scientific reports

OPEN

Check for updates

A quantum-inspired classifier for clonogenic assay evaluations

Giuseppe Sergioli^{1,7^{IXI}}, Carmelo Militello^{2,7}, Leonardo Rundo^{3,4}, Luigi Minafra², Filippo Torrisi⁵, Giorgio Russo², Keng Loon Chow¹ & Roberto Giuntini^{1,6}

Recent advances in Quantum Machine Learning (QML) have provided benefits to several computational processes, drastically reducing the time complexity. Another approach of combining quantum information theory with machine learning—without involving quantum computers—is known as Quantum-inspired Machine Learning (QiML), which exploits the expressive power of the quantum language to increase the accuracy of the process (rather than reducing the time complexity). In this work, we propose a large-scale experiment based on the application of a binary classifier inspired by quantum information theory to the biomedical imaging context in clonogenic assay evaluation to identify the most discriminative feature, allowing us to enhance cell colony segmentation. This innovative approach offers a two-fold result: (1) among the extracted and analyzed image features, homogeneity is shown to be a relevant feature in detecting challenging cell colonies; and (2) the proposed quantum-inspired classifier is a novel and outstanding methodology, compared to conventional machine learning classifiers, for the evaluation of clonogenic assays.

The synergies between machine learning and quantum theory has received a massive increase in the last decades¹⁻⁴. One reason is due to the need for dealing with the current exponential growth of data being captured and stored⁵. Standard procedures frequently exhibit relevant slowdown in performances once these procedures are used in the treatment of big data. The advantages of quantum computation over conventional computation are widely discussed including the drastic reduction in the time complexity of a large set of algorithms. Moreover, recent progress made in the direction of producing real quantum computers suggested the combination between machine learning and quantum computing as a natural connection. However, the discussion involving real quantum computers is not the only way to exploit the properties of quantum theory at the service of machine learning; recent works showed that quantum information can inspire new ways to design machine learning algorithms that are inspired by quantum information. This formalism, known as Quantum-inspired Machine Learning (QiML)⁸, is motivated by the fact that the expressive power of the quantum language makes it possible to gain relevant benefits for computational processes. QiML effectively exploits properties of quantum information theory to increase the accuracy of the process, rather than reducing the time complexity, such as in the case of standard Quantum Machine Learning.

Recently, promising results from QiML have shown to efficiently solve different kinds of classification problems, i.e., the problem of assigning each object of a given dataset to a membership class⁹. In particular, the work⁶ proposed a QiML technique for binary classification inspired by the theory of quantum state discrimination¹⁰, whereby the idea was in that discrimination between quantum states produces a very efficient classification process. The authors compared the QiML algorithm—called the Helstrom Quantum Classifier (HQC)—with other commonly used classifiers, by applying these classifiers to several conventional machine learning repository datasets, and they had obtained results which showed an average supremacy of the HQC compared to the other classifiers. This innovative approach suggested applications of the HQC on real-world datasets. A first attempt of the application of QiML technique to biological datasets have also previously been introduced¹¹.

In this work, we show how the application of quantum information theory to machine learning turns out to be particularly beneficial in the context of biomedical images. In particular, we show a large-scale application of the HQC to support the evaluation in clonogenic assays. A clonogenic assay is a quantification technique of the survival degree of in vitro cell cultures, which is based on the ability of a single cell to grow and form a

¹University of Cagliari, Cagliari, Italy. ²Institute of Molecular Bioimaging and Physiology, Italian National Research Council, Cefalú, Palermo, Italy. ³Department of Radiology, University of Cambridge, Cambridge, UK. ⁴Cancer Research UK Cambridge Centre, University of Cambridge, Cambridge, UK. ⁵Department of Biomedical and Biotechnological Sciences, University of Catania, Catania, Italy. ⁶Centro Linceo Interdisciplinare "Beniamino Segre", Accademia dei Lincei, Rome, Italy. ⁷These authors contributed equally: G. Sergioli and C. Militello. ^{III} email: giuseppe.sergioli@gmail.com colony. To quantify the number and size of cell colonies after irradiation or drug administration (e.g., cytotoxic agents)^{12,13}, a measure to assess the anti-proliferative use of these treatments is required. After some preparatory phases (i.e., plating, incubation, cell treatment¹⁴) the standard procedure includes colony counting with a stereo-microscope^{15,16}. Traditionally, clonogenic assay evaluation is performed by manually counting the colonies composed of at least 50 densely-packed cells. To estimate the effect of the treatment on cell survival, the Plating Efficiency (PE), which is the fraction of colonies obtained from untreated cells, and the Surviving Fraction (SF) of cells after any treatment, are measured¹⁴. From a biological point of view, this quantification-which aims at identifying and quantifying the colonies grown following a specific treatment (e.g., radiation or drug/substance administration)-still represents an open problem. In fact, there are critical issues that are not completely solved yet, such as: (1) the high variability in the scenario related to the specific cell line used, and (2) the subjectivity in human quantification procedures. Depending on the cell line analyzed, the generated colonies can have very different characteristics, such as size, shape and heterogeneity (i.e., some colonies are small with well-defined boundaries and high-contrast compared to the background, whereas others are large and evanescent). A further difficulty of the evaluation process involves colonies which grow considerably and tend to merge together. Along with these high variabilities, human subjectivity can also affect the manual procedure. These issues introduce compelling challenges in manual procedures used in colony detection and quantification. Biologists typically attempt to reduce this lack of reliability, by considering the average of several manual counts.

Considering these challenging scenarios, recent research efforts^{17–19} have proposed an alternative solution to common counting procedures. In particular, rather than quantifying the number of colonies, the area covered by cell colonies is determined. Experimental evidence showed that the area covered by a colony is correlated to the colony number and size. In fact, area-based approaches—which determines the area of the well plates covered by the colonies—represent a useful alternative, allowing us to provide a measure equivalent to the exact count of colonies. To quantify the number of colonies grown after a treatment, a post-processing step, which evaluates the number of colonies contained in the segmented regions, would be integrated into the processing pipeline in area-based approaches. This surrogate measure allows us to overcome some of the problems highlighted above, such as the difficulty of correctly quantifying the colonies which, due to the growth, have merged together.

In this work, an area-based approach is proposed, which is based on imaging characteristics that are not observable by the naked human eye. In particular, we start from the intrinsic assumption that biomedical images often convey information—contained in so-called descriptors (i.e., *contrast, correlation, energy* and *homogene-ity*)—about the phenotype of the underlying physiopathology, which is not always easily identifiable by a simple visual inspection by the human eye. These descriptors can be revealed by quantitative analysis, by converting the images into a high-dimensional dataset, and making it possible to extract further information. In our biological setting, along with the native imaging characteristics—i.e., Red Green Blue (*RGB*) and International Commission on Illumination (CIE) $L^*u^*v^*$ pixel values—these descriptors are used in the classification of colonies vs. background area, where these high-dimensional set of descriptor features makes it possible to enhance the detection of difficult cell lines.

Summarizing, the area-based approach strictly depends on the colonies vs. background binary classification, where the descriptors assume the role of the features. Several algorithms and techniques have already been explored in the classification of colonies vs. background area and, specifically, in the context of clonogenic assays^{17,20-25}. We here introduce a multidisciplinary effort which involves image processing, machine learning, quantum information theory, and cell biology (see Fig. 2a). In particular, we apply the HQC to the binary classification of colonies vs. background area over four different cell lines. Each cell line is given by a dataset where each row in the dataset is a vector that the HQC has to classify as belonging to a colony area or to a background area by using the information provided by the corresponding features. Our experimental study is divided into two stages: (1) we analyze the relevance of different features (descriptors) during the classification process to identify the one that optimizes the accuracy in the colonies vs. background discrimination, and (2) we provide a full comparison between HQC and other conventional classifiers aiming to show that the HQC deserves to be considered as a performant classifier in the real context of clonogenic assay evaluations.

Materials and methods

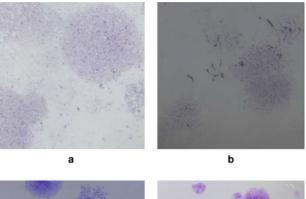
This section first describes the datasets analyzed in our experiments (i.e., the well plates with cell colonies) along with how the features—which are the inputs of the HQC—were extracted and prepared from the Grey Level Co-occurrence Matrix (GLCM) of the well plate images^{26,27}. The section then outlines the setup of the HQC.

Dataset description. The imaging data used for clonogenic assay evaluation were images of 6-well plates (produced by Corning Inc., Corning, NY, USA) regarding four different cell lines: (1) MDA-MD-231 is a human metastatic breast cancer cell line which represents an *in vitro* model of a subgroup of breast cancer, particularly radioresistant and refractory to conventional therapies; (2) U87-MG is a human glioblastoma multiforme cell line; (3) MCF7 is a breast epithelial cell line which is often used in the field of cell biology; and (4) U251 is a human glioblastoma cell line used in brain cancer research and drug development. Figure 1 shows an example of each cell line analyzed in this study.

The images of the well plates were acquired using a common desktop flat-bed scanner, with a resolution of 800 dpi and a 24-bit color-depth. For each well plate image, only a squared area (about 300×300 pixels) composed of about 10^5 pixels was considered to reduce the computational time. Thirty well plates for each cell line were considered, treated with different doses of particles (i.e., protons, photons) and/or cytotoxic agents (e.g., curcumin, SLNB).

Such cell lines considered in this work have different characteristics, with colonies having different size, shape, contrast, and uniformity. In these trials, we considered the most challenging scenarios where MDA-MD-231 and

2



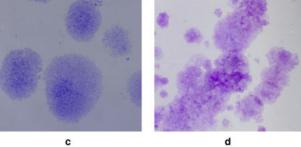


Figure 1. Examples of the wells analyzed in this study. Colony images are displayed for each cell line: (a) MDA-MD-231. (b) U87-MG. (c) U251. (d) MCF7. Images are depicted by a reduced 0.25 factor to the original acquisition size.

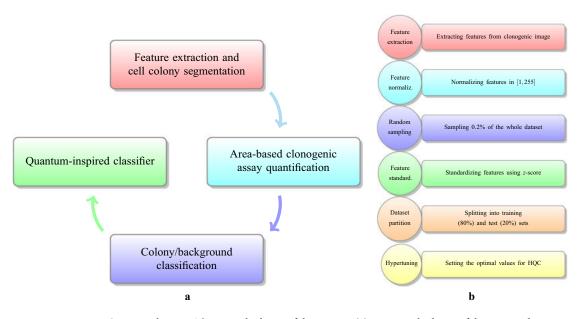


Figure 2. Conceptualization. The general scheme of the process: (**a**) conceptual scheme of the proposed multidisciplinary approach involving image processing, machine learning, quantum information theory and cell biology. (**b**) The pre-processing steps.

U87-MG are cell lines particularly difficult to quantify in clonogenic assays because it produces non-compact colonies, and can sometimes be evanescent because they tend to take up very few crystal-violet, a dye commonly added to the culture plate by biologists to increase the contrast of the colonies.

Dataset preparation. The initial part of the experiment was devoted to the preparation of the datasets. In this experiment, we applied the HQC to the four considered cell lines. For each cell line, we considered 30

images, which were obtained from 30 different well plates. In order to quantify the effectiveness of the classifier and to determine the most discriminative feature, before applying the HQC, each image was segmented to define the ground-truth, which is then used to compare the classification result achieved by the HQC and the competing classifiers. These masks—validated by biologists—were the result of colonies-background segmentation by means of spatial Fuzzy C-Means (sFCM) clustering using the pixelwise entropy feature maps of the well plate. The value 1 (or 0) associated with each pixel within this mask represented the class membership (or not) of the pixel to a colony. Finally, the mask obtained by sFCM clustering underwent a post-processing step which removes small connected-components, to consider only the colonies comprising of at least 50 densely-packed cells¹⁴. The choice of entropy to determine the ground-truth was motivated by a previous work¹⁹, which showed a high correlation between area-based quantification by entropy and manual quantification.

A particular aim of the experiment is to compare different inputs to find out whether, in general, any feature outperforms the others in the classification process. In particular, the six investigated features in our experiment were: the *RGB* and $L^*u^*v^*$ (where L^* represents the lightness, while u^* and v^* denote the chromaticity) color space encodings, as well as the *contrast, correlation, energy* and *homogeneity* descriptors. For this reason, the dataset was split into 6 different datasets (one for each feature) and properly formatted to obtain a file suitable for the HQC. In particular, the obtained segmentation mask (our ground truth) was 'serialized' forming a set where each row, which represents the characteristics of each pixel, is structured as follows: (1) the first two columns represent the two-dimensional coordinates of the pixel, (2) the last column denotes the class label of the pixel (1 if belongs to a colony, and 0 if the pixel belongs to a background), and (3) the middle columns store the values of the features for each pixel. Prior to classification, all the values of the features were normalized in the range [1, 255]. Hence, we performed the experiment over 4 cell lines, each one included 30 different well images that yielded 6 distinct datasets; therefore, the total number of datasets is 720.

Extracted features. For each input image, along with the original encoding in the *RGB* and $L^*u^*v^*$ color spaces, the following feature maps were also extracted from the GLCM, namely: *contrast, correlation, energy,* and *homogeneity*.

More specifically: (1) *contrast* represents a measure of the intensity contrast between a pixel and its neighbor over the whole image, (2) *correlation* denotes a measure of how correlated a pixel is to its neighbor over the whole image, (3) *energy* (i.e., angular second moment) yields the sum of squared elements in the GLCM, and (4) *homogeneity* quantifies the closeness of the distribution of elements in the GLCM to the GLCM diagonal. The feature maps were computed using the MatLab (The Mathworks, Natick, MA, USA) built-in function graycoprops, which relies upon the graycomatrix function.

These GLCM-based local texture descriptors are comprised among the so-called Haralick's features^{26,27}. In particular, the input images were quantitized (i.e., histogram rebinning) by using *L* gray-levels and processed by a sliding squared window of size $\omega \times \omega$ pixels²⁸. The parameters for the feature extraction were: sliding window size $\omega \times \omega = 5$ pixels, number of gray-level bins L = 256. For a detailed description of the mathematical formulation, please refer to Supplementary Material S1.

We compared the various features extracted individually, with the goal of understanding the most discriminative one. In summary, the HQC was tested on the following set of features: (1) *RGB* color space triplet, (2) $L^*u^*v^*$ color space triplet, (3) *contrast*, (4) *correlation*, (5) *energy*, and (6) *homogeneity*. The use of such a procedure, which separately analyzed the 6 image features, rather than a wrapper method for feature selection²⁹ was mostly motivated by computational limitations³⁰. In wrapper methods, the feature selection criterion is based on the performance of a subset of the predictors, by searching for the highest classification performance. Indeed, wrapper methods rely on the classification evaluation for obtaining the optimal feature subset: this search in the feature space is a non-deterministic polynomial-time hard (NP-hard) problem. Exhaustive search methods are computationally intensive and infeasible for large-scale datasets, thus search methods and metaheuristics are typically used to find sub-optimal solutions in the search space³¹. Importantly, overuse of the accuracy estimates in feature subset selection may cause overfitting in the feature subset space due to multiple comparisons and hinders generalization capabilities³². Therefore, in our experiments, we aimed at identifying the most discriminative feature in colony vs. background classification by fairly evaluating several different binary classifiers.

Setup of the HQC. Following standard procedures, pre-processing was applied to the 720 datasets before training the HQC on these datasets. In particular, the pre-processing phase consisted of three steps: (1) random sampling, (2) standardization, and (3) splitting the sampled dataset into development and test sets (80% and 20%, respectively).

The random sampling simply consisted of the random extraction of a subset over each of the initial 720 datasets. Each of the initial dataset has cardinality 301^2 (the number of the pixels) while the sampled dataset has cardinality 181, hence we considered a random sampling pre-processing step that randomly extracted a different 0.2% sample from each of the 720 datasets. In particular, there were 30 datasets for each cell line and each feature, and a different 0.2% random sample was extracted from each of the 30 datasets, to train the HQC. In the standardization step, the six features of the sampled dataset (*RGB, L*u*v*, contrast, correlation, energy* and *homogeneity*) were standardized to have mean equal to 0 and standard deviation equal to 1 by using the individual feature's mean and standard deviation values (i.e., *z*-score standardization).

The HQC was trained on the training set and hypertuning is performed simultaneously using the classifier's four hyperparameters: (1) the rescaling factor, (2) the encoding method, (3) the number of copies taken for the density matrices, and (4) the class weights assigned to the quantum centroids in the HQC.

The first hyperparameter, the rescaling factor, involves the multiplication of the values of each feature with a scalar factor. As already shown³³, even though this procedure is generally not beneficial for conventional

classification approaches, a suitable choice for the rescaling factor can produce relevant advantages for the HQC in terms of the improvement to the classifier's performance. We considered rescaling factors in the set {0.5, 1, 1.5, 2}. The second hyperparameter was the encoding method that was adopted. In order to apply the HQC, we need to encode each row data X (a real vector whose elements are the the respective features) into a density matrix (also called *density pattern*), ρ_X , which is the standard mathematical object representing a quantum state. In our experiment we considered two different encoding methods: the stereographic encoding (SE) and the amplitude encoding (AE). Intuitively, the SE is inspired by geometrical considerations and associates each real vector X to a point of a hypersphere with unitary radius, which has a natural interpretation in the standard quantum scenario. On the other hand, the AE is based on the idea of keeping the information about the amplitude of the vector by considering this as a particular feature³⁴. Both the SE and AE were previously detailed³⁵. The third hyperparameter was given by taking a certain number of *copies* for each row vector **X** of the encoded training set (which has now been encoded into density matrices). Formally, taking a certain number of copies is provided by tensor products of the density patterns ρ_X with itself (i.e., $\rho_X \otimes \rho_X \otimes \ldots \otimes \rho_X$), obtaining a new set of density patterns. The idea for this procedure originates from quantum information theory where-unlike in the classical case—taking copies of a given state ρ provides additional information with respect to the initial state. In particular, considering more copies of the states can increase the probability of providing a correct discrimination between two quantum states⁶. Let us remark how this is relevant because it suggests that the performance of the HQC could be, in principle, improved by increasing the number of the copies for each density pattern obtained from the initial dataset. In the experiment, we considered a number of copies equal to {1, 2, 3, 4} for the image features *RGB* and $L^*u^*v^*$; and $\{1, 2, 3, 4, 5\}$ for the image features *contrast*, *correlation*, *energy* and *homogeneity*. The last hyperparameter was represented by two types of class weights assigned to the two quantum centroids in the HQC. The first type, called equiprobable, assigns equal weights of 1/2 to both of the two quantum centroids; the second type, called weighted, assigns to each centroid a weight which is proportional to the cardinality of the respective classes⁶. The pre-processing and hypertuning steps are outlined in Fig. 2b. The performance metrics considered in the experiment were the balanced accuracy and Area Under the Receiver Operating Characteristic (AUROC) scores. The balanced accuracy score was chosen to ensure the evaluation of the classification task of a pixel as either a colony or a background are both equally relevant. The AUROC score was chosen to enable the evaluation of the overall performance of a classifier. To obtain the combination of hyperparameters which maximizes any of the two performance metrics, we first partitioned the development set into 5 subsets of the same cardinality. According to the most common experimental procedures, during the development phase, we performed a 5-fold cross-validation. The model performance for each combination of hyperparameters is obtained by averaging the validation set's performance over the 5 rounds.

The same procedure was performed to determine the best combination of hyperparameters for the other 18 (generally, high performing and well-established) conventional machine learning classifiers. The 18 classifiers considered were: AdaBoost, Bernoulli Naïve Bayes, Dummy Classifier, Extra Trees, Gaussian Naïve Bayes, Gradient Boosting, Linear Discriminant Analysis, Logistic Regression, Multi Layer Perceptron, Nearest Centroid, Nearest Neighbors, Passive Aggressive Classifier, Perceptron, Quadratic Discriminant Analysis, Random Forest, SVM (with linear kernel), SVM (with polynomial kernel), and SVM (with RBF kernel). For the performance metric AUROC score, three classifiers—Nearest Centroid, Passive Aggressive Classifier and Perceptron—were excluded from this performance metric analysis due to the unavailability of the predicted class probabilities required in the AUROC score calculation.

The HQC was also compared with these 18 other classifiers (for the balance accuracy score) or 15 other classifiers (for the AUROC score) by determining the best image feature (among *RGB*, $L^*u^*v^*$, *contrast*, *correlation*, *energy*, or *homogeneity*) and the best classifier—i.e., the HQC or the other 18 (or 15) classifiers—which yielded the highest performance on the test set, individually for each of the two performance metrics, balance accuracy and AUROC scores respectively.

Experimental results

Experimental tests were carried out exhaustively, in order to quantify the effectiveness of the classifier and to establish the most discriminative feature (in terms of colonies vs. background). As a reference for comparing the HQC classification results against the other standard classifiers, we used the ground-truth masks previously calculated and validated by experimental biologists. These masks were the result of colonies-background segmentation by means of sFCM clustering using entropy as a discriminant¹⁹. The mask obtained by the sFCM clustering, prior to be used as ground-truth, underwent a post-processing step (i.e., morphological operations and small connected-component removal), aiming to cope with the noise in the well background and to consider only the colonies composed of, at least, 50 densely-packed cells¹⁴.

We first present the experimental results for the best performing image feature for each of the four cell lines, which can be found under section Supplementary Material S2. The results for each cell line consists of two parts. The first part shows: (1) heatmaps of the balanced accuracy scores over the 30 datasets for the HQC and the other 18 classifiers, obtained by hypertuning the hyperparameters of each classifier in order to optimize the balanced accuracy score; (2) heatmaps of a classifier outperforming ("wins") over another classifier ("losses") out of the 30 datasets; and (3) a table showing the averaged scores over the 30 datasets for each of the 6 image features and 18 classifiers. The second part for each cell line is analogous to the first, where the role of the balanced accuracy score is replaced by the AUROC score. The whole performance evaluation was executed using the test set. The aim of this experimental procedure was to find the most informative feature that classifies a pixel as either a colony or a background, i.e., the feature that maximizes the value of the balanced accuracy and the AUROC scores, respectively.

Cell line	Best image feature	Best classifier	Balanced accuracy	Jaccard index	Dice coefficient
MDA-MD-231	Homogeneity	Helstrom Quantum Classifier	$\textbf{0.959} \pm \textbf{0.036}$	$\textbf{0.918} \pm \textbf{0.080}$	$\textbf{0.955} \pm \textbf{0.046}$
U87-MG	Homogeneity	Helstrom Quantum Classifier	$\textbf{0.919} \pm \textbf{0.050}$	$\textbf{0.790} \pm \textbf{0.121}$	$\textbf{0.877} \pm \textbf{0.078}$
	L*u*v*	Gaussian Naïve Bayes	0.969 ± 0.034	0.892 ± 0.088	0.941 ± 0.050
MCF7	L*u*v*	Helstrom Quantum Classifier	0.965 ± 0.033	$\textbf{0.882} \pm \textbf{0.084}$	$\textbf{0.935} \pm \textbf{0.048}$
	L*u*v*	Multi Layer Perceptron	0.965 ± 0.042	0.898 ± 0.100	0.943 ± 0.059
U251	Homogeneity	SVM - RBF	0.980 ± 0.033	0.948 ± 0.079	0.971 ± 0.047
0231	Homogeneity	Helstrom Quantum Classifier	$\textbf{0.979} \pm \textbf{0.029}$	$\textbf{0.944} \pm \textbf{0.078}$	$\textbf{0.970} \pm \textbf{0.045}$

Table 1. The mean and standard deviation balance accuracy score (with respect to 30 datasets) for the best performing image feature and classifiers (up to and including HQC and classifiers where the score was tied with HQC), with corresponding mean and standard deviation Jaccard index and Dice coefficient, for cell lines MDA-MD-231, U87-MG, MCF7 and U251. The rows in boldface denote the results achieved by the HQC.

Cell line	Best image feature	Best classifier	AUROC	Jaccard index	Dice coefficient
	Homogeneity	Quadratic discriminant analysis	0.957 ± 0.039	0.914 ± 0.083	0.953 ± 0.048
	Homogeneity	Nearest neighbors	0.956 ± 0.039	0.914 ± 0.083	0.953 ± 0.049
MDA-MD-231	Homogeneity	Linear discriminant analysis	0.955 ± 0.049	0.912 ± 0.102	0.951 ± 0.060
	Homogeneity	Gaussian Naïve Bayes	0.954 ± 0.045	0.906 ± 0.095	0.948 ± 0.056
	Homogeneity	Helstrom quantum classifier	$\textbf{0.954} \pm \textbf{0.050}$	$\textbf{0.910} \pm \textbf{0.093}$	0.950 ± 0.055
U87-MG	Homogeneity	Helstrom quantum classifier	$\textbf{0.917} \pm \textbf{0.048}$	$\textbf{0.794} \pm \textbf{0.099}$	$\textbf{0.882} \pm \textbf{0.062}$
	L*u*v*	Gaussian Naïve Bayes	0.969 ± 0.034	0.892 ± 0.088	0.941 ± 0.050
	$L^{*}u^{*}v^{*}$	Bernoulli Naïve Bayes	0.964 ± 0.030	0.844 ± 0.128	0.910 ± 0.083
MCF7	L*u*v*	Quadratic discriminant analysis	0.961 ± 0.036	0.892 ± 0.088	0.940 ± 0.051
MCF/	L*u*v*	Linear discriminant analysis	0.961 ± 0.047	0.899 ± 0.114	0.943 ± 0.071
	L*u*v*	Helstrom quantum classifier	$\textbf{0.960} \pm \textbf{0.041}$	$\textbf{0.869} \pm \textbf{0.139}$	0.923 ± 0.097
	$L^{*}u^{*}v^{*}$	SVM-linear	0.960 ± 0.052	0.894 ± 0.135	0.938 ± 0.086
	Homogeneity	Helstrom quantum classifier	$\textbf{0.978} \pm \textbf{0.027}$	$\textbf{0.944} \pm \textbf{0.068}$	$\textbf{0.970} \pm \textbf{0.037}$
U251	Homogeneity	Nearest neighbors	0.978 ± 0.028	0.944 ± 0.069	0.970 ± 0.038
	Homogeneity	SVM-linear	0.978 ± 0.035	0.945 ± 0.081	0.970 ± 0.048

Table 2. The mean and standard deviation AUROC score (with respect to 30 datasets) for the best performing image feature and classifiers (up to and including HQC and classifiers whose score are tied with HQC), with corresponding mean and standard deviation Jaccard index and Dice coefficient, for cell lines MDA-MD-231, U87-MG, MCF7 and U251. The rows in boldface denote the results achieved by the HQC.

.....

The experimental results shown in Supplementary Material S2 are summarized in Tables 1 and 2. These tables were obtained by extracting the best performing image feature and, for this image feature, the best classifier up to and including the HQC were presented. The corresponding Jaccard index and Dice coefficient values are also shown for each table.

A premise is needed. We observe the colony vs. background classification task on the datasets considered in this paper generally produces a high performance score. An explanation for this is because most of the pixels belonging to a given colony or background class are concentrated together in a large part in each of the images (see Fig. 1). Hence, the performance of most of the classifiers are generally good. For this reason, the performance for a number of classifiers will generally be quite high and the differences in the performances observed among these classifiers are very subtle. The ease of the classification task on these datasets further gives rise to the sufficient need for extracting only 0.2% samples from each of the 720 datasets used in the training pipeline of the classifiers.

The results in Tables 1, 2 and 3 (which we will discuss in more detail below) clearly show that, on average, the best performing image feature and classifier combination is given by *homogeneity* and the HQC.

For cell line MDA-MD-231, Tables S2.1.1 and S2.1.2 (see Supplementary Material S2.1) show the best image feature for both the balanced accuracy and AUROC scores is *homogeneity*. For this image feature, we can observe that the HQC was the best performing classifier for the balanced accuracy score and it was also one of the best performing classifier for the AUROC score (see Tables 1, 2). In previous work⁶, we discussed the potential of the HQC achieving a higher performance is dependent upon the number of copies taken for the density patterns. In other words, increasing the number of copies increases, on average, the performance of the classifier. Consequently, the computation complexity during training increases (whereby the computational complexity is $O(n^m)$, where *n* and *m* are the number of features and number of copies, respectively). In principle, a multiplecore computational platform or server would allow the HQC to achieve a higher performance which leads to potential future experiments to be explored assessing the real limits of the HQC with more powerful computing

www.nature.com/scientificreports/

(a) Dataset	Hyperpar. used in exp.	Hyperpar. used in exp. and rescale=0.5, encod.=amplitude, #copies=6, class weight =weighted	(b) Dataset	Hyperpar. used in exp.	Hyperpar. used in exp. and rescale=0.5 encod.=amplitude #copies=5, class weight =weighted	(c) Dataset	Hyperpar. used in exp.	Hyperpar. used in exp. and rescale=0.5, encod.=amplitude, #copies=5, class weight =weighted	(d) Dataset	Hyperpar. used in exp.	Hyperpar. used in exp. and rescale=1.0, encod.=amplitude, #copies=6, class weight=weighted
1	0.962	0.962	1	0.913	0.935	1	0.935	0.935	1	1.000	1.000
2	0.979	0.979	2	1.000	1.000	2	1.000	1.000	2	1.000	1.000
3	0.950	0.967	3	1.000	1.000	3	1.000	1.000	3	1.000	1.000
4	1.000	1.000	4	0.938	0.938	4	0.878	0.920	4	1.000	1.000
5	0.900	0.900	5	0.941	0.941	5	0.958	0.958	5	1.000	1.000
6	0.977	0.977	6	0.958	0.958	6	1.000	1.000	6	1.000	1.000
7	0.946	0.946	7	0.982	1.000	7	0.944	1.000	7	0.974	0.974
8	0.911	0.955	8	0.938	0.980	8	0.980	0.980	8	1.000	1.000
9	0.774	0.888	9	0.982	0.982	9	0.982	0.982	9	1.000	1.000
10	0.916	0.916	10	0.918	0.918	10	0.918	0.918	10	1.000	1.000
11	0.920	0.920	11	1.000	1.000	11	1.000	1.000	11	0.975	0.975
12	1.000	1.000	12	1.000	1.000	12	0.979	1.000	12	1.000	1.000
13	0.891	0.950	13	0.958	0.979	13	0.979	0.979	13	1.000	1.000
14	1.000	1.000	14	0.960	0.960	14	0.960	0.960	14	1.000	1.000
15	0.947	0.947	15	0.941	0.979	15	0.979	0.979	15	0.962	0.962
16	0.967	0.967	16	0.984	0.984	16	0.984	0.984	16	0.975	0.975
17	1.000	1.000	17	0.981	0.981	17	1.000	1.000	17	0.896	0.917
18	0.971	0.971	18	0.940	0.940	18	0.940	0.940	18	0.927	0.927
19	1.000	1.000	19	0.985	0.985	19	0.985	0.985	19	0.946	0.946
20	1.000	1.000	20	1.000	1.000	20	1.000	1.000	20	1.000	1.000
21	1.000	1.000	21	0.967	0.967	21	0.895	0.929	21	0.950	0.950
22	0.974	0.974	22	1.000	1.000	22	1.000	1.000	22	0.974	0.974
23	0.955	0.955	23	0.984	0.984	23	0.884	0.884	23	1.000	1.000
24	1.000	1.000	24	1.000	1.000	24	1.000	1.000	24	0.980	0.980
25	1.000	1.000	25	0.875	0.875	25	0.879	0.879	25	1.000	1.000
26	0.955	0.977	26	0.946	0.946	26	0.971	0.971	26	0.983	0.983
27	0.946	0.974	27	0.911	1.000	27	0.911	1.000	27	0.982	0.982
28	0.957	0.978	28	0.982	0.982	28	0.982	0.982	28	0.895	0.895
29	0.976	1.000	29	1.000	1.000	29	0.981	1.000	29	0.980	0.980
30	0.853	0.971	30	0.969	0.969	30	0.900	0.900	30	0.982	0.982
Mean	0.954	0.969	Mean	0.965	0.973	Mean	0.960	0.969	Mean	0.979	0.980

Table 3. Performance of HQC when increasing the number of copies by an addition of one copy for cases where HQC does not outperform the other classifiers. (a) For cell line MDA-MD-231, comparison of AUROC score for HQC when increasing the number of copies to 6 for 30 homogeneity image feature datasets. (b) For cell line MCF7, comparison of balance accuracy score for HQC when increasing the number of copies to 5 for 30 $L^*u^*v^*$ image feature datasets. (c) For cell line MCF7, comparison of AUROC score for HQC when increasing the number of copies to 5 for 30 $L^*u^*v^*$ image feature datasets. (d) For cell line U251, comparison of balance accuracy score for HQC when increasing the number of copies to 6 for 30 homogeneity image feature datasets.

infrastructures. Inspired by this motivation, we repeated the experiment by increasing the number of copies by an additional copy for cases where the HQC is not, initially, the best performing classifier. As an example, in Table 3a we show how by adding one more copy, the AUROC score (averaged across 30 *homogeneity* feature datasets) increases from 0.954 to 0.969, making the HQC the best performing classifier for cell line MDA-MD-231.

For cell line U87-MG, Tables S2.2.1 and S2.2.2 (see Supplementary Material S2.2) and Tables 1 and 2 show a subtle but clear supremacy of the image feature and classifier combination of *homogeneity* and the HQC, for both balanced accuracy and AUROC scores. However, it is worth noting that the balanced accuracy and AUROC scores obtained for cell line U87-MG for all classifiers (including HQC) were lower compared to the other three cell lines, indicating the classification task of discriminating a pixel being a colony or a background class to be slightly more difficult for the cell line U87-MG in comparison to the other three cell lines.

Unlike U87-MG, the balanced accuracy and AUROC scores obtained for cell line MCF7 were high, thus indicating this cell line was particularly simple to classify and naturally resulting in the comparison among the best performing classifiers more unstable. For this cell line, Tables S2.3.1 and S2.3.2 (see Supplementary Material S2.3) show the best image feature is $L^*u^*v^*$, and for this image feature, the best classifier was *Gaussian Naïve Bayes* for both the balanced accuracy and AUROC scores (see Tables 1, 2). Even though the balanced accuracy and AUROC scores obtained with the HQC were not considerably different from that of the *Gaussian Naïve Bayes*, we repeated the experiment by considering the HQC with one additional copy (using the similar procedure as

described for cell line MDA-MD-231 above). In Tables 3b and 3c, we show the scores (averaged across 30 $L^*u^*v^*$ feature datasets) of the HQC obtained with the additional copy outperformed (for the balance accuracy score) and equalizes (for the AUROC score) the performance of the *Gaussian Naïve Bayes*.

Finally, for cell line U251, Tables S2.4.1 and S2.4.2 (see Supplementary Material S2.4) show the best image feature for both the balanced accuracy and AUROC scores is *homogeneity*. For this image feature, we can observe the HQC is close to (for the balance accuracy score) or is one of the best (for the AUROC score) performing classifier (see Tables 1, 2). We also note the balanced accuracy and AUROC scores obtained are high, indicating this cell line was also particularly simple to classify and naturally resulting in the comparison among the best performing classifiers more unstable. Again, we repeated the experiment for the balanced accuracy score by considering taking one more additional copy for the HQC and this gave us a further small increase of the performance of the HQC to equalize the performance of the SVM (with linear kernel) (see Table 3d).

