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Alzheimer's Disease Detection using CNN

Deep Learning

(CSE4037)

Slot: B1

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ABSTRACT

Alzheimer's disease (AD) is a neurological disorder. Alzheimer's disease (AD) is the most prevalent chronic disease among the elder people, with a high prevalence. It is a devastating neurodegenerative disease that affects millions of people around the world. There is no particular therapy for Alzheimer's disease. Early identification of Alzheimer's disease can assist patients in receiving appropriate care. Deep learning has gained popularity and success in the field of medical imaging in recent years. It has become the dominant way of assessing medical pictures and it has also sparked considerable interest in the diagnosis of Alzheimer's disease. The suggested methodology uses MRI data to diagnose AD and the Deep Learning algorithm to categorise the current illness. In this project, we propose a deep learning-based approach to detecting Alzheimer's disease using magnetic resonance imaging (MRI) scans trained on the Kaggle dataset.

INDEX TERMS: DenseNet121, DenseNet169, ResNet50, VGG19 and MRI images of Alzheimer's.

I.INTRODUCTION

Alzheimer's disease is a clinical syndrome characterised by progressive deterioration of cognitive and memory abilities. It is a very common disease among the elderly, accounting for 60-80% of dementia types. Although the prevalence of Alzheimer's disease is high, there is currently no cure. There is a long period of time between the appearance of AD and the final diagnosis. Mild cognitive impairment (MCI) refers to patients in the early stages of Alzheimer's disease; however, not all MCI will progress to AD; approximately 30-40% of MCI will progress to AD.

Translational applications of computational neuroscientific approaches have been shown to be extremely beneficial in large-scale mental health trials. This multidisciplinary field of study can aid in modelling the biological processes that govern the healthy and diseased states of the human brain and mapping these processes into observable clinical manifestations. The rapid increase in high-volume biomedical datasets over the last decade. This recent advancement, from a computational standpoint, has spawned the development of tools that incorporate several patient-specific observations into predictions and improve the clinical outcomes of patients suffering from such disorders.

Deep learning algorithms, such as Densenet169 and Densenet121 have recently shown promising results in medical image analysis. We intend to investigate the use of these deep learning algorithms for the detection of Alzheimer's disease using MRI images.This study used MRI images from four classes: Mild

Demented, Moderate Demented, Non Demented, and Very Mild Demented. The dataset is split into two parts: training and testing, with an equal distribution of the four classes in each.On our MRI dataset, we propose using transfer learning techniques to fine-tune pre-trained Densenet169 and Densenet121 models. We will assess our models' performance using various metrics such as accuracy, precision, recall, and F1 score. Our aims is to contribute to the development of accurate and efficient Alzheimer's disease diagnostic tools that can aid in the disease's early detection and treatment.

This condition is characterised by an accumulation of plaques and tangles in the brain, along with the harm and degeneration of brain cells. Dr. Alois Alzheimer was the first to notice it after witnessing a woman die as a result of internal brain tissue changes. The primary cause of this disease, the doctor concluded after scanning the patient's brain after death, was the development of various clumps. They interfered with the brain's ability to coordinate with other body parts.The longest-lasting disease is Alzheimer's, which can cause severe mood swings, confusion, impulsivity, lack of focus, difficulty recognising objects, etc. The final phase is the most challenging.

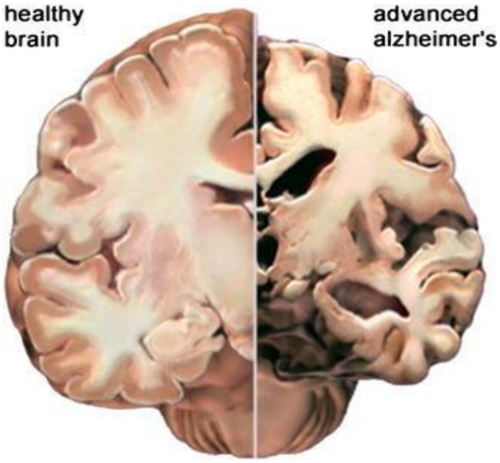

Fig.1.Representing a picture of a Healthy Brain vs Advanced Alzheimer's.

The use of automatic systems capable of distinguishing pathological cases from normal cases based on their magnetic resonance imaging (MRI) scans will greatly aid in the initial diagnosis of Alzheimer's disease. In this study, we review relevant studies that investigate Alzheimer's disease and apply MRI data and Deep Learning (DL) techniques to various Alzheimer's disease datasets.

Magnetic Resonance Imaging (MRI): Magnetic Resonance Imaging (MRI) is a popular diagnostic tool for detecting structural changes in the brain that may indicate the presence of Alzheimer's disease.This imaging technique employs radio waves and magnetic fields to produce high-quality, high-resolution 2D and 3D images of brain structures. There is no harmful radiation produced by X-rays or radioactive tracers. The structural MRI, which measures brain volumes in vivo to detect brain degeneration, is the most commonly used MRI for AD cases (loss of tissue, cells, neurons, etc.). Brain degeneration is an unavoidable progressive component of Alzheimer's disease. MRI provides useful information and data about the activity of the human brain, i.e., how the brain functions. Brain imaging methods based on arterial Blood Oxygenation Level Dependent (BOLD) contrasts and spin-labelling (ASL).

