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RESEARCH ARTICLE

Real-Time Pilgrims Management Using Wearable Physiological Sensors, Mobile Technology and Artificial Intelligence

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ABSTRACT Annually, a huge number of pilgrims visit Mecca to perform Al Hajj ritual. Crowd management is critical in this occasion in order to avoid crowd disasters (e.g., stampede and suffocation). Recent studies stated that various factors, such as the environment, fatigue level, health condition and emotional status have a significant effect on crowded events. This calls for a need for an automated data analytics system that feeds event organizers with information about those factors on real-time, at least from a generalizable sample of crowd subjects, in which proactive crowd management decisions are made to reduce overall risks. This paper develops a novel methodology that fuses mobile GPS and physiological data of Hajj pilgrims collected through wearable sensors to train three classification models: (a) current performed Hajj activity, (b) fatigue level, and (c) emotional level. In a pilot experiment conducted against two subjects, promising results of a minimum of 75% accuracy levels were achieved for the activity recognition and fatigue level classifiers, whereas the emotional level classifier still requires further refinements.

INDEX TERMS Hajj, crowd control, crowd management, physiological sensors, deep learning, machine learning.

I. INTRODUCTION

Hajj is a sacred annual ritual that brings around 2.5 million Muslims worldwide to visit Mecca, the holy ground in Saudi Arabia [1]. With this large population, one of the largest gatherings in the world [2], it is usually the responsibility of the Saudi Arabian government to provide services to all pilgrims, including health management [3]. The Saudi government is making significant efforts to provide services in the highest quality to manage crowds in Hajj, and it seeks, according to its vision, in 2030 to host

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30 million pilgrims. Research, however, shows that one out of 1000 pilgrims may die during these events [4], which proves that the existing methods of managing crowds during Hajj need more investigations and developments [2], [5]. Jihen Fourati et. al. [6] discussed the major problems facing the Saudi Authority in the management of the pilgrimage, which include disasters like fire, suffocation, and stampede, which have led to the loss of a good number of lives. Another author, Abdullah Al Shimemeri [7], summarised that for pilgrims who don't suffer from any medical condition, there is no medical need to worry about the pilgrimage or the associated ceremonies. However, overcrowding is typically a contributing factor to traumas and diseases, including stampedes, mass

panic, and communicable infections for pilgrims. Many of the pilgrims are elderly and have chronic diseases and the stress of Hajj can put them at higher risk of decompensation [8]. From a report that reviews the 2002 Hajj, age-related chronic diseases such as diabetes mellitus (31%), hypertension (27.5%), and hypercholesterolemia (11.4%) were most prevalent in pilgrims aged 65 to 74. More specifically, the study notes that cardiovascular conditions accounted for more than 60% of ICU hospitalizations [7]. In addition to these common problems, the prevalence of COVID-19 has introduced new type of challenges for Saudi Authority when managing pilgrim. Al-Shaery et. al. evaluated COVID-19 control measures that can be adopted by policymakers which will help in curbing of the spread of COVID-19 under the different crowd dynamics induced by the constraints of each ritual [9], [10].

In order to improve crowd health management, the pre-Hajj screening procedures were enforced. This means those intending pilgrims who wish to perform Hajj in the Kingdom of Saudi Arabia would have to ascertain their medical status in order to prove their mental and physical fitness for the energy-sapping journey and exercise. Research shows this enforcement resulted in a significant reduction in health risks [7]. However, the study still shows that in 2013, out of 87% of the Hajj pilgrims who were above 65 years old, 83% faced a high risk of health problems [11]. Deductively, the measures taken to manage and monitor the health of pilgrims during these events are not effective enough.

Several authors have proposed leveraging smart technologies to serve as support systems to help organisers during Hajj season. The use of video surveillance has been one of the most suggested methods to track human congestion in large gatherings. Logesh Rajendran et. al. [12], in their work, suggested an AI-based surveillance system that provides real-time analysis of crowd densities at different locations to the central monitoring room. The accuracy of this method relies heavily on iterating over thousands of images extracted from the real-time videos, which could be slow for the 5000 video surveillance points installed all around Mecca [13]. Shami et al. [14], used a modern convolutional neural network to recognize sparse heads in a large crowd. They argue that the head is the region of a human-body that is most noticeable in a crowded area and may be utilized to count the number of people there. However, a major drawback of their approach is that it will not cover shorter people or children in very dense places that are overshadowed by others, nor can it detect the individual heads of people in dark corners or under shades like trees. Despite how promising these image analysis studies are, they are not scalable enough for very large events like Hajj.

