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Evaluation of a Combined Conductive Fabric-Based Suspender System and Machine Learning Approach for Human Activity Recognition

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ABSTRACT Accelerometer-based human activity recognition (HAR) wearable systems are location-centric and noisy, needing multiple sensors with complex signal processing and filtering mechanisms. A recently reported alternative approach using a wearable suspender integrated with strain sensors and machine learning presented a viable option for nonlocalized measurement with less noise and better recognition capabilities. The washability and wearability of the strain sensor instrumented suspenders due to the physical wires are limited, and the power consumption is higher, which needs to be minimized to extend the battery life of the wearable device. This article proposes an improved body-worn suspender-based HAR system built using a conductive knit jersey fabric material that overcomes the existing strain sensor-based wearable device's limitations and at the same time provides improved sensitivity. The proposed suspender system recognizes 14 human activities using machine learning and deep learning algorithms with the best accuracy of 98.11%. A performance comparison of machine learning models based on two dimensionality reduction techniques using kernel and linear discriminatory analysis was conducted. The kernel-based method outperformed the linear one in recognizing human activities across all classifiers. The durability of the wearable is tested by washing the sensor, and the recognition capabilities were consistent before and after the wash.

INDEX TERMS Conductive fabric sensor, deep learning, e-textile, human activity, human activity recognition (HAR), machine learning, smart textile, wearable.

I. INTRODUCTION

A RELATIVELY active research field in recent years is the area of human activity recognition (HAR) due to the need for pervasive and ubiquitous sensing applications. Automatically identifying and monitoring a person's activity, without interfering with the freedom of movement or privacy is of importance considering the aging population [1]. Computer vision [2] and wearable types [3], [4] form the primary category of HAR classification, with camera-based systems being expensive and prone to privacy and pervasive issues. Human activity groups itself into simple and complex types [5] based on simple single actions, such as standing, sitting, and walking, and complex multiple steps performed simultaneously, such as drinking, eating, and typing while sitting, respectively.

Implementing HAR using smartphones' built-in accelerometers and gyroscope sensors [6], [7], [8] has been an extensive research area with these ubiquitous smartphones and accelerometer-based systems suffering from position localization and drift issues [1], [9], [10]. A good example of this limitation is that an accelerometer on the chest cannot provide sufficient information when a person is working on the computer [4], which is a complex activity. Increasing the number of sensors and combining other sensors for sensor fusion [11] or changing the location can be solutions to overcome this limitation, but it will increase the obtrusiveness of the wearable device and result in complex algorithms [12] and data processing. Accelerometers are more prone to noise requiring smoothening of data, increasing the complexity

TABLE 1. Comparison of existing systems in the literature.

Sensor type	Low Drift	Nonlocalized measurement	Low Noise	Wearability	Power required
Accelerometer [1], [4]	N	N	N	N	Low
Inertial sensors [1], [4]	N	N	N	N	Low
Other sensors [1], [10]	Y	Y	Y*	N	Low
Suspender with strain sensors [13]	Y	Y	Y	Y*	High
Proposed Fabric based suspender system	Y	Y	Y	Y	Low

Other sensors – Stretch, temperature, humidity, light, presence, Wi-Fi, Bluetooth, ECG, EMG, GPS, compass, heart rate, barometer. * - Partial.

of data processing. Older people use their smartphones less frequently and may only sometimes carry them.

Our earlier work [13] addressed these limitations from accelerometer-based systems using a novel smart suspender integrated with strain sensors that are part of daily clothing resulting in low drift, nonlocalized, and less noisy measurements. As the wearable was covering significant portions of the body that resulted in overcoming the position localization limitation with the accelerometer-based systems. This approach had limitations as it was difficult to wash these instrumented suspenders, which limits the device's usage, wearability, and durability. The system had wires running along the suspender length that hinder the natural use of the suspender and less washable. Also, the sensor system's power consumption must be optimized to increase the wearable's battery life.

This article aims to develop a wearable HAR device that seamlessly blends with commonly worn garments, enabling it to effectively monitor human activities. By establishing direct contact with multiple body regions, just like regular clothing does, the proposed device can capture comprehensive data on the subject's movement.

In contrast to the existing accelerometer-based schemes that solely measure acceleration at their specific installation point, the proposed fabric sensor-based device stands out as a less noisy alternative, capable of reliably capturing the human activities with low drift, less noise, and nonlocalized measurements. When compared to the strain sensor-equipped suspender [13] that had limitations in wearability, washability, and power requirements, the proposed fabric-based wearable suspender system surpasses them by providing 1) a reliable measurement of human activities, while maintaining a lower level of noise with increased wearability, washability, and 2) less power requirement. A comprehensive comparison of the existing system with the proposed system is provided in Table 1.

In line with this objective, we propose a new fabric-based wearable suspender sensing system for HAR using machine and deep learning that improves the wearability, durability, and power consumption limitations for the one presented in [13] that used strain sensors. It also overcomes the limitation of the existing accelerometer-based systems by having low drift, less noise, and nonlocalized measurements.

The remainder of this article is as follows. Following a review of related research in Section II, Section III deals with the proposed wearable, its development, data gathering, feature extraction, and classification. Sections IV and V deal with results and discussion, followed by a conclusion.

