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Ataxic person prediction using feature optimized based on machine learning model

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ABSTRACT

Ataxic gait monitoring and assessment of neurological disorders belong to important areas that are supported by digital signal processing methods and artificial intelligence (AI) techniques such as machine learning (ML) and deep learning (DL) techniques. This paper uses spatio-temporal data from Kinect sensor to optimize machine learning model to distinguish between ataxic and normal gait. Existing ML-based methodologies fails to establish feature correlation between different gait parameters; thus, exhibit very poor performance. Further, when data is imbalanced in nature the existing ML-based methodologies induces higher false positive. In addressing the research issues this paper introduces an extreme gradient boost (XGBoost)-based classifier and enhanced feature optimization (EFO) by modifying the standard cross validation (SCV) mechanism. Experiment outcome shows the proposed ataxic person identification model achieves very good result in comparison with existing ML-based and DL-based ataxic person identification methodologies.

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1. INTRODUCTION

Motion disorders plays a key indicator in identifying many diseases as described in [1], [2] such as physical activity, rehabilitation, physical therapy, orthopedics, rheumatology, and neurology. As stated in [1], around 70% of neurological inpatients exhibit abnormal gait activity; thus, gait-based assessment model can be leveraged for early diagnosis [3] of neurological disorder as demonstrated in [4], [5]. The research work mainly focusses on identifying ataxic neurological disorder through gait analysis as demonstrated in [6]. Designing efficient gait-based mechanism that is skilled for automatic detection and nursing of neurological condition aid in enhancing treatment efficiency, diseases management and also further aid in reducing load of healthcare management environment as stated in [7], [8]. Tool and methodologies are needed for efficient detection and diagnosis of neurological disorders as shown in [9], [10]. The significant growth of wireless communication and sensor technology have led to usage of different sensors such as wearable devices [11], video, depth and thermal camera systems [12], microelectromechanical sensor units, and Kinect sensor [13] for monitoring different neurological disorder [14]. Recently, in [15] presented wearable gait sensor are efficient in studying the behavior of scale for the assessment and rating of ataxia (SARA). Similarly, in [16] showed importance of studying gait characteristic of ataxic patient with multiple sclerosis [17], [18].

The machine learning technique have been adopted for detection and diagnosis of different neurological disorder such as flat fall prediction [19], [20], Parkinson [21], Friedreich's ataxia [22]. In [23] presented a deep leaning-based approach for cerebellar ataxic person identification [24] and compared with various machine learning model. All the existing deep learning-based approaches [25], [26] are used for understanding human's natural spatio-temporal kinematics motions [27], [28] and predict motion disorder; the adoption of deep learning method aid in solving feature selection of spatio-temporal data and decision-making issues of machine learning-based approaches. However, the deep learning-based approaches [29] requires very powerful computational resource, requires huge amount of training sample, and poor performance when data is imbalanced. This motivates the proposed study to design an improved feature optimized machine learning model for detecting ataxic person using spatio-temporal Kinematic features. This paper first presents a standard extreme gradient boost (XGBoost) algorithm; then, introduces a misclassification minimization aware weight optimization technique namely feature weight optimization (FWO). Later, an improved feature selection mechanism by modifying standard cross validation mechanism is provided considering presence of imbalanced data. Finally, ataxic person identification model is constructed.

The significance of feature weight optimization extreme gradient boost (FWO-XGB) for ataxic person identification is as follows. The FWO-XGB is very efficient in reducing misclassification using misclassification minimization aware weight optimization method; better specificity and sensitivity assures the efficiency of weight optimization method. The model is efficient in identifying both healthy and ataxic person even when data is imbalanced in nature; this is due to adoption enhanced feature selection method using modified cross validation mechanism. The FWO-XGB achieves better accuracy, specificity, and sensitivity than existing machine learning (ML) and deep learning (DL)-based ataxic person identification model. The FWO-XGB achieves better accuracy, specificity, sensitivity, precision, and F-measure than standard XGB-based ataxic person identification model.

The manuscript organization. In section 2, various existing ataxic person and neurodegenerative disease identification using ML and DL method advantage and limitation is studied. The section 3, the research methodology of FWO-XGB based ataxic person identification is provided. The section 4, the outcome of FWO-XGB based ataxic person identification method over various ML and DL-based ataxic person identification method is provided. Lastly, the research significance is highlighted, and future enhancement is provided.

