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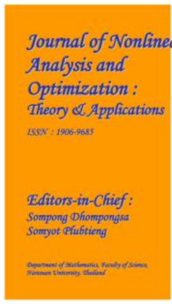

ADVANCING ALZHEIMER'S DIAGNOSIS: A DEEP LEARNING-BASED MULTI-STAGE IDENTIFICATION METHOD

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Abstract:
Multiple ailment detection is a critical area of research that aims to improve healthcare outcomes by detecting multiple diseases in patients at the same time. The traditional approach to disease diagnosis entails identifying a single disease at a time, which is time-consuming, costly, and frequently results in missed diagnoses. Multiple disease detection models that can help diagnose multiple diseases accurately and quickly have been developed because of advancements in machine learning and artificial intelligence. These models identify patterns and predict the likelihood of multiple diseases using data from various sources such as medical records, lab test results, and imaging data. In this article proposing a system which used to predict different stages of Alzheimer disease which includes Non-Demented(normal), Mild-Demented, Moderate Demented, and Very-Mild Demented. For prediction and classification of multiple stages of Alzheimer disease, applied Deep Learning Model known as VGG-16, using brain MRI dataset, which yields the accuracy of98.87%,with99%precision.

Keywords:
Machine Learning; Deep Learning; Artificial Intelligence; Alzheimer; VGG-16

I. INTRODUCTION

In recent times, there has been a huge surge in interest and enthusiasm in researching and developing technology that can aid in the timely detection and prediction of a different multiple diseases. The ability to ascertain diseases early is critical in providing timely and effective treatment, which can greatly improve patient outcomes. Prediction and Classification of Multi-disease detection using Novel Deep Transfer Learning Approaches is the process of identifying and diagnosing multiple diseases using various diagnostic tools and techniques. Forecasting and Classification of Multiple disease is especially significant when a patient exhibits symptoms that could be indicative of several diseases. Traditional diagnostic methods frequently focus on one disease at a time, which can cause diagnosis and treatment to be delayed if a patient has multiple co-existing conditions. Healthcare practitioners may screen for and diagnose communicable disease at the same time when using a multi-disease strategy, which can accelerate the diagnostic process and improve patient care.
Technological advancements, which includes artificial intelligence and machine learning algorithms, have greatly increased the accuracy and efficiency of multiple illness identification. These tools are capable of quickly interpreting large amounts of patient data, including such past medical history, laboratory findings, and imaging studies, in order to identify patterns and make accurate diagnoses. The ability to detect multiple diseases with a single diagnostic test or tool is a promising advancement in medicine that has the possibility to significantly enhance the patient outcomes while also lowering healthcare costs.This article presents a diagnostic system for predicting and categorizing multi-stage Alzheimer's Disease. The system utilizes various Artificial Intelligence and Deep Learning models and methodologies.
Begin with a discussion of the diseases referred to in this article. According to WHO, “Dementia is a condition characterized by cognitive function decline that surpasses the typical effects of biological

aging. Although while dementia mostly affects the elderly, it is not an inescapable consequence of aging". Time of writing, according to the World Health Organization (WHO), there is a global population of about 55 million individuals who are impacted by dementia, with roughly 10 million new cases being diagnosed each year. Dementia arises from several diseases and accidents that impact the brain, either through direct or indirect means. Alzheimer's disease is the predominant form of dementia, comprising around 60-70% of all cases[1]. Alzheimer's disease is currently the seventh most prevalent cause of death globally and one of the primary contributors to impairment and dependence among older individuals worldwide. Dementia encompasses a range of physical, psychological, social, and economic consequences that impact not just individuals with dementia but also their careers, families, and society at large.
In order to create a diagnostic tool for predicting and categorizing illnesses, we will utilize Deep Learning and Artificial Intelligence methodologies and techniques. Machine learning is a branch of artificial intelligence where machines replicate intelligent human behavior. Artificial intelligence systems are employed to perform complex tasks using problem-solving techniques similar to those used by humans [2]. Machine learning (ML) and artificial intelligence (AI) are tightly intertwined subjects that are revolutionizing numerous industries and aspects of everyday existence. Machine Learning (ML) is a subset of Artificial Intelligence (AI) that use algorithms and statistical models to enable computers to learn from data and make predictions or evaluations without explicit programming.

