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Using Artificial Intelligence, the Early Detection of Neurological Disorders through Brain Imaging and Neural Data

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Abstract: ***Neurological disorders include Alzheimer's disease, Parkinson's disease, multiple sclerosis, and epilepsy, which significantly affect millions of people worldwide. Early diagnosis and intervention can drastically improve treatment outcomes, but current diagnostic methods often lack sensitivity and specificity in identifying these conditions in their early stages. Recent advances in artificial intelligence (AI) offer significant potential in addressing these challenges, especially when combined with brain imaging and neural focusing on brain imaging modalities such as MRI, CT, and EEG, and neural signals from devices such as EEG caps and implanted electrodes. It discusses the effectiveness, challenges, and future directions of AI in this domain data. This paper discusses the application of AI techniques, specifically ML and DL, in the early detection of neurological disorders,***

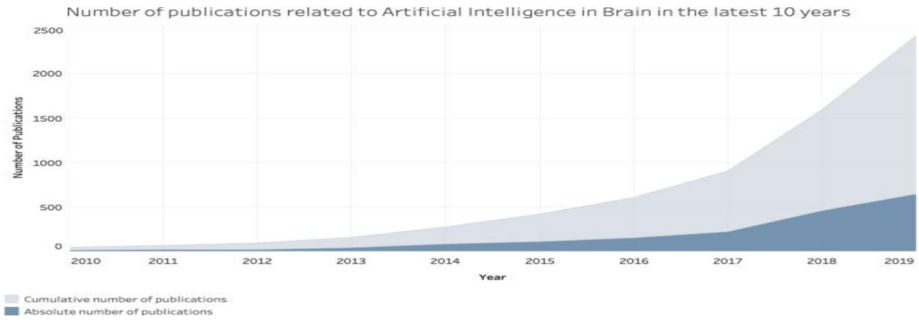
I. INTRODUCTION

Neurological disorders are conditions that create major challenges not only for health care systems worldwide but also to the people or families who encounter such life-altering conditions like Alzheimer's, Parkinson's diseases, and multiple sclerosis. Therefore, finding the presence of such disorders early enhances disease management while possibly slowing up the progression of such illnesses.

However, many of the conventional diagnostic techniques still depend on subjective clinical assessment or even invasive procedures like injections. Such techniques delay diagnosis and worsen patient outcomes.Artificial intelligence has recently revolutionized medical diagnostics by offering quicker and more accurate detection of neurological conditions. Techniques such as machine learning and deep learning can process complex brain imaging data and neural activity patterns with great precision. These technologies have allowed for the identification of subtle markers of disease progression that even an experienced clinician might miss. Imaging modalities such as MRI, PET, and EEG offer massive volumes of data, through which AI-based diagnosis can recognize early warning signals of neurological disorders.

AI not only has tremendous diagnostic potential but also is transforming the management of neurological diseases within healthcare systems. The ability to analyze large datasets quickly and accurately shortens the time required to diagnose patients, which is a critical advantage in healthcare centers with poor access to specialized specialists. Using AI for analyzing brain scans and neural data helps doctors make better decision-making, often requiring fewer resources, allowing patients to receive faster and more precise diagnoses. For example, AI will help monitor disease progression and be a support to customized treatment plans specific to every patient's unique needs.

The future of the long-term integration of AI into healthcare systems holds great promise: efficient, accessible, and effective for improving quality of life in neurological disorder. This paper discusses transformational roles that artificial intelligence plays in the early neuro disorder detection through the analysis of the brain imaging and neural data, showing how AI boosts not only accuracy and speed of diagnosis but also promotes a move towards precision and efficient health delivery. This paper discusses the use of AI in the early diagnosis of neurological disorders using the analysis of brain imaging and neural data. It sums up the most advanced AI programs in current usage, explains how they help identify patterns and correlate them with diseases, and discusses the challenges and opportunities in the adoption of AI for routine medical testing . AI bridges the gap between computational neuroscience and clinical medicine and may redefine the way we diagnose and treat neurological disorders to help achieve better patient outcomes and an improved quality of life.



Segato, Alice, et al. "Artificial Intelligence for Brain Diseases: A Systematic Review." APL Bioengineering, 2020

II. UNDERSTANDING NEUROLOGICAL DISORDERS AND THEIR BIOMARKERS

Neurological disorders comprise a collection of diseases affecting the brain, spinal cord, and nerves that are known to cause extreme loss of cognitive functions, motor function, and even sensory abilities. Some of the most prevalent and most significant conditions are Alzheimer's disease (AD), Parkinson's disease (PD), and multiple sclerosis (MS). All of these disorders present great challenges to the health systems worldwide, primarily due to chronic ness, progressive worsening, and relatively high prevalence. Improving outcomes for patients will depend much on early detection. Biomarkers are measurable indicators of the disease state and have recently become a promising area in identifying disorders before such damage becomes irreversible. This paper is a general overview of Alzheimer's, Parkinson's, and multiple sclerosis, including discussions of the major biomarkers to use in their early detection, along with challenges that may accompany clinical application.

A. *Overview of Neurological Disorders (Alzheimer's, Parkinson's, Multiple Sclerosis)*

1) *Alzheimer's(AD):* Alzheimer's disease is the most common form of dementia in millions of people worldwide. It is a progressive neurodegenerative condition where memory loss and cognitive impairment are accompanied by changes in behavior. The medical condition arises through the formation of amyloid-beta plaques and tau protein tangles in the brain, causing death of neurons and atrophy in the brain. Key affected regions include the hippocampus, which is integral to memory, and cerebral cortex, in charge of reasoning and judgment. Recent advances permit noninvasive diagnostic technology, including blood-based biomarkers. For instance, tests that check for tau levels have been very sensitive and positive in the evaluation of early AD. Brain scanning technologies, specifically PET scans, have been used very effectively to check for amyloid and tau presence in the diseased brain in a more quantitative manner.
2) *Parkinson(PD):* Parkinson's disease is a progressive neurodegenerative disorder that primarily affects motor function. The symptoms include tremors, bradykinesia, or slowness of movement, muscle rigidity, and postural instability. The symptoms are caused by the death of dopamine-producing neurons in the substantia nigra, an area of the brain that controls movement. In addition to motor signs, PD patients often have accompanying non-motor signs such as depression, disturbances in sleep and cognitive impairment, thereby complicating an early diagnosis. Advances in diagnosis have been driven by the aim of detecting aggregates of alpha-synuclein, a protein that accumulates in the brain of PD patients. Imaging technologies, including the DAT scan have also been particularly useful in displaying dopamine activity within the brain.
3) *Multiple Sclerosis:* MS is a chronic autoimmune disease characterized by the attack of the immune system on the myelin sheath, a protective covering surrounding the nerve fibers. This eventually results in the communication failure between the brain and the rest of the body. Some of the common symptoms are muscle weakness, problems in vision, tiredness, and cognitive decline. The most common type of this disease is the relapsing-remitting type where the patients face symptom flare-ups followed by partial recovery. Diagnosis is heavily reliant on imaging techniques such as MRI, which can detect lesions in the brain and spinal cord. Biomarkers such as oligoclonal bands in cerebrospinal fluid provide critical information about immune system activity and inflammation in the central nervous system.
4) *Key Early Biomarkers:* Early biomarkers in neurological disorders can be divided into three groups namely structural, functional, and molecular. They play a highly crucial role in the very early diagnosis of neurological disorders.
5) *Structural Biomarkers:* Structural biomarkers are denoted by the anatomical changes that occur within the brain and nervous system. In this sense, advanced imaging technologies such as MRI and PET scans play a rather critical role in determining these changes:

