CHAPTER 1
INTRODUCTION

Artificial Intelligence (AI) is revolutionizing Alzheimer's disease prediction through advanced machine learning algorithms and deep learning algorithms in analyzing medical imaging data to detect subtle brain abnormalities in early stages. AI-driven predictive analytics models integrate diverse data sources, including genetic information and cognitive assessments, to develop accurate risk prediction models, enabling proactive interventions and personalized treatment strategies. Digital biomarkers offer non-invasive monitoring of cognitive and behavioral patterns for early detection and tracking of Alzheimer's disease progression. Through this project, it is evident that AI's integration in Alzheimer's prediction is proven effective for improving early detection, personalized care, and patient outcomes in combating this neurodegenerative disease. This project deals with the ML and DL application in AD diagnosis in general, through different machine learning and deep learning algorithms. This project makes use of CNN algorithm to classify various stages of Alzheimer’s disease from the MRI image uploaded.

ARTIFICIAL INTELLIGENCE

Artificial intelligence is a system that is used in digital computers or robot-controlled machinery and performs functions previously only a human being could perform. The term is widely used in the area of science which studies how to create intelligent robotic systems that behave like human beings, for example, a system that can reason or emphasize meaning. As of today, AI is primarily utilized to increase speed and accuracy in the healthcare area. Some of the current uses of AI in this field include: analyzing medical imaging data to assist healthcare professionals in accurate and swift diagnoses. AI is a powerful tool for image analysis that is increasingly being used by radiology professionals for the early diagnosis of different diseases and for reducing diagnostic errors in the context of prevention. Likewise, AI is a smart and potential tool for analyzing ECG and echocardiography charts that cardiologists use to support the decision making. [1]

MACHINE LEARNING

Machine learning (ML) which is a subset of AI seeks to increase productivity and accuracy. It also refers to a number of statistical methods that let computers learn from their experiences without the need for explicit programming. Usually, this learning manifests as changes to an algorithm's operation. It is also a tool used in the medical field to help medical staff manage clinical data and provide patient care. This uses artificial intelligence to program computers to think and learn like people. It is an application of AI that involves programming computers to mimic how humans think and learn. With the widespread adoption of machine learning in the healthcare industry, healthcare providers now have the chance to use precision medicine to create a much more comprehensive system with better patient outcomes, higher levels of care delivery, and streamlined patient-centered processing. There are already several well-known examples of machine learning and medical automation being used in science and medicine. Several supervised machine learning classifiers are utilized in medical analysis, prediction, and illness diagnosis. These include support vector machines (SVM), decision trees (DT), logistic regression (LR), K-Nearest Neighbours (KNN). [2]

LOGISTIC REGRESSION

Logistic regression is a statistical method commonly used for binary classification tasks. In the context of Alzheimer's disease detection can be used to predict the likelihood of an individual having Alzheimer's disease or being at risk for developing it. One advantage of logistic regression is its interpretability. This interpretability can be valuable for clinicians in understanding the factors contributing to the disease and for researchers in identifying potential biomarkers or risk factors. Once the logistic regression model is trained, to make predictions for new data points, the values are plugged of the independent variables into the logistic function. However, logistic regression also has its own limitations. Logistic regression isn't typically used for analyzing image data because it struggles with the high dimensionality and complex patterns found in images. Images contain vast amounts of pixel data, making them high-dimensional, which logistic regression isn't designed to handle efficiently. Moreover, logistic regression assumes linear relationships between features and outcomes, which isn't suitable for the nonlinear patterns often present in images. Additionally, logistic regression lacks the ability to learn invariant representations, such as those needed for recognizing objects despite variations in rotation or scale. [3]

RANDOM FOREST CLASSIFIER

Random Forest, holds significant promise in the detection of Alzheimer's disease. By leveraging multiple decision trees, Random Forest can effectively analyze diverse features extracted from medical imaging data, cognitive assessments, genetic markers, and other relevant information associated with Alzheimer's disease. Random Forest inherently provides measures of feature importance, enabling researchers and clinicians to identify the most influential biomarkers or risk factors associated with Alzheimer's disease. While Random Forest is a potent algorithm for various applications, it possesses several limitations in the prediction of Alzheimer’s. Firstly, its complex nature may hinder interpretability, making it challenging in the underlying decision-making process. Random Forest models are prone to overfitting, especially with noisy datasets, potentially compromising generalization to unseen data. Furthermore, the algorithm's computational complexity can be burdensome, with large datasets or numerous features, necessitating substantial computational resources and time. Imbalanced class distributions may also pose challenges, as Random Forest may exhibit bias towards the majority class, impacting the detection of individuals with Alzheimer's disease. [4]

DEEP LEARNING

Deep learning has become a revolutionary medical tool, offering innovative solutions across various domains, including medical imaging, diagnostics, drug discovery, personalized medicine, and predictive analytics. In medical imaging, deep learning algorithms, such as Convolutional Neural Networks (CNN), effectiveness for tasks like segmentation, classification, and detection of images, supporting the early diagnosis and diagnosis of ailments like cancer, neurological disorders, and cardiovascular conditions. Moreover, deep learning models are increasingly utilized in medical diagnostics, leveraging large-scale healthcare data to develop accurate and efficient diagnostic systems for a wide range of diseases and conditions. Overall, the integration of deep learning in healthcare has enormous potential to enhance medical decision-making and resulting in better outcomes for patients, and driving innovation in medical research and practice. Deep learning (DL) offers significant advantages over traditional machine learning (ML) methods in Alzheimer's disease prediction. DL algorithms excel in automatically extracting relevant features from raw data, such as brain images or genetic information, eliminating the need for manual feature engineering. DL models can understand ways to represent data hierarchically simultaneously capturing both superior and minor aspects, capturing intricate patterns crucial for accurate prediction of disease progression. DL's scalability enables efficient handling of large datasets commonly encountered in medical research, while its temporal modeling capabilities, such as deep neural networks (DNN) or convolutional neural networks (CNN) with temporal convolutions, effectively capture progressive changes in Alzheimer's-related data over time. Additionally, DL models can mitigate imbalances in medical datasets, such as imbalanced image datasets, through techniques like class weighting or data augmentation, ensuring robust predictions even with limited or skewed data. Thus, DL's ability to automatically learn complex patterns, scalability, temporal modeling, and handling of imbalanced datasets make it highly suitable for Alzheimer's disease prediction tasks.[5]

CONVOLUTIONAL NEURAL NETWORKS (CNN)