II. BACKGROUND AND RELATED WORK

Most reported systems use accelerometers alone or in combination with other sensors like gyroscopes, magnetometers, compasses, pressure sensors, body temperature sensors, electromyography systems, oximetry sensors, and electrocardiographs, employed as standalone devices or as part of smart devices, such as smartwatches or smartphones [1], [3], [4], [6].

When assessing ambulation activities with a wrist-worn smartwatch, inaccurate activity estimations can occur because of unintentional arm movements [4]. When separating eating behaviors from noneating ones, Dong et al. [14] showed an accuracy of 81% using a wrist-worn accelerometer. A wearable system's ability to recognize a complex activity is significantly hindered during a complex activity such as a person eating while seated.

Chen and Shen [15] tested the smartphone sensor performance for HAR for five different activities in their work. They concluded two significant problems: 1) the diversity of the positions and orientations of the phones and 2) the general accuracy of the sensors in the phones. In [10], it is evident from the trials that when the user stops and sits on a chair, the accelerometer cannot collect the data effectively.

A suspender is an item of everyday clothing, especially for elders. Suspenders with strain sensor was presented in [13] as an alternative to avoid positioning problems associated with accelerometer-based systems. The prototype uses a wearable suspender integrated with three metallic strain sensors as part of a commercial weighing scale on the three ends of the suspender arms that measure the strain produced on the instrumented worn suspenders from various human activities. Strain levels corresponding to human activities are digitized, processed, and the activities are classified. The main limitations of this system are the durability and wearability constraints, physical wires that limit reliability, and the suspender usage and higher power requirements. In this article, we propose an alternate extended and enhanced wearable suspender using a conductive fabric-based sensor material that is stitched on the suspender to overcome the limitations of the recently reported suspender system in [13] and other existing accelerometer-based systems [1], [4], [14], [15].

The output signal from the conductive fabric-based suspender system corresponds to human activities performed but the pattern observed from each activity type cannot be easily deciphered to recognize the activity. Combining machine learning and deep learning methods with the conductive fabric-based sensor, classifying the activities performed using

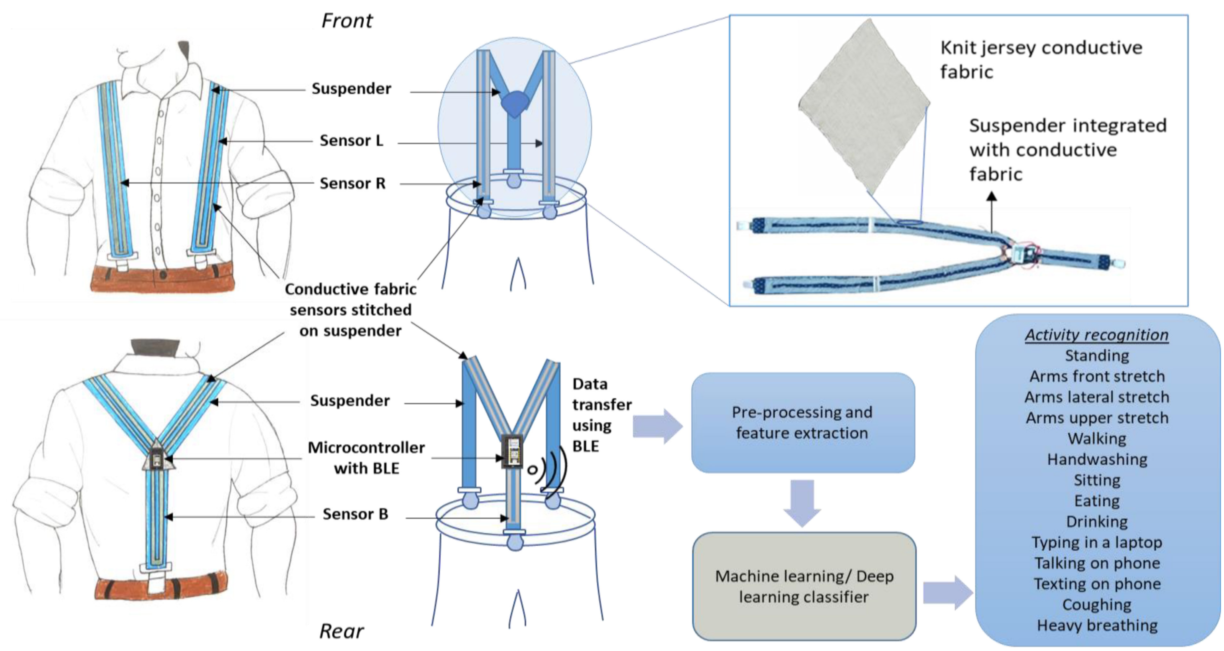


FIGURE 1. Pictorial representation of the proposed suspender system. Sensor-R and Sensor-L are the conductive fabric sensors introduced on the right and left sides of the suspender, and Sensor-B is located at the back. The inset shows the conductive fabric stitched in the suspender.

the output patterns observed from the suspender system results in HAR.

A. DATA PROCESSING FOR HAR

The HAR's preprocessing method uses sliding or transition windows with predetermined periods as part of the time-series segmentation. Standard HAR measurements produce the vector of attributes from each window [16], [17], [18], using the time and frequency domain features as part of extracting the necessary features.

