



An Optimized Convolutional Neural Network for Alzheimer's disease Detection

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Abstract

Alzheimer's disease (AD) is a serious diseases distressing society. AD is a complex disease associated with many risk factors, such as aging, genetics, head trauma, and vascular disease. AD is also influenced by environmental factors such as heavy metals and trace metals. The pathology of AD, including amyloid-peptide (A β) protein, neurofibrillary tangles (NFTs), and synaptic loss, is still unknown. There are many explanations for the causes of AD. Cholinergic dysfunction is a main danger factor for Alzheimer's disease, whereas others believe that abnormalities in the production and treating of A β protein are the primary cause. However, there is currently no accepted hypothesis explaining the pathogenesis of AD. Magnetic resonance imaging is used to diagnose Alzheimer's disease. Our new AD pathogenesis showed 99.77% accuracy with 0.2% efficiency loss and outperformed VGG16, MobileNet2, and Inception V3 without the Adam optimizer and folder hierarchy.

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1. Introduction

Alzheimer's disease (AD) is a nonpathogenic neurodegenerative sickness categorized by mental delay, memory loss, and reduced daily functioning. AD must be diagnosed early and accurately so that it can be treated and cured quickly. Magnetic resonance imaging (MRI) has become an effective method for studying anatomical and functional changes in the brain associated with AD [1].

The selection of a suitable algorithm for medical diagnosis is a combination of science and art. Understanding the various types of machine learning aids in determining a suitable algorithm for effective disease diagnosis. Neural networks (NNs) are modeled based on the structure and functions of organic neurons. An NN is founded on the human brain and improves the learning process. The term Neural Network refers to neurons in the nervous system that process and transmit material using the J48 algorithm. J48 Classifier is a machine-learning choice tree classification technique. The decision tree procedure is based on the branching approach, which increases the output based on the conditions. It has a calm tree-like structure.

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1.1. History of the Alzheimer’s disease

Alzheimer's disease is a brain sickness that increasingly erodes memories and thinking skills, resulting in the inability to do even the most elementary jobs. Most Alzheimer's patients acquire symptoms later in life. Although estimates vary, scientists believe that about 6 million Americans, the majority of whom are 65 years or older, may have Alzheimer's [2]. Alzheimer's disease is currently the seventh greatest cause of death in the United States and the most common kind of dementia in the elderly. Dementia is described as the loss of cognitive function, including the ability to think, remember, reason, and act in a way that influences a person.

The severity of dementia ranges from mild, when it starts to seriously impair a person's capacity to function, and at its worst, when they must depend on other people to carry out crucial everyday chores [2].

Several different brain disorders can lead to dementia. Frontotemporal disorders, vascular dementia, and dementia with Lewy bodies are among more forms of dementia. Most cases of dementia are mixed, meaning they combine elements of two or more different categories. For instance, vascular dementia and Alzheimer's disease are present in certain patients.

Doctors treating Alzheimer's disease found anomalies in a woman's brain in 1906 after her mental ailment had taken her life. Symptoms include unpredictable behavior, speaking difficulty, and memory loss. After his passing, an examination of his brain revealed many anomalies (now known as amyloid plaques) and tangled fibers (Currently known as tau tangles or neurofibrillary tangles). Alzheimer's disease is thought to have plaques and tangles in the brain as some of its main characteristics. The brain's nerve cells' inability to bind together is another trait. Neurons transmit signals from the brain to the muscles and organs, as well as between different areas of the brain [3].

1.2 Signs and symptoms of Alzheimer’s disease

Remembrance issues are often among the first pointers of Alzheimer's-related cognitive weakening. One such indicator is cognitive decline. Mild cognitive impairment (MCI) is a condition that some people with memory loss suffer. Compared to their counterparts, people with MCI have superior memories, but their symptoms do not affect their day-to-day activities.

MCI is also associated with difficulties in moving and problems with smell. Older adults with MCI are more likely to develop Alzheimer's disease, but not all of them. Some may even relapse.

The earliest signs of AD vary from person to person. Many believe that declines in cognitive skills, such as word search, visual/location problems, and poor thinking or decision-making, indicate the early stages of the disease. Researchers are working on biomarkers (biological markers of disease found in the brain, cerebrospinal fluid, and blood) to identify changes in the brain among people with MCI and those who are well-informed but may be at a higher risk for early Alzheimer's disease. More research is needed before this technology can be frequently applied in clinical settings to diagnose Alzheimer's disease.