Along the whole experiment, the calculation of the Jaccard index and the Dice coefficient confirms a good similarity of the sample sets. Moreover, in order to show how, for these clonogenic assay datasets, the 0.2% random sample extraction of the datasets is sufficiently representative, a sub-experiment was performed where the trained HQC model was tested on a new unseen test set extracted from the remaining 99.8% of the datasets. This experiment was done by randomly selecting 10 datasets (out of the 30 datasets) from the best performing image feature for each of the four cell lines. The results are shown in Tables S3.1-S3.4 (see Supplementary Material S3) where we have presented a comparison of the performance on this new unseen test set against the performance on the test set from the 0.2% random sample used in the main experiment. We could see, on average over the 10 datasets, the performance on both of these test sets is generally not considerably different, suggesting that a small training set is sufficient for the HQC to perform well on classification tasks on these type of clonogenic assay datasets. In conclusion, our results showed how the HQC is particularly efficient for the colony vs. background classification in the context of clonogenic assays. Moreover, this work gave rise to the discovery of the homogeneity image feature as the most informative and discriminant feature for this classification. From a biological perspective, this result represented a relevant confirmation regarding the evidence that homogeneity—at the phenotypic level in a radiobiology experiment-might be a very important feature to count the number of colonies in a reliable and reproducible manner and to, finally, determine the surviving fraction of the dose response curves.

Discussion and further developments

The approach proposed in this work was based on fundamental synergies between machine learning, quantum information theory and biological analysis. Overall, the achieved results are accurate and reliable. In fact, from a computational point of view, the used approach, both in terms of features and quantum-like classifier types, allowed us to obtain effective segmentation performance, with results (in particular, considering the balanced accuracy) being very similar to the reference ground-truth. The HQC being proposed, which has already shown⁶ excellent performance even when compared to other quantum-like classifiers, performed well when applied to the problem at hand. Furthermore, the extracted descriptors made it possible to further improve the classifier capabilities, compared to the *RGB* and $L^*u^*v^*$ color space encodings.

From a biological point of view, the results obtained would provide support in the quantification of the well area covered by cell colonies in clonogenic survival assays. Indeed, the main problems still unsolved in a radiobiology experiment for studying the effect of a cell treatment—such as irradiation or drug administration—and quantifying the surviving cells are the high variability related to the specific cell line used, as well as the subjectivity, due to operator-dependence, in evaluation methods. Therefore, it is extremely important to use an approach that allows us to quantify the cell survival in a reliable and reproducible manner to determine the dose response curves, which represent the primary study models in radiobiology.

In the future, we plan to extend the application of the proposed classification approach, which currently provides a clonogenic assay evaluation based only on the colony area alone. We aim to integrate the developed classifier into a processing pipeline together with an *ad hoc* post-processing step allowing us to accurately quantify the number of colonies grown, as required in traditional clonogenic assay evaluations.

From the classifier's perspective, future challenges are the following: (1) develop a *pure quantum* version of the HQC (i.e., the quantum algorithm for the HQC running on quantum computers) which will enable both the advantages of a reduction in time complexity and an improvement in the accuracy at the same time, (2) investigate an optimal strategy exploiting parallel computing to allow us the use of the HQC with higher number of copies (producing a further improvement in the performance), and (3) find a multi-class generalization of the HQC (i.e., to extend the classification capability of the HQC to more than two classes). This would allow us to expand considerably the potential applications to other real-world contexts, including—but not limited to—the field of biomedical imaging.

Data availability

The software for the HQC was developed in Python and the experiment was conducted on a server with 128 GB RAM memory and 16 CPU cores. The software package is available in the public repository https://github.com/leockl/helstrom-quantum-centroid-classifier.

Received: 27 August 2020; Accepted: 15 January 2021 Published online: 02 February 2021

References

1. Biamonte, J. et al. Quantum machine learning. Nature 549, 195-202. https://doi.org/10.1038/nature23474 (2017).

2. Schuld, M. Machine learning in quantum spaces. Nature 567, 179-181. https://doi.org/10.1038/d41586-019-00771-0 (2019).

- Schuld, M. & Petruccione, F. Supervised Learning with Quantum Computers. Quantum Science and Technology 1st edn. (Springer Nature, Switzerland, 2018).
- Schuld, M., Sinayskiy, I. & Petruccione, F. An introduction to quantum machine learning. Contemp. Phys. 56, 172–185. https:// doi.org/10.1080/00107514.2014.964942 (2014).
- Wittek, P. Quantum Machine Learning: What Quantum Computing Means to Data Mining 1st edn. (Academic Press, Cambridge, 2014).
- Sergioli, G., Giuntini, R. & Freytes, H. A new quantum approach to binary classification. PLoS Onehttps://doi.org/10.1371/journ al.pone.0216224 (2019).
- Sergioli, G. Quantum and quantum-like machine learning. A note on similarities and differences. Soft Comput. https://doi. org/10.1007/s00500-019-04429 (2019).
- Manju, A. & Nigam, M. J. Applications of quantum inspired computational intelligence: A survey. Artif. Intell. Rev. 42, 79–156. https://doi.org/10.1007/s10462-012-9330-6 (2014).
- 9. Duda, R. O., Hart, P. E. & Stork, D. G. Pattern Classification 2nd edn. (Wiley, Hoboken, 2000).
- Helstrom, C. W. Quantum Detection and Estimation Theory. Mathematics in Science and Engineering 1st edn. (Academic Press, New York, 1976).
- Sergioli, G. *et al.* Quantum-inspired minimum distance classification in a biomedical context. *Int. J. Quantum Inform.* 16, 1840011. https://doi.org/10.1142/S0219749918400117 (2018).
- Baskar, R., Dai, J., Wenlong, N., Yeo, R. & Yeoh, K.-W. Biological response of cancer cells to radiation treatment. Front. Mol. Biosci. 1, 1–9. https://doi.org/10.3389/fmolb.2014.00024 (2014).
- Minafra, L. et al. Radiosensitizing effect of curcumin-loaded lipid nanoparticles in breast cancer cells. Sci. Rep. 9, 1–16. https:// doi.org/10.1038/s41598-019-47553-2 (2019).
- Franken, N. A. P., Rodermond, H. M., Stap, J., Haveman, J. & Van Bree, C. Clonogenic assay of cells in vitro. Nat. Prot. 1, 2315. https://doi.org/10.1038/nprot.2006.339 (2006).
- Puck, T. T. & Marcus, P. I. Action of X-rays on mammalian cells. J. Exp. Med. 103, 653–666. https://doi.org/10.1084/jem.103.5.653 (1956).
- Freshney, R. I. Culture of Animal Cells: A Manual of Basic Technique and Specialized Applications 7th edn. (Wiley-Blackwell, New York, 2016).
- Guzmán, C., Bagga, M., Kaur, A., Westermarck, J. & Abankwa, D. ColonyArea: An ImageJ plugin to automatically quantify colony formation in clonogenic assays. *PLoS One* 9, e92444. https://doi.org/10.1371/journal.pone.0092444 (2014).
- Militello, C. *et al.* Area-based cell colony surviving fraction evaluation: A novel fully automatic approach using general-purpose acquisition hardware. *Comput. Biol. Med.* 89, 454–465. https://doi.org/10.1016/j.compbiomed.2017.08.005 (2017).
- Militello, C. *et al.* MF2C3: Multi-feature fuzzy clustering to enhance cell colony detection in automated clonogenic assay evaluation. *Symmetry* 12, 773. https://doi.org/10.3390/sym12050773 (2020).
 Barber, P. R. *et al.* Automated counting of mammalian cell colonies. *Phys. Med. Biol.* 46, 63–76. https://doi.org/10.1088/0031-
- Partici, J. Ret al. Model-based automated detection of mammalian cell colonies. *Phys. Med. Biol.* 46, 3061–3072. https://doi.org/10.1006/0001
 Bernard, R. *et al.* Model-based automated detection of mammalian cell colonies. *Phys. Med. Biol.* 46, 3061–3072. https://doi.
- org/10.1142/S02197499184001170 (2001). 22. Chiang, P.-J., Tseng, M.-J., He, Z.-S. & Li, C.-H. Automated counting of bacterial colonies by image analysis. J. Microbiol. Methods
- 108, 74–82. https://doi.org/10.1142/S02197499184001171 (2015).
 Dahle, J., Kakar, M., Steen, H. B. & Kaalhus, O. Automated counting of mammalian cell colonies by means of a flat bed scanner
- and image processing. Cytom. Part A 60, 182–188. https://doi.org/10.1142/S02197499184001172 (2004). 24. Geissmann, Q. OpenCFU, a new free and open-source software to count cell colonies and other circular objects. PLoS One 8,
- e54072. https://doi.org/10.1142/S02197499184001173 (2013).
- 25. Roldán Fajardo, N. et al. A New Automatic Cancer Colony Forming Units Counting Method (Springer, Basel, 2019).
- Haralick, R. M. et al. Textural features for image classification. *IEEE Trans. Syst. Man Cybern* SMC-3, 610–621. https://doi.org/10.1142/S02197499184001174 (1973).
- Haralick, R. M. Statistical and structural approaches to texture. Proc. IEEE 67, 786–804. https://doi.org/10.1142/S02197499184001 175 (1979).
- Rundo, L. *et al.* HaraliCU: GPU-powered Haralick feature extraction on medical images exploiting the full dynamics of grayscale levels. In *Parallel Computing Technologies (PaCT), vol. 11657 of LNCS* (ed. Malyshkin, V.) 304-318, (Springer, Cham, 2019) (978-3-030-25636-4_24).
- Chandrashekar, G. & Sahin, F. A survey on feature selection methods. Comput. Electr. Eng. 40, 16–28. https://doi.org/10.1016/j. compeleceng.2013.11.024 (2014).
- Sun, P., Wang, D., Mok, V. C. & Shi, L. Comparison of feature selection methods and machine learning classifiers for radiomics analysis in glioma grading. *IEEE Access* 7, 102010–102020. https://doi.org/10.1109/ACCESS.2019.2928975 (2019).
- Wang, L. et al. Feature selection based on meta-heuristics for biomedicine. Optim. Methods Softw. 29, 703–719. https://doi. org/10.1080/10556788.2013.834900 (2014).
- Kohavi, R. & John, G. H. Wrappers for feature subset selection. Artif. Intell. 97, 273–324. https://doi.org/10.1016/S0004 -3702(97)00043-X (1997).
- Sergioli, G., Bosyk, G. M., Santucci, E. & Giuntini, R. A quantum-inspired version of the classification problem. *Int. J. Theor. Phys.* 56, 3880–3888. https://doi.org/10.1007/s10773-017-3371-1 (2017).
- Lloyd, S., Mohseni, M. & Rebentrost, P. Quantum principal component analysis. Nat. Phys. 10, 631–633. https://doi.org/10.1038/ nphys3029 (2014).
- Santucci, E. & Sergioli, G. Classification problem in a quantum framework. In *Quantum Foundations, Probability and Information* 215–228 (Springer, Cham, 2018). https://doi.org/10.1007/978-3-319-74971-6_16.

Acknowledgements

G.S. is grateful to Fondazione di Sardegna [project code: F71I17000330002]. R.G. is grateful to RAS (Regione autonoma della Sardegna) [project code: RASSR40341] and to Fondazione di Sardegna, project: "Resource sensitive reasoning and logic" [project code: CUP: F72F20000410007]. K.L.C. is grateful to the project PRIN 2017: "Theory and applications of resource sensitive logics" [projects code: CUP:20173WKCM5 and 20173YP4N3]. This work was also supported by the GeSeTON project Grant (funded by Italian MISE grant n. 489 of 21/02/2018) and by the PBCT PRIN (Progetti di Ricerca di Rilevante Interesse Nazionale PRIN 2017 Prot. 2017XKWWK9).

Author contributions

G.S. and C.M. (as shared first authors) conceived the experiment, analyzed the results and coordinated the research. L.R. conceived the experiment and analyzed the results. L.M. and F.T. extracted the datasets. G.R. conceived the experiment. K.L.C. conducted and analyzed the experiment. R.G. conceived and conducted the

9

experiment. All authors reviewed the manuscript. The corresponding author is responsible for submitting a competing interests statement on behalf of all authors of the paper.

Additional information

Supplementary Information The online version contains supplementary material available at https://doi. org/10.1038/s41598-021-82085-8.

Correspondence and requests for materials should be addressed to G.S.

Reprints and permissions information is available at www.nature.com/reprints.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

© The Author(s) 2021

A quantum-inspired classifier for clonogenic assay evaluations - Supplementary material

Giuseppe Sergioli^{1,*}, Carmelo Militello², Leonardo Rundo^{3,4}, Luigi Minafra², Filippo Torrisi⁵, Giorgio Russo², Keng Loon Chow¹, and Roberto Giuntini^{1,6}

¹University of Cagliari, Cagliari, Italy.

²Institute of Molecular Bioimaging and Physiology, Italian National Research Council, Cefalú, Palermo, Italy. ³Department of Radiology, University of Cambridge, Cambridge, United Kingdom.

⁴Cancer Research UK Cambridge Centre, University of Cambridge, Cambridge, United Kingdom.

⁵Department of Biomedical and Biotechnological Sciences, University of Catania, Catania, Italy.

⁶Centro Linceo Interdisciplinare "Beniamino Segre", Accademia dei Lincei, Rome, Italy.

*Corresponding author: giuseppe.sergioli@gmail.com

ABSTRACT

This file contains all the supplementary material regarding the experimental trials described and carried out in the manuscript "A quantum-inspired classifier for clonogenic assay evaluations". In the first section, detailed descriptions of the extracted texture features are provided. In the second section, we show the experimental results obtained for each of the four cell lines MDA-MD-231, U87-MG, MCF7, and U251, by considering the best performing image feature. The third section is devoted to show the performance of the Helstrom Quantum Classifier (HQC) on a new unseen test set. Finally, in the last section we summarize the full results of the whole experiment, for all the investigated cell lines and image features.

S1. The extracted Haralick's features

We start from the assumption that biomedical images contain information phenotype of the underlying physiopathology, which is not always easily identifiable by simple 'visual' inspection. These information can be revealed through quantitative analysis, by extracting the so called 'descriptors' in order to make it possible to acquire further knowledge on the dominion. The Gray-Level Co-occurrence Matrix (GLCM) computation is the first step to obtain the features.

Formally, let a GLCM with size $L \times L$, where L represents the maximum number of gray-levels according to a given quantization scheme, denote the second-order joint probability function p(i, j) of an image region (where $i, j \in [0, 1, ..., L-1]$) represent a gray-level pair) after the normalization by the total number of pixels. These descriptors are generally called Haralick's features^{1,2}.

Given a squared window of size $\omega \times \omega$ pixels sliding over the whole image³, we computed the following GLCM-based features (with $i, j \in [0, 1, ..., L-1]$):

• contrast $\in [0, (L-1) \times (L-1))$ yields a measure of the intensity contrast between neighboring pixels:

$$contrast(i,j) = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} |i-j|^2 \cdot p(i,j),$$
(1)

contrast = 0 for a constant image;

• correlation $\in [-1,1]$ indicates the degree of correlation between a pixel and its neighbor:

$$\operatorname{correlation}(i,j) = \frac{\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} (i - \mu_x) (j - \mu_y) \cdot p(i,j)}{\sigma_x \sigma_y},$$
(2)

where: $\mu_x = \sum_i \sum_j i \cdot p(i, j), \ \mu_y = \sum_i \sum_j j \cdot p(i, j), \ \sigma_x = \sum_i \sum_j (i - \mu_x) \cdot p(i, j), \ \text{and} \ \sigma_y = \sum_i \sum_j (j - \mu_y) \cdot p(i, j) \ (\text{with } \sum_i \text{ and } \sum_j (j - \mu_y) \cdot p(i, j) \ (\text{with } \sum_j p_i) = \sum_i \sum_j (j - \mu_y) \cdot p(i, j) \ (\text{with } \sum_j p_i) = \sum_i \sum_j (j - \mu_y) \cdot p(i, j) \ (\text{with } \sum_j p_i) = \sum_j \sum_j (j - \mu_y) \cdot p(i, j) \ (\text{with } \sum_j p_i) = \sum_j \sum_j (j - \mu_y) \cdot p(i, j) \ (\text{with } \sum_j p_i) = \sum_j \sum_j p_i \sum_j$ $\sum_{i=0}^{L-1}$ and $\sum_{i=0}^{L-1}$, respectively). This feature is 1 or -1 for a perfectly positively or negatively correlated image, respectively;

• energy $\in [0,1]$ calculates the sum of squared elements in the GLCM:

$$energy(i,j) = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} p(i,j)^2,$$
(3)

energy = 1 for a constant image;

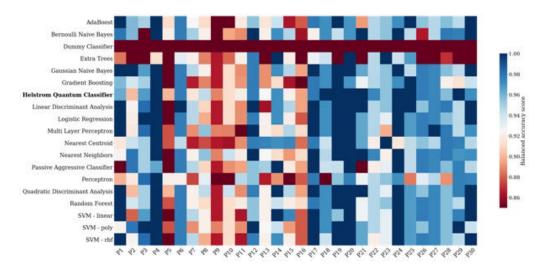
• homogeneity $\in [0,1]$ Returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal:

homogeneity
$$(i, j) = \frac{\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} p(i, j)}{(1+|i-j|)},$$
(4)

homogeneity = 1 for a diagonal GLCM.

S2. Experimental results

This section is divided into four groups, one for each cell line MDA-MD-231, U87-MG, MCF7 and U251, respectively. Each group contains two reports, the first shows: (1) the balanced accuracy score over 30 datasets (for the best performing image feature) for the HQC and the 18 competing classifiers, obtained by hypertuning the hyperparameters of each classifier in order to optimize the balanced accuracy score; (2) heatmaps of a classifier outperforming ("wins") over another classifier ("losses") out of the 30 datasets (for the best performing image feature); and (3) a table showing the averaged balanced accuracy score over the 30 datasets for each of the six image features, RGB, $L^*u^*v^*$, contrast, correlation, energy and homogeneity. The second report is the analogous of the first, where the role of the balanced accuracy is replaced by the AUROC score. All performance evaluation is performed using the test set. The aim of the experimental procedure is to find the most informative image feature in discriminating a pixel between a colony or a background, i.e., the image feature which maximizes the value of the balanced accuracy and the AUROC scores, respectively.



S2.1. Cell line MDA-MD-231

Fig. 2.1.1 | Balance accuracy score of 19 classifiers across 30 homogeneity image feature datasets for cell line MDA-MD-231.

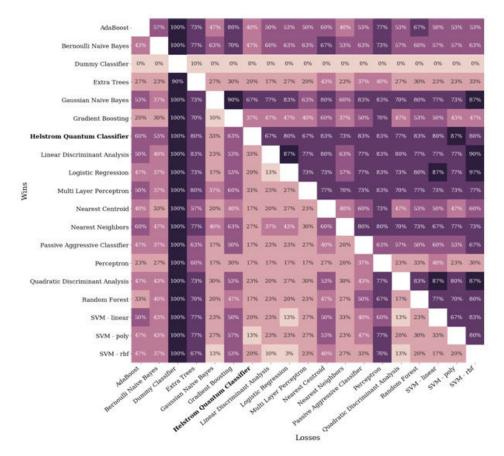


Fig. 2.1.2 | Percentage of datasets where model A ("Wins") outperformed model B ("Losses") out of 30 homogeneity image feature datasets for cell line MDA-MD-231 (balanced accuracy score).

	Image features						
Classifiers	RGB	L*u*v*	Contrast	Correlation	Energy	Homogeneity	
AdaBoost	0.861 ± 0.088	0.878 ± 0.065	0.898 ± 0.065	0.738 ± 0.110	0.936 ± 0.052	0.942 ± 0.046	
Bernoulli Naive Bayes	0.841 ± 0.060	0.855 ± 0.079	0.840 ± 0.097	0.630 ± 0.126	0.854 ± 0.087	0.940 ± 0.057	
Dummy Classifier	0.507 ± 0.047	0.513 ± 0.056	0.506 ± 0.069	0.518 ± 0.042	0.497 ± 0.069	0.485 ± 0.060	
Extra Trees	0.822 ± 0.120	0.839 ± 0.141	0.709 ± 0.163	0.616 ± 0.121	0.767 ± 0.169	0.851 ± 0.139	
Gaussian Naive Bayes	0.855 ± 0.063	0.874 ± 0.084	0.886 ± 0.063	0.711 ± 0.102	0.923 ± 0.067	0.954 ± 0.045	
Gradient Boosting	0.876 ± 0.076	0.874 ± 0.069	0.899 ± 0.063	0.835 ± 0.113	0.941 ± 0.047	0.933 ± 0.050	
Helstrom Quantum Classifier	0.895 ± 0.058	0.883 ± 0.069	0.902 ± 0.070	0.775 ± 0.081	0.938 ± 0.047	0.959 ± 0.036	
Linear Discriminant Analysis	0.850 ± 0.066	0.865 ± 0.080	0.837 ± 0.075	0.660 ± 0.122	0.860 ± 0.089	0.955 ± 0.049	
Logistic Regression	0.882 ± 0.061	0.879 ± 0.086	0.883 ± 0.066	0.657 ± 0.131	0.932 ± 0.056	0.951 ± 0.045	
Multi Layer Perceptron	0.890 ± 0.055	0.885 ± 0.069	0.901 ± 0.069	0.833 ± 0.086	0.942 ± 0.052	0.940 ± 0.091	
Nearest Centroid	0.839 ± 0.058	0.868 ± 0.078	0.846 ± 0.070	0.686 ± 0.114	0.867 ± 0.063	0.941 ± 0.044	
Nearest Neighbors	0.890 ± 0.069	0.875 ± 0.064	0.903 ± 0.073	0.808 ± 0.070	0.942 ± 0.049	0.953 ± 0.040	
Passive Aggressive Classifier	0.831 ± 0.105	0.809 ± 0.113	0.828 ± 0.118	0.607 ± 0.137	0.907 ± 0.062	0.935 ± 0.052	
Perceptron	0.790 ± 0.117	0.832 ± 0.106	0.831 ± 0.112	0.631 ± 0.103	0.914 ± 0.054	0.916 ± 0.060	
Quadratic Discriminant Analysis	0.872 ± 0.065	0.876 ± 0.074	0.876 ± 0.076	0.731 ± 0.112	0.925 ± 0.066	0.957 ± 0.039	
Random Forest	0.874 ± 0.078	0.883 ± 0.074	0.919 ± 0.058	0.827 ± 0.119	0.944 ± 0.043	0.951 ± 0.036	
SVM - linear	0.880 ± 0.063	0.873 ± 0.078	0.880 ± 0.071	0.655 ± 0.141	0.929 ± 0.052	0.949 ± 0.046	
SVM - poly	0.883 ± 0.055	0.892 ± 0.069	0.899 ± 0.065	0.811 ± 0.084	0.926 ± 0.050	0.950 ± 0.042	
SVM - rbf	0.876 ± 0.062	0.874 ± 0.084	0.890 ± 0.069	0.662 ± 0.134	0.931 ± 0.052	0.948 ± 0.046	

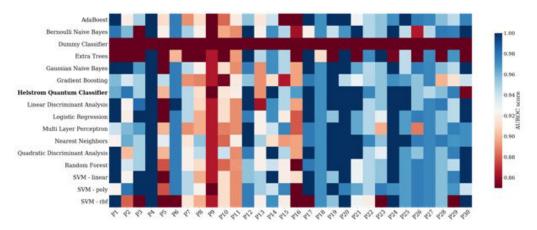


Fig. 2.1.3 | AUROC score of 19 classifiers across 30 homogeneity image feature datasets for cell line MDA-MD-231.

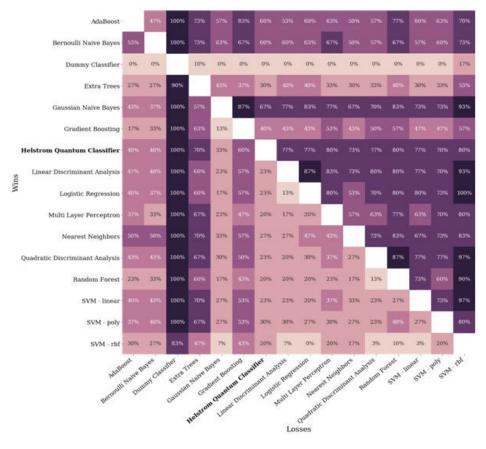


Fig. 2.1.4 | Percentage of datasets where model A ("Wins") outperformed model B ("Losses") out of 30 homogeneity image feature datasets for cell line MDA-MD-231 (AUROC score).

	Image features					
Classifiers	RGB	L*u*v*	Contrast	Correlation	Energy	Homogeneity
AdaBoost	0.874 ± 0.076	0.881 ± 0.067	0.898 ± 0.063	0.739 ± 0.130	0.932 ± 0.051	0.943 ± 0.048
Bernoulli Naive Bayes	0.841 ± 0.060	0.855 ± 0.079	0.840 ± 0.097	0.630 ± 0.126	0.854 ± 0.087	0.940 ± 0.057
Dummy Classifier	0.505 ± 0.027	0.498 ± 0.072	0.484 ± 0.046	0.497 ± 0.070	0.503 ± 0.077	0.497 ± 0.049
Extra Trees	0.813 ± 0.132	0.812 ± 0.159	0.678 ± 0.162	0.615 ± 0.127	0.740 ± 0.178	0.837 ± 0.159
Gaussian Naive Bayes	0.855 ± 0.063	0.874 ± 0.084	0.886 ± 0.063	0.711 ± 0.102	0.923 ± 0.067	0.954 ± 0.045
Gradient Boosting	0.880 ± 0.074	0.868 ± 0.076	0.902 ± 0.066	0.834 ± 0.114	0.930 ± 0.056	0.935 ± 0.039
Helstrom Quantum Classifier	0.879 ± 0.081	0.884 ± 0.066	0.905 ± 0.062	0.787 ± 0.082	0.927 ± 0.058	0.954 ± 0.050
Linear Discriminant Analysis	0.850 ± 0.066	0.865 ± 0.080	0.837 ± 0.075	0.660 ± 0.122	0.860 ± 0.089	0.955 ± 0.049
Logistic Regression	0.872 ± 0.072	0.874 ± 0.088	0.886 ± 0.068	0.660 ± 0.138	0.927 ± 0.051	0.950 ± 0.044
Multi Layer Perceptron	0.889 ± 0.056	0.889 ± 0.057	0.894 ± 0.065	0.804 ± 0.104	0.932 ± 0.041	0.946 ± 0.042
Nearest Neighbors	0.883 ± 0.070	0.877 ± 0.066	0.902 ± 0.064	0.800 ± 0.075	0.937 ± 0.049	0.956 ± 0.039
Quadratic Discriminant Analysis	0.872 ± 0.065	0.876 ± 0.074	0.876 ± 0.076	0.731 ± 0.112	0.925 ± 0.066	0.957 ± 0.039
Random Forest	0.881 ± 0.068	0.878 ± 0.077	0.912 ± 0.062	0.817 ± 0.117	0.943 ± 0.040	0.946 ± 0.043
SVM - linear	0.879 ± 0.064	0.876 ± 0.076	0.881 ± 0.073	0.648 ± 0.135	0.914 ± 0.049	0.953 ± 0.043
SVM - poly	0.880 ± 0.058	0.864 ± 0.082	0.897 ± 0.064	0.805 ± 0.087	0.920 ± 0.052	0.950 ± 0.047
SVM - rbf	0.845 ± 0.115	0.860 ± 0.104	0.831 ± 0.147	0.652 ± 0.132	0.879 ± 0.138	0.843 ± 0.193

Table 2.1.2 | The mean and standard deviation AUROC score (with respect to 30 datasets) for cell line MDA-MD-231

Results exclude Nearest Centroid, Passive Aggressive Classifier and Perceptron.

S2.2. Cell line U87-MG

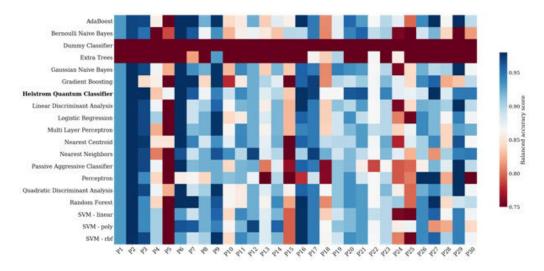


Fig. 2.2.1 | Balance accuracy score of 19 classifiers across 30 homogeneity image feature datasets for cell line U87-MG.

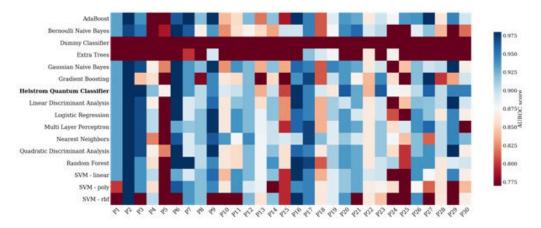


Fig. 2.2.3 | AUROC score of 19 classifiers across 30 homogeneity image feature datasets for cell line U87-MG.

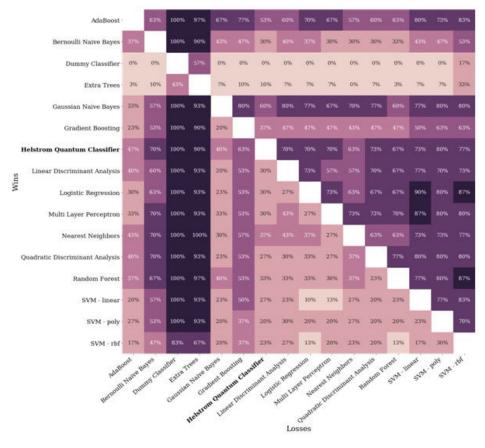


Fig. 2.2.4 | Percentage of datasets where model A ("Wins") outperformed model B ("Losses") out of 30 homogeneity image feature datasets for cell line U87-MG (AUROC score).

	Image features					
Classifiers	RGB	L*u*v*	Contrast	Correlation	Energy	Homogeneity
AdaBoost	0.776 ± 0.117	0.779 ± 0.110	0.864 ± 0.060	0.704 ± 0.105	0.873 ± 0.082	0.898 ± 0.077
Bernoulli Naive Bayes	0.765 ± 0.095	0.788 ± 0.084	0.841 ± 0.070	0.629 ± 0.088	0.771 ± 0.126	0.869 ± 0.082
Dummy Classifier	0.504 ± 0.050	0.504 ± 0.056	0.512 ± 0.055	0.480 ± 0.076	0.505 ± 0.055	0.516 ± 0.058
Extra Trees	0.577 ± 0.098	0.583 ± 0.120	0.529 ± 0.078	0.515 ± 0.043	0.525 ± 0.068	0.613 ± 0.156
Gaussian Naive Bayes	0.734 ± 0.089	0.752 ± 0.096	0.780 ± 0.086	0.674 ± 0.074	0.890 ± 0.065	0.905 ± 0.059
Gradient Boosting	0.815 ± 0.091	0.827 ± 0.085	0.877 ± 0.064	0.758 ± 0.095	0.879 ± 0.075	0.871 ± 0.085
Helstrom Quantum Classifier	0.791 ± 0.099	0.792 ± 0.090	0.838 ± 0.066	0.768 ± 0.075	0.902 ± 0.057	0.917 ± 0.048
Linear Discriminant Analysis	0.752 ± 0.095	0.736 ± 0.085	0.740 ± 0.076	0.639 ± 0.086	0.842 ± 0.107	0.900 ± 0.065
Logistic Regression	0.770 ± 0.100	0.764 ± 0.102	0.805 ± 0.085	0.636 ± 0.086	0.877 ± 0.071	0.897 ± 0.070
Multi Layer Perceptron	0.792 ± 0.109	0.784 ± 0.115	0.840 ± 0.067	0.768 ± 0.079	0.877 ± 0.099	0.901 ± 0.070
Nearest Neighbors	0.793 ± 0.105	0.793 ± 0.090	0.847 ± 0.044	0.739 ± 0.086	0.884 ± 0.076	0.902 ± 0.054
Quadratic Discriminant Analysis	0.773 ± 0.100	0.750 ± 0.102	0.782 ± 0.100	0.667 ± 0.074	0.879 ± 0.081	0.908 ± 0.050
Random Forest	0.808 ± 0.106	0.803 ± 0.100	0.861 ± 0.059	0.763 ± 0.083	0.900 ± 0.070	0.902 ± 0.068
SVM - linear	0.764 ± 0.100	0.751 ± 0.113	0.798 ± 0.088	0.591 ± 0.103	0.891 ± 0.065	0.888 ± 0.076
SVM - poly	0.745 ± 0.119	0.746 ± 0.111	0.780 ± 0.084	0.720 ± 0.091	0.865 ± 0.095	0.864 ± 0.090
SVM - rbf	0.756 ± 0.123	0.741 ± 0.114	0.682 ± 0.157	0.575 ± 0.096	0.859 ± 0.130	0.770 ± 0.179

Table 2.2.2 | The mean and standard deviation AUROC score (with respect to 30 datasets) for cell line U87-MG

Results exclude Nearest Centroid, Passive Aggressive Classifier and Perceptron.

S2.3. Cell line MCF7

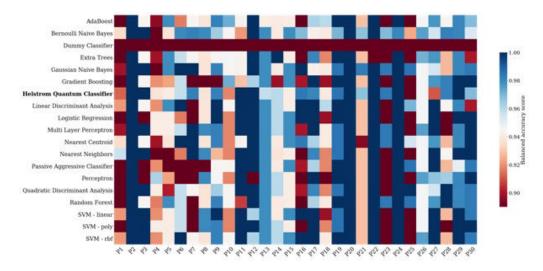


Fig. 2.3.1 | Balance accuracy score of 19 classifiers across 30 L*u*v* image feature datasets for cell line MCF7.

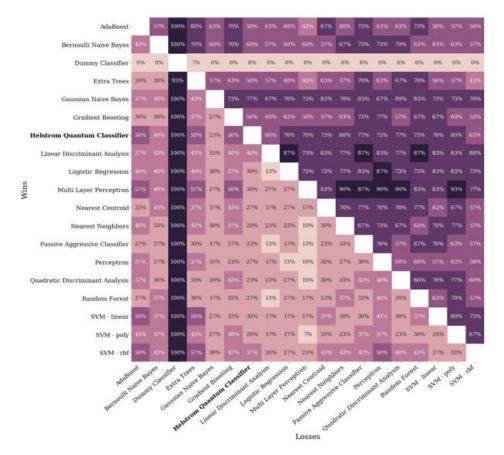


Fig. 2.3.2 | Percentage of datasets where model A ("Wins") outperformed model B ("Losses") out of 30 L*u*v* image feature datasets for cell line MCF7 (balanced accuracy score).