The selection of discriminatory analysis and the choice of machine learning models for evaluation is based on the models that were successful and widely used for HAR problems [1], [5], [8], [16], [19], [20], [21], [22], [23], [24], [25], [26], [27]. The dimensionality reduction is performed using discriminatory analysis methods—linear discriminatory analysis (LDA) [5], [19] and kernel discriminatory analysis (KDA) [8]. Similar to [13], the most used machine learning and deep learning approaches for classifying HAR activities [1], [16], [20], [21], [22], [23], [24], [25], [26], [27], such as k-nearest neighbor (KNN), support vector machine (SVM), support vector classifier (SVC), random forest (RF), decision tree (DT), gradient boosted DT (GBDT), logistic regression (LR), and long short-term memory (LSTM), are used as classifiers to identify the best model for HAR using the proposed suspender sensing system.

III. SYSTEM AND ITS COMPONENTS

A pictorial diagram representation of the proposed conductive fabric-based suspender system is illustrated in Fig. 1. The proposed system consists of a suspender stitched with a textile-based sensor that changes resistance in response to the stretches and compressions the worn suspender experiences due to diverse human activities.

A. SYSTEM DESIGN AND PROTOTYPE DEVELOPMENT

The textile sensor-based suspender system is realized using a conducting knit jersey fabric from Adafruit [28]. This fabric is a bidirectionally stretchable fabric with 63% cotton, 35% silver yarn, and 2% spandex. It has a resistance variation of 1.5 Ω/cm across rows in a stretchier direction and 15 Ω/cm across columns in a less stretchy direction. The material is washable and has a good sensitivity for capturing variations in human activities. This textile sensor is used as an electrode in [29] and [30].

The sensor consists of the conducting fabric cut in the form of a U shape as in Fig. 1, with a length of 52 cm on the left and right arms of the suspender and each leg of the U-shaped sensor on each arm measuring 1 cm width. In the back arm of the suspender, which is shorter, the length of the sensor material is 14 cm, with each leg of the sensor having a 1 cm width. The sensor fabric is stitched on the arms of the suspender using regular nonconducting thread with the help of a standard sewing machine. The ends of each sensor act as the leads for the sensor that are covered using a 10-mm adhesive copper tape to secure the connection between the sensor and microcontroller (μC). The inset in Fig. 1 shows the conductive fabric stitched onto the suspender. Under the two metal buckles of the suspender that are used for adjusting the length, a layer of insulating material is fastened to ensure no interference between the buckles and the fabric sensor.

The end leads from the sensor are connected to a voltage divider with a 1-kΩ pull-up resistor to convert the resistance changes from the body movements of the suspender

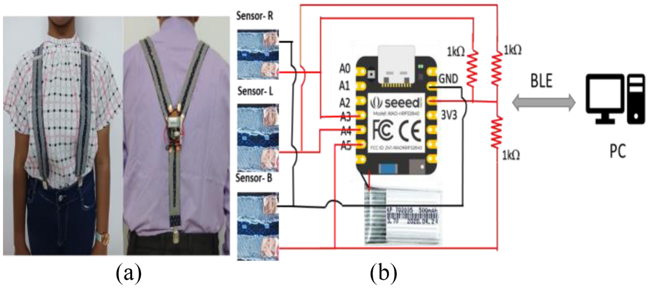


FIGURE 2. **Subjects wearing the prototype of the suspender sensor system. A photograph of the prototype system developed is shown in (a). (b) Functional diagram, i.e., conductive fabric sensors, μC, and wireless data transfer unit.**

to corresponding voltage signals. The voltage divider is powered by a 3.3-V power supply available as part of the μC, where the output voltage V_{out} from the voltage divider is expressed as

$$V_{\text{out}} = R_{\text{sensor}}/(R_{\text{sensor}} + 1k\Omega) \times 3.3 \tag{1}$$

where R_{sensor} is the resistance of the conducting fabric sensor.

The Xiao nRF52840 μC from Seeeduino [31] is thumb-sized (21 mm × 17.5 mm) with Bluetooth low energy (BLE) capabilities which provides ultralow power consumption of 5 μA in deep sleep mode along with battery charge management that makes it a suitable choice for this lightweight, miniaturized, low power wearable application. The analog signals from the sensor are digitized using the 12-bit ADC of the μC, which is then wirelessly sent in real time to mobile and PC. It is logged for activity recognition and identification. The sampling frequency is 20 Hz, which is sufficient to capture all human movements [32]. The power supply for the μC is from a 500-mAh lithium-polymer battery (702035 type), and the whole unit is powered from the 3.3-V supply of the μC.

The voltage divider and the μC, along with the connecting leads from the sensor, are assembled in a tiny board of dimension (4.8 cm × 3.5 cm × 9 cm) and secured on the leather back portion of the suspender where all three arms of the suspender are joined together as shown in Fig. 2. The entire signal processing and transmission setup is very light in weight, ~45 g and also uses low power of 50 mW resulting in 37 h of uninterrupted operation of the wearable device before the next recharge.

B. DATA COLLECTION AND PROCESSING

Eight subjects wore the suspender system, four men and four women, performing 14 activities provided in Table 2. The subjects' height varied from 153 to 177 cm, and their weight varied from 58 to 93 kg, representing a diverse mix of the broader population. Subjects spent 28 min on all 14 activities, and 268 273 data points were collected, with an average of 33 534 data points per subject with a standard deviation of 835. Handwashing activity could not be carried out by subject #4 due to an injury on the left hand. Fig. 3 shows the data collected from each subject. Fig. 4 provides output waveforms of a subject performing all 14 activities.

