PREDICTION OF BRAIN MRI SYMPTOMS FOR ALZHEIMER'S DISEASE DIAGNOSIS USING CNN BASED APPROACH

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ABSTRACT:
The most common cause of dementia in older persons is Alzheimer's Disease (AD). The neurodegenerative changes occur in the brain when an individual has Alzheimer disease. Alzheimer's is a neurodegenerative disease that specifically affects detailed mental analysis through changes in the central nervous system and cognitive functions. Furthermore, official data indicate a significant increase in the number of Alzheimer's disease-related deaths. Thus, the possibility that an Alzheimer's patient would cases might be increased by early diagnosis. Alzheimer's is an unpredictable disease. Treatment efficiency and the amount of minor damage avoided are higher when AD is treated early rather than later. Therefore, this analysis shows that early diagnosis utilizing Convolutional Neural Networks (CNN) reduces the annual death rates from Alzheimer's disease significantly. Hence, in terms of accuracy, precision, and recall, this analysis generates better results.

KEYWORDS: **Alzheimer's Disease, Convolutional Neural Network (CNN), Prediction**
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I. INTRODUCTION

Within the human body, the brain is one of the most important and complex organs. It performs a number of essential tasks, including thinking, problem-solving, making decisions, imagination, and memory. Information and experiences can be saved and retrieved from memory. Our in body memory contains all of the information about our daily lives, which is important in developing the identities and character. It is difficult to experience dementia-related memory loss and the loss of awareness of our surroundings. The most prevalent type of dementia is Alzheimer's disease (AD). People's fears of Alzheimer's disease increase as they age [1]. Alzheimer's patients lose their capacity to recognize their family members, to love or care for others, to follow basic directions, and to communicate with outside factors due to the disease's slow but steady degeneration of brain cells. In more extreme stages, they also lose their capacity to breathe, cough, and swallow. The costs of providing health and social care for the 50 million or so persons affected by dementia worldwide is equal to the largest economy in the world [2].

Furthermore, by 2050, there will be 152 million new cases of AD and other dementias annually, or one new case every three seconds. This is three times the annual number of cases currently reported.

The symptoms of AD can be overlapped with those of Vascular dementia (VD) or normal aging, making the diagnosis more difficult [3]. With the ability to monitor the disease's progression, early and accurate identification of AD is essential for therapy, prevention, and patient care. The goal of various research programs is to use brain imaging, such as Magnetic Resonance Imaging (MRI), to detect Alzheimer's disease. It is capable to determining the quantity and size of brain cells. In situations of AD, it might also demonstrate parietal atrophy.

Short-term memory loss, paranoia, and delusional beliefs that are mistaken as the results of stress or age are symptoms of AD, then AD is a degenerative neurological disorder. About 5.1 million people in the United States have been diagnosed with this disease. Continuous treatment is required to control AD [4]. Although AD is chronic, it could continue for years or possibly for every second of your life. Thus, in order to prevent significant brain damage, it is essential to prescribe medication at the right time. Early disease diagnosis is a time-consuming and expensive process that demands extensive data collecting, the use of advanced prediction algorithms, and the involvement of an experienced doctor. Because automated systems are not susceptible to human mistake, they are more accurate than human evaluation and can be utilized in medical decision support systems. MRI scans, biomarkers (chemicals, blood flow), and numerical data collected from the scans have all been used by researchers to study AD, expanding on previous studies on the disease. As a result, they could determine if an individual was impacted or not. Automating Alzheimer's diagnosis will not only reduce the amount of human interaction but also shorten diagnosis times [5].

Among elderly people, Alzheimer's disease is a common cause of cognitive decline. This AD progression rates from Mild cognitive impairment (MCI) range from 10% to 15% every year. It is possible to consider Mild cognitive impairment (MCI) as a stage of transition between the cognitive decline linked to dementia and the cognitive capacities usually found in people with normal cognitive functioning [6]. Although healthy persons of the same age who lead balanced lifestyles often experience a 1% to 2% yearly mental decline, it is important to remember that there is presently no conclusive medical diagnosis or treatment for this disorder. On the other hand, several strategies can be used to prevent the disease from getting worse [7]. The development of the disease is stopped by prompt and accurate medical diagnosis.