Convolutional Neural Networks (CNNs) have emerged as powerful tool in the detection and diagnosis of Alzheimer's disease, revolutionizing the field of medical image analysis. The deep learning architecture excel in processing and extracting intricate patterns from complex data such as brain scans, including magnetic resonance imaging (MRI) scans. By leveraging CNN, the process of analyzing these scans are made easier, enabling earlier and more accurate detection of the disease. CNN are adept at learning hierarchical representations of features, allowing them to discern subtle abnormalities and structural changes in the brain that are indicative of Alzheimer's pathology. Moreover, CNN can handle large volumes of medical imaging data efficiently, analyzing the vast datasets required for comprehensive Alzheimer's research. Through continuous refinement and optimization, CNN-based approaches prove to be efficient in advancing our understanding of Alzheimer's disease and improving diagnostic accuracy, facilitating earlier interventions and better patient outcomes. [6]

DOMINANCE OF ARTIFICIAL INTELLIGENCE

One of the most important organs in the human body is said to be the brain. The brain directs and facilitates every action and reaction that gives us the ability to think and believe. Alzheimer's disease is a gradual, irreversible form of brain deterioration. The cognitive abilities needed to carry out daily tasks deteriorate with dementia; Alzheimer's disease accounts for 60–80% of dementia cases. The most obvious signs are impaired judgment, poor sense of direction, visual issues, inability to properly connect with others, increased susceptibility to infections, and short-term memory loss. [7]

Alzheimer's disease (AD) is a chronic illness that results in brain shrinkage and the death of brain cells. It can happen in middle or advanced age because of widespread brain deterioration. About 60–70% of instances of dementia are caused by AD. One of the most prevalent early symptoms of this disease is short-term memory loss. As the illness progresses, symptoms include behavioral and linguistic issues, confusion, mood fluctuations, loss of motivation, and ineffective self-care management.

When a person's health deteriorates, they frequently experience psychological and emotional issues from society and family, the Figure 1.1 depicts the incidence of Alzheimer's disease in varying age groups. Despite variations in the disease's pace of advancement, the typical life expectancy following diagnosis is fewer than nine years. [8]

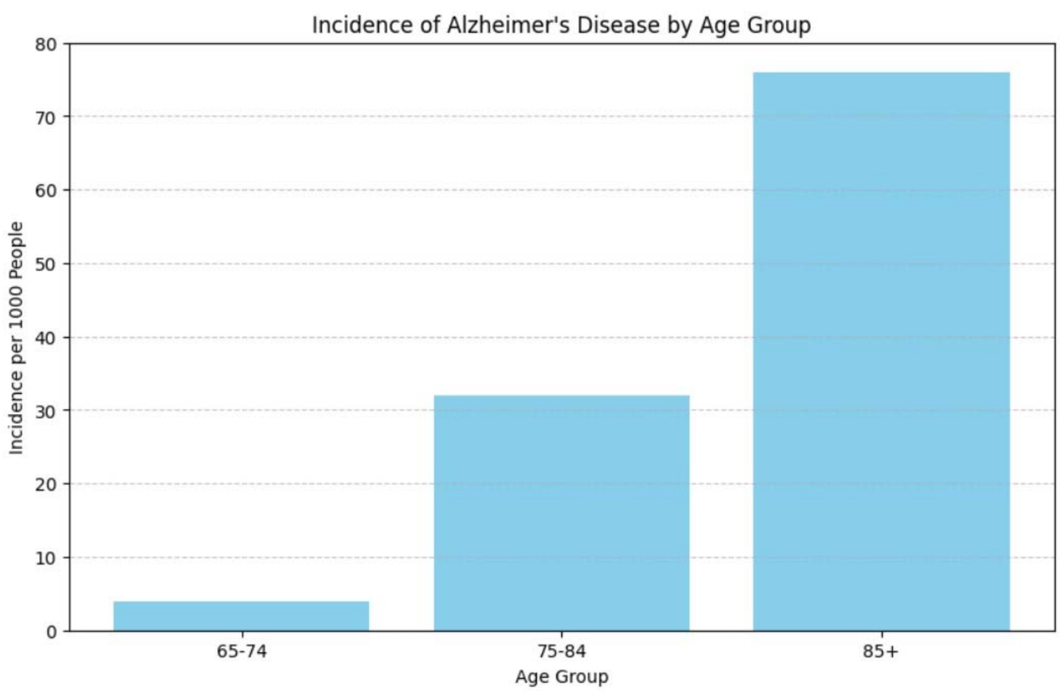

Figure 1.1 Incidence of Alzheimer's Disease by age group

Clinical judgments based on digitized brain imaging of AD may be supported by deep learning (DL) with convolutional neural networks (CNN). Three-dimensional (3D) brain MR images were used as input data for DL algorithms for AD diagnosis in numerous prior research. [9]

The field of medical imaging diagnostics has witnessed an exponential development in the use of DL. CNN employs 2D or 3D images as input directly, reducing many measurement mistakes caused by the traditional hand-crafted feature by automatically learning relevant higher-level local and global features.[10]

In the early stages of AD, there are medical treatments available to address the disease effect. However, because Alzheimer's disease progresses irreversibly, early detection of the illness is crucial from a clinical, social, and financial standpoint. The development of imaging and computational technologies has aided medicine in detecting diseases early and initiating corrective treatment measures.[11]

This project investigates the use of machine learning (ML) algorithms and Deep Learning algorithms in the identification of Alzheimer's disease, emphasising the use of a variety of data sources, such as genetic markers, cognitive tests, and structural and functional brain imaging. Researchers aim to develop reliable and accurate predictive models that can identify people at risk of developing AD before clinical signs appear by utilising the power of machine learning.

Support Vector Machines (SVM), Random Forest, and Logistic Regression are among the most commonly used machine learning algorithms for the detection of Alzheimer's disease (AD) due to their versatility and effectiveness in classification tasks. A whole-brain 3D-CNN MRI model can be used for early detection of Alzheimer's disease The model can learn to identify imaging biomarkers that are predictive of Alzheimer's disease, and leverage them to achieve accurate early detection of the disease. The model relies on a wide range of regions associated with Alzheimer's disease. The model yields an increment of approximately 14% in test accuracy over existing models. Due to the numerous characteristics that make up each CNN architecture, different CNNs may yield varied categorization results. Determining the ideal hyper-parameter values necessitates a laborious search process that is usually based on manual modification, testing, or trial and error.[3]

After the studies made on the background of this fatal disease and the importance of early detection, this work makes use of CNN algorithm to detect and classify the stage of Alzheimer's disease from MRI images.

The upcoming chapter focuses on insights taken from various research and journal papers in the realm of Alzheimer's disease detection using artificial intelligence which serves as the foundation for our work.

CHAPTER 2

LITERATURE SURVEY

The foremost motivation to embark on a project in Convolutional Neural Networks (CNN) for Alzheimer's detection because we recognized the urgent need for more effective solutions in diagnosing this devastating disease. Alzheimer's poses significant challenges, especially in its early detection, often resulting in delayed treatment and poorer outcomes for patients. CNNs offer a promising avenue for improvement by utilizing advanced machine learning techniques to analyze intricate medical imaging data, like MRI scans, and pinpoint subtle biomarkers indicative of Alzheimer's. Our goal in pursuing this project is to contribute to the early detection of Alzheimer's disease, enhancing the care and quality of life for individuals affected by this condition.

