Applying Deep Learning Techniques for Alzheimer's disease Classification: A Comparative study

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Abstract

Alzheimer's disease is a chronic brain condition that causes brain cell death, shrinkage, memory loss, and cognitive difficulties. The major cause of dementia is alzheimer's disease. The functioning of the brain is affected by this disease. In the initial state of alzheimer's disease the loss of memory is quite lower, and that in the late stage individuals receives cognitives disorders. This dangerous disorder requires to be handled in an early stage. Due to the increasing progress of this disease, it is crucial to diagnose the disease in early stage in order to limit further progression of the disease. Common machine learning algorithms do not improve the accuracy of predicting this disease, although deep learning techniques have increased the level of accuracy. My research on current research papers leads to the evidence for image processing, deep learning algorithms outperform common machine learning techniques. Image processing is performed on magnetic resonance imaging data to classify disease using deep learning algorithms. I propose a comparative analysis utilizing distinct deep learning techniques including CNN, RNN and transfer learning to classify alzheimer's disease. Magnetic resonance data is employed for this research, were this study concentrates on individual performance of distinct deep learning methods. From the performance of distinct evaluations from algorithms on magnetic resonance data is easy to differ the algorithms performance and how they differ from each other. This paper highlights performance of distinct deep learning algorithms to classify stages of alzheimer's disease. Convolutional neural networks(CNN), Transfer learning (TL) and Recurrent neural network(RNN) are the deep learning techniques which is used in this analysis. VGG19 architecture was utilized in CNN in order to perform AD classification. My transfer learning model underwent fine-tuning, which includes unfreezing the previously learned model and retraining it in order to enhance the model's performance. The results acquired from classifying the images by using CNN model produced an accuracy of 0.93 percentage whereas transfer learning model used VGG16 architecture which showed 0.98 accuracy.

keywords- Image processing, Magnetic resonance images , deep learning, Machine learning, Alzheimer's disease, dementia, Convolutional Neural Networks(CNN), Recurrent Neural Networks(RNN) and Transfer learning

Contents

1 Introduction

Alzheimer's disease (AD) is a serious condition that affects the hippocampal region Bv and Agrawal (2022) of the brain. Cognitive difficulties are a developing symptom of this disease, which affects people when it is already advanced. It affects roughly 50 million individuals worldwide. Additionally, if the right treatment is given, an Alzheimer's patient's condition can slow down their progress. An individual's cognitive performance is eventually affected by initial symptoms. Although it cannot be cured or reversed, the disease's progression can be slowed down if found in time. Multiple medical methods can be used to diagnose this condition. The early identification of AD is essential for controlling the disease. Therefore, early identification of this disease helps the experts in medical areas to recognize the issue in a very early stage and provide necessary treatments for the AD patients. For the early intervention of disease, various technological techniques are used. By using a machine learning or deep learning techniques, the stages of this disease can be determined. This is performed usually with the patients data that could be image data.

Machine learning algorithms are replaced with deep learning algorithms for better accuracy of the prediction modelsChahal and Gulia (2019). Feature selection and extraction techniques works better with deep learning algorithms. Image processing plays a significant role in determining the patients different stages of the disease. Image processing is performed on magnetic resonance imaging data to detect disease using deep learning algorithms. Magnetic resonance data is used in order to perform image processing. An imaging system detect Alzheimer's disease using a unique algorithm by setting various parameters for the detection. The process involves collecting appropriate features from the brain images to deeply observe and analyse patterns to detect the presence of the condition. Image segmentationShafi and Padha (2019)is method used to perform this task in the MRI data. Image classification is widely used in the medical fields to detect hazardous or incurable diseases like dementia. Through image classification it can easily evaluate metabolic activity of the brain from the collected images which additionally extracts required details from its structure that is used in the classification of AD.

Recent researches in this areas highlighted the significance of solving classification problems through deep learning techniques rather relying on general machine learning methods. Image classifications performed distinctively on deep learning algorithms, taking this into account i have performed my analysis of AD in deep learning methods. Two deep learning techniques are performed in a magnetic resonance data to classify Alzheimer's disease. Convolutional neural networks (CNN) and transfer learning algorithms are used in my analysis. Performance of distinct deep learning algorithms are used to classify stages of alzheimer's disease. Convolutional neural networks(CNN) and recurrent neural network(RNN) are the deep learning techniques which is used in this analysis. VGG19 architecture was utilized in CNN in order to perform AD classification. Convolutional neural network algorithm belongs to deep learning. my recent researches showed that features collected through CNN architecture improved the models accuracy and prediction. region of extraction and classification are the two steps of image classification. These two methods constitutes the main aspect of this analysis. Transfer learning (TL) is another deep learning algorithm used in this study. Transfer learning methods uses a pre-trained model to perform its task to give a more generalized model.TL usually reuse the model to perform for the classification of images.

1.1 Research question

Numerous studies have been done on Alzheimer's disease utilizing various data sets, methodologies, and architectures. These methods combine deep learning methods with general machine learning methods. The early identification of AD is essential for controlling the disease's course. Therefore, early identification of this disease helps the experts in medical areas to recognize the issue in a very early stage and provide necessary treatments for the AD patients. The treatment of Alzheimer's disease requires early detection. Deep learning algorithms were used to analyze a set of data and perform early disease detection. My study employs magnetic resonance data to analyze and compare the same metrics with different algorithmic structures to investigate individual performances of the algorithm. Three different algorithms were utilized in my analysis to classify the disease in various phases. I propose comparing three distinct deep learning algorithms: convolutional neural networks (CNN), recurrent neural networks (RNN), and transfer learning to classify the patients alzheimer's disease using magnetic resonance imaging data. The research questions that surfaced during the analysis:

1. How to improve the level of accuracy and other key metrics for the classification and prospective prediction of AD?
2. What are the approaches for reducing over-fitting in model building?

1.2 Motivation

I think it's important to look into this research topic for a few key reasons. Since this brain condition affects people in a variety of ways, it's critical to take action to identify it early on and prevent it from getting worseAl-Shoukry et al. (2020). Health professionals may be able to learn more about dementia's various stages and develop better treatments for those who have the condition with the help of this classification. It will also be helpful to understand the underlying causes of this condition and slow the disease's progression in the future. As a result, medical professionals to prevent it from getting worse. According to study, if a proper diagnosis is made and treatment is initiated, this brain disorder can be improved. This neurological disorder affects millions of people. Even though the reasons of this condition have already been studied by a number of researchers, any future advances in treating it or any previously unknown causes of it may be found by numerous analyses or classifications. Medical professionals are attempting to comprehend aging and find treatments for this disease. The classification of the phases of dementia can also be used to better understand how Alzheimer's patients' brains change over time, study ways to slow or stop the disease's spread, and diagnose different kinds of dementia.

