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An Image Classification for larger Healthcare Datasets using Machine Learning

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Abstract:- The most anticipated procedures in the present digital era are image retrieval from vast libraries of health care sector data. The objective of this work is to use machine learning techniques to efficiently classify medical images from larger healthcare datasets. In this paper, features are retrieved using GLCM (Grey Level Co-occurrence Matrix) from five different classes of medical images using image properties including dissimilarity, correlation, homogeneity, contrast, ASM, and energy. To extract the attributes utilizing the layers, the photographs are looked at from a variety of angles (0, 45, 90, and 135). Input is made to the trendiest Machine Learning (ML) models using the received feature vectors, that is Random Forest (RF) and Support vector machines (SVM) are used to classify images. Performance evaluation is carried out by contrasting and assessing the experimental results of SVM and Random Forest, two algorithms produces classification accuracy of 95.22% and 96.37%, respectively. When picture classification is done on bigger healthcare datasets, the Precision, Recall, and F1-Score are compared as well, and they are more accurate. In comparison, the feature extraction employing GLCM and ML models can extract better medical image features and achieve higher classification accuracy.

Keywords:- *Grey Level Co-occurrence Matrix, Cloud Computing, Random Forest (RF) and Support Vector Machines (SVM), Content-Based Image Retrieval.*

I. INTRODUCTION

Medical image classification plays an increasingly essential role in the early detection, diagnosis, and treatment of diseases as the desire for quicker and more precise treatment increases, the advancement of physics, electrical engineering. The resolution involves engineering, computer science, and technology. The quality of medical images is improving and the image mode is increasing in quantity. Furthermore, the quantity of the medical industry is rising quickly. Currently, X-ray imaging, magnetic resonance, and computed tomography (CT), imaging (MRI), in clinics, ultrasonic imaging is frequently employed [7].

From prior years, it is possible to observe the importance of disease classification and prediction. To pinpoint the precise source of the disease as well as its symptom, it is vital to be aware of the key traits and features provided in a dataset. With regards to categorizing and assisting in decision-making, artificial intelligence (AI) has demonstrated promising outcomes. A kind of artificial intelligence called ML has sped up a lot of medical research. While Deep Learning (DL), a subset of ML, examines the precise features needed for illness identification and classification by studying the neural network layers [1][13].

The use of technology in the medical industry is expanding quickly, and one aspect of this growth is the simplification of medical imaging procedures through the use of medical imaging techniques. Given that it has replaced the conventional procedures, it alludes to a particular element of medical operations in this dispensation. The development of imaging technology has greatly contributed to the increase of medicine. Traditional methods for diagnosing and clarifying the results of image processing take a long time, are susceptible to human error, and have trouble aligning the overall results with the past because the earlier results are difficult to compare[12].

The important techniques for categorizing images from repositories and collecting their properties—including parameters like distance, angle, resolution, level, and symmetric values—is called content-based image retrieval (CBIR) [1][2]. ML Models Computer Vision (CV) [6].

Feature Extraction entails giving each character a feature vector that will likely end up serving as its identity. Its challenging objectives are to create the similar feature set for several instances of the same symbol while also extracting the features that optimize the recognition rate with the fewest number of components. Current feature extraction algorithms were unable to select the most crucial aspects for a subsequent diagnostic.

Classification plays important role in classifying every single item in a batch of information into one of a predetermined number of classes or groups of things. It is very much essential to predict correctly the mark class for every case in the data is the fundamental aim of

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classification. To do this, it separates the images of the different classes of medical images. Our proposed effort will place a major emphasis on this phase because current approaches do not place a strong emphasis on effectively categorizing Medical images.

This work enhanced the accuracy of the pictures gathered from huge Medical images with deep learning categorization algorithms. Because categorization requires a large quantity of features or parameters, conventional methods like machine learning approaches, were used to conduct extraction with less accuracy. To construct machine learning models with better feature mining and classification techniques to progress the accuracy of medical image classification from larger healthcare datasets.

II. LITERATURE SURVEY

Han JIANG., et al. [1] The author discussed regularly utilized multimodal medical pictures of computed tomography (CT), magnetic resonance imaging (MRI), ultrasound (US), positron emission tomography (PET), and pathology are briefly introduced in this work along with some basic imaging principles. Additionally, supervised learning and weakly supervised learning were used to further categorize the intelligent diagnosis techniques for imaging gland cancer. Conventional ML techniques, such as the K closest neighbor algorithm (KNN), support vector machines (SVM), and multilayer perceptrons, as well as deep learning techniques derived from CNN, make up supervised learning.

Justice Williams Asare., et al. [2] To find practical methods to diagnose anemia, the author conducts a systematic review and investigates current trends and concepts of ML in healthcare services. In this study, we examine the most popular machine learning (ML) algorithms in terms of machine learning, evaluation metrics, picture augmentation, and the source and size of the dataset employed. The outcome is a blatant demonstration that non-invasive techniques, like the use of ML algorithms to identify anemia, are cost-effective and timely.

