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Time Orient Acceleration Gait Pattern Based FOG Prediction on Parkinson Patients Using Deep Learning and Wearable Sensors

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ABSTRACT

The problem of predicting Freeze of Gait (FoG) on Parkinson diseased patients has been well studied. There exists number of approaches in predicting FoG, which uses sensory features, EEG data and so on. However, the methods suffer to achieve higher performance. To handle this issue, an efficient Time Orient Acceleration Gait pattern based FoG prediction model (TOAGP-FoG) is presented in this paper. The model designed to attach accelerometer sensors at different ankle and joints of the body. The sensor signals are recorded at different gait movement in long term. The sensory signals are passed to the central data server which tracks the movement signals. With the time variant signals stored by the model, the method generates Acceleration Gait Pattern with number of features. At each movement, the method analyses the patterns to compute FOG Risk Support (FoGRS) towards various gait movement. The FoG Risk Support is measured according to the movement forces produced by the patient for various gait movement in different time stamp and computes minimum gait force to be produced. Based on the FoGRS value, the method performs FoG prediction. The proposed method improves the performance of FoG prediction with higher accuracy. Other notable aspects of the suggested model include comparable performance, resiliency, real-time prediction capabilities, FOG-specific integration of data, and advanced deep learning methodologies for accurate prediction. The Special Features of TOAGP-FoG include the Multi-Sensor Configuration, Temporal Analysis, Adaptive Thresholding, Dynamic FoG Risk Support (FoGRS), and Enriched Feature Extraction. The TOAGP-FoG model offers an important breakthrough in the predictive modelling of Parkinson's disease since it integrates several features such as temporal flexibility, dynamic FoGRS computation, adaptive thresholding, enriched feature extraction, and multi-sensor configurations.

1. Introduction

The human society faces number of diseases in their lifespan, where some of them affect the quality of life and some of them are claiming the whole life. The medical practitioners suffer to identify and conclude the disease in many occasions. To support the medical practitioner, the

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decisive support systems are designed to provide recommendation for them. However, predicting the disease at the early stage would support the medical practitioner in providing effective treatment for the patients. The Parkinson disease is one among them, which appears on old age people due to neurodegenerative condition. Presence of PD introduces muscular rigidity, bradykinesia, sluggishness, and postural instability on their body which challenge the patient in performing regular activities with more comfortable way. However, FoG (Freeze of Gait) is the most dominant issue identified on the PD patients. This is a kind of mobility problem which make the people to get trouble on walking and leads to fall on ground. Presence of FoG or forthcoming FoG can be identified with the support of earlier traces. For any person, there will be specific momentum would require or some sort of acceleration would be required to proceed with the Gait movement. By monitoring the acceleration and he force produced by the person would be useful in predicting the FoG. However, it requires huge amount of data and by maintaining such huge volume of data, the presence of the FoG can be predicted. By predicting such FoG movement, then it can be alerted to provide enough support for the person. In this case, machine learning can be used as it has been used for variety of problems.

The deep learning models like CNN (Convolution neural network) [7] and LSTM (Long Short Term Memory) [6] has been used in several occasions to handle the problem. However, the method uses variety of features like plantar pressure, frequency features, and EEG features in predicting the possibility of FoG. Still the methods suffer to achieve higher performance in predicting FoG. However, the possibility of FoG can be identified by maintaining number of FoG pattern and by computing risk support towards various class of FoG. Also, the performance predicting FoG can be further improved by considering number of features like the plantar pressure, frequency features, EEG features, accelerating features, weight features and so on. By considering all these, a novel Time Orient Acceleration Gait Pattern Based FoG Prediction model (TOAGP-FoG) is presented in this paper.

To summary, this research proposes a completely new and extremely accurate Time Orient Acceleration Gait Pattern-based FoG prediction model (TOAGP-FoG) to address the limitations of existing methods for predicting Freeze of Gait (FoG) in patients with Parkinson's disease. By strategically positioning accelerometer sensors at different body joints and ankle placements, the simulation is able to gather extensive sensory data over a prolonged duration of different gait movements. The model is more relevant to the particular neurological condition when FoG-specific data integration is prioritised, yet accurate predictions are ensured by the integration of sophisticated deep learning algorithms. Further, the comparative performance for the proposed method, that illustrates greater precision in comparison to existing methodologies, clearly shows its value. By providing a novel approach that uses technology and data analytics to enhance the prediction of FoG in Parkinson's patients, this study makes a substantial contribution to the field and eventually improves patient outcomes and treatment quality. Its usefulness in tackling the complicated nature of Parkinson's disease is highlighted by its real-time capabilities, which further improve by the incorporation of data applicable to FoG and comparative performance analysis. This study aims to offer a practical and efficient solution for long-term monitoring, addressing challenges in FoG prediction accuracy, false ratio occurrences, and time complexity. The goal is to enable more reliable and timely interventions, positively impacting the lives of Parkinson's patients.

