ALZHEIMER'S DISEASE DETECTION USING DEEP LEARNING MODELS

A project report submitted in partial fulfillment of the requirements for the award of the degree of

B.Tech.

in

Electronics and Communication Engineering

BY

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EC499
PROJECT WORK - PART-A
NATIONAL INSTITUTE OF TECHNOLOGY
ANDHRA PRADESH-534101

DECEMBER 2024

BONAFIDE CERTIFICATE

This is to certify that the project titled **ALZHEIMER'S DISEASE DETECTION USING DEEP LEARNING MODELS** is a bonafide record of the work done by

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in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology** in **ECE** of the **NATIONAL INSTITUTE OF TECHNOLOGY, ANDHRA PRADESH**, during the year 2024-2025.

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ABSTRACT

There are many different causes of Dementia, but Alzheimer's Disease is the most usual form. As the condition progress, it limits one's ability to perform any task without aid, and the diagnosis timeline and aging population are expected to cause its prevalence to increase. The conventional ways of detecting Alzheimer's is tiring for both patients, doctors where it involves retrieving the past medical records and having Magnetic Resonance Imaging scans and even neuro-physical testing which can be inconvenient for patients. An early diagnosis of brain diseases makes a big difference when it comes to attempting to cure them. Our work has used Convolutional Neural Network(CNN) to detect Alzheimer's disease earlier than usual by combining it with deep learning. As the obtained dataset from Kaggle is heavily imbalanced, we evenly distributed the data between the categories using SMOTE. Then the model is trained and tested with the categorized MRI data i.e. very mild dementia, mild Dementia, moderate Dementia and NonDementia and finally extract features to examine the results. The results we achieved are compared with the previous attempts on detection of Alzheimer's and came out to be significantly greater in terms of precision and accuracy.

ACKNOWLEDGEMENT

We would like to thank the following people for their support and guidance without whom the completion of this project in fruition would not be possible.

Dr. V. Prakash singh, our project incharge, for helping us and guiding us in the course of this project .

Dr. Puli Kishore Kumar, the Head of the Department, Department of ECE.

Our internal reviewers, **Dr. Puli Kishore Kumar** , **Mr. Iqram Haider** , **Dr. Priya Kumari** for their insight and advice provided during the review sessions.

We would also like to thank our individual parents and friends for their constant support.

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Chapter 1

Introduction

1.1 Background on Alzheimer's disease

A person with Alzheimer's Disease (AD) suffers from a developing neurobiological disorder that affects brain cells to die and atrophy. AD is the prevalent cause of dementia, which causes memory loss and impaired reasoning abilities. Around 6 million people in the U.S of age 65 and above are caused with Alzheimer's disease. Of those 80 percent are above 75 years old. In India it is calculated around 5.3 million people live with dementia of which Alzheimer is the common cause. Dementia with Alzheimer's is classified into four categories: a. Very Mild Dementia: Individuals suffers from memory loss as they age. b. Mild Dementia: Symptoms which includes lack of memory, Behavioral changes, inability to perform routine tasks. c. Moderate Dementia: The day to day life becomes complex for the individuals with moderate dementia, where the patients require extra care and support. d. No Dementia: The patient is healthy and not suffering from Alzheimer's disease.

Alzheimer's is not a curable disease, but an early diagnosis can help prevent the patient from suffering from the later stages. In order to diagnose AD manual detection systems for example: Positron Emission Tomography (PET) were used to track the progression of the various stages of AD, MRI scans and genotype sequencing results were taken for diagnosis.

1.2 Motivation for early detection

Among the most popular fields of research in recent years has been brain-computer interface (BCI), thanks to its applications in areas such as brain fingerprinting, detecting neurological illnesses, tiredness, adaptive e-learning and more. By extracting the most significant characteristics, BCI creates an effective link to interact between the brain and the device. A complex brain structure varying with age and pathology makes it very difficult to detect neurodegenerative diseases in their early stages. Computer-assisted techniques are more successful in detecting these disorders than traditional approaches. A timely diagnosis and identifying of Alzheimer's disease is essential to reducing medical expenses, improving treatment, and preventing brain cell degeneration.

Some of the methods included in an early examination include Positron Emission Tomography (PET), digital imaging methods and genotyping-by-sequencing. It is difficult to take decisions by analyzing different methods. Furthermore, the patients will have to undergo radioactive effects during PET medical procedure. According to our findings, MRIs can provide valuable information on the brain, because they provide flexible imaging, superior tissue contrast, and do not expose the brain to ionizing radiation. It is crucial to develop a model that can take MR images as input and detect whether patients are normal or not. By utilizing a dataset, machine learning can extract knowledge. Computer science, artificial intelligence, and statistics combine to make up this field..

Dementia is a term for a decline in mental ability severe enough to interfere with daily life. Alzheimer's is the one type of dementia. Alzheimer's is the most serious yet common neurodegenerative disease that initially destroys cells of the part of the brain. It's responsible for language and memory resulting in memory loss of the patient and also the ability to perform regular tasks. As there is no cure for Alzheimer's disease, it's better to detect as early as possible to slow down the severity of the disease. Usually to diagnose the disease radiologists use manual methods such as previous medical history, continuous monitoring of the patient to detect the various stages of AD, however these manual methods may lead to errors!