Santwana Gudadhea., et al. [3] This study suggests a joint feature selection method to categorize cerebral hemorrhage CT images. Transform and texturing features make up the joint feature set. Grey level co-occurrence matrix (GLCM), discrete wavelet (DWT), and discrete cosine (DCT) characteristics are combined to create joint features. Brain hemorrhage CT image classification uses ensemble-based ML techniques. A Synthetic Minority Over-Sampling Technique (SMOTE) is used on the training dataset to address the oversampling issue by incorporating new data. The suggested innovative feature extraction mechanism enables the ML-based ensemble classifiers to generate extremely accurate outputs. Six essential features make up the vital feature set, and it is clear that Random Forest achieved the highest accuracy, or 87.22%.

K Aditya Shastry [4] This study attempts to detect PD at an early stage by applying ensemble techniques on the Parkinson's speech dataset (PSV), which consists of numerous sound recordings with 27 input features and one target feature. The significance of each feature was calculated using the Mean Decrease in Impurity (F-MDI), Feature Permutation (F-PER), and Pearson's Correlation (F-CORR) techniques. Several supervised ML baseline models were investigated using the proposed Nearest Neighbor Boosting (NNB) technique, which combines k-Nearest Neighbor (k-NN) and Gradient Boosting (GB).

Daniel., et al. [5] study to assess the state of research in this area and recognize some lessons that may be applied to future studies. This literature review was capable to locate 19 related papers by filtering titles, abstracts, and content in the Google Scholar database to address two research concerns, namely what medical images are typically utilized for COVID-19 classification and what are the methodologies for COVID-19 classification. The results show that chest X-rays are the most frequently utilized data to classify COVID-19, and this study's strategy was transfer learning. Researchers came to the end that using multimodal data and lung segmentation could enhance performance.

Hai Tang., et al. [7] authors outlines a novel technique for extracting image features and classifying images for CT pathological image analysis of the chest and brain. The use of a small quantity of annotated pathological picture data to train the network model and then integrating the characteristics the network generated to categorize the image is described as a semi-supervised learning-based approach.

Veronika Kurilová,. et al. [8] suggests a new technique for locating and recognizing hard exudates in retinal pictures. SVM classifier and a quicker region-based Convolutional neural network (faster R-CNN) object detector were combined to produce fast picture pre-scanning for the localization of exudates. The first findings suggested that pre-scanning the samples with the SVM before applying The deep-network object detector may concurrently get better and speed up the current method for detecting hard exudates, particularly when there is a lack of training data.

A M. Sarhan., et al [9] this study describes a novel method for identifying COVID-19 instances in chest X-ray scans. The suggested system searches the X-ray pictures for discriminative features using the Wavelet transform (WT), and then classifies the recovered features by Support Vector Machines (SVM). A novel threshold scanning technique is used in the projected system to extract just specific high-energy approximation coefficients. The maximum accuracy of the suggested system is 94.5% when the threshold level is 903 and the decomposition level is 2.

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Diogo Pessoa., et al. [10] In this paper, authors provide a novel strategy to encourage the use of Electrical Impedance Tomography (EIT) data and the adoption of differential diagnosis for the fresh clinical applications, along with the creation of various machine learning models to distinguish between EIT data from healthy and unhealthy people. Preliminary outcome have shown accuracy percent ages of 66% in challenging evaluation scenarios and improves upto 96%.

S W Kareem., et al. [11] In order to segment and categorize MRI images for the detection of brain malignancies, this study provides a ML-based methodology. Using the K* classifier, Additive Regression, Bagging, Input Mapped Classifier, and Decision Table techniques, this framework enables the pre-processing, segmentation, feature extraction, and classification of images.

Racheal S. Akinbo., et al. [12] the goal of this study is to advance the creation of ML algorithms for categorizing medical photographs. A noteworthy use of this is the automated classification of medical images, which has the potential for greater predictability and accuracy.

Meghavi Rana., et al. [13] this study is to advance the creation of ML algorithms for categorizing medical photographs. A noteworthy use of the said algorithms is the automated classification of medical images, which has the potential for greater predictability and accuracy. The healthcare industry will advantage from this study by making it easier for academics and medical professionals to quickly and accurately select the best diagnosis method for a particular ailment.

N Pathan,. et al. [14] In this study, we suggest a method for removing ultrasound images. Due to the idea of standard view planes, a posting of predetermined images of the embryo at a particular stage is obtained in the conventional ultrasonography. This contains observable images that have inbuilt abnormalities. This study uses K-NN, SVM, and Neural Network classifiers to consider the order outcome. According to the outcome, the support vector machine classifier performs better than both Neural Networks and K-Nearest Neighbor Classifiers.

III. MATERIALS AND METHODS

The efficient image classification over the medical images is performed using feature extraction and ML Classification models.

