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Fog-Centric IoT Based Framework for Healthcare Monitoring, Management and Early Warning System

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ABSTRACT Internet of things (IoT) and machine learning based systems incorporating smart wearable technology are rapidly evolving to monitor and manage healthcare and physical activities. This paper is focused on the proposition of a fog-centric wireless, real-time, smart wearable and IoT-based framework for ubiquitous health and fitness analysis in a smart gym environment. The proposed framework aims to aid in the health and fitness industry based on body vitals, body movement and health related data. The framework is expected to assist athletes, trainers and physicians with the interpretation of multiple physical signs and raise alerts in case of any health hazard. We proposed a method to collect and analyze exercise specific data which can be used to measure exercise intensity and its benefit to athlete's health and serve as recommendation system for upcoming athletes. We determined the validity of the proposed framework by giving a six weeks workout plan with six days a week for workout activity targeting all muscles followed by one day for recovery. We recorded the electrocardiogram, heart rate, heart rate variability, breath rate, and determined athlete's movement using a 3D-acceleration. The collected data in the research is used in two modules. A Health zone module implemented on body vitals data which categorizes athlete's health state into various categories. Hzone module is responsible for health hazards identification and alarming. Outstandingly, the Hzone module is able to identify an athlete's physical state with 97% accuracy. A gym activity recognition (GAR) module is implemented to recognize workout activity in real-time using body movements and body vitals data. The purpose of the GAR module is to collect and analyze exercise specific data. The GAR module achieved an accuracy of above 89% on athlete independent model based on muscle group.

INDEX TERMS Fog computing, gym activity recognition, health hazard recognition, Internet-of-Things (IoT), machine learning, smart workout.

I. INTRODUCTION

The world today, is witnessing a massive technological turn in every walk of life, focusing particularly on healthcare and physical fitness services. Information and communication technologies are moving with the engineering and medical mechanizations, and have greatly enhanced and monitored healthcare and physical fitness not only at home but outdoor as well. It has been observed that the research of current times is mostly focused on wireless healthcare provisions using smart wearable for remote access. The people of the world are advanced enough to receive instant health alerts by professionals, trainers and clinicians on their smart phones and other gadgets. These systems are utilizing their advanced features and capabilities to bring out useful and productive information from the smart wearable to deliver better healthcare services [1].

Machine learning based fitness monitoring systems in health and fitness domain have supported trainers, coaches and physicians by providing real time decision support and early diagnosis of injuries. The technological enhanced healthcare delivery services can particularly reduce the risks associated with the health of athletes. This improved fitness domain has altered the traditional medical treatments

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to a modern one including their prevention by predicting and detecting the health risks beforehand. Such system are more favorable in reduction of healthcare costs by providing remote delivery of services to trainer and physician. [2]. Nowadays, the focus of health and fitness domain has been evolved to include prevention, and early detection of injuries. For example, athletes, especially beginners who constantly overdo gym workout often experience fatigue, mental exhaustion, and muscle fractures. Such injuries of an exercisers can be prevented by analyzing data acquired from smart wearable in real time [3].

Internet of Things (IoT) along with Fog computing has high impact on several application domains including healthcare in sports [4]. Fog centric IoT is rapidly gaining fame as a novel paradigm reflecting a pervasive presence of things, services, places and networks allowing network devices to collect, communicate and exchange data. IoT based healthcare platform powered with machine learning is one of the most attractive application domain of IoT, focusing on real-time and remote monitoring, improvement of quality of life, patient centric healthcare, early diagnosis of chronic diseases, medical emergencies and reduction in treatment cost [5].

Physical fitness plays a vital role in our lives, physically and mentally fit people can perform there day to day activities better and are less prone to medical conditions. Our modern sedentary lifestyle has resulted in unhealthy weight, which causes diseases like heart, high cholesterol, diabetes, depression, obesity, etc. Physical activity can probably help us reduce the risk of diseases. World Health Organization (WHO) [6] suggests moderate intensity workout of at-least two and half hour or vigorous-intensity aerobic physical activity of 75 minutes for the adults aged between 18 and 64 throughout the week.

The gym and fitness clubs are gaining popularity due to the technological advancements and awareness associated with various advantages of daily exercises. Nowadays, regularizing physical activity sessions appears to be difficult as busy work routines can often impede the execution of exercise plans. Thereby, workout/body fitness centers are becoming necessary for physical workout. While sometimes high-intensity exercises may lead to serious health-related issues. The health state prediction is possible by real-time acquisition and compilation of athlete's health data [3]. To analyze data from wearable, the concern should not be on how much data is collected, but rather, what relations or co-relations can be drawn between data received from different sensors and exercise apparatus. For instance, how do we relate data collected from the smart watch while a person is exercising on the treadmill and while using a bench press?

A major contribution of this paper is the proposition of a framework for exercise specific body vitals data collection, early diagnosis of injuries and alarm in case of any health hazards in a smart gym environment. Which, to the best of our knowledge, has only been done as prediction value based on historical events but not being tracked in real-time. This paper offers the following contributions.

1) Proposition of a framework for a smart gym environment which involves exercise specific health related data acquisition and analysis.
2) Real time early diagnosis of health risks for athletes due to over exertion or over doing exercises. A Fog-centric model is introduced in the proposed framework to respond in real time using mobile application.
3) A novel mechanism of Activity Correlation has been proposed using body movement data and body vitals taken by single device attached to the athlete's body instead of multiple smart devices.
4) The exercise specific data collection and analysis can be used to monitor body's recovery rate, athlete's comfort analysis, exercise intensity analysis etc and also serve as recommendation system for upcoming athletes.
5) Experimentation has been performed in a controlled smart gym environment under observation of trainers, physicians and other domain experts.

The rest of the paper is organized as follows. Section II presents an overview of the recent literature. Section III presents the proposed framework along with Section IV which describes the data collection and transformation process. Section V describes the use of transformed data in two modules, gym activity recognition (GAR) module and health zone (Hzone) identification modules. The section VI providing the experimental validation of the same. Section VII concludes the entire discussion presenting an overview of the contributions and achievements of the proposed framework.

II. PRELIMINARY AND RELATED WORK

IoT and Fog based health monitoring research can be further divided into four categories as described below.

A. FOG-COMPUTING PARADIGM IN IoT

Bonomi *et al.* [7] outlined the vision of Fog/Edge computing paradigm in the field of IoT to deliver a rich set of services and application in sensor based network to overcome the issue related to IoT like latency, mobility, real time manipulation of data, increasing number of nodes, location awareness and storage. Farahani *et al.* [8] presented applicability of IoT in healthcare and medicine by presenting a holistic architecture of IoT eHealth ecosystem using Fog-computing paradigm which defines a healthcare based multi-layer architecture.