2. Related Works

There exists number of approaches around predicting FoG on PD patients. This section details some of them around the problem. A machine learning and walking pattern-based FoG prediction model is presented in [1], which records the pattern using wearable system to support the prediction.

The pressure data collected from various limbs and MAS are used towards predicting FoG in [2], which collect pressure data at various walking trials and frequency features. Based on them, FoG prediction is performed. An LSTM based neural network has been used towards predicting FoG in [3], which collects plantar pressure data to perform FoG prediction. A machine learning classifier is presented in [4], which collects sensor data from wearable system and generates walking patterns and velocity patterns to support FoG classification. A neural network based gait prediction model is presented in [5], where the multi-level perceptron model FGPuMLP, achieves lesser error compared to the logistic regression model. An LSTM based FoG episode prediction model is discussed in [6], which consider different features towards classification. A deep convolution based LSTM model COnv-LSTM is presented in [7], which classify the FoG under three classes according to the angular axes features obtained from spectrogram images. A detailed review on the problem of FoG prediction is presented in [8], which analyses the performance using various data sets.

The performance of various machine learning models like Random forest, SVM, gradient boosting, neural network and RBF are analyzed for their performance against various data sets in [9]. A machine learning model is presented in [10], which uses step-based impaired gait features and conventional FoG detection features to predict the FoG. The variations of gait complexity are recorded to predict the FoG in [11]. The method extracts 3 dimensional acceleration data and performs analysis on topological symptom to perform the task. A frequency analysis-based FoG detection model is presented in [12], where on body acceleration sensors are used to measure the movements of patients to detect FoG. An expert system is designed to classify gait patterns in [13], which computes pearson correlation measure to classify the patterns. The skin conductance and EEG signals are more important in classifying FoG pattern and an anomaly based algorithm is presented in [14] to classify the patterns.

A vision based FoG detection model is presented in [15], which generates a graph convolution neural network to produce directed graph from videos to perform classification. An auto regressive predictive model is presented in [16], which collects movement data from sensors to train the model. With the acceleration data, the method performs classification. An event based anomaly detection model is presented in [17], which extract relevant features and perform classification. A time varying auto regressive moving average model (TV-ARMA) is presented in [18], which computes time varying parameters to transform frequency domain to compute time-frequency spectrum and calculate the FI. A k nearest neighbour algorithm (K-NN) is presented in [19], towards classifying three class of events. A deep gait anomaly detector (DGAD) is presented in [20], which applies transfer learning to perform prediction. A continuous wavelet transform based scheme is presented in [21], which applies time frequency analysis to predict FoG. This study aims to offer a practical and efficient solution for long-term monitoring, addressing challenges in FoG prediction accuracy, false ratio occurrences, and time complexity [22-25]. The goal is to enable more reliable and timely interventions, positively impacting the lives of Parkinson's patients. The challenges mentioned in these works involve noise resiliency, selecting the best scale, meeting patient differences, and being practical in real time [26-27]. Gaining understanding of these difficulties is essential to improve continuous wavelet transform-based methods and widening the area of FoG prediction in Parkinson's disease research [28-30].

3. Proposed Prediction Model

The Time Orient Acceleration Gait pattern based FoG prediction model (TOAGP-FoG) model collects gait features through various accelerometer sensors attached at different ankle and joints of the body. The sensor signals are recorded at different gait movement in long term. The sensory signals recorded are generated into gait pattern and trains with deep neural network. The DNN designed has number of intermediate layers and the neurons are designed to measure FOG Risk Support (FoGRS) towards various gait movement. The FoG Risk Support is measured according to the movement forces produced by the patient for various gait movement in different time stamp and computes minimum gait force to be produced. Based on the FoGRS value, the neurons at the output layer produces different FoGRS value towards different classes. Based on the value of FoGRS, the method performs classification.

