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A study on machine learning-based prediction of cerebellar ataxia using gait analysis and accelerometer data

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Abstract

In the neurological field, predicting Cerebellar Ataxia (CA) is based on analyzing gait values of human actions. Analyzing Gait (AoG) can potentially guide effective treatment strategies. This study aimed to create a machine-learning model for predicting AoG using gait patterns indicative of pre-AoG conditions. During the execution of designed walking tasks to provokeAoG, accelerometers were attached to the lower back of 21 subjects as they performed 12 different walking positions to collect acceleration impulses. The participants engaged in walking exercises for one minute at 12 different walking speeds on a split-belt treadmill, ranging from 0.6 to 1.7 m/s in 0.1 m/s increments. The speed sequence was randomized and concealed from the subjects to minimize fatigue effects. Prior research studies have surveyed machine-learning algorithms such as support vector machine (SVM) and k-nearest neighbors (KNN). These algorithms demonstrate strong performance, especially when the dataset is trivial, and the classification is binary. SVM, KNN, decision trees, and XGBoost algorithms were utilized in the proposed study on the CA dataset. Our findings revealed that the AdaBoost algorithm, with its high precision, offers a more precise categorisation of the severity of CA disease, instilling confidence in the study's findings.

Keywords: Medical imaging; Deep learning; Object detection; Classification; Cervical spine fracture; Convolutional Neural Network (CNN)

1. Introduction

While the motor symptoms of cerebellar ataxia (CA) are widely recognized, numerous non-motor symptoms have also been recognized [1]. Irregular actions and the inability to suppress urges are

Characteristic features of the psychiatric disorders referred to as impulse control disorders (ICDs). Neurology is a well-established area of medical specialization [2], focusing on understanding how the brain directs the body's responses to various events. This research allows us to identify activity irregularities and assess the nervous system's functionality. Disruptions in activity rhythm can contribute to neurological diseases. Neurosurgery primarily addresses brain, spine, and nerve damage, offering treatments for various neurological conditions. Detecting activity patterns [3] in the medical field poses challenges, requiring careful observation of patients' movements to identify conditions [4]. Identifying and pinpointing issues in the early stages of neurological diseases can be particularly challenging. Any lapses in medical care could potentially result in a patient's death. In cross-sectional studies, the prevalence of ICDs and related conditions has been reported to range from 15% to 20% [5–7]. The annual incidence is estimated to be around 10% [8,9], and after five years from the onset of the disease, the overall incidence rises to over 50% [10]. These issues may also impact those who have had Parkinson's disease (PD) for more than five years.

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Neurologists assess the complexity of nervous system disorders to determine their severity, guiding treatment decisions. The brain's capacity is essential for all human activities. Activity patterns reflect the severity of the CA condition. Recent advancements in neurosurgical critical care and neuroimaging technologies enable early treatment of patients with minimally invasive techniques, although managing the condition and ensuring successful treatment can be challenging and life-threatening. An interdisciplinary team [11] comprising various neurospecialists is dedicated to this goal. One of the cerebellar patients' most prevalent and incapacitating symptoms is gait dysfunction, known as analysis of gait (AoG) [12]. AoG is characterized by "a brief, episodic lack of forward motion or a significant decline despite the intention to walk" [13]. It is more prominent during turning, navigating through confined spaces, and initiating walking. AoG significantly restricts mobility, increases the risk of falling, and reduces the quality of life [14–16].As medical treatments advanced rapidly, the range of diseases also expanded. These advancements in medicine have elevated societal standards. Cerebellar Ataxia (CA), a neurological condition, leads to improper coordination of body movements. Muscle strength affects coordination issues during exercises. When there is a compromise in the magnitude and synchronization of limb movements to maintain posture, coordination problems occur.

They experience physical imbalance and struggle to carry out tasks. Early detection of the condition simplifies treatment. Interpreting ensembles may pose greater challenges. Even the best ideas may not always convince decision-makers. Occasionally, even the most brilliant concepts are rejected by the intended audience. Finally, ensembles are more costly to develop, train, and implement. The healthcare sector greatly benefits from artificial intelligence [17]. By accurately predicting the disease, it aids in saving the lives of numerous people. Various algorithms are applied to the activity data and thoroughly scrutinize their results. The analysis outcome is reliable and accurate for forecasting. For the necessary disease prediction analysis, we utilize the support vector machine (SVM) [18], decision tree (DT) [19], and k-nearest neighbor (KNN) [20] algorithms.

