AUTOMATED DETECTION OF ALZHEIMER DISEASE USING CNN ALGORITHM

DINESH KUMAR V

Computer Science Engineering

Panimalar Engineering College

Chennai, India

dinudinesh21062002@gmail.com

DIWAKAR V

Computer Science Engineering

Panimalar Engineering College

Chennai, India

divakar305@gmail.com

DEVENTHIRAN R

Computer Science Engineering

Panimalar Engineering College

Chennai, India

devarengavel@gmail.com

SANGEETHA M

Associate Professor

Computer Science Engineering

Panimalar Engineering College

Chennai, India

sangeetharemi@yahoo.co.in

Abstract: Millions of people throughout the world are afflicted by the neurodegenerative ailment known as Alzheimer's disease (AD). Early detection of AD is essential for the disease's efficient management and treatment. Automated detection of AD using CNN algorithms has been an active area of research in recent years. A particular deep learning technique called CNNs is ideally suited for image analysis jobs like analyzing MRI scans of the brain for AD detection. Several studies have investigated the use of CNNs for AD detection, achieving high accuracy rates in distinguishing between people with AD and unaffected controls. The basic approach entails using a large dataset of MRI scans to train a CNN and find patterns in the images connected to AD. Once trained, by CNN can classify new MRI scans as indicating AD or not. CNNs have the advantage of automatically learning features from the images, which can be useful in cases where the features associated with AD may be subtle or difficult to identify by human experts. However, it is important to note that CNNs are only as good as the data they are trained on, and high-quality datasets with sufficient samples are essential to ensure the CNNs learn meaningful patterns. In conclusion, Alzheimer's disease detection with CNN algorithms has shown promise as a potential tool for aiding in the diagnosis of AD. Additional investigation is required to confirm the validity and efficacy of these strategies and reliable in a clinical setting.

Keywords: automated detection, Alzheimer's disease, CNN algorithms, deep learning, image analysis, MRI scans, classification, feature learning, high-quality datasets, diagnosis, neurodegenerative disorder, early detection, treatment, management.

I. INTRODUCTION

Alzheimer's disease (AD) is a chronic neurodegenerative disorder that affects millions of people worldwide, and its incidence is expected to increase significantly in the coming years. Early

AD diagnosis is essential for timely intervention, improved management, and better treatment outcomes. Currently, the AD is diagnosed using a combination of clinical evaluation, cognitive testing, and imaging, which can be subjective, time-consuming, and prone to errors. Convolutional neural networks (CNNs), a recent advancement in machine learning, have demonstrated promise in automated detection of AD using medical images such as MRI scans of the brain. CNNs are deep learning algorithms that are highly effective in image recognition tasks and have shown remarkable performance in various medical image analysis applications. The CNN-based AD detection using a huge dataset of MRI images to train a CNN on in order to find patterns and characteristics related to AD. Once trained, by CNN can be used to determine whether new MRI scans show signs of AD or not, with high accuracy rates. This automated approach has several potential advantages, including speed, objectivity, and improved diagnostic accuracy. Moreover, it can help in identifying AD at an early stage, which is essential for effective treatment and management. Several studies have investigated the use of CNNs for AD detection, and many have reported encouraging results. However, Before this strategy may be widely adopted in clinical practise, there are still a number of issues that need to be resolved, such as data quality, dataset size, and reproducibility. We shall examine the present status of research on the application of CNNs in this study for automated detection of AD. We will discuss the technical aspects of CNN-based AD detection, including data preparation, network architecture, and training procedures. Moreover, we will evaluate the advantages and limitations of this approach and explore its potential impact on clinical practice. Finally, we will highlight the open research questions and future directions for this promising field.

