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ALZHEIMER'S DISEASE DETECTION USING DEEP LEARNING

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ABSTRACT

Image processing is a technique for applying various procedures to a picture in order to improve it or extract some relevant information from it. It is a kind of signal processing where the input is an image and the output may either be another picture or features or characteristics related to that image. Image processing is one of the technologies that is currently expanding quickly. It is a primary subject of research in both the engineering and computer science fields. For dementia, Alzheimer's disease (AD) is the most prevalent kind. It often shows itself as a steadily declining memory and cognitive function, which makes it difficult for the affected person to live independently and has a significant negative influence on both the affected personand society. At the moment,AD diagnosis depends on medical history analysis, blood testing, behavior analysis, brain imaging, and cognitive testing. But because these processes are arbitrary and uneven, it is difficult to provide a precise forecast for the early phases of AD challenging. A dynamic dual-graph fusion convolutional network is suggested in this paperto enhance the accuracy of Alzheimer's disease (AD) diagnosis. The key contributions of the paper are as follows: The proposed architecture can dynamically adjust the graph structure for GCN to produce better diagnosis outcomes by learning the optimal underlying latent graph, propose a novel dynamic GCN architecture, which is an end-to-end pipeline for diagnosing AD, incorporate feature graph learning and dynamic graph learning, giving those useful features of subjects more weight while reducing the weights of other noise features. Experiments show that our approach achieves great classification results in AD diagnosis while offering flexibility and stability. This project is implemented for the Alzheimer disease classification using Graph convolutional network architecture like CNN with LSTM layer and fit the model in the training and testing and deploy the modelfor getting the test image output and then compare the accuracy of the model for getting the most perfect model for medical image classification and get theaccuracy of CNN- LSTM layer with 98%.

CHAPTER 1 INTRODUCTION

1.1. INTRODUCTION TO IMAGE PROCESSING

Image Processing is a technique to enhance raw images received from cameras/sensors placed on satellites, space probes and aircraft or pictures taken in normal day-today life for various applications. Various techniques have been developed in Image Processing during the last four to five decades. Most of the techniques are developed for enhancing images obtained from unmanned space crafts, space probes and military reconnaissance flights. Image Processing systems are becoming popular due to easy availability of powerful personnel computers, large size memory devices, graphics software etc.

Image processing basically includes the following three steps:

- Importing an image with an optical scanner or digital photography.
- Analysis and image management including data compression and image enhancement and visual detection patterns such as satellite imagery.
- It produces the final stage where the result can be changed to an image or report based on image analysis.

Image processing is a way by which an individual can enhance the quality of an image or gather alerting insights from an image and feed it to an algorithm to predict the later things. There are two types of methods used for image processing namely, analogue and digital image processing. Analogue image processing can be used for the hard copies like printouts and photographs. Image analysts use various fundamentals of interpretation while using these visual techniques. Digital image processing techniques help in manipulation of the digital images by using computers. The three general phases that all types of data have to undergo while using digital technique are pre-processing, enhancement, and display, information extraction.

1.2 Problem Statement

Alzheimer’s disease (AD), the most common type of dementia, is a neuro degenerative disease that deteriorates brain connections, leading to memory impairment and decline in other cognitivefunctions.

The stages of AD can be divided into two stages: Mild Cognitive Impairment (MCI), and Alzheimer’s disease (AD). The MCI stage can be subdivided further into Early Mild Cognitive Impairment (EMCI) and Late Mild Cognitive Impairment (LMCI). Individuals with MCI face a significant risk in progressing into the late stages of Alzheimer’s. MCI patients experience a mild decline in memory and other cognitive functions. At a later stage, the patient would be Unable to respond to the environment or carry on a conversation. Therefore, early AD detectionwould significantly contribute to preventive treatment and help delay cognitive

Deterioration.

Accurate diagnosis of the disease requires a series of examinations: cognitive tests, blood tests, behavior assessments, brain imaging, and medical history analysis. However, the current examination relies explicitly on behavioral assessments and the patient's medical history

As pieces of evidence, which both demand multiple testing sessions by expert doctors over a long period. In this paper, initially read out and load the whole dataset and preprocess all the images in the datasets by the methods such as image re sizing, image filtering, image denoising, image enhancing. Then pre-processed image is fed for extract the features by the method curvelet transform and split the data into train and test for the prediction and classification.

1.3 Objective of the Project

Alzheimer's disease (AD) is the most common form of dementia. It usually manifests through Progressive loss of cognitive function and memory, subsequently impairing the person's ability to live without assistance and causing a tremendous impact on the affected individuals and society. Currently, AD diagnosis relies on cognitive tests, blood tests, behavior assessments, brain imaging, and medical history analysis. However, these procedures are subjective and inconsistent, making an accurate prediction for the early stages of AD difficult. At a same time Artificial Intelligence (AI) has been significantly developed in the recent years and offered substantial advantages in computer-based diagnostic systems. Over the past years, various efficient machine learning (ML) algorithms have been designed to improve disease diagnosis Accuracy. Research interests in this domain include both Support Vector Machine (SVM) and Deep Learning (DL) models.

This paper introduces a curvelet transform (CT) based-convolutional neural network (CNN) (DeepCurvMRI) model for improving the accuracy of early-stage AD disease detection using from Magnetic resonance imaging (MRI) images. The MRI images were first pre-processed using CT, and then a CNN model was trained using the new image representation. These encouraging results are superior to the ones reported in related methods, showcasing the potentiality of DeepCurvMRI in capturing the key anatomical changes in MRI images that

Can be differentiated between various staged of Alzheimer's disease classes.

- To improvise the accuracy with the comparison.
- To minimize the time complexity.
- To enhance the performance analysis.
- To implement the layer of LSTM with the CNN-model for more accurate value.

1.4 Usefulness/Relevance to the Society

In this paper, it demonstrates how Alzheimer disease classification and prediction of diseases in MRI images. In 2018, it was estimated that over 50 million people worldwide were living with dementia, and this number is expected to reach 152 million by 2050. The average life expectancy after AD diagnosis is 3-9 years, as currently, there is no cure for AD. MCI patients experience a mild decline in memory and other cognitive functions. At a later stage, the patient would be unable to respond to the environment or carry on a conversation. Therefore, early AD detectionwould significantly contribute to preventive treatment and help delay cognitive deterioration.
However, the current examination relies explicitly on behavioral assessments and the patient's medical history as pieces of evidence, which both demand multiple testing sessions by expert doctors over a long period. The latter increases the diagnosis cost and brings subjectivity and alterity to the diagnostic outcome. As a result, a more efficient and cost-effective diagnostic system is crucial. Recently, with the advancement in technology, several imaging techniques have been developed, such as Magnetic Resonance Imaging (MRI) Positron Emission Tomography (PET), and Computed Tomography (CT). These techniques are non-invasive, rapid, accurate, and are widely used to obtain additional information about AD diagnosis.

Chapter 2 Literature Survey

2.1 Suhad Al-Shoukry; Taha H. Rassem; Nasrin M. Makbol: 'Alzheimer's Diseases Detection by Using Deep Learning Algorithms: A Mini-Review', 2020

The accurate diagnosis of Alzheimer's disease (AD) plays an important role in patient treatment, especially at the disease's early stages, because risk awareness allows the patients to undergo preventive measures even before the occurrence of irreversible brain damage. Although many recent studies have used computers to diagnose AD.AD can be diagnosed-but not predicted-at its early stages, as prediction is only applicable before the disease manifests itself. Deep Learning (DL) has become a common technique for the early diagnosis of AD.