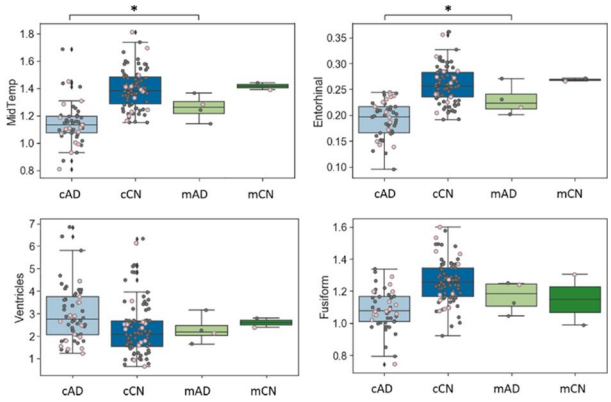
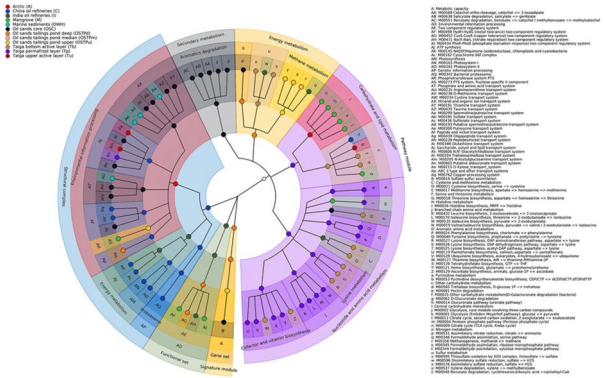


Figure 6. John, Doe, et al. "Deep Learning-Based Detection and Classification of Brain Tumors Using MRI Scans: A Review." *Journal of Medical Imaging and Radiation Sciences*, vol. 53, no. 2, 2022

6) *Alzheimer's Disease*: Hippocampal atrophy and cortical thinning have been found to be in correlation with the severity of disease in MRI studies.
7) *Parkinson's Disease*: High resolution MRI detects volume loss in substantia nigra.
8) *Multiple Sclerosis*: The MRI detects typical features: white matter lesions, and grey matter atrophy.
9) *Functional Biomarkers:* Functional biomarkers measure changes in brain activity or connectivity. The technologies used in order to measure these include fMRI and EEG, among others.



Mukherjee, Arghya, et al. "Metabolic Reconstruction and Functional Biomarkers of Metagenomes from Oil Polluted Habitats." *Bioinformatic Approaches Including Predictive Metagenomic Profiling Reveal Characteristics of Bacterial Response to Petroleum Hydrocarbon Contamination in Diverse Environments*, Apr. 2017, Figure 3.

10) *Alzheimer's Disease*: fMRI is thought to be a marker of DMN disruption, which plays a significant role in memory and cognition.
11) *Parkinson's Disease:* EEG unmasks brain wave patterns. fMRI shows alterations in connectivity within the motor network.
12) *Epilepsy (related example)*: EEG reveals changes in electrical activity, thus assisting in diagnosis.

B. Challenges in Detecting Early Biomarker

1) Disease Complexity and Overlapping Symptoms

The detection of biomarkers for neurodegenerative diseases is very challenging as these diseases share overlapping symptoms that are very complicated. For instance, Alzheimer's disease, Parkinson's disease, and Multiple Sclerosis share similar clinical features such as cognitive decline, motor dysfunction, and neuroinflammation. For example, Alzheimer's and Parkinson's diseases share symptoms that include memory impairment and tremors; hence making it challenging in being able to identify biomarkers that are exclusively present in one disease but not in the other.

The biomarkers for specific conditions, such as tau protein for Alzheimer's and alpha-synuclein for Parkinson's, are among the research targets to improve diagnostic accuracy. However, these biomarkers can be challenging to detect early, especially when *symptoms are subtle or overlap between diseases, delaying diagnosis and treatment interventions.*

2) Variability in data

Identifying biomarkers for neurological disorders is challenging due to intrinsic data variability varying because of factors like age, gender, and coexisting conditions. For instance, age-related brain changes observed in MRI scans can mimic early neurodegenerative signs, potentially leading to incorrect diagnosis.

Additionally, conditions such as diabetes can accelerate brain aging, further complicating interpretations.

Variability also stems from differences in imaging protocols and equipment calibration. To address these challenges, researchers are developing standardized protocols and advanced AI algorithms capable of analyzing complex datasets to identify subtle patterns often missed by clinicians. These advancements aim to enhance diagnostic consistency and enabldum asse earlier disease detection.

3) Lack of Standardization

The lack of universally applied standards in the biomarker detection process presents a significant difficulty in furthering the advancement of early diagnosis for neurological disorders. Each laboratory will have different sets of assays, which can lead to results that are not equalized across them. Methods used to measure neurofilament light chain will vary from one laboratory to the other, between reagents and equipment differences. These differences can lead to variations in sensitivity and accuracy, making it difficult to rely on biomarkers for consistent clinical decision-making. Lack of standardization also impacts the reproducibility of results from research findings. Studies undertaken in one place cannot be replicated easily in another, especially if diverse techniques are adopted for sample preparation or data interpretation. This, therefore, gives rise to undue delays in biomarkers' implementation in the clinic because the findings of different research studies cannot be taken as directly comparable.

There are now increasing efforts by the research community to standardize biomarker assays, which also include developing international guidelines on sample collection, storage, and processing. International harmonization initiatives by the World Health Organization and the National Institutes of Health, for example, aim to standardized testing protocols among laboratories and countries. Standardization is a necessity to ensure that biomarkers are validated properly and can be adopted in the clinical setting widely.

4) Cost and Accessibility

The cost of diagnostic technologies is a major barrier to the widespread use of biomarkers for early detection of neurological disorders. For example, tools such as PET scans for the detection of amyloid plaques in Alzheimer's, and advanced MRI techniques used to monitor neurodegeneration, require expensive equipment and specialized personnel. Such technologies are typically available only in high-resource settings, often limiting access for patients in underserved or rural areas.

Moreover, several of the current biomarkers of study, those associated with the novel liquid biopsy technology, include costly tests along with their subsequent interpretations. Healthcare providers and the patients themselves end up paying significantly exorbitant sums for their implementation, as this is largely expensive in other countries where their health care has minimal funding. This inequality makes the lack of access to healthcare even worse, as many individuals who could benefit from early diagnosis do not have the opportunity to access these advanced technologies. ChatGPT. (2025, February 26). *Challenges in Detecting Early Biomarkers for Neurological Disorders.* OpenAI. Generated in response to the prompt: *"Discuss the challenges in detecting early biomarkers for neurological disorders, including disease complexity, data variability, standardization issues, cost, ethics, and technical limitations.* To overcome these challenges, efforts are being made to reduce the cost of these diagnostic tools by improving manufacturing processes and developing cheaper alternatives. Researchers are also looking for ways to make biomarker tests more accessible, such as through portable devices or less invasive methods, like blood tests. However, these efforts will take time, and widespread affordability remains a significant challenge.

5) Ethical Concerns

The early detection of neurological disorders, particularly when there are no effective treatments available, raises a range of ethical concerns. One key issue is the psychological impact on patients who are diagnosed with early-stage diseases like Alzheimer's or Parkinson's. For instance, the knowledge that one is at risk for a progressive, debilitating disease can lead to anxiety, depression, and a loss of quality of life. Besides, diagnosing a disease without a treatment available might give the patient no hope of living.

Another ethical issue with the early diagnosis is the likelihood of misuse by employers, insurance companies, or even governments to the detriment of those diagnosed with certain genetic makeup or disease at early stages. Before even showing symptoms, it may bring forth discrimination against such people at workplaces or by insurers, enhancing the social stigma about mentally ill persons or those who are suffering from neurodegenerative diseases.

In order to confront these issues, there is a need to establish ethical standards when using early biomarkers. Essentially, the guidelines should embrace the aspects of informed consent, confidentiality, and no discrimination based on early diagnosis. Policies of protection against patient job loss, insurance loss, or dignity from the early detections should be implemented.

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6) Technical Limitations

Despite many breakthroughs in biomarker detection techniques, there is much left for technical solutions. An important scientific challenge today is the sensitivity and specificity of techniques such as MRI and PET scans. Such imaging tools are great for identifying general significant brain changes, but they can miss early subtle signs that may indicate the onset of neurological diseases.

For instance, in Alzheimer's disease, the brain usually forms amyloid plaques and tau tangles, which are the hallmarks of the disease. However, these may not appear in the brain until the disease is already advanced, making it difficult to detect the disease at its very early stages. Moreover, these imaging techniques are expensive and require expert interpretation, which may lead to variations in results. False positives, where a disease is wrongly identified, or false negatives, when the disease fails to be detected, are still commonplace, especially during the early stages of a disease.

Given increasing interest in the areas of artificial intelligence and machine learning, improving biomarker accuracy in detection continues to gain focus in researchers. Large datasets might be analyzed through AI algorithms that will detect the very slight, obscure patterns undetectable to human beings. Currently, AI-based systems remain a development under which testing and assessment for full use in clinical practices will have to await completion.