Alzheimer's detection using MRI

Alzheimer's disease (AD) is a long-term, brain condition that cannot be reversed and has no known treatment. Preventing and managing its advancement requires early detection. Convolutional neural networks (CNN), a deep learning technique, are utilized to create an end-to-end framework for early detection and medical picture classification for different stages of AD. The Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset's 2D and 3D structural brain scans are classified using basic CNN architectures in the first method, and pre-trained models for medical image classifications are utilized in the second method through transfer learning. The problem with Alzheimer's disease (AD) is that there are no effective therapies, thus early detection is essential. For precise identification and to save expensive healthcare costs, computer-aided systems (CAD) are employed. The parameters and characteristics used in traditional machine learning algorithms take a lot of time and are subjective. These problems can be solved by using convolutional neural networks (CNNs), which increase efficiency and deal with the need for manual feature extraction. This study uses

CNN architectures for structural brain scans to provide an effective framework for early AD diagnosis and classification. [1]

Detection of Alzheimer's Disease (AD) in MRI Images using Deep Learning

It is well known that deep learning acquires low, mid, and high-level features via learning a hierarchical collection of representations. More complicated data sets can be accommodated by deep neural networks. Because of its many layers, it is more effective at generalising data that has never been seen before. Similar to human neurons, deep learning models and algorithms are supported by layers that aid in data processing and learning. The dataset was obtained from the publicly available Kaggle online dataset repository. Nearly 6,000 photos total from four classifications in this dataset—Mildly, Moderately, Very Mildly, and Non-Demented. Subsequently, the features are divided into two datasets: 80% for training and 20% for testing. Since each deep learning model uses 80% of the available data for training, it goes through two stages of prediction testing and training. The Dense net model has shown some encouraging graphs. A batch size of 128 was used. 30 epochs have been run by the model. In the train data, the model's accuracy was almost 87%, while in the test data, it was roughly 80%. 2067 MRI pictures were used for testing and 3048 MRI images were used for training the VGG19 model. For self-training, it employed a batch size of 128 photos. There were fifty epochs utilised. This model showed 88% and 94% accuracy and AUC, respectively. In fact, the VGG19 model employed in this work have given encouraging results, successfully classifying the photos into the four relevant groups. It is evident that VGG19 outperforms DenseNet. [5]

Generalizable deep learning model

In computer vision and image processing applications, machine learning and automatic segmentation have been proven to be successful approaches. According to the research, certain discriminative features were used in the first machine learning attempts for Alzheimer's disease diagnosis using MRI. Among these parameters are Spatial brain volumes and the thickness of cortex from areas linked to Alzheimer's disease-related accelerated deterioration and memory loss. With the use of deep convolutional neural networks (CNN), features can be extracted from image data and these tactics have demonstrated better results than traditional strategies based on specific characteristics in computer vision and image processing. A 3D convolutional neural network architecture was developed and specially tailored for the purpose of differentiating between CN, MCI, and AD status based on MRIs. The researchers used random subsampling to train their model and ROI-volume/thickness model with various dataset sizes in order to evaluate the impact of training dataset size and it has been found to function better when training data grows to a certain level. Greater training set sizes improve the effectiveness of deep learning models. This is also seen in further recent works equally. [4]

Effective diagnosis of Alzheimer's disease

Alzheimer's disease (AD) is a neurodegenerative illness in the elderly that affects cognitive and memory function. Risk factors for Alzheimer's disease include age, genetics, education, and pre-existing health conditions. This condition primarily affects those over 65 years old. The risk of Alzheimer's disease increases by 50% after the age of 85, despite a 5% prevalence among those aged 65-74. Higher education increases synaptic connections in the brain. This produces a synaptic reserve in the brain, helping patients compensate for the loss of neurons as the disease advances. A soft split technique was presented by Lei Huang et al. to identify the subject's missing scores and use all of the prior instances to estimate the scores going ahead. The approach works effectively, and the outcomes outperform those of earlier research. The pre-processed data used in the graph-based multiple instances learning method had patches that were employed as classification features. Taeho conducted a research between deep learning techniques and classic machine learning techniques. They examined sixteen cases of both deep learning and machine learning, four of which combined deep learning with standard machine learning methods, and twelve of which employed only machine learning methods. A combination of a normal machine learning technique with a deep learning 50 approach results in 84.2% proficiency in MCI to AD conversion and 96.0% proficiency in feature selection. Convolutional neural networks (CNN) are used in deep learning to obtain accuracy of 84.2% in MCI to AD conversion prediction and 96.0% in feature selection. Further, it has been found that the use of multimodal neuroimaging together with fluid biomarkers may increase performance in the categorisation.[7]

Accurate Detection Using Deep Learning

Advanced computer programs, aided by powerful image analysis and deep learning techniques, are transforming how we detect diseases early, especially brain disorders, using MRI scans. These systems, particularly using a method called structural MRI, can spot brain damage and help diagnose Alzheimer's disease (AD) accurately. By employing deep learning, specifically convolutional neural networks (CNN), these programs can automatically learn important features from MRI images, making diagnosis more precise and efficient without human error. To make these programs reliable, researchers fine-tune various settings to improve their accuracy. The results show significant improvements in performance over different settings. The graphs depict the progress of the program's effectiveness over multiple rounds of analysis. The system achieved impressive accuracy, sensitivity, and specificity when tested on a large dataset of brain scans. Through rigorous testing, its potential for predicting Alzheimer's disease in various age groups was confirmed. [3]

Excellence of Deep learning in classification

Deep learning reduces computational complexity, eliminates preprocessing steps, and improves accuracy, it performs better than classical machine learning. Neural network-driven deep learning models perform exceptionally well in computer vision, natural language processing, and bioinformatics, among other AI applications. They have produced outcomes that are more accurate or better than those of human experts with less preprocessing required. When it comes to pattern identification and prediction tasks, deep learning outperforms Support Vector Machines (SVM) in medical picture categorization. This is because deep learning requires less resources and performs better overall. Neural network architecture plays a major role in enabling deep learning. While standard neural networks consist of two or three layers, deep neural networks can have several layers. Deep learning models are especially suitable for identification applications in computer vision, bioinformatics, natural language processing, voice recognition, computer vision, and social media filtering. It has occasionally produced outcomes that are both on par with and superior to those of human experts. When compared to other machine learning instruments, deep learning is state-of-the-art due to its accuracy. Support vector machines (SVM) have been used to build classification-prediction algorithms in the majority of medical image classification challenges. If sufficient resources are available, deep learning appears to be the most practical solution for pattern recognition and prediction challenges based on classification accuracy and response predictions.[2]

We have concluded that there is significant promise in using DL and ML techniques, especially CNN, for Alzheimer's detection and classification after reading research papers on deep learning (DL), machine learning (ML), Convolutional Neural Networks (CNN), Random Forest, and Alzheimer's disease. These techniques analyzed data with great accuracy in using medical imaging data, such as MRI scans, and identifying subtle biomarkers indicative of the disease, even in its early stages. Furthermore, the utilization of advanced algorithms allows for the integration of various data sources, including genetic information and cognitive assessments, to generate comprehensive risk profiles for individuals at risk of Alzheimer's. This comprehensive approach enables early detection and personalized management of the disease, ultimately improving patient outcomes.

