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Classification and Detection of Alzheimer's Disease: A Brief Analysis

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***Abstract*— Detecting Alzheimer's disease early is crucial for timely intervention and treatment as it is a neurological ailment that gradually impacts daily functioning along with memory, thinking, and reasoning skills. Older people of age over 60, are mostly affected by this ailment. The cause is still unknown and may be hereditary. A lot of methods and approaches have been suggested, however, MRI scans are the most popular ones. A brief analysis of the MRI scans via digitized images is taken into consideration. The person's conditions are categorized into mild cognitive, mild demented, moderate demented, and severely demented. The proposed model is based on a deep learning approach. The optimization of the obtained result is done by tuning. Further, the SoftMax activation function is employed in the model to normalize the output of the neural network. The model has achieved an accuracy of 98.5% achieved. Importantly, this method has the potential to enhance early Alzheimer's diagnosis and detection, thus leading to improvement in patient health.**

Keywords—Alzheimer's Disease, Magnetic Resonance Imaging (MRI), Health, Deep Learning.

I. Introduction

Alzheimer's disease is a devastating and progressive neurodegenerative disorder that primarily affects the brain, leading to severe cognitive impairment and functional decline. First described by Dr. Alois Alzheimer in 1906, this ailment has since become a global health challenge, impacting millions of individuals and their families. Alzheimer's disease is primarily characterized by the accumulation of abnormal protein deposits in the brain. Two main types of protein aggregates play a central role [1]:

- Beta-Amyloid Plaques: These are clumps of beta-amyloid protein that accumulate between nerve cells and disrupt cell function.
- Tau Tangles: Abnormal tau protein forms twisted tangles within nerve cells, leading to impaired cell transport and eventual cell death.

The exact causes of these protein abnormalities are not fully understood, but they are believed to result from a complex interplay of genetic, environmental, and lifestyle factors. The symptoms of Alzheimer's disease typically progress through several stages (Fig. 1), each marked by distinct symptoms [2]:

- Mild Cognitive Impairment (MCI): Early signs may include forgetfulness, difficulty finding words, and challenges with complex tasks.
- Mild Alzheimer's Disease: Symptoms worsen, with memory loss, confusion, personality changes, and difficulty with everyday tasks.
- Moderate Alzheimer's Disease: Severe memory loss, disorientation, and the need for assistance with daily activities become apparent.
- Severe Alzheimer's Disease: In this advanced stage, individuals often lose the ability to communicate, recognize loved ones, and care for themselves.

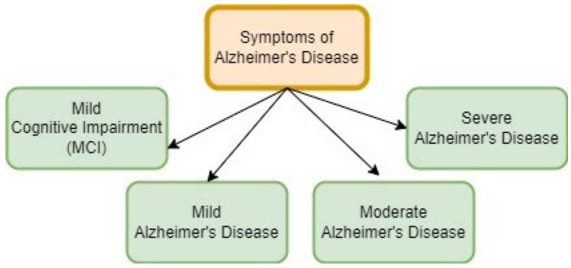

Fig. 1. Symptoms of Alzheimer's Disease.

Memory loss is one of the most troubling signs of Alzheimer's disease. Fig. 2 presents the areas of the brain affected by disease. As the condition advances, people find it more difficult to recall recent events, loved ones' names, and even their own identities. The loss of priceless memories causes both the afflicted individuals and their loved ones to feel extreme emotional agony and vulnerability. In addition to memory loss, Alzheimer's disease impairs a number of cognitive functions, such as thinking, language, and problem-solving skills. The societal impact of Alzheimer's disease takes a heavy toll on affected individuals and their families, with caregiving often becoming a full-time role. It also poses a significant economic burden on healthcare systems. As the global population ages, addressing Alzheimer's disease is increasingly critical [3].