B. IoT BASED HEALTHCARE

Adame *et al.* [9] deployed and tested CUIDATS an IOT based hybrid monitoring system using wireless sensor networks(WSN) and Radio Frequency Identification (RFID). The target was to obtain the patient's location, status, tracking, and assets (wheelchair) tracking in real-time. Mahmud *et al.* [10] designed a user-friendly Smartphone case that can monitor the heart rate and ECG of a person in real-time using wireless sensor networks. Results obtained were promising and consistent.

C. IoT BASED SMART WORKOUT

Thompson and Walter (2019) [11] in their fitness trends survey highlighted that Wearable technology and gym-related exercises like High-Intensity Interval Training (HIIT) and Bodyweight training is among the top 5 spots for 2019 fitness trends. Qi *et al.* [12] collected home and gym activity data using a belt and a wrist device. They applied Artificial Neural Networks (ANN) based learning, achieving high accuracy on activity recognition. Gupta and Sruti (2011) [13] proposed a sports and fitness based architecture named as Digital Fitness Connector (DFC) that leverages existing technologies to monitor different vital signs during a workout session. Patel and Aisling (2015) [14] presented exploratory study on human behavior to adopt technology in the smart workout environment, providing insight into commercially available fitness related products, heart rate monitor, and pedometer. The work provided by Das *et al.* [15] includes home and gym activity recognition and repetitions counting along with comfort analysis deduced from resting and maximum heart rate. The Comfort factor analysis is helpful in selection of more or less weight during gym activities.

Bhatia and Sandeep (2017) [3], presented a framework for real-time analysis and prediction of health conditions during workouts in a smart gym environment. The proposed framework is comprised of three phases namely, monitor, learn, and predict. They collected data related to athlete's health state (heart rate, blood pressure, breath rate, and body temperature), environment (hall temperature, humidity, oxygen supply), nutrition intake, and behavior (anxiety and stress level). Artificial neural networks are used for the intelligent processing of the data and to state health vulnerabilities. Yong *et al.* [16] designed an IoT and Machine learning based intelligent fitness system which includes data acquisition from smart wearable and webcam for data analytic and to act as recommender system to find similar workout routines. An Algorithm for intensities recognition using heart rate data is proposed in [17] based on athlete independent and dependent observations. The authors made use of heart rate data along with accelerator data to improve classification performance.

D. AUTOMATIC EXERCISE RECOGNITION

Morris *et al.* [18] presented gym activity recognition system using a 3-axis accelerator and a 3-axis gyroscope based armband. Ding *et al.* [19] proposed an integrated free-weight exercise monitoring system called FEMO. The FEMO system was used for activity recognition and repetitions counting. A blue tooth connection based wearable system is proposed in [20] to acquire athlete's movements while performing exercises. The proposed system segments groups of exercises and classify which exercise is being performed and counts number of repetitions for that exercise. A simple smart watch based system named MiLift [21] aims to track the workout activities. The MiLift system also categorized exercisers into different classes as resting, walking, running and weightlifting.

III. PROPOSED FRAMEWORK

Trainers working in the gym environment are responsible for conducting a multitude of tasks that requires constant vigilance and thus the need for a smart physical activity monitoring system has arisen. The existing frameworks lack in sensing gym workout, on numerous important and critical workout apparatus, local processing for real-time caution/alarm generation, objective or disease-specific data acquisition and analytic. To analyze data from wearable, the concern should not be on how much data is collected, but rather, what relations or co-relations can be drawn between data received from different sensors and exercise apparatus. For instance, how do we relate data collected from the smart sensor while a person is exercising on a treadmill or using a bench press?

The main advantage of the proposed framework is exercise specific data collection and analysis that can be used to monitor athletes body vitals, recovery rate, comfort factor, exercise intensity, etc. in real time, from which trainers and physicians can add or skip exercises or adjust weight for exercises. The proposed data collection and analysis technique can also be helpful in early diagnosis of health hazards during gym activity. A well trained system can also serve as recommendation system for upcoming athletes. Automatic exercise classification, segmentation, and counting number repetitions are also an important domain of smart gym-related research. There is also a lack of integrating research related to an athlete's health state analysis during and post-workout.

The reference architecture of the proposed framework is presented in Fig. 1. It combines the functionality of research related to smart wearable based body vitals data analysis as well as automatic gym activity classification along with real-time alarm generation in case of any health hazard. This fog-centric IoT based healthcare framework is expected to be efficient in monitoring and management of exercisers in a smart workout environment. The architecture is divided into three layers A) IoT Sensor Network Layer B) Fog-Node and Services Layer and C) Cloud Storage and Analytics Layer. The Fog Node and Services layer is responsible for real-time collection of a huge amount of data generated from the IoT Sensors layer, classify the data, generate an alert to athlete and/or trainer in case of any hazardous situation and forward preprocessed data to cloud storage for storage and analytics. The Cloud Storage and Analytics layer processes the data and generates reports/alerts for athletes, trainers, and concerned physician. Cloud layer of a well-trained system is also expected to generate safe workout plans for new athletes and providing assistance to trainers and physicians. Each layer of the system is described as follows.

A. IoT SENSOR NETWORK LAYER

This layer is used for data acquisition from smart wearables related to physical fitness related characteristics, a person's vital signs monitoring, and body motion according to the exercise apparatus. These smart wearables are capable of

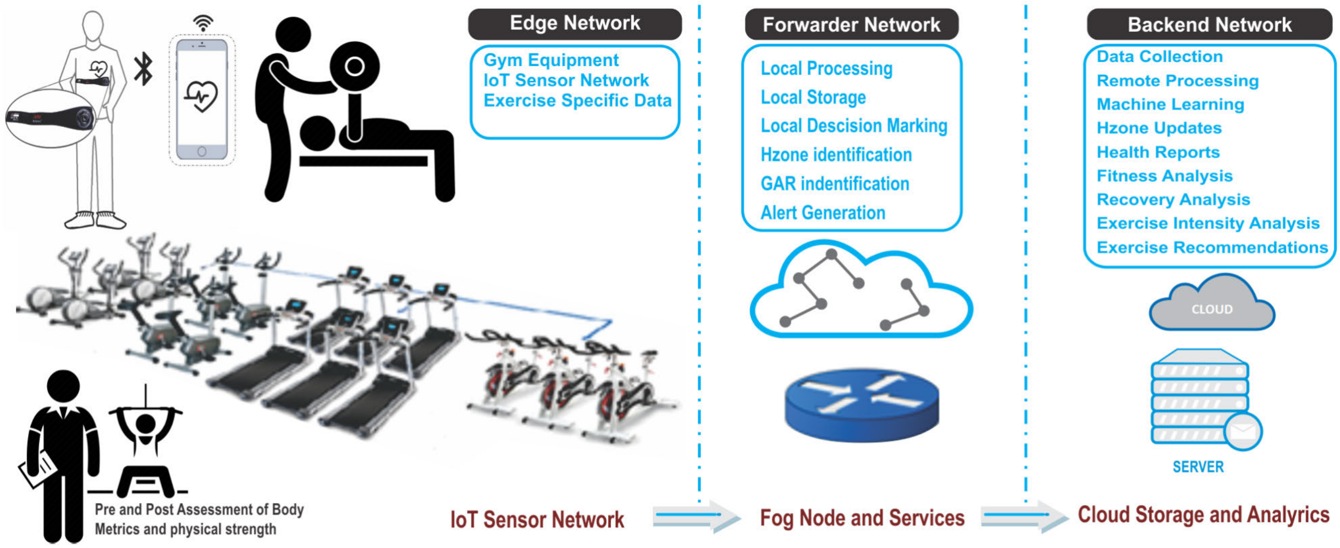

FIGURE 1. Proposed Fog-Centric Healthcare Framework.

