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Evaluation of Machine Learning Models for Breast Cancer Diagnosis Via Histogram of Oriented Gradients Method and Histopathology Images

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Abstract— Breast cancer is the main death rate from malignant growth worldwide and the most frequently diagnosed type of cancer in females. Machine learning systems have been developed to assist in the accurate detection of cancer. There are numerous methods for cancer detection. But histopathological images are thought to be more precise. In this study, we used the HOG features extractor to extract statistical features from histopathology images of invasive ductal carcinoma. We chose the following images at random from the histopathology images: 100, 200, 400, 1000, and 2000. These statistical features were then used to train several algorithms, including the decision tree, quadratic discriminant analysis, extra randomized trees, gradient boosting, gaussian process classifier, naive bayes, nearest centroid, multilayer perceptron, and support vector machine, to identify whether or not the images depict cancerous or noncancerous growth. The algorithms' performance was evaluated depending on the specificity, accuracy, sensitivity, precision, F1_score, and AUC. The algorithms used worked best when the number of images was set to 100. As the number of images went up, their effectiveness went down.

Keywords- Histogram of oriented gradients; Computer-aided diagnosis; Breast cancer; machine learning; Invasive ductal carcinoma

I. INTRODUCTION

Cancer is the disease that accounts for the greatest number of deaths among individuals all over the world [1]. Only in 2018, 18.1 million patients were classified as having cancer, breast cancer (BC) is the principal type [2]. BC is a potentially fatal cancerous tumor that affects women all over the world, surpassing lung and bronchus cancer as the second leading cause of death in women [3]. Number of cases of BC is increasing and is expected to reach 19.3 million by 2025 [4]. Invasive ductal carcinoma (IDC) is the most frequent BC subtype, accounting for approximately 80% of all patients [5]. IDC originates in a breast duct and then spreads to the breast's fibers or fat tissues. It may spread to nearby lymph nodes and other body regions [6]. BC death rates can be reduced with primary detection and accurate diagnosis. To distinguish between malignant and benign cancers, frequent tests and diagnostic scanning, such as MRI, mammography, and ultrasound, are required [7]. Pathological diagnosis with histopathological imaging, on the other hand, is recommended since it provides greater evidence for categorization, evaluation, and investigational treatment, but pathological diagnosis is a time-consuming and exhausting process [8]. Pathologists who are experts may also make errors in diagnosis. Pathologists visually evaluate histology samples under the microscope to detect IDC, which is a difficult operation due to their varying appearance, texture, and structure and is a time-consuming operation. Pathologists would benefit from automation of this tumor type's detection since it would speed up the diagnosis and reduce mistakes. Therefore, computer-aided design (CAD) systems are the optimal approach for classifying histopathological images as cancerous or non-cancerous [9].

The primary goal of this research is to assess the efficiency of machine learning (ML) algorithms for classifying IDC histopathology images of breast cancer by using six criteria. The models use a histogram of gradients (HOG) feature extractor. The collected features are then utilized to train the next algorithms: decision tree, quadratic discriminant analysis, extra randomized trees, gradient boosting, Gaussian Process Classifier, Naïve Bayes, Nearest Centroid, Multilayer Perceptron, and support vector machine. In addition, know the effects of the number of images on classification results.

