Structural MRI classification in Alzheimer's disease using CNN-XGBoost: An early diagnosis

Bassam Mohammad Elzaghmouri [1*], yosef Hasan Fayez Jbara[2], Mohammed Awad Mohammed Ataelfadiel[3], Asef Al-Khateeb [4], Motasem AbuDawas [5], Binod Kumar Pattanayak [6]

[1*]Department of Computer Science .Faculty of Computer Science and Information technology, Jerash University, Jerash, Jordan, Email: b.el-zaghmouri@jpu.edu.jo

[2]Computer Engineering Department, College of Engineering & Information Technology, Buraydah Colleges,

Email: yosef.hasan@bpc.edu.sa

[3]Applied College, King Faisal University, Al-Ahsa, Saudi Arabia, Email: melfadiel@Kfu.edu.sa

[4]Department of Computer Science .Faculty of Computer Science and Information technology, Jerash University, Jerash, Jordan, Email: asef.alkhateeb@jpu.edu.jo

[5]Department of Computer Science, College of Science and Information Technology, Irbid National University, Irbid, Email: Email: motasem_dawas@inu.edu.jo

[6]Department Department of Computer Science and Engineering Institute of Technical Education and Research (ITER) Siksha 'O' Anusandhan (Deemed to be University) Bhubaneswar, Odisha, INDIA>
Email: binodpattanayak@soa.ac.in

*Corresponding Author: Bassam Mohammed Elzaghmouri. Email: b.el-zaghmouri@jpu.edu.jo

ABSTRACT

The sixth most common cause of mortality worldwide is Alzheimer's disease (AD), a progressive neurological condition. Large healthcare data has been a topic of interest for the past ten years due to the digitization that has led to a rise in data captured in medical industries. Lately, various categorization problems have been addressed with deep learning and machine learning techniques, which have demonstrated notable gains in effectiveness. On the other hand, their limited generalization abilities and inadequate model variance provide a problem, as reported in the literature. By using a mixed model that combines machine learning methods and deep learning, this project aims to increase the accuracy of Alzheimer's image classification. Particularly in the area of computer vision, the deep learning approach to machine learning has outperformed traditional machine learning in terms of its capacity to identify complex structures in complex, high-dimensional data. To improve the detection ability to classify images of Alzheimer's disease, this work has presented a hybrid model using CNN a Deep Learning technology, and the XGBoost machine learning. Based on structural MRI images, our findings imply that AD can be accurately classified using CNN-XGBoost algorithms. This may result in the creation of tools for AD diagnosis and aid in enhancing the illness's early identification and management. Using a structural MRI image hold-out test set, we assessed our model's performance. In comparison to other techniques used to classify AD from MRI scans, our model's accuracy of 98.7% is much greater.

INDEX TERMS Alzheimer’s disease, Convolutional Neural, Deep Learning, eXtreme Gradient Boosting, Machine Learning

I. INTRODUCTION

Alzheimer's disease is a neurological condition that is progressive, irreversible, and multidimensional. It gradually damages brain cells, impairing thinking and memory abilities and, in the end, the capacity to perform even the most basic tasks. One of the most prevalent types of dementia is Alzheimer's disease (AD). It affects about 75% of patients with dementia. As per the research showcased by Alzheimer's Disease International, 50 million individuals are grappling with dementia. By 2050, it is anticipated that this number will have increased to 65.37 million. Dementia eventually results from the cognitive deterioration brought on by this illness. For example, in neurodegenerative dementia, the disease starts with moderate degeneration and gets worse over time. Tau protein and beta-amyloid plaques and tangles accumulate in the brain of Alzheimer's disease (AD), a neurodegenerative disease that progresses over time and causes cognitive decline and memory loss. For prompt intervention and the creation of successful treatment plans, early identification of AD is essential. However conventional diagnostic techniques are not always able to identify minute structural alterations in the brain; instead, they frequently depend on subjective interpretation. Figures 1 and 2 show the structural MRI sequences of the T1-weighted MRI images of the patient with Alzheimer's disease and the normal patient.

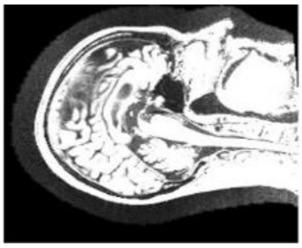

Fig. 1. Alzheimer's disease patient's T1-weighted MRI picture

Fig. 2. Normal patient's T1-weighted MRI picture

The economic burden of dementia is likewise enormous. Researchers usually do their hardest to extract useful information from big healthcare data. A crucial component of the clinical evaluation of patients with probable Alzheimer's is magnetic resonance-based structural imaging. The purpose of this study is to assess the current state of healthcare big data analytics, as well as its potential uses and adoption barriers. The article also covers the large data generated by these healthcare systems and the role big data analytics plays in gaining valuable insights from these data sets. Medical practitioners and academics can more easily recognize Alzheimer's disease thanks to a machine learning algorithm's capacity to classify the brain disorder. The convolutional neural network (CNN), one of the Deep Learning Network architectures, is used in this work to create a trained and predictive model by classifying the brains of people with Alzheimer's disease and healthy brains[1].To identify neurodegenerative diseases, researchers are increasingly using machine learning techniques and data mining technologies due to the rapid growth of data and information on disease aspects. A computer approach based on experience that enhances performance or makes precise detections is called machine learning. Deep learning is one of the machine learning approaches employed, where computer models learn to execute classification tasks directly from MRI scans [2]. The primary goal of deep learning is to automate the process of finding features or effective machine learning representations for various tasks, including the automatic transfer of information from one job to another in parallel [3]. With deep learning, a machine can grade directly from images, text, or audio. Researchers have developed an Arduino UNO-based smart traffic system that analyses spoken messages and modifies light signals accordingly [4]. In the future, reduce the failure rate of neurodegenerative disorders by utilizing different commands. A computer's internal representation, or feature vector, is created from an image's pixel values after it has been trained on numerous labeled datasets. This allows classifiers to recognize or detect input patterns.

Alzheimer’s disease, a common neurodegenerative disorder in individuals over 60, leads to memory loss and cognitive decline due to brain cell death. This research utilizes segmentation techniques and convolutional neural networks (CNN) to analyze MRI images for hippocampal atrophy, achieving 98.2% accuracy in distinguishing between Alzheimer's and normal controls by assessing brain, grey matter, and hippocampal volume variations [20].

In section II, we set forth the goals of the study. In section III, the research background is provided. Section IV provides information on the problem statement. Give opinions regarding the challenging portion in section V. Regarding the motivation portion in section VI, Outline the contribution portion in section VII. Provides a section on limitations in section VIII. Detailed descriptions of related works are found in section IX. Section X provides an overview of the early detection phase; Section XI covers the CNN portion; Section XII elaborates on XGBoost; Section XIII presents CNN-XGBoost; Section XIV covers the Performance Evaluation In Multi-Class Classification portion; Section XV provides the methodology part; Section XVI describes the dataset part; and Section XVII delivers the result and discussion part, and the last section XVIII: contribute the conclusion part.

