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Primary phase Alzheimer's disease detection using ensemble learning model

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ABSTRACT

Alzheimer's disease (AD) is a noteworthy problem for public health. Older people are most impacted by this neurological disease. It leads to memory loss and various cognitive impairments, eventually hindering communication. As a result, research on early AD detection has intensified in recent years. In current research work, we propose an ensemble learning strategy to identify AD by classifying brain images into two groups: AD brain and normal brain. Researchers have recently explored various machine learning (ML) and deep learning techniques to improve early disease detection. Patients with AD can recover from it more successfully and with less damage if they receive early diagnosis and therapy. This research presents an ensemble learning model to predict AD using decision trees (DT), logistic regression (LR), support vector machines (SVM), and convolutional neural networks (CNN). The open access series of imaging studies (OASIS) dataset is used for model training, and performance is measured in terms of various kinds of outcome namely accuracy, precision, recall, and F1 score. Our results demonstrated that, for the AD dataset, the CNN achieved the maximum validation accuracy of 90.32%. Thus, by accurately detecting the condition, ensemble algorithms can potentially significantly reduce the annual mortality rates associated with AD.

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1. INTRODUCTION

Millions of people worldwide suffer from the debilitating condition known as Alzheimer's disease (AD). It is a incurable condition of the brain illness which progressively deteriorates memory and thinking skills, making it challenging for sufferers to carry out even the most basic tasks. The illness causes brain cell destruction and death, which lowers cognitive function and ultimately impairs one's capacity to carry out daily tasks. As a condition worsens, people may have confusion, memory loss, language difficulties, and changes in their typical behavior [1]. This disease is currently diagnosed mostly by cognitive impairment testing, which regrettably does not provide an accurate diagnosis until the patient has advanced past the stage of moderate AD [2]. Detecting primary phase AD is crucial for timely intervention and improved patient outcomes.

Traditional diagnostic methods often struggle due to subtle symptoms and overlap with other cognitive disorders. Ensemble learning models offer a promising solution by combining predictions from multiple algorithms and leveraging diverse data sources, such as neurosurgical and genetic information, to capture complex patterns associated with early-stage AD. This approach aims to enhance diagnostic accuracy and generalization across populations, enabling more effective and personalized interventions in Alzheimer's care [3]. Deep learning, in particular convolutional neural networks (CNN), has revolutionized the area of medical imaging. This cutting-edge neural network designs are especially well suited for interpretation of medical imaging data since they are built to automatically learn and extract hierarchical characteristics from massive volumes of data [4]. Using data from medical imaging tests like magnetic resonance imaging (MRI) scans, CNN have lately shown a lot of promise in diagnosing AD [5], [6]. CNN are the subset of deep learning algorithm that works well for medical image analysis because they can automatically recognize and extract information from images. In this research we investigate the following: i) to train the model with various machine learning (ML) methods on the open access series of imaging studies (OASIS) dataset; ii) to apply a cutting-edge CNN based method for AD identification; iii) to identify AD with high accuracy at an early stage; and iv) to improve the standard of life for patient and their families.