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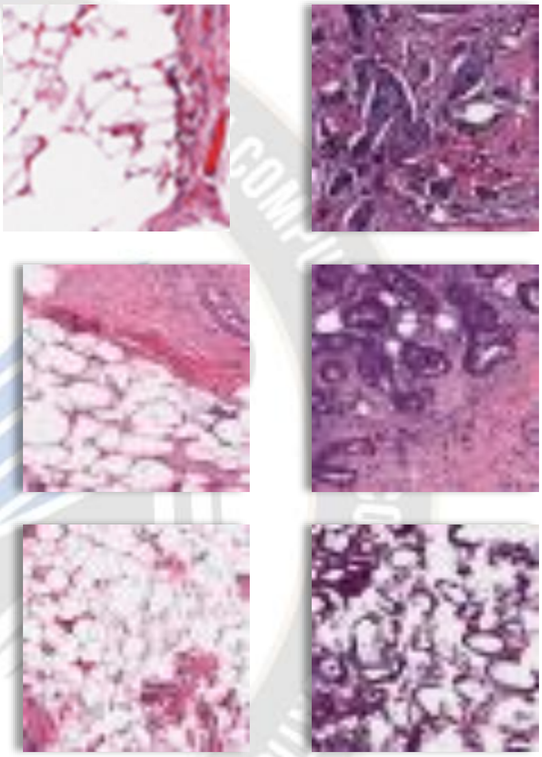
II. RELATED WORK

Researchers have proposed numerous strategies for BC diagnosis in histopathology images in the last few years. ML algorithms are being presented as new revolutionary approaches. Much research has concentrated on feature extraction by using a HOG extractor or other, and finding statistical and textural features. A.D. Belsare et al. (2015) [10] used textural features, and LDA to categorize breast histopathology images, and the spatial-color texture graph segmentation approach is used to separate them as the epithelial lining around the channel. Several features are extracted, including the GRLM, GLCM, and the Euler number. The LDA classifier is compared to KNN and SVM classifiers in terms of performance. Quantitative analyses and experiments demonstrate that the LDA classifier surpasses others with an accurate classification rate of 100% for nonmalignant breast histopathology images and 80% for malignant breast histopathology images, respectively. Taha J. Alhindi et al. (2018) [11] compared classification methods based on local binary patterns, HOG, and the three most prevalent image categorization techniques and a pre-trained deep neural network, which are: ANN, SVM, and DT. All are employed to categorize feature vectors extracted by various feature extractors using KIMIA Path960. The accuracy of classification models applied to the histopathology images was evaluated; SVM achieved the greatest accuracy at 90.52 %. Barath Narayanan et al. (2019) [5] provided an architecture for classification based on CNN on a collection of 27,553 test images, the AUC for IDC detection is 0.94. According to the data, CNN is highly successful at detecting IDC. 27753 images yielded an AUC value of 0.935 (7879 with IDC). Soumya Deep Roy et al. (2021) [12] employed feature extractors to extract textural and statistical features such as SURF, ORB, and SIFT. Features are then concatenated to create a 782-feature dataset. These features are then combined using a variety of classification algorithms, including ERT, AdaBoost, random forest, CatBoost, XGBoost, and MLP, followed by selecting features to produce a dataset with four features for classification. In these experiments, CatBoost achieved a maximum accuracy of 92.55%. Vandana Kate et al. (2021) [13] used the CNN, which is supposed to be able to expand and learn about spatial hierarchies of characteristics by using error backpropagation and convolution-pooling layers. It worked best when used for breast cancer histopathology imaging. With an average accuracy of 98.5 % for 200X scaled images, the proposed model had the best overall performance. When images of various sizes were merged to enhance the input dataset's size, the algorithms were able to classify benign and malignant subcategories by 95.5%. respectively.

III. METHODS

A. *Dataset description*

The classification was accomplished using a histopathology image. The IDC subtype of breast cancer has been determined to be the most prevalent of all breast cancer types [14]. It contains 162 full-mount side images of breast cancer. There are 277,524 and 50x50 image patches, of which 78,786 are IDC(+) and 198,738 are IDC(-) [15]. Figure 1 shows sample histopathology images from the current dataset for both classes. The dataset is freely available through the Kaggle website.



(a) IDC (+) (b) IDC (-)

Figure 1. A sample of images from the current dataset. (a) IDC (+), (b) IDC (-)

B. *Histogram of Oriented Gradients (HOG)*

HOG descriptor is used in image processing and computer vision to improve the detection of objects [16]. When it comes to lighting background, noise, and variation, HOG is an excellent descriptor since it provides distinguishing features. The HOG descriptor focused on the structure or form of an object. HOG exceeds all other edge descriptors by generating histograms for the image's areas depending on the gradient's orientation and amplitude. [17]. HOG is explained in Figure 2.