1.3 Role of deep learning in medical diagnosis

The ML is done through training a computer to produce the output based on its past experience to solve a given problem. Machine learning can be applied in a variety of fields in order to solve problems quicker than humans, and therefore be more efficient, and reduce time spent on repetitive tasks. Nowadays, because of the reduction in the cost of computing power and memory. This allows processing and analyzing huge amounts of data to generate insights. Additionally, Deep Learning is a subset of ML and an advanced mode of analyzing and learning information from raw data that computers are able to replicate, much like how humans are able to do, with a computer. Deep learning is becoming increasingly popular for diagnosing diseases. Several Machine learning approaches have been proposed recently to aid in this diagnosis, providing doctors with more information to make informed decisions

We use Deep Neural Networks (DNNs) for feature extraction using deep learning techniques in the proposed model. A solution to underfitting is to use sampling techniques especially oversampling to resolve class imbalance. DL performs classification on given MR images using the cortical surface of the brain as input. Using a dementia-specific (Alzheimer's) dataset, the models are evaluated by 3 NonDemeneted, Moderate Dementia, Mild Dementia and Very Mild Dementia obtained from Kaggle. Utilizing the CNN technique, we extract discriminating features for AD classification by improving the accuracy. By using this model, we can accurately classify the stages of AD.

Implementing Deep Learning algorithm efficiently to identify the stage of the Alzheimer's disease patient. Analyzing the various performance metrics of the deep learning algorithm.

Chapter 2

Review Of Literature

Deep Learning for Early Detection and Decision-Making in Alzheimer's Disease: Studies emphasize the use of deep learning techniques, such as convolutional neural networks (CNNs) and Vision Transformers (ViT), to classify AD using brain imaging data like MRI and PET scans. CNNs excel in feature extraction from visual data, and Vision Transformers further enhance the model's ability to capture global contextual features. These techniques improve classification accuracy and help in understanding visual biomarkers associated with AD. However, their overreliance on specific datasets and lack of generalization for real-world AD diagnosis remain challenges, along with computational demands and limited data diversity.[1]

Optimized Deep Learning with Inception V3 for Alzheimer's Classification: The Inception V3 architecture is optimized for datasets with limited size by reducing the parameter count, improving efficiency, and minimizing overfitting risks. This method shows high accuracy for early-stage AD detection by focusing on essential biomarkers. However, challenges include overfitting on small datasets and potential for misclassification. These issues can be mitigated through advanced regularization techniques and larger, more diverse training datasets.[2]

Machine Learning Approaches: SVM and Ensemble Techniques: Support Vector Machines (SVM) and Artificial Neural Networks (ANNs) are widely used for AD prediction due to their robustness in handling non-linear relationships. Ensemble learning methods, which combine multiple models, provide incremental learning capabilities that are useful for modeling sequential data like cognitive decline trajectories. However, these methods often suffer from local minima problems in ANN training and limited feature extraction capacity compared to deep learning models like CNNs. [3]

Deep CNN Architectures with Magnetic Resonance Imaging (MRI): CNNs tailored for MRI data achieve high accuracy in detecting and classifying AD. These models utilize spatial information effectively, offering superior performance for larger datasets. Nonetheless, they require substantial computational resources and annotated data. Addressing these limitations involves leveraging pre-trained models and transfer learning to reduce the dependency on large labeled datasets.[4]

Future Directions To improve diagnostic reliability, researchers highlight the importance of multimodal approaches that combine data from MRI, PET, and clinical biomarkers. Additionally, creating standardized benchmark datasets can streamline model comparisons and validation. Efforts to integrate explainable AI (XAI) techniques will also make predictions more interpretable for clinical use.

Chapter 3

Aim and scope of present investigation

3.1 Aim

This project aims to detect the stages of the Alzheimer's disease by using deep learning techniques.

3.2 Scope of the present investigation

Alzheimer's disease is a progressive neurological disorder that causes the brain to shrink (atrophy) and brain cells to die. Alzheimer's disease is the most common cause of dementia. As the disease progresses, a person with Alzheimer's disease will develop severe memory impairment and lose the ability to carry out everyday tasks. A number of medicines may be prescribed for Alzheimer's disease to help temporarily improve some symptoms but there is no permanent cure. An accurate, timely diagnosis gives you the best chance to adjust, prepare and plan for the future, as well as access to treatments and support that may help. An early detection can give a patient a better chance to cure and recover. It is crucial to develop a model that can take MR images as input and detect whether patients are normal or not. Computer science, artificial intelligence, and statistics combine to make up this field. been applied in the healthcare sector.Deep Learning is a subset of ML and an advanced mode of analyzing and learning information from raw data that computers are able to replicate, much like how humans are able to do, with a computer. Deep learning is becoming increasingly popular for diagnosing diseases. We use Convolutional Neural Networks (CNNs) for feature extraction using deep learning techniques in the proposed model. A solution to underfitting is to use sampling techniques especially oversampling to resolve class imbalance. DL performs classification on given MR images using the cortical surface of the brain as input.

3.3 Existing system

Early detection of this disorder is being researched to slow down the abnormal degeneration of the brain, reduce medical care cost reduction, and ensure improved treatment. In Existing system machine learning algorithms are used to predict the Alzheimer disease using psychological parameters like age, number of visit, MMSE and education. Different modalities are used for AD study include MRI, Positron Emission Tomography (PET), and genotype sequencing results. It is time-consuming to analyze different modalities to take a decision. Furthermore, the patients can encounter radioactive effects in the modalities like PET. Previously researchers performed 3D tissue segmentation of white matter, gray matter, and cerebrospinal fluid from MR images after skull striping using FSL tool, calculate the surface fractal dimension from segmented brain tissue. From the survey , Numerous techniques exist for AD classification using machine and deep learning. However, the high model parameter and class imbalance in the multiclass AD classification is still an issue.

3.3.1 Disadvantages

The existing model shows significant accuracy only when MMSE score, education, etc., is given. The patients can encounter radioactive effects in the modalities like PET. 3D MRI scan is hard to train and time consuming process.

