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Deep learning-based alzheimer disease detection techniques

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***Abstract*---**Alzheimer disease (AD) is one of the most common degenerative illnesses of the elderly worldwide. It is a progressive neurological condition that impairs cognitive memory. As a result, Alzheimer's sufferers struggle to recall daily activities, recollect family members, and solve logical problems. Medication which reduces the creation of proteins, block data communication between brain neurons and it can also delay the course of Alzheimer's disease. Mild Cognitive Impairment (MCI) seems to be a common disorder that does not usually progress to Alzheimer's. It is difficult to find patients with modest cognitive decline who may acquire Alzheimer's. As a result, creating deep learning-based disease detection techniques to assist clinicians in detecting prospective Alzheimer's patients is crucial. The performance comparison of the Imaging, Electronic Health Record (EHR), and Single nucleotide polymorphisms (SNP) datasets is evaluated using the metrics Accuracy, Sensitivity, Specificity, and Multi Area. Different mistakes are added under the curves for gradient calculation. This study's findings are as follows: results on standard datasets show that the proposed feature selection algorithms discover a sub-optimal minimal level feature set from a larger input feature set for diagnosing Alzheimer's disease, with higher values for system performance in terms of Accuracy as well as losses against training and Accuracy and losses against validation. These results can demonstrate the model's suitability for the purpose.

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1. Introduction

One of the highly difficult diseases towards treatment is Alzheimer Disease (AD). Alzheimer disease usually means Senile Dementia, is decreasing neurological disorder with gradual losing memory and cognition. Alzheimer disease is the fourth biggest effect of mortality worldwide after stroke, cardiovascular disease, and cancer. It has become the highly dreaded disease by taking over from cancer. More people are killed than combined breast cancer and prostate cancer. Alzheimer's disease has progressively destroyed the body and leads to death. In 2018, Alzheimer's disease has at least 50 million people in it, according to World Health Organization (WHO) data, has 4–8 % of people, at the age of 65. After the age of 85, the chance will rise to 35% for Alzheimer Disease [1][2]. Now, Alzheimer disease pathophysiology is still unknown. It is generally believed to be linked to the extracellular and the Neurofibrillary Tangles (NFT) deposition of Amyloid-β (Aβ) that cause loss or damage to synapses and neurons [3][4]. Early on, Alzheimer's disease is characterized by "Mild Cognitive Impairment" (MCI), which is caused by the transition from advancing age to Alzheimer's disease. Natural aging symptoms are often mistaken as MCI. In a few years, 44 % of MCI patients is developed Alzheimer's disease [5]. Psychotherapies and medication are effectively slow the progression of MCI, allowing patients to enhance their quality of life. Alzheimer's disease research is currently most significant topic in medical research. Every year, at least US$ 100 billion is spent on Alzheimer's disease diagnosis and treatment.

1.1 Deep Learning

A multi-layer computational paradigm, Deep Learning (DL), for data representation on many abstract levels [6]. Despite the fact that deep learning had tremendous progress in computer field, identifying and classifying medical pictures remains a big difficulty. It has advanced considerably in the interpretation of medical pictures in recent years. Deep learning method for distinguishing between MCI and Cognitively Normal (CN), AD and MCI, AD and CN. Accuracy levels are 95.9 % (AD versus CN), 75.8 % (MCI versus AD), and 85.0 % (CN versus MCI) [7]. A thorough Boltzmann machine is utilized to eliminate the features underneath from “Positron Emission Tomography” and “Magnetic Resonance Imaging” images, while the “Support Vector Machine” procedure is employed for final categorization. But there is a procedure that simply employs four-layer networks, which makes it complicated to separate abstract image features.

“Convolutional Neural Network” (CNN) considered as great artificial neural network feed-forward class. It is the most important technique of deep learning for picture recognition and classification. It is directly utilizing the two-dimensional pictures as data entry and then learns automatically from the data that the conventional (conv) hand-held extraction functions produce to prevent various calculation mistakes. It can extract better characteristics to describe the delicate lesion locations [8-10]. It is utilized to distinguish between normal, healthy human brains, and Alzheimer disease [11]. It uses CNN for AD brains with an accuracy rate of 96.86% in a healthy person's brain [12][13]. The pictures of "Structural Magnetic Resonance Imaging" (SMRI) and "Functional Magnetic Resonance Imaging" (FMRI) are combined and utilized to classify Alzheimer disease using networked LeNet-5 and networks. While more accuracy should be achieved by only healthy aging people and Alzheimer's patients are recognized, and the procedure is not utilized in "Magnetic Resonance Imaging". Error is calculated in the backpropagation step in equation 1.

