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Fall and Normal Activity Classification via Multiple Wearable Sensors

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***Abstract*—A fall detection and classification system is crucial for reducing the severe consequences of falls, which account for the leading cause of accidents on construction sites. Wearable sensors are one of the technologies used to detect falls. Although much academic work has been dedicated to the study of this class of systems, little attention has been paid to the evaluation of simpler algorithms prior to training on complex ones. This study utilizes the open-source UP Fall Detection Dataset and proposes that effective data processing and simpler baseline models give better results for fall-direction classification. Several data-processing techniques like windowing and filtering are used prior to using simpler baseline models like Neural Network (NN), K-Nearest Neighbor (kNN), Support Vector Machine (SVM), Naïve Bayes (NB) and Discriminant Analysis (DA) Classifiers. It is also investigated how to minimize multisensor cost while achieving acceptable detection accuracy. Based on this robustness analysis, fine kNN and wide NN yield 99.5% accuracy for all five wearable sensors. In comparison, using the best of these sensors (belt and pocket) results in 99% accuracy, with accuracy of all 11 individual activities exceeding 93%. The findings of this study bode well for the development of real-world fall-prediction systems as they enable accurate fall direction identification.**

Keywords—fall detection, wearable sensors, machine learning, construction safety

I. Introduction

Falling is often dangerous and could cause serious injury or even death if medical attention is not provided promptly. Fall monitoring systems with reliable and effective fall-prevention features would reduce the incidence of serious fall-related injuries and improve quality of life for those in the fall risk group. Although falls can be detected and classified in many different areas, the construction industry has especially high fall-accident-related workplace safety hazards due to the confined and complex work environment [1–3]. It has been found that a considerable amount of academic and commercial work has been concentrated on identifying fall events as accurate and fast as possible [4,5].

Over the last few decades, sensor-based technology has been widely used to monitor workers' safety and health [11], [12], as well as identify various activities [13,14], and the protective equipment (PPE) they wear [6,7], such as hard hats [8,9], and safety hooks [10]. Sensors are primarily used in studies related to FFH safety in order to identify unsafe behavior and prevent FFH injuries [15–17]. These sensors can also detect workers' movements and body postures [3,13]. Three major factors were taken into account by Yang et al. [14]: recognizing unsafe behaviors, processing data, and recognizing actions. Workers' unsafe behaviors reported by them that led to accidents were initially classified. While performing the lab experiment, they attached the sensor to the workers' bodies (waist) to collect data about their movement (acceleration and angular velocity). With the accelerometer data extracted, the support vector machine (SVM) methodology was used to predict (classify) the unsafe behavior of the worker. Nevertheless, the system's accuracy was 98.6% for predicting unsafe behaviors and 60.96% for predicting safe behaviors. The predictor system did not perform well when predicting behaviors associated with movements outside the training set because movements are highly complex and unpredictable at the site.

Numerous wearable sensors-based datasets have been proposed for fall and normal action detection. [18] uses DLR dataset collected from an IMU accelerometer attached to a belt to detect falls and normal activities using Bayesian analysis. Consequently, it achieves 100% recall and 80% precision. [19] uses MobiFall dataset collected from smartphone inertial sensors in trouser pockets to detect various fall directions and normal actions using kNN, which yielded fall detection and classification accuracy of 99% and 83%, respectively. Vilarinho e al. [20] uses smartphone and smartwatch inertial data to classify 12 types of falls with an accuracy of 68%. Using accelerometers worn in two pockets on two smartphones, the tFall dataset in [21] is used to classify eight types of falls with an accuracy of 95%. Using 5 wearable IMU sensors' data, [22] proposes a large-scale UP Fall Detection dataset whose statistical features are extracted to achieve accuracy and precision of 95% and 74%.

This study uses UP Fall Detection dataset and proposes a stable tilt angle-based data-processing approach, resulting in a significant increase in detection accuracy to 99.5%.