This imaging technique utilities radio waves and magnetic fields to generate high-quality and high-resolution 2D and 3D images of brain structures. No harmful radiations from X-rays or radioactive tracers is generated. The most commonly used MRI for AD cases is the structural MRI, which measures brain volumes in vivo to detect brain degeneration (loss of tissue, cells, neurons, etc.). Brain degeneration is an inevitable progressive component of AD.

Advantages:

- It may generate the prediction accurately.
- Compared to other techniques, Single-Photon Emission Computed Tomography (SPECT) is more economical than the other techniques

Dis Advantages:

- Classification takes so many time to process the images.
- Wavelet transform has major limitation is its inability to identify curved edges, which in
- Some cases causes false alarms.

2.2 Savita Dahiya; S. Vijayalakshmi; Munish Sabharwal: 'Alzheimer's disease Detection using Machine Learning: A Review', 2021

Researchers use a variety of novel approaches to classify Alzheimer's disease. Machine learning, an AI branch use probabilistic technique that allow system to acquire knowledge from huge amount of data. In this paper we represent a analysis report of the work which is done by researcher in this field. Research has achieved quite promising prediction accuracies however they were evaluated the the non-existent datasets from various imaging modalities which makes it difficult to make the fair comparison with the other methods comparison among them. It has achieved quite promising prediction accuracies however they were evaluated the the non- existent datasets from various imaging modalities which makes it difficult to make the fair comparison with the other methods comparison among them. In this paper, we conducted a studyon the effectiveness of using human brain MRI scansto detect Alzheimer's disease and ended with a future discussion of Alzheimer's research trends.

Advantages:

It also use the labelled dataset

Dis Advantages:

- It uses the LSTM and regression model for the prediction.
- Regular neural networks have been criticized for their poor classification performance when trained on the raw/un-preprocessed data.

2.3 Vrashikesh Patil; S L Nisha: 'Detection of Alzheimer's Disease Using Machine Learning and Image processing', 2021

The Alzheimer disease is caused by the Excess secretion of β−amyloidal peptide (Aβ) proteins

between neurons. The current study is focused on ventricular space and total brain area, which will be less for persons with Non dementia and higher for Alzheimer patients. A comparative study is made to detect the Alzheimer based on Region of interest (ROI) technique which utilizes image processing for classification. And Machine learning (ML) + image processing based Technique on MRI images for classification purpose. The inputimages were preprocessed for contrast equalization and noise reduction purpose, then ventricular space of Alzheimer's and Non-Alzheimer image were calculated in the form of ratio which will be acting as deciding factor in the "Decision tree" Algorithm. Ventricular volume for Alzheimer patients will be greater than Non dementia patients, acting as deciding factor. Present technique has been tested with confusion matrix for accuracy where we got up to 95 % accurate results. This has got upper hand to other technique which is able to give 86% accuracy using Region of interest (ROI) based technique. This technique can be used in medical field for detecting Disease in patients.

Advantages:

It only gives the machine learning for the classification and predication.

Dis Advantages:

- It only gives the classification for the limited number of classes.
- Time is too long for the classification purpose.

2.4 S. Pavalarajan; B.Arun Kumar; S.Shahul Hammed; K. Haripriya; C. Preethi; T. Mohanraj: 'Detection of Alzheimer's disease at Early Stage using Machine Learning', 2022

Identification of dementia is an important concern in medical image processing. Alzheimer is a common kind of dementia. Objective of distinguishing people with normal brain ageing from those who would develop Alzheimer's disease, this paper presents an effective machine learning model that successfully diagnosed AD, cMCI, ncMCI and CN which are being detected during pre-stages by itself. Four machine learning models were designed for identifying this disease. This is classified as a classification problem, and the classification algorithms tested include logistic regression, support vector classifier, decision tree, and random forest classifier. The models are fine-tuned by choosing optimal values for parameters that influences the accuracy of the model. The optimal parameters are found using a K-fold cross validation score, and the models are generated using that. The dataset used in the model is longitudinal cross sectional data from OASIS. It has been inferred from the results that random forest classifier performs well than the other models.

Advantages:

The accuracy of the algorithms used is nearby 90%

Dis Advantages:

Time is too long for the response

2.5 Pratik M. Sonar; Sourabh S. Walke; Raman R. Bane: 'Alzheimer's Disease Detection using Machine Learning Techniques in 3D MR Images', 2020

This study proposes a new method for the detection of Alzheimer's disease (AD) using first- order statistical features in 3D brain Magnetic Resonance (MR) images. Alzheimer's disease is a neurodegenerative disorder that affects elderly people. This is a progressive disease and early detection and classification of AD can majorly help in controlling the disease. Recent studies use voxel-based brain MR image feature extraction techniques along with machine learning algorithms for this purpose. Grey and white matter of the brain gets affected and damaged due to AD and so studying these both prove to be more effective in predicting the disease. The proposed work uses 3D structural brain MR images to separate the white and grey matter MR images, extract 2D slices in the coronal, sagittal and axial directions and select the key slices from them for performing feature extraction on them. Feature extraction is applied on top of these slices to calculate the first-order statistical features and the prominent feature vectors generated by PCA are selected for further study. In the classification phase, different classifiers take the selected features as its input to predict the classes AD (Alzheimer's disease) or HC (Healthy Control) based on the observations in the validation set.

Advantages:

It only gives the prediction.

Dis Advantages:

- Limited amount of datasets
- It cannot predict the stages of AD and type of the AD

CHAPTER 3 SYSTEM ANALYSIS

3.1 Existing System

In existing system, it uses the little amount of test images to predict the classes of the diseases and also use the simple CNN to fit the model and also get the accuracy of 90% for testing the image dataset. A novel CT-based CNN model that improves AD stage prediction accuracy usingMRI images.

The model incorporates Fast Discrete CT (FDCT) for feature extraction across multiple

Scales and orientations. Followed by a shallow CNN network for the multi-class classification (Non-Demented (ND) vs. Very Mild Demented (VMD) vs. Mild Demented (MID) vs.

Moderate Demented (MOD))

- A novel Curvelet Transform-based Convolutional Neural Network approach is proposed, which provides a more effective and faster method for AD diagnosis.
- Fast Discrete Curvelet Transform is applied as a feature extraction tool for AD MRI image classification for the first time.
- It requires less number of training parameters, giving a high classification accuracy in a shortperiod.

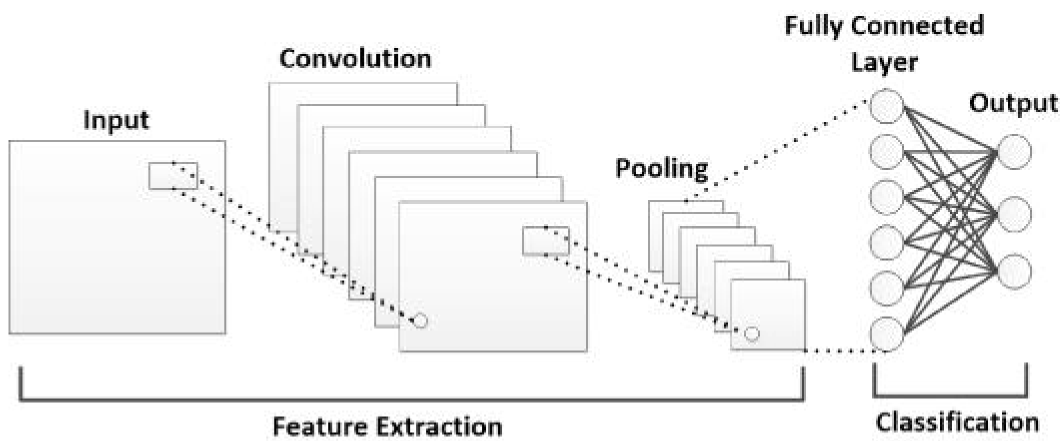
Disadvantages

- The data loss is more when compared with the other conventional methods.
- Time of response is too low.
- Time taken is maximum for the data collections.

