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Extracting the Features of Diseases Using Fast Fourier Transform and Convolutional Neural Network

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Abstract-Alzheimer's disease causes long-term harm to brain cells, particularly in the hippocampus. In persons aged 65 and up, this disease is the leading cause of dementia. This neurological disorder worsens with time and cannot be cured. Alzheimer's disease can cause irreversible brain damage, therefore catching it early is crucial. In order to stop the progression of the disease before it becomes irreversible, prompt and precise therapy is required. In this paper, we offer a Deep Learning-based method for enhancing the precision of classification by the use of the Convolutional Neural Network (CNN). In this study, we examine the EEG data, extract characteristics using Fast Fourier Transform (FFT), and then use convolutional neural networks (CNNs) to categorize the condition.
Keywords: Alzheimer's disease, Brain, Deep Learning, Prediction,

I.Introduction

Alzheimer's disease is a neurodegenerative disorder characterized by progressive cognitive decline, memory loss, and impaired daily functioning. It is the most common cause of dementia, affecting millions of individuals worldwide. As the global population continues to age, the prevalence of Alzheimer's disease is expected to rise, placing an increasing burden on healthcare systems and society as a whole. Early detection and prediction of Alzheimer's disease are crucial for enabling timely intervention, treatment, and support for affected individuals and their families.

There are three distinct times in the development of AD. The first stage of Alzheimer's disease, in which damage to brain nerve cells begins, is difficult to distinguish from normal since the affected individual shows no outward symptoms. The next level of cognitive decline is known as mild cognitive impairment (MCI), and it manifests itself in the form of difficulties with thinking. At this point in time, individuals do not need constant assistance from others to carry out their everyday lives. The Alzheimer's stage is the highest one. People in this stage undergo more radical mental and behavioral shifts, and increasingly exert control over their routine physical activities.

No drug now available can cure AD, however several can slow its progression. Scientists in Bengaluru have just uncovered the tiny particle TGR63, which can evade the instrument that leads to dysfunctional neurons in Alzheimer's disease. Alzheimer's patients produce cerebrospinal fluid in their brain tissues, cerebral cortex, and brain chambers. These effects are used to monitor the development of AD.

In recent years, there has been a growing interest in the application of deep learning techniques, particularly Convolutional Neural Networks (CNNs), in various domains, including medical research. CNNs have shown remarkable success in image classification, object detection, and pattern recognition tasks. Their ability to automatically learn hierarchical features from raw data makes them well-suited for analyzing complex medical imaging data, such as magnetic resonance imaging (MRI) scans and positron emission tomography (PET) images.

The use of CNNs for Alzheimer's disease prediction holds great promise in improving diagnostic accuracy and providing valuable insights into the underlying mechanisms of the disease. Traditional methods of diagnosing Alzheimer's disease rely heavily on clinical evaluation, cognitive tests, and neuroimaging scans, which can be subjective and prone to variability. CNNs offer the potential to enhance the accuracy and efficiency of Alzheimer's disease prediction by automatically extracting relevant features from medical images and making predictions based on learned patterns.

One of the key advantages of CNNs is their ability to learn spatial hierarchies of features. This is particularly valuable in the context of Alzheimer's disease prediction, as neuroimaging data provides rich spatial information about the brain. CNNs are capable of capturing both local and global patterns in brain images, allowing for a more comprehensive analysis of disease-related abnormalities. By leveraging these learned features, CNNs can identify subtle structural changes in the brain that may serve as early indicators of Alzheimer's disease, even before clinical symptoms manifest.

The process of using CNNs for Alzheimer's disease prediction typically involves several stages. Firstly, a large and diverse dataset of neuroimaging scans is collected, consisting of both healthy individuals and those diagnosed with Alzheimer's disease. These scans are preprocessed to ensure data quality, including steps such as normalization, registration, and artifact removal. The preprocessed images are then used to train the CNN model, where the network learns to extract discriminative features that differentiate between healthy and Alzheimer's disease-affected brains. The trained model is then evaluated on a separate test dataset to assess its performance in predicting Alzheimer's disease.

