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Feature Extraction, Performance Analysis and System Design Using the DU Mobility Dataset

SWAPNIL SAYAN SAHA[1], (Student Member, IEEE), SHAFIZUR RAHMAN[1], MIFTAHUL JANNAT RASNA[1], TAREK BIN ZAHID[1], A. K. M. MAHFUZUL ISLAM[2], (Member, IEEE), AND MD. ATIQUR RAHMAN AHAD[3], (Senior Member, IEEE)

[1]Department of Electrical and Electronic Engineering, University of Dhaka, Dhaka 1000, Bangladesh
[2]Institute of Industrial Science, The University of Tokyo, Tokyo 113-8654, Japan
[3]Department of Intelligent Media, Osaka University, Suita 565-0871, Japan

Corresponding author: Md. Atiqur Rahman Ahad (atiqahad@du.ac.bd)

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ABSTRACT The University of Dhaka mobility data set (DU-MD) is a human action recognition (HAR) data set consisting of 10 classes and 5000 observations from 50 subjects recorded using wrist-mounted sensors embracing accelerometry. The data set exhibits sufficient statistical diversity in physiological parameters and a noteworthy correlation between similar activities with coveted quantitative and qualitative features, suitable for training machine learning models. On the other hand, the wrist-mounted approach parallels the future commercial scenarios. In this paper, we explore how the quantitative features of the DU-MD have been extracted and selected. Existing machine learning models used in HAR, in particular, support vector machines, ensemble of classifiers, and subspace K-nearest neighbours have been applied to our data set for activity and fall classification, with outcomes being compared with benchmark and similar data sets. With a HAR classification accuracy of 93%, fall detection accuracy of 97% and fall classification of 68.3%, quantitative performance metrics have either approached or outperformed other data sets, making this data set suitable for application in hardware-independent healthcare monitoring systems. Finally, we construct an algorithm with our data set based on performance metrics, and suggest some strategies for large-scale commercial implementation.

INDEX TERMS Human action recognition (HAR), activities of daily living (ADL), wearable, accelerometer, machine learning algorithms, feature extraction, statistics, support vector machines, decision trees, nearest neighbor methods.

I. INTRODUCTION

The University of Dhaka Mobility Dataset (DU-MD) [1] is being developed to complement the application and development of hardware-independent machine learning motion detection models for existing ubiquitous wrist-mounted motion detection systems such as activity trackers and fitness bands, with focus on fall detection in senior citizens. The open-source DU-MD embraces the wearable approach in Human Action Recognition (HAR) and uses the principle of accelerometry to aid classification of Activities of Daily Living (ADL) or fall detection [2].

Qualitative comparison with widely-used benchmark and existing HAR datasets [3] has been studied in the literature [1]. These datasets are summarized in Table 1.

The shortcomings of the benchmark dataset illustrated in literature [1], which the DU-MD attempts to address are:

- Only UMAFall [10] considers fall waveforms. Other datasets are hence not suitable for fall detection.
- In case of HAR, HAD and HAPT dataset [6], [7], [9], placement of data logger does not parallel the commercial landscape of wearables in HAR; it is not feasible or practical to attach smartphones or data loggers around the waist or chest.
- With the exception of the HASC dataset [5], most datasets were crafted in a controlled environment (using maximal protective measures) with a few test subjects, sacrificing realism.

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TABLE 1. Summary of some benchmark HAR datasets.

Dataset	Subject Count	ADL Count	Principle	Sample Count
UCB WARD [4]	20	13	Accelerometry; Gyrometry	1298
HASC [5]	540	6	Accelerometry	6700
UCI HAR [6]	30	6	Accelerometry; Gyrometry	10299
USC HAD [7]	14	12	Acclerometry; Gyrometry	840
Opportunity [8]	12	20	Acclerometry; Gyrometry; Magnetometry	3371
UCI HAPT [9]	30	6+6*	Acclerometry; Gyrometry	10929
UMAFall [10]	17	11**	Acclerometry; Gyrometry; Magnetometry	531

*Considers 6 postural transitions (transition from one action to another).
**UMAFall considers 3 types of falls besides classic ADL. Rest of the datasets have no fall waveforms.

- Machine learning models classifying a diverse class of ADL require a large sample count ($\sim> 5000$), a large subject count ($\sim> 30$) with statistical variance in physiological parameters such as age, weight and height to prevent bias [11]. Table 1 portrays that the WARD, HAD and UMAFall [4], [7], [10] fails in first two criteria.

The coveted characteristics of the DU-MD are as follows:

- Subject count: 50
- ADL count: 10 (Walking, sitting, lying, jogging, staircase climbing, staircase down, standing, falling via unconsciousness, falling via heart attack and falling via slipping while walking).
- Principle: Accelerometry using a wrist-mounted data logger; The newly developed open-source Internet of Things (IoT) kit from IIS, University of Tokyo, known as the Trillion Node Engine Project, was used to assemble the data logger [12].
- Sample Count: 5000 (each person provided 10 samples of each ADL, amounting to 100 samples per person).
- Three types of realistic falls taken into account for fall detection.
- Signals sampled at 30 Hz to ensure detailed ADL waveform.
- Minimal protective equipment in testbed.
- Promising statistical diversity of physiological parameters and correlation between similar signals. Average weight and height of the test subjects matched the average adult weight and height [1].

Kolmogorov-Smirnov (K-S) test was performed on age, weight and height of 25 of the 50 subjects in literature [1] to ensure sufficient statistical diversity. No bias was observed in weight and height whilst a small bias was observed in age, which was corrected by augmenting the significance level of the test to 0.1. The results are duplicated in Table 2.

Kruskal-Wallis (K-W) one-way ANOVA was performed on 10 walking ADL from a random test subject and outlined in literature [1]. Each ADL contains 101 sample points. The results are duplicated in Table 3.

At the 0.05 level, the populations are not significantly different, which justifies that similar ADL are statistically coherent and uniform.

The coveted features, amalgamated with statistical justification of the dataset, now demands further analysis. In this paper, we explore the following:

TABLE 2. Results from K-S test on age, weight and height [1].