2. RELATED WORK

This section studies various methodologies for detecting ataxic patient using gait characteristics. In [30], focused to identify whether it is possible to identify person with ataxia using gait features and also focused to establish ataxia severity and its risk. They collected videos from 80 people, where 65 people exhibit spinocerebellar ataxias and remaining 24 people are health subject. Each people were asked to perform certain task to collect gait feature for SARA. They collected different gait feature such as speed, stability, swing, step length, and step width. The model attained an F1-score of 80.23% and accuracy of 83.06% for risk prediction. In similar manner achieved 0.7268 of Pearson's correlation coefficient and 0.6225 of mean absolute error. The model work well for classifying data that is not present during training time. Alongside, carried out feature importance study, which shows increased instability, decreased walking speed, and wider steps are gait features plays significant role in ataxia severity. In [31] showed ataxia can be identified by understanding human external features i.e., when people exhibit balance disorder and poor coordination., which shows that certain part of body are affected by the disease. Further, there are other internal aspects that may cause ataxia. Thus, external features and doctor clinical experience are combined to achieve better diagnosing of ataxia. Generally, ataxia is confused with other ailment leading to confusion and delay in treatment and its prognosis. The contemporary diagnostic tools can be used with better precision; however, cost is significantly higher. Recently, sensing technique with non-contact with patient are used for differentiating cerebellar ataxia and sensory ataxia. They used microwave sensing for collecting gait features and performed Romberg's test. Then, the data collected are pre-processed using principal component analysis and are trained with ML models such as random forest (RF), support vector machine (SVM), and back propagation neural network (BPNN). The model achieved accuracies of 91.1%, 98.9%, and 97.8% using RF, SVM, and BPNN respectively. In [32] showed that the quality of life is significantly reduced due to gait disorder due to different musculoskeletal and neurological disorder. The gait stereotypes are measured using motion sensors which offers good quality information. Nonetheless, higher data size led to data reduction and computation challenges. The approaches compared several data reduction mechanism and machine learning models used for ataxia person and health person classification. The experiment is conducted using 43 persons out of which 20 are health and remaining 23 are ataxic. The data pre-processed with distributed stochastic neighbour embedding combine with RF algorithm achieves a higher accuracy of 98%. In [33] studied to classify hereditary ataxia using gait features collected from motion sensors. They focused in establishing minimum gait feature required to perform hereditary ataxia classification using ankle-based motions sensors. They considered total 28 participant out of which 14 are health and remaining 14 are hereditary ataxia patient. The spatio-temporal gait features are extracted considering stride window size of 10. Then, for reducing the gait features using ankle sensors Hill Climbing model is used are trained with different ML models such as multi-layer perceptron (MLP) and k-nearest neighbors (KNN) model; the model achieved an accuracy of 96%.

In [23] studied the benefit of using accelerometer sensor for extraction of gait features and trin it with deep learning model such as convolution neural network for classifying whether a person is ataxic or healthy. In conducting experiment total 35 patient are considered out of which 19 people are health and 16 are ataxic person. The DL-based classification algorithm is compared with standard ML-based model such as two-layer neural network (TLNN), SVM, and Bayesian network. They identified accuracies varies with respect to placement of sensors and DL-based method achieves an accuracy of 95.8. However, the model performs badly considering limited training sample and when data is imbalanced in nature. In addressing the research limitation, the following research methodology is presented.

3. PROPOSED METHODOLOGY

The section introduces a methodology of feature optimization model for designing effective ataxic person identification model. In this work first provide mathematical representation of gradient Boosting tree; then, provide the detailed discussion of feature weight optimization to reduce misclassification and feature optimization process to handle data imbalance. The architecture of proposed ataxic person identification model using enhanced ML model is given in Figure 1.

