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Deep Learning and IoT-Enabled Framework for Accurate Classification and Monitoring of Alzheimer's Disease Based on EEG Signal Analysis

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***Abstract*—Alzheimer's disease is a brain ailment that impairs thinking, memory, and behaviour. The efficacy of Brain-Computer Interface (BCI) systems must be enhanced to increase their prevalence in the biomedical sector. The biomedical sector is crucial for precise and efficient patient diagnostics using digital signal processing and wireless sensor network technologies. Alzheimer's disease (AD) is an irreversible brain disorder. Inadequate Alzheimer's disease diagnosis in the early stages, together with exact identification, may aid in halting the progression of the illness. Precise and effective detection and categorization of Alzheimer's disease enhance quality of life and increase life expectancy for patients. The advanced deep learning technology surpasses traditional machine learning methods in classifying complex configurations in high-dimensional composite data, particularly in digital signal processing. The deep learning application for the early detection and accurate classification of Alzheimer's disease might be suggested for a neuron-signal methodology in extensive data analysis. This research paper proposes an intelligent decision-making system (IDMS) for the diagnosis and categorization of Alzheimer's disease (AD) and the continuous monitoring of patients utilizing connected wearable devices. Methods for measuring neuronal synchrony are proposed to diagnose and characterize Alzheimer's disease.**

Keywords: Brain-Computer-Interface (BCI), Alzheimer's disease (AD), Intelligent Decision-Making System (IDMS), Adaptive Harmonic Noise Model Wiener filter (AHNMF), Digital Signal Processing (DSP), PCA, ICA, EMD, DCNN, IoT.

I. Introduction

Principal Component Analysis (PCA) and Independent Component Analysis (ICA) are two approaches employed to identify distinct characteristics from EEG signals. The Fast Fourier Transform (FFT) is a frequency domain method applied to EEG signals to infer frequency domain characteristics. The EEG signal is decomposed into a series of narrowband signals utilizing the Hilbert-Huang Transform (HHT), which has been favored for its capability to evaluate signal properties. The sub-band signal is further decomposed into stationary spatial sequences by empirical mode decomposition (EMD), resulting in a sequence referred to as the Inherent Mode Function (IMF). The suitable IMF for feature extraction from EEG data is chosen.The relevant feature vector from IMF can be used to estimate the estimated entropy value of the EEG signal. We should gather a larger quantity of EEG signals from both healthy individuals and patients with diseases for signal analysis. All features are aggregated and saved in a database during the training phase of deep learning. The equivalent energy spectrum and secondary spectrum are assessed to classify the signals according to their characteristics.

The extensive database is established to enhance the effectiveness of IDMS. The Deep Convolutional Neural Network (DCNN) is trained using integrated frequency, time, and other channel information from EEG signals. The DCNN will train all database characteristics and develop the IDMS system for testing and real-time EEG signals. The real-time EEG signal of any patient can be provided for the DCNN testing phase. The real-time EEG testing signal undergoes all of our unique phases, including filtering, augmentation, and feature extraction. The testing features are evaluated and recorded in DCNN. The testing aspects are juxtaposed with the training phases of DCNN. The IDMS will determine if the EEG signal is normal or abnormal based on the comparison. All patient information is shown in a Graphical User Interface (GUI) that will be sent to the Internet of Things (IoT). The security algorithm will be designed to safeguard patient information, ensuring data confidentiality in the cloud through the use of IoT.

The Health Security System (HSS) is crucial in the medical sector for IoT cloud storage. In the medical field, Confidential Health Information (CHI) is a growing patient-centered system for the sharing of health information, frequently outsourced to third-party servers for storage. In the medical field, while the primary focus is often on life preservation, it is equally essential to maintain data access to interconnected network systems that safeguard personal information, such as health records. Consequently, many privacy and security issues may arise, as CHI is susceptible to penetration by unidentified third parties. Information security regulates access to private medical data by granting uncomplicated permissions to authorized individuals.

II. Literature Survey

Numerous research organizations and independent laboratories globally are engaged in body sensor networks and have proposed a personal atmosphere (PAM) project for mental health monitoring. The objective of the program is to monitor the signatures of patients with bipolar disorder (BP). The PAM consists of two layers: a personal ambient management system (PAM-I) and a specific technology framework for environmental monitoring (PAM-A). The individual and the residence have been outfitted with health monitoring systems. Bluetooth is a protocol that links mobile phones and body sensors. It also links mobile phones and personal computers. Although authors are primarily concerned with applications for wireless mental health surveillance when patient confidentiality is necessary, they do not address patient privacy.