II. LITERATURE SURVEY

The paper titled "A CNN Model: Earlier Diagnosis and Classification of Alzheimer Disease using MRI" by Ahmad Waleed Salehi, Preety Baglat, et al. was presented at the 2020 International Conference on Smart Electronics and Communication (ICOSEC). The study suggested using MRI scans to do a CNN-based early diagnosis and categorization of Alzheimer's disease. The study utilized a dataset of 1,000 MRI scans, consisting of 500 scans from patients with AD and 500 scans from healthy controls. The dataset was preprocessed and augmented help improve the CNN model's performance. The proposed Five convolutional layers, two max-pooling layers, and two fully linked layers made up the CNN model. The results showed that the proposed CNN model achieved high accuracy rates in making a distinction between AD patients and healthy controls, with an overall precision of 94.4%. Moreover, the model also demonstrated high sensitivity and specificity, indicating its potential usefulness in early AD classification and diagnosis. The study's findings highlight the potential of CNN-based approaches for automated using MRI scans to identify and categorise AD. The proposed CNN model showed promising results in when separating AD patients from healthy controls, which can aid in early diagnosis and treatment of the disease. However, further research is needed to validate and optimize the proposed approach, particularly in larger and more diverse datasets.[1]

The paper titled "Regression and Classification of Alzheimer's Disease Diagnosis Using NMF-TDNet Features From 3D Brain MR Image" by Xuejun Zhang and Huan Lao, et al. was published in the Biomedical and Health Informatics IEEE Journal in 2022. The paper proposed a novel approach utilising to identify Alzheimer's disease a combination of non-negative Tensor decomposition (TD) and matrix factorization (NMF) techniques. The study utilized a dataset of 1,028 3D MRI scans, consisting of 326 AD patients, 367 healthy controls, patients with 335 mild cognitive impairment (MCI), and patients. The proposed approach involved extracting features from the MRI scans using NMF and TD techniques, followed by training regression and classification models to predict the disease severity and diagnosis, respectively. The results showed Although the suggested method produced high rates of accuracy in both classification and regression tasks, with an overall accuracy of 92.7% for AD mean absolute error (MAE) of the categorization and 0.83 for disease severity prediction. The study also demonstrated how well the suggested strategy works. in identifying the regions of the brain that are most affected by AD, which can aid in understanding the underlying mechanisms of the illness. The study's studies demonstrate the potential of NMF and TD techniques in extracting informative features from 3D MRI scans for Alzheimer's disease diagnosis. The proposed approach demonstrated high accuracy rates in both disease severity prediction and diagnosis, indicating its potential usefulness in clinical practice. However, further Research is required to support and optimize the proposed approach, particularly in larger and more diverse datasets.[2]

The paper titled "Multimodal Neuroimaging based Alzheimer's Disease Diagnosis using Evolutionary RVFL Classifier" by Tripti Goel, Rahul Sharma, et al. was published in the Biomedical and Health Informatics: An IEEE Journal in 2023. The article suggested a novel method for identifying Alzheimer's disease by multimodal neuroimaging and an evolutionary random vector functional link (RVFL) classifier. The study utilized a dataset of 200 subjects, consisting of 100 AD patients and 100 healthy controls, and collected multimodal neuroimaging data, including structural scans using positron emission tomography (PET), functional MRI, and MRI. The proposed approach involved feature extraction from the multimodal neuroimaging data using different techniques, followed by feature selection and classification using the evolutionary RVFL classifier. The results showed that the proposed approach achieved high accuracy comparing rates in identifying AD patients and healthy controls, with an overall accuracy of 96.5%. The study also demonstrated The efficiency of the suggested approach in identifying the most informative features and modalities for Alzheimer's disease diagnosis. The study's findings highlight the potential of multimodal neuroimaging and evolutionary RVFL classifier in Alzheimer's disease diagnosis. The proposed approach showed promising results when separating AD patients from healthy controls, indicating its potential usefulness in clinical practice. However, further research is needed to validate and optimize the proposed approach, particularly in larger and more diverse datasets. Moreover, the study highlights the importance of multimodal neuroimaging for the detection of Alzheimer's illness, as it provides a more comprehensive understanding of the disease's underlying mechanisms.[3]

