Improving Human Activity Recognition using ML and Wearable Sensors

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Abstract – The Internet of Things (IoT) generates massive amounts of data everywhere through sensors of every kind which are disseminated in a variety of objects. This data contains incredibly valuable information useful for multiple applications. Knowing the context in which it was generated is extremely important and constitutes one of the first steps in extracting the knowledge it contains. Thereby, Context-Aware Learning (CAL) has become an important area of research as machine learning (ML) is a fast and ever-evolving technology. Wearable devices, ranging from accelerometers (ACC), frequently used, to magnetic field sensors, are used to monitor and recognize human activities (HA). Beyond ML Algorithms (MLA), accurate Human Activities Recognition (HAR) or context identification, depends not only on the kinds of sensors used but also on their location. In this paper, we study the impact of three types of sensors: ACC, gyroscope (GYR), and magnetometer (MAG); and their locations on the performance of MLA for HAR. Our results show that magnetic field sensors, less frequently used in the literature, placed at a specific location, provide the best performance in terms of HAR. Using a publicly available dataset, PAMAP2, we implement and evaluate the performance of HAR using five MLA: Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QLA), K-Nearest Neighbors (KNN), Decision Tree (DT), and Random Forest (RF). Our results show that the success rate of these algorithms is 98.3%, 90.4%, 97.6%, 99.9%, and 100% respectively, which exceeds the results obtained in a previous work based on the same dataset.

Keywords: IoT; context-aware learning; sensors; sensors' location; machine learning; human activity recognition; feature extraction.

I. INTRODUCTION

IoT is one of the most important subjects that attract a lot of attention in the research community as well as in industry. IoT has several applications that can be grouped into 8 areas [1]: Smart Mobility, Smart Grid, Smart Home/Building, Public Safety and Environmental Monitoring, Medical and Healthcare, Industrial Processing, Agriculture and Breeding, and Independent Living. The number of IoT devices in 2021 is approximately 13.8 billion [2]. Meanwhile, the total market size was estimated at $388 billion U.S. in 2019 and is expected to exceed $1 trillion in 2030 [3]. IoT devices generate massive amounts of data which contain valuable information that can be used in a variety of applications. Extracting knowledge from this data is challenging, particularly for real-time applications. An important step of this knowledge extraction is identifying the data context. Thereby, CAL has become an important area of research as ML is a fast and ever-evolving technology. Among other applications, CAL was often used for physical/human activities (HA) monitoring and health applications [4]. Data is collected using wearable sensors: ACC, GYR, MAG, GPS, heart rate (HR), etc. The type of sensors collecting the data and their location on the human body can greatly affect the accuracy of context identification. To the best of our knowledge, none of the previous research works have studied the impact of the type of sensors used and their location on the performance of MLA on HAR. In this paper, we study the impact of the three types of sensors: ACC, GYR, and MAG; and their location on the performance of MLA on HAR. For this purpose, we used PAMAP2 [5], [6], a dataset of HA collected from a variety of sensors (ACC, GYR, MAG, temperature, HR). We implemented and evaluated the performance of HAR using five MLA: LDA, QDA, KNN, DT, and RF. Our results showed that the success rate of these algorithms is 98.3%, 90.4%, 97.6%, 99.9%, and 100% respectively, exceeds the results obtained by M. Arif and Kattan [7] on the same dataset.

The contributions of this paper are the following:

1. We improved the success rate of HAR in comparison with the previous work based on the same dataset.
2. We proved that sensor location on the human body is crucial for improving HAR and found that placing the sensor on the chest provided the best results compared to other locations such as the ankle and hand.
3. We showed that considering all sensors data (here, 3 sensors, 18 activities) provides better performance than partial sensors data (1 sensor, 12 activities).
4. We demonstrated that increasing the window size (WS) enhances the learning algorithm performance i.e., better success rate and lower execution time.
5. We established that data from MAG, often ignored in previous works, improve the learning algorithm performance, and provide better results than commonly used ACC data.