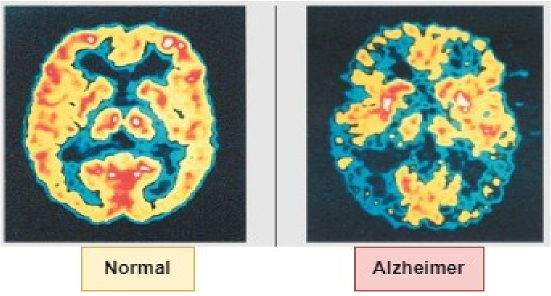

Fig. 2. Areas of the brain affected by Alzheimer due to dementia.

Some common methods and approaches for classifying and detecting Alzheimer's disease [4] are depicted in Fig 3. Clinical Assessment consists of clinical interviews, cognitive tests, and functional assessments.

- Clinical Interviews: Medical professionals conduct detailed interviews with patients and their families to gather information about cognitive decline, behavioral changes, and medical history.
- Cognitive Tests: Neuropsychological tests, such as the Mini-Mental State Examination (MMSE) and the Montreal Cognitive Assessment (MoCA), assess memory, attention, language, and other cognitive functions.
- Functional Assessment: Evaluating a person's ability to perform daily tasks, such as managing finances or remembering appointments, can provide insights into cognitive decline.

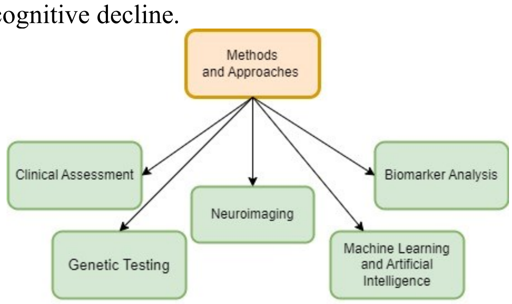

Fig. 3. Methods and Approaches for Classifying and Detection.

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Neuroimaging consists of MRI, PET, and SPECT:

- Magnetic Resonance Imaging (MRI): MRI scans can reveal structural changes in the brain, such as atrophy of the hippocampus, which is a common sign of Alzheimer's disease.
- Positron Emission Tomography (PET): PET scans can measure brain glucose metabolism and the accumulation of beta-amyloid plaques, a hallmark of Alzheimer's disease.
- Single Photon Emission Computed Tomography (SPECT): SPECT scans can also assess cerebral blood flow and identify areas of reduced activity in the brain.

Biomarker Analysis comprises CSF and blood biomarkers. In Cerebrospinal Fluid (CSF) Biomarkers, an analysis of CSF can reveal abnormal levels of proteins associated with Alzheimer's disease, such as beta-amyloid and tau. In blood biomarkers, researchers are developing blood tests to detect biomarkers indicative of Alzheimer's disease, such as elevated levels of certain proteins or genetic markers.

Machine Learning and Artificial Intelligence algorithms can analyze neuroimaging data, genetic information, and biomarkers to predict the likelihood of Alzheimer's disease or classify individuals as either healthy or affected. Deep learning models have shown promise in detecting subtle patterns and predicting disease progression based on neuroimaging data.

In Genetic Testing, the genetic factors play a role in Alzheimer's disease. Genetic tests can identify certain risk factors, such as the APOE ε4 allele, which increases the risk of developing AD. The research Studies show that participation in research studies and clinical trials may involve advanced diagnostic techniques and access to emerging detection methods [5].

A definitive diagnosis of Alzheimer's disease often requires a combination of these approaches, and early detection can be challenging as symptoms can overlap with those of other cognitive disorders. Moreover, ongoing research is continually improving the understanding of Alzheimer's disease detection and classification, leading to the development of more accurate and reliable diagnostic tools. Early detection can enable timely intervention and access to available treatments and support.