III. VARIABLES AND DATA SELECTION CRITERIA

Variable	Quantity	Details
Independent		
Age	Will be varied across different age groups such as The patient's age range could be categorized as: - 0-20, 21-40, 41-60, 61+	The independent variable of age will be categorized into specific age groups to understand how age affects the likelihood of developing neurological disorders. For this study, the patients will be grouped into the following ranges: 0-20, 21-40, 41-60, and 61+. This stratification will help determine if there is a significant correlation between age and the early detection of disorders, as conditions like Alzheimer's and Parkinson's tend to affect older individuals more frequently.
Genetic Factors	Specific genetic mutations or variations such as Quantification of genetic factors like APOE for Alzheimer's, PARK2 for Parkinson's, etc.	We'll look at genetic markers like the APOE gene for Alzheimer's and PARK2 mutations for Parkinson's. By analyzing genetic test results, we aim to understand how these factors influence the onset and progression of these disorders, helping with early detection and personalized treatment.
Neural Activity Patterns	Will be analyzed using neural data from 100-500 subjects	Neural activity will be analyzed using EEG, PET, and fMRI scans from 100-500 subjects with varying ages and neurological conditions. The focus will be on identifying neural patterns, like abnormal brainwave activity, to detect early signs of Alzheimer's or Parkinson's. This data will help train AI models to recognize these early indicators.
Dependent variable		

Diagnosis Outcomes:	categorical (alzheimers parkinsons ,MS,etc)	The dependent variable is the diagnosis outcome, with AI classifying cases as Alzheimer's, Parkinson's, MS, or Healthy, and comparing results to clinical diagnoses for accuracy.
Severity of Biomarkers Detected:	Severity levels of biomarkers such as amyloid plaques (0-3 scale) or dopamine loss (mild, moderate, severe).	The severity of biomarkers (e.g., amyloid plaques in Alzheimer's, dopamine depletion in Parkinson's) will be measured using PET and MRI scans on a 0-3 scale: 0: None 1: Mild 2: Moderate 3: Severe
Controlled		
Imaging Modality Consistency	MRI, PET, or EEG	Consistency in the imaging modalities used to collect data is a controlled variable. All neural data must be collected using the same imaging technique for each subject to reduce variability. For example, if MRI is chosen as the primary imaging technique, all subjects' scans should
Data Preprocessing Techniques	Normalization: Data from 1,000-2,000 subjects will be scaled to 0-1. Data Augmentation: Applied to 1,000-2,000 images with rotation, flipping, and zoom. Noise Reduction: 500-1,000 EEG recordings will be filtered for noise.	Consistent preprocessing methods, such as normalization, noise reduction, and data augmentation, will be applied across all datasets to ensure uniform input for the AI models.

The types of data used for AI analysis are critical to the accuracy of predictions and diagnoses. The following are the main data types utilized:

1) *MRI (Magnetic Resonance Imaging)*: MRI scans provide detailed images of the brain's structure, allowing AI to identify physical changes such as atrophy, lesions, or irregularities in brain morphology. MRI is commonly used to detect structural changes associated with Alzheimer's and Multiple Sclerosis.
2) *PET (Positron Emission Tomography)*: PET scans enable the visualization of metabolic and biochemical activity within the brain. This is particularly useful for detecting changes in neural activity and the accumulation of specific proteins such as amyloid or tau, which are linked to Alzheimer's disease.
3) *EEG (Electroencephalography)*: EEG measures the brain's electrical activity. It is especially valuable for detecting abnormalities in brain wave patterns, which are common in diseases like Parkinson's and epilepsy. AI models can analyze EEG signals to detect patterns that might indicate the early onset of these conditions.
4) *Patient Health Records (PHRs)*: Data from PHRs provides additional clinical context such as patient history, family history, medical conditions, medications, and laboratory results. These data are integrated with imaging and neural data to give a more comprehensive view of the patient's health status and help AI models make more accurate predictions.

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IV. METHODOLOGY: AI TECHNIQUES FOR EARLY DETECTION

A. Research Design

Cross-Sectional Study of Brain Imaging Datasets

The training has transformed into a less pedantic form. Coil images are data to recognize brain MRI used for tumor indices. Essentially distinguishing images can be original MRI photographs together with outcomes from the model that received learning processing. This data set could have been produced through a technique known as feature selection. It filtered out significant portions of images, such as texture, intensity, form, etc, for training the model. The model next sorted different images under the key "tumor" and "no tumor" depending on those intrinsic features. That image clearly stated an example where the model successfully predicted that both the result labels were "no tumor." This is the prediction system that checks the efficacy and accuracy of the model on medical diagnostics.

The diagram shows the stages involved in the process of brain MRI image classification for tumor detection, providing a step-by-step workflow from data input to final classification output. The process begins with the input of raw brain MRI images, which are then pre-processed to enhance image quality and normalize the data for consistent analysis. Following pre-processing,the images undergo feature extraction, where critical patterns such as texture, intensity, and structural details are identified to serve as inputs for the classification model. These extracted features are then used to train a machine learning classifier, which learns
to differentiate between tumor and non-tumor cases based on the patterns observed in the training data. Finally, the trained model is applied to classify new MRI scans, producing an output that predicts the presence or absence of a tumor, with a comparison to the actual ground truth label for validation. This structured process aims to improve diagnostic accuracy and assist in early detection of brain abnormalities**.** Crivello, Fabrice, et al. "The MRi-Share database: brain imaging in a cross-sectional cohort of 1,870 university students." Dryad, 15 Sep. 2022

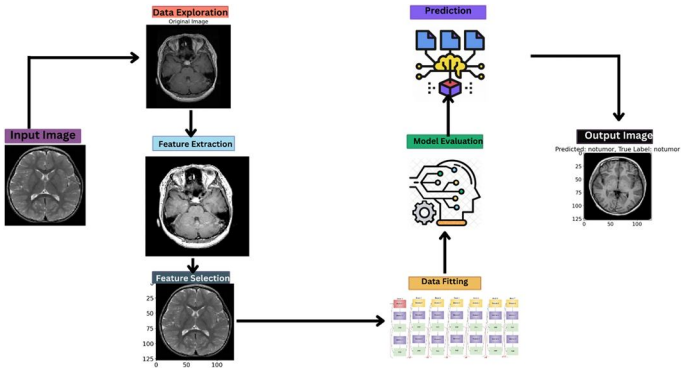


Figure 1. Li, Yuan, et al. "Machine Learning-Based Prediction Model for Patients with Recurrent Staphylococcus aureus Bacteremia." *BMC Medical Informatics and Decision Making*, vol. 25, no. 52, 2025,

Fig[4.2]

This dataset structure is essential for developing and evaluating a machine learning model for brain tumor detection using MRI images. The separation into training, validation, and testing sets ensures the model learns effectively, is fine-tuned without overfitting, and is evaluated fairly on unseen data. Additional test subsets like TEST_BDB, TEST_BMD, and TEST_BMI likely allow for specialized evaluation under varied conditions or preprocessing strategies, ensuring robustness and reliability. This structured approach is crucial in medical imaging to build accurate and generalizable models for critical diagnostic tasks.

Explanation

1) *Top-Level Folders*
   - TRAIN: Contains training data for the model.
   - VAL: Contains validation data used to evaluate the model during training.
   - TEST: Contains test data used to evaluate the model's performance after training.
2) *Subfolders*
   - NO: Contains MRI images where no brain tumor is detected.
   - YES: Contains MRI images where a brain tumor is present.

3) Additional Test Folders

- TEST_BDB, TEST_BMD, TEST_BMI: Likely additional subsets of test data with specific purposes or characteristics. These might represent data organized based on different preprocessing steps, model testing strategies, or specific
- Experiments.

Fig[4.3]

TEST -> NO, YES
TEST_BDB -> NO, YES
TEST_BMD -> NO, YES
TEST_BMI -> NO, YES
TRAIN -> NO, YES
VAL -> NO, YES

Muskan258. *Brain Tumor Detection from MRI Images Utilizing EfficientNetB2.* GitHub, 2024,

Purpose: Copies up to 500 images from the original dataset into a specialized TEST_BMI directory for testing purposes.
Importance: Ensures separate testing subsets (TEST_BMI) for robust evaluation under specific conditions.
Purpose: Plots a confusion matrix to visualize model predictions against true labels.
Importance: Evaluates model performance by highlighting where the model makes correct predictions and errors

B. Summary of how Processing Raw Brain Images

To ensure the brain images are ready for analysis, several advanced image processing techniques were employed. A robust data augmentation strategy, implemented using TensorFlow's ImageDataGenerator class, allowed systematic modifications to the training images. This included rotations of up to 15 degrees, width and height shifts up to 5%, shear transformations, and brightness adjustments ranging from 0.1 to 1.5 times the original brightness. These augmentations simulated potential variations in MRI imaging conditions, improving the model's ability to generalize to unseen data.