The paper is organized as follows: in section II, a literature review is provided, in section III, we present our approach, followed by the experimental results and discussion in section

IV. Concluding remarks are provided in section V while the list of references is in section VII.

II. Literature Review

Research in IoT covers a large spectre of research interests [1]: sensing and data collection, network issues, security, applications, implementation, sensing the environment and learning, etc. CAL [8]–[10] applied to HAR is our main interest in this paper. Several research papers were published on HAR [7], [11] and context identification using a variety of MLA. Data were collected either from mobile phones' sensors or from Inertial Measurement Units (IMU). The most commonly used sensors were ACC, GYR, HR and MAG. A variety of scenarios involving a group of individuals were established for monitoring and collecting HA data. A scenario defines the activities to be monitored, their type, time, and period as well as the number of subjects involved.

Arif and Kattan [7] used ACC to classify different physical activities, including twelve physical activities and nine subjects. Time domain features were extracted from sensors placed on three locations: wrist, chest, and ankle. Using KNN, Rotation Forest, and Neural Network algorithms for activities classification, they achieved a success rate of 98%. Sarcevic et al. [11] extracted and compared features from time and frequency domains for human movement classification. They showed that time-domain features provide a higher classification success rate than frequency domain features. Sukor et al. [12] studied HAR using smartphone-embedded ACC data. They applied Principal Component Analysis (PCA) based features and compared time and frequency domains with several MLA. Chelli and Patzold [13] used acceleration (ACC) and angular velocity data for fall detection. Artificial Neural Network (ANN), KNN, Quadratic Support Vector Machine (QSVM), and Ensemble Bagged Tree (EBT) algorithms were tested. Instead of 66 features from ACC data only, they used 328 features from the autocorrelation from both the ACC and the angular velocity data. They were able to significantly improve the performance of these algorithms. Radivojević et al. [14] worked on ACC data from a smartwatch for HAR without any features. In training, the RF algorithm provided the best result; however, in testing, the Deep Neural Network (DNN) algorithm was the best for HAR.

Several other research works were published in CAL in relation to HAR. Fan et al. [15] proposed a transfer learning based collaborative tensor factorization method to achieve personalized context-aware online activity prediction. With only 30% of observed time and location contexts, they can improve activity prediction by 40%. Vaizman et al. [16] showed the difficulty of recognizing human context in the wild i.e., unscripted behavior and unconstrained phone usage. They collected data from sixty subjects with the subjects' personal smartphone and smartwatch provided by the authors for the purpose of their study. Agac et al. [17] proposed a context-aware activity recognition algorithm, which dynamically activates appropriate sensors, sampling rates and features according to the type of activity. In terms of results, they achieved 22% energy economy compared to static parameters sampling. Das and Almhana [18] proposed a CAL system in which they showed the importance of implementing lightweight learning algorithms on mobile devices which have a limited computing and energy power.

Unfortunately, most of the previous research works in HAR and CAL rely mainly on ACC data. In this work, we consider ACC, GYR and MAG sensor data and their location to evaluate their impact on HAR. A publicly available dataset, PAMAP2 [6], is used.

III. Approach

Our approach consists of the following steps:

A. Data selection and preprocessing. As previously mentioned, we will use and provide a brief description of the PAMAP2 dataset [6]. Also, we will describe some cleaning and formatting steps.
B. Feature extraction. Mainly, we will extract all necessary parameters or features for MLA.
C. MLA selection. We will explain the choice of each algorithm.

Subsequently, we will evaluate the performance of MLA, compare our results with the previous work [7], and study the impact of sensors location on performance.

A. Data Selection and Preprocessing

Reiss and Stricker [19] created and made publicly available the PAMAP2 dataset [6]. It was collected from nine individuals according to a specific scenario which includes eighteen different physical activities such as lying down, sitting, standing, walking, running, cycling, and others. Three IMUs were used and placed on the wrist, chest, and ankle. They include a variety of sensors such as HR, temperature, 3D-ACC data (scale ±16g), 3D-ACC data (scale ±6g), 3D-GYR data, 3D-MAG data, and orientation. For more information about the dataset, please see [19].

We were particularly interested in this dataset as they were collected from independent wearable sensors which can provide 30% more accurate data than sensors embedded in smartphones [20]. Furthermore, the scenario used for this dataset covers a variety of representative human activities. Also, it includes an important number of instances, a total of 3,850,505 instances.

We completed some preprocessing on the dataset. Mainly, we removed unwanted data: HR, 3D-ACC data (scale ±6g), and orientation as they are not needed for our work. Also, we removed all rows with erroneous values such as NaN (Non a Number). Finally, we concatenated all rows and sorted them according to their timestamp.

