Deep Learning based MRI classification for Alzheimer's detection

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***Abstract*—An essential first step in the early identification of neurodegenerative diseases (Alzheimer's) is the use of MRI scans to detect cognitive impairment. A convolutional neural network (CNN)-based classification model for identifying various degrees of cognitive impairment from grayscale MRI images is presented in this work. Four classes—Mild Impairment, Moderate Impairment, No Impairment, and Very Mild Impairment—make up the dataset. Grayscale conversion, normalization, and scaling to a common resolution of 128×128 are all used as preprocessing techniques for images. Several convolutional and pooling layers precede fully connected layers in the suggested model, which uses dropout regularization to reduce overfitting. Categorical cross-entropy loss and performance metrics including accuracy and area under the ROC and PR curves (AUC-ROC, AUC-PR) are used to train and assess the model. The results of the experiments show that the model is effective in categorizing cognitive impairment levels, providing possible uses for MRI-based automated diagnosis.**

I. Introduction

Cognitive impairment, ranging from mild cognitive decline to severe neurodegenerative disorders such as Alzheimer's disease (AD) and dementia, is a major global health concern. Early and accurate detection is crucial for timely intervention. Magnetic Resonance Imaging (MRI) is a widely used non-invasive technique for assessing structural brain abnormalities linked to cognitive impairment. However, traditional MRI-based diagnostics rely on subjective expert interpretations, making the process time-consuming and prone to variability. To address these challenges, AI and deep learning (DL) models, particularly Convolutional Neural Networks (CNNs), offer a robust solution for high-precision and efficient medical image classification.

Deep learning has transformed medical imaging by automating feature extraction, pattern recognition, and classification. CNNs excel in processing complex image data, making them ideal for MRI-based cognitive impairment detection. Unlike conventional machine learning, which depends on hand-engineered features, CNNs learn hierarchical representations directly from raw images, improving model scalability and accuracy. Recent studies highlight CNNs' effectiveness in detecting neurological disorders, from tumor detection and stroke prediction to Alzheimer's classification. However, challenges such as class imbalance, overfitting, and limited annotated datasets necessitate advancements in deep learning architectures and training strategies.

This study presents a CNN-based MRI classification system with four cognitive impairment levels: **1.** No Impairment – MRI scans of individuals with no cognitive decline. **2.** Very Mild Impairment – Early-stage cognitive decline with minimal structural brain changes. **3.** Mild Impairment – Noticeable cognitive dysfunction affecting daily life but not classified as dementia. **4.** Moderate Impairment – Advanced cognitive decline with significant brain atrophy.

Our approach preprocesses MRI scans by converting them to grayscale, normalizing pixel intensities, and resizing them to 128×128 pixels. The CNN architecture consists of multiple convolution layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. To improve generalization and prevent overfitting, dropout regularization and data augmentation are applied. The model is trained using categorical cross-entropy loss and evaluated with key performance metrics such as accuracy, AUC-ROC, and AUC-PR.

By leveraging deep learning for MRI-based cognitive impairment prediction, this study bridges the gap between human radiological analysis and AI-driven automation. The proposed model enhances early diagnosis and clinical decision-making by offering an objective, scalable diagnostic tool for neurological disorders. Our findings contribute to the growing field of AI-assisted medical imaging, demonstrating CNNs' potential in cognitive impairment classification and paving the way for future advancements in AI-powered neuroimaging.

