DEEP LEARNING-BASED MRI CLASSIFICATION FOR EARLY DETECTION OF ALZHEIMER'S DISEASE

A PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

This is to certify that this project report entitled **"DEEP LEARNING-BASED MRI CLASSIFICATION FOR EARLY DETECTION OF ALZHEIMER'S DISEASE"** is the bonafide work of **"Mr. Dhanushrinivas K (Reg. No. CH.SC.U4AIE23011), Mr. Jakka Aniketh Reddy (Reg. No. CH.SC.U4AIE23020), Mr. Nammi Bhargav (Reg. No. CH.SC.U4AIE23-037), Mr. Nethi Sathwik (Reg. No. CH.SC.U4AIE23039), Mr. Sunil Raj D (Reg. No. CH.SC.U4AIE23055), Mr. Talasila Balaji (Reg. No. CH.SC.U4AIE23056)"** who carried out the project work under my supervision as a part of the End Semester Project for the course 22BIO211 - Intelligence of Biological Systems 2.

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ABBREVIATIONS

AD	Alzheimer's Disease
MRI	Magnetic Resonance Imaging
CNN	Convolutional Neural Network
SVM	Support Vector Machine
XGBoost	Extreme Gradient Boosting
RF	Random Forest
PCA	Principal Component Analysis
AUC-ROC	Area Under the Receiver Operating Characteristic Curve
AUC-PR	Area Under the Precision-Recall Curve
MP-RAGE	Magnetization-Prepared Rapid Gradient-Echo
ReLU	Rectified Linear Unit
MCC	Matthews Correlation Coefficient
TPR	True Positive Rate
FPR	False Positive Rate

NOTATION

x_i	Input MRI image
y_i	Corresponding class label
f_θ	CNN classification function
$H \times W$	Image resolution (height × width)
C	Number of cognitive impairment classes
θ	CNN model parameters
k	Kernel size in convolutional layers
W_{mn}	Weight matrix in convolution operation
$ReLU(z)$	Rectified Linear Unit activation function
S	Pooling region in max pooling
F_i	Extracted feature vector from CNN
$PCA(F_i)$	Principal Component Analysis transformation
P_{meta}	Prediction probability from stacked classifier
η	Learning rate in optimization
T	Number of decision trees in Random Forest
MCC	Matthews Correlation Coefficient
$AUC - ROC$	Area Under the Receiver Operating Characteristic Curve
$AUC - PR$	Area Under the Precision-Recall Curve

ABSTRACT

Early detection of Alzheimer's disease is crucial for effective intervention, and MRI-based analysis plays a significant role in identifying cognitive impairment. This study presents a Convolutional Neural Network (CNN)-based classification model to detect different levels of cognitive impairment using grayscale MRI images. The dataset consists of four categories: No Impairment, Very Mild Impairment, Mild Impairment, and Moderate Impairment. Image preprocessing includes grayscale conversion, normalization, and resizing to 128×128 pixels. The proposed CNN model comprises multiple convolutional and pooling layers, followed by fully connected layers, with dropout regularization to minimize overfitting. The model is trained using categorical cross-entropy loss and evaluated using accuracy, AUC-ROC, and AUC-PR metrics. Additionally, a hybrid model integrating CNN-based feature extraction with machine learning classifiers (SVM, XGBoost, and Random Forest) is introduced to enhance classification robustness. Experimental results indicate that the CNN model achieves high accuracy in cognitive impairment classification, while the hybrid approach improves generalization. These findings emphasize the potential of deep learning in MRI-based automated Alzheimer's detection, bridging the gap between radiological expertise and AI-driven diagnosis.

Keywords: Alzheimer's Detection, MRI Classification, Convolutional Neural Network (CNN), Cognitive Impairment, Deep Learning, Machine Learning, Image Processing, Hybrid Model, AUC-ROC, Medical Imaging.

CHAPTER 1

INTRODUCTION

1.1 GENERAL BACKGROUND

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.

1.2 ROLE OF AI AND DEEP LEARNING IN MEDICAL IMAGING

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.

1.3 CHALLENGES IN COGNITIVE IMPAIRMENT DETECTION

Despite the advantages of CNNs in medical imaging, several challenges persist, including class imbalance, overfitting, and limited annotated datasets. Addressing these challenges requires advancements in deep learning architectures and training strategies to enhance model performance and reliability in real-world applications.