	Image features						
Classifiers	RGB	L*u*v*	Contrast	Correlation	Energy	Homogeneity	
AdaBoost	0.959 ± 0.046	0.940 ± 0.070	0.827 ± 0.106	0.699 ± 0.099	0.851 ± 0.111	0.875 ± 0.092	
Bernoulli Naive Bayes	0.951 ± 0.048	0.964 ± 0.030	0.717 ± 0.124	0.661 ± 0.107	0.718 ± 0.133	0.837 ± 0.118	
Dummy Classifier	0.505 ± 0.064	0.509 ± 0.041	0.494 ± 0.048	0.484 ± 0.044	0.500 ± 0.057	0.491 ± 0.044	
Extra Trees	0.858 ± 0.150	0.914 ± 0.125	0.507 ± 0.037	0.526 ± 0.061	0.523 ± 0.078	0.585 ± 0.124	
Gaussian Naive Bayes	0.943 ± 0.043	0.969 ± 0.034	0.641 ± 0.095	0.715 ± 0.091	0.886 ± 0.069	0.882 ± 0.078	
Gradient Boosting	0.934 ± 0.080	0.939 ± 0.062	0.814 ± 0.103	0.706 ± 0.088	0.844 ± 0.093	0.866 ± 0.110	
Helstrom Quantum Classifier	0.949 ± 0.052	0.965 ± 0.033	0.798 ± 0.109	0.775 ± 0.081	0.875 ± 0.059	0.892 ± 0.065	
Linear Discriminant Analysis	0.947 ± 0.047	0.961 ± 0.047	0.626 ± 0.097	0.685 ± 0.098	0.781 ± 0.139	0.874 ± 0.095	
Logistic Regression	0.946 ± 0.055	0.948 ± 0.060	0.638 ± 0.107	0.674 ± 0.095	0.866 ± 0.097	0.856 ± 0.096	
Multi Layer Perceptron	0.946 ± 0.052	0.965 ± 0.042	0.760 ± 0.106	0.718 ± 0.089	0.867 ± 0.089	0.856 ± 0.111	
Nearest Centroid	0.923 ± 0.056	0.964 ± 0.032	0.770 ± 0.117	0.739 ± 0.095	0.851 ± 0.068	0.890 ± 0.063	
Nearest Neighbors	0.951 ± 0.056	0.947 ± 0.063	0.769 ± 0.109	0.759 ± 0.075	0.861 ± 0.075	0.854 ± 0.101	
Passive Aggressive Classifier	0.945 ± 0.048	0.943 ± 0.051	0.690 ± 0.120	0.616 ± 0.145	0.787 ± 0.145	0.770 ± 0.154	
Perceptron	0.938 ± 0.056	0.923 ± 0.094	0.652 ± 0.167	0.630 ± 0.145	0.774 ± 0.122	0.795 ± 0.149	
Quadratic Discriminant Analysis	0.959 ± 0.050	0.961 ± 0.036	0.638 ± 0.096	0.710 ± 0.111	0.883 ± 0.072	0.872 ± 0.089	
Random Forest	0.948 ± 0.064	0.956 ± 0.044	0.816 ± 0.112	0.740 ± 0.097	0.851 ± 0.113	0.860 ± 0.110	
SVM - linear	0.955 ± 0.050	0.956 ± 0.052	0.654 ± 0.138	0.696 ± 0.107	0.868 ± 0.110	0.873 ± 0.108	
SVM - poly	0.940 ± 0.054	0.949 ± 0.060	0.762 ± 0.108	0.730 ± 0.080	0.862 ± 0.078	0.874 ± 0.105	
SVM - rbf	0.950 ± 0.053	0.962 ± 0.048	0.681 ± 0.134	0.697 ± 0.108	0.868 ± 0.112	0.877 ± 0.102	

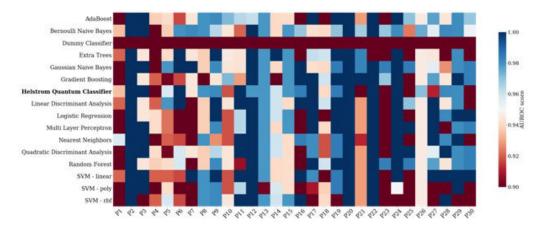


Fig. 2.3.3 | AUROC score of 19 classifiers across 30 L*u*v* image feature datasets for cell line MCF7.

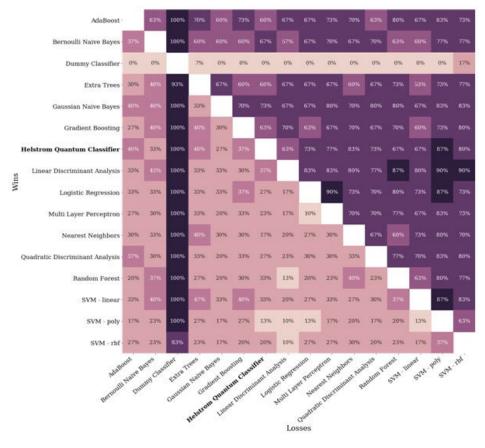


Fig. 2.3.4 | Percentage of datasets where model A ("Wins") outperformed model B ("Losses") out of 30 L*u*v* image feature datasets for cell line MCF7 (AUROC score).

Table 2.3.2 The mean and standard deviation AUROC score (with respect to 30 datasets) for cell line MC	F7
--	----

	Image features					
Classifiers	RGB	L*u*v*	Contrast	Correlation	Energy	Homogeneity
AdaBoost	0.944 ± 0.076	0.951 ± 0.058	0.821 ± 0.110	0.704 ± 0.107	0.845 ± 0.103	0.857 ± 0.102
Bernoulli Naive Bayes	0.951 ± 0.048	0.964 ± 0.030	0.717 ± 0.124	0.661 ± 0.107	0.718 ± 0.133	0.837 ± 0.118
Dummy Classifier	0.475 ± 0.066	0.506 ± 0.073	0.504 ± 0.041	0.506 ± 0.051	0.496 ± 0.069	0.493 ± 0.051
Extra Trees	0.856 ± 0.148	0.918 ± 0.129	0.505 ± 0.025	0.511 ± 0.038	0.509 ± 0.043	0.527 ± 0.068
Gaussian Naive Bayes	0.943 ± 0.043	0.969 ± 0.034	0.641 ± 0.095	0.715 ± 0.091	0.886 ± 0.069	0.882 ± 0.078
Gradient Boosting	0.911 ± 0.112	0.952 ± 0.060	0.773 ± 0.121	0.719 ± 0.091	0.820 ± 0.092	0.837 ± 0.117
Helstrom Quantum Classifier	0.955 ± 0.045	0.960 ± 0.041	0.753 ± 0.120	0.766 ± 0.090	0.866 ± 0.078	0.883 ± 0.071
Linear Discriminant Analysis	0.947 ± 0.047	0.961 ± 0.047	0.626 ± 0.096	0.685 ± 0.098	0.780 ± 0.141	0.874 ± 0.095
Logistic Regression	0.943 ± 0.062	0.950 ± 0.054	0.637 ± 0.108	0.672 ± 0.095	0.853 ± 0.115	0.848 ± 0.107
Multi Layer Perceptron	0.953 ± 0.056	0.950 ± 0.054	0.770 ± 0.120	0.700 ± 0.103	0.850 ± 0.082	0.869 ± 0.104
Nearest Neighbors	0.948 ± 0.045	0.947 ± 0.061	0.767 ± 0.115	0.751 ± 0.087	0.862 ± 0.080	0.850 ± 0.110
Quadratic Discriminant Analysis	0.959 ± 0.050	0.961 ± 0.036	0.638 ± 0.096	0.710 ± 0.111	0.883 ± 0.072	0.872 ± 0.089
Random Forest	0.949 ± 0.066	0.953 ± 0.057	0.811 ± 0.116	0.733 ± 0.100	0.838 ± 0.133	0.852 ± 0.104
SVM - linear	0.946 ± 0.054	0.960 ± 0.052	0.635 ± 0.135	0.687 ± 0.113	0.849 ± 0.126	0.858 ± 0.130
SVM - poly	0.887 ± 0.093	0.927 ± 0.063	0.713 ± 0.125	0.682 ± 0.113	0.841 ± 0.107	0.866 ± 0.121
SVM - rbf	0.872 ± 0.144	0.859 ± 0.176	0.586 ± 0.111	0.601 ± 0.121	0.839 ± 0.142	0.717 ± 0.200

Results exclude Nearest Centroid, Passive Aggressive Classifier and Perceptron.

45 S2.4. Cell line U251

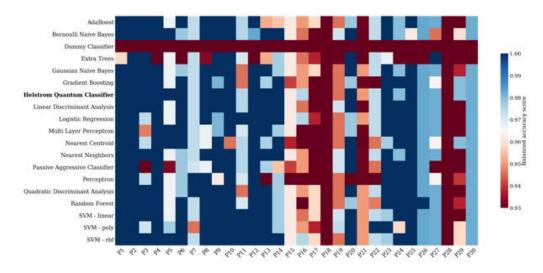


Fig. 2.4.1 | Balance accuracy score of 19 classifiers across 30 homogeneity image feature datasets for cell line U251.

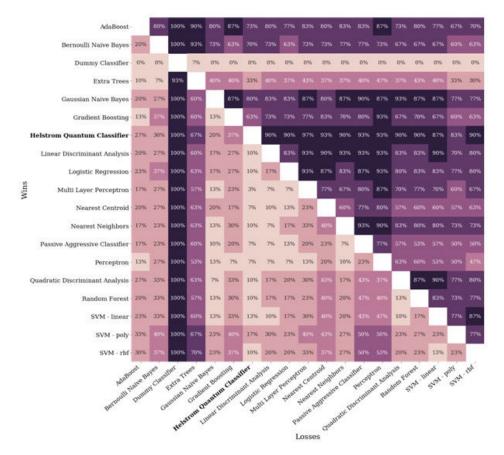


Fig. 2.4.2 | Percentage of datasets where model A ("Wins") outperformed model B ("Losses") out of 30 homogeneity image feature datasets for cell line U251 (balanced accuracy score).

	Image features						
Classifiers	RGB	L*u*v*	Contrast	Correlation	Energy	Homogeneity	
AdaBoost	0.911 ± 0.049	0.909 ± 0.046	0.969 ± 0.027	0.771 ± 0.081	0.968 ± 0.045	0.972 ± 0.032	
Bernoulli Naive Bayes	0.890 ± 0.047	0.903 ± 0.043	0.934 ± 0.055	0.649 ± 0.108	0.859 ± 0.118	0.967 ± 0.059	
Dummy Classifier	0.504 ± 0.068	0.494 ± 0.058	0.495 ± 0.049	0.485 ± 0.057	0.495 ± 0.051	0.509 ± 0.069	
Extra Trees	0.832 ± 0.126	0.865 ± 0.098	0.714 ± 0.188	0.571 ± 0.110	0.692 ± 0.206	0.867 ± 0.164	
Gaussian Naive Bayes	0.908 ± 0.052	0.912 ± 0.051	0.969 ± 0.030	0.698 ± 0.084	0.964 ± 0.033	0.976 ± 0.027	
Gradient Boosting	0.917 ± 0.049	0.907 ± 0.054	0.958 ± 0.034	0.845 ± 0.064	0.965 ± 0.039	0.970 ± 0.035	
Helstrom Quantum Classifier	0.917 ± 0.045	0.907 ± 0.039	0.966 ± 0.032	0.792 ± 0.070	0.973 ± 0.024	0.979 ± 0.029	
Linear Discriminant Analysis	0.892 ± 0.062	0.904 ± 0.047	0.916 ± 0.065	0.674 ± 0.087	0.935 ± 0.058	0.975 ± 0.036	
Logistic Regression	0.911 ± 0.051	0.918 ± 0.044	0.965 ± 0.030	0.677 ± 0.087	0.964 ± 0.031	0.976 ± 0.031	
Multi Layer Perceptron	0.915 ± 0.045	0.924 ± 0.046	0.965 ± 0.035	0.837 ± 0.087	0.968 ± 0.034	0.969 ± 0.035	
Nearest Centroid	0.892 ± 0.051	0.892 ± 0.048	0.927 ± 0.033	0.694 ± 0.091	0.923 ± 0.048	0.967 ± 0.038	
Nearest Neighbors	0.914 ± 0.046	0.907 ± 0.050	0.969 ± 0.032	0.836 ± 0.078	0.974 ± 0.036	0.974 ± 0.033	
Passive Aggressive Classifier	0.875 ± 0.070	0.881 ± 0.070	0.951 ± 0.050	0.575 ± 0.111	0.958 ± 0.047	0.959 ± 0.046	
Perceptron	0.902 ± 0.054	0.889 ± 0.060	0.945 ± 0.060	0.586 ± 0.117	0.951 ± 0.039	0.952 ± 0.056	
Quadratic Discriminant Analysis	0.923 ± 0.053	0.924 ± 0.051	0.972 ± 0.028	0.712 ± 0.085	0.969 ± 0.033	0.976 ± 0.028	
Random Forest	0.926 ± 0.048	0.918 ± 0.047	0.973 ± 0.033	0.815 ± 0.086	0.970 ± 0.044	0.974 ± 0.034	
SVM - linear	0.916 ± 0.047	0.914 ± 0.051	0.970 ± 0.027	0.656 ± 0.103	0.975 ± 0.028	0.976 ± 0.035	
SVM - poly	0.925 ± 0.052	0.911 ± 0.064	0.972 ± 0.027	0.821 ± 0.072	0.970 ± 0.031	0.978 ± 0.025	
SVM - rbf	0.913 ± 0.051	0.917 ± 0.053	0.969 ± 0.032	0.667 ± 0.100	0.976 ± 0.027	0.980 ± 0.033	

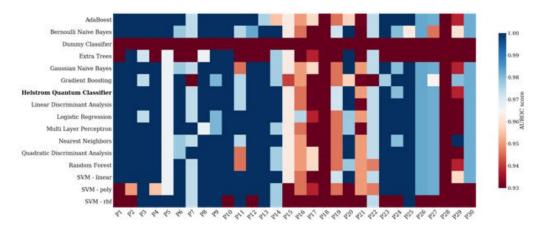


Fig. 2.4.3 | AUROC score of 19 classifiers across 30 homogeneity image feature datasets for cell line U251.

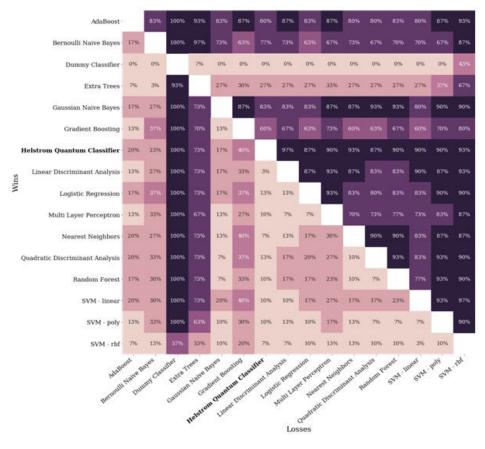


Fig. 2.4.4 | Percentage of datasets where model A ("Wins") outperformed model B ("Losses") out of 30 homogeneity image feature datasets for cell line U251 (AUROC score).

	Image features					
Classifiers	RGB	L*u*v*	Contrast	Correlation	Energy	Homogeneity
AdaBoost	0.920 ± 0.046	0.911 ± 0.048	0.971 ± 0.027	0.741 ± 0.099	0.967 ± 0.045	0.975 ± 0.034
Bernoulli Naive Bayes	0.890 ± 0.047	0.903 ± 0.043	0.934 ± 0.055	0.649 ± 0.108	0.859 ± 0.118	0.967 ± 0.059
Dummy Classifier	0.500 ± 0.050	0.492 ± 0.049	0.499 ± 0.059	0.502 ± 0.054	0.503 ± 0.055	0.511 ± 0.055
Extra Trees	0.808 ± 0.152	0.843 ± 0.110	0.653 ± 0.177	0.558 ± 0.098	0.673 ± 0.186	0.838 ± 0.155
Gaussian Naive Bayes	0.908 ± 0.052	0.912 ± 0.051	0.969 ± 0.030	0.698 ± 0.084	0.964 ± 0.033	0.976 ± 0.027
Gradient Boosting	0.924 ± 0.052	0.906 ± 0.046	0.964 ± 0.031	0.830 ± 0.060	0.966 ± 0.040	0.968 ± 0.034
Helstrom Quantum Classifier	0.899 ± 0.057	0.907 ± 0.053	0.948 ± 0.063	0.797 ± 0.093	0.966 ± 0.031	0.978 ± 0.027
Linear Discriminant Analysis	0.892 ± 0.062	0.904 ± 0.047	0.916 ± 0.065	0.674 ± 0.087	0.935 ± 0.058	0.975 ± 0.036
Logistic Regression	0.911 ± 0.050	0.917 ± 0.046	0.962 ± 0.030	0.676 ± 0.088	0.962 ± 0.036	0.975 ± 0.034
Multi Layer Perceptron	0.921 ± 0.046	0.918 ± 0.051	0.965 ± 0.034	0.830 ± 0.093	0.962 ± 0.034	0.971 ± 0.040
Nearest Neighbors	0.914 ± 0.051	0.907 ± 0.050	0.964 ± 0.040	0.823 ± 0.062	0.972 ± 0.036	0.978 ± 0.028
Quadratic Discriminant Analysis	0.923 ± 0.053	0.924 ± 0.051	0.972 ± 0.028	0.712 ± 0.085	0.969 ± 0.033	0.976 ± 0.028
Random Forest	0.921 ± 0.050	0.925 ± 0.049	0.975 ± 0.025	0.836 ± 0.076	0.973 ± 0.038	0.972 ± 0.035
SVM - linear	0.916 ± 0.049	0.909 ± 0.047	0.962 ± 0.030	0.651 ± 0.103	0.971 ± 0.030	0.978 ± 0.035
SVM - poly	0.897 ± 0.063	0.901 ± 0.062	0.952 ± 0.061	0.801 ± 0.089	0.969 ± 0.030	0.955 ± 0.051
SVM - rbf	0.849 ± 0.150	0.833 ± 0.156	0.776 ± 0.221	0.634 ± 0.114	0.871 ± 0.189	0.723 ± 0.240

Results exclude Nearest Centroid, Passive Aggressive Classifier and Perceptron

S3. Performance of HQC on a new unseen test set (for the best image feature for each cell line)

In this sub-experiment the trained HQC model was tested on a new unseen test set extracted from the remaining 99.8% of the datasets. This experiment was done by randomly selecting 10 datasets (out of the 30 datasets) from the best performing image feature for each of the four cell lines. We show a comparison of the performance on this new unseen test set against the performance on the test set from the 0.2% random sample used in the main experiment.

Table 3.1 Balance accuracy and AUROC score for HQC on the test set used in the experiment and a new unseen test set for 10 randomly selected homogeneity image						Table 3.2 Balance accuracy and AUROC score for HQC on the test set used in the experiment and a new unseen test set for 10 randomly selected homogeneity image					
feature d	atasets for cell line	MDA-MD-231			feature d	atasets for cell line	U87-MG				
Datasets	Balanced accuracy Test set used in the experiment	Balanced accuracy New unseen test set	AUROC Test set used in the experiment	AUROC New unseen test set	Datasets	Balanced accuracy Test set used in the experiment	Balanced accuracy New unseen test set	AUROC Test set used in the experiment	AUROC New unseen test set		
P5	0.900	0.943	0.900	0.943	P1	0.931	0.947	0.931	0.947		
P6	0.977	0.921	0.977	0.921	P2	0.985	0.953	0.985	0.954		
P7	0.916	0.897	0.946	0.896	P5	0.869	0.908	0.869	0.908		
P8	0.944	0.937	0.911	0.943	P9	0.943	0.928	0.943	0.940		
P14	0.971	0.935	1.000	0.933	P10	0.891	0.894	0.891	0.897		
P15	0.921	0.869	0.947	0.888	P14	0.898	0.868	0.898	0.870		
P23	0.955	0.968	0.955	0.967	P21	0.964	0.910	0.929	0.901		
P26	0.977	0.947	0.955	0.944	P22	0.867	0.868	0.839	0.870		
P27	0.974	0.953	0.946	0.951	P25	0.871	0.893	0.871	0.893		
P30	0.971	0.951	0.853	0.811	P27	0.980	0.869	0.960	0.871		
Mean	0.951	0.932	0.939	0.920	Mean	0.920	0.904	0.912	0.905		

Table 3.3 | Balance accuracy and AUROC score for HQC on the test set used in the experiment and a new unseen test set for 10 randomly selected L*u*v* image feature datasets for cell line MCF7

Datasets	Balanced accuracy Test set used in the experiment	Balanced accuracy New unseen test set		AUROC New unseen test set
P6	0.958	0.955	1.000	0.958
P8	0.938	0.949	0.980	0.951
P9	0.982	0.958	0.982	0.955
P13	0.958	0.966	0.979	0.970
P14	0.960	0.978	0.960	0.978
P16	0.984	0.959	0.984	0.951
P19	0.985	0.977	0.985	0.976
P23	0.984	0.967	0.884	0.947
P25	0.875	0.867	0.879	0.886
P26	0.946	0.980	0.971	0.946
Mean	0.957	0.956	0.960	0.952

Table 3.4 | Balance accuracy and AUROC score for HQC on the test set used in the experiment and a new unseen test set for 10 randomly selected homogeneity image feature datasets for cell line U251

Datasets	Balanced accuracy Test set used in the experiment	Balanced accuracy New unseen test set	AUROC Test set used in the experiment	AUROC New unseen test set
P2	1.000	0.985	1.000	0.977
P7	0.974	0.962	0.974	0.962
P15	0.962	0.956	0.962	0.898
P18	0.927	0.971	0.927	0.971
P20	1.000	0.960	1.000	0.959
P21	0.950	0.964	0.950	0.964
P22	0.974	0.941	0.974	0.948
P27	0.982	0.965	0.982	0.973
P29	0.980	0.926	0.938	0.932
P30	0.982	0.976	0.982	0.968
Mean	0.973	0.961	0.969	0.955

S4. Experimental results - extended version

This section contains tables showing the experimental results for the balanced accuracy and AUROC scores for the six image features RGB, $L^*u^*v^*$, *contrast*, *correlation*, *energy* and *homogeneity*, for each of the four cell lines MDA-MD-231, U87-MG, MCF7 and U251 respectively.

200 201 201 201 201 201 201 201 201 201	P.0. 0.947 0.947 0.947 0.947 0.974 0.9774 0.9774 0.9774 0.9774 0.9774 0.9774 0.9774 0.9774 0.9774 0.9774 0.9774 0.9774 0.97777 0.97777 0.97777 0.97777 0.97777 0.97777 0.97777 0.97777 0.97777 0.97777 0.977777 0.977777 0.9777777777777777777777777777777777777	200 1.000 3.886 3.886 3.886 3.055 0.002 0.005 0.057 0.057 0.055 0.055 0.055 0.055 0.055 0.055 0.055 0.0570 0.0570 0.0570000000000	0.0 017.0 07.7 00000000
P29 5 0.9408 6 0.5710 7 0.9410 7 0.9410 7 0.9410 7 0.9410 7 0.9410 7 0.9410 7 0.9410 8 0.9410 9 0.9410 <td< td=""><td>P29 9 0.918 9 0.918 9 0.918 9 0.918 9 0.938</td><td>P29 5 0.969 5 0.969 7 0.489 7 0.484 7 0.494 7 0.494 7 0.494 7 0.494 7 0.494 7 0.494 7 0.494 7 0.494 1000 0.994 9 0.996</td></td<> <td>P29 71017 0.5700 5 0.7700 6 0.5500 0 0.5000</td>	P29 9 0.918 9 0.918 9 0.918 9 0.918 9 0.938	P29 5 0.969 5 0.969 7 0.489 7 0.484 7 0.494 7 0.494 7 0.494 7 0.494 7 0.494 7 0.494 7 0.494 7 0.494 1000 0.994 9 0.996	P29 71017 0.5700 5 0.7700 6 0.5500 0 0.5000
P28 0.58555 0.58555 0.58555 0.58555 0.585555 0.585555 0.585555 0.585555555555	P28 0.913 0.913 0.913 0.913 0.921 0.921 0.939 0.939 0.939 0.8399 0.8390 0.83900 0.83900 0.83900 0.83900000000000000000000000000000000000	P28 0.905 0.921 0.921 0.929 0.829 0.829 0.829 0.829 0.829 0.821 0.822 0.9229 0.9229 0.9229 0.9229	P28 0.458 0.458 0.458 0.458 0.500 0.500 0.795 0.7958 0.5938 0.425 0.425 0.425 0.4418 0.4418 0.4418 0.5938 0.4418 0.5938 0.4418 0.5938 0.4418 0.5938 0.4418 0.5938 0.5938 0.5937 0.5937 0.5937 0.5937 0.5937 0.5937 0.5937 0.5937 0.5937 0.5937 0.5937 0.5937 0.5937 0.5937 0.5937 0.5938000000000000000000000000000000000000
P27 P27 0.796 0.789 0.473 0.789 0.820 0.812 0.812 0.812 0.812 0.821 0.821 0.821 0.821 0.822 0.822 0.821 0.0821 0.08	P27 0.947 0.947 0.947 0.972 0.972 0.972 0.972 0.972 0.972 0.972 0.972 0.972 0.972 0.972 0.972 0.972 0.972 0.972 0.972 0.972 0.972 0.9777 0.97777 0.97777 0.97777 0.97777 0.97777 0.97777 0.97777777 0.9777777777777777777777777777777777777	P27 0.971 0.925 0.925 0.925 0.975 0.975 0.975 0.975 0.975 0.975 0.975 0.975 0.975 0.975 0.975 0.975 0.975 0.975 0.975 0.975 0.975 0.975 0.9770 0.97700 0.97700 0.97700 0.97700 0.97700 0.97700 0.977000 0.9770000000000	P27 0 819 0 819 0 818 0 818 0 818 0 819 0 810 0 810 0 880 0 880 0 0 880 0 0 0
P26 0381 0381 0428 0428 0428 0428 0428 0428 0428 0428	P26 0.871 0.871 0.871 0.5750 0.5275 0.9229 0.9229 0.9259 0.9259 0.8571 0.9259 0.9259 0.9259 0.9259 0.9251 0.9257 0.9257 0.92571 0.92571 0.9257 0.92571 0.9257 0.92571 0.92571 0.9257 0.92571 0.92570 0.92570 0.92570 0.92570 0.92570 0.925700 0.925700 0.925700 0.925700 0.925700 0.925700 0.9257000 0.9257000000000000000000000000000000000000	P26 0.799 0.824 0.824 0.824 0.824 0.824 0.824 0.824 0.825 0.825 0.825 0.924 0.825 0.916 0.916 0.916 0.916 0.916 0.916	P26 0303 0303 0303 0307 0500 0744 0381 0381 0,793 0,793 0,794 0,79
P25 0 803 0 805 0 805 0 0 805 0 0 805 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	P25 0.952 0.881 0.605 0.976 0.976 0.976 0.929 0.976 0.976 0.976 0.976 0.976 0.976 0.976 0.976 0.976	P25 0.921 0.921 0.921 0.9777 0.97770 0.97770 0.97770 0.97770 0.97770 0.97770 0.97700 0.97700 0.97700 0.9770000000000	P25 0.745 0.721 0.721 0.816 0.816 0.816 0.816 0.816 0.816 0.816 0.816 0.753 0.816 0.753 0.816 0.753 0.816 0.753 0.816 0.753 0.816 0.745 0.816 0.816 0.745 0.816 0.8260 0.8260 0.8260 0.8260 0.8260 0.8260 0.8260 0.82600000000000000000000000000000000000
P24 0.917 0.863 0.500 0.917 0.590 0.91700000000000000000000000000000000000	P24 0.835 0.835 0.9380 0.93800 0.93800 0.93800 0.93800000000000000000000000000000000000	P24 0.891 0.711 0.711 0.711 0.716 0.716 0.711 0.821 0.9210 0.921 0.921 0.921 0.921 0.921 0.9210 0.9210 0.9210 0.9210 0.9210 0.9210 0.9210 0.9210 0.92100000000000000000000000000000000000	P24 0.593 0.674 0.670 0.600 0.600 0.703 0.703 0.703 0.703 0.703 0.753 0.753 0.753 0.753 0.753 0.753 0.753 0.753 0.753 0.773 0.773 0.660 0.7730 0.7730 0.7730 0.7730 0.7730 0.7730 0.7730 0.7730 0.7730 0.770
P23 P23 0.590 0.590 0.590 0.590 0.890 0.890 0.890 0.890 0.890 0.890 0.890 0.890 0.890 0.890 0.890 0.890 0.890	P23 0.978 0.899 0.978 0.9964 0.9957 0.9957 0.915 0.9780 0.97800 0.97800 0.97800 0.97800000000000000000000000000000000000	P23 0.920 0.754 0.754 0.754 0.755 0.859 0.859 0.859 0.859 0.859 0.850 0.857 0.868 0.857 0.850 0.857 0.850 0.857 0.850 0.857 0.850 0.857 0.857 0.850 0.857 0.857 0.850 0.857 0.8500 0.8500 0.8500 0.850000000000	P23 0.742 0.742 0.742 0.746 0.766 0.776 0.776 0.776 0.776 0.778 0.778 0.778 0.778 0.778 0.778 0.778 0.778 0.778 0.778 0.778 0.780 0.781 0.782 0.782 0.782 0.782 0.782 0.770 0.782 0.776 0.776 0.776 0.776 0.776 0.776 0.776 0.776 0.776 0.776 0.776 0.776 0.776 0.776 0.776 0.7776 0.7776 0.7776 0.7776 0.7776 0.7776 0.7770 0.7776 0.77700 0.77700 0.77700 0.77700 0.77700 0.77700 0.77700 0.77700 0.77700 0.77700000000
P22 P22 1,000 1,000 0,545 0,567 0,567 0,567 0,979 0,979 0,979 0,979 0,979 0,979 0,979	P22 P21 0.921 0.921 0.921 0.921 0.921 0.921 0.921 0.921 0.921 0.921 0.921 0.921 0.921 0.921 0.921 0.921 0.921	P22 0.925 0.850 0.820 0.921 0.921 0.922 0.923 0.923 0.920 0.900 0.946 0.946 0.946 0.950 0.955 0.950 0.955 0.9500 0.9500 0.9500 0.9500 0.950000000000	P22 0.770 0.770 0.500 0.500 0.770 0.770 0.770 0.770 0.770 0.8640 0.771 0.8640 0.8677 0.8640 0.8677 0.8640 0.8677 0.8660 0.8667 0.8667 0.8667 0.776 0.8667 0.770 0.760 0.770 0.760 0.770 0.760 0.760 0.760 0.760 0.760 0.760 0.760 0.760 0.770 0.760 0.770 0.760 0.770 0.760 0.770 0.760 0.770 0.760 0.770 0.760 0.770 0.760 0.770 0.760 0.770 0.760 0.770 0.760 0.770 0.760 0.770 0.760 0.760 0.770 0.760 0.760 0.760 0.770 0.760 0.770 0.760 0.770 0.760 0.770 0.760 0.770 0.770 0.770 0.770 0.770 0.770 0.770 0.770 0.770 0.770 0.770 0.770 0.770 0.770 0.770 0.770 0.77000 0.77000 0.7700000000
P21 P21 0.978 0.857 0.857 0.855 0.943 0.835 0.750 0.943 0.835 0.750 0.835 0.835 0.835 0.835 0.835 0.835 0.835 0.835 0.835	P21 0.864 0.864 0.727 0.509 0.738 0.738 0.754 0.754 0.755 0.754 0.751 0.781 0.771 0.781 0.771 0.781 0.771 0.781 0.771 0.781 0.7777 0.781 0.7777 0.781 0.7777 0.781 0.7777	P21 0.972 0.890 0.579 0.579 0.579 0.972 0.972 0.972 0.972 0.972 0.973 0.973 0.974 0.973 0.974 0.974 0.974 0.974 0.974 0.973	P21 0.577 0.577 0.577 0.510 0.510 0.511 0.512 0.512 0.550 0.550 0.550 0.550 0.550 0.550 0.550 0.551 0.555 0.551 0.555 0.551 0.555 0.551 0.5550 0.5550 0.5550 0.5550 0.5550 0.5550 0.5550 0.5550 0.55500 0.55500 0.55500 0.55500000000
P20 0.2505 0.2505 0.2505 0.2505 0.2506 0.2506 0.2506 0.2506 0.2506 0.2505 0.250	P20 0.921 0.921 0.941 0.540 0.941 0.946 0.946 0.946 0.946 0.851 0.946 0.946 0.951 0.946 0.946 0.946 0.946	P20 0.974 0.974 0.255 0.255 0.946 0.972 0.972 0.946 0.972 0.944 0.972 0.973 0.973 0.973 0.974 0.974 0.974 0.974 0.974 0.974 0.974 0.974 0.974 0.974 0.974 0.974 0.974 0.974 0.974 0.977	P20 0.900 0.905 0.905 0.975 0.975 0.975 0.975 0.887 0.887 0.887 0.887 0.887 0.887 0.887 0.887 0.887 0.887 0.887 0.887 0.887 0.877 0.887 0.877 0.975 0.075 0.000 0.0750 0.0750 0.0750 0.0750000000000
P19 0.275 0.275 0.276 0.295 0.276 0.275	P19 0349 0.042 0.0585 0.0585 0.0885 0.885 0.885 0.885 0.885 0.885 0.885 0.885 0.885 0.885 0.885 0.885 0.885 0.885 0.885 0.885 0.885 0.885 0.885 0.985 0.0865 0.0855 0.0855 0.0855 0.08550 0.08550 0.08550 0.08550000000000	P19 0.909 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200	P19 01333 01333 01434 01435 014550 014550 014550 014550 014550000000000
P18 0.858 0.858 0.858 0.923 0.923 0.923 0.885 0.885 0.885 0.885 0.885 0.942 0.943 0.944 0.9430 0.9430 0.9430 0.9430 0.94300000000000000000000000000000000000	P18 0.941 0.578 0.578 0.579 0.979 0.979 0.979 0.979 0.979 0.979 0.979 0.979 0.979 0.979 0.979 0.979 0.979 0.979 0.979	P18 0.929 0.929 0.929 0.945 0.	P18 0.734 0.734 0.734 0.734 0.734 0.734 0.734 0.734 0.734 0.913 0.913 0.913 0.913 0.735 0.735 0.735 0.734 0.734 0.734 0.734 0.734 0.735 0.734 0.0734 0.0733 0.0733 0.0734 0.0734 0.0734 0.0733 0.0733 0.0734 0.0733 0.0734 0.0733 0.0743 0.07430 0.07430 0.07430 0.07430 0.07430 0.07430 0.07430 0.07430 0.07430 0.07430 0.07430000000000000000000000000000000000
P17 P17 0.396 0.396 0.946 0.946 0.971 0.971 0.971 0.971 0.971 0.971 0.971 0.971 0.971 0.971 0.971 0.971 0.971 0.971	P17 912 0.838 0.838 0.517 0.517 0.517 0.517 0.517 0.896 0.896 0.896 0.896 0.896 0.896 0.896 0.895 0.912 0.912 0.912 0.912 0.912 0.912	P17 0.9330 0.9330 0.9330 0.9330 0.9330 0.9330 0.9330 0.93300 0.9330000000000	P17 0.397 0.397 0.0740 0.0740 0.0740 0.0741 0.0741 0.0741 0.0741 0.0741 0.0762 0.0762 0.0762 0.0772 0.0772 0.0772 0.0772
P16 0.938 0.938 0.500 0.500 0.9380 0.93800 0.93800 0.93800000000000000000000000000000000000	P16 0.709 0.709 0.520 0.520 0.520 0.681 0.681 0.608 0.608 0.714 0.608 0.714 0.608 0.608 0.608 0.698 0.698 0.698 0.698 0.698 0.698	P16 0.784 0.784 0.500 0.500 0.500 0.784 0.786 0.786 0.786 0.784 0.784 0.784 0.7866 0.7866 0.786 0.786 0.786 0.786 0.786 0.786 0.786 0.786 0.7860	P16 0.649 0.649 0.500 0.500 0.500 0.648 0.648 0.648 0.648 0.648 0.648 0.648 0.657 0.657 0.657 0.657 0.657 0.758 0.5700 0.5700 0.5700 0.570000000000
P15 0.774 0.778 0.778 0.778 0.778 0.778 0.778 0.778 0.778 0.778 0.778 0.778 0.778 0.778 0.778	P15 0.757 0.757 0.541 0.541 0.821 0.821 0.762 0.762 0.762 0.746 0.757 0.821 0.746 0.746 0.757 0.821 0.746 0.746 0.746 0.746 0.821 0.821 0.821 0.821	P15 0.804 0.804 0.804 0.596 0.873 0.801 0.825 0.804 0.822 0.801 0.822 0.801 0.822 0.801 0.822 0.801 0.822 0.823 0.801 0.822 0.821 0.821 0.822 0.821 0.822 0.821 0.754	P15 0.519 0.519 0.500 0.501 0.501 0.481 0.481 0.481 0.481 0.481 0.481 0.481 0.481 0.500 0.501 0.500 0.501 0.500 0.513 0.513 0.513 0.513 0.513 0.513 0.513 0.513 0.513 0.513 0.513 0.513 0.513 0.513 0.515 0.5500 0.5500 0.5500 0.5500000000
P14 P14 0.025 0.025 0.026 0.021 0.021 0.021 0.021 0.021 0.021 0.021 0.021 0.021 0.021 0.021 0.025 0.022 0.025 0.022 0.022 0.025 0.022	P14 P14 0.505 0.505 0.505 0.505 0.805	P14 0 890 0 890 0 899 0 898 0 899 0 813 0 814 0 813 0	P14 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
P13 P13 0 8158 0 8158 0 8168 0 916 0 915 0 916 0 916 0 916 0 916 0 916 0 915 0	P13 0 1795 0 1795 0 1707 0 1708 0	P13 0 890 0 80	P13 1765 1765 1765 1784 1784 1789 1789 1789 1789 1789 1789 1789 1789
P12 P12 P12 P12 P12 P12 P12 P12	P12 P12 0.967 0.967 0.967 0.967 0.917 0.917 0.917 0.967 0.977 0.977 0.977 0.977 0.977 0.977 0.977 0.977 0.977 0.977	P12 0.975 0.97	Lig 211 211 211 211 211 211 211 21
P11 1 0 01281 0 01282 0 01283 0 0128 0 0	P11 1 0 0946 0 0 0946 0 0 0946 0 0 0948 0 0 0458 0 0 0458 0 0 0458 0 0 0458 0 0 0451	P11 1 0.881 0.882 0.881 0.0882 0.882 0.0882 0.882 0.0982 0.914 0.914 0.952 0.905 0.952 0.905 0.952 0.929 0.929	P.1 P.1 1.02 2.02 2.02
P10 F 0.739 C 0.739 C 0.739 C 0.739 C 0.739 C 0.739 C 0.731	P10 T 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	P10 P10 0578 0.978 0578 0.978 0578 0.070 0579 0.070 0579 0.070 0579 0.070 0579 0.070 0579 0.070 0579 0.070 0579 0.070 0570 0.070 0570 0.070	P10 F 0.757 0 0.757 0 0.757 0 0.757 0 0.756 0 0.708 0 0.709 0 0.714 0 0.8190 0 0.8191 0 0.8191 0 0.8191 0 0.8191 0 0.8191 0 0.8191 0 0.8191 0 0.8191 0 0.8191 0 0.8191 0 0.8191 0 0.8192 0 0.8192 0 0.8192 0 0.8117 0 0.8117 0 0.8117 0 0.8117 0 0.8117 0 0.8117 0 0.8117 0 0.8117 0 0.8117 0
Pass Pass <th< td=""><td>P P 0.000 0.000 0.000</td><td>7 7 0.945 0 0.845 0 0.845 0 0.812 0 0.812 0 0.812 0 0.812 0 0.812 0 0.812 0 0.812 0 0.812 0 0.812 0 0.812 0 0.812 0 0.938 1 0.938 1 0.938 1 0.938 1 0.938 1 0.938 1 0.945 1 0.945 1 0.945 1 0.945 0 0.945 0</td><td>8 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2</td></th<>	P P 0.000 0.000 0.000	7 7 0.945 0 0.845 0 0.845 0 0.812 0 0.812 0 0.812 0 0.812 0 0.812 0 0.812 0 0.812 0 0.812 0 0.812 0 0.812 0 0.812 0 0.938 1 0.938 1 0.938 1 0.938 1 0.938 1 0.938 1 0.945 1 0.945 1 0.945 1 0.945 0 0.945 0	8 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
Para 2015 10 10 10 10 10 10 10 10 10 10 10 10 10	7 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2		
P7 P9 P7 P9 P8 0.51 0.851 0.53 0.851 0.53 0.851 0.15 0.852 0.15 0.853 0.15 0.854 0.15 0.855 0.15 0.856 0.15 0.859 0.15 0.859 0.15 0.859 0.15 0.859 0.25 0.859 0.25 0.859 0.25 0.859 0.25 0.859 0.25 0.859 0.25 0.859 0.25 0.859 0.25 0.859 0.25 0.859 0.25 0.859 0.25 0.859 0.25	5		Proceedings of the second seco
MIDA-MII P P P P P P P P P P P P P	Max Max <thmax< th=""> <thmax< th=""> <thmax< th=""></thmax<></thmax<></thmax<>	P P P 1 P 0	All line
Pic Provident Process	P	State State <th< td=""><td></td></th<>	
Processor Processor 0 0.917 0.917 0 0.917 0.917 0 0.917 0.917 0 0.917 0.917 0 0.917 0.917 0 0.917 0.917 0 0.917 0.917 0 0.917 0.917 0 0.917 0.917 0 0.917 0.917 0 0.917 0.917 0 0.917 0.917 0 0.917 0.917 0 0.917 0.917 0 0.917 0.917 0 0.917 0.917 0 0.917 0.917 1 0.917 0.917 1 0.917 0.917 1 0.917 0.917 1 0.917 0.917 1 0.917 0.917 1 0.917 0.917	damages fo provide the second	All and a constraint of the second se	Pic Pic Pic Pic Pic 0.500 Pic
Plat Pat Pat 0.552 0.553 0.543 0.543 0.543 0.543 0.543 0.543 0.543 0.543 0.543 0.543 0.543 0.543 0.543	 Fathers P4 P4 0.59 0.99 	P4 P4 091 091 091 091 091 091 091 091 091 091	P.4 (64) (64) (64) (64) (64) (64) (64) (64
B image fs P3 0.366 0.250 0.250 0.250 0.200 0.217 0.217 0.217 0.217 0.217 0.217 0.210 0.21	Prev Image 2015	Eq. (10, 10, 10, 10, 10, 10, 10, 10, 10, 10,	Comparison in the first provide the provident in the
P2 P2 0.647 0.647 0.057 0.057 0.051 0.051 0.058 0.068 0.068 0.068 0.068 0.0580 0.0580 0.0580 0.0580 0.0580000000000	P2 0.789 0.789 0.780 0.500 0.500 0.850 0.850 0.850 0.8200 0.82	P1 000 000 000 000 000 000 000 000 000 0	P20. com P21 0.583 0.583 0.583 0.583 0.583 0.493 0.493
P1 P1 P1 03555 03555 03557 03557 02557 02557 02557 02557 02557 02557 02557 02557 02557 02557 02557 02557 02555 02555 02555 02555 02555 027555 027555 027555 027555 027555 027555 027555 027555 027555 00	er 0.734 0.734 0.734 0.734 0.734 0.734 0.734 0.3344 0.8257 0.8257 0.8257 0.8257 0.8267 0.82755 0.82755 0.82755 0.827555 0.8275555 0.	C 3 500 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	CONCOMENTIAL CONCOMENTA CONCOMENTE
Characterization 0.000	Balls 4.1 Halanced accuracy score (her. Mit. 24) 100 Chronition 1 7 7 15 Addition 1 7 15 15 Addition 1 7 15 15 Addition 0.30 0.30 0.31 0.39 0.33 Demain Cashier 0.31 0.39 0.30 0.34 0.39 0.35 Demain Cashier 0.39 0.39 0.30 0.30 0.34 0.39 0.35 Demain Cashier 0.34 0.39 0.38 0.39 0.39 0.31 0.31 Demain Cashier 0.34 0.39 0.38 0.39 0.33 0.31 0.31 Cashier Cashied 0.34 0.39 0.32 0.31 0.31 0.31 0.31 0.31 0.31 0.31 0.31 0.32 0.32 0.31 0.31 0.31 0.31 0.31 0.31 0.31 0.31 0.31 0.31 0.31 <th< td=""><td>Classifiers All Balanced accuracy serves and Allows (Classifiers Plu) (Classifiers P</td><td>Table 4.1 Balanced accuracys Late 4.1 Balanced accuracys Addisor balanced accuracys addisor barrow Sares consoling the Barrow consoling the Barrow</td></th<>	Classifiers All Balanced accuracy serves and Allows (Classifiers Plu) (Classifiers P	Table 4.1 Balanced accuracys Late 4.1 Balanced accuracys Addisor balanced accuracys addisor barrow Sares consoling the Barrow consoling the Barrow