TABLE 2. **Activities—categories.**

Activity name, code	Activity class	Activity type
Standing (STA)	Ambulatory	Simple
Arms front stretch (AFS)	Exercise	Complex
Arms lateral stretch (ALS)	Exercise	Complex
Arms upper stretch (AUS)	Exercise	Complex
Walking (WAL)	Ambulatory	Simple
Hand washing (HWA)	Daily activities	Complex
Sitting (SIT)	Daily activities	Complex
Eating (EAT)	Daily activities	Complex
Drinking (DRK)	Daily activities	Complex
Typing on laptop (TYP)	Daily activities	Complex
Talking on phone (OPH)	Daily activities	Complex
Texting on phone (TXT)	Daily activities	Complex
Coughing (COU)	Diagnostic	Complex
Deep/Heavy breathing (HBR)	Diagnostic	Complex

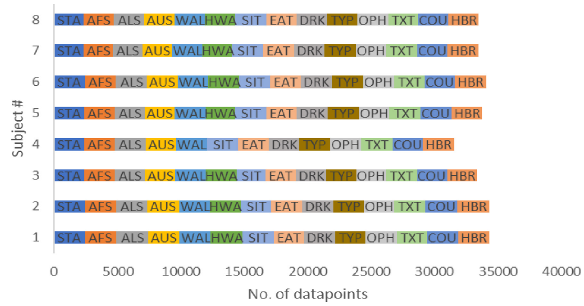


FIGURE 3. **Subject wise data collected on activities.**

From the waveforms, it is clear that using the data from the three sensors captures distinct patterns that represent each activity.

The schematic of the stages involved in the classification of human activities is provided in Fig. 5. The data from the three sensors of the suspender is preprocessed by normalizing and segmentizing the time-series data. The extraction of features forms the next stage, where the time and frequency domain-based features are extracted from each time-segmented data window. Dimensionality reduction of the features is performed using discriminatory methods to reduce the complexity of the multiple dimensions while retaining the feature information. Finally, we use eight different classifiers utilizing machine learning and deep learning techniques to recognize human activities and to identify the best-performing classifiers for the proposed suspender system.

C. PREPROCESSING

Due to the varying length of the suspender between the front and the back arms, the resistance variation between the front two sensors and the back varies significantly. Hence, the normalization of the values X_n is done on every datapoint X_i for a sensor using the maximum and minimum values $X_{\max}$ and $X_{\min}$, respectively, as given in

$$X_n = X_i - X_{\min}/(X_{\max} - X_{\min}). \tag{2}$$

The normalized time-series data obtained is segmented using a sliding window to determine the features. For the current