II. A STORY OF ALZHIEMER'S DISEASE

The history of AD is a collection of information from papers that were looked for in GoogleScholar. Only papers published between 2008 and 2019 were chosen and only the most recent publications were taken into consideration. The datasets used to study AD and 4 classes of images of like Mild Demented, Moderate Demented, Non Demented, Very Mild Demented,were the main focus of our study. The methods and procedures employed by earlier researchers were examined.

III. LITERATURE REVIEW

Khan et al. [1] compared the effectiveness of imputation and non-imputation methods using the Random-Forest classifier. They discovered that the non-imputation method has an accuracy of 83% while the imputation method has an accuracy of 87%. The subjects were further divided into demented and non-demented groups.

Escudero et al. [2] suggested an ML method utilising biomarkers in their paper. They put to the test a custom disease classifier using a technique for learning locally weighted and biomarkers. The methodology makes an initial classification attempt before deciding which biomarker to order. They separated the MCI patients who converted to AD within a year from those who did not.

Alam [3] claimed that early disease detection can stop the spread of illness. He used structural magnetic resonance imaging (MRI) to extract brain images from the repository. In order to project the data onto the available linear space, he proposed using kernels. The data was then classified using a Support Vector Machine (SVM). He achieved a respectable accuracy of 93.85%.

X. Zhang et al. (2019). [4] propose a deep learning approach to detect Alzheimer's disease from MRI images in their study "Early Detection of Alzheimer's Disease Using Deep Learning Techniques." The proposed method extracts features from MRI images and then uses an SVM to classify the images as normal or AD.The

CNN used in the study is made up of multiple convolutional layers, pooling layers, and finally fully connected layers. The CNN is trained on a large dataset of MRI images, including normal and Alzheimer's disease images. The CNN learns to extract discriminative features from images that allow it to differentiate between normal and AD images.

Shi et al. (2017).[5] in there paper "Nonlinear feature transformation and deep fusion for Alzheimer's Disease staging analysis" proposes a new Alzheimer's Disease (AD) staging analysis method that combines nonlinear feature transformation and deep fusion techniques. Using a nonlinear kernel function, the original data is transformed into a high-dimensional feature space, and then a deep fusion model is used to combine features from multiple modalities, including structural magnetic resonance imaging (MRI) and cerebrospinal fluid (CSF) biomarkers.

Hadeer A. Helaly [6] conducted research on the use of deep learning approaches for Alzheimer's disease early detection. The study used magnetic resonance imaging (MRI) data to assess the performance of various deep learning algorithms in detecting Alzheimer's disease in its early stages.A dataset of MRI scans from patients with Alzheimer's disease, mild cognitive impairment, and healthy controls was used in the study. The MRI images were preprocessed before being fed into various deep learning algorithms, such as convolutional neural networks (CNNs) and autoencoders. The accuracy, sensitivity, specificity, and area under the receiver operating characteristic (ROC) curve were used to evaluate the performance of these algorithms.

Dr. Bryan [7] observed that variations in cross-site and cross-vendor estimations constrained the use of AI in cerebral blood flow imaging techniques for Alzheimer's disease. Such types can be strongly standardised in human vision, but they require significant advancements in learning how to avoid dangers from ignored and underrepresented measurable mistakes.

Tausifa Jan Saleem 2022.[8] The paper "Deep Learning-Based Diagnosis of Alzheimer's Disease" suggests a deep learning-based approach to Alzheimer's disease diagnosis (AD). The authors hope to create a reliable and accurate diagnostic tool that will aid physicians in making early and accurate diagnoses of Alzheimer's disease. The proposed method extracts features from magnetic resonance imaging (MRI) data of patients with Alzheimer's disease and healthy controls using a convolutional neural network (CNN). The authors trained and tested the model using two publicly available datasets.

The authors concluded that their deep learning-based approach has the potential to help physicians make accurate and timely diagnoses of Alzheimer's disease. They did, however, state that more research is needed to validate the results on larger datasets and to investigate the clinical utility of the proposed method. Overall, the paper presents a promising method for detecting Alzheimer's disease early and accurately using deep learning techniques.

Ahmed Arafa et.al.(2022).[9] in there paper "Early detection of Alzheimer's disease based on the state-of-the-art deep learning approach: a comprehensive survey" they proposed a deep learning-based approach for early detection of Alzheimer's disease using structural MRI images. A convolutional neural network (CNN) and a fully connected neural network are used in the proposed model. The CNN extracted features from the MRI images, and the fully connected neural network was used for classification. The proposed method achieved an accuracy of 95.4% for Alzheimer's disease diagnosis, demonstrating its potential for early detection of the disease.

