The Journal of Computational Science and Engineering (TJCSE)
ISSN 2583-9055 (Media Online)
Vol 3, No 7, July 2025
PP 83–103

Detecting Alzheimer's Disease With Deep Learning

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Abstract
Alzheimer's disease (AD) is a neurological condition that worsens over time and has a major influence on memory, daily life, and cognitive function. For prompt intervention and to improve patients' quality of life, early identification of AD is essential. This study uses the MobileNet algorithm, a portable and effective deep learning architecture, to suggest a novel method for predicting Alzheimer's disease. In order to categorize and forecast Alzheimer's disease in its early stages, the MobileNet model is trained on medical imaging datasets, such as MRI or CT scans. The suggested solution is appropriate for deployment on resource-constrained devices, such as smartphones or embedded systems, because it makes use of MobileNet's computational efficiency to guarantee scalability and accessibility. To attain high accuracy, robustness, and generalizability, the model is subjected to extensive preprocessing and training. Evaluation of performance is conducted using metrics such as accuracy, precision, recall, and F1-score, demonstrating the effectiveness of the proposed solution

Keywords:
Convolutional neural network (CNNs) ,Magnetic Resonance Imaging (MRI), Feature Extraction, Transfer Learning, Cognitive Decline, Accuracy.,Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI),Neurodengenerative Disorders, Brain Atrophy, Dementia, Deep Neural Network(DNNs).

1. Introduction

Alzheimer's disease (AD) is a neurological condition that worsens over time and impacts daily activities, memory, and cognitive function. Effective intervention, which slows the progression of the disease and enhances the patient's quality of life, depends on early detection. Clinical evaluations, cognitive testing, and neuroimaging procedures like CT (Computerized Tomography) and MRI (Magnetic Resonance Imaging) scans areRecurrent neural networks (RNNs) and convolutional neural networks (CNNs[1]1), which show potential in datasets like OASIS and ADNI, aid in development. Data modalities like MRI, PET, and CSF are frequently used. Cognitive tests and neuropsychological tests provide valuable insights. Researchers employ transfer learning, data enrichment, and feature extraction. Using classification models, high sensitivity, specificity, and accuracy are achieved. Excel Gradient Boosting, Random Forest, and Support Vector Machines (SVM). Deep learning models outperform conventional machine learning methods. Multimodal fusion and ensemble learning improve detection accuracy. Class imbalance, interpretability, and data quality are some of the challenges. Future directions could include explainable AI, personalized medicine, and real-world applications. Widespread usage requires clinical integration and validation. Notable contributions are made.

Utilizing sophisticated preprocessing methods like augmentation, normalization, and picture scaling. A pre-trained MobileNet model is modified to categorize various stages of AD using transfer learning to improve model performance. Metrics like accuracy, precision, recall, and F1-score are used in performance evaluation to guarantee dependability.all part of traditional diagnostic methods. However, manual diagnosis can be costly, time-consuming, and prone to human mistake, which restricts its general use.
With its increased accuracy and efficiency, deep learning has become a potent tool for automating medical picture processing.This system's deployment on cloud-based or mobile platforms makes AD detection easier to access and cuts down on diagnostic delays. This AI-powered method offers a quick, dependable, and effective way to diagnose Alzheimer's disease early on while also increasing scalability and lowering healthcare expenses. One of the upcoming improvements is the incorporation of explainable AI (XAI).

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2. Literature Survey

The following gives an overview of the various methodologies used by various authors for disease prediction using machine learning methodologies. We can observe that there is fine comparison made between major deep learning algorithms whether they are able to predict the presence of the disease with a greater accuracy, achieving optimal performance. The research efforts presented by the authors in the following papers are focused in developing and evaluating a web-based tool for disease prediction

In [1], reviewed the use of machine learning and deep learning algorithms in diagnosing Alzheimer's, highlighting their potential in early detection.

In [2], proposed a hybrid gene selection pipeline combined with deep learning methods to improve classification accuracy, demonstrating significant improvements.

In [3], utilized convolutional neural network (CNN) models with pre-existing architectures and transfer learning to predict Alzheimer's disease, showing promising results.

In [4], conducted a comparative study using multiple transfer learning models for Alzheimer's classification, further supporting the efficiency of transfer learning in this domain.

In [5], advanced this work by using volumetric CNNs with transfer learning for both classification and visualization of Alzheimer's disease, offering insights into structural brain changes.

In [6], demonstrated the feasibility of automated classification of Alzheimer's and mild cognitive impairment using a single MRI scan with deep neural networks, simplifying the diagnostic process.

In [7], emphasized the importance of neuroimaging data in the classification and prognostic prediction of Alzheimer's through machine learning approaches.

In [8], presented a mini-review showcasing the application of deep learning algorithms in Alzheimer's detection, reaffirming their growing relevance.

In [9], proposed a deep learning method for automatic recognition of Alzheimer's from MRI data, achieving notable accuracy rates.

In [10], reviewed various machine learning and deep learning techniques employed in diagnosing Alzheimer's, providing a comprehensive overview of advancements in this area.

