IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 10, Issue 6, June 2022

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.165

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |

|| Volume 10, Issue 6, June 2022 ||

| DOI: 10.15680/IJIRCCE.2022.1006101 |

Dementia Prediction using Dense Net169 Model

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ABSTRACT: Dementia is a progressive disease and it is the most prevalent neurodegenerative disorder. It is believed that the people with mild cognitive impairment are at high risk of developing this disease. According to the annual report released by the Alzheimer's Association R 2020, Dementia is the sixth leading cause of death in the United States and little bit in some other countries too. Thus, there is a need of educating people about this disease, reducing the risks by militating the necessary precautions to disseminate its affect by diagnosing it at early stages. It is also important to propose some recent advancement in this research which can help in early prediction of the disease using machine learning techniques. This paper work intends to develop the novel algorithm by proposing changes in the designing of capsule network for best prediction results and making the model computationally efficient. The research is conducted on the image dataset from Kaggle to diagnose the labels for four classes, as Non- demented, Moderate Demented, Mild Demented and Very Mild Demented. The novelty lies in conducting the in-depth research in identifying the importance of features, correlation study between factors and density of data showing status of factors by studying hierarchical examination of all the data points available using exploratory data analysis. Several optimization functions are conducted on the variables and feature selection is done to make the model faster and more accurate. The claims have been validated by showing the correlation accuracy at several iterations and layers with an admissible accuracy by using Deep Learning Algorithm. The dementia prediction will happen for all the four classes: Non- demented, Moderate Demented, Mild Demented and Very Mild Demented with their accuracy values which lies different for different Images.

I. INTRODUCTION

Dementia is a devastating illness which results gradual loss of memory and some other cognitive abilities which we can mostly identified in people more than 60 age groups. Alzheimer is a progressive disease which can destroy memory and other important functions of Brain. In this disease, Brain cell connections and the cells themselves degenerate and die, and also destroying memory and some other important mental functions like memory loss and so on. A Dementia diagnosed person cab live only for four to eight years only but, there are some people who live for twenty years as well because it completely depends on different factors. Various biological and neuropsychological studies discover that it can be predicted at its early stage and useful to take treatment in a proper direction. It actually starts from a specific region like subcortical and then increases to the cortical mantle which results in most common effect which is memory loss and it also slows down the ability to do any task. In most of the researches shows that MCI, a highly heterogeneous phenotypic spectrum, has very less considerable memory deficits thanAlzheimer / dementia disease and these MCI may convert to dementia because some of the studies shows that it was discovered that 10%-15% MCI patients converted to dementia within a short passage of time. Therefore, MCI needs to be taken care with special attention in order to stabilize the chance of this disease. In a research is given that"The development of dementia can be predicted several years before which are helpful in controlling the progress of this. Biomarkers, magnetic resonance imaging (MRI), genetic data, cerebrospinal fluid, Positron emission tomography (PET) have attracted interest in identifying the early symptoms of dementia. MRIs do not involve ionizing radiation and are economical than PET and minimal invasive than cerebrospinal fluid (CSF). MRI provides multi-mode information for the brain's structure and function. MRI works successfully in distinguishing healthy people with AD survivors. MRI results can identify the sMCI (stable MCI) and pMCI (progressive MCI). These clinical and neuroimaging data have been used to extract feature information voxels, classify different groups and use it with several cognitive measures to produce various predictions, obtaining an area under Receiver operating characteristics (ROC) and authentication curve (AUC). Neuroimaging techniques are progressing very fast that makes it difficult to integrate large scale high dimensional multimodal neuro-imaging data. Thus, computer aided

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machine learning approaches are adopted for integrative analysis. Linear discriminant analysis (LDA), linear program boosting method (LPBM), logistic regression (LR), recursive feature elimination has been used for early detection of disease. For any machine learning approach, architectural design and pre-processing steps should be predefined. For classification, the most popular four ways are feature extraction, feature selection, dimensionality reduction and feature based classification algorithm selection. Multiple optimization stages are required." In this paper, we will do analysis by using convolutional neural network, DenseNet169 for the classification and prediction of four different classes of Dementia: Non-Demented, Moderate Demented, Mild Demented, Very Mild Demented. We will use dataset for the training and validation of the different images. The dataset description will discuss in further section. By using the dataset as images for different classes, we will do prediction based on the different classification that how much that particular type of dementia belongs to that type which will help to analyse the type of data very easily and efficiently. The dataset we have taken all are in the form of images as .jpg. In the dataset, there are two types of data as Train dataset and Test dataset. In each type, there are more classes, in which the type of dementia images are separated and those different classes are: Non- demented, Moderate demented, Mild demented and Very mild demented. The main objective of doing this paper is that it will do the fast analysis of the demented structure and will analyse the accurate results which will help to analyse the proper class of dementia in a person and helps to cure that. By increasing the number of epochs of DenseNet model will increase the accuracy to getting the type of dementia and also decreases the model loss.