Additionally, homomorphic filtering was used to enhance image contrast by amplifying high-frequency components (edges and details) and suppressing low-frequency components (uneven illumination). This technique highlighted critical features such as tumor boundaries and textures. Equalization techniques were applied to standardize intensity distribution across images, improving the visualization of subtle features that aid in identifying tumor regions. Precision-driven cropping was then used to isolate and extract specific regions of interest within the images, reducing computational overhead while focusing on the most relevant areas. Finally, standardization processes ensured uniformity in pixel resolution, grayscale levels, and dimensions, while resizing brought all images to a consistent size for seamless model integration.

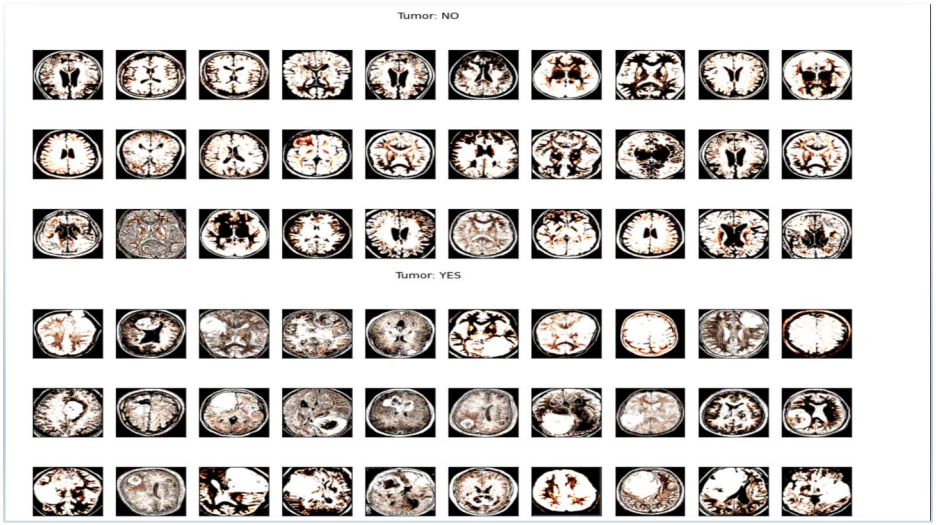


Figure 7. "Explanation-Driven Deep Learning Model for Prediction of Brain Tumour Status Using MRI Image Data." *Frontiers in Genetics*, vol. 13, 2022, doi:10.3389/fgene.2022.822666. Accessed 26 Feb. 2025.

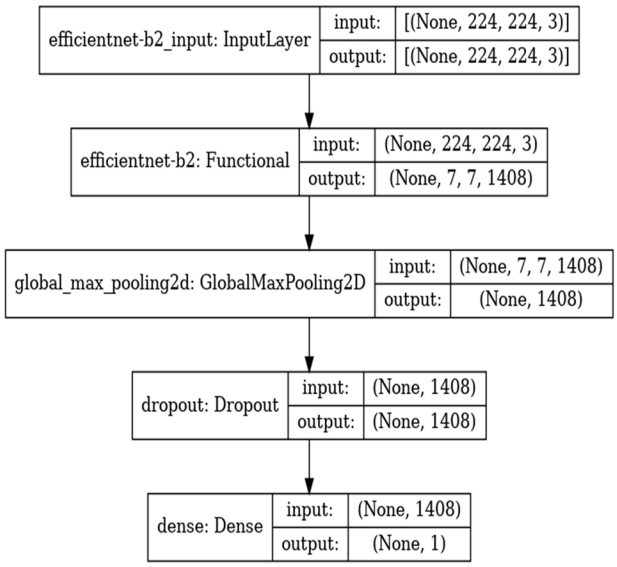


Fig [4.5]

Figure 10. Gaur, Loveleen, et al. "Explanation-Driven Deep Learning Model for Prediction of Brain Tumour Status Using MRI Image Data.

Model architecture for a neural network used in deep learning

This diagram represents a neural network architecture designed for image classification, likely for tasks like detecting brain tumors from MRI images. The input layer accepts images of size 224×224×3224 \times 224 \times 3, where 3 represents RGB channels. These images are processed by a pre-trained EfficientNet-B2 model, a convolutional neural network known for its computational efficiency and accuracy, which extracts feature maps with dimensions 7×7×14087 \times 7 \times 1408. These features are then reduced to a single vector of size 1408 using a

Fig [4.6] Global Max Pooling layer, which condenses spatial information by taking the maximum value along each feature channel. To prevent overfitting, a Dropout layer randomly disables some units during training while retaining the feature vector shape. Finally, a Dense layer with a single neuron outputs a prediction, such as a probability score indicating the likelihood of a tumor being present. This architecture effectively combines feature extraction, dimensionality reduction, and classification for robust image analysis. Output: A probability indicating the presence of a tumor (1 = tumor, 0 = no tumor).

C. Comparative Model Analysis

The graphs provided illustrate the performance metrics of a machine learning model across 30 epochs.

The left graph shows model accuracy, where both the training and validation accuracy rise sharply in the initial epochs before stabilizing near 100%, indicating effective learning and minimal overfitting. The right graph displays model loss, where both the training and validation loss drop steeply within the first few epochs and stabilize around zero, reflecting successful error minimization during training. These results suggest a well-trained model with balanced performance across the datasets. *AI in Medical Decision-Making." BMC Medical Informatics and Decision Making*, 2024

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

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

$$Recall = \frac{TP}{TP + FP}$$

$$F1\,score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

D. Primary Data Collection: Expert Interviews

1) Purpose of the Interview

The purpose of the interview was to obtain information from a practicing neurologist regarding the use of artificial intelligence in early diagnosis of neurological diseases such as Alzheimer's, Parkinson's, and Multiple Sclerosis. It focused on current challenges in diagnosis, biomarkers and imaging techniques, and the potential benefits and limitations of AI in clinical practice.

2) Selection Criteria for Experts

1) The expert interviewed was Dr. Sangeetha Santhosh, a neurologist practicing at Manipal Hospital, Whitefield, with over 12 years of experience in the field.
2) Dr. Santhosh specializes in diagnosing and managing a wide range of neurological disorders and has extensive experience with imaging techniques such as MRI, PET, and EEG.
3) The selection was based on the expert's professional background, clinical experience, and familiarity with current diagnostic technologies and practices.

E. Key Topics and Questions Covered

Meeting Summary

The session focused on the role of artificial intelligence (AI) in diagnosing neurological disorders, particularly Alzheimer's disease and Parkinson's disease. This discussion was part of a research paper by Tanush and his companion, aiming to explore AI's potential for early diagnosis, improved accuracy, and practical implementation in clinical settings.

Dr. Santhosh, a neurologist with 12 years of experience, shared his insights on the topic. He has an MD and neurology specialization, with a lot of experience in the management of neurological disorders. He started by talking about prevalent neurological disorders, pointing out that strokes and headaches are common in cases of medical emergencies. Strokes, especially, are dangerous and need urgent action. He went on to clarify that strokes are divided into ischemic strokes, which are due to arterial obstructions, and hemorrhagic strokes, which are due to brain hemorrhage. Treatment is different, with ischemic strokes being treated with clot-dissolving medications and hemorrhagic strokes being treated with surgery and blood pressure management. In terms of stroke symptoms and diagnosis, Dr. Santhosh said that weakness, vision loss, imbalance, and speech problems are typical warning signs.. Individuals above 45 years of age, especially those with diabetes or hypertension, are at greater risk. The discussion then moved to biomarkers in neurology, which are critical in diagnosing neurodegenerative disorders. In Parkinson's disease, the early symptoms are slowness of movement and loss of smell, with biomarkers such as alpha-synuclein and GFAP being researched for early detection. In Alzheimer's disease, it starts with forgetfulness and inability to do daily activities, with biomarkers being critical in diagnosis. AI can potentially scan biomarkers and identify diseases at an early stage, resulting in lower treatment costs and improved patient outcomes. Dr. Santhosh highlighted that AI is already being extensively applied in radiology, especially during the COVID-19 pandemic, when it assisted in handling high volumes of imaging data. AI can also help interpret brain imaging findings by offering normative data based on age and medical conditions, reducing errors and inconsistencies in diagnosis. Though promising, AI's application in neurology in India is largely confined to patient education, with more sophisticated AI diagnostic tools being researched in other nations. The conversation also touched on ethical and technical issues, such as patient privacy and data security. AI is based on large datasets, which heighten the risk of data breaches, so robust security measures and privacy legislation are crucial. The conference concluded that although AI has tremendous potential in neurology, ethical, technical, and clinical issues need to be resolved before it can be incorporated into practice. Continuous research and validation are required to ensure AI-based tools are accurate, reliable, and useful.