The Johns Hopkins University-developed MEDiSN system, which tracks patients in hospitals and emergency rooms, has been the subject of recent media coverage [2]. This includes a number of clinical gadgets (sometimes referred to as "PMs"), battery-operated motes, and medical indicators that are used to collect physiological data from patients (e.g., blood oxygenation, pulse rate, pulsation rate, etc.). Furthermore, the authenticated login for the backend controller sensor network is kept secret, but only approved customers are able to access and monitor it [5]. Because of this, the author's understanding of their security procedures has not been thoroughly discussed from a security standpoint.

[4]Implementing the medical picture segmentation system with the histogram-dependent approach. The method evaluates the image's threshold value using the p-tile approach and utilizes the edge details derived from the edge maximization methodology. The regions from the satellite image are segmented based on the threshold value, which is then effectively utilized to assess the tumour existing in the image. [5] Creating an adaptive thresholding strategy based on genetic algorithms for the picture segmentation system. The approach evaluates the picture window dimensions according to the entropy characteristics. The entropy characteristic facilitates the segmentation of pictures into distinct sections by the application of a parallel genetic algorithm. The algorithm determines the segmentation based on the selection, mutation, and crossover functions. The operator-based segmentation methodology efficiently segments the picture compared to Huang's pyramidal window merging method. The device output is ultimately assessed for consistency and error rating based on experimental findings and analysis.

[6] Enhancement of the MRI image's capacity to detect brain tumour's by reducing conjecture. The author uses a variety of filter strategies, including the medium-length, average, Wiener, and wavelet filters, to reduce the image noise quality and increase the image quality. The strategy eliminates noise while removing it without degrading the quality of the edges, which solely contain information on the tumour itself. In the end, the output is assessed in accordance with the high signal-to-noise ratio requirements for the suggested device capacity.

[7]Brain tumors are examined via many medical imaging techniques, including ultrasound, MRI, CT, and X-rays. Certain noise that eliminates the complete system output affects these photos. The noise is therefore produced by the use of several filters, while the wavelet transforms and isolates the noise without affecting the information regarding the edges. Subsequently, the high-quality images are utilized for tumor isolation in the following phase, ensuring complete accuracy. [8] Segmenting the effective tumor zone from the MRI picture via various preprocessing techniques. The use of various filters, which reduce noise, utilizes three distinct series: T1, T2, and DWI, for the preprocessing of collected pictures. Various attributes derived from the pre-processed picture are input into the classifiers to analyze the tumor efficiently. The system's efficiency correlates with the particular statistical approaches employed.

[9, 10] Utilize the MRI image to develop the tumor detection system. The Gabor filter improves the produced pictures by the use of Gaussian principles. Subsequently, the tumor region is segregated utilizing Otsu thresholding techniques predicated on the threshold value. Various normal characteristics are collected from the segmented region to distinguish between normal and abnormal photos in the dataset. The computer output is subsequently compared with the auditory representation and other conventional segmentation techniques.

[11-12] Research demonstrates that the disruption and anomalies in the blood-brain wall might develop early in the illness's progress. A collection of brain cells known as the neurovascular unit interacts with injected fibrinogen. They like to clarify the connection between neuronal and synaptic degeneration and vascular pathology associated with Alzheimer's disease in this review.

III. Expected Output and Outcome of the Research

The anticipated outcome is a prototype that integrates hardware and software for the detection and identification of Alzheimer's disease and the continuous monitoring of patients with IDMS. A wireless sensor combined with software will be developed for EEG signal collection. The obtained analog EEG signal must be digitized for storage. The noisy EEG signal is processed using a digital filter. The digital filter may be engineered to eliminate various noise components in the EEG signal. The DSP processor is utilized for filter design. The filtering parameters are computed to validate the filter's efficacy. The EEG data is further processed using a DSP enhancement method to boost signal quality. The relevant characteristics are assessed and shown for categorization purposes. The decision-making for IDMS may be achieved using DCNN to classify whether a particular real-time EEG data is influenced by AD. The automated and integrated IDMS system may be constructed utilizing the features recorded in a database. The database is crucial for signal categorization with deep learning.

