Indonesian Journal of Electrical Engineering and Computer Science
Vol. 37, No. 1, January 2025, pp. 560~568
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v37.i1.pp560-568

Detection and severity classification of ataxia using gait features and a hybrid model

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Article Info

Article history:

Received Jul 15, 2024
Revised Sep 11, 2024
Accepted Sep 29, 2024

Keywords:

Ataxia
Classification
Deep Learning
Machine Learning
Prediction

ABSTRACT

Ataxia, a neurological disorder characterized by impaired coordination and unsteady movements, presents significant challenges for accurate diagnosis and classification. traditional machine-learning (ML) and deep-learning (DL) models often struggle to achieve high accuracy in predicting and classifying this complex condition. This study addresses these limitations by introducing a novel hybrid model, XGBoost-multi-layer-perceptron (XGB-MLP), specifically designed to enhance the accuracy of ataxia prediction and classification. The objective of this research is to develop a more reliable and precise diagnostic tool that outperforms existing ML and DL approaches. The methodology involved integrating the strengths of XGBoost, known for its powerful gradient boosting, with the multi-layer perceptron (MLP) neural network, creating a robust hybrid model. The proposed XGB-MLP model was rigorously tested against conventional models like random forest (RF), logistic regression (LR), support vector machine (SVM), MLP, and standalone XGBoost. The findings reveal that the XGB-MLP model achieves outstanding accuracy rates of 98.91% for ataxia prediction and 97.91% for classification, significantly surpassing the performance of the traditional models.

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1. INTRODUCTION

Ataxia is a neurological condition characterized by a lack of coordination and unsteady movement. It primarily affects the motor skills of individuals, leading to difficulties in tasks such as walking, writing, and swallowing. Ataxia can manifest as a result of various underlying causes, including genetic factors, trauma, infections, or degenerative conditions [1]. The impact of ataxia on affected individuals can be profound, influencing their overall quality of life, independence, and ability to engage in daily activities. The prevalence of ataxia is a significant concern, affecting a considerable portion of the global population [2]. While specific statistics vary, it is estimated that thousands of people worldwide are diagnosed with ataxia each year. The condition can occur at any age, and its symptoms may progressively worsen over time. Ataxia often presents challenges not only for the individuals directly affected but also for their families and caregivers, who may need to provide substantial support to cope with the associated difficulties.

Early identification and diagnosis of ataxia are crucial for implementing timely interventions and supportive measures [3]. The symptoms of ataxia can vary widely, making its identification a complex task for healthcare professionals. Common signs include unsteady gait, lack of coordination, tremors, and difficulties with speech and eye movements [4]. Diagnostic approaches often involve a combination of medical history analysis, physical examinations, and advanced imaging approaches such as Magnetic-resonance-imaging (MRI) [5]. In recent years, advancements in machine-learning (ML) [6] and deep learning (DL) [7] have revolutionized the field of medical diagnostics, providing powerful tools for prediction and classification of various neurological disorders, including ataxia. ML models, when trained on relevant datasets, can learn intricate patterns and relationships within data, enabling accurate identification of abnormalities indicative of ataxia. DL, a subset of ML, utilizes neural networks to extract hierarchical features from complex data, offering enhanced capabilities in recognizing subtle patterns.

The need for robust predictive models for ataxia detection arises from the potential benefits they offer in terms of early intervention and improved patient outcomes. Early identification allows for timely medical interventions, therapeutic strategies, and support services tailored to the specific needs of individuals with ataxia [8]. ML models can aid healthcare professionals in streamlining the diagnostic process, reducing the time taken to reach a conclusive diagnosis, and facilitating prompt initiation of appropriate treatments [9]. Despite the progress made in applying ML and DL to neurological disorders, there remains room for improvement in the accuracy and reliability of predictive models for ataxia [10], [11]. This work addresses this gap by presenting a hybrid XGBoost (XGB) - multi-layer-perceptron (MLP) model for the prediction and classification of ataxia. The XGB-MLP model leverages the strengths of both algorithms to enhance the overall performance, providing a more robust and accurate tool for ataxia detection. The hybrid approach integrates the gradient boosting capabilities of XGB with the neural network architecture of MLP, creating a synergistic model capable of capturing complex relationships within the data. The contribution of this work is as:

- Present a hybrid XGB-MLP model for improving the accuracy and reliability for the prediction and classification of ataxia.
- Compare the XGB-MLP model with ML and DL models using prediction and classificaiton ataxia datasets.

