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A Framework for the Diagnosis and Classification of Alzheimer's Disease Using Deep Convolutional Neural Network

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Abstract- *The disease most frequently associated with dementia is Alzheimer's. It's a disease that worsens over time, starting with modest memory loss and potentially progressing to the inability to have a conversation or react to your surroundings. Certain regions of the brain responsible for cognition, memory, and language are affected by Alzheimer's disease. This paper uses a biomedical image as a dataset in building a smart system for the diagnosis of Alzheimer's disease. The biomedical image used here is that of Alzheimer's disease. The dataset consists of about six thousand three hundred and twenty-three images (6323) images. Feature engineering was applied to the dataset in selecting relevant/important features from the dataset, and also making use of the hot_label_encoder function in labeling the dataset into the categories which they fall under. After this process, we made use of a pre-trained weight by means of transfer learning. This was done in other to have better training data. The parameters used in fine-tuning the pre-trained weight are dropout=0.2, loss= loss='categorical_crossentropy, optimizer=Adadelta, number of classes=4, batch_size=32, epoch=50. The new model was trained on 50 training steps. After training, the model was evaluated in terms of model accuracy and model loss. The evaluated result of the proposed model shows that the model had an accuracy result of about 99.99%. This shows that the model is in a good performance.*

Keywords- *Alzheimer disease, Convolutional Neural Network, Diagnosis, Python Flask*

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I. Introduction

As the world's population ages, so does the number of people diagnosed with dementia. Recent estimates place the number of people affected by dementia at 50 million [1], with 60–70% having Alzheimer's disease (AD) [2]. Alzheimer's disease, one of the most prevalent neurodegenerative disorders, is associated with significant cognitive decline and behavioural problems. Among the most well-known forms of dementia affecting people aged 65 and up, Alzheimer's disease causes a gradual decline in cognitive abilities until everyday tasks become extremely challenging [3]. The subtle progression of disease makes patients increasingly reliant on their loved ones. Forecasts suggest that by 2050, one in every 85 people will be affected and that this proportion will double over the next two decades [4]. "1. Dense layers of protein deposited outside and between the nerve cells," and "2. Abnormally high levels of amyloid beta" are two of the most frequently reported abnormalities in the brains of patients with Alzheimer's disease. Secondly, tangled areas of damaged nerve fibres inside the nerve cells. In addition, these plaques and tangles have been utilised in the diagnosis of Alzheimer's disease [5].

Wide ranges of explorations in view of social medicine, epidemiology, and molecular medicine have been carried out and most hold the view that Alzheimer's Disease is caused by multi-dimensional factors related to physiology, psychology and sociology [6]. The ways of screening for a patient with Alzheimer's Disease rely heavily on clinical manifestations and neuropsychological scales including Mini-mental State Examination (MMSE), Montreal Cognitive Assessment (MoCA), Activities of Daily Living (ADL), and Global Decline Scale (GDS). These approaches are practicable for patients with advanced Alzheimer's Disease, whereas early detection will be key to preventing, slowing and stopping Alzheimer's disease. Therefore, experts and scholars around the world have made active exploration in predicting Alzheimer's Disease, concentrating on risk factors and biomarkers. The accumulation of the protein beta-amyloid outside neurons and an abnormal form of the protein tau inside neurons are two of several changes believed to contribute to the development of Alzheimer's Disease [7].

Patients with Alzheimer's disease have some symptoms, such as mood and personality changes, loss of mental functions and memory, and difficulty in performing daily activities, routine tasks, reading, writing,

speaking, and understanding what people are talking. There are three major stages (very mild, mild, and moderate) of the disease [8]. The treatments have the most impact at the early stage. Therefore, early diagnosis has a vital role in patient care and future treatment to delay its progression. Abnormalities in the amygdala and hippocampal regions give important information to diagnose Alzheimer's disease. These abnormalities can be seen in images obtained by different imaging techniques, which are usually Magnetic Resonance (MR)- based imaging, Diffusion Tensor based Imaging (DTI), and also Positron Emission Tomography [9].

