Machine Learning For Detection and Classification of Alzheimer's: An Analysis of Current Trends and Future Possibilities

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Abstract : Early diagnosis is a major aspect for treating any disease and Machine Learning (ML) plays a vital role in speeding up the diagnosis process and increase the efficiency of existing treatment strategies. A short yet effective review of the current trends in diagnosing Alzheimer's with the help of Machine Learning has been done in this paper. This This review will help in our future work or other contributors working on Drug Repurposing Techniques. In this review, we have found that the Models used in various studies such as ANN, SVM, DNN, CNN etc have achieved accuracy greater than 90% which is a good sign for future work. Upon analysis we have found that various studies have used MRI images for classifying Alzheimer's. With advancements in computer aided systems, production of quality information from the image processing techniques has introduced various challenges and these challenges are tried to resolve through ML. As the number of studies focusing on the use of ML has increased, the efficiency of the diagnostic systems has also increased and are helping the medical community.

***Index Terms* – Machine Learning; Alzheimer's; Image Processing; Drug Repurposing; Computer aided systems**

I. INTRODUCTION

Alzheimer's Disease (AD) is the most prevalent form of dementia, affecting mostly the older citizens and for which there is no treatment [1]. Progressive memory loss and cognitive dysfunction are the symptoms [1]. It consists of various symptoms, varying in nature [2]. At the most severe stage, it causes cognitive impairment, behavioral issues, loss of semantical, lexical and pragmatic language processing [2]. Unfortunately, there are very few treatments available against Alzheimer's. However, potential medications and remedies are available and are found effective if implemented at early stages [3]. As the world's population ages, AD becomes a significant issue [2]. According to the United Nations' 2017 World Population Ageing Highlights [4], there are nearly a billion people aged 60 and up, more than double the number in 1980. As a result of the global decrease in the fertility rates and improved living conditions, that number is expected to double again by the year 2050 [4]. At the same time, the use of technology by seniors is on the rise [2]. According to the Pew Research Center for Internet and Technology, 40% of elderly people in the United States owned a smartphone in 2017, up from 35% in 2013 [5]. Companies all over the world are redefining their goals and missions in order to adapt to societal changes and meet the growing demands of an aging population [2]. While companies work on products to ensure the safety and independence of seniors, researchers are looking into the limitations of current Alzheimer's disease (AD) detection methodologies and recognizing the need for more accurate tests [2]. Existing research on Alzheimer's is based on medical images. With the advancements in Artificial Intelligence (AI) and Computer Aided Diagnosis (CAD), classification and Early prediction of Alzheimer's has become a research hotspot in recent years [6]. The machine learning revolution has shown that computers can solve problems that were previously considered to be impossible for them to solve. Computers have become an important part of almost every field, and their continued use would have a significant impact on how these fields function. Diagnostic medicine is an example of such an area, where computers and machine learning algorithms are increasingly assisting in both tracking and diagnosing patients [7].

Machine learning algorithms may also detect information that a human eye might miss, as shown by the use of machine learning to detect early-onset Alzheimer's disease (AD) [7]. The standardized criteria set out by Dubois et al. [8] are commonly used to diagnose probable AD. They must have memory loss combined with abnormal biomarker results, a proven genetically dominant AD mutation in the immediate family, or macroscopic visible changes in the brain identified through neuroimaging. Atrophy of the hippocampus is the most common of these modifications, which becomes more obvious as the disease progresses [7-8]. It can be difficult to correctly identify it in prodromal AD, but recent advances in computer-aided diagnosis (CAD) using machine learning have made it easier by providing automated procedures for generating diagnoses with accuracies of around 90% [7][9][10]. Despite the fact that these CAD systems are usually focused on machine learning, they take a somewhat different approach. The different models require varying amounts of prior knowledge about the data set [7], which is an important difference.

The goal of this paper is to analyze the current progress in the field of Machine Learning (ML) for diagnosing Alzheimer's. This paper provides an in depth analysis of the current trends and also suggests the future possibilities in diagnosing Alzheimer's. Rest of the paper is structured as follows. Section 2 deals with the related work. Current methods for Medical Imaging for diagnosing Alzheimer's is explained in Section 3. Section 4 deals with the future possibilities and the paper is concluded in Section 5.

