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Article

Advance of AI-Based Predictive Models for Diagnosis of Alzheimer's Disease (AD) in Healthcare

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Abstract: The effects on the elderly are disproportionately Alzheimer's disease (AD) is one of the most prevalent and chronic types of dementia. Alzheimer's disease (AD), a fatal illness that can harm brain structures and cells long before symptoms appear, is currently incurable and incurable. Using brain MRI pictures from a publicly accessible Kaggle dataset, this study suggests a prediction model based on Convolutional Neural Networks (CNNs) to help with the early detection of Alzheimer's disease. Four levels of dementia have been applied to the 6,400 photos in the collection: not demented, slightly demented, moderately demented, and considerably mildly demented. Pixel normalization, class balancing utilizing data augmentation techniques, and picture scaling to 128×128 pixels were all part of a thorough workflow for data preparation. To improve the gathering of spatial dependence in volumetric MRI data, a 3D convolutional neural network (CNN) architecture was used. We used important performance measures including F1-score, recall, accuracy, precision, and log loss to gauge the model's effectiveness. A review of the available data indicates that the total F1-score, accuracy, recall, and precision were 99.0%, 99.0%, and 99.38%, respectively. The findings demonstrate the model's potential for practical use in early AD diagnosis and establish its robustness with the help of confusion matrix analysis and performance curves.

Keywords: Alzheimer's Disease, Machine Learning, CNN, Brain MRI, Early Detection, Medical Imaging, Data Augmentation, Predictive Modeling

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1. Introduction

The abundance of biological data is growing more and more important as the medical industry enters a new age [1]. Precision medicine considers a number of patient data points, such as variations in lifestyle, environment, EHR, and molecular characteristics. In this particular instance, its stated goal is to ensure that the right treatment is delivered to the right patient at the right time.

The human brain, a highly complex organ comprising over 100 billion neurons interconnected through trillions of synapses, serves as the central hub for the body's nervous system. It governs essential functions such as cognition, voluntary movement, coordination, balance, memory, learning, executive planning, and emotional responses [2]. Due to its central role in body function regulation, any abnormal disruption in brain activity can have widespread and catastrophic consequences, leading to neurodegenerative disorders such as AD.

The gradual, irreversible neurological condition known as AD results in the brain's build-up of amyloid plaques and neurofibrillary tangles, which impairs cognition and causes behavioural abnormalities. Figure 1 illustrates the many phases of AD. The most prevalent kind of dementia is identified via an MRI [3], In the United States, the sixth most common cause of death, AD has a major negative impact on national health and the world economy. In 2018, the financial impact of managing AD reached approximately $277 billion, largely due to medical care, caregiver burden, and lost productivity.

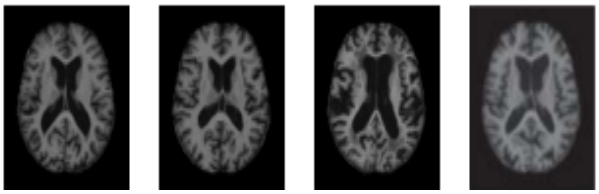

Figure 1. Example of Different Brain MRI Images Presenting Different AD Stage

Despite the severity of AD, current diagnostic methods remain suboptimal. Traditional diagnostic approaches, including cognitive assessments, MRI, PET, and CSF analyses, are often invasive, expensive, and impractical for widespread screening [4][5]. Moreover, definitive diagnosis of AD frequently occurs post-mortem, limiting opportunities for early intervention. In spite of some of the biomarkers measurable via imaging and CSF that are abnormal Many years passed before any clinical signs appeared., using them more in diagnosing patients early on continues to be a critical task [6].

The emergence of ML and AI has opened up new possibilities for getting beyond these restrictions. ML tools offer automated, scalable analysis of the complex and high-dimensional healthcare data, such as images, electrophysiology, and clinical records [7]. Through the discovery of subtle as well as non-obvious patterns found in these datasets, the ML models have promise for improving early AD diagnosis accuracy and supporting innovative clinical decision-making.