Machine learning algorithms used today are imprecise and unreliable. When doing the analysis, these algorithms encountered problems with overfitting and underfitting. Various machine learning methods Dashtipour et al. (2021) have been used to identify the disease's early stages, but more recent deep learning algorithms have done it more precisely. I proceeded with magnetic resonance data to classify the stages of Alzheimer's disease in order to answer my research topic. I analyzed my data using the most popular deep learning techniques, including convolutional neural networks, transfer learning, and RNNs, each of which has a distinct architectures. Convolutional neural network model used VGG19 architecture, whereas transfer learning model used VGG16 architecture which is actually based on Resnet network. The methodology section of this paper provides further information regarding deep learning algorithms and their architectures.

2 Literature survey

2.1 Introduction

Deep learning algorithms are effectively used for early Alzheimer's disease identification. This is well demonstrated in the studies of current researchers. In my paper, I use deep learning techniques to do analysis on MRI data to predict alzheimers disease. Many current surveys use deep learning algorithms to perform classification analysis with high efficiency. Neural network models or deep learning models are used to tackle image classification challenges.My research investigation attempted to increase the accuracy of the existing models, considering that there are a few studies that analyze MRI data from patients with Alzheimer's using deep neural techniques.

Recent studies have employed MRI data to do feature selection and predictive modeling, among other techniques.I employed a magnetic resonance imaging dataset for my analysis. When it comes to image classification, Convolutional Neural Network (CNN) models outperformed other approaches.In this study, I analyzed Alzheimer's disease using the magnetic resonance imaging dataset using three distinct deep learning algorithms. These three algorithms are transfer learning, recurrent neural network (RNN), and convolutional neural network (CNN). Three algorithms are evaluated equally and best approach is chosen from them. all the alogirthms uses distinct architecture with multiple layers.

2.2 Performance of Deep learning techniques

Neural networks performed much better in feature extraction and image classification when compared to a machine learning systemZaabi et al. (2020). This study is primarily concerned with two tasks. The first is feature extraction, and the second is classification. They cut out only the essential portions of the images after dividing them into squares. I find this activity to be quite challenging because some of the image is overlooked or not well observed. This could result in the loss of an essential component of an image.In this research, the transfer learning model outperforms the CNN model.

Another paper Liu (2022) that predicts early and late stages of Alzheimer's disease likewise demonstrates the great accuracy of the transfer learning model. Combining a bootstrap model and a transfer learning model reduced overfitting and increased model stability. They chose the training sets for this at random. Since they had limited samples, they separated the sample bags into five groups of three. Since my dataset now includes larger images, completely avoided these techniques. moreover, only recently attempted to import a specific model and assigned a classifier and output layers for that particular model.

The most effective supervised learning strategy, which outweighed other supervised methods, is CNN. According to a recently released article Gao and Lima (2022), CNN's biggest drawback is that it takes a long time to train. The lengthy training period of CNN models was a problem I encountered in my analysis. This was a significant problem I considered when conducting my analysis. Number epoch values will progressively lengthen the data's training period. I therefore agreed with the paper's claim based on my experience and analysis.This research implies that CNN performs better than any other supervised models. Overfiiting difficulties, which I also encountered in my analysis, was one of their primary problems.The problem of insufficient sample data was overcome utilizing data generating techniques. Python has libraries like keras which contains dataimsge generator class which allows to perform task,that make it easier to carry out this activity. This assignment consists solely of creating new images from old ones. This has the drawback that it could possibly lead to overfitting issues.

In deep learning models, raw data is used as input to create a system that will enable the acquisition of a range of features from the training data. Another benefit is that it provides the best possible performance according to end-to-end learning, in which all processing pipelines are optimized at the same timeOh (2019). CNN models are strong models that use data with a grid structure, for instance MRI scans. The most common of these is the alexnet architecture. As a result, various fields receive diverse exposure on CNN. By using the right regulation techniques, these strategies achieved remarkable results. Accuracy of AD analysis has always been improved by deep learning approaches.

A wiseDNN model for Alzheimer's identification was carried out using baseline MRI data and clinical scores. creation of a supervised network and image patch extraction from a raw image. To fully utilize all of the training subjects, loss function is appliedLiu et al. (2020).Finding the right information from the images is one of the frequent challenges experienced when performing AD analysis.examining possibly significant brain areas for investigation The CNN model was created using a landmark-based deep learning technique for feature extraction and classification. The fixed sizes of the picture patches employed for this research took into account the structural changes brought on by dementia. By constructing a weight loss function in the neural network, they were able to analyze weakly labelled participants as opposed to the fully labelled subjects employed in earlier methods.

An accuracy of greater than 75 percentage was obtained for the prediction model using a framework that included longitudinal domain dataLee (2019). Because the model's performance in making predictions was just so poor, it was decided to reduce accuracy. When compared to alternative models that only employ one type of data, the cognitive performance model was found to be the most accurate. Despite having a greater sample size for neuroimaging data than for cognitive function or CSF biomarkers, the accuracy of the neuroimaging data model was lower. Measurements of diverse brain development and function are available from neuroimaging scans gathered from MRI and other pictures generated by FDG-PET Donghuan Lu (2018). It is expected that using several different picture modalities may yield more data that will aid in the early detection of Alzheimer's disease. A multimodal deep neural network was used to construct a deep learning-based system to classify persons with AD. Following study to identify those with mild cognitive impairment (MCI), the approach has an accuracy rate of 82 percent.

In one of the papersSimeon Spasov (2019), a model called Alexnet with grouped convolutional layers and efficient parameters was developed. The two different problems are likely to be predicted using similar data modifications. technique increases the number of training samples for the extractor network, reducing overfitting. While there are few factors that explain the discrepancies in the data shared between the two discriminating problems, balancing between the two tasks put smooth limits on the network parameters, which may prevent overfitting issues. Four-dimensional vectors are extracted by the feature extractor for the two classification issues.Using max pooling, which enables getting the highest values from an image patch, spatial demension was decreased. The clinical features are taken care of in this dense block layer. Each layer performs specific functions.Convolutional layers that are implemented separately and do not rely on pooling processes. A few convolutional blocks were made specifically to minimize the dimensionality of the MRI pictures used as input data. The remaining feature extraction is done on several convolutional blocks.

