



M.KUMARASAMY
COLLEGE OF ENGINEERING
NAAC Accredited Autonomous Institution

Approved by AICTE & Affiliated to Anna University
ISO 9001:2015 Certified Institution
Thalavapalayam, Karur – 639 113.



ALZHEIMER'S DISEASE PREDICTION

A PROJECT REPORT

GURUMEETA S R (927621BAD012)

PRANISHKA N (927621BAD037)

YUVASHREE S (927621BAD063)

In partial fulfillment for the award of the

degree of

BACHELOR OF TECHNOLOGY

in

ARTIFICIAL INTELLIGENCE AND DATA SCIENCE

M.KUMARASAMY COLLEGE OF ENGINEERING, KARUR

ANNA UNIVERSITY:: CHENNAI 600 025

JUNE 2024

M.KUMARASAMY COLLEGE OF ENGINEERING
(Autonomous Institution affiliated to Anna University, Chennai)
KARUR – 639 113

BONAFIDE CERTIFICATE

Certified that this project report “**ALZHEIMER’S DISEASE PREDICTION USING CNN ALGORITHM**” is the bonafide work of “**GURUMEETA S R [927621BAD012], PRANISHKA N [927621BAD037], YUVASHREE S [927621BAD063]**” who carried out the project work under my supervision. Certified further, that to the best of our knowledge the work reported herein does not form part of any other minor project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate

SIGNATURE

Dr.T.SARAVANAN, Ph.D.,
ASSISTANT PROFESSOR,
Department of Artificial Intelligence and
Machine Learning
M.Kumarasamy College of Engineering,
Thalavapalayam,
Karur-639113.

SIGNATURE

Dr.R.RAJA GURU, M.Tech, Ph.D.,
HEAD OF THE DEPARTMENT,
ASSOCIATE PROFESSOR,
Department of Artificial Intelligence
M.Kumarasamy College of Engineering,
Thalavapalayam,
Karur-639113.

ABSTRACT

Alzheimer's disease (AD) is a progressive neurodegenerative disorder characterized by cognitive decline and memory loss, posing significant challenges for early detection and intervention. In this project, Convolutional Neural Networks (CNNs) are used for the prediction of Alzheimer's disease using brain imaging data. Alzheimer's disease (AD) is the leading cause of dementia in older adults. There is currently a lot of interest in applying machine learning to find out metabolic diseases like Alzheimer's and Diabetes that affect a large population of people around the world. Their incidence rates are increasing at an alarming rate every year. In Alzheimer's disease, the brain is affected by neurodegenerative changes. As our aging population increases, an increase in individuals, their families, and healthcare will experience diseases that affect memory and functioning. These effects will be profound on the social, financial, and economic fronts. In its preliminary stages, Alzheimer's disease is hard to predict. A treatment given at an early stage of AD is more effective, and it causes fewer minor damage than a treatment done at a later stage. Several techniques such as Decision Tree, Random Forest, Support Vector Machine, Gradient Boosting, and Voting classifiers have been employed to identify the best parameters for Alzheimer's disease prediction. Predictions of Alzheimer's disease is based on Open Access Series of Imaging Studies data, and performance is measured with parameters like Precision, Recall, Accuracy, and F1-score for ML models. The proposed classification scheme can be used by clinicians to make diagnoses of these diseases. It is highly beneficial to lower annual mortality rates of Alzheimer's disease in early diagnosis with these ML algorithms.

Keywords: Alzheimer Disease, Convolutional Neural Networks, Neurodegenerative, Decision Tree, Random Forest, Support Vector Machine

TABLE OF CONTENTS

CHAPTER NO.	TITLE	PAGE NO.
	ABSTRACT	
	TABLE OF CONTENTS	
	LIST OF FIGURES	
	LIST OF ABBREVIATIONS	
1	INTRODUCTION	1
	1.1 BACKGROUND	2
	1.2 PROBLEM STATEMENT	4
	1.3 OBJECTIVE	4
2	LITERATURE REVIEW	6
3	PROJECT METHODOLOGY	12
	3.1 DESCRIPTION OF THE WORKING FLOW OF PROPOSAL SYSTEM	13
	3.2 MRI DATASET	13
	3.3 DATA PREPROCESSING	14
	3.4 PROPOSED METHOD-CONVOLUTIONAL NEURAL NETWORK	14
4	RESULT AND DISCUSSION	16
	4.1 EVALUATION METRICS	17
6	CONCLUSION	20
7	REFERENCES	22

LIST OF FIGURES

FIGURE NO.	TITLE	PAGE NO.
3.1	WORKING FLOW OF PROPOSED SYSTEM	13
3.2	REPRESENTATION OF CONVOLUTIONAL NEURAL NETWORK (CNN)	14
3.3	BUILDING BLOCK OF CNN	15
4.1	CONFUSION MATRIX FOR THE PREDICTION OF ALZHEIMER'S DISEASE	17
4.2	COMPARISON OF THE PERFORMANCE METRICS OF FOUR PROPOSED MODELS	18
4.3	TRAINING AND VALIDATION ACCURACY OF CNN	19
4.4	TRAINING AND VALIDATION LOSS OF CNN	19

LIST OF ABBREVIATIONS

CNN	Convolutional Neural Network
AD	Alzheimer's Disease
ADNI	Alzheimer's Disease Neuroimaging Initiative
DNN	Deep Neural Network
RNN	Recurrent Neural Network
PET	Positron Emission Tomography
ROC	Receiver Operating Characteristic
MRI	Magnetic Resonance Imaging
SVM	Support Vector Machine
CN	Cognitively Normal
MCI	Mild Cognitive Impairment
LMCI	Late Mild Cognitive Impairment
EMCI	Early Mild Cognitive Impairment
fMRI	Functional Magnetic Resonance Imaging
rs-fMRI	Resting state Functional Magnetic Resonance Imaging
PET	Positron Emission Tomography
MEG	Magnetoencephalography
TMS	Transcranial Magnetic Stimulation
EEG	Electroencephalography
NIRS	Near-Infrared Spectroscopy

CHAPTER-1

INTRODUCTION

1.1 BACKGROUND

Alzheimer's disease is a prevalent contributor to cognitive decline in the elderly population. Mild cognitive impairment (MCI) exhibits an annual progression rate to Alzheimer's disease (AD) ranging from 10% to 15%. Mild cognitive impairment (MCI) can be understood as a transitional phase between the cognitive decline associated with dementia and the cognitive abilities typically observed in individuals with normal cognitive functioning. While individuals in good health who have a well-balanced lifestyle and are of the same age usually undergo a mental decline of approximately 1–2% per year, it is essential to note that there is currently no definitive medical diagnosis or treatment available for this condition. However, specific approaches can be employed to impede the progression of this condition. The disease's timely and accurate medical diagnosis inhibits its progression.