3.2 Methodology Proposed

- In Proposed system, it trains the lot of images to test the model and also design theadvanced layers of the model to fit the model.
- Try to minimize the time for fitting the model and also increase the accuracy by using the more preprocessing techniques.
- To implement the LSTM layer for the time embedding concept to minimise thecomplexity.

CNN is a robustness method that is frequently used in computer vision, and it falls under thecategory of supervised learning strategies. Given that CNN introduced the weight sharing approach to address the issue of parameter explosion, it can expedite the training process. Applications for it include pre-processing images and face rearrangement. The convolution layer, pooling layer, and fully linked layer make up the three primary parts of the CNN architecture. The filter (kernel) with a predetermined size is moved through the output of the preceding layer by the convolution layer to apply the linear operation.



LSTM:

Recurrent neural networks (RNNs)—of which LSTM is a particular kind—are widely used to interpret time-series data. Every layer in the typical RNN depends on both the previous and current outputs in addition to the input received. However, the issue of vanishing gradients is one of the primary training challenges for the typical RNN. Equation 1 illustrates how gradients are used to update a neural network's weight values. On the other hand, learning is not greatly

enhanced when a gradient value back propagates through time and gets incredibly small. Small gradient adjustments affect the RNN, particularly in the early layers. As a result, it cannot retain the data for lengthy sequences.

New weight=weight−learningrate∗gradient

Explanation for Model:

Conv2D Layers: These layers perform 2D convolution on the input image. The first layer has 32 filters, each of size (3, 3), with 'same' padding to keep the spatial dimensions the same. The subsequent layers increase the number of filters, capturing more complex features as you go deeper into the network.

MaxPooling2D Layers: These layers perform max pooling operation for down-sampling, reducing the spatial dimensions of the feature maps.

Dropout Layers: Dropout is applied after each MaxPooling2D layer to prevent over fitting by randomly dropping a fraction of the neurons during training.

Flatten Layer: This layer flattens the 2D output from the convolutional layers into a 1D array, preparing it for the subsequent fully connected layers.

Reshape Layer: Reshapes the flattened output into a 3D tensor, suitable for the LSTM layer. LSTM Layer: A Long Short-Term Memory layer with 64 units. LSTM layers are recurrent layersthat can capture sequential patternsin the data.

Dense Layers: Fully connected layers with ReLU activation, followed by dropout forregularization.

Output Layer: The final layer with softmax activation for multi-class classification (4 classesin this case).

Compilation: The model is compiled using the Adam optimizer, categorical cross entropy loss (suitable for multi-class classification), and accuracy as the evaluation metric.

Advantages:

- Time taken is limited, when compared with the existing.
- Easy to retrieve the data.
- Data loss is low.

CHAPTER 4 IMPLEMENTATION

4.1 Software Requirements

- O/S : Windows 7 or Windows 10.
- Language : Python
- Tool : Spyder 3.9
- Front End : Anaconda Navigator – Spyder
- Back End : Anaconda Navigator – Spyder Console
- System : Pentium IV 2.4 GHz
- Hard Disk : 200 GB
- Mouse : Logitech
- Keyboard : 110 keys enhanced
- Ram : 4G

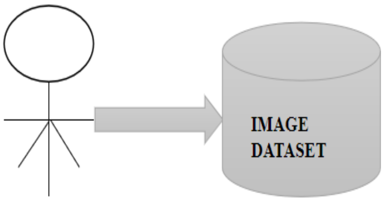
4.2 List of Modules

1. Data selection and loading
2. Data preprocessing
3. Data splitting
4. Feature extraction
5. Classification
6. Prediction
7. Performance analysis

4.3 Module Description

4.3.1 Data selection and loading

- The process of choosing the proper data source, kind, and collection tools is known as dataselection.
- Data relevant to the analysis are chosen and retrieved from the data gathering procedure during data selection, which comes before the real practice of collecting data.
- The dataset used in this experiment for the image captioning.



4.3.2 Data pre-processing

The aim of pre-processing is an improvement of the image data that suppresses unwilling distortions or enhances some image features important for further processing, although geometric transformations of images (e.g. rotation, scaling, and translation) are classified

among pre-processing methods here since similar techniques are used.

Noise Reduction:

Noise in an image can be caused by various factors such as low light, sensor noise, and compression artifacts. Noise reduction techniques aim to remove noise from the image while preserving its essential features. Some common noise reduction techniques include Gaussian smoothing, median filtering, and wavelet denoising.

Image Re-sizing:

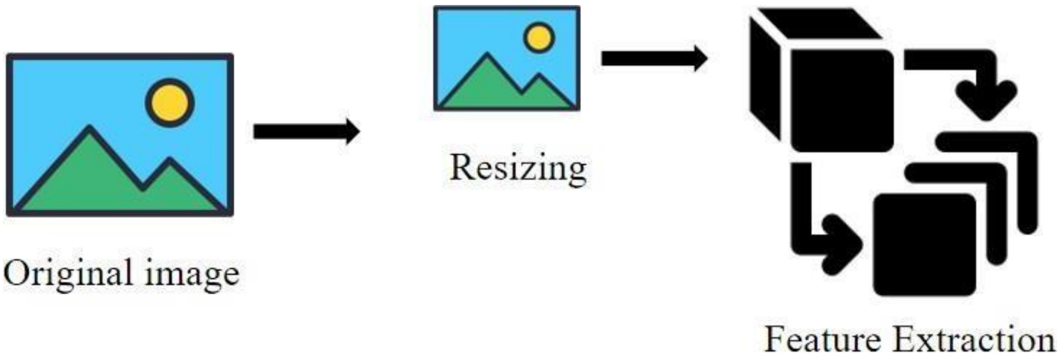
Image re-sizing techniques are used to adjust the size of an image. Re sizing can be done to make an image smaller or larger or to change its aspect ratio. Some typical image re-sizing techniques include nearest neighbor interpolation, bi linear interpolation, and bi cubic interpolation.

Segmentation:

Segmentation techniques are used to divide an image into regions based on its content. Segmentation can be helpful in applications such as medical imaging, where specific structures or organs must be isolated from the image. Some standard segmentation techniques include threshold, edge detection, and region growing.

Feature Extraction:

Feature extraction techniques are used to identify and extract relevant features from an image. These features can be used in object recognition and image classification applications. Some standard feature extraction techniques include edge detection, corner detection, and texture analysis.



4.3.3 Data splitting

Region Splitting is a technique that starts with the whole image as a single region and recursively divides it into smaller regions based on some homogeneity criterion. Splitting image data into train, validation, and test sets is a crucial step in machine learning model development. It helps to prevent over-fitting, evaluate model performance, and ensure that the model generalizes wellto new, unseen data. The best and most secure way to split the data into these three sets is to have one directory for train, one for dev and one for test.

