2024 Third International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE)

Early detection of Alzheimer's Disease and Dementia Using Deep Convolutional Neural Networks

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Abstract*—Alzheimer's disease (AD) is a progressive disease of the nervous system of the brain that weakens the brain functions which leads the patient to bedridden. Overall dementia cases are approximately 75% of elderly people above 65 years of age worldwide. Early detection AD cases constitute nearly 2-5%. Detecting Alzheimer's disease earlier is a difficult and challenging task, which requires human experts and MRI reports. An alternative approach for early detection such as a convolution neural network has been proposed in this paper with more reliable and cost-efficient. From the 3D MRI image report, Alzheimer's Disease and Dementia are detected and also the AD stages are diagnosed using CNN. The CNNs datasheet on sMRI of the brain is loaded in the online database. The image Classification task is analysed and evaluated using the ADNet. This analysis utilizes Magnetic Resonance (MR) brain images and Convolutional Neural Network (CNN) architecture with a deep learning pipeline. The challenging task is to classify Magnetic Resonance (MR) brain images based on the AD stage into Mild dementia (MD), Very Mild Dementia (VMD), Non-dementia (ND), and Moderate Dementia (MoD). The results are outperformed with a high accuracy of 99.94%.

***Keywords*—Convolutional Neural Networks, Magnetic Resonance, Deep Learning, 3D Brain MRI, Alzheimer's Disease, Dementia**

I. INTRODUCTION

Alzheimer's disease is the most common cause of dementia. AD is the nervous disease of the brain and the people affected with AD can show the symptoms like memory loss, difficulty in understanding, what people are saying and struggle in accomplishment routine tasks and personality and mood changes. The cost associated by generating health and social care for dementia equals world's 18th largest economy[1]. This assessment allows to understand disease's massive impact on the economy. Statistics indicate that Alzheimer's will affect around 1 in 10 people over the age of 65. Unfortunately, no effective cures exist for this disease, and no one is immune. Most people find it hard to accept getting old and weak. Matured persons over age of 50+ struggle with this concern, which has doubled due to fear of losing their memory. Alzheimer's Disease victims, their careers, and their family endure a horrible experience. Memories of loving moments, recognition of family members, and childhood experiences are lost for someone with Alzheimer's Disease. They can no longer follow simple instructions.

Most Alzheimer's Disease research initiatives currently focus on developing new drugs or investigating the disease through the study of its biological markers. Due to expansion of computer science, numerous approaches utilizing capabilities of data science and machine learning have emerged to investigate Alzheimer's Disease. Regrettably, researchers were compelled to focus on biological markers of Alzheimer's Disease and largely overlook its behavioral due to data limitations and challenges.

"The aim of the research is to conduct a comprehensive study of Alzheimer's Disease risk factors by utilizing both behavioral and biological markers. This approach is undertaken in the hope of enabling the early prediction. Comprising the bulk of work related to the endeavor, short-term studies on Alzheimer's Disease have been conducted. These studies have predominantly focused on diagnosing the disease from a biological standpoint[2]. The diagnostic methods employed in these studies have relied heavily on the use of positron emission tomography (PET) and single-photon emission computed tomography (SPECT) for brain scans. This situation arises due to the presence of limitations in the discovery of data pertaining to risk factors for Alzheimer's Disease. As a result, challenge lies in searching for most accurate method to predict at a early stage before any symptoms. The achievement of this challenge will be instrumental in aiding and enhancing research into "Early Treatments" and diagnosis at the onset.

In this paper, a dataset related to Alzheimer's Disease that includes information on both behavioral and biological markers, using a machine learning algorithm and CNN is analyzed. At present, there is no known cure for the majority of dementia types, but treatments, guidance, and assistance are accessible. Traditional Machine Learning algorithms need human intervention to extract features, whereas Convolutional Neural Networks can automatically extract features without the need for manual intervention. Instead, it fully automates the process[3].

The balance of this paper is planned as following sections; Section II discusses related works. Section III includes methodology. Section IV defines results, and finally, section V is the conclusion and future work.

