An Interpretable Deep Learning Approach to Detect Alzheimer Using MRI Images

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***Abstract*—Alzheimer's disease (AD) is a serious neurological condition that causes loss of long-term memory, cognitive difficulties, disorientation, inconsistent behavior, and eventually death. AD also destroys brain cells needed for cognitive function. The main focus of our research is to provide an efficient model for the rapid diagnosis of Alzheimer's disease. In this research, we design and demonstrate an interpretable deep-learning approach to detect Alzheimer's using MRI images. For the experiment, brain MRIs are utilized, and by using this data, the model is able to determine the disease. For Alzheimer's patients in different stages, this model uses multi class categorization (MildDemented, ModerateDemented, NonDemented, VeryMildDemented). For this research, we experimented with four different architectures of Convolutional Neural Networks. VGG-19 had 92.65% accuracy, DenseNet-169 89.18%, ResNet-50 V2 87.84%, and Inception V3 80.10%. By comparing model performance, the result may be improved by up to 92.65%, and the system is built using the best architecture (VGG19). Despite a shortage of data, the results accurately identified and categorized Alzheimer's disease and its stages. Lastly, GradCam (Gradient-Weighted Class Activation Mapping) is implemented to make the application of Explainable AI(XAI) apparent. Therefore, the proposed system would enable the detection and interpretation of Alzheimer's disease effectively.**

***Index Terms*—MRI, Deep Learning, Convolutional Neural Networks (CNN), Multiclass Classification Approach, VGG-19, ResNet50 V2, DenseNet-169, Inception V3, Augmentation, Explainable AI (XAI), Gradient-Weighted Class Activation Mapping(GradCam).**

I. Introduction

A. Overview

Alzheimer's disease, a common cause of dementia in elderly individuals, destroys one's the cognitive ability and weakens it gradually. Also, it is the most prominent neurological condition that damages the brain permanently. Dr. Alois Alzheimer, who invented Alzheimer disease in 1906, by detecting damages in a woman's brain tissues. That woman died from this disease, and the disease was named after its inventor. Dr. Alois invented irregular cell clumps and clotting cell bundles. According to medical science, those are denoted amyloid and neurofibrillary plaques. At the same time, Alzheimer's disease hinders the capacity to concentrate, steadily lessening the patient's memory and hampering their day-to-day life. [1] Alzheimer's disease is an illness that becomes worse over time. Significantly impaired is one of the early and prevalent signs of Alzheimer's disease. This could be a symptom of a stroke, therefore anyone experiencing it should see a doctor immediately. Alzheimer's disease results in psychological or behavioral changes, memory lapses, intellectual disability, identification difficulty, communication with others, thinking difficulties, and other symptoms. Being older doesn't always mean that the condition gets worse, though Alzheimer's disease is recognized to harm those aged 65 and beyond.

In this era, this disease is one of the most alarming difficulties in medical science. The mortality rate of Alzheimer's and other dementia-affected people hit 14,993, or 2,09% of total deaths in Bangladesh, according to WHO statistics. [2]

Depending on the severity of the condition, AD goes through different phases. Mid-stage indications might create problems with financial transactions, roaming, and having problems, along with physical and psychological changes.

The signs of the disease get worse when it is in the final stages. A quick and accurate diagnosis is crucial in order to handle this. At this phase of the disease, the signs might not be as those of Alzheimer's disease. However, family members and acquaintances can comprehend their condition, and physicians can identify the indications using the right testing equipment. In this phase, people who are suffering can perform their regular work with others' support. [3]

In this research, we describe and consider different methods for estimating and categorizing human MRI scans into the following four categories, which are very mild demented, mild demented, moderate demented, and non-demented. In order to identify Alzheimer's disease using MRI data, fragmentation and categorization of pictures are crucial. Determining the various phases of dementia in its physical entity would aid in treating it at different phases, as we feel it is crucial to recognize the symptoms as soon as feasible. Here, we evaluate ResNet-50 V2, Inception V3, Densenet169, and Explainable AI (XAI), and those perform well on our dataset. Due to the importance of early Alzheimer's disease diagnosis to our research, we will be analyzing the images and data in a way that maximizes precision and accuracy. Using appropriate CNN architectures, we produce more appropriate outcomes with higher efficiency for our study on the identification and categorization of AD and its phase than in earlier studies. In our study, we employed an MRI image dataset that behaved admirably and produced better outcomes.