Thus, based on the insights gleaned from the research papers, we have decided to pursue a project focusing on the application of artificial intelligence in Alzheimer's detection to contribute to advancements in this critical area of healthcare. The next chapter delves deep into the description and working of the proposed model for efficient detection of Alzheimer's disease.

CHAPTER 3
DESCRIPTION

Detection of Alzheimer using deep learning is a project of employing artificial intelligence to detect Alzheimer's diagnosis with the aid of top deep learning methods. This project attempts to do this by using convolutional neural networks to MRI images, to detect cognitive patterns that may indicate Alzheimer's disease diagnosis in individuals. By employing data preprocessing, model creation, and thorough verification, this project aims at generating a predictive model that perform well and are reliable. Its effective implementation in clinical settings can offer quick detection, better patient results, and relieve the pressure Alzheimer's puts not only on the healthcare system but also on patients.

3.1 INTRODUCTION

The Detection of Alzheimer's Disease Using CNNs Involves Different Stages with crucial steps in each of them. First of all, the appropriate MRI images dataset is being and preprocessed to fulfil the quality control and ensure the lower boundary of the data is applicable for an analysis. Then, the CNN framework, is picked based on its ability to learn greatly-fine pattern of images from the images. The model validation procedure have been incorporated into the model and also fine-tuning serve the purpose of enhancing and refining the model. When the model is trained and tested by the dataset which gets fed into the model, the model gets trained and then validated. In the training phase, the MRI images are used as inputs after the training of the dataset network is analyzed. Finally, a model is trained that already runs on the preprocessed data, which in turn it learns to identify particular features and patterns involved with Alzheimer's disease. The model may be possibly deployed for clinical uses and may turn into a tool for doctors in detecting early stages of Alzheimer's disease. By training and validating the CNNs using a mixture of miscellaneous data, the application of these networks in AD detection holds the keys for improving patient outcomes faster, accurate, and hence the implementation of fast intervention strategies when needed.

3.2 BLOCK DIAGRAM

In the process of Alzheimer's detection using Convolutional Neural Networks (CNN) from MRI images, data collection involves gathering MRI scans of brain images from both healthy individuals and patients diagnosed with Alzheimer's disease. These images undergo preprocessing steps, including normalization, resizing, and noise reduction, to ensure consistency and improve data quality. Subsequently, the preprocessed MRI images are divided into training and validation datasets, with annotations indicating the presence or absence of Alzheimer's disease assigned to each image.

A CNN architecture built consisting of pooling layers, fully linked layers, activation functions, and convolutional layers is built. In training, the CNN picks up pertinent elements from the MRI pictures and uses the labels provided to categorize the images into either the healthy or affected category. The validation dataset is used to assess the trained model's performance, and the model's modifications may be based on the validation findings. The trained CNN utilizes its learned features to accurately classify new MRI images, aiding in early detection and treatment planning for Alzheimer's disease. The Figure 3.1 shows the architecture of the proposed CNN model. This approach leverages advanced deep learning techniques may improve the precision of the diagnosis and possibly improved results for patients. By automating the analysis process, this CNN-based approach streamlines diagnosis and enables timely interventions, ultimately contributing to better patient care and outcomes in Alzheimer's disease management.