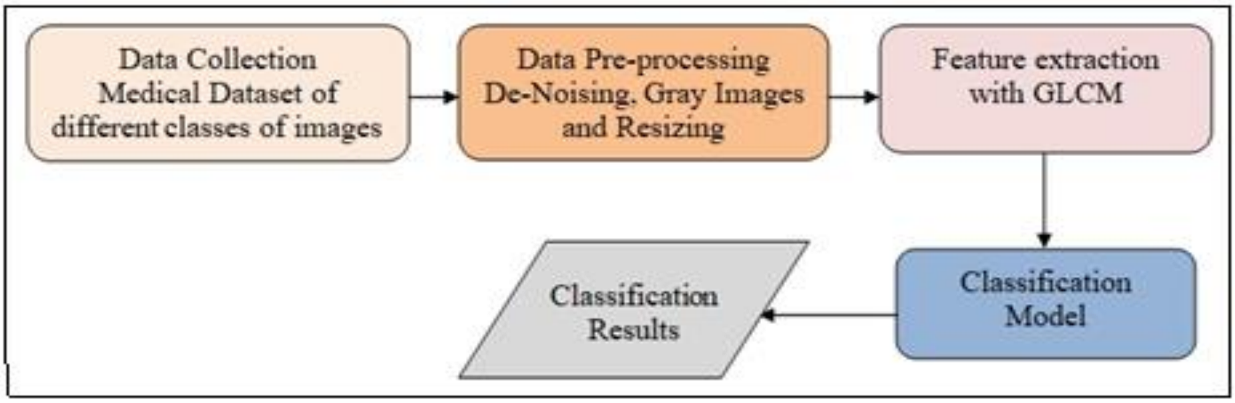

Fig 1 Workflow Model of Classification Process

The above are the stages that this medical picture classification system takes. Figure 1 shows the workflow model of the classification process.

A. Data Collection

The varied number of input images of each dataset collected from web sources and used in experiments. The input for this experimentation consists of 5 classes of images with a minimum size of 4MB and a maximum size of 95MB. Table 1 depicts the total amount of data sets as well as the number of images in each dataset and picture categorization classes. Figure 2 depicts the sample images of medical dataset.

Table 1 Medical Image Dataset

Class#	Target Class	Data Size (MB)	Total Images of each class
1	Alzheimer	4.89	937
2	Brain Tumor	19.8	993
3	Breast Cancer	29.5	952
4	Covid-19	82	945
5	Tuberculosis	95	701
Total			**4525**