II. RELATED WORK

Support Vector Machine (SVM) is a stable and most widely used technique for classification and regression problems [11-12]. Due to the high performance capabilities SVM is a widely used technique [13]. Various studies have been done for detecting and classifying Alzheimer's. In [13], the authors have used various classifiers such as RCNN, SVM etc for diagnosis of Alzheimer's and achieved an accuracy of 98.12%. In [1], a comparison between various Machine Learning (ML) models such as SVM, Fast RCNN, and Faster RCNN is done. In [14] the authors have analyzed 1167 Brain MRI scans and developed a ML model for classifying the scans into three subtypes such as cognitive normal aging, mild cognitive impairment and AD. Several groups have investigated and continue to investigate the potential of electroencephalograms (EEGs) for diagnosing AD or early stages of AD in the last decade [15]. One of the key reasons for concentrating on the early stages of Alzheimer's disease is that the drugs available today are most effective at this point [15-16]. The key advantage of EGG recording systems over other traditional or conventional methods is that they are inexpensive and portable [15-16]. As a result, EGG has the ability to be used to test a large population for Alzheimer's disease much more quickly than we can now [15-16]. Preprocessing is needed before EEG signals can be used for analysis, as described in [17]. This is done to eliminate interference from electrical devices, such as 50 or 60 Hz power supply signals, electromyographic signals elicited by muscle action, and ocular artifacts caused by eye movement or blinking [15]. This is critical because if these signals aren't filtered, they can skew EEG analysis and lead to incorrect conclusions [17]. Electromyographic behavior is thought to be restricted to higher frequencies (above 40 Hz) [17]. To remove these objects from EEG data, a low pass filter is frequently used [15][17]. The summary of the contributions by the authors is provided in table 1.

Table 1: Comparison/Summary of Various Models developed

Authors	ML Models Suggested	Accuracy (%)
[18]	Linear CVM	72.5
[19]	RBF SVM	98
[20]	Ensemble SVM	97.5
[21]	DW-S^2MTL + Linear SVM	95.09
[22]	NGF + SVM	91.8
[23]	MK Boost + SVM	94.65
[24]	MDTFS + MDTC	81.5
[25]	Random NN Cluster	92.3
[26]	Subspace Alignment	84.6
[27]	LSTM	85.6
[28]	ANN	100
[29]	rMLTFL	95.2
[30]	ANN + BGRU	89.69
[31]	TrAdaBoost	93.75
[32]	PCA + FFNN	90.06
[33]	NGF + SVM	91.8
[34]	CNN(TL)	96.25
[35]	ANN	91.25
[36]	GA + ELM	86

The Testing and Training Time For Machine Learning Models were Compared in Figure 1 and Figure 2 respectively.

