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Advancing Early Diagnostic Accuracy for Alzheimer's Disease Through the Integration of Machine and Deep Learning Paradigms by Applying Multisource Datasets

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Abstract— **Alzheimer's disease (AD) is a progressive neurodegenerative disorder with a critical need for early and accurate diagnosis. In this research, various machine learning (ML) and deep learning (DL) techniques are employed for identifying reliable biomarkers for early-stage AD detection. This research paper presents a comprehensive approach utilizing a myriad of artificial intelligence (AI) and machine learning (ML), i.e., self-attention mechanisms with Convolutional Neural Networks (CNN) model has been proposed for predicting the onset of AD. The study has compared these models including Gaussian Naive Bayes (GNB), Decision Trees (DT), Random Forest (RF), XGBoost, Voting Classifier (VC) where the proposed Feature based CNN (F-CNN) network produces the highest classification accuracy, sensitivity, recall, AUC and F1 scores by utilizing datasets such as the Alzheimer's Disease Neuroimaging Initiative (ADNI). The proposed approach holds promise for early detection and intervention in AD, potentially enabling clinicians to intervene before the onset of clinical symptoms. The findings of this research could significantly contribute to improving patient outcomes and advancing our understanding of Alzheimer's disease pathology.**

Keywords— **Alzheimer's Disease, Machine Learning, Deep Learning, Convolutional Neural Network, Evaluation Metrics**

I. INTRODUCTION

In the recent years, the dementia has remained one of the most significant disease in the whole world. Also, it has been observed that dementia has affected more than 40% of the induvial in lower edged and middle edged income countries. From WHO reports, it has been found that around 60 million people are affected due to dementia, out of which 35 million people having Alzheimer Disease (AD) [1,2]. As there is steady increase of proportion of the older people in each of the countries, the projected rise of AD disease has marked to be 82 million in the year 2030, further added to 50 million by 2040. According to the reports from US reports, around 7 million people are affected which is approximately 13% of the total population. It has been predicted that the number would be sharply increased to around 14 million if it is not detected early. In order to track the progress with AD, there are certain characteristics such as historical family background and existence of genes that are present in almost all of the patients [3,4]. Since there has been no permanent cure for the Alzheimer Disease, countries from all over world are finding different ways for providing human care at a minimum cost.

From the above studies, it has been shown that the AD has been a strong intense area of research during recent years [5,6]. The risk of getting AD is due to inheritable factors which amounted to nearly 80% of the total cases. Therefore, identifying the specific genes which cause AD that has proven to be more complicated, which has been found to be one of the rarest disease. Depending the type of phenotype, onset of the disease, and different family backgrounds are main drivers for occurring Alzheimer Disease as shown in Fig.1.

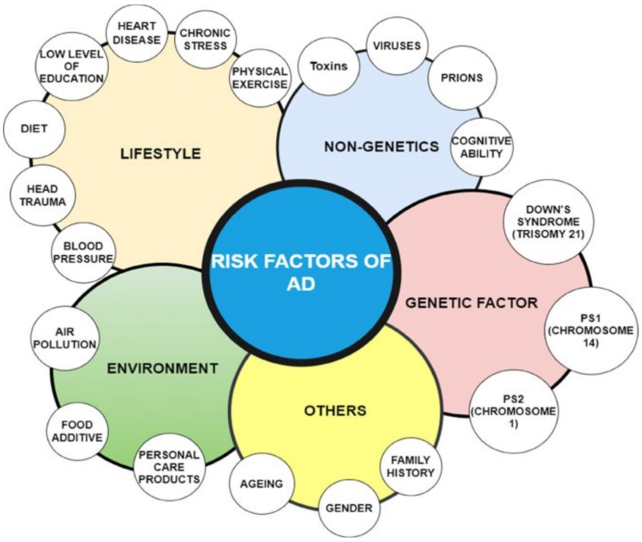

Fig.1. Different risk factors concerning the progression of AD

Recently, Deep Learning has emerged one of the sub areas in the Artificial Intelligence in predicting the onset of Alzheimer Disease [7,8]. During the literature studies, it has been discovered that the accuracy and prediction is much higher when compared with traditional based Machine Learning techniques. The application different DL algorithms have been summarized in [9,10] for diagnosing some of the neurological disorders where AD has been considered as one of the important disease.