II. Literature Review

[10] used a fully convolutional network and multilayer perception for the diagnosis ofAlzheimer's and categorising cases. The MR scans of people's brains come from a database available online.From their results, the DenseNet-121 model achieves a very respectable average performance rate of 88.78% when compared to the other models discussed. However, the DenseNet model is computationally slower than many of the other models discussed because it employs so many convolutional operations. One common technique for improving the efficiency of a convolutional operation is called "depth-wise convolution." Therefore, the authors replaced the convolution layers in the first DenseNet-121 architecture with depth-wise convolution layers to speed up the execution time. Furthermore, the model's performance was enhanced by the new architecture by an average of 90.22%

[11] used a convolutional neural network (CNN) layer with an architecture similar to Alexnet with some parametric changes in extracting features. Thirteen (13) manually extracted features based on a grey-level co-occurrence matrix were also utilised to evaluate the effect of these features on ranking. Misclassification can be avoided by utilising a feature selection tool in conjunction with feature ranking algorithms (e.g., Mutinffs, ReliefF, Laplacian, UDFS, etc.) and by putting these algorithms and tools through their paces using a variety of machine-learning approaches (e.g., Support Vector Machine, K-Nearest Neighbor, and Subspace Ensemble) and test conditions. With a 7:3 ratio of random holdout partition of training to testing image sets and also with fivefolds of cross-validation on the same set using a standardised template, the performance of the results is satisfactory, with classification accuracy around 98 percent to 99 percent.

[12] examined the retina, especially the retinal vasculature, as an alternative for conducting screens for dementia patients caused by Alzheimer's disease. Highly modular machine-learning approaches were applied across the full pipeline. Utilizing data from the UK Biobank, the pipeline obtained an average classification accuracy of 82.44%. Additionally to the excellent classification accuracy, they included a saliency analysis to improve the interpretability of this pipeline. The saliency study confirmed what other research has found, that small vessels within retinal pictures provide the most relevant information for identifying Alzheimer's disease.

[13] made a mathematical model for this classification task, they employ a CNN architecture, VGG-16, trained on the ImageNet dataset, and used as a feature extractor with the help of the transfer learning technique known as PFSECTL. The Alzheimer's Disease Neuroimaging Initiative (ADNI) data set is used for the experiments. The validation set accuracy of the described method for 3-way classification is 95.73%.

[14] propose a densely connected convolution neural network with a connection-wise attention mechanism to learn the multi-level features of brain MR images for AD classification, the authors. The proposed method correctly identified 97.35% of AD patients versus healthy controls, 87.82% of MCI converters versus healthy controls, and 75.79% of MCI converters versus non-converters. Their proposed algorithm has improved upon the classification performance of some neural networks and methods reported in recent studies, placing it among the top ranks in distinguishing MCI subjects who are at high risk of conversion to AD.

[15] applied the 3-dimensional (3D) gray-level co-occurrence (GLCM) method to evaluate the textural features of the image, and used Fisher's coefficient to select the appropriate features for classification. In the last stage, they implemented a deep learning multi-layer perceptron (MLP) model, which they divided into three types, namely, AD-MCI, AD-NC, and MCI-NC. The classification accuracy of the proposed deep learning model was confirmed in the cases of AD-MCI (72.5%), ADNC (85%), and MCI-NC (75%). They also evaluated the results obtained using a confusion matrix, support vector machine (SVM), and K-nearest neighbor (KNN) classifier and analyzed the results to objectively verify their model. They obtained the highest accuracy of 85% in the AD-NC.

[16] made use of 1820 T2-weighted brain MRI volumes, including 18,017 voxels from 635 AD MRIs, 548 MCI MRIs, and 637 CN MRIs. They presented a method to use CNN model for the categorization of brain voxels in order to isolate grey matter. After applying a Gaussian filter, the voxels are employed in a skull stripping technique, which removes any unnecessary tissues. In the next step, hybrid improved independent component analysis is used to divide the voxels into smaller groups. The CNN takes grey matter segments as its input. Using their proposed method, they conducted a clinical valuation, and they were able to acquire an accuracy of 90.47%, a recall of 86.66%, and a precision of 92.59%.