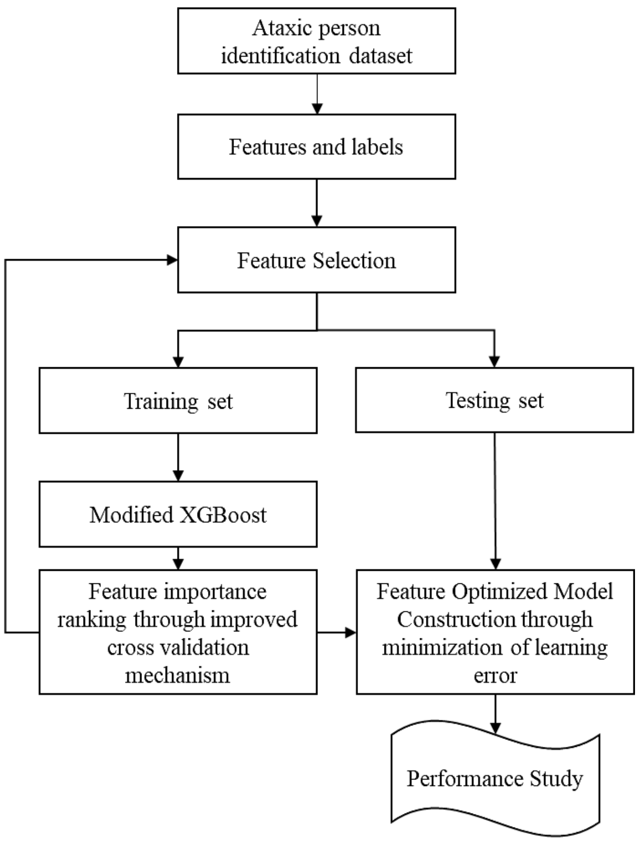

Figure 1. Proposed machine learning model for Ataxic person identification

3.1. XGBoost prediction algorithm

The XGBoost algorithm are very efficient in the field of classification task across different domain such as education, agriculture, healthcare. The XGB takes the input y_j and the corresponding actual label is defined using parameter z_j and the initial prediction outcome prior to sigmoid is defined through parameter a_j and the objective function of XGBoost algorithm is expressed through following equation.

$$M^{(u)} = \sum_{j=1}^{o} m\left(z_j, A_j^{(u-1)} + g_u(y_j)\right) + \rho(g_u) + d \tag{1}$$

where the loss function is defined through parameter $m(.,.)$, the parameter ρ is used for penalizing the model complexities, u defines respective tree, $\rho(g_u)$ defines regularization operation penalty parameter and constant are represented by parameter d. The second-order Taylor expansion are expressed using (2),

$$g(y + \delta y) \approx g(x) + g'(y)\delta y + \frac{1}{2} g''(y)\delta y^2 \tag{2}$$

then substituting (2) into (1) we get,

$$M^{(u)} \approx \sum_{j=1}^{o} \left[m\left(z_j + A_j^{(u-1)}\right) + h_j g_u(y_j) + \frac{1}{2} i_j \left(g_u(y_j)\right)^2\right] + \rho(g_u) + d \tag{3}$$

where h_j is computed as (4),

$$h_j = \frac{\partial M}{\partial a_j} \tag{4}$$

and i_j is computed as (5),

$$i_j = \frac{\partial^2 M}{\partial a_j^2} \tag{5}$$

in (3) the constant term are removed for simplifying the computation at instance u as (6)

$$M^{(u)} \approx \sum_{j=1}^{o} \left[h_j g_u(y_j) + \frac{1}{2} i_j \left(g_u(y_j)\right)^2\right] + \rho(g_u) \tag{6}$$

In fitting the gradient boosting tree model the parameter such as h_j and i_j need to be established. The standard loss function of gradient boosting tree in solving binary classification problem is obtained through cross entropy loss function as (7),

$$M = -\sum_{j=1}^{o}\left[z_j \log(\hat{z}_j) + (1 - z_j)\log(1 - \hat{z}_j)\right] \tag{7}$$

In (9), the parameter $\hat{z}_j$ is computed as (8)

$$\hat{z}_j = \frac{1}{[1+\exp(-a_j)]} \tag{8}$$

and for activation sigmoid function is used and we obtain (9).

$$\frac{\partial \hat{z}_j}{\partial a_j} = \hat{z}_j(1 - \hat{z}_j) \tag{9}$$

3.2. Misclassification minimization aware weight optimization for XGBoost algorithm

The traditional XGB-based classification is primarily focussed in minimizing the loss function; however, the weights for both correctly and wrongly classified class remain same. However, in this work feature weight optimized (FWO) learning method is presented for minimizing misclassification. In FWO, a larger weight is given to misclassified class for error induced by positive sample; thus, higher importance is given to positive samples. In Table 1, binary classification weight matrix is provided.