The working structure of proposed model is presented in Figure 1, which has been explained in detail in this part.

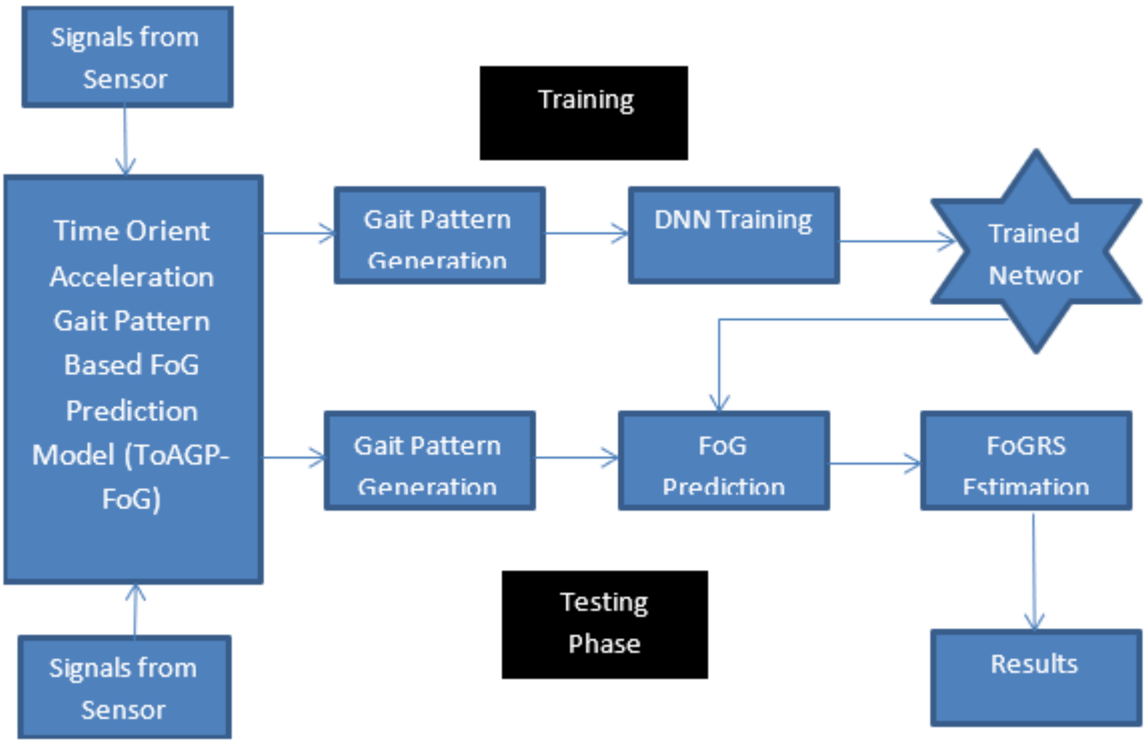

Fig. 1. Architecture of proposed model

3.1 Gait Pattern Generation

The proposed model monitors the gait accelerometer sensors connected with various limbs and knee of the person. From each sensor, the model reads the sensor signals and produces values of pressure, ankle movement, weight, ECG signals and so on. Such features are extracted and generates a Gait Pattern according to the features considered. The following are the features being considered for the gait pattern. Ankle pressure, knee pressure, spin pressure, ankle degree, knee degree, knee weight, ankle weight, blood pressure, pulse rate, limb pressure and so on. Such features are extracted and produced as a gait pattern. Such patterns generated are used to train the network and the same has been used to perform classification.

Gait Pattern Generation Algorithm:

Input: Sensor Signals Ses, Ecg signal Ec
Output: Gait pattern Gp.
Start
    Read Ses and Ec.
    Ankle pressure Ao = $AnklePressure \in ses$

knee pressure Kp = KneePressure ∈ ses
Spin pressure Sp = SpinPressure ∈ ses
Ankle degree Ad = AnkleDegree ∈ ses
Knee degree Kd = KneeDegree ∈ ses
Knee weight Kw = kneeweight ∈ ses
Ankle weight Aw = AnkleWeight ∈ ses
Blood pressure Bp = BloodPressure ∈ ses
Pulse Rate Pr = PulseRate ∈ ses
Limb Pressure Lpr = LimbPressure ∈ ses
Gp = {Ap, Kp, Sp, Ad, Kd, Kw, Aw, Bp, Pr, Lpr}
Stop

The Gait pattern generation algorithm extracts various feature from the sensors and Ecg signals to support FoG prediction.