Parameter	DF	Statistic	$P > D$	Inference
Age (yrs)	25	0.34132	0.0042	At 0.05 significance level, data not drawn from normal distribution.
Weight (kg)	25	0.18228	0.33696	At 0.05 significance level, data drawn from normal distribution.
Height (m)	25	0.18228	0.33696	At 0.05 significance level, data drawn from normal distribution.

TABLE 3. Results from K-W one way ANOVA [1].

	χ^2	DF	$P > \chi^2$
C	100	100	0.48119

- Construction of a feature vector from a given sample window and selecting important features.
- Quantification of the performance of the dataset by applying existing state of the art classification algorithms used for HAR.
- Performance comparison with similar ADL from benchmark datasets, as well as performance analysis of fall classification.
- Proposing a real-time system architecture and algorithm to be used with our dataset.

Detailed explanation, figures and analysis supporting the discourse in Section I, as well as qualitative details of the dataset, assembly of the datalogger and the assumptions/scenarios of the testbed, can be found in literature [1]. The raw (unprocessed) DU-MD is available at: `eee.du.ac.bd/DU-MD` and `aa.binbd.com/mobility.html`

II. METHODOLOGY

Classification problems in HAR generally involve signal preprocessing, segmentation, feature extraction and classification/training [13], [14].

- Pre-processing involves high-frequency noise removal and separation of body and gravitational acceleration components.
- Segmentation involves separating the signal into minute components via a 'window'. Sliding windows, event-defined windows and activity-defined windows are widely used in HAR [13].
- Feature extraction involves constructing a feature vector that contains several quantitative aspects of the signals, some of which may help in differentiating each class of actions.
- Finally, supervised classification involves training a machine learning model using a labeled processed/segmented dataset along with the feature vector. Common models in HAR include Support Vector Machines (SVM), K-Nearest Neighbours (KNN) and Convoluted Neural Networks (CNN).

TABLE 4. Extracted features of the DU-MD.

01. Mean-X	02. Mean-Y	03. Mean-Z
04. Median-X	05. Median-Y	06. Median-Z
07. STD-X	08. STD-Y	09. STD-Z
10. Var-X	11. Var-Y	12. Var-Z
13. Min-X	14. Min-Y	15. Min-Z
16. Max-X	17. Max-Y	18. Max-Z
19. MAD-X	20. MAD-Y	21. MAD-Z
22. IQR-X	23. IQR-Y	24. IQR-Z
25. Entropy-X	26. Entropy-Y	27. Entropy-Z
28. PeakFreq-X	29. PeakFreq-Y	30. PeakFreq-Z
31. VSMean	32. VSMedian	33. VSSTD
34. VSVar	35. VSMin	36. VSMax
37. VSMAD	38. VSIQR	39. SlopeChange-X
40. SlopeChangeY	41. SlopeChangeZ	42. VSSlopeChange
43. ZeroCross-X	44. ZeroCross-Y	45. ZeroCross-Z
46. VSZeroCross	47. MeanCA-X	48. MeanCA-Y
49. MeanCA-Z	50. VSMeanCA	51. MeanCV-X
52. MeanCV-Y	53. MeanCV-Z	54. VSMeanCV
55. Kurtosis-X	56. Kurtosis-Y	57. Kurtosis-Z
58. VSKurtosis	59. Skewness-X	60. Skewness-Y
61. Skewness-Z	62. VSSkewness	63. Range-X
64. Range-Y	65. Range-Z	66. VSRange
67. PCA-X	68. PCA-Y	69. PCA-Z
70. VSPCA	71. DS-X	72. DS-Y
73. DS-Z	74. MeanVecNorm-X	75. MeanVecNorm-Y
76. MeanVecNorm-Z	77. MeanZScore-X	78. MeanZScore-Y
79. MeanZScore-Z	80. MeanRemove-X	81. MeanRemove-Y
82. MeanRemove-Z	83. VecNormMeanRem-X	84. VecNormMeanRem-Y
85. VecNormMeanRem-Z		

A. SIGNAL SEGMENTATION AND PREPROCESSING

Rather than applying autonomous segmentation windows, we have manually segmented each signal to account for unequal sample size of each instance such that each action waveform was reduced to a window of 101 samples ($\sim$ 3.3 seconds). A 4th order IIR Butterworth low-pass filter with a cut-off frequency of 20 Hz (Filter A) was chosen and then applied to the waveforms to remove high frequency accelerometer noise; such an approach to noise removal and chosen cut-off frequency has been justified quantitatively in literature [6] and [15]. To separate gravity acceleration (GA) components from body acceleration (BA) components, a 4th order IIR Butterworth low-pass filter with a cut-off frequency of 0.3 Hz (Filter B) was implemented and output of Filter A was fed to Filter B; the BA components were then calculated by subtracting the output of Filter B (GA components) from output of Filter A [15]. The output of Filter B (GA components) was then used to generate a feature vector.

B. FEATURE VECTOR CONSTRUCTION

Classic features mentioned in literature [6], [15], and [16] such as mean, median, standard deviation (STD), maxima/minima, median absolute deviation (MAD), interquartile range (IQR), entropy, the score of principal components, vector sum (VS) parameters and frequency domain parameters were calculated for the processed signals. A new set of features involving wavelet transforms [17], namely mean approximation coefficients (CA) and mean diagonal detail (CV) coefficients for Symlet Wavelet Transform (sym2, level 5), as well as dominant sign of a signal (DS) were also employed for performance analysis. Table 4 summarizes all of the 85 extracted features.

- Mean: The arithmetic mean/average is given by:

$$\overline{x} = \sum_{i=1}^{n} \frac{x_i}{n} \tag{1}$$

where n = number of samples and x_i = ith sample value.

- Median: The median of a class is given by:

$$M = L_m + C\left(\frac{N/2 - F}{f_m}\right) \tag{2}$$

where L_m = lower boundary of median class, C = class size, F = cumulative frequency before median class, N = total frequency and f_m = frequency of median class.

- Standard Deviation (STD): The standard deviation of a sample class is given by:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \overline{x})^2}{n-1}} \tag{3}$$

where n = number of samples, $x_i = i^{th}$ sample value and $\overline{x}$ = sample mean.

- Variance: The variance of a class is given by:

$$S = \sigma^2 \tag{4}$$

where σ = standard deviation

- Maxima (Max) and Minima (Min): Provides the maximum and minimum values of a particular signal.
- Median Absolute Deviation (MAD): The median absolute deviation is given by:

$$M.A.D. = \sum_{i=1}^{n} \frac{x_i - M}{n} \tag{5}$$

where n = number of samples, x_i = ith sample value and M = median.