The automated and integrated intelligent decision-making system may be utilized to detect the existence of Alzheimer's disease. The Python-based Graphical User Interface must be demonstrated to monitor cerebral functions. The IoT cloud storage system may be implemented for the storage of all data, including acquisition, processing, and database construction.

Data encryption and decryption are feasible for maintaining privacy and security in IoT cloud storage.. The Health Security System (HSS) software package will be developed for securing patient information during transmission and reception of IoT cloud. The integrated device can be established for AD detection and classification for real time EEG signal of patients.

IV. Origin of the Research

The human brain generated electrical signal is called as electroencephalograph (EEG). Alzheimer's disease (AD) is a neurological condition characterized by brain cell death that results in memory loss and cognitive impairment. This kind of Alzheimer's is degenerative; it starts out mildly and gets worse over time. However, limited hospitals usually cannot have adequate supplies for intensive identification training. While there is an increasing amount of information exchanged in scientific research, it is not always evident whether a system built on one database is well suited for other resources. In comparison to a system that was built on the first little dataset, the accuracy increased by about 20%.

The outcomes demonstrated that the suggested remedy is a novel and effective BCI technique that can only be used in clinics with a small amount of learning data. The correct diagnosis of Alzheimer's disease (AD) using traditional deep learning techniques is a subject of ongoing research, and deep learning-related techniques are now frequently employed as an alternative to AD diagnoses. Cognitive Impairment (CI) is characterized by the deterioration of memory function in the human brain, which may potentially develop to Alzheimer's Disease (AD). Due to the many aspects of Alzheimer's disease, neocortical disconnection syndrome has manifested. The historical statistics indicate that 6-25% of cognitive impairment (CI) transitions to Alzheimer's disease (AD) annually, while 0.2-4% of the general population progresses to AD, revealing that CI serves as a precursor to AD. The disintegration of coordination between the cortex and hippocampus has been a crucial focus of study to explore the origins of cognitive impairment in Alzheimer's disease. To investigate neural interaction, the quantitative assessment of connectedness between time series from different brain regions is termed "functional connectivity". The discovery of the human brain as a composite system has facilitated the identification of elements that may effectively detect practical diseases in the human brain.The EEG signal reflects functional instances to assess cognitive disorders and serves as an investigative tool, however analytical ambiguity persists even after first medical interventions.

Vast research has previously been carried out to find the distortions in EEG signals. Changes in local cerebral blood flow are found to be one of the triggers of anomaly in AD EEG signals [1]. The BCI is an alternate contact mechanism between a person and machine that relies not on the usual output neural impulses of the human brain, nor on the muscle. Typically, the method begins by observing the user's brain behaviours before moving on to the signal phase to recognize the user's actions. The external system receives the resultant signal and monitors it in accordance with the signal identification. The EEG signals produced when actively visualizing different movements can be translated into specific tasks, as has been shown in the communication services for patients in lockdown states—one of the rather large range of applications for which BCI is now being used. Brain attributes are linked as feedback impulses to the motor visualization activities. Throughout BCI structures focused on motor imaging (MI), the interpretation of body motions is followed by a constrained event-based coordination / de-synchronization (ERS)/event-based de-synchronization.

Since deep learning techniques are particularly difficult to apply to the production of a comprehensive EEG classification process due to several effect factors like noise, channel differentiation, and high-dimensional EEG features, they have only recently been included into the EEG-based BCI scheme. A stage of data processing where signals are reduced in dimensional space and are interpreted by new data without significant data loss would be part of an ideal classification system. After all functional aspects of the inputs are eliminated during data processing; the system architecture is the next step in this process. Considering several challenges previously discussed, the effective use of deep learning techniques for EEG signal classification is undoubtedly successful.

The electrode position in the scalp is depicted in figure 1. The EEG data were obtained by a high-density retrieval program from three patient categories (CNT, MCI and AD). Three separate combinations of the electrodes were regarded beginning from this. Pre-processing of the signals was conducted by MATLAB and Python. Pre-processed EEGs is used as data acquisition algorithm input signals. To measure the practical communication, for a given frequency spectrum, the Lagged Linear Connectivity (LLC) matrix has been determined for each set of regions of interest (ROIs). The design and development of digital filter using Minimum Mean Square Error log-spectral amplitude (MMSE-LSA), noisy EEG data can be pre-cleaned. The mean squared error cost function is used in the Bayesian estimating process known as the MMSE-LSA technique.