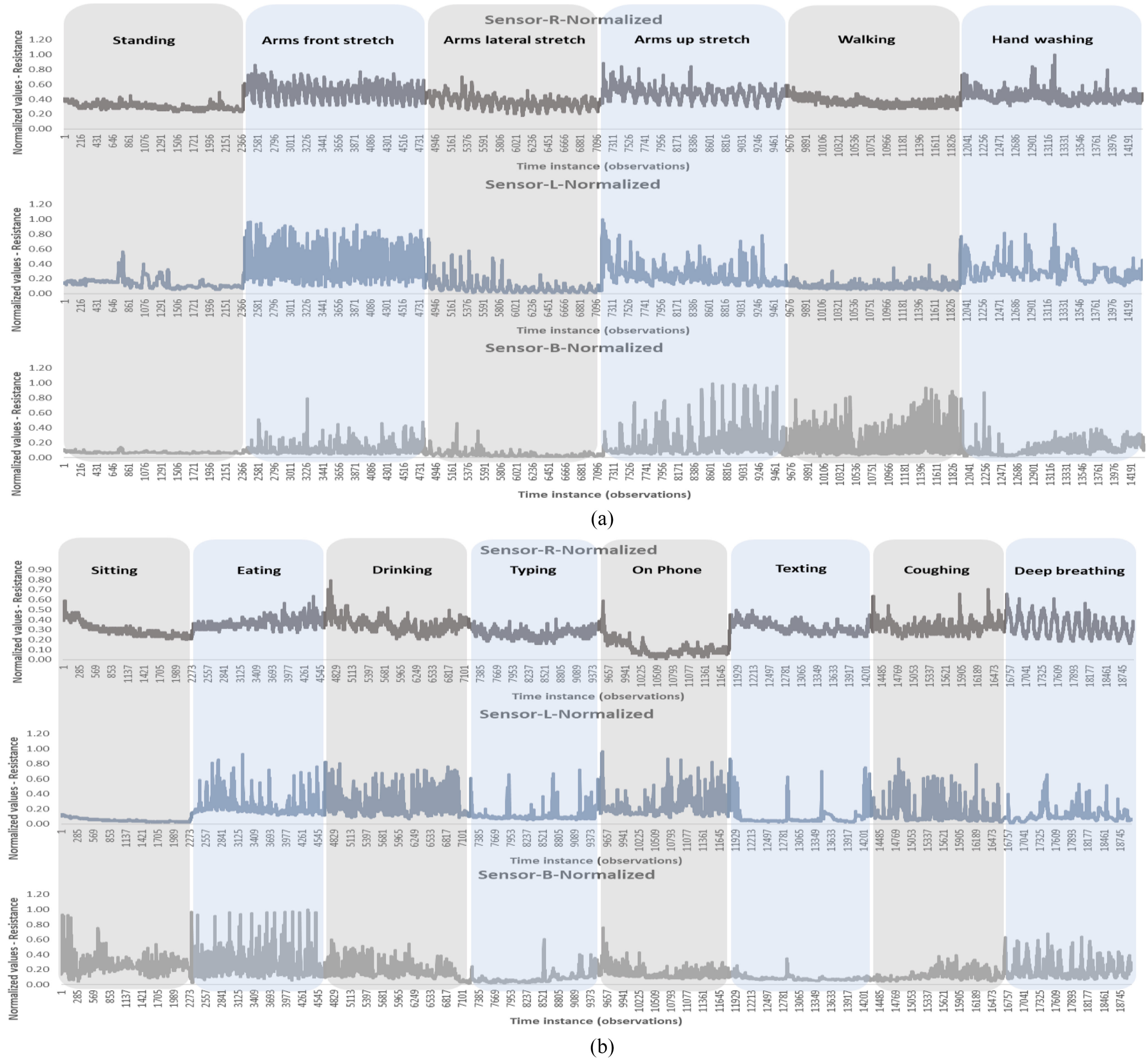


FIGURE 4. **Sensors' output waveforms for a subject performing activities wearing the conductive fabric-based suspender. Waveforms in the top (a) are observed when the user is performing activities while standing and the one in the below (b) shows the waveforms when the user is performing activities while sitting.**

work, we chose 500 observations as the sliding window and 20 as the step size to balance the segmentation precision and computational load. As reduced window size resulted in reduced precision of identified activities, this window size is selected for this work.

D. FEATURE EXTRACTION

Post segmentation, the feature extraction step from each time segment was carried out using time and frequency domain signal features. Fourteen feature groups corresponding to 47 features encompassing the time and frequency domains were extracted resulting in a comprehensive feature set as shown in Fig. 5.

Table 3 provides the list of feature extraction functions used, description, and the number of features.

1) TIME-DOMAIN FEATURES

Statistical time-domain features, such as mean, standard deviation, mode, maximum, minimum, interquartile range, signal magnitude area, first four autoregression coefficients, correlation coefficient, signal entropy, skewness, and kurtosis, were extracted from each time segment.

2) FREQUENCY-DOMAIN FEATURES

In order to obtain the frequency-domain feature, the fast Fourier transformed values are used to obtain the signal

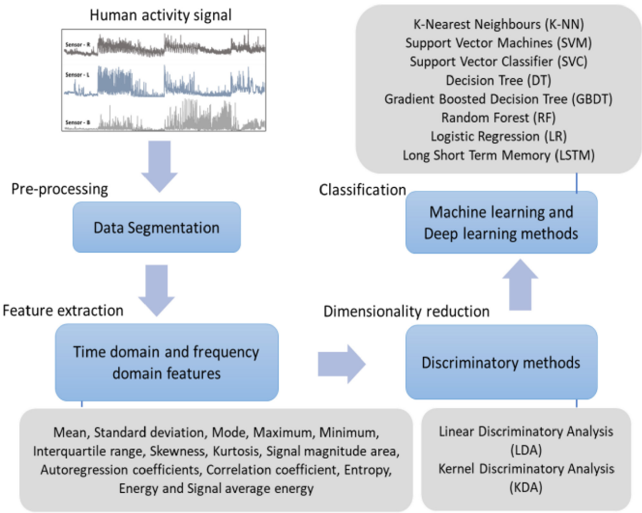


FIGURE 5. Schematic of the machine learning processing for classification.

TABLE 3. List of feature extraction functions.

Function	Description	# features
Mean	Mean value of time window	3
Std deviation	Standard deviation of time window	3
Mode	Mode within the time window	3
Maximum	Maximum value within the time window	3
Minimum	Minimum value within the time window	3
Signal area	Signal magnitude area across sensors	1
Autoregression	First 4 autoregression coefficients	12
Correlation	Correlation across the sensors	3
Energy	Average of Sum of squares of FFT	3
Average energy	Average energy across sensors	1
Interquartile range	Interquartile range of window	3
Entropy	Signal entropy of time window	3
Skewness	Signal skewness of time window	3
Kurtosis	Signal kurtosis of time window	3

spectral energy levels for each sensor across various activities. The average of the spectral energy across these three sensors is also utilized in feature extraction.

All features were extracted from each sensor of the suspender except for signal area magnitude and average energy, which are computed as an aggregate from all three sensors. A total of 13 389 time segments were created with 47 features, with each segment labeled with the corresponding activity, and this forms the input feature space for machine learning and deep learning algorithms.

E. DIMENSIONALITY REDUCTION

For reducing the dimensionality of the feature space, LDA and KDA are used. LDA and KDA reduce dimensions by finding a lower-dimensional representation that maximizes class separation, achieved by minimizing within-class scatter and maximizing between-class scatter [5], [8], [9]. LDA uses the linear function, whereas KDA uses the radial basis function (RBF) to achieve the reduced dimensionality. The dimensionality of the input dataset is reduced from 47 to 13 using LDA and KDA. The adjustable parameters used are threshold value for singular value and the number of components which is set to 0.001 and 13, respectively. The feature subspace is reduced to lower dimensions using the eigenvectors obtained from scatter matrices where each eigenvector corresponds to the combination of features from the original feature space. As an example, the primary dimension in the reduced dimension uses the top contributing features of mean standard deviation, minimum, and energy of left and back sensors, respectively. Similarly, other dimensions are derived based on the combination of input features.