In addition to their diagnostic capabilities, CNNs can also contribute to the development of personalized treatment strategies for Alzheimer's disease. By analyzing individual brain images, CNN models can predict disease progression and identify patients who are more likely to benefit from specific interventions or therapies. This personalized approach has the potential to improve treatment outcomes and optimize resource allocation in healthcare settings.

II.Review Of Literature

Sinharoy, Rajarshi & Sen, Anupam (2023) The rise and significant socioeconomic implications of Alzheimer's disease (AD) have made it a key study focus in recent years. Therefore, diagnosing AD is crucial for providing appropriate treatment. Monitoring the transition from the inevitable cognitive decline that comes with age to the more catastrophic decline that comes with dementia is widespread practice since early identification of Alzheimer's disease (AD) is crucial for effective treatment. Since quick progress in the field of GANs techniques has now been applied in the clinical research sector, the deep learning method for early detection and automated categorization of AD has suddenly attracted a lot of attention. The use of convolutional neural networks (CNN) and magnetic resonance imaging (MRI) of the brain to diagnose Alzheimer's disease has shown great promise in recent years. Many research publications have concentrated on prediction rather than addressing the shortage of real data. This paper's primary contribution is a set of DCGANs designed to accomplish this goal by synthesizing MRI scans. This study provides proof of concept by cascading DCGANs that simulate Alzheimer's disease's progression and using SRGANs to improve MRI scan resolution. The goal of this study is to provide an early indicator of whether or not a person may develop Alzheimer's disease. This study presents a Deep Learning-based technique using CNNs, DCGANs, and SRGANs to enhance classification and prediction accuracy to 99.7% while also handling the lack of data and the resolution of the data.

Senthil Kumar, A.M., et al., (2023) Alzheimer's disease (AD) is the most common form of Dementia in older adults and a neurological disorder. Hippocampal degeneration is the part of the brain affected by this disorder. Early diagnosis of Alzheimer's disease is crucial for reducing the severity of the disease and preventing permanent brain damage to the patient. For people aged 65 and over, it becomes dangerous, and even fatal, to do so. CNN computations were performed to get the desired result. When compared to standard approaches, the proposed method's 20 percent increase in characterization accuracy demonstrates that the neural organism is a significant benefit when analyzing neurological diseases. Our research paves the basis for future comparative studies of neurological disorders within intelligent medical care systems. The primary goal of this research is to predict Alzheimer's disease and build a useful model through the use of Hybrid AI calculations that coordinate SVM with CNN and component extraction and determination. MRI scans are used to collect the data. The suggested method uses a convolutional neural network (CNN) computation to distinguish between stages of Alzheimer's infection, such as moderate-unbalanced and no ill.

Zia, Muhammad et al., (2022) Alzheimer's disease (AD) is a common form of dementia characterized by memory loss and cell death in the brain. When people's brainpower drops low enough, they can no longer function on their own. There is presently no treatment for AD. Extracting diagnostic information from MRI images for AD is quite challenging. There is no room for error in the diagnosis and evaluation of AD, no matter how skilled the medical assistant. In order to train the model and detect illness, the Algorithm necessitates a sizable dataset. However, AD loses some of its predictive power when faced with ambiguity in the dataset, such as intra-class similarity in photos. This research offered a strategy for addressing the aforementioned problem. The proposed method utilizes a Convolutional Neural Network (CNN). Using MRI data obtained from Kaggle, the recommended set of rules in CNN is put into action. In addition, the information was split into four categories. MATLAB was used to plan the experiment. Features retrieved from the MRI dataset with pre-trained convolutional neural network (CNN) models AlexNet and MobileNetV2. AlexNet and MobileNetV2 are combined as CNN pre-training models. F2-CNN For feature fusion, a hybrid approach is presented. To extract the best features for each pretrained model, a feature selection approach is done to an honed dataset. Finally, the best characteristics for predicting AD are classified. The evaluation was made in terms of precision. The findings of this study might have positive implications for healthcare.

