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PERFORMANCE EVALUATION OF CLASSIFIERS ON ACTIVITY RECOGNITION FOR DISASTERS MITIGATION USING SMARTPHONE SENSING

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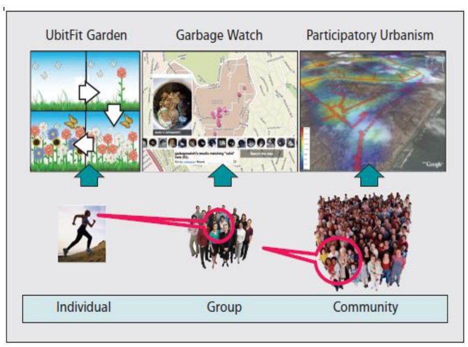
Sadiq, Fatai Idowu[b], Ali Selamat[a,b], Roliana Ibrahim[b]

[a]UTM-IRDA Digital Media Center of Excellence, University Teknologi Malaysia, 81310 UTM Johor Bahru, Johor, Malaysia
[b]Faculty of Computing, University Teknologi, Malaysia, 81310 UTM Johor Bahru, Johor, Malaysia

*Corresponding author
aselamat@utm.my

Graphical abstract



Abstract

Activity recognition (AR_s) is a classification problem that cuts across many domains. The introduction of AR_s accuracy which may be significantly low with decision tree algorithm and the use of smartphone sensing in previous studies has proven its relevance for effective disaster mitigation in our society. Smartphone sensing is an approach found to be useful for activity recognition to monitor people in large gatherings due to the power of embedded sensors on the handheld devices. In this paper, a multitask activity recognition architecture is proposed for proper monitoring of people in large gatherings to control disaster occurrences in crowd, flood, road and fire accidents using related activity scenario in time of danger. We implement the proposed architecture to determine the outcome of activity recognized with K-nearest neighbour (KNN) for k= 3 and 4 to compare performance to that of weka using accelerometer and digital compass (dc) sensors on the same dataset. The results of AR_s accuracy of 100% and 99% in weka, 85% and 89% with KNN shows an improved performance in both tools. The performance of Multilayer Perceptron (MLP), Support Vector Machine (SVM), Naives baye (NB), Decision tree (DT), against KNN were investigated using precision, recall and f-measure in weka as well. The results show significant improvement with performance parameters on accelerometer and dc against the use of accelerometer sensor only with KNN and DT having low number of classified activity recognized on training and testing data.

Keywords: SmartPhone sensing, multitask activity recognition, disaster mitigation, classification, and performance evaluation

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1.0 INTRODUCTION

Human activity is a common phenomenon in everyday life. These activities are found everywhere, i.e. ubiquitous either in offices or in our homes [1]. Nowadays, the presence of smartphones and their continuous growth has made recognition of human activities a possibility with the help of several inbuilt sensors that come with the smartphones [2, 3]. These sensors include accelerometer, gyroscope, digital compass etc., which are inbuilt sensors on the smartphones. It assigns real value estimates of acceleration along x, y, z coordinates from which velocity and displacement can be measured [4].

It is often used as motion detector [5], and for body-posture sensing [6]. Previous studies have shown that Activity Recognition (AR_s) accuracy and mobile sensing towards context-awareness is a challenging problem in context-aware systems and applications [7-9]. Smartphone helps to gather relevant information and knows users more than they know themselves [10]. However, human activity monitoring with the help of sensors on the smartphone is a new research area. Automatic recognition of user activities using different contextual data for enhancement of pervasive systems using context-awareness application is still in its infancy [2, 11], considering its potential to offer more adaptable, flexible and user friendly services [11].