TABLE 1. Description of dataset and smart wearable used for data acquisition.

Sr.	Data	Parameters	Smarts Wearable
1	Physiological Data	Gender, age, height, weight, prior health state, trainer and family physician etc.	
2.	Body Vitals	Heart Rate, Breathing Rate, Skin Temperature, hear rate variability (HRV) etc at 1Hz frequency. Breathing wave form (bwform) at 25Hz frequency. ECG waveform (ecgwform) at 250Hz.	Zephyr bioharness 3
3	Body Movement/Posture	Vertical, Lateral and Sagittal movement at 100Hz frequency.	Zephyr bioharness 3
4	Workout Data	Exercise name, exercise apparatus, weight and number of repetitions.	Smartphone application

sensing and transmitting data using wireless communication technology. Data to be acquired in the proposed framework is divided into four subcategories. Table 1 describes the data collected and smart wearables used in the research. Personal data includes physiological data of the athlete. A physiological fitness index (*PFI*) is calculated on physiological data of the athlete to index the current health state, give in equation 1. In the equation, f represents the current health state (good, normal and poor) and $I_1, I_2, \ldots I_n$ score of each physiological parameter of the athlete.

$$PFI = P(\frac{f}{I_i \cup I_2 \ldots I_n}) \tag{1}$$

The body vitals data includes electrocardiogram (ECG), heart rate (HR), heart rate variability (HRV), breath rate (BR) and body movement includes Vertical, Lateral and Sagittal axes data obtained in real-time using the Zephyr Bioharness 3 device (BH3) [22].

B. FOG NODE AND SERVICES LAYER

Fog-Computing paradigm is particularly chosen to minimize the issues related to IoT healthcare applications like latency, mobility, real-time manipulation of data, location awareness, and storage. The Fog Node and Services layer acts as a bridge between IoT Sensor Network Layer and Cloud Storage and Analytics Layer. It is used for data accumulation, preprocessing, classification, alarm generation in case of any health state vulnerability in real-time, and forwarding the processed data to cloud storage. The data classification component of this layer is subdivided into two modules, 1) Classification of athlete's health state into five categories based on body vitals and workout data with health zone received from the cloud layer. It generates an alert to athletes and trainers in case of any health hazard or in case of a target health zone is reached during a workout session. 2) Automatic gym activity recognition (GAR) module which is implemented using Long Short-Term Memory (LSTM) [23] to identify the workout activity in real-time.

C. CLOUD STORAGE AND ANALYTICS LAYER

IoT devices generate a huge volume of data that is transmitted to the cloud via the intermediate fog node for permanent storage and analytics. The data analytics module at the cloud layer is responsible for applying data mining and machine learning techniques for analysis of data and to depict new patterns. It has 2 modules target health zone selection, storage, and smart reporting. Target health zone is selected on the basis of the physiological data, any prior disease, workout routines, exercise apparatus used and improvement is the physical state by using particular workout equipment using equation 1. The Health zone is periodically reported to the fog node. Fog node makes a decision of alarm on the basis of hazardous health zone or when a target health zone is achieved. Storage and smart reporting module allow athlete trainers and health professionals to remotely monitor data and workout history. The trained system can also act as a virtual trainer which can be used for the generation of workout plans for new athletes as per their physiological data.

TABLE 2. Weekly workout plan targeting each muscle group.

Sr.	Chest Workout	Arms Workout	Shoulder Workout	Back Workout	Legs Workout	Core Body Workout
1	Butterfly	Bicep Curl Barbell	4x4 Dumbbell	Pull Ups	Squats	Leg Raises
2	Cable Crossover	Triceps Dips	Front Raise	Front Pull Down	Leg Press	Crunches
3	Chest Press	Bicep Curl Dumbbell	Back Shoulder Press	Lower Pulley	Leg Extension	Cross Bicycles
4	Decline Press	Dumbbell Extension	Up Right Row	Vertical Traction	Leg Curl	Plank
5	Dumbbell Fly	Preacher Curl	Front Shoulder Press	Back Pull Down	Abductor	Mountain Climber
6	Incline Press	Cable Extension	Lateral Raise	1 Arm Dumbbell Row	Dductor	Leg Scissor
7	Push Ups	High Pulley Curl	Shrugs	Barbell Row. T. Bar Row	Lunges	Boat

IV. DATA COLLECTION AND TRANSFORMATION

We collected four types of data in a controlled smart gym environment with the help of domain experts which are physiological, body vitals, body posture, and workout data. This section describes all aspects of the data collection in a gym environment and transformation process.

A. THE PHYSICAL ACTIVITIES

In this research, athletes are given a weekly workout plan depicted in Table 2, six-days a week targeting each muscle group a day and one day for recovery. A total of six weeks data is collected based on the weekly workout plan. A total of forty two physical exercises are performed, organized into six groups according to target muscle group. The first five are chest, arms, shoulder, back and legs which require gym apparatus. The sixth exercise group named core body belongs to exercises that are beneficial for improvement of posture, flexibility, and balance which don't require gym apparatus. Each workout is associated with one day of the week and is to be finished in one session. These exercises are mostly related to body building and weight training programs. These exercises are commonly used by practitioners and their descriptions are widely known.

Repetitions, sets, rest interval between two sets, and workout routines are the basis of any workout plan that uses these exercises in a systematic way. A repetition (or rep, in short) is one complete motion constituting a gym exercise, such as one front raise, one bench press, or one arm curl. To complete one rep, the athlete begins from a starting position, goes through a sequence of motions and returns to the starting position. A set is a group of consecutive reps of an exercise. It can be considered one round of that exercise. For example, eight repetitions can be one set of bench press. The number of reps an athlete does for an exercise depends on the levels of his fitness and his goals for doing that exercise program. A set/exercise is followed by a small period of rest. Generally, this resting period is between 20 seconds to 1 minutes. The rest interval allows the exercised muscle to recover enough for the next set of the exercises. Three sets of each exercise is performed in a session. After completing all the exercises the athlete starts next set of these exercises. The whole group of exercises done during a complete session is called a workout.