Previously, manuval extraction was performed for Alzheimer's analysis, which needed a significant amount of time and resources for image processing. While in more recent times, automatic categorization has been used with various feature extraction techniquesWei Feng (2020).For deep learning techniques in the study, baseline images were employed.A model called 3D-CNN-SVM was suggested for the classification of Alzheimer in one of research papers. In earlier research, 3D-CNN was also shown to be helpful for the detection of Diseases, but not for the multi-classification of AD. algorithm can help imaging experts with screening and diagnosis without running the danger of radiation exposure related to the ternary classification using MRI modality. In comparison to the most recent models mentioned in earlier studies, 3DCNN-SVM performs better.

To extract features from the primary portion of the brain, a 3D densenet model was used. A single model performed worse than multimodal. By down sampling and eliminating voxels with zero values, large voxel MRI images were transformed into reduced voxel imagesManhua Liu (2020).In cases when the method demands for the modification of existing data, data augmentation was also carried out to expand the amount of data.This was accomplished in my analysis, where I used Keras library classes to do this assignment.

For hippocampal analysis Han (2019), a hybrid convolutional recurrent neural network is deployed. Other techniques were unable to extract the necessary features for this investigation. Additionally, segmentation methods failed to extract the desired characteristics from an image. This RNN/CNN hybrid model was used. Segmentation was used to crop 3D picture patches and create binary masks. Individual 3D densenet creation increased the patches' ability to extract the necessary features from the hippocampus. Then, the features that were retrieved are integrated with additional connected layers for classification using an RNN model. With this strategy, multilayer features are fully learned, potentially improving the classification of Alzheimer's disease. Machine learning models accurately and overcame some limitations to diagnose Alzheimer's diseaseJi Hwan Park (2020).The difficulty to data and examine clinical phenotypes shows its possible role in predicting the probability of developing Alzheimer's disease when combined with data-driven machine learning. In comparison to other methods, the model's performance, with an AUC of 0.89 percent, forecasted the baseline disease with a fair amount of accuracy. The measured, balanced set and unstructured set showed varied little variances in model performance while the models were being compared. The disease's significant clinical aspects were discovered by the model. The qualities chosen are in line with the risk factors discovered in related investigations. The characteristic of Alzheimer's disease that was shown to be most closely related to this analysis was a drop in hemoglobin levels.

Brain damage was independently tracked using MRI data. Manual feature engineering, which takes a significant amount of time, was made possible by machine learning methodologies. For an Alzheimer's detection, a 5-fold cross-validation framework Abrol et al. (2019)was utilized, and the dataset was tested over 100 and 50 epochs. On AD classes, a cross validation approach was used to examine the impact of including more convolutional layers. I encountered overfitting issues when altering the hyperparameters, such as batch size and epochs, in my analysis.

A convolutional neural network's many layers may employ functions like batch nor-

Models/Methods	Percentage of accuracy	Reference
Transfer learning (TL)	92.86%	https://ieeexplore.ieee.org/document/9364155
Optimal transport-kernel based TL	0.78%	https://alzres.biomedcentral.com/articles/10.1186/s13195-021-00915-3
Feature extraction methods	80%	https://www.researchgate.net/publication/357070704_
Volumetric CNN & TL	86.60% & 73.95 %	https://doi.org/10.1038/s41598-019-54548-6
Multimodal DL	86%	https://www.nature.com/articles/s41598-018-37769-z
Multimodal & multiscale DL	86.3%	https://pubmed.ncbi.nlm.nih.gov/29632364/
Parameter efficient DL	86%	https://pubmed.ncbi.nlm.nih.gov/30654174/
3D CNN -SVM	89.40%	https://pubmed.ncbi.nlm.nih.gov/32498641/
CNN-RNN	91%	https://www.sciencedirect.com/science/article/abs/pii/S0165027019301463
Resnet	83%	https://www.sciencedirect.com/science/article/pii/S0165027020301242

Figure 1: AD Classification performances

malization and average pooling Bringas et al. (2020). The normalizing function enabled the model to generalize more accurately and learn more quickly. The pooling procedure reduces the dimensionality of the data .A convolutional neural network model for Alzheimer's disease is constructed utilizing five fully connected layers. The classification of Alzheimer's disease is based on volume and dimensions. One of the main tasks is choosing the appropriate voxel from image patches. Specificity and sensitivity are provided by choosing the appropriate location. Alzheimer's disease is studied using properly segmented grey matter from the voxelBasheera and Satya Sai Ram (2020). In CNN, feature extraction is done layer by layer. It is challenging to extract necessary features from the brain due to its complex structureLiu et al. (2022). Feature extraction from image patches is possible with a multiscale CNN model. The initial data is separated to gain the white matter and grey matter for the model's training and AD detection in order to create an efficient model.

MRI data were used for an AD study, and the BWO technique was used to segment the tissues. This strategy is used with segmentation and clustering. By taking into account the bias field and intensity of each tissue, it introduces temporal consistency restrictions that make it possible to handle the temporal changes in homogeneitiesRaghavaiah and Varadarajan (2022). Additionally, clinical data is integrated with a hybrid Texture, Edge, Color, and Density feature extraction approach to provide information on the patient's emotional state. To increase classification accuracy, a hybrid rotation forest deep neural network is developed. Rotation forest is employed to provide a training feature subset for the deep auto encoder. Using a deep learning method that has been proposedLi et al. (2021), the number of neurons is counted when the neuronal soma is found in the neuronal images. The neuronal images were divided into few cubes in this manner, and a Convolutional Neural Network (CNN) classifier was then used to identify the neuronal soma.This approach successfully identified neurons from the raw images with greater speed and accuracy.

One of the papersAgarwal D (2021) emphasizes how transfer learning is superior to all other deep learning methods. When the 3D CNN Model and transfer learning model were coupled, it attained an accuracy of roughly 98 percent. In a study report, neuroimaging biomarkers and their characteristics are examined. The model findings are influenced by well defined features. With a limited amount of training datasets, overfitting becomes a concern. In my study of MRI data using the TL methodology, overfitting was dealt with utilizing the data augmentation method.

