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Renaissance for Alzheimer’s Disease Detection using ML DL Techniques

Bhaskara Rao B[1], Srinath Reddy Y. P[2], Sai Deepika K[3], Sai Kiran P[4], Bhargavi K[5], Sai Deekshitha A[6]

[1,2]Department of Computer Science and Engineering (Data Science) Rajeev Gandhi Memorial College of Engineering and Technology(Autonomous), Nandyal, Andhra Pradesh, 518501

[3,4,5] Student, Department of Computer Science and Engineering (Data Science), RGM College of Engineering &Technology, Nandyal, Andhra Pradesh, India.

bhaskararaobrd@rgmcet.edu.in[1],srinathreddy0387@gmail.com[2],katakamsaideepika442@gmail.com[3] kiransai7029@gmail.com[4], kollibhargavireddy48@gmail.com[5], saideekshithasaideekshitha7@gmail.com[6]

Abstract:

The early diagnosis of Alzheimer’s disease (AD) is very important in ensuring proper intervention in a timely manner so that patients can be managed better and have better outcomes. Earlier, cognitivedata and numerical patient information were used with conventional machine learning (ML) methods for early detection. One of the past ensemble-based approaches trained up to seven ML classifiers that included Decision Tree, Random Forest, SVM, ANN, and AdaBoost, gaining 93.92% accuracy. However, deep learning integration and optimal feature extraction was not present in that study. This study proposes a novel deep learning (DL) approach using advanced feature selection by Decision Tree and Random Forest, and Synthetic Minority Over-Sampling Technique (SMOTE) for class balancing. A hybrid deep learning approach based on Convolutional Neural Networks (CNN) and Artificial Neural Networks (ANN) is presented. The model provides efficient, scalable, and adaptive, and a robust Alzheimer’s disease (AD) detection for the real-life patients. The models are trained successfully with patients' data from Kaggle.The model provides effic ient early AD detection with better accuracy and stability.

Keywords*:* Alzheimer’s Disease (AD), Cognitive Data, Machine Learning (ML), Deep Learning (DL), Decision Tree (DT), Support Vector Machine (SVM), Random Forest (RF),Synthetic Minority Over-Sampling (SMOTE), Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN)

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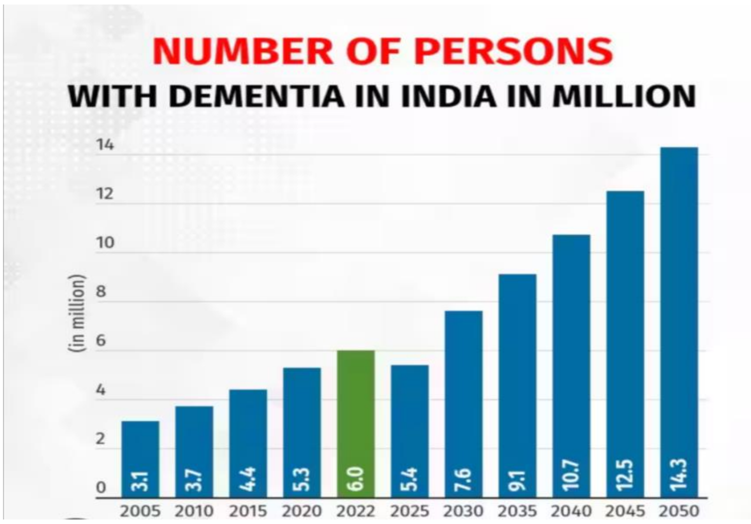
1. Introduction

Alzheimer's disease (AD) is a long-term neurodegenerative disorder affecting predominately memory, cognitive functions, and behaviour. AD is the most prevalent aetiology of dementia, affecting around 60-70% of all cases worldwide. AD is symbolized by the aggregation and deposition of abnormal proteins in the brain, such as beta-amyloid plaques and tau tangles, which eventually lead to nerve loss of function, followed by brain deterioration.

The early symptoms of AD usually include mild forgetfulness, difficulty remembering recent events, and inability to manage complex tasks. Sometimes as the disease progresses, these patients go through various forms of direct cognitive shortfalls involving confusion, failure to recognize familiar people, and language and decision-making problems. In advanced stages, individuals may become unable to perform their daily chores, they become highly disoriented, and require constant care.

In India, due mainly to increased life expectancy and the increasing age of the population, the health-care burden from AD and other forms of dementia is rising. Recent estimates suggest that about 7.4% of India's population aged over 60 are believed to be afflicted by dementia, translating to approximately 8.8 million individuals. This number is projected to go as high as 11.4 million by the year 2050, pointing to an urgent need for improved early detection and intervention strategies. Furthermore, cultural and socioeconomic issues posed by Indian society regarding the awareness and recognition of AD, as well as therapeutics, remain quite daunting.



Detection of AD, nonetheless, poses a challenge, as its complex pathology and its symptoms overlap with other neurodegenerative conditions makes it very difficult for early detection. Most conventional tests, such as neuropsychological assessment, cognitive tests, and imaging techniques like MRI and PET scan, serve to help an expert diagnose AD so that treatment

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may be initiated as early as possible. Unfortunately, these methods take considerable time, incur a high cost, and are often inaccessible by a significant segment of the population as they are considerably expensive.

Our proposed work created a novel framework using deep learning (DL) for the early detection of AD and involves numerical data of any patient. The modelling works based on a framework combining advanced feature selection techniques, like decision tree, and random forest models to extract the best cognitive features for the diagnosis of AD. To deal with the problem of class imbalance of the existing AD datasets, we implement SMOTE, which will generate synthetic samples for the minority class and thus enhance model generalization and reduce bias.

