Enhancing Early Detection and Classification of Alzheimer's Disease Stages Using Deep Learning and LIME for Interpretability

P Mokshit ,P Syam Prasad, N Sumanth Reddy, Dr Rimjhim Padam Singh
Department of Computer Science and Engineering,
Amrita School of Computing, Bengaluru,Amrita Vishwa Vidyapeetham, India
bl.en.u4aie21094@bl.students.amrita.edu, bl.en.u4aie21103@bl.students.amrita.edu, bl.en.u4aie21091@bl.students.amrita.edu, ps_rimjhim@blr.amrita.edu

***Abstract*—The issue of transparency prevails in diagnostic methods, which is the main challenge of Alzheimer's Disease. This work implements the tools of Explainable AI that bring about transparency and decision-making capabilities for clinicians and patients. This paper focuses on analyzing state-of-art deep learning algorithms namely, customized CNN, InceptionV3, DenseNet121, AlexNet, VGG16, and ResNet50 for detecting Alzheimer's disease. The model learning and outputs obtained from these models are also explained using the XAI tool named LIME. The clear explication of the models' decision-making processes effected by XAI tools like LIME can improve diagnostic accuracy and foster trust, and that can offer a great chance for the doctors to offer a better care for patients, who are suffering from AD.**

***Index Terms*—XAI, Neural network architectures, Deep learning algorithms, LIME, CNN, ResNet, DenseNet, InceptionV3, VGG16**

I. Introduction

Alzheimer's is a complex health issue that affects millions worldwide and has far-reaching consequences for patients and their families as well as national healthcare systems. AD, a chronic neurological disorder, is a progressive condition and it is characterized by short-term memory loss, cognitive decline, and impaired daily functioning. The initial and early diagnosis is what provides the basis for good treatment and intervention, which in turn, improves the clients' outcomes and their quality of life. New approaches based on deep learning and AI have demonstrated the reliability in diagnosing AD through neu- rological imaging data. In this type of scans, there are the minimal changes in brain structure that may be an early sign of the disease. Convolutional Neural Networks (CNNs) have developed as a key pillar for advanced image analysis. The aim of this research is analyzing deep learning techniques including convolutional neural networks (CNN), InceptionV3, DenseNet, AlexNet [1] , VGG16 [6], and ResNet for Alzheimer's disease detection. These cutting edge networks with CNN architectures are known to have the ability to learn such complex features from images, which makes them a perfect choice for medical image analysis. We target the implementation of these models in order to achieve clinical accuracy in classifying brain images and ascertaining AD status.

Moreover, we use the Explainable AI technology LIME to give an understanding of the internal processes of the deep learning models we use. The Explainable AI is the essential part of improving the interpretability and reliability of AI-built diagnostic systems. It makes the clinicians to underpin the model predictions which help validate the proposed methodologies and improve these in order to achieve higher diagnostic reliability and patient care effectively.

II. Related Work

Ruhul et al. [2] conducted a thorough research which aimed at classifying Alzheimer's disease using brain images. The research applied various approaches including SVM, KNN, Random Forest, and ANN. The accuracy of 93% outperformed all others for the ANN-based classification. Rahul's research demonstrates the utility of artificial neural networks in diagnosing Alzheimer's disease by integrating information from brain imaging outcomes. This finding suggests the use of machine learning approaches in the algorithms can go a long way in upgrading diagnostic techniques towards alzheimer's disease. Through the comprehensive survey, Doaa et al. [3] examined the area of early Alzheimer's disease detection, classification. It highlights the in-depth deep learning methods with their application to the MRI and the PET imaging modalities. The system does a thorough job of assesing the different preprocessing techniques and faces challenges involved in both image and classification processing stages in particular. This work aims to review cutting-edge techniques and extract general implications about the intricacies of Alzheimer's disease diagnosis. Finally from this probe, the survey looks to join in the progress of diagnostic tools and methodologies that are fighting Alzheimer's disease. Modupe et al. [4] had to use a brand-new deep learning model that combines PET with MRI scans for the diagnosis of (AD). The model achieves a good classification accuracy of 73. 90% after experimenting. With this novel technique, one can see the possible combination of various modalities leading to improvement of diagnostic sensitivities in the case