1.4 PROPOSED CNN-BASED MRI CLASSIFICATION SYSTEM

This study presents a CNN-based MRI classification system for detecting four levels of cognitive impairment:

- **No Impairment** – MRI scans of individuals with no cognitive decline.

- **Very Mild Impairment** – Early-stage cognitive decline with minimal structural brain changes.
- **Mild Impairment** – Noticeable cognitive dysfunction affecting daily life but not classified as dementia.
- **Moderate Impairment** – Advanced cognitive decline with significant brain atrophy.

1.5 PREPROCESSING AND MODEL ARCHITECTURE

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 convolutional 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.

1.6 SIGNIFICANCE AND CONTRIBUTIONS

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 the potential of CNNs in cognitive impairment classification and paving the way for future advancements in AI-powered neuroimaging.

CHAPTER 2

LITERATURE SURVEY

2.1 DEEP LEARNING APPROACHES IN ALZHEIMER'S DETECTION

Recent studies have demonstrated the effectiveness of deep learning models, particularly Convolutional Neural Networks (CNNs), in detecting Alzheimer's disease from MRI scans. 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.

2.2 TRANSFER LEARNING AND FEATURE EXTRACTION

Several studies have implemented AI developments, particularly CNNs such as DenseNet and ResNet, to detect Alzheimer's automatically from MRI scans. Transfer learning (e.g., VGG-19) and CNNs help detect Alzheimer's stages from clinical images, and data augmentation mitigates dataset limitations. Preprocessing techniques such as normalization and rescaling enhance detection accuracy.

2.3 HYBRID MODELS AND ENSEMBLE LEARNING

Fine-tuning ResNet-50 with Softmax, SVM, and Random Forest enhances Alzheimer's diagnosis by addressing dataset limitations and overfitting. New approaches based on structural MRI employ 3D CNN and transfer learning using models like VGG16 and ResNet to improve accuracy. Siamese and Conditional Triplet networks have also been used to overcome data imbalance, enabling better early diagnosis.

2.4 CHALLENGES IN EXISTING APPROACHES

Despite their success, CNN-based models face challenges such as class imbalance, overfitting, and computational complexity. Some studies have illustrated the ability of CNNs to surpass feature-based approaches in classifying Alzheimer's from MRI, recommending the combination of genetic and clinical information for greater accuracy. Reducing 3D MRI scans to 2D alleviates computational complexity, improving classification accuracy.

2.5 COMPARISON OF MODELS AND PERFORMANCE METRICS

Various models have been compared based on accuracy and efficiency. CNN models such as EfficientNet-b0 enable neuroimaging-based early Alzheimer's diagnosis through end-to-end learning and transfer learning fusion. Research shows that hybrid models combining GoogLeNet, DenseNet-121, and traditional feature extraction techniques (DWT, LBP, GLCM) with FFNN provide promising results. A 12-layer CNN has achieved an accuracy of 97.75% in some studies. Additionally, Mask R-CNN has been employed for computer-aided automatic segmentation of brain MRI scans, achieving high classification accuracy.

CHAPTER 3

METHODOLOGY

3.1 DATASET AND PREPROCESSING

The dataset for this study comprises Magnetic Resonance Imaging (MRI) scans classified into four cognitive impairment severity levels associated with Alzheimer's disease (AD):

- **No Impairment**: MRI scans of individuals without detectable cognitive decline.
- **Very Mild Impairment**: Early signs of cognitive decline, often indicative of early-stage Alzheimer's.
- **Mild Impairment**: Greater impairment, not severe enough to meet dementia criteria.
- **Moderate Impairment**: Evident cognitive decline, generally associated with moderate Alzheimer's disease or other dementia.

The dataset is organized by class, with MRI images in JPEG, PNG, or JPG formats as shown in **Figure 1**. Images are preprocessed into grayscale and resized to 128×128 pixels to standardize input for the deep learning model. These images are extracted from brain MP-RAGE scans, capturing detailed structural brain information, and labeled by medical experts to ensure classification accuracy. The dataset is split into training, validation, and test sets to evaluate model performance.