- Interquartile Range (IQR): The IQR is given by:

$$IQR = Q_3 - Q_1 \tag{6}$$

where $Q_3 = 3^{rd}$/Upper Quartile, $Q_1 = 1^{st}$/Lower Quartile.

$$Q_i = L_Q + \frac{h}{f_Q}\left(\frac{iN}{4} - c\right); \quad i = 1, 2, 3\ldots \tag{7}$$

where L_Q = lower boundary of quartile group, h = quartile width, c = cumulative frequency before quartile group, N = total frequency and f_Q = frequency of quartile group.

- Signal Entropy: Entropy refers to the statistical randomness in a sample, or the average information in a signal. It is defined as:

$$H(X) = \sum_{k=1}^{n} P(x_k) log_2\left(\frac{1}{P(x_k)}\right) \tag{8}$$

where $x_k = k^{th}$ sample value and $P(X)$ is a probability distribution function.

- Largest Frequency Component (PeakFreq): The peak/largest frequency component is found out by first finding out the Fast Fourier Transform (FFT) of the signal

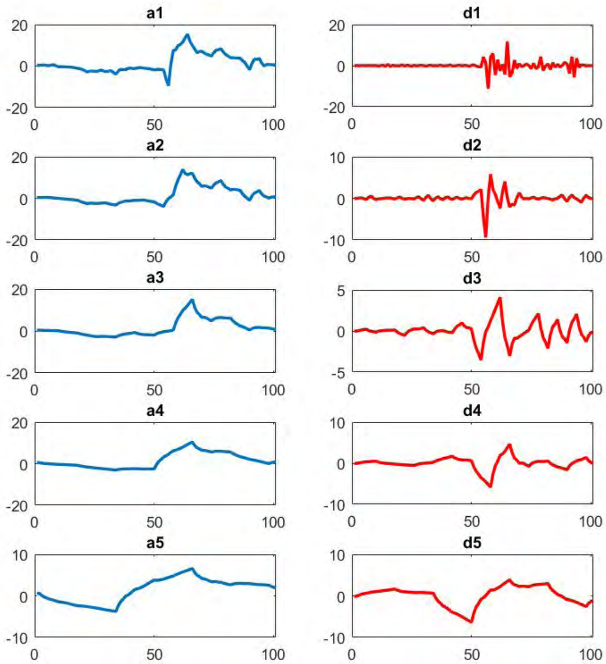

FIGURE 1. Plot of approximation and detail coefficients of a "walk" signal after Symlet wavelet transformation.

and then deciphering the frequency at which the largest response is observed from the spectrum.

- Vector Sum (VS): The vector sum of a signal in three dimensions is given by:

$$S = (\sqrt{{A_x}^2 + {A_y}^2 + {A_z}^2}) \tag{9}$$

where A_x, A_y and A_z are the *x, y* and *z* components of a signal.

- Sign change of Slope (SlopeChange): This is done by finding out the slope (differentiating with respect to time) of the signal at every point and then listing the changes in sign to signify the direction of motion of the curve.
- Zero Crossing (ZC): This is used to detect the points at which the signal crosses zero on the time axis. Mathematically:

$$y = 0 = f(x) \tag{10}$$

where *f(x)* is the polynomial that provides the values of y. At x axis intercept, $y = 0$.

- Approximation Coefficients (CA) and Mean Diagonal Detail Coefficients (CV): A wavelet transform involves decomposing an original signal using a series of filters such that the output of the high pass filter provides some coefficients (called detail coefficients), while the output of the low pass filter provides approximation coefficients. These two groups of coefficients describe the original signal. Figure 1 shows the Wavelet Analyzer Toolbox in MATLAB in action which can be used to obtain the aforementioned coefficients.
- Kurtosis: The peakedness or kurtosis is given by:

$$\mu_4 = \sum (x - \overline{x})^k \cdot f(x) \tag{11}$$

where all values of x are summed over, and *f(x)* is the probability distribution function of x.

- Skewness: The skewness of a distribution is given by:

$$\gamma = E\left(\frac{X - \overline{X}}{\sigma^2}\right)^3 \tag{12}$$

where $\overline{X}$ is the mean and σ^2 is the standard deviation.

- Range: Range of a signal is the difference between the maximum and minimum value of the signal.
- Score of Principal Components (PCA): The k^{th} factor score of principal components (an approximation of actual signal in terms of two other vectors containing essential patterns to describe the signal) of a signal is given by:

$$t_{k(i)} = x_{(i)} \cdot w_{(k)} \tag{13}$$

where x_i is the input data vector, $w_{(k)}$ are k^{th} loadings.

- Dominant Sign (DS): The number of positive and negative samples in a signal are compared and then 1 is assigned to the signal if number of positive samples exceed or is equal to negative samples; a 0 is assigned to the signal is negative samples exceed positive samples.
- Mean Vector Normalization (MeanVecNorm): The samples of a signal are divided by the signal's vector sum and then the mean value of the resulting signal is taken.
- Mean Z Score (MeanZScore): The z score of each signal is calculated using the formula:

$$Z = \left(\frac{X - \overline{X}}{\sigma}\right) \tag{14}$$

Afterwards, the mean value of the new signal is calculated.

- Mean Removal (MeanRemove): Each sample of a signal is subtracted from the mean and then the mean of the new signal is calculated.
- Vector Normalization and Mean Normalization (VecNormMeanRem): Vector normalization is carried out on a signal, and then the mean of the new signal is subtracted from the samples of the new signal. The mean of the resulting signal is then calculated.

All mathematical equations have been referenced from [18]–[22].

C. FEATURE AND CLASS SELECTION

After analyzing with some classifiers and observing the parallel coordinate plot of each feature, as well as standard deviations of the features, 39 features were finally chosen for classifier training empirically, shown in Table 5.

Figure 2 shows the standard deviations/parallel coordinate plot of all the features (assuming 0 mean).

The number of classes were reduced from 10 to 8 by grouping three types of falls into one class since classifiers

TABLE 5. Best features of the DU-MD dataset.