Another method proposed is the use of wireless technologies such as WiFi, Bluetooth, and radio frequency, for monitoring people in a particular location. People interact with different devices during Hajj, making this approach feasible. According to E. A. Felemban et al. [3], the Internet of Things (IoT) is an all-encompassing platform that enables us to connect computer devices with mechanical and

digital equipment while enabling data transfer over the network without direct physical contact. Marwa F. Mohamed's work [15] introduces the adoption of IoT for crowd data acquisition and friendly communication between the administrators and pilgrims via mobile devices. It is advised to assist pilgrims in learning about empty streets, unpopulated locations, and helping them find their groups. Mohamed proposed a novel technique - Near Field Communication (NFC), which can be enabled on mobile devices. The pilgrim's information was included in the application (name, address, nationality, group number, languages, health condition, etc.) and NFC bracelets with all the information contained in them were provided to individuals without NFC mobile phones. [3].

The research paper is organised as follows. Section II reviews related work. Section III outlines the methodology and the system development and framework. Section IV describes our experiments and discusses the results. Finally, section V concludes this work and highlights some future work as well.

II. LITERATURE REVIEW

The study literature review presents previous studies on how to handle Hajj crowds. It consists of two components: automated crowd management and sensors that can detect when individuals are fatigued. The automation of crowd management discusses the crowd management techniques that the Hajj authorities would use to control the people during Hajj activities. Recent research on monitoring and detecting fatigue are reviewed based on the proposed methods and technologies' reliability for detect fatigue.

A. AUTOMATED CROWD MANAGEMENT

People who attend events rarely receive adequate instructions or training on how to use the venue and perform other tasks related to the event [16]. Therefore, it is recommended to provide adequate education and training to those participating in the event. If this does not occur, and the relevant authorities do not limit the number of participants, the situation will be difficult to manage. In addition, when examining stampedes that have occurred in the past 15 years, it is evident that some crowds could not be controlled or stopped (See [6], [16]). Therefore, it would be extremely helpful to reduce the likelihood of catastrophic events by providing adequate facilities for the management of congested gatherings. Crowd management must be studied to get closer to reality and to develop decision support systems, as the vast majority of research has dealt with the problem in a static context and employed exact or approximate resolution methods [6], [17]. The organization of the pilgrimage was assisted by researchers from a variety of disciplines. For instance, computer scientists have utilized computer vision and location-based techniques to aid in the administration of the pilgrimage [18], [19].

Prior research has examined how big data tools [3] and urban analytics [18] can be incorporated into decision support systems, as well as how they can be used to manage and

monitor crowds. Aldahawi [3], provides a framework for big data that facilitates the adoption and use of big data applications for Hajj and Umra events, including the most important use cases for these pilgrimages. Alabdulkarim et al. [18], have proposed urban analytics with a focus on trends and challenges in the Hajj using a variety of technologies, including Unmanned Aerial Vehicles (UAVs) and Mobile Crowd Sensing and Computing (MCSC). Additionally, studies have proposed solutions to regulate crowd movement at specific locations: Rami Al-Jamarat [20], Arafat to Muzdalifah [21] and Tawaf [17].

Researchers [20], [22] propose a crowd management system that employs image classification and an alarm system. A Convolutional neural network (CNN) model was trained with geo-referenced images to determine whether a given crowd was overcrowded, crowded, semi-crowded, or normal. This study's findings are useful for keeping track of the pilgrims. An agent-based modelling simulation platform is presented to demonstrate the efficacy of this solution. Moreover, [16] has developed a disaster management and health management system with separate but complementary subsystems. There is evidence and a simulation of the proposed system's operation, as well as an algorithm for detecting early-stage stampedes. Four mobile applications for disaster relief, blood donation, patient complaints, and emergency alerts have been developed using smartphones as sensors as part of a larger healthcare management subsystem.

B. RELIABILITY OF SENSORS FOR DETECTING FATIGUE

Health-related fatigue, insomnia, and circadian rhythm disruptions may all affect a person's ability to execute at their best. As a result, decision-making abilities, memory sharpness, the capacity to make judgments, reaction speed, and situational understanding may be significantly impaired. For instance, fatigue may arise if a significant mental workload is maintained for an extended period. Multiple factors, including neurophysiological, perceptual, and cognitive systems, contribute to mental stress [23]. This is the amount of a system's information-processing power that is allocated to a certain activity. The amount of work a person must do depends on their age, health, past work experience, motivation to perform the job, the techniques they use to execute the task, and their own physical and mental condition. Considering this, understanding the fatigue of a pilgrim and how it impacts their role performance in a range of settings should aid in the management of the environment, therefore enhancing the performance and well-being of the pilgrim.