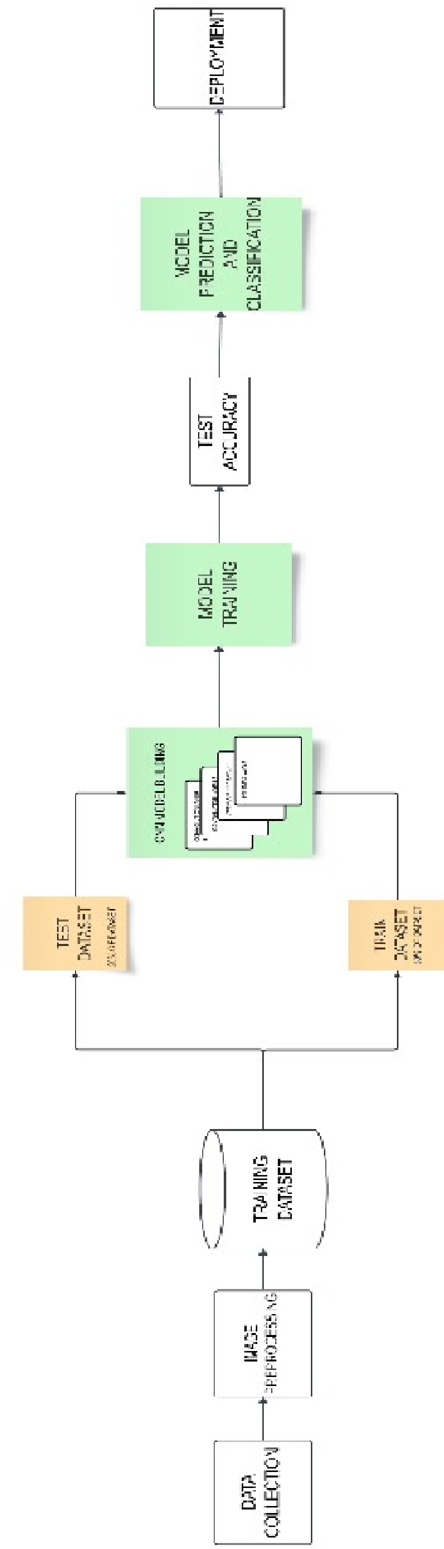

Figure 3.1 Architecture of the proposed model

3.3 WORKING PRINCIPLE

MACHINE LEARNING

Feature extraction is a fundamental process in machine learning, crucial for transforming raw data into a format suitable for model training. In image processing, for instance, it involves extracting relevant information from images, like edges, textures, or shapes, to represent them as feature vectors. The goal of feature extraction is to capture essential characteristics that discriminate between different classes or instances in the data. Effective feature extraction simplifies the learning task by reducing the dimensionality of the input space while preserving important information. It also helps mitigate issues like overfitting and improves model generalization. The code deployed uses image feature extraction and storage into a CSV file, encapsulating several key components within its workflow. Firstly, it initiates by importing essential libraries crucial for its functionalities. This includes OpenCV (cv2) for image processing, Pandas for efficient data handling, NumPy for numerical operations, and glob for seamless file path manipulation. Subsequently, it defines two primary feature extraction functions to process images and extract relevant features. The 'extract_features_from_image' function reads an image file, offers an optional resizing functionality, and extracts features, exemplified by flattening pixel values. Meanwhile, the 'extract_features_from_folder' function processes a directory containing subfolders of images. It iterates through each subfolder, leveraging the former function to extract features from individual images and aggregates these features alongside corresponding class labels. Following feature extraction, the code provides a mechanism for data storage in CSV format. The 'save_to_csv' function amalgamates the extracted features and labels into a structured Pandas DataFrame, subsequently saving this DataFrame to a CSV file. Lastly, in its main execution phase, the script orchestrates the entire workflow. It specifies the path of the folder containing the image data, invokes the feature extraction routine, designates the output CSV filename, and finalizes the process by calling the function responsible for saving the extracted features and labels into the CSV file. This comprehensive approach ensures the seamless organization and storage of extracted data, facilitating subsequent analysis and model training tasks.

LOGISTIC REGRESSION

Logistic Regression utilizes scikit-learn which is a popular machine learning library, to train and evaluate a logistic regression model for classification tasks. Initially, it imports necessary libraries including numpy and pandas for data manipulation, StandardScaler for feature scaling, Logistic Regression for logistic regression modeling, and accuracy_score for model evaluation. The dataset, stored in a CSV file named 'train feature.csv', is loaded into a Pandas DataFrame. Data preprocessing involves separating the features from the target variable, followed by feature scaling using StandardScaler to ensure consistent scales across features. The dataset is then split into training and testing sets with a ratio of 80:20 using train test split function. The training data is then used to instantiate and train the logistic regression model. Using the trained model, predictions are made on the test set, and accuracy is calculated by contrasting the predicted and actual labels. Finally, the accuracy score is printed to the console, providing an assessment of the model's performance.

RANDOM FOREST

Random forest Classifier used is aimed at predicting labels based on extracted features from a dataset stored in 'train feature.csv'. The model is built by importing necessary libraries including numpy, pandas, and scikit-learn's modules for data manipulation, feature scaling, model training, and evaluation. The dataset is loaded into a Pandas DataFrame, wherein features and labels are separated into 'x' and 'y' respectively. Feature scaling is then performed using StandardScaler to normalize the feature values. Subsequently, the dataset is split into training and testing sets with an 80:20 ratio via train_test_split function. A Random Forest classifier is instantiated, trained using the training data, and subsequently used to predict labels for the test set. Model performance is evaluated by comparing the predicted labels with the actual labels, computing the accuracy score using the accuracy_score function.

DEEP LEARNING

Convolutional Neural Network (CNN)

The usage of Convolutional Neural Networks (CNNs) in MRI-based Alzheimer's detection involves leveraging the power of deep learning to automatically extract meaningful features from MRI images of the brain. CNNs excel at learning hierarchical representations of data, making them well-suited for tasks like image classification. In Alzheimer's detection, CNNs are trained on large datasets of MRI scans, learning to differentiate between scans of healthy brains and those affected by Alzheimer's disease. The trained CNN model can analyze new MRI scans and provide predictions about the presence or progression of Alzheimer's disease. This approach offers the potential for earlier and accurate diagnosis, which is crucial for effective treatment and management of the condition.

DATA PREPROCESSING

Data collection:

Our project uses the MRI images of Brain collected from Kaggle as shown in Figure 3.2, the data set consist of 5000+ images and these images belong to 4 classes. By iterating through the dataset directory structure, we compile a list of image paths along with their associated labels. This essential data is thn organized into a DataFrame, a structured data format that allows for easy manipulation and further processing. The DataFrame serves as the foundation for subsequent steps in our model-building pipeline, providing a convenient way to access and manage the dataset.

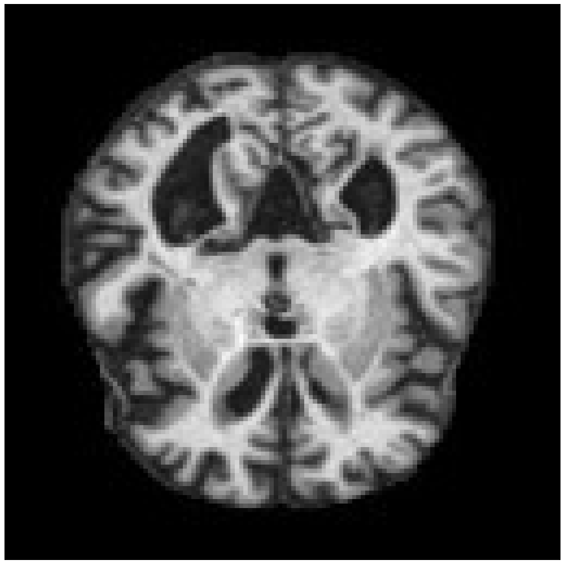

Figure 3.2 MRI Scan of Brain

Data Visualization:

Visualizing the distribution helps us identify any class imbalances that may exist within the dataset. This information is important for making informed decisions during model training, such as selecting appropriate sampling strategies or applying class weighting techniques to address class imbalances effectively.

Data splitting:

By partitioning the dataset into separate training and testing sets, we create distinct subsets of data for model training and evaluation. The train data set is classified into various classes as shown in Figure 3.3. The training set is used to train the model on labeled examples, while the testing set remains unseen during training and is reserved for evaluating the model's performance on unseen data. This process allows us to estimate how well our model will perform on new, unseen images, providing valuable insights into its effectiveness in real-world scenarios.