01. Mean-X	02. Mean-Y	03. Mean-Z
04. Median-X	05. Median-Y	06. Median-Z
07. STD-X	08. STD-Y	09. STD-Z
10. Min-X	11. Min-Y	12. Min-Z
13. Max-X	14. Max-Y	15. Max-Z
16. Entropy-X	17. Entropy-Y	18. Entropy-Z
19. PeakFreq-X	20. PeakFreq-Y	21. PeakFreq-Z
22. VSSTD	23. VSVar	24. VSMin
25. VSMax	26. VSIQR	27. MeanCA-X
28. MeanCA-Y	29. MeanCA-Z	30. Range-X
31. Range-Y	32. Range-Z	33. VSRange
34. PCA-X	35. PCA-Y	36. PCA-Z
37. DS-X	38. DS-Y	39. DS-Z

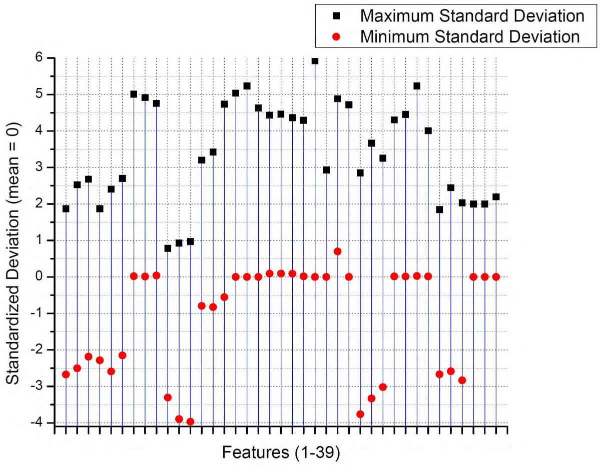

FIGURE 2. Standard deviations of selected features.

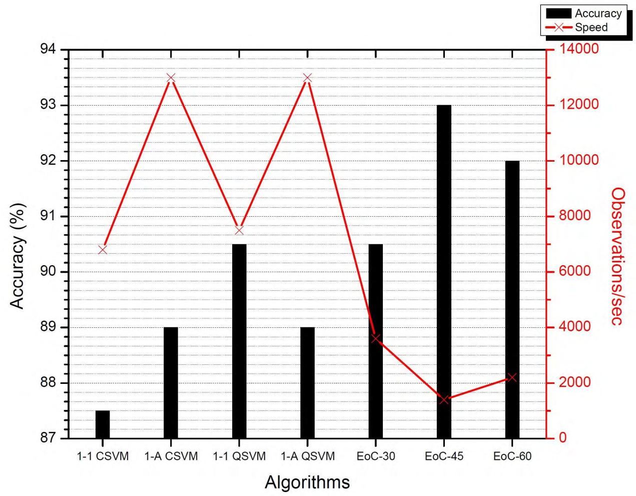

FIGURE 3. Accuracy and speed of several algorithms on the dataset.

TABLE 6. Confusion matrix of EoC-45 on DU-MD.

True Class	Predicted Class								TP	FN
Jogging (J)	**100**								100	0
Laying Down (LD)		**95**	5						95	5
Sitting (Si)		5	**95**						95	5
Staircase Down (SD)				**90**	5			5	90	10
Staircase Up (SU)				10	**85**		5		85	15
Standing (St)					10	**85**		5	85	15
Walking (W)					5	5	**90**		90	10
Falling (F)				3	2			**95**	95	5
	J	**LD**	**Si**	**SD**	**SU**	**St**	**W**	**F**		

TABLE 7. Confusion matrix of 1-1 QSVM on DU-MD.

True Class	Predicted Class								TP	FN
Jogging (J)	**95**							5	95	5
Laying Down (LD)		**90**	10						90	10
Sitting (Si)		10	**90**						90	10
Staircase Down (SD)	5			**85**	5			10	85	15
Staircase Up (SU)				10	**80**		5	5	80	20
Standing (St)					5	**80**	5	10	80	20
Walking (W)			5				**95**		95	5
Falling (F)				3	2			**95**	95	5
	J	**LD**	**Si**	**SD**	**SU**	**St**	**W**	**F**		

TABLE 8. Performance comparison with other benchmark datasets.

Dataset	Classes	Instances	Features	SVM (%)	EoC (%)
HAR	6	10299	561 [13]	96 [13]	97 [13]
HASC	6	6700	144 [15]	95.3 [13]	95.5 [13]
HAPT	6+1*	10929	561 [13]	94.2 [13]	97 [13]
DU-MD (40%)	**7+1♮**	**2000 (out of 5000) ♭**	**39 (best of 85)**	**90.5**	**93**

*6 postural transitions have been considered one class (transitions).
♮ 3 types of falls grouped into one class to improve performance.
♭ At the time of writing, 2000 instances were available for training.

were facing problems in distinguishing between three types of falls.

III. RESULTS

A. PERFORMANCE OF HUMAN ACTIVITY CLASSIFICATION (ALL CLASSES)

Several existing HAR algorithms such as Support Vector Machines (SVM) [6], K-Nearest Neighbours (KNN) [23] and Ensemble of Classifers (EoC) (we have used bagged decision trees) [13] were tested on the dataset consisting of 2000 observations, 8 classes and 39 features. Out of all the algorithms, SVM and EoC exhibited promising performance on our dataset, with EoCs exhibiting an accuracy from 90.5% $\sim$ 93% and SVMs exhibiting an accuracy from 87.5% $\sim$ 90.5%. The variations include:

- One-vs-One Multi-Class Cubic SVM (1-1 CSVM)
- One-vs-All Multi-Class Cubic SVM (1-A CSVM)
- One-vs-One Multi-Class Quadratic SVM (1-1 QSVM)
- One-vs-All Multi-Class Quadratic SVM (1-A QSVM)
- EoC; Bagged Decision Trees with 30 learners (EoC-30)
- EoC; Bagged Decision Trees with 45 learners (EoC-45)
- EoC; Bagged Decision Trees with 60 learners (EoC-60)

For validation, the dataset was partitioned randomly with a holdout ratio of 1:9 (holdout validation); a low holdout ratio was chosen since the dataset was relatively small. The performances of these classifiers are summarized in Figure 3.