Table 1. Binary classification matrix

	Actual ataxic person (Positive)	Actual non-ataxic person (Negative)
Predict Ataxic person (Positive)	TP (O_{11})	FP (O_{01})
Predict non-ataxic person (Negative)	FN (O_{10})	TN (O_{00})

The feature weight optimized XGB (FWO-XGB)-based ataxic person identification model considers the misclassification instance only. Thus, let $O_{00} = O_{11}$, $O_{10} = b(b > 0)$, and $O_{01} = 1$, the loss function using feature weight optimized influence is established using (10),

$$M_b = -\sum_{j=1}^{o}\left[bz_j \log\left(\hat{z}_j\right) + \left(1 - z_j\right)\log\left(1 - \hat{z}_j\right)\right] \tag{10}$$

where b defines feature weight optimized influence. In above equation additional loss will be considered on false positive if b is lesser than 1; however, b is greater than 1, no additional loss will be considered for false negative. The first-order derivative h_j is computed using (11):

$$h_j = \frac{\partial M_b}{\partial^2 a_j} \tag{11}$$

The above equation can be refined as (12),

$$h_j = \hat{z}_j\left(1 - z_j + bz_j\right) - bz_j \tag{12}$$

and second-order derivative I_j is computed using (13)

$$I_j = \frac{\partial M_b}{\partial^2 a_j^2} \tag{13}$$

The above equation can be refined as (14),

$$I_j = \hat{z}_j\left(1 - \hat{z}_j\right)\left(1 - z_j + bz_j\right) \tag{14}$$

The performance of featured weight optimized XGB can be seriously impacted when data is imbalanced in nature; thus, required effective feature optimization mechanism for designing ideal ataxic person identification.

3.3. Feature optimization for imbalanced data

In the standard K-fold cross validation, the feature subset for training classification model is created in by dividing the dataset in random manner with equal size. Then, remaining $K - 1$ are used for construction of ataxic person identification model. Finally, the model is selected that minimize the prediction error considering grid l. The standard cross validation is obtained as (15),

$$CV(\sigma) = \frac{1}{M}\sum_{k=1}^{K}\sum_{j\in G_{-k}} P\left(b_j, \hat{g}_{\sigma}^{-k(j)}\left(y_j, \sigma\right)\right) \tag{15}$$

The proposed feature optimized cross validation is obtained as (16)

$$CV(\sigma) = \frac{1}{SM}\sum_{s=1}^{S}\sum_{k=1}^{K}\sum_{j\in G_{-k}} P\left(b_j, \hat{g}_{\sigma}^{-k(j)}\left(y_j, \sigma\right)\right) \tag{16}$$

A two-step cross validation mechanism is defined. First, main feature is chosen from feature subsets; later, feature extracted in previous steps is used for building high accuracy ataxic person identification model. In. (15) and (16), for choosing good $\hat{\sigma}$ for optimization of ataxic person identification model obtained through following (17),

$$\hat{\sigma} = \underset{\sigma\in\{\sigma_1,\ldots,\sigma_l\}}{\arg\min}\ CV_s(\sigma) \tag{17}$$

In (16), M represent dataset size used during training, $P(\cdot)$ are the loss function, and $\hat{g}_{\sigma}^{-k(j)}(\cdot)$ represent method used for computing its coefficients. After extracting good features in iterative manner using (16), the features are ranked $r(\cdot)$ to attain high accurate ataxic person identification model using (18),

$$r(a) = \begin{cases} 0 \ \ if\ n_j\ is\ not\ selected \\ 1 \ \ if\ n_j\ is\ selected\ as\ optimal\ prediction\ model\ j = 1,2,3, \ldots, n \end{cases} \tag{18}$$