We have developed a hybrid model that incorporates Convolutional Neural Networks (CNNs) with an Artificial Neural Network (ANN). CNN learns complex cognitive patterns and spatial correlations among the selected features, while ANN learns hierarchical features from the tabular data for better classification. The final output of detection is obtained by concatenating CNN and ANN predictions in a manner that tends to be robust and precise.

We tested our approach on a dataset obtained from Kaggle which include numerical patient records (3149 records)that relevant for AD detection. The formulated architecture is both efficient and scalable to real-world applications in consideration of its adaptability to healthcare settings. Final results show that our deep learning approach gives better accuracy, robustness, and efficiency in the detection of AD as compared with classical ML models combination.

2. LITERATURE SURVEY

The 2020 research paper, Machine Learning Approach to Preliminary Diagnosis of Dementia by Fubao Zhu, Xiaonan Li, Haipeng Tang, and Zhuo, published in Hindawi Journal proposed an ML based machine learning approach for the early diagnosis of dementia. There were classifiers like Random Forest, AdaBoost, Logit Boost, Neural Networks (NN), Naïve Bayes, and Support Vector Machines (SVM) for classifying patients in this study. The model, which saved manual labour in diagnosis, gave 87.2% accurate prediction for dementia, which is a moderate score and further development can be done considering the issues like size of dataset used, inconsistent feature selection, and class imbalance observed in the study. This paper had contributed significantly towards the idea of utilising ML in cognitive disorder detection.

The 2020 IEEE Xplore paper, Alzheimer's Disease Detection Using Machine Learning Algorithms, J. Neela Veni and M. S. Geetha Devasena, discussed the effectiveness of DT and SVM for AD identification. The study has shown that SVM model performs better with 85%

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accuracy when compared to DT, with a small pool of cognitive data observations. Although the models were moderate, the major disadvantage was a small number of features utilized for training the models, urging its optimization. It, however, laid the groundwork for research on how common-sense machine learning plays a role in the detection of AD.

The 2022, Early-Stage Alzheimer's Disease Prediction Using Machine Learning paper by C. Kavitha, Vinodhini Mani, and Ibrahim, covered a review of the working of multiple classifiers, namely Random Forest, DT, SVM, XGBoost, and voting classifiers to achieve an improvement in the accuracy of prediction in Alzheimer's disease. The model achieved an accuracy of 86.92% with MRI-based image features added; this research emphasized this model where multilabel combined classification would help in better disease detection. However some drawbacks were pointed out, which include the small size of the dataset, lack of deep learning models within its framework, and sometimes leading to overfitting scenarios.

In 2020, the Research Gate paper, Diagnosis of Alzheimer's Disease using Machine Learning Approach by Akash Rajak and Ajay Kumar investigated the use of Random Forest, DT, SVM, Logistic Regression, and AdaBoost for AD classification. They attained accuracy of 84.21%, with RF and AdaBoost being particularly stable models. However, the study is based on a small amount of data (373 records) and some models might have overfitting case in action. Such research offered an insight into the delicate trade-offs between model complexity and performance.

In 2023, research paper Adaptive Voting-Based Ensemble Machine Learning Approach for Early Detection of Alzheimer's Disease by Md. Irfan, S. Sharestani, and M. Elkhodr, which proposed an ensemble method of 7 ML models. They integrated DT, SVM, KNN, ANN, Logistic Regression, AdaBoost techniques using adaptive voting ensemble since the inception of ensemble learning. It achieved accuracy in the region of competitive 93.92%most of which is possible only due to NCA-F inclusion for feature selection, thus projecting 12.12% better than its predecessors. Though this unique methodology provided a clear break-through of ensemble method utilisation in disease detection. However, the procedure intensified the computation intensity and no deep learning models were recommended, and this approach showed there are class imbalances in the data used.

3. PROPOSED METHODOLOGY

The proposed deep learning-based framework for early Alzheimer disease diagnosis is developed along hybrid lines by harnessing Convolutional Neural Networks (CNNs) and Artificial Neural Networks (ANNs) that apply automatic feature selection and classification. Contrary to earlier models based on machine learning that relied overly on handcrafted

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features and cognitive tests, this model automates these processes, improving classification accuracy through the derivation of complex patterns in the numerical patient data.

Here we follow a structured pipeline process. Initially, the method comprises data preprocessing that cleans and normalizes the dataset. As medical datasets often suffer from an high imbalance in classes, SMOTE has been used to achieve a more uniform distribution of the classes so as to enhance model reliability.

Feature selection through DT and RF models helped in identifying the most prominent cognitive predictors of Alzheimer's disease progression which reduced model complexity and improved model interpretability.

For the next step, these features become model input for a hybrid deep learning model(CNN + ANN). While the CNN learns a spatial relationship among features and complex feature dependencies, the ANN learns hierarchical features from the tabular data for better classification. The predictions became the inputs of the concatenation layer, which helped in producing the final detection output utilising both the models.

The architecture we suggested is trained using a publicly available data set retrieved from Kaggle, which is a collection of numerical patient data in the context of Alzheimer's disease. The performance of the model is evaluated in the terms of usual metrics that are accuracy, precision, recall, and F1-score.