Alzheimer's is a dangerous, progressive diseases that affects the nerve system and brain. A strong and successful treatment plan, as well as more effective therapies, are made possible by early Alzheimer's disease diagnosis. When it comes to recognizing Alzheimer's disease, for the purpose of identifying plaque and diagnosed locations, Magnetic resonance imaging (MRI) is a useful diagnostic tool [8]. Accurately identifying regions diagnosed by Alzheimer's disease using magnetic resonance imaging is one of the main goals of the research. Two perspectives are available to consider the problem. The first part of the issue is the categorization process itself, where it is necessary to identify which images exhibit symptoms of Alzheimer's disease and which do not. The zoning's characteristics are another issue, as they require the identification of places impacted by Alzheimer's [9]. Using magnetic resonance imaging, segmentation and classification approaches are needed to find plaques in the brains of Alzheimer's patients. The goal of zoning techniques is to segregate damaged brain regions from healthy ones and to divide different types of brain tissue [10].

Numerous machine learning techniques have been used to classify AD cases, and the model performance is good. In general, traditional learning-based approaches involve three steps: first, the brain's Regions of interest (ROIs) are determined; second, the ROIs are used to choose the features; and third, classification models are constructed and evaluated. The features engineering process is the main issue in traditional learning-based approaches (manual selection and extraction), which significantly affects the model's performance. Recently, DL has emerged as a methodology that is revolutionary when compared to traditional machine learning techniques. The features engineering process is the main issue in traditional learning-based approaches, while manually obtaining the features from the classifier and going through a separate technique, DL has automated the feature extraction process without requiring human specialists. Convolutional neural networks, or CNNs, have recently been able to classify images with extremely high accuracy and precision.

Thus, this paper explains techniques to predict brain MRI symptoms for the diagnosis of Alzheimer's disease utilizing a CNN-based methodology. Following is the arrangement of the remaining content: In Section II, the literature survey is explained; section III explains technology of prediction of brain MRI symptoms using CNN. The section IV explains result analysis of this method. Finally, the method is concluded in section V.

II. LITERATURE SURVEY

Islam A., Reza S. M. S. and Iftekharuddin K. M., et.al [11] presented a stochastic model for MRIs of the brain that can be used to describe the tumor texture. For complicated MRI appearances, the model utilizes Multifractional Brownian Motion (MBM). A new algorithm is developed to extract spatially varying multifractal features. The method is compared to Gabor-like multiscale texton feature and extends the AdaBoost algorithm. Experimental results show the model's efficacy in automatic tumor segmentation for 14 patients with over 300 MRIs. The results are more consistent and outperform advanced methods on average for patients with available ground truth.

Manogaran G., Hassanein A. S., Shakeel P. M., Malarvizhi Kumar P. and Chandra Babu G., et.al [12] To automatically identify anomalies in the Region Of Interest (ROI), an enhanced orthogonal gamma distribution-based machine-learning technique is used to examine the under- segments and over-segments of brain tumor regions. Incorrect edge matching in the abnormal region causes more data imbalances, which are sampled by matching the edge coordinates and sensitivity, the machine learning technique is used to estimate the selectivity parameters. The most effective automatic technique for identifying tumors and non-tumor areas is evaluated for efficiency and accuracy by gathering and examining the benchmark medical image database. A mathematical approach was used to determine the algorithm's mean error rate. Based on experimental data, the system is evaluated. It was found that the machine learning methodology combined with the orthogonal gamma distribution method could detect brain cancers with an accuracy of 99.55%. This study advances the field of analyzing and detecting brain abnormalities in the medical field without the need for human interaction.

Hamamci A., Karaman K., Kucuk N., Engin K. and Unal G., et.al [13] suggested a contrast-enhanced T1 weighted magnetic resonance image-based cellular automata-based seeded tumor segmentation technique. Standardizing both the volume of interest and seed selection, the approach has connection to graph-theoretic techniques. In order to handle heterogeneity tumor segmentation, a sensitivity parameter is added and the shortest path problem is solved using the iterative Cellular Automata (CA) framework. On a tumor probability map, an implicit level set surface is evolved for spatial smoothness. In order to evaluate the radiation therapy response, the algorithm differentiates between necrotic and enhancing tumor tissue composition. Validation studies show 80%-90% overlap performance, robustness, and efficiency in computation time.