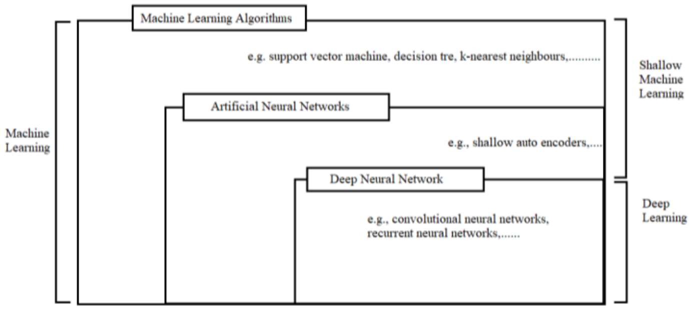

Fig 1Deep Learning

AI refers to machines that can do functions typically associated with human intelligence, such as recognizing speech, understanding natural language, and making decisions. Artificial intelligence (AI) can be categorized into two types: narrow or weak AI, designed for performing certain tasks, and general or strong AI, capable of carrying out any intellectual task that a human can do. Machine learning and artificial intelligence (AI) have been widely utilized in several fields such as healthcare, finance, marketing, and transportation in recent years. To mention a few applications, MLand AI may be used to forecast consumer behavior, identifyfraud, analyze medical imaging, and drive autonomously. The success of ML and AI is due to their capacity to analyze andderiveinsightsfrommassiveamountsofdatathathumanswouldbe unable to process in a reasonable length of time. ML and AImay also learn and develop over time, making them especiallyhelpfulforactivitiesthatrequireconstantchangesorimprovement.
Notwithstanding the numerous benefits of machine learning and artificial intelligence, there are worries about its influence on society, notably in areas such as privacy, job displacement, and prejudice. As the area of ML and AI evolves, it is critical to explore these challenges and guarantee that these technologies are created and applied responsibly and ethically.
Deep Learning: DL is a type of machine learning that focuses on training artificial neural networks to accomplish intricate tasks, such as recognizing images and audio, processing spoken language, and enabling autonomous driving. DL algorithms are intended to comprehend and develop over time by understanding massive volumes of data and learning through patterns and relationships in the data. To highlight a few applications, they may be exploited for object detection, natural language processing, audio recognition, and medical picture analysis. Deep learning has been having a substantial influence on an array of industries, particularly healthcare, finance, and manufacturing.
Deep learning, for example, is being employed in healthcare to enhance the precision and speed of radiography, identify and diagnose diseases including cancer and Alzheimer's disease, and build

appropriate intervention regimens. Deep learning's effectiveness stems from its capacity to learn and improve through experience, as well as its ability to analyze massive amounts of data fast and reliably. Deep learning, on the other hand, necessitates vast quantities of processing power and data, which might be prohibitively expensive for some applications. Despite the plethora of benefits, there are concerns surrounding deep learning's potential influence on society, notably in areas such as privacy, job displacement, and prejudice. As the area of deep learning evolves, it is critical to explore these challenges and guarantee that new technologies are created and deployed responsibly and ethically.

II. RELATED WORK

The cosmos of infinite information and knowledge has a significant amount of earlier effort. Many writers and researcher delivered lots of machine learning tactics and methodologies for forecasting and classification of different categories of illness.

To address these issues, Liu et al. proposed a method that estimates pMCI from the neuroimaging initiative using unsupervised novelty detection methods. Non-imaging data were compared to learning under binary supervision such as SVM (Support Vector Machine) and RF (Random Forest). They used layered cross-validation optimization to optimize the modified F measure and ensure the proposed system's maximum generalization by increasing TNR (True Negative rates) and decreasing FNR (False Negative Rates). Their vast experimental findings confirmed the effectiveness of algorithms KNN 71%, GMM 72%, and ELM 72.5% performed comparable to supervised binary SVM 74% with 20% constant MCI misinterpretation civility and were much superior than RF 47%. Additionally, they observed that employing ND methods, the non-invasive, easily accessible, and low-cost cognitive and functional evaluation was the most efficient predictor of pMCI within 2 years. They also presented a simple and low-cost pMCI prediction approach which does not involve contextual information [4].