3.2 DNN Training

The proposed model trains the deep neural network with number of intermediate layers. The pattern sets generated are read and for each patter, the method generates a neuron. The neurons are initialized with the pattern features and are designed to measure the risk support value. The neurons are designed to compute risk support on various class of features. The intermediate layers measure the risk support and pass to the other layer neurons. Finally, the output layer neurons measures the overall risk support towards various class produce the result to the user.

Algorithm for gait pattern with DNN:

```
Input: Gait pattern set Gps
Obtain: DNN.
Start
        Read Gps.
        Generate deep neural network DNN.
        For each pattern gp
                Generate a neuron N.
                Initialize N with pattern gp.
                For each intermediate layer l
                        Connect the neurons with others.
                End
        End
        For each layer l
                For each neuron N
                        Compute gait risk support Grs.
                        Pass to other layer neuron.
                End
        End
Stop
```

The deep neural network has been trained by the gait pattern generated by the model. For each pattern a neuron is generated and the network is trained to measure the risk support for the patterns and forward the value to the other layer neuron. The trained network is used to perform classification.

3.3 *FoG Prediction & FoGRS Estimation*

The proposed method performs FoG prediction by extracting the features and framing the gait pattern. The gait pattern generated is passed to the network trained. The neurons at the intermediate layer estimates FoG risk support towards various class of features. The FoG risk support represents how efficient the feature would influence the arrival of FoG on the patient. Accordingly, the method computes Ankle Risk support (ARS), Knee Risk Support (KRS), Limb Risk Support (LGS), Echo Risk support (ERS) and Spine Risk Support (SRS). Using all these measures, the method computes the value of FoGRS to support prediction. According to the value of FoGRS, the method classifies the class of gait as normal, pre fog and Fog.

Algorithm for *FoG Prediction & FoGRS Estimation*:
Input: Gait Pattern Gp, DNN
Obtain: Class C
Start
Read Gp, DNN.
Pass Gp to DNN
For each layer l
For each neuron n

Compute Ankle Risk support (ARS) = $\frac{\sum_{i=1}^{size(l)} Distl(i).Ap,Gp.ap)}{\sum_{i=1}^{size(l)} Distl(i).Aw,Gp.aw)} \times \frac{\sum_{i=1}^{size(l)} Distl(i).Ad,Gp.ad)}{No.of.Neurons}$

Compute Knee Risk Support (KRS) = $\frac{\sum_{i=1}^{size(l)} Distl(i).Kp,Gp.Kp)}{\sum_{i=1}^{size(l)} Distl(i).kw,Gp.kw)} \times \frac{\sum_{i=1}^{size(l)} Distl(i).Kd,Gp.Kd)}{No\ of\ neurons}$

Compute Limb Risk Support (LGS) = $\frac{\sum_{i=1}^{size(l)} Distl(i).Lp,Gp.Lp)}{\sum_{i=1}^{size(l)} Distl(i).Lw,Gp.Lw)} \times No.of.neurons$

Compute Spine Risk Support (SRS) = $\frac{\sum_{i=1}^{size(l)} Distl(i).Sp,Gp.Sp)}{\sum_{i=1}^{size(l)} Distl(i).Ad,Gp.ad)} \times No.of.neurons$

Compute Echo Risk Support (ERS) = $\frac{\sum_{i=1}^{size(l)} Distl(i).Bp,Gp.Bp)}{\sum_{i=1}^{size(l)} Distl(i).Pr,Gp.Pr)} \times No.of.neurons$

End
Compute FogRS = $\frac{ARS}{KRS} \times \frac{LGS}{SRS} \times ERS$
End
Class C = Choose the class with maximum FoGRS.
Stop

The FoG prediction algorithm computes FoG risk support towards various class of FoG and based on the value of FoGRS, the method identifies the class of the sample.

4. Results and Discussion

The proposed model has been hardcoded with python and has been evaluated for its performance under various constraints. The performance of the method has been measured and compared with others. This section details the results obtained and presents detail explanation on the results.