The sole criterion for the selection of these exercises was that they are common and widely known. Many of the exercises in this study (e.g., bench press) are done by beginners while some others are done by intermediate to advanced practitioners. We have selected best possible groups of exercises

FIGURE 2. Zephyr bio harness.

targeting each muscle group, in real life, an individual's workout program may have more or less exercises, but that does not have any bearing on our experiments.

B. THE DATA COLLECTION PROCESS

There were a total of 4 athletes, comprised of young males between the ages of 25 and 40. On a given day, each athlete performed all the exercises scheduled in the workout of that day targeting a single muscle group. Each exercise was performed 3 times (3 sets). The sets for an exercise were performed with a small resting period. The number of reps and the weights used varied according to the physical fitness of the athlete. The reps and weights were constant for an athlete for all the 3 sets of the same exercise. For example, an athlete did 3 sets of bench press with 40 kg weight and 10 reps in each set. An exercise and set of an exercise may take variable amounts of time to complete. For example, an athlete might take 1 minutes to complete one set of bench press, while he might take only 30 seconds to complete a set of bicep curls.

The data was collected by a commercially available device called Zephyr Bio Harness 3 (BH3) [20]. The device was strapped on an athlete's chest during each workout session for real-time body vitals and body movement data acquisition as shown in Fig. 2. The data collected by the Bio-Harness was transferred to a laptop via a USB connection. Data collected from BH3 and mobile app is used for Hzone and GAR module.

A mobile application was used to record athlete's name, exercise name, start time, end time, number of repetitions performed, rest time between sets and exercises, equipment used and the weight used. This data was appended later on to the raw signal data to complete the dataset. A manual record of information related to the gender, age, height, weight, prior health state, trainer, and family physician, etc. of the participants was also made. This was done once, at the beginning of the entire data collection process.

All the athletes are given a six-week full-body workout plan, six-days a week targeting each muscle group a day and one day for recovery. Thus, we have 36 days of exercise data and each day's workout has seven exercises multiplied by 3 (3 sets / exercise) multiplied by 4 (4 athlete performed those exercises). The data collection process for each athlete took on average 50 minutes on a daily basis for six consecutive weeks. Thus, we have 4 athletes $\times$ 50 minutes/day/athlete $\times$ 6 days/week $\times$ 6 week of exercise data.

Initially, the process started with 10 athletes, but due to the strenuous nature of the workouts and the daily consistency required over a six week time period, only 4 athletes ended up completing the program.

A different gym in a different climate may introduce a bias into the data collection process, even with the same athlete. However, we believe, that it does not minimize the importance of our process or the relevancy of our results.

C. THE RAW SENSOR DATA

The body vitals data is captured when our athletes perform exercises by wearing Zephyr BH3 device which was transferred to a laptop via a USB connection. The Zephyr device creates separate raw files for each category of data i.e body movement, breathing and electrocardiogram (ECG) data. A summary file is also created using Zephyr's internal algorithm at 1Hz frequency which is used in Hzone module. More details and format of raw data obtained from the device is as follows:

1) Acceleration data file: the format is <timestamp, vertical, lateral, sagittal>. The data is collected at 100 Hz.
2) Breathing data file: the format is <timestamp, Breathingwaveform>. The data is collected at 25 Hz.
3) Heart rate data file: the format is <timestamp, EcgWaveform>. The data is collected at 250 Hz.
4) Summary data file: the format is <timestamp, Heart Rate, Breathing rate, posture, heart rate variability, core temperature >. The data is collected at 1 Hz.

Each file contains data generated during the 7 exercises (3 sets/exercise) done by an athlete on a given day. Since there are 4 athletes, we have $4 \times 4 = 16$ raw data files generated for each day of workout. The workout plan was for 6 weeks with 6 workouts in a week. Thus we have a total of 36 days and $(4 \times \times 4 \times 36 =)576$ raw data files.

Workout data is collected using a mobile application to store athelete-ID, workout category, exercise name, number of reps, weight used and start time and end time of the exercise. The raw data is augmented with the workout data, by linking the time stamp information of raw files and the mobile application based recorded exercise start and finish time.

D. DATA PRE-PROCESSING

The collected dataset is in four categories, physiological, body vitals, body posture, and workout data. Physiological data is recorded manually, while workout data is recorded using a mobile application. Body vitals and posture data is collected using the Zephyr bio harness device.

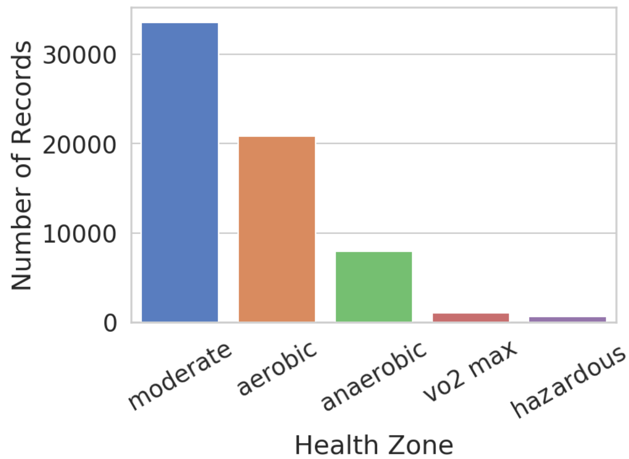

FIGURE 3. **Hzone categories and their record count.**

Body vitals data at 1Hz frequency is used to divide an athlete's health state into five categories based on Fox and Haskell formula [24] for Hzone module. These categories are moderate, aerobic, anaerobic, VO2 max, and hazardous.

The body movement data received at 100Hz frequency, is used for GAR module along with ECG data, breathing data, and body vitals summary data. Given the separate sampling rate of 100Hz for body movement data, 25Hz for breathing data, 250Hz for ECG and 1Hz for summary data we had to scale all data to 100 Hz for GAR module. The data of ECG, breathing, summary data and workout is transformed to 100Hz frequency with the body movement data to create our dataset for the GAR module.

Hzone and GAR modules are based on the body vitals, posture, and activity data collected using BH3. The Hzone module is based on body vitals data collected at 1Hz frequency depicted in Fig. 3. GAR module uses accelerometer, breathing and ECG data collected at 100Hz frequency, to recognize each exercise based on workout category information. ECG and breathing data are considered to identify exercises with similar posture but different arms movement which is not detected by the BH3 device. There are 6 workout categories while each category is based on 7 exercises performed in a session. Since we need labelled data samples for training and testing supervised learning based classification models, each transformed instance is tagged with the activity that was performed based on workout data obtained from the mobile app. Fig. 4 depicts exercise wise instance count for each workout performed.

V. EXPERIMENTATION

The collected data was used to study the feasibility and performance of the proposed framework. Two groups of experiments were conducted, one for exercise recognition and another for monitoring the health state of the exerciser.

