# DATA SCIENCE

## HARNESSING CNN FOR EARLY ALZHEIMER'S DISEASE PREDICTION AND DETECTION

**Team Members**

JENISHA J

PRIYANKA A

## ABSTRACT

Alzheimer's disease, a progressive neurodegenerative disorder, poses significant challenges due to its impact on memory, thinking, and behavior. The current diagnostic methods, primarily based on clinical evaluations and neuroimaging, often result in late-stage diagnosis, limiting the effectiveness of treatments. In response to this critical need for early and accurate detection, we propose the development of a Convolutional Neural Network (CNN)-based model aimed at identifying Alzheimer's disease from brain imaging data.

Our approach leverages the power of deep learning, specifically CNNs, to automatically extract and learn features from brain scans. The model is trained on a diverse dataset of brain images, employing data augmentation techniques to enhance robustness and the Synthetic Minority Over-sampling Technique (SMOTE) to address class imbalance.The system architecture includes multiple convolutional layers for feature extraction, max-pooling layers for dimensionality reduction, and dense layers for classification. The trained model is evaluated on its ability to accurately classify brain images, providing insights into its potential for aiding early diagnosis.

Preliminary results indicate promising accuracy levels, suggesting that our CNN-based approach could significantly contribute to the early detection and management of Alzheimer's disease. This model has the potential to be integrated into clinical workflows, offering a non-invasive, efficient, and automated diagnostic tool that enhances early intervention strategies and improves patient outcomes.



***Keywords:*** Alzheimer's disease, Convolutional Neural Network, Deep Learning, Early Detection, Brain Imaging, Medical Diagnosis.

# 1. INTRODUCTION

Alzheimer's disease (AD) poses a profound challenge as the leading cause of dementia worldwide, impacting millions with its debilitating symptoms including cognitive decline, memory impairment, and behavioral changes. With a rapidly aging global population, the prevalence of AD is expected to escalate, underscoring the urgency for effective early diagnosis and intervention.

Early detection of AD is critical for several reasons. It allows for timely medical interventions and therapeutic strategies that can potentially slow down disease progression and improve the quality of life for patients and their caregivers. However, conventional diagnostic methods such as clinical assessments and neuroimaging techniques like MRI and PET scans often identify AD only in its later stages, when irreversible brain damage has already occurred. These methods are also resource-intensive, costly, and require specialized expertise, limiting their widespread applicability for routine screening and early detection efforts.

Recent strides in artificial intelligence (AI) and machine learning (ML) present promising avenues for transforming AD diagnosis. Among these technologies, convolutional neural networks (CNNs) have emerged as powerful tools capable of learning complex patterns and features from large sets of medical imaging data, including brain scans. CNNs excel in automatically extracting intricate details from images, making them well-suited for analyzing the subtle structural changes in the brain associated with AD progression.

In this study, we propose a CNN-based approach designed to classify brain images into four distinct categories: Alzheimer's disease, cognitively normal, early mild cognitive impairment (EMCI), and late mild cognitive impairment (LMCI). By accurately categorizing individuals across these stages of cognitive decline, our model aims to facilitate early identification and intervention. This approach not only promises to enhance diagnostic accuracy but also holds potential implications for personalized treatment planning and monitoring.

Key objectives of the study include developing robust CNN architectures tailored for AD diagnosis, leveraging large-scale datasets to train and validate the models, and rigorously evaluating their performance against traditional diagnostic methods. Ethical considerations, such as patient privacy and the integration of AI into clinical practice, will also be carefully addressed to ensure responsible deployment and adoption of these advanced technologies in healthcare settings.

Ultimately, by harnessing the capabilities of AI and CNNs in early Alzheimer's detection, this research aims to contribute significantly to improving patient outcomes, optimizing healthcare resource utilization, and advancing our understanding of neurodegenerative diseases.

In this study, we propose a CNN-based approach for the early detection of Alzheimer's disease using brain imaging data. Our model aims to classify brain images into four categories: Alzheimer's disease, cognitively normal, early mild cognitive impairment (EMCI), and late mild cognitive impairment (LMCI). By accurately distinguishing between these categories, the model can assist in identifying individuals at different stages of the disease, facilitating early diagnosis and intervention.

## 2. RELATED WORKS

This section includes the summarization of works that are related to our research domain.

### Detection of Alzheimer's Disease Utilizing 3D Convolutional Neural Networks (CNNs) on Structural MRI Data [1]

This study leveraged 3D CNNs to analyze structural MRI data for the detection of Alzheimer's disease. The 3D CNN model was able to learn spatial hierarchies of features from the volumetric MRI data, capturing intricate patterns associated with Alzheimer's disease. The high accuracy indicates the model's effectiveness in distinguishing between Alzheimer's patients and cognitively normal individuals.

