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ALZHEIMERS DISEASE DETECTION BY USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT: Alzheimer's disease (AD) is a neurological illness. It primarily affects memory of older adults of above 65 years of age. So, this condition is to be detected accurately in early diagnosis. Therefore, manual diagnosis by medical professionals is becoming more inaccurate and time-consuming because many patients suffering with this disease. By using a variety of methods, AD has been diagnosed and classified. However, early diagnosis methods need to be accurate. There is multiple brain imaging techniques are utilized to idetify abnormalities in the brain, along with Computer Tomography (CT) scans, Positron Emission Tomography (PET), and Magnetic Resonance Imaging (MRI), which are preliminary tests for the detection of AD. The MRI scan is used to detect the structural changes and death cells seen in the brain of an AD patient effectively. The treatment can slow down the progression of the disease by identifying the risk for these patients well advance the appearance of symptoms. Therefore, by using this Artificial Neural Network (ANN) disease is predicted accurately. This ANN method will detect the disease accurately, even it reduces the prediction time. Hence, this method shows better results.

KEYWORDS: Magnetic Resonance Imaging (MRI), Artificial Neural Network (ANN), brain imaging, Deep Learning, neurodegenerative disease, Alzheimer's Disease (AD)

I. INTRODUCTION

Alzheimer's disease (AD) is known as dementia. This condition will develops when memory cells sustain irreversible damage. The memory will be lost, when the tissues of visual cortex deteriorate as well as function of nerve cells' ability decreases. Person will struggle with everyday skills like speaking, writing, and reading as AD affects the normal brain's ability function[1].

The serious side effects like heart failure as well as breathing problems will be observed in patients in final stages of illness. Accurately diagnose AD in early stages is still extremely challenging, even symptoms take a long time to appear. So, patients' conditions become worsen as the illness increases [2]. Therefore, patient an extending their life if accurately diagnose.

AD is neurodegenerative brain illness and it is incurable, and it common observed in elderly people, typically affecting those 65 and older. The main characteristic β-amyloid (Aβ) has extracellular plaques and an intracellular neurofibrillary tangle contains tau [3]. The cognitive ability imbalance is main symptom and it is observed 10% of cases in an early onset.

AD impacts communication, memory focus, understanding and reasoning. Professionals only treat the patients suffering with symptoms of AD.The day-to-day functions are affected by Alzheimer, which causes cognitive impairment[4]. Delusional, paranoia, short-term memory loss, and, stress or age are symptoms of AD, then AD is a degenerative neurological disorder. About 5.1 million people in United States have been diagnosed with this disease.

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, that is important to have treatment. Early disease diagnosis is time-consuming as well as expensive process that demands extensive data collecting, the use of advanced prediction algorithms, and the involvement of an experienced doctor. The automated systems will shows accurate results, but comparing to manual system it has errors. So, automated systems are used in medical decision support systems [5].

Numerical data which is collected from MRI as well as biomarkers (chemicals, blood flow), that is 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 AD will not only reduce the amount of human interaction but also shorten diagnosis times.

The medical professionals will diagnosis AD in early stages. Because of the vast number of patients and volume of data, it is hard to manually evaluate medical photographs with accuracy and speed [6]. The clinician or medical specialist personally reviews a small number of records as well as offers an analysis based on their expertise and experience. For examining vast amount of patient imaging data, there is a chance that incorrect analysis will lead to more issues. Therefore, an automated solution is required.

Among elderly people, AD is common cause for cognitive decline. This AD progression rates from Mild cognitive impairment (MCI) range from 10% to 15% every year[7]. 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. 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. The development of the disease is stopped by prompt and accurate medical diagnosis [8].

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. Accurately identifying regions diagnosed by AD using MRI is the main goals of 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].

The remaining paper is organised as follows: section-II presents a literature survey, section-III shows alzheimers disease detection by using ANN; section IV explains result analysis; section V concludes the paper VI references.

II. LITERATURE SURVEY

E. Ç. Polat and A. Güveniş, et.al [11] by using mutual information index-based similarity automated identification of Alzheimer's disease of fluorodeoxyglucose (FDG) PET computing method is applied. By using the leave-one-out approach and Receiver Operating Characteristic (ROC) curves performance was evaluated. The diagnostic reliability is indicated by area under the curve (AUC) with 0.857±0.0261. Based on mutual information, image similarity technique findings are observed and the other technique computer-aided diagnostic (CAD) system is validated with visual and black box methods.

