Survey on prediction, classification and tracking of neurodegenerative diseases

Veena Dhavalgi, H R Ranganatha
Department of Information Science and Engineering, Sapthagiri College of Engineering, Bengaluru, India

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ABSTRACT

Neurodegenerative diseases (NDD) such as Alzheimer's, Parkinson's, and Huntington's disease are complex conditions that progressively impair neurological function. In recent years, machine learning (ML) techniques have shown considerable promise in the prediction, tracking, and understanding of these diseases, offering potential for earlier diagnosis and better patient outcomes. However, despite the advances, significant challenges remain in accurately predicting and classifying NDD due to their heterogeneous nature and the complexity of underlying biological processes. This survey aims to explore the current developments in the prediction and classification of neurodegenerative diseases using ML. The primary objective is to analyze various methods and techniques employed in the early diagnosis of NDD, focusing on ML algorithms, neuroimaging techniques, and biomarker analysis. The survey systematically reviews and categorizes existing studies, highlighting their methodologies, strengths, and limitations. Through an extensive literature review, the survey identifies key challenges such as the need for large, high-quality datasets, the integration of multi-modal data, and the interpretability of ML models. Findings suggest that while ML holds significant potential for advancing NDD research, addressing these challenges is crucial for its successful application. The survey concludes with a discussion on future research directions, emphasizing the importance of interdisciplinary approaches and the development of robust, transparent, and generalizable ML models for the early detection and diagnosis of neurodegenerative diseases.

Corresponding Author:

Veena Dhavalgi
Department of Information Science and Engineering, Sapthagiri College of Engineering
Bengaluru, India
Email: veenadresearch@gmail.com

1. INTRODUCTION

Neurodegenerative diseases (NDD) are a group of conditions characterized by the progressive loss of structure or function of neurons, which are the cells that transmit information in the brain and spinal cord [1]. Some examples of NDD are alzheimer's disease (AD), parkinson's disease (PD), ataxia disease (ATD), huntington's disease (HD), and amyotrophic lateral sclerosis (ALS) [2]. These diseases can cause a decline in cognitive, physical and emotional abilities, and can ultimately lead to death. There is currently no cure for most NDDs, and treatments are primarily focused on relieving symptoms and slowing the progression of the disease. The early detection of the disease can help for the treatment [3]. In the recent years, machine learning (ML) models are currently being used for the prediction and classification of the NDD [4]. Also, the ML models can be used to aid in the diagnosis of NDDs [5]. These models can analyze patterns in various data types such as brain imaging, genetic information, and cognitive test scores to identify markers of the disease [6]. One type of ML model commonly used for this purpose is a deep-learning (DL) neural network, which can automatically identify complex relationships and patterns in data [7]. Another type of model is a decision-tree (DT) or random-forest (RF), which can classify individuals based on the presence or absence of specific disease markers [8]. However, it is important to note that ML models for NDD diagnosis are still in the early stages of development and are not yet widely used in clinical practice [9].

Further, the internet of things (IoT) also play a large role in the identification of neurodegenerative diseases [10]. IoT devices can collect data from various sources such as wearable sensors, smart home devices, and medical equipment to monitor individuals for early signs of the disease [11]. This data can then be analyzed using ML algorithms to identify patterns and markers that are indicative of a particular NDD. For example, wearable sensors can be used to track changes in gait and movement patterns, which can be early indicators of PD [12]. Smart home devices can monitor changes in sleep patterns and behavior, which can be indicators of AD [13]. Medical equipment can collect data on brain activity and imaging, which can be used to identify changes in brain structure and function [14]. It is important to note that while IoT devices have the potential to play a role in early disease detection, they should always be used in conjunction with other diagnostic tools and should not be relied upon as the sole method for diagnosis. Additionally, privacy and security concerns must be considered when using IoT devices to collect sensitive health information [15].

Moreover, in the recent years, some tracking devices and various sensors are being used for tracking a NDD patient [16]. These tracking devices usually comprise of RSS tracking or real-time locating systems (RTLS) [17] or bluetooth low energy (BLE) tracking [18] or angle of arrival (AoA) tracking [19]. RSS tracking, or real-time locating systems (RTLS), is a technology that can be used to track the location and movements of individuals, including patients with NDDs. RTLS can be used to monitor patients in real-time and provide valuable information about their activities and movements. Bluetooth Low Energy (BLE) tracking is a technology that can be used to track the location and movements of individuals, including patients with NDDs. BLE technology uses small, low-power wireless sensors to transmit data about the location and movements of an individual to a central device, such as a smartphone or tablet. Angle of arrival (AoA) tracking is a technology that uses the difference in signal arrival time at multiple receivers to determine the position and location of a device or individual. In the context of tracking Neuro-Degenerative (ND) patients, AoA tracking can be used to monitor a patient's movements and activities in real-time.