1.1. Motivation and Contributions of the Study

This study's motivation stems from the growing number of Alzheimer's patients and Early detection techniques are desperately needed in order to provide timely intervention and enhance patient outcomes. Diagnostic modalities based on the cognitive assessment and clinical evaluation, as the common ones, may not identify early phases of the illness. Making use of medical imaging and ML advancements, predictive models can now actively identify small patterns in brain scans that could be the signs of the first low wave of Alzheimer's. This study makes use of cutting-edge DL methods to improve diagnostic precision and assist medical professionals in identifying the illness early. The following are the study's main contributions:

- Utilizes a publicly available Alzheimer brain MRI dataset from Kaggle, providing real-world imaging data suitable for Alzheimer's disease classification.
- Enhances dataset quality through pre-processing procedures like class balancing with data augmentation, picture scaling, and normalization, ensuring consistency and addressing class imbalance.
- Distinguishes between normal and Alzheimer's-affected brain images using a CNN architecture designed for image classification.
- Evaluates the model's performance employing many measures, including F1-score, recall, accuracy, and precision, to ensure a robust evaluation framework.
- Promotes timely identification and detection which consequently may reduce the negative outcome from late diagnosis and have implications for capacity building in healthcare as well as allocation of healthcare resources.

1.2. Justification and Novelty of paper

This study suggests new DL approach to classify AD using MRI brain images that use a 3D CNN to get beyond the limitations of traditional diagnostic methods. The method's capacity to operate with 3D MRI data makes it novel compared to 2D CNNs since it enables the extraction of more intricate characteristics and enhances spatial context. Since it offers an automated, accurate, and scalable solution that may be prepared for testing in clinical settings to promote early-stage detection, the deployment of a DL architecture specifically created for Alzheimer's disease categorization constitutes a noteworthy development in the field. The high accuracy rate of this approach distinguishes it from the current solutions and shows the potential for dramatically modifying diagnostic practices and patient results during Alzheimer's disease therapy.

1.3. Organization of the paper

The structure of the paper is as follows A thorough analysis of the most recent studies on AD early detection in Section II. Section III details the methodology, data gathering, pre-processing, model construction, and assessment procedures. A comparative analysis of model performance and experimental data is presented in Section IV. Section V wraps up with important takeaways, restrictions, and possible avenues for further study in predictive modelling for AD.

2. Literature Review

This section reviews and emphasizes predictive analytics and early detection methods, focusing on developing predictive models for ML in AD Several works have been studied, including:

Afzal et al. (2019) A frequent neurodegenerative disease that has no known treatment is AD. Although AD phases may be identified with the use of computer-aided diagnostic methods, it is still up for debate whether to categories individuals as being free of dementia, suffering from mild, moderate, or very mild dementia. It has been suggested to use data augmentation in a transfer learning-based method for 3D MRI outperforming cutting-edge methods using pictures from the OASIS dataset with 98.41% and 95.11% accuracy rates, respectively [8].

Ahmed et al. (2019) research on automatic AD diagnosis is still being conducted, and DL-based methods are gaining traction. However, gathering data from several modalities is costly and time-consuming. In order to improve accuracy, get around overfitting, and examine brain landmarks for diagnosis, research focuses on sMRI. The study employs a patch-based methodology, SoftMax cross-entropy, and basic convolutional neural networks. 90.05% accuracy was attained using the dataset from Cohort Study on Alzheimer's and Related Dementias in Gwangju. The model's output is comparable to that of cutting-edge techniques [9].

Silva et al. (2019) propose a model that uses magnetic resonance imaging and deep feature extraction to diagnose AD. The model uses the MIRIAD database to differentiate AD from healthy controls. The model is a CNN-based model and is trained by using RF, SVM, and KNN algorithms. The 0.8832, 0.9607 and 0.8745 accuracy results of the model are testament of its effectiveness and reliability [10].

Altaf et al.'s (2018) a system that recognises and classifies the study's presentation of AD using textural clues from MRI brain pictures. On the AD neuroimaging initiative dataset, the system outperforms cutting-edge methods in terms of specificity, sensitivity, and multi-class classification accuracy (98.4% for the normal class and 79.8% for the AD class) [11].

Mahyoub et al. (2018) This study uses ML prediction models and classification techniques to investigate the categorization and ranking of risk variables for AD. The study covered a wide range of participants, including 183 healthy controls, 127 AD

patients, there were 177 individuals with minor cognitive impairment at the beginning, 161 at the end, and so forth. Even though the initial training values were 0.92 sensitivity, 0.935 specificity, and 0.771 precision, the final results were 0.741 sensitivity, 0.515 specificity, and 0.286 accuracy. The project's overarching goal is to improve the identification and assessment of AD risk factors [12].