The dataset exhibits class imbalance, with fewer images in advanced stages, necessitating techniques like data augmentation and regularization for fair classification across all classes. The dataset is defined as:

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

where $\mathbf{x}_i$ is an MRI image of size $H \times W$, and y_i is its class label. Images are normalized to pixel values in $[0, 1]$:

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

The categorical label y_i is encoded as a one-hot vector $\mathbf{y}_i \in R^C$:

$$\mathbf{y}_i = [y_{i1}, y_{i2}, \ldots, y_{iC}], \quad y_{ij} = \begin{cases} 1, & \text{if } j \text{ is the correct class} \\ 0, & \text{otherwise} \end{cases}$$

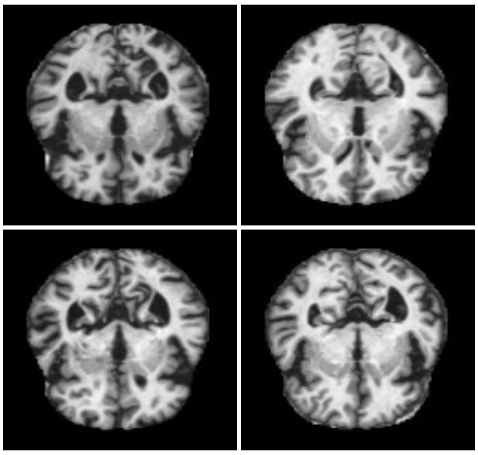

Figure 3.1: Sample MRI image from the dataset.

3.2 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:

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

Each convolutional layer 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.

3.3 HYBRID MODEL: CNN FEATURE EXTRACTION WITH STACKING CLASSIFIER

The hybrid model enhances Alzheimer's classification by integrating CNN-based feature extraction with a stacking ensemble of SVM, XGBoost, and Random Forest, with final decisions made by a Logistic Regression meta-classifier.

3.3.1 FEATURE EXTRACTION USING CNN

The 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. Features are reduced in dimension via Principal Component Analysis (PCA):

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

3.3.2 BASE CLASSIFIERS AND STACKING

Reduced-dimension features $\mathbf{F}'_i$ are used 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 applied with:

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

- **SVM**: Identifies the optimal decision boundary:

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

Classifier predictions are combined by a Logistic Regression meta-classifier:

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

3.3.3 FINAL PREDICTION AND COMPARISON WITH CNN

The final predicted class is:

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

Compared to the standalone CNN model, the hybrid model improves classification accuracy and generalization, particularly on class-imbalanced data. Performance is evaluated using:

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

where:

$$\text{AUC-ROC} = \int_0^1 TPR(FPR)\, d(FPR), \quad \text{AUC-PR} = \int_0^1 P(R)\, dR$$

3.4 CLASSIFICATION AND TRAINING

The softmax activation function is used in the output layer to obtain 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 during 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 Adam optimizer:

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

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

3.5 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 True Positive Rate (TPR) and False Positive Rate (FPR) are:

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

The Precision-Recall AUC is:

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

where Precision P and Recall R are:

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

3.6 COMPARISON WITH THE CNN MODEL

Compared to the standalone CNN model, the hybrid approach combines deep learning (CNN feature extraction) and conventional machine learning (SVM, XGBoost, and Random Forest) to leverage their strengths. Experimental results show enhanced classification accuracy, especially on class-imbalanced datasets, with performance evaluated using:

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

CHAPTER 4

RESULTS AND DISCUSSION

4.1 CNN MODEL PERFORMANCE

The CNN model achieved a high classification accuracy of 96.29% on training and 98.58% on validation, indicating good generalizability. Loss values of 0.0941 (training) and 0.0529 (validation) suggest convergent stability. Macro-averaged precision of 0.9861, recall of 0.9851, and F1-score of 0.9855 demonstrate its ability to discriminate between cognitive impairment classes. The ROC-AUC value of 0.990 further confirms its discriminative power.

The confusion matrix (Figure 5) shows accurate classification across all impairment levels, with minor misclassifications between No Impairment and Very Mild Impairment, possibly due to overlapping structural characteristics. The ROC curve (Figure 4) supports the model's robustness, with AUC scores nearing 1.00 for all classes, reflecting its reliability for AI-assisted Alzheimer's diagnosis.

4.2 HYBRID MODEL PERFORMANCE

The hybrid model, incorporating CNN-based feature extraction and a stacking classifier (SVM, XGBoost, and Random Forest), achieved a training accuracy of 96.94%, test accuracy of 90.77%, F1-score of 0.9078, ROC-AUC of 0.9826, and MCC of 0.8770, indicating high generalizability and robustness. The classification report shows perfect accuracy for Moderate Impairment (F1-score = 1.00), with F1-scores of 0.92 and 0.85 for Mild and Very Mild Impairment, respectively. No Impairment (F1-score = 0.85) exhibited minor misclassifications, likely due to subtle initial cognitive decline patterns.