B. Problem Statement

Alzheimer's disease is the leading cause of dementia globally. More than 55% affected by dementia reside in low- and middle-income countries. There are over 9 million new cases of dementia each year across the world, which equals one new case occurring every 3.3 seconds over the duration of a year [4].

Due to the severe loss in brain function that occurs in the final stages of Alzheimer's disease, patients are more vulnerable to the possibly deadly effects of dehydration, starvation, and infection [5]. Even in the early stages, it is difficult for a doctor to detect the disease and its severity. Therefore, it is imperative to establish a rapid method for determining the kind and severity of an illness [6].

Alzheimer's disease requires extensive, costly treatment and supervision. Since people who suffer from Alzheimer's disease are mentally and physically exhausted and spend their days in fear of death. To reduce their suffering, working in this field is necessary for this century. Day by day, people do research in this area using machine learning (ML), in which the model is experimented with prior data for the purpose of identifying specific diseases. Also, in this situation, proficiency and precision are crucial, but they are very hard to get. Appropriate training for the system is vital since the goal of our study is to diagnose Alzheimer's disease from a brain MRI. After conducting the study, previous experts in this domain achieved previously unheard-of achievements, but they encountered challenges in putting their findings into practice. It is very time-consuming and hard to perform properly to train the algorithm using AD-impacted brain images to produce a proper assumption. Moreover, applying a method that gives the desired and effective result is essential. Deep learning, a significant approach to machine learning, is required for this study. Using brain scans and brain disorders as input, we have developed a deep learning methodology that's more effective than anything else on the market right now. This approach also has a higher level of accuracy than earlier ones. We created a deep learning system using brain scans and brain diseases. This method is also more precise. Using VGG 19, Resnet50 V2, DenseNet 169, and Inception V3, we created a multiclass classifier to diagnose brain diseases.Using an explainable AI (XAI) technique for assessing the disease discovered on the brain image data, it is possible to identify the condition accurately. Finally, this approach requires much more testing time. Despite various obstacles, this study aims to overcome them by finding solutions, learning new concepts, and dispelling uncertainty [7].

II. Literature Review

Yousif A. Hamda, Konstantin Simonov, and Mohammad B. Naeem suggested an MRI approach for detecting brain tumor edges [8].BCET requires noise removal and augmentation for proper diagnosis. The second stage's output is clustered using Fuzzy c-Means (FCM). Canny edge detection finds delicate edges in the last phase. We used images of Alzheimer's disease with different locations, pathologies, forms, sizes, densities, and damaged tissue around the tumor space for the experimental study. Finally, MATLAB software finds and removes brain MRI cancers. The proposed methodology has yielded noise-resistant results from empirical material studies. Geometric analysis and segmentation errors were up to 10-15% better than expert estimates in malignant tumor cases.

In this research, Martin Cenek, Masa Hu, Gerald York, and Spencer Dahl demonstrate how to use image processing to diagnose brain pathology [9]. Images reveal brain function. This method presents brain-processed information. Radiography, MRI, nuclear medicine, ultrasound, and infrared imaging can assess brain soft tissue. MRI is used to train brain abnormality detection algorithms (MRI). An MRI of the brain creates axial anatomical plane slices, and horizontal brain cross-sections separated by 0.2 to 6.0 mm along the vertical axis (spinal axis). Depending on the imaging devices and brain imaging requested, the final picture sets can have 170 to 1,500 photos.

This research utilised neuroimaging biomarkers to detect Alzheimer's and dementia noninvasively. A larger work includes this paper. The Alzheimer's algorithm uses sMRI pictures. They employed several preprocessing methods to decrease magnetic resonance brain imaging with T1 weighted volumetric to a two-dimensional space for three projections. They saw the brain three ways. OASIS and MIRIAD were

integrated to obtain more MRI samples. The highest detection accuracy was 82%. The suggested model requires no further feature extraction or selection operations on the patient's brain MRI image. After generating the best CNN model and setting its parameters, the model can assess new health data without human intervention [10].