Salehi et al. [5] employed MRI pictures, a Convolution Neural Network was developed using the ADNI 3 dataset to detect and classify Alzheimer's disease at an early stage. The dataset consisted of 1512 cases of mild Alzheimer's disease, 2633 cases of normal individuals, and 2480 cases of Alzheimer's disease. The model demonstrated a notable accuracy of 99% in comparison to several other comparable endeavors. They conducted a comparison between their results and previous research that utilized machine learning methods with the OASIS dataset. The findings showed that when working with large amounts of data, such as medical data, deep learning approaches can be a more effective option than traditional machine learning techniques.

Yet, due to similarity in illness manifestations, detecting such diseases effectively from acquired neuroimaging data is extremely challenging. Noor et al. objectively reviews and compares the efficacy of existing deep learning-based algorithms for detecting neurological illnesses MRI image data collected utilizing many methods of treatment, which would include functional as well as structural MRI. The Convolution Neural Network surpasses other approaches in diagnosing neurological illnesses, according to a performance evaluation of many DL designs across various diseases and imaging modalities. Furthermore, a few contemporary research concerns and possible future study areas are mentioned. [6].

Hashmi et al. [7] presents an innovative method for utilizing deep learning models, including "Xception, ResNet18, DenseNet121, InceptionV3, and MobileNetV3". Their strategy involves a weighted classifier that optimally utilizes measured suggestions. Supervised learning is employed when a network uses available information, both in terms of quality and quantity, to make predictions for a specific goal. Transfer learning is utilized as a tool to enhance the precision of a deep learning prototype during its development and validation. In order to enhance the training dataset in a logical manner, partial data supplementation methods are employed. The proposed weighted classifier outperforms all of the independent criteria. Hence, the model is evaluated not only based on its test performance, but also in terms of its Area Under the Curve (AUC). The final proposed weighted classifier model achieves a test accuracy of 98.43% and an AUC score of 99.76% by using irrelevant features from the "Guangzhou Women and Children's Hospital Center Pneumonia Dataset". In summary, the following methods can be used to assess the risk of pneumonia and aid radiologists in their work.

Convolution neural networks (CNNs) beat humans in medical picture data recognition. In summary, Zhenjia et al. utilized the "Kaggle dataset consisting of 5216 training and 624 testing scans" to classify chest X-ray pictures into two categories: normal and pneumonia. Extensive study was conducted using five standard network techniques to identify these disorders in the dataset. The observations were compared, allowing for the improvement of the "Mobile Net Network Structure" and achieving a higher accuracy rate compared to earlier methods. Furthermore, the improved "Mobile Net Network Structure" can be extended to other deployment sites [8].

Zhang et al. [9] introduced a system that surpasses classification algorithms when it comes to binary supervision. They achieved this by utilizing the "X-VIRAL Dataset," which consists of "5,977 patients with viral pneumonia but without COVID-19, and 37,393 cases of non-viral pneumonia or healthy individuals." In addition, while assessing selectivity and sensitivity on the X-COVID dataset, which consists of 106 COVID-19 cases and 107 normal controls, their model achieves an AUC of 83.61% and a sensitivity of 71.70%. These results are comparable to the performance recorded by radiologists. To resolve this challenge, Sharma et al. concerned a deep learning-based system named VGG19 is deployed, which isolates pneumonia versus healthy lungs. The aforementioned study used a “Chest X-ray dataset of 5856 images” to distinguish pneumonia from normal lungs. The accuracy rate was 93%. Moreover, to validate the new program, overall efficiency characteristics of the earliest model are compared to previous research, with the suggested framework exceeding the forth approaches. This work might be employed in hospitals and medical implementations in the years ahead [10].

Nilanjan et al. [11] used traditional deep learning models, including "AlexNet, VGG16, VGG19, and ResNet50," along with a SoftMax classifier, to evaluate the experimental test. Program VGG19 demonstrates superior classification accuracy, surpassing previous techniques by 86%. The Ensemble Feature Scheme is employed to create a tailored VGG19 network, which combines the distinctive characteristics obtained from CWT, DWT, and GLCM analysis with the Deep-Features learned through Transfer-Learning. The performance of the updated VGG19 was assessed using SVM-linear, SVM-RBF, KNN classifier, Random-Forest, and Decision-Tree classifiers. Based on the data, the VGG19 model with the RF classifier achieves a 95% accuracy rate. In a similar experiment using chest radiographs modified with a threshold filter, the VGG19 model with RF classifier demonstrated a classification accuracy of 97%.