B. Feature Extraction

For the MLA, we needed to extract some data features. Several research works [7], [11], [16], [21] proposed certain criteria for feature extraction that we used for our work. As a matter of fact, we extracted sixteen features from time-domain (see *TABLE 1*) and nine features from frequency-domain (see *TABLE 2*), with a variety of WS ranging from 64 (6.4s) to 1536 (2min 33.6s). We compute the vector magnitude signal as the Euclidean norm of the 3D-sensor measurement at each moment using equation (1). *Fast Fourier Transformation* (FFT) was used to obtain frequency domain.

$$S[t] = \sqrt{S_x[t]^2 + S_y[t]^2 + S_z[t]^2} \qquad (1)$$

Where $S_x[t]$, $S_y[t]$, and $S_z[t]$ are the sensors reading at time t for *x, y,* and *z* axes respectively.

TABLE 1. TIME-DOMAIN FEATURES

Mean Absolute Value [11]	$\frac{1}{N}\sum_{i=1}^{N}\lvert x_i\rvert$
Windowed MAV 1 [7]	$\begin{cases}1; & 0.25N \le i \le 0.75N \\ 0.5; & otherwise\end{cases}$
Windowed MAV 2 [7]	$\begin{cases}1; & 0.25N \le i \le 0.75N \\ \frac{4i}{N}; & 0.25N > i \\ \frac{4(N-i)}{N} & 0.75N > i\end{cases}$
Harmonic Mean [7]	$\frac{N}{\sum_{i=1}^{N}\frac{1}{x_i}}$
Skewness [7]	$\frac{E(x-\mu)^3}{\sigma^3}$
Kurtosis [7]	$\frac{E(x-\mu)^4}{\sigma^4}$
25th percentile [16]	$x_r, \quad r = round(0.25 * N)$
50th percentile [16]	$x_r, \quad r = round(0.50 * N)$
75th percentile [16]	$x_r, \quad r = round(0.75 * N)$
Simple Squared Integral [7]	$\sum_{i=1}^{N} x_i^2$
Highest value [11]	$\max(x_i)$
Lowest value [11]	$\min(x_i)$
Slope sign changes [7]	$\{x_i > x_{i-1} and\ x_i > x_{i+1}\}\ OR\ \{x_i < x_{i-1} and\ x_i < x_{i+1}\}, 1 \le i \le N$
Root Mean Square [11]	$\sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$
Standard deviation [11]	$\sqrt{\frac{\sum_{i=1}^{N}(x_i-\bar{x})^2}{N-1}}$
Wilson Amplitude [7]	$\sum_{i=1}^{N-1} f(\lvert x_{i+1}-x_i\rvert); \ f(s) = \begin{cases}1; & s > th \\ 0; & otherwise\end{cases}$

Where N is the WS; x_i is the data in the window; $\bar{x}$ is the average amplitude of N; i is the index; r is the rank of data; *th* is the threshold.

TABLE 2. FREQUENCY-DOMAIN FEATURES

Spectral Energy [11]	$\sum_{i=1}^{M} Y_i^2$
Median Frequency [11]	$\sum_{i=1}^{MDF} Y_i = \sum_{i=MDF}^{M} Y_i = \sum_{i=1}^{M} Y_i$
Mean Frequency [11]	$\sum_{i=1}^{M} f_i Y_i / \sum_{i=1}^{M} Y_i$
Mean Power [11]	$\sum_{i=1}^{M} Y_i / M$
Peak Frequency [21]	$\max(Y_i), \quad i = 1, \ldots, M$
Spectral Moment 0 [21]	$\sum_{i=1}^{M} Y_i$
Spectral Moment 1 [21]	$\sum_{i=1}^{M} Y_i f_i$
Spectral Moment 2 [21]	$\sum_{i=1}^{M} Y_i f_i^2$
Spectral Moment 3 [21]	$\sum_{i=1}^{M} Y_i f_i^3$

Where M is the Number of points in frequency axis; Y_i is value of the amplitude spectrum of ith point; f_i is the frequency of ith point.