Zubair [10] claimed to have found a way to detect Alzheimer's disease. He used a five stage machine learning pipeline process for the detection, with a sub-stage for each stage. This pipeline was subjected to a number of classifiers. The random forest Classifier, he reasoned, had superior performance metrics.

IV.PROPOSED WORK

It is well known that deep learning learns a hierarchy of representations in order to learn low, mid, and high-level features. Complex data sets can be adapted to by deep neural networks. Its multiple layers make it better at generalising previously undiscovered data. Different algorithms make use of Deep Learning's fundamental expertise and train and test them on a variety of datasets.

Similar to human neurons, deep learning has layers that help in the model's or algorithm's ability to learn from and process data. As they move through the layers, these layers process the data that is provided to them as input and learn through the process. The deep learning model finally produces the predicted output after passing through the final layer and applying an activation function. Once we have the training accuracy, we can use the deep learning model to predict or detect anything we want when we use a different dataset of a similar type. Well, in plain working terms, this is what deep learning achieves.

A.DATASET

The dataset, which was taken from the free and public Kaggle online dataset library, has not yet been used in any other research projects or studies. The dataset is open-source. Nearly 6,000 images from this dataset are divided into four classes: Mildly, Moderately, Very Mildly, and Non-Demented. The features are then split between a train dataset and a test dataset. Each deep learning model has two phases, training and testing, where it predicts the data that is given to it. Since 80% of the data is used in training, this means that each deep learning model has two phases. Both models use the same dataset, which is separate from the original Kaggle dataset, and are divided in an 8:2 ratio, with 80% of the dataset being used for training and 20% being used for validation.

B.METHODOLOGY:

Data collection: Collecting MRI scans from patients with Alzheimer's disease and control subjects who are in good condition. Our dataset is already pre-processed dataset which is taken from Kaggle.

Model Selection: deciding on deep learning models like VGG19, DenseNet, and ResNet, and configuring them by changing hyperparameters like learning rate, batch size, and number of layers.

Model training: Using a loss function and an optimizer to train the deep learning models on the pre-processed and supplemented dataset. The models are trained over a predetermined number of epochs, and metrics like accuracy, loss, and validation accuracy are used to track the training process.

Model evaluation: Analyzing the performance of the trained models on a different test set using metrics like accuracy, sensitivity, specificity, and area under the receiver operating characteristic (AUC) curve. The models' performances are contrasted, and the top model is chosen.

Interpretation: To understand how the deep learning models are making predictions, analyse the learned features and visualise the activation maps.