Deep learning has recently emerged as a cutting-edge technique with several medical applications, especially in the detection and classification of Alzheimer's disease. Deep learning can efficiently evaluate complicated medical data, including brain imaging and biomarkers, using cutting-edge models like CNN and RNN. These algorithms enable accurate diagnosis of anomalies associated with Alzheimer's by extracting complex patterns and features from large datasets. The merging of CNN and Tuner Optimization, two deep learning approaches, has shown promising results for the early detection of Alzheimer's disease [6][7]. The CNN is a deep learning model that complements by offering a reliable classifier for categorizing diseases precisely. Tuner optimization aids in time savings and increases the effectiveness of the suggested model by automating the kernel function and locating the model's optimal parameters.

II. Related Work

This section presents the work done by researchers in detecting Alzheimer's disease in the last few years. Their research helped in attaining knowledge and gaining experience in this field of research.

In [8] the study analyzed brain MRI images to classify Alzheimer's disease stages using Convolutional Neural Network (CNN) models. Using a dataset of 2182 objects, 29 models were evaluated for accuracy, precision, sensitivity, and specificity. The model achieved the highest accuracy rate of 92.98%. These findings could aid early detection of Alzheimer's disease.

The authors in [9] present a novel Alzheimer's Disease model using Brain Image Analysis. The model removes unwanted regions and extracts features like texture, histogram, and scale-invariant transform from magnetic resonance images. Using the GGWO technique, it achieves 96.23% accuracy compared to existing schemes.

In [10], the authors present an eigen-brain-based computer-aided diagnosis system that accurately distinguishes Alzheimer's disease (AD). The system uses MRI data, eigen-brain generation, and ML to identify 30 AD-related brain regions. The system achieved an accuracy of 92.36% demonstrating its potential for improved early diagnosis and understanding of Alzheimer's disease.

In [11], authors came up with a blood screening tool for aiding in diagnosing mild cognitive impairment and Alzheimer's disease. The researchers examined 1649 people to check their proteomic profiles. And after all the testing and research the model gave accurate results up to 94%. Table I presents the summary of work done as per the models used and their results achieved by researchers in detecting Alzheimer's disease.

TABLE I SUMMARY OF WORK AS PER USED MODELS AND THEIR RESULTS

Reference	Models	Accuracy
[9]	CNN	75%
[12]	Ensemble Model	89.77%
[13]	BAT-SVM	95.3%
[14]	SDDNN	93.31%
[15]	BO-SVM	92.3%
[16]	ML	92.36%
[17]	CNN-PSO	97%
[18]	GAN	96%
[19]	CNN	92.98%
[20]	MultiAz-Net	92%

III. METHODOLOGY

An in-depth discussion of the thorough methodology used in the research is provided in this section. The dataset used to train the model is described along with an explanation to get the dataset ready for analysis. Fig. 4 shows the methodology.

The deep learning and fine-tuning for Alzheimer's disease diagnostic study methodology is based on a rigorous and comprehensive approach [22]. For the early diagnosis and comprehension of Alzheimer's disease, data collection is crucial. In order to identify Alzheimer's disease, researchers must collect a wide range of data, including genetic profiles, medical histories, cognitive tests, neuroimaging scans like MRI and PET scans, and even information from wearable technology or from online repositories like GitHub, Kaggle, etc. which contains various datasets regarding the same disease.

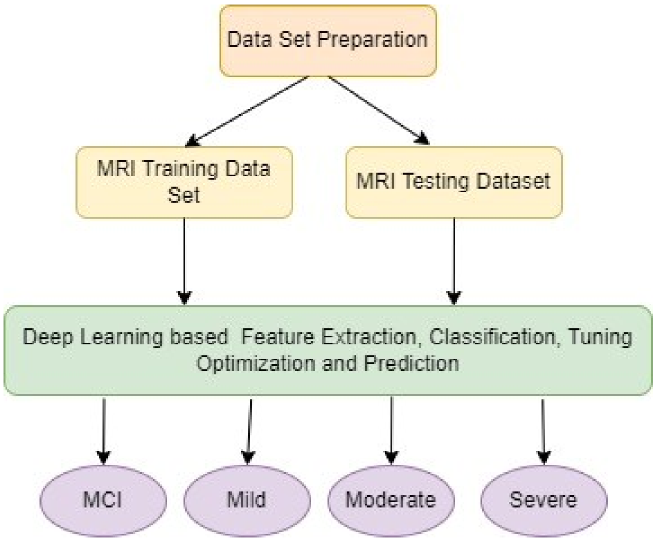

Fig. 4. Methodology.