The feature subset is obtained using (19)

$$F_s = \{r(n_1), r(n_1), \dots, r(n_n)\} \tag{19}$$

For different K-folds instance good features with maximal score are computed as using (20)

$$F_{s_k} = \{r(n_1), r(n_1), \dots, r(n_n)\} \tag{20}$$

After that how many a respective feature has been chosen for K feature subsets have been identified for construction of final features is obtained through (21)

$$F_{s_{final}}=\{f_s(p_1), f_s(n_2), \dots, f_s(n_n)\}, \tag{21}$$

where $f_s(\cdot)$ defines instance where n^{th} feature is chosen or not and is established using (22).

$$F_s(a) = \begin{cases} 0 \;\; if\ q_j\ is\ chosen\ lesser\ than\ \frac{K}{2}\ times, j = 1,2,3, \dots, n \\ 1\;\; if\ q_j\ is\ chosen\ greater\ or\ equal\ to\ \frac{K}{2}\ times, j = 1,2,3, \dots, n \end{cases} \tag{22}$$

Using above equation feature importance of different gait features are first established. Then, based on extracted features the proposed ataxic person identification model is constructed. This allows the proposed FWO-XGB based ataxic person identification model in significantly improving the overall prediction accuracy in comparison with other DL-based and ML-based ataxic person identification schemes. In next section the performance evalution is done using standard ataxia dataset.

4. PERFORMANCE EVALUATION

This section studies the performance achieved using proposed FWO-XGB based ataxic person identification model over standard XGB-based classification model. Further, the model is compared with existing machine learning [32] and deep learning-based [17], [23] ataxic person identification model. The proposed and other existing ataxic person identification model is implemented using Anaconda python framework. The experiment is conducted using dataset collected from [34], [35]. The dataset composed of spatio-temporal data measured through Kinematic v2 sensor of 19 cerebellar ataxic person and 65 healthy persons. The accuracies, sensitivity, specificity, precision, and F-measure are metrics used for validating the classification algorithm performance. The specificity is computed as (23),

$$Specificity = \frac{TN}{TN+FP} \tag{23}$$

where TP defines true positive, FP defines false positive, TN defines true negative, and FN defines false negative. The sensitivity is computed as (24),

$$Sensitivity = \frac{TP}{TP+FN} \tag{24}$$

The accuracy is computed as (25),

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{25}$$

The precision is computed as (26),

$$Precision = \frac{TP}{TP+FP} \tag{26}$$

The F-measure is computed as (27),

$$F - measure = \frac{2*Precision*Sensitivity}{Precision*Sensitivity} \tag{27}$$

4.1. Specificity and sensitivity performance

This section provides performance study of specificity and sensitivity metrics in classifying whether a person is ataxic or healthy. The proposed FWO-XGB is compared with total five existing machine learning algorithm [32] such as random forest (RF), AdaBoost, radial basis function support vector machine

(RBF-SVM), linear regression (LR), and XGB and one deep learning (DL) neural network algorithm [17], [23]. The graphical outcome of specificity is computed using (23) is given in Figure 2. Similarly, the graphical outcome of sensitivity is computed using (24) is given in Figure 3. From both Figures 2 and 3 we can interpret that FWO-XGB outperform all existing ML and DL-based ataxic person identification methods.