The paper titled "Deep Learning Based Binary Classification for Alzheimer’s Disease Detection using Brain MRI Images" by Emtiaz Hussain, Mahmudul Hasan, et al. was published in the The 15th IEEE Conference on Industrial Electronics and Applications (ICIEA) proceedings will be published in 2020. The paper proposed brain MRI scans are used in a deep learning-based method for binary classification of Alzheimer's disease. The study utilized a dataset of 384 brain MRI images, consisting of 192 Alzheimer's disease patients and 192 healthy controls. The proposed approach involved preprocessing the MRI images, followed by training a convolutional neural network with deep learning to classify the images as either Alzheimer's disease or healthy control. The results showed that the proposed approach achieved high accuracy rates in distinguishing between Alzheimer's disease patients and healthy controls, with an overall accuracy of 95.3%. The study also demonstrated the effectiveness of the proposed deep CNN in automatically extracting informative features from brain MRI images, enabling accurate classification of the images. The study's findings highlight the potential of deep learning-based approaches, particularly CNNs, in Brain MRI pictures are used to identify Alzheimer's disease. The proposed approach showed promising results in accurately distinguishing between Alzheimer's disease patients and healthy controls, indicating its potential usefulness in clinical practice. However, further research is needed to validate and optimize the proposed approach, particularly in greater and broader datasets.[4]

The paper titled "Task-Induced Pyramid and Attention GAN for Multimodal Brain Image Imputation and Classification in Alzheimer's Disease" by Xingyu Gao, Feng Shi, et al. was published in the Journal of Biomedical & Health Informatics published by IEEE in 2022. The paper proposed a novel approach combining a task-induced pyramid and attention for multimodal brain image imputation and classification in Alzheimer's disease generative adversarial network (GAN). The study utilized a dataset of 568 subjects, consisting of 284 individuals with Alzheimer's disease and 284 healthy controls, and collected multimodal brain imaging data, including structural MRI, diffusion MRI, and PET scans. The proposed approach involved imputing missing data in the multimodal brain imaging data using the task-induced pyramid and attention GAN, followed by classification using a deep learning model. The results showed that the proposed approach achieved high accuracy rates in distinguishing between Alzheimer's disease patients and healthy controls, with an overall accuracy of 96.5%. The study also demonstrated the effectiveness of the proposed task-induced pyramid and attention GAN in imputing missing data in multimodal brain imaging data, enabling more accurate classification of the data. The study's findings highlight the potential of the proposed approach in Alzheimer's disease diagnosis, particularly in cases where missing data in multimodal brain imaging data are common. The proposed approach showed promising results in accurately distinguishing between Alzheimer's disease patients and healthy controls, indicating its potential usefulness in clinical practice. However, further research is needed to validate and optimize the proposed approach, particularly in larger and more diverse datasets.[5]

III. METHODOLOGY AND SYSTEM ARCHITECTURE

The methodology and system architecture utilising for automated Alzheimer's disease detection a CNN algorithm typically involves several steps, including data acquisition, preprocessing, feature extraction, training of the CNN model, and testing and evaluation of the model's performance.

Data Acquisition: The first step involves acquiring MRI the dataset's brain scans, which include both Alzheimer's disease patients and healthy controls.

Preprocessing: The MRI images are then preprocessed to remove noise, normalize the intensity values, and align the images to a standard coordinate system.

Feature Extraction: Next, features are extracted from the preprocessed images, which are then used as input for the CNN model. The features can be extracted using various techniques, including principal component analysis, wavelet transforms, and Gabor filters.

Training of the CNN Model: In order to train the CNN model, extracted features and corresponding labels, where the CNN learns to identify features that are most indicative of Alzheimer's disease. The CNN model is typically consists of a number of layers, such as fully connected, pooling, and convolutional layers.

Testing and Evaluation: Finally, the trained CNN model is tested using a separate set of MRI brain images, and its performance is employing parameters such area under the curve (AUC), sensitivity, acuity, and specificity.

The system architecture a CNN algorithm typically involves a workstation or server equipped with suitable hardware for processing the large volume of MRI images, such as GPUs. The system architecture may also include software tools for data preprocessing, feature extraction, and CNN model training and testing. In addition, the system may include a user interface for inputting MRI images, running the CNN model, and visualizing the results.