II. OBJECTIVES

Neurons in the brain gradually die as a result of the neurodegenerative brain illness Alzheimer's. It results in the brain cells' ability to operate being lost. Brain cortex shrinking is a result of advanced Alzheimer's disease. An individual grows dependent on his carers as a result of this shrinkage. Promising findings in the field of disease identification utilizing brain MRI data have also been reported by recent research. Although CNN models have yielded good accuracy results for MRI data thus far, very few articles have described the characteristics or picture regions that contribute to this accuracy. We need to come up with strategies to identify it as soon as possible because this is a serious issue that affects a sizable portion of society. The advancement of patients with Alzheimer's disease from the MCI to the AD stage can be slowed, but the disease cannot be stopped. Therefore, early AD diagnosis is highly desirable to improve patient quality of life. Neuroimaging has assessed aberrant brain modifications associated with AD more easily. CNN-XGBoost is a potent tool for identifying pattern and form features in image data. This research outlines how to enhance the functionality of a neural network to classify sliced MRI scans. Accurately labelling structural features in magnetic resonance imaging (MRI) brain scans is the primary goal of neuroimaging.

This paper presents a neural network's functionality optimization for sliced MRI scan classification. Neuroimaging's principal objective is to accurately characterize structural characteristics in magnetic resonance imaging (MRI) brain scans. We are aware that one of the greatest ensemble learning algorithms for a variety of machine learning uses is XGBoost. But researchers suggest a hybrid model for the next two stages after analysing how CNN operates and discovering that convolution layers are utilized to choose and extract features for the classification. Using the high-level features that CNN extracted, we employ XGBoost directly to predict popularity during the regression analysis stage.

III. BACKGROUND

Large-scale medical record analysis now has more options because of the integration of AI-driven methods in consumer products for the healthcare industry. Researchers present a new methodology that leverages AI-driven techniques to extract meaningful insights from large medical datasets, enabling more accurate and efficient healthcare decision-making.

Alzheimer's disease is a long-term neurodegenerative condition that damages brain tissue, leading to dementia and an irreversible decline in cognitive abilities. There is no known cure for it, and its causes are still unclear. Therefore, it is important to detect AD early to halt its progression. The options for large-scale medical record analysis have increased with the entry of deep learning-based technologies into the end-user healthcare sector. We introduce a novel approach that uses deep learning-driven methods to glean valuable insights from huge medical datasets, facilitating more precise and effective healthcare decision-making. However, neuroimaging tools are currently helpful in diagnosing diseases, and deep learning techniques have lately emerged as a crucial methodology used with these tools. The reason is that they can automatically deduce an ideal representation of the data from raw photos without requiring prior feature selection, meaning that there is less need for image preparation and more objectivity in the process. However, the wide variations in brain image types make it difficult to train a trustworthy model.

IV. PROBLEM STATEMENT

The main perspective of the researchers is that a hybrid feature-based classification method is proposed along with clinical data [5]. The impact of employing structural MRI images for feature extraction is studied with good accuracy. When it yields better multi-class classification outcomes, unlike other mixed ensembled methods, the suggested method uses multi-class classification to classify Alzheimer individuals.

V. CHALLENGES

Though it presents several difficulties and barriers, using big data in disease prevention has enormous promise. The dimensionality of data is one of the main obstacles. There is an increased danger of data breaches when health data is gathered, saved, and processed for big data applications. Using deep learning models can help solve issues with technology infrastructure and offer a more scalable and effective method of managing large amounts of healthcare data. This CNN with XGBoost methodology has benefits for accessing and analyzing MRI data to provide a more accurate diagnosis. Large-scale research and integrated data analysis from many sources are also made possible by the simpler collaboration between the two technologies. A potent indicator of the degree and course of the neurodegenerative component of Alzheimer's disease (AD) pathology is atrophy as assessed by structural magnetic resonance imaging (sMRI).

It was comparing Dementia Pathology with Structural Imaging. Given its ability to distinguish AD from CN, structural MRI imaging is acknowledged as a crucial diagnostic technique for AD. Numerous studies currently demonstrate that sMRI is a reliable biomarker of the advancement of AD. The integration of sMRI images from multicenter studies can be done without much consequence, according to publications on sMRI data from multicenter studies like ADNI.

VI. MOTIVATION

Memory loss, difficulty learning new things, and poor judgment are the main problems that older people in society encounter. This results from harm to brain tissue, which may later cause Alzheimer's and cognitive decline. When this progresses to Alzheimer's disease (AD), it is typically discovered. In the last ten years, machine learning (ML) has proven extremely beneficial for numerous computer vision applications, particularly picture classification. In particular, CNN is good at extracting spatial characteristics. Unfortunately, picture noise can readily tamper with CNN's single-layer classifier, which lowers classification accuracy. The classifier is built using the activation function. The sophisticated ensemble model XGBoost is utilized to remedy the issue by making up for a single classifier's inability to categorize image features [6]. To further distinguish the extracted picture attributes, a CNN-XGBoost image classification model was applied. Primarily, the model consists of two parts: the feature extractor CNN is utilised to automatically extract spatial features from images, and the feature classifier XGBoost is utilized to classify features extracted after convolution. According to the set of image results, the proposed model does better in picture categorization.

VII. CONTRIBUTION

Medical image processing is one of the many sectors where deep learning has recently drawn a lot of interest in issue-solving. The proposed deep pipeline in this study uses magnetic resonance imaging

(MRI) scans to develop a convolutional neural network-based pipeline for detecting Alzheimer's disease and its stages. An individual with Alzheimer's disease may find it challenging to work alone because to a progressive loss of morality that causes problems like a slow decline in behavior, cognition, and social skills. Our comprehensive study model for predicting individual diagnosis of Alzheimer's Disease (AD), Cognitive Normal (CN), and Mild Cognitive Impairment (MCI) is based on input images of Magnetic Resonance Imaging (MRI). We combined CNN and XGBoost to make an Alzheimer's disease diagnosis—our suggested model's accuracy, which is a significant advancement over the existing model.

VIII. LIMITATION

Currently, there is no established method for evaluating cognitive domains in AD patients other than memory impairment. Additionally, little is known about the neuropathological mechanisms underlying AD and normal ageing, especially in the senior population when a similar clinical picture may have a different neurobiological underpinning. The importance of early diagnosis stems from its potential to enhance future prediction, personalize therapy, and advance the study of disease development and clinical heterogeneity. It is necessary to adopt a united front. Misdiagnoses are a common problem in neurological facilities because diagnostic techniques are still quite basic and perhaps even restricted. The standard techniques for diagnosing AD include extensive neuropsychological testing, patient evaluation, blood sample analysis, and imaging to rule out other, reversible types of cognitive impairment. The primary limitation of the current approaches is the absence of a useful illness stage. The study of amyloid and tau is a useful method since it provides information on specific protein changes in the brain. Different learning approaches, including supervised, unsupervised, and reinforcement learning, should be compared and contrasted. Use well-liked ensemble methods to enhance model performance, such as stacking, boosting, and bagging.