Several natural or pathological abnormalities in the body's physiological systems may result in fatigue. Fatigue can be linked to abnormalities with the central nervous system, the peripheral nervous system, or the neuromuscular system. It may be either physical or mental depending on the kind of stress. Physical and mental fatigue are the result of activity and stress, respectively, and both lead to a decline in physiological and behavioural performance [24], [25]. For online monitoring, existing non-invasive technologies are

generally based on the following five principles: subjective assessments, performance-related methods, biomathematical models, behavioural-based methods, and physiological signal-based methods [26], [27].

Electronic sensors are the most effective method for detecting physiological signs [28]; nevertheless, there are certain drawbacks, including electrical safety problems, electromagnetic interference, and a remarkably short linear time response period. In contrast, the plastic optical fibre sensor can be used to monitor the subject's heart rate and breathing rate as well as analyze the subject's dynamic posture in a variety of positions, such as while running, walking, standing, crouching, or laying [29].

Fatigue may be detected by physiological signal-based methods such as electroencephalograms (EEG), heart rates (HR), and electromyograms (EMG). As an example, electroencephalograms (EEG) have long been accepted globally for monitoring driver alertness and sleepiness on the road [30], [31], [32], [33], [34].

Using smartwatches, a support vector machine with primary distinguishing factors is utilized to detect fatigued driving [35], [36]. Utilizing principal component analysis, these 13 features were determined. The suggested method is 83.29 percent accurate in identifying driver fatigue or a normal condition. Non-pathological fatigue (self-reported) and multimodal sensor data is linked using supervised and unsupervised machine learning techniques following imputed missing time series data using a recurrent neural network-based algorithm [37]. During this research, 27 healthy participants and 405 days of data were collected. Daily surveys on fatigue and other physiological markers are obtained in addition to multimodal detector panel data on physical activity and vitals. The most important results came from unsupervised representation learning of multimodal sensor data with causal convolutional neural networks and random forest as a classifier that was trained on physical tiredness labels. The random forest was made better by using information about physical activity and vital signs, such as the amount of energy used and the number of steps, the pulse and how it changes, and the rate of breathing. Thus, multimodal sensor data can be used to teach, measure, and improve subjectively observed measures of non-pathological fatigue.

Wearable smart electrocardiogram (ECG) devices are considered as a feasible approach for determining the mental fatigue level of a person by [38]. The research recruited a total of 35 healthy students from a public university in China. A wearable device was attached to each participant's body and transmitted data to their smartphone via Bluetooth. Each participant was required to complete an 80-minute test. Throughout the experiment, eight measures of heart rate variability (HRV) were recorded every five minutes; after feature selection, six measurements remained. Four approaches are used to identify fatigue: logistic regression, naive Bayes, support vector machines, and k-nearest neighbors (KNN). The KNN algorithm is better than the others. The most important

indicators of heart rate variability for detecting mental fatigue are the mean of NNs (the time between two normal heart rates), the proportion of consecutive NNs that vary by more than 50 milliseconds divided by the total number of NNs, total spectral power, and low frequency.

Real-time determination of mental fatigue needs a deep convolutional auto-encoding network trained on biometric data acquired from smart bands (galvanic skin response, heart rate, changes in the time intervals between consecutive heart beats, skin temperature) [39]. The suggested method is verified by analyzing biometric data obtained from six volunteers over a period of six weeks. The accuracy of fatigue detection was found to be 82.9% based on experimental data. To sum up, in addition to laws, rules, and regulations designed to aid in ensuring workplace safety, fatigue detection and prediction technologies will be crucial in future [27], [39].

As was already indicated, a complete solution has not yet been implemented despite major research efforts to find creative methods to automate the information and data collecting needed for crowd control. A comprehensive and capable solution that addresses the two biggest problems in this field, namely the heterogeneity of Hajj rituals and activities, and the intricacy of the variables that affecting pilgrims physical and psychological status. No prior research study that the authors are aware of has explored the use of physiological sensors to train Hajj rituals activity recognition classifiers, as means of complementing an automatic and real-time data analytics system for crowd management.

III. METHODOLOGY

The research methodology consists of the following steps to design and develop an end-to-end framework for pilgrims tracking:

- 1) Data collection framework building
 - a) Physiological signals and wearable sensors selection
 - b) Data acquisition and fusion using smartphone
 - c) Real-time data collection and storage
- 2) Data pre-processing and feature extraction
- 3) Machine learning model development and validation

The following subsections describe how each step was carried out during a pilot study intended to validate this framework. The prototype was evaluated on a group of subjects who engaged in a variety of rituals and activities such Tawaf, Saai, prayer, and Doaa. The steps taken to build the data collection framework is depicted in Figure 1.

