A Machine Learning Approach to Early Detection and Prediction of Alzheimer's Diseases from MRI Scan Images

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ABSTRACT

: Alzheimer's disease (AD) is classified as a debilitating neurological disorder that primarily impacts individuals in advanced age. Individuals diagnosed with Alzheimer's disease experience significant cognitive impairment, particularly in the domain of memory. Memory loss in individuals diagnosed with Alzheimer's disease is attributed to the progressive degeneration and shrinkage, known as atrophy, of certain regions within the brain, including the hippocampus, amygdala, and other associated areas. The identification and classification of Alzheimer's disease pose significant challenges in the realm of research, primarily due to the considerable number of individuals affected by the disease and the lack of reliable diagnostic methods. Furthermore, the conventional process of identifying Alzheimer's disease is becoming increasingly time-consuming.

To address this problem, it is imperative to employ Artificial Intelligence systems that leverage machine learning techniques for AD categorization and identification. This study presents a methodology for AD classification utilising image-based techniques, specifically employing the Speed-Up Robust Feature (SURF) algorithm. In addition, the values of the SURF features are inputted into a machine learning classifier. The system's performance was evaluated by comparing it with five distinct machine learning classifiers, namely Support Vector Machine, Random Forest, Decision Tree, Logistic Regression and XGBoost classifiers. In order to assess the proposed Alzheimer's disease (AD) system, it is necessary to gather a benchmark OASIS longitudinal dataset. This dataset has two distinct classifications, namely AD disease and Normal. The experimental findings demonstrated that the Logistic Regression classifier exhibited superior accuracy compared to other four classifiers.

Keywords— Alzheimer’s disease; machine learning; disease detection; disease prediction; Memory loss; neurological disorder and SURF features.

I. INTRODUCTION

Alzheimer's disease (AD) is a neurodegenerative ailment that affects cognitive function and mental health. Individuals afflicted with this particular ailment have a decline in cognitive abilities, including but not limited to thinking, reading, and writing. In more extreme instances, they may even exhibit memory impairment to the extent of forgetting their own identities. Alzheimer's disease (AD) is the most often seen form of dementia, characterized by the presence of beta-amyloidal plaques inside cerebral neurons. Consequently, individuals in this category may necessitate the assistance of a career on a full-time basis [1]. The estimated prevalence of Alzheimer's disease is around 6% among those aged 62 years, whereas there is a notably higher incidence of around 30% among individuals aged 80 years and above in industrialized nations. With the global increase in life expectancy, there is a projected significant growth in the number of individuals affected by

Alzheimer's disease. According to a recent study [2], Alzheimer's disease (AD) ranks as the eighth leading cause of mortality in India.

Approximately 13 million individuals in India are engaged in the provision of unpaid care, valued at $241 billion, to a population of 7 million individuals afflicted with Alzheimer's disease [3]. Over the past twenty years, there has been a notable 10% decrease in the mortality rate associated with heart attacks, whereas conversely, the mortality rate attributed to Alzheimer's disease has experienced a substantial increase of 150%. Merely 18 percent of the elderly individuals within this cohort receive adequate care and routine medical examinations. In the year 2020, there was a notable rise in the financial burden associated with Alzheimer's disease and other forms of dementia, amounting to a total of 300 billion dollars. This substantial economic impact is further compounded by the alarming frequency at which individuals are affected by Alzheimer's disease or dementia, with a new case occurring almost every 60 seconds [3]. The three phases that culminate in Alzheimer's disease (AD) are normal healthy control (NC), moderate cognitive impairment (MCI), and Alzheimer's disease. In order to achieve an accurate diagnosis of Alzheimer's disease (AD), it is necessary to first transition the patient's first stage of dementia to Mild Cognitive Impairment (MCI) [4]. Timely identification and suitable intervention can effectively mitigate the progression of Alzheimer's disease to a severe state. The reduction in size of the cerebral cortex is a prevalent factor that exerts a substantial influence on the human brain [5]. The cortical volume of the diseased individual undergoes reduction, whereas the process of normal atrophy predominantly affects the hippocampus. This region of the brain is accountable for cognitive processes such as cognition and memory consolidation. A decline in functionality within this region leads to cortical atrophy and enlargement of the ventricles. Alzheimer's disease can be diagnosed through various methods that necessitate comprehensive clinical data, including a thorough medical history, physical and neurobiological examination, utilization of the Neuropsychiatric Inventory-Questionnaire (NPI-Q), Functional Assessment Questionnaire (FAQ), Clinical Dementia Rating (CDR), Mini-Mental State Examination (MMSE), Global Deterioration Scale (GDS), and additional clinical evaluation parameters established by the National Institute of Ageing for the purpose of diagnosing Alzheimer's disease [6].