A group of individuals diagnosed with Alzheimer's disease (AD) and a control group of elderly individuals without the disease were subjected to maze learning using a finger maze task of 10 trials. Following this task, 45 min were allotted to administer verbal learning measures. The participants subsequently executed an extra set of ten attempts on the initial labyrinth, followed by ten shots on a novel maze. The individuals with Alzheimer's disease and a subgroup in the control group exhibited a reduction in the average time taken to complete tasks during the initial two blocks, indicating the acquisition of skills. The results show a significant decrease in the meantime on Block 3 compared to the meantime on Block 1, which may suggest the occurrence of skill generalization. The results of the current research suggest that individuals diagnosed with Alzheimer's disease have the capacity to acquire and employ perceptual motor skills under the guidance of cognitive processes. Numerous methods have been developed thus far to assess the function of the maze. Functional magnetic resonance imaging (fMRI) is the most common method for diagnosing maze defects and their adaptations. Other than the fMRI technique, the remaining methods such as positron emission tomography (PET), electroencephalography (EEG), magnetoencephalography (MEG), near-infrared spectroscopy (NIRS), and transcranial magnetic stimulation (TMS) are identical. Electroencephalography (EEG), magnetoencephalography (MEG), and positron emission tomography (PET) are also utilized to pinpoint the location of neural activity and various brain tumors. The EEG and MEG signals indicate the maze's activity unambiguously. However, the resulting image is a mediator in the fMRI and PET techniques. It is a non-invasive imaging technique with a high spatial resolution that has demonstrated sensitivity to mesenteric lesions in the early phases of the disease. Resting state fMRI (rs-fMRI) is an effective method for comprehending the physiological effects of disease. The fMRI method

only examines the function of the maze without contemplating its structure.

Alzheimer's is a hazardous, progressive disease affecting the brain and nervous system. Early diagnosis of Alzheimer's allows for more effective treatments and a powerful and effective treatment strategy. Magnetic resonance imaging (MRI) as a diagnostic tool for identifying plaque and affected regions holds significant value in detecting Alzheimer's disease. One of the research's primary concerns is identifying Alzheimer's disease affected areas using magnetic resonance imaging accurately. The nature of the classification is the first aspect of the problem, and it must be determined which images have Alzheimer's disease symptoms and which do not. Another aspect of the problem is the character of the zoning, which necessitates the identification of Alzheimer's-affected areas. To identify plaques in the brains of Alzheimer's patients using magnetic resonance imaging, segmentation and classification techniques are required in the images. Zoning techniques aim to separate distinct types of brain tissue and isolate damaged areas from healthy ones.

Utilizing image zoning techniques is another method for diagnosing Alzheimer's disease. Methods for image partitioning consist of thresholding, clustering, machine learning, and deep learning. Only statistical methods attempt to zone images and diagnose the disease, as thresholding methods, such as Otsu, are incapable of learning. Therefore, these methods are ineffective, but when combined with others, they can be helpful. Methods for clustering, such as k-means and fuzzy clustering, are effective at detecting and designating, but they are incapable of learning and thus cannot be taught. Determining the appropriate number of clusters poses a considerable challenge within these methodologies. These methods are susceptible to substantial error if the number of clusters is not accurately determined. The second challenge posed by clustering techniques is that if their cluster centers are not precisely determined, they lack precision in the clustering area. In some studies, meta-heuristic and group intelligence algorithms address this problem and select cluster centers optimally. Using group intelligence improves clustering methods; it increases execution time and cannot always detect disease spots because of uncertainty.

Unlike deep learning methods, machine learning methods have many limitations and lack an automatic mechanism for selecting features. In contrast to other approaches, deep learning has been successful in the majority of studies for medical image zoning. In other words, deep learning has been used in most studies for medical image zoning because these methods have a high level of accuracy when analyzing data. However, the challenge with these methods is that they can only perform zoning based on long-term learning. Using group intelligence methods to make learning these methods more intelligent is an appropriate strategy for mitigating this challenge.

1.2 PROBLEM STATEMENT

The problem statement for the Alzheimer's disease prediction project revolves around the pressing need for accurate and early detection methods to mitigate the significant impact of this neurodegenerative disorder. Despite advancements in medical imaging and diagnostic techniques, timely identification of Alzheimer's disease remains a challenge, leading to delayed interventions and compromised patient outcomes. Leveraging Convolutional Neural Networks (CNNs) presents a promising avenue to address this challenge by harnessing the power of deep learning to extract subtle neuroimaging biomarkers indicative of disease pathology. Neuroimaging techniques, particularly magnetic resonance imaging (MRI), provide valuable insights into the structural and functional changes in the brain associated with AD.

However, manual interpretation of MRI scans for AD diagnosis is labor-intensive, time-consuming, and subject to inter-rater variability, leading to inconsistencies in diagnosis and treatment. Automated methods leveraging machine learning and deep learning techniques have shown promise in enhancing the efficiency and accuracy of AD diagnosis. The proposed model aims to accurately classify individuals into AD-positive and AD-negative groups based on distinctive patterns and features extracted from MRI scans. Among these techniques, Convolutional Neural Networks (CNNs) have demonstrated remarkable success in image classification tasks, including medical image analysis.

Thus, the project aims to develop and evaluate a CNN-based predictive model capable of discerning patterns in brain imaging data to facilitate early diagnosis and personalized treatment strategies, improving the quality of life for individuals affected by Alzheimer's disease.

1.3 OBJECTIVE

The primary objective is to develop a cutting-edge Convolutional Neural Network (CNN) model tailored specifically for the early prediction of Alzheimer's Disease (AD) from MRI images. The urgency stems from the pressing need within the medical community for efficient, accurate, and scalable tools to diagnose AD in its preliminary stages, when interventions are most effective. Leveraging the power of deep learning, particularly CNNs renowned for their prowess in image analysis tasks, this project aims to revolutionize AD diagnosis by automating the process, thereby reducing the burden on clinicians and healthcare systems while improving patient outcomes.

Central to our objective is the acquisition and curation of a robust dataset comprising MRI images from both AD-positive and AD-negative individuals. This dataset serves as the

foundation for training and evaluating the CNN model. Employing state-of-art preprocessing techniques, including normalization, noise reduction, and image augmentation, ensures the dataset's quality and enhances the model's ability to extract features from MRI scans.