of AD detection. The proposed model is able to utilize deep learning techniques, as well as integrate diverse data sources. This model then represents the cutting-edge of research on the diagnosis of Alzheimer's disease, and it has the potential to contribute to better early detection strategies. Hina et al.[5] along with the group revealed a ground-breaking real-time Alzheimer's disease detection system that applied deep learning and transfer learning features. AlexNet model is used to gather deep features and subsequently the experiments are performed with SVM, KNN, and RF algorithms. The accuracy obtained of was 92. The high accuracy of 85% for deep CNN Just restates the concern that the transfer learning is effective in having a high accuracy for multiclass classification in performing Alzheimer's disease detection. The subsequent research is a significant step forwards in the field that reveals tangible proof of the suitability of using deep learning and transfer learning models as a way of increasing Alzheimer's disease detection systems' accuracy and efficacy.

Rajeswari et al. [6] sought and performed several transfer learning techniques to predict the Alzheimer's disease. They schemes like vgg-16, ResNet-50, and Xception as well with ADNI dataset of 6100 images. The dataset was divided into two categories: For each model is trained using 20 epoch and VGG obtained 98

Pushpa et al. [7] tried different state of the art algorithms of image enhancement to improve the quality and to remove noises such as median filtering and DnCNN. The dataset that is presented in this paper was parallelly acquire from Harvard and proceeded later implemented image segmented techniques based on gray matter and white matter. Techniques, such as threshold based image segmentation, Region based segmentation and Adaptive thresholding, are later used. Next, a cnn model is employed with 2 hidden layers and 1 input layer as well as 1 output layer giving an accuracy of 88%. Hamza et al. [8] implement the neural networks to obtain Alzheimer's predicaments. They used the models such as ResNet50, VGG16, and Inception V3 with the dataset from Kaggle. This entry was on normality, slight confusion, moderate confusion, and no confusion. For testing and training, the dataset was divided into an 80:20% Thirty. The stack of the 50 layers in the ResNet50 architecture consisted of a 1 max polling layer, an average pooling layer and 48 other convolutional layers. On the contrary, VGG16 model consisted of three fully connected layers, sixteen weighted layers and a stack of convolutional ones. Besides, the team applied LIME, an explainable AI tool for the purpose of seeing how the model works. Among the models that were studied, VGG16 performed the best attaining a accuracy of 86. 82% Accuracy. Inception V3 came next with 82.04%, the ResNet50 was 82.56%.

Srividya et al. [9], employed ResNet-50 deep learning algorithm as a primary tool was used. Identification of Alzheimer's disease was examined. They used ADNI2's sMRI data database for data. ResNet model was comprised of the five convolutional layers, which were ended with the classification layer that had both flatten and softmax operations. This model demonstrated 91model equipped with the Adam optimizer has displayed the highest degree of precision and attained a Balanced Accuracy Score of 0. 89. The results showed that VGG with Adam optimizer performs better than other models, such as the SGD, occurring a 94

Ishan et al. [11] proposes that A CNN-based multimodal deep learning is used for the appraisal of neuroimaging data of functional and structural type of Alzheimer's disease classification. From ADNI they get MR image data. Then in succeeding steps they preprocess the data spent to extract features like functional measurements (cortical thickness, ReHo, ALFF, DCw, tsavg) and structural measures (lT1). The multi-channel AlexNet brainless classification is implemented. The outcomes prove that performances in multimodal and unimodal environment are in general comparable. Feature analysis demonstrates the exact brain areas that play their role in classification; it is important to note that there are two significant differences: first of all, one can observe the difference between the CN and the AD groups and secondly, the difference between structural and functional modalities.

Sudar et al.[12] deal with XAI (Explainable Artificial Intelligence) methods, among which (LRP — a local relevance score) is used to diagnose Alzheimer's disease in different stages, using MRI scans of the brain. It is worth mentioning that picture categorization by means of VGG-16 and CNN architecture has also been performed. Four categories of MRI images from 6400 scans, which are the non—demented part, the very slightly demented part, the mildly demented part, and the moderately demented part are included in the dataset. The outcomes of this indicate that LRP and VGG-16 successfully give the pixeled and perm*apable outputs thereby creating a more interpretable model. Comparative study of other algorithms, like CNN, random forest and SVM, with the highest accuracy rates proves that algorithms using the concepts of XAI have an advantage in the Alzheimer's disease analysis perform better in haze removal and boost the contrast level more than the existing techniques.