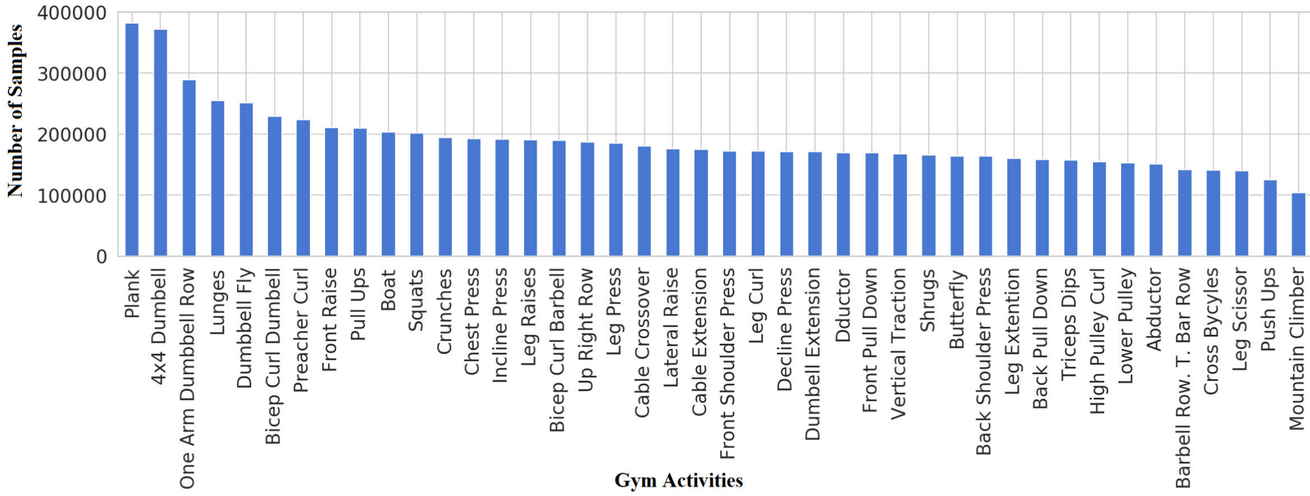

FIGURE 4. **Exercise wise instance count for GAR module.**

This section describes the methodology used to execute our experiments. Section V-A describes the classification algorithm used to build the models. The methodologies used to construct and evaluate the experiments on exercise recognition and health state classification are described in Section V-B.

A. CLASSIFICATION MODELS AND TRAINING

Two separate groups of models were trained, one for exercise recognition and the other for health zone classification. Both the models are Long Short-Term Memory (LSTM) neural networks. LSTM is an extension of recurrent neural network begin widely used in the field of deep learning. LSTM has the advantage over other neural networks by having a feedback connection which can process an entire sequence of data. As the collected data is time series data, so the LSTM model is well-suited for classification of such data.

We implemented a Bidirectional LSTM model with 128 units each, the dropout rate at 0.5, and the relu activation function. The implementation used is in the tensor flow with Keras an open source library for data mining and analysis. The experiments were executed on the Google Colab platform [25].

LSTM comprises different layers of neurons, each neuron has weighted inputs parameters. Layer to layer scaling of input is done with the help of transform function. LSTM model expects fixed-length sequences as training data sequence contains 400 records, which are equal to 4 seconds of activity. Our LSTM model chooses the class label by using the mode of all exercises which are present in the sequence. It is the exercise that occurs most often in the sequence. Splitting of data into training and test data is achieved with the help of setno attribute collected using a mobile app. Each exercise is performed three times in a session. The first two sets of the exercise were used as training data and the third set as test data.

B. METHODOLOGY OF THE EXPERIMENTS

1) METHODOLOGY OF GAR MODULE

Given a set of exercises, the exercise recognition task involves identifying an exercise that is contained within that set. Each exercise represents a different class, for our data set this means forty-two classes. We have set up two types of experiments, one athlete independent and another athlete dependent. Furthermore, for both athlete independent and athlete dependent exercise recognition, we have experimented with two different set-ups. The first consists of training separate models for each muscle group. The second comprises of training only one model and all the classes are part of that model.

Thus we have four experiments:

1) Experiment 1: athlete independent, separate models for each muscle group
2) Experiment 2: athlete dependent, separate models for each athlete and muscle group
3) Experiment 3: athlete independent, one model for all classes
4) Experiment 4: athlete dependent, a model for each athlete and all classes

For experiment 1, data for each muscle group contains data from all the four athletes and a total of seven exercises from that muscle group. This means a muscle group containing 7 exercises is a total data of 108 sets of an exercise (3 sets/week/athlete $\times$ 6 weeks $\times$ 4 athletes). The training and test data is partitioned using the setno attribute, so that the training and test sets both have the same percentage of data from each athlete.

For experiment 2, each athlete has his own data comprising of the sets for a given exercise. This means a total data of 18 sets of an exercise (3 sets/week $\times$ 6 weeks).

Activity recognition models in experiments 1 and 2 are built per exercise based on muscle group. The athlete independent exercise models contains data from all the four

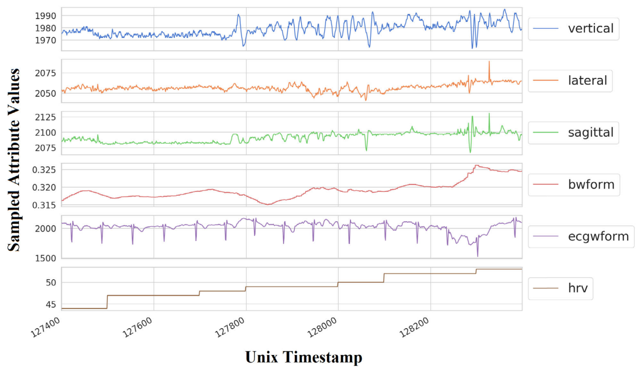

FIGURE 5. Visual inspection of leg press activity data.

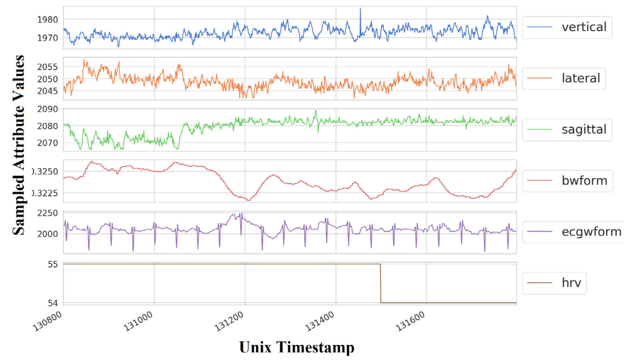

FIGURE 6. Visual inspection of leg extension activity data.