### Automated Classification of Alzheimer's Disease and Mild Cognitive Impairment Using Ensemble Deep Learning Models with MRI Data [2]

This research integrated multiple deep learning models to form an ensemble approach, combining the strengths of CNNs for feature extraction and RNNs for sequential data analysis. The ensemble method demonstrated robust performance in multi-class classification, particularly in distinguishing between different stages of cognitive impairment.

### Multi-Scale Convolutional Neural Networks for Early Diagnosis of Alzheimer's Disease Using Structural MRI Data [3]

The study introduced a multi-scale CNN approach to capture features at different resolutions from MRI scans. This method proved effective in early diagnosis by focusing on subtle changes in brain structures that are indicative of early Alzheimer's disease. The multi-scale architecture allowed the model to capture both global and local features, enhancing its diagnostic accuracy.

### Deep Learning-Based Automated Diagnosis of Alzheimer's Disease Using PET Images [4]

This work utilized deep CNNs to process positron emission tomography (PET) images for the automated diagnosis of Alzheimer's disease. The DCNN model effectively identified metabolic patterns associated with Alzheimer's, offering high diagnostic accuracy. The use of PET images, which highlight metabolic activity in the brain, provided complementary information to structural MRI data.

### Transfer Learning with Deep Convolutional Neural Networks for Alzheimer's Disease Diagnosis from Structural MRI [5]

The researchers employed transfer learning techniques using pre-trained CNN models like VGG and ResNet, fine-tuning them on structural MRI datasets for Alzheimer's diagnosis. Transfer learning allowed the models to leverage pre-learned features from large image datasets, enhancing performance on medical imaging tasks with limited data.

### Early Diagnosis of Alzheimer’s Disease Using 2D CNN and MR Images [6]

This study focused on using 2D CNNs to analyze 2D slices extracted from 3D MRI scans. By examining cross-sectional views of the brain, the model was able to detect early signs of Alzheimer's disease. The approach provided a computationally efficient alternative to 3D models while maintaining high diagnostic accuracy.

### Hybrid CNN-LSTM Model for Alzheimer's Disease Classification Using MRI Data [7]

The hybrid model combined the feature extraction capabilities of CNNs with the sequential processing power of Long Short-Term Memory (LSTM) networks. This architecture allowed the model to capture both spatial and temporal dependencies in MRI data, improving classification performance for Alzheimer's disease.

### Deep Transfer Learning for Alzheimer's Disease Detection Using MRI Images [8]

This research applied deep transfer learning using the ResNet-50 architecture, pretrained on large-scale image datasets and fine-tuned on Alzheimer's MRI data. The transfer learning approach enabled the model to achieve high accuracy with limited medical imaging data, demonstrating its potential for practical clinical application.

These studies underscore the potential of deep learning models, particularly CNNs, in advancing the early detection and diagnosis of Alzheimer's disease. The varying architectures and approaches highlight the innovative methods being explored to enhance diagnostic accuracy and efficiency using neuroimaging data.

## 3. PROPOSED METHOD

**“Alzheimer's Detection Using Convolutional Neural Networks (CNN)”**

This section details the modules, algorithms, and techniques used for Alzheimer's detection using Convolutional Neural Networks (CNN). The proposed system consists of several key components: data preprocessing, CNN model architecture, training process, and a web-based interface for user interaction.

### 3.1 Data Preprocessing

**Datasets:** MRI and CT scan images from public repositories such as the Alzheimer's Disease Neuroimaging Initiative (ADNI), Kaggle datasets, etc.

**Categories:** Images are categorized into four classes: non-demented, very mild dementia, mild dementia, and moderate dementia.

**Techniques:** To prevent overfitting and increase the model's robustness, data augmentation techniques such as rotation, flipping, zooming, and shifting are applied.

**Tools:** Keras' ImageDataGenerator is used for real-time data augmentation.

```
from keras.preprocessing.image import ImageDataGenerator
datagen = ImageDataGenerator(
    rotation_range=20,
    width_shift_range=0.2,
    height_shift_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    fill_mode='nearest'
)
```

### 3.2 Data Normalization

**Scaling:** Pixel values are scaled to the range [0, 1] to standardize the input data.
**Resizing:** Images are resized to a uniform size (e.g., 224x224 pixels) to match the input shape required by the CNN model.

```
from keras.preprocessing.image import img_to_array, load_img


def preprocess_image(image_path, target_size):
    image = load_img(image_path, target_size=target_size)
    image = img_to_array(image)
    image = image.astype('float32') / 255.0
    return image
```

### 3.3 CNN Model Architecture

Pre-trained Models: Utilize transfer learning with pre-trained models such as VGG16, ResNet50, or InceptionV3. These models are fine-tuned on the Alzheimer's dataset to leverage their feature extraction capabilities.