Padole, Joshi and Gandhi (2018) investigate the use of fMRI data from the ADNI dataset for early AD identification. They use a new hypothesis derived from two neurological investigations to identify effective discriminating characteristics from resting-state fMRI data. They use a classifier based on a GCNN to categorise these graph signals, which generalizes CNN to irregular domains. They compare their performance after creating brain diagrams with various connection metrics to find the most appropriate connection metric for each use case. With a classification accuracy of 92.44%, their suggested model performs better than the most advanced AD detection techniques [13].

Research gaps in machine learning-based models for early AD are listed in Table 1, emphasising issues in interpretability, diagnostic accuracy, data diversity, and clinical integration. It also includes a comparative analysis of existing studies based on methodology, key findings, dataset, performance, limitations and future work.

Table 1. Summary on Machine Learning-Driven for Early Detection of Alzheimer's Disease in Healthcare

References	Methodology	Dataset	Performance	Limitations & Future Work
Afzal et al., 2019	Transfer learning + data augmentation on 3D MRI	OASIS	98.41% (single view), 95.11% (3D view)	Class imbalance in dataset; need for balanced multiclass classification of AD stages
Ahmed et al., 2019	CNN ensemble on TVPs of left/right hippocampus	GARD	90.05% accuracy	Focused only on hippocampus; small dataset; overfitting still a concern
Silva et al., 2019	Deep feature extraction + classical ML classifiers (RF, SVM, K-NN)	MIRIAD	RF: 88.32%, SVM: 96.07%, K-NN: 87.45%	Limited region of brain (30 slices); classification only between AD vs. HC
Altaf et al., 2018	Hybrid of clinical + texture features; BoVW model	ADNI	Binary: 98.4%, Multi-class: 79.8%	Moderate performance in multi-class classification; relies on handcrafted features
Mahyoub et al., 2018	ML classifiers on lifestyle, demography, and medical history	Custom tabular dataset	Sensitivity: 0.741, Specificity: 0.515 (test)	Poor generalization; low precision; limited data modalities
Padole et al., 2018	Graph CNN using resting-state fMRI	ADNI	92.44% accuracy	Focused only on fMRI; computationally intensive graph construction

3. Methodology

The proposed methodology focuses on developing a prediction model that uses information use the Kaggle Alzheimer brain MRI dataset to use ML techniques to detect AD early. The workflow, illustrated in Figure 2, begins with comprehensive data pre-processing, including image resizing to ensure uniform dimensions, standardization of pixel intensity levels using normalization, and class balancing using data augmentation to mitigate class imbalance. To facilitate the development and verification of reliable models, Afterwards, the pre-processed dataset is divided into groups for testing and training. A CNN's ability to capture spatial hierarchies in medical imaging data makes it a popular choice for categorization. Key performance indicators including The F1-score, recall, accuracy, and precision are essential for evaluating the model's diagnostic abilities.