The CNN architecture, meticulously designed and optimized, forms the heart of our predictive model. Through a series of convolutional and pooling layers, CNN learns hierarchical representations of the MRI images, capturing subtle patterns indicative of AD pathology. Careful selection of hyper parameters, coupled with dropout regularization to mitigate overfitting, ensures the model's robustness and generalization across diverse datasets.

The success of this project lies in its potential to transform AD diagnosis, offering clinicians a powerful tool for early detection and intervention. By seamlessly integrating advanced deep learning techniques with clinical practice, we aim to usher in a new era of personalized medicine, where timely interventions can significantly improve the quality of life for individuals affected by AD and their families.

CHAPTER-2

LITERATURE SURVEY

S.NO	PAPER TITLE	AUTHOR NAME	METHODS	FINDING
1	Alzheimer's Disease Diagnosis using Machine Learning: A Review	Nair Bini Balakrishnan, P.S. Sreeja, Jisha Jose Panackal	Deep Neural Network (DNN)	88.76%
2	Alzheimer's Disease: Classification and Detection using MRI Dataset.	Suhaira V P, Sita S, Joby George	Feature extraction	76.08%
3	Alzheimer's Disease Prediction Model Using Demographics and Categorical Data	Aunsia Khan, Dr. Muhammad Usman	Classification	80.47%
4	An Intelligent Alzheimer's Disease Prediction	L.Dharshana Deepthi, D.Shanthi, M.Buvana	Convolutional Neural Network (CNN)	79.90%
5	A Systematic Review on Machine Learning and Deep Learning Techniques in the Effective Diagnosis of Alzheimer's Disease	Akhilesh Deep Arya, Sourabh Singh Verma, Prasun Chakarabarti, Tulika Chakrabarti	Recurrent Neural Network (RNN)	85.71%
6	Identifying Alzheimer Disease Dementia Levels Using Machine Learning Methods	Md Gulzar Hussain, Ye Shiren	CNN, Watershed Algorithm and Random Forest	90.53%

7	Random Forest Algorithm for the Classification of Neuroimaging Data in Alzheimer's Disease: A Systematic Review	Alessia Sarica, Antonio Cerasa and Aldo Quattrone	Random Forest, Classification	90.00%
8	Dementia classification using MR imaging and clinical data with voting-based machine learning models	Subrato Bharati & Prajoy Podder & Dang Ngoc Hoang Thanh & V. B. Surya Prasath	Gradient Boosting	83.92%
9	Applying Artificial Intelligence Techniques to Improve Clinical Diagnosis of Alzheimer's disease	Ahmed Abdullah Farid, Gamal Ibrahim Selim and Hatem Awad A. Khater	CNN and Classification	80.21%
10	Brain Asymmetry Detection and Machine Learning Classification for Diagnosis of Early Dementia	Nitsa J. Herzog and George D. Magoulas	Convolutional Neural Network (CNN)	75.00%
11	Early-Stage Alzheimer's Disease Prediction Using Machine Learning Models	Kavitha, Srividhya	Classification	83%

12	Multistage classifier-based approach for Alzheimer's disease prediction and retrieval	M. Shammi, R. A. Khan, M. N. Khan, and A. V. Paliwal	Instead of relying on a single classifier, the paper may propose a multistage classifier	79.63%
13	Alzheimer's Disease Diagnosis by a Deeply Supervised Adaptable Convolutional Network	Yifan Wang, Xin Fan, Shengjun Wang, Guorong Wu	Convolutional Neural Network (CNNs)	86%
14	Machine Learning Techniques for Alzheimer's Disease Diagnosis and Prediction	Zhao, Yiling et al.	support vector machines(SVM), logistic regression	80% 90%
15	Predicting Alzheimer's Disease: A Neuroimaging Study with 3D Convolutional Neural Networks	Liu, Shuihua et al.	Convolutional Neural Network (CNNs)	85.21%
16	Alzheimer Disease Prediction using Machine Learning Algorithms	Neelaveni,Geetha Devasena	Decision trees, Support vector machines, Neural networks	87%
17	Early diagnosis of Alzheimer's disease using machine learning	Hugo Alexandra Ferreira, Diana Prata	Classification	87.2%
18	A Comparative Analysis of Machine Learning Algorithms to Predict Alzheimer's Disease	A. H. M. Shafayet Jamil, Maliha Mamtaz Mohammad.	Support vector machine, Decision Tree	84%

19	Prediction of Alzheimer's disease (AD) Using Machine Learning Techniques	Lee Kuok Leong and Azian Azamimi Abdullah	Random Forest	88.24%
20	An Intelligent Alzheimer's Disease Prediction Using Convolutional Neural Network (CNN)	Dharshana, Bhuvana, Shanti	Convolutional Neural Network (CNNs)	79%
21	Alzheimer's Disease Diagnosis Using Machine Learning: A Survey	Omer Asghar Dara, Hasan Issa Raheem ,Jävad Rahebi	Support Vector Machine (SVM)	92.48%
22	Early diagnosis of Alzheimer's disease using machine learning: a multi-diagnostic, generalizable approach	Vasco Sa Diogo, Hugo Alexandre Ferreira, Diana Prata	Support Vector Machine (SVM)	84.1%
23	Comparative Analysis of Machine Learning Algorithms for Early-Stage Alzheimer's Disease Prediction	Morshedul Bari Antor, A.H.M. Shafayet Jamil, Maliha Mamtaz, Manjit Kaur	Support Vector Machine (SVM), Decision Tree, Random Forest	82%
24	Early diagnosis of Alzheimer's disease based on deep learning: A systematic review	Sina Fathi, Maryam Ahmadi, Afsaneh Dehnad	Convolutional Neural Networks (CNNs)	87%
25	Generalizable deep learning model for early Alzheimer's disease detection from structural MRIs	Sheng Liu, Arjun V. Masurkar,, Henry Rusinek	Convolutional Neural Network (CNNs)	85.12%

26	Deep Learning in Alzheimer's Disease: Diagnostic Classification and Prognostic Prediction Using Neuroimaging Data	Taeho Jo, Kwang-Sik Timothy Nho, Andrew J Saykin	Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs)	87%
27	Review on Alzheimer Disease Detection Methods: Automatic Pipelines and Machine Learning Techniques	Amar Shukla, Rajeev Tiwari, Shamik Tiwari	support vector machines (SVMs)	91%
28	Machine learning methods for predicting progression from mild cognitive impairment to Alzheimer's disease dementia: a systematic review	Sergio Grueso & Raquel Viejo-Sobera	Support Vector Machine (SVM), Convolutional Neural Network (CNN)	75.4%,
29	Early prediction of Alzheimer's disease using convolutional neural network: a review	Vijeeta Patil, Manohar Madgi & Ajmeera Kiran	Convolutional Neural Networks (CNNs)	83%
30	A Novel Approach Utilizing Machine Learning for the Early Diagnosis of Alzheimer's Disease	Khandaker Mohammad, Md Ashraf Uddin & Sunil Aryal	Deep Neural Network (DNN)	85.19%