C. Selection Of MLA

There is a variety of MLA. Based on our literature review, we tested a certain number of them, including Naive Bayes, Logistic Regression, Stochastic Gradient Descent, Support Vector Machines. Finally, we chose the following algorithms and will present their performance results in the subsequent section:

- LDA and QLA classifiers generate a linear and quadratic decision surface, respectively. They are among the simplest MLA, very easy to use, with no hyperparameters to tune. As we will see in the next section, their results are decent, interpretable, and robust.
- KNN classifier is commonly used in the literature. Based on a specific number of neighbours K, defined by the user, it classifies any new point based on its distance from these neighbours. In this paper, we use the Manhattan distance. This method is called "non-generalizing MLA" as it cannot generalize the training model before testing the data. Therefore, it requires a lot of testing time. We used the three (k=3) nearest neighbours in our computation.
- DT requires very little data preparation and training time without affecting its performance results. As a matter of fact, it provides good prediction accuracy. It uses a hierarchical separation of input space, and each node of the tree consists of a simple decision rule 'if-then-else'. The fact that DT input space is divided several times (i.e., deeper and deeper) results in better and more accurate prediction.
- RF provides better and more accurate prediction than DT classifier, however it requires more training time. The accuracy of RF prediction is computed as an average value of its sub-classifiers.

Note that we left all MLA parameters at their default values except for the LDA for the absolute threshold which is set to 1.0e-5.

IV. PERFORMANCE EVALUATION, EXPERIMENTAL RESULTS, AND DISCUSSION

The five selected algorithms were applied to the PAMAP2 dataset [6] to evaluate their respective performance. We evaluated the success rate as function of WS, sensors' location, and source of the data i.e., from which sensor data is received. Finally, we evaluated the execution time as function of WS. Note that all three sensors are embedded in Inertial Measurement Units (IMU).

TABLE 3 shows the success rate as function of WS when data is obtained form three different sensors (ACC, GYR, MAG) located at three specific places: wrist, ankle, and chest. From this table, we observe a constant increase of the success rate with WS except in the case of QDA where the success rate drops slightly for WS 256, 768, and 1024. This is mainly due to the nature of the algorithm which uses a quadratic decision surface rather than a linear one. RT and DT algorithms provided the best results followed in order by LDA, KNN, and QDA. Note that the success rate for RT and DT improved very little after WS= 512.

Let's compare our results to those published by M. Arif and A. Kattan [7] where they used ACC data fed into three ML algorithms, KNN, Rotation Forest (RF), and Neural Network (NN) with a success rate of 98.3%, 98.3%, and 97.6% respectively. Our results are better for RT and DT, but similar for LDA (bold numbers in *TABLE 3*). Note that, here we focus on the best performing algorithms.

TABLE 4 shows similar results as *TABLE 3*; however, only ACC data were used here. Based on the results we obtained in *TABLE 3* and due to space limitation, we will focus on WS from 512 to 1536 where the results were most significant. As in *TABLE 3*, the performance of all algorithms constantly improved when we increased the WS. Again, DT and RT provided the best results, in bold. They are better than those obtained by [7], as mentioned above. The fact that we used 18 activities, 25 features, and 3 sensors' data versus 12, 15, and 1 respectively in [7] appears to improve the performance.

Fig. 1 shows the impact of the IMU's location (hand or chest or ankle) on the success rate for three different WS, 64, 512, and 1536. We used three sensors' data, ACC, GYR, MAG. Here again, the performance of all algorithms improves with the increase of the WS. Placing the IMU on the chest seems in general to give the best performance result, except for KNN where the best position is the ankle. One exception is the case of RF with WS=1512, where performance is extremely close when we place the IMU on the chest (99.9%) or the ankle (100%). The performance of DT and RT algorithms remains the best as we have seen in *TABLE 3* and *TABLE 4*.

Knowing that positioning the IMU on the chest provides the best performance results, we positioned it on the chest and studied the impact of the data source on the performance results, as illustrated in Fig. 2 and Fig. 3. First, in Fig. 2, we considered the data generated from an individual sensor, i.e., ACC, GYR or MAG, then they are combined two by two, ACC/GYR, ACC/MAG and GYR/MAG in Fig. 3. For the three algorithms, LDA, QDA, and KNN, the ACC provides the best results followed by the MAG, except in the case of KNN. In the case of RT and DT, where we obtained the best results as we have previously seen, the MAG gives the best results and remains competitive with ACC in certain cases. From Fig. 3, we can see that ACC combined with MAG provides the best performance results in all cases. Most research published in the literature in this domain used the data generated from ACC, or ACC combined with GYR. Our results show that ACC combined with MAG resulted in the best option.