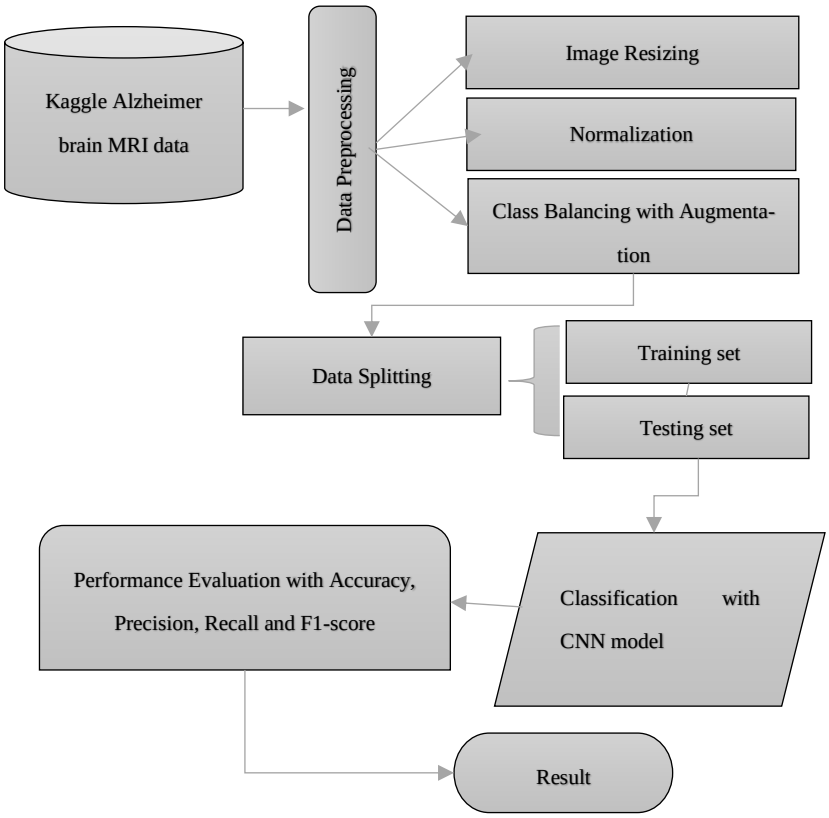

Figure 2. Flowchart for the Early Prediction of Alzheimer Disease

The flowchart below illustrates the general procedures for early ML-based Alzheimer's disease identification:

3.1. Data Collection

The 6400-image MRI dataset of AD was collected using Kaggle. Four classifications were applied to the dataset: slightly deranged, very softly demented, both non-demented and mildly demented. The length of the photographs varied by class, with 896 images in the slightly demented category, 64 in the moderately demented category, 3200 in the non-demented category, and 2240 in the very mildly demented category, for a total of 6400 images. All of the photos in the collection were scaled to 128 x 128 pixels. Figure. 3 displays some images from the Alzheimer's dataset training set.

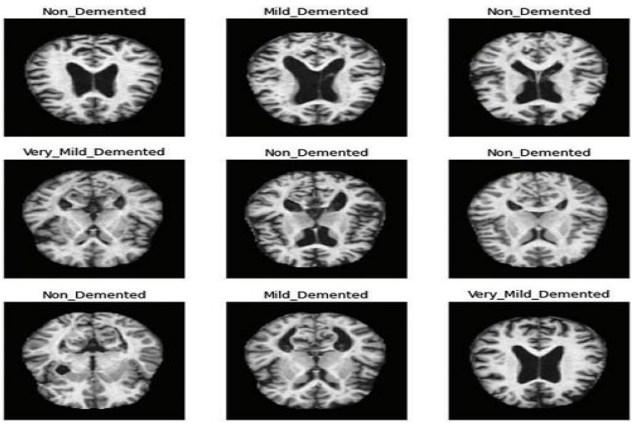

Figure 3. Sample images of the dataset

3.2. Data Preprocessing

Data augmentation and similar methods are used to clean up raw data in preparation for model training, normalization, and picture resizing are used. It boosts model performance, guarantees consistency, and improves data quality. Here is a description of the steps:

- **Image Resizing:** To ensure uniformity across the dataset and to optimize the computational efficiency of the DL model, the resolution of all MRI brain scan pictures was adjusted to 128 × 128 pixels. This resizing process not only facilitates consistent input dimensions required by the CNN architecture but also significantly reduces the computational cost and memory requirements during training and inference.
- **Normalization:** This normalization enhances the model's convergence and speeds up the training process. Each pixel intensity value was divided by 255 to normalize it to a scale of 0 to 1[14]. Z-score normalization calculates the standard deviation σ_{zs} and mean μ_{zs} of the intensities inside the brain mask using the brain mask B for image I. The Z-score was then normalized in Equation (1).

$$I_{z-score}(x) = \frac{I(x)-\mu_{zs}}{\sigma_{zs}} \quad (1)$$

3.3. Data Augmentation

The sample size of minority classes was increased through the deliberate use of data augmentation techniques. By applying random distortions to the pre-existing pictures while preserving their original class labels, these augmentation strategies enhanced the ability of the model to draw broad conclusions from different patterns. In particular, the transformations that were used included rotation by random angles, shearing to create image distortions (whereby a body part is enlarged), zoom both in and out, and horizontal and vertical flipping. These operations managed to artificially increase the size of the dataset and find a way to make a dataset to have more variability and, as we also show in Figure 4, better capable of representing each class after this augmentation phase, we ended up with a total of 10,074 training images, up from 6,400 during the pre-Augmentation phase, which effectively increased the balance of the classes which would fundamentally support more robust learning of the convolutional neural network.