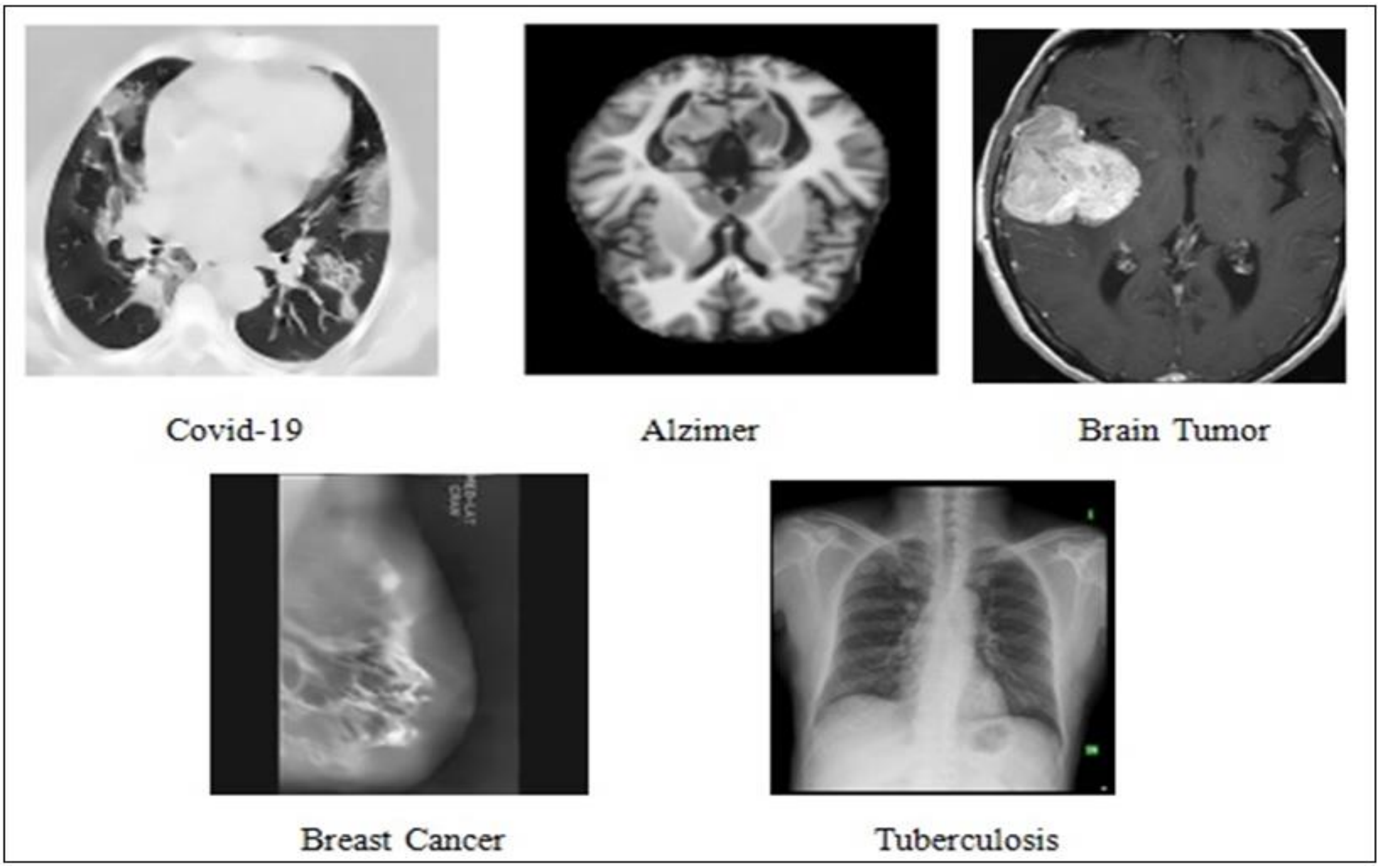

Fig 2 Sample Medical Dataset Images

B. *Texture Feature Extraction*

Feature extraction technique for categorizing images from archives and extracting their properties in terms of variables like distance, angle, resolution, level, and symmetric values. With the help of image properties including dissimilarity, correlation, homogeneity, contrast, ASM, and energy, these extracted values are from the images using the GLCM approach. In order to identify the characteristics using the layers, the photographs are evaluated from a variety of angles (0, 45, 90, and 135 degrees). Figure 3 depicts the sample images features extracted from the medical dataset.

	dissimilarity_0	dissimilarity_45	dissimilarity_90	dissimilarity_135	correlation_0	correlation_45	correlation_90	correlation_135	homogeneity_0
0	30.736916	32.575442	27.894182	32.534729	0.781313	0.764076	0.802819	0.762999	0.455008
1	30.456047	33.104969	28.905615	33.728668	0.780352	0.756658	0.793830	0.750082	0.470101
2	32.560849	34.232700	28.665523	34.308273	0.771272	0.761546	0.808518	0.758617	0.463788
3	33.395452	34.849636	31.126651	34.856920	0.766454	0.755944	0.790607	0.756903	0.420613
4	29.613694	29.885276	23.927337	30.223335	0.828779	0.829478	0.878776	0.827218	0.470974

homogeneity_45	...	contrast_135	ASM_0	ASM_45	ASM_90	ASM_135	energy_0	energy_45	energy_90	energy_135
0.435718	...	3231.741415	0.174483	0.156998	0.171913	0.157505	0.417712	0.396229	0.414625	0.396869
0.451465	...	3585.774454	0.172437	0.155972	0.171425	0.155325	0.415256	0.394933	0.414035	0.394113
0.444993	...	3662.425468	0.178560	0.162075	0.177712	0.162131	0.422563	0.402585	0.421559	0.402655
0.400133	...	3345.376431	0.157093	0.141099	0.158260	0.140762	0.396349	0.375632	0.397819	0.375183
0.456010	...	2937.668314	0.183045	0.166926	0.182494	0.167607	0.427838	0.408566	0.427193	0.409398

Fig 3 Features Extracted using GLCM Method

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C. Classification Models

The derived feature vectors will be passed as input to the two different classification procedures in order to classify the samples of the five classes indicated during the data collection phase. Following are the ML algorithms used for the categorization of medical images.

➢ *Support Vector Machine (SVM)*

Both categorization and regression are performed using supervised machine learning, or SVM. This algorithm's main objective is to find the best plane in an N-dimensional space that can categorize the data points according to several feature space classes. The hyperplane aims for the largest gap that may be achieved between the nearest points of different classes. The size of the space depends on the quantity of features. If there are currently only two input features, the hyperplane is essentially a line. If there are three input features, the hyperplane transforms into a 2-D plane. It becomes difficult to imagine something having more than three features.

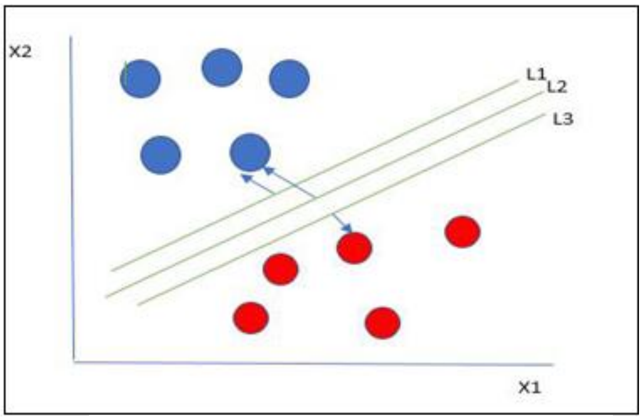

Fig 4 Multiple Hyperplanes Separate the Data of Two Classes

A sensible choice for the best hyperplane is shown in Figure 4, where the hyperplane represents the largest gap or margin between the two classes. Let's take into account two independent variables, x1 and x2, as well as a dependent variable that is also either a blue or a red circle. Let's examine two independent variables, x1 and x2, as well as a single dependent variable, either a blue or red circle.

- *Hyperplane:*

The decision boundary called the hyperplane is used to partition the data points of various classes in a feature space. It will be a linear equation, $w_x + b = 0$, in the case of linear classifications.

- *Kernel:*

The mathematical function known as the kernel is employed in SVM to convert the original input data points into high-dimensional feature spaces, allowing for the easy determination of the hyperplane even when the data points are not linearly divisible in the innovative input space. Radial basis function (RBF), linear, polynomial and sigmoid is a few of the frequently used kernel functions.