Raj et al.[13] conducted, ANN and CNN dl models could effectively diagnose Alzheimers disease through brain images. EfficientNetV2 pretrained weights are applied and the data set includes 5121 training and 1279 testing images. Results show high efficiency of the methods, AD/CNN achieving 100moderate demented. Via wide experimenting, they got satisfying outcomes, whereas VGG16 was the one with the highest accuracy of 86

Janani et al. [15] tackled one of the major problems in Alzheimer's disease and other mild cognitive disorders: the sporadic nature of the data due to reliance on only one method of data gathering (single data modality), which leaves room for improvement in the prediction of AD progress. They gave a new idea of using DL for merging MRI imaging, SNP genetic data and clinical tests. The paper articulates the use of 3D-convolutional neural networks on imaging data and stacked denoisw auto-encoders if it can be found from the biochemical and genetic data for real-time detections of AD. Multi-modality data integration was able to produce a superior performance, which was expressed by the accuracy rate, precision, recall and mean F1 score that were remarkably high, these results were consistent with AD established literature, while the top features were identified. Kechojaate et al. [16] looked into throwing light on the difficult concept of early detection in Alzheimer's Disease as the biomarker changes are tiny and detectable only through neuroimaging. They conducted a literature review of around 100 publications published since 2019 that laid emphasis on the basic deep architectural models for AD diagnosis, such as CNN, RNN and generative models. Moreover, they read about fifty articles on the most frequently-popular topics or buildings. They examined graph-based architectures, explainable models, and attention processes, classifying problems into three areas: adoption, integration, and clinical acceptance both among the healthcare providers and the general public. A clinical research paper will be concluded by the discussion of future aspects and recommendations for additional work on AD diagnostics.

Alejandro et al. [17] have worked on the design of an early time alarm system of the Alzheimer disease by making use of the sagittal magnetic resonance images (MRI) that are underutilization in the diagnosis henceforth mostly blinded. Approaching with the help of Transfer Learning, the researchers relied on the sagittal MRI images from the ADNI and the oasis datasets. The experiment ended with the findings AD related injury can be detected using sagittal MRI with a close match with horizontal plane MRI outcomes. Tt also underlines the impact of occipito frontal MRI on the diagnosis of AD. Proposed approach combines the deep learning technique and transfer learning experimenting with ANN ResNet feature extractor and SVM classifier, which provides the desirable detection outcomes for AD diagnosis. Esra et al. [18] got involved into the research and exploration of the possibility of applying the basic yet meaningful information deduction method mutual information index for differentiating between normal and Alzheimer's related cases from the PET study FDG.

The preprocessing was done with the help of 102 healthy and 95 diseased Alzheirmer's FDG PET images from ADNI which is U. S. A unit of imaging data repository for adults with neurological disorders. A substantiality index was designed for the images, and it facilitated the separation between AD and health controls. In performance of diagnostics by leave-one-out approach reliability yields to 0. 857±0. 0261, shown after ROC curves checking. Research shows the feasibility of a computer-aided system that could be used for secure diagnosis or as a supplement to the existing ones without training and sophisticated features computation tasks.

III. Dataset Description

The dataset available on Kaggle comprises two main folders: "train" and "test" with each data-set having four distinct stages of Alzheimer's disease protocols. The stages of severity that are RAWCOLD dementia are MildDemented, VeryMildDemented, NonDemented, and ModerateDemented to illustrate the wide range and complexities of cognitive impairment in this disease. This "train" folder has an impressive amount of data. From this data, you can observe various stages of Alzheimer's disease. To be more precise, I have images of different severities of MildDemented 717 images, of VeryMildDemented 1792 images, and of NonDemented 2560 images and 52 images of ModerateDemented. The "test" dataset gets it structure inspired by the "training" dataset, although its class instances numbers are significantly less. The example is, there are 179, 448, 640 pictures of MildDemented, VeryMildDemented and NonDemented respectively and only there are 12 of pictures of ModerateDemented.