The confusion matrices [24] of EoC-45 and 1-1 QSVM are shown in Tables 6 and 7. Table 8 shows comparative performances of DU-MD with the HASC, HAPT and HAR benchmark datasets using SVM and EoC. Accuracy (%) in correctly classifying ADL has been used as a performance metric for all datasets.

Several important inferences can be made from Table 8.

- Compared to the benchmark datasets, we used fewer features (hence less processing power required), fewer instances but more classes. This caused a lag in accuracy

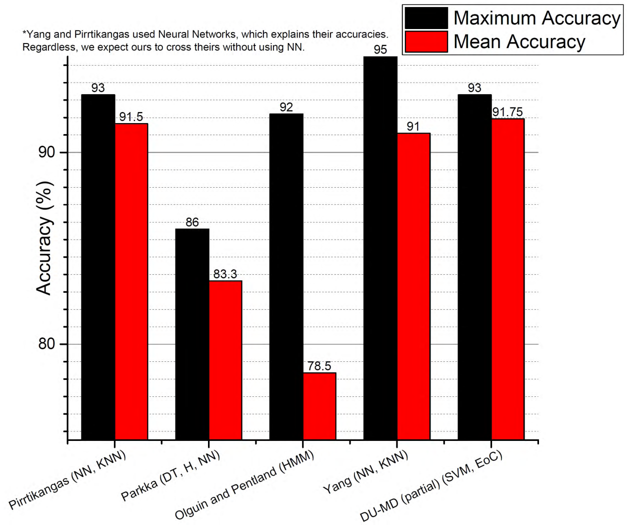

FIGURE 4. **Performance of our dataset in activity recognition compared to other HAR datasets using wrist mounted sensors/combination. DU-MD exceeded mean accuracy of all datasets.**

of 4-6 percent when compared with other datasets, since we provided insufficient training examples with a large number of classes. We expect the accuracies to approach the benchmark accuracies when we complete processing the entire dataset of 5000 observations after the rest of the observations are obtained.

- HAR and HAPT used waist-mounted mobile phones as sensors, while HASC used a mobile phone carried around inside a pocket. Whilst such approaches are not always practical as discussed earlier, a study by Cleland *et al.* [25] found out that wrist-mounted HAR systems perform slightly poorly compared to other locations of the body. So it is no surprise that the performance of DU-MD is slightly degraded compared to other datasets. In fact, Figure 4 shows some notable datasets in wrist-mounted HAR systems and their performances as mentioned in literature [25], compared to our dataset. Figure 4 shows that our dataset outperformed all other datasets marginally (without using neural networks, heuristics, or other deep learning models). Furthermore, HASC, HAPT and HAR datasets are not applicable in fall detection systems. However, our dataset has fall waveforms and the classifiers detected falls with an accuracy of 93-97% and a modal accuracy of 95%.

The Receiver Operating Characteristic Curve (ROC Curve) [24] for fall detection using EoC-45 and 1-1 QSVM are shown in Figure 5, while Figure 6 shows performance of our dataset for fall detection compared to performance of other datasets [26]–[30]. Note that these manuscripts attempt several different algorithms to improve their fall detection accuracies while we apply a single classifier. Neural networks and deep learning principles were used to improve fall detection as shown in Figure 6.

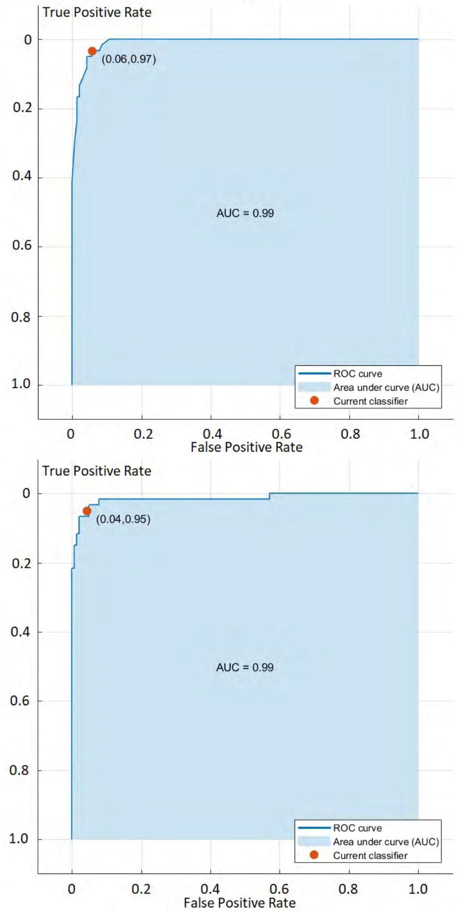

FIGURE 5. **(Top) ROC curve for QSVM; (Bottom) ROC curve for EoC-45.**

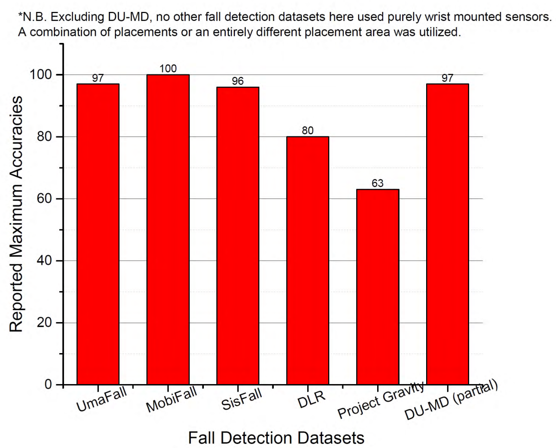

FIGURE 6. **Performance of our dataset in fall detection compared to other fall detection datasets. Datasets not using machine learning have been ignored.**

B. PERFORMANCE OF FALL CLASSIFICATION

For fall classification (differentiating between three falls), Subspace K-Nearest Neighbour (S-KNN), with 60 learners and a subspace dimension of 15 yielded an accuracy of 68.3% on the 600 fall waveforms with 39 features and 3 fall classes.