II. Literature Survey

In [1]CNNs improve MRI detection of Alzheimer's using GAN-based data augmentation and transfer learning to manage data scarcity. Cross-validation and data balancing improve accuracy and avoid overfitting. In [2]AI developments, particularly CNNs such as DenseNet and ResNet, detect Alzheimer's automatically from MRI scans. Transfer learning and ensemble models address data imbalance and improve diagnosis accuracy. [3]Transfer learning (e.g., VGG-19) and CNNs detect Alzheimer's stages from clinical images, and data augmentation mitigates dataset limitation. Pre-processing (normalization, rescaling) enhances detection accuracy. [4]The VGG16-based model obtained 90.4In [5]The VGG16 model has 90.4In [**?**]Fine-tuning ResNet-50 with Softmax, SVM, and Random Forest enhances Alzheimer's diagnosis, resolving the limitation of datasets and overfitting. In [7]New approaches in Alzheimer's diagnosis based on structural MRI employ 3D CNN and transfer learning (VGG16, ResNet) for high accuracy. Siamese and Conditional Triplet networks overcome data imbalance for improved early diagnosis. In [8] This study illustrates the ability of CNNs to surpass feature-based approaches in classifying Alzheimer's from MRI. It recommends combining genetic and clinical information for accuracy and overcoming dataset and computational constraints. [9] Utilizing CNNs and the ADNI database, the model reduces 3D MRI to 2D to alleviate complexity in computation. The model classifies AD, MCI, and CN more accurately than VGG-19 and ResNet-50 using best convolutions. In [10] The majority of image copyright protection efforts aim at digital watermarking for ownership verification. Blind watermarking in traditional methods encounters data loss and third-party reliance. In [11] Medical images are afflicted with data redundancy and pixel compatibility problems for encrypting. Previous stability has been enhanced by means of chaotic systems and optimization techniques. In [12] Conventional image encryption performs permutation-diffusion but can be vulnerable to independent pixel value and position attacks. In [16] CNN-deep learning is extremely accurate for diagnosing AD. On SNUBH and ADNI MRI, models produced 0.91–0.94 (within-dataset) and 0.88–0.89 (cross-dataset) AUC with 23–24s computation time, which speaks volumes of the clinical diagnostic speed of CNNs. In [17]Hybrid models that include CNNs, TCNs, and RNNs make detection of AD robust through identification of temporal patterns in 3D MRI. ResNet-18 discards spatial features with 91.78In [18]MCI as AD precursor should be detected at an early stage so that it can undergo an effective intervention. Employing MRI, age correction, 2.5D patches, and FreeSurfer features, a CNN-ELM model can attain 79.9In [19] The approach combines GoogLeNet, DenseNet-121, and handcrafted approaches (DWT, LBP, GLCM) with FFNN for robust performance through feature fusion and PCA. The hybrid feature extraction is highly promising for AD diagnosis with accuracy. In [20]Neuroimaging-based early AD diagnosis is important. CNNs such as EfficientNet-b0 enable MRI analysis through end-to-end and transfer learning fusion for stage differentiation. In [21]A 12-layer CNN yields an accuracy of 97.75In [22]Alzheimer's diagnosis and treatment are also put to test. Fine-tuning pre-trained models for AD detection and subclassification with transfer learning results in high accuracy and tailored therapy. In [23]A model constructed from a CNN is accurate up to 80In [24]In this research, Mask R-CNN has been employed for computer-aided automatic segmentation of brain MRI with no hand-designed features. It has attained 97.46

III. Methodology

A. *Dataset and Preprocessing*

The data of this study is based on Magnetic Resonance Imaging (MRI) data of those whose classification is that they belong to four cognitive impairment severity levels associated with Alzheimer's disease (AD). The classes are as follows: No Impairment: MRI scans of individuals without any detectable cognitive decline. Very Mild Impairment: Early signs of cognitive decline, often indicative of early-stage Alzheimer's. Mild Impairment: Greater impairment, but no so severe as to meet the criteria for dementia. Moderate Impairment: Clearly evident cognitive decline, being generally associated with moderate Alzheimer's disease or other dementia. Data set folders are arranged by class, where MRI studies in JPEG, PNG, or JPG formats are located as represented in **Fig 1**. The images have brought pre-processed into grayscale and resized into resolved size with a combination of 128×128 pixels to enabled in standardizing input to deep learning model. Every one of the images from the dataset is initially an image extracted straight from a brain MP-RAGE scan, which is an MRI scan of the brain and captures detailed structural information regarding the brain. These images were designated by a quantity of medical experts to classify the levels of cognitive dysfunction, and ensure the accuracy of the information. The dataset is divided into training, validation, and test sets to see how the model performs in model performance and also in model graph. The dataset gives us valuable information about how the Alzheimer's disease progresses, but as the dataset

