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Research Article

Pengru Xu, Junhui Zhou, Nasreen Kausar, Chunlei Lin, Qianqian Lu, Ebrahim Ghaderpour*, Dragan Pamucar, and Ardashir M. Zadeh*

A new machine learning approach based on spatial fuzzy data correlation for recognizing sports activities

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Abstract: Wearable sensors (WS) play a vital role in health assistance to improve the patient monitoring process. However, the existing data collection process faces difficulties in error corrections, rehabilitation, and training validations. Therefore, the data analysis requires additional effort to reduce the overall problems in sports rehabilitation. The existing research difficulties are overcome by applying the proposed spatial data correlation with a support vector machine (SDC-SVM). The algorithm uses the hyperplane function that recognizes sportsperson activities and improves overall activity recognition efficiency. The sensor data are analyzed according to the input margin, and the classification process is performed. In addition, feature correlation and input size are considered to maximize the overall classification procedure of WS data correlation using the size and margin of the input and previously stored data. In both the differentiation and classification instances, the spatiotemporal features of data are extracted and analyzed using support vectors. The proposed SDC-SVM method can improve recognition accuracy, $F1$ score, and computing time for the varying WS inputs, classifications, and subjects.

Keywords: machine learning, data classification, fuzzy data correlation, feature extraction, SVM, wearable sensors

MSC 2020: 94D05, 68Q32, 62H20

1 Introduction

A wearable sensor (WS) for rehabilitation is used to monitor the sportsperson's day-to-day activities and gives the appropriate feedback to improve their movements. The rehabilitation center has a database list regarding the sportsman's performance, which is easy to identify the risk of injury and fatigue [1,2]. The sensor senses the

*** Corresponding author: Ebrahim Ghaderpour,** Department of Earth Sciences, Sapienza University of Rome, Piazzale Aldo-Moro, 5, 00185 Rome, Italy, e-mail: ebrahim.ghaderpour@uniroma1.it
*** Corresponding author: Ardashir M. Zadeh,** Multidisciplinary Centre for Infrastructure Engineering, Shenyang University of Technology, Shenyang 110870, China, e-mail: a.mzadeh@sut.edu.cn
Pengru Xu, Junhui Zhou: Department of Public Physical Education, Zhejiang Guangsha Vocational and Technical University of Construction, Dongyang 322100, China
Nasreen Kausar: Department of Mathematics, Faculty of Arts and Science, Yildiz Technical University, 34220, Esenler, Istanbul, Turkey
Chunlei Lin: Department of Education and Engineering, Zhejiang Guangsha Vocational and Technical University of Construction, Dongyang 322100, China
Qianqian Lu: Department of Education and Engineering, Administrative Office, Zhejiang Guangsha Vocational and Technical University of Construction, Dongyang 322100, China
Dragan Pamucar: Department of Operations Research and Statistics, Faculty of Organizational Sciences, University of Belgrade, Belgrade, Serbia; Department of Industrial Engineering & Management, Yuan Ze University, Taoyuan City, Taiwan; Department of Mechanics and Mathematics, Western Caspian University, Baku, Azerbaijan, e-mail: dragan.pamucar@fon.bg.ac.rs

data, which is called an aggregation process and is the preliminary step for every sensor network. The aggregated data are processed for further processing based on the sensor application, which includes medical, sports, commercial, and others [2]. Reliable communication between the sportsperson and the rehabilitation center should be done to avoid data loss. The sportsman wears a WS based on his or her activity [3]. For example, if the sportsman is athletic, the sensor is worn on the legs and wrist to determine whether the action is normal or abnormal. This way, the data are forwarded to the rehabilitation center to find the person's behavior. The notification is sent to the person by indicating to control the activity and take a rest. The workout is analyzed at every fixed interval [4,5].

The aggregated data from the sensor have different time-based information; the data correlation is used to achieve better communication. Correlation is classified into two categories such as temporal and spatial correlation [6]. The spatial correlation states the space data in three dimensions, e.g., it includes the location of data, such as geographical areas [7]. Since temporal data are based on the period of the geographical area, data retrieval is in the specified time interval. For rehabilitation, the material data give a better result; herein, the person's activity is monitored based on time [8]. As a result, reliable communication is carried out between the sportsman and the rehabilitation center. The temporal data are correlated based on the sensed information on the allocated time interval. In this study, the similarity of the data is matched by using prediction-based methods [4,6]. If the correlation increases, communication achieves a better correlation in the network. The correlation is derived in two positive or negative levels; positive means good, and negative means no correlation occurs [5,9].

A better correlation is achieved to improve communication between the sportsman and the rehabilitation center. Data correlation is done by evaluating the sensor's size, time, and position [10]. Correlation analysis based on multiple decision-making and machine learning methods has been introduced for reliable solutions. In rehabilitation, handling WS data and analyzing them based on features are complex and time-consuming [11]. Therefore, classification and learning methods are introduced to provide precision-based solutions and retain complex-less analysis. The process of data analytics helps to improve recognition accuracy through correlation [12]. The challenge is extracting the necessary data features and correlating them through precise analytical models to improve accuracy. Therefore, analyzing relies on multilevel processing, requiring decisive and adaptive processing to enhance the correlation solutions in rehabilitation assistance [10,13]. In analyzing immense volumes of data, analytical models pose other exclusive challenges for machine learning (ML) and data analysis, containing fast-moving streaming data, format variation of the raw data, greatly distributed input sources, the trustworthiness of the data analysis, poor quality data, noisy and high dimensionality, scalability, and imbalanced input data. During the early phases of learning a sport-specific activity, motor skill acquisition processes are generally prioritized above strength and performance in rehabilitation. Attentional concentration and task-specific feedback based on advanced deep neural networks are useful in sports activity recognition procedures. Instructions that encourage an exterior focus (directed at the movement impact) are more successful than those that encourage an interior focus (directed at the performer's body movements) in studies exploring the role of the patient's focus of attention. Focusing on something outside the body allows for greater ease of motor control and more efficient movement.