A. PHYSIOLOGICAL SIGNALS AND WEARABLE SENSORS SELECTION

Various wearable sensors for acquiring physiological signals were compared, evaluated and considered for this system (refer to Table 1). Although, there is a huge number of physiological signals monitoring kits available in the market, we limited our hardware evaluation to the kits depicted in Table 1. This decision was made due to two reasons. First, those tool kits have Android APIs which will facilitate the

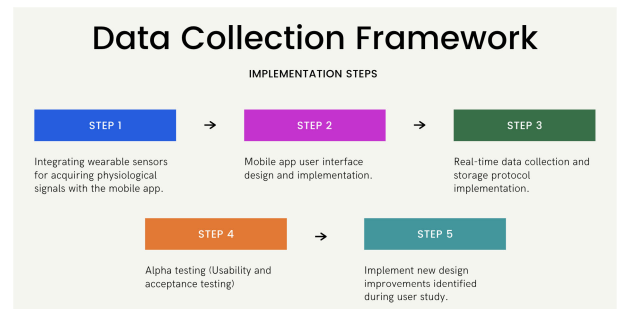


FIGURE 1. Data collection framework.

TABLE 1. Physiological signals measuring wearables toolkit.

Name	Type	Biometric measured	Drawbacks	Price
Zephyr belt-type BioHarness sensor	chest belt	ECG, skin temperature, HR, HRV, respiration rate, Body motion	Had to be worn bare-chest, no EDA sensor	\$631.4
MC10	patch	ECG, EMG, Body motion	Limited physiological signals tracked and expensive	\$2,500
Empatica’s E4	wristband	skin temperature, blood volume pulse (BVP), EDA	Expensive and no respiration rate sensor	\$1,690
Microsoft Band 2	wristband	HR, body motion, skin temperature, galvanic skin response, beat-to-beat interval	The SDK is no longer supported by Microsoft	\$250
Fitbit Sense	wristband	EDA, skin temperature, HR	No access to EDA sensor data using Fitbit APIs	\$380

integration between the data generated by the kit and the developed app. Second, those kits support the continuous and real-time monitoring of a broad range (e.g., BVP –500 to 500, skin temperature –40 to 115°C) of physiological signals. After considering tradeoffs between conveniences to wear, cost and number of physiological signals monitored, a decision was made to use both Zephyr belt-type BioHarness sensor and Empatica’s E4.

Zephyr belt-type BioHarness provides respiration rate signal but the user is required to wear it on a bare chest to get an accurate reading. This might not be convenient for many studies. However, the setting of the current study makes it a convenient measurement instrument since pilgrims perform Hajj activities with a bare-chest (see Figure 2).

B. DATA ACQUISITION AND FUSION USING SMARTPHONE

A mobile application was designed and downloaded onto the subjects’ phones. The app was developed for Android supported mobile devices. The app was written in the native Android development language, Java. The app was designed to record and fuse location data, raw physiological signal data, user input corresponding to Hajj Rituals, and their emotional and physical status.

1) LOCATION DATA

Table 2 summarizes the location data collected using the mobile. We used Android ACCESS_FINE_LOCATION

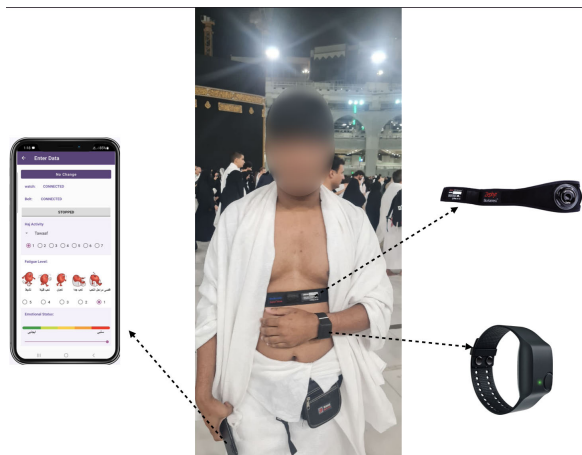


FIGURE 2. Subject wearing Zephyr belt-type and E4 watch and carrying the mobile with the custom built application.

TABLE 2. Location data collected using the application.

The location data	Definition
Altitude	The location’s elevation in meters above the WGS84 datum.
Longitude	The longitude, measured in degrees.
Latitude	The latitude, measured in degrees.
Speed	This location’s data shows current speed in m/s.
Time	Unix epoch time of the specified location, in milliseconds since the start of the Unix epoch (00:00:00 January 1, 1970 UTC).
Accuracy	The predicted horizontal accuracy radius at the 68th percentile confidence level, measured in meters, for the specified location.
Bearing	The bearing is between 0 and 360 degrees. It shows the horizontal travel direction, regardless of the orientation of the device.

permission since it enables the location API to ascertain an exact position as feasible using the location providers that are accessible, such as WiFi and mobile cell data as well as the Global Positioning System (GPS). GPS latency is the interval between when the time when the location data is measured and when it is recorded or transmitted. GPS readings are taken from a mobile device and recorded immediately by the mobile app in the same mobile; therefore GPS latency in this case can be negligible.