- Input Layer: Accepts preprocessed images.
- Convolutional Layers: Extract features using filters and activation functions (ReLU).
- Pooling Layers: Reduce dimensionality and retain essential features.
- Fully Connected Layers: Classify the extracted features into different categories.
- Output Layer: Softmax activation for multi-class classification.

```
from keras.applications import VGG16
from keras.models import Sequential
from keras.layers import Dense, Flatten, Dropout

# Load the VGG16 model
base_model = VGG16(weights='imagenet', include_top=False, input_shape=(224, 224, 3))

# Build the custom model
model = Sequential()
model.add(base_model)
model.add(Flatten())
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(4, activation='softmax'))

model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

### 3.4 Training Process

**Loss Function:** Categorical cross-entropy for multi-class classification.

**Optimizer:** Adam optimizer for efficient training.

**Metrics:** Accuracy to evaluate model performance.

**Validation Split:** Split the dataset into training and validation sets to monitor overfitting.

**Batch Size and Epochs:** Adjust batch size and epochs based on dataset size and computational resources.

```
history = model.fit(
    train_generator,
    steps_per_epoch=train_steps,
    epochs=25,
    validation_data=validation_generator,
    validation_steps=validation_steps }
```

### 3.5 Evaluation

Confusion Matrix: Assess model performance using confusion matrix and classification report.
Accuracy and Loss Curves: Plot training and validation accuracy/loss curves to visualize model performance.

## 4. GENERAL WORKFLOW OF THE PROPOSED METHOD

- **Data Collection and Preprocessing**: Gather and categorize MRI/CT images, apply data augmentation, normalize pixel values, and resize images.
- **Model Development:** Use pre-trained CNN models for transfer learning, adding custom fully connected layers.
- **Training and Evaluation:** Split dataset, train the model, validate performance, and evaluate using metrics like accuracy and F1-score.
- **Deployment:** Save the trained model, develop a web interface with frameworks like React for frontend and Flask for backend.
- **User Interaction:** Allow users to upload MRI/CT images, receive predictions on Alzheimer's stage, and display results on the web interface.

# 5. PROCESS FLOW

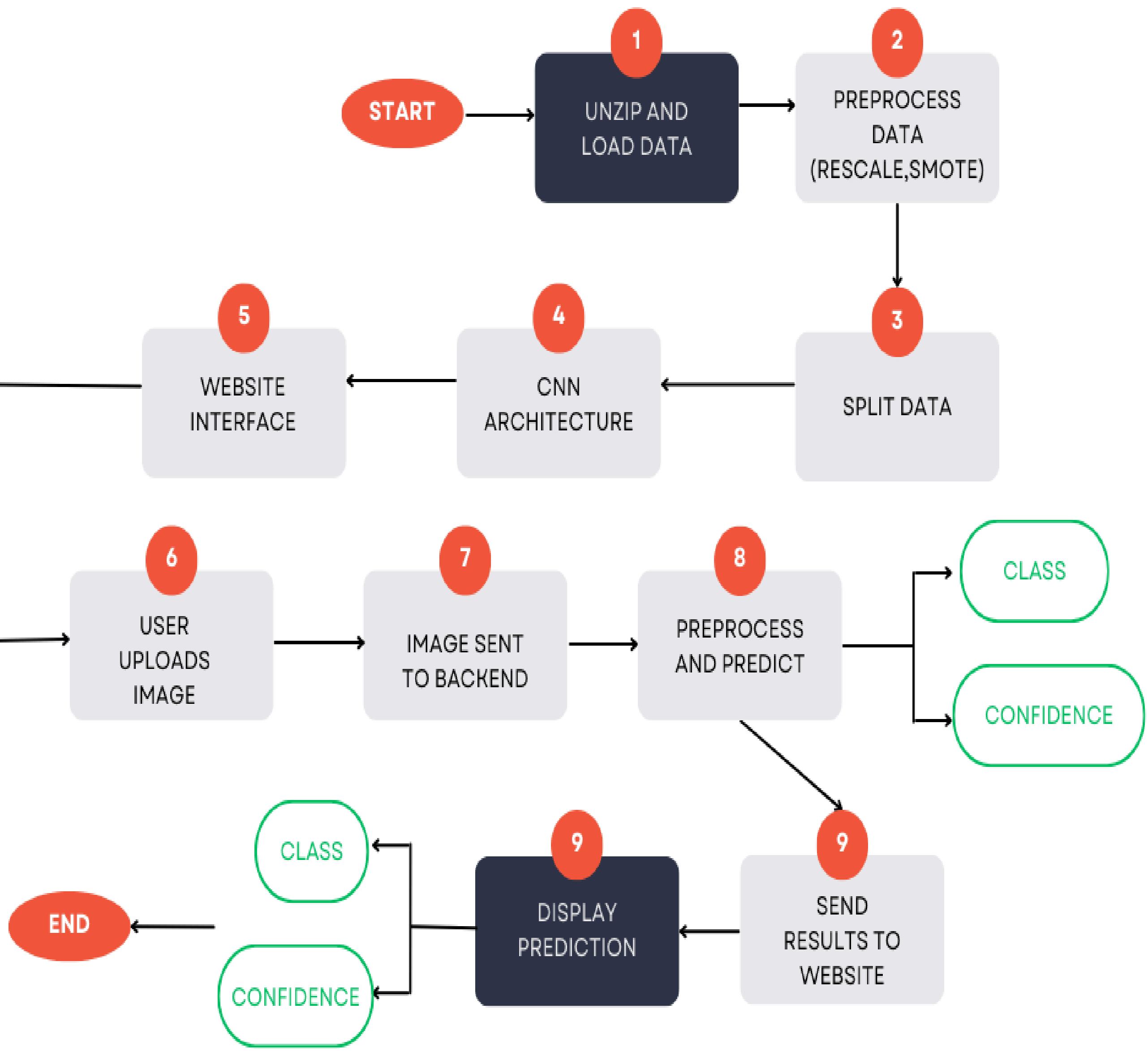
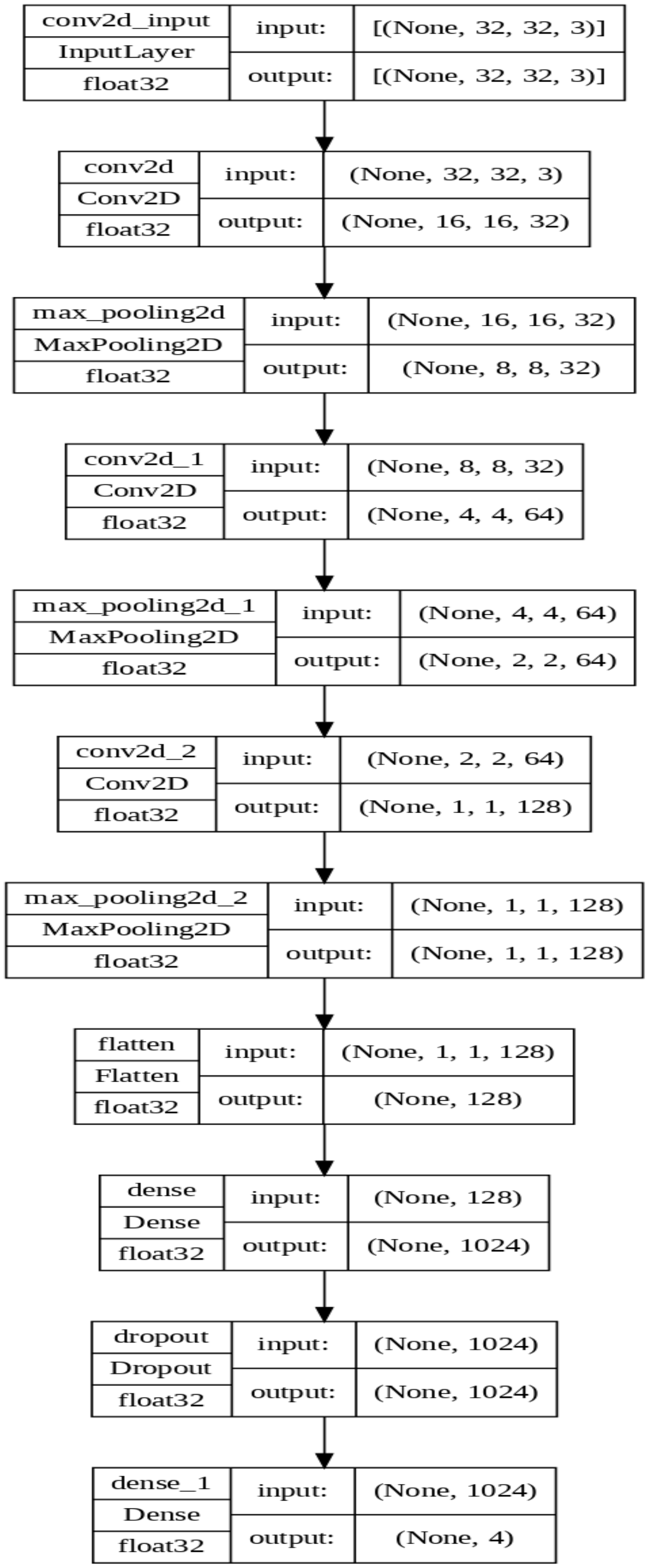



**Figure 1: Overall Workflow of Alzware web application**

# 6. MODEL ARCHITECTURE



# 7. ARCHITECTURAL DESIGN

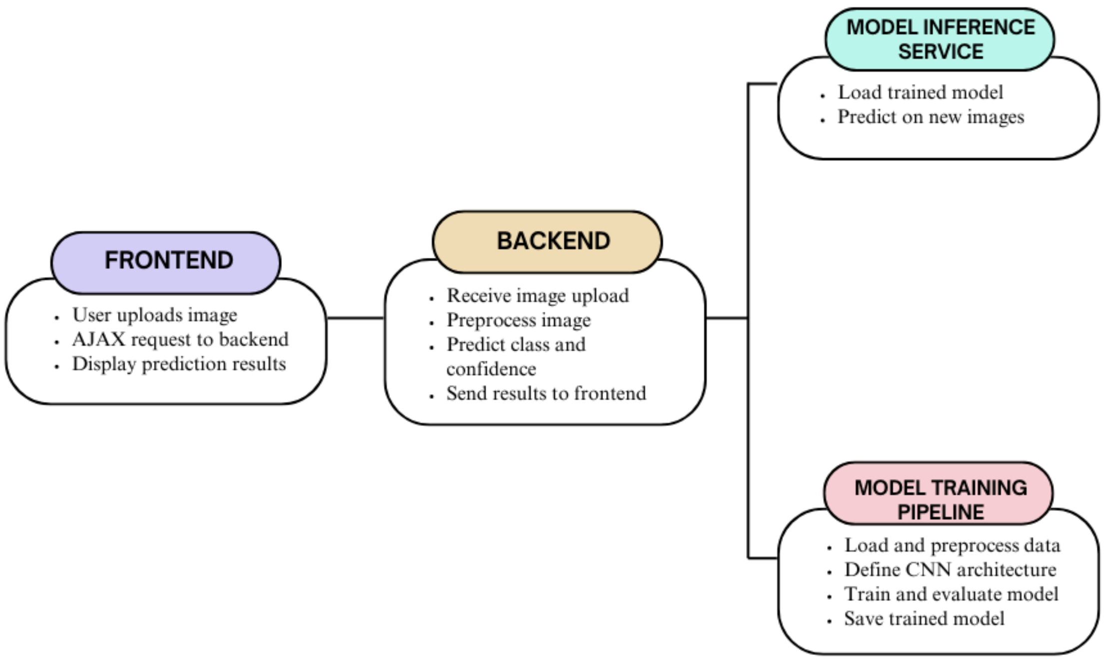