Table 4.5 Balasced accuracy score for 30 energy image featu	core for 30	energy imag	te feature	datasets	for cell line	MDA-MI	0-231																				and the second s	
Classifiers	d Id	2 P3	Pa	PS.	-	-				1	P12	P13	P14			1	1	1		1	1	P24	STA	P26	P27	P28	P29	P30
AdaBoog	0.944 0.	323 0.8	50 15	100	0 0			-			1/60	696.0	0.944						203			E060	5160	0.955	1947	0.855	196.0	856.0
Dumny Classifier		0.620 0.5	00 05	00 0.6	100 0 2013 (12) 0 513	0.539	9 0.519	9 0.500	00500	10354	0.451	0.500	0.517	0.512 0	0.500 0.	0.516 0.	20 005 0	005.0 005.0	0 0.442	0.500	0.343	0.483	0.500	0.547	0.648	0.500	0.500	0.460
Extra Trees	0.778 0.		00 0.5	51 0.5	0	•				0	1.000	0.929	0.911	-			Ŭ		800	Ĩ		0.821	516.0	0.500	0.944	0.841	0.893	116.0
Gaussian Naive Bayes	0.944 0.	385 0.840	40 0.5	93 0.9	0 0	0 0					1,000	0.969	0.944	-				7	7 0			196.0	1.000	0.890	126.0	0.932	1.000	0.938
Mattern Deserve Charles				00 00							DOD!T	0.000	1000						0.0			190.0	1000	10001	ates o	0.000	1000	0.016
Linear Discriminant Analysis			80 98	83 0.9	0						0560	0.976	116.0				1		23			0.857	0.900	0 773	0.867	0.864	5680	0.896
Logistic Regression	0 944 0	0.385 0.765	59 0.5	93 1.0	0	0				0	1 000	0.969	0.944				100	Ĩ		-		0.964	6.975	1.000	0.974	0.838	0.978	8[6:0
Multi Layer Perceptron			10 0 t	93 1,0	0	0				1	1,000	0.969	0.944				~		10	~		0.964	279.0	1,000	1/20	861.0	0.978	0.958
Nearest Centroid			29 0.8	57 0.8	0	•	1				5260	0.969	0.821				~	Ĩ	33			0.857	526-0	0.806	0.921	0.836	0.893	0.801
Nearest Neighbors	0.982 0.	0.825 0.85	57 0.5	43 0.9	0	•				2	1.000	0.969	0.921				~	Ĭ	7	7		19610	1.000	0.962	0.946	0.955	0.964	856.0
Passive Aggressive Classifier	0.873 0.	346 0.340	50 0t	64 0.9	0	•		~			0.941	6960	0.944				Ŭ	Ĩ	8			0.921	\$75.0	605'0	0.974	0.\$55	0.943	0.885
Perception	0.909 0.	2	33 0.9	29 0.9	44 0.83	(3 0.93	5 0.93	13 0.861			0.941	0.976	0.944				~		88			0.964	516.0	0.923	0.974	0.855	0.964	0.938
Quadratic Discriminant Analysis	0.944 0		\$0 0.E	60 66	44 0.88	68 0.83	9 1.00	0 0.835			1160	0.969	0.944				7	Č.	23	-		0.964	1.000	6.935	0.974	2560	1.000	0.958
Random Forest	0.944 0		57 0.5	07 1.0	16'0 00	17 0.92	1 100	0 0.36			1.000	0.969	0.944	-			-		22			6963	5260	606.0	160	0,855	1.000	0.958
SVM - Inear	9 ++60		66 0.8	93 1.0	00 0.81	10.89	6 1.00	0 0.835			1.000	0.969	0.944	-			-		343			196.0	516.0	0.955	16.0	0.838	0.964	0.938
SVM - thf	0 1750	0.885 0.769	50 05 80 05	93 10	00 0.65	10 0.87 19 0.92	06.0 1 1	0.341	6		1/6/0	0.969	0.944						868			196.0	0.975	0.955	0.974	0.888	0.9645	816.0
Table 4.6 Balanced accuracy score for 30	core for 30	homogeneit	oity image f	oature dat	asets for c	oll line MI	0.4.MID-231	11																				
Classifiers	P1 P	2 P3	P4	P5	P6	Ld	PS	8	P10	1	P12	P13	P14				-			8		P24	P25	P26	P27	P28	P29	P30
AdaBoost	1.000 0.	958 0.9	50 1.0	00 0.9	11 0.9)	1 0.92	0	0		0	0.955	0.916	0.941				"		Ū	1	Ĩ	1/60	1.000	0.955	0.946	0.957	0.945	1.000
Bernoull Naive Bayes	~	°	36 1.0	00 0.9	21 0.97	0	126.0 0	ø			1.000	0.921	1/60				Ĩ	7		~	-	1.000	0.944	0.865	0.946	0.978	0.976	1.000
Dummy Classifier	0	603 0.5	510 0.4	18 0.5	0	0	0	0	2		0.427	0.500	0.500				~	Ĩ	3	2		0.500	0.495	0.518	0.500	0.500	0.500	0.384
Ettra Trees	0.885 0.	500 0.5	00 00	13 0.8	0	•	0	ø			1160	0.850	1.000				°	7	2	~		19610	0.967	0.733	0.835	0.870	0.812	0.794
Gaussian Naive Bayes	1.000 1.	6.0 000	57 1.0	00 0.8	0	•	0	0			116.0	163'0	116.0				2			~		1.000	0.944	116.0	16.0	156.0	0.945	000.1
Gradient Boosting	0.958 0.		50 1.0	00 0.8	0	0	•	Ö			2260	168'0	0.912				7	Ĩ		-		126.0	1.000	116-0	974	0.921	6.914	1+6:0
Heistrom Quantum Classifier			57 1.0	00 0.9	0	0	0	ø			116-0	0.925	1/6.0				7					1.000	1.000	116.0	0.974	0.957	1.000	0.971
Linear Discriminant Analysis		•	83 1.0	00 0.8	2	•	•	G			1.000	0.862	0.971				7			-		1.000	1.000	0.955	160	0.978	0.945	1.000
Logistic Regression			00 1.0	00 0.8	0	2	0	ø		2	116.0	0.921	1/60				7	2	73			1.000	0.967	1160	0.974	0.957	0.945	1.000
Muthi Layer Perception	_	0.917 0.981	83 1.0	00 0.5	•	0	•	ø		Ξ.	1.000	0.921	0.912				7	7	73			1.000	196.0	116-0	1.000	0.978	0.945	1/6.0
Nearest Centroid	Ĩ	60 156	50 1.6	00 0.8	0	0	•	e.			1160	0.975	0.971				7		7	3		0.916	0.944	0.955	976'0	0.978	0.976	0.946
Nearest Neighbors	0.923 0.	679 0.9	50 1.0	00 0.8	0	-	•	ē			1.000	0.925	0.912				7	7		-		1.000	H60	1160	974	0.978	0.969	1/6/0
Passive Aggressive Classifier	0.798 0	6.0 616	50 03	64 0.8	0	0	•	ø.	168.0 8	1	0.955	0.950	1.000				-	7	22	-	0.932	1.000	0.944	116-0	0.974	0.957	0.976	946-0
Perception	0.899 0	917 0.9	83 1.0	00 03	21 0.92	•	5 0.93	2 0.72			0.955	0.866	0.891				-	-	7			0.971	0.386	0.933	0.946	168.0	9/6.0	0.975
Quadratic Discriminant Analysis	1.000 0	902 0.9	50 1.0	00 0.9	00 0.91	0.92	1 0.94	14 0.365			0.977	0.921	1.000				7	7				1.000	0.967	9355	16.0	0.957	0.976	1.000
Random Forest		25	50 1.0	00 0.8	16.0 11	10 0.92	16'0 1	0.365			0.955	0.921	0.941				5	534 		-		1.000	0.967	116.0	16.0	0.957	0.945	1.000
SVM - linear	_	0.881 0.967	57 1.0	00 0.8	33 0.97	16.0 11	6 0.92	0.865			0.955	0.921	1.000				-	2	73			1.000	0.967	116.0	0.974	0.957	0.976	1.000
Vod - MVS			00 10	00 0.8	0.91	0.891	0.92	1 0.381		0.63.0	1.000	0.925	116:0	0.893 0	0.879 1.	0000	0.1 172.0	000 1.000	0.964	0.947		1000	1950	5550	160	0.957	1.000	1160
2 V M - 101	1,000	COL: 0 576 0	23 4.0	20 N.S	12 0.21	10.94	0 0.03	000	7160	1,304	1/2/1	176.0	1/2/1								226.0	1.000	106.0	1360	12/4	106.0	CH4CID	1.000
Table 4.7 MTBOC score for 10 BCB (more feature detects	1 D.C.B (man	to feature of	and a start of the	A N III IIII	CITA MIN	111	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	
Classifiers	d Id	Ed 5	P4	Sel	P6	Ld	Ps	17	17	17	51d	P13	P14	17	17	17	17	17	17	2	17	17	P15	P26	P27	P28	P20	P30
AdaBoost	0.855 0	804 0.6	8 0.8	82 0.9	0	0		Γ		Γ	0.885	0.858	0.925	ľ	Ĩ				1	10	Γ	Γ	0.863	0.931	0.796	0.885	0.980	0.803
Bemoels Naive Bayes	0.738 0.	756 0.755	8.0 25	97 0.8	839 0.720	0.850	006.0	0.857	0.741	0.814	168.0	0.916	0.866	0.778 0	0 878.0	0 9960	1865 0.7	0.761 0.875	5 0.828	0.843	0.904	0.863	0.807	0.894	0.739	0.856	0.878	0.871
Dummy Classifier	0.500 0	500 0.470	20 0.5	00 0.5	0	0	2				0.500	0,463	0.526		Ĩ	Ĩ		~	<u> </u>	0			0.500	0.500	0.558	0.500	0.548	0.544
Extra Trees	0.855 0.	500 0.500	00 05	21 0.9	0	0	2	Ĩ			0.935	0.818	0.866			Ĩ	0	~	~	0			0.784	0.500	0.820	0.907	0.938	0.896
Gamssian Naive Bayes	0.795 0.	316 0.504	94 0.5	97 0.9	•	0	2		Ĩ		0.891	0.955	0.871		Ĩ	Ĩ		Ĩ	~	0		~	0.807	6.913	0.739	0.\$56	0.918	0.846
Gradient Boosting	0.397 0.	0.686 0.769	80 65	51 0.8	0	0		Ĩ	Ĩ	0	178.0	0.935	0.896	~	Ĩ	Ĩ	1	Ĭ	Ĩ	-		Ĩ	0.836	0.950	0.820	0.907	0.980	0,837
Heistrom Quantum Classifier	0.857 0.	0.837 0.618	18 0.7	95 0.9	0	0	2				0.885	0.916	0.950		Ĩ	Ĭ		~	1	0			0.863	0.931	0.812	0.899	0.980	0.896
Linear Discriminant Analysis	0.837 0.		34 0.8	42 0.9	0	0	2		0	0	0.870	0.916	0.900			Ĩ		~	~	0			0.756	0.881	0.812	0.899	0.940	0.866
Logistic Regression	0.857 0.	0.920 0.651	51 0.8	80 06	0	0	2				0.899	0.916	0.896	Ĩ	Ĩ	Ĩ		Ĩ	Ĩ	~		Ĭ	0.836	0.931	0.820	0.907	0.980	0.891
Multi Layer Perception	0.857 0.	784 0.301	0.1 0.5	97 0.9	0	0	5		1	0	0.907	0.962	0.921		Ĩ	Ĩ		~	7	-		ĩ	0.889	0.913	0.789	0.907	0.980	168.0
Nearest Neighbors	0.857 0.	668 0.7	0.2	60 06	0	•	1		0		0.849	0.962	0.921			Ő		~	ॅॅ	0		~	0.863	0.881	0.851	106:0	0.980	0.866
Quadratic Discriminant Analysis	0.877 0	760 0.534	84 0.8	90 0.8	0	0	2	~			0.863	0.916	0.896		Ĩ	Ĩ	1		7	0		~	0.808	0.913	0.882	0.899	0.980	0.807
Random Forest	0.855 0.	784 0.785	85 0.8	82 0.9	0	0	2			-	0.907	0.935	0.925	~	Ĩ	Ĩ	1	Ĩ	7	-		1	0.863	0.913	0.796	0.907	0.980	0.866
SVM - linear	0.857 0	798 0.384	84 0.8	9.0 16	0	0	2				0.877	916.0	0.925	-		0		~	×	•		~	0.863	0.963	0.820	106'0	0.930	0.921
SVM - poly	0.835 0	784 0.817	17 0.8	60 0.9	0	0	8				0.893	0.916	0.921					~	1			-	0.890	0.863	0.851	0.849	0.980	0.896
SVM - rbf		857 0.8	84 0.0	95 0.5	0	0		1			0.599	0.916	0.925	1		1		1	1	٦		1	0.836	0.963	0.789	106:0	0.980	0.871
Retails sociade Nearest Cennoid, Passry Agg	Aggressine Class	uther and Percey	ptron.																									
Table 4.8 AUROC score for 30 L*u*v* in	" at a to a lo	tane feat	ure datasets	for cell lis	line MDA-MD	10-231	I	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	I	
Classifiers	PI P		P4	PS		PT	84	17			P12	P13	P14			17	17	17		17	17		P25	P26	P27	P28	P29	P30
AdaBoost	0.825 0.	851 0.838	38 0.5	43 0.8	0	2		ľ			0.967	0.795	0.906	[⁻		Ĩ	Γ		1	1	[[0.952	0.929	0.947	0.885	0.897	0.947
Bernoulk Naive Bayes	0.904 0.	366 0.3	44 0.9	07 0.9	0		2		Ĩ		0.944	0.692	0.859			1	1	Č	3	-			0.881	0.871	0.946	0.863	0.918	0.946
Dummy Classifier	0.353 0.	500 0.5	500 0.5	00 0.5	0	0	2		1		0.500	0.503	0.400			1	7	-	2	õ			0.464	0.685	0.462	0.604	0.485	0.355
Extra Trees	0.799 0.	632 0.500	0		-	-	1				0.967	0.762	0.929			1		~					506-0	0.500	0.974	0.500	0.917	0.920
Generation Making Barner	0 202 0	PUT O ADT	c	00 000							0.067	2000	1300										9000	103.0	1 000	0 800	0 955	0.017
Gentleret Boostine	0 780 0	140 0.828									1000	10.764	0.616				27						ALC: N	108.0	LTO U	1001	0.918	1000
Matetron Omatum Cheelflor	0 1110	1000									1 047	0.746	0.88.0										0.070	158.0	U OIN	1100	0.016	0.974
These Principalities Andreis	0.000										1 267	012.0	0.016										0.00	110.0	0.016	100.0	01010	0.074
Lateat Lascrumant Analysis	0.890		.		-						104.0	0+/-0	0.900										676.0	122.0	0760	16910	0.938	5/60
Logistic Regression	0	882 0.938		943 0.9	•	-					0.967	0.708	0.906										0.921	668'0	0.946	0.863	0.958	0.974
Mah Layer Perception	0.890	382 0.822	•		•						116.0	0.811	0.851						8.6		-		0.952	1950	9460	0.929	0.938	0.946
	0.890 0	778'0 798	20 27	40 66	-						1060	708.0	0.882						1				476.0	676.0	14/6/0	0.405	816.0	1440
Quadratic Discriminant Analysis	0.935	157 0.922	22 0.5	45 0.9	0 0	•		-			1060	0.802	0.900					-					10.952	0.857	140	0.899	0.938	1960
CULT United	0 000.0		20 10 10								10.067	212.0	0.000										0.001	1.0.1	197.0	CT0.0	800.0	144510
SVM - mole	0 200		100	10 0.0			-				0.038	0.676	0.815										0.076	1CE U	0.07	0.885	0.018	0.974
June - MAS	0.390 0.		22 0.5	60 60	1906 0.87	10.867	0 771	1 0.780	0.733	0.722	196.0	0.762	906.0	0.771	0 698 0	0.932 0	0.938 0.5	0.842 0.946	005.0 9	0.895	516.0	1160	296.0	0.857	2160	0.899	0.938	0.974
Results exclude Nearest Centroid, Passive Agp	Aggressive Clan	other and Proces	ptron.																									

Table 4.9 AUROC score for 30 contrast image feature datas Classifiers P1 P2 P3	D contrast	mage for	PS PS	P4 F	MB	P6 P		8	14 8	114 014	214	P13	P14	PIS	P16	714	P18	14 614	P20 P2	P21 P22	114	164	574	P26	124	P28	P29	P30
AddBood	0.835 0	678.0	6/20										0.830	0.784	0.800										1.000	0.874	0.969	1960
Demous Naive Dayes			0.478	0 1310 0									0.567	0.481	0.500										10400	1760	1400	0.500
Extra Trees			0 500				-				1		0.811	0.697	0.500				88					9454 775	1 600	0.762	0.594	0.932
Gaussian Naive Bayes			0.862 (•			1	~			-		0.839	0.878	0.800				1						1.600	0.897	1.000	0.955
Gradient Boosing	0.891 0		0.879 (•									0.892	0.819	0.784										196.0	0.850	1.000	1.000
Heistrom Quantum Classifier	÷.		0.912 (•			-	~			~		0.839	0.864	0.784						-		Č		1.000	0.945	1.000	246.0
Linear Loscimmant Analysis			SHOUL				3	-					C08.0	109.0	0.800										0660	608.0	COM:0	0.909
Logistic Regression	0 0.000 0		1000										202.D	0.040	0.000				20						2/2/0	676.0	1.000	2006.0
Number of the second of the			0.800					-					0.010	0.016	0.000				202						1 000	0.000	0.001	0.055
Oradicate Discriminant Analosis			0 210								1		0.813	0.768	0.800				317						1 200	0.000	0.976	0.965
R ardom Forest	0.855		0 204										0.865	TUS U	0.800				20						1 000	123.0	1 000	1100
SVM - Inear			0.879	0 068.0	765		1				1		0.865	0.819	0.800										1.000	0.929	0.976	0.932
Vod - MV2			0.845	0.917 0	906	0 1080	0.914 0						0.785	0.804	0.800										1.000	0.905	1.000	0.955
SVM - th	-		0.879 (0.917 0	962			1					0.839	0.784	0.500					6			Ĩ		1.000	0.929	1.000	0.955
Results exclude Neseest Centroid, Passive Aggre	Aggressive Claudite	mains and P.	and Perception.																									
	Contraction of the	Contraction of the local division of the loc	000000000000000000000000000000000000000	100 March 100 Ma															1	1	1	1	1	1	1	1	1	1
Table 4.10 AUNOU Score lot 30 correla	30 COLTEM	Bon Image	on image leature da	itasets lot	ł		Ľ		ľ	ľ	ľ	ľ					ľ	Ľ	ľ	F	ľ	ľ	ľ	ľ				1
Classifiers			2		1	1	1	1			1	ľ	P14	LIS	110	LI.				1		ľ		1	174	1.18	P.19	P30
Adational			<55C D										0,803	00+00	1000	162.0		2							0750	0.731	1110	06/10
Demode Narve Bayes			0050										0.720	1750	00200	0.740									818.0	804-0	0000	0.730
Durinty Classifier			610.0		5									00500	NCC D	0050									0.440	170'0	00000	100-0
EARTH Trees	0.500 0	00500	0.500			22	2						0.007	0.003	00200	10001									0.857	0.500	0.500	0.700
Gaussian Name Dayes			0 019 0		5.5		2						0.010	199-0	0.048	0.016									DCP/D	0.110	7000	0.020
Unament Docenting			410.0										0.100	0.00	0.007	0.010									1000	01210	10.014	0.754
Linese Discriminant Anchuis			0 600				1						0.677	0.481	0.576	141									0.850	0.500	0.577	0.700
T addition II entreaction			0 400		1								0.655	0.481	1250	172.0									0.250	0 500	UCS U	0.703
Midhi I aver Percention			0 785		1	337						1	0.878	0.739	0.790	0.741					, .				0.850	10 017	0.906	0.807
Neurose Neiddhore			2 289.0			07	0						0.700	0.630	0.845	0.914									0.850	0.784	0.000	C1.C U
Onadvarie Discriminane Analysis			D 581		-								0.713	U SUD	A774	0.887									0.840	1 798	0.789	EUX U
Random Format			0 535	0.920	0.843 0	0 202.0	0 867 0	0 795 0.8	0.851 0.858	38 0.635	5 0.851	0.789	0.885	0.679	0.610	0.960	0.935 0	1 005	000 0.5	0.815 0.699	0 742	0.844	0.819	0.881	0.850	0.958	0.969	0 865
SVM - linear	0.750 0	0.502 0	0.500	0	1	22			Ĩ	0			0.748	0.442	0.500	0.710	Ĩ	Ĩ	Ĩ	-		Ĩ	Ĩ	1	0.850	0.500	0.500	0.730
SVM - poly			0.852 (177	1	12	1		Ĩ			~	0.877	0.718	0.681	926.0			Ĩ		0	Ĩ			0.850	116.0	0.851	0.782
SVM - rbf	0.750 0		0.500 (<u>ر</u>	32	ē		Ĩ			7	0.748	0.460	0.500	0.772	Ĩ	Ĩ	1	9	0	Ĩ	Ĩ	1	0.826	0.500	0.500	0.730
Raudis exclude Nearest Centroid, Passive Aggr	Aggressive Cla	witter	and Perception.																									
				A CONTRACTOR OF	- 18	100 1 1 100 1 10 10 10 10 10 10 10 10 10																					1	1
Table 4.11 AUROC score for 30 energy image feature data	30 energy	image fea	fure datas	ets for cell	line MDA	107-01V-V			10	Ľ	1	1	110	Die	DIA	-10	010	10	-0		110	110	1	ľ		910	0-0	010
A delivere	0.071 0	0.000	0.067	1	0 000	016 0	010				1		0.044	0.000	A DW	0.010			1						0.017	0.000	0.0cl	0.000
Remote Name			0.000		100	0 1991	0 000						E to o	0.641	0.5%	2000					5.6				1000	0.690	0.044	0.017
Dummy Classifier			0.500	0.705 0	434 0	0 005 0	200	1496 0.5	1567 0.500	00 0 000	0 0.565	005.0	0.500	0.544	285.0	0.250	0 263 0	500 0	0 200 0.50	SES 0 005 1	35 0.500	0 0.547	0.500	0.638	0.500	0.417	0.505	0.500
Extra Trees		0.500 0	0.500 (-	612	Ĩ	856 0		Ĭ		2	Ĩ	0.877	0.892	0.500	606-0	Ĩ		Ĩ	Ĩ	0	Ĩ		Ĩ	0.944	0.500	0.821	516.0
Gaussian Naive Bayes	0.944 0	0.885 0	0.840 (0	944 1		1 668	Ĩ	Ĭ			Ĩ	0.944	0.867	0.683	186.0	7		Ĩ		0	Ĩ		Ĩ	0.974	0.932	1.000	0.938
Gradient Boosting	0.927 0	0.846 0	0.929 (•	972 6	°	1 126		č			Ĩ	0.944	0,811	076.0	0.962	7		7	Ĩ	0	Ĭ	Ĩ	7	0.921	0.855	156.0	0.958
Helstrom Quantum Classifier	0.927 0	0.846 (0.786 (0	946	Ĩ	921 0	Ĩ	Ĩ	0		Ĭ	0.921	0.814	636.0	186.0	Ĩ		7	2	0	Ĩ	0	Ĩ	0.946	0.955	0.964	0.917
Linear Discriminant Analysis	0.778 0	0.846 0	0.786 (0.893 0	944	Ĩ	0 515		Ĩ		1	Ĩ	0.911	0.867	0.500	0.916	Ĩ		~		0	Ĩ	1	Ĩ	0.867	0.864	0.893	0.896
Lonistic Repression	0.944 0	0.885 0	0.786 (1 568.0	000	Ĩ	921 0		Ĭ			Ĩ	0.944	0.893	0.858	186.0			Ĩ		0	Ĩ	Ĩ		0.974	868.0	0.978	0.938
Multi Layer Perceptron	0.909	0.885 (0.857 (0.893 0	972	~	943 0			2	1	Ĩ	0.944	0.867	6.983	13610	Ĩ		Ĩ	Ĩ	0	Ĩ	Ĩ	Ĩ	0.974	0.838	0.943	0.938
Nearest Neighbors	0 1961 0		0.857 0	0.871 0	916		9 126					~	0.921	0.783	6.983	186.0	Ĩ		Ĩ	1	0	Ĩ		Ĩ	0.920	0.955	0.964	0.938
Ousdratic Discriminant Analysis	0.944 0		0.840	0 893 0	944 0	0 688	1 668		Ĭ			Ĭ	0.944	0.841	0.683	186.0	1		Ĩ		0	Ĩ		Ĭ	0.974	0.932	1.000	0.958
Random Forest	0.927 0		0.857 (0.964 1	000	0 1161	943					~	0.944	0.865	\$16.0	186.0	1		~		0			Ĭ	0.974	0.838	1.000	0.958
SVM - hnear	0.944 0	0.385 0	0.786 4	1 563.0	000		0 668		Ĭ		1	1	0.944	0.867	0.858	136.0	Ĩ		~	Ĩ	0	Ĩ		Ĭ	0.974	0.932	0.964	0.938
Vin - poly			0.786 (0.857 0	H	0 946 0	0 1561	Ĩ	Ĩ			Ĩ	0.838	0.841	6.983	0.897	Č		Ĭ	Ĩ	0	ĩ	0		1947	0.536	0.943	626.0
SVM - rbf	0.889 0	0.500 0	0.500 (0.893 1	000		1 126		Ĭ			1	0.944	0.867	0.858	1961	័	2	1		ໍ		1	Ĭ	0.974	863.0	0.964	0.938
Rendts exclude Nearest Centroid, Passive Agg	1	ive Classifier and Percept	underse																									
1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	A Reserved	the state of the state	A Real Property of the Letter	A LOUGH AND A	and the second se	THE OWNER OF													l	l	l	l	l	l	l	l	l	l
Classifiers	I Id	and Annual Col	P.4	d Harris	No. Coll III	d 94	1 107-01	8		17			p14	pit	p16	71d	ľ	17	Г	17	17	17	17	17	P27	P28	D20	P30
AdaRoost	1 000	0.0M	0.000	-	011	077 0	80t 0		1	1			0.041	0.818	0.840	1000	1		1	1	Г	1	T	1	0.074	0.967	0.045	0.075
Rentold Name Ranet			0.746		110	0 110	0 050			0			1160	0.947	0.867	1001									10.016	810-0	0.076	1 000
Dummy Classifier			0.526		005	0 097	0 107					27	0.490	0.570	0 500	0.461			1	-					0 500	0.604	0.500	0.456
Extra Trees	0.846 0		0.500	0	767 0	0 000	812 0			1		3	0.971	0.947	0.500	1.000			1	1					0.972	0.739	0.960	0.706
Gaussian Naive Baves	1 000	1 000	1967		0 173	0 116	946 0					52	116.0	116.0	0.895	1 000			1						116.0	126.0	0.945	1.000
Gentlers Routine	0 956		0.940		011	0 110	108						0.010	0.865	0.804	0.976									7/8/0	0.890	0.014	176.0
Materian Occupier Charling			0.000		1	- 110	0 910						1 000	0.007	0.067	1 000			1						0.016	0.067	0.076	10.053
There is a subset of the subse			100.0		-	000	-					88	1001	1000	0.000					1					and a	0.078	0.000	1000
Linear Lascimmant Analysis			0,783		179.1		014						1/6/0	1460	0.895	1.000				2					120	8/4/0	CH40	1000
Logistic Kepression	1.000		1.000	1,000	1833	0 1160	010					200	1/6/0	0760	0.879	0001				2					160	166.0	cH(n)	1.000
bruin Layer Perception	0.941	1000	106.0		005	1167	148.4					201	166.0	0.974	0.812	215.0									120	106.0	0/6/0	116.0
Conductor Discriminate Analysis			0.000	0 000 1	000	0 010	110					2.5	1 000	CTO D	0.000	0000			20						100	0.007	0.076	1 000
Pardom Farset			0.950	0 000 1	100	0 (10)	110						0.941	000	0.240	0.078									100	0.967	0.915	1 000
SVM - linear	1 000		1 000	0 000 1	833 0	0 1161	946 0					200	1.000	0.920	0.912	1 000			Ĩ	1					0.974	256.0	0.976	1 000
SVM - poly		616.0	1.000	1.000 0	1877 0	0 1761	0.946 0	100 1261	0.795 0.9	0.912 0.890	116.0 0	0.950	0.941	0.974	0.840	1.000	1 1/6/0	000 01	976 0.5	1.964 0.947	110.0 14	1/20 1	1950	116.0	0.974	0.957	0.969	0.941
SVM - rbf		0.381 0	0.500	1.000 0	3 005	0 00510	916 0						1/6-0	0.920	0.500	0.500						-			0.974	0.957	0.500	1.000
Results exclude Nearest Centroid, Passive	Aggressive Cla	unifier and P.	workphon.																									