For example, any tracking technology (RSS, RTLS, BLE, AoA) can be used in the form of wearable devices, such as smartwatches or wristbands, to track a patient's activity levels, sleep patterns, and gait. The data collected by the wearable device can be analyzed to identify changes in the patient's behavior and movements that may be indicative of a decline in cognitive or physical function. It is important to note that while the tracking technology can provide valuable information about a patient's disease progression, it should be used in conjunction with other tracking methods to provide a comprehensive picture of a patient's condition. Additionally, privacy and security concerns must be considered when using tracking technology to track individuals, as the collected data can be sensitive and personal in nature. The main contribution of the survey is to

- Study the various methodologies for prediction and classification of neurodegenerative disease.
- Study the various methodologies for prediction and classification of ataxia disease.
- Study the various methodologies for prediction and classification of parkinson disease.
- Study the various methodologies for prediction and classification of alzheimer disease.
- Study the various ML and deep learning methodologies used for the prediction and classification of the neurodegenerative diseases.
- Study the various tracking methods used to track the patient having a neurodegenerative disease.

2. LITERATURE SURVEY

2.1. Methodologies for the prediction and classification of neurodegenerative disease

ALS, HD and PD are just a few examples of NDD that affect the daily lives of many individuals all over the globe. Selzler *et al.* [20], they have extracted the important features required for the classification of the NDD from the NDD dataset using the signals that are emitting from the gait-dynamics. In this work, they have employed support-vector-machine (SVM), DT and k-nearest-neighbor (KNN) to classify several sets of features, and then discuss the accuracy of these methods. Moreover, this research proposed a system that operates in real time with an accuracy of above 82%. Berke Erdaş *et al.* [21], they provided a study proposing a DL-based technique for assessing gait pattern that takes the data from the quick-response in order to create a robust and accurate disease-severity grading method for the NDD like PD, ALS and HD. In order to find a way to precisely classify the severity of diseases, this set of data was transformed into regression using the DL approach of convolutional-neural-networks (CNN). In addition, in order to show the efficacy of the findings acquired using the newly developed strategy, traditional ML methods, like RF, multilayerperceptron (MP), KNN and extremely-randomized-trees (ERT), ensemble-ML (EML) techniques, like as stacking and voting, were utilized on 1-dimensional data. The results demonstrated that the 2-dimensional CNN method outperformed the others in the majority of instances.

Shusharina *et al.* [22] reviewed the interesting possibilities for future study of ML techniques towards the treatment of NDD as well as mental disorders. The paper summarizes the most up-to-date findings from studies of neurodegeneration and mood disorders. Aguayo *et al.* [23], they have trained 3 deep-neural-network (DNN) algorithms for identifying the NDD. The 3 algorithms were Densenet (Dense-Convolutional), Feed-Forward and Tab-Transformer. In this work, they have additionally trained two other algorithms which have been constructed on the Cox method. These two algorithms were CoxSF (selected features) and CoxEn (elastic-net-regularization). Among these five algorithms, the Tab-Transformer showed best accuracy (83.4 percent). Termine *et al.* [24], the researchers highlight how recent research has shown that deep-learning offers a possibility to improve their understanding of NDD like Parkinson's and Alzheimer's by bringing together previously presented biomedical datasets.

2.2. Methodologies for the prediction and classification of ataxia disease

Numerous neurology and muscular disorders dramatically lower quality life expectancy and are accompanied by gait abnormalities [25]. Motion sensors allow for accurate modeling of gait variations. Nevertheless, they generate an enormous quantity of information, the analysis of which can be difficult. Vyšata *et al.* [25], they evaluated and classified several data-reduction strategies for usage in healthcare. By using a RF classifier pre-processed using T-Distributed Stochastic-Neighbor-Embedding, they were able to attain an accuracy rate of 98% when differentiating among a set of healthy people and those diagnosed with ataxic-gait collected from a database of forty-three people (20 healthy, 23 ataxic), developing 418 sections of gait-pattern. Prochazka *et al.* [26], explored the idea of training CNN method to differentiate among normal gait and ataxic-gait utilizing accelerometric information. The results of their classification method were compared with the results achieved by traditional approaches, such as the SVM, Bayesian approaches, as well as the two-layer neural-network design containing features approximated as its relative-power in specified frequency ranges. Based on their findings, selecting optimal sensor locations could boost accuracy between 81.2 percent at the level of the foot to 91.7 percent at the cervical spine. The accuracy was improved to 95.7 percent by integrating the given input information into the DL method using five distinct layers.