3. Methodology

This study uses MobileNet, a portable and effective deep learning architecture, to create an Alzheimer's disease (AD) prediction model in a methodical manner. There are several steps in the process, Including data collection, preprocessing, model training, evaluation, and deployment comprising gathering data, preprocessing, training models, assessing them, and implementing them.

1.Information Gathering

Medical imaging datasets are employed, including CT (Computerized Tomography) and MRI (Magnetic Resonance Imaging) images.
Labeled pictures of AD and non-AD cases can be found in publicly accessible databases such as OASIS (Open Access Series of Imaging Studies) and ADNI (Alzheimer's Disease Neuroimaging Initiative). The dataset is divided into three stages: Alzheimer's disease, mild cognitive impairment (MCI), and normal.
Labeled pictures of AD and non-AD cases can be found in publicly accessible databases such as OASIS (Open Access Series of Imaging Studies) and ADNI (Alzheimer's Disease Neuroimaging Initiative).
The dataset is divided into three stages: Alzheimer's disease, mild cognitive impairment (MCI), and normal.

2. Preprocessing Data

Resizing: Every image is scaled to fit the 224x224 pixel input size that MobileNet requires. Normalization: To increase the stability and convergence of the model, pixel intensity levels are normalized. Data augmentation: Methods including flipping, rotation, contrast enhancement, and noise addition are used to improve generalization and diversify datasets.

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3. Model Training and Selection

The architecture of MobileNet: Its lightweight design and use of depthwise separable convolutions allow it to maintain great accuracy at a lower computational cost. Learning Transfer: A MobileNet model that has been pr.e-trained using ImageNet

4. Assessment of the Model

Performance indicators are used to assess the trained model: Accuracy: Indicates how accurate a prediction is overall. Reliability in Alzheimer's case classification is ensured by precision and recall.

F1-score: Provides reliable performance by striking a balance between recall and precision. Confusion Matrix: Offers a thorough analysis of classification performance.

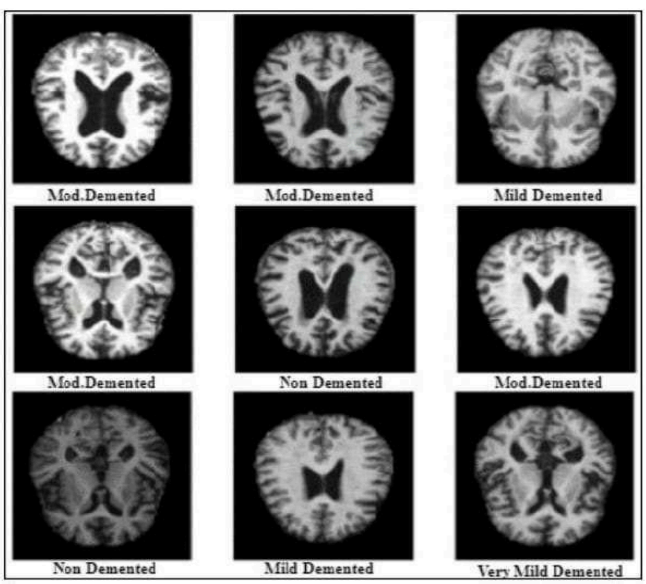
5. **Accessibility and Deployment**

The finished model is designed for embedded systems, cloud platforms, and mobile devices. On devices with limited resources, such as smartphones, Edge AI guarantees real-time AD detection. To help physicians with early diagnosis, the technology can be included into medical facilities and applications.

6. Upcoming Improvements

Hybrid Models: For increased accuracy, MobileNet is combined with other architectures (such as ResNet or Vision Transformers). Explainable AI (XAI): Visualizing model decisions through the use of tools such as Grad-CAM. Improving patient tracking and diagnosis history through integration with EHR systems.

STAGES OF ALZHEIMER'S DISEASE



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MRI image in Dataset

4. **Experimental Setup and Implementation**

Deep Learning Model Module

Description:

The Deep Learning Model Module is responsible for implementing and training a convolutional neural network (CNN)-based classifier for the detection of Alzheimer's disease. The implementation can be carried out using either TensorFlow or PyTorch frameworks, depending on developer preference or project requirements. For the model architecture, one can opt for a custom CNN designed specifically for the dataset, or leverage pretrained models such as VGG16, ResNet50, or DenseNet121, combined with fine-tuning techniques to improve performance. The model uses the categorical cross-entropy loss function, which is suitable for multi-class classification problems. For optimization during training, the Adam optimizer is used, as it is efficient and widely adopted for deep learning tasks.

Metrics: accuracy, precision, recall

```
# Sample model snippet (Keras)
model = Sequential([
  Conv2D(32, (3,3), activation='relu', input_shape=(224,224,3)),
  MaxPooling2D(),
  Flatten(),
  Dense(64, activation='relu'),
  Dense(3,
  activation='softmax')
])
```

2. Prediction & Inference Module

Description:

Loads trained model and predicts the class of uploaded MRI images. Implementation:

This module is designed to load the trained deep learning model and predict the class of user-uploaded MRI images. The implementation involves loading the saved model weights to ensure consistency with the training phase. Once a user uploads an MRI image, it is preprocessed in the same manner as the training data, including resizing, normalization, and possibly converting to grayscale or RGB depending on how the model was trained. After preprocessing, the image is passed through the model to obtain the predicted class, indicating whether the image shows signs of Alzheimer's disease or not.