A. Collection of Datasets

In the model, the dataset is taken from Kaggle. First, a dataset comprising a range of Alzheimer's and healthy patients is obtained [21]. Then it is divided into training and testing datasets. A total of 30363 MRI brain scan pictures are obtained and divided into four different categories: MCI, Mild demented, moderately demented, and severely demented as shown in Fig.5.

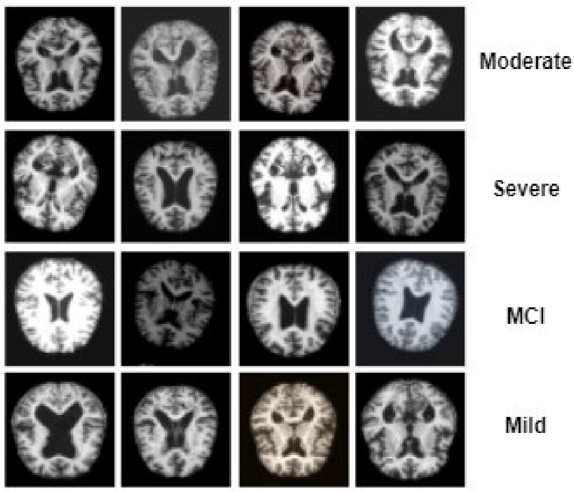

Fig. 5. Dataset Sample.

These photos are taken from a variety of people and have a rich source of data, including insights on changes in brain function, structural changes, concentrations of possible biomarkers, and genetic predispositions. The combination of information from many sources, such as MRI scans and other pertinent data, contributes significantly to the knowledge of Alzheimer's disease and makes it easier to make an early diagnosis, which is essential for successful treatment and intervention.

B. Dataset Classes

Fig. 6 shows the classes of dataset pertaining to MCI, Mild, Severe, and moderate MRI images taken into consideration.

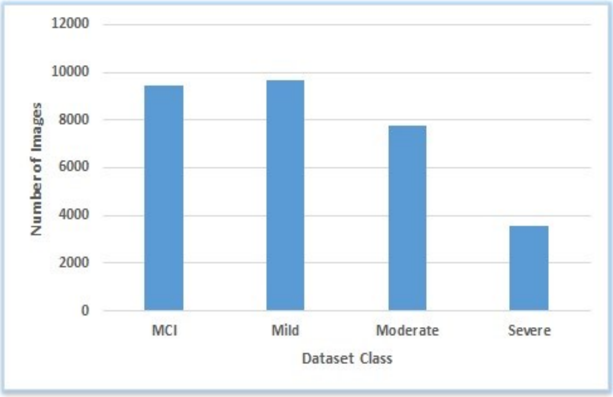

Fig. 6. Distribution of Dataset Class-wise.

C. *Pre-Processing*

Pre-processing is an important step in accurately evaluating data to detect Alzheimer's disease. In the context of detecting Alzheimer's disease, pre-processing refers to crucial procedures designed to enhance the accuracy and integrity of data prior to analysis. Data normalization is one of these techniques, which entails bringing a variety of data categories into a consistent range to prevent any one category from dominating the analysis owing to scale differences. It is also possible to utilize noise reduction techniques to get rid of unnecessary distortions or oscillations that could cover up significant patterns. Methods for selecting or extracting features, that highlight the most critical data characteristics that aid in illness differentiation, are equally important. The alignment of spatial data in neuro-imaging may also be a part of pre-processing in order to make accurate comparisons across several scans. The proposed model takes input features that describe patients' characteristics, such as age, genetic markers, brain imaging data, and cognitive test scores and sample MRS's. The collective dataset of MRI scanned images of the brain is divided in the ratio of 80:20 where 80% goes for training the model and the remaining 20% is used for testing the model. The pre-processing establishes a strong basis for extensive and accurate analysis, enabling researchers to draw conclusions and patterns from intricate and varied datasets. This increases the accuracy of Alzheimer's disease diagnosis and detection. Also, the model identify and retain only the most relevant features using deep learning thus reducing noise and potentially improving model accuracy.