2) PHYSIOLOGICAL DATA

To collect the subjects’ physiological signals, two commercially available sensors were used: Zephyr belt-type Bioharness and E4 wristband. Figure 2 shows a subject wearing the two sensors.

Table 3, summarizes the subjects’ physiological data collected using Zephyr Bioharness and E4. Some of the physiological signals were available from the two sensors such as the Temperature, whereas other physiological signals were only recorded by one sensor, such as respiration rate which was available only from Zephyr. E4 watch use an infrared thermopile sensor to measure skin temperature with an accuracy (sensitivity) of ±0.2°C within the range of 36-39°C.

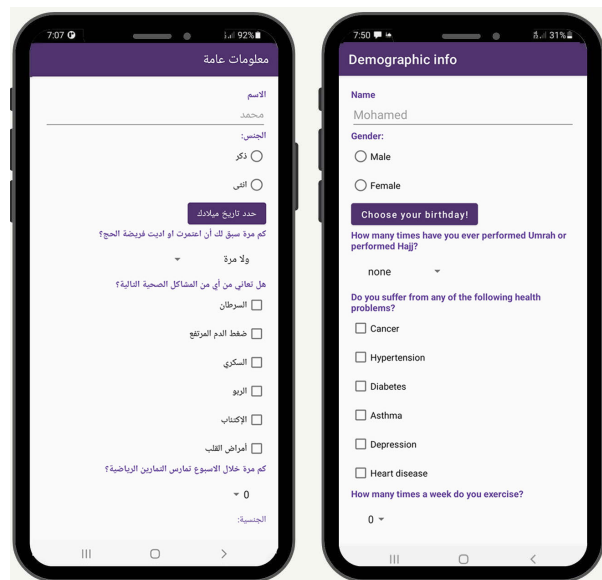


FIGURE 3. Demographic information UI Arabic and English interface.

3) DEMOGRAPHIC AND ANNOTATION DATA

The smartphone app also acted as an annotation logging tool, pairing with the two sensors via Bluetooth to continually collect the physiological information. The mobile application consists of two main user interfaces: (a) Demographic User Interface (UI) used to collect demographic data from the subject (See Figure 3), and (b) Annotation User Interface (UI) used to collect information about the Hajj activities they are currently performing, their emotional status and their physical status.

The demographic data included subject’s name, gender and nationality. Also the answer to the following questions were recorded.

- 1) Have you performed Hajj or Umra before?
- 2) Do you suffer from any of the following chronic diseases (cancer, high blood pressure, diabetes, Asma, depression or heart disease)?
- 3) How often do you exercise per week?

Using the annotation UI (refer to Figure 4), subjects were able to record 4 different types of Hajj activities: Tawaf (7 rounds), Saai(7 rounds), Prayer (Sunna, Fard) and Doaa. Also, the subject can record fatigue level in visual discrete scale of 5 where 1 means “not tired” and 5 means “Extremely tired”. The emotional status on visual continuous scale (0-100) where 0 means “Extremely negative” emotion and 100 means “Extremely positive” emotion.

C. REAL-TIME DATA COLLECTION AND STORAGE

The gathered information was stored in the phone external storage as a comma separated value (CSV) file. It was also saved in Room MySQL database in the mobile internal storage. Whenever there is internet connectivity, a copy of the collected data was sent to Firebase a cloud storage.

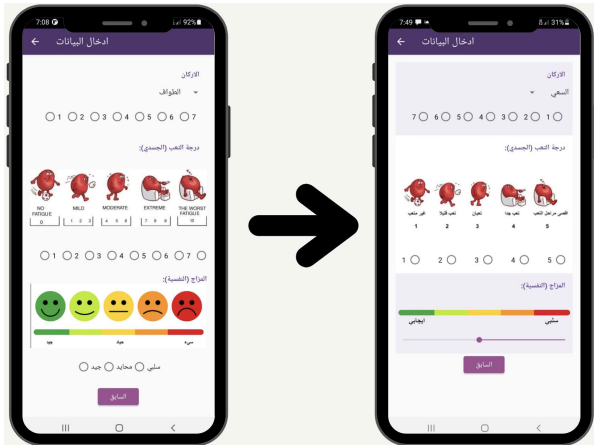


FIGURE 4. Annotation UI (before and after usability and acceptance testing).

TABLE 3. Physiological data collected using the mobile application.