Recent studies have shown evidence that the use of multimodality data has potential for the detection and classification of Alzheimer's disease. Positron Emission Tomography (PET), Computed Tomography (CT), Magnetic Resonance Imaging (MRI), X-rays, and the patient's clinical records are all instances of multimodal data [7]. Despite the fact that magnetic resonance imaging (MRI) has demonstrated more efficacy in Alzheimer's disease (AD) detection compared to computed tomography (CT) scans, there are certain concerns associated with both conventional and manual disease identification methods. The subsequent points encompass a range of concerns:

The aforementioned methods are characterized by a significant investment of time and a substantial requirement for diagnostic expertise, specifically in the context of data labeling, to ensure an accurate diagnosis, particularly during the first phases. In the context of supervised approaches, it is worth noting that the pre-processing procedures employed for manual feature extraction may be susceptible to errors. Additionally, the extraction of low-level features from many imaging modalities may not yield the most ideal outcomes.

The subsequent sections of this article are organized in the following manner: In the second section, a literature study is conducted on the conventional approaches used for classifying Alzheimer's disease. Section 3 of this paper examines the suggested procedures for the selection and pre-processing of MRI scan images. It also outlines the process of extracting features from the data and then classifying diseases using machine learning algorithms. In Section 4, a comparison is made between the experimental findings of several conventional classifiers. Section 5 encompasses both the concluding remarks and prospects for further research.

II. LITERARURE SURVEY

The over the last few decades, researchers have developed image processing methods including artificial intelligence and machine learning for AD detection. For accurate Alzheimer's disease categorization using machine learning, there are various stages. Always start with pre-processing, then feature extraction, then classification. Classification always follows pre-processing, feature extraction, and classification. Khedher et al. [8] introduced a new classification method based on Independent Component Analysis (ICA) and supervised learning for automatic classification of segmented brain MRI from Alzheimer's disease Neuro Imaging Initiative (ADNI) subjects. Three phases comprise the ICA method. The first one normalises and segments MRI using SPM software. After that, the average image of NC, MCI, or AD individuals is calculated. Fast ICA is then applied on these average pictures to extract IC that represent each class's features. Finally, every brain picture from the database is projected onto this individual components basis for feature extraction, and a Support Vector Machine (SVM) classifies. AD recognition from NC had 87.5% accuracy, 90.4% specificity, and 84.6% sensitivity. The experimental findings show that this unique method can differentiate AD, MCI, and NC patients.

After extracting the Master Features of the pictures using a rapid discrete wavelet transform (DWT), Siddiqui et al. [9] used Principal Component Analysis to analyse them. Five decision models are given different primary feature vector subset sizes. J48 decision tree, K-Nearest Neighbour (KNN), Random Forest (RF), and LS-SVM with polynomial and radial basis kernels are classification models.

Li and his colleagues [10] solved picture segmentation, a tough challenge. This method uses a two-level segmentation scheme, dividing background and target. In their new strategy for automatically visual mining MRI images, Cruz-Roa and colleagues [11] used Bag of Features (BoF) to show that BoF is a good choice for MRI image representation because it can extract implicit patterns for automatic annotation with 80% accuracy. It was shown that BoF represents MRI pictures well. This technology's applicability are expanded by factorising non-negative matrices using the BoF approach. To obtain information similarly, Kavita et al. [12] use piecewise feature extraction and artificial neural networks.

In 2017, Long et al. [13] developed a machine learning method to distinguish AD or MCI patients from healthy elderly subjects and predict AD conversion in MCI patients by calculating and evaluating brain regional morphological differences. Every pair of subjects' distance was quantified using symmetric diffeomorphic registration, followed by an embedding approach and a classification learning technique. The new method distinguishes mild AD from healthy elderly by 86.5% using the whole-brain grey matter or temporal lobe as ROI, progressive MCI from healthy elderly by 91.74%, and stable MCI by 88.99% using amygdala or hippocampus as ROI. The pair-wise macroscopic shape difference between groups has been maximised by this deformation-based method, increasing differentiation power.

The Rueda et al. [14] MRI imaging AD classification methodology is automated. In application, the model was 83% accurate. To detect Alzheimer's disease early, Bansal et al. [15] used naive bayes, random forest, MLP, and SMO. With the OASIS dataset, CFSSubsetEval's feature selection technique yielded 82.6% accuracy. With neuropsychological data from 16 OASIS characteristics, the earlier study's results were accurate. We investigated whether brain MRI images might extract enough features for classification.