the same of the second of the store The second submerses i durit wood it	COTS TOT TO	Kive me	A PERSON AND IN COLUMN AND INC AND IN COLUMN AND IN COLUMNA AND IN COLUMN AND IN COLUMN AND IN COLUMN AND IN COLUM	STATUTE IN	r cell mars	S Person and a second s																						
Classifiers	d la	Ed 1	z	54	P6	1.d	84	2	P10	PII									P21	P22	P23	P24	P25	P26	P27	P28	P29	P30
AdaBoost	0 168.0	920 0.87	S 0.78	1 0.71	0	0.877	0.753	0.366	0.770	158.0		1			1			1	0,792	0.848	0.911	0.784	0.569	0.484	0.774	0.813	0.704	0.897
Bernoull Naive Bayes	907 0.	77.0 277	3 0.83	1 0.63	•	0.693	0.916	0.827	0.590	0.935									0.733	0.762	0.855	0.539	6.653	0.722	0.774	0.650	0.724	0.897
Dumny Classifier	1300 0.	500 0.50	0 0.60	2 0.50	0	0.528	0.500	0.466	0.500	0.516									0.505	0.500	0.429	0.500	0.522	0.406	0.500	0.500	0.500	0.490
Extra Trees	1500 0.	S00 0.50	0 0.50	0 0.50	0	0.500	0.591	0.344	0.500	0.753									0.500	0.654	0.667	0.542	0.500	0.500	0.500	0.500	0.556	0.844
Gaussian Naive Bayes	1,786 0.	10.01	0 0.75	0 0.62	0	0.668	0.851	0.827	1/9/0	0.844									0.813	0.737	0.933	0.564	0.700	0.553	0.664	0.668	0.667	0.890
Gradient Boosting (0.013	695 0.83	3 0.78	1 0.80	•	0.815	0.916	0.921	0.792	0.916									0.875	0.813	0.933	0.782	0.684	0.484	0.824	0.753	0.722	0.921
Heistrom Quantum Classifier	0.826 0.	120 161	2 0.83	1 0.82	•	0.752	0.897	0.397	0.734	0.935									0.795	0.758	0.867	0.756	69910	0.638	0.507	0.692	0.638	0.832
Latest Decrumant Analysis	0 1787	CE.U CUM	C('0 5	10.0	0	711.0	611.0	0/10	76/10	1120									21/10	0./88	006.0	47/10	0,000	0.484	9440	0.006	100010	0.854
Logbar Regression	0.047	CIE/0 000	12/10 E	50.0 F		C11.0	0.010	176.0	28/-0	016.0									0.767	0.610	0.000	111.0	0.000	1040	0.078	0.020	11270	046.0
	0 106	12.0 277	130 E	1 0.65	, 0	0.653	0.871	0 807	0.676	0.962									0 835	0 706	0.877	0.461	0 700	1 553	0.686	0.610	0.660	0.850
Nearest Neighbors	0.913 0.	123 0.813	3 0.76	3 0.73	0	0.732	0.799	0.890	0.713	0.787									0.855	0.841	0.765	0.785	0.569	0.684	869.0	0.672	0.651	0.906
	0 8/61	317 0.87	E9/0 S	1 0.63	-	0.773	0.727	0.390	169 0	0.320									0.730	0.730	0.855	0.621	0.506	0.569	0.719	0.612	0.744	0.738
	943 0.	869 0.85	5 0.83	1 0.59	0	0.835	0.677	0.897	0.742	0.806									0.710	0.756	0.865	0.545	0.481	0.606	0.500	0.240	0.657	0.844
Quadratic Discriminant Analysis	0 1061	151 0.87	S 0.73	1 0.64	•	0.793	0.871	0.835	0.742	0.890									0.855	0.787	116.0	0.725	0.484	0.569	0.769	0.668	0.760	0.844
Random Forest	957 0.	886 0.83	3 0.78	1 0.82	0	0.835	0.825	676 0	0.756	0.890									0.875	0.841	0.933	0.757	0.600	0.484	0.895	0.690	0.538	0.921
	821 0.	841 0.85	5 0.75	0 0.64	•	0.793	0.773	0.835	0.742	0.916									0.813	0.842	0.855	0.699	0.700	0.484	0.698	0.690	0 722	0.914
	0.921 0.	869 0.855	\$ 0.63	9 0.752	2 0.832	0.813	0.825	0.866	0.756	0.774	0.819 0	0.744 0.	0.716 0.7	0.732 1.000	0.757	0.818	0.833	0.825	0.857	0.759	616:0	0.810	0.538	0.584	0.540	0.630	159'0	0.938
	0 883 0	341 0.87	\$ 0.73	1 0.64	0	0.813	0.773	0.897	0.756	916.0	2	1							0.813	0.842	0.855	669'0	0.600	0.484	0.698	0.690	0.722	0.832
and the second is the				-		Contraction of the local division of the loc																						
Table 4.14 Balanced accuracy score for 30 L*u*v* image for	core for 3	L'u'V' Ini	age featury	e datasets	for cell lin	L87-MG	1	į	1														1					
Classifiers		Ed .	z	3		H	24	2	PIO	FII			1						P21	P22	524	124	P15	P26	124	P28	62d	P30
AdaBoost	0.793 0.	\$75 0.93	1 0.86	3 0.57	•	0.770	0.800	0.841	0.704	0.861								2	0.831	0.882	0.815	0.832	0.684	0.735	0.664	0.685	0.804	0.832
Bernoul Naive Bayes	0 01/1	830 0.86	3 0.83	0.76	-	0.835	0.826	0.846	692.0	0.902								-	0.826	0.756	996	0.729	0.853	0.735	0.761	0.635	0.831	0.832
Dumny Classifier	0.500 0.	249 0.50	0.50	0 0.50	-	0.500	0.707	0.500	0.508	0.446							-	-	0.483	0.622	0.500	0.608	0.500	0.439	0.504	0.500	0.500	0.500
	0.500 0.	200 070	0 0.50	050 0	•	0.571	0.500	0.825	0.500	0.787							-	-	0.550	0.789	0.778	0.638	0.500	0.500	0.500	0.500	0.500	0.799
Gamssian Naive Bayes	0,750 0,	510 0.58	1 0.71	3 0.64	-	0.786	0.881	0.821	0.745	0.902								-	0.844	0.804	606-0	0.671	0.669	0.735	0.841	0.660	0.737	0.828
		985 0.950	61.0 0	4 0.84	•	0.814	0.931	0.916	0.769	0.881									0.794	0.796	0.927	0.776	6960	0.610	0.886	0.685	0.941	0,862
Helstrom Quantum Classifier	0.813 0.	150 076.0	3 0.84	4 0.70	•	0.719	0.826	0.925	0.843	0.843								20	0.857	0.882	0.889	0.842	0.922	0.784	0.744	0.660	0.819	0.887
Linear Discriminant Analysis	0.750		0.70	0 0.64		0.671	0.850	0.775	692.0	0.846								22	0.863	0.741	0.833	0.673	0.700	0.625	0.761	0.706	0.731	0.824
Logistic Regression	0.750	750 0.850	0 0.81	3 0.64	3 0.538	0.778	0.831	0.896	0.769	0.902									0.913	0.772	0.889	0.729	0.700	0.610	0.761	0.685	0.731	0.853
Muhi Layer Perceptron	855 1.	Ĭ	1 0.73	1 0.55	-	0.792	0;6;0	6.975	0.763	0.881								-	0.913	0.827	0.944	0.830	0.953	0.735	0.789	0.685	0.979	0.841
Nearest Centroid	0 069'	84S 0.86	3 0.82	6 0.79	•	0,871	0.844	0.875	0.704	0.843									0.794	0.787	0.853	0.695	699'0	0.735	0.737	0.660	0.861	0.837
Nearest Neighbors	1.795 0.	595 0.86	3 0.76	3 0.61	2	0.778	0.813	0.896	808.0	0.822							-	2	0.707	0.811	0.889	0.832	0.753	0.705	0.761	0.765	0.902	0.841
Passive Aggressive Classifier	1.750 0.	135 0.83	9 0.84	4 0.80	Ĩ	0.750	0.826	0.812	0.825	0.798								0	0.894	0.772	0.855	0.497	0.753	0.735	0.636	0.685	0.710	0.799
Perceptron	1752 0.	735 0.81	3 0.85	0 0,50	0 0.654	0/800	0.881	0.774	0.662	0.331								-72	0.802	0.558	606.0	0.452	0.753	0.735	0.595	0.635	0,840	0.816
Quadratic Discriminant Analysis (1,750 0.	735 0.83	1 0.69	4 0.57	1 0.577	0.786	0.813	0.821	0.787	0.902								100	0.863	0.710	0.927	0.694	0.600	0.750	0.726	0.685	0.808	0.857
	1772 0.	16.0 281	3 0.86	3 0.71	4 0.808	0.849	0.881	0.916	0.346	0.561								an a	0.863	0.882	0.889	0.821	0.753	0.750	0.506	0.685	116 0	0.832
	0 0112	750 0.90	61.0 0	4 0.57	1 0.577	0.764	0.831	0.846	0.769	0.881							-	27	0.913	0.772	0.833	0.752	0.600	0.735	0.778	0.685	0.846	0.853
	0.835 0.	360 0.300	0 0.76	3 0.610	0 0.748	0.835	0.863	0.828	0.668	0.784	0.784 0	0.575 0.1	0.916 0.6	0.606 0.843	3 0.756	0.917	0.730	0.775	0.876	0.749	0.778	0.764	0.753	0.610	0.789	0.685	0.843	0.749
SVM - rbf 0	1750 0.	750 0.850	0 0.54	4 0.57	1 0.615	0.756	0.831	0.846	167.0	0.531	1	121					1	1	0.913	0.772	0.944	0.729	0.684	0.625	0.778	0.685	0.846	0.828
A REAL PROPERTY OF A REA	and the second se		and contraction of	00-000	The second s	Contraction of the																						
Table 4.15 Balanced accuracy score for 30	core for 3	contrast image lea	age leatur	e datasets	for cell in	e UST-MG	2	1										Ľ										
Classifiers	-	C4	-	5		H	2	-	PIO	III	1	1			T		T	1	121	111	21	124	2	P.20	124	P.28	P.29	P30
AdaBoost	1.89/	560 00V	0000 0	0.80	0	0140	0.803	0.887	67670	1760			10					-	0.685	0.890	0.780	0.820	18.0	108.0	2010	0.897	0.840	0.610
Demoute Name Bayes	0 0191	100 037	660 L	1.0.0		816.0	168.0	ICR'D	1.885	106-0									176.0	0.844	0.843	198.0	1000	108.0	707.0	0.8.0	006.0	0.120
Durinty Cassibilit	1900 U	200 0.20	02.0 0			0.048	0.587	10014	1000	0.015								202	0.500	0.667	0.449	0.270	0.504	005.0	0.500	0.500	0.500	11910
EAUS LIVES	1 100 1	1000 000	NC. N - N	00'n 0		004.0	10C/0	CC0.0	0000	2000								200	0.000	100.0	100.0	0.06.0	201.0	0000	005.0	0.200	0.620	110/0
Gentleret Boostine	1 101		12.0 1	200.0 E		0.017	136.0	1000	836.0	1000									283.0	1000	10.00	0.814	0.845	012.0	107.0	10110	113.0	0.787
Haletrom Ownedum Charifier	1774	190	130 1	10.00		0.012	0.861	0.857	0/0/0	1001									0.007	0.818	0.840	0.887	TUDU	0.950	0.780	0.635	0.863	0.041
I more Discriminant Anshuis	0 1951	110 053	1970 1	0.63.0		0.744	0.740	0.857	0 Rak	174.0									0 744	010.0	1090	0.870	0.716	P CR D	0.647	204.0	0.600	0.806
T and the Descention Analysis	U UIL		1000 0 0	100 0 0		0.010	192.0	0.001	1011	10.01								222	0.000	0.600	111.0	110 0	0.716	TLA U	0.498	0.611	0.660	0.000
Logistic Kegtessam	0000	720 0.35	K0'0 4	noin n		0.918	19/10	10800	1460	1/2/0	2016							20	C687.0	0.830	15/10	0.614	0.755	1.5.4	0.055	108/0	0.00.0	0.808
Num Layer Perception	0 CCE/0	04-0 0C4	4 0.18	1 0.01		V(8).0	10.031	1000	1400	1060									0.049	0.010	108.0	799.0	0.50	0.879	0.710	CC0.0	C0/ .0	0.110
	SCC D	130 050	1080	0.80		0.830	0.881	0.847	1071	1 262								-	11.2.0	0.876	0.872	0.821	0 081	0.230	0.710	CES U	0.750	0.841
Province Associations	0 10L	10.0 000	100 N	12.0		0.041	10010	1000	01740	0.640									0.014	0.000	1.601	0.617	1040	1.614	0.570	0.010	002.0	0.000
Passive Aggressive Cassiller	0 C6/1	19'0 000	1000 A	0.0	5 4	10970	201.0	108.0	0.748	1.007								22	10.0	708.0	760.0	0.014	0.000	1960	870.0	0.800	0.100	0.000
Conducto Discriminane Andreis of	1 10	0.00	01.0 0	190		0.770	0.000	1/20/0	1960	1000								252	0.690	002.0	Las o	0.961	0.610	1001	887 U	1757 0	0.400	0.781
Citate and Longituments Analysis	1 000	000 0100 0100	00'0 v	10 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	0000 0	0.010	0.000	1000	100 0	1000								840	200.0	0.044	74010	100.0	010/0	1.605	0.751	1.61.0	0.000	1010
CUMP Reserve	100	70470 01400	00.0	14.U 0	5 6	012.0	100.0	100.0	10070	1050									289.0	0.946	0 744	118.0	11 8.45	inera u	0.408	0.651	0.700	0.904
	0.813 0.	950 0.92	7 0.84	4 0.812	2 0.918	0.918	0.863	0.857	0.923	0.835	0.864	0.877 0.	0.871 0.7	608/0 662/0	9 0.857	0.780	0.899	0.813	0.849	0.7955	0.899	0.851	0/6/0	0.790	0.668	0.780	0.900	0.702
SVM - rbf (0.813 0.	900 0.889	9 0.70	0 0.73	-	0.918	0.831	0.832	0.962	0.871	1	2		- 1					0.885	0.945	0.710	0.811	0.845	0.824	0.688	0.851	0.700	0.808
a second second	-	and a second sec	and the second s		1	Concession of the local division of the loca																						
Balanced accuracy	SCORE FOR 30	correlation	image feat	fure datas	ets for cell	100 L87-M	De De	8	010	110	10				Ľ		Ľ		140	640	110	P14	210	P14	510	ard.	010	D10
AdaBoost	750 0	794 0.74	4 0.50	0.76		0.700	0,769	0.842	0.710	0.670	0 744 0			1	ľ	1	1	Г	0.726	0.732	0.893	0.631	0.483	0.638	0.677	0.878	0.734	0.724
Bernoulli Naive Baves	1781 0.	851 0.65	5 0.54	5 0.50	0	0.697	0.551	0.688	0.726	509/0	0.644 0						1	27	109/0	0.632	0.647	0.661	0.500	0.669	0.520	0.621	0.685	0.803
Dummy Classifier	1500 0	190 0.61	5 0.50	0 0.43	0	0.537	0.505	0.500	0.500	0.547	0.500	67			Ĩ		1	1	0.500	0.440	0.467	0.552	0.390	0.500	0.354	0.500	0.500	0.500
Extra Trees	1500 0.	S00 0.50	0 0.50	0 0.50	•	0.528	0.500	0.500	0.500	0.500	0.500	27			1			1	0.500	0.622	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.710
Gaussian Naive Bayes	1,700 0.	753 0.70	65 0 59	1 0.64	-	0.699	0.613	0.665	269.0	0.587	0.611 0	17			Ĩ			100	0.695	0.707	0.752	0.624	0.500	0.669	0.635	0.729	0.702	0.832
Gradient Boosting	800 0	864 0.80	0 0.67	0 0.83	0	0.753	0.952	0.842	0.616	0.773	0.867 0	17			Ĩ		1	1	0.781	0.728	0.918	0.725	0.545	0.653	0.820	0.755	0.750	0.749
Heistrom Owantum Classifier	913 0	10 252	2 0.65	7 0.67	•	0.781	0.852	0.809	0.686	0.737	0.855							10	0.765	E59 D	0.920	0.677	0.640	0.644	0.725	0.736	0.753	0.724
Linear Discriminant Analysis	0.531 0.	389'0 624	8 0.57	3 0.57	0	0.728	0.618	0.598	0.695	0.545	0.677 0	83			~		1		0.609	101.0	0.690	0.528	0.500	0.653	0.585	0.593	0.602	0.774
Logistic Regression (1.531 0.	20 624	\$ 0.59	1 0.52	0	0.728	0.618	0.598	26910	0.545	0.644 0	3					1	7	0.609	0.707	0.690	0.528	0.500	0.653	0.585	0.593	0.602	0.744
	1231 0	851 0.74	4 0.73	69'0 6	•	0.753	0.753	0.865	0.757	0.737	0.821 6	12						-	0,664	0,719	0,878	0.725	0.636	0.584	0.834	0.612	0.833	0.703
Nearest Centroid	0.844 0.	878 0.69	2 0.65	7 0.67	0	0.730	0.683	0.764	0.677	0.737	0.742 0	2					1	1	0.636	0.682	0.755	0.622	0.498	0.675	0.626	0.659	0.672	0.891
	0.813 0.	00.0 080	2 0.76	1 0.69	0	181.0	0.801	0.320	0.702	0.857	0.877 6	56			~			67	0.636	0.753	0.898	0.756	0.744	0.638	0.806	0.626	0.868	0.703
: Classifier	0.583 0.	878 0.50	120 0	3 0.52	0	0.592	0.567	0.642	0.567	0.445	0.688 0	2			~	0	7	1	0.749	0.565	0.673	0.561	0.636	0.644	0.500	0.476	0.435	0.703
Perceptron (1857 0.	846 0.69	4 0.60	6 0.65	0	0.620	0.559	0.632	0.600	6.673	0.765 0	2			~		1		0.644	0.682	0.630	0.560	0.500	0.500	0.562	0.654	0.484	0.762
Quadratic Discriminant Analysis	1.681 0	75.0 0.67	1 0.59	1 0.643	3 0.710	0.697	0.602	0.586	0.781	0.630	0.677	1627 0.	0.702 0.6	0.628 0.644	0.532	0.649	127.0	0.878	0.640	0.762	0.753	0.662	0.562	699.0	0.685	0.528	0.618	0.719
Random Forest	0 800	0.706	0.00	0.00	•	0.733	0.965	0.870	2600	0.735	0.811							20	0.757	0.705	0.918	0.705	202.0	0.684	0.750	0.787	108.0	0.782
SVM - Intear	0020	0//0 08/	0000	0.00		0.728	0050	8600	C6010	202.0	110.0	993 						20	115.0	10/10	06010	125.0	005.0	0000	0000	1450	0.002	0.774
fund - sex c	0 0051	010 010	090 9	0 0 20		0.782	120.0	0.508	0.656	0 565	0.577 0	5.5							0.577	202.0	0.690	0.600	0 500	005.0	0 400	5050	0.607	0.774
141 Mar 10 10				ALC: No.			14.11.1	Arrest	and a	Viete	100 L								1100	1000	lever.	Preve.	Press.	Post	W.cvv	Ware	N.vrm	1000

Table 4.17 Balanced accuracy score for 30 energy image feat	score for 30	energy im	age featu	re dataset	s for cell li	ne U87-M	U													li									÷.
Classifiers	d Id	Pa Pa	P	A	-	2	-	7		7	P12	P13	P14	P15			1	7		1	1	7		7	1	P28	P29	P30	
AdaBoost Remode Native Ranae	0 126.0	50 0046	10 10	0 703	0 C						0.620	0.748	026.0	0.538	0.0											0.873	0.700	176-0	
Dumny Classifier	0.560 0.	500 0.2	28 0.	0 005	0.5	500 0.5	518 0.5	0.500 0.500	005-0 0	0.500	0.500	0.500	0.578	0.659	0.500 0	452 0	0.500 0.	0.438 0.46	1463 0.538	8 0.500	0.500	665.0	0.500	0.382	0.500	0.490	0.375	0.500	
Ettra Trees	0.500 0.	542 0.1	00 00	00 00;	0	•	2	~		1	0.500	0.500	0.500	0.500	0			~ _		~	-	č				0.500	0.500	0.700	
Gaussian Naive Bayes	0.944 0.	958 0.5	0 +86	137 0.	0	0	20				0.838	0.849	0.869	0.906	•							Ĩ.,			1	0.837	0.900	0.866	
Gradient Boosting	0.8/1		00510	0.	0 0	•		-			CC60	0.800	0.920	2260	0.4			23				-				188.0	0.800	016:0	
Heistrom Quantum Classifier		1.895 U.S	0.784 0.1	-0 115	0 0						1550	0.915	0.630	00610	0.9											108.0	0060	0.910	
Latest Locannan Analysis 1 seites Barrarian	0 0 0 0	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	1 000 T 100				3				110.0	0.600	176.0	276.0											22	018.0	0.600	0.841	
Muth Laver Percentron	0 110		984 0.9	-0 SE6	0						0.911	0.778	0.841	866.0				27								0.519	0.900	0.946	
Nearest Centroid	0 946 0	010 016	922 0.1	1/1 0	0	0	1			1	0.853	0.856	0.817	0.906	Ĩ			1		Ĩ				1	7	0.816	0.953	0.841	
Nearest Neighbors	0.944 0.	918 1.0	000 0.	NS5 0.	0	0	Ĩ			1	0.955	0.814	0.841	0.922	Ĉ	0	1	Ĩ		Ĩ		ĩ	Ĩ	0	2	0.822	0.984	1/6:0	
Passive Aggressive Classifier	0 606.0	960 035	984 0.1	836 0.	0	0	Ĩ			1	0.833	0.800	0.879	0.706	°		1	Ĭ		Ĭ				1		0.840	0.800	0.816	
Perception	0.964 0.	940 010	0.800 0.5	968 0.	710 0.9	38 0.9	2	~			0.838	0.849	0.670	0.922	Ĉ		7	7		Ĭ		1	Ĩ	Ĩ	9	0.756	0.800	0.950	
Quadratic Discriminant Analysis	0.889 0.	958 0.5	0.984 0.1	137 0.	793 0.9	38 0.9	3			1	0.633	0.849	0.869	0.891	Ő		1	5		č			Ĩ.			0.857	0:900	0.800	
Random Forest	0.944 0.	960 1.0	000 000	952 0.	752 0.9	38 0.9	9				0.933	0.800	0.920	0.984	ě	0				Ĭ		~				0.531	0.800	056.0	
SVM - linear	0.927 0.	50 095	984 0.5	0.0	835 0.9	20 0.9	Ĩ				0.911	0.814	0.920	906.0	•			Ĩ		Ĩ				0	2	0.840	0.900	0.841	
VM - poly	0.927 0.	0.938 0.9	0.584 0.1	134 0.	710 0.9	20 0.9			Ο.		0.838	0.828	0.903	0.922	0					Č		č				0.551	006:0	0.841	
SVM - rbf	0.927 0	960 036	84 0.5	03 0	835. 0.9	20 0.9					0.838	0.814	0.903	0.906 (0							1				0.840	0.900	0.841	i.
Table 4.58 Released accuracy score for 30	cente for 20	homory	maley image	fasture d	stacate for	coll line 7	STAG	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	i.
Classifiers	d Id		P.	A	P6	Ld	PS	8	01d	17	51d	P13	P14		17		1d 18	0 P2(17	17	17	17	17	[7	17	P28	P20	P30	i.
AdaBoost	0 031 0	970 079	0 03	0 858	-	0	0	Î	1	1	0.921	0.837	0.878	1	1	1	0			1	1	1	Γ	Ĩ		0.864	1.000	1.895	
Bernoull Naive Baves	0.931 0	970 019	952 0.	744 0.	7	0	0	.0			0.871	0.854	0.833		~		0		1	~	-			Ĩ	1	0.840	169/0	0.816	
Dummy Classifier	0.500 0.	0.333 0.1	0 005	500 0.	0	0	•	0			0.500	0.500	0.365				0	Ĩ	Ĩ	~		Ĩ	Ĩ	Ĭ		0.500	0.500	0.466	
Ettra Trees		0.750 0.4	125 0.5	900 00	0	0	0	0			0.500	0.500	0.500		1		0	Ĭ	Ĩ	~		Ĩ	Ĩ	Ĩ	2	0.500	0.500	0.658	
Gaussian Naive Bayes	0.931 0.	50 586	0 690	0 698	1	000 0.9	0	0	2		0.921	0.837	0.918				0	Č	ૼ	~		Ĩ	Ũ	Ĩ	2	0.902	1.000	0.868	
Gradient Boosting	0	985 0.1	0.844 0.1	858 0.	-	0	0	0			0.921	0.899	0.877		Ĩ	0	0	Ĭ	ĩ	~		1	Ĩ	~	2	0.822	0.833	0.895	
Heistrom Quantum Classifier	0.931 0.	985 1.0	000 01	834 0.	1	0	0	0			0.921	0.878	0.898		0		0		~	~		~	Ĩ	č	2	0.831	0.946	0.947	
Linear Discriminant Analysis	0.931 0.	50 586	969 0.1	0 698	698 1.0	00 0.8	•	•			0.921	0.857	0.918				0	Ĩ	Ĩ	~		~	Ĩ	Ĭ	1	0.902	1.000	0.895	
Logistic Regression	0.931 0.	985 0.5	696 01	03 00	636 1.0	00 0.8	2	0	Ĩ	0	0.921	0.831	0.918		Ξ.		0	0	ĩ	~		Ĩ	Ĩ	7	2	0.864	0.944	0.868	
Muhi Layer Perceptron	0.931 0.	50 5850	696 0.1	10 10	636 1.0	00 0.9	•	°			0.921	0.861	0.918				0	Ŭ	Ĩ	~			Ĩ.	Ĩ	с. 	0.\$40	0.927	0.921	
Nearest Centroid	0.931 0.	50 586	0 9/4	151 0.	851 1.0	00 0.9	0	°	Ĩ		0.921	0.875	0.920		~		0	č	Ĩ	~		~		Ĩ	2	0.840	196 0	0.865	
Nearest Neighbors	0.931 0.	50 586	696 01	906 0.	716 0.9	64 0.8	•	0			1/6/0	0.878	0.898		~		•		Ĩ	~		~		Ĩ		0.902	0.944	0.947	
Passive Aggressive Classifier	0.931 0	985 0.9	0 694	0 698	653 1.0	00 0.9	610 016	920 0.92		1	0.921	0.804	0.878		Ĩ.,		a		<u></u>	~						0.878	1,000	0.895	
Perceptron	0.931 0.	585 07	0.938 0.1	11 0	608 0.8	57 0.8	0	0			1/8/0	0.668	0.897				0					-				0.822	1.000	0.684	
Quadratic Discriminant Analysis	0.951 0	50 586	606	606	823	00	•				126.0	0.878	816.0				•		20							0.902	1.000	0.868	
Random Forest	0.931 0.	0.985 0.5	0.938 0.1	111 0	053 1.0	00 03	19 0.9	060 020			126.0	198.0	0.938				• •		20							0.843	0.539	0.895	
O V DI - MDCM			0 400 U		0.0 0.0	20 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	200	2000 00			1220	0.001	0.949				9.9			-						0.619	10.0	0.640	
SVM - thf			50 6960	0 500	0.0 530.0	8.0 62	60 06	82.6.0 50	E 0.842	0.938	0.921	183.0	816.0	0.796	0 6460	0 946	0.364 0.1	888 0.9	935 0.929	9 0.865	0.897	10807	0.753	0.938	0.958	0.902	0.944	0.868	
																					Ľ								
Table 4.19 AUROC score for 30 RGB image feature datasets	30 RGB inta	ige feature	datasets	for cell lin	ine US7-MG																								
Classifiers	PI P	2 P.	h	h	-		٦		7	7		P13	P14		-	1	1	-		7		-	7	-	P27	P28	P29	P30	
AdaBoost	0.863 0.	920 076	133 0.	731 0.	0	Ĩ			Ξ.	1		0.721	0.584		Ĩ.,	Ĉ	Ĩ	Ĩ	Ĩ	~		°		Ĉ	0.807	0.813	0.649	0.897	
Bemodi Naive Bayes	0.907 0.		10 11	10 10	636 0.7	780 0.6	0.093 0.9	0.827	0 0 2 9 0	0.935	0.763	0.738	0.709	0.793	0 385 0	0 101	713 0.1	0.7	EET.0 227.	0.762	0.855	0.539	0.653	0.722	0.774	0.650	0.724	0.897	
Durniny Classifier	0.512 0.	200	.568 0	183 0.	•		20	-				0.500	0.453			•		•	-			0		9	0.500	0.487	0.577	0.500	
Extra Trees	0.043	0 000	00200	0 000	0.0	С.)						H	0.500			0.4		•	7			0.4		9.6	0.500	0.500	0.500	0.500	
Canissian Name Bayes	02/0	200 0.2	0.710 U.	0 00								1/0.0	01/10											P. 1	0000	0.008	/00:0	0.890	
Gradent Boosting	0.915 0.		0 76/0				0					0.811	0.761			•		-				• •		•	C68'0	0.735	0.722	0.859	
Heistrom Quantum Classifier	0.935 0.		223 07	10 10								10.044	0.098			•								•	0.769	0.735	0.658	0.914	
Latest Locationatil Attaiyats			U 222 U	in nci			8					0,135	1023											2	960 n	0000 n	10010	0.684	
Logistic Kegression			0.813 0.	00 00	0			-				0./11	01/10			0.1								9.4	0.698	0.000	0.760	856.0	
Muth Layer Perception		0.085	0.805	00			-					11.0	0.096			0.1									0.824	C 607.0	0.722	0.882	
Nearest Neighbors			0.813 0.7	10	•		20					0.811	0.09%									0.1		•	0.698	0.795	1590	0.900	
Quadratic Discriminant Analysis	0.907 0.	0.851 0.1	0 675	161	•							0.711	0.030			•			1					•	0./09	0.608	0./60	0.844	
Random Forest	0.935 0	386 0.1	0.833 0.	181 0.	•		-					0.788	0.709			•		-	2			0		-	0.824	0.753	0.593	0.914	
SVM - Intel	0 17210		0 558.0	0.00								1/0/0	01/10											•	0.698	0,048	0.722	0.914	
SVM - DOV			0./05 0.	00	0 1							110.0	500.0			0				2					0.540	0.712	0.220	866.0	
D V 261 - 1101 0.002	anine Clas	0 procession	andered	.n n:o				1	1	1		1/0/0	01/10		1	2				1	1	1		2	0.000	0.040	0.122	0.054	
and a local state of the second state of the s																													
Table 4.20 AUROC score for 30 L*u*v*	30 L*u*v*1	image feature data:	ire datase	ts for cell	line US7-A	IG																							
Classifiers	P1 P	2 bi	P4	P	-	2						P13	P14			1		7	P20 P21	P22						P28	P29	P30	
AdaBoest			0.	Ĩ	•	0						0.627	0.807			~	2	÷.	20	-			ĩ	1	2	0.735	0.843	0.832	
Bernoull Naive Bayes		130 01	0	\$26 0.	0.0 0.0	692 0.8	835 0.8	0.826 0.846	6 0.769	0.902	0.501	66510	0.803	0.685	0.902 0	0.655 0	0 5681	0.728 0.7	23	~	0.946	6.729	0.853	0.735	0.761	0.635	183.0	0.832	
Dumny Classifier			0	Ĩ	0	0	2					0.500	0.518		٦,	ĩ	1	Ĩ	20	6			Ĩ	7	2	0.500	0.532	0.438	
Extra Trees	0.500 0.	0.500 0.50	0 005-0	Ĩ	9	0	2	Ĩ	1	1		0.500	0.588		ĩ	Č	7	7	8	1			Ĩ	7	7	0.500	0.500	0.765	
Gaussian Naive Bayes	0.750 0.	610 015	0	Ĩ	0	0	2					0,632	0.710		0	Ĩ	7	Ĭ	3				ĩ	0	7	0,660	0,737	0.828	
Gradient Boosting	0.772 0.	50 586	0.931 0.	Ĩ	0	0	2		0			0.654	0.719			~	ста 	<u> </u>	20				1			0.774	0.941	0.837	
Heistrom Quantum Classifier	0.855 0.	955 0.5	0 1860		0	0	3					0.632	0.769			ĩ	1		2	3			Ĩ.,		2	0.685	0.831	0.787	
Linear Discriminant Analysis	0.750 0.	750 0.1	0.500 0.7	Ĩ	•	•	2		0			0.604	0.681		0	ĩ		~	5	Ĩ			ĩ	0	8	0.706	0.731	0.824	
Logistic Regression	0.750 0.	750 0.1	1.850 0.1	Ĩ	•	0	7	ĩ		0		0.604	0.656			Ĩ	1	1		-				1	1	0.685	0.731	0.853	
Mahi Layer Perceptron	0.855 0.	1625 0.1	10 9/3	Ĭ	•	•	2	ĩ				0.605	0.774			~		1	2				0	2	7	0.660	116:0	0.891	
Nearest Neighbors	0.792 0.	750 052	620 0	763 0.	9	0	2		0			0.656	0.857			~	2	-	55	2			Ĩ			0.765	0.902	0.857	
Quadratic Discriminant Analysis	0.750 0.	735 0.1	\$31 0.4	0 166	0	0	3			2		0.604	0.735			~	0	~		2						0.685	0.808	0.857	
Random Forest	0.772 0.	860 0.5	0.950 0.1	10 10	0	0						0.656	0.744			~		~		-					2	0.635	0.902	0.807	
SVM - linear	0.750 0.		300 0.	10 16	•	•	1					0.576	0.681		-	~ ·		~	23		-				-	0,685	0.846	0.853	
SVM - poly	0.835 0.		0.900 0.	103 0.		0 1						0.005	0.735					-	20							0.618	0.692	0.749	
SVM - rbf	0.750 U	500 0.1	0.850 0.1	544 U.	0	-		1				0,032	120 0			1										CEO 0	0.808	0.833	i.
Kestats extrate rearest centroid, Paratre Agg	Appression Line	WITH AND PHILES	-boost																										