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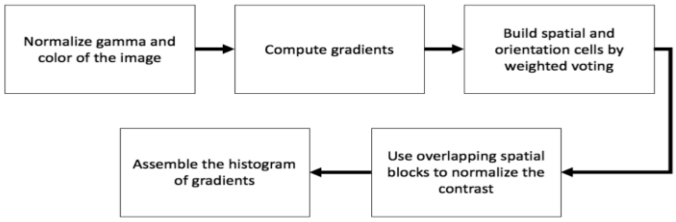

Figure 2. Flowchart summarizing the estimation of HOG [18]

C. Models

A Decision tree (DT) is an approximation of a piecewise constant. A decision is a recursive split of the instance space that is used to classify. DT is easy to understand and interpret. The cost of utilizing the tree is proportional to the number of data points required to train it. DT able to deal with both numerical and categorical data. DT capable of dealing with problems that have a large number of possible outcomes [19]. Quadratic discriminant analysis (QDA) is an individual covariance matrix estimated for each class of observations. A problem with QDA is that it can't be used to make things smaller in size. QDA is more flexible than linear discriminant analysis (LDA) in that it does not require equal variance and covariance. To put it another way, the covariance matrix for each class in QDA might be different. When you have a short training set, LDA is preferable to QDA. On the other hand, QDA has suggested if the training set is very big and the classifier's variance isn't a key concern [20]. The Extra Randomized Trees (ERT) algorithm is one of the types of bagging methods. The basic point of the average method is to build a huge number of estimators exclusively and then average their results. The combined estimator is typically superior to any of the single-base estimators since its variance is reduced [21]. Gradient Boosting (GB) is one of the methods of boosting. GB refers to an extension of boosting to arbitrary differentiable loss functions. GB is a ML approach to improving a model's predictive value by continuously improving its predictive value [22]. The gradient is the gradual change that occurs during the procedure. Boosting is a means of speeding up the increase in prediction accuracy to a very high level. Both binary and multi-class classification are supported by GB [23]. The Gaussian Process Classifier (GPC) takes a probabilistic and practical approach to learning in kernel machines, giving it a competitive advantage in terms of model architecture interpretation, integrated learning, and model selection treatment [24]. In comparison to other popular classifiers, GPC offers three significant advantages. First, GPC is capable of dealing with high-dimensional and nonlinear difficulties that arise during travel mode detection. Second, GPC generates probabilistic outputs rather than deterministic classification findings, which accounts for the inherent model uncertainty in travel mode identification. Third, GPC is a non-parameterized model, which means that it may tune hyperparameters directly using training data [25]. Logistic Regression (LR) is a method for predicting a classified independent variable from a set of dependent variables. LR is a technique for forecasting the outcome of a categorical dependent variable. As a result, the output must be either discrete or categorical [26]. LR can quickly discover the most efficient categorization factors and can categorize observations based on a variety of data sources [27]. Naive Baye (NB) is a Bayes' Theory-based classification approach and also the condition of predictor independence, where a feature's presence in a class is unrelated to the incidence of any other characteristic [28]. The NB classifier is simple to build and extremely successful when dealing with large amounts of data. This method is commonly used for text categorization and difficulties involving several classes [29]. A nearest centroid classifier (NC) is a classifier that identifies a group of training samples according to their centroid (mean) distance from the observed item or data. The empirical data and multiple class centroids' distances are ranked, and the closest distance is chosen [30]. A Multilayer Perceptron (MLP) has a hidden layer or layers (except for one input and one layer of output). In comparison to a single layer perceptron, MLPs are capable of learning non-linear functions [31]. Weights are linked to all connections. However, only three weights are used (w0, w1, and w2). Three nodes comprise the input layer. The bias node is set to 1. Both X1 and X2 are used by the other two nodes as external inputs (which are quantities depending upon the given data) [32]. Support vector machine (SVM) is the most important task to find a hyperplane that can distinguish between similar and different classes of data [33]. The algorithm is still effective even when the numeral of dimensions exceeds the numeral of samples because it only uses a small portion of the decision function's training points (known as support vectors), it consumes less memory, and high degree of stability because of the reliance on support vectors rather than data points. SVM can handle the numerical prediction problem [34].