Mean-while, smartphone sensing and activity recognition has proven to be relevant in many domains healthcare [12], sports [13], daily activity [14] etc. It is still new in crowd disaster mitigation scenario following a stampede occurrence that claimed lives of over hundred people in India [15]. Crowd disaster mitigation utilizes activity recognition to predict on set the possibilities of a stampede in a crowd through the movement of participants and their behavioural patterns using AR_s accuracy for crowd disaster mitigation [15]. This paper presents the relevance of AR_s in disaster related scenario particularly crowd and show possible experimental results of AR_s on smart- phone sensing using different classifiers with machine learning techniques following the recent state-of-the-art [15], study in crowd disaster that shows the significance of individual AR_s accuracy to determine the possibility of stampede occurrence in crowded environments [15]. Figure 1 shows a typical example of individual, group and community where stampede is possible[16]. The used of activity recognition in disaster mitigation [15], was motivated following the recommendation made in Bao *et al*. [17], where they emphasized the importance of recognition on activities such as walking, sitting etc., for stampede prediction. The rest of the paper is organized as follows: Section 2 briefly describes related works using smartphone and selected activities for recognition. Section 3 presents proposed architecture and other relevant concept, Section 4 and 5 explain the experimental results, discussion and contributions while Section 6 presents the conclusion and recommendations for future work.

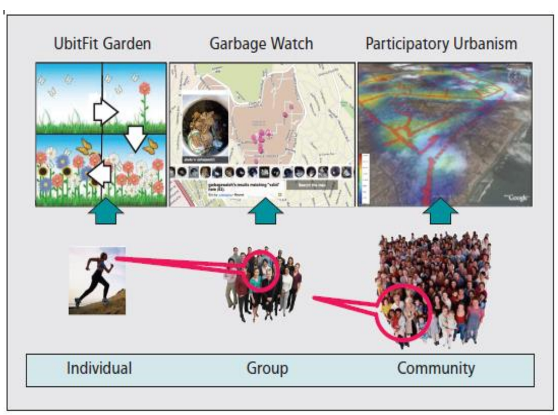

Figure 1 Smartphone sensing is effective across crowd, arising from individual, group and community where stampede may occur. *Source*: [16]

2.0 RELATED WORK

Smartphones have opened new research direction for human applications where the user serves as a source of context information and the smartphone as a sensing tool [18]. Activity recognition with wearable sensors has been a hot research field in the last decade. Much research work has been done to recognize physical activities such as sitting, standing, running and so on for wellbeing management [18, 19], where a Multiclass Support Vector Machines (SVMs) for the classification of smartphone inertial data achieved 96% of test data on 6 Activity Daily Living (ADL) using time and frequency domain feature vectors in [1, 18, 19].

In khan *et al.* [20], both higher activities and simple–low level physical activities such as walking, running were considered using nonlinear discriminatory approach with SVMs on 15 activities and time domain as feature vectors was implemented to achieve 99%, 94% and 92% accuracy in offline and online subjects respectively. Off-line recognition may be employed where online recognition is not adequate [1]. However, online recognition of smart phones yielded much better classification performance of 92% accuracy with clustered KNN on 4 activities with 5 subjects, while hoping to investigate the performance of a decision tree in future work [1]. Dela *et al.* [20, 21], proposed an approach for accuracy of activity recognition capable of higher accuracy with 98% on 8 activities without compromising efficiency. The study provides access to higher granularity activities using accelerometer sensors [20]. Radianti *et al*. [22], proposed a novel smartphone based communication framework using machine intelligent process sensor readings for emergency situations. They remarked that context-aware, and activity recognition are challenging forms of research, due to sensing capability coupled with their applications, within an environment. Activities fall within higher–level and simple-low level based on previous studies [20, 21].

Besides, the problem and domain under review will determine the activities suitable for use. In this paper, the activity experimented are walking, jogging, standing, still and peak shake while-standing etc., due to their considerations in [15] and presence in most gatherings for example at airports, stadiums during football matches or churches during worship [15]. The human activity recognition research has emerged as an important research area over the past decade because a variety of applications rely on sensing and recognizing users activities, including health [12] and environment monitoring applications [21], security and surveillance application [22]. Most importantly the state-of-the-art [15], used activities such as walking, jogging, standing, still and peak shake while standing to monitor IAR through smartphone sensing, the essence of the recognition is to monitor human movement behavior individually and in groups. The study which used decision tree algorithm, recorded 92% AR_s accuracy analyzed in weka [15], the AR_s accuracy was further used to determine the probability of stampede detection for abnormal movement behaviour in a crowded scenario using 20 subjects with smartphone sensing for effective mitigation of crowd disaster. Kose *et al*. [1], whose study investigated KNN in weka and achieved 92% AR_s hope to compare with DT in future.