Afiya Begum & Prabha Selvaraj (2022) The field of healthcare is now well-known for the success of deep learning techniques, which are particularly well-suited to the field of medical imaging. Alzheimer's disease (AD) is a persistent condition of the neurological system that causes cognitive decline and memory loss in elderly people. Medical help and possible therapy for Alzheimer's disease depend on early and precise identification of the disease. In contrast to typical machine learning algorithms, deep learning algorithms are capable of adequately analyzing the massive dataset and extracting higher-level characteristics from it. This paper introduces a deep convolutional neural network (DCNN) technique that may be used to identify AD and its progression across different settings. For this purpose, we employ a deep convolutional neural network (DCNN) and a three-dimensional densely connected convolutional neural network (3D-DCNN). When it comes time to categorize diseases, the DCNN and 3D-DCNN characteristics are combined. The ADNI dataset is used for experimental investigation of Alzheimer's disease. The suggested AD-3DCNN model has the greatest accuracy for predicting AD stages when compared to other pre-trained models such as Xception, inception V3, mobile Net, and dense Net. Precision, recall, and F1 score correctness are some other performance criteria used to assess a system's efficacy.

Kaur, Swapandeep et al., (2021) Alzheimer's disease (AD) is a neurodegenerative disorder characterized by the slow death of brain cells. Dementia leading to dependence on others is the primary factor in the development of AD. A common symptom of early-stage AD is a loss of recall for recent discussions or events. Later on, memory loss may become so severe that the individual is unable to carry out even the most basic of duties. In the early stages of the condition, the drugs now available may temporarily ameliorate symptoms. Since there is currently no cure for Alzheimer's disease, early diagnosis is crucial. The automated detection of Alzheimer's disease is crucial since clinical therapies are so costly. Very mildly demented, mildly demented, averagely demented, and non-demented photos of AD were utilized to train a deep learning model based on a convolutional neural network. The accuracy of 98.9%, the classification error rate of 0.01%, and the specificity of 0.992 were all determined to belong to the moderately demented class. The false-positive rate was also reduced to 0.007 percent.

Yousry Abdulazeem, et al., (2021) Health care innovations in the present decade have captured the public's attention because of their potential to help people live healthier, longer lives. Alzheimer's disease (AD) is the most prevalent form of dementia and neurodegeneration. Caregiving expenses for those with Alzheimer's disease are expected to soar. A computer-aided approach for prompt and precise AD categorization is thus essential. In comparison to traditional machine learning approaches, the benefits of deep-learning algorithms are substantial. Promising findings have been found in several recent studies using brain MRI images and convolutional neural networks (CNN) for the diagnosis of Alzheimer's disease. Therefore, our research suggests an end-to-end paradigm for AD-classification based on convolutional neural networks. On the Alzheimer's disease Neuroimaging Initiative (ADNI) dataset, the suggested framework obtained 99.6%, 99.8%, and 97.8% classification accuracies for the binary classification of AD and Cognitively Normal (CN). Experiments using several classes of data showed that the suggested framework could correctly categorize 97.5% of the ADNI dataset.

Basheera, Shaik & Ram, M. (2020) A large gap now exists between the ability to foretell Alzheimer's Disease (AD) from MCI and CN. Recently developed neuroimaging, when combined with machine learning algorithms, may aid in the early detection of Alzheimer's disease by recognizing patterns in medical imaging. The shrinkage of the brain in both healthy adults and those with early-onset Alzheimer's disease seems to be same. As part of this effort, we put out a model that better distinguishes between MCI and CN in order to boost the early identification of AD. The methods of binary and multiclass classification, 4463 By splitting the slides in half, one set is used for training, while the other is used for testing, AD-CN is able to attain perfect accuracy, sensitivity, and specificity at the subject level. The diagnostic performance for AD-MCI is 96.2% accurate, with 93% sensitivity and 100% specificity. In the instance of CN-MCI, these figures are as follows: 98.0% accuracy, 96% sensitivity, and 100% specificity. The AD-MCI-CN has a reliability of 86.7%, a sensitivity of 89.6%, and a specificity of 86.61 %. Using 10x cross validation, the model was able to successfully distinguish between CN and MCI with a 98.0% success rate. Compared to past work processes, the findings provided by our proposed framework for predicting AD from MCI and CN are substantially more accurate, allowing for earlier diagnosis of AD.