Using MRI scans, Gad et al. [16] examined two classification methods to identify older people with Normal Cognitive (NC), Alzheimer's disease (AD), and MCI. The dataset has 120 subjects—40 ADs, 40 MCIs, and 40 NCs. Before extracting twelve features, K-Nearest Neighbour (KNN) and Support Vector Machine (SVM) were used to filter and normalise each subject. Two classification approaches were examined after feature selection. In order to choose the traits that best identify classes, permutations and combinations are used. Best average accuracy was 97.92% using SVM polynomial order three, and best was 95.833% using KNN with K=6, and K=7 for random test data selection using SVM and KNN. Within the three clinical groups, classification accuracy is high.

Lama et al. [17] compared the use of structural Magnetic Resonance (sMR) images to distinguish AD, MCI, and HC subjects using SVM, IVM, and RELM. Important feature vectors are selected via greedy score-based feature selection. To handle complex data distributions, a kernel-based discriminative method is used. These classifiers are compared for volumetric MR image data using ADNI datasets. According to ADNI dataset trials, RELM with feature selection can improve AD classification from MCI and HC people.

In 2017, Xiao et al. [18] explored multi-feature combination correlation technologies and improved the SVM-RFE method using covariance. The newly presented approach is effective based on comparative trials using available ADNI database. Additionally, multi-feature combination outperforms single-feature approach.

Oppedal et al. [19] used RF to distinguish NC, AD, and LBD using local binary pattern (LBP), three orthogonal planes (TOP), and white matter (WM) legions or normal-appearing WM as a ROI from T1-weighted MRI. With 109 participants, they achieved 79% accuracy on the three-class issue NC vs AD vs LBD and 97% accuracy on the two-class problem NC versus AD using 10 folds nested cross validation.

Similar to Liu et al. [20], neural network auto-encoders, a softmax regression layer, and 83 ROIs from MRI and PET were used to distinguish NC, MCIs, MCIc, and AD patients. The Alzheimer's Disease Neuroimaging Initiative (ADNI) data set of 77 NC, 102 MCIs, 67 MCIc, and 85 AD yielded 77.4% accuracy on the four-class challenge.

Chaplot et al. [21] suggest feeding Self Organising Maps wavelets using MR brain pictures. These brain MR images are categorised as normal or abnormal by appearance. We improve classification accuracy using this study. El-Dahshan et al. [22] developed a tri-phase AD classifier in 2010 using recovered features and dimensionality reduction to classify Alzheimer's disease from magnetic resonance images. Researchers identified the most relevant categorization characteristics using DWTs, PCAs, FP-ANNs, and k-NNs. Classification accuracy was at least 87% using these approaches. Joshi S et al. [23] used multi-layer perceptrons, bagging, decision trees, Co-active Neuro-Fuzzy Inference Systems (CANFIS), and genetic algorithms to categorise Alzheimer's disease. The CANFIS classification method was 88.55% accurate.

It has been demonstrated that the manual and conventional processes that were previously discussed are ineffective due to the substandard results that they provide when applied to both the training and testing datasets. A typical method for classifying Alzheimer's disease is presented here. This method makes use of Support Vector Machines (SVM), decision trees, and Multilayer Perceptron. The aforementioned constraints were taken into consideration when developing this method.

III. PROPOSED METHODOLOGY

In this part, we will provide a proposed framework for the early identification and categorization of Alzheimer's disease. The process of illness identification may be divided into two main stages: feature extraction and classification. In the initial phase, the features of the benchmark dataset are retrieved through the utilisation of Speed up Robust Features (SURF) approaches. The feature values that have been gathered are subsequently inputted into conventional classifiers such as Support Vector Machines (SVM), Decision Trees, and Logistic Regression. The architectural representation of the proposed model for Alzheimer's disease is seen in Figure 1.