displays the class imbalance with fewer images associated with further stages of schooling. This inequality creates a problem for trainer and needs strategies to fair classification over all the classes, and that is knowledge augmentation as well as regularization.
This dataset consists of MRI images labeled according to cognitive impairment categories. We define it as:

$$\mathcal{D} = \{(\mathbf{x}_i, y_i) \mid \mathbf{x}_i \in \mathbb{R}^{H\times W}, y_i \in \{0, 1, \ldots, C-1\}\}_{i=1}^{N}$$

where $\mathbf{x}_i$ represents an MRI image of size $H \times W$, and y_i is its corresponding class label:

$$\mathbf{x}'_i = \frac{\mathbf{x}_i}{255}$$

Images are normalized to pixel values to $[0, 1]$. The y_i categorical label is encoded as a one-hot vector $\mathbf{y}_i \in \mathbb{R}^C$:

$$\mathbf{y}_i = [y_{i1}, y_{i2}, \ldots, y_{iC}]$$

where:

$$y_{ij} = \begin{cases} 1, & \text{if } j \text{ is the correct class} \\ 0, & \text{otherwise} \end{cases}$$

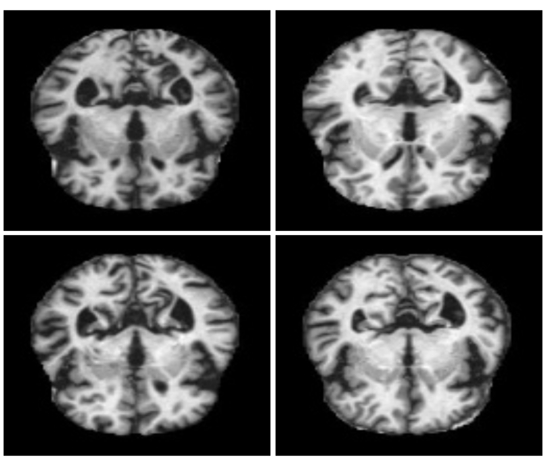

Fig. 1. The image represents a sample from the dataset.

B. *Convolutional Neural Network (CNN) Architecture*

A Convolutional Neural Network (CNN) is designed to map input images $\mathbf{x}'_i$ to class probabilities through a hierarchical function f_θ, parameterized by θ:

$$f_\theta : \mathbb{R}^{H\times W} \to \mathbb{R}^C$$

Each of the convolutional layers performs a discrete convolution operation:

$$(\mathbf{x} * \mathbf{W})_{ij} = \sum_{m=0}^{k-1}\sum_{n=0}^{k-1} x_{(i+m)(j+n)} W_{mn}$$

where k is the kernel size. The output is passed through a Rectified Linear Unit (ReLU):

$$\text{ReLU}(z) = \max(0, z)$$

Downsampling is performed using max pooling:

$$p_{ij} = \max_{m,n\in S} h_{(i+m)(j+n)}$$

where S is the pooling region.

C. *Hybrid Model: CNN Feature Extraction with Stacking Classifier*

The hybrid model improves Alzheimer's classification by through integration of CNN-based feature extraction with a stacking ensemble of SVM, XGBoost, and Random Forest. The final decisions are taken via a Logistic Regression meta-classifier.