3 Research Methodology

In order to classify the stages of Alzheimer's, I applied an image classification technique to Magnetic resonance imaging (MRI) data. In this analysis, the performance of various algorithms is analyzed. Convolutional neural networks (CNN), Recurrent neural networks (RNN), and transfer learning (TL) are some of the algorithms. I looked over a number of research papers that discuss the crucial classification schemes for Alzheimer's disease. I decided to carry out my analysis using the aforementioned techniques. In order to create CNN model, i used VGG architecture. So, to put it simply, VGG is indeed a deep CNN that has been used to classify images. This architecture consists of 19 levels. Resnet was surpassed by VGG because VGG is optimized for deep networks. Transfer learning model VGG16, a deep neural network model, was employed. This architecture has 16 layers total, including three dense layers, 5 max pooling layers, and 13 convolutional layers. I choose to utilize CNN VGG19 since it is simple to integrate with other deep learning techniques like transfer learning and RNN. The last model I ran my image data was a CNN-RNN model, which combines CNN and RNN techniques.

3.1 Convolutional Neural Network(CNN)

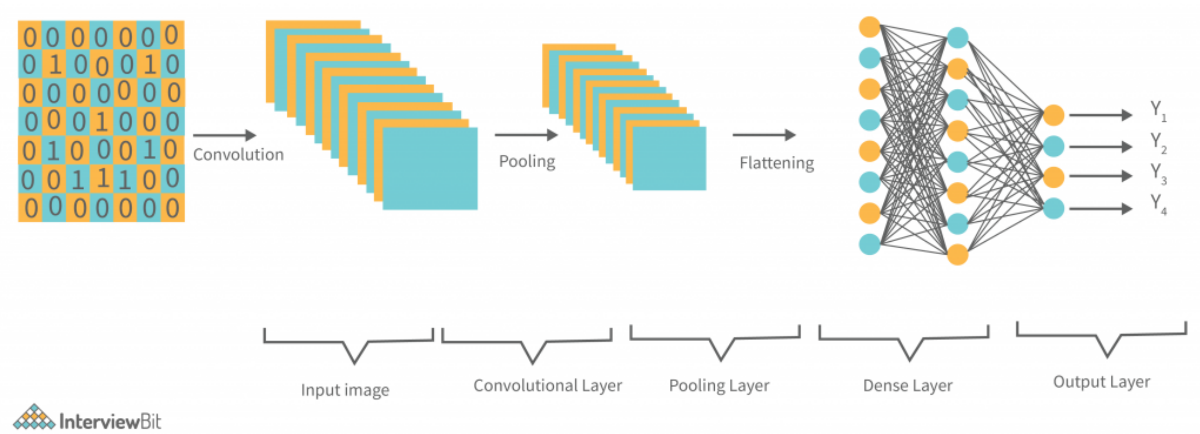


Figure 2: CNN architecture
cnn (n.d.)

The Convolutional Neural Network (CNN or ConvNet) is merely a subclass of Neural Networks that is exclusively employed for image processing applications. After analyzing the image data, its built-in convolutional layer minimizes the high dimensionality of the images without sacrificing any of their information. It defines the red component in the first matrix, the green component in the second, and the blue component in the final matrix to explain the color that each pixel of the image displays. Consequently, a 3 by 3 pixel image produces three separate 3x3 matrices. The convolution layer specifies a filter that controls the size of the partial pictures and a step length that controls how many pixels we continue between calculations, reducing the dimensionality of the image. The pooling layer comes next, whose computational view is similar to the convolution layer with the exception that, depending on the application, we only take the average or maximum value from the output. This saves minute details in a few pixels that are essential to completing the task. The final layer is fully connected, using rigidly layers to lower the image's size and relinks each individual sub-image in order to determine connections and do classification.

3.2 Recurrent neural networks (RNN)

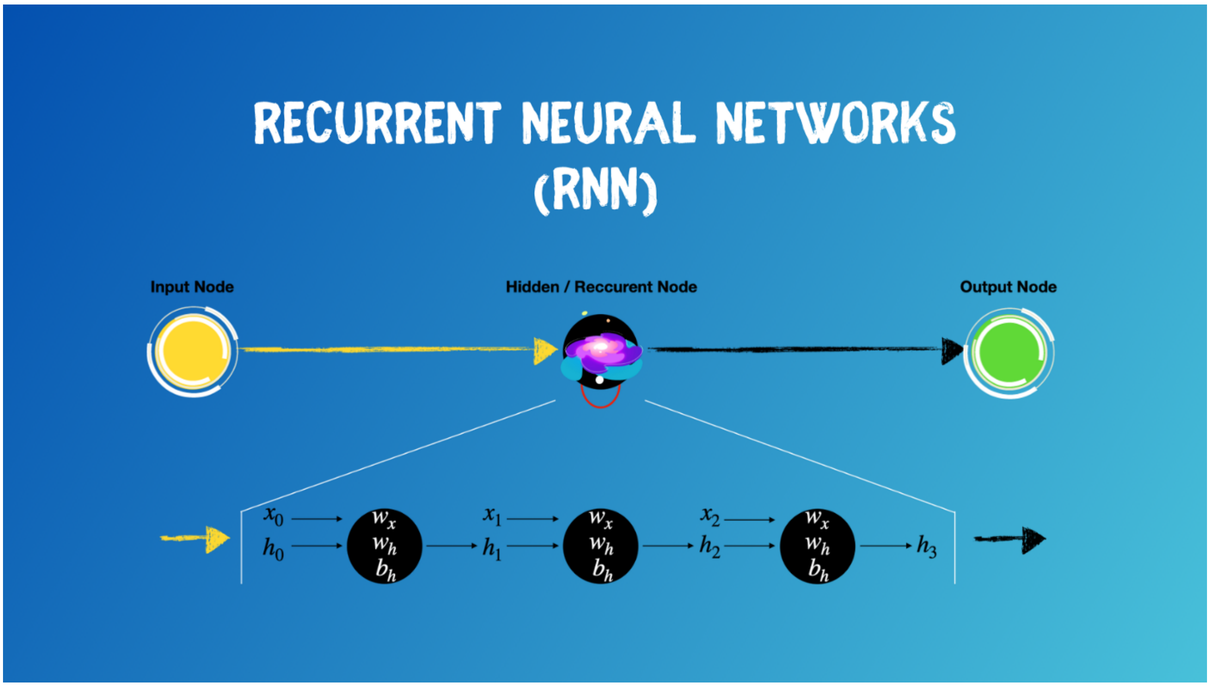


Figure 3: RNN architecture
rnn (n.d.)