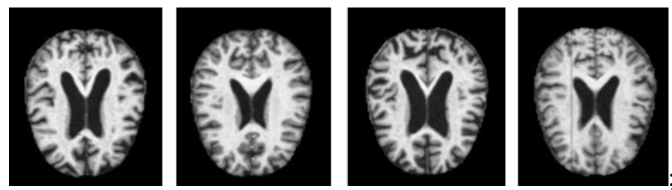
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Fig. 1. Dataset

IV. Proposed Methodology

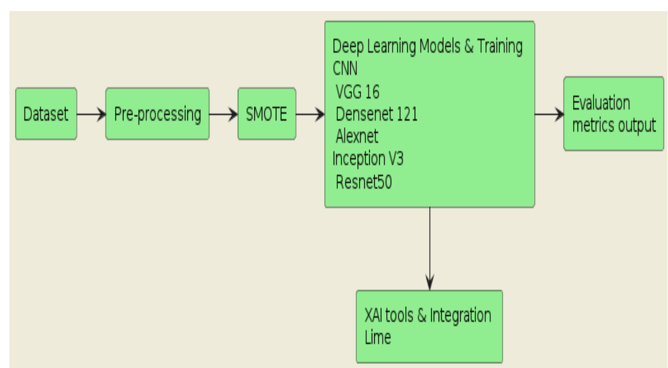

Fig. 2. Workflow of Deep Learning Model Development with XAI Integration

In this work, a deep learning framework based on Explainable AI (XAI), for the detection and diagnosis of Alzheimer's Disease (AD) is presented. The framework consists of data collection, preprocessing, model training and interpretation as its main stages. Our dataset was an MRI brain scans collection that went through augmentation, preprocessing, and balancing to make it as effective as it could be. Multiple CNN architectures were tested, and xAI tool LIME was used in model interpretability of the predictions.

A. Data Collection

The dataset used in this study was obtained from the Alzheimer's Dataset, which includes MRI scans of brain images categorized into four classes: "NonDemented," "VeryMildDemented," "MildDemented," and "ModerateDemented." The data set was to be partitioned into training and test folders.

B. Data preprocessing

To boost the quality as well as the generalization of our dataset, we made use of the ImageDataGenerator class in Keras to apply quite a number of data augmentation techniques. These methods that the algorithm used were rescaling pixel values to [0, 1] range, changing angle of image within 20 degrees range and applying zoom transformations within 0 – range. The transformation I will apply is shifting images 20% horizontally and vertically, and performing horizontal and vertical flips as well. These transformations were applied to provide an artificial wider and more diversified dataset, making the network less prone to overfit.

The data set was separated into training, validation and test sets. The dataset was then split into training and validation partitions to estimate the model accuracy as a function of training. SMOTE function was used to handle the class imbalance situation by creating synthetic samples for the deficient classes, resulting in the percentage of classes being equal.

C. Model Architecture

We employed six state-of-the-art Convolutional Neural Network (CNN) architectures: We opted for, particularly, InceptionV3, DenseNet, AlexNet, VGG16, ResNet, and a custom CNN version as models. They were all chosen, due to their proven skill in learning the details that may be too complicated to be identified by humans using imaging, which is makes them suitable for medical image analysis.

Max-pooling and normalizing stages come after multiple convolutional layers in AlexNet's deep convolutional network architecture. This architecture greatly enhances performance on difficult visual identification tasks by its well-known capacity to identify complicated patterns and features in images. Deep layer architecture and robustness allow AlexNet to handle complex image classifications, such those needed in Alzheimer's disease medical diagnosis.

1) CNN: The designed CNN architecture consisted of two or three convolutional layers, all of which are accompanied with ReLU activation function and the subsequent max-pooling layers for decreasing the size of the spatial dimensions. The final category of the neural network consisted of layer placed at the end which consisted of a softmax activation function to determine the class probabilities. In overfitting prevention, dense layers with dropout were implemented. The convolutional layers were also pre-conditioned using the He initialization so as to be able to accelerate the convergence of the network. Stochastic dropout with a rate of 0.5 was employed after each convolutional layer and batch normalization was used as well for training stability and speed up. Moreover, to reduce over fit and improve model's ability to generalize, techniques like rotation and flipping were used in data augmentation.