Jinnai et al. obtained a dataset consisting of 5846 clinical scans of pigmented skin lesions (PSL) from a total of 3551 scans for their research. The PSL encompassed both malignant and benign malignancies. The evaluation data set was created by randomly arranging 666 cases and selecting one image per participant, while the input sequence was started by labeling 4732 scans and 2885 scan cases with bounding boxes. The training dataset was used to train a somewhat faster convolution neural network (CNN) that focuses on specific regions. This network was then evaluated against the testing dataset for validation. In addition, the identical tests were carried out by ten dermatologists who are certified by a board and ten trainees specializing in dermatology. The precision of their diagnosis was compared to that of FRCNN. In the context of six-class classification, the FRCNN model achieved an accuracy of 86%, while the BCDs and TRNs models achieved accuracies of 79% and 75% respectively, as stated in reference [12].

Arthur et al. [13] introduce a Computer-Aided Diagnostic (CAD) system that categorizes manually segmented scans into three diagnostic classes: melanoma, nevi, and seborrhea keratosis. In order to enhance the precision of the CAD system, they are contemplating the implementation of a groundbreaking ensemble topology that utilizes convolution neural networks, which are evidently influenced by factorization and ensemble measures. Contrary to previous methods, this strategy utilizes a directed acyclic network to combine Boolean CNNs for the purpose of detecting melanoma. Our solution outperforms multiclass CNNs, an ensemble of multiclass CNNs with typical aggregation methods, and other similar attempts in terms of balanced accuracy. Specifically, our system achieved an accuracy of 76% on the ISIC 2018 public dataset. The results of our study indicate that utilizing a directed acyclic graph is a highly effective method for developing a reliable and resilient automated diagnostic system for classifying dermoscopic images into multiple categories.

Ibraheem et al. [14] utilized pixel-based segmentation along with feature extraction algorithms to showcase a non-invasive automated method for distinguishing between "Malignant Melanoma" and

"Seborrhea Keratosis (BKL)". The proposed technique utilizes pixel-based features to identify the fundamental distinctions between benign keratosis lesions (BKL) and malignant melanoma. The utilization of the dot approach enabled the representation of individual pixels' color and texture distributions in the processed image, leading to a distinct contrast between pigmented skin lesions and unaffected skin regions. The experimental data demonstrate that the representational result obtained using gradient boosted trees is promising and surpasses other state-of-the-art approaches, with an accuracy of 97.5%, Dice measure of 98.5%, sensitivity of 98.3%, and specificity of 92.1%.

Sevli et al. introduced a convolution neural network (CNN) model for the purpose of classifying seven different skin conditions in the "HAM10000 Dataset". The programs had a grouping efficiency of 91%. Upon comparing the effectiveness of the programs to other research released thus far, it was found that they surpassed the bulk of them. The model was integrated with a web-based application and underwent two stages of testing by a panel of seven dermatologists. During the initial phase, it was observed that the engine had a practical success rate of 90% in identifying skin lesions [15].

Prior to the Convolution Neural Network, a framework is presented for the identification of distinct characteristics of Alzheimer's disease in MRI scans. The proposed approach by Surya et al. [16] constructs a program that takes into account the four phases of cognitive decline. By performing a specific diagnostic, the suggested method generates high-resolution statistical likelihood layouts of disease progression in the brain. These layouts are then fed into a multilayer perceptron, resulting in realistic and clear representations of an individual's likelihood of developing Alzheimer's disease. To mitigate the problem of misinterpretation, it is advisable to evenly distribute the parts across the courses. The "Kaggle MRI Image Dataset" has a notable issue of class imbalance. A proposed method for diagnosing dementia stages using MRI scans is the implementation of a DEMentiaNETwork, which achieves a 95% accuracy rate.

In their study, Javeed et al. [17] aimed to thoroughly validate diagnostic systems that rely on machine learning automation techniques. They employed many data modalities, including images, clinical features, and speech data. They conducted a comprehensive search for literature on dementia, machine learning, feature selection, data modalities, and automated diagnostic systems spanning the years 2011 to 2022. The selected resources underwent meticulous examination and extensive deliberation. ML models that utilize image data exhibit superior performance compared to other data approaches, such as clinical feature-based data and voice data, for predicting dementia. This study also emphasized the limitations of previously suggested automated dementia methods and suggested potential remedies for these challenges.