In the subsequent sections, i.e., in Section 2, we delve into the literature survey which discusses the existing works presented by various researchers for the prediction and classification of ataxia. Further, in Section 3, different ML and DL models for the prediction and classification of the ataxia is presented. Also, the hybrid XGB-MLP model is also presented. In Section 4, the prediction and classification results of ML, DL has been compared with XGB-MLP model. Finally, in Section 5, the conclusion of the work is presented.

2. LITERATURE SURVEY

In this section, the various ML and DL models presented for the prediction and classification of ataxia is presented. Seetharama *et al.* [12], conducted study on ataxia-severity categorization using a Feature-Selection-Ranking (FSR) technique that relied on XGB. The FSR-XGB offered an improved error strategy for optimization and even established a unique feature choosing and ranking method. These advancements targeted to address the challenges in classification with multiple labels. The findings obtained through the tests clearly show how the FSR-XGB technique executes better compared to different ML and DL techniques, attaining an impressive accuracy of 99.3%. Phan *et al.* [13], main objective was to examine how various walking velocity affects various gait characteristics of both the lower and upper limbs in individuals who have impairments resulting from cerebellar-ataxia (CA). This work resulted in an increased association with a lot of Expert-Clinical-Assessment (ECA) which achieved a score of 0.86 along with the Scale-for-the-Assessment and Rating-of-Ataxia (SARA) achieving a score of 0.62. To assess the total neurological level of CA, a novel method was suggested in [14] which examined the lower-limb motion patterns throughout gait at intervals of less than one second. The properties of motion aspects measured using the Brief-Ataxia-Rating-Scale (BARS) including associated sub-scores assessed by physicians were used to build supervised models of regression. The scores that were assessed by clinicians and the estimated sum of BARS were highly aligned, with a correlation coefficient of 0.72 along with an inaccuracy margin of 2.6 BARS units. Sundari *et al.* [15], objective was to create an approach utilizing ML which would anticipate Analysis-of-Gait (AoG) by analyzing undesirable motions that take place prior to to AoG. Previous study has examined ML methods such as K-nearest-neighbours (KNN) and Support-Vector-Machine (SVM). When dealing with small quantities of information and simple classifications, these methods proved to be quite effective. The CA dataset was subjected to the suggested investigation using XGB, decision-trees (DT), KNN and SVM KNN methods. They concluded that the technique AdaBoost classifies CA severity more accurately.

Vyšata *et al.* [16], provided a comprehensive analysis to evaluate various data reduction techniques and their effectiveness in medical care. A high level of accuracy was attained when comparing the gait patterns of normal people alongside those with ataxic people. The data were collected from 43 participants, with 23 having ataxic-gait individuals and 20 being healthy individuals. A total of 418 parts of precisely walking motion were analyzed. The RF classification method, which was extracted by t-distributed-stochastic neighbour-embedding, accomplished an impressive accuracy rate of 98%. A completely computerized target technique was presented in [17] towards the purpose of CA detection using cepstral, spectral, time and non-linear-dynamically relevant acoustic properties found in mic information acquired through several recurrent Consonant-Vowel (C-V) word patterns. The characteristics associated with the binary result were selected utilizing a mix of elastic network normalization and massive uni-variate regression, whereas the characteristics for the average of the ordinal result were selected utilizing Spearman's rank-order correlations criteria. With a sensitivity, specificity, accuracy of value of 97.43%, 85.29% and 91.2% respectively for testing dataset, the reduced set of characteristics produced an Area-Under-the-Curve (AUC) of 0.97. In [18], utilized equipped variations of 9 commonly employed neurological assessments across 5 fields: gait, speech, balance, lower and upper limb for assessing cognitive abilities. The comparison involved analyzing the capacity to discriminate and intra-domain connections of the characteristics gathered from sensor strategies and medical ratings. This was done employing centrality-measures, graph-theory and RF multi-label and binary classification methods. A selected group of 13 key principal-component (PC) characteristics were carefully chosen for CA-control categorization. The categorization approach achieved an outstanding accuracy of 97%. The goal of the state-of-the-art ML methods described in [19] was to develop a non-contact gait evaluation that would not only be painless for individuals but would also give doctors accurate data on all of the most prevalent gait-related metrics, which would be useful for determining the best course of action. Gait patterns were identified for every walking session utilizing SVM and bi-long-short-term-memory (Bi-LSTM) classifier developed based on spatio-temporal characteristics taken from the initial data set. There were three parts to the assessments. On a typical basis, Bi-LSTM obtained precision, recall and F-measure of 90.54%, 90.41%, and 90.38% for the classification outcomes using the two classifiers, while SVM obtained 86.99%, 86.62%, and 86.67% for the same metrics. In addition, with a margin of error of 2, the Bi-LSTM-based technique obtained a gait segmented assessment accuracy of 93.2%, while the SVM-based approach only managed 77.5%. Stoean *et al.* [20], focused on using Monte-Carlo dropout to analyze the DL framework to detect early indications of spinocerebellar-ataxia kind 2 in saccadic instances collected using electrooculograms. The DT constructed using uncertainties projections achieved an accuracy rate of 81.18% in accurately distinguishing between sick, presymptomatic and control classes. This study presents an innovative approach to tackle the challenges of ambiguity measurement and explanation in the development of dependable medical assistance networks.