3.4 Proposed system

It is considered important to develop a better computer-aided diagnostic system that can interpret MRI imaging and determine whether patients are healthy or have Alzheimer's disease. Conventional deep learning systems use the cortical surface to input the CNN to perform AD classification on raw MRI images. In this proposed work, We believe that the MRI modality benefits from its greater imaging flexibility, excellent tissue contrast, lack of ionizing radiation, and ability to provide useful information on human brain anatomy. This paper proposes a model that uses the convolutional neural network to extract the discriminative features. Class imbalance is addressed using the Synthetic Minority Oversampling Technique (SMOTE) technique. The model is developed from scratch to classify the stages of AD more accurately by reducing its parameters and computation cost. The models are evaluated by training them over the MRI dataset from the Kaggle. The dataset comprises four types of dementia such as Mild Dementia (MID), Moderate Dementia (MOD), Non-Demented (ND) and Nondementia(ND).

A new convolutional neural network architecture is proposed with relatively small parameters to detect the types of dementia which is suitable for training a smaller dataset SMOTE technique is used to address the class imbalance problem in the dataset is by randomly duplicating the minority class of images in the dataset to minimize the overfitting problem. We created the generalized model that learns from the smaller dataset with reduced parameters and computation cost, which still performs better for AD diagnosis. We also compared the proposed model with deep features and hand-crafted features to detect AD stages in terms of Accuracy, AUC and Cohen's kappa score.

3.4.1 Advantages

A neural network architecture is proposed with relatively small parameters to detect the types of dementia which is suitable for training a smaller dataset SMOTE technique is used to address the class imbalance problem. We created the generalized model that learns from the smaller dataset with reduced parameters and computation cost.

Chapter 4

Approach and Algorithmic Framework

4.1 Deep Learning Overview

Deep Learning is a subfield of machine learning concerned with algorithms inspired by the structure and function of the brain called artificial neural networks. It is essentially a neural network with three or more layers, these neural networks attempts to mimic the human brain through a combination of data inputs, weights, and bias, allowing it to learn from large amounts of data. These elements work together to accurately recognize, classify, and describe objects within the data.

There are different types of neural networks to address specific problems or datasets. For example, Convolutional neural networks (CNNs), used primarily in computer vision and image classification applications, can detect features and patterns within an image, enabling tasks, like object detection or recognition. Recurrent neural network (RNNs) are typically used in natural language and speech recognition applications as it leverages sequential or times series data.

4.2 Steps to Download and Install Python

Download the Latest version of the Python executable installer .Watch the PIP list where pip is the package installer for python. Now upgrade the pip and setup tools using the command ENVIRONMENT INSTALLATION FOR PYTHON Jupyter Notebook is an open-sourced web-based application which allows you to create and share documents containing live code, equations, visualisations, and narrative text. It is a server-client

application that allows editing and running notebook documents via a web browser. The Jupyter Notebook App can be executed on a local desktop requiring no internet access. pip install pandas pip install matplotlib pip install notebook
Installation-`(https://jupyter.org/install/)`

4.3 Python Libraries

There are many libraries in python.In those, we only use a few main libraries needed

4.3.1 NUMPY library

NumPy is an open source numerical Python library. NumPy contains a multidimensional array and matrix data structures It can be utilized to perform a number of mathematical operations on arrays such as trigonometric, statistical, and algebraic routines like mean, mode, standard deviation, etc.,
Installation-`(https://numpy.org/install/)`

4.3.2 PANDAS library

Pandas is a high-level data manipulation tool developed by Wes McKinney. It is built on the Numpy package and its key data structure is called the Data Frame. Data Frames allow you to store and manipulate tabular data in rows of observations and columns of variables. There are several ways to create aDataFrame.
Installation- `(https://pandas.pydata.org/getting_started.html/)`

4.3.3 MATPLOTLIB library

Matplotlib is a comprehensive library for creating static, animated, and interactive visualizations in Python. Matplotlib makes easy things easy and hard things possible. Use interactive figures that can zoom, pan, update, visualize etc..,
Installation- `(https://matplotlib.org/users/installing.html/)`
pip install seaborn
pip install pillow
Here we use pyplot mainly for plotting graphs. matplotlib.pyplot is a collection of

functions that make matplotlib work like MATLAB. Each pyplot function makes some change to a figure: e.g., creates a figure, creates a plotting area in a figure, plots some lines in a plotting area, decorates the plot with labels, etc.

4.3.4 SEABRON library

Seaborn package was developed based on the Matplotlib library. It is used to create more attractive and informative statistical graphics. While seaborn is a different package, it can also be used to develop the attractiveness of matplotlib graphics.
Installation- `(https://seaborn.pydata.org/installing.html/)`

4.3.5 PILLOW library

The Python Imaging Library adds image processing capabilities to your Python interpreter. This library provides extensive file format support, an efficient internal representation, and fairly powerful image processing capabilities. The core image library is designed for fast access to data stored in a few basic pixel formats. It should provide a solid foundation for a general image processing tool.
Installation- `(https://pillow.readthedocs.io/en/stable/installation.html/)`

4.3.6 TENSORFLOW library

TensorFlow is a framework created by Google for creating Deep Learning models. Deep Learning is a category of machine learning models (=algorithms) that use multi-layer neural networks. TensorFlow is a great tool which, if used properly has innumerable benefits. The major uses of the library include classification, perception, understanding, discovering, prediction and creation.
Installation- `(https://www.tensorflow.org/install/)`

pip install scikit-learn

pip install tensorflow

pip install keras

4.3.7 KERAS library

Keras is a powerful and easy-to-use free open source Python library for developing and evaluating deep learning models. It is an open-source software library that provides a Python interface for artificial neural networks. Keras acts as an interface for the TensorFlow library. Keras follows best practices for reducing cognitive load: it offers consistent simple APIs, it minimizes the number of user actions required for common use cases, and it provides clear and actionable feedback upon user error.
Installation- `(https://keras.io/getting_started/)`

4.3.8 SCIKIT-LEARN library

Scikit-learn is a free machine learning library for the Python. It features various algorithms like support vector machine, random forests, regression and kneighbours, and it also supports Py(thon numerical and scientific libraries like NumPy and SciPy.
Installation- `(https://scikit-learn.org/stable/install.html/)`
Here use scikit-learn's regression methods for prediction purpose.