III. Materials and Methods

The architectural design comprises different components. The components show the different interactions and processes that are carried out in the proposed system for the diagnosis of Alzheimer's disease. A detailed interaction of the architectural design of the proposed system can be seen in Figure 1.

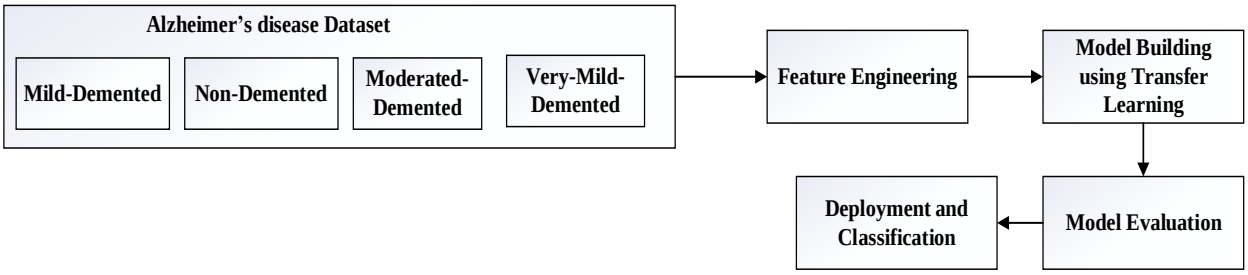

Figure 1 Architecture of the proposed system

Alzheimer Disease Dataset: The Alzheimer's disease dataset comprises six thousand three hundred and twenty-three (6,323)images. A sample of the dataset can be seen in figure 2. The images are of different categories of Alzheimer's disease. The categories of the dataset are:

1. **Mild-Demented:** In the mild dementia stage, people may experience: Memory loss from recent events. Individuals may have an especially hard time remembering newly learned information and ask the same question over and over. Difficulty with problem-solving, complex tasks, and sound judgments.
2. **Non-Demented:**These are categories of people that do not have Alzheimer's disease.
3. **Moderate-Demented:** During the moderate dementia stage of Alzheimer's disease, people grow more confused and forgetful and begin to need more help with daily activities and self-care.
4. **Very-Mild-Demented:** People will experience further mental decline as well as worsening physical capabilities once the disease progresses to the point of severe dementia. Severe dementia often can cause loss of memory, loss of physical capabilities, such as walking, sitting, and holding one's head up, and, eventually, the ability to swallow, control the bladder, and bowel function.