C. Fang *et al.*, [12] based CAD system it provides new gaussian Discriminant Analysis (GDA) that based on held-out test data set and tenfold cross validation. In the suggested system, tenfold cross validation, distinguishes CN group from MCI and AD with an average accuracy, F1 score, specificity and sensitivity with 96.00%, 97.20%, 88.67% and 99.14% respectively; for separating MCI from AD, the average specificity of 91.25%, sensitivity of 79.09%, accuracy of 87.43% and F1 score was 79.82%.

Y. Tu *et al.*, [13] provides a new isometry-invariant shape descriptor for analysis of brain morphometry, and cortical surface to unit sphere is first computed by global area-preserving mapping. By using support vector machine (SVM) classifier 248 amyloid-beta-negative normal control patients are separated from 135 amyloid-beta positive individuals with a clinical diagnosis of MCI. AD-related dementia from age-matched, healthy aging people are separated accurately by using shape descriptor

S. Luz, et.al [14] presents detection of Alzheimer's type dementia by examining vocalization features that are easily retrieved from spontaneous speech. The speech transcriptions of the patient didn't depend on this technique, and by using Bayesian classifier using features extracted from basic algorithms. The voice activity detection as well as speech rate tracking is achieved an accuracy of 68%. The suggested method patients 'n = 214' and elderly controls 'n = 184' for data set of spontaneous speech recordings.

Afdel. K, Bakkouri. I, Catheline. G, and Benois-Pineau. J et.al [15] by using Gated Recurrent Fusion Unit (GRFU) and 3D(D-Dimensional) Multi-scale Feature (3DMF) blocks provided new CAD system. By using standard sMRI imaging modalities, this technique is used for screening patients with input of Hippocampal Volumes Of Interest (VOI). The extraction of multi-scale attributes by using 3D Convolutional Neural Network (CNN), and it is fed into Gated Recurrent Units (GRU), then performance is enhanced.

F. Alvarez *et al.*, [16] multimodal fusion and to analyze data the data is captured and extract pertinent features by using a novel system. To enhance patient's quality life, in health monitoring settings, the system athers signals from various sources, initiates suitable actions and recognizes user behavior and context. The versatile, multipatient and multimodal approaches are observed in this technology, which is found in other methods. Therefore, identifying abnormal action in daily life this system provides similar or better outcomes.

U. M and M. Baskar, et.al [17] propose a generic flow map that can be used in many different situations, including the detection of brain tumours. The many accessible datasets are given for use in evaluating brain tumour algorithms. There is a need for research that identifies brain tumours with decent efficiency and fair effort, therefore this article compares the performance of recent literature additions as Accuracy, Sensitivity, Specificity, as well as time consumption.

Ashraf.I Ishaq.A, Kuthala.V, Rustam.F, Alfarhood.S and Mallampati.B, *et al*., [18] to detect brain tumors, features of MRI machine learning-based method is proposed. To train suggested model, characteristics of 3Dimensional and 2Dimensional-UNet segmentation are considered from MRI like gray level dependence matrix, run length matrix values, statistics, size zone matrix, co-occurrence matrix and Shape. By combining benefits of two machine learning models, K-nearest neighbor (KNN) and gradient boosting classifier (GBC) for soft voting criteria is considered to enhance the performance of hybrid model.The reason for combining GBC and KNN is better performance. The model's accuracy is 64%.

S. Ahdi Rezaeieh, A. Zamani and A. M. Abbosh, et.al [19] two-module computerized method aimed at increasing the speed and accuracy of brain tumor detection. The first module, termed the Image Enhancement Technique, utilizes a trio of machine learning and imaging strategies—adaptive Wiener filtering, neural networks, and independent component analysis—to normalize images and combat issues such as noise and varying low region contrast. The second module uses Support Vector Machines to validate the output of the first module and perform tumor segmentation and classification. our method exhibited significant improvements in contrast and classification efficiency.

Bianchi A., Bhanu B. and Obenaus A., et.al [20] To enhance the identification of Mild traumatic brain injury (mTBI) lesions, discriminative voxel-level classifier is described 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 hard estimate of lesion at prior time point, as suggested by 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.