- *C: The regularization parameter*

C in SVM balances margin maximization with misclassification penalties. It determines the fine for exceeding the margin or incorrect classifying data items. With a higher value of C, a stronger penalty is applied, which leads to a narrower margin and possibly fewer misclassifications.

The Eq (1) for the linear hyperplane can be written as:

$$w^T + b = 0 \qquad \text{Eq (1)}$$

The hyperplane's normal vector, or the direction perpendicular to it, is represented by the vector W. The offset or separation of the hyperplane from the starting point down the usual vector w is represented by the parameter b in the equation.

The formula for calculating the separation between a data point x_i and the decision boundary is in Eq (2).

$$\textbf{data point}\ d_i = \frac{w^T x_i + b}{||w||} \qquad \text{Eq (2)}$$

Where ||w|| denotes the Euclidean norm of the normal vector W and the weight vector w.

Eq (3) for the Linear SVM classifier.

$$y = \begin{cases} 1 \ : \ w^T x + b \geq 0 \\ 0 \ : \ w^T x + b \leq 0 \end{cases} \qquad \text{Eq (3)}$$

➢ *Types of Support Vector Machine*

SVM can be split into two major categories based on the characteristics of the decision boundary.

- *Linear SVM:*

A linear decision boundary is used by linear SVMs to separate the data points into various classes. Linear SVMs are ideal when the data can be accurately linearly segregated. This indicates that the data points can be completely divided into their particular classes by a single straight line (in 2D) or hyperplane.

- *Non-Linear SVM:*

When data cannot be divided into two groups by a straight line (as in 2D), non-linear SVM can be used to categorize the data. Nonlinear SVMs may manage nonlinearly separable data by utilizing kernel functions.

➢ *Kernel Functions in SVM*

A function called the kernel converts low-dimensional input space into higher-dimensional space. The kernel does several incredibly complex data transformations before determining how to segregate the data based on the chosen labels or outputs, Eq (4) represents mathematical functions.

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$$\textbf{Linear} : K(w, b) = w^T x + b$$

$$\textbf{Polynomial} : K(w, x) = (\gamma w^T x + b)^N$$

$$\textbf{RBF} : K(w, x) = \exp(-\gamma ||x_i - x_j||^n)$$

$$\textbf{Sigmoid} : K(x_i, x_j) = \tan(\alpha x_i^T x_j + b) \quad \text{Eq (4)}$$

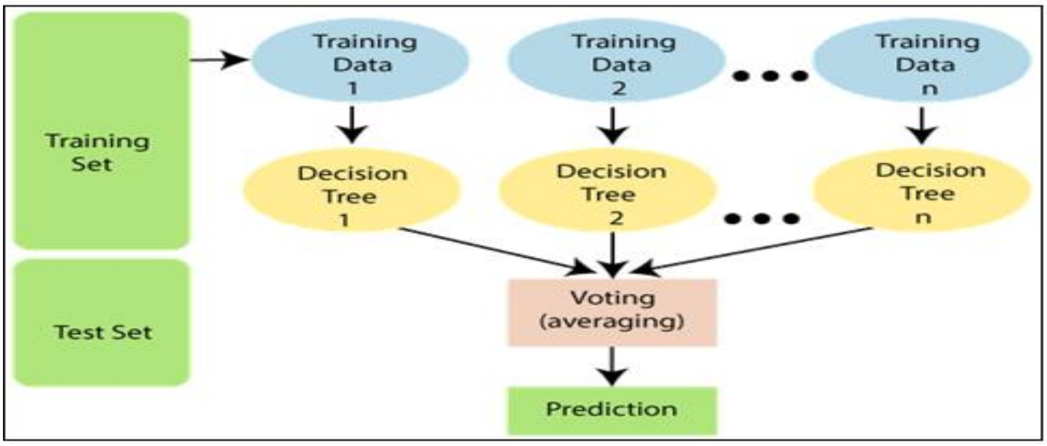

Fig 5 The Basic Structure of RF Model

In order to boost the projected accuracy of the input dataset, the RF classifier averages the results from many decision trees applied to various subsets of the input dataset. As shown in Figure 5, the RF employs forecasts from all of the decision trees rather than just one to predict the outcome based on which predictions earned the most votes.

- *Random Forest Algorithm:*

✓ It requires small training time than other algorithms.
✓ It predicts outcomes with a high degree of accuracy and works well even with a huge dataset.
✓ Even if a sizable portion of the data is missing, accuracy can still be preserved.
✓ Working process of RF Algorithm

N decision trees are joined to create the random forest, and then in the second stage, forecasts are created for each of the first phase's trees.

The algorithm steps as shown below.

✓ Choose arbitrary K data points from the training set.
✓ Construct the decision trees connected with the particular data points (Subsets).
✓ Select the number N for decision trees that need to build.
✓ Repeat Step 1 & 2.
✓ Find the forecasts for each decision tree for fresh data points, and then assign the novel data points to the class that receives the majority of votes.

- *Random Format (RF)*

The supervised learning method includes the well-known ML algorithm Random Forest. It can be utilized for both categorization and Regression issues.