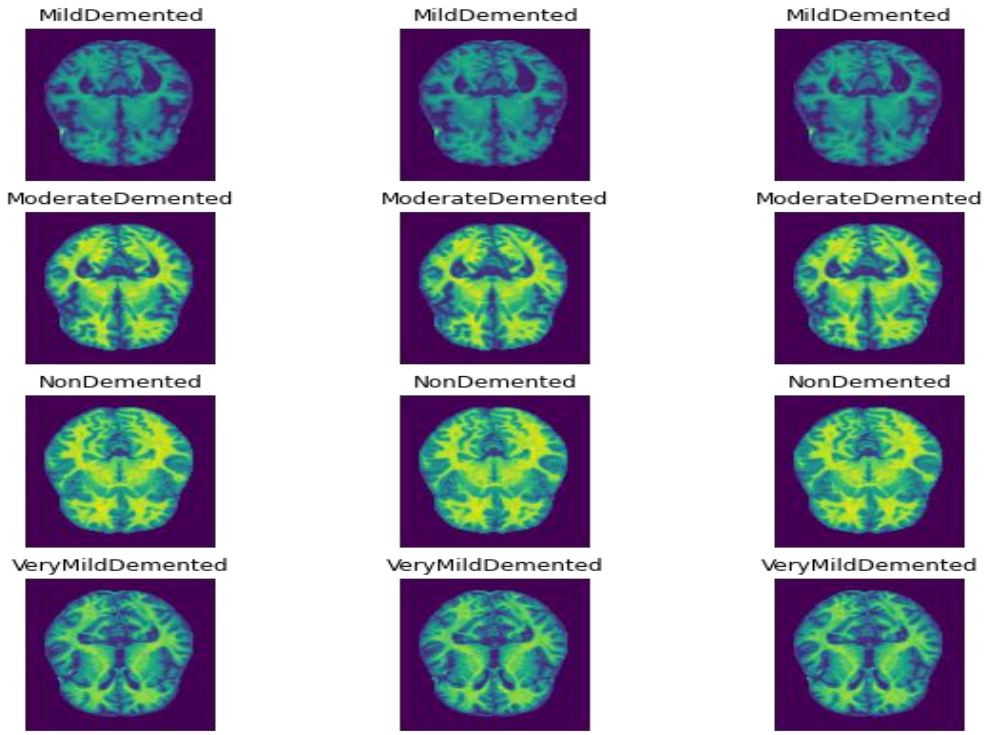

Figure 2 Alzheimer Disease Dataset

Feature Engineering: Feature Engineering encapsulates various data engineering techniques such as selecting relevant features, handling missing data, encoding the data, and normalizing it. It is one of the most crucial tasks and plays a major role in determining the outcome of a model.

Model Building with Transfer Learning: Fine-Tuning Convolutional Neural Networks for Biomedical Image Analysis: Actively and Incrementally. Intense interest in applying convolutional neural networks (CNNs) in biomedical image analysis is widespread, but its success is impeded by the lack of large, annotated datasets in biomedical imaging. The step by step algorithm of transfer learning can be seen below:
Step1: Obtain a pre-trained model. The first step is to choose the pre-trained model that would like to keep as the base for training a model for classifying Alzheimer's Disease
Step 2: Create a base model (CNN).
Step 3: Freeze layers
Step 4: Add new trainable layers.
Step 5: Train the new layers.

Step 6: Fine-tune the new model by inputting some parameters like activation function, and epochs.

Model Evaluation: A classification report was used in evaluating the performance of the proposed model. A classification report is a performance evaluation metric in machine learning. It is used to show the precision, recall, F1 Score, and support of your trained classification model.

Deployment and Classification: The trained model will be saved into a file and will be deployed to the web for conducting real-time analysis and classification of Alzheimer's disease.

IV. Experimental Results and Discussion

This system uses a biomedical image as a dataset in building a smart system for the diagnosis of Alzheimer's disease. The biomedical images used here are of Alzheimer's disease. The dataset consists of about six thousand three hundred and twenty-three images (6323) images. The images were of four categories, of which three were of different stages of Alzheimer's disease, and the image folder contains images that are free from Alzheimer's disease. The three stages of Alzheimer's disease include mild demented, moderate demented, and very mild demented. An analysis was carried out on the dataset, in other to know the categories of people that are mostly affected by Alzheimer's disease and their age difference. This can be seen in Figure 3 and Figure 4. Feature engineering was applied to the dataset in selecting relevant/important features from the dataset, and also making use of the hot_label_encoder function in labeling the dataset into the categories which they fall under. After this process, we made use of a pre-trained weight by means of transfer learning. This was done in other to have better training data. The pre-trained weight can be seen in Figure 5. After downloading of the pre-trained weight, we fine-tuned the pre-trained weight to suit the Alzheimer's dataset. The parameters used in fine-tuning the pre-trained weight are dropout=0.2, loss= loss='categorical_crossentropy, optimizer=Adadelta, number of classes=4, batch_size=32, epoch=50. The summary of the new model can be seen in Figure 6. The new model was trained on 50 training steps. This can be seen in Figure 7. After training, the model was evaluated in terms of model accuracy and model loss. This can be seen in Figure 8 and Figure 9The evaluated result of the proposed model shows that the model had an accuracy result of about 99.99%. This shows that the model is in a good performance. The model was then saved and deployed to the web using the flask framework. The flask framework was used in building a smart system that will be used for the diagnosis of Alzheimer's disease.