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3. User Interface Module

Description: Allows users to interact with the system ,upload image, get predictions, download reports.

Implementation:

The User Interface Module enables users to interact seamlessly with the system by providing options to upload MRI images, receive predictions, and download diagnostic reports. This module can be implemented using web frameworks such as Streamlit, Flask, or Django, depending on the required level of customization and complexity. The interface includes key components such as a file uploader for image input, a submit button to trigger the prediction process, and a display area where the system presents the predicted result. Additionally, users are given the option to download a report, typically in PDF format, summarizing the prediction and any relevant model insights.

4. Report Generation Module

Description:Generates a detailed report of the diagnosis and model confidence.

Implementation:

The Report Generation Module is responsible for creating a comprehensive diagnostic report based on the model's output. This report includes the predicted class of the MRI image, the model's confidence level, and other relevant information to support the diagnosis. The implementation uses libraries such as fpdf, reportlab, and matplotlib to generate well-structured and visually informative PDF documents. Each report contains the uploaded MRI image, the prediction along with the confidence score, and the date and time of the analysis. Optionally, the report may also include a heatmap generated using Grad-CAM to visually highlight the regions of the brain that contributed most to the model's decision, adding interpretability to the output.

5. Grad-CAM Visualization Module (Optional)

Description: Displays heatmaps highlighting regions contributing to the prediction.

The Grad-CAM Visualization Module is an optional component designed to enhance interpretability by displaying heatmaps that highlight the regions of an MRI image contributing most to the model's prediction. This helps users, especially medical professionals, understand which parts of the brain the model focused on while making its decision. The implementation can be done using libraries such as keras-vis, tf-explain, or torchcam, depending on the deep learning framework in use. The generated heatmap is then overlaid on the original MRI image, allowing users to visually identify the activation zones that influenced the prediction.

6. Security & Data Handling Module

Description: Ensures safe upload, temporary storage, and deletion of sensitive medical data.

The Security & Data Handling Module is crucial for ensuring the safety and privacy of sensitive

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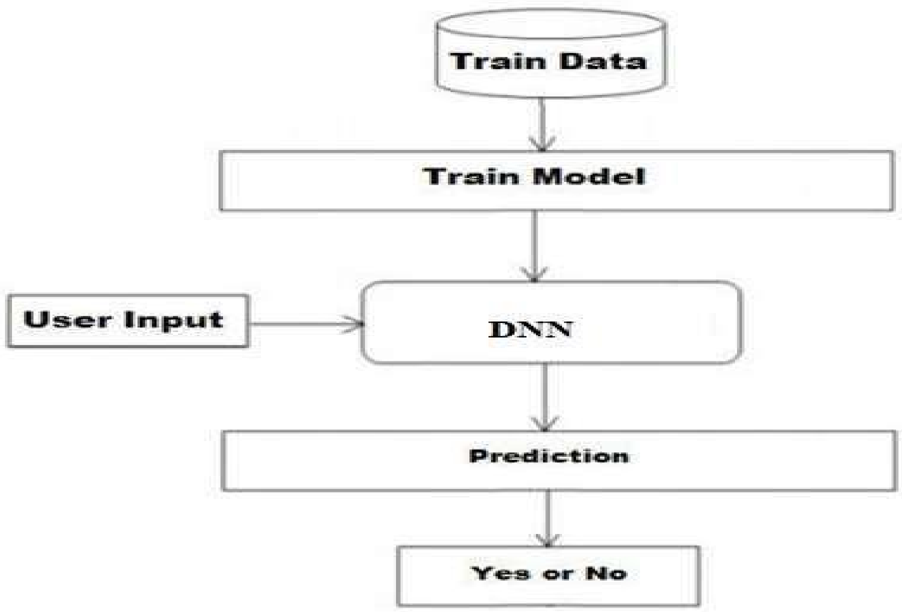
medical data, particularly MRI images. This module is responsible for securely handling file uploads, ensuring that any medical data processed through the system is stored temporarily and deleted automatically after processing. For secure file handling, tools such as werkzeug or tempfile
can be used to safely manage file uploads and prevent vulnerabilities. After processing the image and generating the prediction, the system automatically deletes the uploaded file to ensure that no sensitive data remains on the server. If the application is deployed online, it is essential to use HTTPS to encrypt the communication between the user's browser and the server, further ensuring the privacy and integrity of the data.

5. Proposed System



- The user input is received by the web application using HTML forms.
- The Web application makes use of HTTP modules to send and receive the data to the API's.
- The API's will receive the user input in the form of a JSON object (key-value pair).
- Trained DNN Models in the form of pickle files are consumed by the flask file housing at the local system
- The trained models are called by passing the user input JSON object
- Prediction result is sent as a response to the API calls.

Trained DNN Models were used to predict the presence of Dementia or Alzheimer Disease. Pre-processed standard datasets were used to train the models post normalizing the dataset using Standard Scalar.

Post training the models, these models where extracted as pickle files and are stored at a local location which is used by the flask framework to call the trained model by passing in the user input.

this project, algorithm has been implemented. In case of the likelihood of the features us assumed to be Gaussian i.e. all continuous values x associated with class y are distributed according to Gaussian distribution.