Acosta-escalante *et al.* [27], researchers analyzed information gathered from 14 hereditary-ataxias (HA) patients as well as 14 healthy individuals who had iPhone motion sensors put on their legs to determine how few gait parameters are necessary for effective and unobtrusive HA individual's recognition. The results showed that MLP and KNN and methods were able to obtain 96 percent accuracy rate for classification utilizing 2 gait-patterns, while just right foot sensor data were needed for MLP, hence reducing the level of intrusion. Nunes *et al.* [28], researchers showed that it is actually possible to differentiate between NDDs. Time-series data describing the separation of the index and middle fingers and the resulting structures were analyzed for information. Classification approaches for ataxia achieved receiver-operating-curve (ROC) that were close to 0.91. Yang *et al.* [29], they offered a learning system that makes use of magnetic-resonance imaging (MRI) data to distinguish between various forms of ataxia of the cerebellum as well as to forecast the functional rating associated with the condition. Simulations demonstrated the effectiveness of their method in distinguishing among four classes and in making reliable predictions about these classes.

2.3. Methodologies for the prediction and classification of Parkinson disease (PD)

The nervous system is the primary target of PD, an irreversible neurological disorder. Delaying the progression of PD requires its diagnosis and treatment at an early stage. Huang *et al.* [30], they offer a new technique for adaptable unsupervised selection of features by using manifold training with longitudinal data that is multimodal. In order to aid in early identification of PD, they performed classification as well as diagnostic score predictions simultaneously and presented an efficient iterative improvement approach. To ensure the reliability of the suggested method, they conducted extensive research employing the parkinson's-progression-markers-initiative (PPMI) dataset. The outcomes demonstrated that this technique outperformed the current standard methods in long-term data classification and diagnostic score prediction. An innovative and effective similar spatially pattern-based technique was presented in [31] for identifying PD in two distinct settings: without treatment as well as on treatment. Several ML methods were examined in order to determine the best way to categorize the characteristics that were extracted. These methods included: RF, SVM, KNN and quadratic/linear discriminant evaluation. The findings showed that the maximum accuracy in classification is found in feature extractions from the beta and alpha bands. Yang *et al.* [32], proposed the hierarchical-boosting-dual-stage-feature-reduction ensemble-method (HBD-SFREM). To reduce features in two steps, the closest-neighbor feature selection approach was built into the multidimensional extraction of features approach. In order to increase approach recognition efficiency, the AdaBoost method repeatedly performed the dual-stage feature elimination pairing to get occurrences having more accurate features.

Priya *et al.* [33], utilized local-binary-pattern (LBP) approaches for analyzing gait patterns in humans prior to identification through feature extraction. Statistic-features were created and examined, then a test called the Kruskal-Wallis test was employed to determine which features are most useful. An artificial-neural-network (ANN) was then used to perform classifications using the determined set of features. With 96.57 percent sensitivity, 96.28 percent accuracy and 95.94 percent specificity, the presented symmetrically-gradient pattern (SWLNGP) approach outperformed the state-of-the-art methods. A method for anticipating the severity of PD was presented in [34], which made use of DNN as well as the Parkinson's Telemonitoring-Voice Dataset presented by the UCI. A wavelet-based splitting fuzzy method was used to classify the features once the initial signal information was processed employing the signal's distortion reduction normalization method. The extracted speech abnormalities information classification was also found to be more accurate (99.8 percent) than PD prediction, suggesting that it represents a superior measurement for severity anticipation.

2.4. Methodologies for the prediction and classification of Alzheimer disease

Predicting the long-term course of a disease like AD, which is a progressive NDD, is crucial [35]. Zhao *et al.* [35], presented a NDD prediction architecture. It consists of two components: a three-dimensional multi-information generative-adversarial-network (mi-GAN) for predicting exactly what a person's entire brain might appear involving within a certain period, as well as a three-dimensional DenseNet-based multiple-class classification system enhanced using focal loss algorithm to identify the diagnostic phase of a person's predicted brain. The alzheimer's-disease-neuroimaging-initiative (ADNI) was used for evaluating the proposed architecture. When comparing real MRI scans from year 4 to their produced images, the structural-similarity-index (SSIM) was found to be 0.943, demonstrating that their mi-GAN achieved outstanding results. Ni *et al.* [36], ImageNet and ADNI database were utilized to train a two-phase transferred learning approach predicated upon the ResNet-50 architecture, where achieved accuracy of 90%.