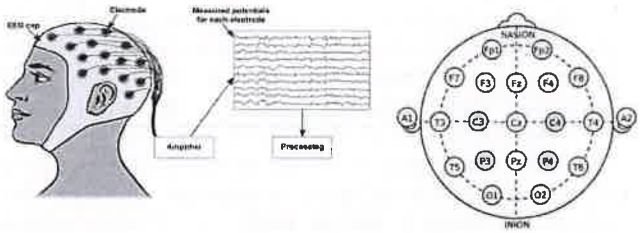


Figure 2: Block Diagram of Digital filter for DSP Processor

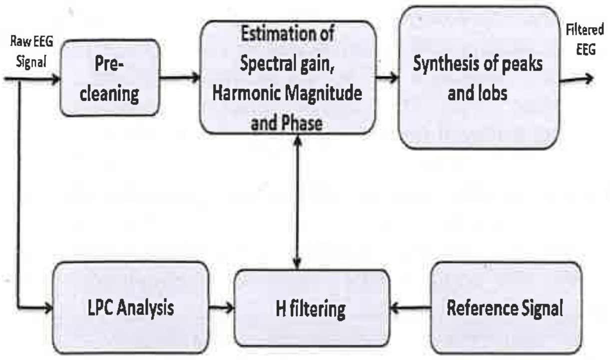


Fig. 2. Block Diagram of Digital filter for DSP Processor

Pre-cleaning provides the primary benefit of de-emphasizing the spectrum's noise-corrupted region. Pre-cleaning the signal before using it for signal analysis is crucial because it increases robust pitch estimation, improves spectrum accuracy, and yields an approximation of speech and noise information. The stimulated EEG signal's harmonic component is represented as

$$E^T S = \sum_{k=1}^{v(m)} M_k(m)\cos(2\Pi(kT_0(m)+\Delta_k(m))+\theta_k(m)). \quad (1)$$

In this case, (m) denotes the number of harmonics, T0 (m) denotes the magnitude, and the vectors E and S correspond to the harmonic amplitude and harmonically related sinusoids, respectively. Harmonic magnitudes are determined through the optimum period T0 under clean conditions.

$$e_h(m) = E^T S + d(m). \quad (2)$$

The LPC spectral envelope is used to describe the signal's harmonic amplitude and phase, which is subsequently translated into a correlation function. Correlating the LPC coefficients in this way allows for the attainment of spectral alteration. We are able to include the H∞ tracked spectral envelope in this setup.

V. Methodology

This study proposes a unique technique for the Intelligent Decision-Making System (IDMS) aimed at the identification and recognition of Alzheimer's Disease (AD) and the ongoing monitoring of patients. The main objective is to provide a thorough framework for the early identification of Alzheimer's disease and to categorize medical data for various stages of the condition. This research employs a deep learning methodology, namely a convolutional neural network (CNN). The initial four phases of AD can be delineated using several categories. Additionally, each combination of AD phases is categorized using a distinct binary brain tumor detection classification approach. Medical picture categorization and the diagnosis of Alzheimer's disease utilize distinct methodologies. The initial method employs 2D and 3D convolution with fundamental CNN architectures to address anatomical brain imaging in both 2D and 3D from the Alzheimer's dataset.

A online application for assessing Alzheimer's is advised utilizing the optimal qualifying design plans. Remote monitoring of Alzheimer's disease is beneficial for both physicians and patients. Furthermore, it evaluates the patient's symptoms to determine their current position on the AD spectrum and offers corresponding advice. The experimental results demonstrate that the suggested structures are efficient, uncomplicated designs that effectively save time and effort while decreasing computing demands, memory requirements, and overfitting.

VI. Acquisition of EEG Signals

The EEG signal acquisition block diagram is displayed in Figure 3.