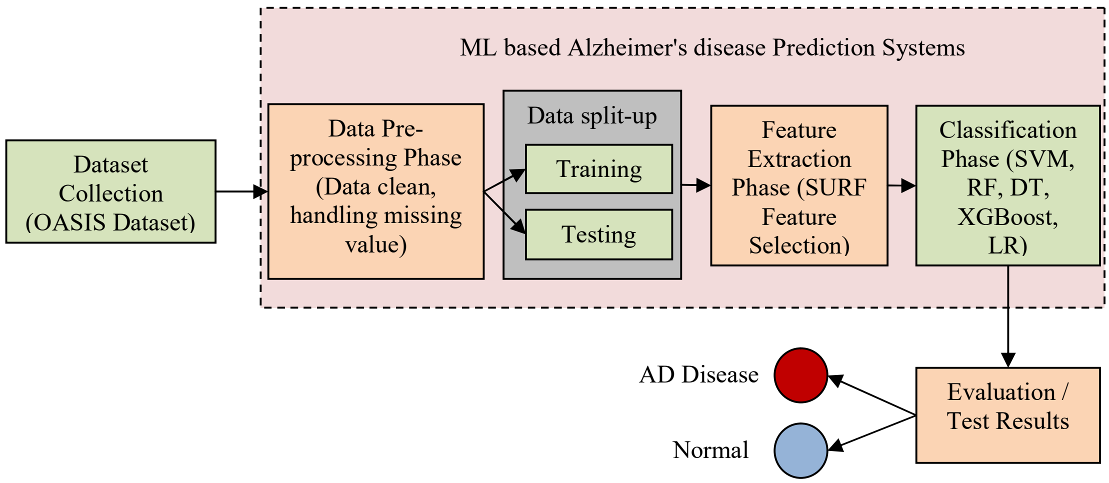

Figure 1: Architecture of ML based Alzheimer's disease Prediction Systems

A. Dataset Collection

In order to make accurate predictions regarding Alzheimer's disease, this study [24] makes use of a longitudinal data collection. The first thing that has to be done is to figure out how cross-sectional the data at a certain baseline or over a particular time period are. After that, a comprehensive data analysis is performed, which consists of comparing the major research components and the related data gathered on each visit. This is done after the previous step has been completed.

Table 1: Decsriptions about OASIS Dataset

S. No.	Attributes	Descriptions	Range
1.	Visit	Number of visits during study	-
2.	MR delay	Delay	-
3.	M/F	Gender (Male, Female)	-
4.	Age	Age in Years	-
5.	EDUC	Education in Years	Min-6, Max-23
6.	SES	Social and Economical Status	Min-1 Max-5
7.	MMSE	Examination of Mini-mental state	Min-4, Max-30
8.	CDR	Clinical dementia rating	Min-0, Max-2
9.	eTIV	Estimated total incremental value	Min-1106.0, Max-2004
10.	nWBV	Normalize total brain volume	Min-0.64, Max-0.83
11.	ASF	Atlas scaling factor	Min- 0.87, Max- 1.58

Within this study, there are a total of 150 participants who have provided MRI data. Their ages range from 60 to 96 years old. During the course of the trial, each patient underwent the scan procedure on at least one occasion. Each and every patient has a right-handed dominant dominant. At the time of the preliminary assessment, 64 individuals were recognized as having dementia, while 72 were classified as not having dementia; this ratio did not change over the course of the investigation. The description of the OASIS longitudinal dataset and corresponding attribute ranges are seen in Table 1 and Figure 2.