We employ the ensemble technique to enhance the precision of predictions from machine-learning methods [21]. The combined predictive ability of these features has not been extensively studied. Only three studies [22] have reported research and patient-level forecasts. In all three studies, researchers utilized logistic regression with neuro-clinical and genetic data and then used the receiver operating characteristic (ROC) curve to assess the prediction performance (ROC AUC). The absence of cross-validation or a replication cohort in any of these experiments affected the accuracy of performance outcomes [23].

We utilized machine-learning approaches to predict neuro-clinical data. We used two longitudinal cohorts to train and cross-validate the obtained models and assess their applicability to other cohorts. With information on the patient's clinical history and genotyping, we aimed to estimate the risk of ICDs at the next appointment. Ensemble approaches combine multiple models rather than relying solely on one, aiming to increase the accuracy of predictions. Integrated models significantly enhance the accuracy of the findings, leading to the increasing prominence of ensemble approaches in machine learning.

2. Related work

Rukhsar S [24]. This section discovers various procedures for detecting ataxia patients using gait characteristics. The aim was to investigate the feasibility of using gait to i) identify individuals with ataxia-related gait characteristics (threat prediction) and ii) assess the severity of ataxia. They collected 155 videos of 89 individuals, including 24 individuals with controlled spinocerebellar ataxia (SCAs) and 65 individuals with SCAs (or at risk of developing them), performing the gait task of the Scale for the Assessment and Rating of Ataxia (SARA) at 11 clinical locations in eight states across the United States. In addition, they devised a strategy for isolating the subjects from their environment. They built several features to record aspects of gait, such as step width, step length, speed, swing, and stability. Their recommended method for predicting risk is 83.06% accurate and has an F1 score of 80.23%. Further, their future method for estimating severity has a mean absolute error (MAE) of 0.6225 and a Pearson's-correlation-coefficient-score (PCCS) of 0.7268, both statistically significant results. Their proposed method maintained superior results when tested on data from non-training sources. Moreover, the feature-importance evaluation shows that their proposed method correlates higher ataxia severity with broader steps, slower walking speed, and more instability.

Zhang et al. [25], ataxia is a symptom that occurs when the human body experiences difficulties with balance and coordination. While there are various possible internal causes of ataxia, the condition is often diagnosed based on external characteristics and the physician's clinical experience. In their study, they utilize a contactless sensing method to distinguish cases of sensory ataxia from cases of cerebellar ataxia. They collect data on Romberg's tests and gait analysis using a microwave sensing system, then preprocessing and training the method using machine-learning techniques. Considering time series parameters for Romberg's test, all three methods achieve 96% or better accuracy in this task. For gait identification, Principal Component Analysis (PCA) is employed to reduce dimensionality, with accuracy rates of 97.8%, 98.9%, and 91.1% for back-propagation neural network, support vector machine (SVM), and random forest (RF), respectively.

Shanmuga Sundari M et al. [26], Difficulty walking is a common symptom of various debilitating neurological and orthopedic conditions. Accelerometers enable the accurate simulation of gait patterns, but they produce a large volume of data that can be challenging to analyze. This study evaluated various techniques for clinical data reduction and the categorization of resulting data. Using data collected from 43 subjects (20 healthy subjects, 23 ataxic subjects), resulting in 418 sequences of normal gait patterns, a maximum accuracy of 98% was achieved using an RF classifier pre-processed by t-distributed stochastic neighbor segmentation to distinguish between healthy individuals and those with an ataxic gait.