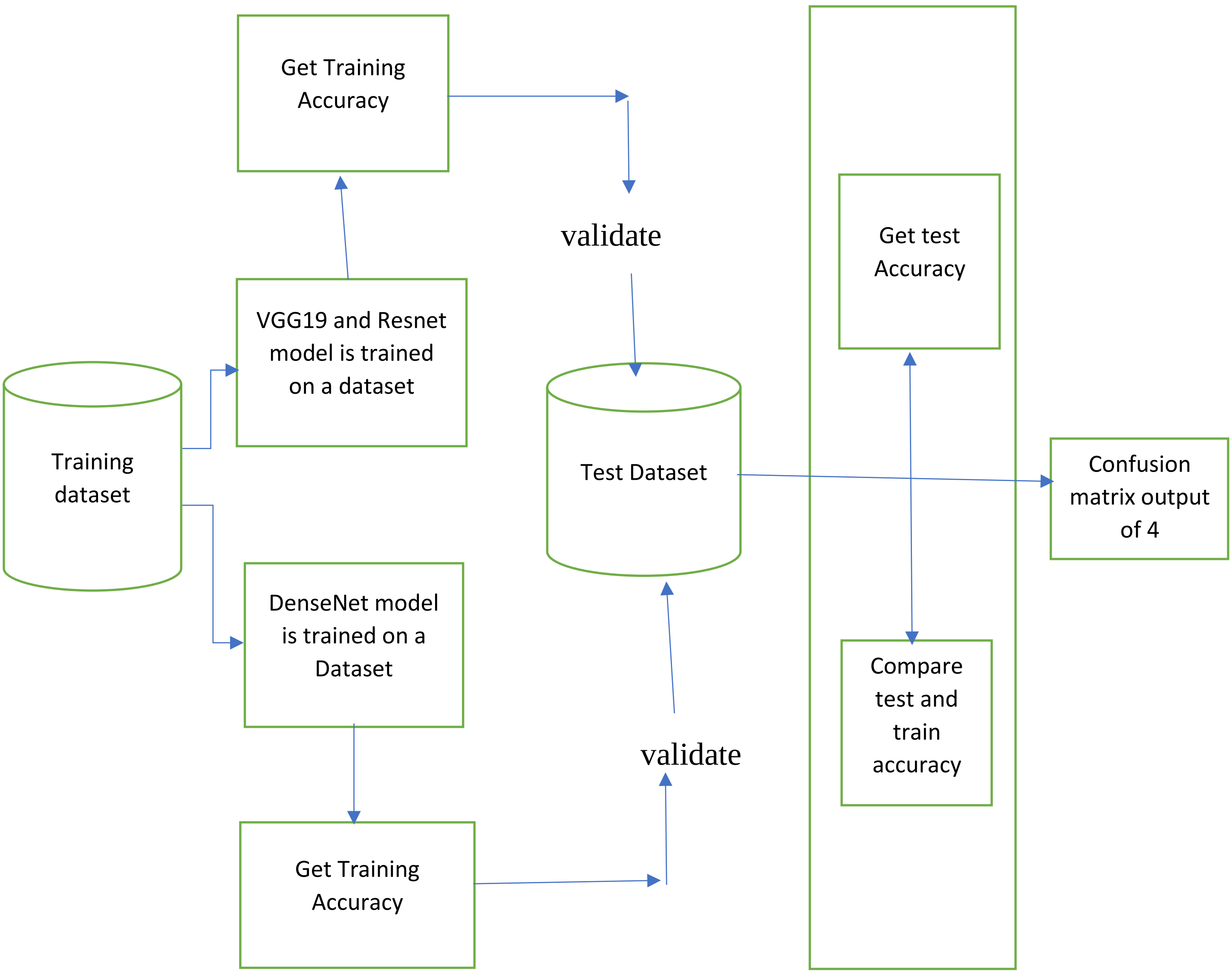

Fig.2.Proposed Methodology

The system architecture diagram represents the system's conceptual and behavioral features. It is simply a view that demonstrates how the database is utilised to obtain the dataset and then how this data is used in our project modules to train the various models.

The data is obtained from the training dataset and then delivered to the models, as shown in the architecture diagram above. The testing or validation accuracy is then determined by validating it against the test dataset. After comparing the accuracy, the diseased photos are extracted from the dataset. Mild Demented, Moderate Demented, Non Demented and Very Mild Demented are the four classifications used. The architecture diagram also demonstrates how the project's various parts interact with one another, how they work together to produce the expected outcomes, and how each module must be connected to the others in order for the project to function together.

RESULTS AND DISCUSSIONS:

a).Densenet121 model

The Densenet121 model has demonstrated respectable picture classification accuracy. The model has shown some interesting graphs. A batch size of 128 was employed. 5 epochs of the model have been completed. The model's accuracy is 0.7973, which indicates that it successfully identified 79.73% of the data. With a precision of 0.71, the model is right 71% of the time when it predicts a good outcome. With a recall of only 0.3197, the model performs good at spotting positive outcomes when they are present in the data. The model is relatively good in differentiating between positive and negative cases, according to the AUC score of 0.8296. The model is functioning properly, as evidenced by the F1 score of 0.4372, which measures the balance between precision and recall.

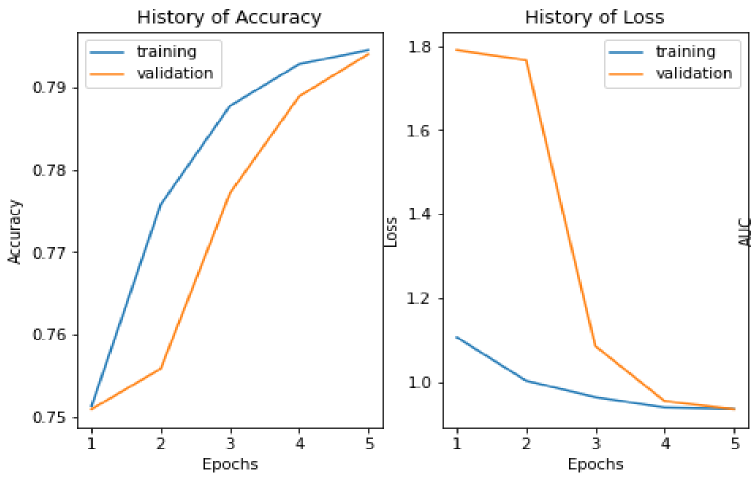

Fig.3.Model Accuracy and model loss in DenseNet121.