2) VGG16: VGG16 can be described in the manner that it is simple yet deep model, which is built up of 16 layers of convoational layers with small receptive fields of 3x3. When it comes to the architecture in a way that captures hierarchical features, it works rather well because these characteristics prove to be quite important in image classification. It maintains a relatively standard design of convolutional layers in addition to max-pooling layers where the layers continue to compound the features learned. Furthermore, the convolutional layers in VGG16 use a higher number of filters in the deeper layers yielding higher accuracy for complex patterns and fine details.

3) Resnet: ResNet incorporates residual links or skip connections for the network using them as identification mapping. The network now learns the mapping of the two identities and hence finalizing a deeper network training becomes easier. That is why the use of this type of architecture helps to avoid the vanishing gradient issue and makes it possible to train extremely deep networks. Moreover, the design of ResNet is such that the gradients can flow more easily through the network which means that convergence is usually enhanced. This approach of saving information present in previous layers also aids in better performance and accuracy in comprehensive evaluations.

4) Densenet: Densely Connected Networks also known as DenseNet work on feed-forward type of connection in that every layer is connected to a layer of the next stage. All of these aspects help solve the challenges of disappeared gradients, reusing features, and making the models more efficient. Further, because DenseNet does not require feature maps to be discarded and relearned new ones, it requires considerably fewer parameters. This dense connectivity also results in higher gradient flow, improved conspicuity, and feature reuse – all of which, in turn, lead to better generalization and more compact models.

5) InceptionV3: InceptionV3 incorporates network-in-network architecture where convolution operations are performed progressively at each layer of the network along with downsampling. The availability of modeling some of the features at the fine to coarse components of the visual content, successively enhances the attention span of the model eventually enhancing holistic image tasks. In this architecture, multiple filter sizes are used inside a single module, which make it capable of learning the spatial features at once. Moreover, the factorized convolution restricts computational cost while enhancing the capability of InceptionV3 handling high-dimensionality input..

D. Explainable AI

To enhance the interpretability of our deep learning models, we integrated the Local Interpretable Model-agnostic Explanations (LIME) tool across all six CNN architectures: CNN, InceptionV3, AlexNet, DenseNet, VGG16, and ResNet. LIME works by perturbing input data and observing the corresponding model outputs to reveal how different features influence predictions locally. This method helps in understanding the decision-making process of these otherwise opaque models by highlighting key features that drive predictions.

V. Results

The evaluation of six CNN-based models—InceptionV3, DenseNet, AlexNet, VGG16, ResNet, and a standard

CNN—utilizes precision, recall, F1-score, and accuracy to measure performance. Classification reports detail each model's effectiveness, while LIME visualizations enhance the interpretability and transparency of their predictions, building trust in their capabilities.

Parameters/models	AlexNet	Customized CNN	VGG16	REsNet	DenseNet	InceptionV3
Training: Validation: Testing	70:15:15	70:15:15	70:15:15	70:15:15	70:15:15	70:15:15
Batch size	32	32	32	32	32	32
Image height and width	128,128	128,128	128,128	128,128	176,176	128,128
Activation Function	Relu, softmax	Relu, softmax	Relu, softmax	Relu, softmax	Relu, softmax	Relu, softmax
Optimizer	adam_optimizer	adam_optimizer	Rmsprop optimizer	adam_optimizer	rmsprop_optimizer	adam_optimizer
Loss Function	categorical_cross entropy	categorical_cross entropy	categorical_cross entropy	categorical_cross entropy	categorical_cross entropy	categorical_cross entropy
Metrics	Accuracy, Precision, Recall, F1 Score	Accuracy, Precision, Recall, F1 Score	Accuracy, Precision, Recall, F1 Score	Accuracy, Precision, Recall, F1 Score	Accuracy, Precision, Recall, F1 Score	Accuracy, Precision, Recall, F1 Score

TABLE I
COMPARISON OF DIFFERENT MODELS BASED ON VARIOUS PARAMETERS.