1.3 Causes Alzheimer’s disease

Many people are concerned that they might have Alzheimer's, particularly if there is a family history of the condition. A family history of the illness does not ensure that it will manifest. That being said, this might indicate that you have this illness. Alzheimer's disease risk is influenced by a person's heredity. Gene variations or mutations that might result in disease are examples of genetic risk factors. Alzheimer's disease comes in two flavors: early onset and late onset. They both possess genetic material. The two approaches' differences are listed in Table 1.

Table 1: Distinctions between early- and late-onset diseases:

Disease	Appear Age	Type	Reason
Late-Onset Alzheimer’s Disease	Middle 60s	More common type	Apolipoprotein E4 gene
Early-Onset Alzheimer’s Disease	30s and middle 60s	Very rare	Gene changes passed to child

In recent years, significant progress has been made in many areas, including learning and medical imaging analysis. Deep learning forms such as convolutional neural networks (CNN) and recurrent neural networks (RNN) have proven to be capable of relearning data representations. Raw, accurate, and useful medical image [1].

Alzheimer's disease diagnosis using deep learning models based on MRI shows great promise. Using the power of deep neural networks, complex patterns and abnormalities in brain MRI that are the hallmark of Alzheimer's can be effectively identified. Deep learning models can capture relationships between brain images, make them more accurate, and help diagnose AD and learn to discriminate [2].

One of the advantages of deep learning models in diagnosing Alzheimer's disease is that they extract advanced features directly from MRI scans, thereby eliminating the need for manual analysis. Previous methods often relied on skilled hand tools and could not cover all the aspects of the disease. Deep learning models can learn relevant features from raw MRI data, making it possible to identify new and useful biomarkers that are not previously known [3]. Additionally, deep learning models can use large datasets that are useful in the context of AD research. With access to large MRI databases, learning models can be trained on diverse and comprehensive datasets, allowing them to learn more about the pathology of Alzheimer's disease [4].

The purpose of this study was to understand the potential of deep learning techniques in MRI-based diagnosis of AD. Alzheimer's disease has been diagnosed. Deep neural networks were used to extract features from brain MRI images and classify them as healthy or Alzheimer's patients. Accuracy and speed of detection through deep learning are needed to be increased, thereby enabling early diagnosis and intervention [5].

Deep learning models for detecting Alzheimer's disease with MRI will revolutionize clinical practice by providing an effective tool for diagnosing Alzheimer's disease. This will help doctors make informed decisions, intervene early, and monitor the disease effectively. In addition, insights from deep learning models may lead to a better understanding of the neurobiological mechanisms underlying AD [6].

Deep learning methods for MRI-based diagnosis of Alzheimer's represent a very promising method by which neuroimaging can be performed efficiently and will allow for improved patient care [7]. The use of deep neural networks help in the development of accurate, effective, and easily scalable diagnostic technologies that will aid in the early detection and management of AD.

2. Literature Survey

Alzheimer's disease is a neurological condition related with aging. This suggests short-term memory loss, which is a sickness. The patient experienced memory loss because of recent occurrences. According to the world health organization (WHO) estimations, the global prevalence of AD was 0.441% in 2015 and will increase to 0.556% by 2030. In the medium term, perceived mental retardation progresses from moderate to severe and dependence on caregiver's increases. In the final stage, the patient's thoughts and behaviors change, and he becomes more dependent on his work [8].

The genetic elements were discussed specific biological processes potentially associated with the AD disease [9]. Some of the participants discuss ways that treatment can be addressed at each stage of the disease continuum, contributing to the discussion of what should guide scientists [10]. The single targeting of the amyloid peptide (A β) protein monomer is sufficient to enhance the inhibitory effect of A β -anticalin in the early stages of disease [11]. It has been shown that the cellular mechanisms underlying A β -dependent neuronal dysfunction may be active before plaque formation [12].

A method for detecting brain diseases has been previously proposed [9]. MRI scans are divided into four categories: Alzheimer's, normal, Parkinson's, and tumors. Inceptionv3 and VGG19 were used as the feature extractors before training the model. They extracted convolutional features from these models [10]. Random forest was used to classify the received features. Inceptionv3 and VGG19 networks were used to train 6754 MRI samples. 1046 samples were collected for analysis. A random forest classifier was used to classify the MRI scans into four groups: Alzheimer's, normal, Parkinson's, and tumor. Combining deep learning models with machine learning classification to recognize different types of brain diseases.