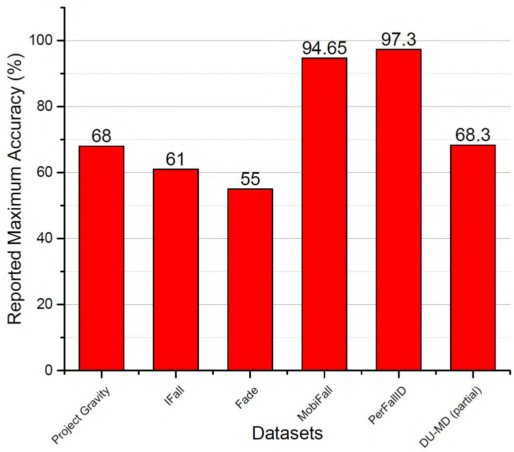

FIGURE 7. **Performance of our dataset in fall classification compared to other fall classification datasets [25], [29], [30].**

TABLE 9. **Confusion matrix of S-KNN after fall classification.**

True Class	Predicted Class			TP	FN
Fall (Heart Attack)	**62**	19	19	62	38
Fall (Slipping)	19	**72**	9	72	28
Fall (Unconscious)	20	10	**71**	71	29
	Fall(Heart Attack)	Fall (Slipping	Fall (Unconscious)		

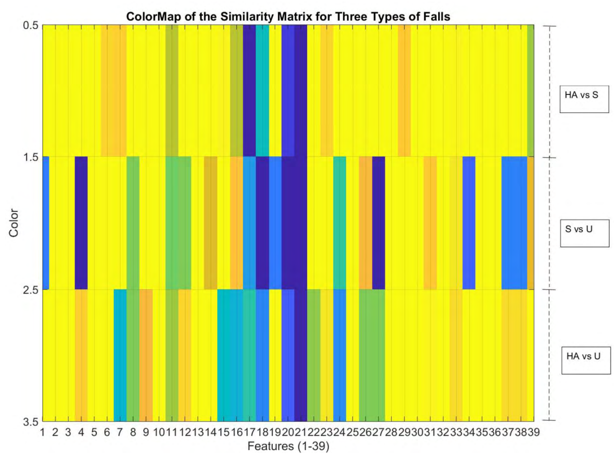

FIGURE 8. **Similarity matrix of the three classes of falls for each feature (1-39) shown in RGB color map, which indicates similarity of each class with the other.**

12-fold cross validation was used to protect against bias. Figure 7 shows performance of other similar datasets when classifying various types of fall.

The confusion matrix of fall classification using S-KNN is shown in Table 9.

The color map of the similarity matrix of the three types of falls shown in Figure 8.

The falls that we are trying to classify have similar waveforms with only the initial window before the actual fall being different as explained in literature [1], whereas other fall classification datasets focused on detecting the direction of falls (e.g., falling backwards or forwards or sideways), which explains the relatively low accuracy of our fall classifier compared to other fall classification datasets as shown in Figure 7. This is also confirmed by a color map of the similarity matrix of the three types of falls shown in Figure 8, which indicates the correlation of the features for each type of fall against each other (heart attack vs. slipping, slipping vs. unconsciousness and heart attack vs. unconsciousness). The matrix clearly indicates that many features are similar to each other, further explaining the low accuracy.

The confusion matrix in Table 9 indicates that the classifier is only 62% accurate in case of heart attacks. In order to improve this, we suggest using a non-invasive heart rate monitor to verify whether the predicted action actually refers to a heart attack or not. Such a combination has already been applied in literature [31] with promising results, however, we aim to detect heart attacks using commercial heart rate monitors found within fitness bands to align with the philosophy of our dataset goals rather than using discrete heart rate sensors for heart attack detection [32].

IV. IMPLEMENTATION STRATEGIES

Application of existing fitness bands in activity tracking and heart rate monitoring such as the Xiaomi Mi Band, Apple Watch, Samsung Gear Fit, Garmin Vivofit, FitBit Flex etc. regarding accuracy and precision have been studied and justified in literature [33]. Reported accuracies are as high as 99.1%. As a result, fitness bands can be used as the intended sensor whilst processing is to be carried inside a smartphone.

Inside residential and restricted environments, the smartphone can be kept within allowable communication range of the activity tracker and act as the processing node. Multiple activity trackers can tap one processing node, which may be useful in hospitals and retirement homes. Special RFID Tag Systems mentioned in papers [34], [35] can also be used to monitor both external and internal motion signatures of subjects using a single harmonic RFID tag rather than using multiple fitness trackers, with the action recognition kernel of the system being trained using our dataset.

In external environments or places where Internet is unavailable, it is expected that the user will carry both the sensor node and the processing node. Energy consumption in smartphones executing HAR algorithms have been studied extensively in papers [30], [36] and all smartphones are going to be equipped with innate energy-efficient machine learning processors / neural engine SoC (such as ARM ML or Apple A11) mentioned in literature [38] and [39] in near future. Several aspects of using the smartphone as a processing node, such as dataset generation, hardware-friendly machine learning algorithms and online activity recognition has been discussed extensively and justified in by Ortiz [39].

A. PROPOSED ALGORITHM

Figure 9 shows the suggested algorithm to be used in real time systems trained using our dataset. The raw data is obtained in real time from an accelerometer coupled with a heart rate monitor. The interfacing software parses the data and passes

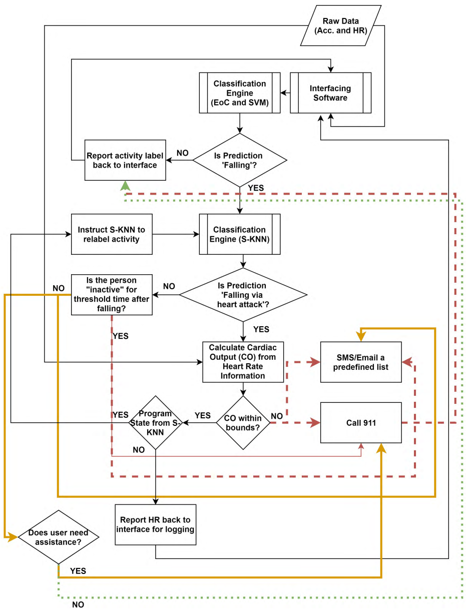

FIGURE 9. Proposed algorithm to be used in real time for systems trained with our dataset. Red lines indicate highly dangerous event flow, orange lines indicate moderately dangerous event flow, green lines indicate low danger event flow.