IX. RELATED WORK

For prompt intervention and the creation of successful treatment plans, early identification of AD is essential. CNNs' capacity to decipher complex relationships inside images makes them an effective tool for AD detection. By analysing magnetic resonance imaging (MRI) data, CNNs can identify minute patterns and anomalies that may indicate AD. This creates opportunities to comprehend the fundamental mechanisms of the illness in addition to facilitating more precise and trustworthy diagnosis. These studies demonstrate the efficacy of CNN-based methods in detecting biomarkers associated with AD and differentiating between normal and pathological brain tissue. CNNs provide a data-driven, scalable, and objective method of diagnosing AD by utilising the enormous volumes of data found in neuroimaging databases. Convolutional neural networks (CNNs), a prominent deep learning (DL) technique, were paired with transfer learning (TL) techniques like InceptionV3, ResNet50, VGG16, and VGG19, as well as a support vector machine (SVM) classifier, to increase prediction accuracy. Using a variety of performances and network measures, extensive simulations were looked at to demonstrate the viability of the proposed paradigm. on a sizable dataset of mammography pictures that were accurately identified [7]. Regarding an emergency patient One issue that worries medical personnel is that they sometimes have to transfer patients to various hospitals. To assist researchers in connecting with their studies, the following research will be conducted in the field of neurodegenerative research. In a particular scenario, the researcher suggests an improved framework for traffic control and management that uses a mobile agent paradigm to automate the regulation of traffic congestion. The adaptable suggested executive system executes systematic control more effectively in a vehicle ad hoc network (VANET) scenario [8].In light of the many scenarios outlined by the aforementioned research, determined that certain deep learning algorithms can be beneficial for processing vast amounts of images to attain high levels of accuracy. In addition to precise segmentation, volume measurement is crucial.

Although AD currently has no known cure, numerous medications are being developed, and a discovery of a treatment is anticipated shortly. Support vector machines (SVM), k-nearest neighbours (KNN), random forests (RF), and other ensemble classifiers are just a few of the many classification methods and techniques that are supported by machine learning. Because of its excellent sensitivity and accuracy in handling high-dimensional data, the SVM method is the most often used of them.With labels assigned to the subjects, the SVM classification approach offers a first step in the recognition of data from the training dataset that includes well-characterized individuals in recognised states.With its crucial role in expanding diagnostic skills across multiple domains, Convolutional Neural Networks (CNNs) have become a cornerstone in medical imaging. Specifically, in the field of neuroimaging, CNNs have proven to be remarkably effective in tasks like organ segmentation and illness identification, which has led to a notable improvement in healthcare outcomes. Brain networks (NNNs) are well-suited to handle the particular difficulty posed by the intricate nature of brain pictures, which feature minor abnormalities and complex architecture. CNNs specifically offer a viable route towards early diagnosis and intervention in the context of Alzheimer's disease (AD) detection. CNNs' capacity to decipher complex relationships inside images makes them an effective tool for AD detection. An increasing amount of research highlights CNNs' importance in AD detection. These studies demonstrate the efficacy of CNN-based methods in detecting biomarkers associated with AD and differentiating between normal and pathological brain tissue. CNNs provide a data-driven, scalable, and objective method of diagnosing AD by utilising the enormous volumes of data found in neuroimaging databases. In conclusion, CNNs are a game-changing advancement in neuroimaging that has significant ramifications for AD diagnosis and detection. By deciphering complex connections seen in photos, they can provide a new way for early intervention and customised treatment plans, which will ultimately improve the care that people suffering from this deadly illness receive. Using very logical Swarm intelligence methodologies, Swarm intelligence analyses and reviews the technology-based advanced applications of IoT.Here, future research on various indifferent analytical reviews may aid in improving the diagnosis [9]. Robust and deeper feature representation is made possible by machine learning techniques like deep learning. Accuracy in the binary phase of Alzheimer's disease is obtained by integrating information from MRI images using autoencoders. According to their suggestions, structural modelling and independent component analysis are useful methods for identifying atrophy patterns in specific brain MRI regions. Segmenting MRI images into smaller pieces was another suggested approach, as it was thought that each segment covered significant cognitive processing domains. By separating each 3D MRI image utilising integrated methods and DenseNet, a new state of the art in three categories. A good development of phased accuracy is demonstrated by the several works that use VGG16 structures trained in a series of MRI images [10]. Various research technologies will be utilised to improve the detection of neurodegenerative diseases. Using sensors and actuators, billions of smart devices connected to an IoT environment may communicate with one another. This ability to communicate effectively across IoT globally requires extensive security provisioning. Researchers describe the main privacy and security concerns along with potential solutions, taken from the writings of several academics in the area [11]. The intelligent routing protocol was proposed in the study is based on the Ant Colony Optimisation (ACO) technique. It finds the shortest path between a source and a destination, applies power-aware techniques to save energy and prolong the link's lifespan, and uses digital signatures, watchdogs, and path raters to detect and prevent blackhole and grayhole attacks. The suggested plan is studied through simulation for a variety of network parameters, and it is discovered to be more effective than the fundamental AODV routing protocol[12].Different researchwork uses the notion of Mobile Agents to propose a monitoring technique for ensuring that the Quality of Service (QoS) standards are met during competent routing. The suggested QoS platform includes an intelligent mobile agent that uses the longest critical path approach at the forwarding node to pick itself as the best alternative among all neighbour nodes, and monitors and controls the QoS processing duties. Comparing the simulation findings with other similar systems, they demonstrate a greater packet delivery ratio and somewhat lower overhead bandwidth consumption.A highly effective real-time scheduler design at the network layer with enhanced RMA (Rate Monotonic Algorithm) and EDF (Earliest Deadline First) scheduling is presented in the research paper along with an efficient Quality of Service architecture that uses inter-layer communication to schedule multiple real-time applications efficiently without missing any deadlines[13]. In comparison to other comparable cross-layer-based methodologies for video file transmission, simulation findings in NetSim ver 8 ensure healthier network performance in terms of better packet delivery ratio, jitter, and network lifetime.The many energy levels, including single energy levels (LEACH, IEBRP), distributed energy levels (DEEC), and multi-energy levels (M-SEP), are the topics of attention[14]. The design algorithms of the LEACH, IEBRP, DEEC, and M-SEP protocols are then compared. The lifetime of sensor networks was finally determined with the aid of four new matrices: First Node Died (FND), Some Node Died (SND), Half Node Died (HND), and Last Node Died (LND). The researcher simulated all four protocols using the C platform. The authors of the researchwork have created a real-time, reliable, and energy-efficient routing protocol for MANETs. Their method differs in that it determines which node should transport the packet to its destination by first calculating the intermediate node's packet processing rate, bounded delay, and remaining residual battery power. To properly select a load-balanced way from source to destination, the cost function computed using the aforementioned three parameters, and the state of the congested node is additionally verified. According to simulation results, the suggested protocol outperforms the traditional AODV protocol in terms of packet delivery ratio, network lifetime, throughput, and delay [15].The AODV ad hoc routing protocol has been improved with the Power Aware AODV (PAAODV) protocol for ad hoc networks[16]. The main idea behind PAAODV's design is to minimize power consumption as much as possible in an ad hoc network without compromising network connectivity. It has the effect of greatly reducing the total power used in the transmission of overhead packets. On the other hand, the data packets can be transmitted using greater power. This study improves the on-demand routing protocol known as AODV to PAAODV and uses the network simulator NS-2 to simulate and validate its functionality.The researcher discusses some security concerns that are arising from network issues among robots and suggests PD-ROBO, a dynamic MANET-based automated convention with a dedicated Intrusion Detection System (IDS) structure that uses a portable operator method to prevent replay attacks in mechanically based MANETs[17].