F. CLASSIFICATION

We have used eight machine-learning models to evaluate the HAR classification performance using the custom-made sensors deployed as part of the suspenders. KNN, SVM, SVC, RF, DT, GBDT, LR, and LSTM were deployed on the reduced feature space from LDA and KDA, respectively. The objective of using multiple models and techniques is to find the best-performing model and the suitable dimensionality reduction methodology for addressing the HAR problem for the proposed suspender system. All the models and classifiers are implemented using Python using appropriate machine learning and deep learning functions and packages. Hyperparameters are tuned using gridsearchCV from sci-kit learn, which implements a fit and score method for doing an exhaustive search over the specified parameter values for an estimator. Fivefold cross-validation is performed on all the models.

KNN works by finding the nearest neighbors of a new data point and predicting its value based on the values of its neighbors, and the tuned hyperparameter value of 1 is used for k in both LDA and KDA. The search space for the hyperparameter k was the values between 1 and 5.

SVM and SVC find the optimal hyperplane to separate data into different classes with a maximum margin between them. SVM uses RBF kernel, and SVC uses linear one to accomplish the model. The SVC model uses the tuned hyperparameter values of C at 0.5 and 0.25 for LDA and KDA, and SVM uses C and gamma values of 1 and 1, 0.125 and 0.01 for LDA and KDA, respectively. The search space for hyperparameter C for SVC used was 0.25, 5, 1, 2, 4, and 8. For SVM, the search space used for C and gamma hyperparameters was 0.125, 0.25, 0.5, 1 and 0.01, 0.1, 1, and 2, respectively.

A DT builds a tree and recursively partitions it based on the most informative feature with max depth parameter tuned at 9 and 8 for LDA and KDA. The maxdepth hyperparameter search space used in this study was between 4 and 10. GBDT is an ensemble algorithm that combines multiple DTs by iteratively improving the accuracy using gradient descent. The max depth and no of estimators were tuned at 6 and 130 and 5 and 120 for LDA and KDA. The number of estimators hyperparameter search space used was between 120 and 150 and for maxdepth hyperparameter, it was between 3 and 10. RF builds multiple DTs and combines their predictions with high accuracy and low overfitting. The max depth and no of estimators were tuned to be 14 and 130 for LDA and 4 and 10 for KDA. The number of estimators hyperparameter search space used was between 10 and 200 and for maxdepth hyperparameter, it was between 4 and 15. LR uses the maximum likelihood to estimate the probability of membership in a category, and the C value was 20 in both LDA and KDA, respectively. The search space used for C values was 20, 25, 30, 35, and 40.

In the deep learning LSTM model, the input feature vector forms the input layer, followed by two layers of 512 hidden memory nodes. A rectified linear unit (ReLu) activation function is used between input and across hidden layers. The output layer uses the Softmax function with categorical cross entropy used as the loss function. A batch size of 16 with 25 epochs is used. In order to evaluate the classifiers, the following metrics are calculated:

$$\text{Accuracy} = (TP + TN)/(TP + TN + FP + FN) \quad (3)$$

$$\text{Precision(PR)} = TP/(TP + FP) \quad (4)$$

$$\text{Recall(RC)} = TP/(TP + FN) \quad (5)$$

$$\text{F1 score} = 2 \times (PR \times RC) / (PR + RC). \quad (6)$$

TP is true positive, TN is true negative, FP is false positive, and FN is false negative.

Accuracy measures the overall correctness of the model's predictions across all classes and is calculated as the fraction of all predictions that are correct. As HAR is a multiclass problem, precision quantifies how well the model predicts a specific class compared to other classes, and recall measures the ability of the model to correctly identify instances of a specific class. The performance scores at an overall model level are presented as an average of the individual class scores for precision, recall, and F1 scores.

As in [33], it is worth noting that the accuracy, precision, and other metrics are used in the context of evaluation of the machine learning classifier performance and do not indicate the measurement of the sensor directly.

IV. RESULTS

The input dataset is split into train and test datasets before classification. After being trained on the train datasets, the models are tested using the test datasets. Fig. 6 outlines the different data collected from the subjects used for training the machine learning model that enables the base model created by learning the various activity patterns from every user thereby resulting in a trained model. The trained model is evaluated for its performance by testing the learned machine learning model with a new set of test data from the user to ensure that the models are evaluated aptly using unseen data from the user simulating the real-life situation. Using the input dataset of 13 389 inputs with 47 features, we employed a split of 70:30, yielding 9372 rows for training and 4017 for testing. To guarantee that the model learns appropriately, we have utilized a ratio of 80:20 for LSTM.

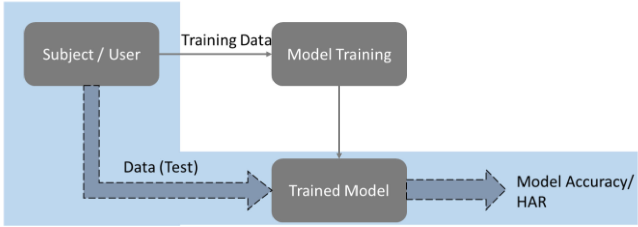


FIGURE 6. Schematic of the evaluation of machine learning models. Data (Test) is not part of the training data.