IV. IMPLEMENTATION

Ten models based on the HOG feature extractor are constructed for the purpose of classifying the dataset. The cell size of 8x8 and cell per block size of 4x4, orientation 9 are used for computing the features. We were randomly selected from the IDC histopathology images as follows: (a) 100images including (50 normal, 50 abnormal), 200 images including (100 normal, 100 abnormal), 400 images including (200 normal, 200 abnormal), 1000 images including (500 normal, 500 abnormal), and 2000 images including (1000 normal, 1000 abnormal) respectively. The HOG model's feature vectors are used as inputs to the classifying algorithms; the extracted features are given to DT, QDA, ERT, GB, GPC, LR, NB, NC, MLP, and SVM individually. The Python programming language setup is utilized for the experiments, together with the Anaconda distribution's supporting libraries. The Scikit-Image [35] library

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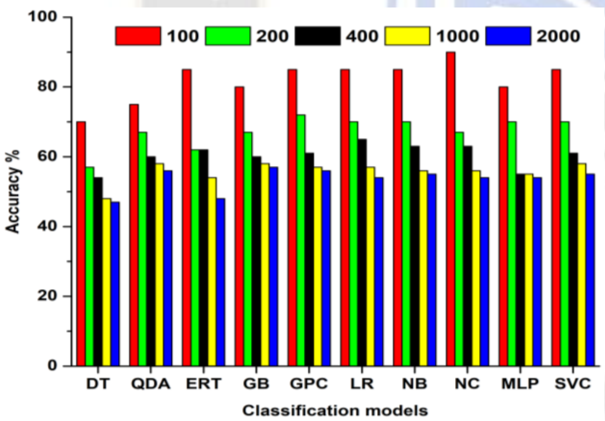
is employed for HOG feature extraction and DT, QDA, ERT, GB, GPC, LR, NB, NC, MLP, and SVM classification algorithms.

V. RESULTS AND DISCUSSION

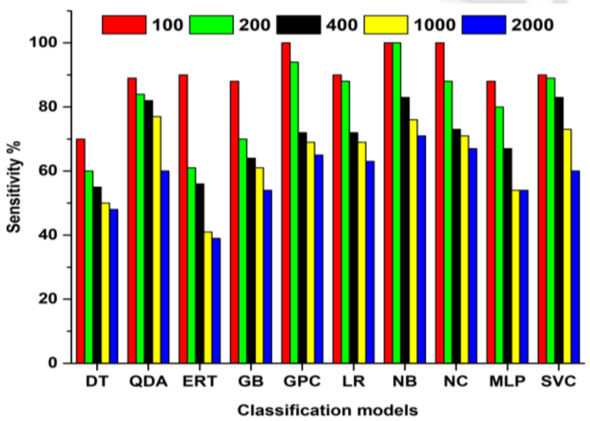
In this research, we randomly chose 100, 200, 400, 1000, and 2000 histopathology images with IDC and used the HOG features extractor to extract statistical features from the images, then applied the algorithms DT, QDA, ERT, GB, GPC, LR, NB, NC, MLP, and SVM to classify these features as benign or malignant tumors. Accuracy, sensitivity, specificity, precision, F1_score, and AUC were used to assess models' performance. Table 1 displays the accuracy, specificity, and sensitivity of each algorithm. As seen in table 1, the highest accuracy value was 90 when the number of images was 100 and the NC algorithm was used. The greatest sensitivity value was 100 when the number of images was 100 and the GPC and NC algorithms were used, while the greatest sensitivity value was 100 when the number of images was 100, 200 and the NB algorithm was used. The maximum specificity was 90 utilizing QDA and GB algorithms, with 100 images. As shown in figures 3 (a), (b), and (c), the accuracy, sensitivity, and specificity decrease as the number of images increases.