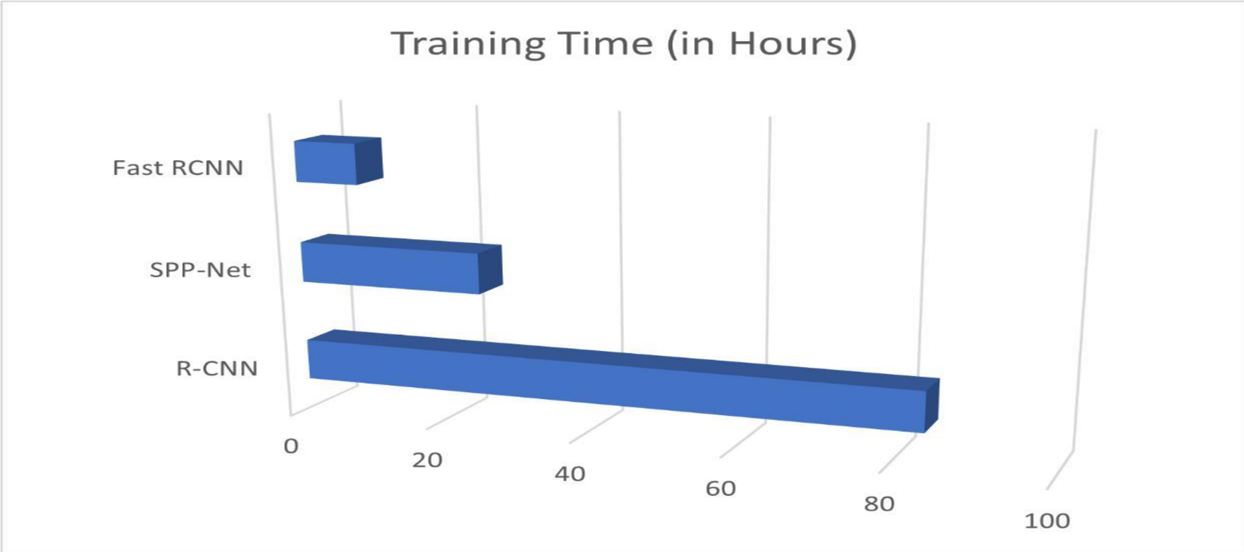

Figure 1: Comparison of various Models on the basis of training time [12]

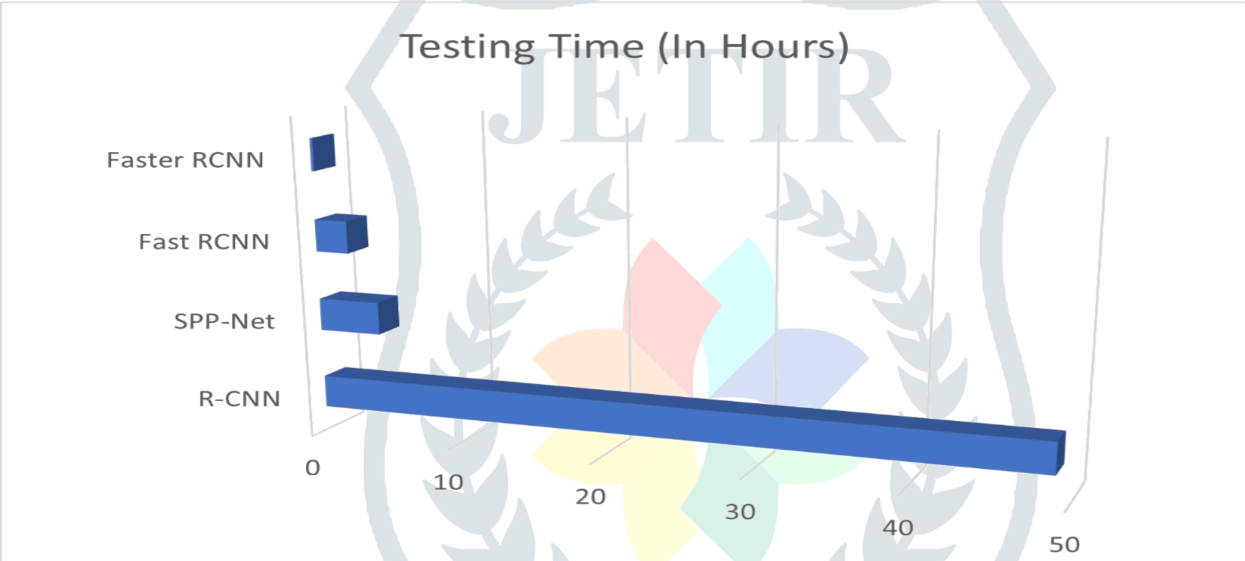

Figure 2: Comparison between different ML models on the basis of their testing time [12]

III. Medical Imaging For Diagnosing Alzheimer's

A medical Image is made up of pixels or voxels, representing the internal structure or functioning of an anatomical area [1]. It is a discrete representation that maps the numerical values with spatial position as a result of sampling or reconstruction process [1]. Neuroimaging, also known as Brain Imaging is a non-invasive method of visualizing the functions of the brain as well as its behavior and pharmacology [1]. Neuroimaging has been divided into two broader categories such as Structural Imaging: that provides information about the loss of various components of tissue of the brain like neurons, synapse, etc [37]. The workflow of a computer aided system (CAS) is shown by figure 3.