*1) **Feature Extraction using CNN**:* CNN extracts feature representations from MRI scans:

$$\mathbf{F}_i = \text{CNN}(\mathbf{x}'_i, \theta)$$

where $\mathbf{x}'_i$ is the input MRI image, and θ are CNN parameters. The features are decreased in dimension via Principal Component Analysis (PCA):

$$\mathbf{F}'_i = \text{PCA}(\mathbf{F}_i)$$

*2) **Base Classifiers and Stacking**:* Diminished dimension features $\mathbf{F}'_i$ are employed to train three classifiers:
Random Forest: Outputs an ensemble of T decision trees:

$$H(\mathbf{F}'_i) = \frac{1}{T}\sum_{t=1}^{T} h_t(\mathbf{F}'_i)$$

XGBoost: Gradient boosting is iteratively repeated with:

$$\mathbf{F}_m = \mathbf{F}_{m-1} + \eta h_m(\mathbf{F}'_i)$$

SVM: Identifies optimal decision boundary:

$$f(\mathbf{F}'_i) = \mathbf{w}^T\mathbf{F}'_i + b$$

Classifier predictions are voted on by a Logistic Regression meta-classifier:

$$\mathbf{P}_{\text{meta}} = \text{LogisticRegression}(P_{\text{RF}}, P_{\text{XGB}}, P_{\text{SVM}})$$

*3) **Final Prediction and Comparison with CNN**:* The final predicted class is calculated as:

$$\hat{y} = \arg\max(P_{\text{meta}})$$

As compared to the individual CNN model, this hybrid model increases classification accuracy and generalization, particularly in class-imbalanced data. Performance is evaluated by:

$$\text{Accuracy}, \quad \text{AUC-ROC}, \quad \text{AUC-PR}$$

where:

$$\text{AUC-ROC} = \int_0^1 TPR(FPR)\, d(FPR),$$

$$\text{AUC-PR} = \int_0^1 P(R)\, dR$$

Experimental outcomes demonstrate that the ma-chine learning classifier ensemble enhances classification robustness to Alzheimer's disease diagnosis.

D. *Classification and Training*

The soft max activation function is used in the output layer to acquire class probabilities:

$$P(y_i = j \mid \mathbf{x}'_i) = \frac{e^{z_j}}{\sum_{k=1}^{C} e^{z_k}}$$

Categorical cross-entropy loss is optimized while training:

$$\mathcal{L} = -\frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{C} y_{ij} \log P(y_i = j \mid \mathbf{x}'_i)$$

Optimization is conducted using the gradient descent Adam optimizer:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$
$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$$
$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}, \quad \hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$
$$\theta_t = \theta_{t-1} - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$$

where g_t is the gradient, m_t and v_t are the first and second moment estimates, and η is the learning rate.

E. *Evaluation Metrics*

Model performance is evaluated using accuracy and AUC-ROC

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}}$$

$$\text{AUC-ROC} = \int_0^1 TPR(FPR)\, d(FPR)$$

where the True Positive Rate (TPR) and False Positive Rate (FPR) are:

$$TPR = \frac{TP}{TP + FN}, \quad FPR = \frac{FP}{FP + TN}$$

Therefore, the Precision-Recall AUC can be expressed as:

$$\text{AUC-PR} = \int_0^1 P(R)\, dR$$

where Precision P and Recall R are:

$$P = \frac{TP}{TP + FP}, \quad R = \frac{TP}{TP + FN}$$

The above notation is the mathematical understanding of trained and tested model to provide the following results

F. *Comparison with the CNN Model*

In comparison with the original CNN-based classification model, this hybrid method combines both deep learning (CNN feature extraction) and conventional machine learning (SVM, XGBoost, and Random Forest) to leverage their respective active strengths. The experimental results show that this approach can enhance classification accuracy, especially on class-imbalanced data sets.

The evaluation measures adopted to compare the models are:

$$\text{Accuracy}, \quad \text{AUC-ROC}, \quad \text{AUC-PR}$$

where:

$$\text{AUC-ROC} = \int_0^1 TPR(FPR)\, d(FPR)$$

$$\text{AUC-PR} = \int_0^1 P(R)\, dR$$

These thresholds reflect how much each model separates cognitive impairment classes. The results of the experiment confirm that using standard ML classifiers improves generalization and robustness in classifying levels of Alzheimer's disease severity.