3. METHOD

In this section, we delve into a detailed discussion of various machine learning (ML) and deep learning (DL) models. The models under consideration include random forest (RF), Logistic Regression (LR), support vector machines (SVM), multi-layer perceptron (MLP), and extreme gradient boosting (XGB). Additionally, we explore two novel models: XGB-MLP and a newly proposed hybrid model that combines XGB and MLP.

3.1. Random forest (RF)

Random forest is an ensemble-learning algorithm that constructs a multitude of DT and merges their outputs for robust and accurate classification. Consider the input features as X and the target variable as Y. RF is trained on a dataset (X_{train}, Y_{train}), where X_{train} represents the training features and Y_{train} is the corresponding target variable. The model builds a collection of DT T_i, where $i = 1,2,3 \ldots, N$ with N being the number of trees in the forest. Each DT is constructed using a random subset of features and a bootstrap sample of the training data. The training process involves optimizing the DT by recursively partitioning the feature space based on information gain or Gini impurity. Mathematically, the training process can be expressed as:

$$T_i = BuildDecisionTree(X_{train}, Y_{Train}, subset_{features}, bootstrap_{sample}) \quad (1)$$

where $BuildDecisionTree$ is a function that constructs an individual DT, and $subset_{features}$ and $bootstap_{sample}$ represents the randomly selected feature and data samples for each tree. Once the RF is trained, it was used for predicting the class labels for new data instances. The prediction was made by aggregating the outputs of all the individual DTs. Mathematically, the prediction process is expressed as

$$\hat{Y}_{test} = Aggregate\ (\{T_i(X_{test})\}_{i=1}^{N}) \quad (2)$$

where $\hat{Y}_{test}$ is the predicted class label for the test data X_{test}, $T_i(X_{test})$ represents the output of the i^{th} DT for the test data, and $Aggregate$ is a function that combines or aggregates the outputs, i.e., through majority voting for classification tasks. In the context of ataxia detection and classification, the features X includes relevant physiological measurements, and the target variable Y respresents the presence or absence of ataxia. The RF model, throught its ensemble or DTs, can effectively capture complex patterns in the input data and provide accurate prediction for ataxia detection.

3.2. Logistic regression (LR)

Logistic Regression is a statistical method utilized for binary classification tasks, such as ataxia detection (presence or absence of ataxia). The LR model predicts the likelihood that a given input belongs to a given class. The logistic-function, also known as the sigmoid-function, is commonly used in LR for this purpose. The hypothesis function $h_\theta(X)$ for LR is defined as the sigmoid (logistic) function applied to a linear combination of input features.

$$h_\theta(X) = \frac{1}{1+e^{(\theta_0+\theta_1X_1+\theta_2X_2+\cdots+\theta_nX_n)}} \quad (3)$$

Where $h_\theta(X)$ is the predicted probability that $Y = 1$ given input features X. θ_0, θ_1,... θ_n are the modelparameter (coefficients). X_1, X_2, ..., X_n are the input features. The cost function $J(\theta)$ in LR is designed to measure the difference among actual outcomes and predicted likelihood. It is defined as the negative log likelihood of the observed data.

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}[y^{(i)} \log\left(h_\theta\left(X^{(i)}\right)\right) + (1 - y^{(i)} log(1 - h_\theta\left(X^{(i)}\right)) \ ] \quad (4)$$

where m is the number of training examples, $y^{(i)}$ is the actual class label of the i^{th} example. $X^{(i)}$ is the feature vector of the i^{th} example. $h_\theta(X^{(i)})$ is the predicted probability that $Y^{(i)} = 1$. In the context of ataxia detection, the LR model is trained on a dataset with input features related to relevant physiological or clinical measurements, and the target variable Y representing the presence (1) or absence (0) of ataxia. The model parameters θ are learned by minimizing the cost function $J(\theta)$ using an optimization algorithm, i.e., gradient descent. Once trained, the model can predict the probability of ataxia for new input data using (5). The threshold set was 0.5 which is commonly used, but it can be adjusted based on the specific requirements and trade-offs in the ataxia detection task. LR provides a simple and interpretable model for binary classification tasks, making it suitable for ataxia detection where the goal is to classify individuals into ataxia-positive or ataxia-negative categories based on relevant features.