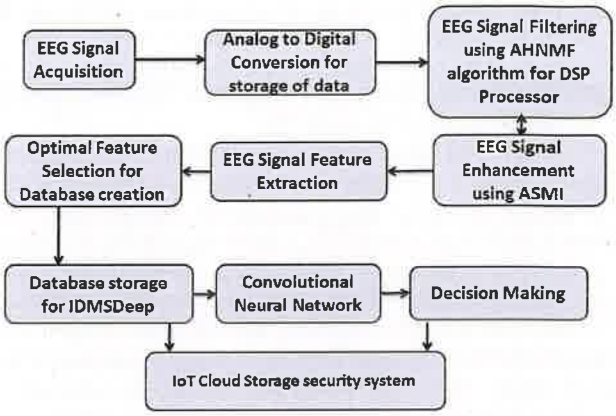


Fig. 3. Architecture diagram of proposed methodology

Our objective is to develop a lightweight, battery-powered EEG signal collecting device that utilizes wireless sensors positioned on the patient's head. The emergence of this novel foldable technology can effectively address the issue of EEG scalability by reconfiguring devices for smaller or more intricate applications. Development of a device capable of transmitting raw EEG data over Bluetooth or Wi-Fi, acquiring 16 to 64 EEG channels at sampling rates between 250 Hz and 1000 Hz.

Additionally, device analysis has made use of simple yet effective measurement techniques. In addition to validating the system's operation against authorized datasheet requirements and for practical applications, testing can also be used to undertake regression studies of specific associated EEG devices using the suggested standard assurance methodologies. It is possible to design an analog front end (AFE) that is reliable and precise. There are a number of AFE products on the market that could cast doubt on analog EEG signals. The primary brain EEG oscillating waves do not require high-sampling output AFE since they oscillate within the low frequency range of 0–40 Hz. As such, AFEs with low channel assistance, strong noise reduction capabilities, and high acquisition quality will be given top consideration.

VII. DESIGN AND DEVELOPMENT OF DIGITAL FILTER (DF) AND ENHANCEMENT

The DSP algorithm could be developed for filtering raw EEG signal. The input EEG signal consists of various types of noises such as random noise and Gaussian noise. The noises should be adaptively filtered to get filtered EEG signal. The Adaptive Harmonic Noise Model Wiener filter (AHNMF) is applied to eliminate different noise content from the EEG signal. The algorithm for digital filter is developed for Digital Signal Processor (DSP). The DSP processor is the part of an integrated device. Further, the EEG signal has to be enhanced by applying Adaptive Significance Magnitude Improvement (ASMI) algorithm that used to improve the quality of EEG signal in terms of amplitude and magnitude.

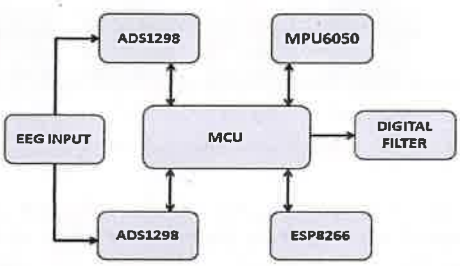


Fig. 4. Block diagram for data acquisition

The original EEG signal acquired from human is poor in quality and noise content in nature due to various factors it will amplified and filtered with the help of figure 4. The EEG signal is undergone for pre-processing using AHNMF digital filter and ASMI enhancement technique using DSP processor. In the next phase, the requirements for database generation are executed.

EEG signal classification

A substantial database is established to enhance the effectiveness of IDMS. The Deep Convolutional Neural Network (DCNN) is trained using integrated frequency, time, and other channel information from EEG signals. The DCNN will train all database characteristics and develop the IDMS system for testing and real-time EEG signals. The real-time EEG signal of any patient can be provided for the DCNN testing phase. The real-time EEG testing signal undergoes all of our unique phases, including filtering, augmentation, and feature extraction. The testing features are evaluated and recorded in DCNN. The testing functionalities are juxtaposed with the training phases of DCNN. The IDMS will determine if the EEG signal is normal or abnormal based on the comparison.

As shown in figure 5 as a method of machine learning, deep learning (DL) teaches computers to solve problems in the same way that people do. Large-scale multimodal neuroimaging data has been generated thanks to the rapid development of NM with DL's assistance, which has sparked interest in early diagnosis and automated categorization of Alzheimer's disease.