Sensor	Physiological data
Empatica E4	Temperature GSR Iner plus interval (IBI) BVP X acceleration Y acceleration Z acceleration
Zephyr Bioharness belt	Heart Rate Respiration Rate Posture Activity and acceleration Heart Rate Variability GSR

D. DATA PRE-PROCESSING AND FEATURE EXTRACTION

Table 4 presents a statistical summary of physiological data collected from two subjects using an Empatica E4 wristband. Both subjects’ BVP, GSR, and IBI results are distributed throughout a range. The mean BVP for subject 1 is -0.42 with a standard deviation of 3.72 , whereas the mean BVP for subject 2 is 8.47 with a standard deviation of 23.51 . Likewise, the means for GSR (0.81 vs. 5.62) and IBI (0.47 vs. 0.64) are comparable. Temperature readings have a similar set of data. Acceleration data for x, y, and z are shown with varying means, standard deviations, minimum and maximum values for the two subjects. It is well-known that sensor data is noisy and some data points might be missing due to several reasons. For example, every sensor makes use of a unique Bluetooth device with a varied Bluetooth transmission range. Some might be more reliable and can send data to the mobile from a longer distance while others might not be as reliable. In addition, we are integrating data from multiple sensor types. Those sensors log data at varying frequency. For example, the E4 wristband has 4 sensors each logs data at a different frequency:

- Blood Volume Plus (BVP) sensor at 64Hz
- Temperature sensor at 4Hz
- Accelerometer at 32Hz
- Electrodermal activity sensor (EDA) at 4Hz

TABLE 4. Statistical summary of physiological data collected using Empatica E4 wristband.

Physiological data	Statistics	Subject 1	Subject 2	
BVP	Min	-3.68	-1.19	
	Max	8.35	88.35	
	Mean	-0.42	8.47	
	Std Dev	3.72	23.51	
GSR(micro Siemens μS)	Min	0.81	0.00	
	Max	0.81	6.56	
	Mean	0.81	5.62	
	Std Dev	0.00	2.30	
Inter Beat interval (IBI)	Min	0.47	0.36	
	Max	0.47	0.64	
	Mean	0.47	0.60	
	Std Dev	0.00	0.10	
Temperature ($^{\circ}C$)	Min	37.47	28.29	
	Max	37.47	34.39	
	Mean	37.47	33.51	
	Std Dev	0.00	2.14	
Acceleration (g)	Min	x	-17	-70
		y	44	-64
		z	12	-19
	Max	x	-5	-4
		y	81	-16
		z	32	3
	Mean	x	-9.32	-59.72
		y	54.51	-23.22
		z	25.99	-14.74
	Std Dev	x	5.13	23.00
		y	7.22	16.72
		z	7.54	8.06

Zephyr Bioharness belt was logging data at 1Hz. The location data was recorded at a frequency of 0.1 Hz. Therefore, a protocol for missing values replacement was formulated for this study. Since our data is time-series data, we used the last observation carried forward (LOCF) method. When a value is absent, the most recent value that was seen is used in its stead. Despite being straightforward, this approach strongly presupposes that the value of the result is unaffected by the missing data, which is quite plausible in our present environments. We utilized Next Observation Carried Backward (NOCB) to fill initial missing values after using LOCF to fill inner missing values. Similar to LOCF, NOCB operates in the other direction by carrying the initial observation backward from the missing value. To prepare the data for deep learning, a sliding window strategy was used on each sensor output. We applied a sliding window and created a set of successive fixed-size windows with a fixed degree of overlap. Let us denote the 7-sensors inputs as sequences of length T, namely,

$$Temp = (Temp_1, \dots, Temp_t, \dots, Temp_T) \quad (1)$$

$$BVP = (BVP_1, \dots, BVP_t, \dots, BVP_T) \quad (2)$$

$$IBI = (IBI_1, \dots, IBI_t, \dots, IBI_T) \quad (3)$$

$$GSR = (GSR_1, \dots, GSR_t, \dots, GSR_T) \quad (4)$$

$$AccX = (AccX_1, \dots, AccX_t, \dots, AccX_T) \quad (5)$$

$$AccY = (AccY_1, \dots, AccY_t, \dots, AccY_T) \quad (6)$$

$$AccZ = (AccZ_1, \dots, AccZ_t, \dots, AccZ_T) \quad (7)$$

where $Temp_t, \dots, IBI_t$ and BVP_t denote the window of Temp, ..., IBI and BVP at time slice t. All of the generated windows are considered to be the new training data examples. We then