To aid in the development of better strategies to facilitate early AD detection, Miltiadous *et al.* [37] assessed six supervised ML approaches for classifying processed EEG data of AD and Fronto-Temporal dementia (FTD) individuals. The suggested approach had an accuracy of 78.5 percent when using DT for identifying AD and 86.3 percent when using RF to identify FTD. Odusami *et al.* [38] presented a DL-based approach for the prediction of mild-cognitive-impairment (MCI), earlier MCI (EMCI), later MCI (LMCI), and AD. The ADNI fMRI database was utilized for this analysis where the adjusted ResNet18 system obtained an accuracy of 99.99%. Machado *et al.* [39], provided an ontology-based computing approach which can identify highly risky activities for individuals having AD by receiving physiological information through various IoT applications. Average prediction accuracy was 97.4%, with the simulator generating 1026 situations to use as input. Odusami *et al.* [40], a multiclass-classification of AD utilizing the MRI set was performed using a ResD hybrid technique employing Resnet18 as well as Densenet121. When classifying data, the two pre-trained technique outputs were concatenated. The suggested ResD approach achieved a mean absolute (macro) accuracy of 99.61%.

2.5. Machine learning and deep learning methodologies

Venugopalan *et al.* [41], they utilize DL for classifying the individuals into AD, MCI, and CN by integrating analysis of image ([MRI]), genomic (Singular-Nucleotide -Polymorphisms [SNPs]), and medical test information. They showed that DL methods outperformed simple algorithms such as SVM, DT, RF and KNN using the ADNI dataset. Basher *et al.* [42], slice-wise geometric features gathered from the right and left hippocampi of sMRI data was suggested for prediction in the diagnosis of AD. DNN and a CNN were combined to form the suggested approach. Using the retrieved geometric features associated with the right and left hippocampi, the suggested method accomplished mean averaged accuracy for classification of 94.02 percent and 94.82 percent, respectively. Sharma *et al.* [43], the DeTrAs: DL-based Internet of Healthcare-Framework for the Aid of AD was presented. DeTrAs comprised of three different stages. First, a recurrent-neural-network (RNN) based AD anticipation method was presented that makes use of sensory motion information. Second, an ensemble method has been proposed for abnormality monitoring for AD individuals that consists of two components: a CNN-based emotion identification framework a time-stamped window-based Natural-Language-Processing framework and Internet of Things-based support process is provided for patients with AD. When compared to other current ML algorithms, DeTrAs is shown to be approximately 10-20 percent more accurate in its evaluations.

The goal of the research presented in [44] was to examine the possibility of using vision-based and ML approaches to distinguish between various gait characteristics linked to accidents on surfaces that are flat. Automated classification of three separate gait characteristics was achieved using 4 distinct classification strategies: long-short-term-memory (LSTM), CNN, SVM and KNN. In total, 750 datasets were obtained, with 80 percent used for the training of algorithms and 20 percent used for analysis. The findings showed that both

KNN and SVM were more accurate than LSTM and CNN. Pallikonda and Varma [45], explained methods to apply DL to the problem of recognizing and classifying cases of AD. Throughout this study, researchers establish benchmarks for various parameters like recall, precision, specificity accuracy and F-measure.

2.6. Tracking methodologies

Ullrich *et al.* [46], the researchers offered a collection of data that includes real-world unsupervised and gait 4x10-Meter-Walking-Tests from 40 PD individuals, all collected continually throughout the course of a two-week period using foot-worn inertial tracking devices. By applying a RF Classifier to every individual aggregated walking session along with day information yielded the maximum overall accuracy of 74 percent. Using a multi-depth camera movement monitoring system, the researchers of [47] demonstrated a fully automated and effective method of falling risk evaluation. Haslam-Larmer *et al.* [48], researchers intended to learn more about how real-time-locating-systems (RTLS) information can be used to improve medical measurements and medical decision-making for individuals having MCI who are receiving treatment in nursing homes. The findings have been used for a variety of purposes, from tracking the extent of activity to informing clinical choice-making and to serve as a prediction of dementia. The validity of medical indexes generated from RTLS data and the utility of such data in decision-making require additional research. Gugliandolo *et al.* [49], they have proposed a monitoring system for the PD patients and other patients which have NDD. In this monitoring system, they have designed an embedded board which consists of four accelerometers. Guamán *et al.* [50], this study demonstrated the ability to record biosignals from individuals suffering from NDD like epilepsy disease (ED), AD, and PD in real-time and save them for later examination. From all the above study, the issues have been identified and the challenges faced by various methods has been presented in the next section.