TABLE 1. THE ACCURACY, SENSITIVITY, AND SPECIFICITY FOR ALL EMPLOYED ALGORITHMS.

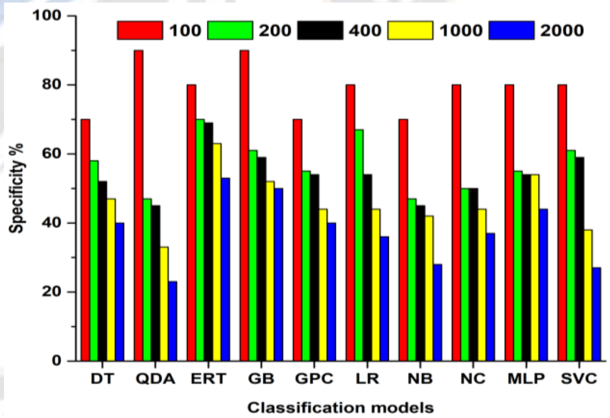
	Accuracy					Sensitivity					Specificity				
No. of images / Models	**100**	**200**	**400**	**1000**	**2000**	**100**	**200**	**400**	**1000**	**2000**	**100**	**200**	**400**	**1000**	**2000**
DT	70	57	54	48	47	70	60	55	50	48	70	58	52	47	40
QDA	75	67	60	58	56	89	84	82	77	60	90	47	45	33	23
ERT	85	62	62	54	48	90	61	56	41	39	80	70	69	63	53
GB	80	67	60	58	57	88	70	64	61	54	90	61	59	52	50
GPC	85	72	61	57	56	100	94	72	69	65	70	55	54	44	40
LR	85	70	65	57	54	90	88	72	69	63	80	67	54	44	36
NB	85	70	63	56	55	100	100	83	76	71	70	47	45	42	28
NC	90	67	63	56	54	100	88	73	71	67	80	50	50	44	37
MLP	80	70	55	55	54	88	80	67	54	54	80	55	54	54	44
SVC	85	70	61	58	55	90	89	83	73	60	80	61	59	38	27



(a)



(b)



(c)

Figure 3. (a)The accuracy, (b) Sensitivity, (c) Specificity, for employed algorithms.

Table 2 displays the precision, F1_Score, and AUC for commonly used algorithms. The maximum precision value was 87 when the number of images was 100 and the GB algorithm was utilized. The highest F1_score was 90 with 100 images utilizing the NC algorithm. When the number of images was 100 and the NB algorithm was applied, the greatest AUC value was 0.97. Calculating the AUC for NC is impossible. This limitation is imposed by the model. This is demonstrated clearly in figures 4, 5, and 6. As the number of images increases, the precision, F1_Score, and AUC for the various ML algorithms reduce.

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TABLE 2: THE PRECISION, F1_SCORE, AUC FOR USED ALGORITHMS

	Precision					F1_Score					AUC				
No. of images / Models	**100**	**200**	**400**	**1000**	**2000**	**100**	**200**	**400**	**1000**	**2000**	**100**	**200**	**400**	**1000**	**2000**
DT	70	63	54	47	43	70	62	52	48	48	0.7	0.48	0.57	0.48	0.54
QDA	85	67	54	53	53	74	70	67	66	63	0.89	0.71	0.77	0.58	0.61
ERT	81	72	57	55	46	85	63	59	45	44	0.91	0.74	0.66	0.51	0.55
GB	87	65	60	59	56	77	71	60	60	59	0.83	0.82	0.64	0.58	0.63
GPC	76	66	62	55	53	86	75	65	61	61	0.96	0.75	0.65	0.55	0.6
LR	81	72	61	55	52	85	72	67	61	60	0.91	0.64	0.65	0.54	0.59
NB	76	66	60	55	52	86	75	70	64	62	0.97	0.86	0.65	0.6	0.54
NC	83	66	59	54	52	90	71	70	60	60	-	-	-	-	-
MLP	80	62	61	54	53	80	72	60	58	53	0.88	0.77	0.61	0.56	0.59
SVC	81	68	62	54	53	85	71	67	64	61	0.96	0.74	0.65	0.55	0.6