II. RELATED WORKS

Due to the lower cost of MRIs compared to PET images and CSF, most researchers have concentrated on studying MRI data. In the past few years, machine learning and deep learning models have been utilized in analyzing medical images like CT scans and MRIs. Deep neural networks can automatically extract features from MRI images, analyze brain MRIs, and detect the stages of Alzheimer's disease, serving as a comprehensive learning model[4]. Researchers created a model that decreases the number of features in order for the model to identify patients with Alzheimer's disease. They utilized a linear support vector machine (SVM) to

2024 Third International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE) | 979-8-3503-1860-9/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICDCECE60827.2024.10548493

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develop a multimodal classifier for brain PET and MRI images, employing a random forest classifier [5].

An approach combining SVM and kernel principal component analysis was implemented to reduce features and extract information from MRI images. The model was tested on the OASIS datasets and achieved an accuracy of 92.5%. The wavelet entropy and biography-based optimizers were introduced to achieve a 100% accuracy rate on 64 brain images using a six-fold cross-validation model[6]. A new method using a gray level occurrence matrix and voxel based morphometry was created to enhance the accuracy of extracting and selecting features from datasets of patients with Alzheimer's disease. Two classifiers were created to extract and reduce features from T2-weighted MRI images. A classification system for different stages of Alzheimer's disease was created in order to collect samples for the ADNI study [7]. The researchers utilized a sparse auto-encoder model to classify three stages of AD and achieved an accuracy of 95%, resulting in an overall accuracy of 79.8% for all stages. ADNI dataset needed. utilized a three-dimensional CNN model for the identification of small brain bleeds. Long-term and short-term memory, as well as time series data in three layers, were utilized to incorporate past patient information into the current task. Experiments show an overall performance of 82.05% for multi-classification of AD patients. In 2016, the inceptionV3 model was created to assist in the early detection of Alzheimer's disease and achieved a high receiving operating characteristic (ROC) is 95% and sensitivity 80% [8].

A novel automated approach using deep learning technology was suggested for diagnosing Alzheimer's disease. 235 participants were chosen at random from OASIS, and the experiments showed an accuracy rate of 88%[9]. While deep neural networks need to be trained on a large number of samples, there are situations where this many examples may not be accessible. In order to address the issue of having limited data, few-shot learning techniques have been developed to allow the model to be trained with only a small number of examples. Only a small number of training examples are required for these algorithms. Hence, the primary objectives of few-shot learning are to demonstrate strong generalization to new examples and attain high accuracy using minimal data. Researchers have been employing machine learning methods to construct classifiers for diagnosing AD by using imaging data and clinical measures[10]. These studies have found that Deep CNN can be used for automated diagnosis of Alzheimer's disease (AD) and mild cognitive impairment (MCI) by analyzing 3D brain MRI scans. The studies identified notable structural differences, such as in the hippocampus and entorhinal cortex, between healthy brains and brains affected by AD. Various types of imaging techniques, including structural and functional Magnetic Resonance Imaging (sMRI, fMRI), Position Emission Tomography (PET), Single Photon Emission Computed Tomography (SPECT), and Diffusion Tensor Imaging (DTI) scans, can detect alterations in the brain cells associated with Alzheimer's disease.

Numerous studies have utilized these neuroimaging methods for diagnosing Alzheimer's disease. Furthermore, data from different sources have been integrated to enhance diagnostic accuracy. Recently, deep learning models like Convolutional Neural Networks have shown excellent results in the field of analyzing medical images[11]. Deep learning methods have the ability to uncover concealed patterns within neuroimaging data and effectively identify disease-related abnormalities. The researchers have created a sparse autoencoder model to classify patients with Alzheimer's disease, Mild Cognitive Impairment (MCI), and individuals in good health. The researcher used sparse autoencoders and a 3D CNN model to train for diagnosing Alzheimer's disease.

A complex deep belief network model and applied manifold learning to detect Alzheimer's Disease from MRI images. a three-dimensional Convolutional Neural Network model for diagnosing Alzheimer's Disease. A deep learning model that combines unsupervised and supervised methods was used to classify patients with Alzheimer's disease (AD) and mild cognitive impairment (MCI)[12]. Using fMRI data and a deep LeNet model to detect Alzheimer's disease. We developed a model using an autoencoder network for diagnosing Alzheimer's disease and utilized various intricate SVM kernels for classification. Low to mid-level features have been obtained from magnetic current imaging (MCI), MCI-converted structural MRI, and PET data, which was then used for classification using a multi-kernel approach and demonstrated better performance on the ADNI dataset.