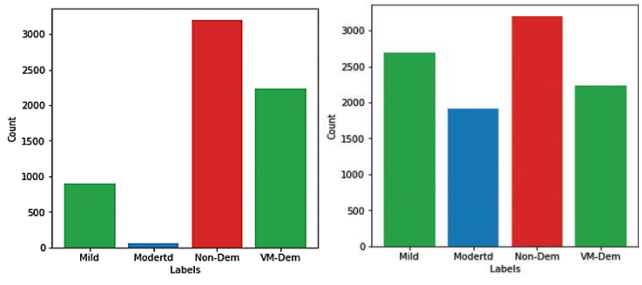

Figure 4. Alzheimer's Dataset Before and After Augmentation

3.4. Data Splitting

Data splitting is a widely adopted technique for model validation, where a dataset is split into two separate subsets, one for testing and one for training. A 20% testing set and an 80% training set made up the dataset for this investigation.

3.5. Proposed Convolutional Neural Network model (CNN)

CNN that draws inspiration from the human visual system is comparable to traditional CNN [15]. However, the spatial information of 3D medical pictures cannot be

efficiently extracted by 2D-CNN structures, which are developed for 2D image analysis. Use the 3D convolution kernel rather than the 2D one as a result. In order to learn the multi-level features hierarchically, the 3D convolutional kernel may be built by alternating between convolutional and down sampling layers. Lastly, get feature maps using the CNN model. A collection of kernel filters is used by the convolutional layer to convolve the input image [16]. In order to learn the multi-level features hierarchically, the 3D convolutional kernel may be built by alternating between convolutional and down-sampling layers. Lastly, get feature maps using the CNN model. The convolutional layer stores the input picture and convolves it using a set of kernel filters. In conclusion, the CNN model allows for the production of multiple feature maps. $W_{kj}^{l}(\delta_x, \delta_y, \delta_z)$ encodes the voxel coordinates for a certain 3D picture in the j-th 3D kernel weight as x, y, and z, respectively. These are the k-th feature maps of the l-1 layer as F_k^{l-1}, the kernel size that corresponds to x, y, and z is δx, δy, and δz, respectively, and it links the k-th feature maps of the l-1 layer to the j-th feature maps of the l layer. According to the kernel filter, the convolutional answer is represented as u_{kj}^{l}(x, y, z). Equation (2) then defines the 3D convolutional layer.

$$u_{kj}^{l}(x, y, z) = \sum_{\delta_x} \sum_{\delta_y} \sum_{\delta_z} F_k^{l-1}(x + \delta_x, y + \delta_y, z + \delta_z) \times W_{kj}^{l}(\delta_x, \delta_y, \delta_z) \quad (2)$$

After convolution, activate the features in Equation (3) by adding a ReLU:

$$F_j^{l}(x, y, z) = \max\left(0, b_j^{l} + \sum_k u_{jk}^{l}(x, y, z)\right) \quad (3)$$

The j-the 3D feature map was produced by using several convolution kernels' response maps, is added together to get $F_j^{l}(x, y, z)$, where b_j^{l} is the bias component derived from the l-the layer's j-the feature map. To give smaller and more effective features, a max-pooling layer is introduced after the convolutional layer. There may be some resistance to the changes seen in Figure 5 since the max-pooling layer reduces the size of the features as one progresses through the levels.

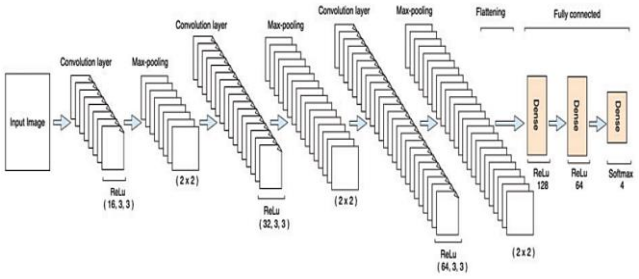

Figure 5. Structure of the CNN Model

3.6. Performance Metrics

In every ML process, performance metrics are essential. In this investigation, a confusion matrix including TP, FP, TN, and FN was used for assessment. These variables were used to construct important assessment metrics incorporating F1-score, accuracy, precision, and recall:

The forecast for those patients who were determined to be disease-free is TN [17], The predictions for patients without an illness who were later discovered to have one are denoted by FN, those with a disease who were later shown to have a disease by TP, and those with a disease who were later found to have no disease by FP.

