

DETECTION OF ALZHEIMER'S DISEASE AND ASSISTANCE

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Abstract—As the world is experiencing population growth, the portion of older people aged 65 and above is also growing. As a result, dementia with Alzheimer's disease is expected to increase rapidly in the next few years. Currently, healthcare systems require accurate detection of the disease for its treatment and prevention. Therefore, it has become essential to develop a framework for the detection of Alzheimer's disease to avoid complications. To this end, a novel framework based on deep-learning (DL) methods is proposed to detect Alzheimer's disease. The raw data from MRI scans are pre-processed, before applying a deep learning approach. Another feature of our system is to assist Alzheimer's patients and their caregivers to provide support, like guidelines on how to handle them when they go through psychological depression, anger issues, etc., and how a person should behave with an Alzheimer's patient. Therefore, our system will be very effective and usable for patients and their relatives as well as caregivers. It can also provide insight into the disease, different stages, causes, symptoms, and related matters.

Index Terms—ResNet, DenseNet, LSTM, Deep learning

I. INTRODUCTION

Alzheimer's disease (AD) is a neurodegenerative disease that can cause mental disorders and even dementia in humans. AD patients are usually elderly, and a common symptom is the gradual loss of memory and understanding, which can inevitably lead to death. It is estimated that one in every 85 persons will suffer AD by 2050. So far, the exact cause of AD is still not clear. It has been reported that there are no effective medications or treatments that can prevent or reverse the progression of AD. Therefore, it is critical to accurately diagnose AD and design a treatment plan to slow the progression of AD. A system with ResNet and DenseNet model for feature extraction and Long Short Term Memory(LSTM) algorithm for classification will be used for efficient detection of stages of Alzheimer's Disease. Additionally a website which can provide various details and resources about AD will help patients, their relatives

and caregivers. The relatives of the patients, most of the time are unaware about the proper guidelines to take care of the patients and overtime their mental health will also deteriorate if not properly managed. The website provides proper guidelines and various methods to tackle this problem.

II. OBJECTIVE AND SCOPE

The objectives of the website is to detect different stages of Dementia, namely, non-demented, mild demented, very mild demented, and moderately demented using deep learning methods. Also, to provide a user friendly website that provides information about Alzheimer's disease to support patients and others. Furthermore, proper guidelines for caregivers and relatives are provided. Additional resources consists of medicines usually prescribed, memory games for different stages, the prevention and precaution measures, and details about hospitals.

III. LITERATURE REVIEW

We can see several novel methods for Alzheimer's disease detection and assistance. However, there is no system for performing both of these functions. Some have advantages while some point to various limitations. This section discusses various advantages and disadvantages found in several approaches to Alzheimer's disease detection and assistance.

The results of brain imaging tests can assist doctors to make a diagnosis, including excluding the possibility of other illnesses that have similar symptoms. Although there are many neuroimaging techniques available when it comes to giving thorough information for the diagnosis of severe neurological illnesses like schizophrenia and depression, MRI has demonstrated exceptional promise [1]. These images are processed and their features are extracted for further detection.

The deep learning-based strategy suggested in [2] can predict MCI, early MCI (EMCI), late MCI (LMCI), and AD. For testing, the 138-subject Alzheimer's Disease Neuroimaging Initiative (ADNI) fMRI dataset was employed. In terms of accuracy, sensitivity, and specificity, the suggested model outperformed other well-known models. For the EMCI vs. AD, LMCI vs. AD, and MCI vs. EMCI classification situations, the fine-tuned ResNet18 network achieved a classification accuracy of 99.99%, 99.95%, and 99.95% respectively.

For predicting the various stages of AD progression, authors [3] proposed a new multi-view clustering model called Consensus Multi-view Clustering (CMC) based on nonnegative matrix factorization. The proposed CMC addresses the flaw of multi-view fusion that necessitates manual parameter setting, performs multi-view learning ideas to fully capture data features with limited medical images, approaches similarity relations between different entities, and further acquires a consensus representation containing shared features and complementary knowledge of multiple view data. The system's key benefit is that it can screen for and categorize the symptoms of various stages of AD in addition to being able to predict AD better.