4.4 Modules Implementation

A modular design reduces complexity, facilities change (a critical aspect of software maintainability), and results in easier implementation by encouraging parallel development of different part of system. Software with effective modularity is easier to develop because function may be compartmentalized and interfaces are simplified. Software architecture embodies modularity that is software is divided into separately named and addressable components called modules that are integrated to satisfy problem requirements.

Modularity is the single attribute of software that allows a program to be intellectually manageable. The five important criteria that enable us to evaluate a design method with respect to its ability to define an effective modular design are: Modular decomposability, Modular Comps ability, Modular Understand ability, Modular continuity, Modular Protection. The following are the modules of the project, which is planned in aid to complete the project with respect to the proposed system, while overcoming existing system and also providing the support for the future enhancement.

4.4.1 Data Pre-processing

The dataset is derived from the Kaggle an open source platform, which contains around 5121 images comprising of four classes namely moderately demented, very mildly demented and non-demented, mildly demented. The dimension of images used in the dataset is of form 224x224. The images are reshaped into 176x176. The SMOTE technique is applied to the dataset to solve the class imbalance problem in the dataset by randomly duplicating minority classes in the dataset to match the majority classes. With the random state of 42, the minority classes oversampled using SMOTE technique. The benefits of using SMOTE include the ability to reduce knowledge loss and minimize over-fitting. Table 2 shows the dataset distribution after SMOTE technique increased to 10240 images, with each class contains 2560 images. It as machine learning engineers use this data to fine- tune the model hyper parameters. Data collection, data analysis, and the process of addressing data content, quality, and structure can add up to a time-consuming to-do list.During the process of data identification, it helps to understand your data and its properties; this knowledge will help you choose which algorithm to use to build your model. A number of different data cleaning tasks using Python Pandas library and specifically, it focus on probably the biggest data cleaning task, missing values and it able to more quickly clean data. It wants to spend less time cleaning data, and more time exploring and modeling.

Some of these sources are just simple random mistakes.Other times, there can be a deeper reason why data is missing.It's important to understand these different types of missing data from a statistics point of view.The type of missing data will influence how to deal with filling in the missing values and to detect missing values, and do some basic imputation and detailed statistical approach for dealing with missing data. Before, joint into code,it's important to understand the sources of missing data. Here are some typical reasons why data is missing: User forgot to fill in a field, Data was lost while transferring manually from a legacy database, Due to Non-availability of data, Users chose not to fill out a field tied to their beliefs about how the results would be used or interpreted, Variable identification with Uni-variate, Bi-variate and Multi-variate analysis: import libraries for access and functional purpose and read the given dataset General Properties of Analyzing the given dataset Display the given dataset in the form of data frame, show columns, shape of the data frame, To describe the data frame, Checking data type and information about dataset, Checking for duplicate data, Checking Missing values of data frame, Checking unique values of data frame, Checking count values of data frame, Rename and drop the given data frame.

Class	Training Images	Testing Images
Mild Demented	717	179
Very Mild Demented	1792	448
Non-Demented	2560	640
Moderate Demented	52	12

Table 4.1: Dataset Distributed in obtained Dataset

Class	Training Images	Testing Images
Mild Demented	2560	179
Very Mild Demented	2560	448
Non-Demented	2560	640
Moderate Demented	2560	12

Table 4.2: Dataset Distributed after applying SMOTE

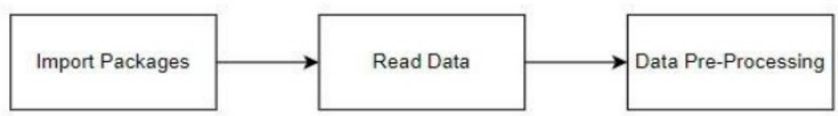

Figure 4.1: Pre-Processing Diagram

4.4.2 Data Validation and Preparing Process

Importing the library packages with loading the given dataset. To analyzing the variable identification by data shape, data type and evaluating the missing values, duplicate values. A validation dataset is a sample of data held back from training your model that is used to give an estimate of model skill while tuning model's and procedures that you can use to make the best use of validation and test datasets when evaluating your models. Data cleaning / preparing by rename the given dataset and drop the column etc. to analyze the uni-variate, bi-variate and multi-variate process. The steps and techniques for data cleaning will vary from dataset to dataset. The primary goal of data cleaning is to detect and remove errors and anomalies to increase the value of data in analytics and decision making

4.4.3 Exploration data analysis of visualization

Data visualization is an important skill in applied statistics and machine learning. Statistics does indeed focus on quantitative descriptions and estimations of data. Data visualization provides an important suite of tools for gaining a qualitative understanding. This can be helpful when exploring and getting to know a dataset and can help with identifying patterns, corrupt data, outliers, and much more. With a little domain knowledge, data visualizations can be used to express and demonstrate key relationships in plots and charts that are more visceral and stakeholders than measures of association or significance. Data visualization and exploratory data analysis are whole fields themselves and it will recommend a deeper dive into some the books mentioned at the end.

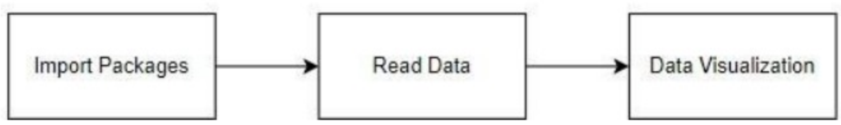

Figure 4.2: Data Visualization Diagram

4.4.4 Comparing Algorithm with prediction in the form of best accuracy result

It is important to compare the performance of multiple different deep learning algorithms consistently and it will discover to create a test harness to compare multiple different deep learning algorithms in Python with scikit-learn. It can use this test harness as a template on your own problems and add more and different algorithms to compare. Each models will have different performance characteristics. Using resampling methods like cross validation, you can get an estimate for how accurate each model may be on unseen data. It needs to be able to use these estimates to choose one or two best models from the suite of models that you have created. When have a new dataset, it is a good idea to visualize the data using different techniques in order to look at the data from different perspectives. The same idea applies to model selection. You should use a number of different ways of looking at the estimated accuracy of your algorithms in order to choose the one or two to finalize. A way to do this is to use different visualization methods to show the average accuracy, variance, and other properties of the distribution of model accuracies.