One of the applications of one of the Deep Learning models, i.e., RCNN model has been applied for diagnosing the disease [11]. Also, the application of neuroimaging data has been applied for treatment of AD. The application of Deep Learning methods has been spread in the different areas of medical fields, especially in the diagnosing and predicting brain disorders. The most popular network is Convolutional Neural Network (CNN) or the different forms has been evaluated in terms in predicting accuracy of predicting disease. Artificial Neural Network (ANN) is one of the subtypes of CNN which contains a network of different interconnected neurons that are mainly used for predicting and classifying AD [12,13]. Moreover, the efficient error functions are computed which are limited by the single layered perceptron level. Gradient descent optimization technique has been applied for minimizing the error functions.

Most of the studies has considered as the binary classification tasks by applying ML models. Multi-kernel SVM classifier model has been applied in order to learn the features obtained from various datasets such as ADNI and OASIS [14]. One of the limitations of SVM is to classify the subjects with more than two classes where prior knowledge is required. In this paper, we have proposed Feature based CNN (F-CNN) model has been proposed for differentiation AD from Normal patients by acquiring T1 weighted scans from ADNI dataset.

II. Description of Dataset

For this research work, we have taken The Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset which was established in the year 2004 [15]. In this dataset, different biomarkers have been applied for validating and detecting the effectiveness. However, it has been found that the original dataset that was formed contains different slices of the brain images. These slices were in ordered form by taking the position where the training of the images is performed at first one but testing images are the latter ones. The original dataset was reframed as “Alzheimer Dataset (4 classes of Images)” where the images are randomly selected as training, validation and testing.

In this dataset, T1-weighted MRI images have been considered where 32 horizontal slices of the brain are divided into 4 classes, namely, Mild Dementia, Moderate Dementia, Non-Dementia, and Very Mild Dementia. For each of the classes, 28 subjects have been taken as Mild Dementia and 2 subjects are considered as Moderate Dementia. Also, 100 subjects for non-Dementia and 70 subjects have been considered as Very Mild Dementia classes.

III. Proposed Methodology

In this proposed technique, there are sequence of steps are required for processing the T1 weighted MRI images. This figure outlines a workflow for machine learning data processing and analysis, specifically in the context of Alzheimer's disease using the OASIS dataset. The process is broken down into several distinct steps:

1. **Dataset Collection:** Data is collected from the Alzheimer Dataset (4 classes of Images) dataset from Kaggle Website.

2. **Preprocessing:** The preprocessing step involves three tasks:
   - Feature Selection: A method such as Select K Best is used to choose the most relevant features from the dataset.
   - Feature Scaling: Standardization of features is performed using Standard Scaler to ensure all input features have the same scale.
   - Handling Missing Data: Missing values in the data are dealt with by replacing them with the mean values of the respective features.

3. **Data Splitting:** The pre-processed data is then split into two parts: 80% for training the model and 20% for testing its performance.

4. **Applying Machine Learning Algorithms**: Various machine learning algorithms are applied to the training data. These include Gaussian Naive Bayes (GNB), Extreme Gradient Boosting (EGB), Decision Tree (DT), Random Forest (RF), Gradient Boosting (GB).

5. **Evaluate the Result:** After training, the models' performance is evaluated using the test data to see how well

they can predict and classify new data. The overview of all the steps of proposed methodology have been shown in the Fig.2.