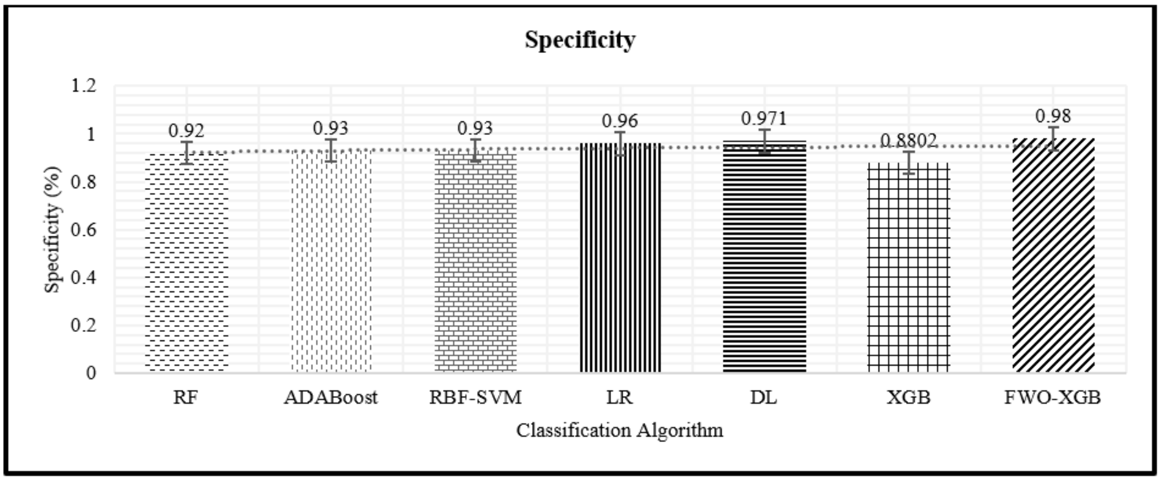

Figure 2. Specificity performance of different ML and DL algorithms for ataxic person identification

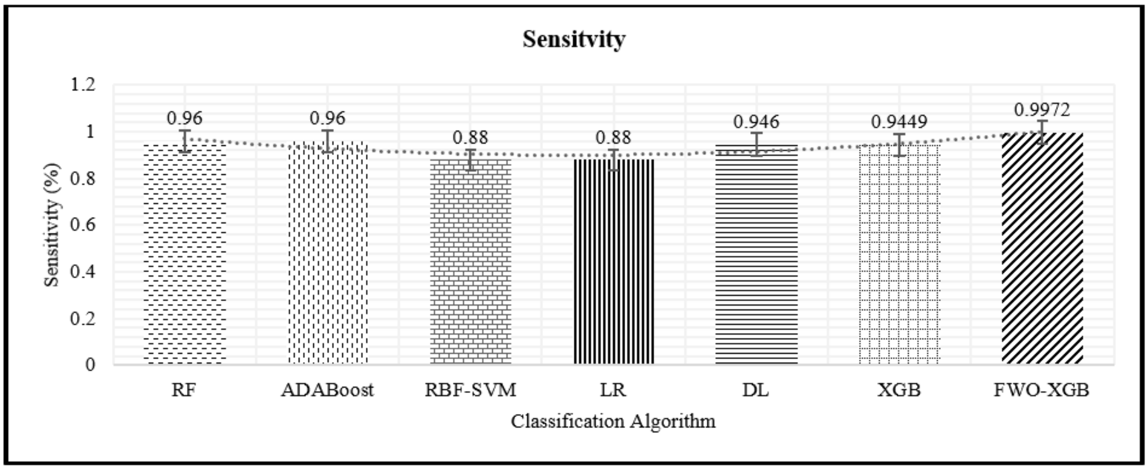

Figure 3. Sensitivity performance of different ML and DL algorithms for ataxic person identification

4.2. Accuracy performance

This section provides performance study of accuracies metrics in classifying whether a person is ataxic or healthy. The proposed FWO-XGB is compared with total eight existing machine learning algorithm [32] such as RF, AdaBoost, RBF-SVM, LR, XGB, Bayes, SVM, two-layer neural network (TLNN), and one DL neural network algorithm [17], [23]. The graphical outcome of accuracy is computed using (25) is given in Figure 4. From Figure 4 we can interpret that FWO-XGB outperforms all existing ML and DL-based ataxic person identification methods.

4.3. Classification performance of XGB vs FWO-XGB

This section provides performance study of standard XGB and proposed improved XGB version i.e., FWO-XGB in terms of accuracy, sensitivity, specificity, precision, and F-measure. The graphical outcome of classification performance is given in Figure 5. From Figure 5 we can interpret that FWO-XGB outperform all standard XGB-based ataxic person identification methods.