Recurrent neural networks (RNNs) are a particular kind of artificial neural network that are used to process time series data or data that contains sequences. Only data points that are unrelated to one another should be used with feedforward neural networks. But if the data is organized in a way that each data point depends on the one before it, change the neural network to take these dependencies into account. In order to construct the subsequent output of the sequence, RNNs contain the idea of "memory" that enables them to store the states or information of prior inputs. In this scenario, combining CNNs and RNNs enables us to work with images and word sequences.

3.3 Transfer Learning

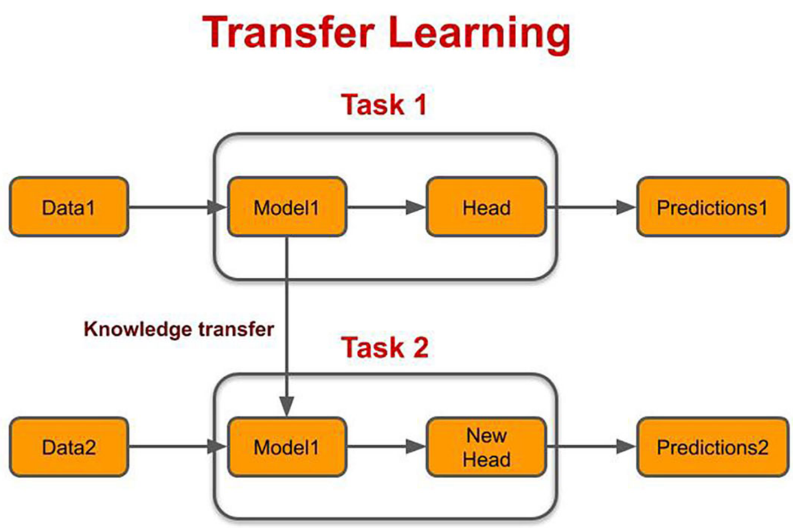


Figure 4: Transfer Learning
tl (n.d.)

A model created for one task is used as the basis for another using the machine learning technique known as transfer learning. Pre-trained models are used as the foundation for developing neural network models for computer vision and natural language processing tasks, which are essential for deep learning in these domains. It is one of the prominent approaches in deep learning. Pre-trained models are stored networks that have previously undergone training on a big dataset, generally for a large image-classification task. Use the pretrained model as is or use transfer learning to tailor it to a specific task. Transfer learning model VGG16, a deep neural network model, was employed. This architecture has 16 layers total, including three dense layers, 5 max pooling layers, and 13 convolutional layers.

4 Design and Implementation Specification

Examining the area of interest extraction includes separating the images into distinct blocks and extracting only significant characteristics from them, primarily from the hippocampus region of the brain. Deep learning metrics are then applied a second time to recognize visual patterns in CNN, which enables areas of brain scans to be removed and then classified as belonging to a normal or Alzheimer's brain. Transfer learning, on the other hand, includes classifying images based on characteristics gathered from the VGG architecture. The dataset is originally the most crucial component of the study. The prediction dataset is an open-source dataset that is accessible through *Kaggle* (n.d.)

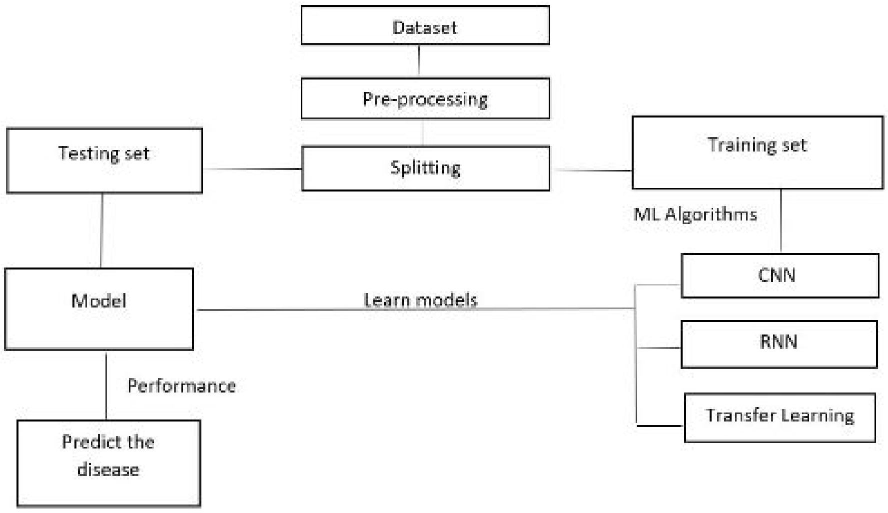


Figure 5: Block diagram of the system

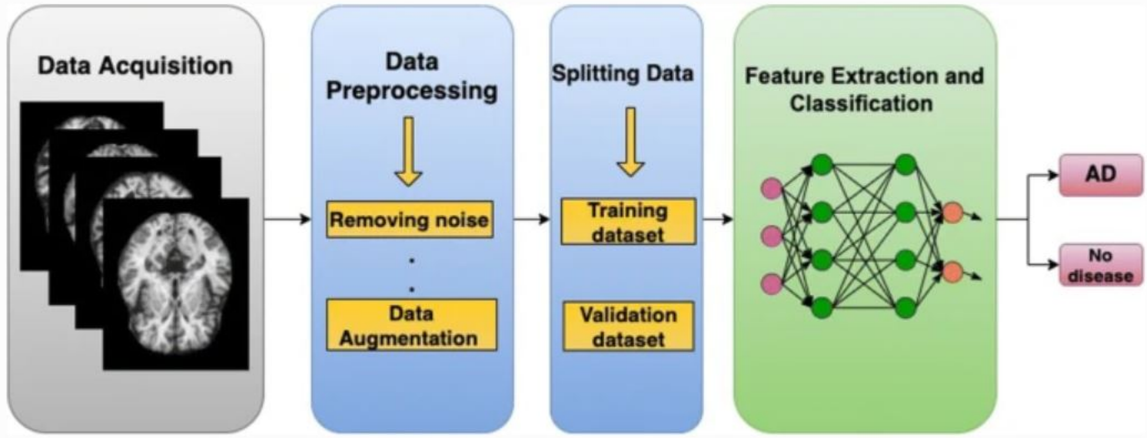
In this dataset, which includes train and test data, I selected the train, test, and validation data. The classification process, which splits the various objects into several classes based on a number of classification criteria, is the most important step in this system. This scenario has two subjects (normal brains and brains with AD). After the blocks have been obtained, the classification stage will be completed in order to do the evaluation using one of three classification methods: CNN, RNN, or Transfer Learning.