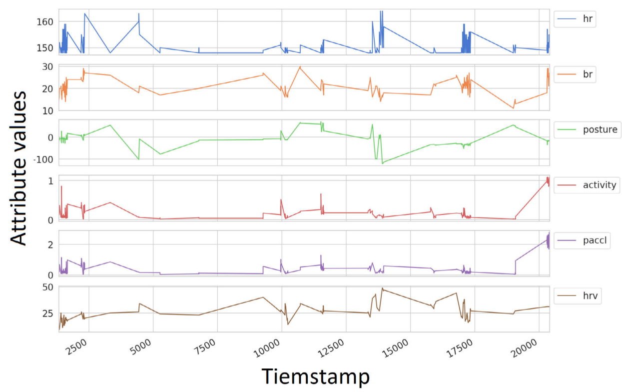

FIGURE 7. Visual inspection of health zone data.

athletes and we have 6 models (one for each muscle group). The athletes dependent models have data from only one athlete and we have a total of 24 models (4 athletes × 6 models, one for each athlete-muscle group).

For experiment 3, data contains data from all exercises done by all the four athletes. This means a total data of 3,024 sets of exercises (42 exercises/athlete × 3 sets/week × 6 weeks × 4 athletes). One model is trained recognizing all the exercises. The data is split in the ratio of 2:1 for training and testing. The split is stratified for each athlete, i.e. 12 sets of an exercise for training and 6 sets for testing from the 18 sets done by that athlete.

For experiment 4, we have 4 datasets one for each athlete. Each dataset contains data from all exercises done by the athlete. This means a total data of 756 sets of exercises (42 exercises × 3 sets/week × 6 weeks). Four models are trained, one for each athlete. Each model is trained to recognize all the exercises.

For experiments 3 and 4, each exercise has its own class. All the four experiments are executed using the LSTM neural network and the six attributes listed before are used.

An important question is about the attributes that can be used for discriminating between exercises. We have experimented with different combinations and in this paper we are focusing on body vitals (breathing, ECG and heart rate variability data) and accelerometer data (vertical, lateral and sagittal axes). The inclusion of body vitals data for the exercise recognition task is a novelty and thus has significance in the larger field of activity identification with similar chest movements. The visual inspection of each component of the GAR module data for leg press and leg extension activities is depicted in Fig. 5 and Fig. 6. We can identify differences in each axis of the signal and body vitals across these activities.

2) METHODOLOGY OF HZONE MODULE

Given the heart rate (hr), breathing rate(br) and heart rate variability(hrv) of an athlete while doing exercises, the health state recognition task involves identifying the exercise zone of the athlete. This information is useful for generating an alarm in the case of 'abnormal' heart rate. There are five health zones moderate, aerobic, anaerobic, VO2 max and hazardous based on value obtained from equation 1 and Fox and Haskell formula [24]. For our experiments, each zone has its own class.

For Hzone experiment, dataset contains data from all exercises done by all the four athletes. One model is trained identifying the health status during all the exercises. The data is split in the ratio of 2:1 for training and testing. The split is stratified for each athlete, i.e. 12 sets of an exercise for training and 6 sets for testing from the 18 sets done by that athlete.

The attribute selected for Hzone module are heart rate(HR), breathing rate (BR), heart rate variability (hrv), posture, activity and peak acceleration (paccl) of body. The visual inspection of each component of the Hzone dataset for anaerobic health zone is depicted in Fig. 7.

VI. RESULTS

This section presents and analyzes the results of all of the experiments conducted in the study. The results are presented first for the GAR module in subsection A, which is responsible for gym activity recognition and then for the health zone (Hzone) module in subsection B. 1) Automatic gym activity recognition (GAR) to decrease the overhead of using multiple sensors or manually selecting gym activity using the mobile application. Accuracy, precision, recall, and F-measure evaluation metrics are used to evaluate the GAR and Hzone module. 2) Hzone module, which is responsible for identifying the health State of an athlete during the activity, will also alarm in case of any health hazard. Mobile application is used for alarm generation and data acquisition.

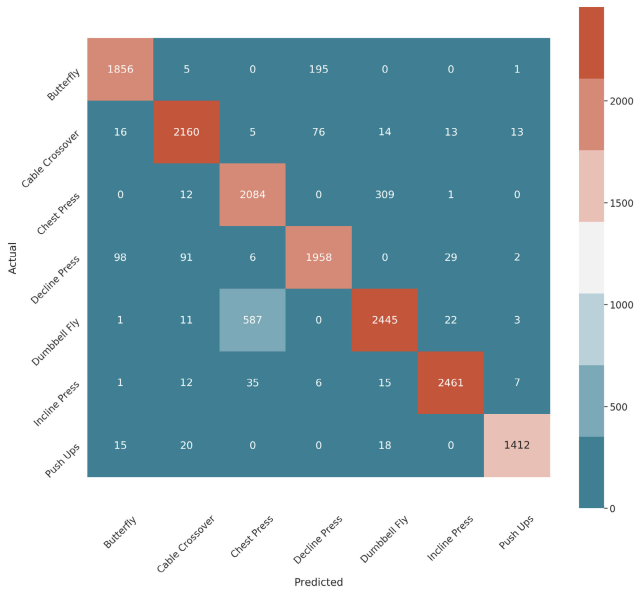

FIGURE 8. Confusion matrix of GAR module on chest workout.

A. GAR MODULE

This section provides the results for all the gym exercise recognition experiments. We have set up a total of four types of experiments, two experiments based on athletes, first is athlete independent and second is athlete dependent. There are two more experiments based on exercises and athlete, first is for each muscle group and second is for all 42 exercises. The results for the first group based on all athletes and muscle group are better as compared to athlete independent model. The results on the model comprises of all 42 exercises are low as compared to the model which is based on muscle group. The results for each experiments are discussed in the following sub sections.

1) EXPERIMENT 1: ATHLETE INDEPENDENT, SEPARATE MODEL FOR EACH MUSCLE GROUP

In this experiment, dataset for each exercise contains data from all the four athletes exercises based on muscle group. Our trained LSTM model of the GAR module learned well on chest workout with accuracy more than 89% and loss around 0.38 on 100 epoch.

Confusion matrix for GAR module predictions accuracy as shown in Fig. 8, module outperformed with only one notable exception include the misclassification of Chest press for dumbbell fly and vice versa. Although both exercises have similar body posture with a slight change in arms movements which is not detected by Zephyr as it only detects chest movement, here the inclusion of body vitals data brought more accuracy in the classification of these exercises. Cable cross over, dumbbell fly, and incline press are activities with the highest accuracy.

The inclusion of body vitals data for the GAR task is very significant in identifying activity with similar body movements. Fig. 9 summarizes the results from chest workout in form of precision, recall and fscore for each activity. Cable crossover has the highest recall value and Chest press has a low score overall. It can be concluded that the experiment 1 of GAR module predicted well with high precision, recall and fscore.

TABLE 3. Athlete dependent accuracy and loss of GAR module on chest workout.

Sr	Athlete ID	Accuracy	Loss
1	A1	85.65%	0.35%
2	A2	88.00%	0.31%
3	A3	84.27%	0.51%
4	A4	80.00%	1.02%

TABLE 4. Precision, Recall and Fscore for each athlete on chest workout.