Eman Marzban, et al., (2020) Some neurodegenerative disorders, such as Alzheimer's disease (AD), are seeing an uptick in the use of machine learning algorithms for classification and/or prediction of onset, which may be attributable to the availability of data and advancements in computing capacity. This study's goal was to develop a shallowly-architected and processed network that could accurately classify people with Alzheimer's disease (AD) and mild cognitive impairment (MCI) compared to healthy controls (HC). The ADNI dataset was used in this investigation. Gray-matter (GM) volumes and diffusion maps were used as inputs to a convolutional neural network (CNN) used for categorization. Overall, 185 scans were used to determine HC, 106 to determine MCI, and 115 to determine AD. The stacking mean diffusivity (MD) and GM volume were used in a ten-fold cross-validation procedure, yielding an AUC of 0.94 and 0.84, respectively, along with 93.5 and 79.6 percent accuracy, 92.5 and 62.7 percent sensitivity, and 93.9 and 89% specificity for the AD/HC and MCI/HC classifications. Incorporating data from structural MRI and Diffusion Tensor Imaging (DTI) for the purpose of classification is explored here, with the inclusion of both modalities shedding light on the effect of using deep learning. We believe this is the first research to evaluate the effect of several scans per individual and to provide the ideal strategy for confirming the system's resilience. The findings hold their own in the current literature, which bodes well for the development of more effective treatments and preventative measures against AD.

Basheera, Shaik & Ram, M. (2019) Diagnosing Alzheimer's disease (AD) early and correctly has become more important in recent years. The use of MCI and CN for predicting AD has recently gained popularity. In the early stages of AD, doctors employ neuroimaging and computer-aided diagnostic methods to categorize the disease. The majority of existing machine learning methods rely on a set of manually selected characteristics. Many medical imaging applications have recently used deep learning. In order to classify AD, current deep learning algorithms use raw MRI images and cortical surface as input to the convolution neural network (CNN). Alzheimer's disease reduces brain volume and alters the structure of gray matter. We employed 1820 T2-weighted brain MRI volumes, divided into 18,017 voxels, comprising 635 AD MRIs, 548 MCI MRIs, and 637 CN MRIs. We suggested a method to classify brain voxels based on their gray matter content using a convolutional neural network. The voxels are improved using a Gaussian filter, and then the skull stripping technique is employed to get rid of the extraneous tissue. Then, hybrid improved independent component analysis is used to divide those voxels into groups. The CNN takes gray matter segmentation as its input. Using our suggested method, we conducted a clinical valuation, and we were able to acquire an accuracy of 90.47%, a recall of 86.66%, and a precision of 92.59%.

Ziqiang Guan, et al., (2019) For the purpose of classifying Alzheimer's disease using brain MRI images, a variety of deep learning models have been built. Several of these models boast impressive performance, with some reaching 95% accuracy in three-class categorization. However, it is also uncommon for these research to make comparisons in performance across models that were trained on various subsets of a dataset or that used different image preprocessing approaches, making it impossible to objectively evaluate model performance. In addition, many of these studies do not include specifics necessary to reproduce their experiments, such as hyperparameters, the precise MRI scans utilized, or their source code. To address these issues, we provide a detailed analysis of several deep learning approaches and architectures applied to the whole ADNI picture collection. When comparing the performance of the most popular convolutional neural network models, we find that (1) classification using 3D models provides a 1% improvement in our setup, at the cost of significantly longer training time and more computation power, (2) pre-training yields minimal (\$0.5%\$) improvement in model performance with our dataset, and (3) most popular convolutional neural network models yield similar performance when compared to each other. Finally, we do a quick comparison between two picture preprocessing tools, FreeSurfer and Clinica, and find that Clinica's spatially normalized and segmented outputs improved model prediction accuracy from 63% to 89%.

III.Methodology

The suggested study use EEG data to categorize the affliction's progression. In this study, we present a novel deep convolutional neural network architecture for improving classification performance on multi-channel human EEG signal data. The following sections make up this work:

- Pre-Processing
- Feature Extraction
- Classification

The architecture of the proposed work learns to identify diseases based on signals provided as input.