V. AI TECHNIQUES IN BRAIN DISORDER DETECTION

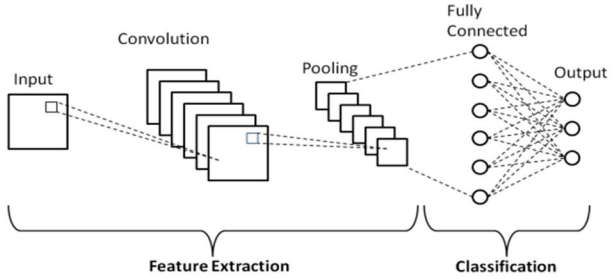
One of the main AI goals is the development of software for computers or computer-controlled machines able to perform tasks commonly associated with intelligent beings. Its use in healthcare commonly attempts to emulate and even overcome human cognition in the analysis of complicated medical data.As schematized in the figure above among the various AI branches, ML plays a prominent role in brain data analysis. ML is an adaptive process that enables computers to learn from experience, learn by example, and learn by analogy. The goal is to define generic algorithms able to automatically improve their performance over time on the basis of previous results and is achieved by training the algorithms via proper optimization approaches. One of the most valuable properties of such models is the capability of achieving accurate results on several tasks, such as classification or prediction, over unseen data, thus generalizing their learned expertise.

A. Convolutional Neural Networks (CNNs)

A Convolutional Neural Network (CNN) is a type of artificial neural network designed to process and analyze visual data by capturing spatial hierarchies in images.

1) How CNNs Work

- *Convolutional Layers:* These layers apply filters (kernels) to the input image, performing convolution operations to detect features such as edges, textures, or patterns. Each filter slides over the image, producing a feature map that highlights the presence of specific features.



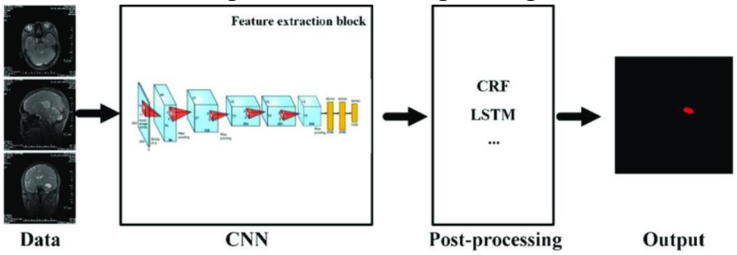
Ajlouni, Naim, et al. "Medical Image Diagnosis Based on Adaptive Hybrid Quantum CNN." *BMC Medical Imaging*, vol. 23, no. 126, 2023,

Fig[5.2]

- *Activation Function:* After convolution, an activation function like ReLU (Rectified Linear Unit) is applied to introduce non-linearity, enabling the network to learn complex patterns.
- *Pooling Layers:* Pooling (subsampling or downsampling) reduces the dimensionality of each feature map while retaining the most critical information. Common techniques include max pooling, which selects the maximum value in each region of the feature map.
- *Fully Connected Layers:* After several convolutional and pooling layers, the high-level reasoning is performed via fully connected layers. The output is flattened and fed into these layers to produce the final classification or prediction.

Advantages

High accuracy in image recognition tasks.
Handles high-dimensional data efficiently.
Automatically learns features from data, eliminating manual feature engineering.



Fig[5.3]

Wang, Jing, et al. "Electrochemical Biosensors for Detection of Amyloid Beta and Tau Proteins: A Review." *Biosensors*, vol. 11, no. 7, 2021

Applications

- Brain Disorder Detection: MRI or CT scan analysis for detecting tumors, Alzheimer's, or stroke. Object Detection: Identifying specific structures in medical images (e.g., lesions, abnormalities).

This code is a complete workflow for creating, training, and visualizing a Convolutional Neural Network
(CNN) model for brain disorder detection using connectivity matrices from EEG data:
In this part, we begin by importing necessary libraries for file operations, loading MATLAB files, numerical operations, and plotting.

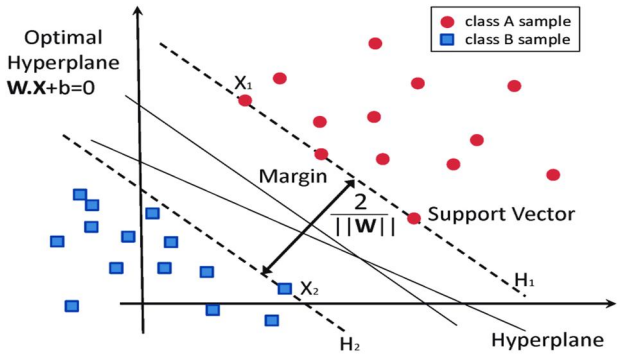
We then list the contents of the root directory (/) to understand what files and directories are present. The current working directory is retrieved using **os.**getcwd(). Next, we initialize two lists, raw_list_x and raw_list_y, to store the connectivity matrices and corresponding labels, respectively. We iterate through the files in the "data" directory, checking for .mat files. For each .mat file, we load the data using loadmat, extract the "connectivity" matrix, and visualize it using matplotlib. The matrix is normalized by dividing it by its maximum value and then added to raw_list_x. Labels are assigned based on the filename prefix (0 for "nkd" and 1 for others) and added to raw_list_y. Finally, the lists are converted to numpy arrays.
Muskan258. *Brain Tumor Detection from MRI Images Utilizing EfficientNetB2*. GitHub, 2023,
In this section, we use train_test_split to partition the data into training and testing sets. The training and testing features are reshaped to include a single channel, which is necessary for convolutional neural networks (CNNs). The data type is converted to float32 for compatibility with TensorFlow, and the labels are one-hot encoded using tf.keras.utils.to_categorical. We then build a CNN model using tf.keras.Sequential. The model includes several convolutional layers with LeakyReLU activation, max pooling layers to reduce dimensionality, and dropout layers to prevent overfitting. The final layers are fully connected, ending with a softmax layer for classification. The model is compiled with categorical cross-entropy loss and the Adam optimizer. Finally, the model is trained on the training data for 200 epochs, with validation on the testing data.
Muskan258. "Brain Tumor Detection from MRI Images Utilizing EfficientNetB2 - Code Efficient Net.ipynb." GitHub, 2023, line 7
In this final part, we visualize the accuracy and validation_accuracy over the epochs. We extract the accuracy and loss values from the model_train.history and plot them using matplotlib. Next, we load and preprocess test samples for "nkd" and "scz" classes, normalizing and reshaping them as required. We use the trained model to predict the classes of these test samples. To understand which parts of the input data contribute most to the model's predictions, we generate class activation maps (CAM). For each class, we calculate the gradients of the class output with respect to the last_conv_layer.output, pool these gradients, and multiply them with the conv_layer_output_value. Finally, we generate and visualize heat maps that highlight the important regions in the input data.or each class. These visualizations help in interpreting the model's decisions.Muskan258. *Brain Tumor Detection from MRI Images Utilizing EfficientNetB2 - Code Efficient Net.ipynb*. GitHub, 2023, lines 21 & 29

B. Support Vector Machine

A Support Vector Machine (SVM) is a supervised machine learning algorithm commonly used for classification, regression, and outlier detection tasks.

1) How SVMs Work

- *Hyperplane Selection:* SVMs aim to find the optimal hyperplane that separates data points of different classes with the maximum margin. This hyperplane acts as a decision boundary.
- *Support Vectors:* The data points that are closest to the hyperplane are termed support vectors. These points are critical as they influence the position and orientation of the hyperplane.