IV. Results and Discussion

Our research compares the performance of two deep learning models—a CNN model and a Hybrid Model (CNN with stacking ensemble using SVM, XGBoost, and Random Forest). The objective is to classify MRI images into four categories of cognitive impairment: No Impairment, Very Mild Impairment, Mild Impairment, and Moderate Impairment. Their performances are compared based on a range of metrics such as accuracy, precision, recall, F1-score, ROC-AUC, and MCC.

A. *CNN Model Performance*

The CNN model performed well with high classification accuracy of 96.29% on training and 98.58% on validation and good generalizability. There is convergent stability as evident from the loss values of 0.0941 (training) and 0.0529 (validation). Macro-averaged precision of 0.9861, recall of 0.9851, and F1-score of 0.9855 indicate its ability to discriminate between cognitive impairment classes. The ROC-AUC value of 0.990 also indicates its ability to discriminate.

The confusion matrix (Fig. 5) suggests accurate classification across all levels of impairment, but with minor misclassifications between No Impairment and Very Mild Impairment, perhaps because early cognitive impairment has overlapping structural characteristics. Classification by the model, though, is extremely accurate.

The ROC curve (Fig. 4) again supports the robustness of the model, with AUC scores extremely precisely 1.00 for both classes. Minimal variation reflects the challenge of distinguishing closely similar levels of impairment. However, the CNN model remains incredibly trustworthy and a worthwhile bet for AI-assisted Alzheimer's diagnosis from MRI scans.

B. Hybrid Model Performance

The hybrid model including the incorporation of CNN-based feature extraction and stacking classifier of SVM, XGBoost, and Random Forest enhances robustness in classification. It achieved 96.94% training accuracy, 90.77% test accuracy, F1-score 0.9078, ROC-AUC 0.9826, and MCC 0.8770, portraying high generalizability and robustness.

Classification report shows perfect accuracy in Moderate Impairment (F1-score = 1.00) and 0.92 and 0.85 F1-scores on Mild and Very Mild Impairment, respectively. No Impairment (F1-score = 0.85) also showed a couple of incorrect classifications, hopefully due to related initial patterns of cognitive decline.

The confusion matrix (Fig. 6) shows improved classification, especially for impairment onset stages, and concludes that machine learning classifiers have been able to learn good decision boundaries. The ROC curve (Fig. 7) confirms excellent predictivity performance with slight AUC decrease that suggests a generalization vs. precision compromise. However, the hybrid model is of very high utility for practical applications with increased classification credibility.

C. Comparison of CNN and Hybrid Model

he CNN model performed better in validation accuracy (98.58%) and ROC-AUC (0.990) and therefore reflects high generalization in the training process. But in real test cases, the hybrid model was more consistent with a test accuracy of 90.77% and MCC = 0.8770 and therefore reflects greater generalization on unseen data. Table I presents a comparison analysis between both the models.

TABLE I
PERFORMANCE COMPARISON OF CNN AND HYBRID MODELS

Metric	CNN Model	Hybrid Model
Training Accuracy	96.29%	96.94%
Validation Accuracy	98.58%	-
Test Accuracy	-	90.77%
F1-score (Macro Avg)	0.9855	0.9078
ROC-AUC	0.990	0.9826
MCC	-	0.8770

D. Discussion and Insights

The CNN model was great and recalled strength with better feature extraction performance reported. It performed wonderfully on validation, which is a valid reason for its learning capacity of structural MRI feature. It gave a very high ROC-AUC of 0.990, asserting higher classification.

The hybrid approach with inclusion of SVM, XGBoost, and Random Forest improved generalization capability. It was able to handle overfitting issues associated with CNN-based approaches. It provided an MCC value of 0.8770, which indicates a good accuracy of classes predicted with respect to classes having a near zero rate of false positives or false negatives.