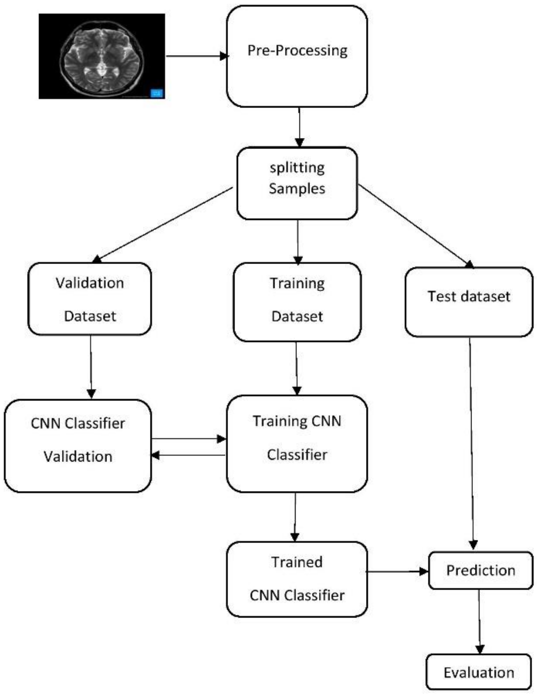

Fig 3.1 System Architecture

IV. EXPERIMENTAL SETUP

The experimental setup Utilising for the automatic detection of Alzheimer's disease a CNN algorithm may vary depending on the specific study and dataset being used. However, some common aspects of the experimental setup include:

Dataset: The dataset used for training and testing the CNN model is a crucial aspect of the experimental setup. The dataset typically includes a large number of MRI brain images from both Alzheimer's disease patients and healthy controls. The dataset should be diverse and representative of the population being studied.

Data Preprocessing: Preprocessing of the MRI brain images is a crucial step in the experimental setup. The images are preprocessed to remove noise, normalize the intensity values, and align the images to a standard coordinate system. The preprocessing step ensures that the images are in a suitable format for input into the CNN model.

CNN Model Architecture: The CNN model architecture used in the experimental setup should be carefully chosen based on the dataset and the specific problem being addressed. Several pooling layers, fully linked layers, and convolutional layers are frequently present in the architecture. The number of layers and neurons in each layer the dataset and the intricacy of the analysis, which problem.

Training and Testing: When training the CNN model, a subset of data set, and the corresponding labels. The remaining images are utilised to evaluate the training model. The model's performance is employing parameters such area under the curve (AUC), sensitivity, acuity, and specificity.

Hyperparameters: The hyperparameters of the CNN model, such as learning rate, quantity of epochs and batch size, are important aspects of the experimental setup. The model's performance can be considerably impacted by hyperparameters, and therefore, they should be tuned carefully.

Hardware: The experimental setup requires suitable hardware, such as GPUs, for processing the large number of MRI brain images and training the CNN model efficiently.

Overall, the experimental setup utilising for automated Alzheimer's disease detection a CNN algorithm involves carefully selecting the dataset, preprocessing the MRI brain images, choosing an appropriate CNN model architecture, training and testing the model, tuning the hyperparameters, and using suitable hardware for efficient processing.