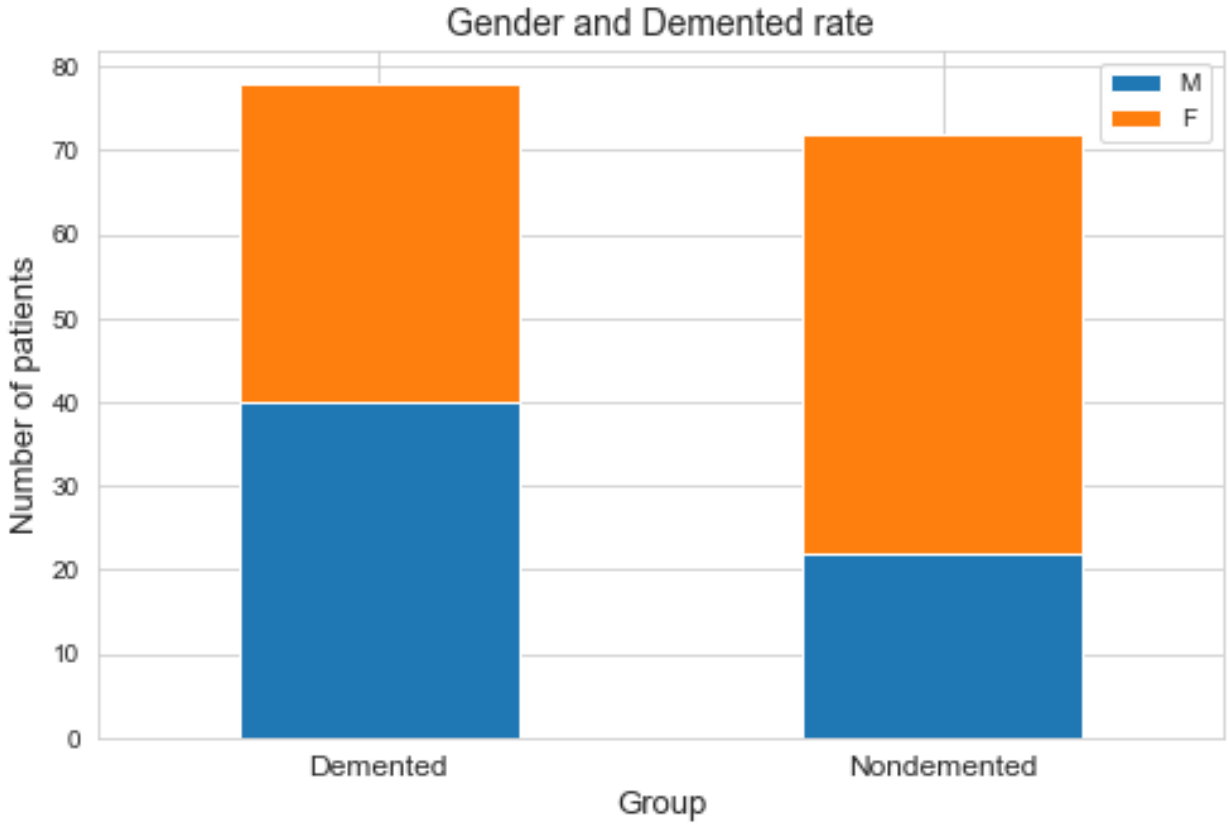

Figure 3: Histogram of demented and Nondemented
The histogram shows that females are more demented than men.