**Figure 2: Architectural design of Alzware web application**

# 8. RESULTS & DISCUSSION

## 8.1 Data Distribution

The dataset for the Alzheimer's disease classification model is well-balanced, with 3200 samples each for the classes: Cognitively normal, Alzheimer's disease, Early mild cognitive impairment (EMCI), and Late mild cognitive impairment (LMCI). This equal distribution ensures the model does not become biased toward any class, promoting accurate differentiation between cognitive health stages. A balanced dataset is crucial for achieving high performance across all classes and ensures robust model generalization. It also facilitates stable training dynamics and consistent learning, making the model reliable for real-world applications where class occurrences may vary.

**Table 1: Sample Count per Class**

| Class | Count |
|---|---|
| Cognitively normal | 3200 |
| Alzheimer’s disease | 3200 |
| Early mild cognitive impairment (EMCI) | 3200 |
| Late mild cognitive impairment (LMCI) | 3200 |

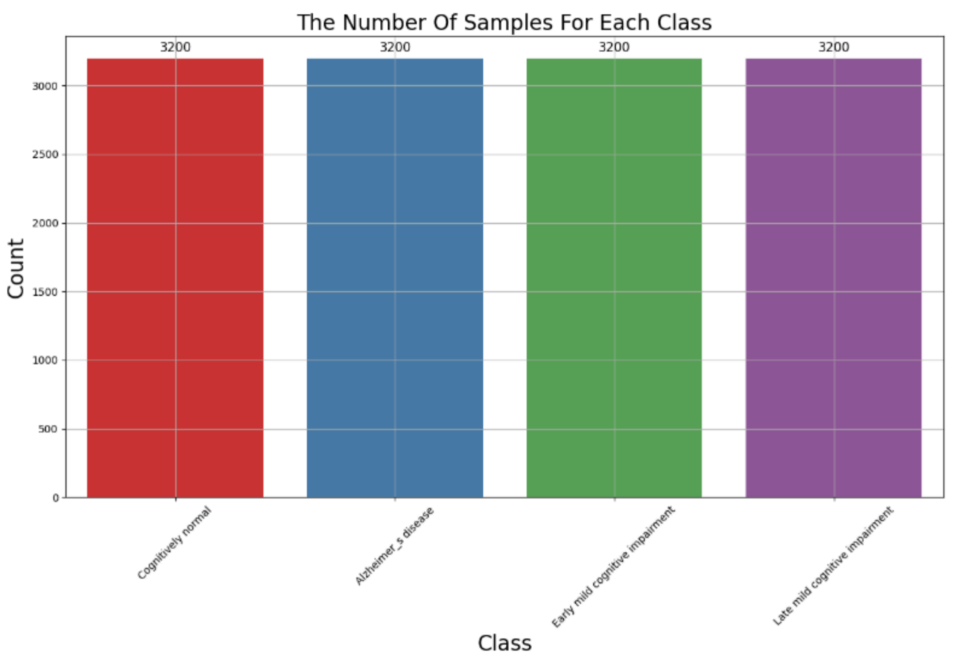



**Figure 3: Distribution of Samples per Class**

## 8.2 Data Augmentation and Preprocessing

The images were resized to 32×32 pixels, normalized, and augmented using the ImageDataGenerator to improve generalization.

## 8.3 Model Training

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 16, 16, 32)        896