D. *Feature Extraction and Classification*

Feature extraction and classification in deep learning involves transforming raw data into a format that is suitable for training a machine learning model, particularly deep neural networks [23]. In deep learning, feature extraction can occur at different levels. In the methodology convolutional Neural Networks (CNNs) are used to automatically learn intermediate-level features from images. These features represent patterns and objects within an image. The reason for using CNN is that it supports automatic feature extraction. In deep learning classification is the process of assigning a label or category to an input based on the features extracted from it. It is a supervised learning task, and deep learning models are often used for classification tasks. CNNs are widely used for image classification. They excel at capturing spatial patterns and hierarchies of features in images. The output layer of the neural network typically uses activation functions like SoftMax (for multi-class classification) or Sigmoid (for binary classification) to produce probability distributions over the classes. Here the SoftMax function is used. The SoftMax function is mentioned in Eq. (1).

$$SM = e^{zi} \Big/ \sum_{j=1} e^{zj} \qquad \text{Eq. (1)}$$

Here SM is SoftMax, e^{zi} is the exponential of the input vector, and e^{zj} is the exponential of the output vector. The softmax function plays an important role in converting the raw model output into class probabilities by exponentiating the scores and then normalizing them. The probabilities are then used to make predictions. The sum of the probabilities for all classes will be equal to 1 and it will help in obtaining the probability that a given patient belongs to either the Alzheimer's or non-Alzheimer's class.

Classification error represents the fraction of predictions made by the model that were incorrect. It is typically expressed as a percentage for better interpretation. The proposed model has a low classification error indicating model efficiency, as it means that the model is making fewer misclassifications. These are presented in the form of a confusion matrix Fig. 7. It depicts the probability of correct and incorrect predictions of Alzheimer's disease cases into mild, MCI, severe, and moderate. The incorrect prediction percentage is nearly 1 to 1.5 out of the total MCIs trained, whereas the correct predictions are nearly 98.5%.

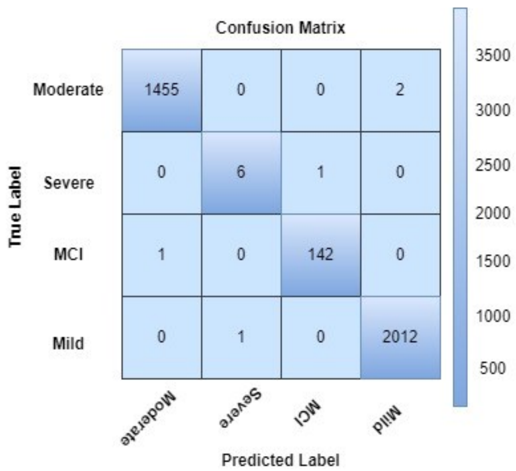

Fig. 7. Confusion Matrix.

The Classification Error (CE) is calculated as in Eq. (2)

$$CE = (FP + FN) / (TP + TN + FP + FN) \qquad \text{Eq. (2)}$$

where FP: False Positives, FN: False Negatives, TP: True Positives and TN is True Negatives

E. *Tuner Optimization and Prediction*

By doing tuner optimization in the proposed model, the model automatically searches for the best hyperparameters. Hyperparameters are settings that are not learned during the training process but must be specified beforehand. The aim of using tuner optimization is to find the optimal combination of hyperparameters to improve the accuracy in detecting Alzheimer's disease.