III. Materials and Methods

A. Patients Data collection

The Patient data is collected from the T1-weighted cross-sectional MR brain scans. The datasheet is collected from the OASIS database, which included both training and testing MR brain images. OASIS-3 is the newest iteration of the OASIS project, designed to provide neuroimaging datasets to researchers at no cost. OASIS-3 is a comprehensive dataset that includes neuroimaging, clinical, cognitive, and biomarker information for individuals experiencing normal aging and Alzheimer's Disease (AD). The dataset includes 6400 images in total and is categorized into 4 classes based on the seriousness of Alzheimer's disease. In particular, various patients' ND, MoD, MD, and VMD.

There are 3200 images for ND, 64 for MoD, 896 for MD, and 2240 for VMD classes. Figure displays the numbers of cases in each category utilized for testing and training, along with examples of MR images for the four groups. The Block diagram of the proposed Alzheimer's Disease diagnosis framework us shown in Fig.1.

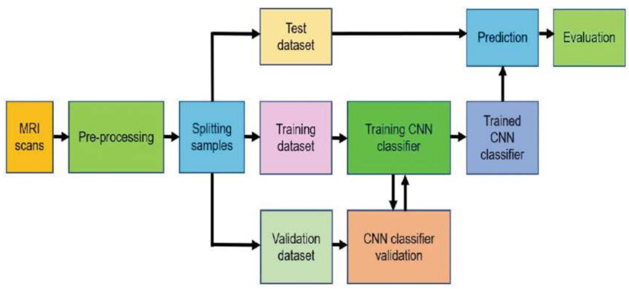

Fig. 1. Block diagram of the proposed Alzheimer's Disease diagnosis

The neural network is composed of a total of 6 layers. The initial layer is a Convolutional layer. In this stage, a filter is passed over the input images in order to generate a feature map. Next, a pool layer is utilized to carry out a reduction operation. Following that, another convolution layer and pooling layer are included to carry out the same process. Following that, a fully connected layer is employed, through a dropout of 80%. The dropout technique was implemented to avoid the bias towards specific neurons. The fully connected layer consists of 248768 neurons. 248768 neurons were specifically required due to the presence of two max pooling layers with 2 strides on both axes. these steps decrease dimensions of 3-dimensional image from $50\times50\times91$ to $13\times13\times23$, converting original image into a feature map is shown in Fig.2.

Before impending dense layer, 64 feature maps are formed. Therefore, the number of neurons in the dense layer came out to be $13\times13\times23\times64 = 248768$ in order to map all of these feature mappings to layer for feed forward operations. The output layer comes last, and it consists of just two neurons that together produce a single hot array that indicates the presence or absence of Alzheimer's. ReLU activation function was applied to the completely linked layer and its two convolutions.

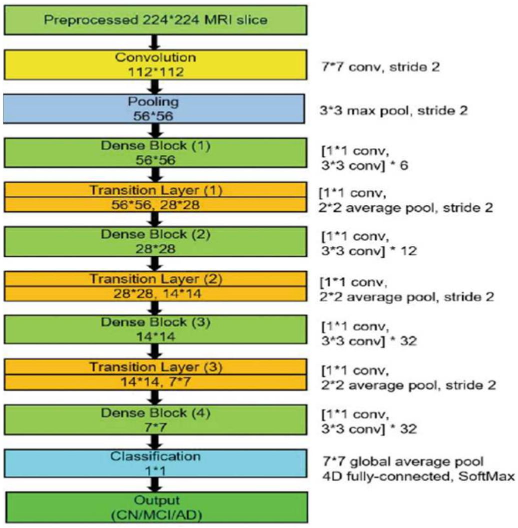

Fig. 2. Deep CNN architecture

The neural network was tested in the above-described configuration. Additionally, overfitting was evidently occurring. In every convolution, 50% dropout was added to address the overfitting issue. Therefore, we have utilized 0.80 and 0.50 as dropout probabilities throughout our entire model. Additionally, the data was randomly divided via cross validation into train and test sets. The neural network's performance significantly improved after that is shown in Fig.3.