Given a continuous attribute x in training data, the data is first segmented by the class

Then, the mean and variance of x in each class is computed. If μ be the mean of the values in x associated with class y, then let d2 be the variance of the values in x associated with class y.

Suppose there is some observation value v then, the probability distribution of v given by class y, p(x=vy), can be computed by plugging into the equation for a normal distribution

6. Code Snippets

Building and Training a Convolutional Neural Network (CNN) Model

```
import    numpy    as    np
import pandas as pd
import    matplotlib.pyplot    as    plt
import cv2
import
tensorflow
import os

import
glob  labels
= []
for img in os.listdir('Dataset/'):
   img_folder = os.path.join('Dataset/',img)
   for       img_path       in       glob.glob(os.path.join(img_folder,"*.jpg")):
      labels.append(img)
len(labels)
```

```
images = []

def pre_process(img_path):
model.compile(optimizer=Adam(learning_rate=0.001), loss='categorical_crossentropy', metrics=['accuracy'])
model.summary()
history = model.fit(X_train, y_train, validation_data=(X_test,y_test),epochs=10,batch_size=32,verbose=1)
model.evaluate(X_test,y_test)

model.save('alzehmer_model.h5')
```

7. **Requirement Specification**

Data Acquisition: Use MRI, PET, and possibly CSF or blood-based biomarkers. Datasets should be big, varied (in terms of age, gender, and ethnicity), and well-annotated with clinical diagnoses. To reduce variability and increase the robustness of the model, use consistent image acquisition protocols. Use robust preprocessing steps, such as noise normalization, picture registration, and reduction to improve the quality of the data The term “maging equipment” describes the instruments used to take pictures of the brain. It isn't depicted in full, but it probably involves scanners for PET (Positron Emission Tomography) or MRI (Magnetic Resonance Imaging). These technologies offer comprehensive information on the anatomy and physiology of the brain.

The brain image is a visual depiction of the structure of the brain that is produced by imaging technology. Most likely, the diagram's central image is a cross-sectional (slice) depiction of the brain.

Image Segmentation: In this step, the brain image is processed to distinguish between various tissue types or areas. This could involve differentiating between cerebrospinal fluid, white matter, and grey matter. It aids in identifying the precise topics of interest for additional research.Feature Extraction After segmenting the image, pertinent features are taken out. These characteristics could include:

The size and volume of several brain regions, such as the hippocampus, which is essential for memory, are measured using volumetric methods.

Form and structural attributes: Cortical folding patterns and layer thickness in the brain. Metabolic activity: Uptake of glucose in various parts of the brain (important for PET scans).

Connectivity: The exchange of information between various brain regions.

AI-powered image recognition: This is the application of artificial intelligence, more especially machine learning models. An AI model that has already been trained is fed the retrieved features. Based on a sizable dataset of brain scans with established diagnoses, our program has trained to identify patterns linked to Alzheimer's disease. Identifying Alzheimer's Disease: After analyzing the features, the AI model offers a categorization or a likelihood that Alzheimer's disease is present. This could be a more thorough evaluation of the disease's stage and severity, or it could be a binary classification (Alzheimer's/No Alzheimer's). The diagram essentially depicts a pipeline:

Data Acquisition: Getting the brain image using scanners.Preprocessing: Preparing the image for analysis through segmentation.Feature Engineering: Extracting meaningful measurements from the image.Data preprocessing: To prepare the raw data for model training, this step entails cleaning and converting it. This include dealing with missing values, eliminating duplicates, and formatting data appropriately. Feature Selection: To train the model, the most pertinent features (variables) are selected from the dataset. This lowers complexity and enhances model performance.

Data splitting: The prepared dataset is separated into two or three subsets: a validation set, which is used to adjust the model's hyperparameters and avoid overfitting, a training set, which is used to train the model, and occasionally a separate test set, which is used to assess the model's performance in the end.

Assessment:

Model Training and Evaluation: This is the fundamental stage in which training data is used to train a machine learning algorithm. The data's linkages and patterns are discovered by the model. Here, "evaluation" most likely refers to preliminary examinations conducted during training.

Model Validation: The model's performance is evaluated on unseen data using the validation set. By doing this, the model is improved and overfitting is avoided. A magnifying glass is displayed over a green checkmark in the design, signifying a thorough and successful validation result. **Model Prediction:** Following training and validation, the model can be applied to forecast new unseen information. The image displays an upward-trending line graph that represents the predictive power of the model.

Performance Evaluation: The last phase entails assessing the model's performance using suitable metrics or, if available, on a held-out test set. This gives an unbiased assessment of the model's likelihood of doing well in actual situations. Performance measures are visually represented in the graphic, most frequently in the form of charts and graphs.