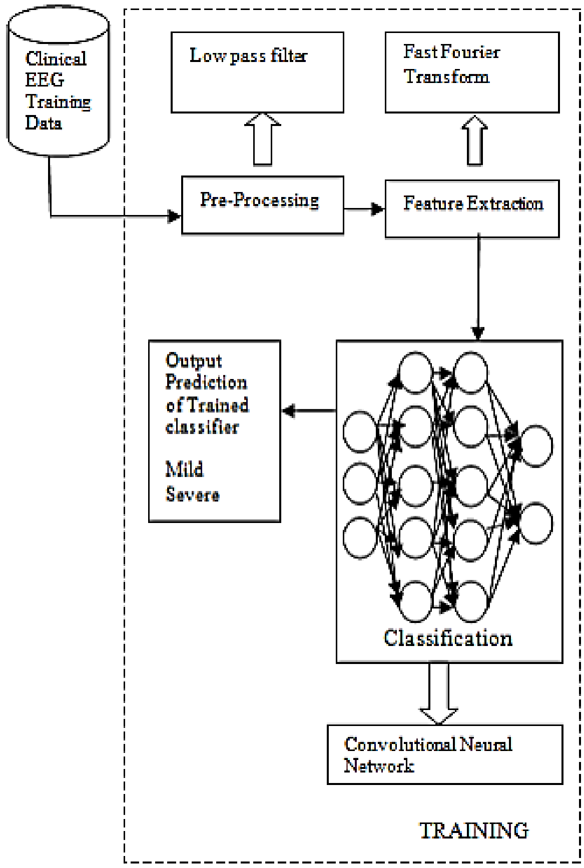


Figure 1 Training phase Model of Prediction System

Training of the prediction system is depicted in Figure 1 design. As an input, we provide the clinical dataset; after applying a Low Pass Filter and Fast Fourier Transform to it, we extract features to feed into a Convolutional Neural

Network. Based on the input attributes, it makes predictions about the output. Variable inputs are used to train the model.

Figure 2 is an architectural representation of the system testing procedure. Input samples and testing data are pre-processed using the Low Pass Filter, and features are retrieved using the Fast Fourier Transform, before being used to train the classifier. The collected characteristics are then used to make a prediction about the output (mild/severe illness stages).

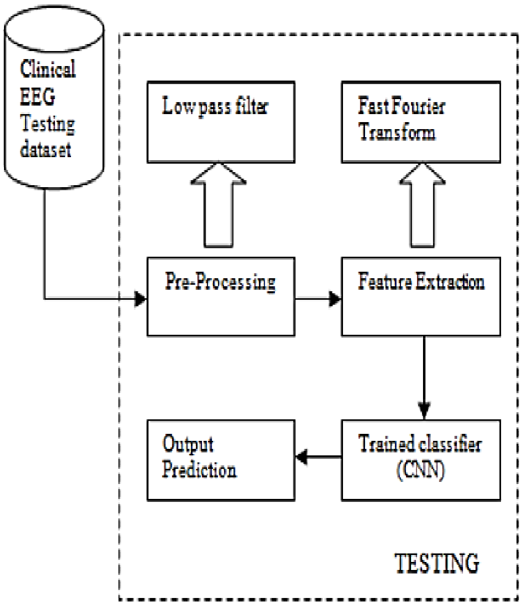


Figure 2 Testing phase Model of Prediction System

IV. Experimental Results

Matlab is used to assess the effectiveness of the proposed technique by feeding it an EEG signal in EDF format. Figure 3 depicts the original signal after being predicted and pre-processed. Time is compared to signal strength in this graph.

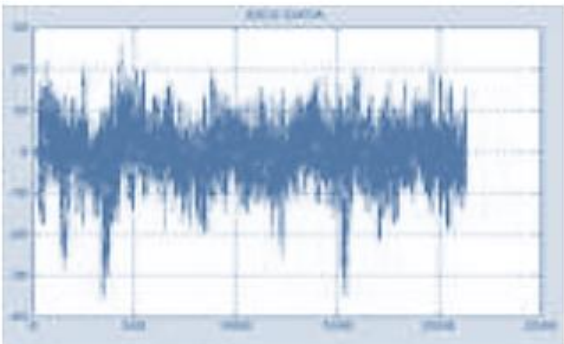


Figure 3 EEG signal for the input data

After the signal has been preprocessed, it is put into a Fast Fourier Transform, from which a number of useful properties are extracted, including the power spectrum's amplitude, the frequency vector and the order of the signal, the signal coefficients, and the average of the relevant band's power signal. Figure 4 illustrates how to acquire the power signal. A plot of frequency vs. amplitude is used to display this.