In the next section, you will discover exactly how you can do that in Python with scikit-learn. The key to a fair comparison of algorithms is ensuring that each algorithm is evaluated in the same way on the same data and it can achieve this by forcing each algorithm to be evaluated on a consistent test harness.

Pre-processing refers to the transformations applied to our data before feeding it to the algorithm. Data Preprocessing is a technique that is used to convert the raw data into a clean data set. In other words, whenever the data is gathered from different sources it is collected in raw format which is not feasible for the analysis. To achieve better results from the applied model the data has to be in a proper manner. CNN deep learning algorithms are executed in a given dataset

False Positives (FP): A person who will pay predicted as defaulter. When actual class is no and predicted class is yes. E.g. if actual class says this passenger did not survive but predicted class tells you that this passenger will survive.

False Negatives (FN): A person who default predicted as payer. When actual class is yes but predicted class in no. E.g. if actual class value indicates that this passenger survived and predicted class tells you that passenger will die.

True Positives (TP): A person who will not pay predicted as defaulter. These are the correctly predicted positive values which means that the value of actual class is yes and the value of predicted class is also yes. E.g. if actual class value indicates that this passenger survived and predicted class tells you the same thing.

True Negatives (TN): A person who default predicted as payer. These are the correctly predicted negative values which means that the value of actual class is no and value of predicted class is also no. E.g. if actual class says this passenger did not survive and predicted class tells you the same thing.

$$\text{True Positive Rate (TPR)} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{False Positive Rate (FPR)} = \frac{\text{FP}}{\text{FP} + \text{TN}}$$

Accuracy: The Proportion of the total number of predictions that is correct otherwise overall how often the model predicts correctly defaulters and non-defaulters.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Accuracy is the most intuitive performance measure and it is simply a ratio of correctly predicted observation to the total observations. One may think that, if we have high accuracy then our model is best. Yes, accuracy is a great measure but only when you have symmetric datasets where values of false positive and false negatives are almost same.

Precision: The proportion of positive predictions that are actually correct.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. The question that this metric answer is of all passengers that labeled as survived, how many actually survived? High precision relates to the low false positive rate. We have got 0.788 precision which is pretty good.

Recall: The proportion of positive observed values correctly predicted. (The proportion of actual defaulters that the model will correctly predict)

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

Recall(Sensitivity) - Recall is the ratio of correctly predicted positive observations to the all observations in actual class - yes.

F1 Score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account. Intuitively it is not as easy to understand as accuracy, but F1 is usually more useful than accuracy, especially if you have an uneven class distribution. Accuracy works best if false positives and false negatives have similar cost. If the cost of false positives and false negatives are very different, it's better to look at both Precision and Recall.
General Formula:

$$\text{F-Measure} = \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}}$$

$$\text{F1-Score} = \frac{2 \times (\text{Recall} \times \text{Precision})}{\text{Recall} + \text{Precision}}$$

4.5 Algorithm and Techniques

4.5.1 Algorithm Explanation

Deep learning algorithms play a crucial role in determining the features and can handle the large number of processes for the data that might be structured or unstructured. Although, deep learning algorithms can overkill some tasks that might involve complex problems because they need access to huge amounts of data so that they can function effectively. Deep learning algorithms are highly progressive algorithms that learn about the image that we discussed previously by passing it through each neural network layer. The layers are highly sensitive to detect low-level features of the image like edges and pixels and henceforth the combined layers take this information and form holistic representations by comparing it with previous data. Convolutional neural network (CNN) popularly known as ConvNets majorly consists of several layers and are specifically used for image processing and detection of objects.CNNs process the data by passing it through multiple layers and extracting features to exhibit convolutional operations. The Convolutional Layer consists of Rectified Linear Unit (ReLU) that outlasts to rectify the feature map. The Pooling layer is used to rectify these feature maps into the next feed. Pooling is generally a sampling algorithm that is down-sampled and it reduces the dimensions of the feature map. Later, the result generated consists of 2-D arrays consisting of single, long, continuous, and linear vector flattened in the map. The next layer i.e., called Fully Connected Layer which forms the flattened matrix or 2-D array fetched from the Pooling Layer as input and identifies the image by classifying it.

4.5.2 Used PythonPackages

Sklearn:In python, sklearn is a machine learning package which include a lot of ML algorithms.Here, we are using some of its modules like train-test-split, DecisionTreeClassifier or Logistic Regression and accuracy-score. NumPy:It is a numeric python module which provides fast maths functions for calculations.It is used to read data in numpy arrays and for manipulation purpose. Pandas:Used to read and write different files.Data manipulation can be done easily with data frames. Matplotlib:Data visualization is a useful way to help with identify the patterns from given dataset. Data manipulation can be done easily with data frames.

4.5.3 Convolutional Neural Network

A convolutional neural network, or CNN, is a deep learning neural network designed for processing structured arrays of data such as images. The CNN architectures are the most popular deep learning framework. CNNs are used for a variety of applications, ranging from computer vision to natural language processing. Convolutional neural networks can operate directly on a raw image and do not need any preprocessing. A convolutional neural network is a feed-forward neural network, often with up to 20 or 30 layers. The power of a convolutional neural network comes from a special kind of layer called the convolutional layer. The architecture of a convolutional neural network is a multi-layered feed-forward neural network, made by stacking many hidden layers on top of each other in sequence. It is this sequential design that allows convolutional neural networks to learn hierarchical features. The hidden layers are typically convolutional layers followed by activation layers, some of them followed by pooling layers. The key building block in a convolutional neural network is the convolutional layer. We can visualize a convolutional layer as many small square templates, called convolutional kernels, which slide over the image and look for patterns. Where that part of the image matches the kernel's pattern, the kernel returns a large positive value, and when there is no match, the kernel returns zero or a smaller value. Convolutional networks are used for alternating between convolutional layers and max pooling layers with connected layers (fully or sparsely connected) with a final classification layer. The learning is done without unsupervised pre-training.Each filter is equivalent to a weights vector that has to be trained. The diagram below represents CNN architecture.
The following are definitions of different layers shown in the above architecture:

1. Input Layer: As input, normalized MRI image datasets are given as the first layer of the presented neural network model.