P Gokila Brindha, M Kavinraj, P Manivasakam, and P Prasanth stated that one possible precursor to cancer is abnormal cell expansion in the brain, known as a tumor. MRI scans are the most commonly used method of detecting a brain tumor. MRI images can reveal unusual tissue growth in the brain. Numerous studies have been conducted to diagnose brain tumors using machine learning and deep learning algorithms. When these algorithms are applied to MRI data, they can predict brain tumors in less time and with greater accuracy. The radiologist can benefit from these predictions, which help them make quick decisions. In the proposed work, the performance of a self-defined Artificial Neural Network (ANN) and a Convolution Neural Network (CNN) in detecting the presence of a brain tumor is investigated [11].

MCI and brain network activity change as Alzheimer's disease advances, according to Roberto Fontana and Mario Agostini. In people and AD mouse models, the quest for early network breakdown biomarkers is underway. Local field potentials in dentate gyrases of PS2APP rats with APP Swedish and PS2 N141I mutations were examined. We found network hyper-synchronicity three months after intracellular amyloid-beta accumulated. Beta/Gamma frequency band network hyperactivity and amplitude-phase cross-frequency coupling in six-month-olds match the disease's histopathology. Although mice expressing either the PS2-N141I or the APP Swedish mutant alone displayed hyperactivity and hyper synchronicity, PS2APP animals aged six months or fewer showed an increase in cross-frequency coupling before cognitive impairment [12].

Rohit Bakshi and Alan J. Thompson uncovered additional MS research and treatment using MRI. Advanced MRI techniques should be tested for diagnosis and phenotyping. Photo post-processing should yield more valuable data. Field strengths should improve magnetic resonance spectroscopy. Metabolites can be discovered. Diffusion imaging simplifies regional lesion functional assessment. Cell-specific MRI contrast agents may be developed. Imaging myelin water fractions provides precise composition measurement. Ultra-high-field MRI is more sensitive but faces additional technological challenges. This article addresses current MS MRI achievements and expected breakthroughs in the spinal cord, optic nerve, perfusion, and functional MRI imaging. New MRI technologies may detect, monitor, and comprehend MS's causes [13].

Structural MRI analyses by Robert W. McCarley, Cynthia G. Wible, and Martha E. Shenton show that schizophrenia is more than just a neurotransmission issue. Peer-reviewed studies with matched controls were examined from 1987 to May 1998. 77% and 67% of instances have enlarged lateral and third ventricles, respectively, while 81% have standard brain/intracranial contents. Despite frontal lobe impairment, structural magnetic resonance scans showed a 55% volume decrease in anomalies. In this instance, MRI may not detect even tiny frontal lobe volume changes. About half of parietal and occipital lobe experiments succeeded. Most cortical gray matter investigations (86%) indicated volume decreases were not uniform but concentrated in certain locations. Two-thirds of studies on the thalamus, corpus callosum, basal ganglia's subcortical structures, and cavum septum pellucid (which causes brain swelling) yield positive results (CSP). However, a rising body of evidence suggests progressive and neurodegenerative features that support a 2-hit schizophrenia notion, for which a cellular explanation is being researched. Most evidence supported this. Clinical symptoms and MRI data are examined, as is the growing evidence that structural abnormalities in affective disorders and schizophrenia disorders are separate [14].