- *Hyperparameters of RF Classifier*

✓ *max_depth:* In Random Forest, the longest path from a tree's root node to its leaf node is considered the tree's maximum depth.
✓ *min_sample_split*: Specifies the minimal amount of observations that must be present in a given node in order for the decision tree in a RF to divide that node, By default, 2.
✓ *criterion:* the feature that assesses a split's quality. The terms "gini" and "entropy" are supported criteria for the Gini impurity and information gain, respectively.
✓ *max_sample:* The amount of the original dataset that is allocated to each individual tree is determined by the max_samples hyperparameter.
✓ *min_samples_leaf:* N decision trees are joined to create the random forest, and then in the second stage, forecasts are created for each of the first phase's trees. Default value: 1.
✓ *n_estimators:* quantity of trees in the forest.
✓ *max_features:* This is comparable to the maximum amount of attributes that can be given to each tree in a random forest.

Entropy aids in the development of a suitable decision tree for the optimum splitter selection. The purity of the sub-split can be measured using entropy. Gini impurity's internal operation and entropy's internal operation in the Decision Tree are both fairly comparable. Both are applied in the Decision Tree algorithm to build the tree by splitting it based on the relevant qualities, although they are computed in quite different ways. Both methods have extremely similar core workings, and both are utilized to compute the feature/split following each new splitting. However, if we compare the two approaches, Gini Eq (5) Impurity is more effective in terms of computational power than entropy Eq (6).

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$$E(s) = \sum_{i=1}^{c} -p_i \log_2 p_i \quad \text{Eq (5)}$$

$$Gini(E) = 1 - \sum_{j=1}^{c} p_j^2 \quad \text{Eq (6)}$$

IV. EXPERIMENTAL SETUP AND RESULTS

The ML classification models applied to the medical dataset of 5 different classes such as Alzheimer, Brain Tumor, Breast Cancer, Covid, and Tuberculosis. The preceding studies, conducted with diverse datasets utilizing the Jupyter Notebook platform and the Python language, yielded results that were sufficiently accurate. In medical dataset of five classes 70% of images are used for training and 30% images are used for the Testing purpose. The performance metrics used to analyze the models is Accuracy, Precision, Recall and F1-Score. Although SVM and Random Forest models are used, the features derived from images using GLCM plays a significant part in this research.

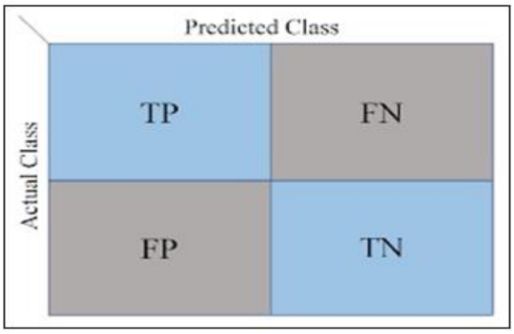

Fig 6 Typical Structure of Confusion Matrix

The Confusion Matrix can be used to forecast by a machine learning system. For validation, a 2*2 matrix is created with computed and actual classes as rows and columns as given in Figure 6.

Every time, the method is applied to both calculated and real class members, with the outcomes being used for analytics and decision-making. Equations determine the correctness of iteration with regard to the instances, where each value is derived from a different example. The Eq (7) to Eq (10) are used to find the Accuracy, Precision, Recall and F1-Score respectively.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad \text{Eq (7)}$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad \text{Eq (8)}$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad \text{Eq (9)}$$

$$\text{F1-Score} = 2 * \frac{Precision * Recall}{Precision+Recall} \quad \text{Eq (10)}$$

- *Support Vector Machines (SVM)*

Table 2 depicts the Precision, Recall, F1-Score and Accuracy for the classes of medical images using SVM with dissimilar kernels such as Linear, RBF and Poly.

Table 2 SVM Classification Performance Metrics for Different Classes of Images

Class	Precision	Recall	F1-Score	Accuracy (%)
		SVM-Linear		
Alzheimer	1.00	0.96	0.98	**95.22%**
Brain Tumor	0.97	0.97	0.97	
Breast Cancer	0.89	0.95	0.91	
Covid	0.94	0.93	0.94	
Tuberculosis	0.98	0.95	0.96	
	95.6	95.2	95.2	
		SVM-RBF		
Class	**Precision**	**Recall**	**F1-Score**	**76.83%**
Alzheimer	0.95	0.87	0.91	
Brain Tumor	0.84	0.69	0.76	
Breast Cancer	0.76	0.67	0.71	
Covid	066	0.87	0.75	
Tuberculosis	0.56	0.79	0.65	
		SVM-Poly		
Class	**Precision**	**Recall**	**F1-Score**	**73.38%**
Alzheimer	0.94	0.83	0.88	
Brain Tumor	0.90	0.62	0.73	
Breast Cancer	0.69	0.69	0.69	
Covid	0.69	0.86	0.76	
Tuberculosis	0.31	0.79	0.44	

However, the SVM-Linear has improved performance with feature extraction comparatively with SVM-RBF and SVM-Poly. Based on the data, a confusion matrix was built and compared to SVM-RBF and SVM-Poly to determine the optimal accuracy levels. When we look at the findings of each kernel, we see that the data consistency level vary based on the type of kernels using and the type of dataset.