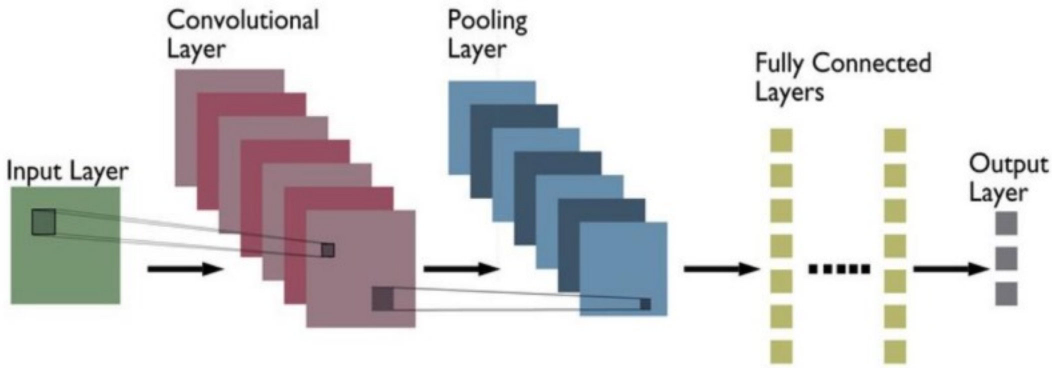

Figure 4.3: CNN Architecture Representation

2. Convolutional layer: Convolutional layers are made up of a set of filters (also called kernels) that are applied to an input image. The output of the convolutional layer is a feature map, which is a representation of the input image with the filters applied. Convolutional layers can be stacked to create more complex models, which can learn more intricate features from images.

3. Pooling layer: Pooling layers are a type of convolutional layer used in deep learning. Pooling layers reduce the spatial size of the input, making it easier to process and requiring less memory. Pooling also helps to reduce the number of parameters and makes training faster. There are two main types of pooling: max pooling and average pooling. Max pooling takes the maximum value from each feature map, while average pooling takes the average value. Pooling layers are typically used after convolutional layers in order to reduce the size of the input before it is fed into a fully connected layer.

4. Fully connected layer: Fully-connected layers are one of the most basic types of layers in a convolutional neural network (CNN). As the name suggests, each neuron in a fully connected layer is Fully connected- to every other neuron in the previous layer. Fully connected layers are typically used towards the end of a CNN- when the goal is to take the features learned by the previous layers and use them to make predictions.

For example, if we were using a CNN to classify images of animals, the final Fully connected layer might take the features learned by the previous layers and use them to classify an image as containing a dog, cat, bird, etc.

5. Dense Layer: By using flatten layer, high-dimensional data becomes column vectors, which follows the convolutional layer, and then there is a dense layer, which does the same functions as a neural network.

6. Dropout Layer: The dropout is regularization technique for neural networks. During training, neurons in the hidden layers are randomly dropped out of the dropout layer. By eliminating some of the neurons, this layer minimizes overfitting in the model.

4.5.4 Optimization Algorithm

As the optimal algorithm, the proposed model is trained with the Adaptive Moment Estimation (Adam) algorithm. This method is very efficient when working big data set or parameters. This algorithm is a combination of the root mean square propagation algorithm and gradient descent algorithm.

4.6 Workflow Diagram

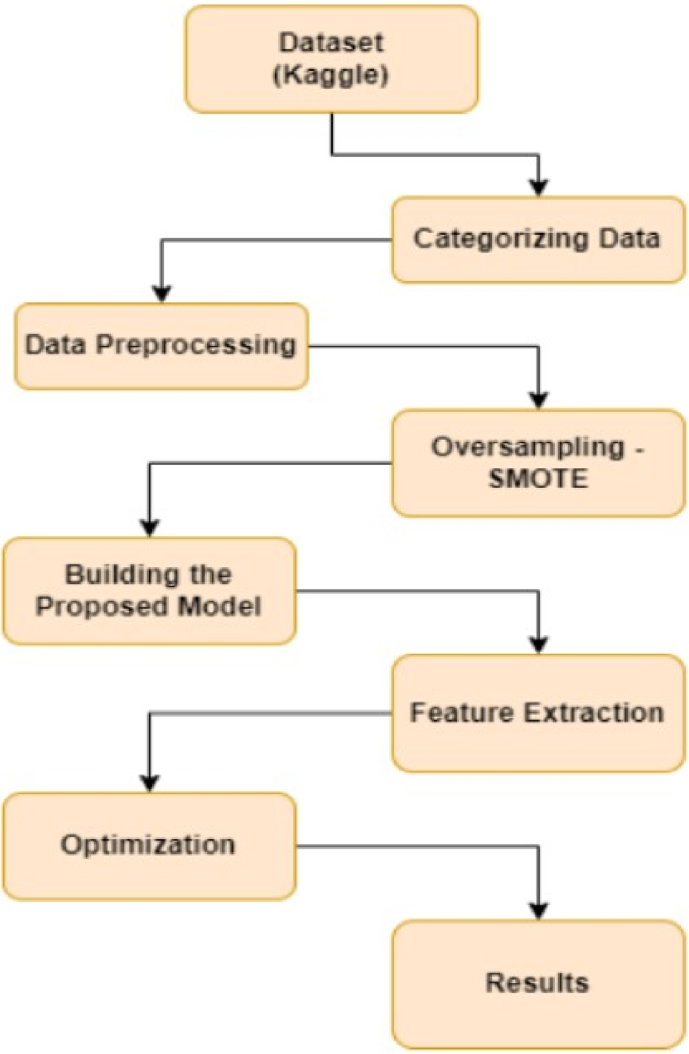

Figure 4.4: Workflow Diagram

Chapter 5

Results and Performance analysis

5.1 RESULTS

The model training is performed using parameter 25 epoch. The model attains a test accuracy of 97% and training accuracy of 98matrix is used to calculate the each and every class metrics

