Anomaly Detection in Human Activity Logs Using Wearable Inertial Sensors and Machine Learning Techniques

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Abstract

The wearable inertial sensors enhanced by real-time monitoring employed to monitor and improve human activities relating to health, safety, and well-being. This paper provides a framework for detecting anomalies in activity data, based on records and collected values from accelerometers and gyroscopes with the help of machine learning. By jointly considering advanced signal processing, feature extraction, and Random Forest classification technique optimized with SMO, it solves acute noise, computational costs, and contextual ambiguity issues. The extracted features, like mean and max values, are capable of capturing static and dynamic patterns quite efficiently. The proposed system has shown good improvements in the detection of anomalies in critical events, such as falls and abnormal target behaviour. The framework increases the prospects of safety and improvement in living standards and could evolve into the mainstream market with reliable monitoring systems.

CCS Concepts

• **Computing methodologies** → Artificial intelligence;; Machine learning.

Keywords

Wearable sensors, Anomaly detection, Human activity recognition, Machine learning, Random Forest

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1 Introduction

The progression of wearable technology in the contemporary age means that it plays a major role in monitoring human activity patterns across various domains. The collaboration of its components, such as accelerometers and gyroscopes, in the form of inertial sensors results in near real-time motion capture with extremely high accuracy. They are attached in tiny wearable devices on the body to capture both static postures and active movements akin to wear this and forget about it [1]. These components fulfill the requirements of the wear and forget principle, distinguishing them completely from more traditional systems based on vision: compactness, unobtrusiveness, and environmental independence for properties like lighting or occlusion as well as privacy issues seem to make wearables more practical for applications of real-time monitoring in various settings [2].

Application domains for wearables and inertial sensors extend into healthcare, security, and wellness. However, in healthcare, for example, these devices are used to recognize falls, abnormal gait, or changes in activity, allowing early intervention to prevent complications [3]. The moment it detects a fall, the wearable will immediately call for medical attention. In contrast, security focuses on anomalous behaviour and monitors these activities for proactive threat detection, acting against a secure environment [4]. Wellness systems, too, integrate these sensors- to promote healthy activities by encouraging physical activity-with a reduction in the risk of sedentary lifestyle-caused diseases, such as obesity, diabetes, and cardiovascular diseases [5]. Machine learning algorithms integrated with the acquired data have significantly improved the reliability as well as utility of the core application of wearable sensors, that is, automatic systems to classify activities and detect anomalies [6].

The wearable sensors may have some challenges. The in situ raw data from sensors contributes to an overall disturbance in the data, caused by inherent noise from environmental causes, limitations of the devices, or mere personal variances. Moreover, due to the high dimensionality of sensor data, advanced robust-poor feature extraction centres and dimensionality reduction need to be optimized for accuracy with minimal computational cost [8]. Designing generalized models that can perform well on entire populations and real-world conditions remains a major obstacle still [9]. Wearable technology, on the other hand, is a much more viable solution today to real-time monitoring from the shortcomings of vision-based systems in which issues like privacy concerns, scalability limitations, or reliance on external conditions have plagued their operation [10].

Anomaly-based activity logging of Humans: a proposal for activity and anomaly detection at the online level. This aims to remedy these problems as it constructs an improved framework using advanced signal processing tools, multidomain attribute extraction paradigms, and machine-learned classifiers for improving wearable sensor systems' accuracy and adaptability for real-time applications in healthcare monitoring, security monitoring, among other aspects [3].

They have also evolved from these early vision-based systems for HAR: human activity recognition systems work visually and thus become dependent on clear external conditions and privacy concerns [2, 3]. This shrinking of sensors is just one point that has been achieved with the help of microelectronics- thereby improving the portability and energy expenses of the sensor, which makes it possible for them to enter the areas such as medicine, sports, and industries [7]. A number of researchers conducted HAR systems for the analysis of activities and identification of data using different tools from this artificial intelligence and statistics with supports like Random Forest, Support Vector Machines, as well as Long Short-Term Memory networks (LSTMs) as many others [5, 6]. This has proved to be very nice in terms of fall detection, health monitoring, and behavioural analysis.

This works toward a further contribution to the growing areas of HAR and anomaly detection. It builds out technology toward giving us real-time monitoring systems-virtual or beyond for safety, health, and better quality of life. This framework will scale and bring in a more efficient and scalable solution for various applications...