III. Methodology

A. Working Process

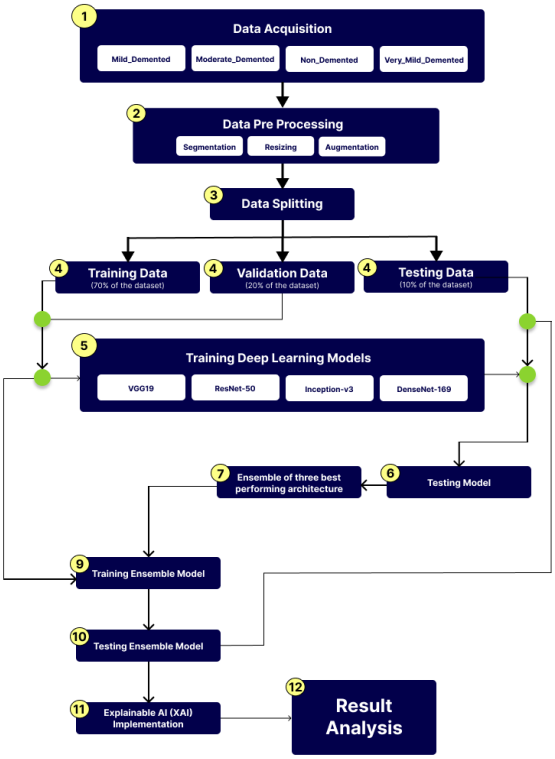

Fig. 1. *Workflow Diagram*

B. Dataset

In order to detect Alzheimer's disease in its earliest stages, we plan to collect datasets of MRI pictures and then divide them into four different categories. Initially, we started gathering the datasets from various websites on the internet. However, it is difficult to find better datasets, such as MRI scans, and sophisticated datasets are required in order to

reliably diagnose the early stages of Alzheimer's disease. MRI scans are only one example. As a result, we scoured the internet and other similar sources to find MRI image datasets that might be trusted. If we are going to be successful in diagnosing Alzheimer's disease, the dataset of MRI images that we use must be of the highest possible accuracy and validated by health organizations. After conducting research on those datasets, we discovered a standard dataset that goes by the name "Dataset Alzheimer." This dataset is an excellent fit for the investigation that we are conducting because it has four distinct image classifications [15]. As a direct consequence of this, we came to the conclusion that this dataset would be ideal for our research.

C. Data Sample

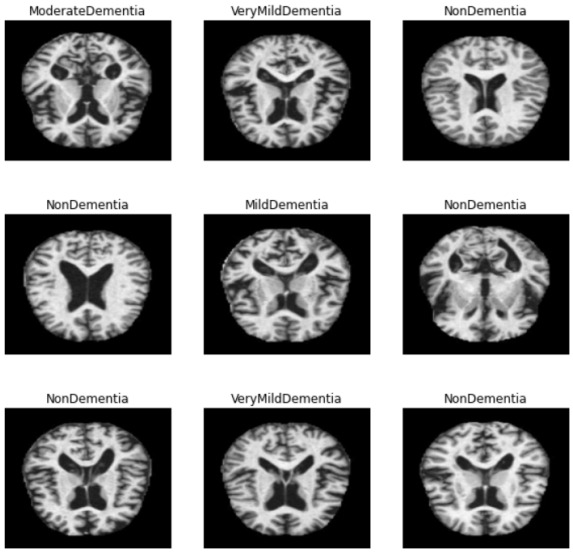

Fig. 2. *Sample Data from the Dataset*

In the above figure, there are 4 classes of Alzheimer's MRI images. Those are the categories according to dementia. Four Classes are MildDementia, ModerateDementia, NonDementia, and VeryMildDementia. There are 3200 affected images and 3200 non-affected images in our normal brain MRI image dataset.

IV. Data Pre-processing

A. Image Resizing

To begin with the dataset preprocessing, we wanted to make sure that each image had its own individual ID. Next, we've modified the dimensions of every picture to the standard (224 x 224). The photos are then rescaled to 1/255 their original size [16] as part of the dataset's formatting. And we process every single image in the training, validation, and test datasets.The data was split into Training, Validation and Test sets for a 70:20:10 ratio respectively. Data augmentation was done on the training images to help increase the accuracy of the training model and reduce overfitting. Feature extraction was carried out by first feeding the images through a convolution layer, then max-pooling layer.

B. Normalization and Scaling of Images

In order to reduce data duplication, unnecessary picture details are removed from the normalization process. Component analysis ensured data collecting consistency. PCA can minimize a large dataset without losing important data. Creating and merging flat fields normalizes brain MRI data. Dynamic flat fields reduce projection intensity normalization errors [17].This action used ImageDataGenerator. Each pixel in an image is multiplied by the same ratio and applied to the others to normalize data. All of our data came from.jpg files, including magnetic resonance imaging images of healthy and sick human brains.