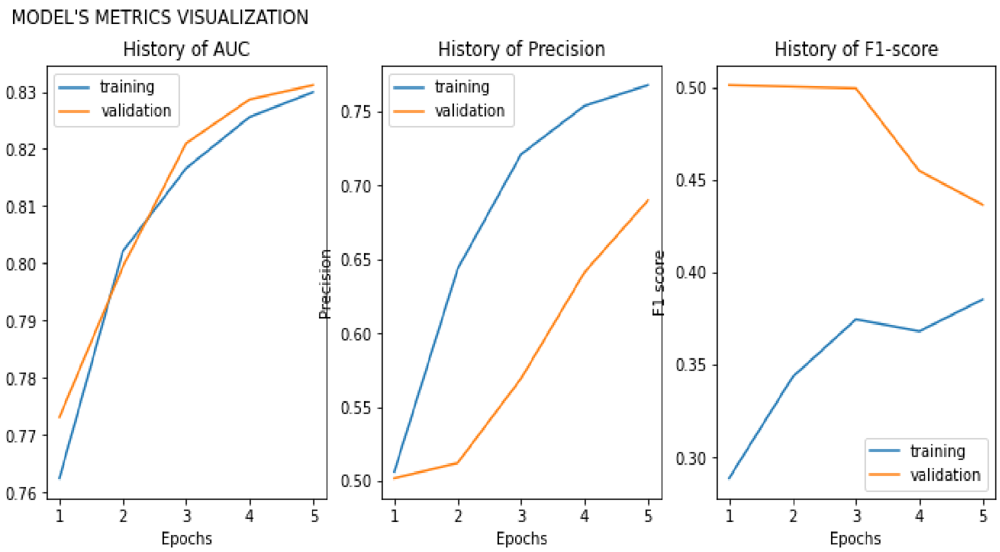

Fig.4.Model AUC and model Precision and F1-score in DenseNet121.

b).Densenet169 model

The Densenet169 model has demonstrated respectable picture classification accuracy. The model has shown some interesting graphs. A batch size of 128 was employed. 5 epochs of the model have been completed. The model's accuracy is 0.7908, which indicates that it successfully identified 79.08% of the data. With a precision of 0.7317, the model is right 73.17% of the time when it predicts a good outcome. With a recall of only 0.2580, the model performs poorly at spotting positive outcomes when they are present in the data. The model is relatively good in differentiating between positive and negative cases, according to the AUC score of 0.8320. The model is not functioning properly, as evidenced by the F1 score of 0.3777, which measures the balance between precision and recall.

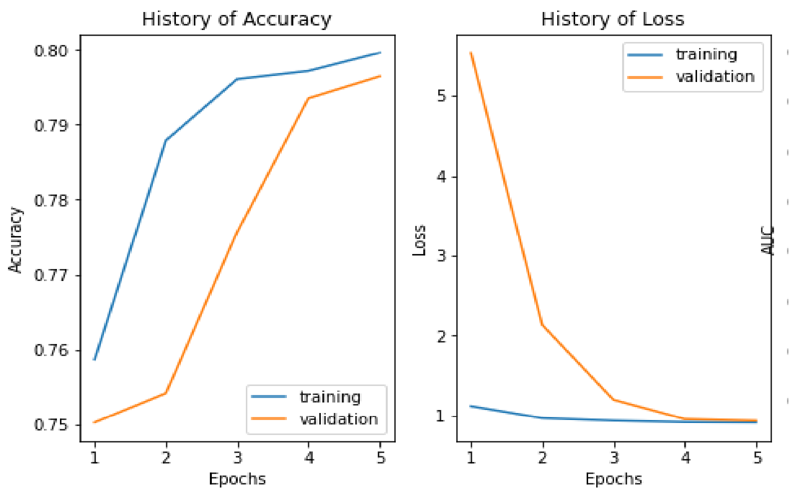

Fig.5.Model Accuracy and model loss in DenseNet169.

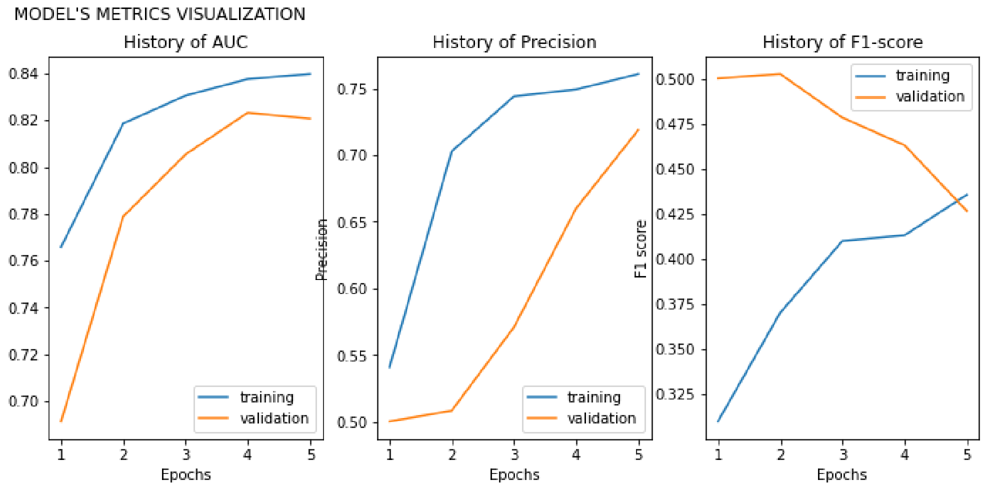

Fig.6.Model AUC and model Precision and F1-score in DenseNet169.

c). VGG19 model

The VGG19 model was evaluated on MRI images. A batch size of 128 photos was used to train it. It was decided to use 5 epochs.The model's accuracy is 0.75, which indicates that it successfully identified 75% of the data. With a precision of 0.0, the model is right 0% of the time when it predicts a good outcome. With a recall of only 0, the model performs poorly at spotting positive outcomes when they are present in the data. The model is relatively good in differentiating between positive and negative cases, according to the AUC score of 0.7969. The model is not functioning properly, as evidenced by the F1 score of 0, which measures the balance between precision and recall.