II. METHODOLOGY

DenseNet169 Deep learning convolutional Model is mainly used for the classification. It contains different layers which performs particular operation like Normalization, Activation and Dropout and passes it through particular dense Block and classify the given input MRI image.

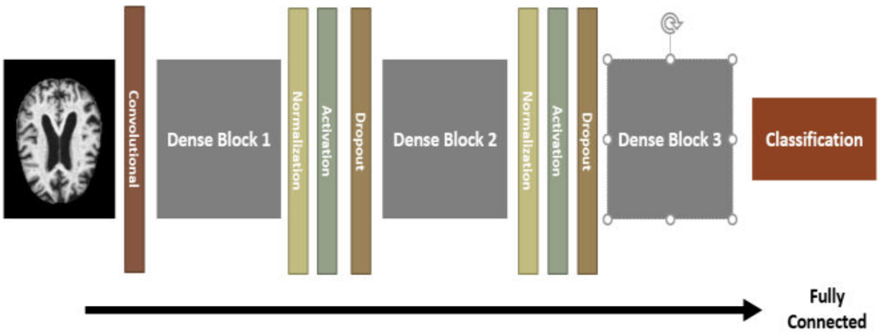

Fig 1: DenseNet169 Model

In this paper, we are working with DenseNet169 Model, which is one of the best models for doing classifications and such processes. So, here we are using the basic methodology for doing such implementation and it is shown as under figure.

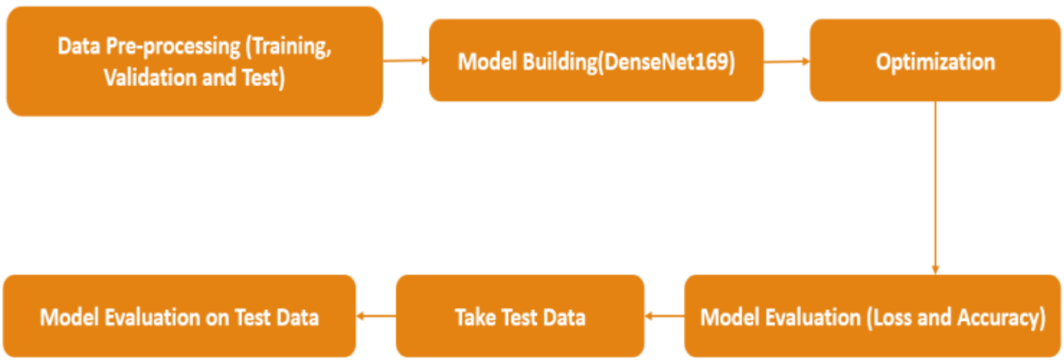

Fig 2: Methodology

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First we need to apply the basic step which is data pre-processing in which we can do some normalization as well as we are applying this pre-processing step for training, test and validation data. After normalizing the images, we will start with model building method and here we are using DenseNet169 Model. After applying all the layers to it we can go for the next step which is optimization and then do the model evaluation by checking the loss and accuracy for the training data. At last, we will apply this model evaluation for Test data through which we can easily analyse the image belongs to which particular demented type.