2.1 Problem Background

Classification problem in AR_s research is found across many domains [15, 23, 24]. The demand for security in public space is gaining attention nowadays due to increasing in crowd disaster [15]. At the same time, we live in a pervasive era where mobile devices are everywhere, and these devices are connected to more than ever with sensors capable of sensing every ongoing situation around us to reduce the danger associated with disaster using simple low level activities referred to in Section 2.0.

2.2 Methodology

The method used in this paper, is based on smart phone sensing, which comprises three steps: 1) collection of sensor data using selected number of subjects and activities such as walking, jogging, standing, still and peak shake while standing etc., 2) preprocessing and extracting features and 3) training classifiers. It is important to mention that weka was used for the data analysis, and K-NN algorithm was implemented using java program to note any change in the results of the same sets of sensor data.

2.2.1 Experimental Setup

To the best of our knowledge, the proposed model which involves working in crowd domain to perform learning and recognition of activities suggesting other related disaster scenario is an innovative approach. Researches in Activity Recognition (AR_s) have used certain number of peoples to perform experiment in different kinds of human activity scenarios such as health [12], sports [13]; transportation [24] etc. Also, in this paper, a set of experiment was conducted to obtain the HAR dataset for crowd scenario, with 4 Subjects volunteers (Males). The subjects are between 21-30 years of age. Each of them was informed on the rules for selecting the activities, the position to place the smart phone and how to perform the activity in such situations. Samsung Galaxy X2, Samsung Galaxy Grand 2, and Gionee are used for this purpose. Each participant places the smartphone on their hand, and tied it to their waist. The selected activities considered are walking, standing, jogging, still, peak shake while-standing [1, 15, 25]. Each of the participants performed each of the activities specified for 10 minutes (600 ms) using the same position which was chosen based on the evidence from previous studies [3, 15, 26]. The data acquisition reading occurs every second. Example of raw data from the accelerometer sensor readings while recognizing each activity in the experiments are recorded on x, y z, axes, and another sensor reading, which is digital compass, are shown in Table 1. The recognized activities are pre-processed to extract meaningful information from the sensor (raw data) collected with the help of android mobile application. The activity classification is carried out using assign label value i.e. true label as the classified label on the crowd controller (server).

Table 1 Crowd scenario for AR_s dataset from Smartphone sensors raw data on activity recognized

A	ax	ay	az	dc	Cl
w	-0.9	3.6	14.4	234	-1
w	10.4	9.7	10.3	49	1
J	3.5	-6.8	-2.34	145	1
J	-1.9	4.1	0.83	209	1
S	4.0	5.1	7.3	118	-1
S	-4.6	-1.4	8.6	237	-1

Key : Unit for ax,ay, az = (m/s^2) ;
dc =digital compass
w = walking; J = jogging and s = standing
A = class label (activity); Cl = class values

2.2.2 K-nearest Neighbor (K-NN) Algorithm

K-NN is a supervised learning algorithm that handles the output of new instance query based on classified majority of k-nearest neighbour category. It is a lazy learning algorithm. The algorithm is commonly applied in pattern recognition, and used neighbor-hood classification as the prediction value of the new query instance. Research has shown its performance in previous studies in AR_s [1, 3], but we have no knowledge of its application till now in activity recognition related to disaster scenario. Its accuracy can be severely degraded by noise and irrelevant features if not properly handled[3].

A major drawback of "majority voting" classification is that classes with more frequent examples normally dominate the prediction of the new vector. However, to overcome this drawback, it takes into account the distance from the two test point in each of the K-nearest neighbours. In order to calculate the distance between the points in multidimensional spaces, we define x, y where each point represents n-dimensional vector, i.e.