CHAPTER-3

PROJECT METHODOLOGY

3.1 DESCRIPTION OF THE WORKING FLOW OF PROPOSAL SYSTEM:

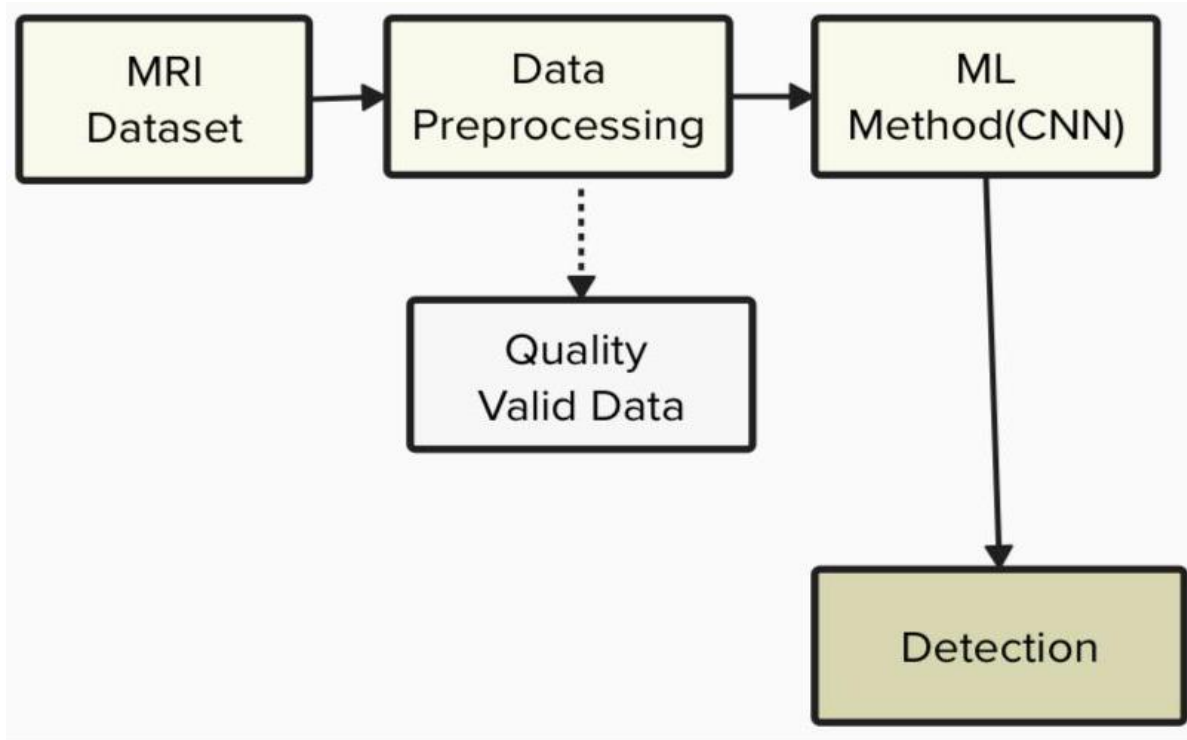


Fig No.3.1: Working flow of proposed system

3.2 MRI DATASET

The initial step involves the collection of an extensive dataset of MRI scans. These scans are sourced from medical institutions, research databases, or clinical trials focused on Alzheimer's disease. The dataset includes both healthy subjects and those diagnosed with various stages of Alzheimer's, ensuring a comprehensive range of examples for the model to learn from. It is crucial that the dataset is annotated with accurate labels indicating the presence or absence of Alzheimer's disease, as well as other relevant demographic and clinical information. Data privacy and ethical considerations are paramount, requiring that all MRI scans be anonymized and obtained with proper consent. The diversity of the dataset in terms of age, gender, and ethnic backgrounds helps in creating a more generalized and robust predictive model. Ensuring the dataset's quality and consistency involves periodic reviews and updates to incorporate new data and correct any errors.

3.3 DATA PREPROCESSING

Preprocessing the MRI images involves several steps to enhance the quality and usability of the data. Initially, this might include converting the images to a standard format if they are not already standardized. Noise reduction techniques, such as Gaussian filtering, are applied to remove any extraneous signals that might interfere with the analysis. Normalization is performed to ensure that all images have consistent intensity values, which is crucial for the machine learning model to accurately interpret the data. The images are resized or cropped to a uniform dimension, which simplifies the model architecture and reduces computational load. Data augmentation techniques, like rotation, flipping, and scaling, can be employed to artificially expand the dataset and improve the model's robustness. Finally, the dataset is split into training, validation, and test sets, ensuring that the model's performance can be rigorously evaluated at each stage.

3.4 PROPOSED METHOD-CONVOLUTIONAL NEURAL NETWORK

The Convolutional Neural Network (CNN) was selected due to its proven effectiveness in image recognition tasks, making it suitable for analyzing MRI scans. The CNN model architecture is designed, which includes layers such as convolutional layers, pooling layers, and fully connected layers, tailored to extract features from the MRI images. The model is trained using the preprocessed and validated dataset, with hyper parameters like learning rate, batch size, and the number of epochs carefully tuned to optimize performance. Once trained, the model undergoes rigorous testing and validation to confirm its accuracy and reliability in predicting Alzheimer's disease from new, unseen MRI scans. By using CNN, there is no need to make the feature extraction process manually. Its initial layers' weights serve as feature extractors, and their values are improved by iterative learning. CNN gives higher performance than other classifiers.