3. ISSUES AND CHALLENGES

From the above literature survey, the issues and challenges for the prediction and tracking of a neurodegenerative disease can be given as follows:

a) Data quality and availability: A major challenge in predicting neurodegenerative diseases using ML is the quality and availability of data. ML models require large amounts of high-quality data to train and validate predictions. However, data for neurodegenerative diseases is often limited and may not be representative of the population as a whole, leading to potential biases in the model.
b) Heterogeneity of symptoms: The wide range of symptoms that can be associated with neurodegenerative diseases makes it challenging to train ML models to accurately predict the disease.
c) Lack of ground truth: In many cases, the true diagnosis of a neurodegenerative disease can only be confirmed after death, making it difficult to validate the predictions of ML models.
d) Overfitting: ML models have the potential to overfit to the training data, meaning that they perform well on the training data but do not generalize well to new data. This can be a major issue in the prediction of neurodegenerative diseases, where the data is limited and the symptoms are heterogeneous.
e) Explain-ability: ML models are often considered "black boxes" because it is difficult to understand how they make predictions. This can be problematic in the prediction of neurodegenerative diseases, where it is important to understand the reasoning behind the predictions.
f) Integration with clinical practice: To be useful in clinical practice, ML models must be integrated into existing clinical systems and workflows. This can be challenging, as there are often regulatory, logistical, and technological barriers to overcome.
g) Ethical considerations: The use of ML for the prediction of neurodegenerative diseases raises important ethical considerations, such as the potential for discrimination and the impact on patient well-being.
h) Long-term data collection: Neurodegenerative-diseases can take years or even decades to develop, making it challenging to collect long-term data for tracking purposes.

Despite these challenges, the use of ML for the prediction of neurodegenerative diseases is an active area of research, and many researchers are working to overcome these challenges and develop more accurate and effective models. This includes the development of new ML algorithms, the integration of multiple data sources, and the use of explainable AI techniques to improve transparency and trust in the predictions. Hence in the next section a possible solution for these problems has been given.

4. POSSIBLE SOLUTION

From the issues and challenges, there is a need for an advanced ML technique for the detection of the neurodegenerative diseases utilizing a combination of ML and IoT sensors. Further, a feature selection feature has to be presented in the ML technique so that the prediction of neurogenerative disease gives an accurate result. Also, to avoid the overfitting issues, the ML technique has to address the issue of class imbalance in the binary as well as the multi-label data. Furthermore, the proposed ML technique has to validated using different datasets to ensure that the ML technique provides accurate result for the prediction of the neurodegenerative disease. For keeping tabs on the NDD patient, a tracking technique can be introduced. The ML technique has to be evaluated by using accuracy, precision, recall and F1-score. Furthermore, when evaluating a classification model, it is important to consider both precision and recall, as well as accuracy, as each provides a different perspective on the model's performance. The choice of evaluation metric depends on the goals of the classification problem and the consequences of false positives and false negatives.

5. CONCLUSION

The use of ML for the prediction and tracking of neurodegenerative diseases has shown promising results in recent years. With the increasing availability of data, ML algorithms are able to learn complex patterns in the data and make accurate predictions. However, there are still many challenges that need to be addressed, such as the quality and availability of data, the heterogeneity of symptoms, and the ethical considerations of using ML in healthcare. Despite these challenges, the field of ML for neurodegenerative diseases is rapidly growing, and many researchers are working to develop more accurate and effective models. In particular, the integration of multiple data sources, such as imaging, genomics, and clinical data, has shown great potential for improving the accuracy of predictions. In this work, we study various problems faced by the ML techniques, their advantages and their disadvantages for prediction and tracking of the neurodegenerative patients. On the basis of this the issues and challenges have been given. To address the issues and challenged, this paper proposed a solution for the given problem of prediction and tracking of neurodegenerative disease. Furthermore, in the future, ML models for neurodegenerative diseases are likely to play an increasingly important role in healthcare, providing early detection, improved tracking, and better understanding of these complex and debilitating diseases. As these models continue to develop, it is important to consider the ethical, regulatory, and practical implications of their use in clinical practice.

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CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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BIOGRAPHIES OF AUTHORS

Veena Dhavalgi achieved BE in computer science and engineering from Visveswaraya Technological University in 2012 and M. Tech in computer networking from Visveswaraya Technological University in 2015. She has experience of 3 years. She can be contacted at email: veenadhavalgi@sapthagiri.edu.in.

Dr. H R Ranganatha achieved M. S in Software systems at BITS, PILANI in 2001 and further pursued PhD in computer networking from Jain University, Bengaluru in 2017, He has teaching experience of 31 years and 7 years of research experience. He can be contacted at email: hodise@sapthagiri.edu.in.