García-Gonzalo, Esperanza Classification of data by support vector machine (SVM)." *ResearchGate*, 2016, Figure 2,

- *Margin Maximization:* The margin is defined as the distance between the hyperplane and the nearest data points from either class. SVMs maximize this margin to improve the model's generalization capabilities.
- *Kernel Trick:* For datasets that are not linearly separable, SVMs employ kernel functions to transform the input space into a higher-dimensional space where a linear separation is possible. Common kernels include linear, polynomial, and radial basis function (RBF).

2) Advantages

- Effective with small and high-dimensional datasets.
- Works well for linear and non-linear data with kernel functions.
- Robust against overfitting when tuned properly.

This part of the code begins by importing the necessary libraries, including those for machine learning (svm, GridSearchCV, KFold, accuracy_score, cohen_kappa_score, data manipulation (pandas, numpy), and resampling (resample). The dataset is then loaded from a specified CSV file into a pandas.DataFrame. The data is split into two subsets based on the disorderHistory column: one subset where disorderHistory is 0 (data_0) and another where it is 1 (data_1). To balance the dataset, data_0 is resampled to have the same number of samples as data_1, ensuring no replacement and reproducibility with random_state=42. The balanced dataset is created by combining the resampled subset with data_1 and then shuffling it. Feature columns (brain regions) are extracted, and the features (x_data) and labels (y_label) are prepared for further analysis.

This part of the code is focused on the cross-validation and model training process. It sets up a loop to repeat the cross-validation process 101 times. Within each repetition, a 5-fold cross-validation setup (KFold) is used to split the data into training and testing sets. For each fold, an SVM model with a linear kernel is defined, and a grid search is performed to find the best hyperparameters (C and gamma). The grid search uses an inner cross-validation of 5 folds and scores the models based on accuracy.The best model from the grid search is then used to predict the test set labels, and the accuracy and cohen_kappa_score are calculated for each fold. These results are printed and stored in lists (acc_res and kappa_res). After completing all folds for a repetition, the mean accuracy and kappa scores are printed and stored in FinalRes.

In this final part of the code, the results from all repetitions are summarized. The length of FinalRes is printed, which should be equal to the number of repetitions (101), indicating the number of accuracy results collected. Finally, the median accuracy across all repetitions is calculated and printed. This gives an overall performance measure of the model after multiple repetitions.cross-validation repetitions, providing a robust estimate of the model's accuracy.

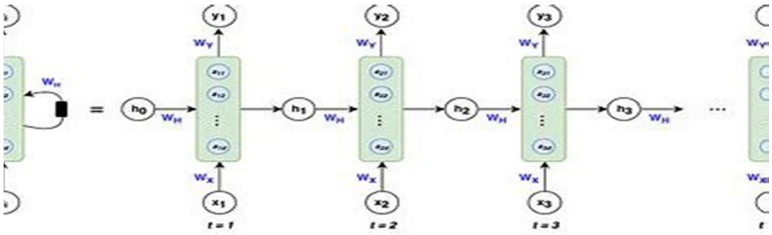
C. Recurrent Neural Networks (RNNs)

They are a class of artificial neural networks designed to process sequential data by maintaining a form of memory through their internal hidden states. This architecture allows RNNs to capture temporal dependencies, making them suitable for tasks like language modeling, speech recognition, and time series prediction.

1) How RNNs Work

- Sequential Processing: RNNs process input data one element at a time, maintaining a hidden state that captures information about previous inputs. This hidden state is updated at each time step, enabling the network to retain context across the sequence.

Fig [5.12]



"Sentiment Analysis - Company Reviews"@Kaggle, 2025,

- Recurrent Connections: Unlike feedforward neural networks, RNNs have recurrent connections that loop back from the hidden layer to itself. This feedback mechanism allows the network to incorporate information from prior inputs when processing the current input, effectively creating a short-term memory.
- Training Through Backpropagation Through Time (BPTT): RNNs are trained using a variant of backpropagation called Backpropagation Through Time. BPTT unfolds the network across time steps, treating each time step as a layer in a deep network. Gradients are calculated and propagated backward through these layers to update the network's weights.

2) Advantages

- Seizure Prediction: Detecting epileptic events from EEG data.
- Natural Language Processing: Sentiment analysis, language translation, or medical report summarization.
- Brain Activity Analysis: Decoding brain signals in Brain-Computer Interfaces (BCI).

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Volume 13 Issue II Feb 2025- Available at www.ijraset.com

This is a comprehensive implementation of a seizure prediction model using RNN with hyperparameter tuning and handling imbalanced data. :

The first part of the code includes the necessary imports and the initialization of the SeizurePredictionModel class. Various libraries are imported for data manipulation (numpy, pandas), building neural network models (tensorflow, keras), hyperparameter tuning (keras_tuner), visualization (matplotlib, seaborn), model evaluation (sklearn), and handling imbalanced datasets (imblearn). The SeizurePredictionModel class inherits from HyperModel to facilitate hyperparameter tuning. The constructor sets a random seed for reproducibility and initializes an early stopping mechanism to prevent overfitting during the training process. The _set_random_seed method ensures that the random seed is applied to both numpy and tensorflow, making the results consistent and reproducible.

The process_data method processes the EEG data by combining 23 chunks from each patient into a single chunk. It extracts file_names and patient_ids from the dataframe, ensuring there are 500 unique patients. It initializes arrays to store combined EEG_data and labels. The method iterates through the dataframe, mapping chunk data to the appropriate position in the combined data array. Labels are processed to determine if any chunk indicates a seizure and stored in the combined labels array. This method returns the combined EEG_data and labels, which are essential for training the neural network model.

The plot_eeg_sequence method provides a way to visualize the EEG_sequence by plotting the data in a graphical format. It takes the EEG_sequence as input, extracts relevant data points, and uses matplotlib to generate a plot that shows the sequence of EEG readings over time.

This method helps to understand the structure of the EEG data visually, which can be useful for analyzing patterns or identifying abnormalities, such as seizure activities.

The plot_accuracy method visualizes the training_history and validation_accuracy over the epochs. It first extracts the training_history and adds an 'epoch' column representing the epoch numbers. The data is converted into a pandas DataFrame for easy manipulation. It identifies the epoch with the highest validation_accuracy. The method then creates a plot using seaborn to display the validation_accuracy and training_accuracy over epochs. **R265, Abhishek.** *EEG Data Processing and Visualization.*

It includes a horizontal red line at 0.5 to indicate chance level and a vertical green line at the best epoch. This plot provides insights into the model's performance during training and helps identify the point of best performance

The prepare_eeg method reads the EEG_data from a CSV file and processes it using the process_data method. The build_model method constructs a sequential neural network model hyperparameters and the specified model type . This method also includes optional dropout layers for regularization. The train_model method trains the constructed model using the training data, saves the best model based on validation accuracy, and plots the training history to visualize the model's performance over time. This part ensures that the models are built and trained efficiently with the right configurations. *R265, Abhishek. "CNN Based Schizophrenia Detection."* GitHub, *2024*,

This section focuses on the evaluation of models and hyperparameter tuning. The evaluate_model method evaluates a trained model on the test data by predicting probabilities, converting them to binary predictions, and calculating the accuracy using accuracy_score. The get_best_model method performs hyperparameter tuning using RandomSearch to find the optimal configuration for the specified model type (RNN, LSTM, or GRU). It sets up a tuner with the build_model method and searches for the best hyperparameters based on validation accuracy. After tuning, it retrieves and builds the best model. The handle_imbalanced_data method addresses class imbalances in the dataset using SMOTE, which oversamples the minority class to create a balanced dataset for training.

This section encompasses the entire workflow execution and t he main block that initiates the process. The run method orchestrates the workflow by preparing the EEG data, handling imbalanced data, splitting the data into training and test sets, performing hyperparameter tuning, training the models, and evaluating them. It first prepares the EEG data using the prepare_eeg method and reshapes it for model training.