Nowadays, various ML approaches have been utilized in order to improve the diagnosing power of Alzheimer's disease [1]. In [39] the authors developed a technique which was able to achieve a high precise individual definition of stable and progressive mild cognitive impairment (MCI) regardless of the MCI subtypes. They have used a DTI baseline data for conducting a study of 35 Normal Condition (NC) and 67 MCI subjects recruited from Geneva and Lausanne countries based on SVM. In [40] the authors used the Alzheimer's Disease Neuroimaging Initiative (ADNI) database to predict the conversion of amnestic MCI to Alzheimer's Disease (AD) using SVM with radial basis function kernels. The authors have discarded the other subtypes as the amnestic subtype was found to be the most widely studied in the prodromal phase of AD [40].

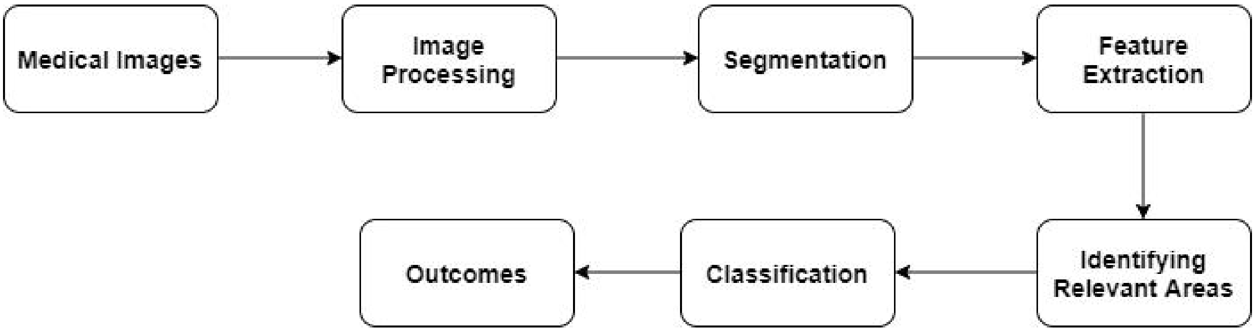

Figure 3: Workflow of the Computer Aided System (CAS) [38]

In [41] the authors have suggested a sparse autoencoder (AE) and 3D convolutional neural network (3D-CNN) for predicting the patient's status of AD by using the structural and functional magnetic resonance image (MRI) data of 2015. The major difference between this method and other methods is that it uses full MRI images from the data, which produces better results than the methodology suggested by [1] based on brain slices or 2D CNN. In [42] the authors have used stacked autoencoders for detecting simultaneous time series of various organs from the MRI data by extracting various visual and temporal characteristics from an unlabeled multi-modal DCE-MRI data. Unlike the standard autoencoders, used in [1], implemented pooling operations after each sheet, effectively compressing the features of increasing large input region. The authors in [43] have shown a 3D convolutional deep learning (CDL) architecture for taking out the characteristics from the brain and was not limited to a non-enhanced T-1-weighted MR videos [1]. The overall summary of the studies done by using various ML techniques [38] are shown in figure 4.

