Machine Learning–Driven Prediction and Pattern Analysis of Sedentary Behavior in Adults for Preventive Health Monitoring

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Dr. A. Ambeth Raja
Associate Professor,PG & Research Department of Computer Science
Thiruthangal Nadar College, India

Mrs. D. Malathy
Research Scholar, PG & Research Department of Computer Science
Thiruthangal Nadar College, India

Dr. V. Devi
Professor, PG & Research Department of Computer Science
Thiruthangal Nadar College, India

Dr. K. Somasundaram
Head, Associate Professor, Department of Computer Application
Thiruthangal Nadar College, Chennai

Abstract

In terms of its implication on health in adults, sedentary behavior is widely reported as an associated risk factor of chronic diseases such as cardiovascular disease, obesity, metabolic problems and deterioration of mental health. Most conventional monitoring methods depend on self-reporting mechanisms which are often not precise in terms of temporal representation and susceptible to reporting bias. We present a machine learning based framework for the prediction of and modeling of patterns of adult sedentary behavior utilizing the data obtained from wearable sensors on activity and physiological metrics. Detailed preprocessing and feature engineering was applied to extract measures such as sedentary duration, transitions to and from physical activity, posture distribution, heart rate trends and indications of energy consumption. Five prediction models, including Logistic Regression, Random Forest, Support Vector Machine, Gradient Boosting and a deep learning based Long Short-Term Memory network, are trained and compared. To achieve robust and generalization accuracy, a weighted ensemble combination of Random Forest, Support Vector Machine and stacked LSTM predictions are further proposed. Based on stratified cross-validation experimentations, deep learning models outperformed classical classifiers significantly and stacked LSTM offered the best performance in modeling the temporal characteristic. In sum, the proposed ensemble framework demonstrated top performance in prediction and modeling (97.1% in accuracy, 96.5% in F1-score, 0.99 in AUC). The performance was consistent over various time segments throughout the day through temporal modeling and robust against the presence of noise and its impact in real world wearable applications. It is concluded that combination models offer highly accurate methods for identifying periods of prolonged sedentary behavior and for prediction of future risks.

Keywords: Sedentary Behaviour, Health, Machine Learning, Prediction

Introduction

Sedentary behavior—defined as a sitting or reclining waking behavior characterized by a low energy expenditure—is an increasingly prevalent issue of public health at the world level. The levels of sitting/reclining in adults have increased considerably and rapidly in the context of the urbanization, mechanization and a shift from manual labor occupations to office jobs. Chronic sitting/reclining is associated with several health problems including cardiovascular disease, obesity, type 2 diabetes, musculo-skeletal disorders and cognitive impairment. Further, accumulating evidence indicates that individuals that meet guidelines for physical activity in their daily life may still suffer from negative health outcomes associated with high duration of uninterrupted sedentary bouts [1, 4].

Traditional ways of monitoring behavior has primarily been using questionnaires or retrospective observation [4]. Such tools might give reasonable data but have issues like memory bias, impression and insufficient data. More recently, rapid increase in number of wearable devices, smart phones, and Internet of Things (IoT) devices has enabled collecting significant amount of physiology and other data for a long period [5, 8]. Such data can support various analytical methods for detailed observation, early detection of chronic inactivity and generating alerts.

Machine learning is becoming an attractive methodology for large and high dimensional data analysis, and the modeling of persistent and stubborn patterns of human behavior. Both supervised and unsupervised ML algorithms and deep learning methods such as Long Short-Term Memory (LSTM) neural network have been demonstrated to be suitable for predicting activity outcome, identifying anomaly of activity behavior and forecasting of activity trend [9, 12]. Based on the temporal, contextual and physiological status, ML based approaches can overcome existing limitations and produce recommendable results [13, 15].

In this study we propose a machine learning framework that predicts and studies recent patterns of sedentary behavior in adults. Its primary goal is to identify prolonged periods of sedentary behavior, investigate behavioral trends and forecast potential sedentary risks from physiological and activity features. The framework promises a scalability solution for continuous health monitoring and early intervention to mitigate sedentary risks.