The confusion matrix (Figure 6) demonstrates improved classification, especially for early impairment stages, suggesting effective decision boundaries learned by the machine learning classifiers. The ROC curve (Figure 7) confirms strong predictive performance, with a slight AUC decrease indicating a trade-off between generalization and precision.

4.3 COMPARISON OF CNN AND HYBRID MODEL

The CNN model outperformed in validation accuracy (98.58%) and ROC-AUC (0.990), reflecting strong generalization during training. However, the hybrid model showed greater consistency on unseen data, with a test accuracy of 90.77% and MCC of 0.8770. Table 1 presents a comparative analysis.

Table 4.1: 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

4.4 DISCUSSION AND INSIGHTS

The CNN model excels in feature extraction, achieving high validation performance (ROC-AUC of 0.990). The hybrid model, incorporating SVM, XGBoost, and Random Forest, enhances generalization (MCC = 0.8770), mitigating overfitting issues common in CNN-based approaches. Challenges in classifying No Impairment and Very Mild Impairment (lower F1-scores) suggest overlapping structural patterns in early stages. Hyperparameter tuning, deeper networks (e.g., attention or transformer-based), and larger datasets with 3D MRI features could further improve performance.

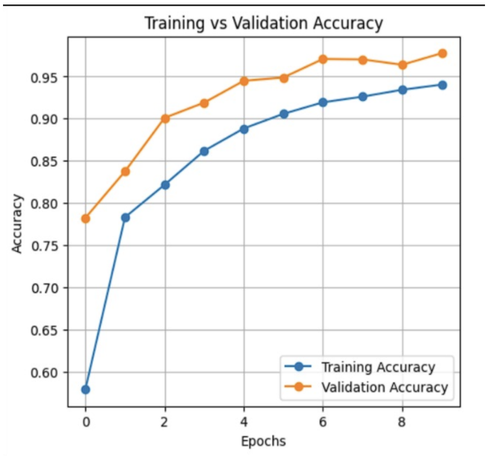

Figure 4.1: Training vs. Validation Accuracy over Epochs.

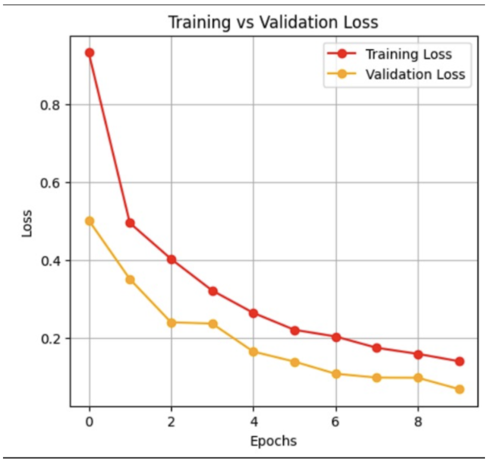

Figure 4.2: Training vs. Validation Loss over Epochs.

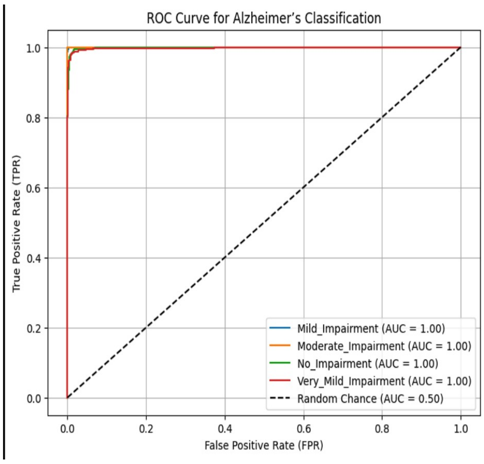

Figure 4.3: ROC Curve for the CNN Model.

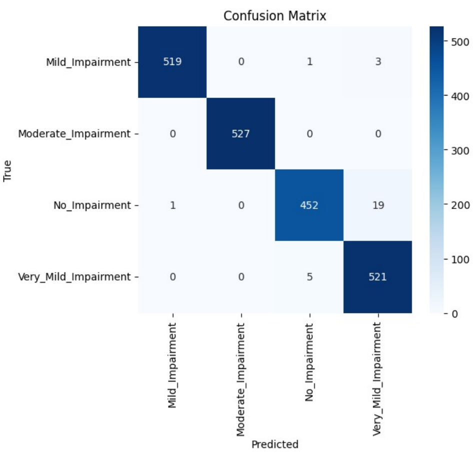

Figure 4.4: Confusion Matrix for the CNN Model.