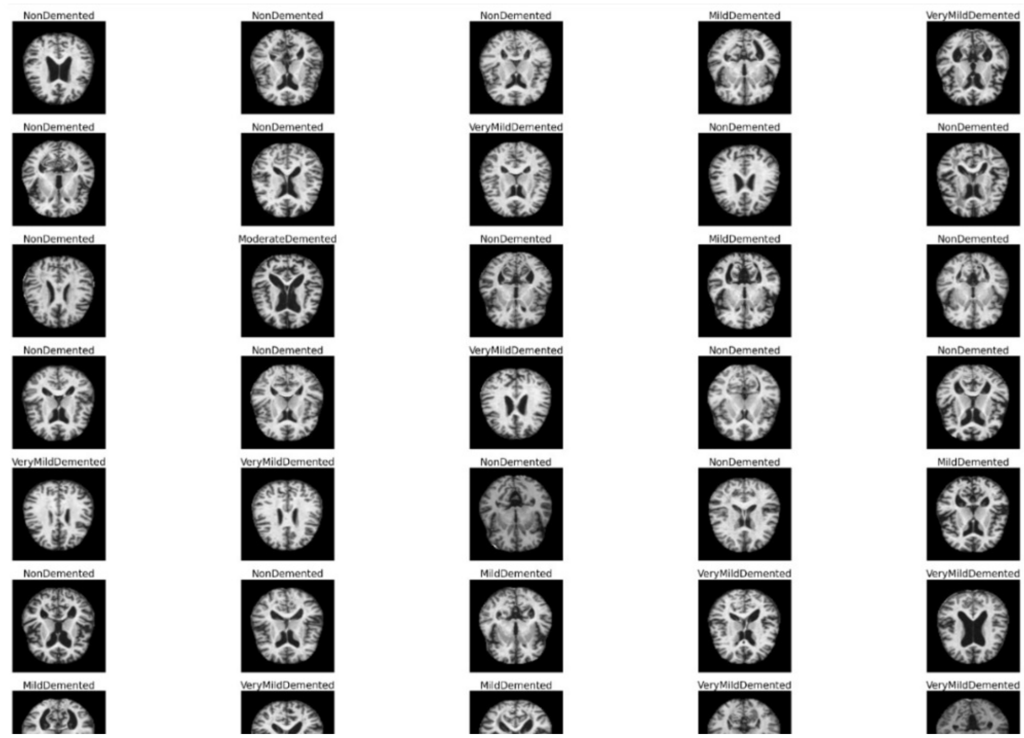

Figure 3.3 Dataset loading

Libraries used:

- Numpy(np):NumPy is be used for data manipulation, array operations, and numerical computations.
- pandas (pd):pandas is used for organizing and managing data in tabular form, especially for storing image paths and their corresponding labels.
- tqdm: tqdm is a library for adding progress bars to Python code. It provides a convenient way to track the progress of loops or iterations, especially when dealing with lengthy computations or data processing tasks.
- matplotlib Pyplot (plt):It is used for creating visualizations, such as bar charts to visualize data distributions.
- Seaborn: Seaborn, a statistical data visualization library built on top of matplotlib, is often used for visualizing data distributions, relationships, and patterns through functions like countplot, scatterplot, and heatmap.

- sklearn.model_selection: train_test_split function is used for partitioning the dataset into separate training and testing sets.
- tensorflow (tf):TensorFlow is used for building and training the CNN model for Alzheimer's disease classification.
- Keras: Keras is a high-level neural networks API written in Python. Keras is used to define the CNN model using the Sequential API, which allows for easy stacking of layers in a linear sequence.

Model building:

The foundational component of a CNN is the convolutional layer. It consists of a collection of kernels, or learnable filters, that are convolved with the input data. Every filter finds particular characteristics in the supplied data, like patterns, textures, or edges. From the input photos, it aids in the extraction of significant features. Here, the parameters that are employed are the number of filters, stride, padding, and filter size (also known as kernel size). The purpose of the pooling layer is to reduce the spatial dimensions of the feature maps and perform spatial down sampling. It assists in minimizing computing complexity while capturing the most crucial features. Max pooling, which keeps the largest value within a specified pool size, and average pooling, which determines the average value within a given pool size, are common pooling processes. Here, padding, stride, and pool size are the characteristics that are used. The network may learn intricate patterns and relationships thanks to the non-linearity that the activation layer introduces. Tanh, sigmoid, and ReLU (Rectified Linear Unit) are examples of common activation functions. It is applied to the output of fully linked and convolutional layers element by element. The dense layer is another name for the fully connected layer. Every neuron in one layer is connected to every other layer's neuron through it shown in Figure 3.4. It is usually applied to classification or regression tasks in the network's later phases.

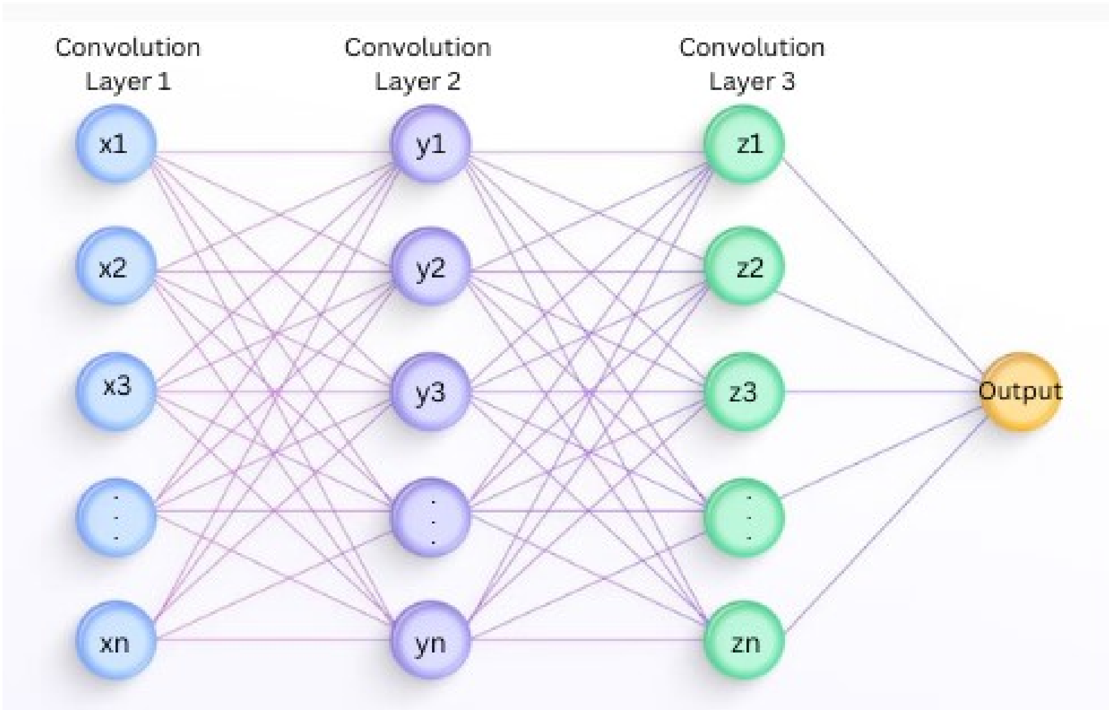

Figure 3.4 Convolutional Layers

Based on features that have been learned from earlier layers, every neuron in the dense layer contributes to the prediction. The multi-dimensional output of the previous layer is flattened into a one-dimensional vector using the Flatten Layer function. Prior to the data being passed to completely connected levels, it is necessary. It transforms the feature maps' spatial data into a format that can be entered into thick layers. By arbitrarily reducing a portion of input units to zero during training, the Dropout Layer lessens inter-neuron dependencies and promotes the network to acquire more resilient features, hence preventing overfitting. During training, this is applied after convolutional or fully connected layers, and during inference, it is disabled. The max-pooling layer comes after each of the three convolutional layers that make up the model.