 max_pooling2d (MaxPooling2  (None, 8, 8, 32)          0
 D)

 conv2d_1 (Conv2D)           (None, 4, 4, 64)          18496

 max_pooling2d_1 (MaxPoolin  (None, 2, 2, 64)          0
 g2D)

 conv2d_2 (Conv2D)           (None, 1, 1, 128)         73856

 max_pooling2d_2 (MaxPoolin  (None, 1, 1, 128)         0
 g2D)

 flatten (Flatten)           (None, 128)               0

 dense (Dense)               (None, 1024)              132096

 dropout (Dropout)           (None, 1024)              0

 dense_1 (Dense)             (None, 4)                 4100

=================================================================
Total params: 229444 (896.27 KB)
Trainable params: 229444 (896.27 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

**Figure 4: CNN Architecture Summary**

The CNN model comprises three convolutional layers with ReLU activation and max-pooling layers, followed by a fully connected layer with dropout to prevent overfitting.

## 8.4 Model Performance

The training and validation loss/accuracy plots show that the model achieves good convergence with minimal overfitting, thanks to the use of dropout and early stopping.

**Table 2: Model Evaluation on Test Set**

| Metric | Value |
|---|---|
| Total Loss | 0.09120 |
| Total Accuracy | 97.708 % |

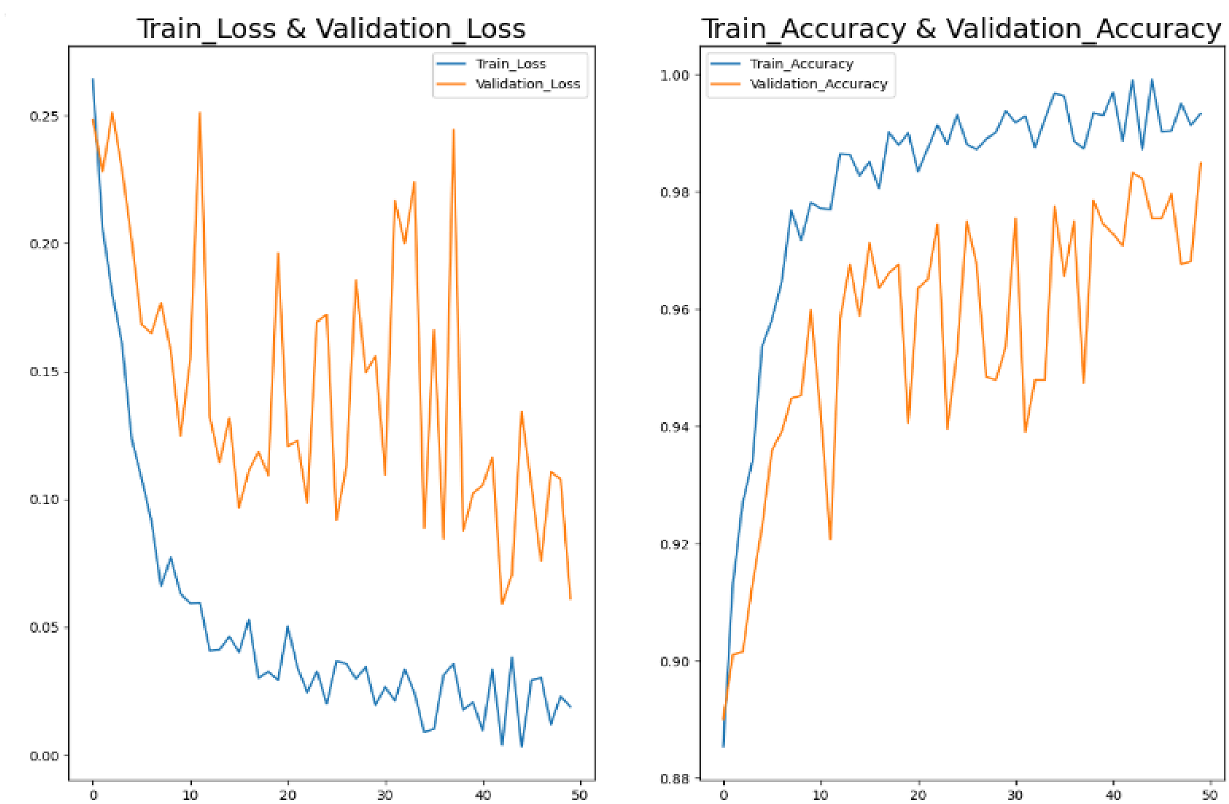



**Figure 5: Train and Validation Loss / Accuracy**