Several approaches have been studied in the literature to help doctors diagnose this illness. A thorough analysis of AD was provided by Kavitha *et al.* [7], who also investigated the impact of two ML techniques that aid in the early detection of the illness. The author covered crucial study subjects like the data sets utilized and the methods of evaluation performed. They offer a paradigm that facilitates a deeper comprehension of the state of the field and draws attention to the obstacles and possibilities for creative and valuable study. The study demonstrated the optimal ML technique for the Alzheimer's disease neuroimaging initiative (ADNI) dataset. Using the suggested classification scheme by Diogo *et al.* [8], clinicians can identify these illnesses. By using these ML algorithms for early diagnosis, annual death rates from AD can be significantly reduced. On the AD test data, the suggested approach yields superior findings with the highest evaluated average accuracy. Compared to previous studies, the accuracy score on this test is significantly higher. Cheung *et al*. [9] addressed the limitations of previous research by proposing an ML-based diagnostic tool for moderate cognitive impairment (MCI) along with AD. The tool is specifically multi-diagnostic and was trained as well as evaluated using two separate data sources. It has multiple acquisition protocols, and tests generalization across datasets and protocols. The proposed method is entirely new in the context of AD and is based on baseline scans and a follow-up diagnosis, regardless of progression, has transparent performance reports, and analyzes potential clinical applicability. An unsupervised domain adaption deep learning technique was used by Zaabi *et al*. [10] to improve the generalization of a novel retinal photograph-based deep learning architecture for the primary detection of AD cases. This algorithm was created, validated, and tested. When distinguishing between patients suffering from AD-dementia along with those without the condition, the proposed deep learning algorithm performed consistently and accurately. Alroobaea *et al*. [11] used the CNN and transfer learning as two distinct approaches for AD detection. There are two primary processes in the suggested method: region of interest extraction and classification. To find the area of the image that contains the hippocampal region of the brain, the image is first divided into blocks. Researchers evaluated CNN and transfer learning techniques in the second phase. The achieved results demonstrate that the categorization of images employing transfer learning produces a better result rate when compared to CNN. Singh *et al*. [12] proposed the use of ML techniques for AD identification. The ADNI along with OASIS datasets are used in the classification model evaluation process. The findings of the experiment demonstrated that, while employing the ADNI dataset, algorithms namely logistic regression (LR) along with support vector machines (SVM) yielded the best accuracy values, while LR and random forests produced the best results when using the OASIS dataset. Zhao *et al*. [13] highlighted the summary of current studies on deep learning algorithms for diagnosing AD. From the literature survey done, it is observed that detecting early-stage Alzheimer's with ML faces certain challenges like limited data, poor generalization across populations, and the black-box nature of models, which reduce clinical trust. Also, early symptoms are subtle and overlap with other conditions thereby complicating detection. Therefore, this research includes deep learning technique which can automatically extracting complex patterns from large datasets and hence can improve accuracy by reducing the need for manual feature selection. The main contribution of the current research is an analysis of how well ML along with deep learning detect AD. The study focuses on using ML and artificial intelligence to diagnose AD.

2. PROPOSED METHOD

2.1. Proposed methodology

An effective strategy has been developed to improve the detection of AD. The proposed method is divided into following steps as presented in Figure 1. The objective of this methodology is to build predictive models using LR, decision trees (DT), SVM, and CNN to categorize patients with a likelihood of AD with

respect to clinical, genetic as well as imaging data. The steps in the methodology includes collection of data, preprocessing it, extracting features, training the model, evaluating it, and comparing it.

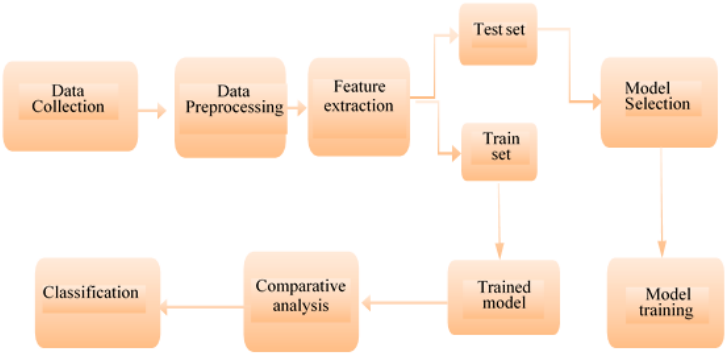

Figure 1. Proposed methodology architecture

2.1.1. Data collection

In this research OASIS dataset is utilized which seeks to prepare MRI datasets of brain publicly available for future research. There are three kinds of datasets available: OASIS-1 (cross-sectional) MRI data in young, middle aged, non-demented and demented older adults, OASIS-2 (longitudinal) MRI data in non-demented and demented older adults whereas OASIS-3 is an expansion of earlier dataset collections [14]. We have used OASIS-2 and OASIS-3 datasets for the detection of Alzheimer. On these datasets, we apply both classical ML techniques (LR, SVM, DT) and modern deep learning (CNN) for effective and comprehensive Alzheimer's prediction.