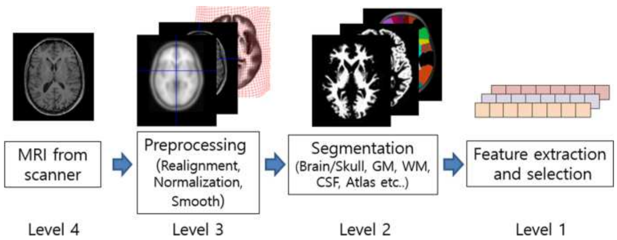

Fig. 3. Stages of image extraction and selection

IV. RESULTS

During data collection, MRI images deteriorate low variation occurs because the optical equipment is not bright enough. To address this issue for the improvement of MRI scans, image improvement techniques are typically used to rectify or enhance the distribution of pixels over a wide range of intensities. For this reason, we first used picture normalization to reduce the image pixel intensity values. The sMR image examples for different Dementia stages: (a) None Demented(ND), (b) Moderated Demented (MoD), (c) Mild Demented (MD), and (d) Very Mild Demented (VmD), from left to right, respectively is shown in Fig.4. Fig. 5. The sMR image rescaling and resize, (a) before and (b) after resizing.

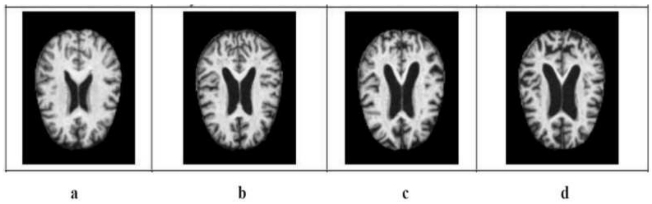

Fig. 4. sMR image examples for different Dementia stages: (a) None Demented(ND), (b) Moderated Demented (MoD), (c) Mild Demented (MD), and (d) Very Mild Demented (VmD),

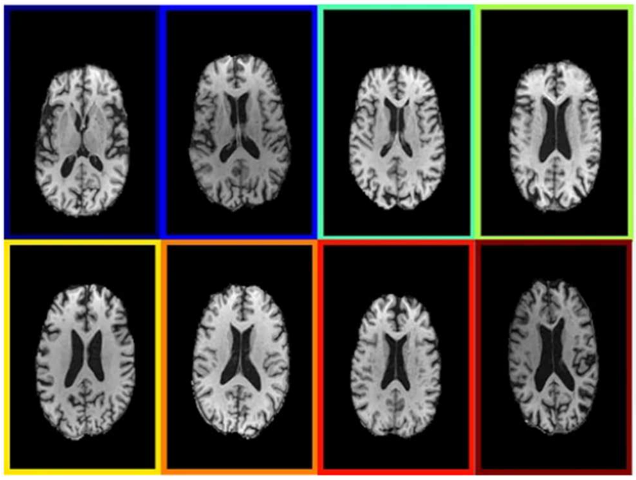

Fig. 5. The sMR image rescaling and resize: (a) before and (b) after resizing.

In Convolutional Neural Networks, a kernel or filter moves over the image pixel by pixel and automatically identifies and chooses the features. Due to the progress in GPU computing and cloud computing, Convolutional Neural Networks and various other Deep Learning methods have become the preferred solution for these challenges. With 3D brain MRI data has been challenging due to their complexity and time-consuming nature. Advanced techniques involving magnetic fields, radio waves, and field gradients, MRI technology creates detailed images of the inside of the body without the need for invasive procedures. MRI scans typically produce images of the body in axial planes, which involve slicing the body from front to back. Each of these slices is a standard two-dimensional image. Fig. 6, shows the samples of data augmentation images.

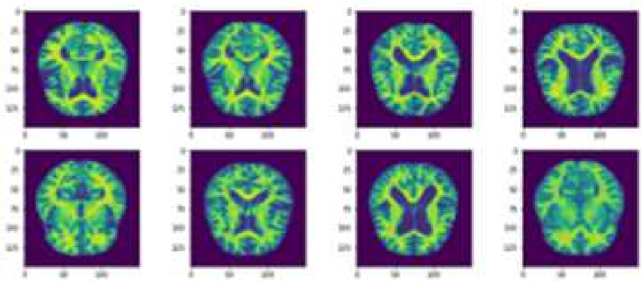

Fig. 6. Samples of data augmentation images.