In the field of deep learning, loss is more of a function; unlike accuracy, it is not expressed as a percentage and represents the total of all the mistakes the machine made throughout training and validation. Any hyperparameter of the deep learning model, such as the batch size of images for training and the number of epochs, can be altered to lessen loss.

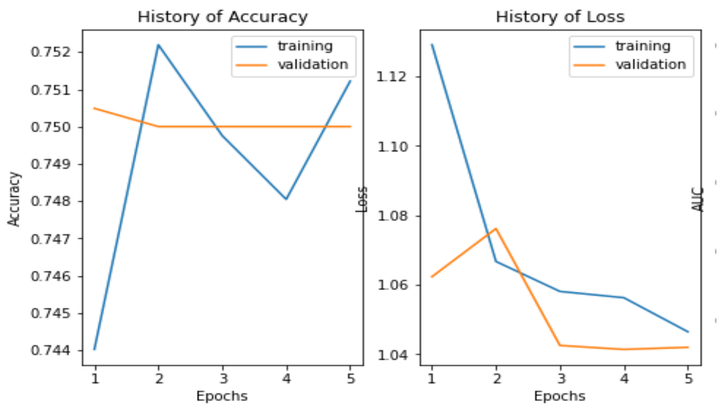

Fig.7.Model Accuracy and model loss in VGG19.

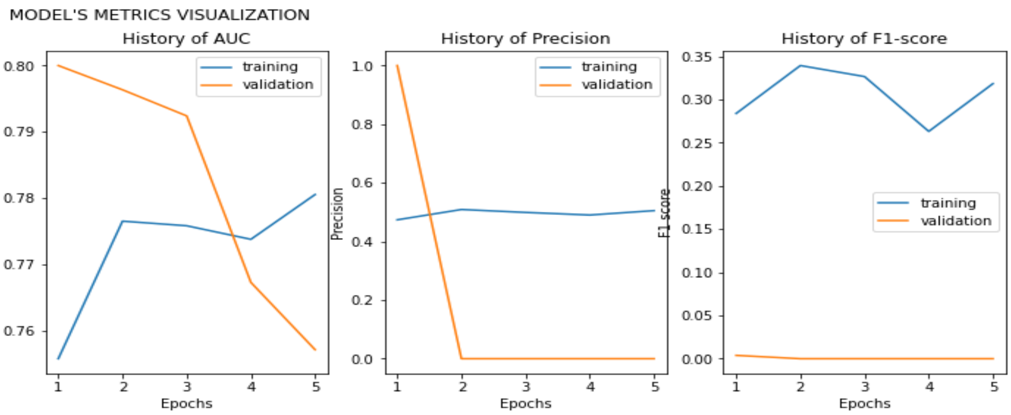

Fig.8.Model AUC and model Precision and F1-score in VGG19.

d). ResNet50 model

The data was classified using a ResNet50 model. The model's accuracy is 0.7498, which indicates that it successfully identified 74.98% of the data. With a precision of 0.4286, the model is right 42.86% of the time when it predicts a good outcome. With a recall of only 0.0023, the model performs poorly at spotting positive outcomes when they are present in the data. The model is relatively good in differentiating between positive and negative cases, according to the AUC score of 0.7894. The model is not functioning properly, as evidenced by the F1 score of 0.0045, which measures the balance between precision and recall.

The ResNet50 model appears to be outperforming on this dataset. But the precision and recall are poor and the accuracy is fair, respectively. This indicates that the model is not very effective at locating positive cases, which is probably a problem if that is the classification task's main objective. To enhance the ResNet50 model's performance on this dataset, it might be necessary to experiment with different models or change its parameters.

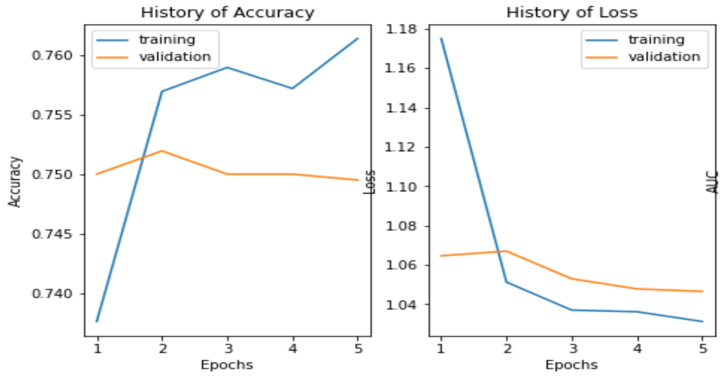

Fig.9.Model Accuracy and model loss in ResNet50.