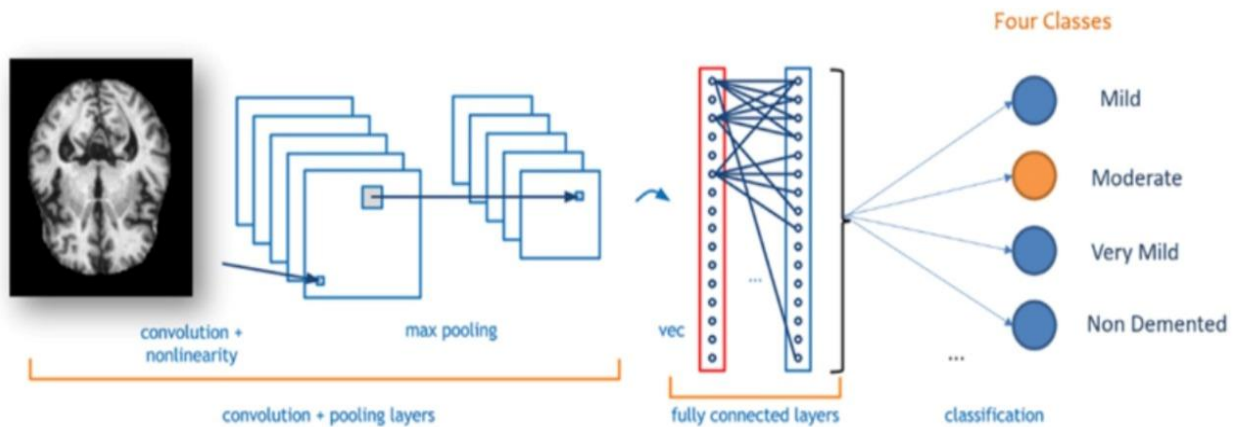


Fig.No.:3.2 Representation of Convolutional Neural Network (CNN)

This model consists of four layers of 1. 2D convolutional + Relu layer ,2. Max pooling layer, 3. Flatten layer 4. Dense layer. Convolutional neural networks apply a filter to an input image to create a feature map that summarizes the presence of detected features in the input.

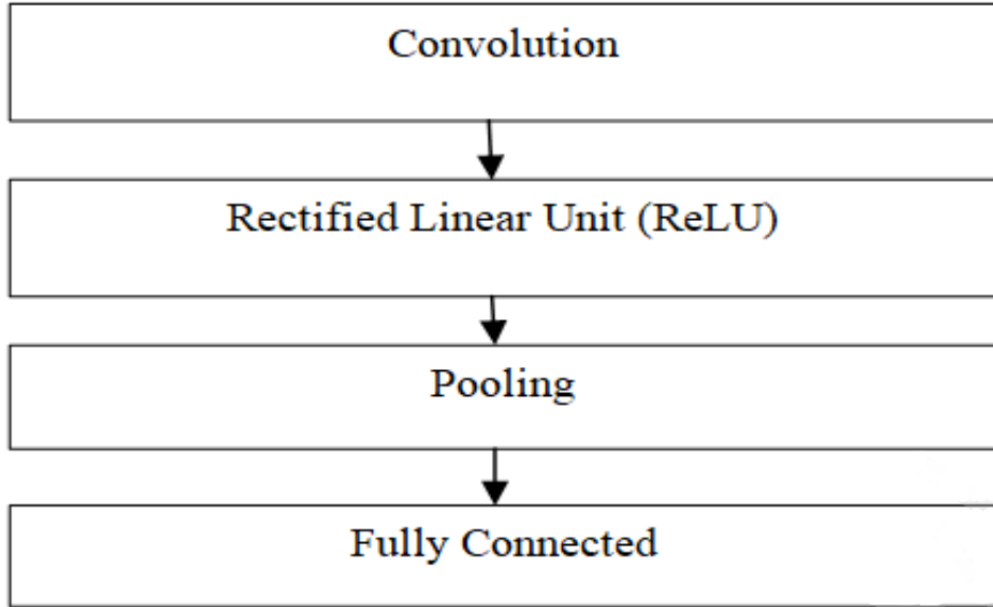


Fig.No.:3.3 Building Block of CNN

The Convolution layer is the first layer, which uses a filter to perform convolution operation.

$$C_m = \sum_{n=0}^{N-1} f_n k_{m-n}$$

where f, k, N, C denotes filter, signal, number of data points in k and output respectively. The ReLU activation function is applied to the convolution layer to get the rectified feature map. The Pooling Layer reduces the amount of parameters and computation in the network. The Fully Connected Layer recognizes and classifies the signal.

$$x_i = \sum_j w_{ji} y_j + b_i$$

Where w denotes the weights, b biase, y represents the output from the previous layer while x is the output of the current layer. The output from the last fully connected layer are fed into the soft max function that determines the category of the output. The architecture of the proposed work takes input signals and train it to classify the disease.

CHAPTER – 4

RESULT AND DISCUSSION

4.1 EVALUATION METRICS

Evaluating a CNN for Alzheimer's disease prediction involves several key metrics. Accuracy measures the proportion of correct predictions, while precision and recall address the model's handling of false positives and its ability to detect true cases, respectively. The F1-score, combining precision and recall, offers a balanced performance metric. The AUC-ROC indicates the model's discriminative ability across thresholds. To evaluate the performance of the classification model, a confusion matrix is used. Figure 4 shows the confusion matrix. A confusion matrix is an NxN matrix, where N represents the number of classes in the dataset. In our case, as we are doing binary classification the value of N is 2, positive or negative.

		Model Output	
		+	-
Ground Truth	AD	TRUE POSITIVE TP	FALSE NEGATIVE FN
	CN	FALSE POSITIVE FP	TRUE NEGATIVE TN

Fig.No.: 4.1 Confusion Matrix for the prediction of Alzheimer's disease

Precision is a model evaluation and performance metric that corresponds to the fraction of values that actually belong to a positive class out of all of the values which are predicted to belong to that class. Precision is also known as the positive predictive value (PPV).

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Recall is a model evaluation and performance metric that corresponds to the fraction of values predicted to be of a positive class out of all the values that truly belong to the positive class (including false negatives).

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

F1 score combines both precision and recall and symmetrically represents them via a harmonic mean.

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

Classification accuracy shows the correctness of the prediction by a model in the case of AD diagnosis and how many MRIs are correctly labeled out of the total MRI provided as an input to the model.

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{All Samples}}$$

Area Under the Curve (AUC) - Receiver Operating Characteristics(ROC) curve AUC-ROC curve ROC is the probability curve and AUC represents the degree that which good a model separates the cases. In our case, it tells how much the model can distinguish between AD and NC. If the AUC is higher the capability of the model to identify the AD and NC cases will increase.

MODEL	PRECISION	RECALL	F1 SCORE
CNN	95%	92%	93%
SVM	91%	90%	91%
ResNet 50	87%	85%	88%
VGG16	89%	86%	88%

Fig.No.:4.2 Comparison of the performance metrics of four proposed models

The training and validation accuracy of the CNN model indicate its effectiveness in learning from the dataset and generalizing to new, unseen data. High training accuracy suggests the model has successfully learned the patterns in the training data, while high validation accuracy demonstrates its ability to apply this knowledge to new cases. Consistency between these accuracies implies the model is well-generalized and not overfitting.