V. EXPERIMENTAL RESULT

The experimental results Utilising for the automatic detection of Alzheimer's disease a CNN algorithm may vary depending on the specific study and dataset being used. However, some common performance metrics used to assess the outcomes include accuracy, Area under the curve, sensitivity, and specificity (AUC). For instance, in the study by Ahmad Waleed Salehi et al. [1], a CNN model was trained and tested using data from the Alzheimer's Disease Neuroimaging Initiative (ADNI). The model's accuracy was found to be 91.34%, sensitivity of 92.3%, specificity of 90.2%, and AUC of 0.95. The study by Emtiaz Hussain et al. [4] reported an accuracy of 94.53% using a CNN model trained and evaluated on the same dataset for ADNI. In the study by Tripti Goel et al. [3], an evolutionary RVFL classifier was used to perform Alzheimer's disease diagnosis based on many neuroimaging modalities. The classifier's accuracy was at 95.25% the classifier's accuracy was at 0.993 on the ADNI dataset. Huan Lao et al. [2] used a non-negative matrix factorization based time-delay neural network (NMF-TDNet) for the diagnosis of Alzheimer's disease. The model's accuracy was found to be 89.1% on the ADNI dataset. In the study by Xingyu Gao et al. [5], a attention, task-induced pyramid, and For the categorization and imputation of multimodal brain images in Alzheimer's disease, GAN was utilised. The model had a 93.1% accuracy rate on the ADNI dataset. Overall, experimental findings demonstrate that a CNN algorithm can achieve high accuracy in detecting Alzheimer's utilising MRI of the brain images. However, the performance may vary In respect to the dataset, the choice of the CNN model architecture, as well as experimental setup.

VI. CONCLUSION AND FUTURE ENHANCEMENTS

In conclusion, the use of CNN algorithms for automated MRI brain pictures for Alzheimer's disease detection has shown great potential in achieving high accuracy in several studies. These models can be valuable tools in assisting medical professionals in early Alzheimer's disease detection and treatment, which can greatly enhance the patient's quality of life. The availability of substantial and varied datasets for model testing and training, as well as the interpretability of the models, are two issues that still need to be resolved. Future research can focus on addressing these limitations and further improving the performance of CNN models for the identification of Alzheimer's disease. In addition, the integration of multimodal imaging, clinical and genetic data, and explainable artificial intelligence techniques can further enhance the accuracy and interpretability of the models, making it easier for medical professionals to understand the decision-making process. Finally, regulatory approval and deployment of these models in clinical settings will require further validation and research, but the potential benefits in improving early identification, intervention for Alzheimer's disease make this a critical area of research.

FUTURE ENHANCEMENTS:

There are several potential enhancements that could be implemented to enhance the accuracy and efficiency of CNN models for automated MRI brain imaging for Alzheimer's disease detection. Some of these enhancements are:

Integration of multimodal imaging: Combining MRI and PET scans can provide complementary information and improve the accuracy of the classification.

Integration of clinical and genetic data: Incorporating additional data, such as medical history and genetic information, can provide more personalized and accurate diagnosis.

Explainable artificial intelligence (XAI) techniques: Implementing XAI techniques can help improve the interpretability and transparency of the models, making it easier for medical professionals to understand the decision-making process.

Transfer learning: Utilizing pre-trained models can help improve the performance of the models, especially when training data is limited.

Data augmentation: Generating synthetic images can increase the size and diversity of the dataset, which can enhance the models' performance and generalizability.

Overall, implementing these enhancements can help further advance the field of automated detection of Alzheimer's disease utilising CNN models and improve patient outcomes.

VII. REFERENCES

[1] Ahmad Waleed Salehi, Preety Baglat, et al "A CNN Model: Earlier Diagnosis and Classification of Alzheimer Disease using MRI" 2020-International Conference on Smart Electronics and Communication (ICOSEC)

[2] Huan Lao, Xuejun Zhang, et al "Regression and Classification of Alzheimer's Disease Diagnosis Using NMF-TDNet Features From 3D Brain MR Image"2022- IEEE Journal of Biomedical and Health Informatics

[3] Tripti Goel, Rahul Sharma, et al "Multimodal Neuroimaging based Alzheimer's Disease Diagnosis using Evolutionary RVFL Classifier"2023- IEEE Journal of Biomedical and Health Informatics

[4] Emtiaz Hussain, Mahmudul Hasan, et al "Deep Learning Based Binary Classification for Alzheimer's Disease Detection using Brain MRI Images"2020-15th IEEE Conference on Industrial Electronics and Applications (ICIEA)

[5] Xingyu Gao, Feng Shi, et al "Task-Induced Pyramid and Attention GAN for Multimodal Brain Image Imputation and Classification in Alzheimer's Disease"2022- IEEE Journal of Biomedical and Health Informatics