The experimental setup considered for the performance evaluation of the proposed model is presented in Table 1. The table provides details about the experimental setup for the research, outlining key factors related to the data set and the parameters used in the study. In short, a significant FoG data collection of 50,000 samples collected from 500 users make up the setup for the experiment. The paper deals with a multiple-class assignment where there are 3 different classes related to parameters connected to footfall or gait. These specifics offer a basis for understanding the scope, variety, and objectives of the research's investigations.

Table 1
Experimental setup

Key	Factor
Data set	FoG data set
Number of samples	50000
No of users	500
No of classes	3

The accuracy in predicting FoG in PD patients are measured and presented in Figure 2, where the TOAGP-FoG has produced higher results. The accuracy in predicting FoG in PD patients are measured and presented in Table 2, where the TOAGP-FoG has produced higher results. The table provides an analysis of Freezing of Gait (FoG) prediction accuracy for various methods used in the study. In summary, the table provides the ability to compare the precision of FoG predictions derived from different methods. According to the evaluation metrics utilised in the study, a techniques.

Table 2
Analysis on FoG prediction accuracy

Method	Value
FGPuMLP	73
Conv-LSTM	78
TV-MRNA	82
TOAGP-FoG	97

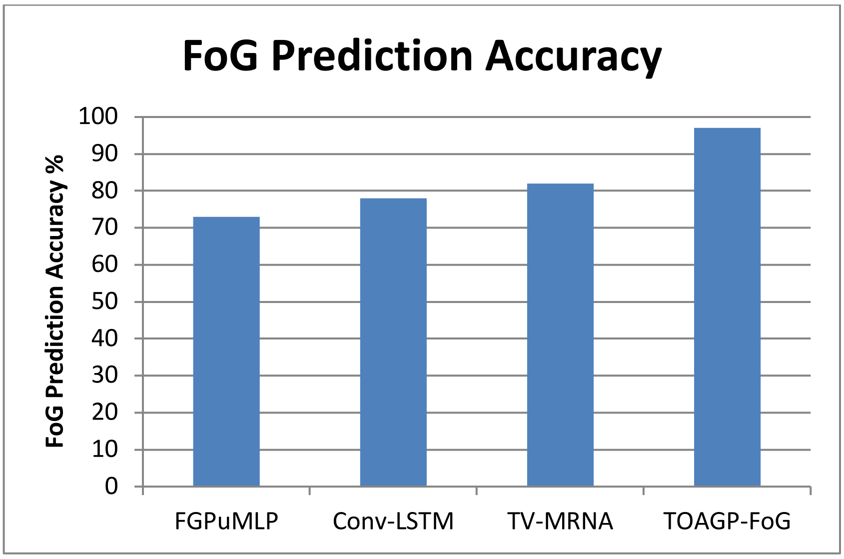

Fig. 2. Analysis on fog prediction accuracy

The false prediction ratio produced by different methods are analyzed and presented in Table 3, where TOAGP-FoG has produced less false prediction ratio than other.

Table 3
Analysis on false ratio in FoG

Method	Value
FGPuMLP	27
Conv-LSTM	22
TV-MRNA	18
TOAGP-FoG	3

The ratio of false prediction introduced by different methods is measured and presented in Figure 3, where the TOAGP-FoG has produced less false prediction compare to others.

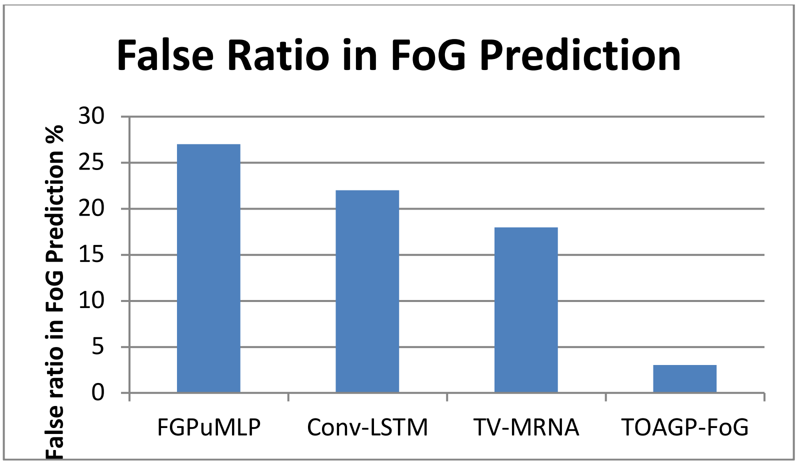

Fig. 3. Analysis on false ratio in FoG prediction

The table provides an analysis of the false ratio in Freezing of Gait (FoG) prediction for various methods used in the study. In summary, the table makes the ability to assess the false ratio in FoG prediction immediately between different methods. The method is more accurate in distinguishing between actual FoG events when the false ratio % is lower, indicating fewer incorrect predictions.