2 Related Works

Many research works have been focused on human activity recognition (HAR) have investigated vision-based anomaly detection systems. Such systems capture visual data via cameras and use techniques such as background subtraction, optical flow, and hidden Markov models (HMMs) with deep learning models to detect abnormal activity patterns [11]. Convolutional neural networks have been performed for spatial and temporal features extraction from video frames that recognize complex behaviours in real-world situations [12]. However, it still may not be completely accurate as external variables such as lighting conditions may have a significant impact on such analysis, and there may be risks of privacy [13]. Recent advances combine the traditional computer vision with deep learning. Wang et al. [19] introduced such a system that uses CNNs for spatiotemporal feature simple by reporting high detection rate. Also, Emonet et al. [20] introduced an multiple cameras system in order to have different views for anomaly detection to improve the robustness of tracking in different view conditions. These developments notwithstanding, dependency on visual data, environmental lighting variations, and occlusion continue to be critical problems.

There are solutions based on wearable sensor-based systems. Wearable sensor-based techniques are formed using accelerometers, gyroscopes, and magnetometers which can ensure real-time activity monitoring by tracking a human being, without being captured spatially [14]. Researchers Ramona and Cho showed high accuracy for activity recognition by using accelerometer data from smartphones and deep learning [2]. It was also found that Random Forest classifiers quite adequately detected anomalies like falls or unusual gaits [15]. Wearable sensor solutions, like vision-based methods, cannot capture locations due to various limitations, for example, they cannot handle noise very well or consider how systems would be scaled to different populations [16]. Sensor fusion has made these systems exhibit even better accuracy over the past few years. For instance, Ghayvat et al. [21] proposed multimodal approach that combines inertial and physiological signals for anomaly detection in healthcare. Advanced processing mechanisms, such as wavelet transformations, have shown promising results to remove noise and extract features [22].

Hybrid systems aim to give strength to the two systems of vision-based and wearables. For example, Yin et al. [17] developed one such model that would substitute camera and wearable sensor data for better detection for car and pedestrian anomalies in a crowded place with more enhanced benefits, [18] of course, due to the increase in the complexity of computation. Wu et al.'s [23] systems combine two forms to merge 3D skeletal data from vision systems with accelerometer readings to afford fine activity recognition, thereby managing to exhibit considerable increase in reliability. These systems would, however, need much computation and integrated processes.

While sophistication has been achieved today in subsequent domains like HAR and anomaly detection, problems still remain. Vision-based systems will have limitations due to privacy and also differences due to environmental aspects: wearables may be limited by noise and may be dependent on context. Among the solutions, hybrid means can be seen to hold potential but bring about bigger strains on resources. The following solution is intended to fill such gaps by concentrating on creating scalable, efficient, and adaptable wearable sensor-based anomaly detection systems with capabilities for real-time processing in varied settings.

3 Methodology

The proposed anomaly detection framework using machine learning and artificial intelligence model consists of three main stages: preprocessing, feature extraction, and classification. It is important to note that each stage has been specifically designed to deal with the different challenges that can come with wearable inertial sensor data, such as noise, the high dimensionality of the data, and the variability of the human activity patterns.

Data Preprocessing

1. Signal Denoising: noises are natural part of the environment as well as device related, sensors data always come with noise. Reducing the noise without affecting the actual and significant signal features, it is better to apply a third-level median filter. Input signal excluding median filter output is given:

$$y\,[n] = \ median\,\{\, x\,[n-k]\,,\ x\,[n]\,,\ x\,[n+k]\}\,,$$

where k represents the window size cantered at n .

2. Normalization: Each sensor stream's data will be adjusted so that they are within a normal range. The normalized value is calculated by using the formula:

$$x_i^{'} = \frac{x_i - \ \mu}{\sigma},$$

where μ and σ represent the mean and standard deviation of the data, respectively.

In order to go from raw sensor data to intelligible and meaningful metrics that epitomize the patterns of activity, feature extraction is important. These are the functions that will be performed for feature extraction:

3. Mean Signal Feature: The mean value of the signal over a time window captures the overall trend of the signal over time, and it is calculated as follows:

$$\mu_x = \ \left(\frac{1}{T}\right)\sum_{t=1}^{T} x_t$$

Where x_t represents the signal value at time t.