2.1.2. Data pre-processing

Data preprocessing requires number of stages to develop the dataset before modeling. Handling missing data is addressed using statistical techniques like mean, mode, and median imputation. Feature scaling is applied to normalize or standardize continuous variables such as age, clinical scores, and genetic markers to ensure consistency across models. To enhance model performance, data augmentation methods like random rotations are applied to MRI/positron emission tomography (PET) images, reducing over-fitting, and improving generalization in CNN models. Dimensionality reduction using method namely principal component analysis (PCA) reduce the feature space for structured data, mitigating the curse of dimensionality, while CNN-based feature extraction is employed to automatically capture relevant features from image data.

2.1.3. Model selection

Four predictive models are developed for AD classification. LR serves as a simple linear model to classify binary outcomes (Alzheimer's vs. non-Alzheimer's) using clinical, demographic, and genetic markers, with L1 or L2 regularization to prevent over-fitting. SVM is used with linear as well as radial basis function (RBF) kernels to classify Alzheimer's risk based on clinical, demographic, and genetic data, and hyperparameter tuning will be done through grid search to optimize kernel parameters (C, gamma). CNN focuses on analyzing MRI or PET scan data, leveraging convolutional along-with max-pooling layers for feature extraction whereas fully connected layers to classify the data, with consideration of pretrained models namely ResNet for transfer learning and optimization via the Adam optimizer with learning rate scheduling. Lastly, DT models split data based on demographic, clinical, and genetic features, with cost-complexity pruning to prevent over-fitting and hyperparameter tuning (e.g., tree depth, minimum samples split, and leaf nodes) via cross-validation to refine model performance.

2.1.4. Model training

The training strategy begins with an 80:20 train-test splitting, where 80% associated with the dataset is utilized for training and 20% dataset is applied for testing during initial model development. To ensure robust model assessment, K-fold cross-validation (where K=5) is applied. In cases of class imbalance between Alzheimer's and non-Alzheimer's samples, technique namely synthetic minority over-sampling technique (SMOTE) is utilized to address this issue. For hyperparameter tuning, grid search method is combined with cross-validation to optimize the performance of each model.

2.1.5. Model evaluation

The proposed model will be evaluated employing several parameters to assess their performance. Accuracy will provide an overall measure of model performance, while precision and recall will specifically

evaluate the model's capacity to correctly recognize true positives. The F1-score will be used to balance precision and recall, which is particularly important in imbalanced datasets.

2.1.6. Comparison of models

Following model evaluation, the effectiveness of DT, SVM, CNN, and LR models are compared using metrics comprising accuracy, precision, recall, and F1-score [15]. Beyond these indicators, factors like model complexity (e.g., CNNs are more complex compared to LR), interpretability (e.g., DT and LR are easier to interpret), and computational resource requirements (e.g., CNNs typically require more computational power and memory) are considered in selecting the most suitable model for predicting AD. Furthermore, the ability of each model to withstand overfitting and its generalizability to unknown data are also evaluated to ensure reliable performance in predicting AD.

2.2. Description of dataset

We will employ longitudinal MRI data from OASIS-2. There are 150 people in the sample having longitudinal MRI data, ranging in age from 60 to 96. Every patient underwent a minimum of one scan [16], [17]. Each individual has a right hand. 72 of the people underwent an investigation and were labeled as "nondemented". 64 of the participants in the study were initially diagnosed as "demented" at the time of their visits. 14 individuals were first diagnosed as "non-demented," however during a follow-up visit, they were categorized as "demented". These belong under the category of "converted". Table 1 shows the list of features from the dataset.