Sr	Exercise	Precision		Recall		FScore	
		A1	A2	A1	A2	A1	A2
1	Butterfly	0.99	0.97	0.99	0.99	0.99	0.98
2	Cablecross over	0.99	0.99	1	0.98	0.99	0.99
3	Chest Press	0.52	0.77	0.46	0.35	0.5	0.48
4	Decline Press	0.99	0.99	0.99	1	0.99	0.99
5	Dumbbell Fly	0.63	0.66	0.68	0.92	0.65	0.77
6	Incline Press	0.98	0.99	0.99	0.99	0.99	0.99
7	Push Ups	0.99	0.98	0.99	0.99	0.99	0.98

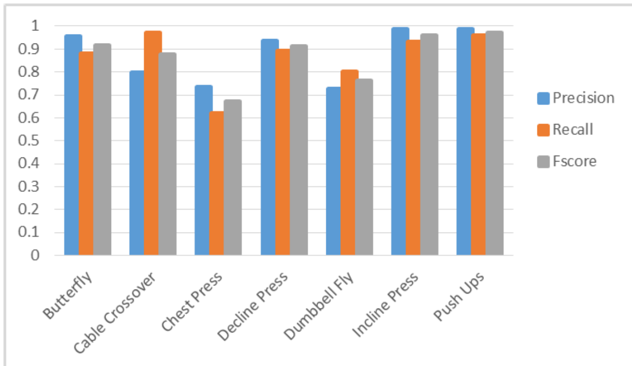

FIGURE 9. Precision, Recall and Fscore on chest workout.

2) EXPERIMENT 2: ATHLETE DEPENDENT, SEPARATE MODEL FOR EACH ATHLETE AND MUSCLE GROUP

In this Section, experiments are performed on athlete's own data built per muscle group. A total of 4 athelete's data were processed and LSTM model of the GAR module learned well on chest workout with accuracy above 83% on athletes (A1). The athlete dependent accuracy and loss of each athlete are depicted in Table 3. The best accuracy of athlete dependent model is 88% while other athlete's accuracy is below this. The accuracy of the athlete independent model in experiment 1 is higher than the athlete dependent model. So, we can conclude that the GAR module predicts well despite the athlete dependency. The confusion matrix for GAR module predictions for first athlete (A1) is shown in Fig. 10. As we have seen in the confusion matrix of experiment 1 in Fig. 8 there are few misclassifcations of chest press with dumbbell fly and vice versa. Similar results are found for athlete dependent models.

Table 4 summarizes the athlete dependent results from chest workout in form of precision, recall and fscore for each activity.

TABLE 5. Precision, Recall and Fscore for all exercises.

EID	Chest			Arms			Shoulders			Back			Legs			Core Body		
	Pr	Re	Fs	Pr	Re	Fs	Pr	Re	Fs	Pr	Re	Fs	Pr	Re	Fs	Pr	Re	Fs
1	0.87	0.87	0.87	0.91	0.88	0.89	0.77	0.67	0.72	0.68	0.80	0.74	0.73	0.77	0.75	0.80	0.93	0.86
2	0.58	0.66	0.61	0.67	0.75	0.71	0.86	0.83	0.84	0.66	0.66	0.66	0.87	0.87	0.87	0.94	0.87	0.90
3	0.79	0.79	0.79	0.76	0.83	0.79	0.95	0.80	0.87	0.94	0.89	0.91	0.78	0.78	0.78	0.86	0.84	0.85
4	0.65	0.77	0.71	0.68	0.68	0.68	0.83	0.68	0.75	0.70	0.67	0.69	0.70	0.83	0.76	0.82	0.84	0.83
5	0.81	0.82	0.82	0.68	0.78	0.73	0.71	0.66	0.69	0.78	0.72	0.75	0.84	0.79	0.82	0.91	0.92	0.092
6	0.80	0.63	0.70	0.78	0.82	0.80	0.83	0.72	0.77	0.78	0.77	0.77	0.91	0.83	0.87	0.91	0.89	0.90
7	0.81	0.82	0.82	0.97	0.90	0.94	0.77	0.79	0.78	0.93	0.94	0.94	0.96	0.91	0.94	0.84	0.77	0.80

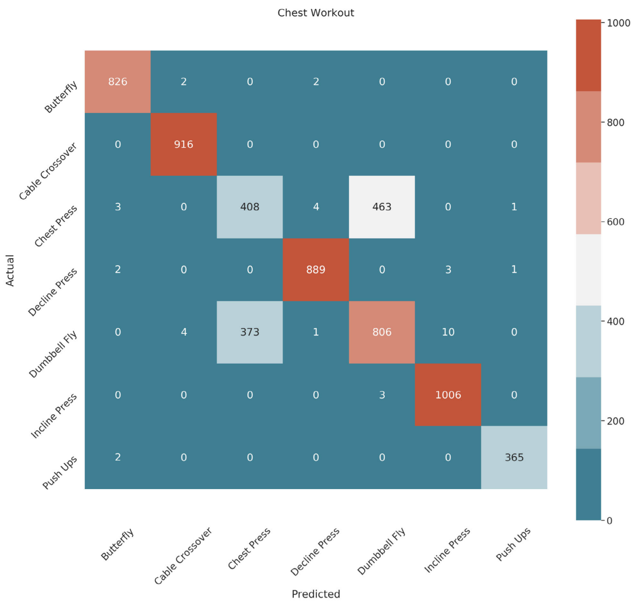

FIGURE 10. Athlete A1's confusion matrix of GAR module.

3) EXPERIMENT 3: ATHLETE INDEPENDENT, ONE MODEL FOR ALL CLASSES

Experiment 3 is based on complete dataset, which include all the athletes, muscle group and activities. A single model is trained to recognize all the 42 exercises. The single athlete independent model with all classes came up with 80.25% accuracy and 1.3% loss. The results of experiment 3 are low as compared to the experiment 1 and 2, due to the reason that in experiment 1 we have seven classes to test and in experiment 3 we have tested on 42 classes. from experiment 1 and 3 it can be conculud that GAR module performs well on muscle group dependent models. Table 5 summarizes the results of this experiment in form of precision, recall and fscore for each activity where EID is the exercise number of each muscle group as depicted in Table 2 and precision, recall and fscore are depicted as Pr, Re and Fs respectively.

4) EXPERIMENT 4: ATHLETE DEPENDENT, ONE MODEL FOR ALL CLASSES

Experiment 4 is based on athelte wise data, which contains single athlete's data of all muscle group and all activities. A single model is trained to recognize all the 42 exercises of the athlete. This athlete dependent model with all classes came up with 83.6% accuracy and 0.81% loss for first athlete and 84.2% accuracy and 0.41% loss for second athlete with an average accuracy of 82% on all athletes.

TABLE 6. Precision, Recall and Fscore of Hzone module.