X. EARLY IDENTIFICATION

The diagnosis of dementia is not too difficult, but the early detection of AD remains a clinical issue. As a result, new imaging techniques that can identify AD in its early stages as well as biomarkers linked to the pathological alterations are required. Comprehending the patient's disease stage is crucial for the treatment plan, prognosis, and proper enrollment in clinical trials. Alzheimer's patients remain unknown, except in a few cases where genetic abnormalities have been identified. The majority of challenges and opportunities for the future lie in the successful integration of several disease pathways to enable early diagnosis and efficient deep-learning methods for treating AD. Early diagnosis of AD is made possible by the combination of neuroimaging methods and cognitive evaluation tools. These tools do, however, have several drawbacks that must be addressed, including their high cost, restricted availability, low sensitivity or specificity, and invasiveness. Researchers can work with the patient's caregiver to develop intervention plans that address the unique strengths and limitations of the study through early identification. This will ultimately enhance the patient's quality of life and lead to better diagnosis outcomes. With an early diagnosis, patients can benefit from individualized, customized learning programs that will intellectually challenge and stimulate them. This article discusses the advantages and difficulties of early diagnosis in AD, including the usefulness of biomarkers in conjunction with CNN-XGBoost techniques, and illustrates these issues (using a clinical scenario). In conclusion, we offer a few recommendations based on researchers' experiences for early diagnostic disclosure of AD.

XI. CNN

The models are trained on a vast array of datasets and a multi-layered Convolutional Neural Network (CNN) architecture. Alzheimer's disease is automatically classified in medical imaging through the application of deep learning. Convolutional Neural Networks (CNNs) are a popular deep learning technique employing picture data. One popular deep learning technique, CNN uses a model that learns to do classification tasks directly from image, video, text, or voice input. Deep learning is a subset of machine learning. To recognize images, CNN leverages patterns rather than human feature extraction. It learns directly from image data. Convolution and down-sampling are CNN's two most significant procedures. While sampling reduces the dimension of the data, convolution extracts features from it. Weight sharing, pooling, and local connectivity are features of CNN that set it apart from other neural networks.

Certain statistical features should roughly match other features since the image possesses unique intrinsic qualities. To create it, a weighted matrix is shared by every convolution filter. The computation becomes easier and there are fewer parameters when weight sharing is used. Feature mapping takes place throughout the pooling process. For every input depth slice, the pooling layer modifies the spatial size of each one independently. To minimize the number of parameters, it gradually shrinks the representation space, which lowers the compute and memory footprint and controls overfitting. A CNN typically consists of layers that alternate between convolution and subsampling, becoming fully linked as it approaches the final output layer. The secondary extraction computations are completed and the pooling process is carried out by the pooling layer, which is a mapping feature layer. A pooling layer comes after each convolution layer, and CNN's unique double-feature extraction structure gives it excellent distortion tolerance for the input images. Using the Keras Sequential API, where adding layers is as simple as starting with the input and adding one at a time. The convolutional layer (Conv2D) is the first. It is comparable to a set of teachable filters. For the first two convolutional layers, chosen select 32 filters, and for the final two, 64 filters. Each filter uses the kernel filter to change a specific area of the image. As shown in Fig. 3, the proposed CNN architecture's detail is as follows:

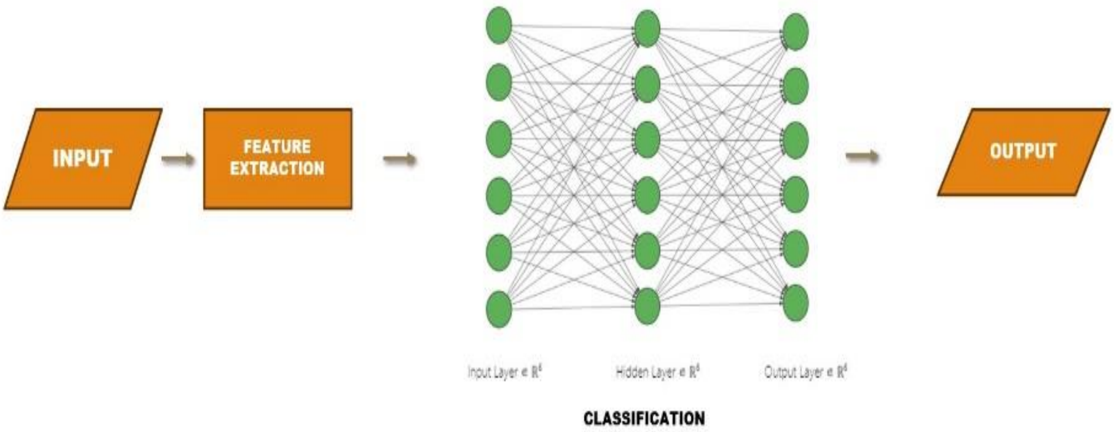

Fig. 3. The proposed CNN architecture

Throughout the entire image, the kernel filter matrix is applied. One way to think of filters is as a picture change. CNN can extract from these altered photos elements that are applicable globally. The pooling layer in CNN is the second crucial layer. All that this layer does is serve as a downsampling filter. It selects the maximum value after examining the two nearby pixels. These are employed to lower computational expenses and, to a lesser degree, lower overfitting. Select a pooling size so that the downsampling is more crucial the higher the pooling dimension. CNN can combine local features and learn more global features of the image by combining convolutional and pooling layers. Dropout is a regularisation technique in which a percentage of the layer's nodes are arbitrarily disregarded for every training sample, hence setting their weights to zero. This forces the network to learn features in a distributed manner by dropping a portion of the network at random. This method also lessens overfitting and enhances generalization.

The application of the rectifier activation function gives the network nonlinearity. To create a single 1D vector from the final feature maps, utilize the Flatten layer. After a few convolutional/maxpool layers, this flattening phase is required to employ fully linked layers. All of the local features discovered by the earlier convolutional layers are combined in it. Ultimately, the features were employed in two fully connected layers, resulting in a classifier that is only artificial neural networks. A more thorough justification of the rationale behind specific architectural choices and their impact on the model's overall efficacy would be beneficial. The Convolutional Neural Network (CNN) is trained using the prepared data in the third phase. To enhance this phase further, hyperparameter tuning is done to determine the optimal parameters and, consequently, the optimal outcomes. The model is tested and its categorization is assessed using quality metrics in the fourth phase. We analyzed the model's output in the last stage and concluded that the model's accuracy was 98.7%.