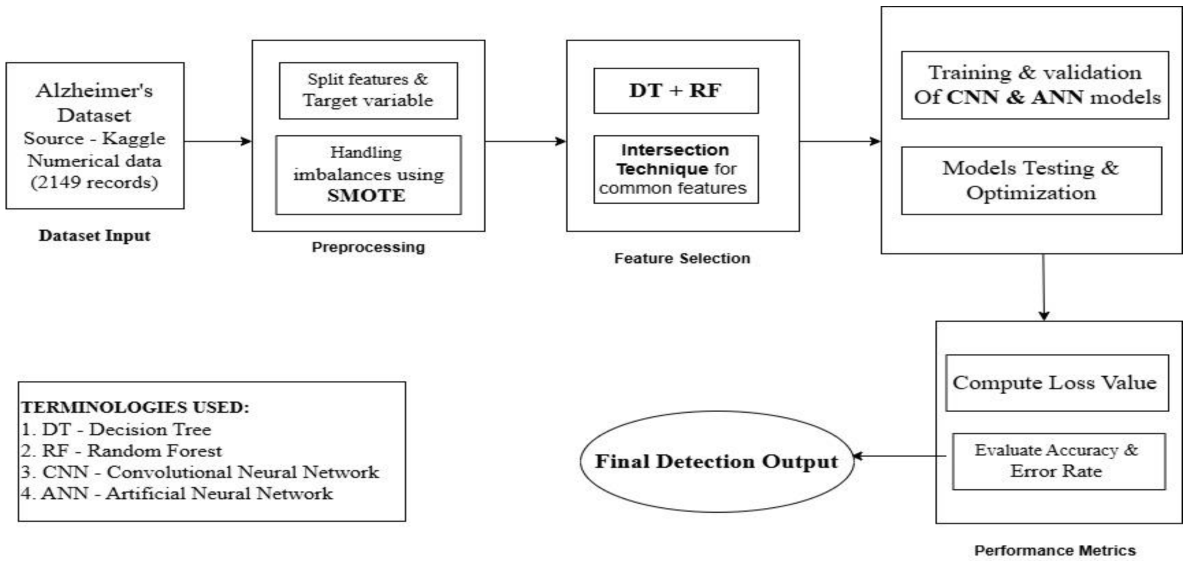

Fig.1 Framework for Alzheimer's disease detection using CNN, ANN Models

The Fig 1 block diagram of the proposed method is illustrated in Fig. 1, which explains the flow of data from preprocessing to classification and also how the whole process is done in a step-by-step manner.

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The present approach combines ML-based feature selection with DL-based detection in order to boost model robustness, predictive accuracy, and generalization when deployed on independent datasets. This integrated model will provide a highly scalable, efficient AI solution for early AD diagnosis, enhancing clinical decision-making and improving patient care.

4. DATASET & PREPROCESSING:

The dataset is collected from the Kaggle website, and the data collected contains cognitive and clinical features that are very important in the detection of Alzheimer's disease (AD). The data set is structured and helps to distinguish between Cognitively Normal (CN) individuals and those who have symptoms of Alzheimer's disease (AD). The dataset aided in both pre-classification and early identification of the diseased. The data chosen was a seamless fit for training Machine Learning and Deep Learning models involved in the process. The dataset collected has no missing values and is therefore cleaned and all the categorical variables are pre-processed and encoded perfectly to a suitable format (numerical values) by the authors, which helped to ensure compatibility with the models trained.

The dataset comprises of 3,149 patient records with a total of 35 attributes that are helpful for detecting the patient’s condition. Dataset used clearly involves patient background data that contains demographics, medical histories, lifestyle factors, cognitive assessments, and clinical biomarkers. This dataset contains 22 integer features related to patient details, risk factors, and medical conditions, 12 continuous features representing cognitive test scores and biomarker levels.

Some of the demographic factors include age, gender, ethnicity, and educational background, while the lifestyle attributes reveal BMI, physical activity, dietary habits, smoking and alcohol history, and sleep characteristics. Medical conditions covered include cardiovascular disease, diabetes, depression, hypertension, and history of head injuries, all of which can directly or indirectly affect cognitive health. From clinical measurements such as blood pressure and cholesterol levels, the dataset draws additional insight into the health profile of the patient.Cognitive and behavioural assessments help assess functions of memory, activities of daily living, and behavioural changes susceptible to Alzheimer’s diseases. The diagnosis feature acts as the target (dependent) variable, segregating patients into Cognitively Normal (CN) and Alzheimer’s disease (AD). The dataset contains 2 redundant features, namely, the PatientId and the DoctorInCharge feature, since they do not aid in detecting a patient suffering from Alzheimer’s disease. To ensure optimal model performance, these features were excluded prior to training the CNN and ANN models.

The data set consists of 2030 cognitively normal (CN) and 1,119 Alzheimer's disease (AD) samples, thus establishing the class imbalance situation where the normal samples greatly

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outnumber the diseased. The imbalance problem was solved with the Synthetic Minority Over-sampling Technique (SMOTE).