$x = (x_1,x_2,x_3,\ldots\ldots x_m)$, $y = (y_1,y_2,y_3\ldots\ldots y_m)$.

The distance measuring function is taken using the distance function, d_E (x, y) between two points are measured using the Euclidean distance formula or d_A(x,y) distance function that measures absolute distance between the two points using Eq.(1) and (2).

$$d_E = (x,y) = \sqrt{\sum_{j=1}^{m}(x_j,y_j)^2} \quad (1)$$

$$d_A(x,y) = \sum_{j=1}^{m}\left|x_j,y_j\right| \quad (2)$$

2.2.3 Weka Tool

Weka is regarded as a black box since it is available for data analysis with ease of task, and it is widely accepted and has been used by many researchers [1,15], for data analysis using machine learning algorithms [25, 27]. As a result of being an open source[27, 28], and flexibility for data pre-processing, clustering, classification, regression, visualization, and feature selection shows the benefits of weka to data analysis[27].

3.0 PROPOSED ARCHITECTURE

Figure 2 shows the proposed architecture of multitask AR_s, which can be used to monitor disaster related scenario using smart phone sensing in an environment. The architecture consists of the following: a.) Internet facilities (Wi-Fi, hotspot), b.) Different disaster scenarios, c.) Related human activity for recognition, d.) Smartphone and application with sensing sensors for data collection using context information, e.) Server for sensor data backup, f.) Pre-processing Server for sensor data backup and g.) Pre-processing.

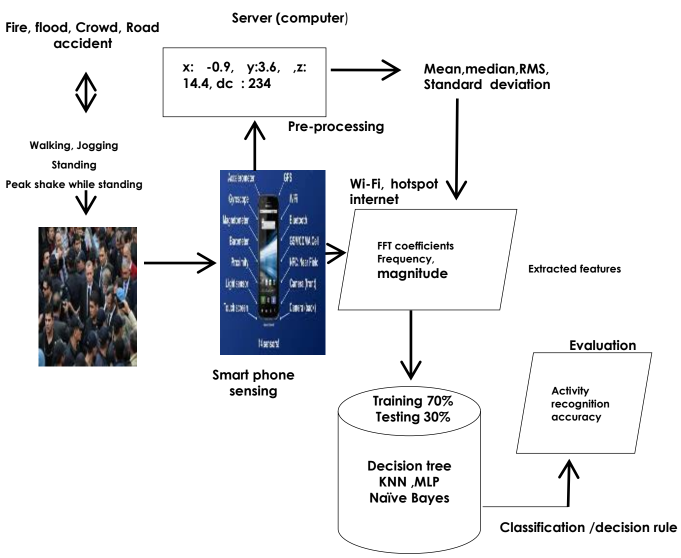

Figure 2 Proposed architecture for multi-task AR_s

3.1 Internet Facilities

These are facilities necessary for communication and facilitation of smartphone sensing, and context information interaction with users (people), environment, computing resources etc. The context helps to actualize the AR_s. It is important to note that AR_s is only possible when the mobile software is available on the smart phone of all the target participants.

3.1.1 Different Disaster Scenario

The scenario in Figure 2 such as flood, road, fire accidents and crowd disaster for example may have related activities to be recognized using various contexts such as time, environment, and location etc., [29]. This is facilitated by activity monitoring using sensors on the smartphone to reduce risk which may lead to disaster with the help of early warning alerts through the interface shown in Figure 3 refer to [30] for details on the interface. While the computer (server) used to capture the selected activities recognized during the experiment is as shown in Figure 4.