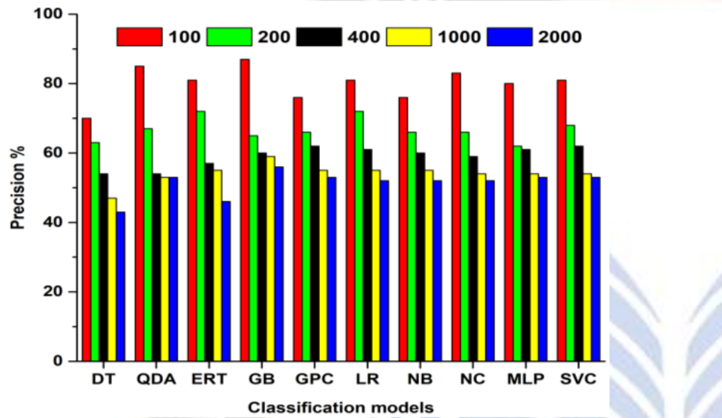

Figure 4. The precision of employed algorithms

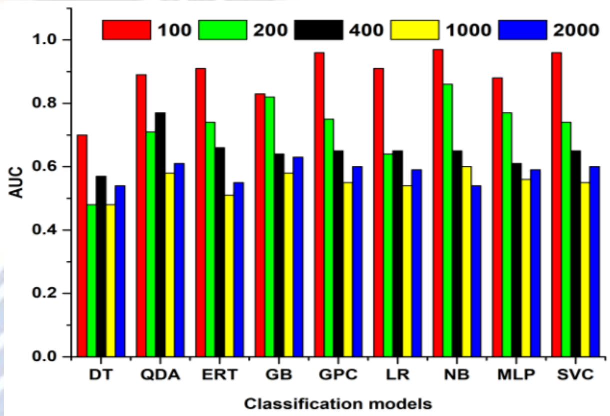

Figure 6. AUC of employed algorithms

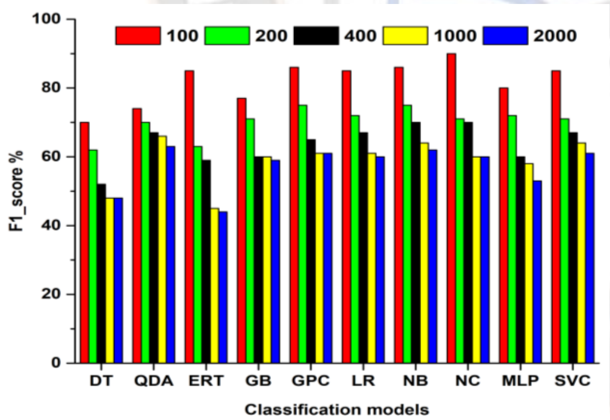

Figure5. The F1_Score of employed algorithms

VI. CONCLUSION

BC identification is critical for optimizing recovery rates. Therefore, prediction accuracy can be improved by the use of CAD. Because of this, researchers focused their efforts on developing methods to assist physicians in making precise and appropriate diagnoses while also reducing the percentage of human errors. This study aims is to assess the efficacy of ML algorithms for classifying IDC Breast Cancer Histology Images using six different criteria. The models use the HOG feature extractor. Then the feature vectors are used as input to train different algorithms. The results listed above show that the algorithms were effective when the number of images was 100, but their performance decreased as the number of images increased, which may indicate that ML is ineffective when a large number of images and this type of images are used. Therefore, we suggest this problem may be solved by utilizing deep learning algorithms.

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