The ratio of accurate predictions for attacks TP [18] and Equation (4) defines accuracy as TN relative to the sum of all instances that were tested.

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \quad (4)$$

The definition of this is the percentage of positively classified situations where the projected outcome was accurate. In terms of mathematics, it is provided as expressed in equation (5).

$$Precision = \frac{TP}{(TP+FP)} \tag{5}$$

This percentage is the ratio of accurate forecasts to TP ground data occurrences. Positively labelled cases are classified by it. In terms of mathematics, it is provided as Equation (6):

$$Recall = \frac{TP}{TP+FN} \tag{6}$$

In cases when there is an imbalance across classes, the performance of a categorization model might be evaluated using the F1 score. The recall and accuracy harmonic mean offers a compromise between the two, as seen in Equation (7).

$$F1 = 2 \times \frac{Precision \times Recall}{Precision+Recall} \tag{7}$$

A classification loss function called log loss is used to assess how well ML systems perform. The log loss model's value will get more accurate the closer it gets to zero. Equation (8) is the formula used to calculate log loss.

$$L_g = \frac{-\sum_{y=1}^{n}\sum_{x=1}^{n} f(x,y)\log(p()x,y)}{n} \tag{8}$$

These performance metrics are utilized for comparative analysis and to evaluate the model's performance in disease prediction.

4. Result Analysis and Discussion

This study analyses the findings from propose models applied to AD prediction. Experiments were conducted using Python 3.9 with TensorFlow 2.12 and Scikit-Learn 1.3 on a 64-bit Windows 11 system outfitted with an NVIDIA RTX 3080 GPU, 32 GB of RAM, and an Intel Core i9 processor (3.70 GHz, eight cores). The CNN model's performance is shown in Table 2, which shows that it classified Alzheimer's disease with exceptional accuracy. It recorded 99.38% accuracy, ensuring highly precise overall classification. A 99% recall rate validates the model's ability to identify real instances, while a 99% accuracy rate suggests few false positives. The robustness is shown by the F1-score of 99%, which strikes a compromise between precision and recall. These indicators show the model's effectiveness and dependability for precise clinical diagnosis.

Table 2. Performance of CNN for Alzheimer's disease prediction

Performance Metrics	Convolutional Neural Network
Accuracy	99.38
Precision	99.0
Recall	99.0
F1-score	99.0

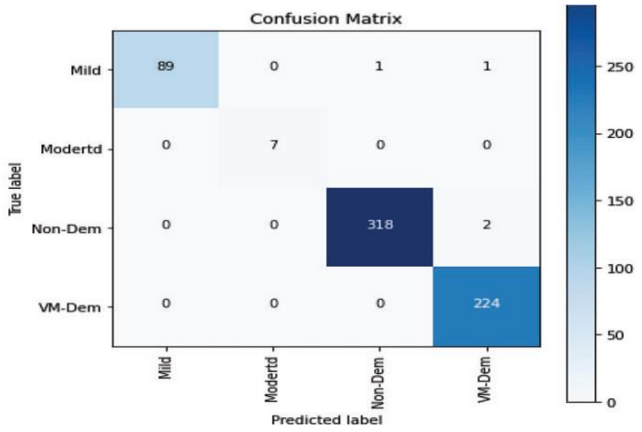

Figure 6. Confusion Matrix for CNN

An Alzheimer's prediction CNN model is evaluated using the confusion matrix across Mild, Moderate, Non-Demented, and VM-Dem stages as depicted in Figure 6. High counts on the diagonal (89 Mild, 7 Moderate, 318 Non-Dem, 224 VM-Dem) indicate correct classifications. Off-diagonal values reveal misclassifications, like 1 Mild case incorrectly predicted as Non-Dem and 2 Non-Dem cases as VM-Dem, revealing details on the precise areas of inaccuracy in the model.