A training set and a testing set are created from the preprocessed dataset. This preprocessing includes scaling, edge smoothing, segmentation, and the removal of any unwanted noises. We'll use the training set to test the suggested algorithms, which include RNN, CNN, and transfer learning techniques. In a CNN model with a 19-level architecture, I utilize Convolution layers. Due to VGG's deep network optimization, Resnet was outperformed by it. Deep neural network model VGG16, a transfer learning model, was used. There are thirteen convolutional layers, five max pooling layers, three dense layers, and a total of 16 layers in this design. A CNN-RNN model, which combines CNN and RNN approaches, was the most recent model I ran on my image data. After our investigation, a better accuracy performance from this model was wanted.The data contains Magnetic resonance imaging (MRI) images. It has 4 different classes of images both in training as well as testing datasets. The classes as follows:Mild Demented,Moderate Demented,Non-Demented,Very Mild Demented. I used python programming language to carry out my project analysis.

4.1 Image Acquisition

The initial stage of image processing is image acquisition. In image processing, this stage is often referred to as preprocessing. The image must be retrieved from a source and the data was collected from kaggle.com. The data contained train and test datasets. Through Python libraries, images are imported and loaded. The libraries used to complete this work are Pillow — Image.open, Matplotlib — plt.imread(), and OpenCV — cv2.imread() () Io.imread from Scikit-Image ().

Fig. 3



The Process of Diagnosis Alzheimer Disease

Figure 6: AD Diagnosis process
ad (n.d.)

4.2 Analyze and manipulate image

Before dividing the dataset and plotting the images according to the labels, redefining the image's size, defining hyperparameters, setting global variables to pull images for analysis, and trying to visualize the images before converting them into arrays and normalizing the color values are all examples of pre-processing. Adding to an image will increase the dataset. I completed this task using the Keras library. It has an imagedatagenerator class that has some characteristics that makes it possible to carry out this activity. Preparing the dataset for training involves dividing the data into a test and training set. This work entails labeling pathways, resizing photos, setting hyperparameters for training, and more.

The following step involves importing and visualizing the inception model. Here, created a training data array with categories and picture pixel values. additionally, used varied epoch and batch settings to train the model and increased batch and epoch values to test for more accuracy. When my model was given different epoch and batch size parameters, there was a noticeable change.

4.3 Generating output

In a CNN model with a 19-level architecture, I used Convolution layers. Due to VGG's deep network optimization, Resnet was outperformed by it. The library that primarily supports VGG architecture is called Keras. A particular form of input preprocessing is anticipated by each Keras Application. Before providing inputs to the model for VGG19, call tf.keras.applications.vgg19.preprocess input on them. The input images are first converted from RGB to BGR using the function vgg19.preprocess input, after which each color channel is zero-centered without scaling with respect to the ImageNet dataset. The CNN model produced an accuracy of 93 percent using the parameters epoch = 500 and batch = 64. This model has an F1 score of 0.93, meaning it has few false negatives and few false positives.

A Transfer learning (TL) model was performed using a CNN model that had already been divided and preprocessed. Prefetch datasets are created for better performance, images are resized to fit models, base model vgg16 is imported and loaded, and variables for the classifier and output layer are defined. Due to VGG's deep network optimization, Resnet was outperformed by it. Deep neural network model VGG16, a transfer learning model, was used.There are thirteen convolutional layers, five max pooling layers, three dense layers, and a total of 16 layers in this design. Importing all the libraries I'll need to create VGG16 is the first important step in performing my analysis. I have employed the sequential technique because I'm building a sequential model, which calls for the sequencing of the model's layers. My transfer learning model underwent fine-tuning, which includes unfreezing the previously learned model and retraining it in order to enhance the model's performance.

ImageDataGenerator was imported from keras.preprocessing. Easily importing data with labels into the model is the aim of ImageDataGenerator. It is a very helpful class because it offers numerous functions to resize, rotate, zoom, flip, and other things.subsequently make an ImageDataGenerator object for both training and test data while giving the folder containing the training data. All of the data in the folder will be automatically labeled by the ImageDataGenerator. following begins with initializing the model and indicating that it is a sequential model. I transmit the input to the dense layer after completing all the convolutions, and to do that, I flatten and add the vector that results from the convolutions. According to the model's confidence, the softmax layer will output a value between 0 and 1. Additionally, with the establishment of the softmax layer, the model is complete. thereafter model is compiled. lastly, examining the model's summary.

5 Evaluation

The evaluation of any deep learning model's performance is the most crucial step in model construction. Different evaluation metrics are associated with classification and regression tasks in machine learning, respectively. Precision-recall metrics, for example, are helpful for a variety of jobs. Before deploying our model in production on untried data, we should be able to increase its overall predictive power. Classification and regression are two instances of supervised learning, which makes up the majority of machine learning applications.

When a deep learning model is applied to unexplored data, fails to evaluate it using a variety of assessment measures and relying simply on accuracy can result in inaccurate predictions.The effectiveness of classification can be evaluated in numerous ways. The most used measurements include accuracy, confusion matrix, log-loss, and AUC-ROC. One popular statistic for categorization issues is precision-recall.

5.1 Accuracy

The probability that the classifier predicts properly is how accuracy is calculated. The ratio of the number of accurate predictions to all predictions can be used to define accuracy.

5.2 Confusion matrix

A performance measure for deep learning classification issues when the output can be two or more classes is the confusion matrix. There are combinations of projected and actual values in the table.

5.3 Precision

How many of the cases that were predicted accurately yet ultimately proved to be positive may be explained by precision. When false positives are more significant than false negatives, precision is helpful

5.4 Recall

Recall details the proportion of real positive cases that our model was able to properly anticipate. When False Negative is more significant than False Positive, it is a valuable metric.

Images are classified using the 19-layer VGG architecture and the CNN model. VGG outperformed Resnet because it is designed for deep networks. Deep neural network model VGG16, a transfer learning model, was used. Convolutional neural networks and transfer learning are the two algorithms whose performance is assessed using the evaluation metrics listed above in this section. Details about the performance of our method are provided in the classification report of our model. The below shown classification describes the classification report of the CNN Model with VGG19 architecture.

	precision	recall	f1-score	support
0	0.90	0.95	0.93	40
1	0.95	0.90	0.92	40
accuracy			0.93	80
macro avg	0.93	0.93	0.92	80
weighted avg	0.93	0.93	0.92	80

Figure 7: Classification report of the model.