II. Dataset Overview

This study uses benchmark UP Fall Detection dataset [22] for sensing the normal and fall activities using wearables. The data is collected in controlled laboratory room. Five Mbientlab MetaSensor wearable sensors are used to collect raw data from the 3-axis accelerometer and the 3-axis gyroscope. These wearables are located in the left wrist, under the neck, at right pocket of pants, at the middle of waist (in the belt), and in the left ankle, as shown in Fig. 1. The sensor position has always been a challenge in fall detection and human activity recognition. According to [23,24], waist, thigh (pocket), wrist, chest, foot are the preferred locations for accelerometers and accelerometers embedded in smart devices. The IMU in the left wrist simulates that the participant is wearing a smart watch. Whereas the IMU in the right pocket simulates the place for wearing a smart phone. The sensor positions are chosen considering a right-handed person. The raw data of 3-axis accelerometer and 3-axis gyroscope is acquired corresponding to the activities shown in Table I.

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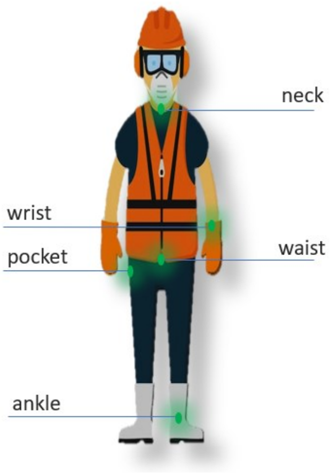

Fig. 1. Position of 5 wearable sensors on workers' body

TABLE I. LIST OF ACTIVITIES PERFORMED BY SUBJECTS WEARING 5 WEARABLE SENSORS

Activity ID	Description	Duration (seconds)
1	Falling forward using hands	10
2	Falling forward using knees	10
3	Falling backwards	10
4	Falling sidewards	10
5	Falling while sitting	10
6	Walking	60
7	Standing	60
8	Sitting	60
9	Picking up an object	10
10	Jumping	30
11	Laying	60

III. DATASET PROCESSING

The methodology of worker activity recognition adapted on IoT sensor data comprises of five steps: 1) data acquisition, 2) window selection 3) feature extraction, 4) feature selection and 5) machine learning (ML) based classification. Detailed description of these steps is presented in this section.

A. Data Acquisition

The data acquired in UP Fall Detection dataset is from 6-axis IMU sensors synchronized for 11 activities performed by 17 healthy individuals, each making three attempts. The raw data of 3-axis accelerometer and 3-axis gyroscope is acquired corresponding to the activities shown in Table I.

B. Window Selection

To learn the temporal features of the raw data signals of IMU sensor, features are extracted from data of different window sizes. Windows of one, two and three seconds are chosen to analyze the accuracy of fall detection system. The data size is varied as per different window and overlapping settings as shown in Table II.

TABLE II. WEARABLE SENSORS DATA SIZE CORRESPONDING TO DIFFERENT DATA WINDOWING

Window Size (seconds)	Number of Data Samples
0	294678
1	68680
2	67147
3	65604

C. Feature Extraction

The accelerometer exhibits a high pitch on a small-scale movement owing to the noise while recording the data. Therefore, noise in the data is suppressed by using a low pass filter and a complimentary filter. The raw data signals within a certain window and overlapping setting are processed to obtain stable and compensated values. The raw data is as follows:

1. Measurement of acceleration along the x-, y-, and z-axes by the accelerometer (acc_x, acc_y, acc_z). In the z-axis direction, the acceleration data reflect the acceleration due to gravity (+9.8 m/s2).
2. Measurement of angular velocity along x- and y-axes with a gyroscope ($gyro_x$, $gyro_y$). When rotating counterclockwise around an axis, angular velocity is positive.

These raw signals are processed as follows:

1. The accelerometer's roll angle between z- and x-axes (also referred to as theta θ) in degrees, given by the following equation:

$$\Theta_{acc} = \frac{-atan2\left(\frac{acc_x}{9.8}, \frac{acc_z}{9.8}\right)}{2\pi} \times 360 \tag{1}$$

2. The accelerometer's pitch angle between z- and y-axes (also referred to as phi φ) in degrees, given by the following equation:

$$\Phi_{acc} = \frac{-atan2\left(\frac{acc_y}{9.8}, \frac{acc_z}{9.8}\right)}{2\pi} \times 360 \tag{2}$$