Figure 2 shows the dataset outcome for the different dementia stages. As seen in Figures 3 and 4, the brain volume ratio of the non-demented category is greater than that of the demented category. This is commonly believed to be the result of diseases that cause the tissue in the brain to shrink. When comparing the demented patient category to the non-demented patient category, there is a greater age distribution of 70-80 years old. We assume that individuals with such an illness have a lesser chance of living, with only a few ninety years remaining. Also, it illustrates that the non-demented category's mini-mental state examination (MMSE) scores were significantly more than those of the demented category. Figure 5 shows that the category with dementia has a slightly higher estimated total intracranial volume. Figure 6 shows that the category with dementia has a higher normalize whole brain volume. Figure 7 depicts that demented individual have longer lifespans than non-demented individuals.

Table 1. Qualities of the information

Attribute	Description
EDUC	Years of education
SES	Socioeconomic Status
MMSE	Mini mental state examination
CDR	Clinical dementia rating
eTIV	Estimated total intracranial volume
nWBV	Normalize whole brain volume
ASF	Atlas scaling factor

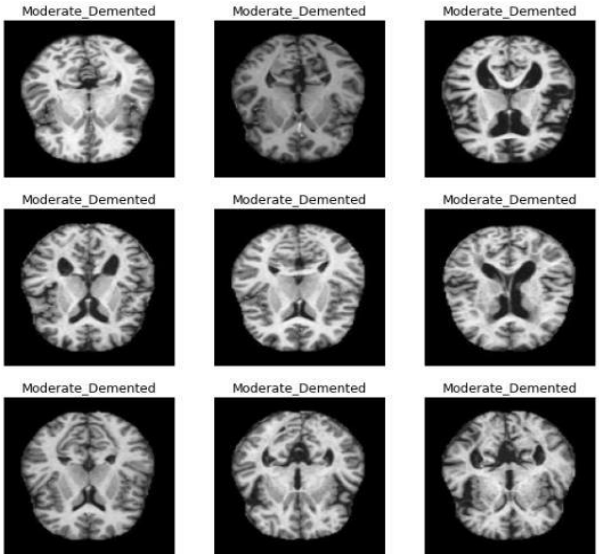

Figure 2. Dataset outcome of different dementia stages [7]