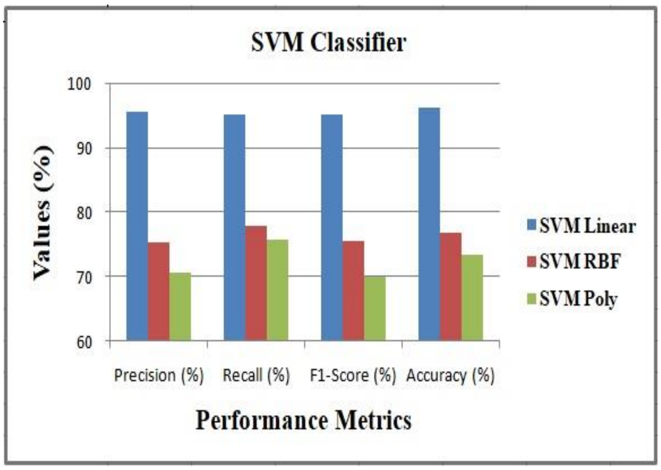

Fig 7 Comparative Analysis of SVM with Dissimilar Kernels for Medical Dataset.

The performance metrics for each SVM-kernel is graphically shown in Figure 7. However, when this SVM-Linear is used with GLCM feature extraction, the picture classification accuracy is about 95.22% compared to SVM-RBF and SVM-Poly accuracy of 76.83% and 73.38% respectively.

- *Random Forest (RF)*

Table 3 and 4 shows the Classification report for the classes of medical images using RF classifier with different criterion such as Entropy and gini with varied max_depth values 5, 8 and 12.

However, the RF-entropy and RF-gini with max_depth of 12 shows better performance with feature extraction comparatively with Max_depth of 5 and 8. Based on the data, a confusion matrix was built and compared with both criteria's determine the optimal accuracy levels.

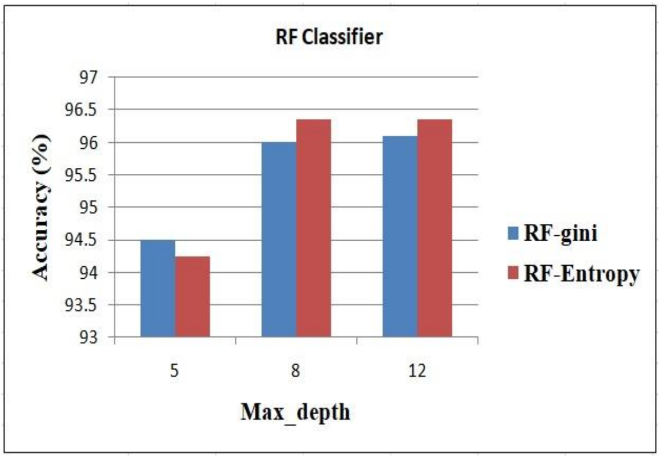

Fig 8 Comparative Analysis of RF with Dissimilar Criterion and Depth for Medical Dataset.

When we look at the findings of each criterion, we see that the Accuracy level almost remains same with both the criterion, but it varies with different tree depth, accordingly this result shows that accuracy levels can be improved by increasing the depth of a tree in RF.

Table 3 Report on RF Classification using the Entropy Criterion

Class	Precision	Recall	F1-Score	Accuracy (%)
RF (criterion = 'Entropy', max_depth = 5)				
Alzheimer	1.00	0.99	1.00	**94.25%**
Brain Tumor	0.94	0.91	0.92	
Breast Cancer	0.95	0.93	0.94	
Covid	0.90	0.96	0.93	
Tuberculosis	0.90	0.91	0.91	
RF (criterion = ' Entropy ', max_depth = 8)				
Class	**Precision**	**Recall**	**F1-Score**	**96.37%**
Alzheimer	1.00	0.99	1.00	
Brain Tumor	0.95	0.97	0.96	
Breast Cancer	0.96	0.95	0.96	
Covid	0.95	0.97	0.96	
Tuberculosis	0.95	0.92	0.93	
RF (criterion = ' Entropy ', max_depth = 12)				
Class	**Precision**	**Recall**	**F1-Score**	**96.37%**
Alzheimer	1.00	0.99	1.00	
Brain Tumor	0.95	0.98	0.96	
Breast Cancer	0.96	0.95	0.95	
Covid	0.96	0.97	0.97	
Tuberculosis	0.94	0.92	0.93	

Table 4 Report on RF Classification using Gini Criterion

Class	Precision	Recall	F1-Score	Accuracy (%)
RF (criterion = 'gini', max_depth = 5)				
Alzheimer	1.00	0.99	1.00	**94.52%**
Brain Tumor	0.95	0.92	0.93	
Breast Cancer	0.95	0.94	0.95	
Covid	0.90	0.96	0.93	
Tuberculosis	0.91	0.90	0.91	
RF (criterion = 'gini', max_depth = 8)				
Class	**Precision**	**Recall**	**F1-Score**	**96.02%**
Alzheimer	1.00	0.99	1.00	
Brain Tumor	0.95	0.96	0.95	
Breast Cancer	0.95	0.95	0.95	
Covid	0.94	0.97	0.96	
Tuberculosis	0.95	0.91	0.93	
RF(criterion = 'gini', max_depth = 12)				
Class	**Precision**	**Recall**	**F1-Score**	**96.11%**
Alzheimer	1.00	0.99	1.00	
Brain Tumor	0.95	0.96	0.96	
Breast Cancer	0.96	0.95	0.96	
Covid	0.94	0.97	0.96	
Tuberculosis	0.94	0.92	0.93	

Figure 8 depicts the performance metrics for each RF-criterion shown graphically. However, when this RF-gini, RF-Entropy with max_depth of 12 is used with GLCM feature extraction, the image classification accuracy is reached upto 96.37% compared to the max_depth 5 and 8 respectively. Further even if tree depth increases, but accuracy remains constant.