Wang W., Bu F., Lin Z. and Zhai S., et.al [14] study aims to promote the use of computer-aided detection technology in brain tumor detection by constructing a model using convolutional neural networks and MRI detection technology. The model segments and recognizes MRI brain tumors, improving recognition efficiency and rate. It also combines artificially selected features with machine learning features for enhanced diagnostic results. The model's practical effects and theoretical reference for future research are demonstrated through performance analysis experiments.

A. Demirhan, M. Törü and İ. Güler, et.al [15] Brain MR images can be segmented into tumor, edema, white matter, gray matter, and cerebrospinal fluid using the newly developed tissue segmentation algorithm. The approach strips the skull prior to segmentation using T1, T2, and Fluid Attenuated Inversion Recovery (FLAIR) MR images of 20 patients with glial tumors. An unsupervised learning approach is used to train the Self-organizing map (SOM), then learning vector quantization is used to optimize it. In order to generate the input feature vector, stationary wavelet transform coefficients are used. 91% for white matter (WM), 87% for gray matter (GM), 96% for cerebrospinal fluid (CSF), 61% for tumors, and 77% for edema are the average dice similarity indexes according to the results.

Z. Huang et al., [16] A Convolutional neural network based on complex networks (CNNBCN) is provided for the classification of brain tumors using magnetic resonance imaging, and it has a modified activation function. A network generator transforms the randomly generated graph algorithms that create the network structure into a computable neural network. The improved CNNBCN model has a 95.49% accuracy rate, higher than other models and lower test loss than ResNet, DenseNet, and MobileNet models. This model enhances neural network design methodology and improves brain tumor image classification.

Mohamed Shakeel P., Tobely T. E. E., Al-Feel H., Manogaran G. and Baskar S., et.al [17] Infrared sensor imaging technology is used to evaluate Machine learning-based back propagation neural networks (MLBPNN). The computational complexity of neural differentiating information then significantly reduced when the system was broken down into a small number of subsystems. The most important features are chosen using a multifractal detection technique to lower complexity after the features are extracted using the fractal dimension algorithm. Through the use of a wireless infrared imaging sensor, this imaging sensor is integrated to screen a patient's health and offer helpful control over the ultrasonic measurement level. This is especially useful in the event that an elderly patient living in a remote area occurs.

Fabelo H. et al.,[18] The goal of the European project HELICoiD (HypErspectraL Imaging Cancer Detection) was to define tumors in real time during neurosurgery procedures using hyperspectral imaging. The process for creating the first hyperspectral database of human brain tissues in-vivo is presented in this work. Information in the visual and near infrared ranges was recorded using a specially designed hyperspectral acquisition devices. In the 450–900 nm spectral range, the system performed better. After obtaining 36 hyperspectral pictures from 22 patients, a semi-automatic algorithm was utilized to label more than 300,000 spectral signatures. All data is available in a public repository.

S. Ahdi Rezaeieh, A. Zamani and A. M. Abbosh, et.al [19] a 3-D slot-rotated antenna that provides wide and unidirectional performance at low microwave frequency bands are created for a microwave head-imaging system. The antenna reduces size while improving directivity and bandwidth using traditional methods. The working frequency is lowered and the bandwidth is increased by using folding procedures, parasitic patches, and four sequences of staircase-shaped slots. With a measured (Voltage Standing Wave Ratio) (VSWR) fractional bandwidth of 87%, the final design has dimensions of 0.11 λ×0.23 λ×0.05 λ. An artificial head phantom is scanned using the antenna in 20° angle steps using a wideband microwave transceiver. The antenna is an effective choice for head imaging applications due to its small size, large operational bandwidth, unidirectional radiation, and detection viability.

Bianchi A., Bhanu B. and Obenaus A., et.al [20] To enhance the identification of Mild traumatic brain injury (mTBI) lesions, a discriminative voxel-level classifier is proposed and integrated with innovative low-level static and dynamic context factors. Initial estimates of a lesion are provided by visual features, such as various texture evaluations. Contextual features are obtained from the first estimate of new proximity and directional distance fed into a different classifier. Using only the visual data, this feature makes use of the first lesion estimate's spatial information. The separation from a hard estimate of the lesion at a prior time point, as suggested by the posterior marginal edge distance context feature, represents dynamic context. In comparison to other modern techniques, the method is validated using a temporal mTBI rat model dataset, showing improved dice scores and convergence. There is also an analysis of the approach's versatility to different datasets and the significance of the features.