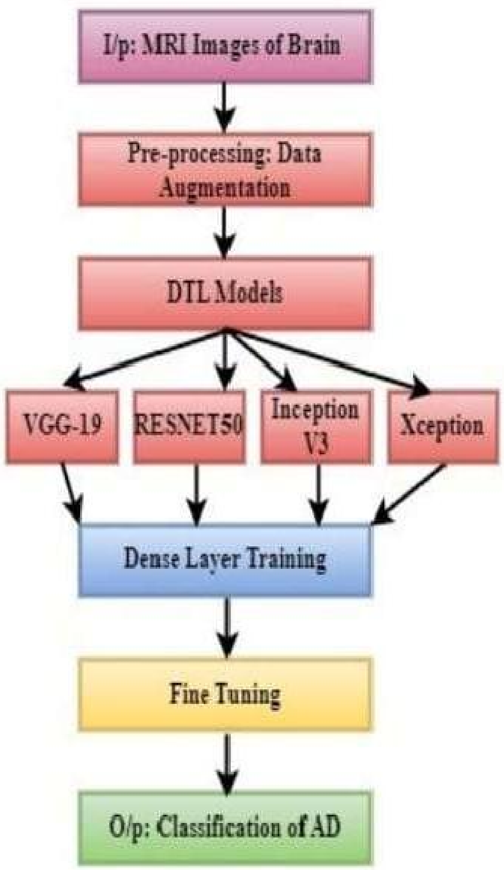


Diagram of the Architecture for ADClassification

8. **Dashboards**

   1- LANDING PAGE

   The landing page is where the accuracy of the platform of prediction will be shown, number of datasets images used for traning the model will be shown.

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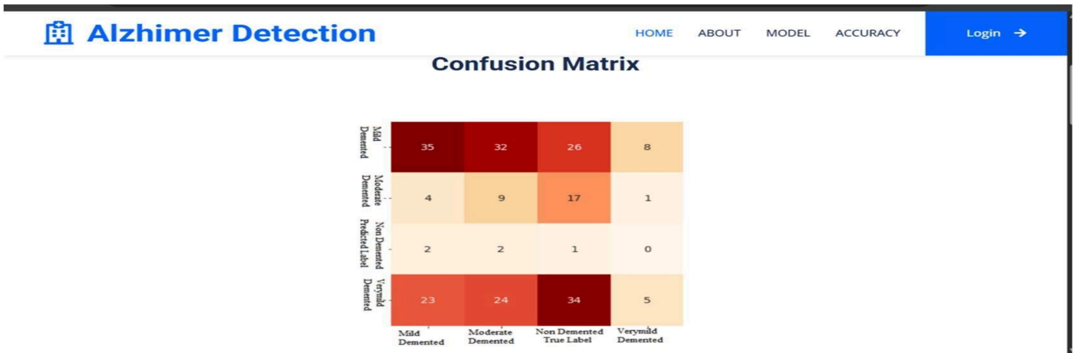
2- CONFUSION MATRIX

The confusion matrix for the Alzheimer's detection model reveals how well the model classifies different stages of dementia. It includes four classes: Mild Demented, Moderate Demented, Non Demented, and Very Mild Demented. The model performs best in identifying "Mild Demented" and "Very Mild Demented" patients, with 35 and 34 correct predictions respectively.



3- DIFFERENT CASES ON DATASET

There are 4 different cases on dataset, mild demented, moderate demented, non demented, very mild demented. Along with number of MRI images of each cases in used for training the model.

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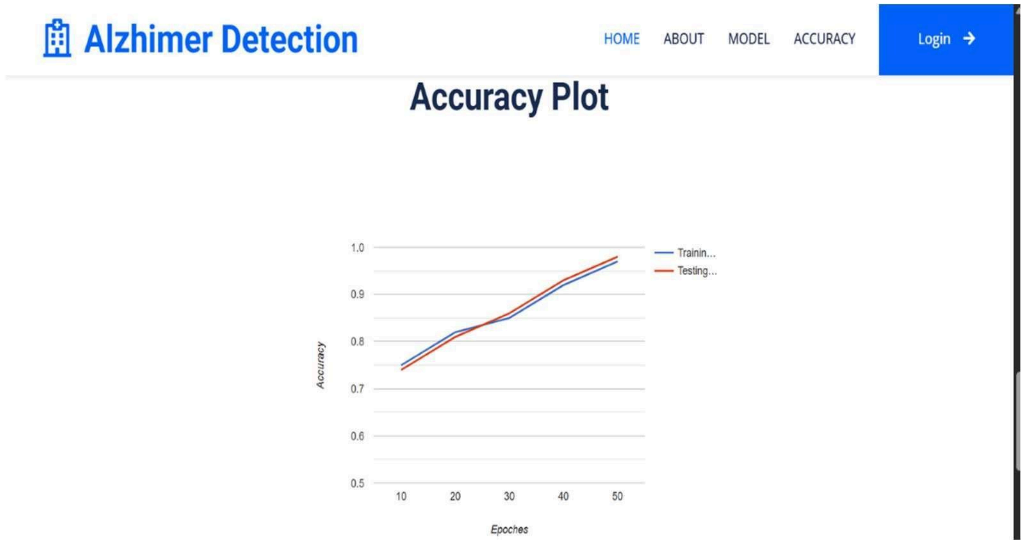
4- ACCURACY PLOT

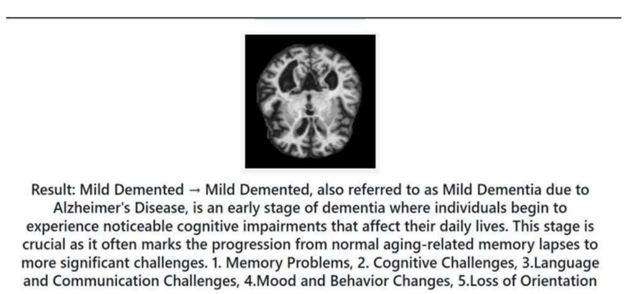
Here the users will be able to see, accuracy plot of our model on both testing and training dataset.