Neighborhood Component Analysis (NCA) -based Hybrid CNN Model for Classification of Alzheimer's Disease was proposed but has low accuracy in large epochs [16]. A multilayer partial network solution (PartialNet) specially designed for AD using MRI. PartialNet has mapping, depth differentiation and depth tracking features. A proposed deep visualization of failure neuroimages to characterize dementia subtypes and expand on non-stereotypical patterns [18]. Data have been collected from studies on cognitive decline of intelligence, but the results are below 90% in large epoch [19].

The hybrid study model revealed early symptoms of AD. These additional hybrid models were designed using different types of machine learning, including machine learning environments, random forests, decision trees, and nearest neighbors. This machine-learning model was used to replace the nonlinear SVM component of the proposed model. The hybrid learning model consists of a combination of Gaussian filters for noise reduction, a collection of neural network models for feature extraction, entropy-based feature metric ranking for feature reduction, and support vector machines [11].

Owing to their size, it is suggested that different levels and features of MRI, brain images, and cascade CNNs be analyzed [12]. Because there is no image segmentation during the preparation of the data, private information is not important. This is the main reason why it is better than other methods. In an additional process, the features were separated and fitted to the model. The working efficiency is as high as 93.26%.

They claimed that 3D Capsule Networks could process images at extremely high speeds. Their method improves detection compared with deep CNNs. They correctly classified AD data with 98.42% accuracy across a joint system [13]. All patients with MCI were recruited from the same institution. They used a CNN to examine 3D T1-weighted images. They use ADNI dataset. They studied the CNN functions for the classification of AD, advanced MCI, and stable MCI. The accuracy of the CNN in distinguishing MCI from stable MCI is 75% [14].

An individual's population and Mini-Mental State Examination scores were analyzed to determine if they were at risk of AD [15]. Human speech pauses and changes in sounds owing to the environment should be considered. By combining genetic algorithms with support vector machines and generalized regression neural networks, the most important feature vectors can be selected without wasting input data supplied into the Bayesian network. Although the proposed method was accurate, the Bayesian network was not acceptable for missing data. To use MRI for the diagnosis of moderate cognitive impairment (MCI) or AD, a classifier was proposed by merging CNN [10]. This classification performance can be further improved using optimization techniques and/or by adding more deep learning models, which can enable the identification of brain regions with greater discriminability.

Many strategies have been employed, such as GRUs and classifiers, to inform the development of AD from MCI [17]. For this purpose, the KNN method includes and preserves missing variables. Although each worker cannot help disrupt this order, it is necessary to support the research model to improve the efficiency of the work. See with a large image-size dataset.

In this case, the KNN imputation procedure is integrated to account for the missing variables and effectively control them. Although each feature alone does not lead to accurate knowledge of the relationship between features, there is no such combination to improve the quality of information to improve the features. Characteristics of the parameter optimization stage. Large amounts of image data supporting the detected models are important.

3. Techniques and Technologies

3.1. Deep Learning

Deep learning is a machine learning technique that employs deep connections to model and solve complicated problems. Deep learning algorithms must learn from large amounts of data by identifying patterns and relationships that humans or machine learning algorithms cannot identify complex problems. These networks can detect patterns in images, audio, text, and other types of data with high accuracy, and their applications are developing in image, natural language, and speech recognition. Deep learning has become a major tool for researchers, data scientists, and developers in areas such as vehicle detection, diagnosis, and prediction.

3.2. Convolutional Neural Architecture

Convolutional Neural Architecture The convolutional neural network (CNN) is a deep learning method that is commonly utilized in image and video analysis. CNN processes the input using multiple convolution and pooling algorithms. The layers of the CNN scan the input for local patterns or features such as edges, corners, and texture. The pooling layer down samples the output of the convolutional layer. In other words, pooling lowers the resolution of the image dimensions but preserves the most important information. This is followed by one or more connected layers conduct categorization or inversion depending on the retrieved features. Through training, the CNN uses backpropagation to select weights that are appropriate for the features and semantic segmentation of each problem. The convolutional neural network components are illustrated in Figure 1.