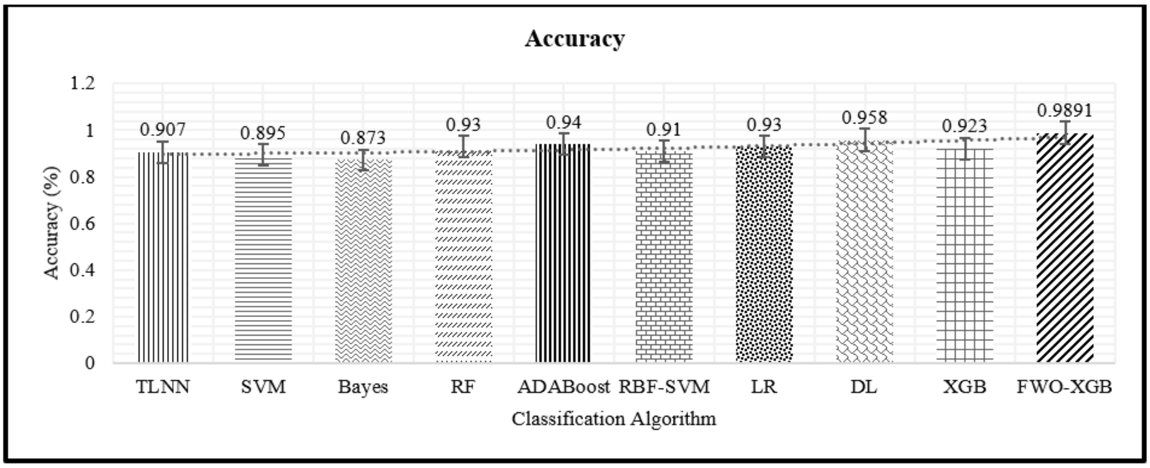

Figure 4. Accuracy performance of different ML and DL algorithms for ataxic person identification

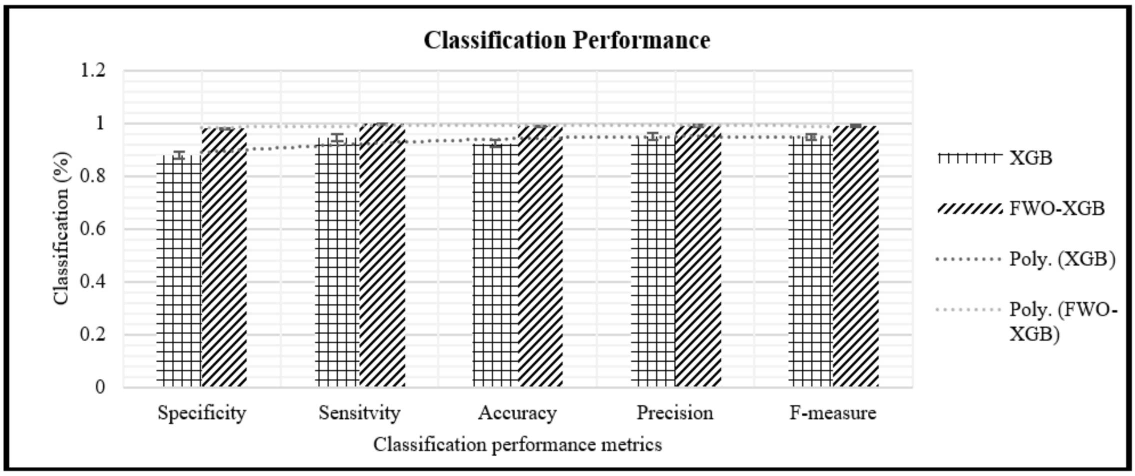

Figure 5. Classification performance for different ROC metrics

5. CONCLUSION

The aim of the study is to employ machine learning technique to classify ataxic person and healthy subject using gait features. The work conducted deep rooted study of various ML and DL method applied for ataxic person identification using gait features and identified its benefits and limitations; the study shows that deep learning method requires larger data to achieve higher accuracy. On the other side, the ML-based methods provide poor accuracies due to high false positives when data is imbalanced in nature. In addressing the research issues this paper introduced a novel feature weight optimization method for XGB to reduce false positive and further, a novel feature selection mechanism by modifying the cross-validation mechanism is introduced that works well even when data is imbalanced in nature. The FWO-XGB is very efficient in identifying which feature impact classification accuracies by minimizing objective error; thus, aid in achieving better accuracy, sensitivity, specificity, precision, and F-measure performance than standard XGB-based ataxic person identification. The future work will consider testing the proposed model on different spatio-temporal dataset. The robustness of FWO-XGB can be validated by testing on multi-label classification dataset. More emphasize to be given in classifying different stages of ataxic using SARA scores.

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