3. Processed roll and pitch from the low pass filter, given by the following equations:

$$\Theta_{lp}(t) = \left(0.95 \times \Theta_{lp}(t-1)\right) + \left(0.05 \times \Theta_{acc}(t)\right) \tag{3}$$

$$\Phi_{lp}(t) = \left(0.95 \times \Phi_{lp}(t-1)\right) + \left(0.05 \times \Phi_{acc}(t)\right) \tag{4}$$

4. Based on accelerometer and gyro measurements and the complementary filter, the tilt angle data is used to generate a quick and relatively vibrational-free response from the design system.

$$\Theta_{comp}(t) = \left(\Theta_{comp}(t-1) + gyro_y(t) \times dt\right) \times 0.95 + (\Theta_{acc} \times 0.05) \tag{5}$$

$$\Phi_{comp}(t) = \left(\Phi_{comp}(t-1) - gyro_x(t) \times dt\right) \times 0.95 + (\Phi_{acc} \times 0.05) \tag{6}$$

The features computed in (3), (4), (5) and (6) are used for further training ML classifiers on workers' wearable sensors data. A machine learning model is then trained or tested using the extracted data features.

D. Feature Selection

ML models are trained by identifying the characteristics that separate the classes. To achieve high accuracy, this allows for the inclusion or exclusion of features. The accuracy of processed features was found to be higher than the accuracy of raw data. Both raw and processed features were used to train the model and to compare the evaluation metrics.

E. ML Classification

The machine learning (ML) models are trained on processed IMU data of fall & normal human activities, to make real-time predictions. Several classification models are trained with labeled data that contains ground truth before this classification and activity recognition task can be performed. The dataset is divided into two parts for training and validation in a 70:30 ratio.

Existing research studies suggest that simpler learning models should be tried first before choosing a complex model for training so that there is a baseline for assessing performance. Furthermore, complex models are more likely to over-fit and consume a lot of resources [25]. Occam's razor [26] dictates that the simpler of the two methods is preferable if performance is similar between them. Therefore, simpler and common supervised machine learning classification algorithms are trained, which are listed as under:

1. Neural Network Classifiers [27]
2. k-Nearest Neighbor Classifiers [28]
3. Support Vector Machine Classifiers [29]
4. Naïve Bayes Classifiers [30]
5. Discriminant Analysis Classifiers [31]

IV. Results

A. Evaluation Metrics

In this study, ML-based trained models are evaluated on the IoT data of wearable devices and are evaluated according to (7), (8), (9), (10) and (11) scores of recall, accuracy, precision, false-negative rate, and false discovery rate. The testing partition of the dataset demonstrates high accuracy. This is because the trend of tilt angle variation is distinctive in each class of various normal and fall relation activities. Hence, this distinction in features of safe and unsafe behavior results in high accuracy of the fall classification system.

$$TruePositiveRate(TPR)\ or\ Recall = \frac{TP}{TP+FN} \tag{7}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{8}$$

$$PositivePredictiveValue(PPV)\ or\ Precision = \frac{TP}{TP+FP} \tag{9}$$

$$FalseNegativeRate(FNR) = \frac{FN}{TP+FN} \tag{10}$$

$$FalseDiscoveryRate(FDR) = \frac{FP}{TP+FP} \tag{11}$$

In these formulas, TP denotes True Positive, FN denotes False Negative, FP denotes False Positive, and TN denotes True Negative.

B. Evaluation Results

The accuracy achieved on the 5 wearable sensors data corresponding to window size of 1-, 2- and 3-seconds is shown in the Table III. The results indicate that in most of the models accuracy increases when window size increases. The highest accuracy in less time on all 5 wearable sensors data is 99.5% achieved from wide neural network model, which stays same even if the window size is increased.