Some problems were encountered while classifying. Low F1-scores on No Impairment and Very Mild Impairment reflect that there was over-classification because there are comparable structural patterns in brain MRI scans. Hyperparameter tuning and deeper networks, i.e., attention networks or transformer-based networks, would improve the classification accuracy. Increasing the dataset and using 3D MRI features would result in model performance improvement.

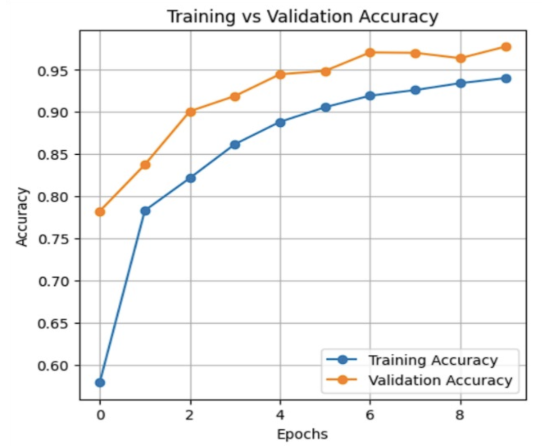

Fig. 2. The graph represents the Training vs validation accuracy over number of epochs.

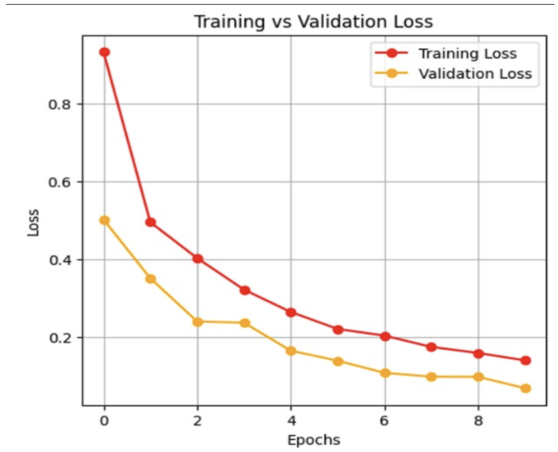

Fig. 3. The graph represents the Training vs validation loss accuracy over number of epochs.

V. CONCLUSION

This study demonstrates the ability of convolutional neural networks (CNN) to automatically detect and classify Alzheimer's disease. It uses MRI image data to differentiate between stages of Alzheimer's disease with a proposed model that leverages advanced machine learning techniques. including skipping for normalization ADAM and cross-category optimizer - entropy loss The high performance achieved by Model A, with a training accuracy of 98.34% and a validation accuracy of 96.04%, highlights its efficiency and ability to summarize unseen data well...