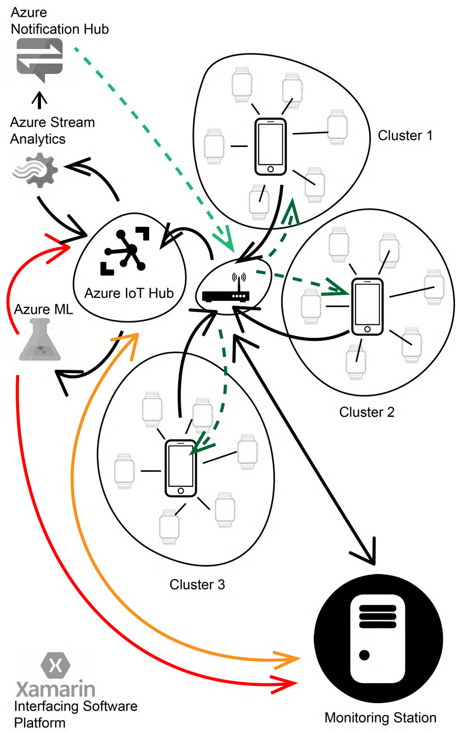

FIGURE 10. Proposed real-time IoT mesh architecture for systems trained using our data in controlled environments (such as hospitals).

it off to the classification engine, either bagged decision trees or support vector machine. If the classifier classifies the data as anything but falling, the data is reported back to the interfacing software. Parallely, the heart rate of the patient is also continuously monitored, and emergency actions (such as calling 911 and informing relatives via email/SMS) are taken if the cardiac output deviates from natural values.

If the classifier detects a fall, then the interfacing software runs a second engine (Subspace KNN) to classify the type of fall. If an abnormality is detected in the cardiac output while the classifier classified the signal due to falling from heart attack, then the classifier immediately classifies the fall as falling due to heart attack; otherwise the system reruns the calculations to check again. Unconsciousness is detected by comparing the period of inactivity against a threshold time for which the person is inactive, after which the system performs emergency actions. If the user is not unconscious but requires assistance, he/she can instruct the interfacing software to do so. Compared to existing commercial fall detection systems, we have fused two sensors on a single fitness band for improved fall classification accuracy and false positive elimination.

B. DEPLOYING ON THE CLOUD

In environments deploying a large number of sensing nodes, cloud-based machine learning services can be used to reduce processing requirements and focus on subject monitoring and data analytics [40]. Figure 10 shows our proposed cloud architecture, based on Microsoft Azure services [41] for deploying real-time systems. Each cluster consists of one receiving node (can be a smartphone or a computer) and several sensor nodes (fitness bands or RFID tags). The sinks arrange the data in a form suitable for processing by Azure Machine Learning Studio. The sinks upload data to Azure IoT Hub and a monitoring station, located inside the same facility as the sinks and sources. The IoT Hub securely stores all vital signs, traces, and physiological information. It streams data in real time to Azure ML [42] and shares data with Azure Stream Analytics occasionally. The ML Studio runs our proposed algorithm for HAR in real time and stores activities (shown in red color) in Azure IoT Hub. Additionally, the classified activities for each subject are sent to the monitoring station. If an emergency situation persists (e.g., a fall is registered), the monitoring station is easily notified. The monitoring station is also able to access all stored data (shown in orange color) securely. Stream Analytics analyzes activities for patterns and custom creates health tips and reminders subjectwise, which are forwarded to the Notification Hub. The Notification Hub sends these notifications to the sinks of the clusters at optimum times (shown in dashed green). The applications shall be developed using the Xamarin Platform for machine-independent applications.

V. CONCLUSION AND FUTURE WORK

In this paper, we quantitatively validated part of the open-source DU-MD that was introduced in the literature [1]. Apart from exhibiting promising statistical diversity in physiological parameters and correlation between similar classes, an average accuracy of 91.75% was obtained when One-vs-One Quadratic SVM and Bagged Decision Trees (Ensemble

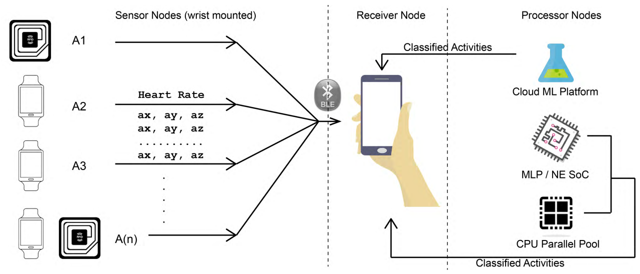

FIGURE 11. **Overview of the suggested real time implementation scheme.**

of Classifiers) were used for HAR with a maximum accuracy of 93% obtained using EoC, which is within 4∼6% of benchmark datasets. Maximum fall detection accuracy was 97%, which exceeded accuracies obtained from most similar datasets. In addition, we obtained a moderate accuracy of 68.3% in fall classification using Subspace KNN as a classifier. We proposed solving the low-accuracy problem in fall-classification by bringing in heart rate monitors into play, found within most fitness bands.

In addition, we qualitatively explored possible implementation strategies of systems to be trained using our dataset. We proposed an algorithm that may be run on such machines and also provided a cloud-based IoT architecture of a large scale system where multiple sensors may be deployed using several services from Microsoft Azure. Implementation schemes for both large scale and small scale deployment were suggested.

Scopes involving future perusal include the application of dense labeling algorithm [43] for automatic segmentation instead of manual or traditional sliding windows. Performance analysis on the entire dataset must be carried out when complete. Performance analysis of our dataset using deep learning models such as convolutional and recurrent neural network [44], [45] is also recommended. 'Real-time' performance analysis of our proposed algorithm by varying the length of the time series (i.e., window size) [46], hence making window size flexible, will be commercially significant, especially quantifying processing requirements and energy efficiency of our proposed algorithm when run on a smartphone. Application of sequential spatial information through the application of Long Term Short Memory (LSTM) network would be important during real time operation. Other possible research areas include deployment and performance analysis of proposed IoT mesh architecture and testing performance of our classifiers over a wide range of fitness bands to test whether the dataset is indeed truly hardware independent.