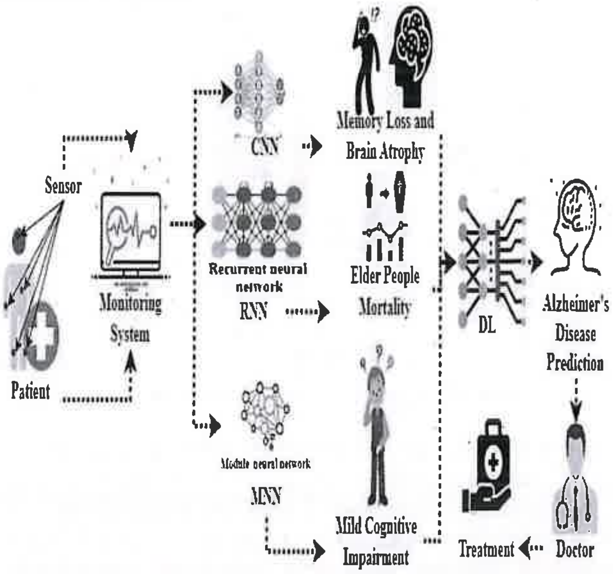


Fig. 5. Deep learning to process and detection of Alzheimer's disease and persistent monitoring of patient

It has been shown that conventional neural networks (CNN) can assist avoid memory loss and keep the body in shape by engaging in physically demanding and mentally stimulating activities like exercise. Various protective effects for the brain were ascribed to these meals, and recurrent neural networks (RNN) have been shown to lower death rates in the elderly and keep brain diseases under control.

A modular neural network (MNN) has been shown to boost cognitive function, reduce the risk of dementia and cardiovascular disease, and alleviate the signs and symptoms of serious depression.

TABLE I. ANNUAL INCIDENCE RATE (%) OF DEMENTIA (ALL CAUSES) AND ALZHEIMER'S DISEASE IN HEALTHY PEOPLE

Age	Dementia	Alzheimer's Disease
60-64	0.11	0.06
65-69	0.33	0.19
70-74	0.84	0.51
75-79	1.82	1.17
80-84	3.36	2.31
85-89	5.33	3.86
90-94	7.29	5.49
95+	8.68	6.68

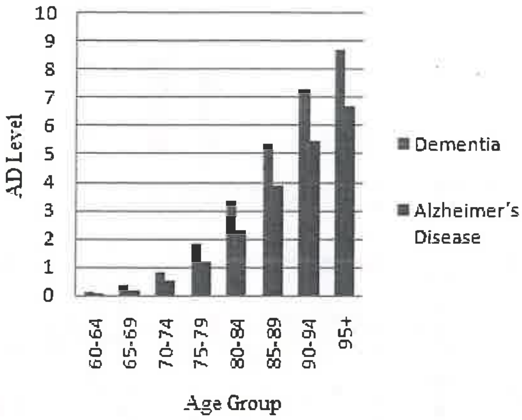


Fig. 6. Annual Incidence Rate Monitoring of Patient

When evaluating the accuracy of different modalities in sample data for Alzheimer's disease (AD) shown in fig 6 and, it's crucial to consider various biomarkers and modalities used for diagnosis and monitoring, including structural Magnetic Resonance Imaging (sMRI) for volumetric measurements, functional MRI (fMRI) for functional connectivity, Positron Emission Tomography (PET) for amyloid-β and tau protein deposition, Cerebrospinal Fluid (CSF) biomarkers for Aβ42, t-tau, and p-tau levels, clinical and cognitive assessments like MMSE, ADAS-Cog, and CDR scores, and genetic markers like APOE genotype. Factors affecting accuracy include image quality, brain region segmentation, age-related changes, tracer specificity, image resolution, partial volume effects, sample handling, rater variability, education and cultural biases, test-retest reliability, genetic complexity, penetrance, and expression. Combining multiple modalities through multimodal fusion, feature selection, and dimensionality reduction can improve accuracy, and using standardized protocols, quality control measures, and machine learning techniques can help account for individual variability and confounding factors, ultimately capturing the complex biology of AD.

TABLE II. ACCURACY OF DIFFERENT MODALITIES

Sample Data	MRI (%)	PET	Multimodal
100	84.32	91	93.25
200	84.51	91.32	94.56
300	86	92.22	95.79
450	87.67	92.41	96.4

Here are the accuracy rates of different modalities for Alzheimer's diagnosis- Multimodal diagnosis model: Classification accuracy of 98.1% using the Alzheimer's Disease Neuro Imaging Initiative (ADNI) dataset shown in table II.