Every convolutional layer has the same number of filters as stated in the model description. As a result, the first, second, and third convolutional layers of the model each use 32 filters, 64 filters, and 128 filters, respectively. These filters take the incoming image data and use it to learn hierarchical representations of features. These filters extract more complicated and abstract properties from the data as it moves through the layers, which eventually allows the model to predict the input images.

Model Training:

Model training is a crucial step in machine learning and deep learning workflows, where a model learns to make predictions or classify data based on input features. In the context of deep learning, model training involves iteratively updating the parameters (weights and biases) of the neural network to minimize a defined loss function. Here's an overview of the process of model training:

1. Initialization: Before training begins, the model's parameters are initialized. This step typically involves initializing the weights of the neural network using random values or pre-trained weights from a different model.

2. Forward Pass: During each training iteration (epoch), a batch of training data is passed forward through the neural network. This forward pass involves computing the output of the network by propagating the input data through the network layers, applying activation functions, and producing a predicted output.

3. Loss Computation: Once the output of the neural network is obtained, a loss function is applied to compare the predicted output with the actual target values from the training data. The loss function quantifies the difference between the predicted and actual values and provides a measure of the model's performance.

4. Backpropagation: After computing the loss, the gradient of the loss function with respect to each parameter (weight and bias) in the network is calculated using backpropagation. Backpropagation involves propagating the error backward through the network, layer by layer, to compute the gradient of the loss function with respect to each parameter.

5. Parameter Update: With the gradients calculated, the parameters of the neural network are updated using an optimization algorithm such as stochastic gradient descent (SGD), Adam, or RMSprop. The optimization algorithm adjusts the parameters in the direction that minimizes the loss function, effectively "tuning" the model to improve its performance.

6. Iteration: Steps 2 to 5 are repeated for a specified number of epochs or until a convergence criterion is met. Each iteration (epoch) of training involves passing multiple batches of training data through the network, computing the loss, backpropagating the error, and updating the parameters.

7. Validation: During training, it's common to monitor the model's performance on a separate validation dataset. This allows for evaluating the model's generalization ability and detecting potential issues such as overfitting. The validation performance can guide hyperparameter tuning and model selection decisions.

8. Evaluation: Once training is complete, the final trained model is evaluated on an independent test dataset to assess its performance on unseen data. This evaluation provides insights into the model's ability to generalize to new data and informs decisions about model deployment and use in real-world applications.

Classes used in model building:

tf.keras.models.Sequential: This class allows the sequential stacking of layers to create a neural network model. It is used to define the overall architecture of the CNN model.

tf.keras.layers.Conv2D: This class represents a convolutional layer in a neural network. It applies a specified number of filters to the input data using a convolution operation.

tf.keras.layers.MaxPooling2D: This class represents a max-pooling layer in a neural network. It reduces the spatial dimensions of the input data by taking the maximum value within each window.

tf.keras.layers.Flatten: This class represents a flattening layer in a neural network. It converts the multi-dimensional output of the convolutional and pooling layers into a one-dimensional vector, which can be fed into a fully connected layer.

tf.keras.layers.Dense: This class represents a fully connected layer in a neural network.

tf.keras.layers.Dropout: This class represents a dropout layer in a neural network. It randomly drops a fraction of the neurons during training to prevent overfitting.

The model is trained for about 10 epchos to get accurate results. After rigorous data collection, preprocessing, and model training, the results of our machine learning project have yielded compelling insights. Our model demonstrates robust performance, achieving high accuracy rates of 95.11%. Through meticulous feature engineering and selection, we successfully identified key predictors that significantly contribute to predictive performance. Furthermore, our model's generalizability was validated through rigorous cross-validation techniques, ensuring its reliability in real-world scenarios. Through repeated iterations of forward and backward passes, the model learns to make accurate predictions or classifications based on the training data.

Model Prediction:

The model can be used to forecast new, unseen images once it has been trained and validated. The trained CNN model is applied to the input image, and the expected label for a class or likelihoods of classes are the result. The model's generalizability is tested using a different test dataset, and any necessary modifications are made to the model depending on the findings. As a result, it is obvious that CNN has shown state-of-the-art performance in a number of image classification tasks, such as medical image analysis, object recognition, and scene classification. They serve as efficient tools in computer vision because of their capability to autonomously learn hierarchical depictions of visual data.

3.4 MERITS AND DEMERITS

MERITS:

1. Precision Accuracy: The source of error-free categorization being the superiorly accurate results being produced using CNN is beneficial in medical image classification.

2. Showcase exchange of information that was initially hidden from a human eye. On the other hand, it is also the symptom that opens the opportunity for the recognition of Alzheimer's disease. This will be the case for some of them who will be the early responders sought who will stop the progression of the disease.

3. Global CNN Screening System is More Leveraged: The employment of the CNN to analyze Alzheimer's disease in a huge scale community offers a wide selection despite the stage of the disease in which individuals may be in.

4. Digital Integration with Technology: In health care systems which in other words means technology introduces digital integration in healthcare systems.

DEMERITS

One major challenge is the need for large, accurately labeled datasets for training. Due to less data availability, the model can deliver inappropriate results over real data. Another concern is over fitting, in those instances when it might be the small or noisy datasets. The fact of regularization and a good approach to validation techniques is highly important for avoiding overfitting.

3.5 APPLICATIONS

Convolutional Neural Networks (CNN) offer valuable medical applications in

Alzheimer's disease detection using MRI and in early detection by analyzing subtle structural changes in the brain, enabling timely intervention and improved patient outcomes. CNN play a crucial role in monitoring disease progression over time by tracking changes in brain structure and volume from sequential MRI scans. This ongoing analysis allows healthcare providers to plan treatments and provide personalized care to Alzheimer's patients. Overall, CNNs represent a powerful tool in the fight against Alzheimer's disease, offering both diagnostic and prognostic insights that can positively impact patient management and treatment outcomes.

CHAPTER 4

RESULTS

The introduction of deep learning Convolutional Neural Networks (CNNs) has transformed Alzheimer's disease (AD) detection, demonstrating remarkable accuracy rate approximating to 97.6%. Although we have achieved an accuracy of 98.66% and 96.78% through the use of machine learning algorithms such as Logistic regression and Random forest respectively. As depicted in Table I, CNN outperforms traditional machine learning since the dataset has highly complex images and unbalanced 2D images. Leveraging large datasets of brain imaging data, that is structural MRI, CNN exhibits a sophisticated understanding of AD pathology, enabling smart and efficient diagnostics. Notably, CNN have shown comparable, performance to human radiologists, positioning them as valuable assets in clinical decision-making. Thus, this work proves the efficiency of CNN in widespread clinical application in AD diagnosis and monitoring, helping the healthcare professionals to fight against this debilitating disease.