Shakila et al. [18] utilize the "Open Access Series of Imaging Studies Dataset" with dimensions of 373X15 to classify the labels as either demented or non-demented. The uniqueness is in doing a "Hierarchical Examination" of all available data points using exploratory data analysis to assess the significance of features, correlation studies between variables, and data density to uncover the condition of components. Diverse variable optimization techniques, along with feature selection, are employed to enhance the speed and accuracy of the model. The claims were validated by reaching a correlation accuracy of 92% across multiple iterations and layers.

Miah et al. [19] conducted a quantitative evaluation of various classifiers' ability to diagnose dementia using clinical datasets. The classifiers included K-nearest Neighbor, decision tree, random forest, Naive Bayes, artificial neural network, support vector machine, and logistic regression. By utilizing open access datasets like the open access series of imaging investigations, the Hypertension neuroimaging project, and the Alzheimer bank datasets, it has been demonstrated that support vector machine and random forest algorithms exhibit superior performance.

Virk et al. [20] stated that segmentation is a crucial component of computer-aided diagnosis (CAD) and medical picture analysis. Their work presented a method for automatically selecting a threshold to segment medical images. The method is based on fuzzy 2-partition utilizing Kapur entropy. The image is transformed into a fuzzy 2-partition by utilizing two parameterized fuzzy membership functions in the Kapur entropy approach. The optimal threshold is achieved by seeking the ideal combination of parameters for the fuzzy membership functions in order to maximize the fuzzy 2-partition Kapur entropy. Integrating the concept of a rapid recursive algorithm and Kapur entropy reduces the complexity of looking for the optimal combination of parameters. The performance of the represented approach is evaluated using multiple medical photos, and the findings are found to be quite promising. The suggested methodology could be included into a CAD system to facilitate the early identification of diseases such as cancer.

In their study, Pritpal Singh et al. [21] emphasized the importance of developing intelligent systems that utilize machine learning techniques to effectively diagnose diseases using patient health data. This work successfully developed a computer-aided design (CAD) system for predicting cardiovascular illness by employing various machine learning techniques.

III. PROPOSED WORK

Machine Learning and Deep Learning are rapidly growing disciplines within the study of Artificial Intelligence (AI) that demonstrate significant promise in diverse domains, such as image classification, natural language understanding, and speech synthesis. Deep learning use multi-layered neural networks to address intricate problems, whereas machine learning utilizes algorithms and statistical models to enable machines to gather knowledge from data and produce recommendations or conclusions.

Intendtoexploretheperformanceofdeeplearningalgorithm on a real-world dataset in this proposed effort. Will concentrate on constructing and evaluating several models for classification issue, where the aim is to predict the class label ofan input instance based on its attributes. We intend to utilize publicly accessible dataset with a high number of examples with many characteristics. The data will be preprocessed and divided into training and testing sets. Afterwards, wetested deep learning model, and assess the performance using measures like “accuracy, precision, recall, and F1-score”.

Data Collection: Data collection and organization for training and testing machine learning models is a crucial step in the machine learning process. The accuracy and reliability of the resulting models can be significantly affected by the quality and quantity of the collected data.

The dataset provided is the Alzheimer MRI Preprocessed Dataset, which consists of images with dimensions of 128 by 128 pixels. The data is sourced from multiple websites, hospitals, and public repositories. The dataset comprises preprocessed MRI (Magnetic Resonance Imaging) images. The dataset consists of four distinct categories of photos. The dataset has a total of 6400 MRI pictures. The dataset consists of 896 photographs of individuals with mild dementia, 64 images of individuals with moderate dementia, 3200 images of individuals without dementia, and 2240 images of individuals with very mild dementia.