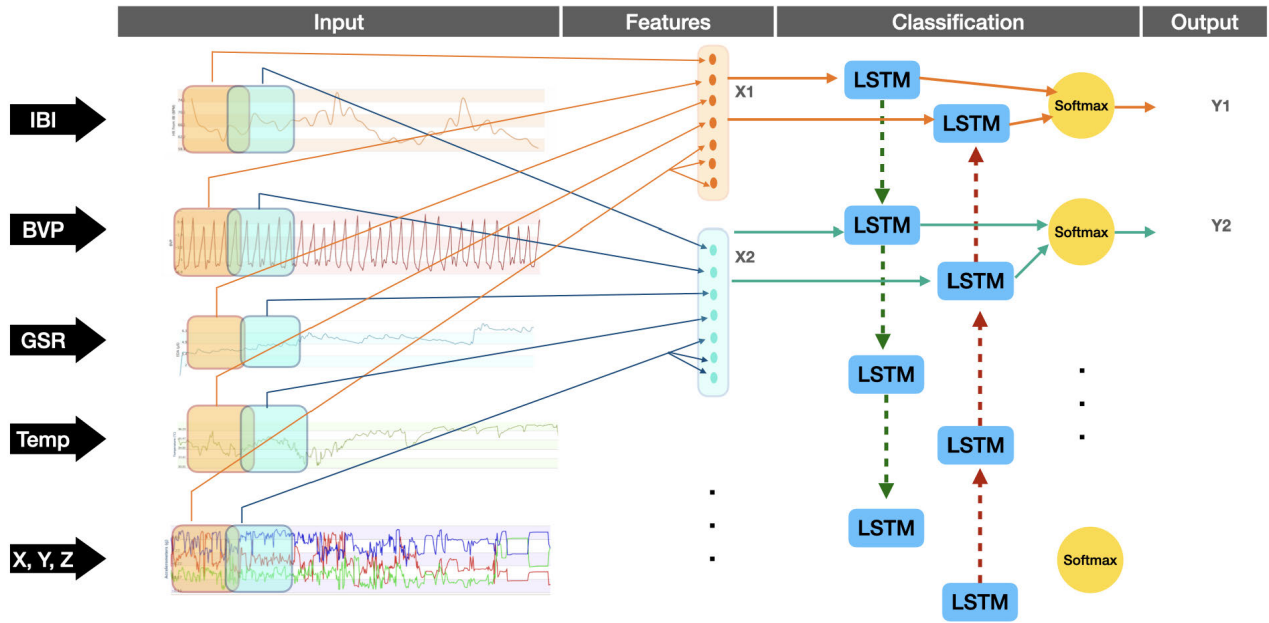


FIGURE 5. The pipeline of the deep learning model based on bidirectional LSTM. The inputs to this system are the IBI, GSR, Temperature (Temp), Acceleration (three channels) and BVP signals. The inputs are segmented into successive fixed-size windows with some degree of overlap (25% overlap). The output of this model depends on the classification task. The created window at time t from each of the 7 signals are concatenated to build the joint representation. The created joint representation at time slice t is then fed into the two layers of LSTM followed by a dense layer and a soft-max layer depending on the classification task.

segmented each channel into consecutive windows with window sizes (0.3 sec) and 25% overlap. The label (category) is chosen based on the mode of all sequence categories. In other words, given a sequence of length time steps, this category was determined to be the most prevalent. The labels are then encoded using a one-hot encoder method.

E. MACHINE LEARNING MODEL DEVELOPMENT

In this stage, we developed and validated Machine Learning (ML) models. For the purpose of this study, we used deep learning to build three different classification models:

- 1) Classification model for predicting the Hajj related activity currently performed by the pilgrim.
- 2) Classification model for predicting pilgrim’s fatigue level (physical status)
- 3) Classification model for predicting pilgrim’s emotional status (psychological status)

Specifically, we used recurrent neural networks (RNN). Deep learning approaches proved to provide similar, and in some cases, superior results to classical classification approaches. RNN succeed in dealing with time-sequential data that embody correlations between close data points in a sequence [40]. Recent studies proposed to use Long-Short Term Memory (LSTM) [41], an RNN approach, which is useful for the classification of time series data. Therefore, we decided to build LSTM classifiers given that all our data are time series data. More specifically, we built Bidirectional LSTM models and evaluated their performance. Bidirectional RNNs improve the accuracy of their predictions of the current state by incorporating future information that is unavailable to unidirectional RNNs.

TABLE 5. Distribution of Hajj activity classes, physical status classes and emotional status classes.

Responses	Class	Subject 1	Subject 2	Two Subjects
Hajj Activity Classes	Tawaf One	57	154	211
	Tawaf Two	14	3	17
	Tawaf Three	2	2	4
	Tawaf Four	11	2	13
	Tawaf Five	1	15	16
	Tawaf Six	1	27	28
	Tawaf Seven	1	20	21
	Saee One	2	0	2
	Saee Two	1	0	1
Saee Three	1	0	1	
	All	91	223	314
Physical Status Classes	1	72	204	276
	2	19	19	38
	3	0	0	0
	4	0	0	0
	5	0	0	0
		All	91	223
Emotional Status Classes	0 — 10	58	41	99
	10 — 30	0	22	22
	30 — 60	0	21	21
	60 — 80	3	49	52
	80 — 100	26	50	76
		All	91	223

IV. RESULTS

The classifiers were built using two subjects’ data. The complete data-set models and results will be published in a separate paper. Before building the classifiers, we visually examined the data (see Table 5). From Table 5, it can be clearly observed that the two subjects log more data at Tawaf’s first lap (denoted Tawaf One in Table 5) and the number of logged data by the pilgrim decreases over time.