$$\frac{\partial E}{\partial W_{ab}} = \sum_{i=0}^{N-m} \sum_{j=0}^{N-m} \frac{\partial E}{\partial W_{ij}^{l}} \frac{\partial x_{ij}^{l}}{\partial W_{ab}} \quad (1)$$

$$= \sum_{i=0}^{N-m} \sum_{j=0}^{N-m} \frac{\partial E}{\partial W_{ij}^{l}} y_{(i+a)(j+b)}^{l-1} \quad (2)$$

Where E denotes the error function, x denotes input, y is i^{th}, j^{th} and m is the filter size, and N is the number of neurons in each layer, l represents layer number, w is the filter weight with a and b indices.

Deep learning is coupled with a brain network resting technique to differentiate between CN, MCI, and AD. For Alzheimer's disease, a deep learning and state-resting brain network-based early diagnosis technique has been developed [14]. The algorithm integrated the "Functional Magnetic Resonance Imaging" (FMRI) photographs with the clinically important data to identify regular aging Alzheimer disease and Magnetic Resonance Imaging. The predictive accuracy percentage is 31.21% higher compared to the conventional approach. A complex AlexNet network model is developed using MRI data for MCI, AD, and CN diagnostics [15]. AlexNet is named ImageNet Champion in 2012, and it has a major impact of Image Processing (IP) in the application of machine learning [16]. The AlexNet is a neural network that is created using and supported by Compute Unified Device Architecture (CUDA). The AlexNet intensive is completely sensitive to AD vs. CN diagnostics. It is developed a multimodal fusion method for Alzheimer disease diagnosis [17]. The use of Positron Emission Tomography (PETs) and Magnetic Resonance Imaging (MRIs) simultaneously, every PET image has a strict registration technique that is matched with the MRI image. The same MRI and PET region are used to extract 93 features. Its method is effective for detecting dichotomous difficulties, but owing to human participation, it is difficult to identify many categorization errors. The studies presented above show that deep learning is identified Mild Cognitive Impairment (MCI) and Alzheimer disease effectively and requires several recommendations for further investigation into AD's secondary diagnosis, as well as ideas for future research.

2. Review of Literature

Janani et al., [18] investigated the single data modes utilised to forecast the stages of Alzheimer disease (AD). The integration of many data modalities yields a comprehensive picture of AD Stage Analysis. Thus, it makes extensive use of Deep Learning (DL) to evaluate imaging, Magnetic Resonance Imaging (MRI) and clinical testing for AD, genetic (Single Nucleotide Polymorphisms (SNPs)), MCI, and control. It is used to stack noise removal drivers to obtain parameters from imaging data, clinical, and genomic. In addition, it provides a novel method for data interpretation to identify high-performance features generated from deep models through clustering and disturbance analysis. These results are being used to illustrate that deep model (like k-nearest neighbors, random forests, support vector machines, and decision trees) much better than shallow models (such as decision trees) in rating, particularly when it comes to search results and relevance. Furthermore, it demonstrates that combining multi-modality data yields more accurate, exact, recoverable, and medium F1 scores than single modality models. The hippocampus or amygdala mind regions and “Rey Auditory Verbal Learning Test” (RAVLT) as the highest characteristics that conform to known AD literature.

Ebrahimighahnavieh [et al.], [19] state that Alzheimer Disease is a leading reason of death in technologically advanced countries. Although the research results were excellent no clinically effective diagnostic techniques based on computer-aided algorithms were available. Deep models have been more popular in recent years, especially in the realm of photography. Deep learning is an extra accurate and traditional machine learning technique in detecting Alzheimer's disease. However, identifying Alzheimer disease remains challenging, or necessitating a highly discriminating representation of the features to differentiate similar brain patterns for classification. It is offering the developments and findings based on a thorough review of over 100 articles It focuses on critical biomarkers, pre-processing processes, and various approaches to data management in single-mode and multimodal research.