Data splitting is when data is divided into two or more subsets. Typically, with a two-part split, one part is used to evaluate or test the data and the other to train the model. Data splitting is an important aspect of data science, particularly for creating models based on data.

It has two types of Test Split:

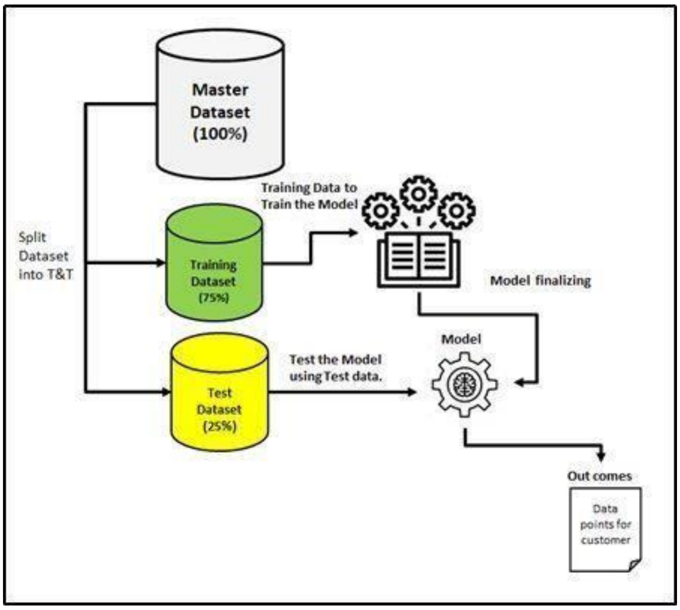
1. Train-Test Split
2. Train-Validation-Test Split

Train-Test Split:

The dataset is divided right into a training set and a trying out set.

Train-Validation-Test Split:

The dataset is split into three subsets – a schooling set, a validation set, and a trying out set.



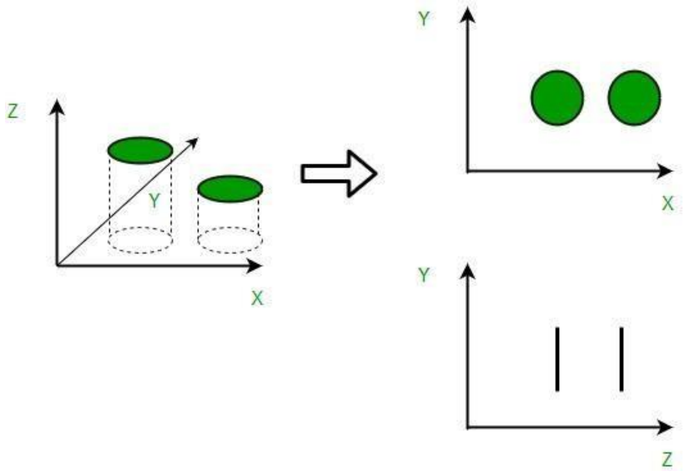
4.3.4 Feature extraction

Feature extraction is a part of the dimensionality reduction process, in which, an initial set of theraw data is divided and reduced to more manageable groups. So when you want to process it will be easier. The most important characteristic of these large data sets is that they have a largenumber of variables.

Feature extraction is very different from Feature selection: the former consists in transforming arbitrary data, such as text or images, into numerical features usable for machine learning.

The process of transforming raw data into numerical features that can be processed while preserving the information in the original data set.

Feature extraction is an effective method used to reduce the amount of resources needed without losing vital information



4.3.5 Classification

Classification is a task in data mining that involves assigning a class label to each instance in a dataset based on its features. The goal of classification is to build a model that accurately predictsthe class labels of new instances based on their features.

Effective use of multiple features of remotely sensed data and the selection of a suitable classification method are especially significant for improving classification accuracy. Non- parametric classifiers such as neural network, decision tree classifier, and knowledge-based classification have increasingly become important approaches for multisource data classification. Our goal is to apply machine learning and deep learning algorithms to discover underlying patterns in the dataset, enabling us to correctly classify data points. Each *image* is, therefore, a *data point*.

Supervised Classification:

Supervised classification is based on the idea that a user can select sample pixels in an image that are representative of specific classes and then direct the image processing software to use these training sites as references for the classification of all other pixels in the image. Training sites (also known as testing sets or input classes) are selected based on the knowledge of the user.

Unsupervised Classification:

Unsupervised classification is where the outcomes (groupings of pixels with common characteristics) are based on the software analysis of an image without the user providing sample classes. The computer uses techniques to determine which pixels are related and groups them into classes. The user can specify which algorithm the software will use and the desired number of output classes but otherwise does not aid in the classification process.

4.3.6 Prediction

Predictive analytics algorithms try to achieve the lowest error possible.

❖ **ACCURACY:**

In multilabel classification, this function computes subset accuracy: the set of labels predicted for a sample must exactly match the corresponding set of labels in y_true.

❖ **LOSS:**

Loss functions in Python are an integral part of any machine learning model. These functions tell us how much the predicted output of the model differs from the actual output.

4.3.7 Performance analysis

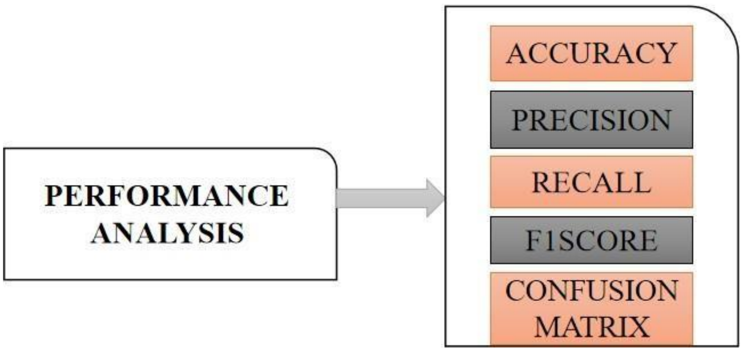
Accuracy:

The set of labels predicted for a sample must exactly match the corresponding set of labels.

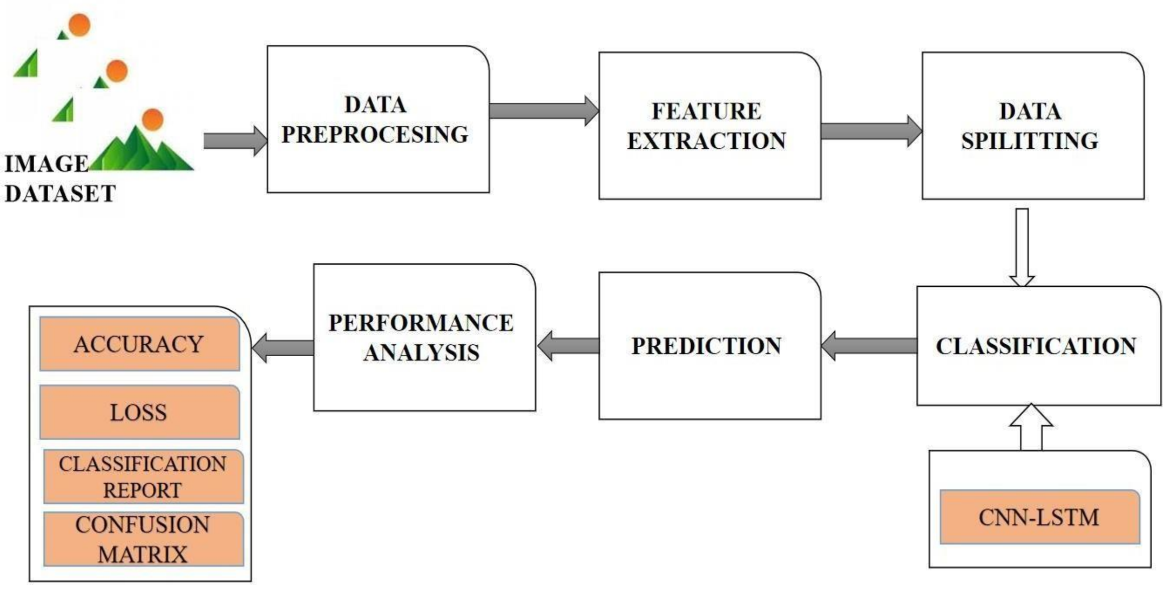
accuracy_score (y_true, y_pred)