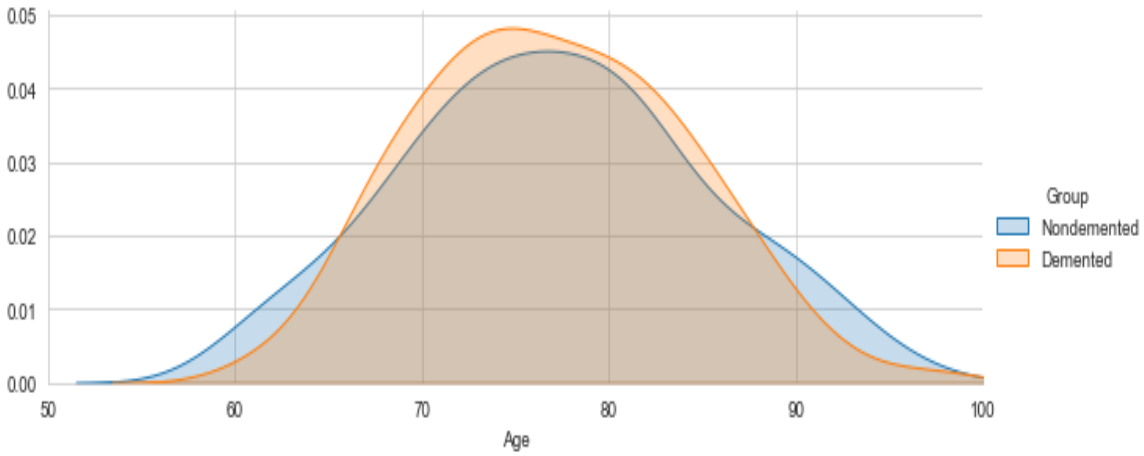

Figure 4 Distribution plot of Demented and Nondemented
The plot shows that from age 60 to 85 are using prone to being demented of Alzheimer's disease

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/resnet/resnet50v2_weights_tf_dim_ordering_tf_kernels_notop.h5
94674944/94668760 [==============================] - 1s 0us/step
(32, 6, 7, 2048)
```

```
In [12]: # freezing base_model layers
base_model.trainable = False
base_model.summary()
```

```
Model: "resnet50v2"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_1 (InputLayer)            [(None, 176, 208, 3) 0
__________________________________________________________________________________________________
conv1_pad (ZeroPadding2D)       (None, 182, 214, 3)  0           input_1[0][0]
__________________________________________________________________________________________________
conv1_conv (Conv2D)             (None, 88, 104, 64)  9472        conv1_pad[0][0]
__________________________________________________________________________________________________
pool1_pad (ZeroPadding2D)       (None, 90, 106, 64)  0           conv1_conv[0][0]
__________________________________________________________________________________________________
pool1_pool (MaxPooling2D)       (None, 44, 52, 64)   0           pool1_pad[0][0]
__________________________________________________________________________________________________
conv2_block1_preact_bn (BatchNo (None, 44, 52, 64)   256         pool1_pool[0][0]
__________________________________________________________________________________________________
conv2_block1_preact_relu (Activ (None, 44, 52, 64)   0           conv2_block1_preact_bn[0][0]
__________________________________________________________________________________________________
conv2_block1_1_conv (Conv2D)    (None, 44, 52, 64)   4096        conv2_block1_preact_relu[0][0]
```

Figure 5 Summary of the Pre-trained weight

By pre-trained weight, we have an already existing model that was trained for classifying various categories of images.

```
model.summary()
```

```
Model: "functional_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_2 (InputLayer)         [(None, 176, 208, 3)]     0
_________________________________________________________________
rescaling (Rescaling)        (None, 176, 208, 3)       0
_________________________________________________________________
resnet50v2 (Functional)      (None, 6, 7, 2048)        23564800
_________________________________________________________________
global_average_pooling2d (Gl (None, 2048)              0
_________________________________________________________________
dropout (Dropout)            (None, 2048)              0
_________________________________________________________________
dense (Dense)                (None, 4)                 8196
=================================================================
Total params: 23,572,996
Trainable params: 8,196
Non-trainable params: 23,564,800
```

Figure 6 Summary of the fine-tuned model.

The model summary shows the total number of trainable parameters. Which is about 8,196, with an output shape of 4.