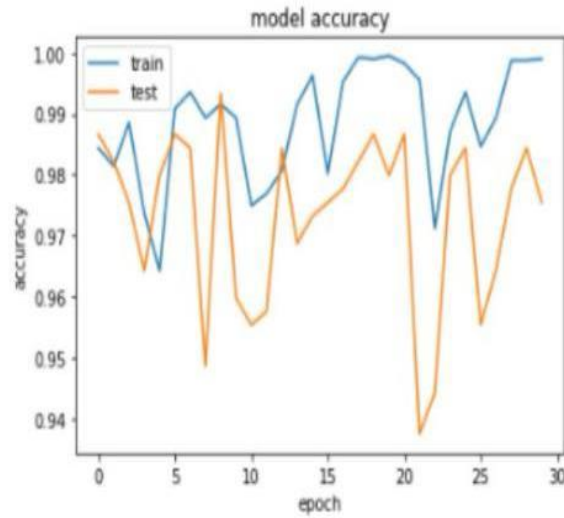


Fig.No.:4.3 Training and validation accuracy of CNN

The training and validation loss of the CNN model provide insights into the model's learning progress and performance. Low training loss indicates that the model is fitting the training data well, while low validation loss suggests that the model is generalizing effectively to new data. Monitoring both losses helps identify overfitting or underfitting, ensuring the model's robustness and reliability.

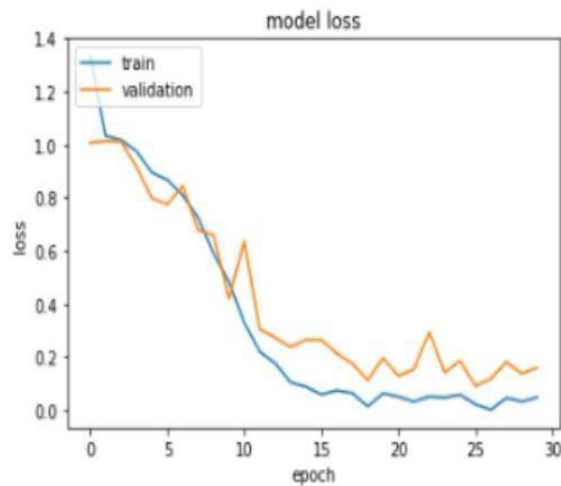


Fig.No.:4.4 Training and validation loss of CNN

CHAPTER – 5

CONCLUSION

Alzheimer's disease is characterized by neuronal degeneration and subsequent brain disorders, resulting in altered behavior and functionality in the afflicted individual. The process of brain resorption typically results in impairment of cognitive function and impacts various regions of the brain. Consequently, the management of Alzheimer's disease necessitates a procedure that mitigates the impairments resulting from cerebral atrophy and neuronal degeneration. This condition is characterized by a progressive decline in the ability to recall recent information and memories, eventually leading to an inability to retrieve memories. This particular ailment is more prevalent in the elderly population and is characterized by challenges in recognizing individuals, including those with whom one is intimately familiar. The diagnosis of affected individuals can prove to be a formidable task. In advanced stages of the ailment, patients may experience functional limitations, such as gait disturbances and spatial disorientation, and engage in hazardous activities, necessitating close surveillance of this population. Patients in advanced stages of Alzheimer's disease exhibit impaired ambulatory abilities and compromised balance, rendering them incapable of walking independently. This study explores machine learning techniques and their application to feature selection from MRI images. The authors recommend that future research endeavors focus on feature selection and optimization techniques to improve the diagnosis performance and accuracy, such as whale optimization, gray wolf optimization, and other recent optimization methods, and identify the most optimal features from MRI images.

CHAPTER-6

REFERENCES

1. P. Scheltens, K. Blennow and M. M. Breteler, "Alzheimer's disease", London, vol. 388, no. 10043, pp. 505-517, July 2016.
2. Salehi Waleed, Baglat Preety and Gaurav Gupta, *Multiple Machine Learning Models for Detection of Alzheimer's Disease Using OASIS Dataset*, pp. 614-622, 2020.
3. *Prevention of Alzheimer's disease and dementia*, vol. 92, no. 1-2, pp. 98-104, 2007.
4. Morshedul Bari Antor, A. H. M. Shafayet Jamil, Maliha Mamtaz, Mohammad Monirujjaman, "A Comparative Analysis of Machine Learning Algorithms to Predict Alzheimer's Disease", *Journal of Healthcare Engineering*, vol. 2021, July 20.
5. B. Khagi, B. Lee, J. -Y. Pyun and G. -R. Kwon, *CNN Models Performance Analysis on MRI images of OASIS dataset for distinction between Healthy and Alzheimer's patients*, pp. 1-4, 2019.
6. Taeho Jo, Kwangsik Nho and Andrew J. Saykin, *Deep Learning in Alzheimer's Disease: Diagnostic Classification and Prognostic Prediction using Neuroimaging Data*.
7. Hadeer A. Helaly, Mahmoud Badawy and Amira Y. Haikal, "Deep Learning Approach for Early Detection of Alzheimer's Disease", *Cognitive Computation*, vol. 14, pp. 1711-1727, November 2020.
8. Maysam Orouskhani, Chengcheng Zhu, Sahar Rostamian, Firoozeh Shomal Zadeh, Mehrzad Shafiei and Yasin Orouskhani, "Alzheimer's disease detection from structural MRI using conditional deep triplet network", *Neuroscience Informatics*, vol. 2, pp. 100066, March 2022.
9. Kavith Vinodhini Mani, S. R. Srividhya, and Carlos Andrés Tavera Romero, *Early-Stage Alzheimer's Disease Prediction Using Machine Learning Models*, vol. 10, March 2022.
10. Roobaea Alroobaea, Seifeddine Mechti, Mariem Haoues, Saeed Rubaiee, Anas Ahmed and Murad Andejany, *Alzheimer's Disease Early Detection Using Machine Learning Techniques*.