TABLE 4. Mean test scores from cross-validation.

Model	KNN	SVM	LSTM	RF	GBDT	LR	DT	SVC
LDA	0.98	0.96	0.96	0.95	0.90	0.5	0.57	0.49
KDA	0.99	0.98	0.99	0.96	0.91	0.97	0.90	0.98

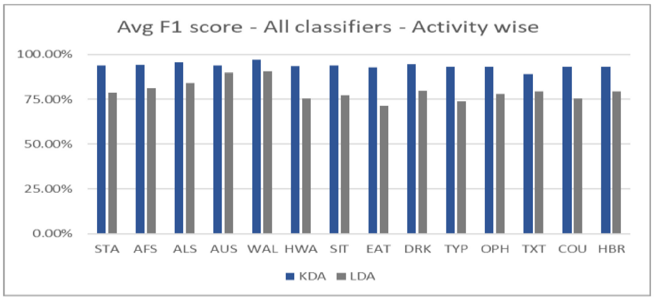
Fivefold cross-validation is used and test scores of cross-validation across the models are provided in Table 4. The average values of performance scores of all the eight classifiers employed with LDA and KDA are listed in Table 5. Five models—KNN, LSTM, SVM, RF, and GBDT—performed well with KDA and LDA. LR and SVC performed well with KDA. LR and SVC showed tremendous improvements in accuracy from 49.39% to 96.04% and from 48.94% to 96.14% with LDA and KDA, respectively. Comparatively, DT did not perform well with both LDA and KDA. With KDA, the best accuracy of 97.16% was obtained using LSTM, whereas the overall best accuracy of 98.11% is obtained with LDA using KNN. Fig. 7(a) provides an activity-wise comparison of average F1 scores for all the classifiers, and Fig. 7(b) provides a similar one for the top 5 performing classifiers.

To evaluate the performance of the wearable device for a new user, a leave out one subject cross-validation was carried out by leaving one subject out of the eight subjects for testing. Seven subjects' data were used for training and the left-out subject's data was used for testing the model. An accuracy score of 72.57% was achieved using the leave one subject out method. The accuracy score is expected to be lower compared to the cross-validation scores [34] obtained using the fivefold method as it provides the evaluation of the wearable device for a new user whose initial data is not trained with the wearable system This score can be improved by training the wearable system with a larger and more diversified population of users.

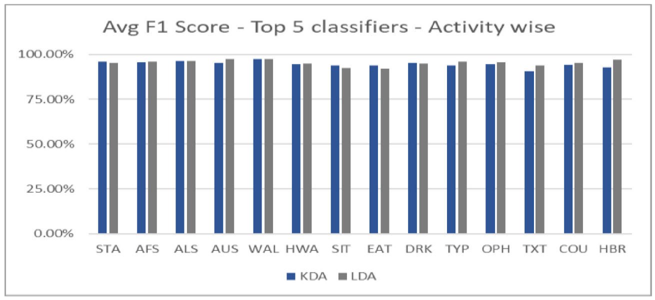
A comparison of the performance of the proposed conductive fabric sensor-based suspender with strain sensor integrated suspender in [13] is provided in Table 6. We have considered a margin of around 3% for F1 scores between the models for comparing them. The training and validation loss for the LSTM across epochs for LDA is 0.18, and for KDA, it is near zero.

TABLE 5. Average values of performance scores across classifiers.

Machine learning/ Deep learning Model	Using Kernel Discriminatory Analysis (KDA)				Using Linear Discriminatory Analysis (LDA)			
	Accuracy	Precision	Recall	F1 score	Accuracy	Precision	Recall	F1 score
K-Nearest Neighbours (KNN)	95.72%	95.79%	95.71%	95.75%	98.11%	98.14%	98.14%	98.14%
Support Vector Machines (SVM)	95.74%	95.86%	95.71%	95.79%	96.51%	97.07%	96.36%	96.71%
Long Short-Term Memory (LSTM)	97.16%	97.07%	97.00%	97.04%	96.19%	96.00%	96.29%	96.14%
Random Forest (RF)	93.45%	93.36%	93.43%	93.39%	95.32%	95.29%	95.36%	94.32%
Gradient Boosted Decision Tree (GBDT)	90.09%	91.36%	90.29%	90.82%	90.47%	90.43%	90.36%	90.39%
Logistic Regression (LR)	96.04%	95.93%	96.14%	96.04%	49.39%	48.86%	48.93%	48.89%
Support Vector Classifier (SVC)	96.14%	96.29%	96.14%	96.21%	48.94%	48.00%	48.50%	48.25%
Decision Tree (DT)	83.35%	85.21%	83.43%	84.31%	64.05%	64.29%	63.71%	64.00%



(a)



(b)

FIGURE 7. Activity-wise comparison of average F1 scores across all classifiers in (a) and (b) shows the classifier results for the top 5 classifiers (KNN, SVM, LSTM, RF, and GBDT).

TABLE 6. Proposed fabric sensor-based suspender with the load cell-based suspender [13].

Model	KNN	SVM	LSTM	RF	GBDT	LR	DT	SVC
LDA	S	S	S	S	S	S2	S2	S2
KDA	S	S	S	S*	S*	S*	S2	S

S - Both fabric and strain sensors performance are similar
S*- The difference in F1 scores between the sensors is within 3 to 4%
S2 - Strain sensor performed well compared to fabric sensor.