V. Used Architectures

In our research, we used five architectures, which are VGG-19, ResNet-50 V2, DenseNet-169, Explainable AI (XAI), and Inception V3. The details of this architecture are given below:

A. Visual Geometry Group (VGG-19)

The VGG-19 network is an intense convolutional neural network. This obtained 92.7 percent top-five test accuracy when using ImageNet, a dataset consisting of over 14 million pictures and 1000 classes, for large-scale image identification. The VGG-19 is a deep-learning model with 19 neural network layers. ImageNet contains a pre-trained network that has been exposed to over a million images. Each filter used a maximum of three by three cells, with a stride of one and a pad of twenty-two [18]. To help construct this model, we leveraged components of ImageNet. Some of the 19 easy-to-train layers in the VGG-19 include convolutional and fully connected layers, as well as max pooling, dropouts, and fully connected layers.

B. Inception-v3

Instead of going deeper and adding additional convolutional layers on top of each other, the third version of the Inception v3 family uses transfer learning [19] to acquire better classifications. In Inception, many alternative levels were used. The emphasis is on expanding the network rather than improving its base. The expanded model has the capability to change between a wide number of symmetric and asymmetric construction elements, including such dropouts, max pool layer, convolutional layers, entirely connected layers, average pooling and contacts. When compared to earlier iterations of Inception, the Regularization Optimizer, Batch Normalization in the Auxiliary Classifiers, 7x7 Convolution layers, and Label Smoothing are just a few of the additional features that we added to Inception v3.

C. Residual Networks (ResNet-50 V2)

ResNet 50 V2 is composed of 50 layers: 48 Convolutional layers, 1 Maxpool layer, and 1 Average pool layer. Each of the four parts of this model—a conversion block and an identification block—makes up the whole. Each of the blocks' 3 convolution layers (as seen in the figure above) uses a 7x7 Kernel for the first convolution and a 3x3 Kernel for the max-pooling [20]. At the first stage of the model, where three residual blocks and three layers are used, batch normalization is commonly deployed. When doing convolution, stride 2 is used to lessen the input and increase the channel size by 1.

D. DenseNet-169

DenseNet-169 is a popular architecture for DL classification tasks, and it is one of the DenseNet family's architectures. It has 169 layers. When compared to its fellow DenseNet architectures with fewer layers, it has far fewer trainable parameters. DenseNet-169 and its siblings are a family of very trustworthy DL architectures because they circumvent the vanishing gradient problem, employ a powerful feature propagation approach, reduce the number of trainable parameters, and promote feature reuse. Convolutional layers, max pool layers, dense layers (completely connected layers), and transition layers are all a part of the architecture. The model's activation function is ReLU, and it uses SoftMax activation for the very last layer in the design [21].

E. Explainable AI (XAI)

Understanding how a Neural Network or Machine Learning model works is difficult. This makes these models "black-boxes." Nobody knows how those models are succeeding. XAI, or Explainable AI, is needed to explain deep Neural Network model behavior. It helps humans understand deep learning models' predictions, which improves communication between automated classifiers and human specialists [22]. Researchers have devised many methods to improve deep learning model precision and interpretability, and some have demonstrated promising results [23]. Grad-CAM, Grad-CAM++, LRP, SmoothGrad, Class Activation Maps (CAMs), etc are examples of it.

F. Grad-CAM

Grad Cam utilizes the gradient of any target concept to build a localization map that highlights the concept-predicting region of interest within the image. The Grad-CAM approach uses a trained CNN, an input image, and a class of interest to generate a class-specific heatmap. It resembles CAM. Any CNN architecture with distinguishable layers can compute Grad-CAM. Grad-CAM solves localization and segmentation issues without supervision [24].

VI. Implementation

A. System Configuration

For this project, we used Jupyter Notebook. The PC instance has a 3.20 GHz i5 10400 CPU, 32 GB of RAM, and a 12 GB graphics processing unit (GPU) with the model designation "RTX-2060". Just so you know, here is a high-level overview of the system we built our project around. Four different architectures, including Inception V3, ResNet-50 V2, DenseNet-169 and VGG-19 have been utilized in our work.

B. Experimental Setup

In TensorFlow, our model library was imported by utilizing the Keras library importer. We developed a base model with three input channels at the end and an input shape of 224x224, our ideal size. Before training, we weighted ImageNet. We've frozen the layers because they don't need training right now. We generated distinct iterations for each model. We use 2D global average pooling and 0.5 data dropout. With the data on a plane, a fully linked layer can be created. After that, we developed a sequential model using our base models, three dense batch normalization layers with 64 batches, kernel initialization with uniform parameters, and the final two layers with 32 batches each. All layers used the ReLu activation function and dropout was 0.5. Our dataset includes data on four forms of dementia, thus we used a 6th layer using a soft-max function and four samples. Our output layer uses multinomial probabilistic predictions. Each batch has 8. Adam, an optimizer whose learning rate adjusted from 0.002 to 0.001 dependent on loss, helped us do this.