Literature Review

Sedentary behaviour has been recognized as an important public health problem as a result of its strong relationship with physical and mental health outcomes. A meta-analysis showed that longer duration spent being sedentary has a high association with developing depression, heart problems and metabolic abnormalities [8]. Similar findings has also been demonstrated in relation to children and adolescents, where patterns of sedentary activity, in addition to sleep and physical activity were correlated with cognitive, psychosocial and social-emotional factors [5,6]. Dumuid et al. Also concluded that time-use equivalence of sedentary, physical activity and sleep behavior will aid the development of health promotion intervention and demonstrated the need of measuring distribution of daily activities in behavioral research [4]. These are evidence to suggest that continuous, reliable, objective monitoring of sedentary behavior is needed for adults, in order to develop health promotion strategy.

The application of ML techniques to activity and sedentary behavior research has allowed for more reliable detection, prediction and personalized interventions. An in-depth review on ML applied in activity, sleep and sedentary behavior research was conducted by Farrahi and Rostami; where it was demonstrated that both supervised and unsupervised ML models can learn significant patterns from high dimensional time series data [2]. Established ML models such as Random Forests, Support Vector Machines (SVM) and Gradient Boosting performed accurately in prediction for activity recognition. Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks are an excellent choice for deep learning architectures which can be leveraged in modeling sequential nature of daily activity.

Recently, several studies have also investigated deep learning (especially LSTM-based networks) for sedentary episode prediction for adults. Vibha et al. Have proposed a stacked LSTM network that can model intricate temporal behavior of inactivity and outperforms conventional ML classifiers [1]. Their model captures long inactive periods and switches between activity using sequential activity and physiological features. Papathomas et al. Have modeled daily steps to predict sedentary behavior, proving that supervised learning can capture the personal behavior patterns for a health-promoting context [3]. Both these works show that sequence-based modeling is particularly useful for describing both rapid changes in activity and longer-term patterns.

In addition to reporting measures of individual activity, inclusion of multi-dimensional data (physical activity, sleep, diet) has improved interpretability and prediction ability. Dumuid et al. Found that inclusion of time-use data over a daily period allows the discovery of an activity equivalence between activity, sedentary, and sleep behaviors [4] which is important for health assessments. Farrahi and Rostami also identified feature engineering (including time aggregation, activity intensity measures and contextual behavioural measures) as having a significant impact on ML model performance [2]. Use of multi-dimensional inputs allow the prediction models to be highly applicable for individually-tailored interventions.

In the field of healthcare, Machine learning has already yielded exciting possibilities for disease detection, risk stratification and the tailoring of intervention strategies [7]. A precise modeling of sedentariness will likely lead to real time monitoring, early warnings on prolonged periods of sedentariness and personalized behavioral interventions that counteract associated risks. This effort is consistent with the world-wide goal of establishing data-driven preventive health systems and demonstrates the translational utility of activity monitoring through wearable sensors combined with sophisticated prediction techniques on adult populations.

To conclude, the literature reviewed outlines a distinct research stream towards using ML approaches including deep learning models like stacked LSTM to predict and characterize sedentary behavior. Multi-dimensional activity, sleep and physiological information contribute to improve the accuracy of the prediction and develop interventions for preventing health-related problems. Nevertheless, the research is still lagging in characterizing individual variation, generalizing to diverse populations and considering behavioral and contextual factors of sitting time which this research aims to contribute.

Proposed Work

This work provides a machine learning based system that estimates and predicts the amount of sedentary activity for adults. This is based on an implementation of classical and deep learning algorithms using both activity and physiological data recorded from wearable sensors that are worn by the participants. The data includes steps count, body posture, heart rate, and metabolic expenditure. After extensive data cleaning and filtering, several key features such as sedentary sitting duration, pattern of transitions between rest and activity states and physiological features were chosen for building the input for multiple supervised machine learning algorithms such as Random Forest, Support Vector Machine, and a stacked LSTM network. To maximize the accuracy on the diverse weak learners, we use weighted ensemble learning to combine individual predictions. The system is aimed at detecting health risk signals of the individuals by examining prolonged sitting behaviors in a specific duration of time as well as predict the individuals' future behavior to promote preventive healthcare.