Classification report:

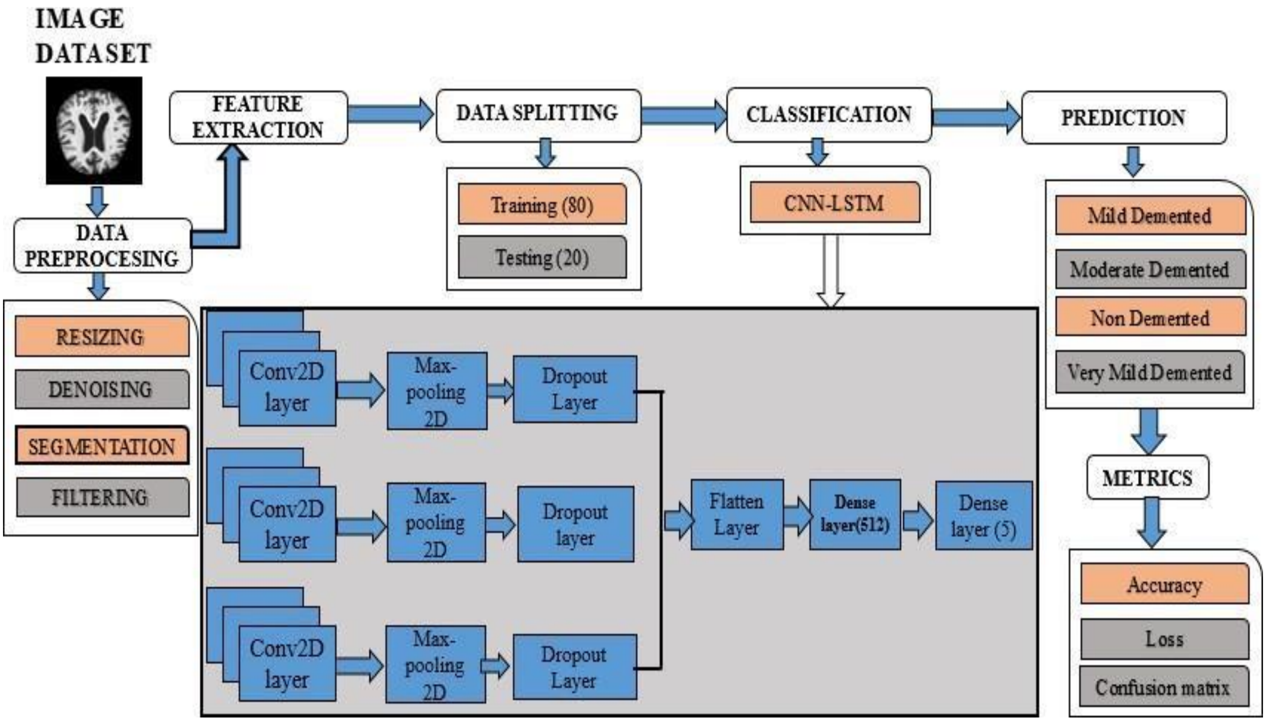
A classification report is a performance evaluation metric in machine learning. It is used to show the precision, recall, F1 Score, and support of your trained classification model.