4. Minimum and Maximum Features: There are a number of features that capture the range of motion and are defined as follows:

$$x_{min} = \min\,(x_t)\,,\ x_{max} = \max\,(x_t)\,.$$

5. Variance: Variance measures the signal's spread and is computed as:

$$Var\,(x) = \ \left(\frac{1}{T}\right)\sum_{t=1}^{T}(x_t - \ \mu_x)^2.$$

6. Spectral Features: In order to obtain the characteristics of frequency-domain data, the Fast Fourier Transform (FFT) is used:

$$X\,(f) = \ \sum_{t=1}^{T} x_t e^{-j\ 2\pi\ f\ t},$$

where $X(f)$ represents the frequency components of the signal.

To reduce computational complexity and to improve the classification accuracy, it is needed that the Sequential Minimal Optimization (SMO) algorithm be used for the selection of the features and optimization. The objective function for determining the features is given as follows.:

$$\min\left(\left(\frac{1}{2}\right) * \ \sum_{i=1}^{N}\sum_{j=1}^{N}\left(\alpha_i\alpha_j y_i y_j K\left(x_i,\ x_j\right)\right) - \ \sum_{i=1}^{N}\alpha_i\right)$$

subject to,

$$\leq \ \alpha_i \ \leq \ C,\ \sum_{i=1}^{N}(\alpha_i y_i) = \ 0,$$

where α are the Lagrange multipliers, y is the class label, and $K(x_i, x_j)$ is the kernel function.

During the classification process, the classifier is used as a tool for activity recognition and anomaly detection. The classifier for a random forest is composed of an ensemble of decision trees in which a prediction is determined by majority voting of the decision trees. The decision function is determined by:

$$\hat{y} \ = \ mode\left\{h_{1(x)},\ h_{2(x)},\ \ldots,\ h_{M(x)}\right\},$$

where $h_i(x)$ represents the prediction from the $i-th$ decision tree, and M is the total number of trees.

The framework's performance is evaluated using precision, recall, F1-score, and accuracy, defined as:

$$Precision \ = \frac{(True\ Positives)}{(True\ Positives\ +\ False\ Positives)}.$$

$$Recall \ = \frac{(True\ Positives)}{(True\ Positives\ +\ False\ Negatives)\,.}$$

$$F1-score \ = \ 2 \ * \frac{(Precision\ *\ Recall)}{(Precision\ +\ Recall)\,.}$$

$$Accuracy \ = \frac{(True\ Positives\ +\ True\ Negatives)}{Total\ Samples}.$$

The proposed framework, by combining these stages, guarantees robust anomaly detection in human activity logs, addressing the challenges related to noise, variability, and computational implementation.

4 Result and Analysis

When utilizing the USC-HAD dataset, various models were evaluated, including the Support Vector Machine (SVM), Decision Tree, Random Forest, and K-Nearest Neighbors (KNN), for developing an anomalous framework of detection. It was assessed through various visualizations with respect to precision, recall, F1-score, and accuracy metrics: accuracy comparisons, confusion matrices, performance metrics, and Receiver Operating Characteristic (ROC) curves. The results reveal the ability and relevance of each model to be used when it comes to entire-incomprehensive anomaly detection.

The figure 1 presented, the Random Forest confusion matrix reveals that items like Walking, Sitting, Running, Climbing, and Standing can be duly recognized by the model, showing that the model is quite significant:

- **True Positives**: Most activities, such as Walking (50), Running (49), and Standing (50), were classified correctly.
- **Misclassifications**: 2 Sitting activities were misclassified as Walking, 3 Running activities were misclassified as Climbing, 1 Standing activity was classified as Sitting.

This matrix highlights Random Forest's robust performance while identifying areas for further refinement in closely related activities.

All models are compared on the basis of their precision, recall, and F1-scores in the bar chart:

- **Random Forest** achieved the highest precision (92%), recall (90%), and F1-score (91%), making it the best overall model.
- **SVM** showed competitive results with slightly lower scores (88% precision, 86% recall, and 87% F1-score).