TABLE 6. Training and testing accuracy of the classification models*.

Classification Accuracy Case	Subject 1	Subject 2	Two Subjects
Hajj Activity	0.9 (0.67)	0.82 (0.56)	0.83 (0.75)
Physical status (fatigue)	0.8 (1)	1 (0.78)	0.98 (0.92)
Emotional Status	0.8 (0.1)	0.54 (0.22)	0.64 (0.42)

*The data enclosed in brackets indicates the verification using the 20% unseen testing data. Using cross-validation with 10 folds, training data is evaluated.

We assigned the data into training and testing sets, allocating 80% of the data to training and 20% to testing. Then, while training the model, 10-fold cross validation was used. The data samples of n-dimensional patterns created by concatenating the BVP, GSR, IBI, and temperature values with the three acceleration values (x, y, z) collected along each Cartesian direction. It is essential to utilize a loss function to characterize the precision of a classification model while solving a classification problem. The loss function specifies how much the results deviate from the actual data. The more precise the findings, the less the loss. As a cost function, we opted for the cross-entropy loss (log loss function). In our experiments, we used a dropout rate of 0.5, a batch size of 32, and the Adam optimizer with 0.001 learning rate. We determined the classification's quality based on how well it performed throughout both training and testing. The accuracy of training was determined by applying the model to the training set. The performance of the model on the test data was evaluated by applying it to that set of data.

The experiments were conducted using Google Collab Notebook. The code is developed in Python 3 using Keras version 2.8.0 and TensorFlow version 2.8.2. The CPU is an Intel(R) Xeon(R) running at 2.20 GHz, and the system memory is 13.29858 GB.

Emotions are said to have two dimensions: arousal and valence, with arousal referring to the intensity of the emotion and valence relating to the distinct emotional state, which is separated into positive, negative, and neutral feelings [42]. In the experiment, only the valence dimension was considered. Table 6 displays the three models' performance on datasets from Subject 1, Subject 2, and the combined dataset including data from both subjects. The accuracy (10-fold cross-validation accuracy of 0.83) of the Hajj activity classification model is shown in Table 6. In addition, the physical status detection model performs very well (10-fold cross validation accuracy of 0.98) but the emotion detection classifier unperformed (10-fold cross validation accuracy of 0.64). This low performance of the emotional state classifier might be attributable to the wide variety of variables that pilgrims can use to describe their emotional condition (0-100, where 0 represents "extremely negative" emotion and 100 represents "extremely positive" emotion). We will no longer use a continuous visual scale, but rather ordinal data classes in the near future. Additionally, we propose capping the total number of such classes to five.

No prior research study -the authors are aware of- has explored the use of physiological sensors to train Hajj rituals

TABLE 7. The comparison of the performance of our proposed model with other state-of-the-art methods for emotional classification from physiological signals and fatigue detection.

Classification Task	Study	ML model	Accuracy
Fatigue Level Classification	zhang et al. [43]	Deep Convolutional Autoencoding Memory network (CAE-M)	82.9%
		one-class SVM (OCSVM)	53.9%
		one-class single-layer LSTM	71.85%
	Our model	Bidirectional LSTM	0.98%
Emotional Status (valence) classification	Nakisa et al [44]	ConvNet LSTM	71.61%
		Xing et al. [45]	LSTM
	Alhagry et al. [46]	LSTM RNN	72.06%
	Our model	Bidirectional LSTM	0.64%

activity recognition classifiers. In the near future, more data will be collected using this framework to build a comprehensive model that can be used to classify and recognize Hajj rituals and activities. Yet, Table 7 was included to compare our results to previous work on fatigue and emotional recognition using physiological signals.

V. CONCLUSION

This research study is proposing an innovative framework for information collection that would help in crowd management. This framework utilize the data captured by mobile GPS and physiological wearable sensors to automate crowd management. Our approach is based on machine learning classification that identify the Hajj and Umra activities. We built machine learning classifiers to identify Hajj's activity, pilgrim's fatigue level and emotional status and reported the resulting accuracy. In future, a more comprehensive set of sensors could be used to build the classification models. Furthermore, feature reduction (dimensionality reduction) could be employed to reduce the number of features, as this simplifies and accelerates the training and classification processes.

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