Yang Xet al. [27], Researchers have utilized motion sensor information to analyze the walking patterns of individuals with neurological disorders, such as hereditary ataxias (HA), over time. Data was collected from 14 individuals with hereditary ataxias (HA) and 14 healthy individuals using iPhone motion sensors attached to their ankles. The aim was to determine the minimum required gait traits for effective and less invasive recognition of HA patients. To reduce the number of gait characteristics and sensor systems, two approaches were developed: i) implementing a local-minimum significant peak requirement to determine the start of each step, resulting in a 10-stride frame from which 56 features were derived, and ii) employing a searching method primarily based on the hill climbing algorithm. The main findings were that using two gait sequences, the k-nearest neighbor (KNN) and multi-layer perceptron (MLP) methods achieved a 96% classification performance. For the MLP method, only variations from the right ankle sensor were necessary, thus reducing intrusion.

J. V. Chandra et al. [28], In this study, accelerometric data is utilized to optimize DL convolutional neural network (CNN) systems, which can then distinguish between normal and ataxic gait. The dataset comprises 860 signal segments from 16 ataxic subjects and 19 control subjects, with the average ages of the two groups being 38.6 and 39.6 years, respectively. The technique involves simultaneously decomposing accelerometric data captured at multiple body locations and sampling at 60 Hertz into their frequency components. The DL algorithm utilizes all parameters between 0 and 30 Hertz. Conventional techniques such as SVM, Bayesian methodologies, and two-layer neural networks, with characteristics evaluated based on relative power in specified frequencies, are among those whose results are compared with those achieved in this classification experiment. The results indicate that selecting the right locations for the sensors can increase accuracy from 81.2% at the foot to 91.7% at the spine. Furthermore, an accuracy of 95.8% was achieved by integrating the input data using a five-layer DL algorithm. However, the model does poorly when dealing with limited training samples and imbalanced data. Also, effective feature weight optimization is required for multi-label classification and importance selection during training. Thus, the current approaches fail to achieve good accuracies. To address this research limitation, the following research methodology is presented.

W. Jamal and S. Das [10] utilized brain connectivity for supervised learning in autism spectrum disorder classification, which has served as a significant milestone for such classifications. A. Abraham and F. Pedregosa [29] ingeniously combined neuroimaging advancements with machine learning using a sci-kit.

The classification of anxiety disorders in social issues has been advanced by the use of BCIS by F. Liu, W. Guo, and Y. Wang, with W. Wang pushing the BCIS further [8]. The estimations and predictions in autism spectrum disorders for youth with ANN have taken the research from [30] to a whole new level, led by A. Narzisi and F. Muratori [31]. The theory pitfalls and guidelines for imaging data of psychological patients with disorders are well-explained, showcased by P. Kassraian Fard and C. Matthis [32].

3. Datasets and preprocessing

3.1. Data sources

Here, we will discuss the public benchmark dataset used in this research and our data augmentation strategy, which aims to address the common issue of data bias in medical datasets.

3.2. The dataset

The dataset created by Rueangsirarak et al. comprises four classes and 45 walking motions, including 10 healthy, 4 with joint problems, 18 with muscle weakness, and 13 with neurological defects. These motions were performed by 45 subjects aged between 61 and 91 years old. Three medical doctors diagnosed the subjects into one of the four classes. Standard clinical tests were used by medical experts for screening and approving voluntary applicants, ensuring they could walk without assistance and had no medical disorder history that could affect walking. Further details can be found in possible.

Using a randomly sampled and population-based approach, we selected five male and 40 female subjects from the list of approved applicants. The gender bias reflects the bias present among voluntary applicants in this community. The Motion Analysis optical motion capture system, which consists of fourteen Raptor-E optoelectronic cameras sampling at 100 Hz, was used to collect the data.

3.2.1. Data Augmentation

The dataset used in this study presents tasks due to its multiple, small-scale, and biased classes of disorders. The number of training samples significantly influences the generalization ability of DL models. To improve the generalization of the DL model, augmentation techniques such as random scaling, noise addition, sign inversion, and motion reversal were applied to produce more training samples for cerebral palsy prediction. However, the techniques mentioned above only address intra-class variations, which means that the augmented data may not effectively alleviate the inter-class similarity problem, as multiple class labels must be considered. To address this, we apply the synthetic data augmentation method mix-up, resulting in a four times larger unbiased dataset. This dataset size is reasonable for our model learning, preventing overfitting and achieving good performance in our experiments.