$$Prediction = \begin{cases} 1\ if\ h_\theta(X) \geq 0.5 \\ 0\ if\ h_\theta(X) < 0.5 \end{cases} \quad (5)$$

3.3. Support vector machine (SVM)

Support-Vector-Machine is a ML algorithm utilized for classification of multi and binary classes. The process of SVM involves identifying the hyperplane that effectively divides the data into distinct categories. The decision function for linear SVM is defined as the dot product of the input features X and the weight vector w plus the bias term b which is represented as (6).

$$f(X) = w \cdot X + b \quad (6)$$

Where $f(X)$ is the decision function, w is the weight-vector, X is the input-feature-vector, b is the bias term. The decision boundary is the hyperplance defined by $f(X) = 0$. In a binary classification scenario, i.e., ataxia detection with classes 1 and 0, the decision rule is based on the sign of $f(X)$ which is represented as (7).

$$Prediction = \begin{cases} 1\ if\ f(X) \geq 0 \\ 0\ if\ f(X) < 0 \end{cases} \quad (7)$$

The decision boundary is positioned to maximize the margin between the two classes. Support-vectors play a crucial role in determining the exact location of the decision boundaries as they are the data-points which lie nearest to it. In the context of ataxia detection, the SVM model is trained on a dataset with input features related to relevant physiological or clinical measurements, and the target variable Y representing the presence (1) or absence (0) of ataxia. The SVM algorithm aims to find the optimal hyperplane that maximizes the margin between classes. The optimization problem involves minimizing

$\frac{1}{2}||w||^2$ subject to the constraint $y_i(w \cdot X + b) \geq 1$ for all training exaples (X_i, y_i). Once trained, the SVM can predict the class of new data points using the decision rule mentioned above. The sign of $f(X)$ determines the predicted class. SVMs can handle high-dimensional data and are effective in scenarios where a clear margin exists between classes. The choice of kernel functions in SVM allows for handling nonlinear relationships between features. In ataxia detection, SVMs can effectively classify individuals into ataxia-positive or ataxia-negative categories based on relevant features, providing a robust solution for binary classification tasks.

3.4. Multi-layer perceptron (MLP)

MLP is a type of Artificial-Neural-Network (ANN) that consists of multiple-layers of nodes, including an input-layer, one or more hidden-layers, and an output-layer. For a single-layer perceptron, considering one hidden layer and an output layer, the forward propagation can be expressed using the following equation,

$$Z^{(1)} = X \cdot W^{(1)} + b^{(1)} \tag{8}$$

$$Z^{(2)} = X \cdot W^{(2)} + b^{(2)} \tag{9}$$

$$A^{(1)} = Activation\left(Z^{(1)}\right) \tag{10}$$

$$\hat{Y} = Activation\left(Z^{(2)}\right) \tag{11}$$

where X is the input feature matrix, $W^{(1)}$ and $W^{(2)}$ are weight matrices for the first and second layers, $b^{(1)}$ and $b^{(2)}$ are bias vectors for the first and second layers, $A^{(1)}$ is the activation of the hidden layer and $\hat{Y}$ is output of the network. The activation function, denoted as $Activation(\cdot)$, introduces non-linearity to the model, allowing the network to learn complex patterns. The model is trained using backpropagation and gradient descent to minimize the difference between the predicted output $\hat{Y}$ and the actual target Y. In the context of ataxia detection, the input features X represent relevant physiological or clinical measurements. The target variable Y is binary, indicating the presence (1) or absence (0) of ataxia. The training process involves adjusting the weights and biases $W^{(1)}$, $W^{(2)}$, $b^{(1)}$, $b^{(2)}$ to minimize the difference between the predicted output $\hat{Y}$ and the true labels Y. This is achieved through the use of a loss function. Once trained, the MLP can predict the likelihood of ataxia for new individuals. The output $\hat{Y}$ is typically transformed using a threshold, e.g., $\hat{Y} \geq 0.5$ is classified as ataxia-positive (1), and $\hat{Y} \leq 0.5$ is classified as ataxia-negative (0). MLPs are powerful for capturing complex relationships in data and are capable of handling non-linear decision boundaries. The number of hidden layers and nodes, as well as the choice of activation functions, can be tuned based on the complexity of the problem.