XII. XGBoost

Beyond gradient boosting, XGBoost achieves accuracy gains through the addition of built-in regularisation. The addition of data is known as regularisation, and its goal is to lower variance and avoid overfitting. Regularised algorithms may also be tried, even if hyperparameter fine-tuning can also regularise data. Simple features like brightness and borders can be the starting point for image processing, or it can go deeper into details like layer thickness to identify things uniquely. The technique of creating samples by altering the training data is known as data augmentation, and its goal is to improve classifier resilience and accuracy. Pre-trained models are now widely accessible. The resulting model will pick up fundamental categorization skills like edge and form recognition. From trained models and a plethora of additional sophisticated categorization classes that can be acquired with the addition of new layers. The model will learn to identify objects that have already been taught if the final few layers of the pre-trained layer are left in place. The decision tree is generally used in the eXtreme Gradient Boosting (XGBoost) technique for regression and classification, which implements the weak predictor principle of the ensemble.

XGBoost is a gradient-boosting implementation that has various additional features added to enhance model performance and execution speed. The challenge lies in enhancing the precision of images used for Alzheimer's diagnosis. Chen and Guestrin created the potent regression and classification algorithm known as XGBoost. A collection of machine learning competition-winning programmers is used in its application. Based on the gradient boosting architecture, XGBoost continuously builds new decision trees to fit a value with residual several iterations, enhancing learner performance and efficiency. In contrast to Friedman's gradient boosting, which utilizes a Taylor expansion to simulate the loss function, XGBoost makes a better trade-off between bias and variance in the model and typically uses fewer decision trees to get greater accuracy. XGBoost is a machine-learning method that is scalable and efficient for tree boosting. It has been widely used in numerous disciplines to obtain state-of-the-art outcomes on multiple data challenges [18]. As an algorithm, the Gradient Booster Because of the decreased model complexity, XGBoost generally adds regularisation to the usual function. To fit the residual error, the first and second derivatives are used. Column sampling is also supported by this approach in lowering computation and overfitting. Hence, larger improvements than the gradient boosting decision tree (GBDT) result in additional hyper-parameters. Reasonably adjusting the hyper-parameters is challenging, though. A reasonable setup necessitates a significant amount of time in addition to the researchers' prior knowledge and experience with parameter tweaking. Sequential decision trees are created using this process, with each tree fixing mistakes made by the one before it. Weights are allocated to independent variables and modified in accordance with how well the model predicts the outcome.

A reliable, accurate machine learning model is produced by this iterative procedure.The results of image classification are obtained by applying this XGBoost Classifier to the highest level of CNN. The following are some benefits of XGBoost over Gradient Boosting:

1. Regularization:
• XGBoost provides improved control over model complexity by incorporating both L1 (LASSO) and L2 (Ridge) regularisation components in the objective function.

2. Parallelization:
• Because XGBoost is designed for parallel computation, it is more scalable and efficient. The process of parallel tree construction is used to do this, and it is especially advantageous for big datasets.

3. Handling Missing Values:
• No need for explicit imputation is required because XGBoost can handle missing values internally.

4. Tree Pruning:
• When building trees, XGBoost uses the "max_depth" and "min_child_weight" parameters to regulate the size and depth of the trees, allowing for more efficient pruning.

5. Cross-validation:
• Cross-validation is included in XGBoost, which streamlines the model selection process. In gradient boosting, cross-validation must be implemented independently.

XIII. CNN-XGBoost

Convolutional Neural Networks (CNNs) and XGBoost combine to generate CNN-XGBoost, which can be used to identify Alzheimer's patients at an early stage accurately. This section uses two components of the CNN-XGBoost model—the feature extractor and the feature classifier—to classify images. Feature extractor CNN first gathers features from the set of images. To train and classify, XGBoost uses the features in the second step.

A. FEATURE EXTRACTOR

To create a lightweight model, this study attempts to investigate how to better combine the neural network's feature extraction capabilities with the decision tree's classification capabilities input layer, three convolution layers, two pooling layers, and one complete connection layer to set the feature extraction make up the special CNN structure for image classification when considering model computation.

B. FEATURE CLASSIFICATION

The deep learning techniques utilized in many healthcare domains such as diagnosing Alzheimer's patients are covered in this study. We use structural MRI scans from the publicly accessible dataset for this purpose. Scientists have utilized a variety of deep-learning models to automatically identify Alzheimer's patients. Among them is the binary classification of patient scans into CN and AD stages. Unlike other classifiers, which only use one model, the ensemble technique uses a collection of different models. In general, ensemble approaches outperform individual machine learning algorithms due to their increased flexibility and adaptability. In this work, an ensemble method is known as "XGBoost. The XGBoost technique is used to increase the models' overall performance after they are assessed using several assessment measures. According to the experimental findings, an average accuracy of 98.7% is attained for each stage of Alzheimer's disease.

XIV. PERFORMANCE EVALUATION IN MULTI-CLASS CLASSIFICATION

Analyze and compare CNN-XGBoost, XGBoost, SVM, reinforcement, and other learning methodologies. Incorporate popular ensemble techniques to enhance model performance. The gradient boosting framework, a subclass of ensemble learning, includes the machine learning method known as XGBoost. XGBoost excels in tasks like regression and classification and can handle large datasets with ease. Additionally, it can process missing values in real-time data with speed and accuracy. XGBoost was used to construct an efficient distributed gradient boosting library. It offers good accuracy when used with CNN as opposed to other machine learning algorithms. One of the main issues with the classification of Alzheimer's patients has been multi-class classification. Multiclass classification remains a difficult issue, even though binary class classification has reached a reasonable level of accuracy. Furthermore, the Evaluation parameters demonstrate this.

The suggested method's sensitivity, specificity, and accuracy are evaluated using the following formulas:

Accuracy = (TN + TP)/ (TN + TP + FN + FP)

Precision=(TP)/ (TN + FP)

Recall=(TP)/ (TP + FN)

F1-score= (2 *Precision* Recall)/ (Precision+ Recall)

TP, TN, FN, and FP stand for true positive (the AD subjects suspected of having AD), true negative (healthy individuals detected as healthy), false negative (AD subjects identified as healthy), and false positive (respectively, the healthy subjects identified as AD patients). The efficacy of the characteristics gathered was verified using four classifiers. RF, SVM, XGBoost, and CNN-XGBoost were the classifiers employed. The quantity of instances where a certain Alzheimer's stage was genuine despite the model's prediction that it was invalid. Different evaluation measures used for classifying Alzheimer's disease are as follows, given the values mentioned above precision. Using thorough experimentation, exhibits exceptional performance metrics, indicating its potential as a resilient and efficient. This report contributes to the current discussion on enhancing AD detection techniques by clarifying these gaps and problems and establishing the foundation for further research efforts in this area.