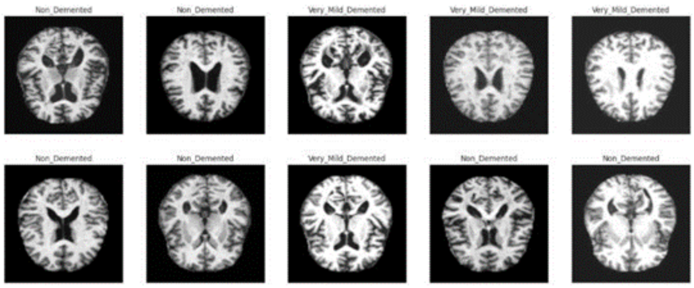

Fig 2. Alzheimer Dataset

The dimension of each image in Alzheimer dataset is of 128 X 128 pixels as represented below.

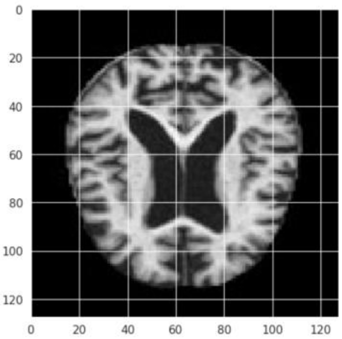

Fig 3.Shape of Data Image

TheAlzheimer datasetaswhole distributedinTrainingandValidationdataset as represented inthefollowingplots.

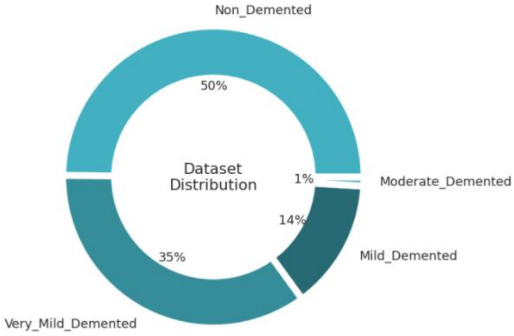

Fig 4. Alzheimer Dataset

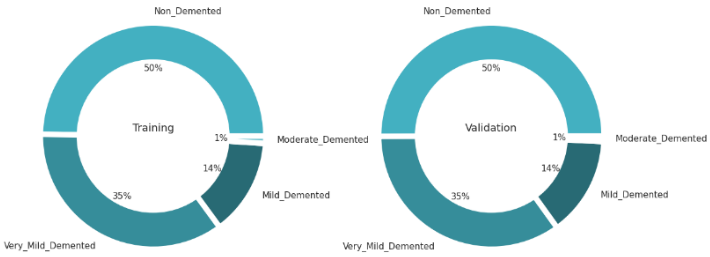

Fig 5. Training and Validation Dataset

Trainingamodelonthishighlyimbalanceddatasetwillcausethemodeltooverfitonthedifferentclassthatisinexcessandfailtolearn patterns from the other classes. Fortunately, there was awaytotacklethisproblem.Usingthecross-entropylossfunctioncreates a bias towards the dominating class. So, applied weightstobalance the lossfunction.Thisiscalledweightedlossfunction.

$$\mathcal{L}_{cross-entropy} = -\frac{1}{N}\sum_{i=1}^{N}[w_p y_i \log(\hat{y}_i) + w_n(1-y_i)\log(1-\hat{y}_i)] \quad (1)$$

Studied the use of deep learning model VGG-16, for the sameclassification job. VGG is quite popular since 2014. In 2014, researchersattheUniversityofOxfordunveiledthedeepconvolutionalneuralnetwork(CNN)architectureknownasVGG(Visual Geometry Group). It refers to the research group whereitwascreated,theVisualGeometryGroup.TheVGGNetasitiscalled, gained notoriety for its 16designisrenownedforbeingbothstraightforwardandefficient layers serve as a classifier, and convolution layers are in chargeofextractingfeaturesfromtheinputimage.

Model: "classifier"

Layer (type)	Output Shape	Param #
block1_conv1 (Conv2D)	(None, 128, 128, 32)	896
block1_conv2 (Conv2D)	(None, 128, 128, 32)	9248
pool1 (MaxPooling2D)	(None, 64, 64, 32)	0
block2_conv1 (Conv2D)	(None, 64, 64, 64)	18496
block2_conv2 (Conv2D)	(None, 64, 64, 64)	36928
pool2 (MaxPooling2D)	(None, 32, 32, 64)	0
block3_conv1 (Conv2D)	(None, 32, 32, 128)	73856
block3_conv2 (Conv2D)	(None, 32, 32, 128)	147584
pool3 (MaxPooling2D)	(None, 16, 16, 128)	0
flatten (Flatten)	(None, 32768)	0
dropout1 (Dropout)	(None, 32768)	0
dense1 (Dense)	(None, 128)	4194432
final (Dense)	(None, 4)	516