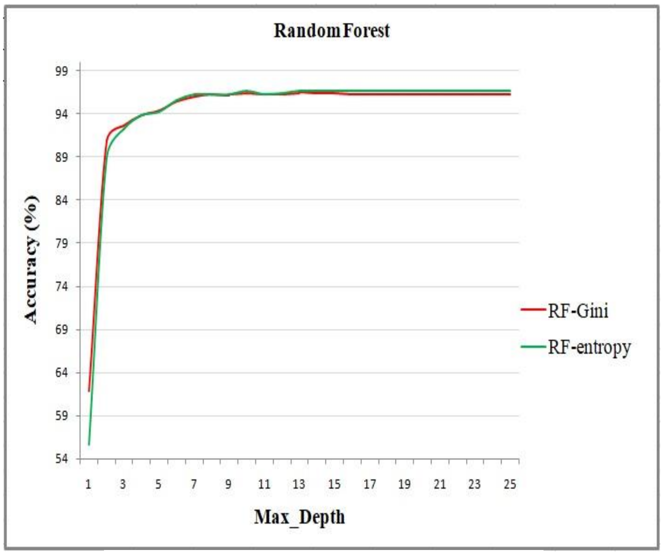

Fig 9 Overall analysis of RF performance

The performance of RF varied with different depth values according to the algorithm, we started analysis by taking parameter Max_depth of a tree form 1 to 25 for both the criterions. As shown in Figure 9 as the depth of a tree increases the accuracy of the model also increased up to the depth value 15, further even depth increases also performance of the RF model remains constant for both the criterions. So this proves that depth of a tree at certain level only increases the efficiency after that it remains constant.

V. COMPARISON BETWEEN SVM AND RF

SVM classifies data based on the hyperplane, while RF needs a depth of tree training. The most useful aspect of SVM ensured that the information would be divided in the best possible way. The two models were trained, their accuracies plotted, and the test accuracy was acquired and compared for 5 classes of medical datasets as shown in Tables 2, 3 and 4.

Figure 10 depicts the accuracy comparision of SVM and RF models by taking the maximum accuracy obtained. We investigated SVM and RF classifiers with GLCM-based features for the proposed system, Using performance matrices for accuracy, precision, recall and F1-Score classifiers are contrasted.

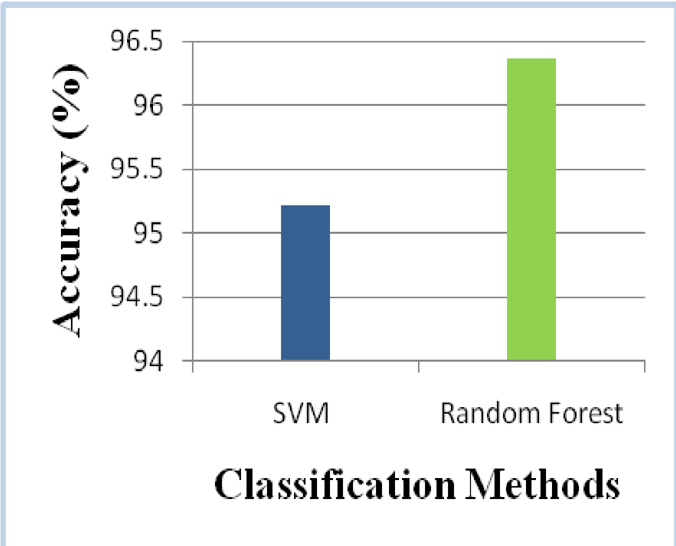

Fig 10 SVM Verses RF

First, the efficiency of a classification model SVM is assessed using diffrent Kernel functions, but we achived an highest accuracy level with SVM-Linear function. Second, the effectiveness of RF is assessed using diffrent Criterion and Depth parameters, but we achived anf highest accuracy with a depth of 12.

VI. CONCLUSIONS

In this work, we developed a medical image classification system for medical data utilizing the most efficient feature extraction technique GLCM, which is a distinguished technique for extracting characteristics from huge image archives. SVM and RF are the most often utilized Machine learning models for classifying accurate pictures with low latency. These models are analyzed with different hyperparameters, which adds additional research ideas into the field to select the suitable hyperparameters for image classifications. When the testing results are compared for both the methods with different parameters the accuracy levels differentiated. Once these models are capable of handling large datasets in real time, it improves medical image classification accuracy by adding feature extraction method GLCM compared to the traditional machine learning approaches. The suggested models provide high accuracy image classification at a rate of 96.37% and 95.22% by RF and SVM respectively. In future, the categorization performance of the Health care images can be enhanced by using deep leaning methods.

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