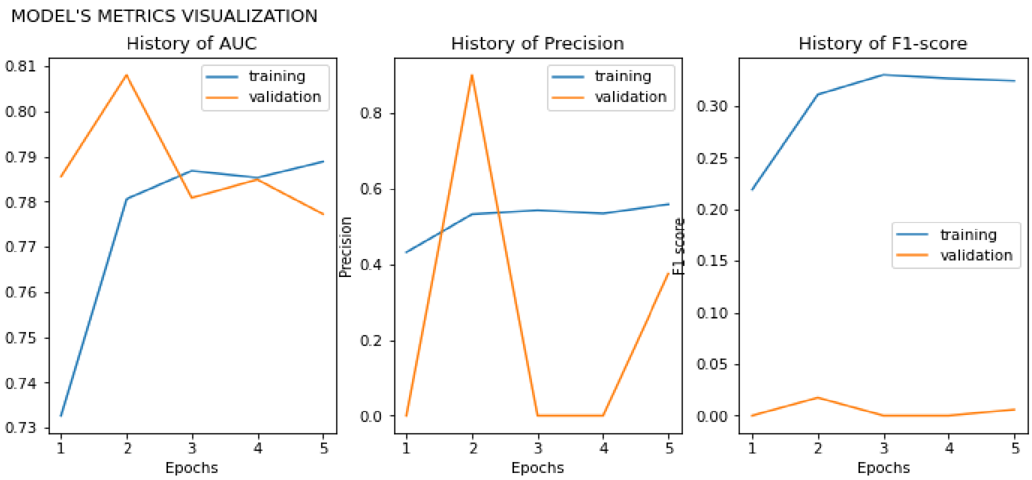

Fig.10.Model AUC and model Precision and F1-score in ResNet50.

CONCLUSION:

The most common cause of dementia is Alzheimer's disease. This paper proposes a method for detecting the disease at an early stage. The models used in this paper successfully classified the images into the appropriate four classes, yielding promising results. We observe that DenseNet121 has highest accuracy compare to VGG19, DenseNet169 and Resnet50. More research is needed to ensure that this model can be implemented in clinical settings, increasing the rate of health care against this specific disease. People should be educated about this disease and they should be encouraged to get themselves checked. We are currently working on putting this model on a website for easier use.

FUTURE WORK:

Future work shall include more deep learning models using keras in order to extend the precision of the Alzheimer disease detection and also we can use some deep learning models that could be designed to provide explanations for their predictions, which could aid in understanding the mechanisms of Alzheimer's disease and aid in the development of effective treatments. The developed models could be integrated into clinical workflows and tested in real-world scenarios to assess their effectiveness and practicality in detecting Alzheimer's disease.

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REFERENCES:

[1]"Usage Of Random Forest Ensemble Classifier Based Imputation And Its Potential In Alzheimer's Disease Diagnosis" by Swaleha Zubair and Afreen Khan

[2]"Machine Learning-Based Method for Personalized and Cost-Effective Detection of Alzheimer's Disease" by Stephen Pears, Colin Green, James Shearer, Javier Escudero, and Emmanuel Ifeachor.

[3] Saruar Alam and Goo-Rak Kwon published "Alzheimer disease classification using KPCA, LDA, and multi-kernel learning SVM" on May 18, 2017.

[4] "Convolutional Neural Networks and Ensemble Learning: A Novel Method for Early Alzheimer's Disease Detection Using Magnetic Resonance Imaging for the Alzheimer's Disease Neuroimaging Initiative" by Tory Frizzell3, Xiaowei Song, Dan Pan, An Zeng, Longfei Jia, (ADNI).

[5] Alzheimer's disease staging analysis using deep fusion and nonlinear feature transformation Author links open a panel overlay by Yani Chen, Pin Zhang, Charles D. Smith, Jundong Liu, Bibo Shi, For the Neuroimaging Initiative for Alzheimer's Disease.

[6]I. Vatanabe, P. Manzine, and M. Cominetti, "Historical Concepts of Dementia and Alzheimer's Disease: From Ancient Times to the Present," Revue Neurologique, 2019.

[7] Richard J. Sundberg: The Chemical Century, by E. R. Adlard. Chromatographia, 2017. "Molecular manipulation and its impact on the 20th century."

[8] L. Keuck, "History as a biomedical matter: recent reevaluations of the initial cases of Alzheimer's disease," History and Philosophy of the Life Sciences, 2017.

[9] "Nanoparticle-mediated brain drug delivery: Overcoming the blood-brain barrier to treat neurodegenerative diseases," Journal of Controlled Release, 2016, by C. Saraiva, C. Praça, R. Ferreira, T. Santos, L. Ferreira, and L. Bernardino.