C. Performance Metrics

1) Confusion Matrix: The confusion Matrix is a measure for the classification skills of machine learning systems that assesses the effectiveness of any program. The confusion matrix has the following elements:

True Positive: values that were both really positive and predicted to be positive were considered true positives.

True Negative: values are those that were both negative and predicted to be negative.

False Positive: values that were genuinely negative but were misinterpreted as positive. This is also known as a Type I error.

False Negative: positive values that were incorrectly considered to be negative. This is also known as a Type II error.

2) Classification Report:

$$Accuracy = \frac{(T.Positive + T.Negative)}{(T.positive + F.positive + T.negative + F.negative)} \tag{1}$$

Precision- it assures that the percentage of true positive samples is found among all positive cases. The precision formula:

$$Precision = \frac{(TruePositive)}{(Truepositive + Falsepositive)} \tag{2}$$

Recall- it reflects the percentage of true positives predicted out of all positives in the dataset. It is sometimes referred to as "sensitivity." The recall formula:

$$Recall = \frac{(TruePositive)}{(Truepositive + Falsenegative)} \tag{3}$$

F1 score- The F1 score assures that accuracy and recall are symmetric. This is the arithmetic mean of recall and accuracy. F1 scoring formula:

$$F1score = \frac{(2PrecisionRecall)}{(Precision + Recall)} \quad (4)$$

VII. Result Analysis

A. Confusion Matrix

Our confusion matrix has four categories which are mild demented, moderately demented, non-demented, and very mild demented. The anticipated label is on the x-axis, while the true label is on the y-axis.

The confusion matrix of VGG-19, ResNet-50 V2, DenseNet-169, and Inception-v3 is shown in Figure-5.1.1, 5.1.2, 5.1.3, and 5.1.4.

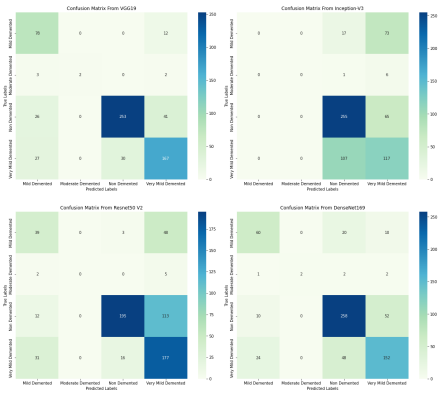

Fig. 3. *Confusion Matrix of All the Proposed Classifier Used on the Datase*

B. Performance Evaluation

We trained four different models with our dataset and evaluated the categorization and test accuracy before trying to come up with an explanation for the classification or prediction of specific MRI images. Our dataset was divided into four categories: non-demented, very mildly demented, mildly demented, and moderately demented. The results of the four models in training and validation after 30 epochs are shown in the tables below. We intended to reveal the findings for further comprehension, but the accuracy does not improve much over longer periods.

TABLE I

VGG-19 Corresponding Numeric Metric Score

Train/Val	Epochs	Accuracy	Loss	Precision	Recall
Train	30 Epochs	0.9908	0.1324	0.9827	0.9806
Validation	30 Epochs	0.9265	0.3783	0.8600	0.9730

TABLE II

Inception-V3 Corresponding Numeric Metric Score

Train/Val	Epochs	Accuracy	Loss	Precision	Recall
Train	30 Epochs	0.8024	0.8988	0.7001	0.3616
Validation	30 Epochs	0.8010	0.8767	0.7364	0.3294

TABLE III

ResNet-50 V2 Corresponding Numeric Metric Score

Train/Val	Epochs	Accuracy	Loss	Precision	Recall
Train	30 Epochs	0.8847	0.5738	0.7851	0.7637
Validation	30 Epochs	0.8784	0.5861	0.7695	0.7686

TABLE IV

DenseNet-169 Corresponding Numeric Metric Score

Train/Val	Epochs	Accuracy	Loss	Precision	Recall
Train	30 Epochs	0.9475	0.1511	0.9068	0.9464
Validation	30 Epochs	0.8918	0.7010	0.7980	0.9020

The results of the four models in training and validation after 30 epochs are shown in the tables below. We intended to reveal the findings for further comprehension, but the accuracy does not improve much over longer periods.