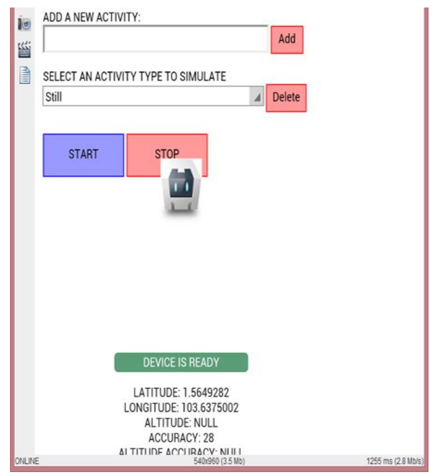

Figure 3 Graphical User interface for AR_s data capture[30]

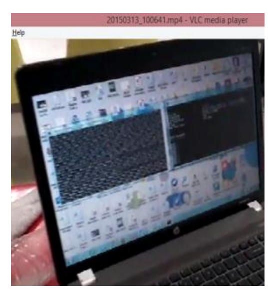

Figure 4 Snapshot from the experiments for jogging activity. *Source:* March 2015

3.1.2 Activity Recognition Cases

The activities considered for crowd scenario, for instance, are walking; jogging, standing; still, climbing up, climbing down, peak shake while standing. Each of these activities monitored through the participants as earlier stated in (Subsection 2.2.1). Similar activities related to other types of disaster specified in Figure 2, can as well be programmed for recognition and monitoring to keep track of every event and sensitize the people around especially the security personnel to avert any danger that the people would encounter using the devices.

3.1.3 Smartphone and Application

This performs the necessary activity monitoring of the user's movement with the help of 'mobileapp' using the embedded accelerometer, gyroscope, digital compass sensors etc. The Mobile device with the help of sensors recognizes different contexts such as time, individual, environment, location to sense and record any form of erratic, panic, abnormal behaviour which may be triggered by sudden or emergency action for example thunder strike, jeep or car horn, sudden noise of someone who encounters danger in a crowded place, this action will force the program sensor to sensitize other nearby participant(s) and security for necessary control measures using data record in Table 1 using Figure 3. Thereafter, the classifier can be used to analyze sensed data for decision making.

3.1.4 Dataset Pre-Processing

The raw values from the accelerometer were pre-processed before the feature extraction. For the pre-processing, we computed the mean for each of the axis x, y, z for accelerometer data captured to remove the random spikes and noise (if any) on the dataset [15]. The median value was obtained to treat the missing values found along the x, y, and z-axes of the same dataset. Each of the three axes was analyzed individually and the statistical metrics such as standard deviation and correlations were obtained to ascertain the stability of the dataset and to distinguish one activity from the other [19, 20, 31]. In the experiment, a time limit of 60 seconds based on a previous study [1], is specified for each activity carried out for 10 minutes which have yielded good results with similar approach.

Moreover, in a gathering of people, individual (participants) usually perform activities randomly. The purpose is to predict the next class of activity performs by any user using the sensors data with relevant contexts [11]. Our assumption is that each participant performs a set of activities while holding the smart phone with the application for recognition, and when the activity is changed to another participant, another set of activities is performed. In general, participants' movement or users' activity recognized is given as a log with smart phone sensors reading: $p = (s_1, s_2, s_3 \ldots s_n)$. where p is the set of sensor's readings, s_1 represents sensor reading 1, s_2 represents sensor reading 2 etc., Given a set $d=(a_1, \ldots, a_m)$ of activity types, a_1, a_2 represent an activity 1 e.g. walking, activity 2 i.e. jogging, an activity is a pair (a,t), where t is an occurrence time of activity.

The outcome of participant class of the activity set for the participant n is an ordered sequence of events:

$$s = [(a_1, t_1), (a_2, t_2), (a_3, t_3) \ldots (a_n, t_n)] \tag{3}$$

such that for all i ε (1,n) and $t_i < t_{i+1}$ for all i ε (1,n-1). Therefore, in case of offline approach $t_i = t_{i+1}$ assuming all the activities occur at once, otherwise we do not have t_i to be equal to t_{i+1} since several activities performed by other participants cannot occur at the same time.

3.2 Computational Features

Out of the eight (8) sensors programmed, accelerometer digital compass sensor values are found to be significant for our analysis and benchmarking for AR_s in [15], the calculated mean, standard deviation, correlation coefficients and root mean square were used in [15]. Other features such as maximum, minimum, median, and Fast Fourier transform (FFT) coefficients were computed from the raw accelerometer sensor x, y, z and digital compass as feature vectors in this study were considered.