[10] "Toward a United States of Health: Implications of Understanding the US Burden of Disease," by H. K. Koh and A. K. ParekhWith Regard to a United States of Health Editorial," JAMA, 2018.

[11] “Attention-based 3D convolutional network for Alzheimer's disease diagnosis and biomarkers exploration, 2019 IEEE 16th International Symposium on Biomedical Imaging,” by D. Jin, J. Xu, K. Zhao, F. Hu, Z. Yang, B. Liu, T. Jiang, and Y. Liu. (ISBI 2019). IEEE, 2019.

[12] Alzheimer's Disease End-of-Life Decision Making Across Cultures, R. H. Blank. Springer 2019 in Singapore.

[13] "The National Institute on Aging and Alzheimer's Association Research Framework: A Commen-tary from the Cochrane Dementia and Cognitive Improvement Group," by J. McCleery, L. Flicker, E. Richard, and T. Quinn.2019's Alzheimer's & Dementia.

[14] N. Hill and J. Mogle, "Protocol for a construct-level replication analysis: Alzheimer's disease risk factors as mediators of subjective memory impairment and objective memory decline," BMC Geriatrics, 2018.

[15] K. J. "Method and apparatus for motilitycontrast imaging," US 20150062592 A1, October 2018. David D. Nolte and John J. Turek.

[16] "Flortaucipir tau pet imaging in semantic variant primary progressive aphasia," Journal of Neurology, Neurosurgery & Psychiatry, 2017. S. Makaretz, M. Quimby, J. Collins, N. Makris, S. McGinnis, A. Schultz, N. Vasdev, K. Johnson, and B. Dickerson.

[17] "Neuroimaging Mark-ers of Global Cognition in Early Alzheimer's Disease: A Magnetic Resonance Imaging-Electroencephalography Study," Brain and Behavior, 2018, by M. Waser, T. Benke, P. Dal-Bianco, H. Garn, J. Mosbacher, G. Ransmayr, R. Schmidt, S. Seiler, H. Sorensen, and P. Jennum.

[18]"Imaging tau and amyloid-proteinopathies in Alzheimer's disease and other conditions," published in Nature Reviews Neurology in 2018, V. L. Villemagne, V. Doré, S. C. Burnham, C. L. Masters, and C. C. Rowe.

[19]Early diagnosis of Alzheimer's disease utilising pib and fdg pet, Neurobiology of Disease, vol. 72, pp. 117–122, 2014. [34] A. D. Cohen and W. E. Klunk.SPECT/PET Findings in LewyBody Dementia, R. Ducksbury, T. Whitfield, and Z. Walker

[20] Heidelberg and Berlin: Springer Berlin, 2014.

[21] "Amyloid imaging in Alzheimer's disease: comparison of florbetapir and Pittsburgh compound-b positron emission tomography," Journal of Neurology, Neurosurgery, and Psychiatry, 2012. D. Wolk, Z. Zhang, S. Boudhar, C. Clark, M. Pontecorvo, and S. Arnold.

[22]"Gabor filters as texture discriminator," I. Fogel and D. Sagi. 1989's Biological Cybernetics.

[23]”An Introduction to Support Vector Machines and Other Kernel-based Learning Methods,” by N. Cristianini and J. Shawe-Taylor. 2000. Cambridge University Press.

[24]"Deep learning in neural networks: An overview," by J. Schmidhuber, 2015's NeuralNetworks.

[25] "Deep learning framework for Alzheimer's disease diagnosis via 3d-cnnand fsbi-lstm," by C. Feng, A. Elazab, P. Yang, T. Wang, F. Zhou, H. Hu, X. Xiao, and B. Lei. 2019 IEEE Access.

[26] "Deep learning," by Y. LeCun, Y. Bengio, and G. Hinton, Nature 2015.

[27] "Deep learning in neural networks: An overview," J. Schmidhuber, NeuralNetworks, 2015.

[28] C. Feng, A. Elazab, P. Yang, T. Wang, F. Zhou, H. Hu, X. Xiao, and B. Lei, "Deep learning framework for Alzheimer's disease diagnosis using 3d-cnn and fsbi-lstm," IEEE Access, 2019.

[29] "Deep learning," Y. LeCun, Y. Bengio, and G. Hinton, Nature, 2015.

[30] "Imagenet classification with deep convolutional neural networks," A. Krizhevsky, I. Sutskever, and G. E. Hinton. May 2017. Communication.

[31] "Research on data augmentation for image classification based on convolution neural networks," J. Shijie, W. Ping, J. Peiyi, and H. Siping, in 2017Chinese Automation Congress (CAC), 2017.

[32] "Gan-based synthetic medical image augmentation for increased cnn performance in liver lesion classification," M. Frid-Adar, I. Diamant, E. Klang, M. Amitai, J. Goldberger, and H. Greenspan,Neurocomputing, 2018.