3.2.2. Process flow of disease prediction

This paper aims to present a revolutionary disease pre-diction method with five key phases, including

- Data preprocessing,
- Noisy data reduction,
- extract feature,
- select the proper feature, and
- Final classification.

3.3. Challenges and Considerations

Predicting neurological diseases like cerebellar ataxia through impaired gait analysis presents several challenges. Accurately detecting and analyzing gait abnormalities requires sophisticated technology and expertise in neurology and biomechanics. The variability in symptoms and progression of cerebellar ataxia adds complexity, as no single gait parameter can reliably predict the disease. Additionally, distinguishing between cerebellar ataxia and other conditions with similar symptoms is challenging, requiring comprehensive clinical assessments. In addition, standardizing gait analysis protocols across different settings is difficult due to variations in equipment, environmental conditions, and patient characteristics. To overcome these obstacles, multidisciplinary cooperation, technological developments, and extensive follow-up research are required to enhance diagnostic precision and optimize predictive models.

4. Machine learning techniques

Neurological disease prediction through impaired gait analysis involves machine-learning techniques, particularly focusing on foot position in cerebellar ataxia. Based on labelled datasets, supervised learning algorithms like Support Vector Machines (SVM), Random Forests, and Gradient Boosting Machines can classify gait patterns as indicative of cerebellar ataxia or healthy controls. Deep learning models such as Convolutional Neural Networks (CNNs) can extract features from gait images or video sequences, capturing subtle variations in foot position and movement patterns. Transfer learning allows fine-tuning pre-trained models using cerebellar ataxia-specific data, while ensemble methods like bagging and boosting combine multiple models to improve prediction accuracy. Unsupervised learning techniques like Isolation Forest or One-Class SVM can detect anomalies in gait data, identifying deviations from normal patterns indicative of cerebellar ataxia. Moreover, model interpretability methods like LIME and SHAP offer insights into the contribution of specific gait features to the prediction, aiding clinicians in understanding and validating model decisions. Longitudinal analysis using Hidden Markov Models (HMMs) or Long Short-Term Memory Networks (LSTMs) can track disease progression over time, predicting future states based on past gait observations. Integrating these machine learning techniques with clinical expertise enhances the accuracy and reliability of neurological disease correctness prediction using impaired gait analysis for cerebellar ataxia.

4.1. Convolutional Neural Networks (CNNs)

In predicting neurological diseases like cerebellar ataxia through impaired gait analysis focusing on foot position, Convolutional Neural Networks (CNNs) play a crucial role. CNNs excel in extracting spatial features from gait images or video sequences, making them well-suited for analyzing foot position variations and movement patterns. By processing gait data at multiple levels of abstraction, CNNs can capture intricate details that might indicate abnormalities associated with cerebellar ataxia. These networks can learn to recognize subtle differences in foot positioning, aiding in identifying characteristic gait patterns indicative of the disease. Moreover, CNNs can adapt to different scales and orientations of gait images, making them robust to variations in the camera under different angles or patient movements. Their ability to automatically learn relevant features from raw data eradicates the need for physical feature engineering, streamlining the prediction process. By integrating CNNs into the analysis pipeline, researchers and clinicians can achieve moderate, accurate and efficient neurological disease prediction using impaired gait analysis for cerebellar ataxia.

4.2. Emerging trends: Exploring beyond CNN's

Exploring beyond CNNs in neurological disease prediction through impaired gait analysis for foot position in cerebellar ataxia reveals several emerging trends. One such trend is the integration of graph neural networks (GNNs), which can predict and model the difficultrelations between different body parts during gait. GNNs enable the representation of gait as a graph structure, capturing dependencies between joints and their movements, which could provide deeper insights into cerebellar ataxia-related abnormalities. Another promising trend is the use of attention mechanisms, particularly in recurrent neural networks (RNNs) or transformer models. Attention mechanisms allow models to focus on relevant regions or time steps within gait sequences, potentially improving the detection of subtle gait anomalies indicative of cerebellar ataxia.