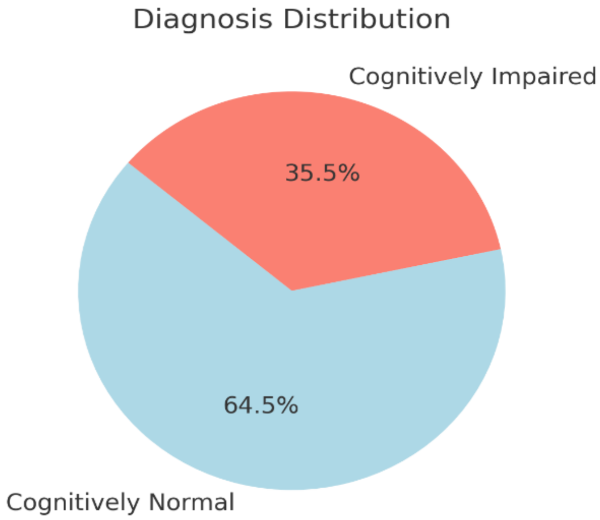

Fig.2 Number of CN and Alzheimer's patients in the data

SMOTE is an oversampling technique that generates synthetic instances for the minority class rather than simply duplicating the instances. In this technique, a single instance of the minority class is selected and the nearest neighbours are computed. New synthetic points are also computed along the line between the two points. This can be mathematically expressed as:

$$\boldsymbol{x_i +\ x_i + \lambda \times (x_{nn} - x_i)}$$

Where:

- x_i is a randomly proposed minority instance.
- $x_{nn}$is one of its nearest neighbours,
- λ is a random number between 0 and 1.

Utilizing SMOTE, for the construction of synthetic AD cases helped in generating a balanced dataset, averting the model from being biased toward the majority class. This increases the predictive capability of the classifier to more effectively differentiate between CN and AD cases and thus results in a more generalized and robust predictive model.

5. FEATURE SELECTION METHODS

After we had balanced our data using SMOTE (Synthetic Minority Over-sampling Technique), we performed our feature selection to determine the cognitive features most relevant to the effective classification of Alzheimer's disease. Choosing the appropriate

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features improves interpretability, decreases computational cost, and helps in making the correct decisions. We had trained 2 models, i.e., Decision Tree (DT) and Random Forest (RF) for feature selection.

Decision Trees (DT) are widely used in feature selection because it ranks the features based on their importance for classification. To uncover each feature's contribution towards recognition of CN vs. AD case, In the DT model, we applied Gini Impurity to identify the important features as it works well for balanced dataset and is computationally faster. The formula of Gini Impurity is:

$$1 - \sum_{i=1}^{c} p_i^2$$

Where:

- C is the Number of classes (CN vs. AD).
- P_i is the probability of class i.

The features with low Gini Impurity are retained, and the ones with the higher value are removed as they have minimal impact on the final detection output.

Next, Random Forest (RF) model, as an extension of DT, constructs multiple decision trees and aggregates their classifications. From Random Forest, we can obtain the Feature Importance Scores, which indicate a feature's contribution towards the classification. For any feature, the importance score is determined based on an average of impurity-decrease contributions across all trees. The formula for finding the feature importance scores is:

$$Importance(F) = \frac{1}{T}\sum_{t=1}^{T}(I_{parent} - (I_{left} + I_{right}))$$

Where:

- T is the total number of trees
- I_{parent} is the impurity of the parent node
- $I_{left} + I_{right}$ are the impurities of the child nodes.

In order to refine the feature selection process further, we performed an Intersection-Based Feature Selection. This assures that only the most
relevant and consistently important features across both models, Decision Tree and Random Forest, will be kept. The intersection operation identifies the common features that both models selected as important and assures that only those features have strong power of prediction and are attributes for training our models.

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This approach provides support for more robust and reliable Alzheimer's Disease detection.

Decision Tree Features	Random Forest Features	Final Features
Age	Age	Age
EducationLevel	BMI	BMI
BMI	AlcoholConsumption	DietQuality
DietQuality	PhysicalActivity	SleepQuality
SleepQuality	DietQuality	CholesterolTotal
SystolicBP	SleepQuality	CholesterolHDL
DiastolicBP	CholesterolTotal	CholesterolTriglycerides
CholesterolTotal	CholesterolLDL	MMSE
CholesterolHDL	CholesterolHDL	FunctionalAssessment
CholesterolTriglycerides	CholesterolTriglycerides	MemoryComplaints
MMSE	MMSE	BehavioralProblems
FunctionalAssessment	FunctionalAssessment	ADL
MemoryComplaints	MemoryComplaints	
BehavioralProblems	BehavioralProblems	
ADL	ADL	

Fig 3. The Selected Features from DT and RF models

This above table basically represents the feature selection comparison table used within the framework of the Alzheimer detection project. It highlights important features selected by Decision Tree and Random Forest models, and final selected features provided by the use of an intersection-based feature selection strategy. These features are thus assumingly robust and reliable because they are common. The finalfeature set composed of Age, BMI, Diet Quality, Sleep Quality, Cholesterol Levels, MMSE, Functional Assessment, Memory Complaints, Behavioural Problems, and ADL which are very helpful for Alzheimer's Disease detection. By focusing on similar and informative features, this approach improves model accuracy, reduces complexity, and increases generalizability.

The correlation matrix underscores the primacy of the selected cognitive features in detecting dementia. Strong correlations are noted with respect to MMSE, Functional Assessment, and Memory Complaints indicate their full weight in making an assessment of cognitive decline. Moderate associations of behavioural features, such as Sleep Quality and Behavioural Problems, suggest they may probably stand as early indicators. Weak correlations with other physiological factors, such as Age, BMI, or Cholesterol level, imply a potential contribution toward overall brain health, but lack hallmark predictive capability. In essence, the matrix affirms that cognitive features play the leading role as indicators of Alzheimer's, while behavioural and physiological factors provide a backing contribution in second place.