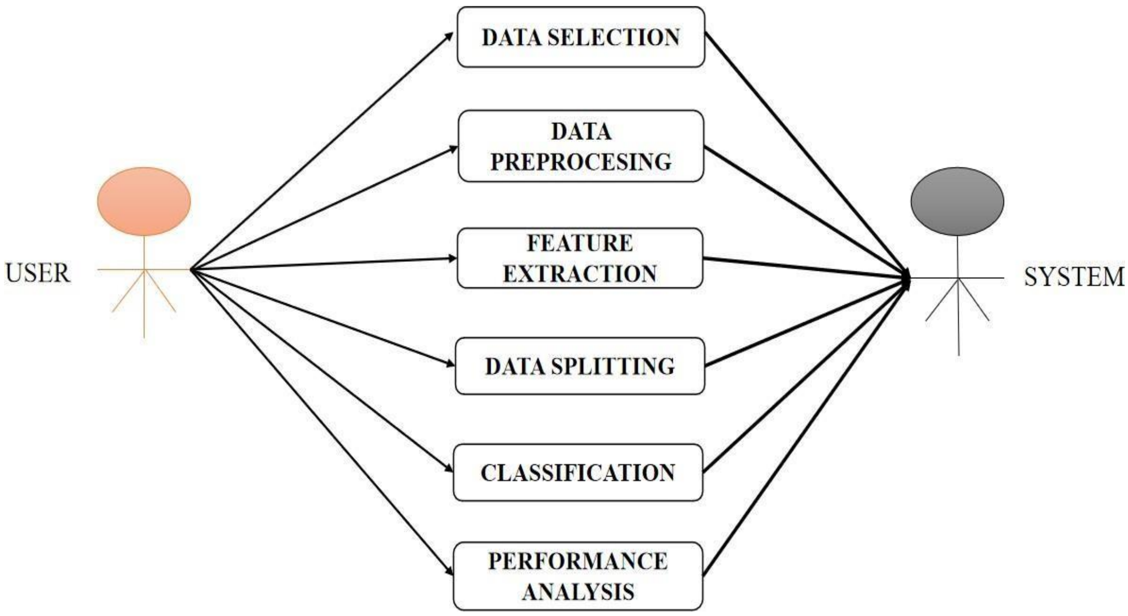
4.3.8 SYSTEM ARCHITECTURE



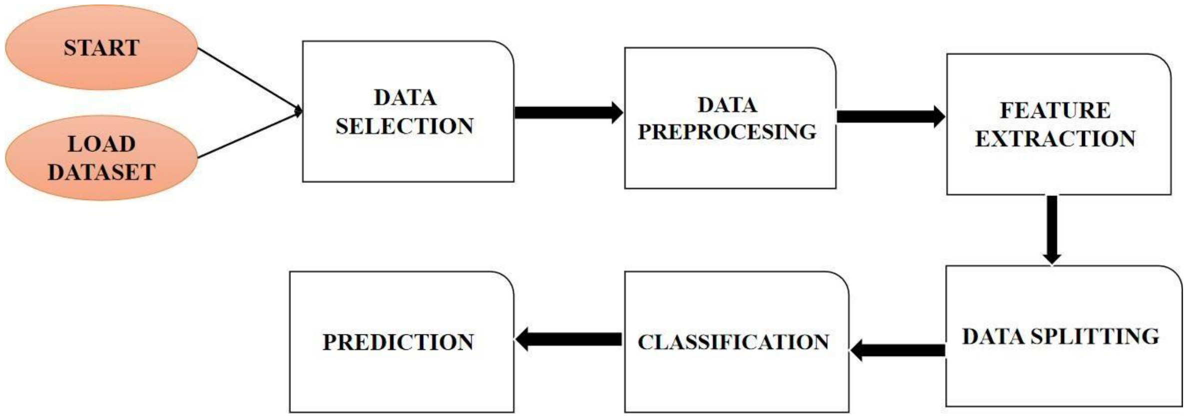
4.3.9 FLOW DIAGRAM



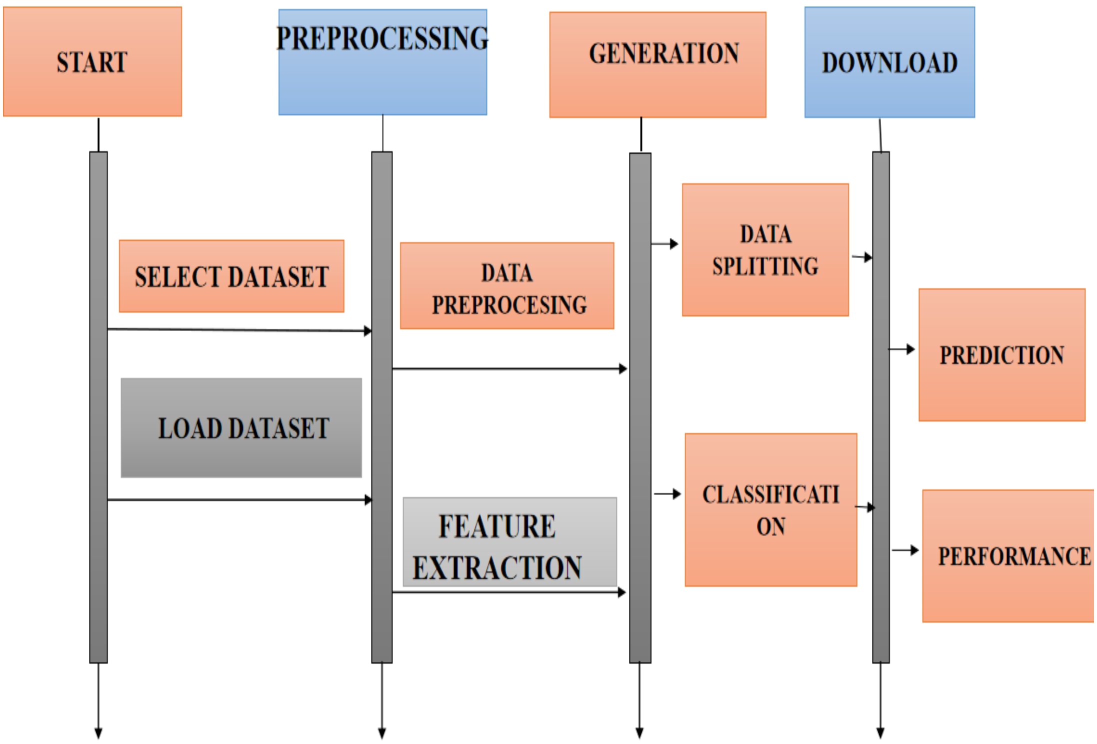
4.3.10 USE CASE DIAGRAM



4.3.11 ER ARCHITECTURE



4.3.12 SEQUENCE DIAGRAM



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CHAPTER 5

EXPERIMENTAL RESULTS

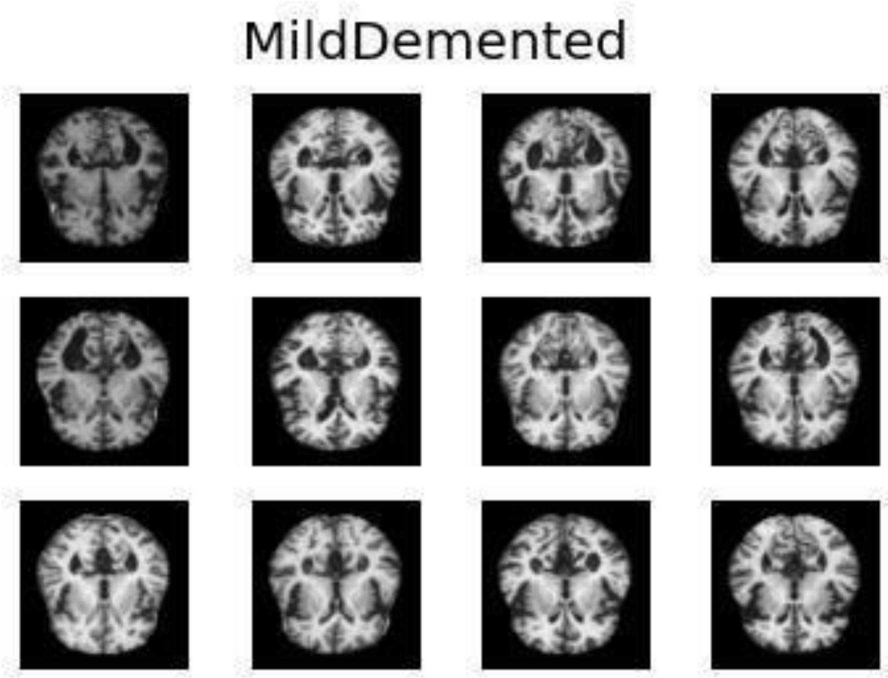
5.1 Assumption

Dataset Used in the Proposed System:

- Mild Demented
- Moderate Demented
- Non Demented
- Very Mild Demented

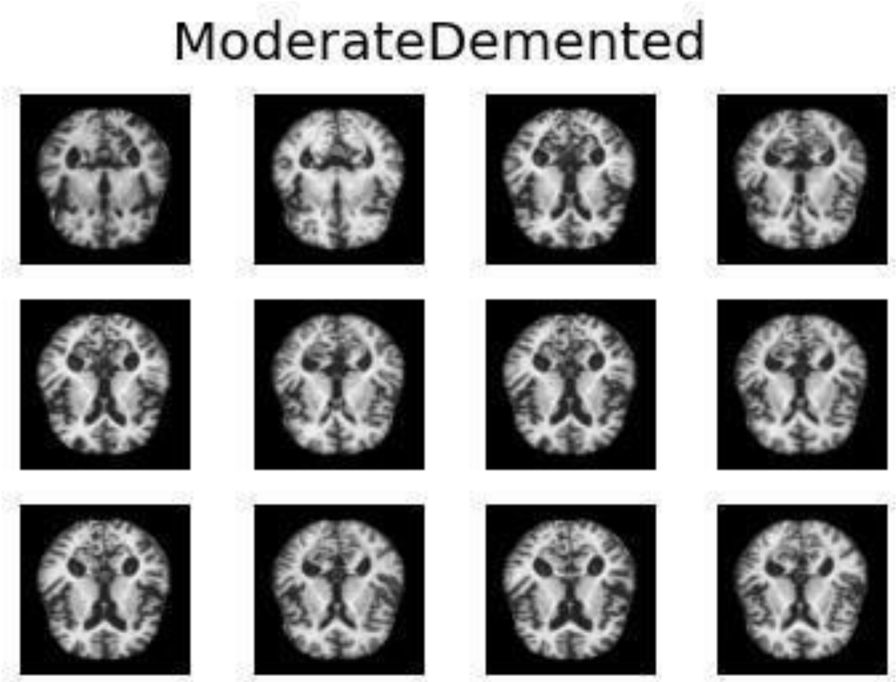
Mild Demented:

Mild dementia is also defined by cognitive impairment and poor performance on objective cognitive assessments that represents a decline from the past, but importantly, dementia requires evidence of significant difficulties in daily life that interfere with independence.