XV. METHODOLOGY

The approach used in this work combines creative architecture with careful dataset selection to create a strong convolutional neural network (CNN) model specifically intended for Alzheimer's Disease (AD) identification.Illustrates the general process methodology. This study's main component, the CNN-XGBoost architecture, was painstakingly created to capture all of the complex subtleties of AD pathophysiology. This architecture meets the critical need for accurate and sophisticated AD detection techniques by combining CNN-XGBoost convolutional blocks with innovative design ideas.It explains the many layers and design ideas of the CNN-XGBoost architecture through a graphic illustration. The following subsections give an in-depth examination of the CNN-XGBoost convolutional blocks, outline the architectural design concerns, and describe the dataset-gathering procedure. The careful consideration that went into creating the CNN-XGBoost architecture is explained in these subsections, highlighting the design's resilience and effectiveness in AD detection. A hierarchical architecture known as a convolutional neural network (CNN) uses several different layers to efficiently handle input data. Beginning with the input layer, the network absorbs 176x208 pixel grayscale images. The data travels through two successive convolutional layers in the first convolutional block once these images are passed through. Basic features are extracted from the input by the first layer, which is a 3x3 kernel Conv2d operation with 32 output channels. The rectified linear unit (ReLU) activation receives standardized inputs thanks to batch normalisation, which also introduces nonlinearity and improves model convergence. Then, using a kernel size that is comparable to the first, the second convolutional layer further compresses these characteristics into 16 output channels. Before max pooling, the data are again subjected to batch normalization and ReLU activation, which downsamples the information by a factor of two. Similarly, the next convolutional blocks further enrich the network's representation of complex features. To create 32 output channels, the second block starts a new 3x3 kernel Conv2d operation using the 16 output channels from the first block. Next, we apply max pooling, batch normalization, and ReLU activation. The third and fourth phases of this method each add to the intricacy and depth of feature extraction. The fourth block increases this to 128 output channels, capturing ever more complex patterns. The third block further converts the 32 channels into 64 output channels.Dropout regularisation, which deliberately removes a tiny percentage of nodes during training, is integrated into the design to prevent overfitting. To prepare the multidimensional data for processing through fully connected layers, a flattening operation transforms it into a one-dimensional vector after the convolutional layers. These layers, which include batch normalization and linear transformations, lower the dimensionality of the data iteratively until class probabilities are produced. This methodical approach is reflected in the CNN-XGBoost architecture, which makes it easier to extract hierarchical features and produces classification outputs that are accurate for different stages of Alzheimer's disease. Two completely connected layers using the "ReLu" activation function come after the convolutional portion. There is also a flattened layer in between. The three classes are eventually reached using a last fully connected layer that has a classification: Although there are no specific treatments or cures for disorders similar to AD, early diagnosis can help patients live better. Magnetic Resonance Imaging (MRI) is the most appropriate technique for the diagnosis of illnesses that resemble AD.Hospitals are using a lot of digital photographs as information, so the amount of medical image archives is expanding rapidly. Digital images are highly useful in forecasting the severity of a patient's illness, and they are used extensively in research and diagnostics. The automatic classification of medical images is an open research challenge for computer vision researchers due to recent advancements in imaging technologies. In the biomedical sciences, from drug delivery systems to medical imaging, machine learning techniques particularly predictive modeling and pattern recognition have emerged as critical tools that help researchers gain a deeper understanding of the problem at hand and find solutions to challenging medical issues. When it comes to categorization and feature extraction at all levels, deep learning is a potent machine learning algorithm. In this study, we trained CNN-XGBoost to distinguish between the typical, healthy brain and the Alzheimer's brain. As much as progress has been made, current detection models still struggle to correctly diagnose AD, particularly when it first manifests. Accuracy and model optimization are further concerns. To fill this important research void, CNN-XGBoost, a sophisticated convolutional neural network architecture designed specifically for AD detection, is presented in this publication. By improving the accuracy metrics and reliability of AD diagnosis, this work aims to overcome the shortcomings of existing approaches. The preprocessed 2D images in the dataset were taken from 3D photos and were gathered from ADNI. The most crucial factor in classifying medical photos according to the appropriate classes is choosing the best classifier. Image classification is useful for predicting which class or category unknown photos belong to. The details of the step-by-step proposed architecture are shown in Fig. 4 and go as follows:

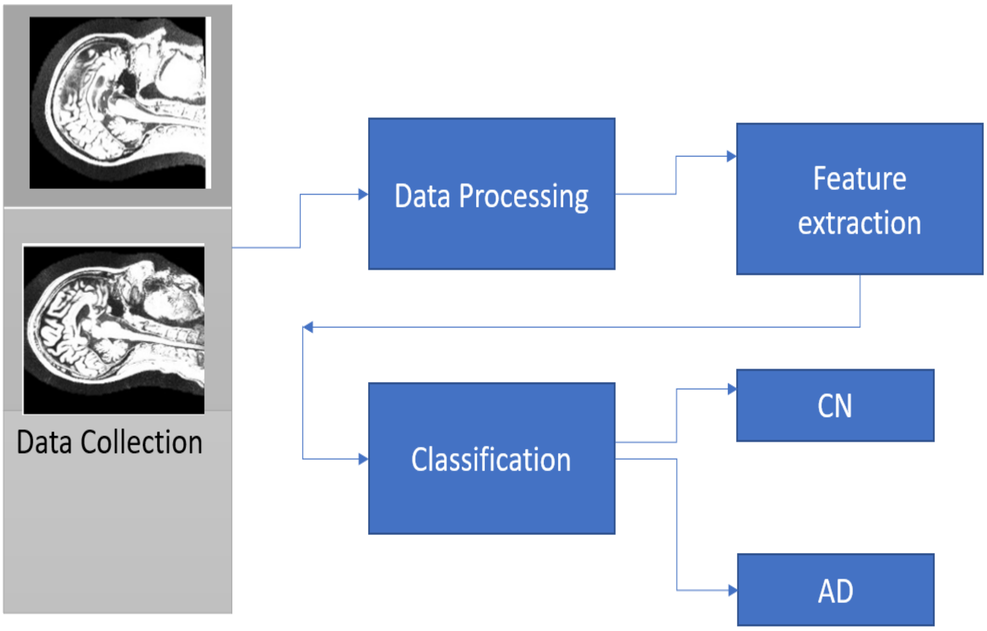

Fig. 4 The block diagram of the classification process

XVI. DATASET

Acquisition of Datasets This study took into account several public databases for the categorization of Alzheimer's disease (AD). The ADNI database shows that structural MRI using T1-weighted images is still the gold standard for MRI investigations on AD, even when other MRI sequences appear promising. Different signal qualities are present in the two basic pictures, T1- and T2-weighted. Patients with Alzheimer's disease, participants with mild cognitive impairment, and older controls are among the study resources and data from the North American ADNI project that are accessible via this website. The Alzheimer's Disease Neuroimaging Initiative (ADNI) is a long-term, multicenter research project aimed at creating biochemical, genetic, imaging, and clinical biomarkers for early Alzheimer's disease (AD) identification and monitoring. Ever since its inception in 2004, this historic public-private collaboration has significantly advanced AD research by facilitating data exchanges amongst researchers globally. Many of these datasets, nevertheless, were in CSV format, which was judged inappropriate for this study's objectives. An organization like the Alzheimer's Disease Neuroimaging Initiative (ADNI) is dedicated. The layer-by-layer result of CNN-XGBoost running on the ADNI dataset [19]. This effort aims to create and propose a method for estimating the presence of Alzheimer's disease by analyzing brain MRI sequences. Furthermore, its manageability is improved by its appropriate size and careful preprocessing, which includes organizing and resizing. The data was presented as separate three-channel (RGB) pictures, each measuring 176 × 208 pixels before being uniformly scaled to 248 x 248 pixels.ADNI gathering, data organization into several standard sets with longitudinal data. Beyond these difficulties, there are no widely applicable standards set for navigation in such a large collection to get image data. Because reproductivity information necessary to produce a comparable subset is typically withheld, a great deal of research articles employ their own sets that were taken from the original ADNI, making it extremely difficult to compare approaches fairly. Our main focus has been on T1-W1 structural MRI scans, analyzing data from 289 subjects, including 37 patients with Alzheimer's disease, 159 patients with mild cognitive impairment, and roughly 93 healthy older people. CNN-based diagnostic MRI analysis (HPC) was conducted using a high-performance Intel Xeor silver 4110 -2.1GHZ -3.5GHz x8 core computer. GPU system that makes use of Nvidia. The GTX1080Ti, the Pascal chipset with the highest ALU count, was used. The cuda(x) is kept in The GPU (Graphics Processing Unit) and also has a channel that a company can set up and several external libraries.