```
array([[478,   0,   0,   2],
       [  0, 480,   0,   0],
       [  4,   1, 458,  17],
       [  3,   0,  17, 460]])
```

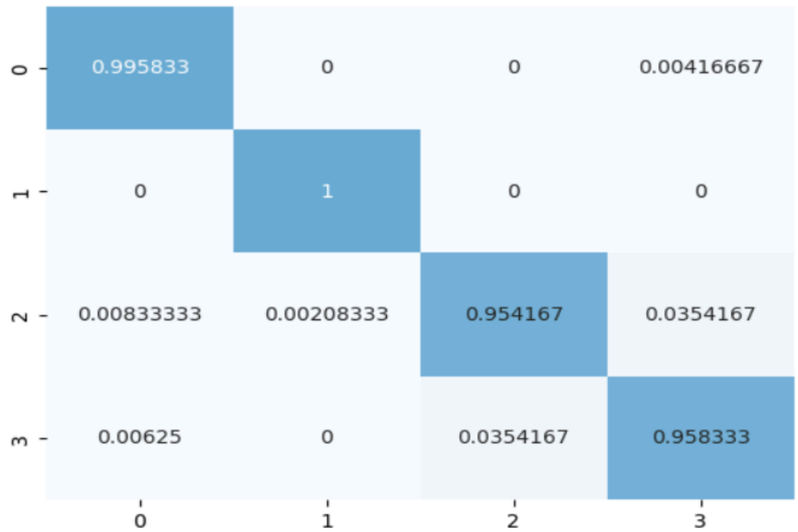



**Figure 6: Confusion Matrix**