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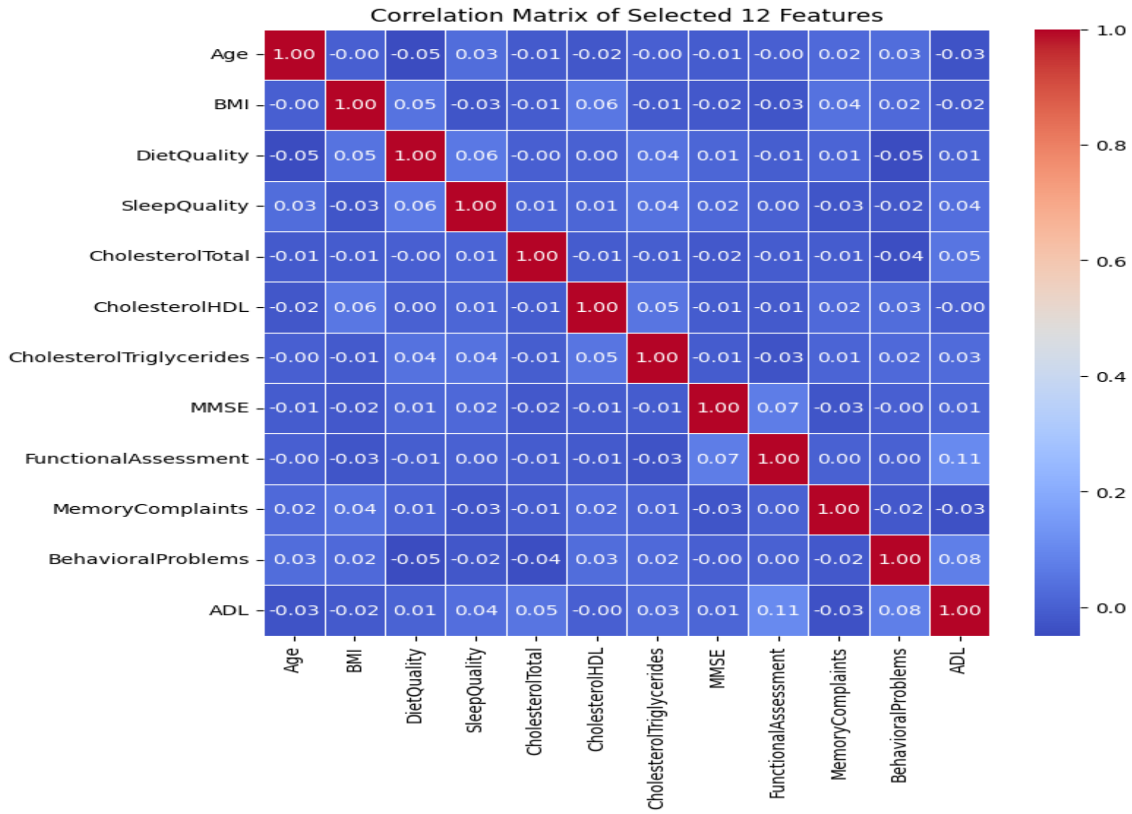

Fig 4. Correlation matrix of final selected features

6. METHODOLOGY

This paper introduces a state-of-the-art hybrid deep learning framework combining Convolutional Neural Networks (CNNs) and Artificial Neural Networks (ANNs) to improve the classification of Alzheimer's disease. The CNN component has an important role in feature extraction through the examination of spatial patterns and hierarchical representations of the dataset. Compared to traditional feature extraction techniques, our proposed system employs a 1D convolutional layer with the goal of discovering complex and subtle patterns, which is especially helpful for structured medical data. This approach allows the CNN to discover important features that are hard to discover using traditional approaches.

Concurrently, the ANN module is responsible for achieving high-dimensional interrelations by examining raw numerical features in fully connected dense layers. These layers allow the model to detect complex interdependencies of diverse cognitive and clinical variables, which are vital for precise disease classification. The application of the two architectures is performed via a concatenation layer utilized to combine the features achieved from the CNN with those processed in

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the ANN. Combining these features increases the model's power to utilize both feature extraction and decision-making abilities, hence enhancing its predictive strength.

To make sure that the model performs very well on unseen data and reduce the chance of overfitting, various regularization methods are employed. Batch Normalization is employed to normalize the learning process and speed up convergence rates, while Dropout is employed to drop out neurons randomly while training the model to avoid over-reliance on certain features. Furthermore, L2 regularization is incorporated to impose penalties on excessively complex weight parameters, hence making the model stable and avoiding unnecessary complexity. In the last step, a sigmoid activation is applied in the output layer to do binary classification between Alzheimer's and non-Alzheimer's. The hybrid model possessed better precision, recall, and F1-score than traditional deep learning models and is a very useful tool for disease classification in our own medicalfield for the patients detection in our medical field.