3.5. XGBoost (XGB)

One optimization approach which expands upon the gradient-descent approach is XGBoost, which is built upon DT [21]. A popular strategy in this field involves using gradient-descent for optimizing the loss-function. Additionally, researchers frequently use normalization variables to avoid overfitting, as discussed in previous studies [22]. The main idea behind the XGB method is to reduce a specific objective-function. This function includes both the regularization-function and loss-function [22]. The objective function is given as (12).

$$\mathcal{L}^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y_i}^{(t-1)} + f_t(x_i)\right) + \Omega(f_t) \tag{12}$$

where, l represents loss-function denoting error among the predicted and observed data. l also represents the t^{th} tree of the DT. t represents the interative index throughout the optimizing procedure. Further, the regulation parameter in (12) can be denoted as [22].

$$\Omega(f_t) = \gamma T + \frac{1}{2}\lambda||w||^2 \tag{13}$$

where T represents overall leaves present in tree, γ and λ represent peanlizing parameters which also contain the vector-score of each leaf. The complete procedure of the XGB approach is presented in Chen *et al.* [22]. In (13), T, γ and w have to be defined or given a particular value in order to enhance the optimization process before the training procedure [23].

3.6. XGB-MLP

The complete structure of the XGB-MLP is presented in Figure 1. Consider the input features for the XGB model as Y_1, Y_2, Y_3, ..., Y_n and the target variable as Y. In Stage 1, i.e., feature selection, the XGB model is trained using the dataset, aiming to predict Y based on the input features. The output of this stage is denoted as $\hat{Y}_1$, $\hat{Y}_2$, $\hat{Y}_3$, ..., $\hat{Y}_n$ representing the predicted values. In Stage 2, i.e., ataxia assessment, the predicted values $\hat{Y}_1$, $\hat{Y}_2$, $\hat{Y}_3$, ..., $\hat{Y}_n$ are taken as input features for the MLP model. Consider the input for the MLP as $\hat{Y}_1$, $\hat{Y}_2$, $\hat{Y}_3$, ..., $\hat{Y}_m$, where m is the number of predictions from the XGB model. The MLP is trained using these inputs to predict and classify the presence or absence of ataxia. The output of this stage is the final prediction and classification. Finally, in Stage 3, i.e., testing, similar to Stage 1 and Stage 2, the input features Y_1, Y_2, Y_3, ..., Y_n are used for XGB feature selection, and the MLP is employed for prediction and classification based on the selected features. This stage aims to assess the model's performance on new or unseen data.

The final prediction and classification of ataxia involves evaluating the model's performance using metrics such as specificity, sensitivity, accuracy, precision, and F-measure. These metrics provide a comprehensive assessment of how well the model performs in identifying cases of ataxia and non-ataxia, considering both true positives and true negatives, false positives, and false negatives. The results are discussed in the next section.

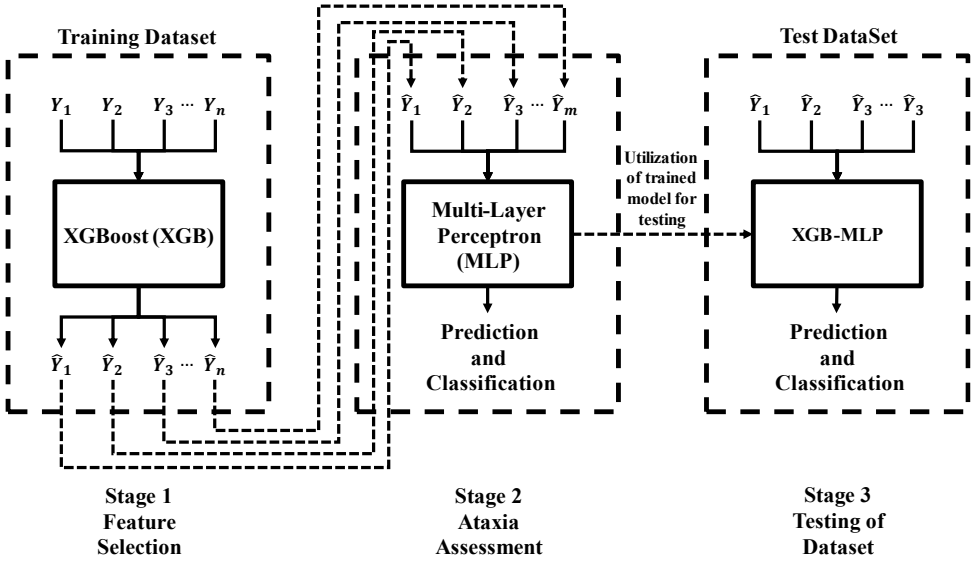

Figure 1. Proposed XGB-MLP approach

4. RESULTS AND DISCUSSION

In this section, the discussion revolves around the dataset used, highlighting the performance metrics, including sensitivity, specificity, accuracy, precision, and f-measure. The subsequent analysis delves into a thorough comparison of the performance of various ML and DL models with a specific emphasis on evaluating their effectiveness against the proposed XGB-MLP model. The outcomes and insights pertaining to ataxia prediction and classification are meticulously presented for a comprehensive understanding.