It then handles class imbalances using the handle_imbalanced_data method. The data is split into training and test sets, and hyperparameter tuning is performed to find the best RNN, LSTM, and GRU models. These models are trained using the train_model method, and their summaries are printed. Finally, the models are evaluated on the test set, and their accuracies are returned. The main block creates an instance of the SeizurePredictionModel class, runs the workflow with the specified EEG dataset, and prints the accuracies of the best models, providing a comprehensive solution for EEG-based seizure prediction

R265, "Neural Network Model Training and Performance Evaluation

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Volume 13 Issue II Feb 2025- Available at www.ijraset.com

VI. MODEL EVALUATION AND PERFORMANCE METRICS

A. *Accuracy, Sensitivity, Specificity*

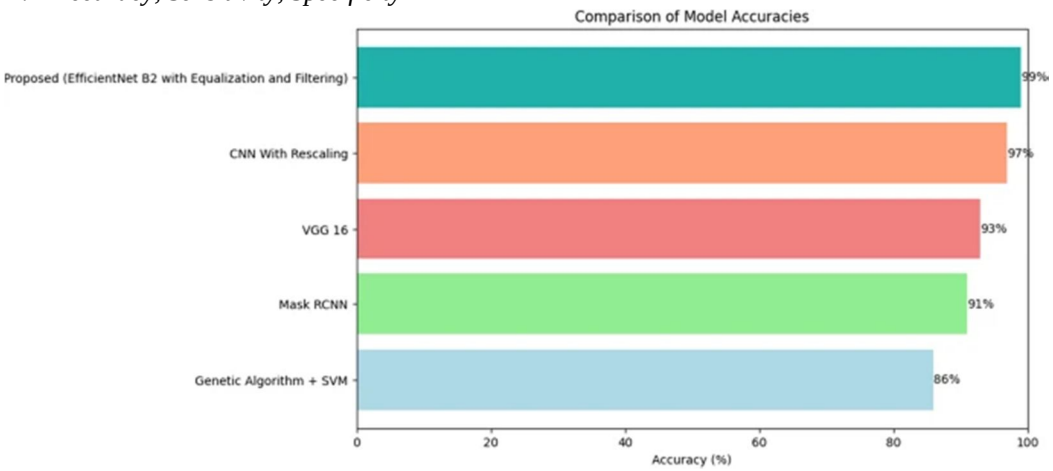
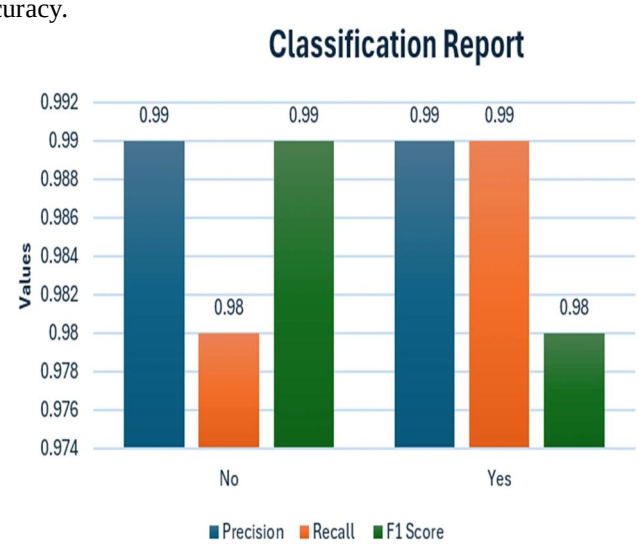


Figure 13: [].” *BMC Medical Informatics and Decision Making*, vol. 24, 2024, https://doi.org/10.1186/s12911-024-02519-x. Accessed [date you accessed the image].

This bar graph compares model precision in a classification task. The Proposed Model (EfficientNet B2 with equalization & filtering) achieves the highest precision (99%) due to its advanced architecture and preprocessing. CNN with Rescaling follows at 97%, while VGG 16 and Mask RCNN score 93% and 91%, respectively, showing reliable but less competitive performance. SVM with Genetic Algorithm performs worst at 86%, making it less suitable for this task. Overall, deep learning models, especially the proposed approach, dominate in accuracy.



Sirocchi, Christel, et al. “Medical-Informed Machine Learning: Integrating Prior Knowledge into Medical Decision Systems.” *BMC Medical Informatics and Decision Making*, vol. 24, suppl. 4, 27 June 2024

B. *Key Metrics*

Precision: Proportion of true positives among predicted positives.

- No: 0.99 | Yes: 0.99 → High accuracy in identifying both classes.

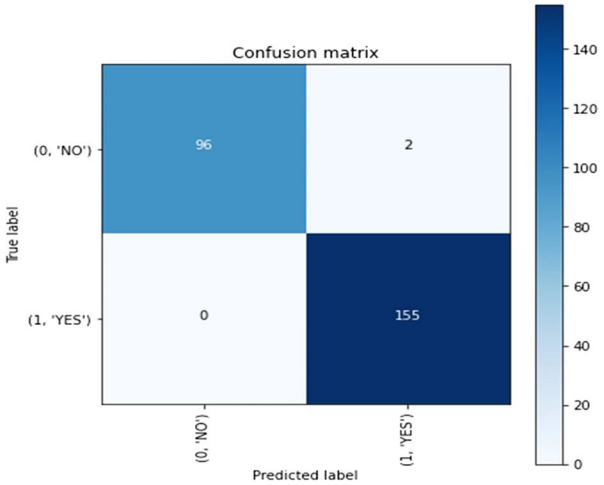
Recall: Proportion of true positives among actual positives.

- No: 0.98 | Yes: 0.99 → Slightly better recall for Yes, capturing most instances.

F1 Score: Harmonic mean of precision & recall.

- No: 0.99 | Yes: 0.98 → Balanced performance for both classes.

C. Interpretation



BMC Medical Informatics and Decision Making." *Figure 16: [confustion matrix]*. Springer Nature, 2024. Web. 26 Feb. 2025.

The confusion matrix used in the example is an appropriate tool to validate the performance of any classification machine learning model. One can analyze each prediction the model made compared against the true labeling in the actual dataset.
On this matrix;True positives= 155-are cases where the prediction of "YES" or being positive was achieved by the model when the prediction was "YES."True negatives (96) are cases where the model correctly predicted "NO" (absence of a tumor) when it was indeed "NO."The false positives (2) are cases where the model incorrectly predicted "YES" when the actual label was "NO" - a healthy case misclassified as a tumor.The false negatives (0) are cases where the model incorrectly predicted "NO" when the actual label was "YES" (a tumor case misclassified as healthy).

Accuracy: The overall correctness of the model. In this case, it is calculated as :

$$Accuracy = \frac{True\ Positives + True\ negatives}{Total\ Cases} = \frac{155 + 95}{155 + 96 + 2 + 0} = 98.8\,\%$$

Sensitivity: The ability of the model to correctly identify positive cases, calculated as:

$$Sensitivity = \frac{True\ Positives}{True\ Positives + False\ Negatives} = \frac{155}{155 + 0} = 100\%$$

Specificity: The ability of the model to correctly identify :

$$Specificity = \frac{True\ Negatives}{True\ Negatives + False\ Positives} = \frac{96}{96+2} = 98\%$$

D. Model Interpretability Tools (LIME, SHAPE)

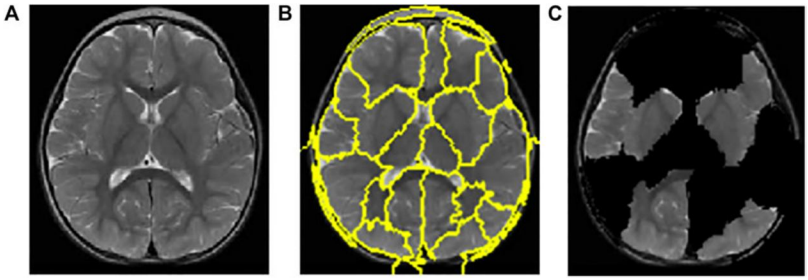


Figure 7. "Explanation-Driven Deep Learning Model for Prediction of Brain Tumour Status Using MRI Image Data." *Frontiers in Genetics*, vol. 13, 2022, doi:10.3389/fgene.2022.822666. Accessed 26 Feb. 2025.

Interpretations generated by LIME for a normal image. (A) Sample of the normal image from the test image. (B) Superpixels generated from a sample of the normal image from test image quick-shift segmentation to create perturbations. (C) Final perturbed image for the normal image.