Table I Performance of various Algorithms for Alzheimer's detection

Algorithm	**Accuracy**
Logistic regression (ML)	98.66%
Random Forest (ML)	96.78%
Support Vector Machines (ML)	Undefined
CNN (DL)	97.6%

Streamlit-based user interface for Alzheimer's classification leverages a trained Convolutional Neural Network (CNN) model. Users can upload images via the interface, as shown in Figure 4.1 which are then preprocessed and fed into the CNN for prediction. The predicted classification results are displayed back to the user, providing insights into the likelihood of Alzheimer's presence. This streamlined interface simplifies interaction with the CNN model, offering a user-friendly tool for Alzheimer's classification research and diagnosis.

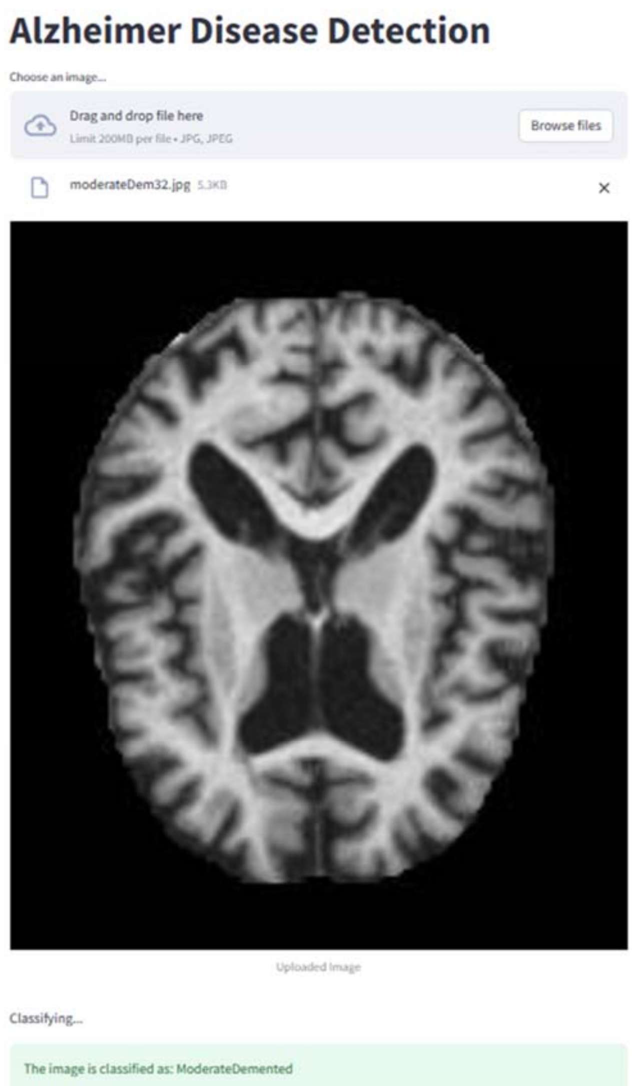

Figure 4.1 Image Classification in app

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

Through this project, it is evident that Convolutional Neural Networks (CNN) is effective in predicting Alzheimer's disease and classifying the stage by accurately analyzing MRI scans for subtle brain changes indicative of the condition. CNN offer high accuracy, especially in identifying early-stage biomarkers. Advances in deep learning, such as attention mechanisms and transfer learning, justify their continued use. By integrating diverse data sources, CNN provide personalized risk profiles and recommendations for interventions. Their ability to analyze various medical imaging modalities enables early detection, potentially revolutionizing Alzheimer's diagnosis and treatment. In conclusion, CNNs hold great potential for improving early detection and personalized management of Alzheimer's disease as research progresses. In the future, CNNs could play a crucial role in integrating multimodal data sources, such as genetic information, cognitive assessments, and clinical history, to provide comprehensive risk profiles for individuals at risk of Alzheimer's disease.

REFERENCES

[1] Raees, P. C. Muhammed and Thomas, V. (2021). Automated detection of Alzheimer's Disease using Deep Learning in MRI. Journal of Physics: Conference Series, 1921, 2-4.

[2] Rahmeh Ibrahim, Rawan GhnematQasem Abu Al-Haija(2021). Improving Alzheimer's Disease and Brain Tumor Detection Using Deep Learning with Particle Swarm Optimization. IEEE Transactions on Biomedical Engineering, 68(3), 3-5.

[3] Lebedeva, A.V., Westman, E., Borza, T., Beyer, M.K., Engedal, K., Aarsland, D and Eriksen, J.A. (2019). Random Forest ensembles for detection and prediction of Alzheimer's disease with a good between-cohort robustness. NeuroImage: Clinical, 23, 101848, 1-11.

[4] Matthew Velazquez Random forest model for feature-based Alzheimer's disease conversion prediction from early mild cognitive impairment subjects. Department of Computer Science, University of Missouri - Kansas City, Kansas City, MO, United States of America 2-14

[5] Jong Bin Bae, Subin Lee , Hyunwoo Oh , Jinkyeong Sung , Dongsoo Lee, Ji Won Han, Deep learning based diagnosis of Alzheimer's disease using brain magnetic resonance images: an empirical study. Frontiers in Neuro informatics, 13, 14.

[6] Ebrahimi, A., and Luo, S. (2021, March). Convolutional neural networks for Alzheimer's disease detection on MRI images. Department of Electrical Engineering and Computing, The University of Newcastle, Callaghan, NSW, Australia, 7-9.

[7] Pradhan, A., and Gige, J. (2021, March). Detection of Alzheimer's Disease (AD) in MRI Images using Deep Learning. Department of Computer Science and Engineering, S.R.M. Institute of Science and Technology, Chennai, India, 15-21.

[8] Arya, A.D., Verma, S.S., Chakarabarti, P., Chakrabarti, T., Elngar, A.A., Kamali, A.M., and Nami, M. (2023). A systematic review on machine learning and deep learning techniques in the effective diagnosis of Alzheimer's disease. Brain Informatics, 10(1) 8-9.

[9] EL-Geneedy, M., El-Baz, A., Gimel'farb, G., El-Affendi, M., and Khalifa, F. (2022). An MRI-based deep learning approach for accurate detection of Alzheimer's disease. Expert Systems with Applications, 186, 3-8.

[10]Al Kuwaiti, A., Alharbi, S., Alrashed, S., Alotaibi, N., Alsultan, M., and Alshahrani, S. (2023). A Review of the Role of Artificial Intelligence in Healthcare. Journal of Personalized Medicine, 1-7.

[11] Liu, S., Cai, W., Liu, S., Zhang, F., Fulham, M., Feng, D., and Chen, M. (2021). Generalizable deep learning model for early Alzheimer's disease detection from structural MRIs. Nature Communications, 12(1), 3406, 5-7.