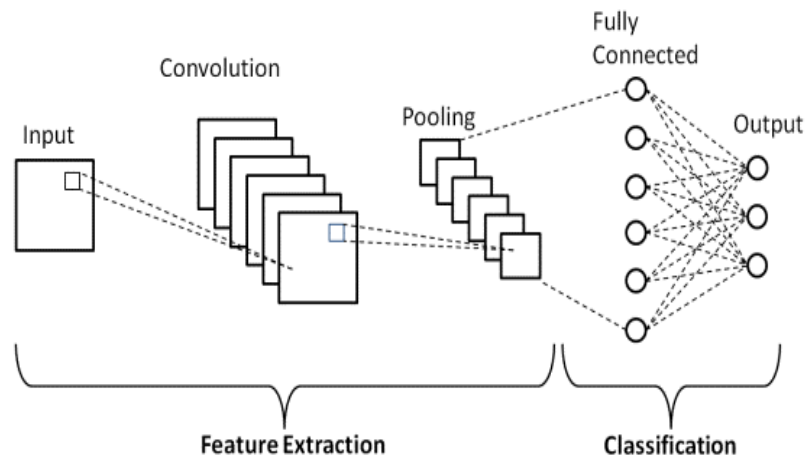


Figure 1. Convolutional Neural Network Components.

A CNN model containing 11 convolution layers with VGG16 uses the Adam optimizer; the folder hierarchy is shown in figure 2.

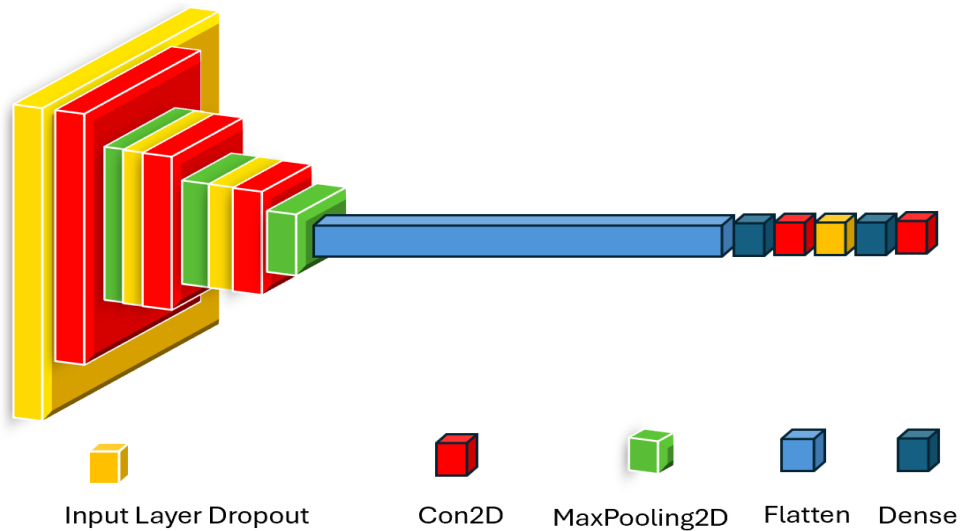


Figure 2. CNN using Adam optimizer.

3.3. Evaluation Method

In Python, the **accuracy score method** was used to calculate the accuracy of the fraction or the number of correct predictions. Accuracy is the ratio of the sum of true positives and true negatives in all predictions, as in Algorithm 1.

Algorithm 1: Accuracy Score Calculation

Start

Y_{true} : True output

Y_{pred} : predicted output

TP=Summation of True positive images

TN= Summation of True negative images

FN= Summation of false negative images

FP= Summation of false positive images

Accuracy_{Score} = $(TP+TN) / (TP+FN+TN+FP)$

Y_{true} = label_{indicator array} / label_{sparse matrix proper}

```

Y_pred= label indication array/ label sparse matrix expected as returned by the classifiers
Accuracy score method =Y_true,
normalize=False
Accuracy score method=Y_true,
normalize=False,
Sample weight=None
Normalization
If (normalization result==true) then
    Return the proportion of appropriately confidential samples.
Else
    return the number of correctly confidential samples.
return Confusion Matrix
End

```

Where TP is the sum of the true positives, TN is the sum of the true negatives, FN is the sum of the false negatives, and FP is the sum of false positives. Accuracy can be also calculated with the help of the accuracy score method from as Algorithm 1.

In multi-label deployment, this function returns true. If all predictions in the model are set to exactly the true list. Then the accuracy of the subset is 1.0, otherwise the accuracy is almost 0.0. Sample **normalization** contains Boolean values (True/False). If true, return the number of true latent patterns in Step 17. Otherwise, it returns the correct part of the latent model in Step 19. **Confusion matrix** is a technique for performance evaluation. It is returned in Step 20 and is used to predict or summarize the content of classification problems.