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, Callic.G.M. Fabelo.H, 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, described method solves these problems. First, a T-distributed stochastic neighbor

technique extension is used to reduce dimensionality, and following that, tissues are categorized using Semantic Texton Forest, and semantic segmentation method is used to show better output. Thorough, validation of the suggested approach has been carried out to show the system's possible therapeutic utility.
C. A. Subasini, A. Hamid, D. C. S and A. Sheeba, et.al [23] propose a novel approach by introducing a dynamic ensemble machine learning algorithm. Leveraging models like MobileNetV2, EfficientNet, ResNet50, Inception, and GoogLeNet, our approach surpasses static models in adaptability. Trained on diverse features and architectures, our method forms an adaptive ensemble that dynamically selects the most effective algorithm at runtime, optimizing classification accuracy. Through a comprehensive evaluation on a diverse dataset, our approach demonstrates superior performance compared to static ensemble models. This dynamic ensemble machine learning technique not only advances medical image analysis but also addresses the need for adaptive and efficient models in practical diagnostic applications. Manogaran.G, Mohamed Shakeel.P, Tobely.T. E. E, Al-Feel.H, and Baskar.S, et.al [24] 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 important attributes are chosen utilizing multifractal detection method to lower complexity after attributes are extracted using the fractal dimension algorithm. Through use of 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*.,[25] describes 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.

III. FRAMEWORK OF ALZHEIMERS DISEASE DETECTION BY USING ANN

In this section, framework of alzheimers disease detection by using ANN is observed in Figure.1.
Intially input is taken as MRI imaes, then from that images the unwanted data is removed. Then features are selected from those images. Features are extracted from that selection. From that data training datset and testing dataset is trained. Then, the ANN is applied to that data. Finally stages of the tumor are evaluated. An MRI picture was used in this analysis. Brain MRI images are utilized as the input; these pictures include information about diseased and non-infected regions. This MRI image is utilized to run the algorithm when the MRI scanning process is complete. The algorithm first looks for the tumour location in the MRI picture. The MRI brain image involves inserting and filtering for Preprocessing. In MRI image some noise is observed, therefore the image is smoothed using an average filter. The smoothed image is forwarded and average filter is a simple and straightforward method for image smoothing. Preprocessing is the process of

preparing data for further processing or analysis. It involves cleaning and organizing data before it's used in a data-driven algorithm. Preprocessing can help to: Remove noise, Enhance contrast, Avoid the influence of undesirable phenomena, and Facilitate subsequent processing. The preprocessing data are some of the benefits: The dependability and precision is enhanced. Preprocessing data can increase dependability, dataset's accuracy and quality by eliminating inconsistent data or missing values based on human or computer errors. In results data is consistent.

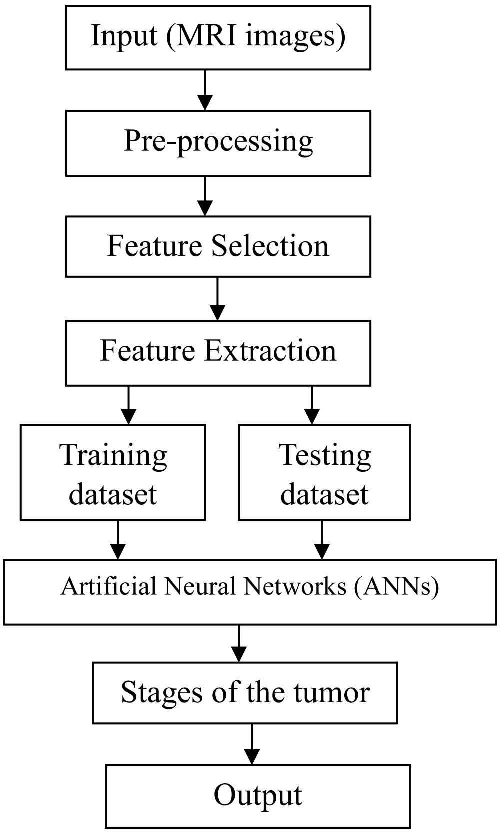

Figure.1: Framework of Alzheimers Disease Detection by Using ANN

Feature selection resolve both by having too little high-value data and having too much low-value data. For choosing features and creating a model by finding the minimum number of columns from the data source. The benefits of feature selection are improved model interpretability, shorter training periods, effective multicollinearity maintenance less overfitting, and better model performance.