This model's accuracy was 0.93, which indicates that it performs well. This model has an F1 score of 0.93, meaning it has false negatives and few false positives. The recall value, which ranges from 0.0 to 1.0, indicates the proportion of positive samples that the model correctly identified as positive. Here, this model's recall value is 0.95. A model with a precision of 1.0 produces no false positives. My model has a precision of 0.9, meaning that it correctly predicts if a disease is demented or not 90 percent of the time. A conclusion that can be drawn from looking at our model's classification report and analyzing its metrics is that my model performed better with VGG19 CNN architecture. The classifier's performance is measured by the values between 0.1 and that is Greater values indicate greater model accuracy. Here, the values range from 0.8 to 1.0, indicating

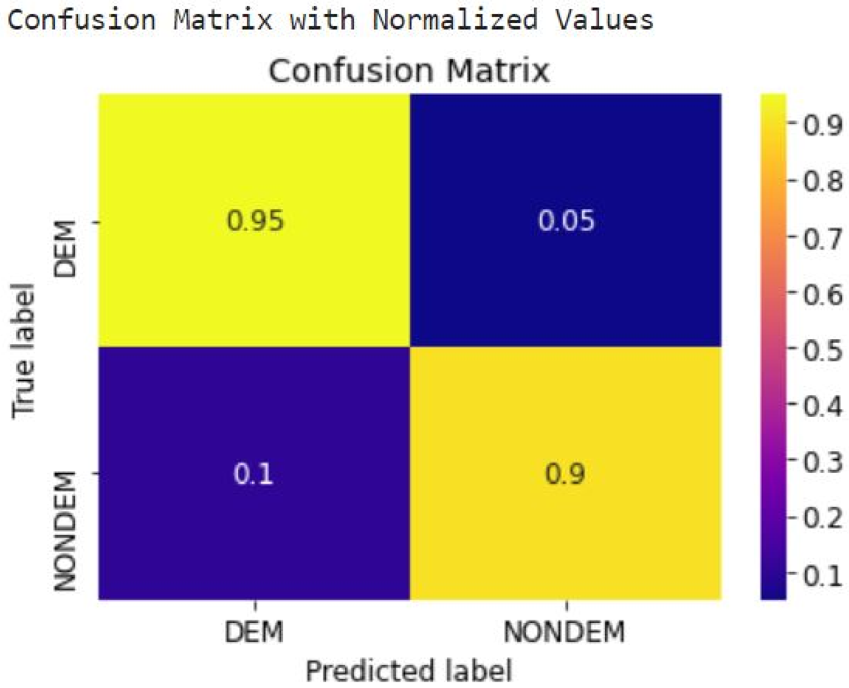


Figure 8: Confusion matrix without normalization.

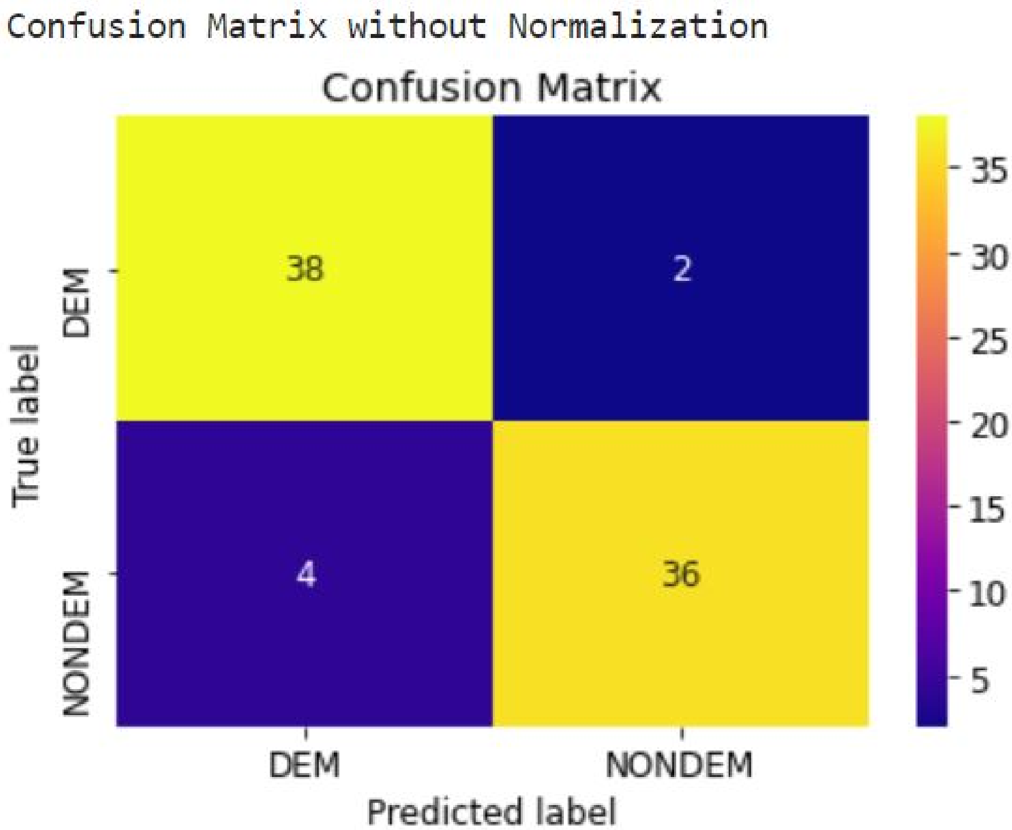


Figure 9: Confusion matrix with normalized values.

a greater threshold and lower classification error. The model is assessed using test data and yields an accuracy of 0.98 and a loss of 0.03 for the transfer learning model created