Zhang et. al., [20] studies revealed that AD is the hardest diseases to treat. Elderly people and families are severely affected by Alzheimer's disease. “Mild Cognitive Impairment” (MCI) is the transition among normal aging Alzheimer's and subsequently converts MCI to AD. The appropriate therapy is missed MCI frequently misinterpreted as signs of normal aging. Mild Cognitive Impairment (MCI) is crucial for the initial analysis and medication of Alzheimer disease the precise diagnosis. This article offers a profound pattern for the auxiliary identification of Alzheimer disease that mimics the diagnostic procedure of the physician. Neuroimaging and cognitive diagnostic tests are often used to identify people who may have Alzheimer's disease. In this study, two separate neural convolutional networks train multi-modal medical pictures. Then, correlation analysis evaluates the stability of the output of two convolutional neural networks.

Ji et al., [21] state that Alzheimer disease leads to further impairment and memory loss. It has a significant impact on patients' lives and is not curable. The detection of Alzheimer disease is helping to initiate proper treatment to avoid further brain damage. Alzheimer disease classification has been subjected to machine learning methods over the past few decades, with results based on physically produced features and multi-stage architectural classifiers. It was utilized the introduction of deep learning, and the end-to-end method of neural networks for pattern categorization. The primary motive of this research would be to design a technique for detecting Alzheimer disease at the initial stage using Magnetic Resonance Imaging (MRI) based on Convolutional Neural Networks

(Conv Nets). Image of grey and white matter MRI slices were utilized as categorization inputs. Ensemble learning processes collaborative learning processes were utilized to enhance classification by combining deep classification findings.

Martinez-Murcia et al., [22] studied that several conventional machines have been applied to Alzheimer disease, including image decomposition segmentation methods such as major component analysis to greater complexities, nonlinear decomposition algorithms. The deep learning paradigm is based on abstract high-level characteristics retrieved from MRI images that dictate the internal distribution of data to low-dimensional manifolds. There is attempting a new Alzheimer disease experimental data analysis based on deep learning in this investigation. By integrating information regarding neuropsychological test results, and clinical data along with pictures obtained only by data-driven degradation of MRI. It is expected to uncover links between the process of neurodegeneration and cognitive disorders. The impact of each automatic coordinate on the brain is then evaluated by examining various combinations of the features. This is accomplished via the use of regression and gradation analysis. Clinical variable quantity with associations over 0.6 in the case of neuropsychological assessment measures such as Mini-Mental State Exam (MMSE) or Advanced Driver-Assistance Systems (ADAS11), reaching a classification precision of more than 80% used for the Alzheimer disease diagnosed.

3. Background Study

Using deep convolutional neural networks, a new strategy for screening Alzheimer's disease was found Recently. To make an early diagnosis of this disease, it is imperative to do a clinical assessment of patients cognitive testing, medical history other pathological assessments. In addition to these clinical procedures, there are numerous other techniques to determine Alzheimer's disease, including cerebrospinal fluid (CSF) analysis, biomarkers, brain imaging (MRI/PET), and blood protein analysis. The discrete wavelet transform (DWT) method was used to generate feature wavelets for classification of Alzheimer's disease to aid diagnosis. This does not provide disease identification; extra processing is necessary using machine learning algorithms.

Hand-crafted feature learning methods like machine learning techniques require painstaking labour to build the features. Deep learning methodologies, like machine learning frameworks, are capable of learning higher-level features from datasets when contrasted with hand-crafted feature learning methods such as machine learning techniques. To model Deep Convolution Neural Network (DCNN), the Spyder software from the anaconda package is utilized, together with the Keras library and Tensor-flow backend on GPU. The experiment results demonstrate 98.57% accuracy using the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset. The datasets were used to optimize using different optimizers and their results were compared to find best optimizer. The complete method was based on Conv-ReLu-maxpooling- conv-ReLu-maxpooling operation to extract the features and classify the disease [23].