Table 4.21 AUROC score for 30 contrast image feature data	50 contrast	unge featu	ire dataset	is for cell li	ne US7-M	0	1																					
Classifiers	PI P.	Fd 7	P4		1	7	1	8	P10	PII	P12	P13 P	Pl4 Pl	P15 P16	714	PIS	P19	P20	P21	P22	P23	P24 P	P25	P26 P2	P27 P2	P28 P2	P29 P3	P30
AdaBoosz		6.0 0.0	64 0.50		•	Ĭ	0	0.921	0.923	0.921		24	2				0.877	0.944	0.835	0.830	69/.0			20	26	20		210
Bernoult Naive Bayes	6 . 4		0 4	950 0.84	0.875		0.4	0.857	0.885	1060		2					1/2/0	0.781	0.921	0.844	0.843			2.2	263			2 2
Dumity Cassiner	-0 -00-0	20 W020	20 760			10	5 4	106.0	005-0	002.0		107					208.0	0.500	0.600	0000	1000		202		333	22		000
Gaussian Narive Bayes						1	0	0.857	0.921	0.835		22					0.885	0.750	0.835	0.851	0.731			1	100	1		200
Gradient Boosting			0				0	0.921	616.0	0.921		2	2				0.842	0.944	0.885	0.890	0.843				88	22		Ci ci
Heistrom Owantum Classifier			0		a	Ĩ	0	0.857	0.885	0.907		10	2				0.877	056-0	0.871	0.874	0.861	1		1	923	22		18/
Linear Discriminant Analysis			0		0	Ĩ	0	0.857	0.846	0.764		1	6				0.834	0.700	P-764	0.725	0.692	1			03	-		908
Logistic Regression	0.730 0.1		0		•	~	0	0.857	0.941	178.0		2	2				0.899	0.800	0.885	0.890	0.731			2	55			806
Muhi Layer Perceptron	0.835 0.5	0.900 0.927	0		•	Ĩ	0	0.857	0.385	0.907		2					0,877	0.900	106.0	0.826	0.843			2				808
Nearest Neighbors			33 0.80	00 0.77	•	Ĭ	0	0.857	0.923	0.849		22					0.863	0.850	0.835	0.826	0.881			2	2			782
Quadratic Discriminant Analysis		0.889	89 0.7	00 0.62	•		0	0.857	0.962	1050		33	3				0.921	0.750	0.885	0.780	0.692		-	22	23			181
Random Forest			64 0.7	50 0.79	•		0	0.857	160	206.0		23					1150	0.781	0.885	0.914	0.881				20	88		182
SVM - Imear		0.1	33 0.60	00 0.60	0 1		0 1	0.857	0.885	1/8/0		201					0.877	0.750	0.585	0.945	0.710			28	263	96		808
Van - poly	0.730 0.1	0.350 0.7	778 0.6	60 0.625 an	SE8.0 21	0.724	0.731	0.857	0.885	0.835		20					0.899	0.800	0.871	0.866	0.899				20			8
2 M - 101 0 - 0 - 0 - 0 - 0 - 0 - 0 - 0 - 0	0 CT07	0	00 0.00	0.00			2	760%	167.0	1/0/0						1	1/6/0	0000	0.200	0/6/0	CT070		T	1				000
Property Concepts - Network - States of a state of	Allound Call		mont																									
Table 4.22 AUROC score for 30 correlat		on insee feature da	sture data	tests for cell	I line L'87.	MG	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l
Classifiers		1d	Pd	M	bi	54	M		014	110				17		ľ	01d	070	14d	644	110	17		17	r	Г		
AddRess	0.750 0	0 244 D 65	c		1	1	0.760		0 520	D CON	ľ	T		Г	T	Г	0.744	0 734	0.710	0.722	1 217	Г	T	Г	1		Γ	PH4
Removed Native Ranses	0.781 0.1		ic				0.551		0.756	0.605							0.614	1890	0.601	0.623	1.647				1			the second
Dommy Classifier							0.470		0.170	0.588		25					005.0	865.0	1.001	165.0	0.400				1			No.
Fare Tease			C		0		0.500		0.500	0 500		25					0 400	0 500	0 500	0.003	0.500				8			100
Gameian Narive Bareet		0.753 0.706	0		0	0	0.618		0.695	0.587			-				0.690	0 820	0.695	0.707	0.752				10	1		-
Gradient Boosting			0		0	0	0.952		0.562	0.815		25	1				0.702	0.897	0.781	0.757	0.815			1	ॅ			69%
Helstrom Quantum Classifier	0.913 0.1		0	17	0	0	0.739		0.734	0.758		102					0.813	0.858	0.765	0.653	0.918			100	್			151
Linear Discriminant Analysis	0.531 0.	0.773 0.688	0	573 0.57	0	0	0.618		569/0	0.545		83	9		1		0.697	0.878	0.609	101.0	0.690	0		9	ੱ	2		774
Legistic Regression	0.531 0.	0.773 0.706	0		0	0	0.613		\$69.0	0.545		9			8		169/0	0.878	0.609	107.0	0.690	1		~	č	~		Ŧ
Muhi Layer Perceptron	0.800 0.1	0.916 0.690	0	137 122	0	•	0.720		0.750	0.755		85	2				0.754	0.916	0.726	0.728	0.755			1	ੱ			774
Nearest Neighbors	0.831 0.	780 0.762	0		0	0	0.820		0.702	0.777		17	9			1	0.700	0.897	0.695	0.632	0.896			7	Ĩ	Ĩ		782
Quadratic Discriminant Analysis	0.681 0.	753 0.671	0		0	0	0.602		18/.0	0.630		80					0.727	0.878	0.640	0.762	0.753	Ĩ		87	ੱ	-		611
Random Forest	0.800 0.	0.734 0.651	61 0.6	0.806	0.855	0.753	0.968	0.876	56970	0.815	0.833 (0.627 0.	0.727 0.7	0.713 0.833	0.753	0.734	0.670	0.897	0.726	0.728	0.898	0 6+1.0	0.625 0	0.669 0.7	0.756 0.7	1.741 0.8	0.108.0	0.782
SVM - linear	0.500 0.	799 0.482	82 0.66	08 0.50	0	0	0.500		0.500	0.585		10					0.727	0.813	109.0	0.707	0.585			1	~	Ĩ		774
SVM - poly	0.831 0.	0.753 0.633	33 0.6	25 0.78	0	0	0.621		0.640	162.0		2	0				0.700	0.916	0.734	0.703	0.753	1			Ĩ			956
SVM - rbf	0.500 0.	799 0.669	69 0.50	00 0.50	0 0.500	0.782	0.583		0.656	0.565		3				1	0.500	0.500	0.577	0.707	0.690			~	័	1		774
Rendts exclude Nearest Centroid, Passive Age	Aggreening Class	effor and Perceptron	uptron.																									
The state of the second s	A LOUGH AND AND	COLUMN DE LA COLUMN	A Manual and	Carlo Commence	TION NO.		l	l		l	l	l	l			l	l	l	l	l	l	l	l	l	l	l	l	I
Classificare	DI CHEFEN	nage leatur	e datasets	De cell III	2	-4	ad	8	010	114			10 10	A DIA			010	0.cd	144		110	17	Ľ	14 24		ca	Ľ	9
A deDirect	0 100 010	- U0	100 000				0.467	0.001	0.804	1 000	T						0.000	1 1000	0.730	0.000	0.016	1						240
AGADOOSI	s e			P 4			100'0	206.0	100.0	1.000		19	5 6				0.000	1.000	001.0	0.0.0	016.0			10	1			9.3
Denom Nave Dayes	0 200	0.400 0.400		005 U 005	U05.0 0	0.500	1000	0.446	185 U	005.0	0.500	0 0001	5 U U05 U	14C	005.0	005.0	0.500	0.500	0.500	0.590	1/0.0	0 10071	0 0050	CO UUS (FU 7121	0.0 ANL	Contraction of the	140.0
Estra Trans	i e						0.500	D.AGA	0 463	0 500							0 577	0 500	0.500	0.500	0.500				1			
Garreign Naive Ranee				9			0.861	69.60	0.807	10 01		197					0 836	1 000	0.872	0 818	0.810							No.
Gradient Booding				1.0	-		0.669	0 971	1220	0.918	200		-				106.0	0 580	C12.0	0.855	0.851				7			Line Line
Haleton Omentum Chevillar							0.011	1 000	0.905	0 880		327					10.076	0.080	0.000	0.818	0.858							ALC NO
These Physics Andreases Andrease			i e	2 C	5 6		0.776	0.0.0	0.840	0.017	-	32	5 6				APR 0	0.486	0.614	0.000	0.000							
T office in second company			2.4		5.0		0.000		and a	1120		20	3.6				0.000	0.000		0.010	0.000				਼			010
Multi T user Descention			100 100	10.0 0.75			0.816	0.020	0.804	0.475		225					0.011	0.080	0.612	0.876	1.007							E S
Navaar Maldhoor				01.0 01.00			140.0	1 000	1000	10011		202					1 202	0.000	CT0.0	0.300	1.817							
Conducto Discriminant Analosis			21 U 23	21 0 75			0.816	176.0	0.070	0.944		863					0.853	1 000	0.916	0.787	1 8 4 8							
Random Forest			000 0.00	58 0.75			0.813	0.000	1.877	0 947							0.044	1 000	0.811	0.845	0.016							050
SVM - hnear	0 7220	0.960 0.984	84 0.9	ES.0 SE	0	0	0.778	6460	0.835	0.972			0				0.598	0.958	0.813	0.858	0.858	0	Ĩ		1	1		112
via - poix			1.000 0.94	68 0.75	12 0.920	0	0.778	0.885	0.835	0.944	1	22	0				0.944	0.833	0.835	0.837	0.878		Ĩ	Ĩ		Ĩ		It
SVM - rbf	27 0	960 0.984	84 0.90	03 0.83	0	0	0.853	0.979	0.835	0.972		3	0	0			0.898	0.958	0.835	0.858	0.820		Ĭ	Ĭ	1			115
Rendts exchade Nearest Centrold, Passree Agg	Aggreence Classifier	uffer and Percepts	ptron																									
100 0 00000 - 100 0000 00000 00000 00000000		Contraction of the second s	10000 F	100 miles			l										l				l	l	l			l	l	I
Classifiers		td t	Td anion	Did strategi	DA DE UN	Dir.	bg	8	DIG	11d		17		Ľ	Ľ		010	D'0	Ind		114	ľ	ľ	Ľ	ľ	1	1	9
AdeRoost	0.011 0.0	1 984 0 9	A6 07	0	-		0.000	0.078	0.845	0.856		1		1		T	0.888	0.014	0.010	0 BAS	0.807		ľ	1	1	1		you you
Bemouls Name Baves		0.970 0.952	0	144 0.78	5		0.869	0.935	0.826	0.858		~					0.876	0.942	0.957	0.893	106.0				ॅ		0	919
Durumy Classifier			0.5		0		0.647	0.453	0.500	0.363		0		0			0.483	0.528	0.500	0.500	0.664			~	Ĩ	•	0	12
Extra Trees	0		0.5	0	0	Î	0.500	0.893	0.500	0.708		2		-			0.877	0.500	0.500	0.864	0.500	Î		1	3	-	0	858
Ganssian Naive Baves	0	695.0 586.0	0.5	•	-	-	076.0	8/60	0.828	0.938		ੌ	22	0			0.944	556 0	0.929	0.865	1.897				Ĩ	-	0	200
Gradient Boosting		0.985 0.844	44 0.8	58 0.71		0	0.778	0.943	0.863	0.855		ੌ	8	0			0.898	0.935	0.871	0.841	0.942			2	1	-	0	565
Heistrom Quantum Classifier			000 0.9	20 0.56	+	0	06.0	6963	0.391	0.598		ੰ	2	0			0.865	0.962	0.929	0.839	0.962				Ĩ	0	0	140
Linear Discriminant Analysis			69 0.Ed	69 0 69		0	0.903	0.957	0.863	0.918		-		0	Ĩ		0.911	163.0	0.929	0.865	0.897			1	~	1	0	565
Logistic Regression	0 156.0		60 6960	03 0.65		0	0.920	\$26.0	0.863	0.938		~	10	0	Ĩ		116.0	0.935	0.893	0.865	0.897	-			Ĩ	0	0	268
Multi Layer Perceptron	0.931 0.1	0	69 0.90	03 0.63	0.929	•	076.0	87.6.0	0.863	0.938	-	~	9	0			0.888	0.935	0.929	0.865	0.916			~	~	•	0	163
Nearest Neighbors	0.931 0.9		30 696	23 0.71	-	-	076'0	0.964	0.935	0.877		ី	1	0			0.538	916.0	0.593	0.865	0.916	•		~	~	•	0	170
Quadratic Discriminant Analysis			0.969 0.80	69 0.82	-	0	606.0	816.0	0.863	0.855		~		0			116.0	0.935	0.929	0.865	0.916			~	~	-	0	898
Random Forest			38 0.5	58 0.03	.	0	06.0	0.943	0.863	0.855		~					116.0	556-0	0.929	0.865	0.897			~ ·	÷.	0	0.0	565
SVM - BRAK	10 156.0	4000 0000	26 U.M	10 0 CD			076'0	1060	19610	0.938				0.0			0.855	01410	0.000	CK910	1620						5 6	8
SVM - thf			200 0.50 0.50	010 0.636	00500 91	SE6.0	076.0	0050	0.500	0.500	1.621	0.861 0.	918 0.7	516.0 061.0	0.946	0.864	0.838	0.935	0.500	0.865	0.844	0 1321	0 6521	0 328 0.5	1500 0.5	1.564 0.7	722 0.8	100
Partie archele Namet Castrold Parties	Asmantite Class	offer and Perrs	where a				-	-	ALC: N	ALC: N				1				ALCON.	M. eres	ALCON.				1	1			1

Table 4.25 Balanced accuracy score for 30 RGB image feature	score for 3	0 RGB im	age featur	e datasets	for cell lin	e MCF7																							
Classifiers	PI	22	5	1	S P	rq 8	Ps	2					P14	PIS	P16	P17	P18		17			171		Π				17	
AdaBoost	0.885	000 0	0 116	0 663	920 1.	000 0:0	•						0.940	0.941	0.800	1.000	086.0		Ĩ.,							8			8
Bernoulli Naive Bayes	0.863	000	34	1881	1 856	000 0.9	0						1.000	1+6'0	696'0	0.942	0.980									20			3
Dummy Cassifier	206.0	0 000	2/4/2	0 000	-0 CRC:	000	0.4						10.022	0.500	0000	0050	805.0	202	202							208			2 5
Consider Votion Barner	190.0	000	0110	-	1 010	2 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0							0.000	1000	0.000	1000	0.060		27							0.03			2.5
Configure Recommendation	208.0	000	150	010		2 0 0 L 10	2 4						0.040	U OH	0.100	1000	0.000		100						50	0.5			2.5
Helstrom Osantum Classifier	526.0	000	1944	0 205	1 205	000 000	0						1 000	176.0	0.984	0.962	0.938		10	2						82			2 22
Linear Discriminant Analysis	0.921	000 0	944 (920 0	920 0.	958 0.8	0						1.000	0.941	1.000	0.955	0.938		ॅ	2						38			
Logistic Regression	0.885	000 0	(389 (962 0	923 0.	\$75 0.8	0						1.000	0.941	0.800	1.000	0.938		1							17			
Multi Luyer Perceptron	516 0	00001	944 (962 0	0 188	875 0.8	0	_					1.000	116.0	006.0	0.955	0.938		7				0		2	22			8
Nearest Centroid	0.899	000	883	902 0	.631 0.	958 0.9	•						1.000	0.941	1.000	6060	0.938		~	39						20	24	-	8
Nearest Neighbors	0.935	000	000	615	.881 0.	958 0.9	0 1						1.000	196.0	0.784	19610	0.938		20							200			
Passive Aggressive Cassiner	24010	1 000	1997	1 106	0 100 I	0.0 0.0							0.000	1100	0060	2000	0.718		50						14	333			2 5
Procession Discriminant Androis	1000	000	-	110	0 000	0.0 0.0							0.960	1000	0001	0.000	0.960									10			
Random Forest	0.885	000	688	963	611 0	0.9	, 0						01940	0.941	0.700	1 000	0.980		ॅ							80			
SVM - linear	0.899	000 0	944 (1941 0	941 0	917 1.0	•						0.980	0.979	00610	1.000	0.938		7						100	17			
SVM - poly	0.863	000 0	927 (0 2051	920 0.	917 1.0	000 0.5	911 816	1.000 0.918	8/2-0-8	1.000	0.979	1.000	116:0	0.800	1.000	0.938	1.000 1	0 000 1	0.912 0	5.0 006.0	0.900 1.0	1.000 0.8	0.860 0.975	196-10 - 54	7 0.927	7 0.850		0.854
SVM - rbf	0.885	000 0	889 (0 663'	641 0	6.0 116	0					2	0.950	616.0	006.0	1.000	0.938		1		-								8
Table 4.76 Balanced accuracy	cone for	"Anana U	imare fea	ture datas	ots for cell	line MCF		l	l	l	l	l	l					l	l	l	l	l	l	l	l	l	I	I	I
Classifiers	Id	1	1 5		e P	rq 2	P8	17					P14	PIS	P16	P17	P18		17	1				1	1		1	1	
AdaBoost	0.885	000 0	944 (0 968.0	0	0	Ē	ľ		1	1		0.940	0.941	0.700	0.962	0960	P	1	[[ľ		1	ľ	[\$
Bernoulk Naive Bayes	0.935	1.000 1	000	1981	0	0						0	0,940	616-0	0.969	0.942	0.940		ॅ					~		25	0		-
Dammy Classifier 0.500 0.500 0.500 0	0.500	0.500 0	0051	522 0	•	•	1						0.467	0.502	0.606	0.500	0.500	~	1	2				~			•		2
Entra Trees	0.885	000 0	10	0 6681	0	•						2	1.000	0.941	0.700	186'0	816.0		Ĩ.,					~		32	0		8
Ganssian Naire Bayes	0.899	000	000	198	-	-						22	0.940	6.6.0	1.000	0.942	0.940							-		20			
Gradent Boosting	0.863	000	t	0 0751	0 0	0							0.876	616.0	006:0	1.000	0.595									22			8 9
Heistrom Quantum Classifier	11610	000		0 000	P +								0.000	146.0	1960	1967.0	0.000								24	202	-		8 5
T anish Researching	0.850	000	123	110								-	0.040	02.00	1000	1000	1 202		337							213			2.5
Multi Laver Perception	0.899	000	000	0 1161	941 0	958 1.0	000 072	96.0 086.0					0.960	616.0	006-0	1.000	0.940		1							202			. 8
Nearest Centroid	0.935	000 0	944 (0 663	-	-	1					-	0.940	616.0	0.984	0.962	0.940		~						107	0.00	-		8
Nearest Neighbors	256.0	1 000 1	000	1878 0	0	1	-					2	0.938	0.941	0.884	186.0	816.0		22					~		20	-		
Passive Aggressive Classifier	0.863	000 0	1833 (920 0	1885 0.	875 0.8	2					- 72	0.940	616.0	006.0	0.962	0.918		~					~		100	0		
Perceptron	0.835	000 0	.778 (1962 0	923 0.	875 0.8	50 68	-				22	0.960	0.941	0.800	1.000	0.378		~					~		50	0		8
Quadratic Discriminant Analysis	0.885	1.000 1	000	1941 0	.902 0.	958 0.9	HH 0.5	950 850					0.960	1+6.0	006'0	186.0	0.918		2					~	33		•		I
Random Forest	0.885	000	944 0	1617 0	0 616	958 0.8	50 681	36.0 816				24	0.940	116.0	0.800	0.962	0.940		~					~	73 		•		z
SVM - linear	1260	000	000	920 0	941 0	958 0.8	50 68	980 1.00				201	0.940	616.0	0001	1.000	0.898		1					° .		763	-		3
SVM - poly	1400	000	000	0 116	.0 IH6	8.0 8c4	20 62 F	10 0.95	31610 73610	1 1 000	0.001	0.979.0	0.960	146.0	0.800	1.000	0.918	1 0001	0001	1 0101	000	0.784 1.0	000 01	0660 0.940	1,000	1/2/0 0	1.000		0001
that i that A m	1000	1 1000	-	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 16			100					0.000	2120		1.000													
Table 4.27 Balanced accuracy score for 30 con	score for 2	0 contrast	trast image fea	ture datas	ets for cell	line MCF	1																						
Classifiers	PI	1	5		d.	d	7				1		P14	PIS	P16	717	P18	7		7	_								
AdaBonst	0.870	0 1861	964 ((753 0	0	•	50					-	0.858	0.721	0.769	0.839	0.677	7	1	7			0.	1	2	62	2		
Bernoul Naive Bayes	0.762	0 068 0	1961	686 0	•	•	20					2	0.650	0.591	0.569	0.741	0.423	2	7					<u> </u>		550	30		21
Dummy Classifier	0.500	02200	202	345	•							722	0.487	0.500	0.500	0.500	0.500	-	20	2						23			8 1
Extra Trees	0000	00010	000	- 104 D		C.0 000		00C-0 000					0.000	00200	0000	0200	0.500									20	20		8 2
Gradient Rooting	0.245	1350	196	0 2.69								20	0.733	0.899	0.853	126.0	0.528	-											
Helstrom Omntum Classifier	878.0	186 0	108 (604 0									0.757	0 801	0.759	0.830	0.427									333			1 25
Linear Discriminant Analysis	0.756	0 70K 0	119	0 101									0 565	0.512	0 500	0.500	0.440	2.5								10		1	
Lonistic Restession	0.756	0.818 0	1687	636 0	•	0						23	0.565	0.532	0 500	0.500	0.462	- 22	1				1			87			5
Multi Layer Perceptron	0.762	0 0680	927 ((638 0	0	0						100	0.733	0.822	0.553	0.897	0.548	100	1	1	1		1	1		-	1		9
Nearest Centroid	0.820	0.839 0	1681	1837 0	0	0							0.713	0.756	0.597	0.858	0.510		~	Ĩ				1		20			Y.
Nearest Neighbors	0.842	0 9160	1211 0	0 S6L	•	•	3						0.673	0.647	0.769	0.962	0.550		~			-				20	-	-	12
Passive Aggressive Classifier	0.734	0.818 0	606	1647 0	•	•		-				23	0.563	0.593	0.600	0.624	0.480	70		-						53			I :
Perception	6770	1/12 D	35/7	0 100	· · · · · · · · · · · · · · · · · · ·	10 01/							71C'0	1424	0.000	165-0	CUPU 0	22								22			0.2
Random Farnet	0.870	000	1001	1748 0	730 0	100 000						0.0	0.83.0	0.801	0.663	0.858	0.673	80				0				102			2.2
	0.770	0 068.0	1853	0 9891	0 172	710 0.8		6.6				-	0.565	0.434	0.500	0.500	0.462		-							115			18
	0.727	0.864 0	0.964 ((732 0	638 0.	6.0 0.86	810 116	0.878 0.645	651.0 63	9 0.705	0.787	0.774	0.753	0.784	0.669	0.878	0.612	0.720 0	0.838 0	0 628	0.776 0.5	0.553 0.6	0.694 0.5	0.500 0.744	H 0.753	3 0.762	2 0.826	0.806	8
	0.699	0 068 0	964	134 0	.718 0.	793 0.8		8					0.607	0.490	0.500	0.533	0.462							Ĩ					\$
Table 4.28 Balanced accuracy score for 30	score for 3	0 correlati	ion image	feature da	tasets for e	ell line M	CF7	I	I	I	I	I	I					I	I	I	I	I	I	I	I	I	I	I	I
Classifiers	PI	1 1	1 5	1	d	a.	1					2	P14	PIS	P16	P17	P18							17		2	7		
AdaBoost	0.610	0.708 0	008 (665	0	•						2	0.733	0.676	0.469	0.734	0.670									2	-		
Bernoult Naive Bayes	100'0	2150	022	0.00									10.10	0.083	0200	1000	7620	20		1						20			
Duminy Cassing	anc.n	000510		101	2 0	5 6							005.0	002.0	anc n	005.0	101-00									202			
Gammin Maine Rooms		0 908.0	1780	COK 0								2.5	0.766	0.673	0 500	0.827	0.60									22			2.5
Gradient Booshing	0.691	0.722 0	744	582 0	0	0						100	0.733	0.550	0.569	0.760	0.668		27							27			1
	0.755	0.839 0	873 (0 566/	•	0	25					-	0.777	0.659	0.791	0.698	0.652	1	55	9						25	-		22
Linear Discriminant Analysis	0.612 0	0 0/970	.780 (0 9651	0	0						-	0.795	0.567	0.600	0.832	0.547			22				7		270	-		12
Logistic Regression	0.595	0.670 0	0.780 (965	•	•	2					78	0.775	0.567	0.600	0.832	0.567	75								22	~	-	12
Multi Layer Perceptron	0.727	0.767 0	873 (261 0	•	•						20	0.773	0.606	0.706	169'0	0.547		33							20			12
Nearest Centroid	9.054	0.852 0	6180	965	0 1	•						72.8	0.735	0.599	0.791	0.774	0.633	28								83			0.0
Passive Assession Classifier	0.492	1877 0	714	0 100								23	0.757.0	0 508	0.500	0.767	0.612									9.5			1 3
Perception	0.548	0 365 0	429	965	• •							-	0.838	0.495	0.428	0.722	0.570			-				1		-	-		
Quadratic Discriminant Analysis	0.705	0.760 0	168 (1575 0	•	•							0.775	0.665	0.500	0.624	0.547							1		20	-		8
Random Forest	0.727	0.741 0	335 (6239 0	0	•		~				2	0.670	0.668	0.584	0.780	0.670	-	53	20				-		26	-	-	8
SVM - Intear	0.083	0.689	1835	575	0 0							200	0.755	0.000	0.500	0.852	0.610	24								202			51 5
SUM - MA	1.681	0 689.0	108 0	0 905	715 0	688 0.6	610 250	0.877 0.67	0.702 0.702	10.769	0.651	741'0	0.755	0.623	00200	0.837	0.630	0 299 0	0 225	0 0/10	0.781 0.1	0 005 0	0.794 0.5	01/00 0050	10 0.653	3 0.853	0.070 8		14010
**** BILL ***	Allow-	- Alex	ALC: N					1					49144	July a	and a	Area	W.Ach										1		

Table 4.29 Balanced accuracy score for 30 energy image feath	score for 3	0 energy is	nage feats	re dataset	s for cell li	ne MCF7						1000												100			1000	10110	ī,
Classifiers	P1 P	4 2	4 P	4 P	A	-	6			7					P16	P17	P18	P19	7			1		7	7	7	7		
AdaBoost	0.812 1	000 0	964 0	774 0.	0	0	2						24	2	0.669	0.878	0.778	0.970	2	-		°.		0		Ĩ	-		
Bernoulli Naive Bayes	0.783 0	1677 0.	\$37 0	771 0.	0.0	690 0.8		0.920 0.8			-		222	24	0.500	0.865	5690	0.500	797	0.0	-				÷.,		0.565	-	
Extra Trees	0 005.0	0 005	0 005	763 0.	0								103		0050	545.0	00200	00200	3323							20			
Gaussian Naive Bayes	0.798 1.	0 000	964 0	795 0.	0	0	1					1	277	1	0.853	0.878	0.778	0.955	273	-		~		1		1	-		
Gradient Boosting	0.742 1	000 0	964 0	777 0.	0.	•							23	20	0.769	0.787	0.737	0.955		-		~			Ĩ	Č	-	~	
Heistrom Quantum Classifier	0.848 0		0 946 0	192 0.	0	0						7	893	2	658.0	6.923	0.300	605 0	23	•					- -			-	
Linear Discriminant Analysis	0.870	0 1	364 0	712 0.	0	0							8.8	800	0.600	1060	0.673	0.485	20	• •					-	1			
Logbar Regression	0.798	000	104	174 0.	6 6	5 4							517		0.884	0.8/8	8//-0	0.65.0	252										
Nearest Centroid	0.804 0		0 116	712 0	0								887		0 922	0.904	0.800	0.864	333								-		-
Nearest Neighbors	0.877 0	0.962 0.	964 0	816 0.	0	0			1	0			10	6	0.809	0.942	0.755	656.0	87	-		~			Ĭ	Ĩ	-		2
Passive Aggressive Classifier	0.784 0	318 0	964 0	774 0.	0	•						100	83	2	0.684	878.0	0.485	0.955	83	-					~	Ĩ	-		
Perceptron	0.870 1	0 000	0.611 0	627 0.	553 0.8	13 0.8	2						8		0.784	0.878	0.732	0.939	8	~		~		1	Ĩ	~	~	~	
Quadratic Discriminant Analysis	0.798 1	000 0	0.964 0	795 0.	6.0 668	58 0.8	2				Ξ.	7	23	2	0.853	0.378	0.798	0.830	23	-		Ξ.	0	Ĩ.,	×.	Ĩ	-		
Random Forest	0.770	000	0.964 0	795 0.	756 0.8	97 0.8	S3 0.5	80 0.7	_				29	8	0.569	878.0	0.715	0.970	22	0					~	Ť.,			
SVM - linear	0.834 1	000	904 0	753 0.	812 0.9	80 0.9	9	60 09					2.2		0.784	0.878	0.778	556 0	7.12						~		0.876	0.844	
SVM - thf	0.854	000	0 364 0	753 0	0.812 0.9	50 0.9	946 0.9	60 09	1120 1160	3 0.790	703.0 0.938	0.875	0.858	0.833	0.784	126.0	0.778	1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2	0 946 0	1 000 0	000	50 0080	00 1061	0 500 0 925	5 0,309	0.929	0.876	0.844	
Table 4.30 Balanced accuracy score for 30	score for 3	homoge	uelty imag	o feature d	atasets for	cell line A	NCF7																						
Classifiers	P1 P1		9	*	P6	Ld	P			7	1		P14		P16	P17	P18	P19		7		7		1	7		7		
AdaBoost	0.848 0	981 0	964 0	774 0.	0	0	0			1		1	0.838		0.869	0.878	0.758	0.830	1		Ĩ	Ĩ.	Ϊ.	ĩ	Ì.	Ĩ	Ĩ		
Bernould Naive Bayes	0.848 0	0 186	964 0	792 0.	a	0	0					-	0.838		0.638	0.885	0.758	0.769		-		~		~		÷.	-	-	
Dummy Classifier	0.497	165	005	457 0.	0 1	200 0.5	0					200	0.500		0200	0.470	0.500	0.500	5.4					-					
Edita trees	0 1/C/0	0 000	0 000	111 0.	5 6	0.0						20	CT0.0		00200	25670	0.000	005-0											
Cerdient Rootine	0.820	000	0 200	10 10	0.0 1501	80 08	5 0	50 100				803	0.818		0.660	1001	0.758	0000	202							1			
Helstrom Omentum Classifier	0 344	0 135	0 196	194	20 956	0.0							0 818		0.010	0.878	0.758	0.016								ॅॅ			
Linear Discriminant Analysis	0.812 0	0 185	964 0	774 0	854 0.9	60 09	0						0.838		0.784	0.897	5690	0250								1			
Lozistic Regression	0.820	-	0 000	774 0.	875 0.8	97 0.9	0	897 0.9				222	0.837	8	0.684	0.897	0.673	0.970	15					~		1	1		
Muhi Layer Perceptron		0 000	0.964 0	774 0.	795 0.8	6.0 79	0					57	0.838	23	692.0	0.878	56970	0.970	1			Ĩ				~			
Nearest Centroid	0.870 0	923 0	964 0	753 0.	812 0.9	60 0.9	0						0.838	6	656.0	0.885	0.758	0.939	-77	-		~		~	2	~	-		
Nearest Neighbors	0.842 0	981 0	0 605	753 0.	812 0.8	55 0.9	0			1		-77	0.858		0.669	0.858	0.717	0.970	27	-				~	2	~			
Passive Aggressive Classifier	0.756 0	0 185	0 916	627 0.	854 0.9	60 0.6	11 0.1	97 0.9	82 0.306	1			0.775	1	0.769	0.890	0.632	0.735	-					~		~			
Perceptron	0.792 1	000 1	0 000	571 0.	700 0.7	93 0.9	50 60	93 0.8					0.818		0.869	0.851	0.400	0.735	-			Ĩ.,		~		~			
Quadratic Discriminant Analysis	0.856 1	000 0	964 0	736 0.	875 0.9	38 0.8	191 0.9	60 80					0.878	3	0.869	0.875	0.735	0.670	20	~		Ĩ		-		~	Ĩ		
Random Forest	0.877 1	0 000	0.964 0	774 0.	827 0.8	13 0.9	50 60	80 0.8		1			0.838		692.0	0.375	0.715	0.970	172			Ĩ		~		Ĩ	~		
SVM - linear	0.870	0 185	0.964 0	10 144	854 0.9	60 09	H6 0.5	60 08				5	0.838	50	0.684	0.878	5697	0.6.0	7			Ĩ.,		~		~			
Vod - MVS	0.870	000 000	0 19610	0 117	837 0.9	0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0	946 0.9	80 0.7	0.780 0.81	7 0.762	2 0.938 2 0.938	716.0	0.835	0.854	696.0	0.875	260.0	0/6/0	0.946	0.900 1	000 001	0.584 0.5	0.963 0.6	0.625 0.562	1 0.598	0.817	516.0	0.922	
101 - WAC	0.040	000	*04	-n -n	2 m + 20	AU 0.2	0		20 40	N'10			0.000		1010	0.010	1010	N/Z/A				1						1	
Table 4.31 AUROC score for 30 RGB image feature datasets	30 RGB im	age featury	e datasets	for cell lin	ine MCF7																								Ì
Classifiers	PI P	d.	3 P	4 P:	5 P6	P7	Ps	Po I	1		1	17	1		P16	P17	P18	P10		7					1	7	1	P30	
AdaBoost	0.921 1	000 0	944 0	920 0.	P41 1.0	00 0.9	0					Ē.	72		0.700	1.000	0860	1.000		7				Ĩ		~	7	1.000	
Bemosli Naive Bayes	0.863 1	000	944 0	881 0	91 856	0	944 0.5	6.0 856	2120 1061	2 0.507	1,000	0.979	1.000	116.0	696.0	0.942	086.0	285.0	1.000	0.929 1	000	1.0	000 003	0.955 0.946	1150 9	0.800	0.913	0.984	
Durany Cassiber	0.500	1999 0	0000	202 0	0 0	6 1	6 4					244	22		167.0	0.444	0.000	002.0								-		005.0	
Extra Trees	0.079	000	0 0000	-0 Z06	•	8.0 0.8	0 4						533		0.000	1050	8550	1,000								23		001.0	
Centional Name Dayes	1 1/20	0 000	1880	STR D	• •	5 6	5 0						87		0.700	1 000	0.500	1 000									-	1.000	
Maleton Oceanin Cheelfine	0.057	000	0 0000	0 010		5 6	5 6								0.040	10001	0.020	1 000								23	1	0.000	
These Disciolates Andreis	1000	000		0 000		s e	5 6					2			1000	1946	0.020	1 000										0.000	
Torisfe Remeation	0.885	0 000	0 088	011 0											0.800	1 000	0.978	1 000								1		0.900	
Muhi Laver Percention	1 (56.0	0 000	0 1880	941 0			0								1.000	1 000	0.398	1 000								1		1 000	
Nearest Neidthors	0.921 1	0 000	1 688	979 0	0	0	0							-	0.984	0.981	0.938	1 000		1						1	1	0.884	
Quadratic Discriminant Analysis	0.921 1.	000 1	0 000	911 0	0	0	0						10	~	1.000	0.962	0.960	0.985		7	Ĩ		Ĩ	Ĩ	1	ॅ	0	1.000	-
Random Forest	0.885 1	000 00	0 1833 0	917 0.	-	0	144 0.5	9.0 8.0				1			0.700	1.000	086-0	1.000						1		~	-	1.000	
SVM - linear	0.885 1	0 000	0.944 0	941 0.	920 0.8	75 0.8	50 68	01 08	<u> </u>				53	-	006.0	556'0	0.938	1.000		1		-		Ĩ			-	006.0	
SVM - poly	0.863	000	0.927 0	938 0.	920 0.8	0.8	50 68	50 50				200	52		0.884	1.000	0.772	1,000								10		0.900	
SVM: - EDI 0.31 Bandhu sechada Nasasat Cannoid Bandon Asse	a Assessing Class	100 miles and P	0 000	0 668	2.0 0.26	2.0	50 C 68	80 I.U							0.500	1.000	761-0	1.000			1							0.900	
and a function of the last of second to the second	£		and a																										
Table 4.32 AUROC score for 30 L*u*v* image feature data	30 L*u*v*	image feat	ure datas	its for cell	line MCF																								
Classifiers	H Id	2 P	4 F	4 b	P6	Fq	Ps	20				7	P14	PIS	P16	P17	P18	PIO					1		7			P30	
AdaBoest	0.385 1	.000	000 0	938 0.	H1 0.9	17 0.9	•						0.940	0.941	0.700	1.000	368.0	1.000					0	1		233		0.969	
Bemoult Naive Bayes	0.935 1	000	000	861 0.	•	-	•					20	0.940	0.979	0.969	276-0	0.940	0.970							2	200		0.953	
Dummy Classifier	0.519 0	1200 00	200	200	•	•	0						0.500	0.500	0.500	0.451	0.500	0.708								20		0.500	
Extra Trees	1 126.0	000	146	599 0.	1		0						1.000	0.616	0060	2050	0.900	1.000							-			00610	
Configure Reconfigure	0.861	1 000	000	-n too	• •	011 010							0.650	010.0	1000	1000	0.000	1000								100		0.984	
Heletron Omntun Classifier	1 Stell	000	000	0 808							1		0.960	0.070	0 984	1 000	0.940	1995										0000	
Linear Discriminant Analysis	0.921	0 000	944 0	920 0.	2		0						096.0	0.941	1 000	1 000	0.960	1 000					17	10		200	-	006.0	
Loristic Remession	0.885	0 000	944 0	911 0	0	0	0					-	0.960	626.0	0.900	1 000	0.898	1 600								100	1	1.000	
Mahi Layer Perception	0.877 1	1 000	000	941 0.	0	0	0					87	0.940	0.979	0.884	1.000	0.940	1.000								87	1	0.984	
Nearest Neighbors	1 256.0	000 1	000 0	\$78 0.	0	0	0						0.960	0.941	0.984	186.0	816.0	0.985								27	1	0.834	
Quadratic Discriminant Analysis	0.885 1	000 1	0 000	941 0.	0	0	•		-			1	0.960	0.941	006.0	186.0	0.918	0.985						0			~	0.984	_
Random Forest	0.885 1	000 0	944 0	938 0	941 0.9	58 0.8	0					-	0.940	0.941	0.700	1.000	0.960	1.000							с.,	20	~	0.984	_
SVM - Inteat	0.921	000	000	920 0.	920 0.9	10	0					202	0.940	1400	1.000	1860	168.0	2860										1.000	
SVM - poly	1 148.0	000	000 444	0 010	0.0 1961	20 CO	589 010 010	20 086 086	2160 7360 2360	1 1 000	1 1000	0.902	856-D	146.0	0.800	606.0	0.938	1005.0	000	1 676.0	000 0	2.784 0.5 A GNO 0.1	0.500 0.50	0.500 0.940	006.0 0	0.778	0.000	0.584	
SVM - rbf 0.8 Reads exchade Nearest Centroid: Paulos Arm	O.G.Cl	utiler and Percent	12z u	-n n26	2.m 956	17 /r.o							10,200	616.0	1.000	0.504	0.540	0.000										20'C'0	
Regards excesso presents victoryon, a sorry	WA THEAT OF	Sulter and con	winds																										