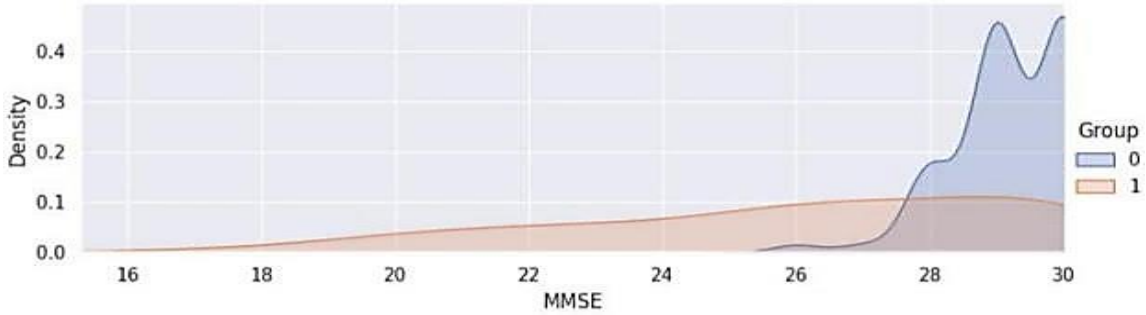

Figure 3. MMSE

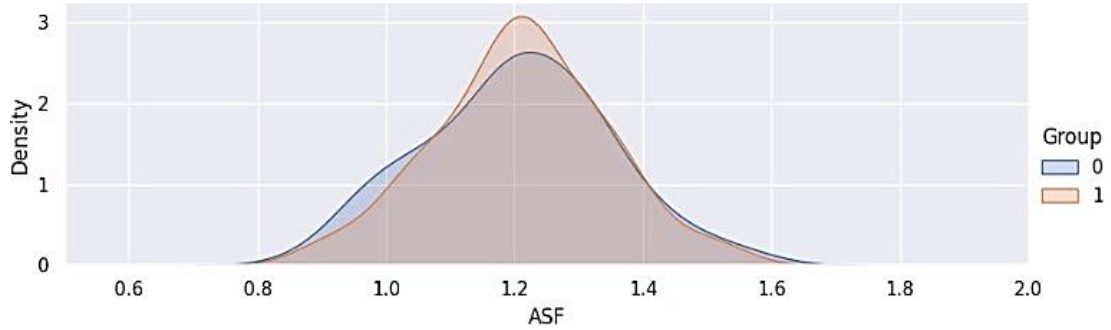

Figure 4. Atlas (volume) scaling factor

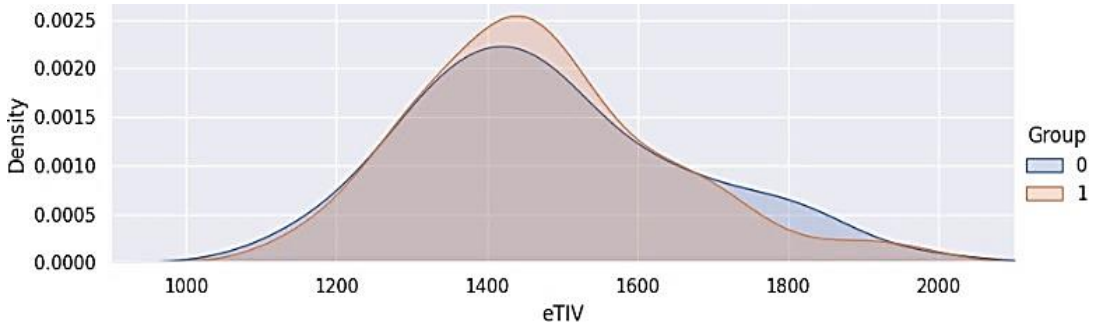

Figure 5. Calculated total intracranial volume

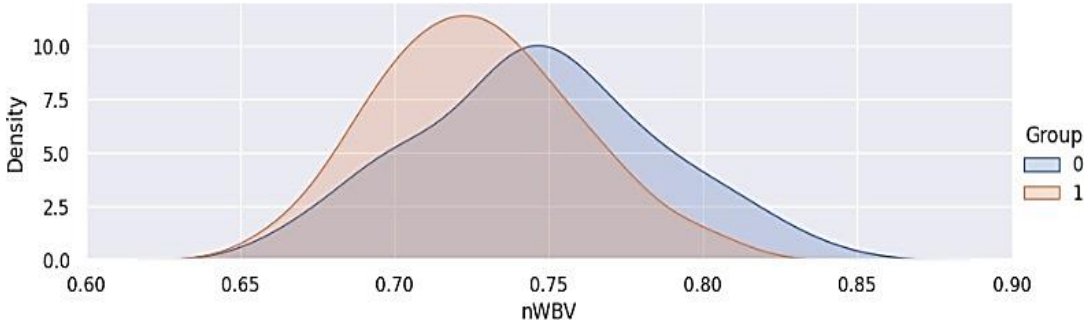

Figure 6. Normalize whole brain volume

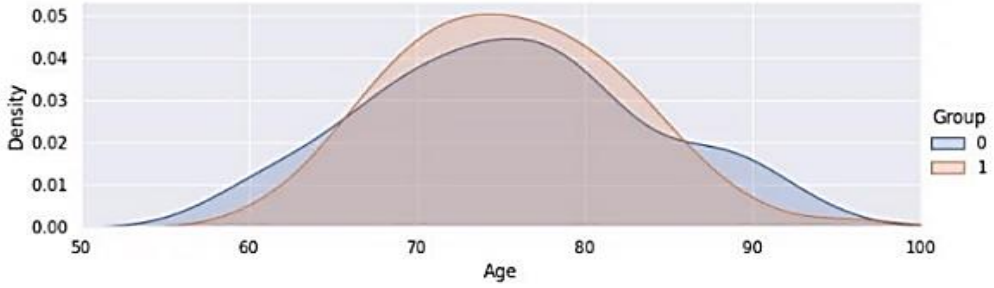

Figure 7. Age in years

2.3. Algorithms utilized for Alzheimer detection

The process of classifying photographs involves using a classifier to divide the various objects into discrete groups based on multiple classification criteria. In this instance, there are two classes: brains without AD and brains with AD. Thus, four classification methods LR, DT, SVM, and CNN are used to complete the categorization procedure once the blocks have been retrieved in order to compare their classification rates.

2.3.1. Logistic regression

LR is employed for binary classification issues and estimates the likelihood that a parameter belongs to a specific group of data by applying the logistic (sigmoid) function. This function maps predicted values to a probability between 0 and 1. The output probability is then compared to threshold to make a binary decision, determining the class of the input based on whether the probability exceeds a certain threshold [18]. The model is represented in (1).

$$P(Y - \frac{1}{X}) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X)}} \quad (1)$$

Where β_0 and β_1 are the coefficients learned during training and X is the input feature. These coefficients are learned using a technique like gradient descent that minimizes a cost function, typically the log-loss (cross-entropy loss) [19].

2.3.2. Support vector machine

Although this technique is mostly employed for classification, SVM is applied for regression jobs as well. It functions by locating the hyperplane that separates the data into the greatest number of classes. This hyperplane is a line in two dimensions and turns into a plane in higher dimensions. In order to provide the best feasible separation between the classes, SVM learning seeks to optimize the difference among this hyperplane and the closest data points from every group [20]. For a given input X and weights w, the decision function is given in (2).