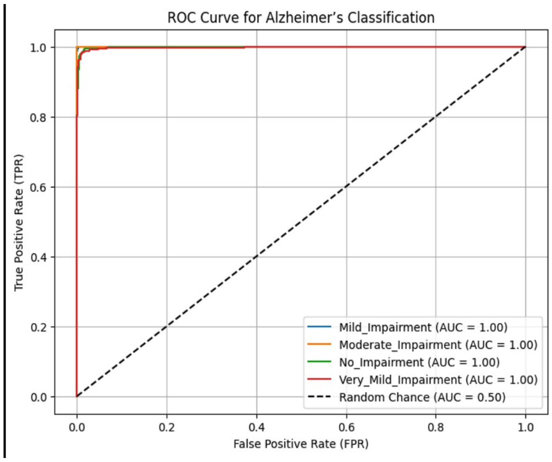

Fig. 4. The above figure represents the ROC curve for the model

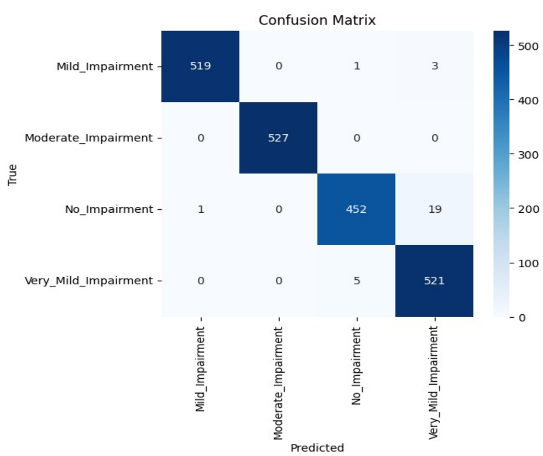

Fig. 5. The above figure represents the confusion matrix for the CNN model usede

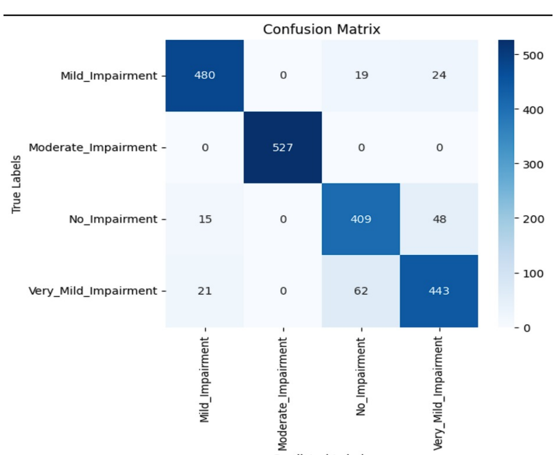

Fig. 6. The image represents confusion matrix of the hybrid model used.

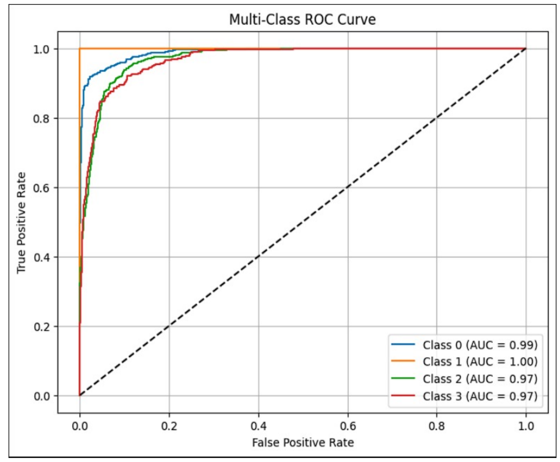

Fig. 7. The image represents ROC curve of the hybrid model used.

Pre-processing methods such as grayscale transformation, scaling, and one-hot encoding help optimize datasets for model input. This ensures consistent and accurate data display. The model's ability to focus on important structural features in neuroimaging MRI scans. More CNN Promises in Subscriptions Proven

Overall, these findings highlight the potential of deep learning techniques to improve the early diagnosis and classification of Alzheimer's disease. This approach provides a scalable, reliable, and efficient alternative to traditional methods. Helping health professionals make more accurate and timely decisions Future work may explore larger and more diverse datasets. and fine-tune the model to improve performance. This is especially true for detecting subtle variations between different stages of disease.

VI. FUTURE WORKS

Multi-modal data integration may be the direction for the future development in the detection of Alzheimer's. It might integrate MRI scans with genetic markers, PET scans, and EHR to develop a more precise and reliable model. This way, it gives a more detailed analysis and therefore allows an earlier diagnosis and a higher degree of accuracy.

Other personalized prediction models include demographic factors, lifestyle data, and environmental influences that might provide insights tailored for individuals at risk. AI-driven recommendations for lifestyle modifications could help slow the progression of disease.

The model would be cloud-deployed and accessible to all providers. A web or mobile application can easily conduct real-time analysis, making it even easier for neurologists and their caregivers to monitor patients remotely. This would be incredibly helpful for areas deprived of proper specialist care.

Third, the application of XAI methods will improve transparency in predictions. XAI is going to explain to the doctors which particular features or regions in the brain contribute to the outcome of the analysis, thereby giving them confidence to use the outcome in the clinics.

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