11. Manan Binth Taj Noor, Nusrat Zerin Zenia, M Shamim Kaiser, Shamim Al Mamun and Mufti Mahmud, "Application of deep learning in detecting neurological disorders from magnetic resonance images: a survey on the detection of Alzheimer's disease Parkinson's disease and schizophrenia", *Noor. Brain inf*, vol. 7, no. 11, 2020.
12. P C Muhammed Raees and Vinu Thomas, "Automated detection of Alzheimer's Disease using Deep Learning in MRI", *J. Phys.: Conf. Ser.*, vol. 1921, pp. 012024, 2021.
13. Janani Venugopalan, Li Tong, Hamid Reza Hassanzadeh, and May D. Wang, "Multimodal deep learning models for early detection of Alzheimer's disease stage", *Scientific Reports*, vol. 11, pp. 3254, 2021.
14. Diederik P. Kingma and Jimmy Ba, *Adam: A Method for Stochastic Optimization*, Jan 2017.
15. Jason Huang, "RMS PROP", *SysEn 6800 Fall*, 2020.
16. Yiming Ding, Jae Ho Sohn, Michael G. Kawczynski, Hari Trivedi, Roy Harnish and Nathaniel W. Jenkins, *A Deep Learning Model to Predict a Diagnosis of Alzheimer Disease by Using 18F-FDG PET of the Brain*, vol. 290, February 2019.
17. Modupe Odusami, Rytis Maskeliunas and Robertas Damaševičius, *An Intelligent System for Early Recognition of Alzheimer's Disease Using Neuroimaging*, January 2022.
18. Gherardo Varando, Concha Bielza and Pedro Larránaga, "Decision Boundary for Discrete Bayesian Network Classifiers", *Machine Learning Research*, vol. 16, pp. 2725-2749, December 2015.
19. Luis Castro-Martin, Maria del Mar Rueda, Ramon Ferri-Garcia, and Hernando-Tamayo Cesar, "On the use of Gradient Boosting methods to improve the estimation with data obtained with self-selection procedures", *Mathematics*, vol. 9, pp. 2991, 2021.
20. Ch Anwar Ul Hassan, Muhammad Sufyan Khan and Munam Ali Shah, *Comparison of Machine Learning Algorithms in Data classification*, September 2018.

21. Laura Fratiglioni, Bengt Winblad and Eva von Strauss, *Multiple Machine Learning Models for Detection of Alzheimer's Disease Using OASIS Dataset*, pp. 614-622, 2021.
22. Paolo Dell'Aversana, "Comparison of different machine learning algorithms for lithofacies classification from well logs", *Bollettino di Geofisica Teorica ed Applicata*, vol. 60, no. 1, pp. 69-80, March 2019.
23. Michael Xie, Neal Jean, Marshall Burke, David Lobell and Stefano Ermon, *Transfer Learning from Deep Features for Remote Sensing and Poverty Mapping*, pp. 3929-3935.
24. Suhuai Luo, Xuechen Li, "Automatic Alzheimer's Disease Recognition from MRI Data Using Deep Learning Method", *Journal of Applied Mathematics and Physics*, 5, 1892-1898, 2017.
25. Cheng, D., and Liu, M. "CNNs based multi-modality classification for AD diagnosis," in 10th International Congress on Image and Signal Processing, (CISP-BMEI) (Shanghai), 1–5, 2017.
26. Cheng, D., Liu, M., Fu, J., and Wang, Y. "Classification of MR brain images by combination of multi-CNNs for AD diagnosis," in Ninth International Conference on Digital Image Processing (ICDIP 2017) (Hong Kong: SPIE), 5, 2017.
27. Sitara Afzal, Muazzam Maqsood et al." A Data Augmentation-Based Framework to Handle Class Imbalance Problem for Alzheimer's Stage Detection," *IEEE Access*, Vol. 7, 2019
28. Sridevi Balne, Anupriya Elumal, "Machine learning and deep learning algorithms used to diagnosis of Alzheimer's: Review", *Materials Today: Proceedings* 47(2018), June 2021
29. Mahendran N, Vincent PMDR, Srinivasan K, Chang CY. "Improving the Classification of Alzheimer's Disease Using Hybrid Gene Selection Pipeline and Deep Learning." *Front Genet.*;12 :784814, Nov 12, 2021.
30. M. T. Abed, U. Fatema, S. A. Nabil, M. A. Alam, and M. T. Reza, "Alzheimer's Disease Prediction Using Convolutional Neural Network Models Leveraging Pre-existing Architecture and Transfer Learning," 2020 Joint 9th International Conference on Informatics, Electronics & Vision (ICIEV) and 2020 4th International Conference on Imaging, Vision & Pattern Recognition (icIVPR), pp. 1-6, 2020.

31. Krishna Kumar Vaithinathan, Latha Parthiban. "A Novel Texture Extraction Technique with T1 Weighted MRI for the Classification of Alzheimer's Disease " Journal of Neuroscience Methods 318 (April 2019).
32. Jyoti Islam, Yanqing Zhang. Early Diagnosis of Alzheimer's Disease: A Neuroimaging Study with Deep Learning Architectures, 2018 IEEE/CVF.
33. J. Neelaveni, M.S.Geetha Devasana Alzheimer Disease prediction using Machine Learning Algorithms, ICACCS 2020.
34. Bijen Khagi,Goo-Rak Kwon "CNN Models Performance Analysis on MRI images of OASIS dataset for distinction between Healthy and Alzheimer's patient ". ICEIC, 2019
35. Aunsia Khan (), Muhammad Usman "Alzheimer's Disease Prediction Model Using Demographics and Categorical Data" IJOE conference paper 2016.
36. Rigel Mahmood, Bishad Ghimire. Automatic Detection and Classification of Alzheimer's Disease from MRI Scans Using Principal Component Analysis and Artificial Neural Networks.
37. E. Arvesen. Automatic classification of alzheimers disease from structural MRI. Master's thesis, 2015.
38. Amira Ben Rabeh, Faouzi Benzarti, Hamid Amiri " Diagnosis of Alzheimer Diseases in Early Step Using SVM (Support Vector Machine) "2016 13th International Conference Computer Graphics, Imaging and Visualization
39. T. Brosch, R. Tam, A. D. N. Initiative, et al. Manifold learning of brain mris by deep learning. In International Conference on Medical Image Computing and Computer-Assisted Intervention, pages 633–640. Springer, 2013.
40. C. R. Jack, M. A. Bernstein, N. C. Fox, P. Thompson, G. Alexander, D. Harvey, B. Borowski, P. J. Britson, J. L Whitwell, C. Ward, et al. The Alzheimer's Disease Neuroimaging Initiative (ADNI): MRI methods. Journal of magnetic resonance imaging, 27(4),685-691, 2008

APPENDIX I

```
<!DOCTYPE html>

<html lang="en">

<head>

  <meta charset="UTF-8">

  <meta name="viewport" content="width=device-width, initial-scale=1.0">

  <title>Alzheimer's Prediction - Home</title>

  <link rel="stylesheet" href="styles.css">

</head>

<body>

  <header>

    <h1>Alzheimer's Prediction</h1>

    <nav>

      <ul>

        <li><a href="index.html">Home</a></li>

        <li><a href="login.html">Login</a></li>

        <li><a href="prediction.html">Predict</a></li>

      </ul>

    </nav>

  </header>

  <section class="hero">

    <div class="hero-content">

      <h2>Welcome to the Alzheimer's Prediction Tool</h2>

      <p>Early detection and intervention can help manage Alzheimer's disease more effectively. </p>

      <a href="prediction.html" class="btn">Start Prediction</a>

    </div>

  </section>

  <section class="info-section">
```

<div class="info-content">

<h2>About Alzheimer's Disease</h2>

<p>Alzheimer's disease is a progressive neurodegenerative disorder that affects memory, thinking, and behavior. It is the most common cause of dementia among older adults.