V. DISCUSSION

A. COMPARISON OF CLASSIFIERS

Five classifiers—KNN, LSTM, SVM, SVC, and LR—provided accuracy greater than 95% with RBF and GBDT providing scores between 90% and 95% with KDA. With LDA, four classifiers—KNN, LSTM, SVM, and RF—scored above 95%, and GBDT scored above 90%. Of the 14 activities performed across all classifiers, two activities—ALS and walking—scored high with an average F1 score above 95% with KDA. All other activities except texting scored an average between 90% and 95%.

Three simple activities had an average F1 score of 94.52%, and the 11 complex activities had an average F1 score of 92.84% across all models. Walking had the highest accuracy score for both LDA and KDA with eating and texting scoring the least, respectively. LR and SVC had more incorrect classifications for typing, eating, and coughing activities. DT had the least score with KDA, and incorrect classifications happened for texting, standing, and arms upper stretching activity. In general, although it was comparable, KDA outperformed LDA counterparts when all classifiers were considered except for KNN, SVM, and RF. It is interesting to note that even though KDA has performed better than LDA from F1 and accuracy scores across all classifiers in Fig. 7(a), the top five performing classifiers have eight activities out of the 14 where LDA has outperformed the KDA as shown in Fig. 7(b). LDA performs well with the top five performing algorithms—KNN, SVM, LSTM, RF, and GBDT, and KDA performs well with all the algorithms except DT.

In comparing the proposed fabric sensor performance with the strain sensor instrumented suspender [13] as in Table 4, KNN, LSTM, and SVM perform at par with strain sensors with LDA and KDA. In contrast, RF and GBDT performance was at par with LDA and within 3%–4% with KDA. KDA performance was comparable for LR and SVC, whereas LDA was not. The performance of DT with LDA and KDA was subpar to strain sensors.

B. PERFORMANCE OF WEARABLE SYSTEM

The results show that the proposed suspender wearable system can perform HAR with accuracy values of 98.11% and 95.72% for KNN with LDA and KDA, respectively.

This conclusion is consistent with [1], having KNN and SVM as popular classifiers for HAR. In addition to recognizing simple activities similar to accelerometer sensors, the proposed wearable system can also identify all 11 complicated activities with an average F1 score of 92.84% across all classifiers. In comparison to [14] and [15], the system is able to identify even complex activities such as eating with scores above 90%.

1) EFFECT OF WASH

The durability of the wearable and change in the resistance of the conductive fabric suspender are evaluated by comparing

TABLE 7. Accuracy scores before and after wash

Model	Before wash		After wash	
	LDA	KDA	LDA	KDA
KNN	98.11%	95.72%	97.88%	95.21%
SVM	96.51%	95.74%	96.00%	95.31%
LSTM	96.19%	97.16%	96.11%	97.16%
RF	95.32%	93.45%	95.04%	88.38%
GBDT	90.47%	90.09%	90.60%	92.30%
LR	49.39%	96.04%	48.19%	95.58%
SVC	48.94%	96.14%	49.22%	95.98%
DT	64.05%	83.35%	63.85%	83.59%

the results before and after the wash. The base trained model before the wash that was trained on all subjects was considered and the test was carried out after the wash with subject #3. This emulates a real-life situation where the wearable system is trained with initial data from the user, the system is evaluated for accuracy of HAR after washing. Table 7 summarizes the classification accuracy across all the classifiers after washing for subject #3 in comparison with before wash results. Table 7 results show that the performance remains consistent.

The power usage of the proposed conductive fabric-based suspender with BLE is 50 mW whereas the one in [13], requires 260 mW. This low power requirement for the wearable helps in 37 h of uninterrupted operation. In order to ensure correct results during extended usage, it is advisable to conduct regular calibration and retraining of the proposed system at periodic intervals.

C. LIMITATIONS

It is imperative to conduct rigorous long-term testing and analysis with more diversified subjects to improve accuracy and reliability over an extended duration. To maximize the device's performance, it is necessary to implement the classifier in the cloud. Addressing these limitations will improve the functionality and usability of the wearable device.

D. FUTURE SCOPE

The wearable prototype unit described in this study was created to test the accuracy and practicality of the suggested approach. The unit requires proper packaging and miniaturization to make it a completely useful unit for regular use. The future area of study may include further developing the present wearable to provide real-time HAR estimate and classification. The state-of-the-art machine learning technique using transformers for processing sequential data may be carried out as a performance study in comparing the classifiers. The design of this wearable can be further studied by deploying the sensor for everyday use.

VI. CONCLUSION

We describe a new wearable suspender with conductive fabric for unobtrusive activity monitoring and identification. Covering most activities, including the complex ones, with fewer sensors and less noise, using a conductive fabric built into the suspender improves the ability to classify HAR effectively. The suggested wearable sensor consistently records the periodicity of human activities compared to accelerometers, which are location sensitive. The proposed suspender system is durable and wearable as it shows repeatable recognition capabilities before and after washing and uses meagre power (50 mW), increasing the wearable device's usage.

Time-series data were gathered, and the prototype of the suggested system was created. A variety of classifiers were applied to compare and contrast the performance of this built system with those dominated by accelerometers in the HAR literature. The suspender system achieved the best recognition accuracy of 98.11% when detecting and identifying simple and complex human activities and assists in performing HAR for a person, young or old, at home or in a community daily.

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