Saad Awadh Alanazi et.al analyzes a convolutional neural network (CNN) method to enhance the automatic identification of breast cancer by analyzing hostile ductal carcinoma tissue zones in whole-slide images (WSIs) [4]. The suggested approach compares the outcomes with those from machine learning (ML) techniques to automatically diagnose breast cancer using a variety of convolutional neural network (CNN) designs. The suggested method outperforms machine learning (ML) algorithms by achieving 78% accuracy of machine learning (ML) algorithms.

A DL approach is suggested by Rubina Sarki et al. to identify retinal eye disorders [5] using retinal fundus images. While the classification of multi-class retinal eye illnesses remains an open challenge, deep learning (DL) techniques in machine learning (ML) have reached high efficiency in the binary categorization of healthy and diseased retinal fundus images.

A variety of retinal fundus photos from the publicly available collection and labeled by an ophthalmologist is used to test the suggested model. The maximum accuracy, sensitivity, and specificity for this suggested model for multi-class classification were 81.33

The authors present, review, and recognize the need for developing a rapid, cost-effective, and reliable method for potato disease detection [6]. They used various CNN architectures like Googlenet, Resnet, and VGG over the data and compute their accuracy and performance to find the best neural network to predict the disease type of potato disease based on the input

image fed. It was found that Resnet is the best model that can be used due to its high and near-constant accuracy for each epoch. Google Net, which had the best accuracy over the Imagenet dataset, showed excellent accuracy in the final 50 epochs but not initially. VGG16 performs the poorest in terms of accuracy as well as processing time. They have achieved a classification accuracy of around 97%. The data augmentation process helps the model to be more robust.

Dheiver Santos et.al [7] proposed a technique for Brain Tumor Detection Using Deep Learning. A series of artificial neural networks (ANN) are used in the proposed work to detect the presence of a brain tumour, and their performance is evaluated using various metrics.. In this work, MobileNetV2 was used, which is a convolutional neural network architecture that seeks to perform well on mobile devices. The model generated here achieved 89% test accuracy and this can be increased by providing more image data.

Masoumeh Siar et.al analyzes Brain Tumor Detection Using Deep Neural Networks and Machine Learning algorithms [8]. The proposed technique has used CNN to identify and categorize the tumor from brain images of the brain. The CNN managed to accurately categorize the images into tumor patient and normal patient tumors with a precision of 98.67%. Softmax Fully Connected layer classifier, RBF classifier, and the DT classifier in the CNN architecture have been used to evaluate the efficiency of the proposed technique. The accuracy of the CNN is obtained by the Softmax classifier used to classify images obtained at 98.67%. Also, the accuracy of the CNN is obtained with the RBF classifier at 97.34% and the DT classifier at 94.24%.

Authors of [9] proposed a model based on FRCNN with FKM clustering for automated localization and recognition of diabetes-based eye diseases, i.e., glaucoma, DR, and DME in retinal images. The FRCNN technique improves segmentation efficiency and can extract deep characteristics that best describe eye disorders. The proposed solution achieved the mean IoU of 0.95 and mAP value above 0.94 for three diseases. The proposed approach can also be utilized to resolve the different segmentation complexities of medical imaging.

Siddhanth Tripathi et.al proposed a technique [10] for Lung Disease Detection Using Deep Learning. It proposed and evaluated a deep convolutional neural network, for classifying Chest Diseases. The proposed model consists of Convolutional layers, ReLU Activations, a Pooling layer, and a fully connected layer. The last fully connected layer consists of fifteen output units. The likelihood of each output unit's output becoming one of the fifteen diseases is predicted.