Math Math <th< th=""><th></th><th>d Id</th><th>bid</th><th>Classifiers P1 P2 P4 P4</th><th>ps</th><th>pé</th><th>L.d</th><th>be</th><th></th><th>P10</th><th>bil</th><th>p12</th><th></th><th></th><th></th><th></th><th></th><th></th><th></th><th>P21</th><th>P22</th><th>P24</th><th>P24</th><th>pre</th><th>P26</th><th></th><th></th><th></th><th></th></th<>		d Id	bid	Classifiers P1 P2 P4 P4	ps	pé	L.d	be		P10	bil	p12								P21	P22	P24	P24	pre	P26				
0 0	AdaBoost	2.834 0.	81 0.9	64 0.6		1	ľ	0.920	1	0.861	0.655	0.878	17		1	1	1		17	0.812	0.944	0.669	0.826	0.500	0.715	0.820	168.0	0.881	1
0 0	Bernoulk Naive Bayes		60 06	64 0.6				0.855		0.706	669/0	0.745								0.560	0.844	0.500	0.813	0.500	0.715	0.786	0.744	108.0	
0 0	Dumny Classifier			0	ал 		~	0.468		0.520	0.500	0.603	-						7	0.500	0.520	0.500	0.520	0.500	0.500	0.500	11510	0.396	
Model Model <th< td=""><td>Extra Trees</td><td></td><td></td><td></td><td>are Geo</td><td>53</td><td>~</td><td>0.500</td><td></td><td>0.500</td><td>0.500</td><td>0.500</td><td>20</td><td></td><td></td><td></td><td></td><td></td><td>22</td><td>0.500</td><td>0.500</td><td>0.500</td><td>0.500</td><td>0.500</td><td>0.500</td><td>0.500</td><td>0.500</td><td>0.500</td><td></td></th<>	Extra Trees				are Geo	53	~	0.500		0.500	0.500	0.500	20						22	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	
Currace in a contract of a	Gaussian Narre Bayes	0 +		0 0			-	0.750	-	259.0	0.542	21970	26						20	0.417	0.750	H8C'D	0.051	0.010	0.538	0/1/0	0.722	10.031	
Matrix Matrix<	Maleton Onetun Cheeffor	*: 6		ė				210.0		0.769	ava u	100.0	10						1	DLL U	0.700	CCC. 0	0.640	1000	1000	1 496	200 U	122.0	
	Linear Discriminant Analysis			i e				0.792		0550	0 562	0.612							23	0.576	0.750	0.584	0.650	0.610	0.538	0.776	0.760	162.0	
matrix is in the second of the s	Logistic Regression	0.756 0.1		0			~	0.833		0.550	0.699	0.612							-	0.510	167.0	0.484	0.631	0.485	0.568	0.776	0.760	0.713	
1 1 <	Muhi Layer Perceptron	0.820 0.5		0.5		5	ੌ	0.833		0.810	0.719	0.920							27	0.795	0.894	0.800	0.644	0.625	0.503	0.786	0.817	0.731	
Mutuality Mutuality <t< td=""><td>Nearest Neighbors</td><td>0.877 0.</td><td></td><td>15 0.7</td><td>95 0.6</td><td></td><td>~</td><td>0.918</td><td></td><td>0.785</td><td>0.891</td><td>668.0</td><td>573</td><td></td><td></td><td></td><td></td><td></td><td>-</td><td>0.740</td><td>0.813</td><td>0.584</td><td>0.663</td><td>0.625</td><td>0.832</td><td>0.786</td><td>0.762</td><td>0.944</td><td></td></t<>	Nearest Neighbors	0.877 0.		15 0.7	95 0.6		~	0.918		0.785	0.891	668.0	573						-	0.740	0.813	0.584	0.663	0.625	0.832	0.786	0.762	0.944	
0 0	Quadratic Discriminant Analysis			15 0.7	07 0.6	2	~	0.703		0.548	0.534	165-0							-	0.438	0.731	0.584	0.650	0.610	0.538	0.776	0.704	0.651	
0 0	Random Forest			64 0.7	36 0.7		~	0.913		0.756	0.820	0.920	2							0,812	142.0	0.600	0.813	0.500	0.857	0.786	0.762	0.931	
1 1	SVM - Inear	0.1		53 0.7	07 0.7		~	0.897		0.523	0.649	0.553	20							0.433	0.650	0.500	0.631	0720	0.538	0.776	0.780	0.731	
Control (1) Control (1) <thcontrol (1)<="" th=""> <thcontrol (1)<="" th=""> <</thcontrol></thcontrol>	SVM - poby	0.727 0		060 0.7	34 0.7		~	0.792	-	109'0	0.834	0.840	20						23	0.669	0.550	0.553	0.650	0.500	0.710	0.776	0.730	0.731	
The function of the func	SVM - rbf		00 07	38 0.7	01 0.7	18 0.0	9 0.760	0.500	1	0.654	0.500	0.500								0.500	0.550	0.500	0.631	0.500	0.504	0.500	0.762	0.531	
Contractional and contractite and contractional and contractional and contracti	Results exclude Neseest Centroid, Passes		fire and Perce	ption																									
Matrix Matrix<	a sector sector		Contraction of the	Concernence of	1000 S 1000			l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	I	
1 1	Taule 4-24 JAUNOU SCORE 100		a mage le	starte cata	201 201 201	i.													Ľ				ł						
0 0	Classifiers		E4								FII	FIZ	1	1				1	1	124	P22	P23	P24	Fis	P20	124	128	P29	
mmm	AdaBoost			•		1					0.506	1/9/0	25					1	-	0.724	0.831	0.469	0.844	0.500	0.626	0.686	0.722	0.613	
000	Bernoalt Narve Bayes			0							0.756	0.612	20							0.740	161.0	0.500	0.752	0200	0.651	0.830	0.633	0.402	
0 0	Duniny Classifier						20				1650	00570	526							0.200	AFC.D	0050	0050	0000	0020	080.0	567.0	0.500	
mmm	EATTA Trees			0		2	2				07200	0.500						-		0.500	0.500	00500	0200	0200	0.500	0.500	0.500	0.500	
Control of a constrained with	Gaussian Naire Bayes			0	7933 2013						0.762	0.651	-							0.812	0.813	0.084	0.844	0.625	0.656	0.686	0.780	0.576	
Terrer 10: 0: 0: 0: 0: 0: 0: 0: 0: 0: 0: 0: 0: 0	Gradetti Boosing			•							0.812	0.721	24							0.730	0.730	0.009	142.0	0.025	0/0/0	0/0/0	1000	0.74	
000	Heistrom Quantum Classifier			• •							0.733	0.760	23						-	0.812	0.894	0.733	0.813	0.955	0.676	0.653	0.873	0.73	
uuu <thu< td=""><td>Linear Lasorinnant Analysis</td><td></td><td></td><td>e 1</td><td></td><td></td><td>22</td><td></td><td></td><td></td><td>0./19</td><td>1000</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>0.812</td><td>0.781</td><td>6000</td><td>14/0</td><td>0000</td><td>5900</td><td>1000</td><td>0.817</td><td>0.0</td><td>•</td></thu<>	Linear Lasorinnant Analysis			e 1			22				0./19	1000								0.812	0.781	6000	14/0	0000	5900	1000	0.817	0.0	•
matrix 0.0<	Logistic Regression	0.595 0.		0.1			73				0.683	0.651								0,069	167.0	0.584	0.794	07200	0.543	0.620	0.853	0.59	
under 0 <td>Multi Layer Perceptron</td> <td>0.762 0.</td> <td></td> <td>0</td> <td>700 200</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td>0.705</td> <td>0.819</td> <td>22</td> <td></td> <td>-</td> <td></td> <td></td> <td></td> <td></td> <td>0.531</td> <td>0.731</td> <td>0.784</td> <td>0.844</td> <td>0.625</td> <td>0.719</td> <td>0.686</td> <td>0.780</td> <td>8</td> <td></td>	Multi Layer Perceptron	0.762 0.		0	700 200						0.705	0.819	22		-					0.531	0.731	0.784	0.844	0.625	0.719	0.686	0.780	8	
0 0	Nearest Neighbors	0.8.0		10.2	93 0.0		38				0.804	0.784	23							0.900	0.794	0.700	0.844	0200	0.705	0.003	0.835	5	
00 00<	Quadratic Discriminant Analysis	0.705		50 16	75 0.7						0.711	0.710	20							0.740	0.831	0.784	0.826	0.625	0.685	0.653	0.927	2	
00 00<	Random Ferest	0		35 0.5	99 0.7						0.755	0.748								0.774	0.800	0.584	0.794	0700	0.735	0.742	0.760	0.85	-
00 00<	SVM - Inear	6		02	15 0.0						0.709	0.651	52						73	0.879	0.781	0.500	0.844	0 200	1090	0.033	60610	0.5	
	SVM - poly			53 0.5	93 0.6		23				0.784	0.538	201							0.833	0.731	865.0	0.826	0.595	0.647	0.630	1190	60	
$ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \$	SVM - rbt	83		00 0.5	12 0.3		1				0./09	0.500		1	1					0.500	0:200	0.500	0.794	0.500	0.601	0.500	606.0	0.770	. I.
Of care for a first mark are raised and off A <th>Kendin suchade Nearest Centroid, Passo</th> <th>Ŧ</th> <th>ther and Perce</th> <th>perom</th> <th></th>	Kendin suchade Nearest Centroid, Passo	Ŧ	ther and Perce	perom																									
	Table 4.35 AUROC score for	0 energy in	age featur	e dataseti	for cell li	ne MCF7	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l		
0101010103 <th>Classifiers</th> <th>d Id</th> <th>P3</th> <th>P4</th> <th>Sd</th> <th>P6</th> <th>Ld</th> <th>BS</th> <th>8</th> <th>P10</th> <th>P11</th> <th>P12</th> <th></th> <th>P14 P</th> <th>Id SI</th> <th></th> <th>1</th> <th>P19</th> <th>P20</th> <th>P21</th> <th>P22</th> <th>P23</th> <th>P24</th> <th>P25</th> <th>P26</th> <th>P27</th> <th>P28</th> <th>P29</th> <th></th>	Classifiers	d Id	P3	P4	Sd	P6	Ld	BS	8	P10	P11	P12		P14 P	Id SI		1	P19	P20	P21	P22	P23	P24	P25	P26	P27	P28	P29	
01 <th>AdaBoost</th> <th>-</th> <th></th> <th>0</th> <th>0</th> <th>0</th> <th>0</th> <th>086.0</th> <th>0.964</th> <th>0.864</th> <th>0.699</th> <th>0.861</th> <th></th> <th>1</th> <th>ľ</th> <th></th> <th></th> <th></th> <th>0.944</th> <th>0.829</th> <th>1.000</th> <th>0.769</th> <th>0.881</th> <th>0.500</th> <th>0.862</th> <th>0.898</th> <th>168.0</th> <th>0.900</th> <th></th>	AdaBoost	-		0	0	0	0	086.0	0.964	0.864	0.699	0.861		1	ľ				0.944	0.829	1.000	0.769	0.881	0.500	0.862	0.898	168.0	0.900	
000	Bemoulli Naive Bayes			0		Ĩ	•	0.920	0.837	0.807	0.856	0.630		1			Ĩ		0.868	0.779	0.500	0.500	0.652	0.500	0.626	0.564	0.575	0.565	
111 <th1< td=""><td>Dummy Classifier</td><td></td><td></td><td>0</td><td>•</td><td>°</td><td>0</td><td>0.612</td><td>0.395</td><td>0.500</td><td>0.500</td><td>0.470</td><td></td><td>9</td><td></td><td></td><td></td><td>Ĩ</td><td>0.402</td><td>0.707</td><td>0.500</td><td>0,422</td><td>0.415</td><td>0.500</td><td>0.500</td><td>566.0</td><td>0.500</td><td>0.500</td><td></td></th1<>	Dummy Classifier			0	•	°	0	0.612	0.395	0.500	0.500	0.470		9				Ĩ	0.402	0.707	0.500	0,422	0.415	0.500	0.500	566.0	0.500	0.500	
w00	Extra Trees			0	-	2	-	0.500	0.500	0.500	0.500	0.500	-			9	Ĭ	Ĩ	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	005-0	0.500	
C 10: 0: 0: 0: 0: 0: 0: 0: 0: 0: 0: 0: 0: 0	Gaussian Naive Bayes			0	-	Ĩ	0	036:0	0.982	0.806	0.790	0.938	2	-	Ĩ	0	Ĩ	Č	0.946	0.900	1.000	0.953	0.913	0.750	0.566	0.876	0.929	0.876	
Chance100 <td>Gradient Boosting</td> <td>0.742 0.1</td> <td></td> <td></td> <td></td> <td>Ĩ</td> <td>0</td> <td>0.813</td> <td>0.835</td> <td>0.836</td> <td>0.627</td> <td>0.822</td> <td>í.</td> <td>1</td> <td></td> <td></td> <td>Ĭ</td> <td></td> <td>0.944</td> <td>0.757</td> <td>1.000</td> <td>0.884</td> <td>0.844</td> <td>0.610</td> <td>0.832</td> <td>863.0</td> <td>163.0</td> <td>0.844</td> <td></td>	Gradient Boosting	0.742 0.1				Ĩ	0	0.813	0.835	0.836	0.627	0.822	í.	1			Ĭ		0.944	0.757	1.000	0.884	0.844	0.610	0.832	863.0	163.0	0.844	
Multi0.0 <th0< td=""><td>Helstrom Ouantum Classifier</td><td>1826 01</td><td></td><td>0</td><td>-</td><td>-</td><td>-</td><td>0.920</td><td>0.893</td><td>0.779</td><td>0.848</td><td>0.941</td><td>27</td><td>1</td><td></td><td></td><td>Ĩ</td><td></td><td>0.920</td><td>0.867</td><td>0.781</td><td>0.884</td><td>0.926</td><td>0.924</td><td>0.950</td><td>0.876</td><td>0.873</td><td>0.876</td><td></td></th0<>	Helstrom Ouantum Classifier	1826 01		0	-	-	-	0.920	0.893	0.779	0.848	0.941	27	1			Ĩ		0.920	0.867	0.781	0.884	0.926	0.924	0.950	0.876	0.873	0.876	
103103036 </td <td>Linear Discriminant Analysis</td> <td>0 0/8/0</td> <td></td> <td>0</td> <td></td> <td>-</td> <td>-</td> <td>019.0</td> <td>0.964</td> <td>0.702</td> <td>0.812</td> <td>0.615</td> <td></td> <td>1</td> <td></td> <td></td> <td></td> <td></td> <td>0.920</td> <td>0.795</td> <td>0.800</td> <td>0.500</td> <td>0.550</td> <td>0.500</td> <td>0.744</td> <td>0.865</td> <td>0.730</td> <td>0.531</td> <td></td>	Linear Discriminant Analysis	0 0/8/0		0		-	-	019.0	0.964	0.702	0.812	0.615		1					0.920	0.795	0.800	0.500	0.550	0.500	0.744	0.865	0.730	0.531	
mu03100030 <th< td=""><td>I onicie Remession</td><td>1 1 2 2 2 2</td><td></td><td>0</td><td></td><td></td><td>1</td><td>0.980</td><td>0.987</td><td>0.889</td><td>181</td><td>0.877</td><td></td><td>2</td><td></td><td></td><td></td><td></td><td>0.946</td><td>0.795</td><td>056.0</td><td>005.0</td><td>0.863</td><td>0 500</td><td>0 391</td><td>363.0</td><td>946</td><td>593 0</td><td></td></th<>	I onicie Remession	1 1 2 2 2 2		0			1	0.980	0.987	0.889	181	0.877		2					0.946	0.795	056.0	005.0	0.863	0 500	0 391	363.0	946	593 0	
(1)(1	Multi Laver Perceptron	1.798 1.1		64 0.7	56 0.7	-	0	0.960	0.760	0.890	0.842	0.822					Ĩ		0.863	0.812	1.000	0.769	0.863	0.750	0.891	0.876	0.946	0.931	
archebie0;	Nearest Neidthors	0 348 01		53 0.7	71 0.5	-		0.960	0.835	0.782	0.348	0.979	18						0.946	0.833	0.881	0 900	0.876	509.0	106.0	292.0	0.762	0.963	
	Onadratic Discriminant Analysis	1 205 1		64 0.7	90 20			035.0	0.964	0.806	0.755	0.938							0.946	0.900	1 000	1 000	0.013	0.750	0.891	0.598	0000	0 894	
01 100 031 030	Random Forest	1.784 1.1		64 0.7	95 0.7	77 0.85	-	086.0	0.760	0.892	0.685	198.0	13	-		0			0.972	0.900	0.950	0.500	0.863	0.500	0.891	868.0	0.946	0.900	_
	SVM - hnear	0.834 1.4		64 0.7	53 0.5	12 0.98		0940	0.964	0.833	0.812	0.938							0.946	0.867	0.850	0.584	0.944	0.500	0.774	0.876	0.946	0.876	
104 0.06 0.51 0.10 0.11 0.06 0.51 0.10 0.51 0.50 0.51 0.50 0.51 0.51 0.50 0.51 0.50 0.51 0.50 0.51 0.50 0.51 0.50 0.51	SVM - poly			64 0.7	53 0.7	36 0.83	0	0+6'0	0.911	0.811	0.870	0.857		-				Ĩ	0.946	0.867	0.800	0.669	0.813	0.610	0.921	0.876	0.780	0.863	
Control Planet pl	SVM - rbf	0.848 1.0		64 0.7	53 0.8	12 0.98	0	0.940	0.964	0.833	0.790	0.938	3	1	ĩ		Ĭ		0.946	0.867	1.000	0.584	0.944	0.500	0.925	0.876	0.929	0.826	
Off control bibliograms Mark for and factor direct for coll bias MAT Off control bibliograms Pin	Rendts exclude Nearest Centroid, Passive	Aggressive Class	fire and Perce	ptron																									
Occarerer RA langearerer durante for calline Alfer. The term of the Alfer Term of th																													
	Table 4.36 AUROC score for	2	ity image	feature di	stasets for	cell line M	CF7	1	1					ľ	ľ	ľ	ľ	ľ											
	Classifiers		2	*d				2	2	P10	HI	LI	P13						P20	P21	P22	P23	P24	P15	P26	124	P28	67d	
res 034 <td>AdaBoost</td> <td></td> <td>81 0.9</td> <td>04 0.7</td> <td>•</td> <td>•</td> <td></td> <td>066.0</td> <td>168.0</td> <td>0.890</td> <td>26/10</td> <td>0.845</td> <td>0.837</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td>146.0</td> <td>0.829</td> <td>186.0</td> <td>6969</td> <td>696.0</td> <td>00200</td> <td>176.0</td> <td>606:0</td> <td>0.835</td> <td>0.900</td> <td></td>	AdaBoost		81 0.9	04 0.7	•	•		066.0	168.0	0.890	26/10	0.845	0.837						146.0	0.829	186.0	6969	696.0	00200	176.0	606:0	0.835	0.900	
	Bernouth Naive Bayes	0	0	0	•	•	~	036:0	0.946	0.778	0.306	0.700	0.857		0				0.946	0.900	0.844	0.500	0.944	0.500	0.950	0.536	116.0	0.870	
visit visit <th< td=""><td>Dummy Classifier</td><td>0</td><td>0</td><td>0</td><td>•</td><td>•</td><td>-</td><td>0.385</td><td>0.615</td><td>0.500</td><td>0.500</td><td>0.500</td><td>0.434</td><td></td><td>•</td><td></td><td></td><td></td><td>0.539</td><td>0.500</td><td>0.500</td><td>0.500</td><td>0.500</td><td>0.470</td><td>0.531</td><td>0.474</td><td>0.562</td><td>0.500</td><td></td></th<>	Dummy Classifier	0	0	0	•	•	-	0.385	0.615	0.500	0.500	0.500	0.434		•				0.539	0.500	0.500	0.500	0.500	0.470	0.531	0.474	0.562	0.500	
100 084 071 031 <td>Extra Trees</td> <td>0</td> <td>•</td> <td>00 0.8</td> <td>16 0.6</td> <td>0</td> <td>-</td> <td>0.500</td> <td>0.500</td> <td>0700</td> <td>0.536</td> <td>0.500</td> <td>0.500 (</td> <td>ĩ</td> <td>0</td> <td>Ĩ</td> <td></td> <td>Ĩ</td> <td>0.500</td> <td>0.500</td> <td>0.500</td> <td>0.500</td> <td>0.500</td> <td>0.500</td> <td>0.500</td> <td>865.0</td> <td>0.500</td> <td>0.500</td> <td></td>	Extra Trees	0	•	00 0.8	16 0.6	0	-	0.500	0.500	0700	0.536	0.500	0.500 (ĩ	0	Ĩ		Ĩ	0.500	0.500	0.500	0.500	0.500	0.500	0.500	865.0	0.500	0.500	
0.00 0.00 0.01 0.01 0.01 0.00 <th< td=""><td>Ganssian Naive Bayes</td><td>***</td><td>0</td><td>64 0.7</td><td>74 0.8</td><td>0</td><td>~</td><td>0.938</td><td>0.982</td><td>0.390</td><td>0.669</td><td>663.0</td><td>0.878 (</td><td>Ĩ</td><td>0</td><td>Ĭ</td><td>Ĩ</td><td></td><td>0.918</td><td>0.829</td><td>0.981</td><td>0.869</td><td>6.96.0</td><td>0.750</td><td>0.916</td><td>0.598</td><td>0.873</td><td>0.894</td><td></td></th<>	Ganssian Naive Bayes	***	0	64 0.7	74 0.8	0	~	0.938	0.982	0.390	0.669	663.0	0.878 (Ĩ	0	Ĭ	Ĩ		0.918	0.829	0.981	0.869	6.96.0	0.750	0.916	0.598	0.873	0.894	
031 034 034 034 034 035 035 035 035 036 031 035 031 <td>Gradient Boosfing</td> <td>0.786 1.0</td> <td>Î</td> <td>64 0.7</td> <td>36 0.8</td> <td>0</td> <td>0</td> <td>0.938</td> <td>0.780</td> <td>0.864</td> <td>0.727</td> <td>0.831</td> <td>0.784 (</td> <td>~</td> <td>0</td> <td></td> <td></td> <td>Ĩ</td> <td>0.835</td> <td>0.500</td> <td>186.0</td> <td>1.000</td> <td>0.913</td> <td>0.610</td> <td>0.774</td> <td>606.0</td> <td>0.946</td> <td>0.881</td> <td></td>	Gradient Boosfing	0.786 1.0	Î	64 0.7	36 0.8	0	0	0.938	0.780	0.864	0.727	0.831	0.784 (~	0			Ĩ	0.835	0.500	186.0	1.000	0.913	0.610	0.774	606.0	0.946	0.881	
011 034 074 015 036 034 037 035 035 036 036 031 <td>Heistrom Quantum Classifier</td> <td>0.870 01</td> <td>0</td> <td>64 0.7</td> <td>36 0.7</td> <td>0</td> <td>•</td> <td>0.897</td> <td>9960</td> <td>0.835</td> <td>0.\$12</td> <td>0.938</td> <td>0.780</td> <td>Ĩ</td> <td>0</td> <td>Ĩ</td> <td></td> <td>Ĵ</td> <td>0.946</td> <td>0.900</td> <td>0.944</td> <td>0.953</td> <td>0.913</td> <td>\$56.0</td> <td>0550</td> <td>0.932</td> <td>0.873</td> <td>0.900</td> <td></td>	Heistrom Quantum Classifier	0.870 01	0	64 0.7	36 0.7	0	•	0.897	9960	0.835	0.\$12	0.938	0.780	Ĩ	0	Ĩ		Ĵ	0.946	0.900	0.944	0.953	0.913	\$56.0	0550	0.932	0.873	0.900	
0 100 100 074 085 087 089 087 099 087 099 091 023 087 049 087 079 084 087 073 079 089 075 079 089 075 100 078 091 050 071 089 083 080 083 0 0430 100 44 071 017 035 039 090 078 049 076 073 040 071 047 048 051 079 049 070 100 070 049 091 050 073 049 047 0 045 049 059 057 047 047 048 075 048 075 040 071 048 059 049 050 079 049 070 070 050 051 049 017 0 045 049 059 057 049 075 049 079 049 079 044 049 040 049 050 079 049 070 070 049 040 070 049 070 050 059 049 041 045 049 050 054 010 050 059 059 059 049 070 044 059 070 049 050 079 050 050 050 050 059 047 000 050 050 050 057 050 057 050 048 051 054 010 054 010 054 059 059 059 041 051 059 059 059 059 059 050 051 050 050 051 050 050 051 051 051	Linear Discriminant Analysis	0 2181		64 0.7	74 0.8	0	0	086.0	0.964	0.835	0.669	0.938	0.878	Ĩ	0			Ĩ	0.890	0.900	136.0	0.869	6.96.0	0.610	0.921	0.932	111	0.913	
100 100 <td>Lonistic Remession</td> <td>1820 11</td> <td>2</td> <td>00 0.7</td> <td>74 0.8</td> <td>0</td> <td>0</td> <td>0.897</td> <td>0.909</td> <td>0.920</td> <td>0.691</td> <td>0.822</td> <td>0.878</td> <td>Ĩ</td> <td>0</td> <td></td> <td></td> <td>Ĩ</td> <td>0.890</td> <td>0.845</td> <td>1.000</td> <td>0.769</td> <td>6.913</td> <td>0.500</td> <td>0.774</td> <td>0.598</td> <td>0.835</td> <td>0.863</td> <td></td>	Lonistic Remession	1820 11	2	00 0.7	74 0.8	0	0	0.897	0.909	0.920	0.691	0.822	0.878	Ĩ	0			Ĩ	0.890	0.845	1.000	0.769	6.913	0.500	0.774	0.598	0.835	0.863	
0 456 0 961 0 969 0 751 0 112 0 553 0 346 0 960 0 759 0 359 0 754 0 50 0 174 0 183 0 759 0 469 0 533 0 717 0 979 0 964 0 900 1 200 0 50 0 507 0 509 0 503 0 101 0 50 0 50 0 5	Multi Laver Percention	1 028.0	60 00	64 0.7	10 10	0		086.0	0.982	0.364	0.727	0.872	0.840	1					0.920	0.917	1.000	0.784	0.963	0 500	0.891	868.0	1 835	598.0	
0158 100 054 075 075 075 091 087 091 087 091 040 019 091 040 019 091 040 011 011 011 011 011 011 011 011 01	Manual Naidhann	DECK DI	9	C U	20 13	c		n ann	0.780	0.226	A 726	uco u	1.781						0 946	0.000	1 000	002.0	0 042	n con	0.940	1 196	0.817	1 041	
0.100 0.64 0.110 0.317 0.372 0.990 0.331 0.371 0.990 0.331 0.371 0.990 0.360 0.331 0.371 0.391 <th0< td=""><td>Onderit Discinitions Andreis</td><td>1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2</td><td></td><td>10 19</td><td>30 95</td><td></td><td></td><td>0.016</td><td>U GAL</td><td>0.918</td><td>0.440</td><td>0.010</td><td>0100</td><td></td><td>9. C</td><td></td><td></td><td></td><td>0.600</td><td>0.000</td><td>0.001</td><td>0 BOA</td><td>1000</td><td>0.670</td><td>0.801</td><td>0 606</td><td>1 817</td><td>0.952</td><td></td></th0<>	Onderit Discinitions Andreis	1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2		10 19	30 95			0.016	U GAL	0.918	0.440	0.010	0100		9. C				0.600	0.000	0.001	0 BOA	1000	0.670	0.801	0 606	1 817	0.952	
Note 0.84 <th0.84< th=""> 0.84 0.84 <th0< td=""><td>Pardom Forest</td><td></td><td></td><td>10 10</td><td>20 91</td><td></td><td></td><td>0.950</td><td>0.851</td><td>012.0</td><td>1 547</td><td>1 541</td><td>1 and 1</td><td></td><td>2.0</td><td></td><td></td><td></td><td>0.642</td><td>0.883</td><td>130-0</td><td>0.700</td><td>190.0</td><td>0 400</td><td>CAR 0</td><td>353 0</td><td>1 417</td><td>0000</td><td></td></th0<></th0.84<>	Pardom Forest			10 10	20 91			0.950	0.851	012.0	1 547	1 541	1 and 1		2.0				0.642	0.883	130-0	0.700	190.0	0 400	CAR 0	353 0	1 417	0000	
0 10 0 10 0 10 0 10 0 0 10 0 0 10 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0	SUM - Heat			2.0 79	10 10			0.960	7960	1 234	ALT O	0.918	0 878		2.0				0.018	0.000	0.061	0.500	196.0	0 500	0 837	1937	1 873	2100	
4. Varie van	SUM - moto	5.0		20 27	a.0 0.0			0.000	0.064	1.811	0.706	0.010			8. C				0.010	0.000	1.000	0.584	0.063	202.0	6.86.9	1.023	1 674	120.0	
	ovar poy	V 200 010	10 10		0 n 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1			0.060	190.0	110.0	0.104	072 D	1160						0.010	0.000	0 COO	10C'D			1000	1000	0.000	100.0	
	SVM - rbt	0.500 v.	81 0.2	00 0.0	12 U.a	0		0.364	1.30+	0.500	C0//0	0.938	0.500	1					0.715	0.500	0.500	0.084	0.500	0.500	0.852	0.932	0.500	0.913	