The table 1 shows configurations and selective performance indices of several convolutional neural networks (CNN) applied to Alzheimer's disease classification. All models employ data split at 70:15:15for training, validation and testing. They use a batch size of 32, while the image resolution is set at 128 x 128 pixels for the five models other than DenseNet, which has an image resolution of 176 x 176 pixels. The activation functions used include ReLU and softmax, while the optimization algorithms used are Adam for most of the models and RMSprop being used on VGG16 and DenseNet. All of the models use categorical cross-entropy as the loss function. Metrics used to measure the performance of the models are accuracy, precision, recall and F1 score.

Accuracy graphs depict how well a model performs during both the training and validation phases across different iterations. These graphs are useful for spotting issues like overfitting, underfitting. Fig 3 depicts illustration of various CNN models training processes. Generally, the models show rapid initial learning, gradually converging with increasing epochs. Models like DenseNet-121, InceptionV3,VGG16, Customized CNN seems to strike a balance suggesting better generalization. Whereas for AlexNet, REsnet50, the training accuracy is slightly higher than validation accuracy, but the gap is minimal, indicating good generalization and limited overfitting.

ResNet, with the highest F1 score of 94, provides extremely reliable predictions, validating the significance of features identified by LIME, enhancing trust in critical applications. DenseNet and VGG16, each with an F1 score of 92, also demonstrate excellent performance, ensuring high confidence in their LIME outputs for precise model tuning. CNN, with an F1 of 89, shows good reliability, though it requires careful scrutiny for potential errors in LIME-exposed features. InceptionV3 and AlexNet, scoring the lowest at 87, necessitate cautious use of LIME to pinpoint inaccuracies and guide significant enhancements. Higher scores (94, 92) bolster trust in LIME outputs for refinements, while lower scores (87) highlight the need for critical evaluations and improvements in model accuracy.

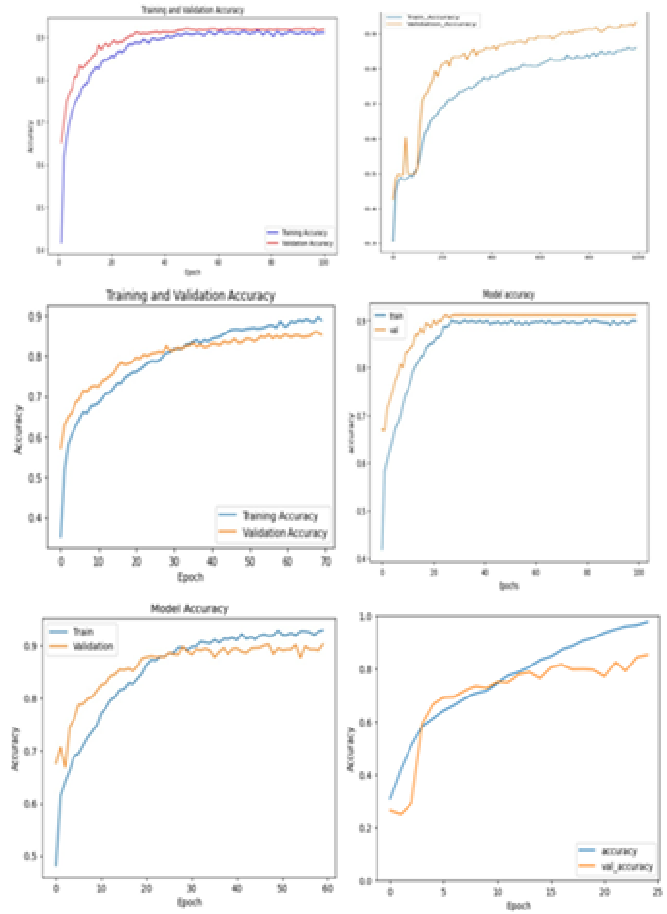

Fig. 3. Accuracy plots obtained for the models analyzed over epochs : top-left: DenseNet-121, top-right- ResNet50, Middle-left: Inceptionv3, Middle right: VGG16, Bottom-left: Customized CNN and Bottom right: Alexnet model