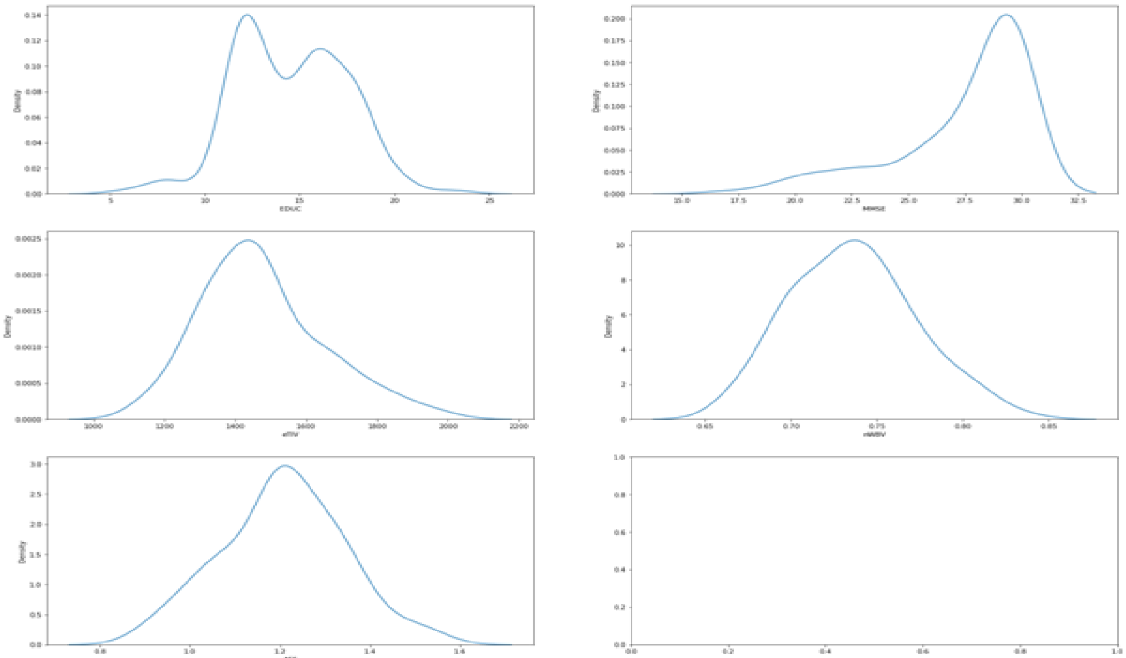

Figure 2: EDUC, MMSE, eTIV, nWBV and ASF attribute ranges

B. Data Pre-processing

Data redundancy and missing values can be found in the raw dataset. The process of managing data includes the extraction and transformation of missing value characteristics. In this study, the preparation of the dataset also includes the activities of selecting features and scaling those features. The OASIS dataset is missing a number of variables across the board. The ML outputs can be affected by missing values, which can also degrade the accuracy of the model. For the purpose of this investigation, we used the mean approach to substitute for missing data. After calculating the mean, or average, of all of the data that was available to us, we substituted that number for any values that were absent.

C. Feature Extraction or Feature Selection:

The Speed up Robust Feature (SURF) approach comprises two distinct steps: a local feature detector and a descriptor. The technique described in this paper is a development in the field of Scale Invariant Feature Techniques [25]. Due to the use of invariant aspects of local similarity for image matching, this method exhibits significantly improved speed and robustness. The initial phase of the SURF methodology involves the production of important points. The last phase involves establishing the invariant descriptor of the aforementioned key points. This descriptor may then be employed for many purposes such as image classification, registration, calibration, and establishing correspondence between two pictures depicting the same object, among other applications. The process of SURF feature extraction involves four distinct processes, which are visually depicted in Figure 3.

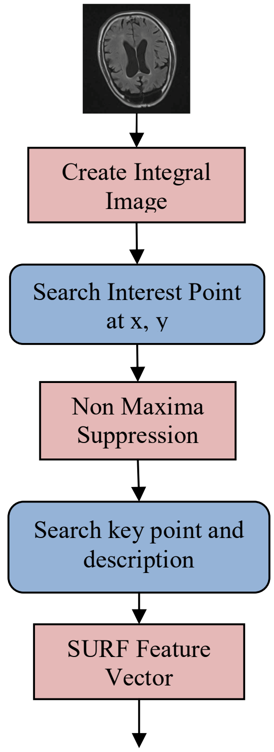

Figure 3: Process of SURF Feature Selection / Extraction

The integral image serves as the initial step inside the SURF (Speeded Up Robust Features) methodology, providing an effective approach to calculate the cumulative total of pixel values in an input picture. Additionally, it may be utilised to compute the mean brightness of the picture. Subsequently, proceed to ascertain the geographical coordinates corresponding to the desired site. A point of interest refers to a specific spot where the border or edge of an item undergoes a quick shift in direction.

Despite the widespread recognition and frequent use of the Harris corner detector, it lacks scale invariance. The difficulty was addressed by employing the Hessian matrix to facilitate automated scale selection. The Scale-Invariant Feature Transform (SURF) algorithm employs a Hessian matrix approximation that exhibits invariance to both scale and rotation, enabling effective point recognition in pictures. Once the feature candidate of the picture has been identified, the non-maxima suppression technique is employed to identify a candidate for the key point. The ultimate stage of the SURF process is articulating the significant finding that has been unearthed. The procedure is finalized by constructing an SURF feature vector for an input picture by the analysis of the pixel distribution of neighboring points surrounding the key point.

D. Classification:

In order to identify and categories cases of Alzheimer's Disease using input images, the SURF characteristics that were retrieved were utilized as input for the classifiers. The performance of various classifiers is contingent upon the dataset and the specific attributes of the images, as evidenced in existing scholarly works. Consequently, a comprehensive assessment has been conducted to evaluate the efficacy of three discrete classifiers, namely Support Vector Machines (SVM), Random Forest (RF), and Logistic Regression (LR). Given their prominent status as classifiers in the academic literature, a concise elucidation of each is presented hereafter.