```
Epoch 1/50
129/129 [==============================] - 19s 146ms/step - loss: 2.2159 - auc: 0.5069 - f1: 0.2130 - acc: 0.2358 - val_loss:
1.9306 - val_auc: 0.5092 - val_f1: 0.1937 - val_acc: 0.2148
Epoch 2/50
129/129 [==============================] - 10s 79ms/step - loss: 2.1803 - auc: 0.5061 - f1: 0.2175 - acc: 0.2343 - val_loss:
1.8844 - val_auc: 0.5137 - val_f1: 0.1977 - val_acc: 0.2188
Epoch 3/50
129/129 [==============================] - 10s 78ms/step - loss: 2.1551 - auc: 0.5096 - f1: 0.2169 - acc: 0.2329 - val_loss:
1.8456 - val_auc: 0.5178 - val_f1: 0.1987 - val_acc: 0.2197
Epoch 4/50
129/129 [==============================] - 10s 80ms/step - loss: 2.0679 - auc: 0.5165 - f1: 0.2149 - acc: 0.2292 - val_loss:
1.8080 - val_auc: 0.5217 - val_f1: 0.2019 - val_acc: 0.2197
Epoch 5/50
129/129 [==============================] - 10s 76ms/step - loss: 2.0927 - auc: 0.5221 - f1: 0.2269 - acc: 0.2412 - val_loss:
1.7753 - val_auc: 0.5252 - val_f1: 0.2055 - val_acc: 0.2227
Epoch 6/50
129/129 [==============================] - 10s 77ms/step - loss: 2.0420 - auc: 0.5229 - f1: 0.2387 - acc: 0.2477 - val_loss:
1.7436 - val_auc: 0.5291 - val_f1: 0.2093 - val_acc: 0.2266
Epoch 7/50
```

Figure 7 Model Training steps

This shows the accuracy and loss values obtained by the model at a different time intervals.

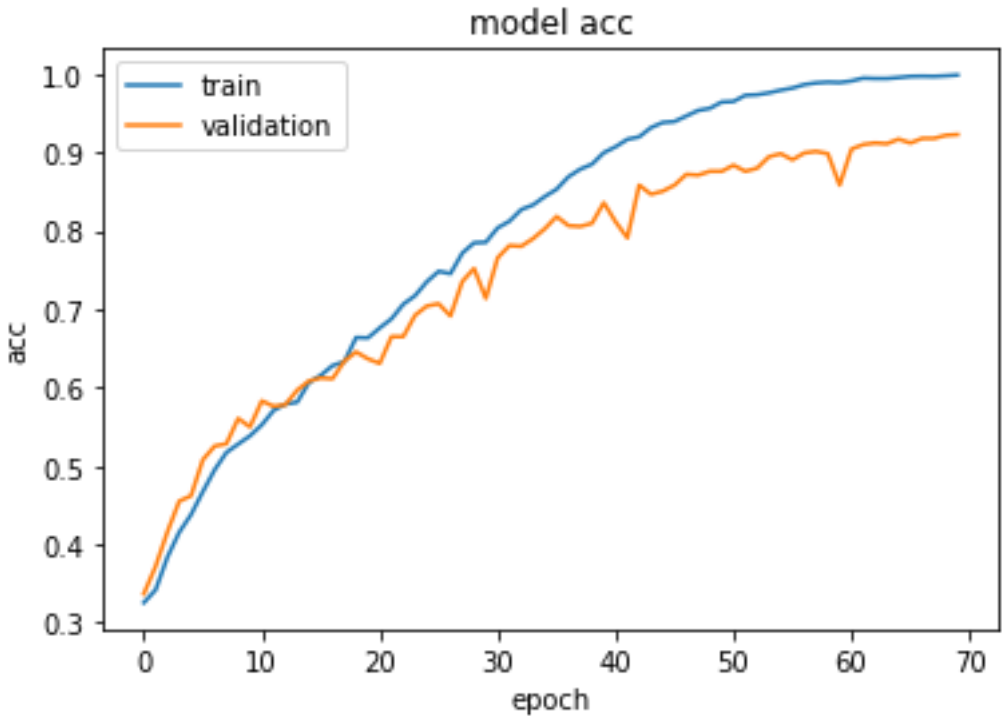

Figure 8: Model Accuracy

This shows the accuracy of the model at different training steps. The accuracy is for both training data and validation data. For training data, the model achieved an accuracy of 99.99% and 91.1% for the validation test.

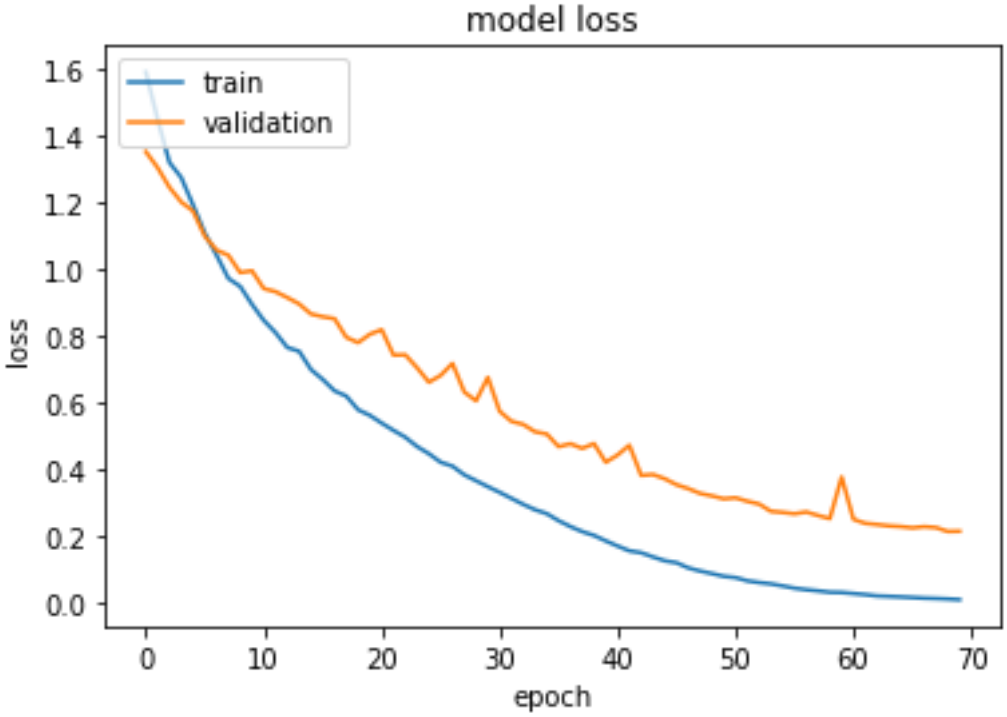

Figure 9: Model loss

This shows the loss values of the model at different training steps. The loss value is for both training data and validation data. For training data, the loss value was below 0.2 and for the validation data, the loss value was 0.21.

V. Conclusion

This system uses a biomedical image as a dataset in building a smart system for the diagnosis of Alzheimer's disease. The biomedical image used here is that of Alzheimer's disease. The dataset consists of about six thousand three hundred and twenty-three images (6323) images. Feature engineering was applied to the dataset in selecting relevant/important features from the dataset, and also making use of the hot_label_encoder function in labeling the dataset into the categories which they fall under. After this process, we made use of a pre-trained weight by means of transfer learning. This was done in other to have better training data. The parameters used in fine-tuning the pre-trained weight are dropout=0.2, loss= loss='categorical_crossentropy, optimizer=Adadelta, number of classes=4, batch_size=32, epoch=50. The new model was trained on 50 training steps. After training, the model was evaluated in terms of model accuracy and model loss. The evaluated result of the proposed model shows that the model had an accuracy result of about 99.99%. This shows that the model is in a good performance. The model was then saved and deployed to the web using the flask framework. The flask framework was used in building a smart system that will be used for the diagnosis of Alzheimer's disease.

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