$$f(X) = w.X + b \quad (2)$$

Where b represents the bias term. The hyperplane is chosen so as to optimize the distance between it and the closest data points, or support vectors.

To find the ideal hyperplane that divides the data for training a SVM, quadratic optimization techniques are applied. The kernel approach is used to translate non-linear data into a higher-dimensional space in which a linear separation is possible. This effectively converts the situation into one where linear classification techniques may be used, enabling SVM to handle complex relationships between features [21].

2.3.3. Decision tree

A DT is used to create a tree-like model by separating the information among subsets according to feature values. It can be applied to jobs involving both regression as well as classification. An internal node indicates a feature, a branch expresses a decision rule, and a leaf node indicates a result or class label. In order to attain the most information gain or impurity reduction, the method uses metrics like mean squared error for regression and Gini impurity or entropy for classification to assess the appropriate split at each node during training. Recursively building the tree results in a model that bases decisions on the feature splits' hierarchical structure [22], [23].

2.3.4. Convolutional neural networks

While its major applications are in the field of image processing along with computer vision, CNNs can also be employed in other fields, including as time-series data. CNNs work by employing convolutional layers to intelligently acquire spatial hierarchies of characteristics from the input data, creating feature maps through the application of convolutional filters. They lower the dimensionality of these feature maps by using pooling layers like max pooling and non-linear activation functions like rectified linear unit (ReLU) to introduce non-linearity. Predictions are based on the learnt features by fully linked layers at the end of the network. Stochastic gradient descent and back-propagation are used in conjunction with end-to-end training to optimize the CNN's performance by modifying its weights [24], [25].