4. Problem Formulation

Alzheimer, an irreparable brain disease impairs thinking and memory while mind size shrinks which is at last prompts disease. Early detection of Alzheimer disease (AD), critical for the advancement of more effective treatment. Deep learning, a cutting-edge machine learning technique, has demonstrated superior performance to classical machine learning at finding subtle structure in complex high-dimensional data spatially in the realm of computer vision. There has recently been increased interest in using deep learning to the early detection and categorization of Alzheimer's disease, as fast advancements in neuroimaging techniques have resulted in the generation of large-scale multimodal neuroimaging data. The majority of current AD and moderate cognitive dysfunction (MCI) research makes predictions using a single data modality, such as AD stage. When different data modalities are combined, it is possible to achieve a comprehensive analysis of staging of AD. Thus, in the current work we have applied deep learning over the individual data modalities and also to integrally analyze genetic (single nucleotide polymorphisms (SNPs)), imaging (Magnetic Resonance Imaging (MRI)) and clinical test data to classify patients into AD stages. In the current work of individual modalities Deep Convolutional Neural Network (DCNN) is used with integral analysis of all three data modalities using concatenation. The validation and optimization of the outcomes is served using gradient computation for error rate detection between actual and generated.

5. Research Objectives

The objectives from the methodology are as follows:

a) To collect the data for all three points i.e., imaging data, electronic health records (EHR) data and SNP data from available sources.
b) To generate a Deep Convolutional Neural Network (DNCC) for individual modality. The DNCC is used with Integral analysis for all three datasets.
c) To validate and optimize the system using gradient computation method.
d) To detect the errors between actual and generated results.

6. Research Methodology

In the proposed methodology there are three datasets taken such as imaging dataset, EHR dataset and SNP dataset. These are discussed below.

6.1. Imaging Dataset

Imaging data sets are used to train and/or test algorithms in a variety of methods. Many data sets used to train convolutional neural networks for image recognition contain hundreds of photos, although smaller data sets are suitable for texture analysis, transfer learning, and other applications. The proposed model employs preprocessing approaches for training and testing on medical images. MRI images degrade during the production process due to low variation induced by the optical equipment's weak brightness. To solve this problem and improve MRI scans, image enhancing techniques, linear contrast stretching was performed on the images to enhance the dispersion of pixels over a broad range of brightness. [24].

6.2. EHR Dataset

Whether there is an electronic health record (EHR) or a clinical database, the goal is the same to help patients lead healthier lives. The electronic chart is an exact replica of the paper chart for a patient. Electronic Health Records (EHRs) are patient-centered, real-time records that provide fast and safe access to relevant information for authorized users. Even though a patient's medical and treatment history is stored in an EHR system, it is also intended to go beyond the typical clinical data collected in a provider's office to provide a more holistic perspective of a patient's care [25]. In order for the electronic health record to be successful, there are three key characteristics: First, the electronic health record empowers authorized physicians to build and maintain health records in a digital format that is accessible to specific other clinicians across multiple health care organizations. A patient's EHR is intended to offer information to healthcare practitioners as well as a variety of other health care providers and institutions, including pharmaceuticals, doctors, diagnostic centers, dispensaries, emergency care, and college and occupational clinics.

6.3. SNP Dataset

The human genome is made up of around three billion nucleotide (DNA base pair) pairs. Only 1% of them differ across people, and nearly majority of them are same among all humans (population). Single Nucleotide Polymorphisms (SNPs)account for a major fraction of these genetic variants. SNPs have been linked to a variety of biological impacts, including the relationship with complicated disorders and diverse reactions to drugs and therapies, according to research. It also offers a number of advantages over microarray gene expressions, including the fact that it is less likely to vary with time. That is, a patient's SNPs at birth will remain the same throughout his or her life [26]. A huge number of genetic variants are currently being identified and evaluated.

The method calls for three stages. Data preparation is first phase; feature extraction from input visuals is the second stage; and the last stage is automatic decision making with Convolution layers, max-pooling levels, and batch normalization layers, three layers of the algorithm performed in concurrently. The classification accuracy was enhanced by using multiple parallel layers in a row. The work-flow model of the proposed methodology is illustrated in the figure 1.