XVII. RESULTS AND DISCUSSION

A. RESULTS

It was shown that 3D convolutional networks perform well in identifying MRI brain scans based on the findings and research conducted on these networks.

Comparatively high accuracy was attained despite time and budget limitations. Comparing the model with 2d convolutions, the accuracy was significantly greater. The people with Alzheimer's disease (AD) and those with mild cognitive impairment (MCI) had the highest degree of uncertainty. This is to be expected as there is no definitive line that separates moderate cognitive impairment from Alzheimer's disease, and the two conditions frequently lead to the same diagnosis. As a result, accurately classifying an individual is difficult. This may lead to data that is incorrectly labeled and a distribution that the model finds difficult to separate. Developing a measure to assess the degree of cognitive impairments would be one way to address this issue. To better improve this model, more studies ought to be conducted. Most significantly, without being limited by time or resources, fine-tuning deep neural networks necessitates several iterations of the same model with various parameters. Research on integrating many specialist models could also be conducted. For instance, the integration of a model that reliably differentiates Alzheimer's disease (AD) from clinically normal (CN) conditions and a model that reliably assesses the degree of AD symptoms. Conclusion and Prospects to diagnose and track the progression of AD, several evaluation tools have been put out over the years. Tasks This study used MRI images to provide a method for dividing Alzheimer's disease into three phases. Using Custom CNN-XGBoost, binary classification is used to categorize subject scans into three distinct categories according to the AD stage. Our model outperforms the traditional methods by a significant margin, achieving the highest precision, recall, and F1 scores on both datasets. Additionally, the suggested model demonstrates enhanced generalization capability and quicker convergence, rendering it more effective and useful for realistic real-world applications. The analysis and use of medical information could be revolutionized by integrating AI-driven methods into consumer electronics for the healthcare industry. This could lead to better patient outcomes and more individualized healthcare solutions. Figures 5 and Table 1 illustrate how well the suggested model performs in comparison to other conventional models.

Table 1: The various categorization comparison analyses are briefly summarised.

Model	Accuracy	Precision	Recall	F1-score
RF	74	69	74	74.2
SVM	70	73	63	60.3
XGBoost	90.6	88.2	90	89
CNN-XGBoost	98.7	90.1	97	95.3

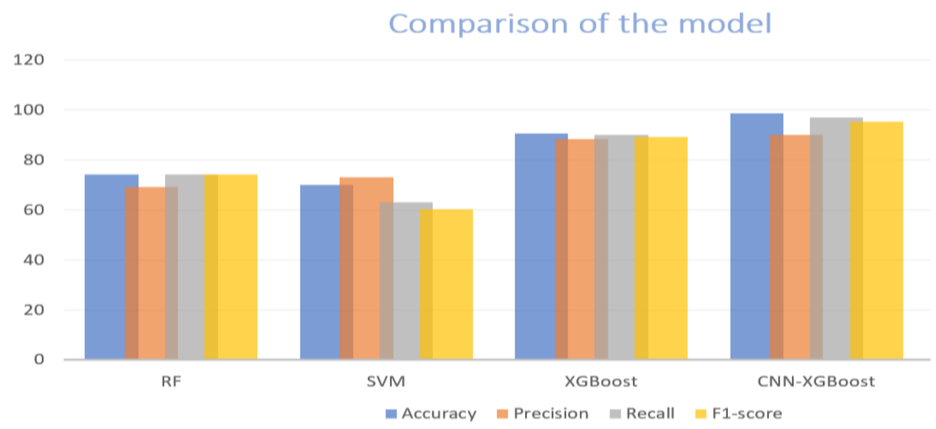

Fig .5 A Comparative analysis of the accuracy performance of the model

Conclusion and Prospects to diagnose and track the progression of AD, several evaluation tools have been put out over the years. Tasks This study used MRI images to provide a method for dividing Alzheimer's disease into three phases. Using Custom CNN-XGBoost, binary classification is used to categorize subject scans into three distinct categories according to the AD stage. Figure 5 below illustrates how the architecture of a CNN-XGBoost aids in the diagnosis process by comparing training and validation accuracy during performance analysis.

Fig. 5. Accuracy Plot Training and Validation Using CNN-XGBoost

B. DISCUSSION

The primary contributions of the current work are outlined below. Initially, we conducted a thorough analysis of the literature on the subject, addressing the shortcomings of several research that also used the ADNI collection. The primary disadvantage is insufficient data to enable easy comparisons. Generally speaking, large datasets are needed for Convolutional Neural Networks and DL-based approaches to be adequately trained, particularly for difficult issues like this one. A popular dataset for studies involving the diagnosis of Alzheimer's disease is ADNI. Due to its well-registered and preprocessed sequences, this dataset provides advantages. Additionally, the skull is cropped out of the pictures, guaranteeing the optimal beginning conditions for any investigation. This is particularly helpful in addressing segmentation issues because masking for white matter, grey matter, and cerebrospinal fluid is accessible. This is why a lot of works favor this dataset over others that can offer a larger number of cases but with poorly processed input, typically raw sequence data. In addition, the way the ADNI collection is arranged into several datasets makes it easier to compare methodologies fairly because images and annotations are readily available. Using XGBoost as a classifier will increase Alzheimer's accuracy with a degree of accuracy. As a result, the accuracy of Alzheimer's disease identification using CNN-XGBoost on images can be increased, as demonstrated by the findings of this study. The quality and quantity of photographs utilized have an impact on the outcome as well. However, given the current state of technical advancements, any technological discovery can be enhanced by subsequent discoveries. Similarly, accuracy can be increased in the identification of neurodegenerative conditions in Alzheimer's images using CNN-XGBoost. The first step in implementing CNN-XGBoost on mammography pictures is gathering datasets. Data preprocessing is the next step in the model-making process, which begins with dividing the data into training and testing sets. This is the final training layer that is applied to the XGBoost Classifier. The primary disadvantages of low-level characteristics are their decreased capacity for discrimination and their domain-specific categorization. A semantic difference between elements of high-level perception in human understanding and low-level comprehension in machines. Classifying this type of medical data is important because it may help construct a predictor model or system that may identify a disease type from normal people or estimate the disease's stage. The most difficult aspect of classifying clinical data, such as those related to Alzheimer's disease, has always been determining which traits are the most discriminative. The structural MRI data of Alzheimer's patients was effectively separated from normal controls using CNN-XGBoost, where test data accuracy was based on trained data.