5- OUTPUT SCREEN

After Patients, sign in into the platform using his designated log in credentials, he will have to upload his MRI images. Those MRI images will be given to our model which will predict the type/stage of Alzheimer disease. The Output will be one of 4 types.

a) MILD DEMENTED



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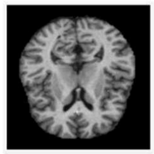
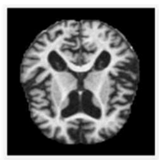
b) NON-DEMENTED



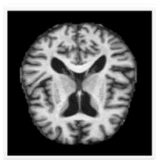
Result: Non Demented → Non-demented refers to individuals who do not exhibit significant cognitive decline or memory impairment severe enough to interfere with daily life. These individuals may still experience normal age-related cognitive changes but remain functionally independent. Understanding this group is crucial in Alzheimer's research and detection, as it helps differentiate between normal aging and early stages of dementia.

c) MODERATE DEMENTED



Result: Moderate Demented → Moderate dementia refers to a middle stage of cognitive decline, typically seen in conditions like Alzheimer's disease. In this stage, individuals experience significant memory loss and difficulties in performing everyday tasks, but they may still be able to engage in some level of independent living with assistance. 1. Memory Problems, 2. Cognitive Challenges, 3.Behavioral Changes, 4.Challenges with Daily Activities, 5.Increased Dependence

d) VERY MILD DEMENTED



Result: Verymild Demented → The Very Mild Demented (VMD) stage is an early phase of Alzheimer's disease and is often considered as part of Mild Cognitive Impairment (MCI). This stage is characterized by subtle symptoms that are usually difficult to detect but can interfere slightly with everyday activities. 1. Memory Problems, 2. Cognitive Challenges, 3.Behavioral Changes, 4.Daily Life Impact

9. **Result Analysis**

The studies are conducted using Python Keras and Tensor Flow. Three convolutional layers are used by the previously trained CNN model to analyze the original 227x227 pixel image. The feature matrix output 13 has 58 dense layers after the image has been converted to 128x128

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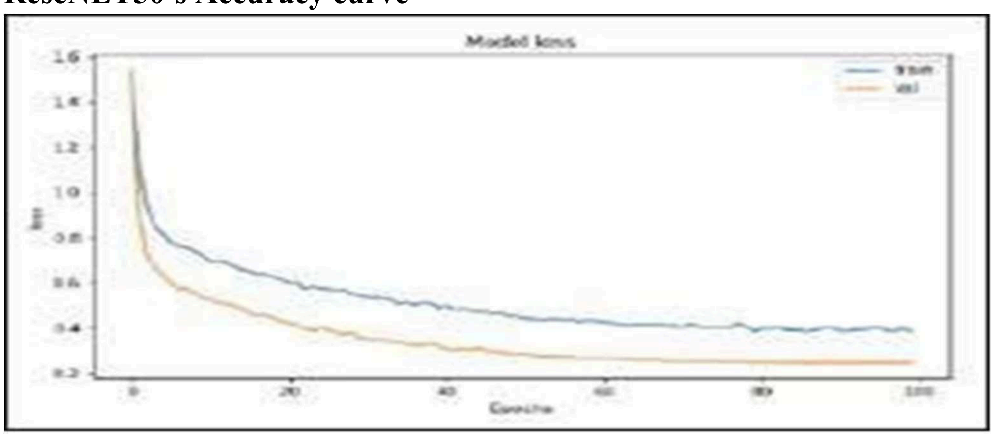
pixels. The optimization technique used in this work is called Adam. It not only helps to minimize loss but also makes it easier to modify the weight and bias parameters. Each test predictive analysis's 100 data epochs are depicted in the following graphics. Each epoch is represented by the x-axis, and loss levels are represented by the y-axis [9,10].

After 80 epochs, the model's training accuracy achieves its peak values after increasing progressively. The validation accuracy, on the other hand, starts to increase from the 40th epoch and reaches 0.90 percent. An example of the precision of the model

Figure 4 illustrates the results obtained in AD detection using a modified VGG-19 algorithm architecture. The validation loss reaches a constant state and converges faster than the training loss after 60 epochs, as seen in Figure 5. This confusion matrix shows how successful the VGG-19 model is. As shown above [13,14], the model can categorize 89% of the photos in the testing data. Architecture: The model accuracy attained by using the RESNET50 model for AD classification is demonstrated by RESNET50. The experiment's findings show that training accuracy stabilized at 0.60% after the tenth epoch, whereas validation accuracy rose to 0.70% by the fifth period. Figure 8 shows that after the 20th period, when the validation loss more rapidly reaches the initial training loss, a stable situation is reached. Confusion matrix, demonstrates the RESNET50 model's efficacy. This indicates that 68% of the photos in the testing dataset can be classified by the model [16–20].