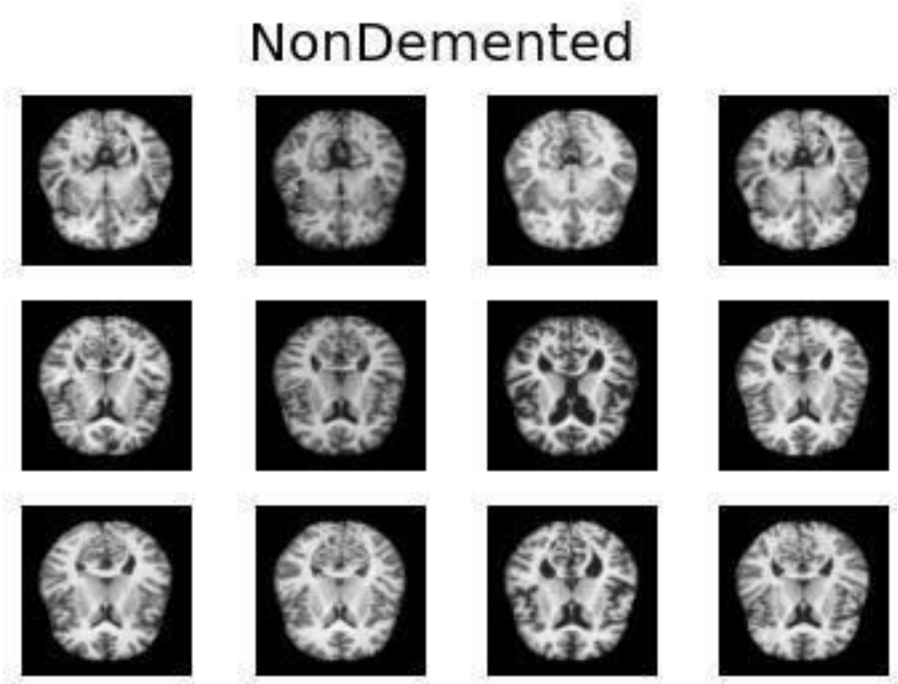
Moderate Demented:

In the moderate stage of AD, patients often begin to require more help with day-to-day life and self-care. This can lead to frustration and anger in patients, and can result in them reacting in unexpected ways. Moderate-stage Alzheimer's tends to be the longest stage, and a patient may remain with moderate disease for many years before the condition again significantly progresses.



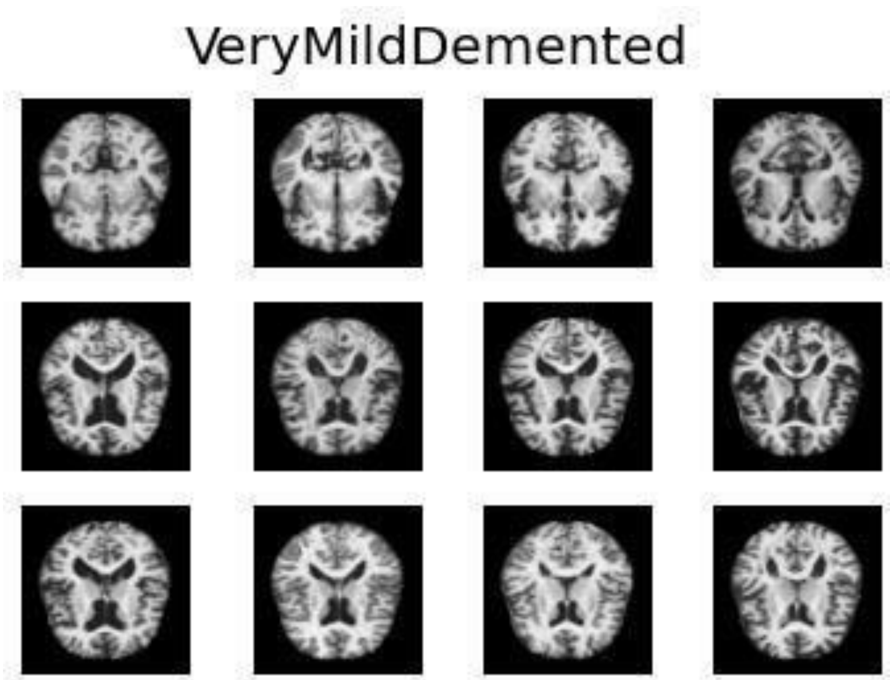
Non Demented:

Non dementia patients often have anxiety themselves is because they cannot comprehend what's going on, and their confusion isn't something that goes away.



Very Mild Demented:

Very mild dementia include memory loss, confusion about the location of familiar places, taking longer than usual to accomplish normal daily tasks, trouble handling money and paying bills, poor judgment leading to bad decisions, loss of spontaneity and sense of initiative, mood and personality changes, and increased anxiety or aggression.

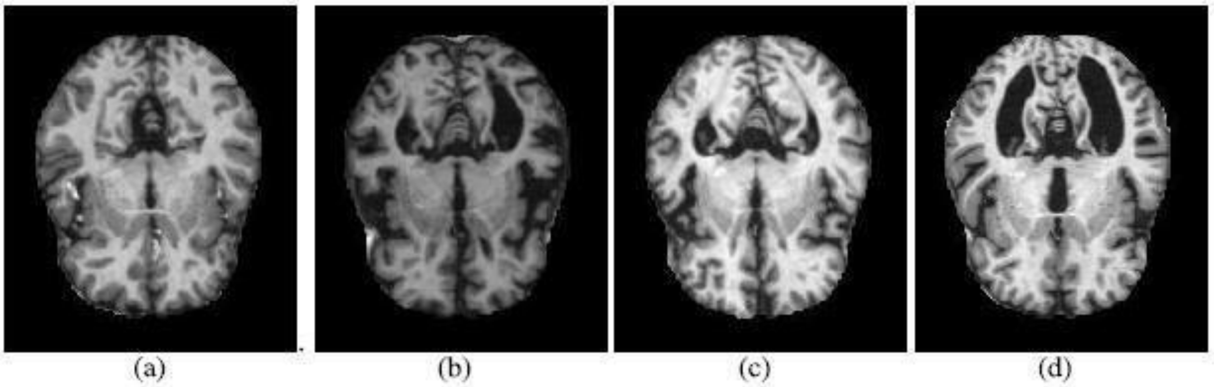


5.2 Benchmark

Existing System Dataset:

Existing system used a novel CT-based CNN model named DeepCurvMRI that improves AD stage prediction accuracy using MRI images. The model incorporates Fast Discrete CT (FDCT) for feature extraction across multiple scales and orientations. Followed by a shallow CNN network for the multi-class classification (Non- Demented (ND) vs. Very Mild Demented (VMD) vs. Mild Demented (MID) vs. Moderate Demented (MOD)) andbinary classification (NDvs. VMD).