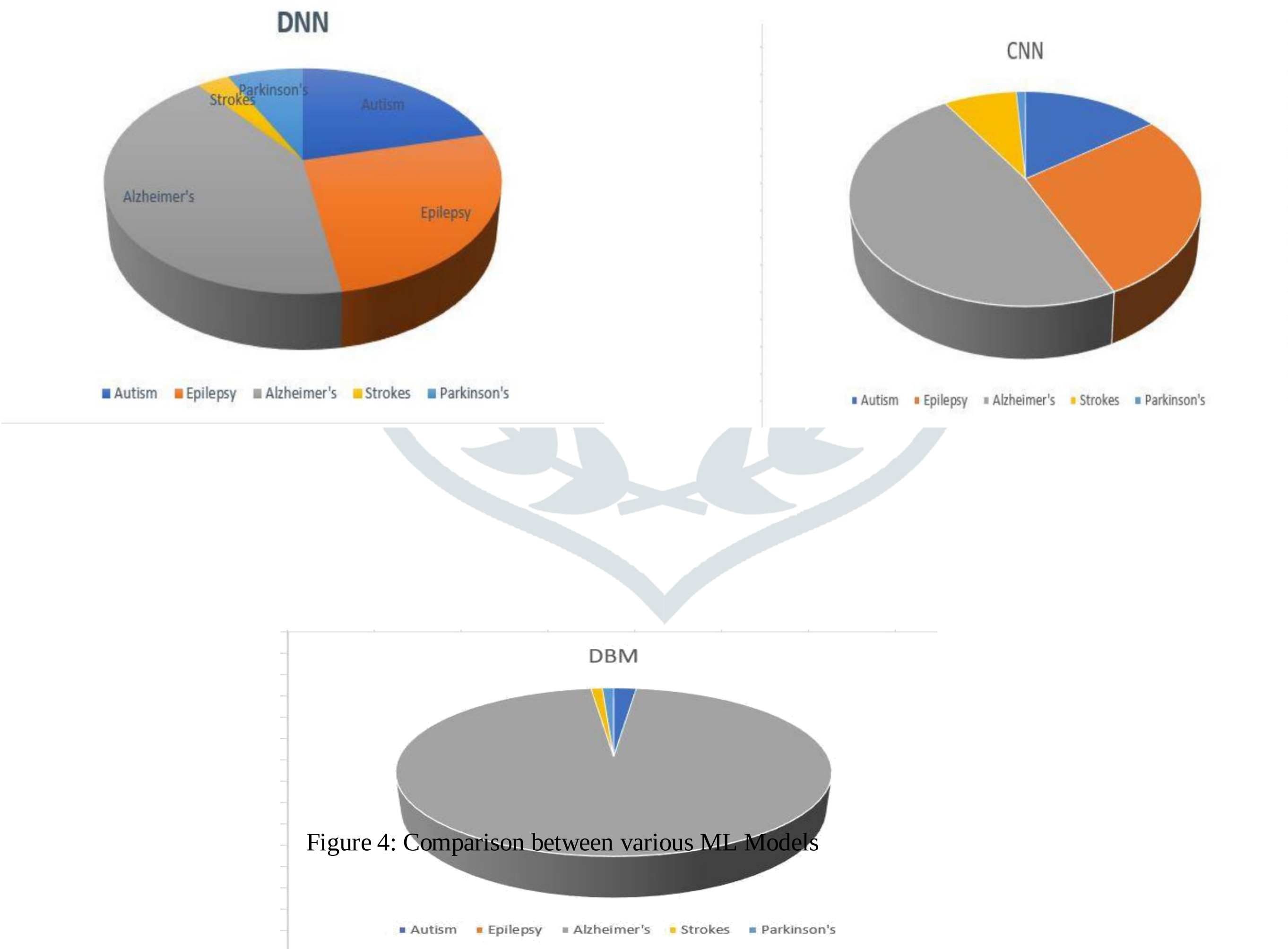

Figure 4: Comparison between various ML Models

IV. Future Directions

The depletion of cholinergic neurons in the brain is a trait of Alzheimer's disease [44]. Various studies have been done for finding an appropriate technique for developing drugs for curing this disease but all efforts remained unsuccessful. Since Drug development is a complex and time consuming process, Machine Learning can help in resolving the complexity of the drug development process. Drug repurposing is the most common technique for drug development [45]. Since there are very few studies available online, our future work will focus primarily on the development of an efficient technique for Drug repurposing. Drug Repurposing is a revolutionary technique as it helps in identification of novel indicators for approved drugs which further helps in development of novel drugs or to increase the efficiency of already existing drugs [46]. In Alzheimer's, the existing therapeutic agents only focus on the symptomatic advantages and do not have any role in disease modification [46]. This challenge needs to be resolved and this is the motivation for our future work. Furthermore, a lot of studies are focused on small or medium datasets of MR images for detecting Alzheimer's. However, due to advancements in machine learning, complex datasets would also be used for more accurate prediction results.

V. Conclusion

The review done in this paper has led to the clear picture that researchers have largely focused on developing Machine Learning models for detecting and classifying Alzheimer's. Work is done using various ML models such as CNN, SVN, ANN and DNN and the accuracy achieved by most of the works was above 90%. However, More studies are required for integrating these detection methods with drug repurposing techniques to be a step closer in treating Alzheimer's. It has also been seen from the review that MRI images were efficiently used with Machine Learning Models for classifying Alzheimer's. Higher success rates are remarkable and will motivate future contributors to suggest more efficient techniques for treating this disease. With continuous advancements in biomedical imaging and machine learning techniques, we hope to find a cure for Alzheimer's in future.

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