Furthermore, federated learning is gaining traction in this domain, enabling collaborative model training across multiple healthcare institutions while preserving patient privacy. This approach facilitates the development of more robust and generalized accurate prediction models by leveraging diverse datasets. Additionally, incorporating multimodal data, such as combining gait analysis with other neuroimaging modalities like MRI or EEG, is becoming increasingly prevalent. Integrating diverse data sources can provide a more comprehensive understanding of cerebellar ataxia and enhance predictive performance.

Lastly, explainable AI techniques are gaining importance to enhance the interpretability of predictive models. Methods such as attention visualization and saliency mapping can provide insights into which gait features contribute most to the prediction of cerebellar ataxia, aiding clinicians in understanding and trusting the model's decisions. By embracing these emerging trends, researchers can advance the accuracy, interpretability, and generalization of neurological disease prediction using impaired gait analysis for cerebellar ataxia, ultimately improving patient care and outcomes.

4.3. Understanding the Training Process

To differentiate between pre-AoG gait and regular walking, boosting pruned C4.5 trees was chosen because it outperformed other strategies for detecting AoG. Before being fed into the classifier, the features were normalized to the range [0,1]. To distinguish pre-AoG from regular walking, only features from the pre-AoG and phases of regular walking were used in themodel training. We assessed and contrasted the model's performance in two different schemes—one patient-dependent and the other patient-independent. A 10-fold validation strategy was used for every subject in scheme 1. In each fold, 30% of the dataset was exploited for the training set and 70% for the testing set.

4.4. The Future of Deep Learning in Ataxia

The future of deep learning in neurological disease prediction using impaired gait analysis for foot position in cerebellar ataxia holds exciting prospects for advancing diagnosis and treatment. One key direction is the integration of multimodal data sources, combining gait analysis with other physiological measurements such as brain imaging or genetic data. This holistic approach can provide a more comprehensive understanding of cerebellar ataxia and improve the accuracy of predictions.

Furthermore, there's a growing emphasis on developing more interpretable deep learning models. Techniques such as attention mechanisms and explainable AI methods will be increasingly important in elucidating how neural networks arrive at their predictions, making the models more trustworthy for clinicians. Another promising avenue is the application of reinforcement learning. By incorporating feedback mechanisms, reinforcement learning can adjust gait analysis protocols or treatment strategies based on patient response, leading to personalized and optimized interventions.

Moreover, the future will likely see advancements in wearable devices for continuous gait monitoring in real-world settings. Deep learning models trained on data from these devices could provide valuable insights into disease progression and treatment effectiveness, enabling early intervention and personalized management plans. Additionally, federated learning approaches will continue to gain traction, allowing models to be trained across distributed healthcare centers without sharing sensitive patient data. This collaborative approach can improve model robustness and generalization while respecting patient privacy.

Lastly, advancements in computational hardware and algorithms will enable the development of more complex and efficient deep-learning architectures tailored specifically for gait analysis in cerebellar ataxia. This includes models that can handle longitudinal data, temporal dependencies, and dynamic changes in gait patterns over time. Overall, the future of deep learning in neurological disease prediction using impaired gait analysis for cerebellar ataxia is promising, with potential benefits for early detection, personalized treatment, and improved patient outcomes.

5. Performance Evaluation of Various Algorithms

Assessing the effectiveness of deep learning models in ataxia analysis is crucial for accurately gauging their value and comparing them to alternative approaches. This section delves into the metrics employed for such evaluations, presents the attained results alongside comparisons, and ultimately provides a comprehensive overview of the impact of deep learning in this particular domain. Various metrics serve as vital indicators for analyzing the efficiency of deep learning models for ataxia.

- Accuracy: Reflects the overall rate of correct predictions across segmentation and classification tasks.
- Precision: Captures the percentage of classified fracture accurately assigned to the predicted quality category.
- Recall: Indicates the proportion of actual fracture of a specific quality category correctly identified by the model.
- F1-score: Blends precision and recall into a single metric, offering a balanced view of the model's performance.

Intersection over Union (IoU): Specifically for segmentation tasks, IoU measures the overlap between predicted and ground-truth segmentation masks, evaluating how well the model identifies individual fractures.