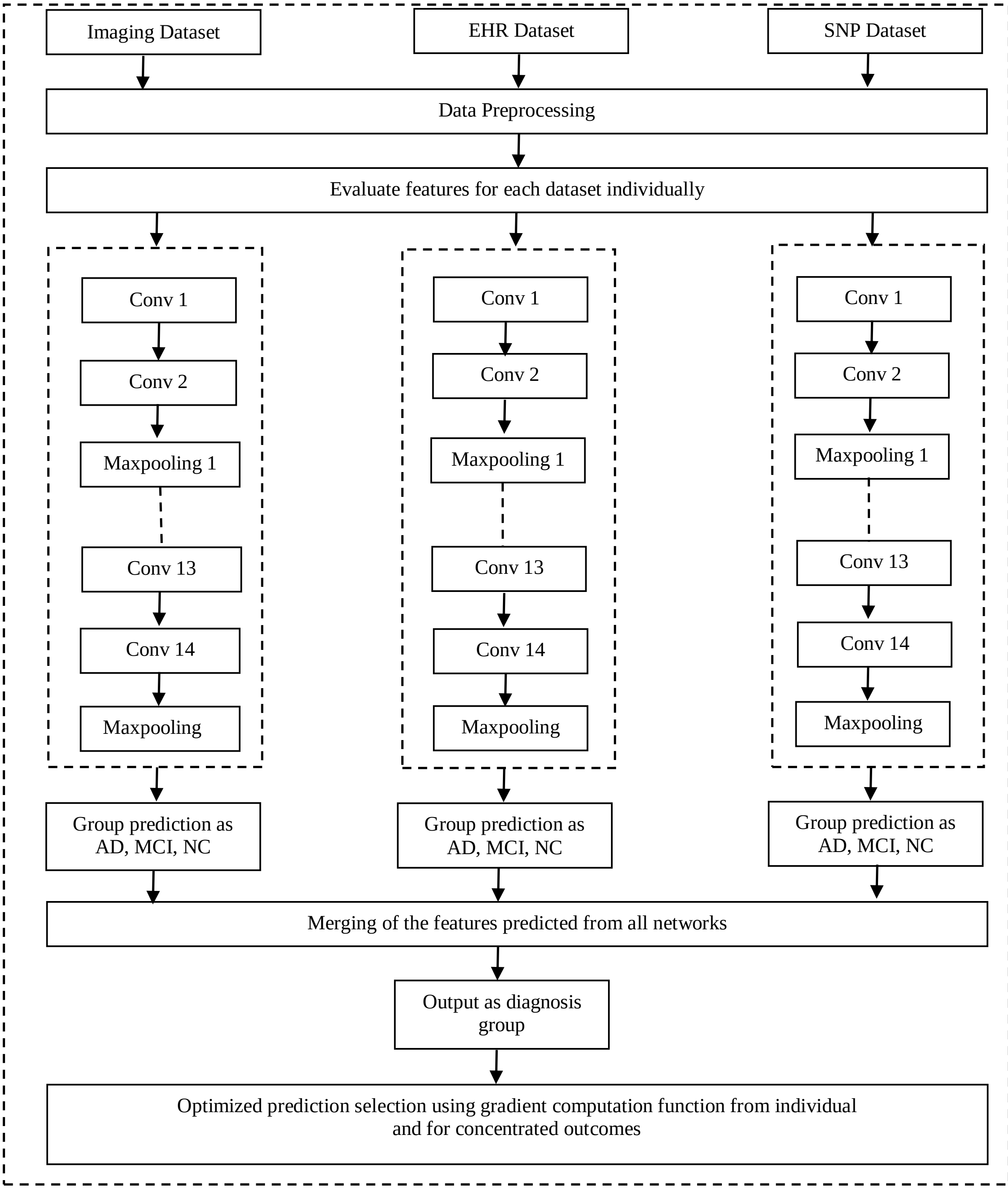

Figure 1. Proposed methodology for AD stage detection

All the steps are as follows:

- In first stage data from the various datasets will take for the evaluation. All three datasets are easily accessible. There are numerous data available about the patients of AD. This information can be used to identifying the different initial symptoms and time of starting of the disease.

- The second phase involves the preprocessing of data and the extraction of features related to AD. After they have been acquired, they must be converted into the appropriate format (JPG, PNG, TIFF, etc.) in order to be used for further processing. This stage involves selecting the most useful information from the datasets in accordance with the requirements.
- In third stage, three layers of work method works parallelly so that the accuracy of the system will improve, and best outcomes can be achieved. In this step three batch normalization layers, five max-pooling levels, and 14 Convolution layers, three layers of the algorithm performed in concurrently for best performance.
- After that outcome of each group is concentrated for further optimization process so that the best results will be found. The optimization is performed using integral analyzer and gradient computing also used for error detection.

7. Expected outcomes

After performing the above method expected outcomes are as follows:

a) Classification accuracy with comparison to existing methods output.
b) Error detection should perform by using gradient computing.
c) Performance of the system in terms of Accuracy and losses against training and Accuracy and losses against validation. These outcomes will show the fitness of the model for objective.

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