DL Models	Accuracy (%)	Recall(%)	F1(%)	Precision(%)
ResNet50	94.00	94.00	94.00	94.00
InceptionV3	87.00	87.00	87.00	87.00
DenseNet	92.00	92.00	92.00	92.00
VGG16	92.00	92.00	92.00	92.00
CNN	89.00	89.00	89.00	89.00
AlexNet	87.00	87.00	87.00	87.00

TABLE II
PERFORMANCE COMPARISON FOR DEEP LEARNING MODELS

A. *Integration of Lime*

In result the Areas highlighted in red are regions in the image that negatively contribute to the model's prediction for the specific class and Areas highlighted in green are regions in the image that positively contribute to the model's prediction for the specific class.Areas in black generally represent the background or parts of the image that do not significantly influence the prediction either positively or negatively

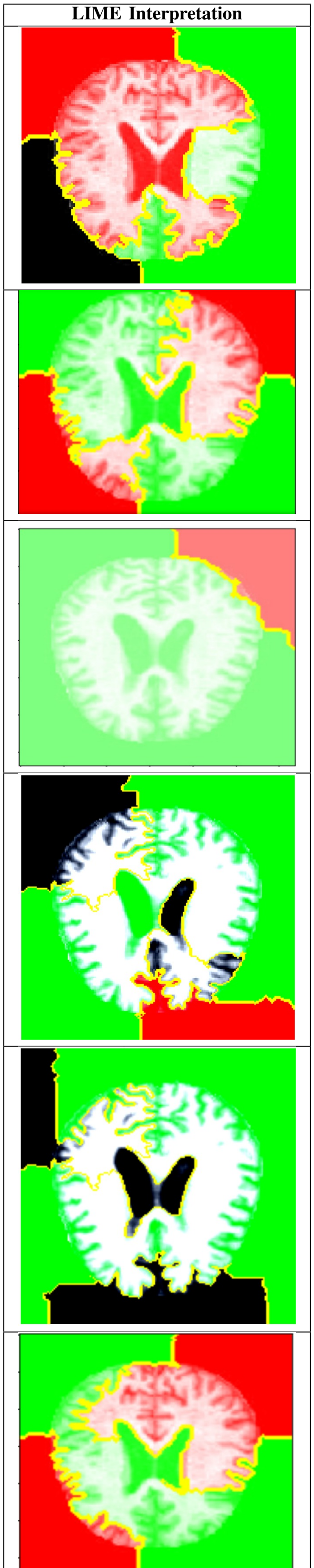

TABLE III
LIME INTERPRETATION OF ALEXNET, CUSTOMIZED CNN, VGG16, RESNET, DENSENET, INCEPTIONV3

The LIME interpretations explain which particular features of an MRI scan of the brain deep learning models focused on when making predictions.These highlighted regions indicate how the model understands and processes the data. Hence, the obtained F1 scores that in some cases is defined as rates of both precision and rates of recall offer an indication of how effectively the models created for the purpose of making accurate predictions have been built. This is why, higher F1 scores offer evidence not only ResNet50 and DenseNet are finding the correct regions of the object at a higher probability level, but they are able to do so with improved reliability and efficiency. Thus, models with higher F1 scores contain further definite and focused LIME visualizations of focus areas and high scores in so far as the model handles the prediction issue.

VI. Conclusion

This study is proposed a novel pattern for implementing the early diagnosis of Alzheimer's Disease with five latest state- art CNN models as well as XAI tools. The findings showed that the model ResNet50 got the highest accuracy 94% consequently VGG16 and DenseNet, with an accuracy 92% . The case of InceptionV3 and AlexNet were almost equal with the performance of 87% accuracy, but CNN model managed to reach 89%.

The addition of LIME gave meaningful feedback on why the particular feature in a brain scan was important in the brain's decision-making model. Despite the explanations we try to give to our proposed AI devices it is crucial to keep in mind that this high transparency is one of the major requirements for both clinical applications and is considered to improve AI reliability and interpretability in diagnostic systems.

After all, the use of CNNs that are specialized as well as XAI provides excellent possibilities for enhancing prognostic accuracy and interpretability of diagnostic models of the Alzheimer's Disease. Further study of the models, the clarification of them, as well as exploring new explainability approaches, might be necessary in order to provide the required decision-making support for the medical staff and implement the improvements in patients' health condition.

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