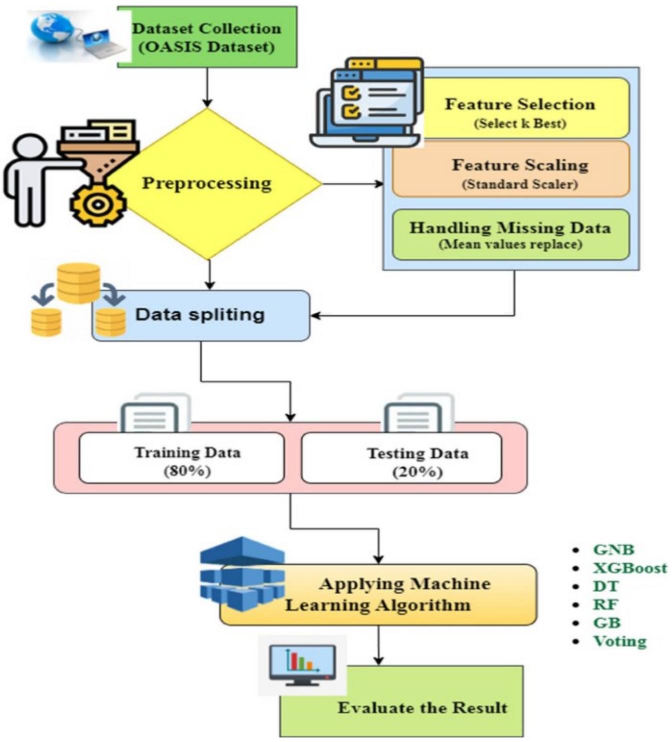

Fig.2 Overall view of proposed methodology

IV. SIMULATION RESULTS AND DISCUSSION

In this section, simulation results have been carried out by applying different Machine Learning algorithms, such as GNB, DT, RF, GB, and voting that are used to classify AD from normal patients. For executing the proposed work, Jupyter notebook has been used as a working environment. Here, 80% of the total images are trained for training and validation purpose whereas the rest 20% of the images are used for testing the models. Evaluation metrics, such as Classification Accuracy, F1 score, Precision, Recall has been applied for classifying Dementia and Non dementia patients. These metrics are required in order to evaluate the quality of different machine learning models. For measuring the accurate performance in each of the models, hyperparameters are optimized by applying cross validation approach. Mathematically, the Classification accuracy formula can be represented as below.

$$\text{Classification Accuracy} = \frac{TP+TN}{TP+FP+FN+TN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

$$\text{F1- score} = \frac{TP}{TP+\frac{1}{2}(FP+FN)} \quad (4)$$

Table 1 describes the different evaluation metrics parameters of seven different ML models.

TABLE 1
VALUES OF EVALUATION METRICS FOR ALL MODELS

S. No	Models	Classification Accuracy	Sensitivity	Recall	F1-Score	AUC Value
1.	GNB	0.67	0.24	0.33	0.29	0.26
2.	DT	0.91	0.67	0.52	0.66	0.42
3.	RF	0.82	0.69	0.55	0.51	0.47
4.	Voting	0.79	0.72	0.43	0.42	0.55
5.	XGBoost	0.74	0.73	0.48	0.33	0.46
6.	GB	0.63	0.61	0.51	0.24	0.28
7.	Proposed F-CNN	0.99	0.82	0.57	0.72	0.75

Table 2 summarizes the performance of various ML models in a binary classification task in order to identify or classify AD from normal patients. Seven different models are evaluated based on five key performance metrics such as Classification Accuracy, Sensitivity, Recall, F1-Score, and AUC Value. Classification Accuracy determines the percentage of total correct predictions made by the model. Sensitivity measures the model's ability to correctly identify positive cases. Recall values determines the percentage in a binary classification context. F1-Score values mean that the harmonic mean of precision and recall. AUC value reflects the area under the receiver operating characteristic curve.

The proposed Feature based CNN (F-CNN) model outperforms the others across almost all metrics achieves at a rate of 99% accuracy and the highest AUC Value at 75% which indicates the superior predictive performance and reliability. On the other hand, the GNB model seems to have the lowest scores in all metrics, suggesting it may be the least suitable model for this task. Models like DT and RF show strong performance in accuracy and sensitivity, but they are still outclassed by the Proposed F-CNN. The Voting and XGBoost methods exhibit moderate results, with the Voting model having a relatively higher AUC Value, suggesting better classification capability than others, despite its lower F1-Score. The values of classification accuracies of different models have been shown in Fig. 3.