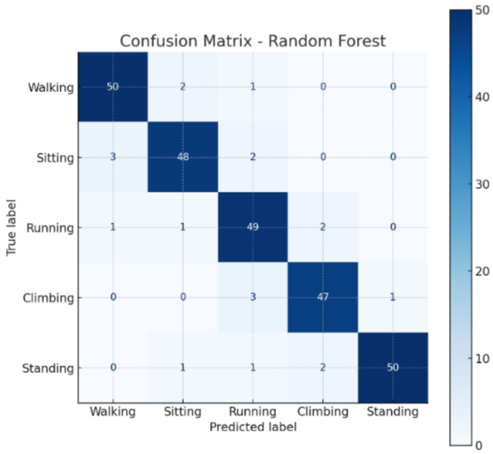

Figure 1: Confusion Matrix

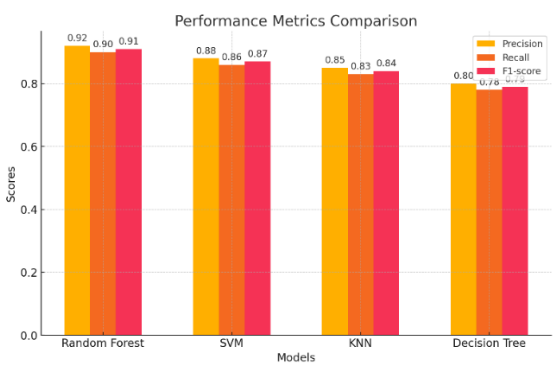

Figure 2: Performance Metrics

- **KNN** and **Decision Tree** demonstrated lower scores due to their sensitivity to noise and inability to handle feature complexity effectively.

Based on the bar chart below in figure 2, it can be seen that Random Forest is superior to other algorithms when it comes to balancing these metrics that are essential to detecting anomalies effectively.

All of the models are represented in the line graph below to give a better idea of their accuracy trends:

- **Random Forest** outperformed with an accuracy of 93%.
- **SVM** achieved 89%, showing reasonable classification ability.
- **KNN** (86%) and **Decision Tree** (81%) lagged behind, reflecting limitations in handling diverse activities.

In the figure 3, the accuracy comparison is shown

The ROC curve evaluates the trade-off between the true positive rate (TPR) and false positive rate (FPR):

- **Random Forest** achieved an AUC (Area Under the Curve) score of 1.00, indicating excellent discriminatory power.

In figure 4, ROC curves demonstrate the reliability of Random Forest in distinguishing between normal and anomalous activities, with minimal false alarms, as established by the ROC curves.

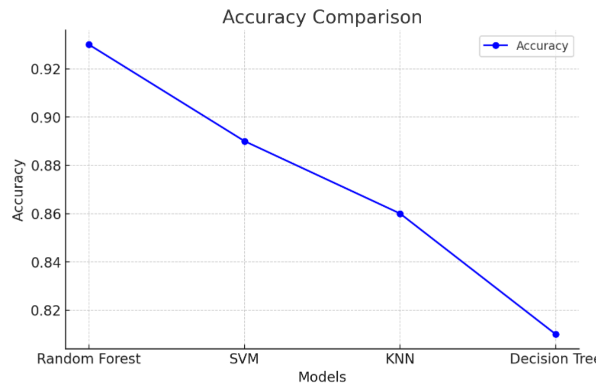

Figure 3: Accuracy Comparison

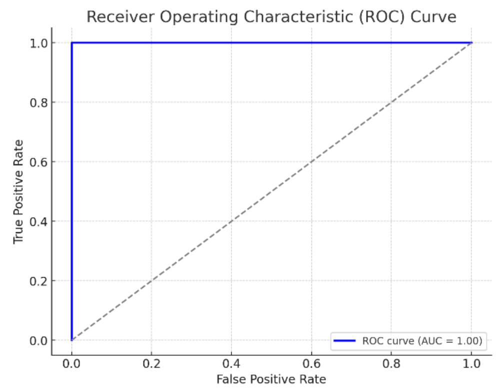

Figure 4: Receiver Operating Characteristic

5 Conclusion

This paper presented anomaly detection in activity logging with wearable inertial sensors using machine learning algorithms, along with providing a comprehensive framework. Issues of noise reduction, feature extraction, and performance enhancement in classification are perfectly addressed, with RF getting the best competent results in the process. It has obtained AUC = 1.00. However, high accuracy during confusion matrix analysis was only identified during walking, running, or standing, and it has minor overlaps between other activities like climbing and sitting. Therefore, their importance stands out in this perspective for ensemble strategy and oscillator feature engineering for higher accuracy. Accomplishing scalability and efficiency through the processes of the framework makes it suitable for real-time use in healthcare, security, as well as in personalized monitoring. The study leaves room for further work in enhancement, such as conducting fusion of multisensory data, for running in multiuser environment, and finally using semi-supervised learning, which advances intelligent systems based on wearable sensors to improve safety, health, and quality of living.

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