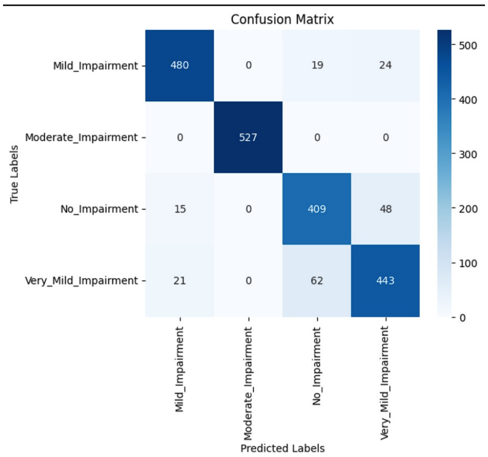

Figure 4.5: Confusion Matrix for the Hybrid Model.

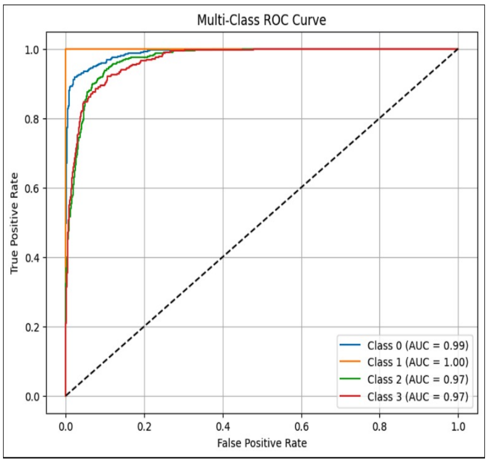

Figure 4.6: ROC Curve for the Hybrid Model.

CHAPTER 5

CONCLUSION

This study demonstrates the efficacy of Convolutional Neural Networks (CNNs) in automatically detecting and classifying Alzheimer's disease using MRI images. The proposed model differentiates between stages of Alzheimer's with high accuracy, achieving a training accuracy of 96.29% and a validation accuracy of 98.58%. Preprocessing techniques such as grayscale conversion, normalization, and one-hot encoding optimize the dataset for model input, ensuring consistent and accurate feature representation. The hybrid model, integrating CNN feature extraction with SVM, XGBoost, and Random Forest, further enhances robustness and generalization.

These findings highlight the potential of deep learning to improve early diagnosis and classification of Alzheimer's disease, offering a scalable, reliable alternative to traditional methods. This approach aids healthcare professionals in making accurate and timely decisions. Future work could explore larger, more diverse datasets and fine-tune models to detect subtle variations between disease stages, further advancing AI-driven neuroimaging.

CHAPTER 6

TECHNICAL REFERENCES

[1] Kwok Tai932 Chui, Brij B. Gupta, Wadee Alhalabi, and Fatma Salih Alzahrani, *An MRI Scans-Based Alzheimer's Disease Detection via Convolutional Neural Network and Transfer Learning*.

[2] Marwa El-Geneedy, Hossam El-Din Moustafa, Fahmi Khalifa, Hatem Khater, and Eman AbdElhalim, *An MRI-based Deep Learning Approach for Accurate Detection of Alzheimer's Disease*.

[3] Hadeer A. Helaly, Mahmoud Badawy, and Amira Y. Haikal, *Deep Learning Approach for Early Detection of Alzheimer's Disease*.

[4] Shagun Sharma, Kalpna Guleria, Sunita Tiwari, and Sushil Kumar, *A Deep Learning Based Convolutional Neural Network Model with VGG16 Feature Extractor for the Detection of Alzheimer Disease Using MRI Scans*.

[5] Mian Muhammad Sadiq Fareed, Shahid Zikria, Gulnaz Ahmed, Mui-Zzud-Din, Saqib Mahmood, and Muhammad Aslam, *ADD-Net: An Effective Deep Learning Model for Early Detection of Alzheimer Disease in MRI Scans*.

[6] Duaa AlSaeed and Samar Fouad Omar, *Brain MRI Analysis for Alzheimer's Disease Diagnosis Using CNN-Based Feature Extraction and Machine Learning*.