TABLE III. ACCURACY ON THE COMBINED 5 WEARABLE SENSORS DATA CORRESPONDING TO WINDOW SIZE OF 1-, 2- AND 3-SECONDS

Model	**Accuracy**		
	Ankle + Neck + Pocket + Belt + Wrist		
	1 sec	**2 sec**	**3 sec**
Neural Network Classifiers			
Narrow NN	95.2	95.9	96.3
Medium NN	98.8	99.1	99.2
Wide NN	**99.5**	**99.5**	**99.5**
K-Nearest Neighbor Classifiers			
Fine KNN	99.3	**99.5**	**99.5**
Weighted KNN	99.2	99.4	99.4
Support Vector Machine Classifiers			
Linear SVM	89.9	91.3	92.2
Quadratic SVM	98.4	98.5	99.0
Naïve Bayes Classifiers			
Gaussian NB	70.3	69.6	68.0
Kernel NB	89.6	90.1	90.4
Discriminant Analysis Classifiers			
Linear DA	71.3	72.5	73.5
Quadratic DA	90.3	90.4	91.6

The contribution of individual sensor in distinguishing 11 activities under consideration is also evaluated using the ML classifiers. This analysis is done to achieve high detection accuracy while decreasing the sensors count and hence the cost. Table IV shows the results on 1-, 2- and 3-seconds windowed data. It can be seen the sensors in pocket and belt give highest accuracy as compared to other wearable sensors.

TABLE IV. ACCURACY ON THE INDIVIDUAL 5 WEARABLE SENSORS DATA CORRESPONDING TO WINDOW SIZE OF 1-, 2- AND 3-SECONDS

Model	**Accuracy**														
	Ankle			**Neck**			**Pocket**			**Belt**			**Wrist**		
	1 sec	**2 sec**	**3 sec**	**1 sec**	**2 sec**	**3 sec**	**1 sec**	**2 sec**	**3 sec**	**1 sec**	**2 sec**	**3 sec**	**1 sec**	**2 sec**	**3 sec**
Neural Network Classifiers															
Narrow NN	78.9	81.5	83.2	74.6	74.1	72.7	82.8	84.7	85.0	81.5	82.5	83.6	71.0	71.4	70.2
Medium NN	84.2	85.8	86.0	80.4	79.9	81.5	88.3	88.6	88.7	87.0	88.3	88.6	76.9	77.8	78.6
Wide NN	87.7	88.6	89.3	83.4	85.1	85.7	92.3	93.3	93.4	90.9	91.8	93.0	83.2	82.8	84.4
K-Nearest Neighbor Classifiers															
Fine KNN K=1	93.3	94.3	**94.5**	92.1	93.0	**93.4**	95.9	**96.3**	96.3	94.9	95.3	**95.8**	90.9	91.5	**92.1**
Weighted KNN K=10	92.6	93.6	94.2	91.5	92.2	92.5	95.3	96.0	95.9	94.5	94.9	95.2	90.2	90.6	91.3
Support Vector Machine Classifiers															
Linear SVM	53.6	54.8	55.3	52.1	53.9	54.2	46.2	46.5	47.9	56.3	57.4	58.4	37.2	38.5	39.8
Quadratic SVM	65.4	71.0	68.3	65.2	65.8	66.9	48.2	48.4	49.8	61.9	62.1	63.2	52.1	52.7	53.7
Naïve Bayes Classifiers															
Gaussian NB	55.1	56.7	57.7	49.9	50.5	51.6	57.0	57.7	58.9	52.5	53.7	51.4	26.1	26.2	25.8
Kernel NB	76.7	77.4	78.5	68.6	67.2	70.5	78.8	80.7	80.7	77.5	78.2	79.6	66.0	67.4	67.9
Discriminant Analysis Classifiers															
Linear DA	49.7	50.5	51.7	26.5	26.3	26.9	41.8	42.8	42.9	38.0	38.3	39.2	44.3	46.7	43.3
Quadratic DA	59.4	60.2	61.5	51.4	51.9	53.9	66.5	68.0	68.9	56.3	58.6	58.7	28.7	29.6	29.7

After analyzing the individual contribution of wearable sensors in distinguishing the 11 activities, the data of significant sensors, i.e., sensors on belt and pocket, are fed to the ML classifiers. Table V shows that using wearable sensors on belt and pocket results in 99.0% accurate activity recognition while reducing the wearable sensor cost. The TPR, PPV, FNR and FDR scores of 11 activities trained on the highly accurate wide neural network are shown in Table VI. The corresponding confusion matrix is shown in Fig. 2.