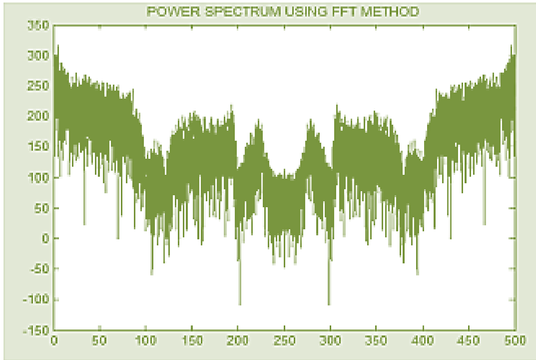
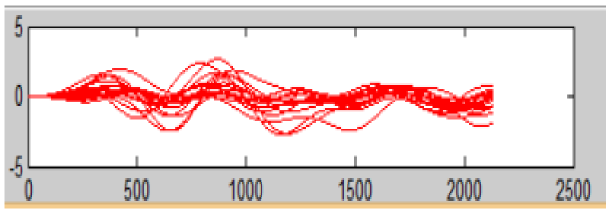
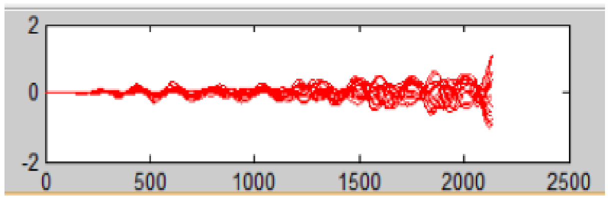


Figure 4 Power spectrums for the given input data

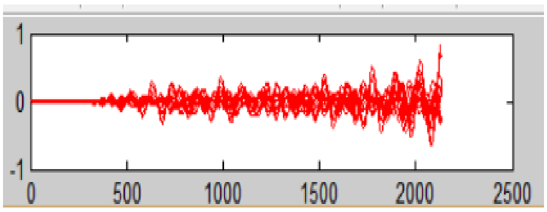
The relative band power signal at various frequencies is shown in Figure 5.The amplitude is displayed along the y-axis, while the number of samples is shown along the x-axis. As can be seen in Figure 5a and 5b, the signals increase in the lower frequency bands (delta and theta), while they decrease in the higher frequency bands (alpha and beta) in Figure 5c and 5d.



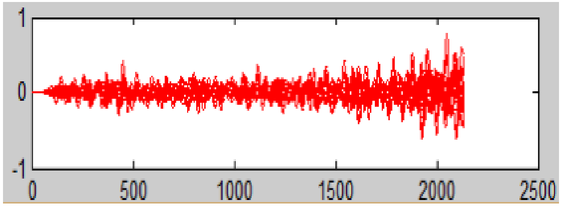
(a)



(b)



(c)



(d)

Figure 5 Different frequency relative band power

The Convolutional Neural Network is fed these signals together with the average relative band power to categorize illness stages.

V. Conclusion

CNNs have the potential to contribute to the development of personalized treatment strategies. By analyzing individual brain images, CNN models can predict disease progression and identify patients who are more likely to benefit from specific interventions or therapies. This personalized approach can optimize treatment outcomes and resource allocation, leading to improved patient care and quality of life. The use of CNNs for Alzheimer's disease prediction represents a promising approach in the field of medical research. By harnessing their capabilities to analyze complex patterns in neuroimaging data, CNNs can contribute to early detection, personalized treatment strategies, and a deeper understanding of the disease. Future research should continue to address the challenges and limitations associated with CNNs, further improving their effectiveness and applicability in the fight against Alzheimer's disease. Ultimately, the integration of CNN-based prediction models into clinical practice has the potential to revolutionize Alzheimer's disease diagnosis, treatment, and patient outcomes.

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