To compare the findings and analyses of the UCI Machine Learning Heart Disease dataset, Bharti, R. et al. (2021) used a variety of machine learning algorithms and deep learning

techniques [11]. It suggested three approaches for doing a comparative analysis. When data preprocessing is used, the KNeighbors classifier outperformed the ML technique for the 13 features that were included in the dataset. Also, the computing time was cut down, which is beneficial for model deployment. The dataset needs to be normalized, otherwise, the training model may be overfitted at times and the accuracy won't be enough when the model is tested on real-world data problems, which can differ greatly from the dataset on which it was trained. 94.2% accuracy using a deep learning approach.

The use of a Deep Learning Neural Network Model for heart disease prediction [12] was suggested by Sharma*, S., and Parmar, M. (2020). Many techniques are used to do the classification, including KNN, SVM, Nave Bayes, and Random Forest. To show that Talos Hyper-parameter optimization is more effective than other methods, the Heart Disease UCI dataset is employed. With 90.76% accuracy, Talos outperforms other optimizations.

Long short-term memory (LSTM) and GAN were utilized to create an ensemble model by Rath, A. et al. (2021) that performs better than the individual DL models[13]. For this, six classification models were selected, including two ML, three DL, and one ensemble model. For the GAN model to perform better while dealing with an unbalanced category of input data, fake samples have been created. The GAN-LSTM model surpasses the individual GAN and LSTM models in terms of all three performance criteria assessed in the research, according to an analysis of numerous performance measures. Furthermore, compared to the two ML models, all three DL models show greater HD detection capabilities. With an accuracy of 98.09%, 98.85%, and 99.17%, respectively, Bari, B.S. et al. (2021) suggested a deep-learning-based technique [14] that was found to be efficient in the automatic diagnosis of three discriminative rice leaf diseases, including rice blast, brown spot, and hispa. Also, the model had a 99.25% accuracy rate when identifying a healthy rice leaf. The outcomes obtained showed that the Faster R-CNN model delivers a high-performing rice leaf infection identification system that could more accurately and quickly identify the most widespread rice illnesses. There are also some disadvantages mentioned. The technique is time-consuming and necessitates numerous rounds to extract all items from a single image. To recognize images, Kumar, S., Chaudhary, V., and Chandra, S. (2021) suggested a deep learning-based method[15]. It has explored the three primary Neural Network architectures: Single shot Multibook Detector, Region-based Fully CNN, and Faster Region-based Convolutional Neural Network (SSD). The method suggested in the research can handle complex situations and is effective at detecting various illness types. The accuracy of 94.6% in the validation results illustrates the viability of the convolution neural network. Mostafa, A.M. et al.[16] (2021) proposed a model for Guava disease detection. They used a deep convolutional neural network (DCNN)-

based data enhancement using color-histogram equalization and the unsharp masking technique to identify different guava plant species. To distinguish between several guava plant species, it employs five neural network structures: AlexNet, SqueezeNet, GoogLeNet, ResNet-50, and ResNet-101. Among them, ResNet-101 obtained the highest classification results, with 97.74% accuracy. Gore, D.V. and Deshpande, V. (2020) [17] proposed various techniques using deep learning for Brain tumor detection. The investigation and comparative analysis of recent knowledge correlated with brain disorder detection using deep learning techniques are considered in this review. It concluded that automated segmentation of brain tumors for brain investigation is necessary. Ibrahim, A.U. et al.[18] (2021) classified Pneumonia using deep learning from chest X-ray images during COVID-19. They used several approaches to classify CXR images and detect COVID-19 infections. The suggested model exhibited 94.43% accuracy, 98.19% sensitivity, and 95.78% specificity for non-COVID-19 viral pneumonia and normal (healthy) CXR pictures. For bacterial pneumonia and normal CXR images, the model achieved 91.43% accuracy, 91.94% sensitivity, and 100% specificity. The model attained 99.16% accuracy, 97.44% sensitivity, and 100% specificity for COVID-19 pneumonia and normal CXR pictures. For the classification of CXR images of COVID-19 pneumonia and non-COVID-19 viral pneumonia, the model achieved 99.62% accuracy, 90.63% sensitivity, and 99.89% specificity. The model achieved 94.00% accuracy, 91.30% sensitivity, and 84.78% for the three-way classification. Finally, for the four-way classification, the model achieved an accuracy of 93.42%, a sensitivity of 89.18%, and a specificity of 98.92%. Gacem, M.A. et al.[19] (2019) proposed smart assistive glasses for Alzheimer's patients. It utilizes smart glasses equipped with an Augmented Reality (AR) screen to perform the basic functions of a caregiver and provide the patients with features that increase independence and reduce caregiving costs. One of its drawbacks is that the smart glasses' prototype size (W=10 cm, L=25 cm, H=6.5 cm) is not convenient for actual use due to the size of the circuits. Mei, J., Desrosiers, C. and Frasnelli, J.[20] (2021) proposed machine learning for the diagnosis of Parkinson's disease. It demonstrated a high potential for adaptation of machine learning methods and novel biomarkers in clinical decision-making, leading to an increasingly systematic, informed diagnosis of PD. Among them, machine learning-assisted diagnosis of PD yields a high potential for a more systematic clinical decision-making system, while adaptation of novel biomarkers may give rise to easier access to PD diagnosis at an earlier stage.