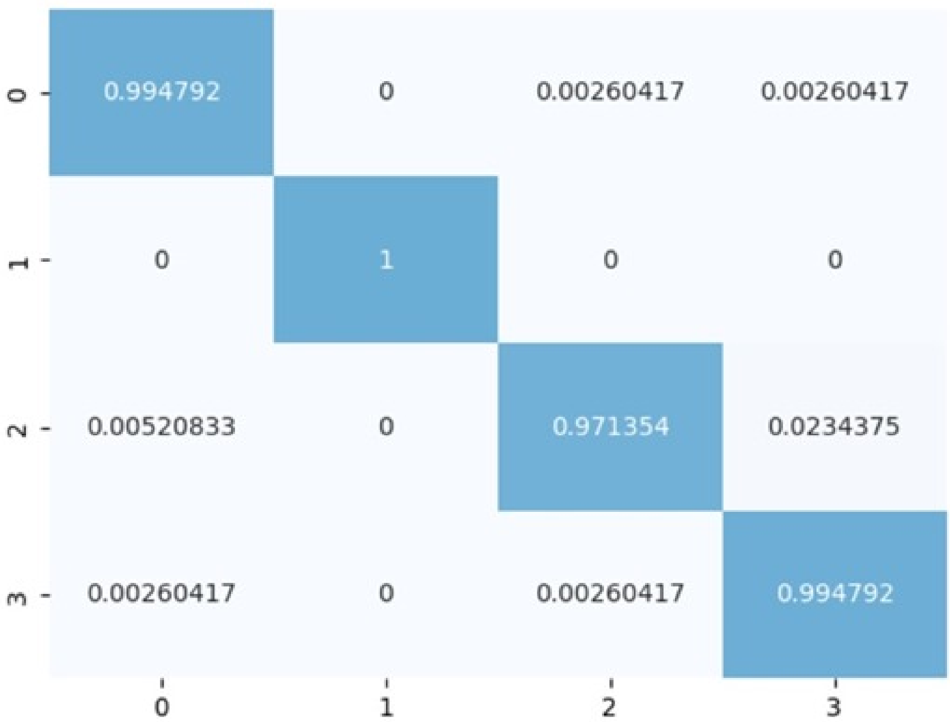

Figure 5.1: Confusion Matrix

In the Confusion Matrix

1. Axes and Classes: The rows represent the true labels (actual classes). The columns represent the predicted labels (model predictions).

2. Diagonal Elements: The diagonal values (e.g., 0.994792 for class 0, 1.0 for class 1) represent the proportion of correct predictions for each class. A higher value indicates better performance for that class.

3. Off-Diagonal Elements: These values indicate misclassifications. For example: 0.00520833 in row 2, column 0 means about 0.5% of true class 2 instances were incorrectly classified as class 0. 0.0234375 in row 2, column 3 indicates that 2.3% of true class 2 instances were misclassified as class 3.

4. Overall Pattern: The model performs very well, with most values concentrated on the diagonal (correct predictions) and small values in off-diagonal positions (misclassifications). Notably, class 1 achieves perfect classification (1.0 on the diagonal).

5.2 Performance analysis and classification report

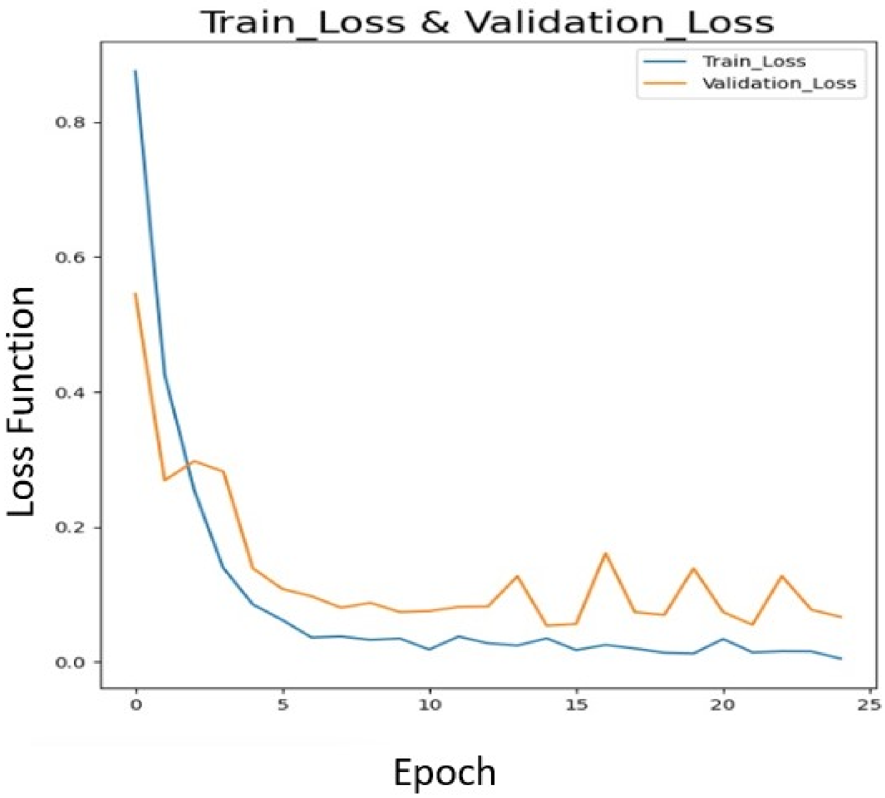

Figure 5.2: Training Loss

This graph shows the training loss and validation loss of a model over 25 epochs.