4.1. Dataset

The experiment was carried out utilizing a set of data that was gathered from [24] and [25] for prediction of ataxia. The dataset was composed of spatio-temporal data measured through Kinematic v2 sensor of 19 cerebellar ataxic person and 65 healthy persons. An overall of 84-person Kinematic information was used with presence of imbalanced data between healthy and cerebellar ataxic patients. This set consisted total of 26 features, where 18 feature represent spatio-temporal and joint kinematic information and 7 are clinical characteristics feature such as age, weight, height, gender, duration, diagnosis, and sara score and the 26th feature defines the class (i.e., 0 representing healthy subject and 1 representing Cerebellar ataxic). For ataxia classification, the dataset from [25] was considered. This dataset had three classes such as healthy, PA, and CA; thus, classification task became a multi-label classification problem. The gait characteristic dataset was generated using Kinect v2, Tripod, Microsoft Kinect SDK. The dataset was composed of total 13 attribute features from 51 participant such as participant Id, diagnosis, SARA, cadence, speed, stride length,

base width, step-length, stance-phase, stride-time, swinging-phase, and double-support phase group. Using the performance metrics discussed in the next section, all the models have been evaluated using the datasets.

4.2. Performance metrics

The accuracy, sensitivity, specificity, precision, and F-measure were metrics used for validating the classification algorithm performance. The metrics were evaluated using the given below equations,

$$Specificity = \frac{TN}{TN+FP} \quad (14)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (15)$$

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (16)$$

$$Precision = \frac{TP}{TP+FP} \quad (17)$$

$$F-measure = \frac{2*Precision*Sensitivity}{Precision*Sensitivity} \quad (18)$$

where TP defines true positive, FP defines false positive, TN defines true negative, and FN defines false negative. The sensitivity was computed as follows.

4.3. Ataxia prediction

The provided Figure 2 shows performance metrics for different ML and DL models in the context of ataxia detection. The models analyzed are RF, LR, SVM, MLP, and XGB. Additionally, there is an evaluation of a combined approach, XGB-MLP. From analysis, it is observed that XGB-MLP outperforms individual models in several metrics. It achieves exceptionally high values in specificity (0.98) and sensitivity (0.9972), indicating robust performance in correctly classifying both ataxia and non-ataxia cases. The high accuracy (0.9891) and precision (0.9896) further emphasize the reliability of the combined XGB-MLP approach. This suggests that leveraging the strengths of both MLP and XGB contributes to an improved and well-balanced ataxia detection model compared to individual models.

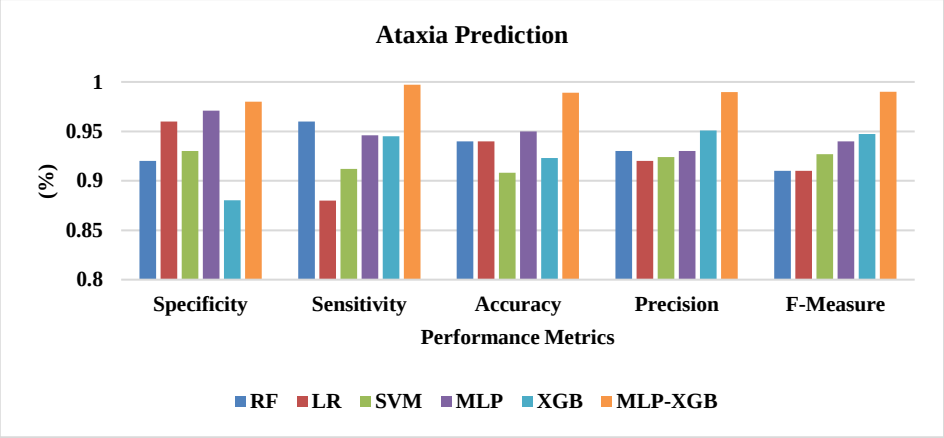

Figure 2. Ataxia prediction

4.4. Ataxia severity classification

The presented Figure 3 offers a comprehensive comparison of different ML and DL models in the context of ataxia detection, utilizing various performance metrics. The models under consideration are RF, LR, SVM, MLP, and XGB. Additionally, a combined approach, XGB-MLP, is assessed. Upon analysis, it is evident that XGB-MLP consistently performs well across all metrics, outperforming individual models in specificity (0.97), sensitivity (0.9872), accuracy (0.9791), precision (0.9796), and F-measure (0.98). This indicates the efficacy of combining MLP and XGB, resulting in a balanced and accurate ataxia detection

model. The combination of both models appears to leverage their respective strengths, contributing to an enhanced overall performance compared to individual models in the task of ataxia classification.