Dataset Description

For this study, adult sedentary behavior data were obtained from publicly available, validated sources to ensure transparency and reproducibility. The datasets include:

Daily Activity and Sedentary Behavior Dataset

- Source: Wearable devices (accelerometers, pedometers, smartwatches)
- Features: step counts, activity duration, posture classification, energy expenditure
- Sampling frequency: 1 Hz
- Participants: 250 adults aged 25–60
- Duration: 30 consecutive days of recording

Data Preprocessing Steps

- Missing Value Handling: Linear interpolation for missing activity or physiological readings.
- Normalization: Min–Max normalization to scale features between 0 and 1:
- Segmentation: Sliding window approach with 30-minute intervals to capture continuous sedentary behavior sequences.
- Labeling: Sedentary vs. active states derived from posture and step count thresholds (step count < 100 steps/30 min labeled as sedentary).

We proposed to use a combination of classic machine learning models, deep learning sequence models, and ensemble approach to predict sedentary behavior. The workflow consists of the following phases:

Phase 1: Feature Extraction

Key features extracted include:

1. **Temporal Features:**
- Duration of continuous sedentary periods ( )
- Frequency of activity transitions ( )
2. **Physiological Features:**
- Average heart rate ( )
- Energy expenditure (EE)
3. **Activity-Based Metrics:**
- Step count (SC)
- Posture distribution ( )

Feature vector for each time segment:

Phase 2: Machine Learning Models

Classical ML Models:

- Random Forest (RF): Ensemble of decision trees. Predicts sedentary class based on feature vectors

  where is the prediction from the decision tree.
- Support Vector Machine (SVM): Maximizes the margin between sedentary and active states:

$$\min_{w,b} \frac{1}{2} \| w \|^2 + C \sum_{i=1}^{N} \xi i$$

subject to

$$y_i(w \cdot X_i + b) \geq 1 - \xi i, \qquad \xi i \geq 0$$

Deep Learning Models (LSTM)

- Captures temporal dependencies in sequential sedentary behavior data.
- LSTM cell equations:

$$f_t = \sigma(W_f \cdot [h_{t-1}, X_t] + b_f)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, X_t] + b_i)$$

$$\ddot{C}_t = tanh(WC \cdot [h_{t-1}, X_t] + b_C)$$

$$C_t = f_t * C_{t-1} + i_t * \ddot{C}_t$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, X_t] + b_o)$$

$$h_t = o_t * tanh(C_t)$$

Where X_t is the feature vector at time h_t, is the hidden state, and C_t is the cell state.

Stacked LSTM Architecture

- Multiple LSTM layers stacked to capture higher-order temporal patterns in prolonged sedentary behavior.
- Output layer: sigmoid activation for binary classification (sedentary vs. active).

$$\hat{y} = \sigma(W_h \cdot h_T + b_h)$$

Phase 3: Ensemble Learning

- Combines predictions from RF, SVM, and stacked LSTM using a weighted voting mechanism:

$$y_{final} = argmax\left(\sum_{m=1}^{M} w_m \cdot y_m\right)$$

where is the weight of model m based on validation accuracy, and is the prediction of model m.

Results and Experimental Evaluation

Experiments were coded in Python 3.10 using Scikit-learn for classical machine learning and TensorFlow 2.12 for deep learning models. The dataset was divided into 70% training, 15% validation and 15% test sets, with stratified partitioning to avoid any bias. The segments are obtained by a 30 min sliding window to obtain a series of continuous sedentary behaviors. Cross-validation of 5 folds was applied to increase the reliability of the model. Optimal values for the hyper-parameters were determined by grid-search, as well as an adaptive learning rate scheduling algorithm.

The metrics for evaluation were Accuracy, Precision, Recall, F1-score, Area Under the ROC Curve (AUC), training time, and inference time.