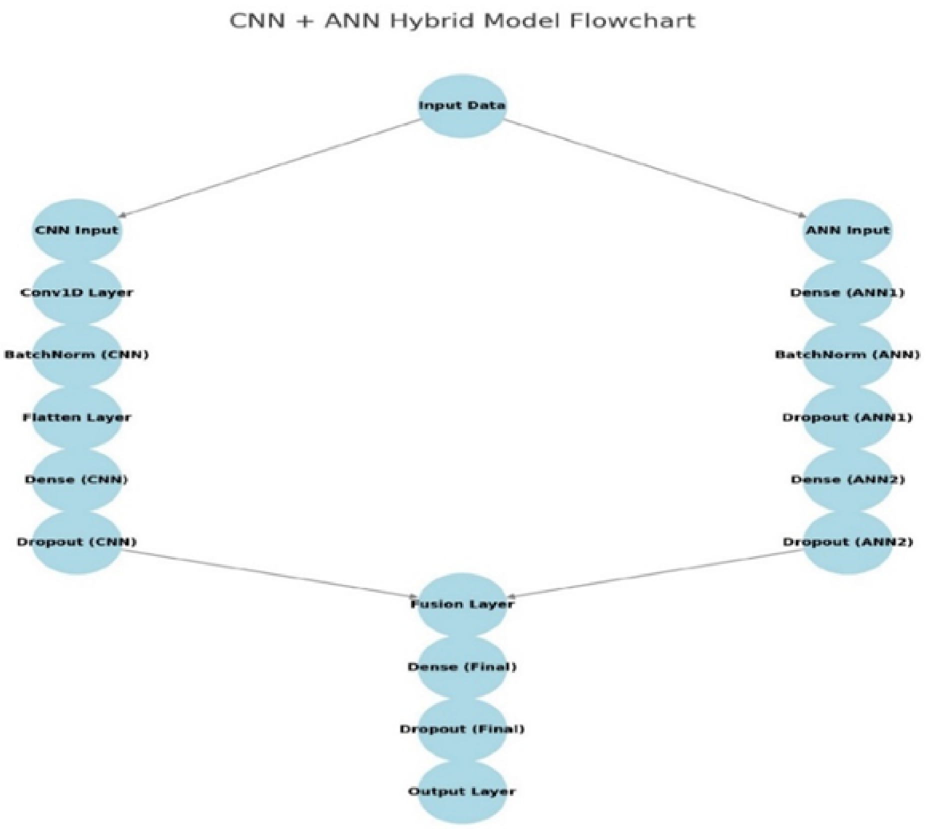

Fig 5. The architecture of the hybrid (CNN +ANN) model

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7. RESULTS AND DISCUSSIONS

After selecting the optimal set of cognitive features using DT and RF classifiers, common features were identified through cross-feature intersectional consistency to enhance feature selection. The refined features selected from there were used to train deep learning models in the form of CNN and ANN for early detection of Alzheimer's Disease. The effectiveness of the proposed models was evaluated through key performance indicators, namely, Accuracy, Precision, Recall, and F1-Score.The key performance indicators are really helpful as the accuracy measures overall correctness, precision minimizes false positives, recall ensures true cases are detected, and F1-Score balances both. Together, they provide a robust evaluation of model performance. The proposed CNN-ANN hybrid model did greatly well in the detection of AD and surpassed many conventional machine learning methodologies. The key performance indicators thus achieved were:

Metric	Score
Accuracy	0.965
Precision	0.965
Recall	0.9507389162561576
F1-Score	0.9578163771712159

Thus, they illustrate that optimized feature selection combined with deep learning remarkably supports Alzheimer's disease detection. The hybrid CNN-ANN approach shows superior performances to traditional classifiers with lower error rates and built classification performance.The Key performance Metrics used are:

1. **Accuracy:** The total number of cases that are correctly predicted as having or not having Alzheimer’s, by the total cases. This shows
how well the model classifies both conditions without focusing on the individual class performance. The model achieved a remarkable accuracy of **96.50%.**

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

2. **Precision:** The percentage of correctly identified Alzheimer’s cases among all cases predicted as positive. It informs how sure the model will be when it predicts someone has Alzheimer’s and will bring down the false alarms (false positives). The precision attained is same as the accuracy rate.

$$Precision = \frac{TP}{TP + FP}$$

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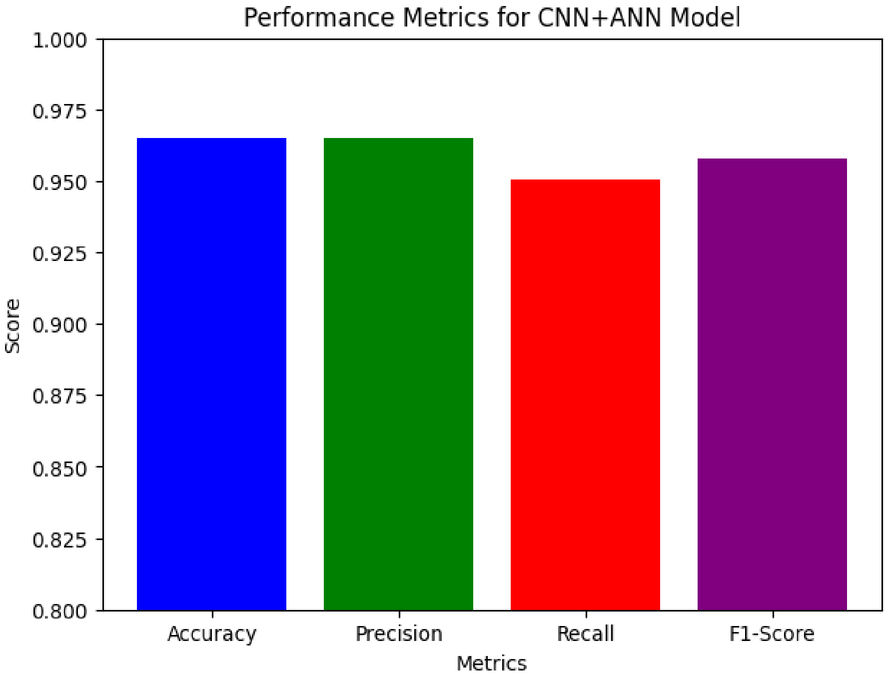

Fig 6. Graphical Representation of performance Metrics

3. **Recall:** The model's ability to actually capture people with Alzheimer's and not miss true patients. A high recall means that there will be few false negatives that are crucial in early detection so as to avoid misdiagnosis. Model's recall (Specificity) is **95.07%**.

$$\boldsymbol{Recall = \frac{TP}{TP + FN}}$$

The model's recall specifies that the model performs well in a generalized way for new data and is good at detecting whether a new patient has the Alzheimer's disease or not.