Fig. 4 shows the execution time for all algorithms as function of the WS. It decreases with the increase of WS for KNN, DT, and RF algorithms and stays relatively stable with minor variation for LDA and QDA. It is obvious that the execution time for DT and RF is much higher than the other algorithms. The execution time for RF algorithm is almost 4 times higher than DT's execution time. Even though DT and RF provide the best performance in terms of success rate, they remain costly in terms of execution time, which makes their implementation in real time challenging.

TABLE 3. IMU'S LOCATION: HAND/CHEST/ANKLE – DATA SOURCES: ACC, GYR, AND MAG

Size	LDA	QDA	KNN	DT	RF
	SR (%)	SR (%)	SR (%)	SR (%)	SR (%)
64	89,0	85,8	81,7	91,9	97,2
128	91,3	85,9	85,7	95,1	**98,8**
256	93,9	84,0	89,2	97,3	**99,7**
512	95,4	96,2	92,9	**98,8**	**99,9**
768	96,7	95,5	94,9	**99,4**	**100**
1024	97,2	89,5	96,4	**99,6**	**100**
1536	**98,3**	90,4	97,6	**99,9**	**100**

TABLE 4. IMU'S LOCATION: HAND/CHEST/ANKLE – DATA SOURCE: ACC

Size	LDA	QDA	KNN	DT	RF
	SR (%)	SR (%)	SR (%)	SR (%)	SR (%)
512	81,5	78,4	70,4	96,7	**99,2**
768	83,7	85,7	75,4	**98,4**	**99,7**
1024	85,2	89,3	79,9	**98,9**	**99,9**
1536	87,5	92,5	85,0	**99,6**	**99,99**

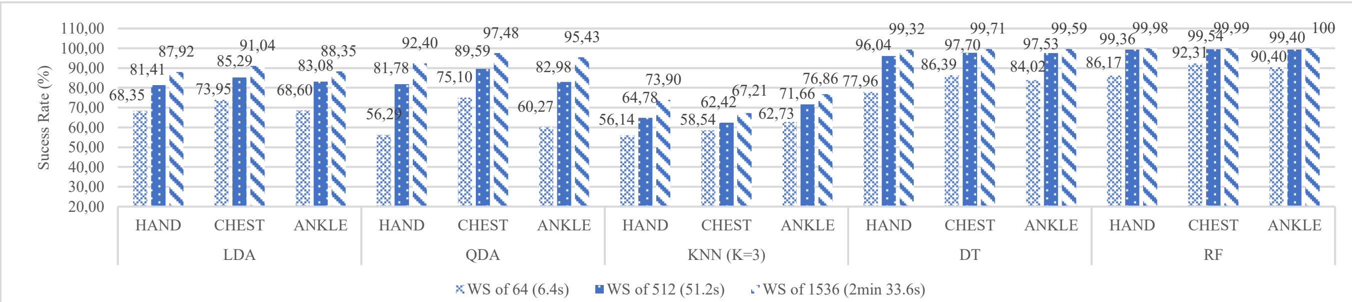

Fig. 1. *IMU's location used separately: HAND, CHEST and ANKLE – Data sources: ACC/GYR/MAG*

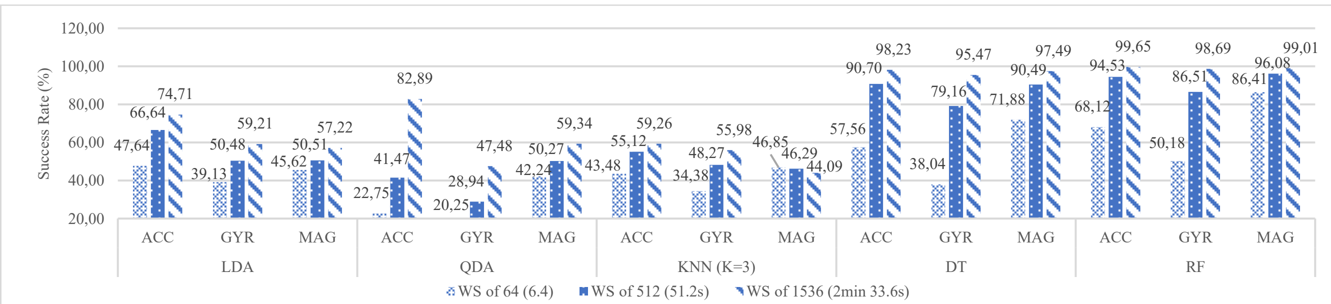

Fig. 2. *IMU's location: CHEST - Data sources from specific sensor: ACC, GYR, MAG*