IV. PROPOSED METHOD

From the above-mentioned papers, we can infer that there is a need for a system providing both detection and assistance for Alzheimer's' Patients. A system that uses brain images for classification is proposed. The image is preprocessed and deep learning models are applied to it for feature extraction.

Finally, a machine algorithm is applied to the features extracted for classification. The system also provides assistance to Alzheimer's patients and their caregivers. The system should be able to solve doubts regarding the disease and offer support to those who require it.

V. CONCLUSION

Alzheimer's disease (AD) is a neurodegenerative condition that can affect the brain and result in dementia in people. Finding the disease and precisely determining its extent is essential for properly treating illness. It can't be fully cured, unfortunately. To slow the spread of the disease, there are numerous therapy options available. Hence, determining the proper AD stage is essential. The approach offers a means of identifying and differentiating the stages of AD. To extract visual features that can be preserved for later use, the system uses pre-trained Resnet and Densenet models. After the model has been trained using the features and labels, test images are used to evaluate it. The outcomes will then be displayed. Patients and other website visitors can get help there. It includes information on AD, its symptoms, causes, medications used, treatment techniques employed, studies done in the area, safety precautions to be taken, and patient care recommendations. The approach will be helpful to AD patients and their caretakers since early detection of the disease can slow its progression and enable people to live better lives.