4. Data Model

First, we gathered our data for model training using Kaggle. After gathering all required images for our training, we used Google drives as a safe and easy storage to store and get our data ready. Kaggle dataset of 6,200 photos was used for training, including 896 images with mild dementia (MD), 64 images with moderate dementia (ModD), 3,200 images without dementia (ND), and 1,966 images with true mild dementia (VMD).

4.1. Data distribution

The data consists of MRI images. The data has four classes of images in both training as well as a testing set: mild demented, moderate demented, non-demented, very mild demented as in figure 3.

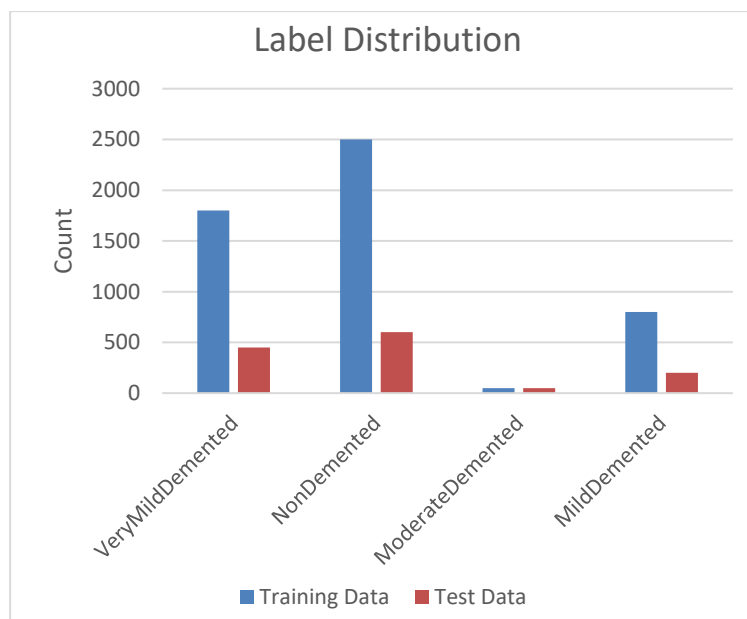


Figure 3. Number of images for each testing set.

The Sample of MRI images of the four classes: mild demented, moderate demented, non-demented, very mild demented are shown in figure 4.

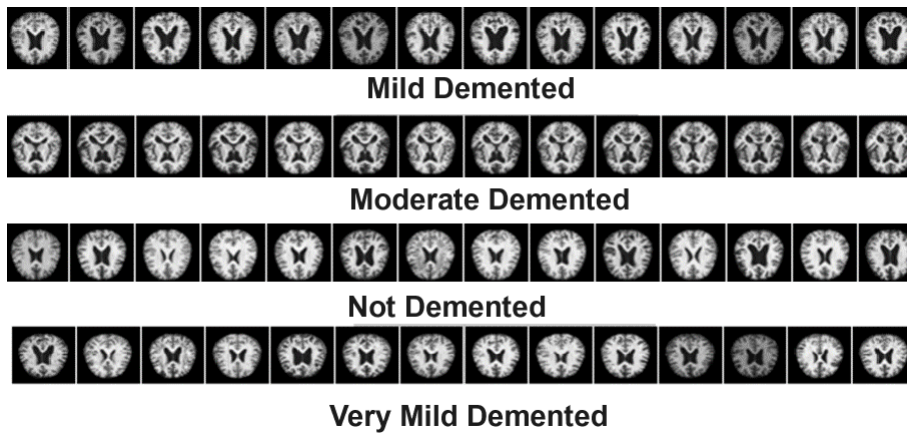


Figure 4. Samples of types.

4.2. Images Preprocessing

Intel Corporation created the Open Computer Vision Library, a software association library aimed largely at computer vision development. The library is free since it is released under an open-source BSD license. It is compatible with most computer platforms and supports both C and C++. OpenCV will help you learn image processing from basics to advanced, like image resizing and image reading.

4.3. Image Resizing

Image scaling refers to image scaling. Scaling is important for a variety of image processing applications, including machine learning. It helps to reduce the number of pixels in an image and has numerous benefits. For example, it can reduce neural network training time since the number of pixels in a picture exceeds the number of input nodes, increasing the model's complexity. It also aids in the growth of the image. The resize method is frequently used to resize, decrease, or increase a picture to meet requirements. OpenCV provides a variety of interfaces for resizing images.