- A novel Curvelet Transform-based Convolutional Neural Network approach is proposed, which provides a more effective and faster method for AD diagnosis.
- Fast Discrete Curvelet Transform is applied as a feature extraction tool for AD MRI image classification for the first time.
- It requires less number of training parameters, giving a high classification accuracy in ashort period.



Brain MRI images from four different classes, i.e.: (a) ND, (b) VMD, (c) MID and (d) MOD

Dis Advantages:

- Along with that, data loss is more when compared with the other conventionalmethods.
- Time of response is too low.
- Along with that, data loss is more when compared with the other conventionalmethods.
- Time taken is maximum for the data collections.

5.3 Metrics

In Existing system it uses the MRI images of four classes, i.e., Non-Demented (ND), Very Mild Demented (VMD), Mild Demented (MID), and Moderate Demented (MOD).

The original image size is 176×208. All images were resized into 208 × 208.

The Accuracy of the Existing system is 90%. But the data loss is more when compared with the other conventional methods. Time of response is too low. Time taken is maximum for thedata collections.

In Proposed system it uses the MRI dataset obtained from the open-source platform Kaggle, which consists of four classes, i.e., Non-Demented (ND), Very Mild Demented (VMD), Mild Demented (MID), and Moderate Demented (MOD).

All images were resized into 176 × 176 so that time taken is limited, when compared with the existing. The Accuracy of the Existing system is 98% by implementing the LSTM layer.

Accuracy:

```
In [28]: print("Train Accuracy:")
    ...: print(trainaccuracy*100)
Train Accuracy:
98.41706132888794
```

CHAPTER 6

CONCLUSION

- Design a disease classifier and also give the suggestion for the diagnosis procedures.
- Generate the advanced level of CNN-LSTM to extract the more features.
- Get the accuracy nearby 98%.
- In scope of the project is to generate the Alzheimer's disease classifier with the efficientaccuracy.
- The suggested model is compared to models based on five variables and to the average ensemble model. The findings indicate that the presented model using CNN results with an accuracy, loss, validation accuracy, validation loss.
- This is superior to other models and can accurately predict the diseases.

APPENDIX- SOURCE CODE

```
import pandas as pdimport numpy as npimport os
from distutils.dir_util import copy_tree, remove_treeimport cv2
import matplotlib.pyplot as pltimport warnings

import tensorflow as tf
from tensorflow.keras.layers import Input, Lambda, Dense, Flatten, Dropout from tensorflow.keras.models import Model
from tensorflow.keras.utils import plot_model
from tensorflow.keras.preprocessing import image, image_dataset_from_directory from imblearn.over_sampling import SMOTE
from tensorflow.keras.preprocessing.image import ImageDataGenerator from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.models import Sequentialfrom tensorflow import keras
from random import randint

default_dir = "/data"root_dir = "./"
test_dir = default_dir + "test/" train_dir = default_dir + "train/"work_dir = root_dir + "dataset/"

if os.path.exists(work_dir):remove_tree(work_dir)


os.mkdir(work_dir) copy_tree(train_dir, work_dir)copy_tree(test_dir, work_dir)
print("Working Directory Contents:", os.listdir(work_dir))

CLASSES = [ 'NonDemented','VeryMildDemented', 'MildDemented', 'ModerateDemented']

IMG_SIZE = 176

IMAGE_SIZE = [176, 176] DIM = (IMG_SIZE, IMG_SIZE)

ZOOM = [.99, 1.01]
BRIGHT_RANGE = [0.8, 1.2]
```

```
HORZ_FLIP = True
FILL_MODE = "constant" DATA_FORMAT = "channels_last"

image_generator = ImageDataGenerator(rescale = 1./255, brightness_range=BRIGHT_RANGE, zoom_range=ZOOM,
data_format=DATA_FORMAT, fill_mode=FILL_MODE,horizontal_flip=HORZ_FLIP)

train_dataset = image_generator.flow_from_directory(batch_size=5200,
directory=work_dir, target_size=(176, 176),shuffle= True)

"""## Visualization"""

def show_images(generator,y_pred=None):labels =dict(zip([0,1,2,3], CLASSES))

# get a lot of images x,y = generator.next()

plt.figure(figsize=(10, 10))if y_pred is None:
for i in range(16):
ax = plt.subplot(4, 4, i + 1)idx = randint(0,50) plt.imshow(x[idx]) plt.axis("off")
plt.title("Class:{}".format(labels[np.argmax(y[idx])]))

else:
for i in range(16):
ax = plt.subplot(4, 4, i + 1)plt.imshow(x[i])
plt.axis("off")
plt.title("Actual:{} \nPredicted:{}".format(labels[np.argmax(y[i])],labels[y_pred[i]]))

# Display Train Images show_images(train_dataset)

data = {'NonDemented':        0,'VeryMildDemented': 0,
'MildDemented':          0,
'ModerateDemented': 0}

# visualizing dataset
for cls in os.listdir(work_dir):
for img in os.listdir(work_dir + '/' + cls):data[cls] = data[cls] + 1
keys = list(data.keys())values = list(data.values())

fig = plt.figure(figsize = (10, 5))

distance = 0.1
separate = (distance, distance, distance, distance)
plt.pie(values, labels = keys,explode = separate,autopct = '%.0f%%', radius= 1.5,textprops={'fontsize': 16})
plt.show()

"""## Feature Engineering and Oversampling""" train_data, train_labels = train_dataset.next()

print(train_data.shape, train_labels.shape) #resampling data

sm = SMOTE(random_state=42)

train_data, train_labels = sm.fit_resample(train_data.reshape(-1, IMG_SIZE * IMG_SIZE *3), train_labels)

train_data = train_data.reshape(-1, IMG_SIZE, IMG_SIZE, 3)print(train_data.shape, train_labels.shape)
```

```
from sklearn.model_selection import train_test_split
train_data, test_data, train_labels, test_labels = train_test_split(train_data, train_labels, test_size = 0.2, random_state=42)
train_data, val_data, train_labels, val_labels = train_test_split(train_data, train_labels, test_size = 0.2, random_state=42)

model = keras.models.Sequential([
keras.layers.Conv2D(16, (3, 3), activation='relu', input_shape = [176,176,3]),keras.layers.MaxPooling2D(),
keras.layers.Conv2D(32, (2, 2), activation='relu'),keras.layers.MaxPooling2D(),

keras.layers.SeparableConv2D(64, 3, activation='relu', padding='same'), keras.layers.SeparableConv2D(64, 3, activation='relu', padding='same'),keras.layers.BatchNormalization(),
keras.layers.MaxPool2D(),

keras.layers.SeparableConv2D(128, 3, activation='relu', padding='same'), keras.layers.SeparableConv2D(128, 3, activation='relu', padding='same'),keras.layers.BatchNormalization(),
keras.layers.MaxPool2D(),keras.layers.Dropout(0.2),
plt.title('Training and Validation accuracy')plt.xlabel('Epochs')
plt.ylabel('Accuracy')plt.legend() plt.show()

model.save(brain.h5')

from pathlib import Pathfrom PIL import Image
from tensorflow.keras.preprocessing.image import load_img, img_to_array#Image path
path = Path('dataset/ModerateDemented/moderateDem0.jpg') img = image.load_img(path, target_size=(176,176))
image_array = img_to_array(img) / 255.0
image_array = np.expand_dims(image_array, axis=0)img_array = image_array.reshape((1, 176, 176, 3))


predictions = model.predict(image_array)#print(predictions)
predicted_label = train_labels[np.argmax(predictions)])
```

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