ReseNET50's Accuracy curve



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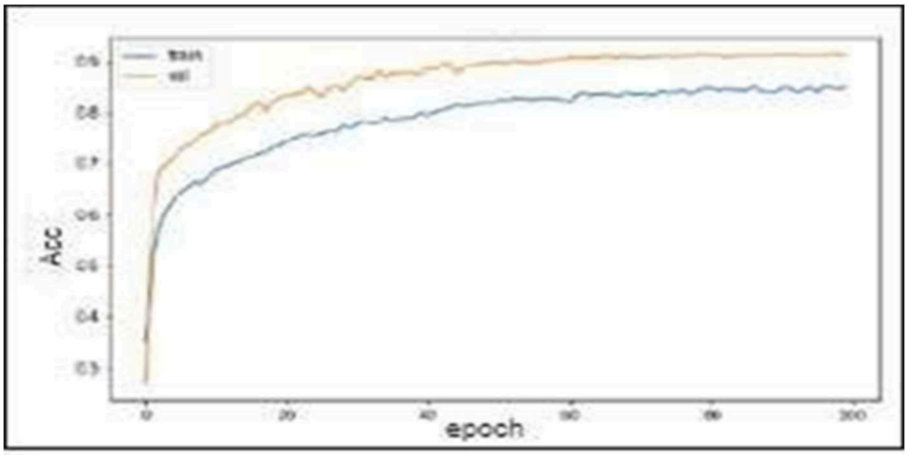
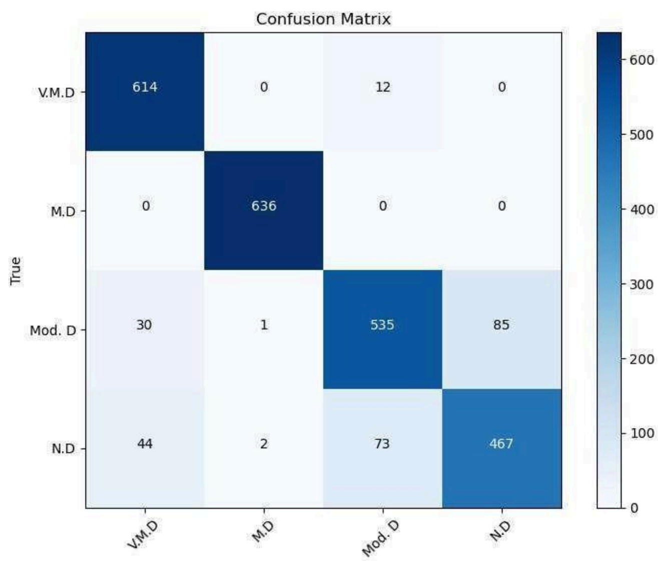
Vgg-19 model's Accuracy curve





Vgg-19 model's Accuracy curve

In comparison to the validation loss, the training loss converges more quickly and stabilizes after the 50th epoch. The effectiveness of the inception-v3 model is demonstrated by the confusion

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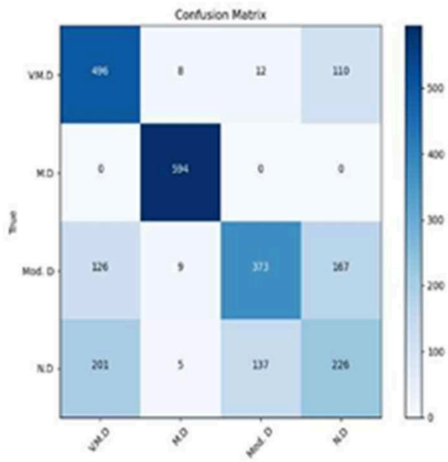
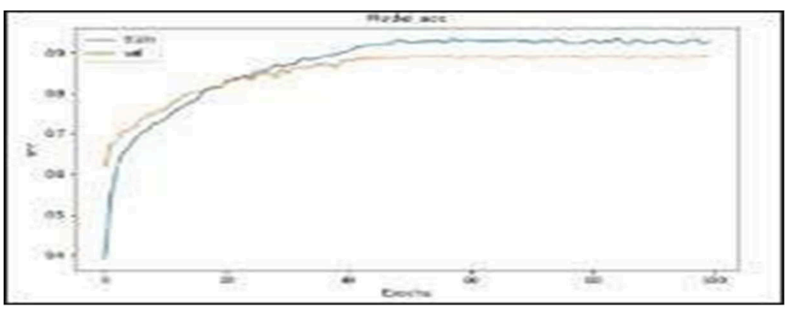
matrix. As demonstrated below, the model can categorize 89% of the photos in the testing set.