IV. Discussion and Result

The proposed model's performance is tested on the basis of the hyperparameters. In this section of the study, the experimental results are presented that are obtained through the evaluation of the model's performance across a range of parameter settings. The presentation of experimental outcomes serves to provide a comprehensive view of how the model performs under different conditions and settings, aiding in the interpretation and analysis of the study's findings.

The parameters on which the model is tested are precision, recall, F1-score, and accuracy. After the testing and adjustments are done to find the accurate model the results of the hyperparameters are as follows: The precision that came out to be for each category is 99% for MCI, 97% for mild, 98% for moderate, and 100% for severe dementia. The recall for the four categories is 96%, 95%, 95%, and 99% respectively. The F1-score for the model was 97%, 98%, 97%, and 99% for each category of Alzheimer's disease. The results are depicted in Fig. 8.

Last, the accuracy calculated for each category comes out to be 98.4% for MCI, 98.5% for mild, 98.4% for moderate, 98.6% for severe, and the overall accuracy for the model was 98.5% (presented in Table II).

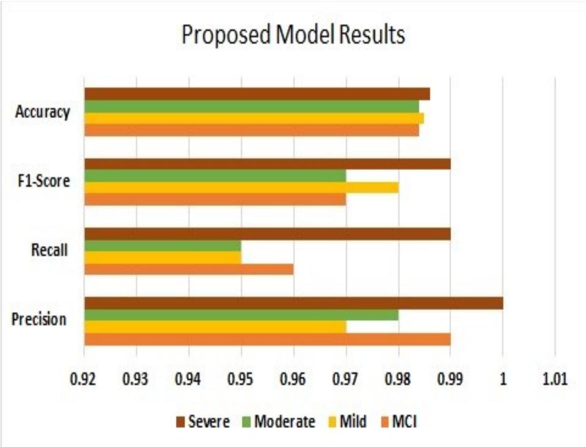

Fig. 8. Model Results.

TABLE II. Hypermetric Evaluation Results

Category	Precision	Recall	F1-Score	Accuracy
MCI	0.99	0.96	0.97	98.4%
Mild	0.97	0.95	0.98	98.5%
Moderate	0.98	0.95	0.97	98.4%
Severe	1.00	0.99	0.99	98.6%

The proposed model was compared with the present methods to check for its accuracy and whether it is more efficient than other concurrent methods. The model was compared with K-Means (94%), Random Forest (95%), and CNN-GAN (97%) respectively. It was found that the proposed model (98.5%) performed better than the rest (shown in Fig. 9).

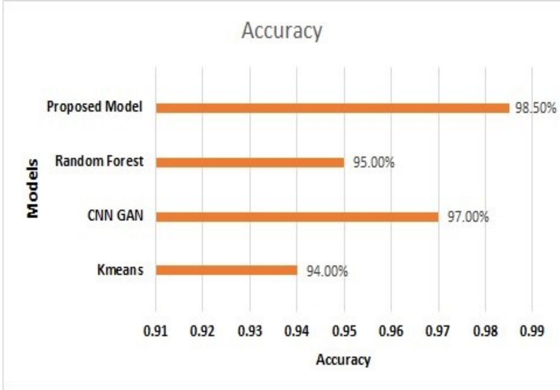

Fig. 9. Comparison Analysis.

Several constraints were found during the research. Handling high-dimensional datasets with a lot of characteristics is one area of concern since it can make computing challenging. Researchers can use methods like feature selection or dimensionality reduction to overcome this problem.

V. Conclusion and Future Scope

This paper presents a robust approach to Alzheimer's disease detection using deep learning techniques, specifically tuning optimization and prediction. The proposed model achieved an accuracy rate of 98.5% during testing which is higher accuracy than the previously reviewed literature and models in comparison. The precision and F1-score metrics affirm its strong performance. The deployment of this model in clinical settings and its integration into healthcare systems can pave the way for early intervention and improved quality of life for individuals affected by Alzheimer's disease. The regular adjustment of crucial parameters, prompted by techniques like grid search or cross-validation in the future, has led to the creation of models that successfully strike the optimal balance between accuracy and generalization.

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