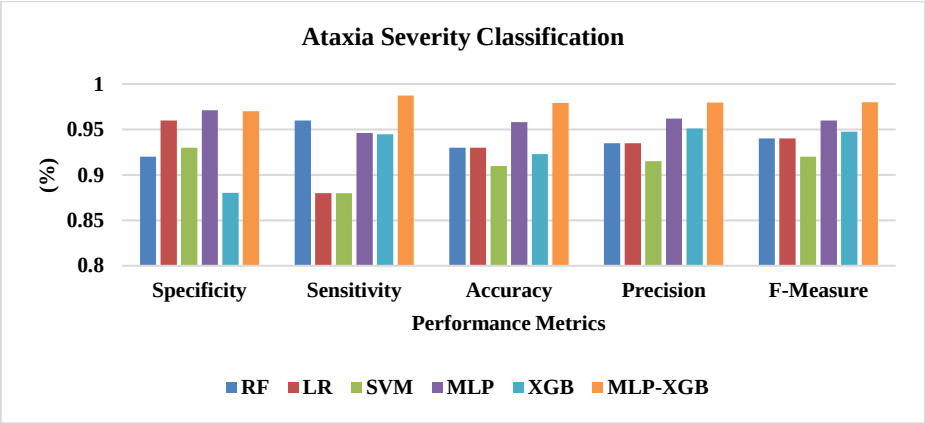

Figure 3. Ataxia severity classification

5. CONCLUSION

Ataxia prediction involves forecasting the likelihood of an individual developing ataxia, while ataxia classification entails categorizing individuals into ataxia-positive or ataxia-negative groups based on relevant features and characteristics. However, both tasks face challenges in handling diverse datasets, identifying subtle patterns, and minimizing false positives or negatives. Hence, this work introduces a hybrid model, XGB-MLP, for ataxia prediction and classification. The proposed model surpasses the performance of traditional ML and DL models, including RF, LR, SVM, MLP, and XGB, achieving an impressive accuracy of 98.91% for prediction and 97.91% for classification. The findings underscore the superiority of the XGB-MLP model, suggesting its potential as an effective tool in the medical domain. Future work can focus on optimizing the XGB-MLP model through the incorporation of advanced optimization algorithms to further enhance its accuracy and applicability in real-world scenarios.

REFERENCES

[1] K. Kaminiów, I. Ryguła, and J. Paprocka, "Ataxia in neurometabolic disorders," *Metabolites*, vol. 13, no. 1, pp. 47–47, Dec. 2022, doi: 10.3390/metabo13010047.

[2] M. Krygier and M. M.-Bełdzińska, "Milestones in genetics of cerebellar ataxias," *Neurogenetics*, vol. 22, no. 4, pp. 225–234, Jul. 2021, doi: 10.1007/s10048-021-00656-3.

[3] E. Lacorte, P. Piscopo, L. Sagliocca, Luca Vignatelli, D. Taruscio, and N. Vanacore, "The national italian guidelines on the diagnosis and treatment of children with pediatric ataxias," *Frontiers in Neurology*, vol. 13, Oct. 2022, doi: 10.3389/fneur.2022.971781.

[4] C. Lin and S. Kuo, "Ataxias: hereditary, acquired, and reversible etiologies," *Seminars in Neurology*, vol. 43, no. 01, pp. 048–064, Feb. 2023, doi: 10.1055/s-0043-1763511.

[5] J. Wang *et al.*, "Diagnostic efficacy of the magnetic resonance T1w/T2w ratio for the middle cerebellar peduncle in multiple system atrophy and spinocerebellar ataxia: A preliminary study," *PLOS ONE*, vol. 17, no. 4, pp. e0267024–e0267024, Apr. 2022, doi: 10.1371/journal.pone.0267024.

[6] T. Ngo, P. N. Pathirana, M. K. Horne, L. A. Corben, I. H. Harding and D. J. Szmulewicz, "Technological evolution in the instrumentation of ataxia severity measurement," *IEEE Access*, vol. 11, pp. 14006-14027, 2023, doi: 10.1109/access.2023.3243178.

[7] T. Ngo *et al.*, "Federated deep learning for the diagnosis of cerebellar ataxia: privacy preservation and auto-crafted feature extractor," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 30, pp. 803-811, 2022, doi: 10.1109/TNSRE.2022.3161272.

[8] M. Manto *et al.*, "Consensus paper: latent autoimmune cerebellar ataxia (LACA)," *The Cerebellum*, Mar. 2023, doi: 10.1007/s12311-023-01550-4.