Support Vector Machine: The Support Vector Machine (SVM) is a type of supervised algorithm that aims to maximize the hyper plane between datasets belonging to different classes. In general, Support Vector Machines (SVMs) are employed to address both linear and non-linear issues. Support Vector Machines with a kernel (SVM-k) are utilized to address the challenges posed by non-linearly separable problems. In contrast, linear SVMs lack a kernel function and are designed to tackle linearly separable problems. The equation representing the hyper plane for the Support Vector Machine (SVM) model is expressed as follows:

$$h(x)=\alpha^T*x+\beta \tag{1}$$

In the context where a weight vector is denoted as α^T and bias is denoted as β, the calculation of the margin, which represents the distance between class instances, is performed based on the training data. The objective of the Support Vector Machine (SVM) is to identify the hyper plane that maximizes the margin, employing an algorithm that aims to achieve the largest margin while minimizing the number of support vectors.

Decision Tree: The Decision Tree (DT) is a non-parametric method used in supervised learning for the purposes of classification and regression. The structure consists of a primary node, a collection of intermediary nodes, and a collection of terminal nodes. The process of categorizing involves the identification of root and internal nodes, which are related with judgments regarding splitting and the corresponding qualities. It is possible to assign a class label to each individual leaf. The DT training phase consists of two distinct parts. The first selection process involves choosing the splitting measures and splitting features. The child nodes' records are partitioned in the second stage based on the decision rule derived from the first phase.

Multilayer Perception: The MLP, or Multilayer Perception, is a widely recognized and extensively utilized model in several research disciplines that need real-time analysis. The term "Feed Forward Network" is often used interchangeably with "Multilayer Perception (MLP)." The model is valuable for discerning non-linearly separable data. The multilayer perception is commonly employed for addressing Classification and Regression (CART) problems characterized by a nonlinear association between the dependent and independent variables. A conventional model consists of an input layer, one or more hidden layers, and an output layer. Every layer consists of artificially created nodes. The nodes are connected to the nodes of their neighboring entities. The multilayer perception is widely recognized as the most prominent neural network in the field of image categorization.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

Within this section, an assessment has been conducted on the recommended approaches for detecting and categorizing Alzheimer's disease at an earlier stage, employing conventional machine learning techniques. The model under consideration was constructed using the Python programming language and the Anaconda integrated development environment (IDE). The computational resources employed for this task were an i5 CPU, 8GB of RAM, and a 1TB hard disc drive.

A. Performance Metrics:

In order to evaluate the effectiveness of the suggested approach, performance assessment measures are utilised. A range of performance indicators, including as Precision (Pr), Recall (Re), Accuracy (A), and F1-measure (F), can be employed to assess the effectiveness of conventional machine learning techniques. The use of the confusion matrix, as seen in Figure 4, facilitates the computation of these metrics. The row represents the actual classes, whereas the column represents the expected classes. Precision is a measure of the degree of quality or correctness, whereas recall pertains to the amount or accuracy of data.

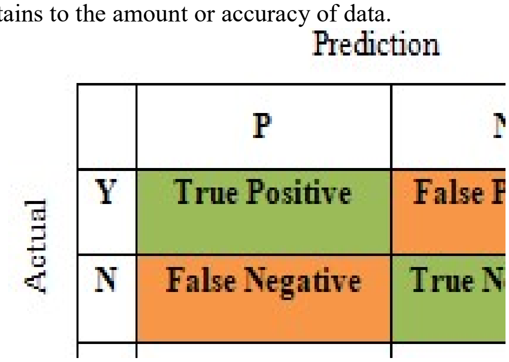

Figure 4: Confusion Matrix

The symbols TP, TN, FP, and FN are used to represent the concepts of true positive, true negative, false positive, and false negative, respectively. The term "TP" denotes an outcome in which the models effectively estimate the positive class. The true negative (TN) value is the result of the models effectively estimating the negative class. The false positive (FP) is an outcome in which the predictive models incorrectly predict the occurrence of the positive class. The false negative (FN) is an outcome in which the models inaccurately predict the negative class.

Precision: Precision (Pr) refers to a measure of accuracy in statistical analysis. It quantifies the proportion of true positive results among all positive Precision is a commonly used performance criterion for evaluating the effectiveness of a proposed system. The metric is employed to determine the ratio of accurately predicted instances in relation to the total number of predictions made. The accuracy may be measured as follows:

$$Pr = \frac{tp}{tp+fp} \quad (2)$$

Recall: Recall, denoted as Re, is a metric used to evaluate the performance of a predictive model. It quantifies the proportion of properly predicted occurrences in relation to the total number of instances.

$$Re = \frac{tp}{tp+fn} \tag{3}$$

Accuracy: The accuracy measure is calculated by dividing the number of correct predictions by the total number of input samples.

$$Ac = \frac{tp+}{tp+fp+tn+f} \tag{4}$$

F1-Score: The F1-Score, also known as the F-measure, is employed as a means to achieve a balance between accuracy and recall measurements. It is calculated as the harmonic mean of these two metrics. The F1-score may be calculated using the following formula:

$$F = 2 \times \frac{Pr \times Re}{Pr+Re} \tag{5}$$

B. Results and Discussions

In this subsection, an evaluation has been conducted on the performance of conventional classifiers such as Support Vector Machines (SVM), Decision Trees (DT), Random Forest (RF), Logistic Regression (LR) and XGBoost classifiers.