H. Su, F. Xing and L. Yang, et.al [21] provides a framework for automatic cell detection that makes use of adaptive dictionary learning and sparse reconstruction. The technique attempts to enhance therapy planning, prognostic and diagnostic stratification, and treatment outcome prediction in cancer diagnosis and treatment. Handling large changes in cell morphology and dividing contacting cells are the key issues. With a F 1 score of 0.96, the approach demonstrated the highest cell detection accuracy out of 32 full slide scanned images after thorough evaluation on a data set of over 2000 cells.

Ravì D., Fabelo H., Callic G. M. and Yang G. Z., et.al [22] For intra-operative margin separation during brain surgery, a new processing pipeline and an innovative dimensionality reduction approach are presented in order to produce an extensive tumor classification map. However, current manifold embedding-based dimensionality reduction methods can be lengthy and may not produce reliable results, which final tissue categorization in the end. By utilizing a two-step process, the suggested framework seeks to address these issues. First, a T-distributed stochastic neighbor technique extension is used to reduce dimensionality, and following that, tissues are categorized using a Semantic Texton Forest, and a semantic segmentation technique is then used to the embedded results. Thorough, validation of the suggested approach has been carried out to show the system's possible therapeutic utility.

III. Prediction Of Brain Tumor By MRI Images For Alzheimer's Disease Diagnosis Using CNN Based Approach

In this section, block diagram prediction of brain tumor by MRI images For Alzheimer's disease diagnosis using CNN based approach is observed in Fig.1. Initially raw data is collected for this analysis. This raw data is given as input for this process. The goal of the MRI dataset pre-processing step is to change the data into a more ideal representation that satisfies the input size requirements of the pre-trained CNN. To enhance the model's performance, after eliminating noise and the skull from the image, they were able to extract the brain from MRI 3D images. Training samples and testing samples are created from the data after pre-processing.

The samples for training data is classified into training sets and validation sets. A specific task, such feature extraction, where the CNN model generates MRI feature vectors from the fully connected layer, is trained on the training set, which is a labeled dataset. Subsequently, three different classifiers receive the feature vectors. The validation set provides an accurate assessment of the way the model matches the training dataset while the model is being modified. The model approaches were evaluated using the test set.

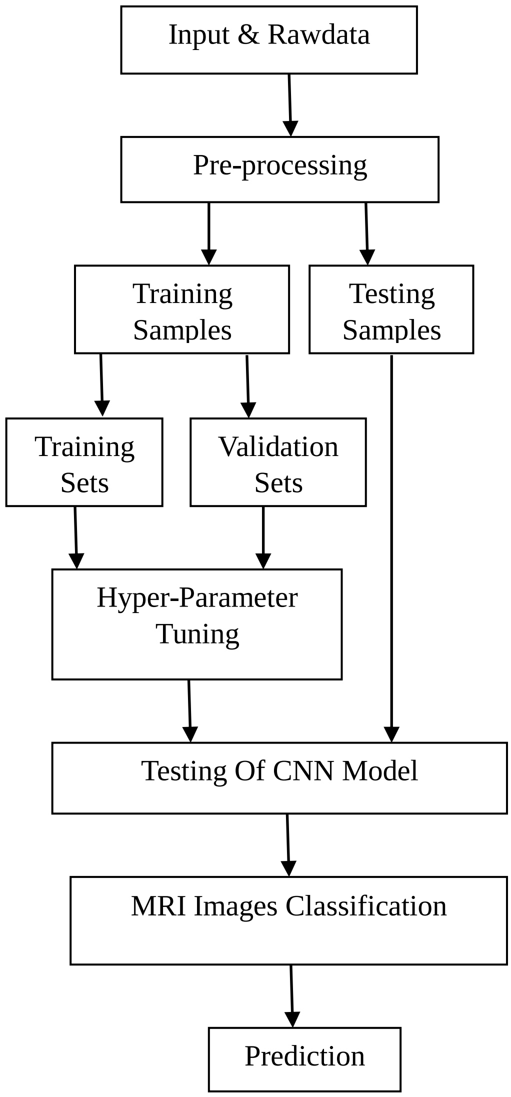

Fig.1: Block Diagram of Prediction Of Brain Tumor By MRI Images For Alzheimer's Disease Diagnosis Using CNN Based Approach