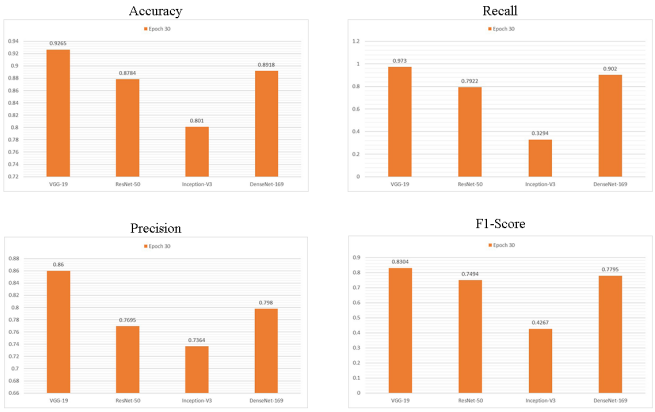

Fig. 4. *Comparisons of Accuracy, Recall, Precision and F1-Score of All the proposed Classifiers*

C. Result Analysis with Grad-CAM

Finally, we applied GradCam to our best-fit VGG-19 model. The regions that determine the predictions made by VGG19 can be visualized by looking at the images that are provided below

In Figure 5, the images Figure 5 (a) are from the non-demented class. The image Figure 5 (b) is of people with mild dementia, and the picture Figure 5 (c) is of people with very mild dementia. By evaluating this interpretation that was made

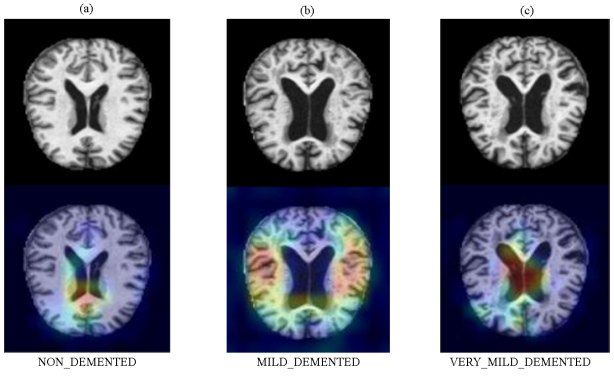

Fig. 5. *Grad-CAM interpretation of the prediction made by VGG19 when an image of (a) Non-Demented, (b) Mild-Demented and (c) Very Mild-Demented is provided as input*

by Grad-CAM, we are able to interpret the prediction made by VGG19 because we can now see that it is looking at the correct regions (regions having a red effect) while predicting image in 5 (b) belongs to the Mild-demented class. This is because we can now see that it is looking at the regions that have the red effect. In a similar manner, we can observe from Figure 5 (c) that VGG19 is looking at the appropriate region while making its prediction regarding the image that belongs to the very mild demented class.

VIII. Conclusion

A. Conclusion

Alzheimer's is a progressive neurological disease that cannot be cured. It damages brain cells. Alzheimer's affects 55 million people globally. It is expected to nearly double every 20 years, reaching 78 million in 2030 and 139 million in 2050 [**?**]. Since nothing is known about how to avoid the condition, we must work to detect or identify it early and make treatment more accessible and understood to more individuals. We analyze and predict early Alzheimer's disease using several neural network models. We demonstrated relevant research and recent experiments on various datasets. We processed the data with ResNet-50 V2, VGG19, DenseNet-169, and Inception V3 and showed the results with Grad-CAM-based XAI. 70% of our data went to training, 20% to testing, and 10% to validation. To summarize, VGG-16 predicted the four classes with 92.65% accuracy, DenseNet-169 89.18%, ResNet-50 V2 87.84%, and Inception-v3 80.10%. This shows promising results that can be enhanced and applied elsewhere. Our Grad-CAM core architecture's adaptability simplifies low-level data and can be applied to different data processing components.

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