These features help to enhance the performance of the various classifiers investigated in our study. Activity recognition is regarded as a classification problem [8, 15, 23] hence the need for machine learning algorithms to help in decision making process, based on the collected information from the extracted information from the phone sensor data using context to make initial scientific hypothesis. In order to classify the human activities for participants in a crowd for example, five machines learning algorithms were investigated using our dataset to select the best performance classifier and activity recognized accordingly to know the actual and predicted class, thereafter return result. The dataset was randomly partitioned into two independent sets, with 70% assigned to training and the remaining 30% for testing [18]. The overall dataset, as the research progresses, may serve the purpose of public dataset in this domain as a contribution, since effort are being made to have public dataset from smartphone sensor for standard evaluation [19]. Statistical properties obtained from raw sensor data and activities recognized with their No. of instances are as shown in Table 2 & 3.

Table 2 Statistical properties computed from raw sensor for AR_s for acceleration a x, ay, az accelerometer & dc sensors

	Statistical properties			
Sensors	**Min.**	**Max.**	**Mean**	**stddev**
ax	-19.54	16.78	-0.01	4.49
ay	-14.52	19.54	2.89	3.46
az	-16.51	19.54	6.92	4.48
dc	0	359.56	161.53	103.47

ax, ay, az:acceleration, stddev: standard deviation

Table 2 presents the statistical properties of the raw data obtained in our experiment. Its raw data were further transformed to time domain using sliding window of window size with 50% overlap in the data analysis. Previous study show that 50% overlap slide window is appropriate for reliable prediction in AR_s[15, 31].

Table 3 Activity recognized and No of instances

Activity	Instances
Peak_shake_while_standing	928
Jogging	46
Standing	886
Still	965
Walking	775
Total	3600

Table 3 shows the list of activities and the number of instances used in this paper.

3.2.1 Creating Crowd Disaster Scenarios

Assuming a scene at the airport, where people gather for the next available flight. Among the passengers, are people coming into the airline station to check in before boarding; this type of action describes walking, those on queue that remain on a spot inform the still or standing actions, jogging or running are encountered in the course of late arrival which is a common occurrence, and may call for peak shake while standing in a critical situation resulting from an attempt to miss one's flight. All these are activities considered and they can be found in any other gathering in stadiums during sports or worship in the church on Sundays or during the convention and even in the mosques on Fridays or market places. Other activities include climbing up and climbing down the staircase, though not used in this study but they are part of our future work. Other researchers have experimented with them in other domains[1,15,16] and in [15], an attempt has been made to show the relevance of the aforementioned activities as displayed in Table 3 for activity recognition for both individuals and in group to provide control measures to avert disaster in a crowded area.

4.0 RESULTS FROM EXPERIMENT

Table 4 shows the java performance of KNN algorithm against Weka tool, using the proposed architecture, referred to in Figure 2. The activity related to any of the aforementioned disasters can also be recognized to sensitize people anytime there is danger. It was noted that activity recognition is reliable for human activity recognition with smart phone sensing [15]. Hence the need for investigation into the approach for recognition of disaster related activity among humans in the environment, so as to reduce disaster risks [32]. This also supports the results of Activity recognition carried out using smartphone applications for transportation services using trained models to classify related activity [26]. The confusion matrix for sensors data used namely; acceleration is shown in the upper part of Table 4. And that of acceleration and dc is shown at the lower part in Table 4 with KNN algorithm having the value of k = 3 for acceleration only and k = 4 for acceleration and dc respectively.