The time complexity of methods in predicting FoG has been measured and presented in Table 4, where TOAGP-FoG has produced less false prediction than others.

Table 4
Analysis on time complexity in FoG prediction

Method	Value
FGPuMLP	79
Conv-LSTM	72
TV-MRNA	65
TOAGP-FoG	32

The time complexity introduced by different methods is measured and presented in Figure 4, where the TOAGP-FoG has produced less time complexity compare to others. The table provides an analysis of the time complexity in Freezing of Gait (FoG) prediction for various methods used in the study. In summary, the table helps one quickly assess the false ratio in a FoG forecast while comparing different methods. When the false ratio% is smaller, indicating fewer inaccurate predictions, the method is more accurate in differentiating among real FoG events. Further, the temporal complexity plot shows TOAGP-FoG's computational effectiveness and shows it as a workable option for real-time FoG prediction. The achieved results, which show the accuracy, discriminative capacity, and computational efficiency of TOAGP-FoG in the challenging task of predicting Freezing of Gait in patients having Parkinson's disease, end the study and validate its efficacy.

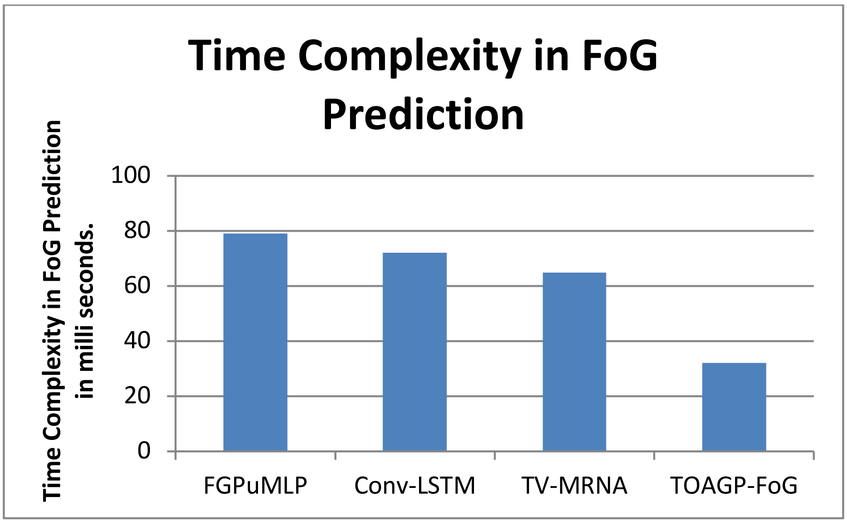

Fig. 4. Analysis on time complexity in FoG prediction

5. Conclusion

This paper presented a novel Time Orient Acceleration Gait pattern based FoG prediction model (TOAGP-FoG). The model collects gait features through various accelerometer sensors attached at different ankle and joints of the body. The sensor signals are recorded at different gait movement in long term. The sensory signals recorded are generated into gait pattern and trains with deep neural network. The DNN designed has number of intermediate layers and the neurons are designed to measure FOG Risk Support (FoGRS) towards various gait movement. The FoG Risk Support is measured according to the movement forces produced by the patient for various gait movement in different time stamp and computes minimum gait force to be produced. Based on the FoGRS value, the neurons at the output layer produces different FoGRS value towards different classes. Based on the value of FoGRS, the method performs classification. The proposed method improves the performance of FoG prediction up to 97% and time complexity up to 32 ms. However, it is essential to acknowledge potential demerits and areas for future work. Demerits and Future Work can be done across High Time Complexity, False Ratio Analysis, Long-term Monitoring Challenges and User Compliance. The future study must focus on improving the computational capability of the model, addressing the root cause for any incorrect forecasts, and confirming its effectiveness in scenarios that involve long-term monitoring. Implementing the suggested FoG prediction model in reality will require user-centered design and methods that enhance user compliance.

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