TABLE V. ACCURACY ON BELT AND POCKET WEARABLE SENSORS DATA CORRESPONDING TO WINDOW SIZE OF 1-, 2- AND 3-SECONDS

Models	**Accuracy**		
	Belt + Pocket		
	1 sec	**2 sec**	**3 sec**
Neural Network Classifiers			
Narrow NN	88.0	88.9	89.1
Medium NN	95.0	96.3	96.1
Wide NN	98.7	98.9	**99.0**
K-Nearest Neighbor Classifiers			
Fine KNN K=1	98.6	98.8	**99.0**
Weighted KNN K=10	98.2	98.6	98.7
Support Vector Machine Classifiers			
Linear SVM	67.2	67.7	68.4
Quadratic SVM	95.4	95.8	96.4
Naïve Bayes Classifiers			
Gaussian NB	63.5	65.9	61.5
Kernel NB	84.0	85.9	85.5
Discriminant Analysis Classifiers			
Linear DA	39.0	39.3	40.2
Quadratic DA	77.9	80.0	80.8

TABLE VI. EVALUATION METRIC SCORES OF 11 ACTIVITIES CAPTURED BY BELT AND POCKET WEARABLES AND TRAINED ON WIDE NEURAL NETWORK

Activity 1				**Activity 2**				**Activity 3**			
TPR	**PPV**	**FNR**	**FDR**	**TPR**	**PPV**	**FNR**	**FDR**	**TPR**	**PPV**	**FNR**	**FDR**
96.2	94.7	3.8	5.3	92.9	94.0	7.1	6.0	95.7	95.9	4.3	4.1
Activity 4				**Activity 5**				**Activity 6**			
TPR	**PPV**	**FNR**	**FDR**	**TPR**	**PPV**	**FNR**	**FDR**	**TPR**	**PPV**	**FNR**	**FDR**
96.9	97.1	3.1	2.9	97.4	94.9	2.6	5.1	99.1	99.5	0.9	0.5
Activity 7				**Activity 8**				**Activity 9**			
TPR	**PPV**	**FNR**	**FDR**	**TPR**	**PPV**	**FNR**	**FDR**	**TPR**	**PPV**	**FNR**	**FDR**
99.7	99.1	0.3	0.9	99.9	99.9	0.1	0.1	97.8	98.5	2.2	1.5
Activity 10				**Activity 11**							
TPR	**PPV**	**FNR**	**FDR**	**TPR**	**PPV**	**FNR**	**FDR**				
98.2	99.4	1.8	0.6	100	99.9	0	0.1				

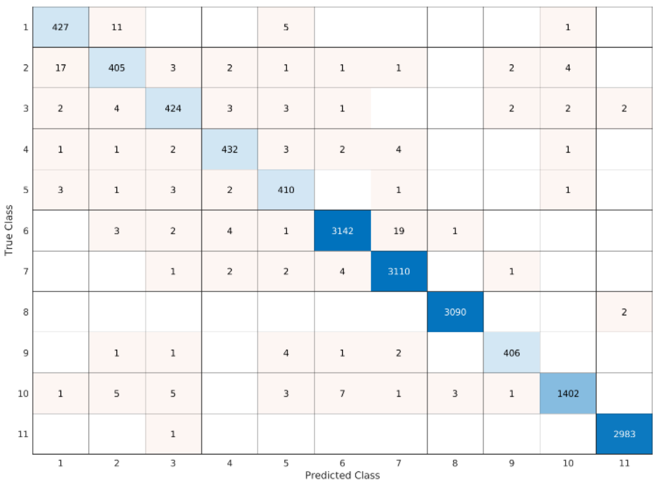

Fig. 2. Confusion matrix of 11 activities captured by belt and pocket wearables and trained on wide neural network model

V. Conclusion

This study uses an open-source large-scale wearable sensors data to propose a stable tilt-angle based fall detection approach. Current detection techniques either rely on statistical features-based processing techniques prior to feeding the data to a machine learning detector algorithm, or they utilize complex models for fall detection. The proposed techniques extract stable tilt angle within a certain data window and uses simpler baseline models to achieve an accuracy up to 99.5%, which is the highest amongst all current approached. This study aims to provide a reliable, fast, and accurate fall and normal action detection approach, so as to ensure that in time medical attention is given in case of fall detection.

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