III. IMPLEMENTATION

The main objective of this paper to predict the different types of dementia on different images with the help of DenseNet deep learning model where we created this model by using some layers and used for the classification for different classes of dementia. In this paper, we have four different classes of dementia: Non-demented, Moderate demented, Mild demented and very mild demented. In this paper we have used some libraries for the implementation of the model and for some other requirements and this is shown in below figure,

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import skimage.io
import os
import tqdm
import glob
import tensorflow

from tqdm import tqdm
from sklearn.utils import shuffle
from sklearn.model_selection import train_test_split

from skimage.io import imread, imshow
from skimage.transform import resize
from skimage.color import grey2rgb

from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import InputLayer, BatchNormalization, Dropout, Flatten, Dense, Activation, MaxPool2D, Conv2D
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
from tensorflow.keras.applications.densenet import DenseNet169
from tensorflow.keras.preprocessing.image import load_img, img_to_array
```

Fig3: Required Libraries

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```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
densenet169 (Functional)     (None, 7, 7, 1664)        12642880
_________________________________________________________________
dropout (Dropout)            (None, 7, 7, 1664)        0
_________________________________________________________________
flatten (Flatten)            (None, 81536)             0
_________________________________________________________________
batch_normalization (BatchNo (None, 81536)             326144
_________________________________________________________________
dense (Dense)                (None, 2048)              166987776
_________________________________________________________________
batch_normalization_1 (Batch (None, 2048)              8192
_________________________________________________________________
activation (Activation)      (None, 2048)              0
_________________________________________________________________
dropout_1 (Dropout)          (None, 2048)              0
_________________________________________________________________
dense_1 (Dense)              (None, 1024)              2098176
_________________________________________________________________
batch_normalization_2 (Batch (None, 1024)              4096
_________________________________________________________________
activation_1 (Activation)    (None, 1024)              0
_________________________________________________________________
dropout_2 (Dropout)          (None, 1024)              0
_________________________________________________________________
dense_2 (Dense)              (None, 4)                 4100
=================================================================
Total params: 182,071,364
Trainable params: 169,259,268
Non-trainable params: 12,812,096
```

Fig 4: Model Summary

In this, we will compile the model by using Tensor Flowkeras Adam optimizer and after this we will define the call-backs for the model like early stopping. After completion of these, we will fit the model with some number of epochs and by using some value for call-back for the model. As the number of epochs increases, the accuracy for detection will increase and the loss will decrease.

Now, we will summarize the loss for the model by using plot library for the model for loss and accuracy with respect to the number of epochs. As we increase the number of epochs, the value for loss decreases and the percentage for accuracy increases. The complete description of this step is discussed under result and discussion section with proper output in plot representation. After this, we will give an image as input and then we will detect the image belongs to which class of dementia with its proper accuracy.

IV. RESULTS

In this section we will discuss about some results that we got after implementing the model for the classification. We will summarize the loss for the model by using plot library for the model for loss and accuracy with respect to the number of epochs. Which comes under model evaluation step.

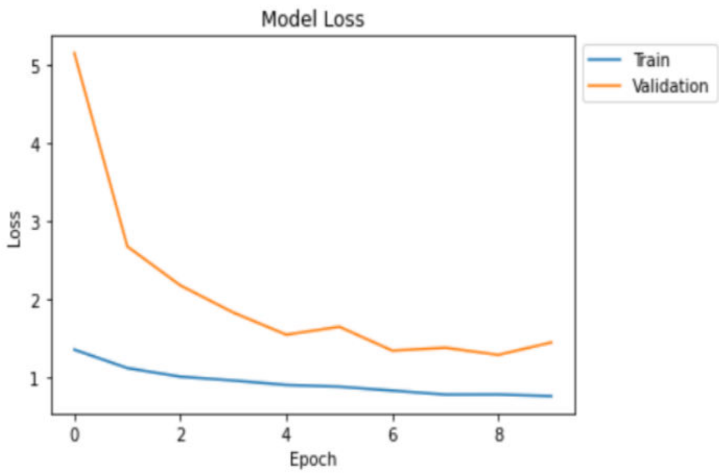

Fig 5: Model Loss Summary

The model loss summary, where we can see that the plot is in between the Loss and the Epochs. As we increase the number of epochs the loss decreases. The blue line is the representation of training dataset and orange line is the

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representation of validation dataset. The number loss is decrease for the detection of dementia when we increase the number of epochs.