A dataset on neurological diseases was utilized in this study. Employing machine-learning algorithms, the study achieved 99.6% accuracy in identifying activity patterns indicative of neurological disease. Specifically, the cerebellar ataxia (CA) disease dataset yielded improved predictions using AdaBoost. Other metrics, such as root mean squared and error values, were also used to generate this forecast. Ultimately, exploring various neural network techniques improved prediction outcomes. Notably, AdaBoost stood out in the comparative analysis. Its strength lies in its ability to detect CA disease early, providing valuable benefits to physicians.

$$\text{Precision} = \frac{TP}{TP+FP} \text{ -----} \textbf{Eq (1)}$$

$$\text{Recall} = \frac{TP}{TP+FN} \text{ -----} \quad \textbf{Eq (2)}$$

$$\text{F1 Score} = 2 \times \frac{P.R}{P+R} \text{ ----} \textbf{ Eq (3)}$$

Table 1 Comparison of results with Baselines on Precision, Recall, F1-Measure, and AUC

Metric	Network	Healthy	Joint Problem	Muscle Weakness	Neurological Defect	Average
Precision	3DJP-CNN	1.00	0.60	0.89	0.92	0.85
	3DRJDP-CNN	1.00	0.75	0.89	0.92	0.89
	2s-CNN	1.00	0.75	0.95	1.00	0.92
Recall	3DJP-CNN	0.95	0.75	0.94	0.85	0.86
	3DRJDP-CNN	1.00	0.75	0.94	0.85	0.89
	2s-CNN	1.00	0.75	1.00	0.92	0.92
F1-	3DJP-CNN	0.95	0.67	0.92	0.88	0.85
	3DRJDP-CNN	1.00	0.75	0.92	0.88	0.89

Measure	2s-CNN	1.00	0.75	0.97	0.96	0.92
AUC	3DJP-CNN	0.95	0.85	0.94	0.91	0.91
	3DRJDP-CNN	1.00	0.86	0.94	0.91	0.93
	2s-CNN	1.00	0.86	0.98	0.96	0.95