The Siamese convolutional neural network, using three branches of ResNet-34, was specifically designed among the DL networks to differentiate between individuals with Alzheimer's Disease (AD) and normal controls (NC) using structural MRI scans

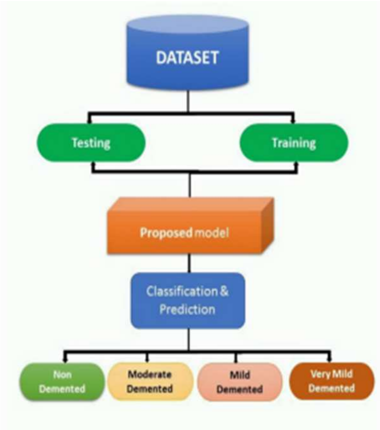

Fig. 7. Flowchart representation for the proposed analysis framework

There are several constructed layers, an input, and an output in the suggested CNN model. Specifically, this work used four two-dimensional (2D) convolutional layers, with a 2D pooling layer in each. Between the input and a kernel, also known as a filter, which serves as a function detector, convolution is a linear operation. The filters have a limited receptive field and are trained to extract specific information from an image into four classification. Flowchart representation for the proposed analysis framework is shown in Fig.7. As seen in Fig.8, measurements of training and testing data loss as well as validation data loss were made during the training phase. We achieved 99.88% training accuracy and 99.94% testing accuracy with our proposed CNN model. The confusion matrix serves as the basis for yet another quantitative analysis. Fig.9. displays the proposed systems confusion matrix. Confusion matrices are helpful for managing and monitoring models in addition to evaluating them.

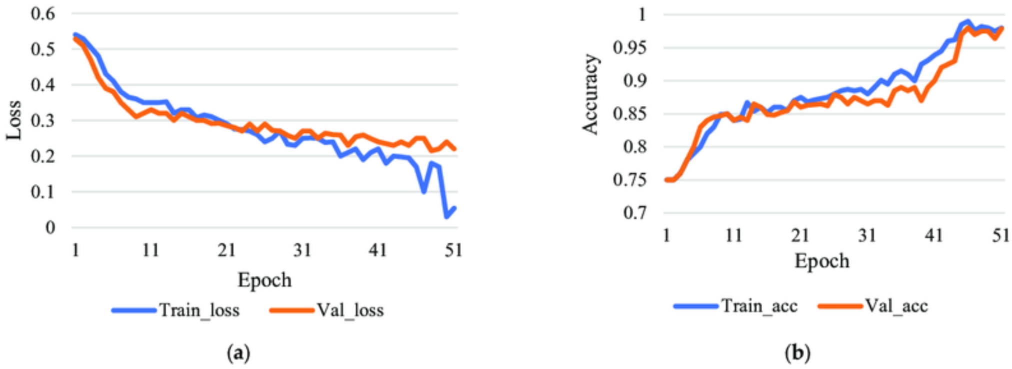

Fig. 8. Training and validation loss and accuracy against the number of epochs

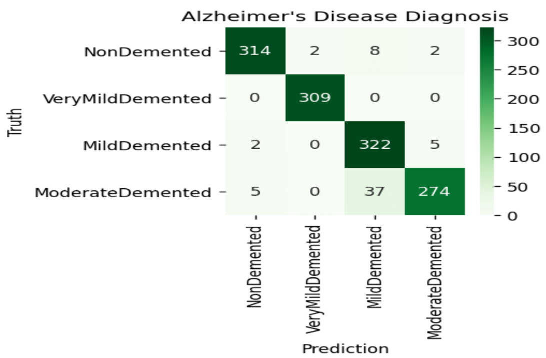

Fig. 9. Confusion Matrix

The produced confusion matrix, which contains the precision, F1-score, and recall, can be used to calculate indices. Typically, the assessment/evaluation of classification models involves the combined use of the confusion matrix and associated metrics. We assessed the proposed CNN model's performance against some of the classification work in brain MR images using CNN models and other ML classifiers in order to highlight its advantages.

V. CONCLUSION

As a result of this paper, a CNN-based pipeline for effectively identifying Alzheimer's disease using brain, structural magnetic resonance imaging has been developed. The accuracy, sensitivity, specificity, and receiving operating characteristic (ROC) of the suggested pipeline were 99.89%,99.84%,99.78%, and 99.68%, respectively. A data collection of brain MRIs was used for testing and validation. The robustness of the method has been proved by analysis, and the higher classification has been validated by contrasting the performance of our framework with that of well-known CNNs. This proposed method is analysed with increased accuracy when employing the appropriate network design selection points to its potential use in forecasting various stages of Alzheimer's disease across a range of age groups. In future work, several datasets using advanced data-mining techniques to improve the efficacy and performance of AD prediction at early stages by utilizing various datasets and stages.

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