3. RESULTS AND DISCUSSION

In this study, we assess a model to diagnose Alzheimer's using the patients' MRI images. A variety of metrics, including specificity, F1-score, precision, accuracy as well as recall, are used to evaluate the model [24], [25]. We divide our categorization rate into two distinct groups (normal range brain along with brain having AD) with respect to the mentioned standards as (3).

$$Classification\ rate = \frac{(No.of\ well\ classified\ images)}{(total\ number\ of\ images)} * 100 \quad (3)$$

As demonstrated in Table 2, we evaluate our suggested method's performance against a few cutting-edge techniques. The comparative analysis and the accuracy given are predicated on a testing dataset. The results shows that the accuracy using the CNN (90.32%) is better than the accuracy using the remaining algorithms. This shows the effectiveness of CNN algorithm. This increases the models' accuracy and decreases the amount of time needed for learning. Thus, greater precision with less time and data. Figure 8 displays an illustration of the accuracy, precision, recall, and F1-score attained by several classifiers.

Table 2. The comparative analysis of all algorithms

Algorithms	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
CNN	90.32	90.54	91.06	49.40
SVM	81.57	82.22	70	37.80
LR	78.94	79.44	70	37.21
DT	81.56	82.50	65	36.35

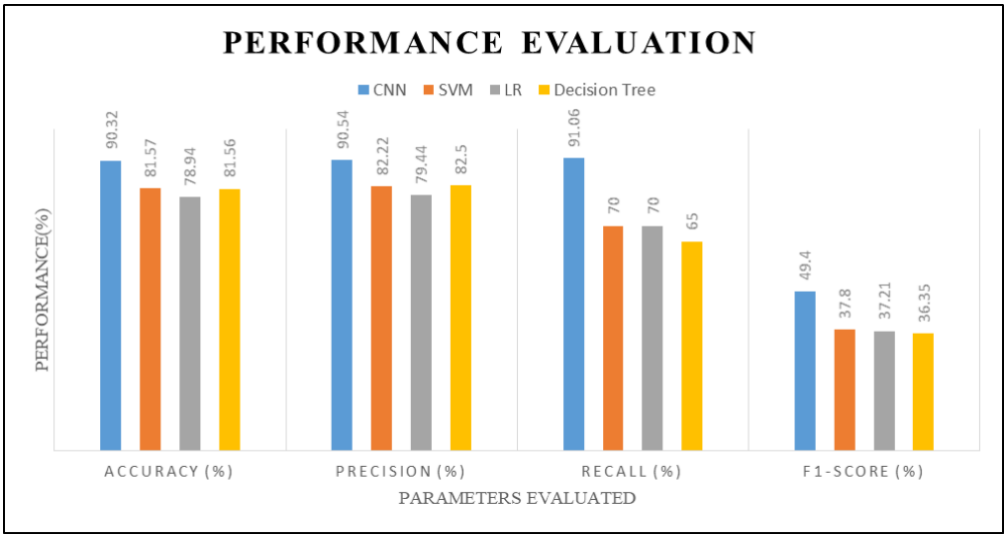

Figure 8. Performance of algorithms

4. CONCLUSION

In our pursuit of advancing healthcare through intelligent machines, our research has underscored a promising approach to enhancing sickness prognosis, with a particular focus on AD. We employed a variety of ML along with deep learning methods in order to analyze patient data, considering a diverse array of

symptoms and conditions to refine our predictive models. Our investigation yielded compelling results, particularly with the CNN algorithm. This proposed model exhibited an exceptional accuracy rate of 90.32% in predicting AD cases. This impressive performance underscores the CNN's capacity to effectively categorize and identify early-phase Alzheimer's, marking it as a standout approach in our study. The future research on ensemble learning for early Alzheimer's detection should improve the interpretability of the models, applicability to different populations, and quality of the data. Ensemble approaches have the potential to enhance diagnostic precision and include multi-modal data by merging various algorithms. It will be possible to implement more precise, dependable, and secure models in healthcare settings by creating explainable models and implementing privacy-preserving strategies. Also, future research should concentrate on growing the dataset to encompass a wider demographic and looking into the use of more sophisticated algorithms and hybrid models.

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