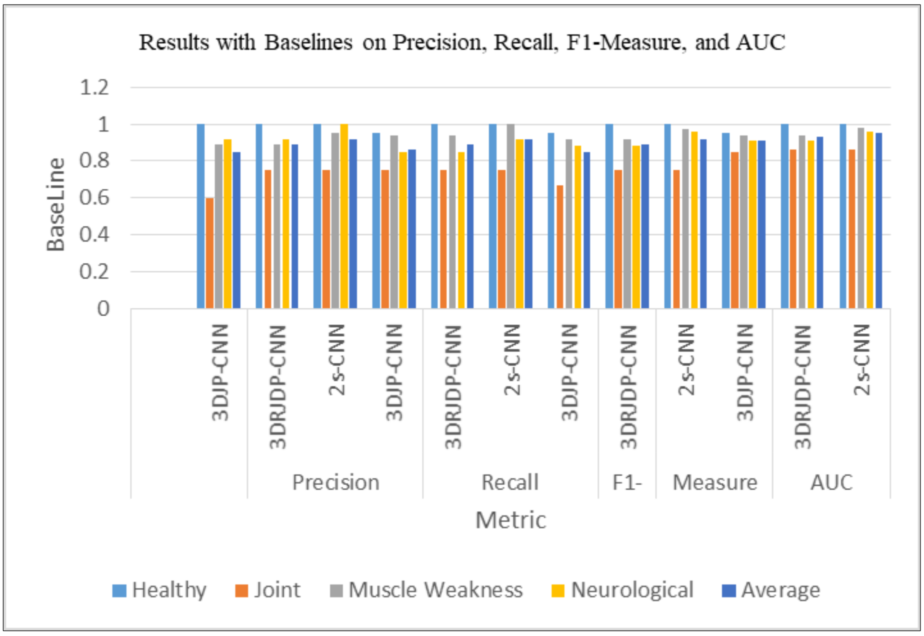

Figure 1 Results with Baselines on Precision, Recall, F1-Measure, and AUC

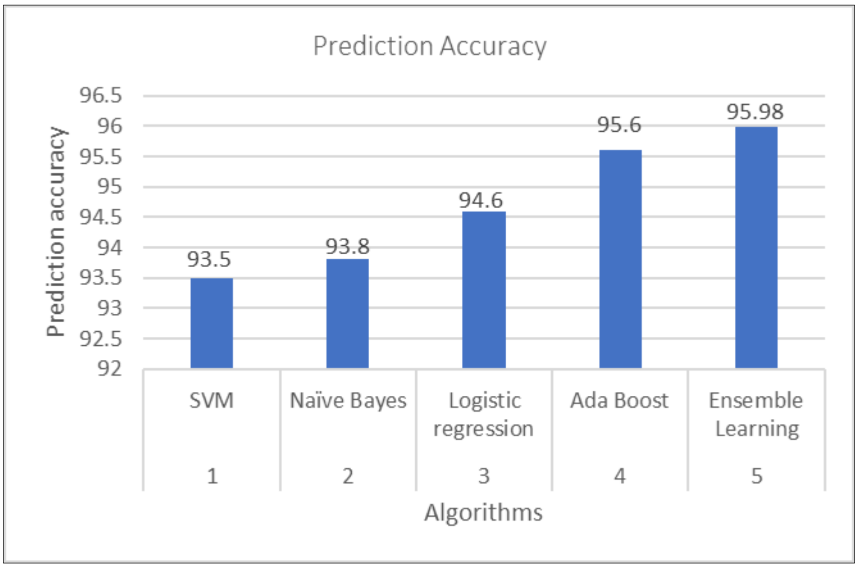

Figure 2 Prediction accuracy using Machine learning algorithms

Table 2 Ensemble learning for using Neurological disease prediction for foot positioning cerebellar ataxia in the proposed network

Sl. No.	Algorithm	Prediction Accuracy
1	SVM	93.5
2	Naïve Bayes	93.8
3	Logistic regression	94.6
4	Ada Boost	95.6
5	Ensemble Learning	95.98

6. Challenges and Future Direction

6.1. Challenges

6.1.1. Data Quality and Quantity

Obtaining high-quality gait data, especially in real-world settings, can be challenging. Additionally, datasets for cerebellar ataxia may be limited in size, making it difficult to train accurate prediction models.

6.1.2. Feature Extraction and Selection

Identifying the most relevant features from a challenge. It requires a deep understanding of both the disease and gait characteristics.

6.1.3. Class Imbalance

Imbalanced datasets, where significantly more samples from one class (e.g., healthy individuals) than others, can lead to biased models. Addressing this imbalance is crucial for accurate predictions.

6.1.4. Generalization

It is essential to develop models that can generalize well across different populations and conditions. The variability in gait patterns among individuals with cerebellar ataxia adds complexity to this challenge.

6.2. Future Directions

6.2.1. Advanced Machine Learning Techniques

Explore advanced machine learning techniques, such as deep learning, ensemble methods, and transfer learning, to improve the accuracy of prediction models. These techniques can more effectively handle complex patterns in gait data.

6.2.2. Longitudinal Studies

Conduct longitudinal studies to collect gait data over time, allowing for a better understanding of disease progression and more accurate predictions.

6.2.3. Multimodal Data Fusion

Integrate data from multiple sources, such as gait analysis, neuroimaging, and genetic information, to enhance prediction accuracy and gain deeper insights into the disease.

6.2.4. Personalized Medicine

Move towards personalized prediction models that account for individual variations in gait patterns and disease progression. This approach can lead to more tailored treatment plans and interventions.

6.2.5. Real-time Monitoring

Develop wearable devices and mobile applications for real-time monitoring of gait patterns. This could enable early detection of changes in foot position and prompt intervention, improving patient outcomes.

6.2.6. Collaboration and Data Sharing

Foster collaboration among researchers and encourage data sharing to create larger and more diverse datasets. This would facilitate the development of robust prediction models and accelerate progress in the field.

7. Conclusion

To diagnose cervical ataxia in the future, addressing issues with data diversity, model interpretability, imbalanced datasets, and clinical integration will be necessary. It is anticipated that ongoing, reliable research and technological developments will result in increasingly complex models and comprehensive strategies that improve ataxia patient care and diagnostic skills.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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