4. **F1score:** The balancing act between precision and recall which is harmonic in nature whereby the correctness of predictions from the model is observed, while also ensuring that the model is sensitive enough not to leave out real patients or make a high number of incorrect predictions in its identification of patients with Alzheimer's disease. The model achieved **96% F1-score** indicates that the model maintains a strong equilibrium between correctly identifying Alzheimer's cases & avoiding misdiagnoses.

$$\boldsymbol{F1 - Score = \frac{2PR}{P + R}}$$

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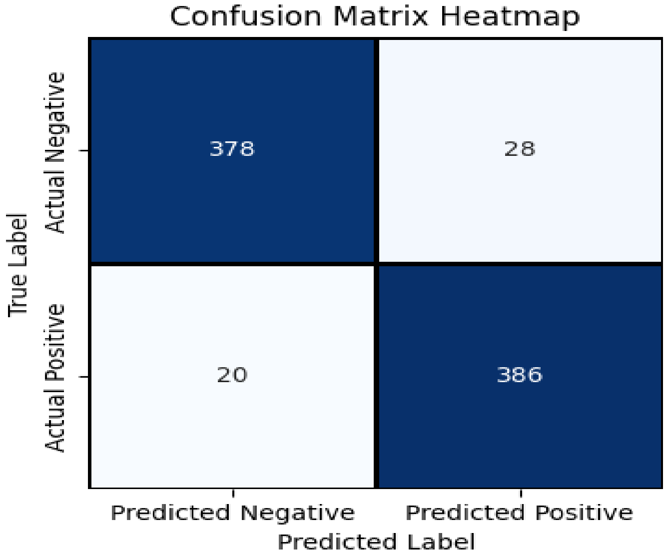
A confusion matrix is drawn on a subset that was used for validation of the model and the model detection performance was as follows:



The given model has reported accurate detections of 378 non-diseased patients (True Negatives) and was capable of also detecting 386 cases with Alzheimer's disease (True Positives), while the model also obtained 28 false-positive predictions and accordingly could trigger adjustments in the downstream clinical workflow. On top of that, 20 genuine Alzheimer's patients ran the risk of potentially being diagnosed as negative (False Negatives) and, therefore, were not treated. While overall performance is impressive because most cases were correctly classified, the feelings of certain questions have been raised around the presence of false positives and false negatives about further improvement.

This is to say that out of 3,149 computed data points, a validation subclass provided a case-based flexibility expressed in the confusion matrix from which the training phase gains experience. Given the low number of false negatives (20) and false positives (28) compared to correctly classified cases, the model shows a rather advanced capacity to be seen as accurate and trustworthy while making predictions for Alzheimer's. A clear consideration of model generalizability, or we can say the model does not overfit on specific distribution of data. Overall, the confusion matrix reflects a highly effective model with poor misclassification, thus making it a reliable detection tool for Alzheimer's.

8. CONCLUSION

The project advances the Detection of Alzheimer's disease by implementing an optimized strategy for feature selection using Decision Trees (DT) and Random Forest (RF) models. The relevant features were selected through an intersection-based selection methodology, so

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inferring noise and improving the quality of inputs for the deep learning models became possible. This improved feature set was next used to train CNN and ANN architectures and achieved considerably improved classification effectiveness.

Comparing with traditional methods, which often fail in dealing with this high-dimensional dataset in terms of feature selection, our methodology provides a better way for generalization and also gave a higher degree of predictive accuracy. The experimental results serve as a strong claim by achieving 96.5% in accuracy, 96.5% in precision, 95.07% in recall, and 95.78% in F1 score. Such metrics demonstrate the model's ability to strike a balance between sensitivity and specificity, hence cutting false classifications while still providing high confidence in its predictions.

By integrating a hybrid feature selection approach with deep learning models, our work provides not only a better-performing framework than the formerly noted conventional ML-based approaches, but also its constituently scalable and really well suited for a real-world application. The subsequent changes will explore the expansion of the data set utilizing unique feature selection techniques and add explainable AI to enhance interpretability in clinical settings. With constant improvement, the proposed method can eventually change the prospect of early detection and diagnosis of Alzheimer's, enabling better and more credible medical decision-making.

9. FUTURE SCOPE

The future work involves the utilizing advanced fine-tuning of hyperparameters, incorporation of models that are more advanced in deep learning, and the enlargement of datasets that can strengthen the model’s generalizability. Real-time involvement and deployment for use as a user-friendly diagnostic tool that will improve the clinical applicability and in turn the assist the medical professionals for an accurate early AD detection.

REFERENCES

[1] Md. Irfan, S. shahrestani, Md. Elkhodr, Early Detection of Alzheimer’s Disease Using Cognitive Features: A Voting-Based Ensemble Machine Learning Approach, Vol 51,No1,IEEEDOI10.1109/EMR.2022.3230820.

[2] Fubao Zhu, Xiaonan Li, Haipeng Tang, Zhuo He,Machine Learning for the Preliminary Diagnosis of Dementia, 2020, Hindawi Journal, https://doi.org/10.1155/2020/5629090

[3] J. Neela Veni, M.S. Geetha Devasena, Alzheimer’s Disease Detection Using Machine Learning Algorithms,2020, IEEE Xplore, 6th ICACCS publication.