A learning algorithm's hyperparameter values are found by applying the optimized algorithm to any data collection. This process is known as hyperparameter tuning. By optimizing a predetermined loss function and maximizing the model's performance, that set of hyperparameters produces better outcomes with fewer errors. CNN model is performed to detect the tumor. CNN operations include convolution, where filters detect features, pooling to downsample retain essential information, flattening to convert data for fully connected layers, activation functions for introducing non-linearity in the model's learning process. The MRI images are then categorized. Other classifiers can be used in place of CNN's Fully Connected (FC) layers. After the classification is predicted.

IV. RESULT ANALYSIS

In this section, result analysis of prediction of brain tumor by MRI images For Alzheimer's disease diagnosis using CNN based approach is observed.

Table.1: Performance Analysis

Parameters	Decision Tree (DT)	CNN
Accuracy	96.1	98.3
Precision	90.5	91.7
Recall	84.8	89.6

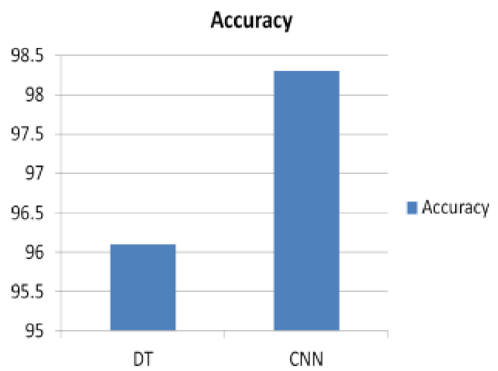

Fig.2: Accuracy Comparison Graph

A comparison graph of accuracy between CNN and decision tree may be seen in Figure 2. CNN displays more accuracy.

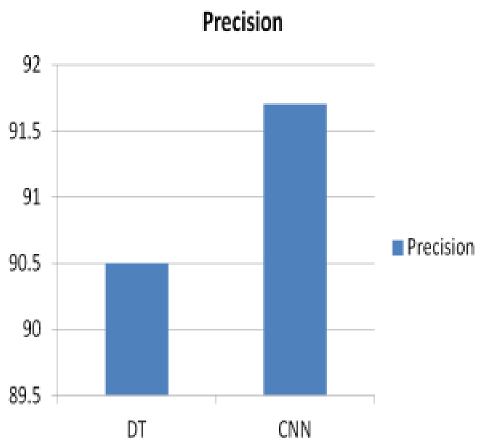

Fig.3: Precision Comparison Graph

A precision comparison graph with a graphical representation is shown between CNN and decision tree. In Fig. 3, CNN's precision is high.

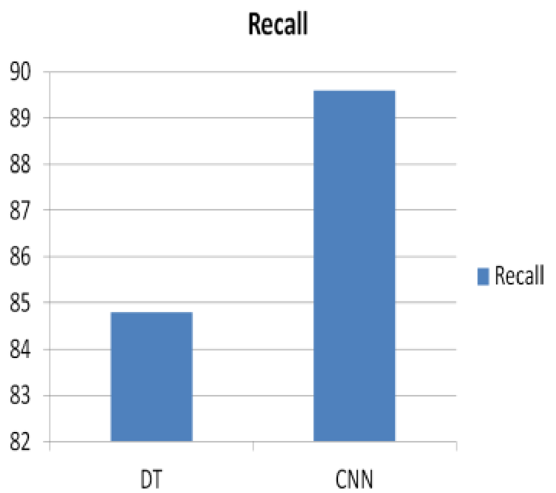

Fig.4: Recall Comparison Graph

Figure 2 shows an accuracy comparison graph between CNN and decision tree. In Fig. 4, recall for CNN is strong.

V. CONCLUSION

In this section, prediction of brain tumor by MRI images For Alzheimer's disease diagnosis using CNN based approach is concluded. Neurodegenerative changes occur in the brain when an individual has Alzheimer disease. As a result, early Alzheimer's disease diagnosis is found in this analysis. Alzheimer's is an unpredictable disease. When AD is treated early on, less minor damage is caused and Compared to addressing it later, the treatment is more effective. Convolutional neural networks (CNNs) are used in this investigation. Hence, this analysis achieves better results interms of accuracy, precision and recall.

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