Table 4.37 Balanced accuracy score for 30 RGB image feature	score for 3	0 RGB im	age featur	e datasets	for cell lin	e U251		1																Ì	1	-			
Classifiers AdaBoost	0.917	925 0	946 0	955 0.	-		139 0.5	21 0.962	52 1.000	P11	0.929	0.921	0.832	0.923	0.871	0.917	0.927 0	0 293 0	P20 P2	0.900 0.9	0.920 1.0	1.000 0.935		0.955 0.91.	2 0.929	9 0.736	0.79	0.871	
Bernoulli Naive Bayes	0.917 6	1875 0	944 0	0 556	0	~	Ĩ					•	0.932	0.923	0.846			1		8				0		0	0		-
Dummy Classifier	0.500	1582 0	1500 0	1500 0.	•	Ĩ	1					9	0.405	0.546	0.500			2		23				•		0	0		0
	0.875 0	0 518.0	0 776	0 555.0								0 0	0.955	516.0	0.812			22		99				10 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0		0 0			
Gradient Boosting	0.917	925 0	946 0	955 1									0.977	0.902	0.896			-		83						0			
	0.917 6	0 0551	944 1	0 000	0	•	Ĩ					9	0.955	626-0	006.0			1		88				-		0	0		
Linear Discriminant Analysis	0.917 0	1875 0	361 6	0 5560	0	~	Ĭ					0	0.955	0.923	0.900									0		0	0		-0
	0.897 0	0 0561	944 0	1.955 0.	0	~	Ĩ					0	0.955	0.923	0.871			~						•		0	0		
Muth Layer Perceptron	0.877	0 0550	9 016	0 555	•							-	0.955	576.0	0.871			20						• •		0 0	0 0		
	108.0	000	1 100	0 220									0.000	2400	0000			-						5.9					
Passive Appressive Classifier	0.877	0 661	944 0	955 0			1					-	0.955	0.941	006.0					22				-		0	0		
	0.917 0	0 056	944 0	0.955 0.	0	-	~					9	0.888	0.816	0.871			22		20				0		0	0		
ininant Analysis	0.897 0	0 519.0	1972 0	1935 0.	0	ő	Ĩ					9	0.977	0.902	0.871			1		-				0		0	0		2
Random Forest	0.917 0	0 006	972 0	0 556	0	~	Ĩ					0	116:0	626.0	0.896			0						0		0	0		
	0.897	0 0561	1944 0	1.955 0.	0	Ĩ						•	0.955	0.923	0.871			-						•		•	0		
SVM - poly	0.877	1950 0	0 272 0	1 5551	000 0.5	9.0 726	0.0 (94)	96.0 556.0				906.0	0.955	6.923	0.896					23				15 0.84	0.964	0.769	0.898		
	0.710	0 0660	1 15	0 ((%)	D	2							CC6.0	6760	0.871									0.84	0.944	D	0		
Table 4 18 Balanced accuracy	trore for 3	AV****10	mare feat	inte datace	its for cell	line 1:241																	l	l	l	l	l	l	l
Classifiers	14	-		R	A PI	Ld 5	Bd .	17						pic	PIS	21d		17				17		17			17		
1. da Room	0.807	0.076 0	014 0	000	-			1		1	1	1		0.073	0.871	0.810						ľ					1	Г	-
Germonth Naive Baves	0.897	0 005	0 115	0 556								10		0.923	0.846	0354			93			~~				202	-		
Dammy Classifier 0.508 0.500 0.539	0.508	1500 0	0 6650	0 005 0	0	2						-7		0.404	0.431	0.561		-7	28			ĩ		1		10	-		
Lutra Trees	0.875 0	0.875 0	1917 0	1,955 0.	0	2	2					77		0.885	0.871	0.875		1	12			~		1		18	Ĩ		
Jamssian Naive Bayes	0.897 6	0 0561	944 0	0.955 0.	0	1						-55		0.902	0.841	0.875	-	1	95	5		~	J			1	-	1	
Gradient Boosting	197	925 0	0 116	0 566	0	2		~						0.902	0.837	0.857		~						1		20	-		
Heistrom Quantum Classifier	897	0.875 0	1 5681	1.955 0.	0	23						1		0.923	0.871	0.854		20	200	8		2		÷.,		50	-		6
mear Discriminant Analysis	1612	0 006 0	1981	955 0	•							22		0.913	00610	0.854		22	20							23			
Logistic Regression	7680	0 0560	1	0 325	•	265								0.923	0.871	0.875			20							26	-		
dan Layer Perception	168.0	1 006.0	000	0 220										126.0	1/8/0	C/80		80	202							202			
	2100	0 000	1 110	0 000	5 C									0.070	0.871	01810			22							22			
Passive Annessive Classifier	0.917	0 0051	839 0	955 0.		6.0 106						200		0.902	0.841	0.784			843							933	0.817		
	0.897 6	0 0561	841 0	581 0	0	25								0.923	0.778	0.801		22	22							20	-		
Quadratic Discriminant Analysis	0.897	0 516	972 0	955 0.	967 0.1	943 0.9								0.902	0.871	0.875			23	22						255	1		-
	0.917 6	925 0	1944 0	0 555 0	967 0.	943 0.5	2							0.923	0.806	0.875		1	22			~		1		20	0.87	5 0.87	
			1,944 0	1,955 0.	967 0.	978 0.5	9					-		0.923	0.871	0.875	-	2	50	8		Ĩ.,				50	0.790	2 0.87	
SVM - poly		0.975 0	0.972 1	000	867 0.5	50 156	0.947 0.9	0.932 1.000	0.975	0.566	0.929	068.0	126.0	0.864	0.871	0.798	0 606 0	0.893 0.	0.978 0.1	0.831 0.8	0.895 1.0	086.0 000.1		0.955 0.840	10 0.964	0.736	0.77	0.853	
	0.897		3 1944	1,955 0	.601 0.	10 816								676'0	0.871	6/8/0											6.0	2 0.87	
Table 4.39 Balanced accuracy score for 30 con	score for 3		trast image fear	ture datas	ets for cell	line U251																							
Classifiers	P1 I		4 6.	d P		7	2			1			1	PIS	P16	P17	1	7		7		-				1	3	-	
AdaBonst	1.000 0	0 1161	1974 0	981 0		2	Ĩ				00		12	1.000	516.0	6260		1				1		1		1			
demode Naive Bayes	0.958 0	946 0	1 1/60	0 000		<u>,</u>	-	-						0.962	006.0	0.920			176	-				Ξ.		200	8	-	-
Dummy Classifier	0.500	200	00510	605										0.484	0.481	0.502			89							23			
Alta litees	0.708	0 0081	1 1081	00020		20								0.840	0.803	0.808		200	20							20	80		
tradient Rooting	000	1 125	000	0 185	945 242									1 000	9160	1950			993										
Helstrom Quantum Classifier	856.0	1 1261	000	000		1								0001	0.975	856.0			2.2							35			
Linear Discriminant Analysis	0.958	921 0	946 0	955 0.		~								0.962	00610	826-0			83	-						63	2		~
Logistic Regression	1.000	0 9#6	1 1/61	0 000'		1		-						1.000	056.0	616'0		-71	-75	-		Ĩ		1		7	2		-
duhi Layer Perceptron	1.000	946	1 1/61	000		0.978 1.0	000 0.8							1.000	0560	8560		-	232	28		-		0 0.983		22	0.875		
vezrest Cetimona Generat Madahare	0001	1 1/2 1	000	0 000		1								0.040	0.976	0.045			897							201			
Passive Annessive Classifier	1 000	0 9:6	974	0 000										626.0	006.0	1560			22							22			
Perceptron	1.000	946 0	974 0	923 0										0.923	0.850	856.0			100	-		~		1		17			
Quadratic Discriminant Analysis	1.000	0 1261	1 1261	0 000'										000 1	0.975	619.0						Ĩ.,	2			8	0.87	26.0 2	
Candom Forest	1.000	1 1/6	000	1 000	000	978 1.6	10 000							1.000	5260	6460			23			-				83	0.935	8 0.98	
SVM - Inteat	000	0 1/60	1 1/51	000	0 106	100 100	000							1 000	516.0	865.0		-	22					0 0.98	10.01	503	0.89	36.0	
SVM - rbf	1 000		0.974 1	0 000	967 0.5	978 1.0	000 000	0.921 0.962	52 1.000	0 0 950	1.000	1.000	116.0	1.000	0.946	\$56.0	0.927 0	0.972 0.	1.0 +96-0	0.950 0.9	974 0.9	186.0 176.0		1 000 0.98	3 1.000	0 0.967	0.85	0.982	
Table 4.40 Balanced accuracy score for 30	score for 3	0 correlati	ion image	feature da	tasets for a	cell line U	U251 no	2	111					114								Ľ							
AddBoost	0.605	812 0	759 0	715 0.	1	0		ľ		0.303	0.736	0.778	0.820	0.718	607.0	0.840	Т	0.759 0.	0.848 0.	1	0.700 0.5	553 0.633		0.780 0.857	7 0.927	7 0.631	0.813	0.871	
Bernoulk Naive Bayes	0.528 6	1657 0	1754 0	0 0050	•	0		.0	-					0.665	0.574	0.763			122			~		1		9			
Dummy Classifier	0.500 0	1494 0	1500 6	0 0051	0			0						0.561	0.500	0.428			3			~		-		0			2
Eura Trees		0 0051	0 611	1,500 0.	•	0	2	0						0.500	0.665	0.538			733	8		1		~		72	8		0
Gaussian Naive Bayes	0.523	0 100	1231 6	0.526 0	•	•		0.1						0.739	0.703	0.739			20			-	- - V			22			0
dradient Boosting	613	0 0681	116	0 55770	•			0.4						158.0	16/-0	0.819			200							20	-		
Linear Discriminant Arabies	0.545	0 1901	1231 0	0 905		5 0		190 0 191						0.700	167.0	0.660			88							587			
odistic Regression	0.545	0 1591	111 0	545				- 0						0.721	0.753	0.662			20										
Multi Laver Percentron	0.690	678 0	946 0	981 0										616.0	0.841	0.801			83							20			
Nearest Centroid	0.553	1724 0	731 0	645 0	0	0		0						0.739	0.653	0.739			12					1		18	85		
	0.732 6	0 1001	0 1680	0 903.0	0	0		.0						0.822	0.841	0.795			22			~				10	-		-
	0.470 0	1410 0	1320 6	528 0	•	0		0						0.756	0.782	0.413			1							9			
Perceptron	0.490	0 1851	1626 0	1.469 0.	•	0		0						0.739	0.678	0.593				-				-		-	3		
nmant Analysis	0.483	0 0	787.0	0.526 0				0.0						0.760	602.0	0.756			9/6	-						92	30		
CUM - Inear	2 282.0	0 1391	781 0	0 005	2 0									0.710	0.753	1000			83							1			
vibe - Body	0.690	682 0	0 1160	696 0				0						0.857	0.891	0.724			85					10		20	1		0.00
SVM - rbf	0.545 6	1.632 0	731 6	500 0	1.653 0.5	500 0.8	811 0.6	0,676 0.81	13 0.649			120	855	0.780	0.782	0.623	0.484 0	1921	1	0.763 0.6		0.732 0.64				1			0
								1																					

	Table 4.41 Balanced accuracy score for 30 energy image feath	energy an	tage leafs	are dataset	is for cell	ine U251																							
Classifiers	PI P	2 P.	A	,	1	-	7			1	7	1	P14	PIS	P16	P17	PIS	P19	P20			-	1	7	1	7	7		
AdaBoost	1.000 1.	000 10	000	0 185									116.0	0.962	1923	0.938	0.927	0940	000								-		
Dummy Classifier		0.524 0.4	458 0.	500 0.		500 0.4		~					0.548	0.500	0.500	0720	172.0	0.500	10910								~		0
Ettra Trees	0.583 0.5	500 0.3	189 0.	500 0.	~		1						0.977	0.923	0.828	1/0/0	0.500	0.500	0.736 (•					~	<u> </u>	~	Ĭ	0
Gaussian Naive Bayes	0.917 1.	000 07	1 740	000		°							0.977	0.962	056.0	0.938	0.927	946.0	0.978	-		° .			~	<u> </u>	-		-
Gradhent Boosting	1000	000	1 000	000									116.0	196.0	0.50	8560	1750	0.920	000										a 4
Heistrom Quantum Classifier	1 000	000 10	1 000	1 000									1,000	076.0	046.0	86610	1000	1150	8/6/0										
Latest Decomman Analysis	1 00670	000	1 1761	1 1 100								-	104.1	116.0	1990	490.0	1760	70/-0	1.076										
Muhi Laver Percentron	1 000	000 1 0	000	000	1								0.977	176.0	9760	2760	0.927	976 0	8191										
Nearest Centroid	0.960	941 0.8	965 0.	923 0.	-	Ĩ		~					0.933	0.938	0.782	826.0	0.927	0.918	0.913 (•					~	ॅ	-		
Nearest Neighbors	1.000 1.0	000 1.0	1 000	000 1.	~	°	3		ĩ	Ĩ			1.000	0.920	216.0	0.920	0.944	0.974	000 0			Ĩ		0	~	Ĩ	7		-
Passive Aggressive Classifier	1.000 1.0	000 072	M1 0.	1 185	-	Ĩ	1		0	Ĭ			0.977	0.941	946.0	0.766	0.927	0.946	9.978 (0		~			Ĩ	Ĩ	~		0
Perceptron	1.000 1.	000 0.5	947 0.	981 0.	2	~	7	~		Ĩ	0		1.000	0.885	0.875	0.899	0.927	0.946	0001	0		~			~	Ĩ	~	č	0
Quadratic Discriminant Analysis	1 (16.0	000 1.0	1. 000	000 1.	-	7				Ĭ			0.977	0.962	0.950	856-0	0.927	1 1/5-0	9.978 (-		~			~	Ĩ		Č	
Random Forest	1.000 1.	000 1.6	000 1	000 1	7	0		-		Ĩ			0.977	0.962	0.925	0.938	0.871	0.946	000 1	0					2	Ĩ	~	ĩ	-
SVM - linear	1.000 1.	000 1.0	000 1	000 1	000 00	7	1			Ĩ			1.000	0.962	946	856'0	0.927	0.946	0001	•					~	Ĩ			13
Vine - poly	1.000	000 10	1 000	1 000	0000	964 0.9	974 1.0	1.000 1.000 N 967 0.981	0 1.000	0000000	1 000	1 000	1.000	0.920	9460	0.938	0.927	976.0	000	0 1661	1 1260	000 000	0.1 100 100 100 100 100 100 100 100 100	1351 0.983	10.962	2 0.912	0.918	C86-0 8	
101 - 10 + 0	1.000	AVV 1-1			MAN 17			1					1.090	11.794	- ALCA	1000	1010	0.67.0	A0471								1		,
Table 4.42 Balanced accuracy score for 30	score for 30	homoge	uelty image	e feature d	latasets fo	r cell line l	U251																						
Classifiers	P1 P.	2 P3	A .	4 7	5 P	Ld S	PS				7		P14	P15	P16	P17	P18	P19	P20 1	7				~	7	7	7		
AdaBoost	1.000 1.0	000 1.0	1 000	000 00	967 1.	000 0.9		1		1			0.955	0.962	056.0	0.958	0.927	0.946) 978 (Ĩ		-			-	Ĩ	0
Bernoull Naive Bayes	1.000 1.0	000 1.0	1 000	000 1	000 00	0							1,000	0.962	946.0	0.917	606.0	216.0	000 1	~	-	Ĩ				័	~	-	5
Dummy Classifier	0.500 0.5	500 0.5	000	500 0.	0	•	8					-	0.500	0.659	0.565	0.623	0.542	0.462	0.396 (2						ĩ	2		0
Extra Trees	0.958 1.0	000 170	000	\$18 O.	0	•	3					2	0.977	0.962	0.946	326.0	0.889	0.500	000	-		Ĩ		•		~	Ĩ	-	0
Gaussian Narie Bayes	1.000	000 170	100	000	•	-							116.0	0.962	0560	\$56'0	0.927	976	000							٣,			. 47
Gradient Boosting	1.000	000	100	000	-	•		-				- 20	1.000	1991	056-0	0.920	0.927	0.946	0.978							~			
Heistrom Quantum Classifier	1.000	000	1 1	000		000 0.9							1.000	20670	516.0	0480	175.0	0540	000							1			
Linear Localitation Analysis	1 0001	11 000	1 10	0 000	1								1 000	104.0	0.076	0100	1750	7/60	ate t							1			
Model Trunc Decomposition	1 000				1								0.071	10000	1000	96.6.0	1750	2000	0.710	1							1		
Newson Controls	1 000 1	50 000	100	1 100	• •							9.07	1.000	0.918	0.871	0.917	0.977	976.0	0001										
INCLUSION CONTRACT				1 000								-	1 1000	0000	110.0	112.0	1720	0440	000										
Denire America Checkler	1 000	10 000		000		0.0 0.0	1					2.5	0.000	0.941	0.940	10 841	1750		000										
Percentron	1 000	50 000	114	000	0 290	01 810	2						0.977	0 864	006.0	0.804	0.927	976 0	263 0	1									
Ousdratic Discriminant Analysis	1 000 1	000 1.0	1 100	000	0 190	0.1 0.1 0							0 077	0.060	0500	0.058	1007	0 046	000	-						1	-		
Random Forest	1 000 1	000 1.0	1 00	0 000	1 1 1	000 000							0.977	0.962	0.900	0.948	126.0	0.946	0.978							1			
SVM - Inest	1 000	000 1.6	000	000	1 1 1 1 1 1	0.0							0.977	0 960	0.946	0.958	0.927	226.0	000							1			
SVM - poly	1.000	000 07	1 2720	0 000	1 1160	000 0.9	946 1.0	1.000 1.000	0 1.000	0 1.000	1.000	1.000	0.977	0.962	056.0	0.938	0.927	0.974	000	1 056.0	1 000 1	000 07	0.1 826.0	1000 0.983	13 0.982	2 0.912	0.958	0.982	a
SVM - rbf	1.000 1.	000 1.6	1 000 1	1 000	000 1.	000 0.9							1,000	0.962	0.975	856'0	0.927	946 0	0001		1			-		1	1		-
Table 4.43 AUROC score for 30 RGB image feature datasets	30 RGB inta	ge feature	datasets	for cell 1	ine U251		1	Ľ	1	1	1	Ľ								1	Ľ	Ľ	1	ľ	Ľ	1	1	Ľ	U
AdeRover	0017 0	050 050	0 10	0 330						1			0.613	0.012	0.804	0.017	0.077	0 602	1 041		1	T							
Bemode Naive Baves	0 2160	875 0.5	10	955 0	933 0	913 0.8	568 0 8	1000 0000	10 0.366	6 0.825	0.929	0.906	0.932	616.0	0.846	0.854	0.927	198.0	1857	0 058.0	.0 868	1261	60 8580	1955 0.84	1840 0.946	0.757	0.833	0.871	
Dummy Classifier		0.440 0.5	500 0	0 005		1							0.482	0.540	0.500	0.500	0.500	0 500	0.500	-							-		. 0
Extra Trees		0.875 0.8	0.889 0.	955 0.	0	1	2					1	0.921	0.885	0.871	0.822	0.833	0.500	0.857 (~				Ĭ	~	Ĩ	~	-	90
Gaussian Naive Bayes			1944 0.	0 555	•	87 	1					1	126.0	0.923	0.871	0.896	0.927	0.541	0.857	0		1			3	Ĩ	-		-
Gradient Boosting	0 216.0	0.950 1.0	000 00	955 0.	0	1	3					Ĩ	0.944	0.902	0.896	0.896	0.927	683	0.964	~	~	Ĩ	Ĩ	Ĩ	~	Ĩ	~	0	
Heistrom Quantum Classifier	0.917 0.5	0.950 0.9	944 0.	955 0.	-	2	2		0			7	0.955	0.923	006.0	0.819	0.889	0.789	0.929 (0	Ĩ	ĩ	0	Ĩ	7	Ĩ	~	0	-
Linear Discriminant Analysis	0.917 0.1	0.875 0.8	0 19810	955 0.	0	С. 		-	7	0	1	č	0.955	0.973	006.0	0.316	0.389	0.842	0.800 (0		Ĩ		Ĩ	~	Ĩ	-	0	*
Logistic Regression	0.917 0.5	0.950 0.5	0 15	955 0.	0	1	8		Ĩ.	0	2	ĩ	0.955	0.923	0.871	0.837	0.891	0.893	178.0	0		Ĩ	Ĩ	Ĩ	~	Ĩ	~	0	
Muhi Layer Perception	0.917 0.1	0.950 0.5	972 0.	955 0.	•	1	5						0.921	0.923	0.871	0.854	168.0	0.867	1.943 (~	Ĩ	Ĩ		1	2	Ĩ	~	0	6
Nearest Neighbors	0 2160	925 0.5	P44 0.	955 0	•		2					-	0.955	626.0	006.0	0,798	0.589	0.921	0.929 (•	-	Ĩ.,			~	Ĭ	~	0	
Quadratic Discriminant Analysis			0 724	935 0.	•	73 		- · ·					0.977	0.902	0.871	0.875	606-0	0.893	0.893	0				Ĭ	~	Ţ	-	0	0
Random Forest	0.917 0.9	0.925 0.5	0.972 0.	955 0.	944 0.	943 0.9	-						0.977	0.923	0.896	0.396	0.927	0.893	0.929	•	-			3	~	7	-	0	
SVM - Intell	160	00000	0 +++	0 000	194	60 164							006.0	676.0	0,871	1.80	176.0	C68.0	1/8/1								-	0.4	
And - to ve			0.00% U	- AUX 0			3						0.000	C7676	1/8/0	to and	1007	749.0							2				
Bardie sechels Names Canonic Bardie American American	Amazine Class	affer and Barrary		.n .ccz	N 666	210 012						1	0.920	57670	17970	0000	1220	76210	0000	"	1			1	1		1	1	
the state of the s																													
Table 4.44 AUROC score for 30 L*u*v* image feature data	30 L*u*v* 1	mage featu	ire datase	ets for cell	line U251	115	I	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	I	l
Classifiers	PI P	2 P3	4	d 7	S P	PT PT		1				7	P14	PIS	P16	P17	P18	P10	11	8			17		17	F	1		
AdaBoost	0.917 0.	950 056	972 0.	909 0.	935 0.	945 0.9		Ĩ				~	0.888	0.923	0.841	0.396	0.927	1 268.0		1			Ĩ	Ĩ	1	1	Ĩ		-
Bemoulk Naive Bayes	0.897 0.5	900 006	944 0.	955 0.	967 0.	913 0.8	2					1	0.955	0.923	0.846	0.854	0.927	0.865		~			Ĩ.		7		~		
Dummy Classifier	0.500 0.1	500 0.5	500 0.	500 0.	0	0						Ĩ	0.448	0.500	0.500	0.421	0.500	0.500		-			Ĩ	2	7	2	1		π.
Extra Trees	0.875 0.1	\$75 0.8	0.861 0.		9	0	2	ĩ	1	0		7	0.955	0.885	0.871	0.896	0.833	0.737				1	Ũ	2	7	8			
Gaussian Naive Bayes	0.897 0.5	950 0.5	944 0.		0	0						~	0.977	0.902	0.841	0.875	0.927	0.593		-			1	0	-		~		
Gradient Boosing	0.877 0.	925 1.6	0 000	an Ve	0	0						1	0.911	0.902	0.866	0.857	606-0	0.892					Ĩ		-		~		193
Heistrom Quantum Classifier	0.917 0.1	500 005	972 0.	2	•	•			Ξ.			7	0.977	576-0	0.871	0.816	0.389	563.0					1		2	3	~		
Linear Discriminant Analysis	0.917 0.5	800 005	1.861 0.		2	•		~				~	0.955	676'0	006.0	0.854	0.889	0.568		~			1	1	20	33	-		
Logistic Regression	0.897 0.1	950 0.5	944 0.		•	0		~				~	0.955	0.923	0.871	0.896	0.891	0.867		7		Ξ.	Ξ.		-		-		
Mahi Layer Perceptron	0.897 0.1	950 1.0	000		•	•	20	-					0.977	0.923	0.871	0.875	0.891	0.567							-	20	-		-
	0 1160	CO 004	1	а () 		8							0.888	0760	0.871	0.810	0.389	9010											
Quadratic Discriminant Analysis	168.0	CO C/6	- 215 O	500 000	-								116.0	0.982	0.8/1	C/8/0	606.0	562.0											
CULL Burne	0 2007	50 U56	0.00										0.906	1000	0.871	0.876	0.880	1 895					1						
SVM - poly	10 2160	\$75 0.5	0.917 0.	955 0.	0.867 0.	943 0.9	947 0.5	0.932 0.955	0550 5	006.0 0	0.929	0.830	0.955	0.902	0.871	0.798	0.889	0.842	978	0.850 0	1 268.0	000	60 0860	955 0.714	14 0.927	7 0.786	0.833	0.871	
SVM - rbf	0	900 006	0.667 0.		0	0						~	0.955	0.923	0.871	0.875	0.871	0.500		~					2	22	~		0
Results exclude Nearest Centroid, Passive Agg	essive Class	utier and Percep-	-brook																										

Table 4.45 AUROC score for 30 contrast image feature data	50 contrast	image featu	ire datase	ds for cell	* U2											1000										and the second se	
Classifiers	PI P	2 P3	P4			1	7		7	FII	1					P18	P19	P20		1	1		1	1	P28	P29	P30
AdaBoog Remode Naive Raves	0.958 0.0	0.0 100	00 03	565-0 000 000	872.0 00	6 0.974	0.967	0.961	0.950	0.900	1 000	0.000 0.5	0001 1000 V880	0060 0	6450	0.927	0.946	0.979	0 056 0	0.918 0.9	256.0 116.0	1 1 000	1260 0	683.0	0.983	0.897	236-0
Dummy Classifier			0.500 0.6							0.347			1.5			0.653	0.500	0.500							0.500	0.500	0.500
Extra Trees			0.306 0.5							0.500		101				0.500	0.500	0.821		-	<u> </u>			1	0.500	0.500	0.500
Gaussian Narve Bayes	1.000	60 1260	1 000 10							218.0		20				606.0	279.0	676.0	89						0.950	0.619	0.982
Helstrom Ownfum Classifier			o d							0.925						0.927	0.737	0.929						847	196.0	0.875	0.982
Linear Discriminant Analysis	0 856.0	0.921 0.946	0			12				0.950			2			0.871	0.893	0.893	2		-				0.643	0.875	0.815
Logistic Regression	1.000 0.		74 1.6	000 0.9			0			0.950						0.927	0.972	0.929						2	0.967	0.875	0.982
Multi Layer Perceptron	0001	0.946 1.0	000 1/0	50 000	0.97	8 1.000				0.950		20				0.927	0.972	156.0						24	1967	0.855	0.982
Desirest regueurs Onsdeste Discrimiser Anslesis	1 000		1 10	CO 000	NO 1 100	1 1 000	2			200		202				1760	0.001	FIND U							10.00	518.0	1000
Random Forest	1.000 0		1 000 1 0	000 1.00	126.0 00	8 1.000				506.0						0 927	0.972	1 000	22						0.967	0.938	0.982
SVM - Inear	1.000 0	1971 0.974	74 1.6	000 0.9	35 0.97	8 1.000	1			0.950			63			606.0	0.946	0.964	22					1	0.967	0.897	0.982
Vod - poly	1.000 0	0	74 1.6	000 0.9	1001 55	0 1.000				575.0						0.927	0.946	0.929	20						0.950	0.875	0.667
SVM - tbf 0.500 0.500 0.500	0.500 0	500 0.5	500 1/0	000 0.5	61 0.97	8 1.000				0.950						0.500	0.500	1 964					T		0.643	0.855	0.500
PERSON SALARSY APPENDIX ADDRESS (1997)	with association		tont																								
Table 4.46 AUROC score for 30 correlat		ion image feature da	ature data	asets for cu	cell line U25	1																					
Classifiers		2 P3	P4	sd Ps	17	1	17	1	P10	PII				-		P18	P19	P20		-	r	П		1	P28	P29	P30
AdaBoost	0.608 0.	0.316 0.7	59 0.5		P	Ĩ	1	[0.812	0.503	P	I?	1	1	1	0.744	0.759	0.820	Г	Ľ	r	Ľ		1	0.521	0.710	0,871
Bernould Naive Bayes		0.657 0.754	0		0	0			0.565	0.665			-			0.556	0.548	0.592	8						0.450	0.753	0.669
Dunny Classifier			•		•	2			07200	0.500		33				115-0	0.500	0.500				2			0.500	0.438	0.617
Eatra Trees			0		0		2	-	0.651	0.500			2			0.500	0.500	0.500	2		1	Ĩ.,			0.500	0.500	0.500
Gaussian Naive Bayes			0	526 0.7	•		2		0.703	0.732		39				0.502	1150	0.635	23						0.643	0.730	0.760
Gradient Boosting			e i		•				0.837	0.803		222				0.891	0.788	0.856						7.6	0.709	0.710	0.815
Helstrom Quantum Classifier			0 4		0 0				1/8/0	0.846		23				168.0	0.784	668'0							0.643	0.733	0.909
Linear Literumant Analysis	0 0000	101.0 100.0			-				6400	0.004		202				0.484	0550	2450							0.043	0.710	0.760
Multi T aver Der entren									0.806	0.887		200				1 987	1813	0.842						20	0.648	0.730	0.961
Nearest Neidthors	0.691 0						1		0.812	0.887		1				0.780	0.867	1980							0.752	0.730	5150
Quadratic Discriminant Analysis	0.483 0		0						0.753	0.732		200				0 593	0.604	0.679							0.610	0.730	0.760
Random Forest		0.791 0.889	89 0.6	\$82 0.9	0.893				0.837	0.916		85				606-0	0.709	0.877	26						0.714	0.813	0.815
SVM - linear	0.545 0	1657 0.703	03 0.5	9.0 0.6	•				0.649	0.694		10				0.484	0.550	0.542				Ĩ		-	0.500	0.730	0.760
Vod - MVVS			17 0.4	896 0.8	H9L 0 608.0	4 0.728	0.721	0.813	0.841	0.857	0 568.0	0.778 0.7	0.753 0.857	168'0 2	0.724	606 0	0.788	156'0	0.763 0	0.810 0.8	0.821 0.938	13 0.545	60/00	0.927	612.0	0.752	0.853
SVM - rbf	5	0.632 0.731	31 0.5	500 0.7	20 0.50	0 0.811	1		0.649	0.500		1		1		0.520	0.500	0.585		1	1	1		1	0.571	0.730	0.760
Raudia exclude Nearest Centroid, Passive Aggr	Aggressive Class	when and Perceptron	thereas																								
Table 4.47 AUROC score for 30 energy image feature data	30 energy in	nage featur	e dataset	s for cell li	line U251																						
Classifiers	P1 P	2 P3	a ,		đ	-	8d		P10	P11	2	2	-	-	714	P18	P19	P20						7	P28	P29	P30
AdaBoost	-		0	0	-	ĉ	1.000		1160	51/6/0			0		0.938	0.927	0.946	1.600	Ĩ				Ĩ		0.824	0.835	0.982
Bernouli Naive Bayes	0.940 0.	0.912 0.838	0 0	827 0.9	955 0.964	4 0.972	660	0.885	1/6-0	10-541	0.807 1	000 07	0.967 0.920	0 0.857	0.958	0.615	0.732	0.548	0.652 0	0.8	0880 0.980	0.729	0.879	0.782	0.505	0.817	0.742
Estra Trans							0.067		0.887	1765		194			0.748	0.667	0 500	0.000							0.500	0.500	0.500
Gaussian Naive Baves							1 000		1 000	1160		22			816.0	0.927	0.946	0.978							0.895	0.918	0.917
Gradient Boosting		000 1.0	0		-	0	1.000		1.000	172.0		100	0		0.938	0.927	0.920	1.000	1						0.824	0.918	0.982
Helstrom Quantum Classifier	0.917 1.	000 1.0	000 0.5	7	0	0	0.967		116-0	1/60			0		856.0	0.927	1.000	0.978	2		Ĩ	0			0.862	0.960	0.927
Linear Discriminant Analysis	0.960 1.	000 0.921	21 1.6	000 1.0	0	°	0.933		1160	116-0			0		0250	0.927	0.762	163.0	Ĩ		Ĩ		0		0.769	0.920	0.982
Logistic Regression	***		74 0.5	1 186	0	1	0.967		1160	160			0		856.0	0.927	9560	0.957			Ĩ.,				0.824	0.940	0.982
Muth Layer Perception		000 10	000 03	01 196	00 0.92		19670	-	1160	1/60		202	0 0		9660	1760	0160	106.0							108.0	0.918	2360
Nearest Neighbors	1.000	000 170	00 17	000 1/6	06.0 00		19670		0001	0140			0 0		0750	1000	120	1.000							0.824	0.950	286.0
Quadratic Literaturation Analysis	1 000 1	000 1000	1 100	1 1 00	NO 1 00		1 000		1000	1000			5.6		1010	176.0	0.046	1 000							10.01	0.016	176.0
SVM - Inear	1 000	000 10	00 1/0	200 1.0	96.0 00		0.967		1 000	126.0			0		856.0	0.927	0.946	1352							0.895	0.898	286.0
yod - MVS	1.000 1		1.000 1.0	000 1.0	00 0.925	0	0.967		126.0	0.946		12	0		0.938	0.927	0.974	1.000							0.879	0.938	0.982
SVM - rbf	00 1	000 1.0	000 1.0	000 1.0	00 0.50	-	0.867		1/6/0	0.500			0		0.958	0.500	0.946	0.935			Ĩ		Ĩ		668.0	0.940	0.500
Rendts exclude Nearest Centroid, Passive Agg	Aggressive Class	wher and Percept	pirros																								
Table 4 481 ATBOC score for 10 ho	TO homomore	after tensors fauture	fasture d	strate for	call line T	161				l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	l	
Classifiers	d Id	2 P3	P4	PS BS	P6	P7	84	8	P10	PII		17	17	1	714	P18	PIO	P20	17	17	17	1	ľ	17	P28	P29	P30
AdaBoost	1.000 1.	000 1.0	00 1.6	000 1.0	-	°	-	1.000	1.000	1.000		1	Γ	ľ	856.0	0.927	0.946	0.957	Γ	r	-	-	Ĩ	ľ	0.845	0.938	0.982
Bernoull Naive Bayes	1.000 1.	000 1.0	1.000 1.0	000 1.0	0	•		1.000	1.000	5/5-0		-		°.	0.917	60610	0.972	1.000			Ĩ	Ĩ		3 	0.631	0.960	0.982
Dummy Classifier	0.428 0.	500 0.5	200 0.5	500 0.4	•	~	0	0.500	0.485	0.500	7	~	2	0	0.500	0.669	0.572	0.500	-			•	Ĩ		0.471	0.530	0.500
Extra Trees	0.833 1.	°	12 0.7	727 0.9	•	-	0	1.000	1.000	0.912		20	2	0	856.0	0.722	0.500	1.000	1			•	-	Ĩ.	0.500	0.583	0.833
Gamssian Naive Bayes	art 1	-	000 1/0	6.0 000	•	•	-	1.000	1.000	0.946		~		0.1	1560	0.927	0.946	1.000		-			•		0.895	0.935	286.0
Gradient Boosting	1.000	50 000	974 1.0	200 002		-		186'0	1.000	21975		~		0.1	0260	0.927	0.946	126.0		-					0.862	0860	2360
These Physics Andreas	1 000		1 10	20 000	• •			1 000	1 000	0.510		20	2	2.0	1160	1750	1001	1 000	1						716-0	0.010	1000
Latest Location Analysis	1 000	000 000	1 10	0.0	1			0.981	1 000	1 600		20			0.978	0 907	0 946	0.078							0.840	0.918	C30 U
Multi Layer Perceptron	1.000		000 1.6	000 000	967 1.000	1	. 0	196.0	1.000	1.000					0.878	0.927	0.946	8/6.0							0.840	168.0	0.982
Nearest Neighbors	1.000 1	000 1.0	00 1.6	6.0 0.9	0	-		1.000	1.000	0.975		-	Ĩ	0	0.396	0.927	0,946	1.000	~		~		Ĩ	Ĩ	0.912	1.000	0.982
Quadratic Discriminant Analysis	-	000 1.0	00 1.0	6.0 0.0	67 0.97	8 1.000		1.000	1.000	946.0		<u> </u>		0	85610	0.927	0.946	1.000							0.895	816.0	0.982
Random Forest	1.000	000 1.0	00 14	20 000 013			** *	1.000	1,000	0.946		~		0 0	10.0	1/2/0	0.946	8/6/0							0.862	0.938	0.982
SVM - ndv SVM - ndv	~ 0	000 10	00 10	955 0.96	67 1.000	0.974	1.000	1.000	1,000	1.000	1.000	1 000 1	000 0.962	2 0.946 5 0.946	1160	0.927	0.946	0.913	0 056.0	1947 1.0	000 1.000	0 1000	0.983	0.982	0.857	0.875	0.833
SVM - thf		200 1.0	00 110	000 1.0				1.000	0.500	1.000					116.0	0.500	0.500	0.500							0.540	0.500	0.500
Rendts exclude Nearest Centroid, Passive	Agmentive Class	wher and Perce	retron																								

References

- 1. Haralick, R. M., Shanmugam, K. *et al.* Textural features for image classification. *IEEE Trans. Syst. Man Cybern.* SMC-3, 610–621, DOI: 10.1109/TSMC.1973.4309314 (1973).
- 2. Haralick, R. M. Statistical and structural approaches to texture. *Proc. IEEE* 67, 786–804, DOI: 10.1109/PROC.1979.11328 (1979).
- **3.** Rundo, L. *et al.* HaraliCU: GPU-powered Haralick feature extraction on medical images exploiting the full dynamics of gray-scale levels. In Malyshkin, V. (ed.) *Parallel Computing Technologies (PaCT)*, vol. 11657 of *LNCS*, 304–318, DOI: 978-3-030-25636-4_24 (Springer International Publishing, Cham, Switzerland, 2019).