ResNet50's Confusion Matrix



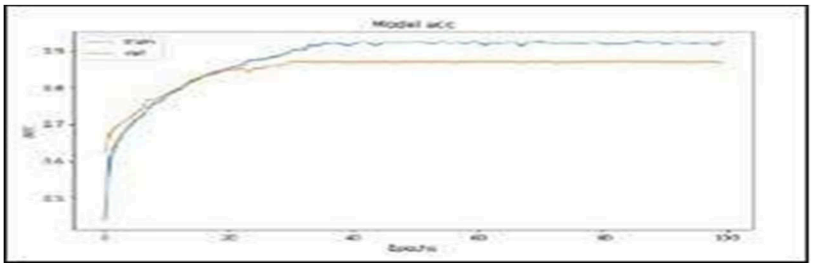
VGG-19 model's Loss Curve



CNN Architecture: Xception displays the attained model accuracy when utilizing the Xception model for AD categorization. During the trial, the training accuracy attained a steady level of 95% following the 40th epoch. The validation accuracy, on the other hand, showed a propensity to rise after the 29th epoch, ultimately hitting 85%. The simulated loss converges faster than the validationloss, as seen by the projected curve loss. The training loss reaches its steady state at the 25th epoch. The performance results of the Xception model are shown as a confusion matrix.
Based on the information provided above, it can be concluded that 87% of the photos in the testing dataset can be correctly classified by the model [21–28].

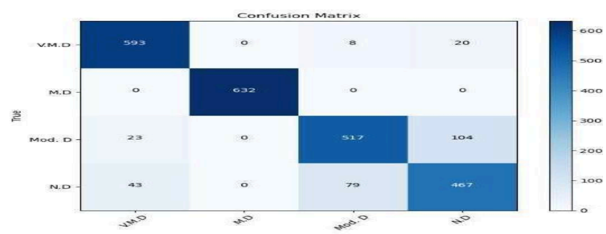
The most useful single-value statistic for this purpose is the Matthew's Correlation Coefficient (MCC), a classification measure that offers a succinct overview of the confusion matrix. The process outlined in equation 4 is used to carry out the computation.The TL models' Balanced Accuracy Score [15] is shown in the following after the optimization procedures have been changed.With a balanced Accuracy Score of 89.94%, the VGG model outperforms the other models when trained using the ADAM optimizer. shows how the MCC of TL models changes with various optimization techniques. When trained with the ADAM optimizer, the VGG model outperforms other models, achieving an MCC of 86.64%.

Inception-v3model'sAccuracy curve

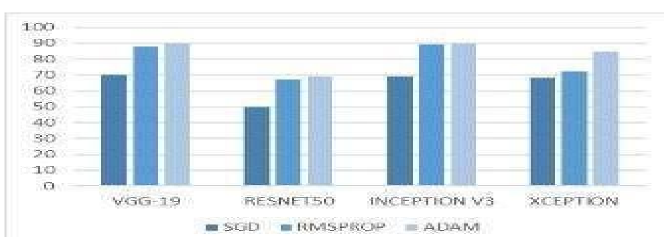


Inception -v3 model's loss curve

Xception model's Confusion Matrix



TL Model's Balance Accuracy Score Comparison



The Journal of Computational Science and Engineering (TJCSE)
ISSN 2583-9055 (Media Online)
Vol 3, No 7, July 2025
PP 83–103

Conclusion

In this study, 6400 MRI images that have been divided into four different categories are utilized to compare DTL models for the classification of AD. The ADASYN is used to carry out the data preparation process. The pretrained CNN model should produce better performance results if training and validation accuracy increase with each epoch. Overfitting problems are expected to occur on the design, specifically when training accuracy increases and validation accuracy decreases. Overfitting causes a model to become overly specialized to a certain set of training data, which leads to predictions for new datasets that are not correct.On the training and tested datasets, VGG-19 outperforms ResNet50, Xception, and Inception-v3 pretrained CNN models, according to the performance studies. Using population-based optimization strategies to train deep CNN models for more predictive analysis of AD is one strategy to advance the research.This study used a convolutional neural network (CNN) model to investigate the possibility of deep learning for Alzheimer's disease detection. The dataset used to train the model was divided into four dementia stages: mild, moderate, very mild, and non-demented. Following ten training epochs, the model demonstrated its capacity to understand intricate patterns in the data and generalize to previously unseen data with a high training accuracy of 98.95% and a validation accuracy of 92.97%. Additionally, analysis of a held-out test set produced an93.20% accuracy, demonstrating the model's potential for real-world use. These findings imply that automated Alzheimer's disease identification using [specify the data type used, such as MRI pictures, patient records, etc. if known] can be accomplished with deep learning approaches, especially CNNs. The model's ability to differentiate between dementia phases is demonstrated by the high accuracy attained.

It's crucial to recognize any potential restrictions, though. The discrepancy between training and validation accuracy raises the possibility of overfitting, which calls for additional research and mitigating measures like regularization or data augmentation.

Future Work

- To enhance the functionality of the prediction disease providing the details of 5 nearest hospitals or medical hospitals to the user input location.
- Provide a user account which allows the user to keep track of their medical test data and get suggestions or support to meet the right specialists or the tests to be taken
- Provide admin controls to upload, delete the dataset which will be used to train the model.
- Automate the process of training the model and extracting pickel files of the trained models

which will be consumed by the API's to predict the disease.

- Mail the detailed report of the prediction engine results along with the information of 5 nearest medical facilities details having location and contrast information

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