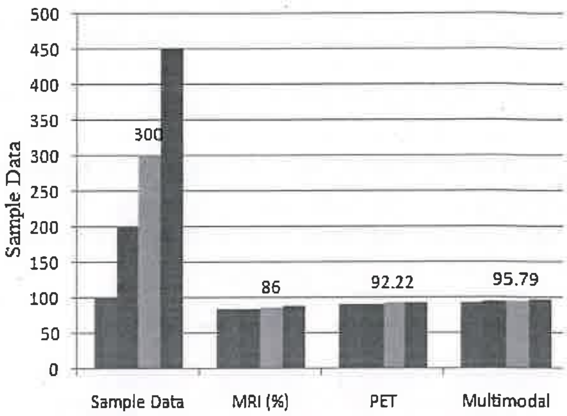


Fig. 7. Alzheimer 's disease Neuro imaging Initiative (ADNI) dataset

Early detection of Alzheimer's disease using DL enhances the likelihood of a positive treatment resultant data set is shown in Fig 7. Individuals who meet the criteria for participation in clinical trials might reap the scientific and medical benefits of participating in these studies because of their earlier diagnosis.

TABLE III DEMOGRAPHY OF SUBJECTS OBTAINED FROM MULTIMODAL NEURO IMAGING

Category	Normal	AD	MCI
Normal	133	166	151
Gender	54/69	68/88	72/70
Age	67-71	65-92	61-82

The subjects span various age groups, including older adults and elderly individuals, and comprise both male and female participants with different educational levels show in fig 8, including those with lower educational attainment. Clinical and cognitive assessments, such as MMSE, ADAS-Cog, and CDR scores, are also considered, along with genetic markers like APOE genotype and may have neuropsychiatric disorders like Alzheimer's disease, mild cognitive impairment, and other dementia-related conditions. The sample size ranges from a few dozen to hundreds of participants, depending on the study, and includes varied ethnic and racial populations, such as Caucasian, Asian, African American, and Hispanic individuals.

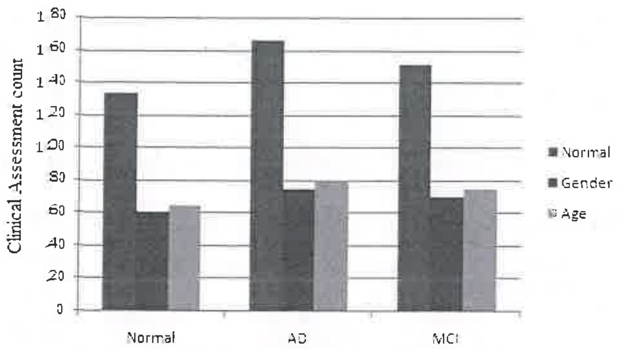
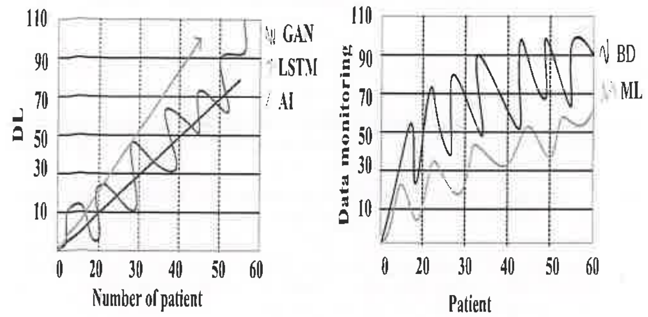


Figure 8. Alzheimer's disease



(a) (b)

Figure 9. (a) Alzheimer's disease for significant in DL
(b) Patients to ensure monitoring data:

Dementia and Alzheimer's disease take an impact on the elderly. Alzheimer's disease is not a natural aspect of aging, although it becomes more severe as patients become deeper. Dementia patients can be better cared for and supported if adequately recognized. People can require assistance to articulate their memories, ideas, and feelings sufficiently. The quality of life of dementia can be significantly improved by finding the correct service. Deep learning has generated superhuman precision in image classification, object recognition, picture restoration, and image segmentation. Even handwritten digits can be detected with this precision. Patient security can be safeguarded by limiting or removing cell devices from patient areas. Because of this safeguard, private documents and information can't be accessed by almost everything.