Table 4 Confusion matrix for classification with accelerometer sensors with java program

a	b	c	d	e	Classified as
248.0	0.0	3.0	0.0	11.0	a:Still
0.0	4.0	4.0	3.0	0.0	b:jogging
3.0	2.0	247.0	29.0	9.0	c:peak shake _ws
2.0	6.0	45.0	179.0	10.0	d:standing
7.0	0.0	12.0	6.0	25.0	e:walking
Accelerometer and dc sensors					
a	b	c	d	e	Classified as
255.0	1.0	0.0	1.0	5.0	a:Still
2.0	3.0	2.0	4.0	0.0	b:jogging
3.0	1.0	255.0	23.0	8.0	c:peak shake _ws
4.0	3.0	37.0	191.0	7.0	d:standing
7.0	1.0	11.0	3.0	259.0	e:walking

The confusion matrix shown in Table 4 indicates the actual activity recognized against the number of activities classified using the 1080 testing data with KNN algorithm. Appropriate feature extraction can help to achieve good results as remarked by [4]. Thus, the AR_s accuracy obtained here will facilitate reliable prediction of stampede occurrence in a crowded area [15]. At the same time more than 1 sensor has shown very good result in previous studies [33].

Table 5 shows the performance of correct and incorrect classification of recognized activities between KNN and other classifiers in percentages. It presents the performance evaluation of 5 classifiers experimented in this study and the results obtained for each of them using weka, and java implementation of KNN to show the influence of dc in addition to the accelerometer sensor with the value of k = 4 and 3 respectively for AR_s using the smart phone sensing with other classifiers performance's parameters. Details displayed in Table 6.

Table 5 Classifiers performance for correct/incorrect classified instances on activity recognized for AR_s

Classifiers	**Instances classify acceleration +dc in %**	
	Correct	**Incorrect**
Naïve bayes	54	46
SVM	64	36
KNN (k=4)**	100	0
(k=3)	99	1
DT	95	5
MLP	77	23
Java implementation of different Acceleration + dc.		
KNN (k=4)**	89	11
(k=3)	85	15

Table 6 Performance evaluation of classifiers on AR_s with acceleration + dc sensors on weka tool

	Performance in %			
Classifiers	**Precision**	**Recall**	**f-measure**	**Accuracy**
Naïve bayes	54	54	51	54
SVM	68	64	60	64
KNN (k=4)**	100	100	100	100
KNN	99	99	99	99
DT *2	95	95	95	95
DT *1	90	90	90	90
DT*[15]	?	?	?	92
MLP	67	66	63	66
		KNN with Java k = 4		
		Acceleration + dc		
KNN **	89	89	89	89
		KNN with Java k = 3		
KNN	85	85	85	85

* = existing approach ; ** = improved performance as the values of k increases with sensor
*1 = *acceleration only*
*2 = *acceleration + dc*

5.0 RESULTS AND DISCUSSION

The implication of misclassification as shown in Table 4 is that an activity meant to be classified and reported to participants/security personnel as 'Peak_shake' while standing' is predicted as 'standing'. This situation needs immediate help to rescue the people affected, but since 'standing' was predicted instead it does not indicate the danger posed by 'Peak_shake' while standing'. Thus the security personnel may not act proactively since 'standing' as shown in (Table 4 of the confusion matrix) was reported instead.

The information that additional sensor may improve accuracy [20], may be true since 85% accuracy for only accelerometer is less than 89% accuracy for accelerometer + dc as shown in Table 5. The properties are exhibited with weka results in the same Table see ** refer to Table 5. The following are the quality measures used in the classification evaluation, in order to calculate the evaluation parameters measure the set of True Positive (TP), False Positive (FP), True Negative (TN), False Negative (FN) are determined and quality measures are calculated as follows:

$$\text{Precision (P)} = \left|\frac{TP}{TP + FP}\right| \tag{4}$$

$$\text{Recall (R)} = \left|\frac{TP}{FN + TP}\right| \tag{5}$$

$$\text{F-measure (fm)} = 2 * \left[\frac{P * R}{P + R}\right] \tag{6}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TP} \tag{7}$$

where TP is the rate of activity predicted correctly to total possibilities, while FP is the vice versa [15]. TN is the correct classification of an activity recognized as not belonging to the class of interest. FN is an incorrect classification of an activity recognized as not belonging to the class of interest when it actually does[24]. It is important to remark that the results obtained with KNN implemented in java program show an improved result in recall, precision, F-measures and accuracy as shown in Table 6.