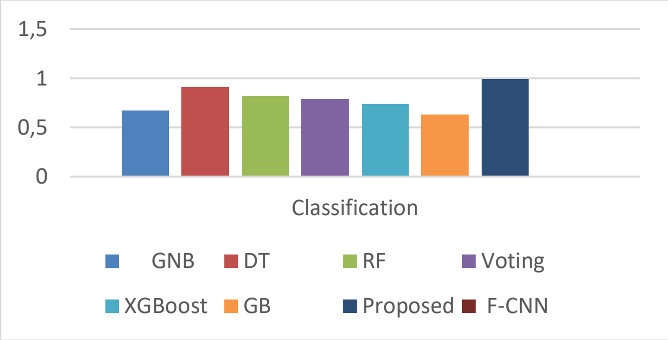

Fig.3 Classification accuracies of different models

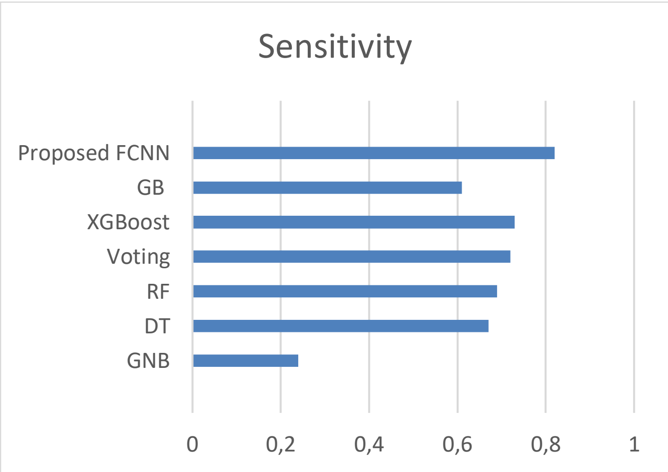

Fig.4 Bar graphs showing the Sensitivity

Fig.4 displays the bar graph where the values of sensitivities of different models are shown. In this figure, the proposed FCNN determines the highest value of 0.8 when compared with others.

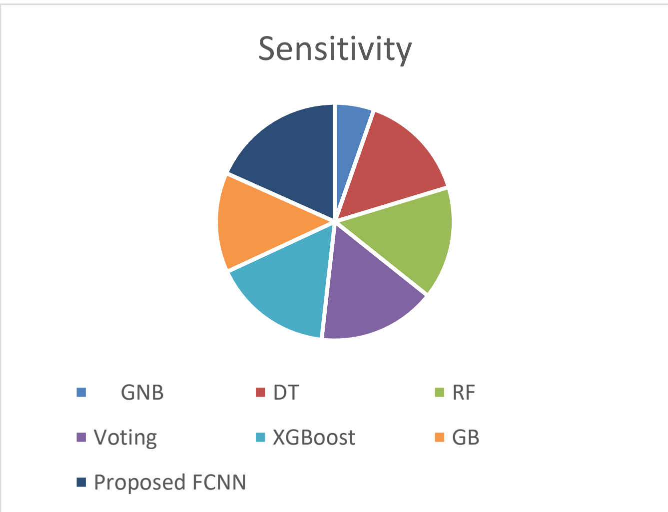

Fig.5 Pie chart showing the proportion area of each of the accuracies

Fig.5 shows the pie chart where the proportion area of the recall accuracies is displayed. From the fig., it has been observed that the proposed FCNN has highest proportion when compared with others.

Fig.6 displays the values of the AUC values of all the models including the proposed Feature based FCNN model in the form of line graph. In this graph, the lowest AUC value of 0.27 is observed in GNB model which is followed by DT, RF, Voting, in increasing order. However, the AUC values has been decreased to 0.42 for XG Boost model which is further decreased to Gradient Boosting at 0.28. But, the proposed F-CNN model shows the highest value of 0.76 due to its feature dependent which act as input of CNN model.

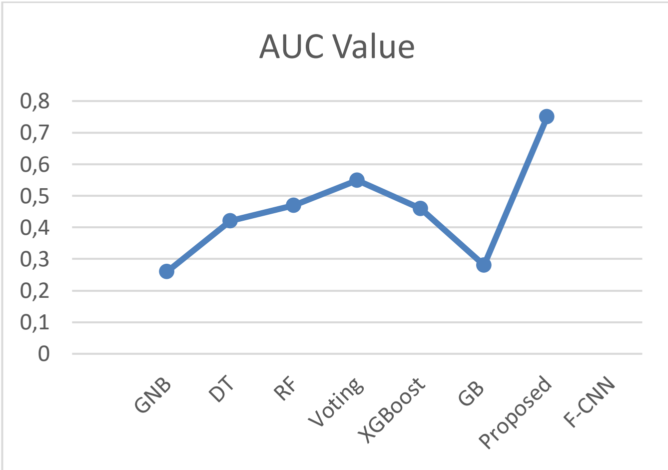

Fig.6 Line graph showing the values of AUC

V. Conclusion and Future Scope

In this work, seven different ML frameworks such as Gradient Boosting (GB), XG-Boost, Decision Tree (DT), Random Forest (RF), Voting, GNB and proposed F-CNN model have been applied for detecting AD at an early stage where T1 weighted MRI scans are obtained from the OASIS dataset. In this research, MRI data is preprocessed for identifying pertinent features for training these models. The performance of each model is evaluated using key metrics such as Classification Accuracy, Sensitivity, Recall, F1Score and AUC-ROC which aims at differentiate between AD patients and healthy individuals accurately. The simulations reveal that the proposed F-CNN model outperforms others in terms of accuracy and AUC-ROC, highlighting its effectiveness as a reliable tool for early AD detection.