Performance Evaluation of Individual Models

As reported in previous work, the prediction of sedentary activity performed better by learning models that rely on ensembles and temporal information than with the static classifier (Papathomas et al., 2021; Vibha et al., 2025). In view of this paper and Table 1 some of the ML and DL models are compared:

Table 1: Comprehensive Performance Comparison of Predictive Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC	Training Time (s)	Inference Time (ms)
Logistic Regression	84.2	82.6	80.9	81.7	0.86	4.8	1.2
K-Nearest Neighbors	86.1	84.9	83.7	84.3	0.88	3.5	2.8
Decision Tree	87.4	86.8	85.1	85.9	0.89	6.2	1.5
Random Forest	91.6	90.8	89.5	90.1	0.93	42.5	4.3
Support Vector Machine	90.3	89.1	88.4	88.7	0.92	35.6	3.9
Gradient Boosting	92.1	91.5	90.7	91.1	0.94	38.2	4.0
LSTM	93.4	92.8	92.1	92.4	0.95	310	6.8
Stacked LSTM	95.2	94.6	94.1	94.3	0.97	465	7.9

As observed from the results, complex ensemble classical models like Random Forest and Gradient Boosting are performing better than simple classifiers owing to their capacity to capture feature interactions and non-linearity as also demonstrated by Farrahi and Rostami (2024). The highest prediction accuracy is observed by deep learning techniques, in particular, stacked LSTM by virtue of its ability to model time dependency among sedentary sequences, as also indicated by Vibha et al. (2025).

Hybrid methods are known to increase the stability and robustness of the prediction for health analytics (Javaid et al., 2022). Hence a weighted ensemble of RF, SVM and stacked LSTM were used:

Table 2: Ensemble Model Performance Comparison

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC	Training Time (s)	Inference Time (ms)
Random Forest	91.6	90.8	89.5	90.1	0.93	42.5	4.3
Stacked LSTM	95.2	94.6	94.1	94.3	0.97	465	7.9
Proposed Ensemble	97.1	96.8	96.2	96.5	0.99	520	8.4

Table 2 shows that all the performance measurements obtained using ensemble model performed best and proves that the heterogeneous ensemble learning successfully balance bias and variance. Even though it takes more computation cost, high accuracy results make it the best model for the preventive health monitoring system.

Within time-use and behavioral health research there has been a focus on the temporal variability of sedentary behavior (Dumuid et al., 2022). The temporal reliability was examined by determining performance in separate time intervals throughout the day.

Table 3: Time-of-Day Sedentary Prediction Performance (Ensemble Model)

Time Period	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC	Avg Sedentary Duration (min)
Morning (6–12)	96.2	95.8	95.1	95.4	0.98	42
Afternoon (12–18)	96.8	96.4	95.9	96.1	0.98	58
Evening (18–24)	97.6	97.1	96.8	96.9	0.99	74
Night (0–6)	95.4	94.9	94.2	94.5	0.97	39

The evening epoch has the greatest extent of sedentariness. This is in line with studies showing associations between higher periods of inactivity and a greater risk of mental and metabolic disorders (Huang et al., 2020). The ensemble approach seems to have a uniform high predictive accuracy for all time segments.

Sensor noise and missing data, to which real-wearable systems are exposed, may also decrease the performance of models (Farrahi & Rostami, 2024). In order to assess robustness, noise was added in a controlled manner.

Table 4: Robustness Evaluation Under Sensor Noise

Noise Level	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC	Signal-to-Noise Ratio (dB)
0%	97.1	96.8	96.2	96.5	0.99	35
5%	95.9	95.3	94.8	95.0	0.98	28
10%	93.8	93.1	92.5	92.8	0.96	22
15%	91.2	90.4	89.9	90.1	0.94	18

It maintained excellent prediction power even under raising noise levels, shows promise for practical health monitoring in real environments (table 4).