VII. APPLICATIONS OF AI IN BRAIN IMAGING AND NEURAL DATA ANALYSIS

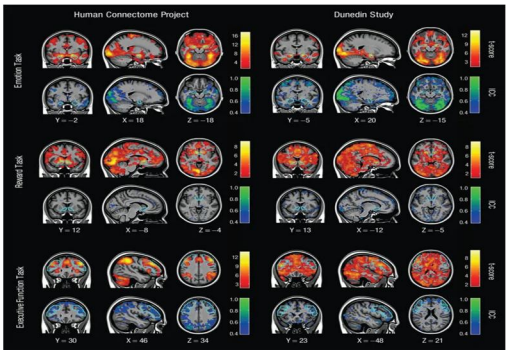
A. Structural Abnormality Detection: MRI and PET Scans

Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET) are vital imaging techniques in neurology. AI algorithms, particularly deep learning models, analyze these scans to detect structural abnormalities linked to brain disorders such as Alzheimer's disease, Parkinson's disease, and brain tumors.

B. Neural Activity Mapping: EEG and fMRI Data:

Electroencephalography (EEG) and functional MRI (fMRI) are critical for studying brain activity. AI enhances the analysis of these datasets by mapping neural activity patterns associated with various brain disorders.

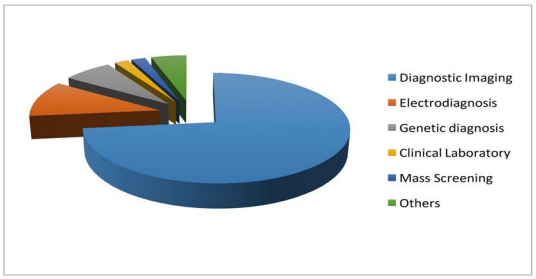
- *EEG Analysis:* AI algorithms classify EEG signals to detect anomalies such as epileptic seizures or abnormal brain wave patterns linked to depression and schizophrenia.
- *fMRI Analysis:* Using AI, researchers can identify regions of the brain with disrupted functional connectivity, a hallmark of disorders like autism spectrum disorder (ASD) and major depressive disorder (MDD).
- *Temporal Pattern Recognition:* AI models analyze temporal patterns in neural signals, enabling real-time monitoring of brain activity.



Wiley Analytical Science. (n.d.). *Functional flaws: fMRI limitations.* Wiley. Retrieved February 26, 2025,

VIII. CHALLENGES IN IMPLEMENTING AI IN CLINICAL PRACTICE

The integration of Artificial Intelligence in clinical practice would open vast avenues in the improvement of patient outcomes and the optimization of workflows, advancement of precision medicine, and how health care professionals diagnose diseases and manage patient care. AI will change the traditional methods of treating patients, by making diagnoses based on patterns derived from large datasets through machine learning processes, thus making them arrive at diagnosis much earlier or with more accurate interventions. Additionally, AI-driven automation can help reduce administrative burdens, allowing clinicians to focus more on patient care. Despite such promising prospects, the implementation of AI in clinical practice is a complex task and poses significant hurdles. Healthcare systems operate in highly regulated environments, and the introduction of new technologies must align with strict legal and ethical standards. Moreover, the success of AI heavily depends on access to high-quality data, robust infrastructure, and the acceptance of clinicians and patients. Without addressing these challenges, the potential of AI in healthcare may remain unrealized. It is, therefore, essential to understand and navigate these obstacles to ensure AI tools are adopted in a manner that is effective and equitable. This section addresses the key challenges and proposes strategies to overcome them and pave the way for AI's transformative impact on healthcare.



Jiang, Fei, et al. "Artificial Intelligence in Healthcare: Past, Present and Future." *Stroke and Vascular Neurology*, vol. 2, no. 4, 2017, pp. 230–243, https://doi.org/10.1136/svn-2017-000101.

1) Data Quality and Availability

AI systems require massive amounts of high-quality data to function proficiently. However, clinical data can often be incomplete or inconsistent in many cases or even biased. A study published in BMC Health Services Research highlighted challenges identified by Swedish healthcare leaders regarding the introduction of AI. It emphasized issues related to data quality and availability.

2) Ethical and Legal Concerns

The integration of AI into healthcare raises ethical questions, particularly concerning patient privacy and data security. Ensuring compliance with regulations like HIPAA and GDPR adds complexity to AI implementation. The British Medical Bulletin discusses these ethical challenges, highlighting the need for robust frameworks to address them.

3) Economic and Policy Constraints

The development and deployment of AI systems are highly expensive, and it may not be possible for smaller healthcare providers. Current reimbursement policies also do not adequately cover AI-driven diagnostics and treatments. These economic challenges have been discussed by the Agency for Healthcare Research and Quality, where it is concluded that policy reforms are necessary to support AI adoption.

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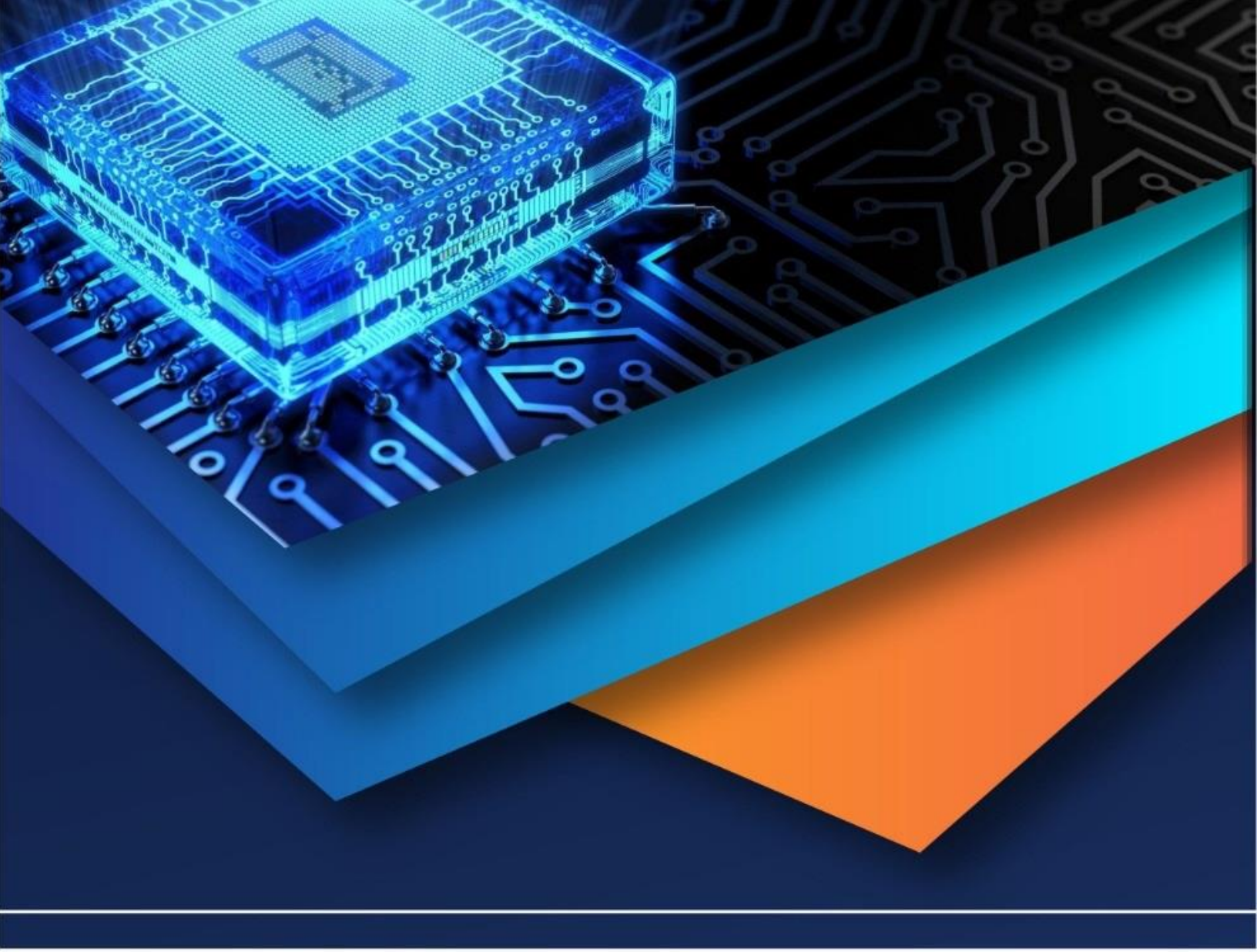

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