Received: 16-11-2024 **Revised: 05-12-2024** **Accepted: 02-01-2025**

[4] C. Kavitha, Vinodhini Mani, Ibrahim, Early-Stage Alzheimer's Disease Prediction Using Machine Learning, 2022, Frontiers Journal, Doi: 10.3389/fpubh.2022.853294

[5] Akash Rajak, Ajay Kumar, Diagnosis of Alzheimer's Disease using Machine Learning Approaches,2020, Research Gate, 342847161 publications

[6] Md. Shahbaz, Shahzad Ali, Aziz, Aneeta Niazi, Amina Umer, Classification of Alzheimer's Disease using Machine Learning Techniques, DOI: 10.5220/0007949902960303, SCITEPRESS

[7] Gill, S. et al. (2020). Using machine learning to predict dementia from neuropsychiatric symptom and neuroimaging data. Journal of Alzheimer's Disease, 75(1).

[8] Tarawneh, R. and Holtzman, D. M. (2012). The clinical problem of symptomatic Alzheimer's disease and mild cognitive impairment. Cold Spring Harbor Perspectives in Medicine, 2(5), a006148.

[9] Martinez-Murcia, F. J., Ortiz, A., Gorriz, J. M., Ramirez, J., and Castillo-Barnes, D. (Jan. 2020). Studying the manifold structure of Alzheimer's disease: A deep learning approach using convolutional autoencoders. IEEE Journal of Biomedical and Health Informatics, 24(1), 17–26.

[10] Sullivan, K. J. et al (2019). Declining incident dementia rates across four population-based birth cohorts. The Journals of Gerontology: Series A, 74(9), 1439–1445.

[11] Shen, T. et al (2019). Predicting Alzheimer disease from mild cognitive impairment with a deep belief network based on 18F-FDG-PET Images. Molecular Imaging, 18, 1536012119877285.

[12] Youn, Y. C. et al (2018). Detection of cognitive impairment using a machine learning algorithm. Neuropsychiatric Disease and Treatment, 14, 2939.

[13] Kruthika, K. R., Maheshappa, H. D., and Alzheimer's Disease Neuroimaging Initiative. (2019). Multistage classifier-based approach for Alzheimer's disease prediction, Informatics in Medicine Unlocked, 14, 34–42.

[14] Veeramuthu, A., Meenakshi, S., and Manjusha, P. S. (2014). A new approach for Alzheimer's disease diagnosis by using association rule over pet images. International Journal of Computer Applications, 91(9), 9–14.

[15] Kang, M. J. et al (2019). Prediction of cognitive impairment via deep learning trained with multi-centre neuropsychological test data. BMC Medical Informatics and Decision Making, 19(1), 1–9.

[16] J. Escudero, E. Ifeachor, J.P. Zajicek, C. Green, J. Shearer, S. Pearson, "Machine learning-based method for personalized and cost-effective detection of Alzheimer's disease", IEEE transactions on biomedical engineering, Vol. 60, no. 1, (2013), pp. 164-168.

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[17] P. R. Hegde, M. M. Shenoy, B. H. Shekar, "Comparison of Machine Learning Algorithms for Skin Disease Classification Using Colour and Texture Features", Proceedings of IEEE International Conference on Advances in Computing, Communications and Informatics, Bangalore, India, (2018) Sep 19-22.

[18] Sivakani GA, Ansari R. Machine learning framework for implementing Alzheimer's disease. International Conference Communication Signal Process. (2020) 12:588 92.
Doi: 10.1109/ICCSP48568.2020.9182220

[19] Khan P, Kader MF, Islam SR, Rahman AB, Kamal MS, Toha MU, et al. Machine learning and deep learning approaches for brain disease diagnosis: principles and recent advances. IEEE Access. (2021) 9:37622 55. Doi: 10.1109/ACCESS.2021.3062484

[20] Williams., Jennifer A, Weakley A, Cook MS, Edgecombe DJ. "Machine learning techniques for diagnostic differentiation of mild cognitive impairment and dementia," In Workshops at the Twenty-Seventh AAAI Conference on Artificial Intelligence. (2018), pp. 71–6.

[21] M. S. Albert, S. T. DeKosky, D. Dickson et al., "0e diagnosis of mild cognitive impairment due to Alzheimer's disease: recommendations from the national institute aging-Alzheimer's association workgroups on diagnostic guidelines for Alzheimer's disease," Alzheimer's & Dementia, vol. 7, no. 3, pp. 270–279, 2011.

[22] D. Bansal, R. Chhikara, K. Khanna, and P. Gupta, Comparative analysis of various machine learning algorithms for detecting dementia, Procedia Computer Science, vol. 132, pp. 1497–1502, 2018.

[23] Zhang, C., and Ma, Y., Eds. (2012). Ensemble Machine Learning: Methods and Applications. Berlin, Germany: Springer-Verlag.

[24] Woods, K., Kegelmeyer, W. P., and Bowyer, K. (Apr. 1997). Combination of multiple classifiers using local accuracy estimates. IEEE Transactions on Pattern Analysis and Machine Intelligence, 19(4).

[25] Q. Zhou, M. Goryawala, Cabrerizo, J. Wang, W. Barker, D.A. Loewenstein, R. Duara, M. Adjouadi, An optimal decisional space for the classification of Alzheimer's disease and mild cognitive impairment, IEEE Transactions on Biomedical Engineering, Vol. 61, no. 8, (2014), pp. 2245-2253.