Total params: 4481956 (17.10 MB)
Trainable params: 4481956 (17.10 MB)
Non-trainable params: 0 (0.00 Byte)

Fig 6.VGG-16ModelSummary

IV. RESULT AND ANALYSIS

Let's look at the findings of research that intended to create amulti-disease detection and prediction framework utilizes noveldeeplearningandmachinelearningapproaches.Theworkentailed evaluating a big dataset of patient health records anddeveloping the deep learning model to predict and classification.Applied the VGG-16 deep learning model on Alzheimer diseasedataset and observed thefollowingresult.

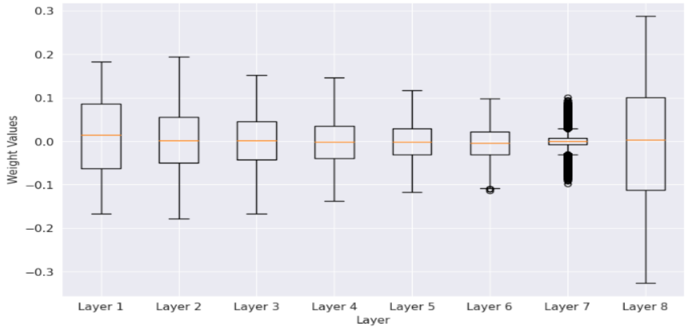

Fig 7. Weight Distribution Across Layers in VGG-16 Model

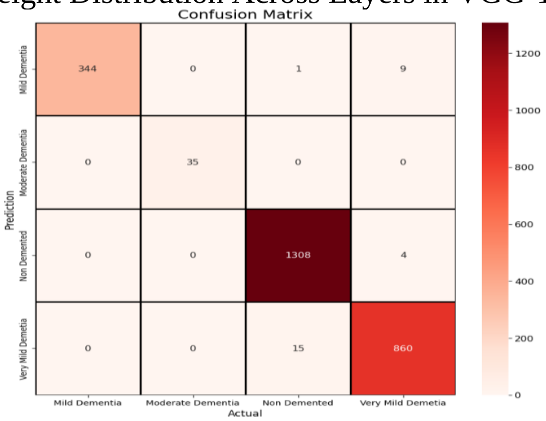

Fig 8. Confusion Matrix

Also applied different optimizer and Regularizer, and obtained the differentresultasrepresentedinthefollowingtable.

Table 1. Different VGG-16 Network Configurations and Performance Measures for Alzheimer Dataset

Layers	Optimizer	Regularizer	Train Accuracy	Test Accuracy
32-64-128	Adam	Dropout(0.3)	99.62	98.68
32-64-128	Adam	Dropout(0.2)	97.67	97.29
32-64-128	Adam	Dropout(0.4)	97.18	96.25
32-64-128	RMSprop	Dropout(0.2)	98.88	98.87