1. Training Loss : Decreases steadily, indicating that the model is learning from the training data.

2. Validation Loss: Initially decreases, showing the model is generalizing well, but begins fluctuating slightly after epoch 10, which might suggest minor overfitting or noise.

Key Observations: Both losses converge and remain relatively low, suggesting a well-trained model. The absence of a large gap between training and validation loss indicates minimal overfitting.

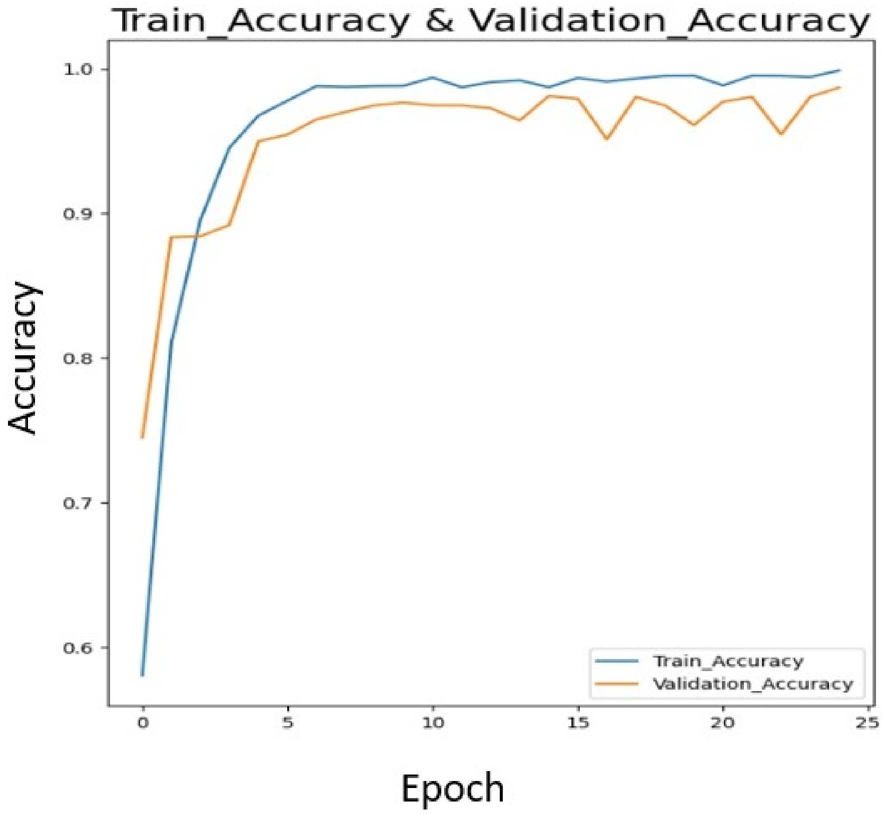

Figure 5.3: Training Accuracy

This graph shows the training accuracy and validation accuracy of a model over 25 epochs.

1. Training Accuracy: Increases rapidly and stabilizes near 1.0 (perfect accuracy), indicating the model learns the training data well.

2. Validation Accuracy: Closely follows the training accuracy, stabilizing around 0.98 after 10 epochs, showing good generalization to unseen data.

Key Observations: Minimal gap between training and validation accuracy indicates low overfitting. The model achieves high and consistent performance on both training and validation datasets.

Classification Report is:	Precision	Recall	F1-Score	Support
0	0.98	1.00	0.99	384
1	1.00	1.00	1.00	384
2	0.95	1.00	0.97	384
3	0.99	0.92	0.96	384
Accuracy			0.98	1536
Macro Average	0.98	0.98	0.98	1536
Weighted Average	0.98	0.98	0.98	1536

Figure 5.4: Classification report

This classification report evaluates the model's performance across four classes (0–3) using precision, recall, F1-score, and support. The model demonstrates excellent precision (0.95–1.00) for all classes, indicating very few false positives. Recall is similarly high, ranging from 0.92 to 1.00, though slightly lower for class 3, suggesting some missed predictions. The F1-scores, which balance precision and recall, are strong across the board (greater than 0.96). Each class has an equal number of samples (384), ensuring the dataset is balanced. Overall, the model achieves a high accuracy of 98%, with both the macro and weighted averages for precision, recall, and F1-score also at 0.98, confirming consistent and robust performance across all classes.

Chapter 6

Conclusion and Future Scope

6.1 Conclusion

In this paper, a custom CNN model is proposed to predict the class of Alzheimer disease among the given classified images. The proposed model has been tested with testing data consisting of four classes and accomplish a 97.8% accuracy. The dataset has a major disadvantage - a class disparity, the SMOTE method is employed to resolve this issue. In this way, it is well suited to identify brain areas often associated with AD and can facilitate physicians' decision making by helping them determine each patient's AD severity level according to the level of dementia.

6.2 Future Scope

The future scope of predicting Alzheimer's disease using convolutional neural networks (CNNs) is vast. It can involve improving model accuracy with advanced architectures and multimodal data integration, such as combining MRI, PET scans, and genetic data. The development of explainable AI tools can help doctors trust and understand predictions. The project can focus on early diagnosis, even at pre-symptomatic stages, and contribute to personalized treatment plans. Real-world deployment could include cloud-based systems or mobile applications. Collaboration with researchers and validation across diverse populations can ensure reliable and unbiased results. Expanding to wearable device data and tracking disease progression over time can further enhance the system's impact, making it a valuable tool in Alzheimer's care and research.

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