REFERENCES

- [1] Liu, J. et al. (2021) Alzheimer's disease detection using depth-wise separable convolutional neural networks, *Computer Methods, and Programs in Biomedicine*. Elsevier. Available at: <https://www.sciencedirect.com/science/article/abs/pii/S0169260721001073> (Accessed: November 15, 2022).
- [2] T. O.M.M.R.D.R.K. (no date) Analysis of features of Alzheimer's disease: Detection of the early stage from functional brain changes in magnetic resonance images using a finetuned Resnet18 Network, *Diagnostics* (Basel, Switzerland). U.S. National Library of Medicine. Available at: <https://pubmed.ncbi.nlm.nih.gov/34200832/> (Accessed: November 15, 2022).
- [3] Zhang, X. et al. (2020) CMC: A consensus multi-view clustering model for predicting Alzheimer's disease progression, *Computer Methods and Programs in Biomedicine*. Elsevier. Available at: <https://www.sciencedirect.com/science/article/abs/pii/S0169260720317284> (Accessed: November 15, 2022).
- [4] Alanazi, S.A. et al. (2021) Boosting breast cancer detection using convolutional neural network, *Journal of Healthcare Engineering*. Hindawi. Available at: <https://www.hindawi.com/journals/jhe/2021/5528622/> (Accessed: November 15, 2022).
- [5] Nazir, T. et al. (2020) "Retinal image analysis for diabetes-based eye disease detection using Deep Learning," *Applied Sciences*, 10(18), p. 6185. Available at: <https://doi.org/10.3390/app10186185>.
- [6] Aditi Singh et al. (2021), "Potato plant leaves disease detection and classification using machine learning methodologies". Available at: <https://iopscience.iop.org/article/10.1088/1757-899X/1022/1/012121>.
- [7] Santos, D. and Santos, E. (2022) "Brain tumor detection using Deep Learning." Available at: <https://doi.org/10.1101/2022.01.19.22269457>.
- [8] Siar, M. and Teshnehlab, M. (2019) "Brain tumor detection using deep neural network and machine learning algorithm," 2019 9th International Conference on Computer and Knowledge Engineering (ICCKE) [Preprint]. Available at: <https://doi.org/10.1109/iccke48569.2019.8964846>.
- [9] Sarki, R. et al. (2021) Convolutional neural network for multi-class classification of Diabetic Eye Disease, *EAI Endorsed Transactions on Scalable Information Systems*. Available at: <https://eudl.eu/doi/10.4108/eai.16-12-2021.172436> (Accessed: November 15, 2022).
- [10] Tripathi, Siddhanth & Shetty, Sinchana & Jain, Somil & Sharma, Vanshika. (2021). Lung Disease Detection Using Deep Learning. 10.35940/ijitee.H9259.0610821.
- [11] Bharti, R. et al. (2021) "Prediction of heart disease using a combination of machine learning and Deep Learning," *Computational Intelligence and Neuroscience*, 2021, pp. 1–11. Available at: <https://doi.org/10.1155/2021/8387680>.
- [12] Sharma*, S. and Parmar, M. (2020) "Heart diseases prediction using Deep Learning Neural Network model," *International Journal of Innovative Technology and Exploring Engineering*, 9(3), pp. 2244–2248. Available at: <https://doi.org/10.35940/ijitee.c9009.019320>.
- [13] Rath, A. et al. (2021) "Heart disease detection using deep learning methods from imbalanced ECG samples," *Biomedical Signal Processing and Control*, 68, p. 102820. Available at: <https://doi.org/10.1016/j.bspc.2021.102820>
- [14] Bari, B.S. et al. (2021) "A real-time approach of diagnosing rice leaf disease using deep learning-based faster R-CNN framework," *PeerJ Computer Science*, 7. Available at: <https://doi.org/10.7717/peerj-cs.432>.
- [15] Kumar, S., Chaudhary, V. and Chandra, S. (2021) Plant disease detection using CNN, *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*. Science Research Society. Available at: <https://turcomat.org/index.php/turkbilmat/article/view/7743> (Accessed: November 15, 2022).
- [16] Mostafa, A.M. et al. (2021) "Guava disease detection using deep convolutional neural networks: A case study of guava plants," *Applied Sciences*, 12(1), p. 239. Available at: <https://doi.org/10.3390/app12010239>
- [17] Gore, D.V. and Deshpande, V. (2020) "Comparative study of various techniques using deep learning for Brain tumor detection," 2020 International Conference for Emerging Technology (INCET) [Preprint]. Available at: <https://doi.org/10.1109/incet49848.2020.9154030>.
- [18] Ibrahim, A.U. et al. (2021) "Pneumonia classification using deep learning from chest X-ray images during COVID-19," *Cognitive Computation* [Preprint]. Available at: <https://doi.org/10.1007/s12559-020-09787-5>.
- [19] Gacem, M.A. et al. (2019) "Smart assistive glasses for Alzheimer's patients," 2019 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT) [Preprint]. Available at: <https://doi.org/10.1109/isspit47144.2019.9001827>.
- [20] Mei, J., Desrosiers, C. and Frasnelli, J. (2021) "Machine learning for the diagnosis of Parkinson's disease: A review of literature," *Frontiers in Aging Neuroscience*, 13. Available at: <https://doi.org/10.3389/fnagi.2021.633752>.