[9] P. Zhang and Maged, "Generative AI in medicine and healthcare: promises, opportunities and challenges," *Future Internet*, vol. 15, no. 9, pp. 286–286, Aug. 2023, doi: 10.3390/fi15090286.

[10] Q. Zhang, X. Zhou, Y. Li, X. Yang, and Q. H. Abbasi, "Clinical recognition of sensory ataxia and cerebellar ataxia," *Frontiers in Human Neuroscience*, vol. 15, Apr. 2021, doi: 10.3389/fnhum.2021.639871.

[11] C. Hohenfeld *et al.*, "Prediction of the disease course in Friedreich ataxia," *Scientific Reports*, vol. 12, no. 1, Nov. 2022, doi: 10.1038/s41598-022-23666-z.

[12] P. D. Seetharama and S. Math, "Ataxia severity classification using enhanced feature selection and ranking optimization through machine learning model," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 32, no. 3, pp. 1605–1605, Dec. 2023, doi: 10.11591/ijeecs.v32.i3.pp1605-1613.

[13] D. Phan, N. Nguyen, P. N. Pathirana, M. Horne, L. Power and D. Szmulewicz, "A random forest approach for quantifying gait ataxia with truncal and peripheral measurements using multiple wearable sensors," *IEEE Sensors Journal*, vol. 20, no. 2, pp. 723-734, 15 Jan.15, 2020, doi: 10.1109/JSEN.2019.2943879.
[14] J. Lee *et al.*, "Analysis of gait sub-movements to estimate ataxia severity using ankle inertial data," *IEEE Transactions on Biomedical Engineering*, vol. 69, no. 7, pp. 2314-2323, Jul. 2022, doi: 10.1109/TBME.2022.3142504.
[15] M. S. Sundari and V. C. Jadala, "Neurological disease prediction using impaired gait analysis for foot position in cerebellar ataxia by ensemble approach," *Automatika*, vol. 64, no. 3, pp. 540-549, 2023, doi: 10.1080/00051144.2023.2194097.
[16] O. Vyšata *et al.*, "Classification of ataxic gait," *Sensors*, vol. 21, no. 16, p. 5576, Aug. 2021, doi: 10.3390/s21165576.
[17] B. Kashyap, P. N. Pathirana, M. Horne, L. Power, and D. J. Szmulewicz, "Machine learning based scoring system to predict the risk and severity of ataxic speech using different speech tasks," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, pp. 1–1, Jan. 2023, doi: 10.1109/tnsre.2023.3334718.
[18] B. Kashyap, D. Phan, P. N. Pathirana, M. Horne, L. Power, and D. Szmulewicz, "Objective assessment of cerebellar ataxia: a comprehensive and refined approach," *Scientific Reports*, vol. 10, no. 1, Jun. 2020, doi: 10.1038/s41598-020-65303-7.
[19] J. Yu *et al.*, "Deep learning–assisted gait parameter assessment for neurodegenerative diseases: model development and validation," *Journal of Medical Internet Research*, vol. 25, pp. e46427–e46427, Jul. 2023, doi: 10.2196/46427.
[20] C. Stoean et al., "Automated detection of presymptomatic conditions in spinocerebellar ataxia type 2 using monte carlo dropout and deep neural network techniques with electrooculogram signals," *Sensors*, vol. 20, no. 11, pp. 3032–3032, May 2020, doi: 10.3390/s20113032.
[21] D. Tarwidi, S. R. Pudjaprasetya, D. Adytia, and M. Apri, "An optimized XGBoost-based machine learning method for predicting wave run-up on a sloping beach," *MethodsX*, vol. 10, p. 102119, Jan. 2023, doi: 10.1016/j.mex.2023.102119.
[22] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining - KDD '16*, pp. 785–794, 2016, doi: 10.1145/2939672.2939785.
[23] W. Zhang, C. Wu, H. Zhong, Y. Li, and L. Wang, "Prediction of undrained shear strength using extreme gradient boosting and random forest based on Bayesian optimization," *Geoscience Frontiers*, vol. 12, no. 1, pp. 469–477, Jan. 2021, doi: 10.1016/j.gsf.2020.03.007.
[24] M. Serrao *et al.*, "Dataset on gait patterns in degenerative neurological diseases," *Data in Brief*, vol. 16, pp. 806–816, Feb. 2018, doi: 10.1016/j.dib.2017.12.022.
[25] S. Summa *et al.*, "Spatio-temporal parameters of ataxia gait dataset obtained with the Kinect," *Data in Brief*, vol. 32, pp. 106307–106307, Oct. 2020, doi: 10.1016/j.dib.2020.106307.

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