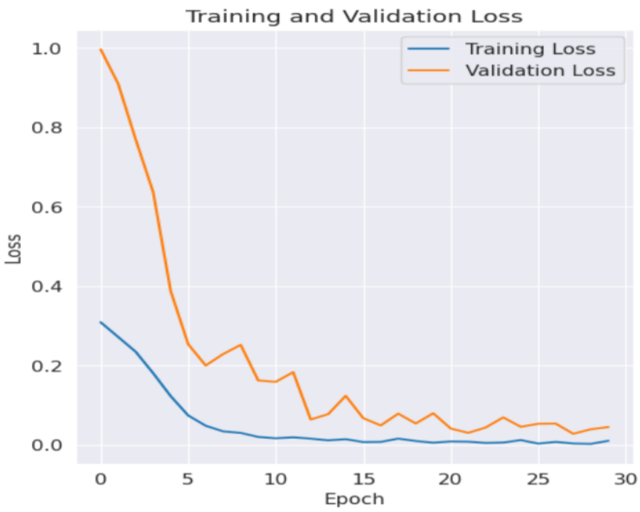

Fig 9. VGG-16 Model Training and Validation Loss

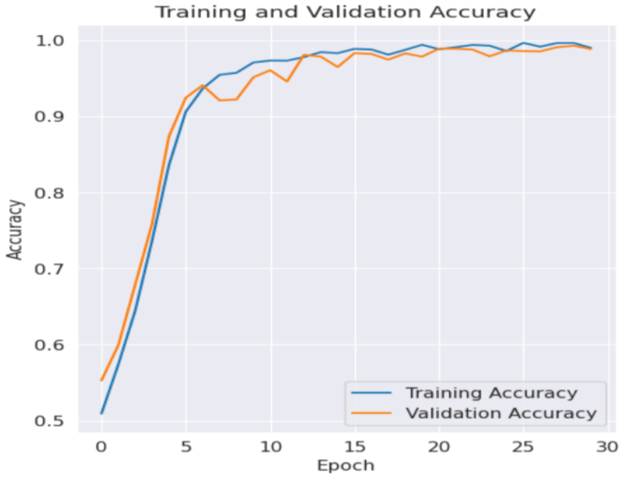

Fig 10. VGG-16 Model Training and Validation Accuracy

On applying 'RMSprop' optimizer with 'sparse_categorical_crossentropy' loss function with dropout (0.2), the VGG-16 model abled to achieve accuracy of 98.87% with 99.33% precision. 99.05% f1-score.

HerearesomesuccessfulclassificationandpredictionofAlzheimerDisease.

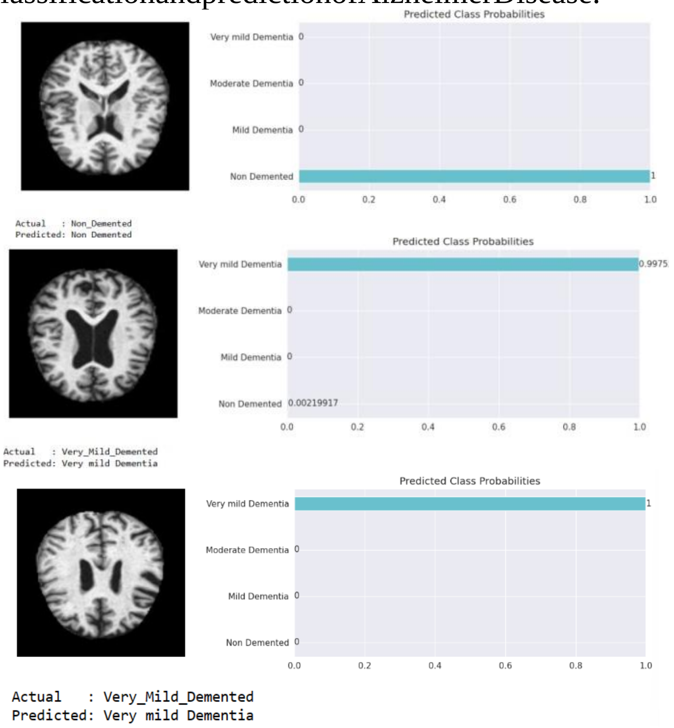

Fig11. PredictionandClassificationofMultipleStagesofAlzheimerDiseaseusingVGG-16

V. CONCLUSION AND FUTURE SCOPE

Finally, the construction of a multi-disease classification and prediction model employing revolutionary deep learning and machine learning approaches has yielded encouraging results in terms of enhancing early detection and treatment of many diseases. The research demonstrates the feasibility of developing accurate and efficient prediction models employing massive datasets and sophisticated algorithms. For Prediction and detection of multiple stages ofAlzheimerDiseaseusingVGG-16deeplearningmodelachieved98.87%accuracy.

Yet, there are still constraints and obstacles to overcome, such as data quality and model biases. Furthermore, the application of these models in real-world healthcare settings must be thoroughly assessed to guarantee successful integration and influence on patient outcomes. The future of multi-disease detection and prediction research will entail the continuous development and improvement of machine learning models, as well as the study of new data sources and techniques. More multidisciplinary collaboration between healthcare practitioners, data scientists, and legislators is also required to guarantee the ethical and responsible use of new technologies. Overall, the potential benefits of multi-disease prediction and classification models are substantial, and further study in this field has the potential to have a large influence on improving healthcare outcomes for people globally.

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