Feature extraction is a process that identifies and extracts important features from raw data to create a more informative dataset. It's a subset of feature engineering, which is the process of improving machine learning model training by reworking data. To reduce dimensionality of dataset, feature reduction is a common optimization technique it eliminates redundant or irrelevant features or by converting extracted features into newly created latent variables which are discriminative than original feature dataset.

Data splitting will divide dataset into multiple sets for training as well as testing machine learning models. A machine learning model that is used to train data is known as training data. If supervised learning or hybrid technique incorporating that approach is used for data labeling or annotation will enhance data. Testing data is a set of data used to examine functionality, performance, and security of a software application or system. It's created or selected to satisfy the input content and execution preconditions required to execute test cases.

In artificial neural networks neurons referred as units, are a component and system is made up of these units grouped in a number of layers. In the data neural networks are needed to uncover hidden patterns and number of units in a layer can range from a dozen to millions.

ANN contains input, output, and hidden layers, it process and learn by transmitting data from outside sources to input layer By using more than one hidden layer, input data is then converted into important data for output layer. The input data receives an result from output layer by ANN.

Stage 0: carcinoma in situation –tumor willn’t spread from past ducts or lobules.
Stage I: The tumor is small and well localized (not morethan 2 cm).
Stage II: The size of tumor varies from 2-4 cm.
Stage III: The tumor size is more than 4 cm.
Stage IV: The cancer will spread to remaining parts like your bones, lungs, liver or brain.

IV. RESULT ANALYSIS

In this section, performance analysis of alzheimers disease detection by using ANN is observed.

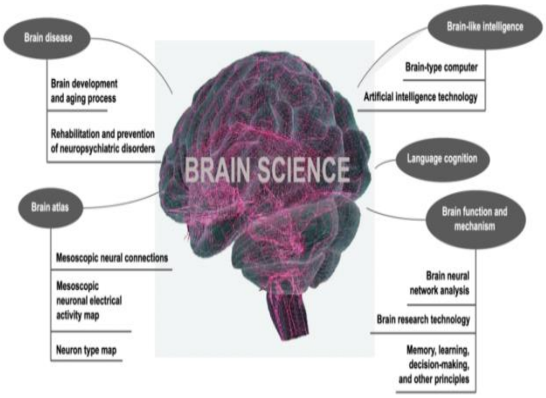

Figure 2: Output Image

Figure 3: Subarachnoid Haemorrhage

Subarachnoid Haemorrhage Predicitng the Result with Accuracy with 75% using Deep Learning (DL) Model.

Figure 4: Intraparenchymal Haemorrhage

Intraparenchymal Haemorrhage Predicting the Result with Accuracy with 75% using DL Model.

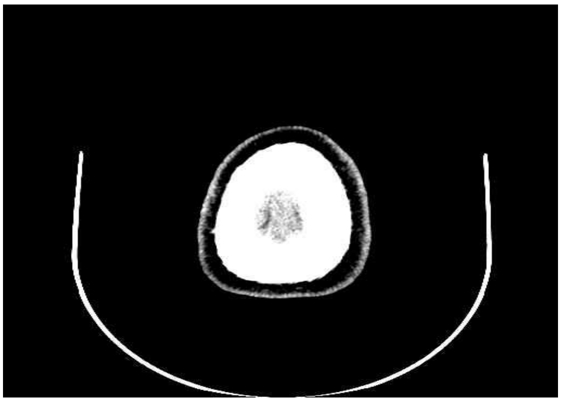

Figure 5. Subarachnoid Haemorrhage

Subarachnoid Haemorrhage Predicitng the Result with Accuracy with 75% using DL Model.

V. CONCLUSION

The most fundamental task is to perform its ability and acquire. AD is a neurological disorder that progressively deteriorates memory, cognitive function, and ability to perform and acquire. Alzheimer's disease (AD) is progressive neurodegenerative illness that is deadly and irreversible. As a result, brain cells deteriorate and it will die. The first sign of AD in middle or advanced age is to buildup protein inside and around neurons. The most common and early signs of the disease is difficulty remembering new information and it typically start in learning-related areas of the brain. For diagnose and characterize Alzheimer's disease, several methods are used and it is an accurate and timely diagnostic solution is required. AD detection approaches using

ANNs based on MRI was implemented and tested. Hence, this system achieves better results in detection of brain tumor at early stage.

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