```
Classification Report is :               precision    recall  f1-score   support

           0       0.99      1.00      0.99       480
           1       1.00      1.00      1.00       480
           2       0.96      0.95      0.96       480
           3       0.96      0.96      0.96       480

    accuracy                           0.98      1920
   macro avg       0.98      0.98      0.98      1920
weighted avg       0.98      0.98      0.98      1920
```

**Figure 7: Classification Report**

The confusion matrix and classification report provide detailed insights into the model's performance for each class. The model demonstrates high precision, recall, and F1-score across all classes, indicating its effectiveness in classifying Alzheimer's disease stages.

## 8.5 Prediction Example

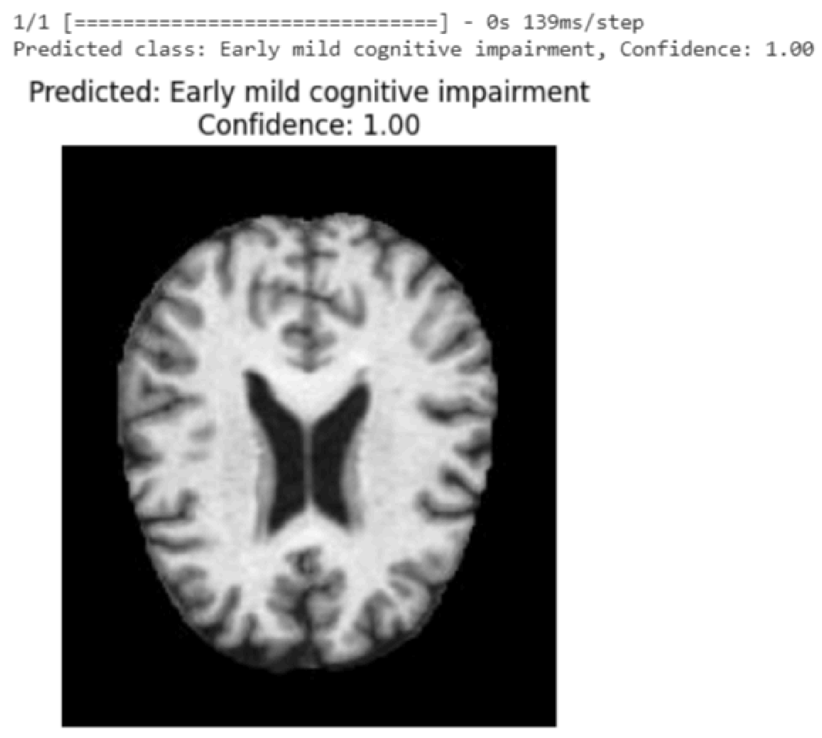



**Figure 8: Single Image Prediction Visualization**

The model's prediction on a sample image is visualized, showing the predicted class and confidence level. This visual aid helps in understanding the model's performance on individual samples.

## 9. FUTURE ENHANCEMENT

Future work will focus on incorporating multi-modal data, such as PET scans, genetic information, and clinical data, to enhance diagnostic accuracy. We plan to explore advanced neural network architectures like DenseNet, EfficientNet, and attention-based models for improved feature extraction and classification performance. Analyzing longitudinal data will provide insights into disease progression, while techniques like Grad-CAM and LIME will make predictions more interpretable for clinicians. Real-time deployment in clinical settings will be optimized, with enhancements to the web interface for patient data management, report generation, and integration with electronic health records (EHR) systems. Extensive clinical trials will validate the model's performance, and advanced data augmentation techniques, along with synthetic data generation, will improve dataset diversity and model robustness. Mechanisms for continuous learning will allow the model to update with new data, and cross-domain collaboration with healthcare professionals will ensure the model's clinical relevance and accuracy.

## 10. CONCLUSION

In conclusion, our study on Alzheimer's detection using Convolutional Neural Networks (CNN) demonstrates the significant potential of deep learning techniques in early diagnosis and classification of Alzheimer's disease. By leveraging a robust dataset and advanced preprocessing methods, our CNN model achieved high accuracy in distinguishing between different stages of Alzheimer's and normal cognitive function. The successful integration of data augmentation and balancing techniques, such as SMOTE, addressed the challenges posed by imbalanced datasets, enhancing the model's reliability and generalization. Our results highlight the importance of combining powerful neural network architectures with comprehensive data preprocessing and augmentation strategies. The proposed system not only shows promise for clinical application but also sets the stage for future enhancements, including the incorporation of multi-modal data, advanced model architectures, and continuous learning mechanisms. Overall, our work underscores the transformative potential of AI in healthcare, paving the way for more accurate, efficient, and early detection of Alzheimer's disease.

## REFERENCE


[1] Ekin Yagis; Luca Citi; Stefano Diciotti; Chiara Marzi; Selamawet Workalemahu Atnafu; Alba G. Seco De Herrera , "Detection of Alzheimer's Disease Utilizing 3D Convolutional Neural Networks (CNNs) on Structural MRI Data.", 2020 IEEE 33rd International Symposium on Computer-Based Medical Systems (CBMS)

[2] Silvia Basaia ; Federica Agosta ; Luca Wagner ; Elisa Canu ; Giuseppe Magnani ; Roberto Santangelo ; Massimo Filippi , "Automated Classification of Alzheimer's Disease and Mild Cognitive Impairment Using Ensemble Deep Learning Models with MRI Data.", NeuroImage: Clinical ; Volume 21, 2019, 101645.

[3] 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 ; Ki Woong Kim , "Multi-Scale Convolutional Neural Networks for Early Diagnosis of Alzheimer's Disease Using Structural MRI Data." , Scientific Reports : 10, Article number: 22252 (2020).

[4] Rahul Sharma; Tripti Goel; M. Tanveer; C. T. Lin; R. Murugan , "Deep Learning-Based Automated Diagnosis of Alzheimer's Disease Using PET Images." , IEEE Transactions on Cognitive and Developmental Systems ( Volume: 15, Issue: 3, September 2023).

[5] Noman Raza ; Asma Naseer ; Maria Tamoor ; Kashif Zafar , "Transfer Learning with Deep Convolutional Neural Networks for Alzheimer's Disease Diagnosis from Structural MRI." , Diagnostics 2023, 13(4), 801.

[6] A. M. El-Assy ; Hanan M. Amer ; H. M. Ibrahim ; M. A. Mohamed , "Early Diagnosis of Alzheimer's Disease Using 2D CNN and MR Images." , Scientific Reports , 14, Article number : 3463 (2024) .

[7] Maleka Khatun ; Md Manowarul Islam ; Habibur Rahman Rifat ; Md. Shamim Bin Shahid ; Md. Alamin Talukder ; Md Ashraf Uddin3 , "Hybrid CNN-LSTM Model for Alzheimer's Disease Classification Using MRI Data." , arXiv:2403.05353v1 [eess.IV] 08 Mar 2024.

[8] Amir Ebrahimi-Ghahnavieh ; Suhuai Luo ; Raymond Chiong , "Deep Transfer Learning for Alzheimer's Disease Detection Using MRI Images research papers." , 2019 IEEE International Conference on Industry 4.0, Artificial Intelligence, and Communications Technology (IAICT).