Electroencephalography (EEG), as seen in Figure 10, is a test to detect irregularities in the brain's electrical activity by analysing the brain's waves. Electrodes consisting of tiny metal discs connected by thin wires are placed on the scalp at various points throughout the procedure. The RNN method to solve the activity of the brain cells generates small electrical charges collected by the electrodes. This involves tests for the capacity to keep track of individual thoughts and for mental agility. Alzheimer's disease can be tracked using this method of testing. As neurons die and are damaged across the brain in Alzheimer's disease, the connections between neural networks can weaken, resulting in the shrinkage of several brain areas.

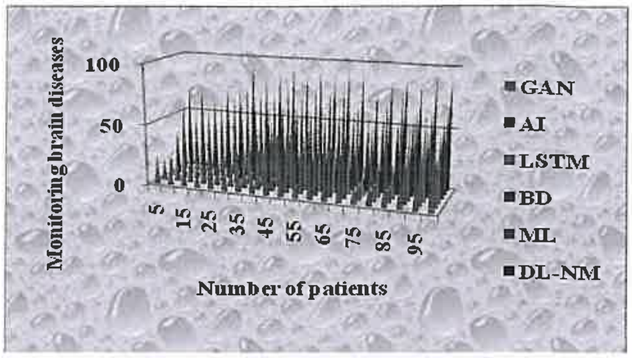


Fig. 10. Monitoring brain diseases of the patient

The diagnostics and clinical procedures that can benefit most from DL methods are those that lead to better patient outcomes. To aid in the identification of age-related conditions, DL-based techniques provide efficient solutions for processing and analyzing complicated medical visual information. The main focuses of current methodologies are finding disease indicators, reporting and identifying human sickness, and keeping an eye on the elderly. DL can incorporate the diverse data collected from elderly patients using wearable technology to track their independent overall health, including cardiac melodies and movements, daily style of life, biometric information, and sentient genes, and can move ahead with the assessment of such unstructured data to pertinent diagnostic information by eliminating anomalies and drawing conclusions useful patterns.

VIII. IoT DATA SECURITY

In an IoT context, gadgets are susceptible to assaults when left unattended. The wireless characteristics of the gadgets facilitate eavesdropping. Appropriate authentication and cryptography methods must be implemented to access devices and their data. Health reports frequently include sensitive data containing personal information that must be properly safeguarded and kept. Consequently, the healthcare system need rigorous privacy restrictions.

All patient information is shown in a Graphical User Interface (GUI) that will be sent to the Internet of Things (IoT). The security algorithm will be designed to safeguard patient information, ensuring data confidentiality in the cloud through IoT integration. The Health Security System (HSS) is crucial in the medical sector for IoT cloud storage. In the medical field, Confidential Health Information (CHI) represents a growing patient-centric system for health information interchange, frequently outsourced to third-party servers for storage. In the medical field, while the primary focus is often on life preservation, it is equally essential to maintain data access to interconnected network systems that safeguard personal information, such as health records. The primary limitation of the S-Box is its static nature during the execution of a security method.

By using the dynamic and random variance of the S-Box technique, the limitation is successfully solved while maintaining patient security for their EEG data. We have proposed a dynamic and random S-Box method utilizing S-Box characteristics essential for secure construction—nonlinearity, bit independence criteria-nonlinearity (BIC-nonlinearity), strict Avalanche criterion (SAC), and bit independence criteria-strict Avalanche criterion (BIC-SAC)—and compared it with other S-Boxes presented in the project. The Two-Fish approach is proposed to facilitate encryption and decryption during the transmission and reception of healthcare data, hence ensuring safe cloud storage and access through IoT.

IX. Conclusion

A unique approach is given for detecting security threats and recovering information to safeguard private data by utilizing a Dynamic and Random S Box model in conjunction with the Two-Fish encryption algorithm. The primary limitation of the S-Box is its static nature during the execution of a security method. The dynamic and random variation of the S-Box approach effectively addresses the constraint while ensuring the confidentiality of patient EEG data. Employing S-Box characteristics essential for secure S-Box construction—nonlinearity, bit independence criteria-nonlinearity (BIC-nonlinearity), strict Avalanche criterion (SAC), and bit independence criteria-strict Avalanche criterion (BIC-SAC)—we have introduced a dynamic and random S-Box methodology and evaluated it against other S-Boxes proposed in the project. The Two-Fish approach is proposed to facilitate encryption and decryption during the transmission and reception of healthcare data, hence ensuring safe cloud storage and access through IoT.

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