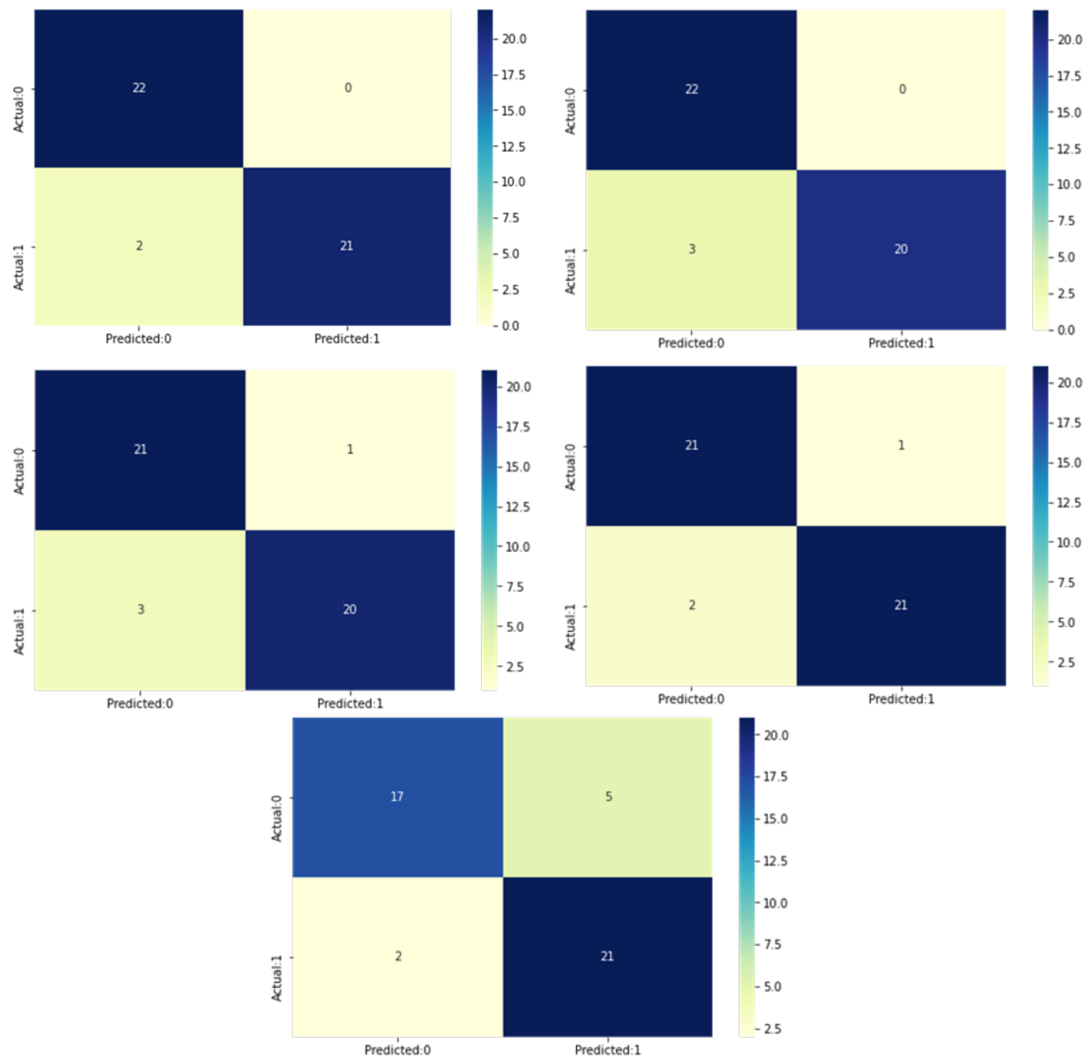

Figure 5: Confusion Matix of LR, SVM, XGBoost, RF and DT

Table 2 presents a comparative analysis of various conventional classifiers, highlighting their performance in terms of Accuracy, Precision, Recall, F1 score, and AUC score. The findings of the categorization of AD disease illness were assessed, marked, and shown in Figure 5.The Logistic Regression had the highest performance accuracy, with a rate of 95.55%. The support vector machine exhibited the second greatest degree of accuracy among the classical classifiers, achieving an accuracy rate of 93.33%. Among the five conventional classifiers, the random forest and decision tree exhibited the lowest level of accuracy, with a rate of 84%. This classifier had the lowest performance among the five classifiers previously described.