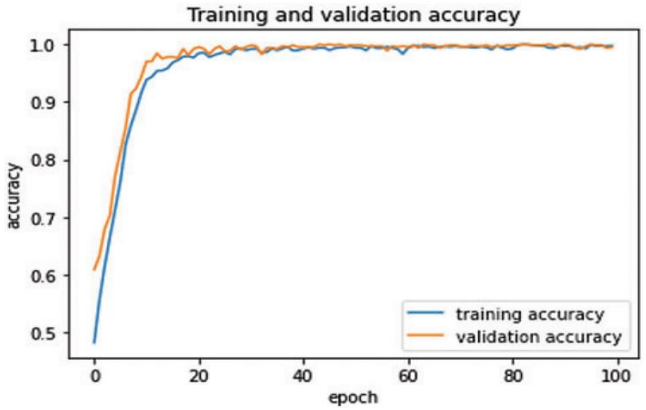

Figure 7. Training and Validation Accuracy for CNN

The accuracy of training and validation throughout 100 epochs is displayed in Figure 7 for a CNN model that predicts AD. Both accuracies increase quickly initially, with training accuracy reaching near-perfect (1.0). Validation accuracy stabilizes around 0.99, closely tracking the training accuracy.

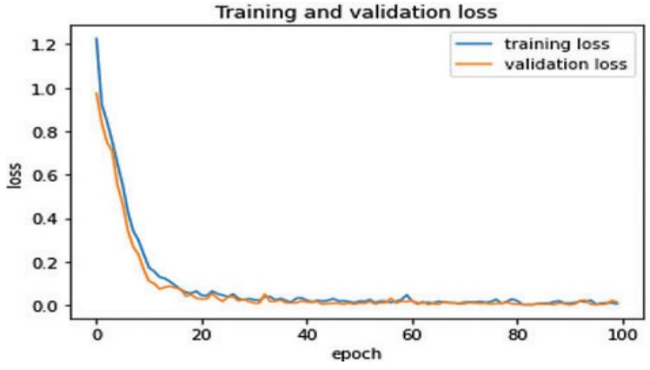

Figure 8. Training and validation loss for CNN

Figure 8's graph displays the validation and training loss of an Alzheimer's CNN model across 100 epochs. Both losses rapidly decline initially and converge near zero. The close tracking of training and validation loss indicates effective learning and good generalization without overfitting.

4.1. Comparative analysis

This section compares the many ML models that are used to forecast AD. A comparison of several models according to their categorization accuracy is given in Table 3. The CNN proved to have superior performance, having an accuracy of 99.38%, which is an indication of its high possibility of learning from complex patterns related to Alzheimer's diagnosis. The opposite is true because the Reset model recorded an accuracy of 82%, the XGBoost model, an accuracy of 80.52%, reflecting relative inappropriateness to address the complexity of the data. The results presented above also demonstrate the robustness and reliability of CNN's clinical decision support model for AD early detection.

Table 3. Comparison of the ML models' performance for Alzheimer's disease prediction

Model	Accuracy
CNN	99.38
ResNet [19]	82
XGBoost [20]	80.52

The proposed method offers significant advantages for early AD prediction. Using a CNN, the model performs well with high accuracy (99.38%), beating traditional methods of ML. Pre-processing involves image resizing, normalization, and class balancing through augmentation means to guarantee the standardization of the data and that class imbalance is eliminated. The model has good application for dependable early detection and enabling prompt therapeutic treatments since it generalizes effectively and has minimal overfitting. The model is suitable for accurate early diagnosis and facilitates prompt therapeutic treatments since it generalizes without a significant amount of overfitting.

5. Conclusion and Future Scope

A timely diagnosis is essential if Alzheimer's disease is to be identified in time for treatment and management. In respect to a large number of AD patients, early detection and even leading a healthy life after diagnosis are crucial to overcoming Alzheimer's. Presenting a DL-based 3D CNN for AD diagnosis utilizing MRI brain images, we provide this work. The model may be a useful diagnostic tool given its excellent accuracy and performance levels. The proposed CNN model successfully distinguished between the Alzheimer's disease four phases. One of the issues to be resolved is, however, there are also certain issues that can be addressed, such as the fact of using a single dataset as a training resource, which might limit the generalization of the model for a wide range of clinical scenarios. Further, interpretability is still an important factor to worry about in medical adoption.

In future work, plan on improving the interpretability of the proposed model by adopting XAI techniques. This would make it possible for medical practitioners to comprehend the AI model's decision-making process better. Further, examining transfer learning, ensemble methods, and multimodal data integration (PET scans and genetic data for further improvements in the model's precision and resilience will be a useful approach. The dataset will also be expanded, including different populations and MR protocols, to make the model more versatile and clinically relevant.

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