[7] Maysam Orouskhani, Chengcheng Zhu, Sahar Rostamian, Firoozeh Shomal Zadeh, Mehrzad Shafiei, and Yasin Orouskhani, *Alzheimer's Disease Detection from Structural MRI Using Conditional Deep Triplet Network*.

[8] Sheng Liu, Arjun V. Masurkar, Henry Rusinek, Jingyun Chen, Ben Zhang, Weicheng Zhu, Carlos Fernandez-Granda, and Narges Razavian, *Generalizable Deep Learning Model for Early Alzheimer's Disease Detection from Structural MRIs*.

[9] Fazal Ur Rehman Faisal and Goo-Rak Kwon, *Automated Detection of Alzheimer's Disease and Mild Cognitive Impairment Using Whole Brain MRI*.

[10] Baowei Wang, Shi Jiawei, Weishen Wang, and Peng Zhao, *SecDH: Security of COVID-19 Images Based on Data Hiding with PCA*.

[11] Shoulin Yin and Hang Li, *GSAPSO-MQC: Medical Image Encryption Based on Genetic Simulated Annealing Particle Swarm Optimization and Modified Quantum Chaos System*.

[12] Guodong Ye, Chen Pan, Xiaoling Huang, and Qixiang Mei, *GSAPSO-MQC: Medical Image Encryption Based on Genetic Simulated Annealing Particle Swarm Optimization and Modified Quantum Chaos System*.

[13] Kurunandan Jain, Aravind Aji, and Prabhakar Krishnan, *Medical Image Encryption Scheme Using Multiple Chaotic Maps*.

[14] A.M. El-Assy, Hanan M. Amer, H.M. Ibrahim, and M.A. Mohamed, *A Novel CNN Architecture for Accurate Early Detection and Classification of Alzheimer's Disease Using MRI Data*.

[15] Kevin de Silva and Holger Kunz, *Prediction of Alzheimer's Disease from Magnetic Resonance Imaging Using a Convolutional Neural Network*.

[16] Jong Bin Bae, Subin Lee, Wonmo Jung, Sejin Park, Weonjin Kim, Hyunwoo Oh, Ji Won Han, Grace Eun Kim, Jun Sung Kim, Jae Hyoung Kim, and Ki Woong Kim, *Identification of Alzheimer's Disease Using a Convolutional Neural Network Model Based on T1-Weighted Magnetic Resonance Imaging*.

[17] Amir Ebrahimi, Suhuai Luo, and Raymond Chiong, *Deep Sequence Modelling for Alzheimer's Disease Detection Using MRI*.

[18] Weiming Lin, Tong Tong, Qinquan Gao, Di Guo, Xiaofeng Du, Yonggui Yang, Gang Guo, Min Xia, Min Du, and Xiaobo Qu, *Convolutional Neural Networks-Based MRI Image Analysis for the Alzheimer's Disease Prediction From Mild Cognitive Impairment*.

[19] Ahmed Khalid, Ebrahim Mohammed Senan, Khalil Al-Wagih, Mamoun Mohammad Ali Al-Azzam, and Ziad Mohammad Alkhraisha, *Automatic Analysis of MRI Images for Early Prediction of Alzheimer's Disease Stages Based on Hybrid Features of CNN and Handcrafted Features*.

[20] Deevyankar Agarwal, Manuel Álvaro Berbís, Antonio Luna, Vivian Lipari, Julien Brito Ballester, and Isabel de la Torre-Díez, *Automated Medical Diagnosis of Alzheimer´s Disease Using an Efficient Net Convolutional Neural Network*.

[21] Emtiaz Hussain, Mahmudul Hasan, Syed Zafrul Hassan, Tanzina Hassan Azmi, Md Anisur Rahman, and Mohammad Zavid Parvez, *Deep Learning Based Binary Classification for Alzheimer's Disease Detection Using Brain MRI Images*.

[22] Muhammad Umair Ali, Kwang Su Kim, Majdi Khalid, Majed Farrash, Amad Zafar, and Seung Won Lee, *Enhancing Alzheimer's Disease Diagnosis and Staging: A Multistage CNN Framework Using MRI*.

[23] Sanjiban Sekhar Roy, Raghav Sikaria, and Aarti Susan, *A Deep Learning Based CNN Approach on MRI for Alzheimer's Disease Detection*.

[24] Madhuri Unde and Abhishek Singh Rathore, *Brain MRI Image Analysis for Alzheimer's Disease Diagnosis Using Mask R-CNN*.