5.1 Contributions

The following are the contributions in this paper:

a) Multitask AR_s architecture for different disaster scenarios such as crowd, flood, road accident and fire is proposed.
b) Proof of concept for AR_s data collection from server instead of smartphone.
c) Simulation using digital compass sensor in addition to acceleration to compare the classifier performance with acceleration only.
d) Performance of Naive Bayes, MLP, SVM, and DT algorithm misclassifications compared with KNN using recall, precision, F-measures, accuracy etc.

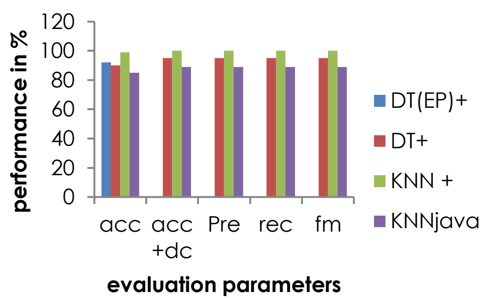

Figure 5 Benchmark of AR_s in weka and the result of KNN with java and DT used being the existing approach

In Figure 5 + referred to weka results with 92% AR_s accuracy in the DT (existing approach) blue against red of 90% refer *1 in (Table 6) using the proposed architecture. KNN recorded 99% using weka in green for the same sensor and 85% for the java implementation purple against 95%, DT red and 100% green using acc + dc sensors in weka. 89% of AR_s for KNN algorithm when k=4 in the said java implementation is as shown in purple colour. *The lesson learnt in this paper is that AR_s results obtained in weka, outperform the KNN java implemented in this study* but both results yields an improved performance when acc + dc sensors are combined using 70% training and 30% testing for same data set collected in this study. The reason will be investigated in future study. However, precision, recall and f-measure are 95% refer *2 in (Table 6), 100% from weka for DT and KNN, and 89% with java implementation respectively. The results achieved accuracy, precision, recall and f-measure from MLP, SVM, Naives baye classifiers are as presented in Table 6.

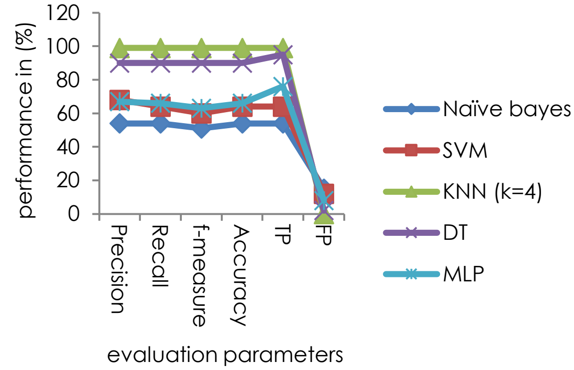

Figure 6 Benchmark of AR_s in weka and the result of KNN implemented with java program

Figure 6 shows that KNN outperform all other classifiers in terms of precision, recall and f-measures follow by DT (existing approach), SVM, MLP and the least being the Naïve Bayes.

6.0 CONCLUSION AND FUTURE WORK

This paper proposed an architecture that can be used for the AR_s to monitor disaster scenarios to facilitate disaster risk reduction in our environment. The success of AR_s in other domains is the reason for this study. It also described smartphone sensing approach for activity recognition capable of handling the disaster with an early warning alert message. The architecture is multitask AR_s since it focuses on different disaster scenario using related activity with the help of embedded sensors on mobile devices. The study has been implemented in Java programs using the KNN algorithm on accelerometer, and digital compass sensors.

The results obtained showed significant improvement in Weka from 99% to 100% and KNN implemented with Java 85% to 89% using both sensors in the same data set collected in this study. It further illustrates the performance of other classifiers such as MLP, SVM and Naives bayes compared to DT and KNN as shown in Table 6. Future work will investigate activity recognition as an online learning using additional disaster related scenarios for activity recognition, to examine the classifier performance against offline learning with similar data sets. Also, to investigate the effect of FFT coefficient and the magnitude in the proposed architecture.

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