Discussion

Machine learning techniques proved capable of modeling and predicting sedentariness in adults with high precision, with deep learning and ensemble-based classical models clearly outperforming standard classifiers. Standard models, such as Logistic Regression and K-Nearest Neighbors had mediocre accuracy levels, suggestive of their capacity to learn simple behavioral patterns, but not sufficiently capable of effectively modelling the inherent nonlinearity and temporal relations within sequences of sedentary activity. Combination of standard classifiers via ensemble learning, such as in Random Forest and Gradient Boosting models, led to significant increases in accuracy, consistent with trends found in related literature.

The above outstanding results of the LSTM and stacked LSTM models reveal that temporal modeling is crucial for sedentary behavior prediction. Models built on LSTM are capable to capture longer terms of inactivity trends, activity transitions and the accumulation of sedentary behavior over time in contrast to static classifiers. The results agree strongly with the latest study of Vibha et al. (2025) where stacked LSTMs beat conventional models due to learning hierarchical representations of activities through time. The results further prove sedentary behavior is a temporal and memory dependent nature.

The presented weighted ensemble model demonstrated the best accuracy and robustness over all experimental settings. Ensemble of Random Forest, Support Vector Machine, and stacked LSTM outputs allowed the combined model to simultaneously decrease the bias and variance, thereby providing constant enhancements for precision, recall, and AUC values. This is in line with recent machine learning in health research work that highlighted the benefits of hybridization for better generalization and trustworthiness (Javaid et al., 2022). This slight rise in computational cost seems an appropriate trade-off to the huge improvements obtained. The results make this model suitable for a real time prevention health monitor.

A further examination of temporal patterns revealed marked variations in sedentary behavior throughout different times of the day. In general, evening hours showed the longest bout duration and the greatest predictability. These patterns align with behavioral health literature demonstrating associations between long inactive periods at night with depression and metabolic disease (Huang et al., 2020). The ensemble model exhibited good performance across all time segments and showed its robustness to shifting lifestyle behaviors and continued monitoring system usability.

We also conducted some robustness tests to evaluate the performance of the proposed framework under normal sensor noise conditions. As the noise level increases the accuracy of the classification gradually decreases. The ensemble model however maintained a considerable classification accuracy and discriminative ability, implying good performance under the inherent imperfection of sensor data typical for health monitoring wearable devices. The importance of robustness to issues such as missing values, signal drift, device variability becomes important in wide-scale deployment in real-world conditions.

From a perspective of preventative health care, the prediction of long sitting bouts and sedentary risks, allow for a better application of behavioural interventions, personalized feedback and adaptable health advice. With the ability to turn wearable data into a personalized health message the described machine learning solution helps people manage their life proactively and minimize the risk associated with sitting-related chronic diseases.

Conclusion

This paper suggested a machine learning, based solution for preventive health monitoring of sedentary behavior in adults. The use of classical and deep learning methods for prediction and pattern recognition of sedentary behavior was discussed. It has been observed that the ensemble based classical models performed much better than simple classifiers in sedentary behavior prediction. Among deep learning models, the proposed stacked LSTM networks, deep learning model was found to achieve best results in sedentary time prediction.

We further proposed the weighted ensemble framework composed by Random Forest, Support Vector Machine and stacked LSTM models was able to offer the higher stable and generalization ability of prediction with the highest performance among all metrics. The time and wise analysis results suggested the model stability on different period of a day and robustness analysis illustrated the model was capable of tolerating sensor noise, hence, suitable for wearable environments. These findings confirmed hybrid machine learning approaches had a potential to be scalability framework for the long- term monitoring in daily life. As a preventive healthcare problem, the continued detection of episodes and the risk prediction of inactivity could not only promote early interventions and customized lifestyle advice, but also lead to intelligent lifestyle regulation. The presented framework will push the development of intelligent health analytics, where massive wearabe data will be utilized for acquiring behavioral intelligence. Further researches are intended to investigate the inclusion of contextual information, such as population load, environmental status and individual emotion, for refining prediction performance and to deploy the model on mobile/edge devices for real time monitoring and health feedback.

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