REFERENCES

[1] Knopman, David S., Helene Amieva, Ronald C. Petersen, Gäel Chételat, David M. Holtzman, Bradley T. Hyman, Ralph A. Nixon, and David T. Jones. "Alzheimer disease." *Nature reviews Disease primers*, vol.7, no. 1, 2021.

[2] Scheltens, Philip, Bart De Strooper, Miia Kivipelto, Henne Holstege, Gael Chételat, Charlotte E. Teunissen, Jeffrey Cummings, and Wiesje M. van der Flier. "Alzheimer's disease." *The Lancet, vol.* 397, no. 10284 pp.1577-1590, 2021.

[3] Van Dyck, Christopher H., Chad J. Swanson, Paul Aisen, Randall J. Bateman, Christopher Chen, Michelle Gee, Michio Kanekiyo et al. "Lecanemab in early Alzheimer's disease." *New England Journal of Medicine, vol.* 388, no. 1, pp. 9-21, 2023..

[4] Self, Wade K., and David M. Holtzman. "Emerging diagnostics and therapeutics for Alzheimer disease." *Nature medicine, vol.* 29, no. 9 pp.2187-2199, 2023.

[5] Self, Wade K., and David M. Holtzman. "Emerging diagnostics and therapeutics for Alzheimer disease." *Nature medicine, vol.* 29, no. 9 pp.187-2199, 2023.

[6] Wong, Winston. "Economic burden of Alzheimer disease and managed care considerations." *The American journal of managed care* 26, no. 8 Suppl , pp.S177-S183, 2023..

[7] Kumari, Rashmi, Shivani Goel, and Subhranil Das. "Mathematical modelling of dendritic complexity mechanism in Alzheimer's disease." In *AIP Conference Proceedings*, vol. 2872, no. 1. AIP Publishing, 2023.

[8] Kumari, Rashmi, Subhranil Das, and Raghwendra Kishore Singh. "Agglomeration of deep learning networks for classifying binary and multiclass classifications using 3D MRI images for early diagnosis of Alzheimer's disease: a feature-node approach." *International Journal of System Assurance Engineering and Management, vol.* 15, no. 3, 931-949, 2024.

[9] Kundu, Rounak, Subhranil Das, and Sudhansu Kumar Mishra. "A comprehensive review of single and double stage object detection algorithms in self driving cars." In *7th International conference for Convergence in Technology (I2CT)*, pp. 1-8. IEEE, 2022.

[10] Das, Subhranil, Abhishek Thakur, Sudhansu Kumar Mishra, Subrat Kumar Swain, and Rashmi Kumari. "Development of Indoor Autonomous Mobile BOT for Static Obstacle Avoidance." In *International Conference on Data Science and Applications*, pp. 59-71. Singapore: Springer Nature Singapore, 2023.

[11] Kumari, Rashmi, Shivani Goel, and Subhranil Das. "A Patch Based 3D CNN Approach for Diagnosing Early Stages of Alzheimer's Disease by Applying OBL-WOA Algorithm." In *8th International Conference on Cloud Computing and Big Data Analytics (ICCCBDA)*, pp. 455-459. IEEE, 2023.

[12] Das, Subhranil, and Rashmi Kumari. "Statistical Analysis of COVID cases in India." In *Journal of Physics: Conference Series*, vol. 1797, no. 1, p. 012006. IOP Publishing, 2021.

[13] Kumari, Rashmi, Subhranil Das, and Raghwendra Kishore Singh. "Ascending Complexity Task GAN and 3D Dense Convolutional Networks for Binary Classification of Alzheimer's Disease." In *International Conference on Data Analytics & Management*, pp. 241-249. Singapore: Springer Nature Singapore, 2023.

[14] Kumari, Rashmi, Shivani Goel, and Subhranil Das. "Using SVM for Alzheimer's Disease detection from 3D T1MRI." In *2022 IEEE 21st Mediterranean Electrotechnical Conference (MELECON)*, pp. 600-604. IEEE, 2022.

[15] Jack Jr, Clifford R., Matt A. Bernstein, Nick C. Fox, Paul Thompson, Gene Alexander, Danielle Harvey, Bret Borowski et al. "The Alzheimer's disease neuroimaging initiative (ADNI): MRI methods." *Journal of Magnetic Resonance Imaging: An Official Journal of the International Society for Magnetic Resonance in Medicine* 27, no. 4, pp. 685-691,2008.