XVIII. CONCLUSION

Alzheimer's disease diagnosis is frequently made using machine-based analysis and prediction algorithms. There are connections between the definition, diagnosis, identification, and relationship of MCI with AD, the moral dilemmas surrounding early diagnosis and disclosures, and how patient-centered research is both required and morally right. The breadth of these investigations is, however, constrained by the poorer accuracy of current methods and the absence of post-diagnosis monitoring tools. This work proposes a unique machine learning-based approach for AD disease monitoring and diagnosis. The diagnosis of AD disorders is achieved using deep learning analysis of structural magnetic resonance imaging (MRI) scans. When CNN and XGBoost were combined, the research revealed that the accuracy results were higher than when CNN was used alone. Hopefully, CNN can be utilized to investigate the precision of Alzheimer's disease identification on the neurodegenerative image. Additionally, the work employed comprehensive and distinct preprocessing techniques to enhance the quality of the data given to the classifier, which in turn had a good effect on its performance. In particular, the study showed how deep learning architectures may be used to diagnose brain abnormalities, which opens up new possibilities for medical diagnostic imaging. The accuracy and effectiveness of recommendation systems can be increased by combining the findings of several models through the use of ensemble learning, a potent technique. To put it briefly, the article provides a basis for future research in healthcare contexts by summarising the body of literature now available on healthcare big data. In subsequent research, we will focus on identifying the many health risks and enabling timely interventions to halt the advancement of illness through various machine and deep learning methodologies.

REFERENCES

[1] Bhatti, U.A., Mengxing, H., Li, J., Bazai, S.U. and Aamir, M. eds., 2024. *Deep Learning for Multimedia Processing Applications: Volume Two: Signal Processing and Pattern Recognition*. CRC Press.

[2] Gazis, A. and Katsiri, E., 2024. Streamline Intelligent Crowd Monitoring with IoT Cloud Computing Middleware. *Sensors*, *24*(11), p.3643.

[3] Sugiharti, E., Arifudin, R., Wiyanti, D.T. and Susilo, A.B., 2022. Integration of convolutional neural network and extreme gradient boosting for breast cancer detection. *Bulletin of Electrical Engineering and Informatics*, *11*(2), pp.803-813.

[4] Biswal, A.K., Singh, D. and Pattanayak, B.K., 2021. IoT-based voice-controlled energy-efficient intelligent traffic and street light monitoring system. In *Green Technology for Smart City and Society: Proceedings of GTSCS 2020* (pp. 43-54). Springer Singapore.

[5] Tooba Altaf, Syed Muhammad Anwar, Nadia Gul, Muhammad Nadeem Majeed, Muhammad Majid. *"Multi-class Alzheimer's disease classification using image and clinical features", Biomedical Signal Processing and Control, 2018*

[6] Reshma Dua, G. Ronald Wallace, Tashi Chotso, V. Francis Densil Raj. "*Chapter 22 Classifying Pulmonary Embolism Cases in Chest CT Scans Using VGG16 and XGBoost",* Springer Science and Business Media LLC, 2023

[7] Pati, A., Parhi, M., Pattanayak, B.K., Singh, D., Singh, V., Kadry, S., Nam, Y. and Kang, B.G., 2023. Breast cancer diagnosis based on IoT and deep transfer learning enabled by fog computing. *Diagnostics*, *13*(13), p.2191.

[8]Rath, M., Pati, B. and Pattanayak, B.K., 2019. Mobile agent-based improved traffic control system in VANET. *Integrated Intelligent Computing, Communication, and Security*, pp.261-269.

[9]Rath, M., Darwish, A., Pati, B., Pattanayak, B.K. and Panigrahi, C.R., 2020. Swarm intelligence as a solution for technological problems associated with Internet of Things. In *Swarm Intelligence for Resource Management in Internet of Things* (pp. 21-45). Academic Pressذ

[10] Raju, M., Thirupalani, M., Vidhyabharathi, S. and Thilagavathi, S., 2021, March. Deep learning based multilevel classification of Alzheimer’s disease using MRI scans. In *IOP Conference Series: Materials Science and Engineering* (Vol. 1084, No. 1, p. 012017). IOP Publishing.

[11] Hosenkhan, M.R. and Pattanayak, B.K., 2020. Security issues in internet of things (IoT): a comprehensive review. *New Paradigm in Decision Science and Management: Proceedings of ICDSM 2018*, pp.359-369.

[12] Panda, N. and Pattanayak, B.K., 2018. Energy aware detection and prevention of black hole attack in MANET. *International Journal of Engineering and Technology (UAE)*, *7*(2.6), pp.135-140.

[13] Rath, M., Pati, B. and Pattanayak, B.K., 2017, January. Cross layer based QoS platform for multimedia transmission in MANET. In *2017 11th International Conference on Intelligent Systems and Control (ISCO)* (pp. 402-407). IEEE.

[14] Rath, M. and Pattanayak, B.K., 2018. Monitoring of QoS in MANET based real time applications. In *Information and Communication Technology for Intelligent Systems (ICTIS 2017)-Volume 2 2* (pp. 579-586). Springer International Publishing.

[15] Rath, M., Pattanayak, B.K. and Pati, B., 2015. Energy competent routing protocol design in MANET with real time application provision. *International Journal of Business Data Communications and Networking (IJBDCN)*, *11*(1), pp.50-60.

[16] Pattanayak, B.K., Mishra, M.K., Jagadev, A.K. and Nayak, A.K., 2011. Power aware ad hoc on-demand distance vector (PAAODV) routing for MANETS. *Journal of Convergence Information Technology*, *6*(6), pp.212-220.

[17] Rath, M. and Pattanayak, B.K., 2019. Security protocol with IDS framework using mobile agent in robotic MANET. *International Journal of Information Security and Privacy (IJISP)*, *13*(1), pp.46-58.

[18] Sugiharti, E., Arifudin, R., Wiyanti, D.T. and Susilo, A.B., 2022. Integration of convolutional neural network and extreme gradient boosting for breast cancer detection. *Bulletin of Electrical Engineering and Informatics*, *11*(2), pp.803-813.

[19] Jiang, Q., 2022. *Application of Hidden Markov Model to Auto Telematics Data and the Effect of Universal Demand Law Change on Corporate Risk Taking in the US Property & Casualty Insurance Industry*. Temple University.

[20] Padmini Mansingh, Binod Kumar Pattanayak, Bibudhendu Pati, Bassam Elzaghmouri and Ahmad Khader Habboush ,2023, PREMORBID BRAIN VOLUME AGAINST ALZHEIMER'S DISEASE USING BIG MEDICAL DATA ANALYSIS,ARPN Journal of Engineering and Applied Sciences, 18(8).