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SWAPNIL SAYAN SAHA (S'15) received the advanced training in small satellite engineering from Beihang University, Beijing, China, and Middle East Technical University, Anakara, Turkey, as part of the First & Second Summer Camp of the APSCO SSS Project in 2017 and 2018. He is currently a Senior majoring in computer engineering with the Department of Electrical and Electronic Engineering, University of Dhaka, Bangladesh. He is also an Undergraduate Researcher and a Lab Operator at FAB LAB DU. He is also the Chief Technology Officer and a Digital Marketing Manager of his own startup named Orion Avionics and Electronics. He is also the Vice-Chair (Technical) of IEEE SBDU, a Social Media Coordinator of the IEEE Bangladesh Section Humanitarian Activities Committee, and an Assistant General Secretary of the Electrical and Electronics Club, EEE, DU. He is the 2018 IEEE Richard E. Merwin Scholar and the 2018 IEEE R10 CS Student Ambassador. Till date, he has co-authored 10 conference publications, one of which achieved a best paper award and has published one data set. He has completed eight projects and has received four grants. His research interests include embedded system design, automation and robotics, applied machine learning, small satellite engineering, and aerospace electronic systems. He is a Student Member of IEEE RAS, IEEE CS, and IEEE AES. He received over 20 awards in national technical/business competitions and the prestigious IEEE AIYEHUM in 2017. He was an invited speaker/trainer in four national seminars/workshops.

SHAFIZUR RAHMAN is currently a Senior majoring in computer engineering with the Department of Electrical and Electronic Engineering, University of Dhaka, Bangladesh. His research interests include applied machine learning, embedded system design, mobile application development, and Web-app development. He was a recipient of the prestigious Digital Khichuri Challenge 2017 and has received seed funds and office space for his own startup from ICT Ministry, Bangladesh. He was also a recipient of over seven national technical/business competitions and has executed two projects.

MIFTAHUL JANNAT RASNA received the B.Sc. degree in applied physics, electronics and communication engineering from the University of Dhaka, Bangladesh, in 2014, and the M.Sc. degree in electrical and electronic engineering in 2016. She is currently pursuing the Ph.D. degree in electrical engineering with fellowship with Princeton University, USA. She is currently a Lecturer in electrical and electronic engineering with the University of Dhaka. Till date, she has co-authored four conference proceedings. Her research interests include biomedical engineering, machine learning, computer vision, signal and image processing, and pattern recognition. She has been a Mentor of IEEE SBDU and has volunteered for several national events and international conferences organized by IEEE SBDU, such as the Bangladesh Electronics Olympiad, IEEE SYWC 2016, and ICIEV 2016.

TAREK BIN ZAHID received the B.Sc. degree in electrical and electronic engineering from the University of Dhaka, Bangladesh, in 2017. Since graduation, he has worked at FAB LAB DU in the field of Bengali character segmentation. Till date, he has co-authored one conference publication and has published one data set. His research interests include computer vision, machine learning, deep learning, and big data analysis.

A. K. M. MAHFUZUL ISLAM (S'11–M'14) received the B.Sc. degree in electrical and electronic engineering, and the M.Sc. and Ph.D. degrees in informatics from Kyoto University, Japan, in 2009, 2011, and 2014, respectively. He is currently a Research Associate with the Institute of Industrial Science, The University of Tokyo, Japan. Till date, he has co-authored seven journal articles, 24 conference publications, and holds two patents. His research areas are include on-chip sensors for variability, temperature, leakage and power, models for performance prediction under the presence of dynamic variations, built-in self-healing techniques, body biasing techniques for energy-efficient LSI operation, low-power circuit techniques, and large-area flexible electronics using organic transistors. He has won several best paper, design, and student presentation awards and is a recipient of several prestigious awards, including the IPSJ Yamashita SIG Research Award, the JSPS Postdoctoral Fellowship for Overseas Researchers, the IPSJ Computer Science Research Award for Young Scientists, and the IEEE SSCS Japan Chapter VDEC Design Award.

MD. ATIQUR RAHMAN AHAD (M'10–SM'15) received the B.Sc. and master's degrees (Hons.) from the Department of Applied Physics & Electronics, University of Dhaka (DU), the master's degree from the School of Computer Science & Engineering, University of New South Wales, and the Ph.D. degree from the Faculty of Engineering, Kyushu Institute of Technology (KIT). He was a Visiting Researcher at KIT. He is currently a Professor of electrical and electronic engineering, DU. He is currently a Specially Appointed Associate Professor with Osaka University, Japan. He works on computer vision, imaging, IoT, healthcare, and so on. He published two books as a single author (available in Springer) and a few book chapters. He has published over 110 journals and conference papers. He has received over 10 international awards in various conference/journal/society. He was invited as a keynote/invited speaker about 50 times in different conferences/universities. He has established several international MOU/collaborations (e.g., Clemson University, the University of Hyogo, RCCIIT, Fukuoka Women University, and Kyushu University). He was a recipient of the JSPS Postdoctoral Fellowship, the prestigious UGC Award 2016, and a number of awards/scholarships.

He is a Member of OSA, ACM, the IEEE Computer Society, IAPR, IEEE RAS, and IEEE SMC. He is the Founder Secretary of the IEEE Computer Society Bangladesh Chapter and the Bangladesh Association of *Pattern Recognition*. He volunteers some societies in Bangladesh and Japan. He has been involved with some academic and editorial activities: e.g., a General Chair of the 2018 7th International Conference on Informatics, Electronics & Vision, Japan, the 2018 2nd International Conference on Imaging, Vision & Pattern Recognition, Bangladesh, and the 7th International Symposium in Computational Medical and Health Technology; a Publication Chair of the 2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC); a Vice Publication Co-Chair and a Vice Award Chair of the Joint 17th World Congress of International Fuzzy Systems Association, the 9th International Conference on Soft Computing and Intelligent Systems, and several other international conferences; an Editorial Board Member of a *Scientific Reports* (Nature) and the *Encyclopedia of Computer Graphics and Games* (Springer); an Associate Editor of *Frontiers* (ICT); an Associate Technical Editor (former) of the *IEEE ComSoc Magazine*; the Editor-in-Chief of the *International Journal of Computer Vision*, *Signal Processing*, the *International Journal of Electronics and Informatics*, and the *International Journal of Environment*. He served as a Guest Editor for *Pattern Recognition Letters* (Elsevier), the *Journal of Multimedia User Interface* (Springer), the *Journal of Healthcare Engineering* (Hindawi), and the *International Journal of Innovative Computing, Information and Control*.