Sr.	Health Zone	Precision	Recall	FScore
1	Moderate	0.992	0.987	0.989
2	Aerobic	0.978	0.976	0.977
3.	Anaerobic	0.886	0.912	0.898
4	VO2 Max	0.267	0.444	0.333
5	Hazardous	0.5	0.889	0.64

B. HZONE MODULE

The Health zone module is the key module of the proposed framework which is based on athlete's health state. The health status identification task is a multi-class classification problem, which for this study includes five classes. The hazardous class is the most important one which can be used for alarm generation. Hzone module outstandingly gave above 97% accuracy in categorizing each health zone. The module converges to its optimum in a few epochs. The accuracy of the training and validation data is very consistent. Table 6 summarizes the results of Hzone module in form of precision, recall and fscore for each activity by presenting their precision, recall and fscore. The results of moderate, aerobic, and anaerobic Hzone are good with scores more than 88%. The VO2 max and Hazardous hzone came up with lower score due to the imbalance of the data set, collecting more data may help in improving these scores.

The confusion matrix for Hzone module is depicted in Fig. 11. Moderate and aerobic health zone categories are with the highest accuracy. The hazardous category is most important in our work as its purpose is to use it as alarm generation. There is minor misclassification of hazardous along with VO2 Max may not be necessarily incorrect, but it is a misclassification considering the available classes. Overall results are satisfactory.

1) COMPARATIVE ANALYSIS

This section presents a comparative analysis between the proposed framework and existing studies as depicted in Table 7. A comparison is made with seven state of the art studies. We divided the present research on gym based activity recognition and health analysis in seven parameters. These parameters are

1) Application domain which provide information about the healthcare domain.
2) Major contribution of the relevant study.
3) Sensing technology used for data acquisition.
4) Activity recognition system implemented or not.
5) Health state analysis method presented.

TABLE 7. Comparative analysis of proposed framework with some different models.

Reference	Application Domain	Major Contribution	Sensing Technology	Activity Recognition	Health State Analysis	exercise specific analysis	Data Storage
Proposed Framework	Healthcare in a smart gym workout.	Automatic Activity recognition and prediction of health hazards in real time.	IoT, fog-computing	Accelerometer and body vitals	Hzone to predict health state and alarm.	Yes	Cloud
[3]	Gym workout-based intelligent healthcare.	CCIoT Framework for monitoring and prediction of health state vulnerability.	IoT	No	PSov to predict health state.	No	Cloud
[12]	Physical Activity and intensity recognition.	Home and gym based activity and intensity recognition using Artificial Neural Netwroks (ANN).	smart wearable	home and gym based activity recognition using two shimmer sensors.	exercise intensity analysis.	No	mobile app
[15]	Physical activity and comfort analysis.	Home and gym based activity recognition along with comfort analysis for adjustment of weights during an exercise session.	smart wearable	hhome and gym based activity recognition	comfort analysis using heart rate data.	No	mobile app
[16]	Healthcare and Physical Activity Recognition.	IoT based activity and fitness monitoring system.	IoT	Web cam	Specific to heart rate.	No	Local
[17]	Physical Activity and intensity recognition.	Algorithm for automatic recognition physical activities and their intensities.	IoT	triaxial Wireless accelerometers and heart rate monitor.	No	No	Local
[20]	Automatic workout Recognition.	IMU based activity classification and reps counting.	IoT	wearable IMU	No	No	Smart watch
[21]	Automatic workout Recognition.	MiLift, workout tracking system with repetition and sets counting.	IoT	smart watch	No	No	Smart watch

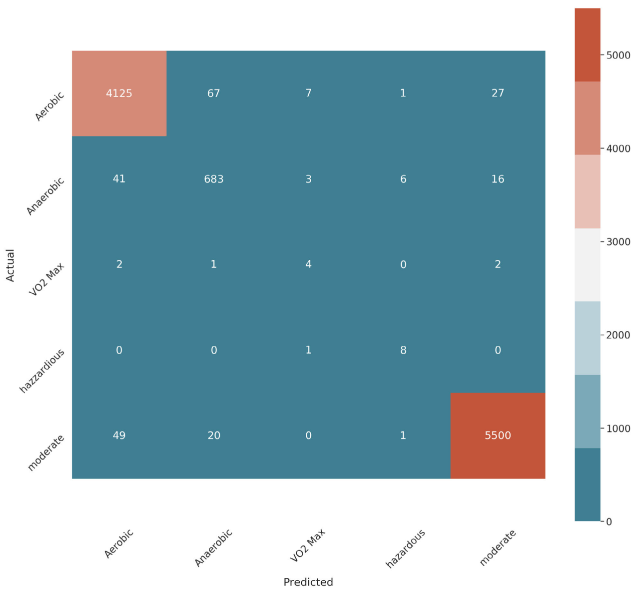

FIGURE 11. Hzone module confusion matrix.

6) Exercise specific health data analysis.
7) Data storage mechanism.

The framework proposed by Bhatia and Sandeep (2017) [3] collects data from multiple sensor to generate Probabilistic State of Vulnerability (PSoV) value using ANN. The PSov is used to predict the health state of the athlete while the framework lacks in real time activity recognition and alarm generation. PSoV value can also be used to Hzone classification as proposed in this research. The research work of Qi *et al.* [12] and Das *et al.* [15] performs home and gym activity recognition with few activities related to gym and they analyzed exercise intensity and comfort level of the athletes. Yong *et al.* proposed webcam based activity recognition which involves use of multiple webcams for each activity recognition, the alert generation mechanism was specific to the heart rate only. The rest of the work was based on the gym activity recognition only.

VII. CONCLUSION

In this research we proposed a fog-centric framework to monitor and manage healthcare in smart gym environment. The framework employs real-time vital signs monitoring, motion data, health state history, physical strength, and body metrics data, and other health-related attributes, which are valuable in the gym environment to analyze physical fitness and avoid health hazards. The framework combines the functionality of research related to body vitals as well as automatic exercise classification along with real-time alarm generation in case of any health hazard to the athlete. We collected exercise specific data which later can be used to analyze the impact of each exercise on the athlete body which forms the basis for recommendation system that can be used for upcoming athletes. The fog computing paradigm is particularly chosen to predict health hazards in real-time on edge networks instead of sending and waiting for a response from the cloud. Outstandingly, the Hzone module can identify the athlete's physical state in five categories with above 97% accuracy. We performed four types LSTM-based Gym activity recognition (GAR) experiments. The overall accuracy of all types of experiments was above 80%. The athlete independent model based on muscle group predicted gym activity with more than 89% accuracy. Results indicate that the Hzone module outperformed in the prediction of the health state of the athlete. GAR results indicate that in most of the exercises we can achieve a high level of accuracy, but as many gym exercises involve similar body posture we add body vitals data with the movement data and achieved improved accuracy. The proposed framework is the foundation to use as a recommendation system for beginners according to their physical state and any health issues.

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