Table 2: Performance Anlaysis of ML Classifiers

S. No.	ML Classifiers	Ac. Score	Pr. Score	Re. Score	F1-Score	AUR Score
1.	LR	95.55	100	91.30	95.45	95.65
2.	SVM	93.33	100	86.95	93.02	93.47
3.	XGBoost	91.11	95.23	86.95	90.90	91.20
4.	RF	84.78	95.45	91.30	93.33	93.37
5.	DT	84.44	100	69.56	82.05	84.78

Table 2 and Figure 6 present the performance outcomes of several conventional classification techniques, including as Support Vector Machines (SVM), Decision Trees (DT), Random Forest (RF), Logistic Regression (LR) and XGBoost classifiers. Table 2 demonstrates that Logistic Regression models exhibit superior performance in comparison to other conventional classifiers, despite the fact that their performance is relatively high.

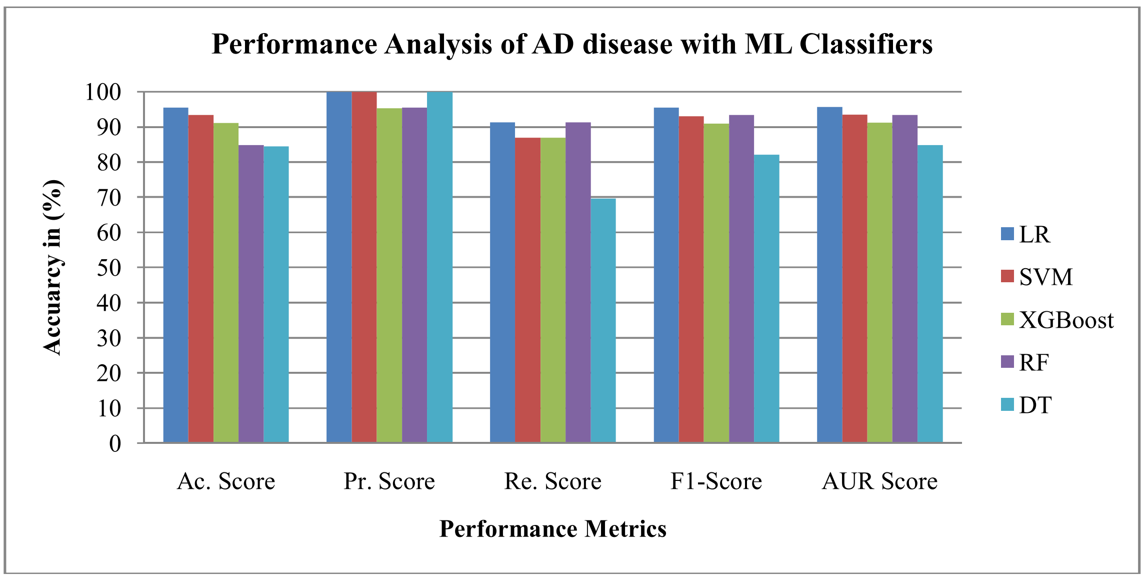

Figure 6: Performance Analysis of AD disease with ML Classifiers

V. CONCLUSIONS and FUTURE ENHANCEMENTS

The detection and categorization of Alzheimer's disease (AD) in MRI scan images is a challenging issue due to the fact that items that belong to the same category might have significantly distinct appearances. Therefore, in order to attain results that are satisfactory, we have presented a Speed-up Robust Feature as a feature extractor. In this research, five standard classification strategies—namely, Support Vector Machines (SVM), Decision Trees (DT), Random Forest (RF), Logistic Regression (LR) and XGBoost classifiers—are investigated. When we tested the proposed models, we discovered that the Logistic Regression performed the best and outperformed the other four traditional classifiers, the decision tree and the random forest gives the lowest percentage of accuracy.

In spite of this, there remains room for improvement in the Alzheimer's disease treatment system. Deep learning techniques may be used to manage large image datasets rather than typical machine learning approaches. These techniques have the potential to minimize complexity while simultaneously improving classification accuracy.

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