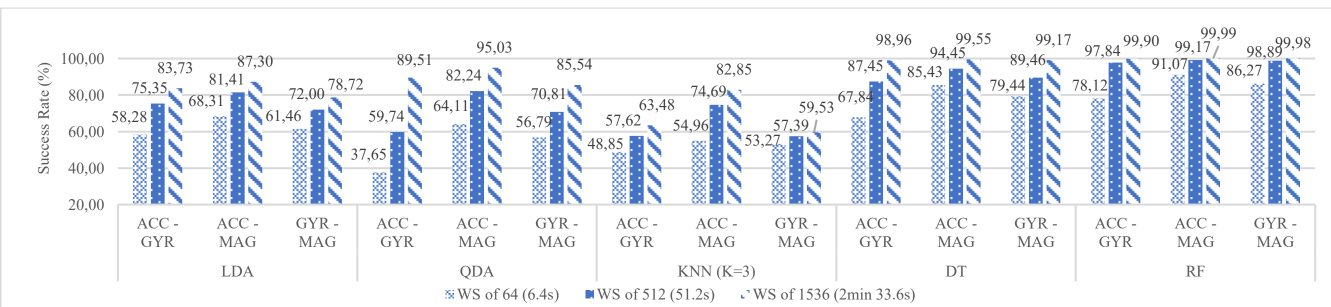

Fig. 3. *IMU's location: CHEST - Data sources from combined sensors: ACC/GYR, ACC/MAG, GYR/MAG*

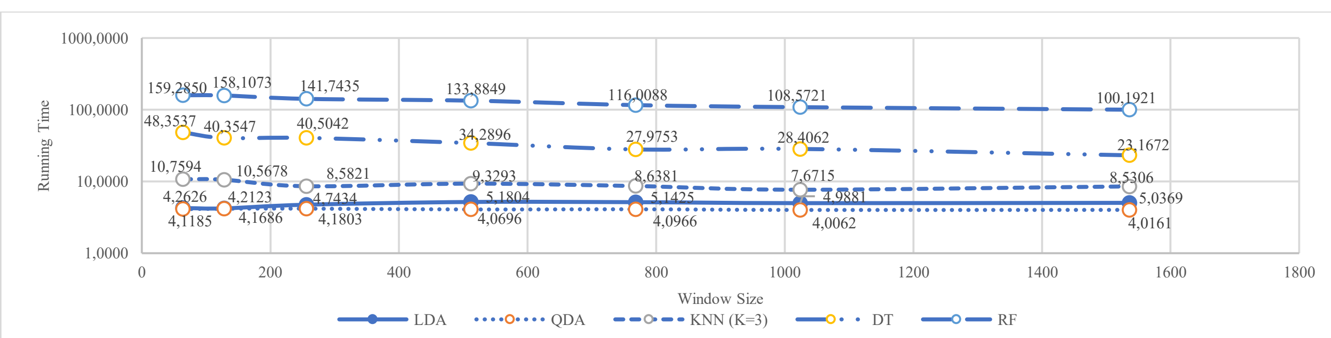

Fig. 4. *IMU's location: Hand/Chest/Ankle – Data sources: ACC/GYR/ MAG*

V. Concluding Remarks and Future Works

In this paper, several MLA were implemented and compared using a publicly available dataset, PAMP2. We reported the performance results of the five best algorithms: LDA, QNA, KNN, DT, RF. As we mentioned before, our results outperform previously published results in terms of prediction accuracy on the same dataset. We showed that the accuracy increases with WS while execution time decreases. Also, we demonstrated that the data source and the location of sensors play important roles in the algorithms' performance. In general, positioning the IMU at the chest produces more accurate results, and combining the data from ACC and MAG also improves the accuracy.

In future works, we are planning to collect our own data and verify if we can implement a system that can predict abnormal context when wearable sensors are used to monitor human health in medical applications. Also, it will be interesting to study how the performance of these MLA will scale with larger amount of data.

VI. ACKNOWLEDGEMENT

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