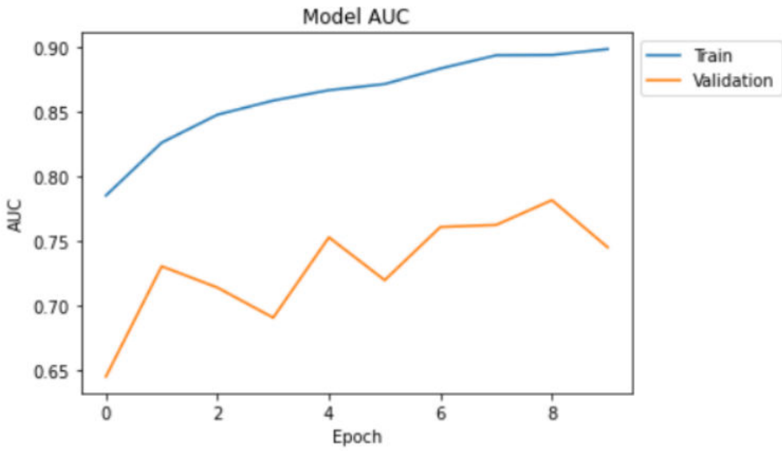

Fig 6: Model Accuracy Summary

In the above figure, we can see that it is completely vice versa with the figure 11. Here we can see that the training dataset is represented with blue line and validation dataset is represented by orange line. Here, we can notice that as the number of epochs is increasing, the accuracy is also increasing. After the completion of training on train dataset, we will move for the next steps of doing testing on test dataset. First, we will evaluate the same for the test data in terms of accuracy and loss with respect to the number of epochs and then we will get the output.

```
10/10 [==============================] - 101s 10s/step - loss: 1.2599 - auc: 0.8381

[1.2599031925201416, 0.8380681872367859]
```

Fig 7: Epoch Value

As we have taken only 10 epochs then it is showing that the decrement in loss for 10 number of epochs is 1.26 and the increment in accuracy for 10 number is around 84%. If we will the increase the number of epochs then we will get more accuracy and very less loss (may be 0). The below figure is the output after giving an image as input and test model will detect the image that with how much accuracy this image belongs to the particular class of dementia among four classes.

```
88.12 % chances are there that the image is ModerateDemented
```

Fig 8: Moderate Demented Image

As we can see that, the output is given as 88.12 % chances that this given image is belongs to mild demented class among four classes of dementia. For now, we did this analysis by using only 10 epochs, but if we will use a greater number of epochs then the output will come with more accuracy for an image and give accuracy of which class it should belong to.

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99.85 % chances are there that the image is NonDemented

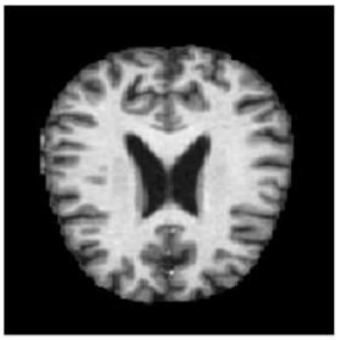

Fig 9: Non-Demented Image

As we can see in the result section, the output is given as 99.85 % chances that this given image is belongs to mild demented class among four classes of dementia, which is a good percentage which shows that this percent it detects the class of dementia. For now, we did this analysis by using only 10 epochs, but if we will use a greater number of epochs then the output will come with more accuracy for an image and give accuracy of which class it should belong to.

V. CONCLUSION

In this paper, we are analysing that the performance of DenseNet169 model (CNN) for the classification of four different classes of dementia: Moderated Dementia, non-dementia, Mild dementia and very mild dementia. The proposed method is using the Deep Learning Model: DenseNet169 transfer training Algorithm for the prediction of Dementia for four classes and we analysed the Dementia image category with its accuracy in percentage value. This implementation is giving us the 99.9% accuracy for detecting the dementia with this deep learning model just need to increase the number of epochs and then we will take it as use for the prediction of the dementia which actually belongs to the different classes: Moderated Dementia, Non-dementia, Mild dementia and very mild dementia. The main objective of doing this paper is that it will do the fast analysis of the demented structure and will analyse the accurate results which will help to analyse the proper class of dementia in a person and helps to cure that. By increasing the number of epochs of DenseNet model will increase the accuracy to getting the type of dementia and also decreases the model loss. In the same way, we can apply more number of epochs to get the high accuracy for the prediction of dementia. As we increase the number of epochs, the loss decreases and accuracy increases.

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|| Volume 10, Issue 6, June 2022 ||

| DOI: 10.15680/IJIRCCE.2022.1006101 |

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