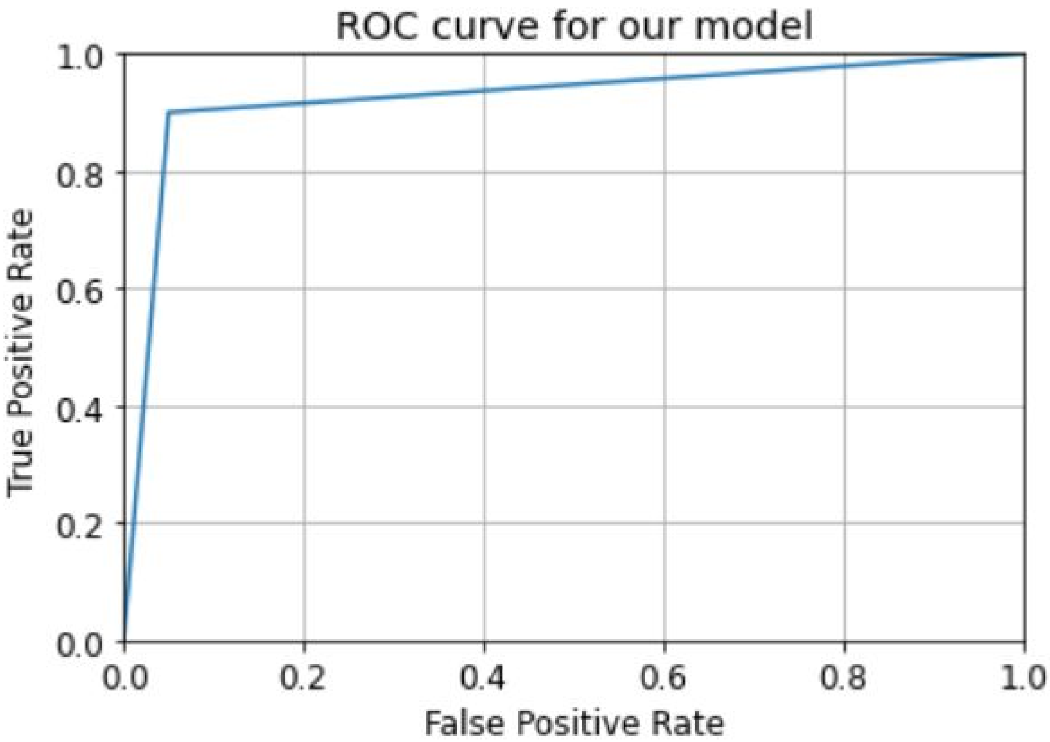


Figure 10: CNN model's ROC curve.

```
model.evaluate(test_data)

-----------------------------------After Fine-tuning model.........................................
64/64 [==============================] - 71s 1s/step - loss: 0.0220 - accuracy: 0.9906

[0.022034764289855957, 0.9906250238418579]
```

Figure 11: Evaluated TL Model after fine tuning

using the vgg16 architecture. The model accuracy in this case is high with a little loss value. A high accuracy with little loss indicates that you had few errors overall. In my case, the first training used 50 as epochs value, and another model was verified using an epoch of 5.

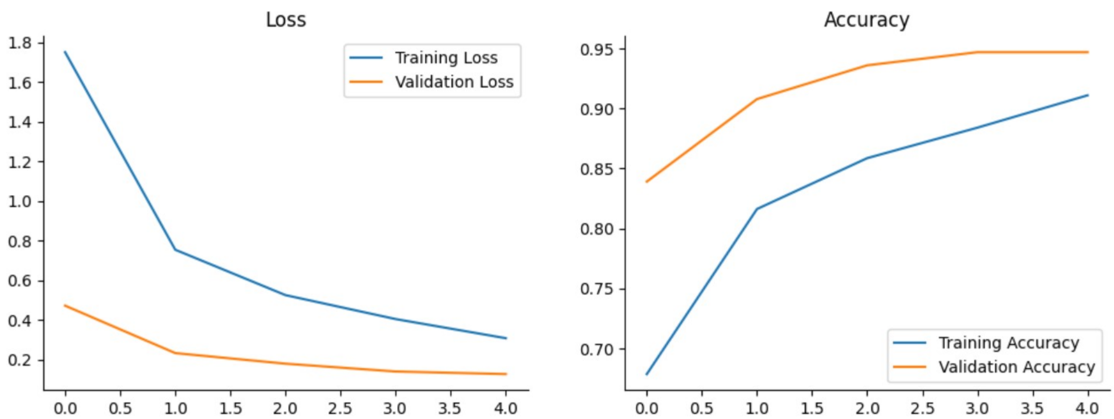


Figure 12: Transfer learning model loss/ Accuracy

6 Conclusion

Deep learning algorithms have taken the place of machine learning algorithms to improve prediction model accuracy. Deep learning algorithms work better with feature selection and extraction approaches. Image processing is important for determining identifying the various disease phases in the patients. Deep learning algorithms are used to do image processing on magnetic resonance imaging data in order to identify disease. Image processing is performed using magnetic resonance data. By adjusting several parameters for the detection, an imaging system may identify Alzheimer's disease using a algorithm.

Deep learning algorithms are used to do image processing on magnetic resonance imaging data in order to classify the disease. To identify Alzheimer's disease, I conducted a comparative analysis using various deep learning approaches, such as CNN, RNN, and transfer learning. This study focuses on the performance of various deep learning techniques individually using magnetic resonance data. It is simple to differentiate between the performance of various algorithm assessments on magnetic resonance data and how they differ from one another. The model's training with a higher epoch value required a lot of time, which was one of the main challenges to determine whether altering the hyperparameters during analysis had a significant influence or not. Data collecting was a challenging task during my analysis.

The performance of various deep learning algorithms to classify the stages of Alzheimer's disease is highlighted in this research. Deep learning techniques employed in this investigation include Convolutional neural networks(CNN) , Transfer learning (TL) and Recurrent neural networks (RNN). CNN's VGG19 architecture was used to conduct AD classification. An accuracy of 0.93 percentage was obtained from identifying the images using the CNN model, although 0.98 accuracy was shown by the transfer learning model with VGG16 architecture.

RNN classification was also performed on this dataset, and an RNN- CNN architecture was attempted to build an RNN model. RNN and CNN were combined in this model.However, the intended model was not provided by the model's implementation. While building the model, some of the methods weren't satisfactory. Using the evaluation measures provided in the evaluation section, the performance of each algorithm was assessed. My analysis raised two research problems, including how to increase accuracy and other crucial metrics for the classification and future prediction of AD, as well as how to limit over-fitting in building the model. In order to overcome overfitting, data augmentation techniques were used during analysis To avoid overfitting during the analysis, more data may be used for training in the future. Additionally, regularization techniques may be applied by modifying the original data's large weights.

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