4.4. Image Reading

To read an image, the image is loaded from a certain file. If the picture cannot be read (due to a missing file, incorrect permissions, or an unsupported or invalid format), this method returns an empty array.

5. Results

A simple CNN model containing 11 convolution layers is compared with VGG16 is using Adam optimizer and folder hierarchy in figure 5 and 6.

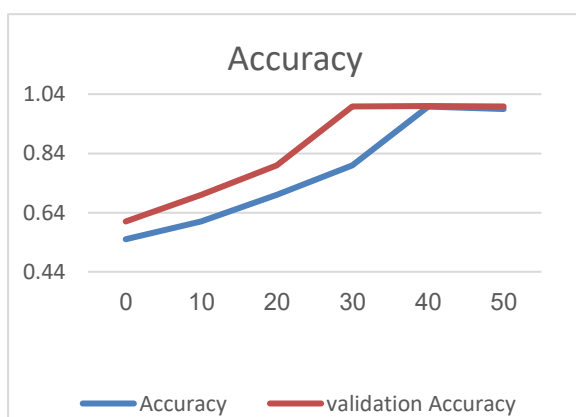


Figure 5. The accuracy of MRI using CNN and Adam optimizer.

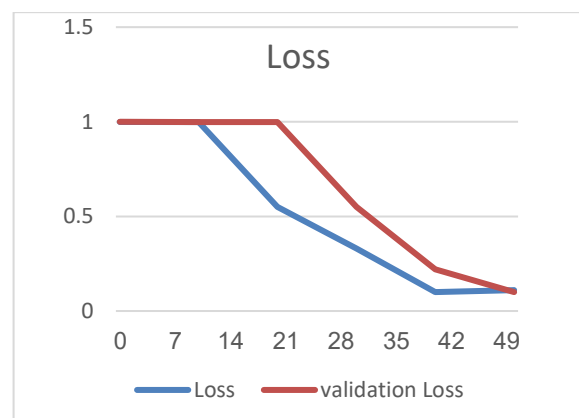


Figure 6. The loss of MRI using CNN and Adam optimizer.

In figure 5, training this model we got accuracy rate (99.77%) and validation accuracy (98.28%). Training this model, we got validation loss (0.2%) in figure 10. This is because VGG16 is using Adam optimizer and folder hierarchy.

6. A comparative Study

CNN models using MobileNet2, VGG16, and inception V3 and are tested to be compared with the proposed model. The accuracy of using MobileNet2 is (65.99%) and the loss is (62.19%) as in figures 7 and 8. MobileNet2 provides low accuracy and large loss.

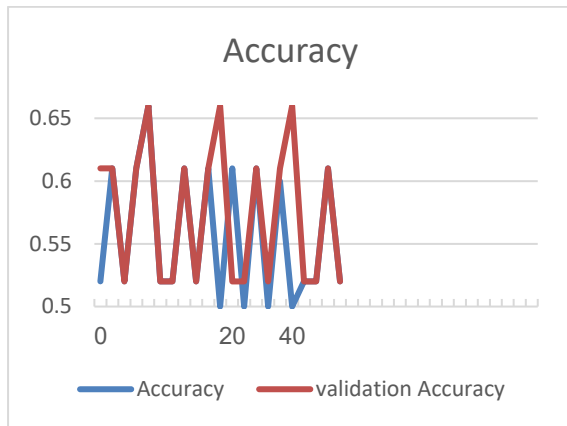


Figure 7. The accuracy of using MobileNet2.



Figure 8. The loss of using MobileNet2.

For VGG16 only, the accuracy is (68.96) and loss 1.2 as in figures 9 and 10 respectively.

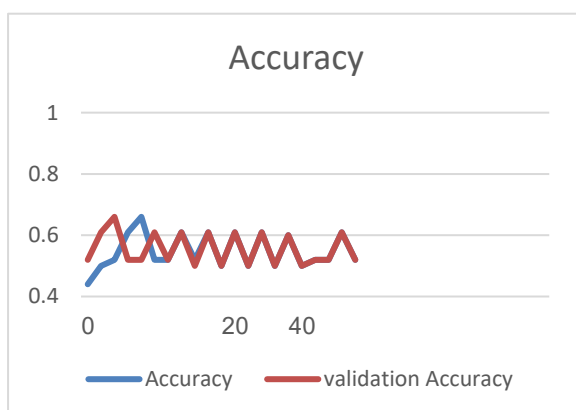


Figure 9. The accuracy of using VGG16 only.