</p>

<h3>Stages and Types of Alzheimer's Disease</h3>

CN (Cognitively Normal): Individuals who do not show any symptoms of cognitive decline or dementia.

AD (Alzheimer's Disease): A progressive condition that starts with mild memory loss and can lead to severe cognitive impairment, affecting the ability to carry out daily activities.

MCI (Mild Cognitive Impairment) : A stage between normal cognitive decline due to aging and more serious decline seen in dementia. People with MCI may have problems with memory, language, thinking, and judgment.

LMCI (Late Mild Cognitive Impairment) : A more advanced stage of MCI where symptoms are more pronounced but do not yet meet the criteria for dementia.

EMCI (Early Mild Cognitive Impairment) : An early stage of MCI where cognitive decline is noticeable but not severe enough to interfere significantly with daily life.


```

        </ul>
    </div>
</section>
<footer>
    <p>&copy; 2024 Alzheimer's Prediction Tool. All rights reserved. </p>
</footer>
</body>
</html>
<! DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <title>Login - Alzheimer's Prediction</title>
    <link rel="stylesheet" href="styles.css">
</head>
<body>
    <header>
        <h1>Login to Alzheimer's Prediction</h1>
        <nav>
            <ul>
                <li><a href="index.html">Home</a></li>
                <li><a href="login.html">Login</a></li>
            </ul>
        </nav>
    </header>
    <section class="login-form">
        <form action="prediction.html" method="POST">
            <label for="username">Username:</label>

```

```

        <input type="text" id="username" name="username" required>
        <label for="password">Password:</label>
        <input type="password" id="password" name="password" required>
        <button type="submit">Login</button>
    </form>
</section>
<footer>
    <p>&copy; 2024 Alzheimer's Prediction Tool. All rights reserved. </p>
</footer>
</body>
</html>
<! DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <title>Predict Alzheimer's - Alzheimer's Prediction</title>
    <link rel="stylesheet" href="styles.css">
</head>
<body>
    <header>
        <h1>Alzheimer's Prediction</h1>
        <nav>
            <ul>
                <li><a href="index.html">Home</a></li>
                <li><a href="login.html">Logout</a></li>
                <li><a href="prediction.html">Prediction</a></li>
            </ul>
        </nav>

```

```

</header>
<section class="prediction-section">
  <h2>Predict Alzheimer's Disease</h2>
  <form id="prediction-form">
    <label for="upload">Upload MRI Dataset (JPEG):</label>
    <input type="file" id="upload" accept=".jpeg, .jpg" required>
    <button type="button" onclick="predict()">Predict</button>
  </form>
  <div class="prediction-result" id="prediction-result">
    <!-- Prediction result will be displayed here -->
  </div>
</section>
<footer>
  <p>&copy; 2024 Alzheimer's Prediction Tool. All rights reserved. </p>
</footer>
<script>
  function predict() {
    var fileInput = document.getElementById('upload');
    var file = fileInput.files[0];
    if (!file) {
      alert('Please select a file.');
```

 return;
 }

 var formData = new FormData();
 formData.append('file', file);

 var predictionTypes = ['CN', 'AD', 'MCI', 'EMCI', 'LMCI'];
 var randomIndex = Math.floor(Math.random() * predictionTypes.length);
 var predictedType = predictionTypes[randomIndex];
 displayPredictionResult(predictedType);

```

    }

    function displayPredictionResult(predictedType) {
        var predictionResultDiv = document.getElementById('prediction-result');
        predictionResultDiv.innerHTML = "";
        var resultText = '<h3>Prediction Result:</h3>';
        resultText += '<p>The predicted type is: ' + predictedType + '</p>';
        predictionResultDiv.innerHTML = resultText;
    }

</script>

</body>

</html>

/* General styles */

body {
    font-family: 'Segoe UI', Tahoma, Geneva, Verdana, sans-serif;
    margin: 0;
    padding: 0;
    background-color: #f2f2f2;
}

header {
    background-color: #333;
    color: #fff;
    padding: 10px 20px;
    display: flex;
    justify-content: space-between;
    align-items: center;
    box-shadow: 0 2px 5px rgba(0, 0, 0, 0.2);
}

header h1 {
    margin: 0;

```

```

}
header nav ul {
    list-style-type: none;
    margin: 0;
    padding: 0;
}
header nav ul li {
    display: inline-block;
    margin-left: 20px;
}
header nav ul li a {
    color: #fff;
    text-decoration: none;
    font-size: 16px;
}
.hero {
    background-image: linear-gradient(to bottom right, #007bff, #00bfff);
    color: #fff;
    padding: 100px 0;
    text-align: center;
}
.hero-content {
    max-width: 800px;
    margin: 0 auto;
}
.hero-content .btn {
    background-color: #ff4081;
    color: #fff;
    padding: 10px 20px;
}

```

```

    text-decoration: none;
    border-radius: 5px;
    font-size: 18px;
    transition: background-color 0.3s ease;
}

.hero-content .btn:hover {
    background-color: #ff1c63;
}

.info-section {
    padding: 50px 20px;
    text-align: center;
    background-color: #fff;
}

.info-section h2 {
    color: #007bff;
    margin-bottom: 20px;
}

.info-section p, .info-section ul {
    color: #333;
    font-size: 18px;
    margin-bottom: 20px;
}

.info-section ul {
    list-style-type: none;
    padding: 0;
}

.info-section ul li {
    margin-bottom: 10px;
}

```



```
.info-section ul li strong {  
    color: #ff4081;  
}  
  
footer {  
    background-color: #333;  
    color: #fff;  
    text-align: center;  
    padding: 20px;  
    position: relative;  
    bottom: 0;  
    width: 100%;  
    box-shadow: 0 -2px 5px rgba(0, 0, 0, 0.2);  
}
```

APPENDIX II