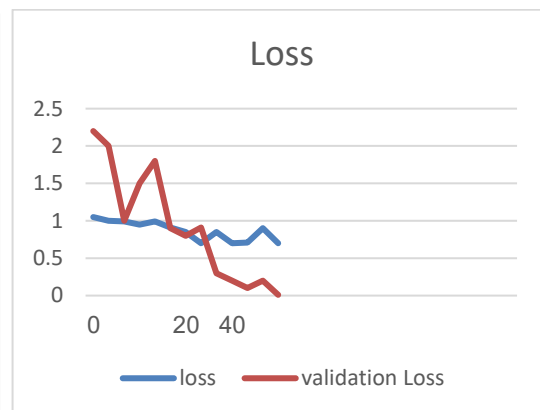


Figure 10. The loss of using VGG16 only.

For InceptionV3, the accuracy is (96.83%) as in figures 11 and 12.

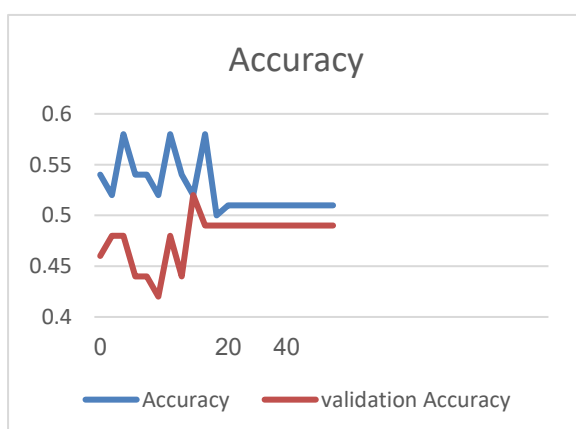


Figure 11. The accuracy of using InceptionV3.

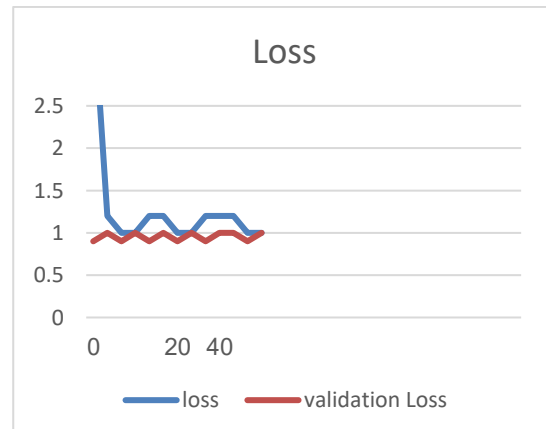


Figure 12. The loss of using InceptionV3.

A simple CNN model containing 11 convolution layers using Adam optimizer and folder hierarchy outperforms VGG16 without Adam optimizer and folder hierarchy, MobileNet2, and Inception V3 even in epoch 50. The identification accuracy of the proposed method outperformed that of other methods for bearing fault diagnosis. This is because it is improved by Adam Optimizer with power exponential learning rate changes the convergence performance of the network, so that the model has the strongest recognition for Alzheimer MRI dataset.

7. Dataset statement

The dataset is available contains image data that was used for this detection problem of Alzheimer's disease is in [Kaggle alzheimers-dataset] and is found in [Kaggle alzheimers-dataset].

8. Conclusion

Alzheimer's disease is a devastating neurological ailment marked by cognitive decline and memory loss. Magnetic resonance imaging (MRI) has emerged as an effective tool for studying structural and functional brain changes associated with Alzheimer's disease. In recent years, deep learning algorithms have excelled in medical image analysis. This study investigates how deep learning techniques can be used to diagnose Alzheimer's disease with an MRI. Deep neural networks were created and trained to automatically extract discriminative features from brain MRI scans and identify individuals as either healthy or Alzheimer's. The suggested deep learning models reduce the need for human feature engineering and leverage the power of large-scale datasets. By capturing complex patterns and subtle abnormalities in brain images, the models achieve high accuracy in AD detection. The results demonstrate the potential deep learning can enhance early diagnosis and intervention in Alzheimer's disease, leading to improved patient care and a better knowledge of the disease's neurobiology.

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