Pal et al. [14] proposed a smart WS for quantitative analysis to improve the quality of experience and information. They used four methods: correlation-based distribution, balanced weight distribution, priority-based distribution, and hybrid distribution. Liu et al. [15] developed a human dynamic motion obtained from the wearable flow-micro inertial measurement unit (MIMU) device. The posture estimates tailored inputs using Kalman-based fusion extracted from accelerations. The flow MIMU is a wireless communication to sense the data from the wearable device.

Sports medical deep learning model-driven using big data is addressed by Su [16]. The stack factor decomposition (SFD) method uses the spatiotemporal features and restricted Boltzmann machine (RBM) [17] to analyze the features of the monitoring activities in the rehabilitation center. In addition, the unsupervised frames are analyzed using 3D convolution RBM. Body area networks used for recognizing human activity to achieve the correlation in the data are presented by Khan et al. [18], where they addressed the feature descriptor, which denotes the local energy-based shape histogram. The data integrate the cloud computing service from the body sensor.

Fialho et al. [19] modeled the prediction of soccer games by artificial intelligence (AI). The forecast is based on preceding data outcomes regarding the sportsperson and results in the output. Their work identified the soccer game using AI technology in a large information set. Human activity recognition (HAR) from the WS using the remote sensing of data streams is designed using fast incremental learning with a swarm decision table [20]. Using a data fusion framework (DFF), different spatial data are identified for recognizing the movements of the sportsman and sent to rehabilitation.

Martinez-Hernandez and Dehghani-Sanij [21] introduced an adaptive Bayesian interference system (BasIS) for detecting walking activity and gait prediction. In their work, the gait was seen from the WS, and three types of walking were analyzed: level-ground, ramp ascent, and ramp descent. Guo and Wang [22] introduced a human motion for segmentation and recognition captured from WS. Their work consisted of two sets of data analyses done by singular value decomposition, where the segmentation was performed first. Then, the motion sequences decreased the data processing time in the network. Zuo [23] developed a human – autonomous for sports training management by the decision-making on a wavelet neural network. First, the data aggregation was done through fuzzy data collection. Then, the decisions were made by the time-based frequency to enhance the feature quality. Finally, Buckthorpe [24] presented sports rehabilitation at late-stage and return-to-sport (RTS). These analyses were done after the anterior cruciate ligament reconstruction, and four approaches were used: neuromuscular performance, re-injury risk, fatigue, and retraining state using RTS.

Multiple WS are used for the covariance matrix to identify fall detection, as proposed by Boutellaa et al. [25]. They detected the arriving fall detection. The features were extracted using the matrix straightforward to improve classification performances. Cogent Labs and DLR captured multiple sensor data. Detecting rehabilitation in a smart home was addressed by Peng [26], where the detection was done by introducing the fuzzy neural network used to detect the gait action from the WS. Movement and instability were identified as the subject moved to further improve accuracy.

Zhang et al. [27] developed fault detection for efficient medical monitoring to find the threshold tuning for sensors using the Bayesian network model. The authors utilized this model for redundant information aggregation on a large scale. The objective was to decrease the inaccuracy rate and enhance fault detection performance. Zhao [28] applied radial basis function (RBF) neural networks to analyze basketball sports person injuries. The sportsperson's activities were continuously monitored, and the collected information was processed with the help of the RBF network. Finally, the algorithm recommended recovering the sportsperson. The developed system ensured 95.4% accuracy compared to the other neural models.

Li et al. [29] introduced convolution neural networks to analyze the sports area and improve overall practical effects. Initially, the sports training area image was processed continuously to predict regional similarity. Then fully connected layer was applied to identify the specific area. Then multi-evaluation standard fusion approach was used to improve the overall sports training performance efficiency. Wang [30] developed a sports training auxiliary decision system using neural networks. Their work intended to minimize entropy loss while analyzing sports data. The collected sports information was processed using the neural network that predicts the correlation and correction between the features. The extracted features were more useful for making the auxiliary decision system.

Zhu et al. [31] applied an improved recursive neural network to identify motion damage in sports. The system intends to minimize injury detection time by frequently analyzing sports incidence. The estimation model uses the recursive network that reduces sports injury and improves the overall physical exercise rate. Li and Li [32] recommended interactive control methods and neural networks to analyze sports training strategies. As a result, the collected sports data have been fused and processed using a neural network. The algorithm examined the interaction between the human and machine that improved the training efficiency by up to 20%. According to the various opinions, sports data, training information, and injury details are continuously examined with the help of machine learning techniques. However, the system requires feedback from the sportsperson to improve the overall data analysis rate. This is achieved with the help of the WS-related spatial correlation and the support vector machine (SVM) approach.

Qiu et al. [33] suggested multi-sensor information fusion based on ML for real applications in HAR. This article begins by providing an overview of the most widely used WS, smart wearable devices, and major end-use scenarios. Many models or channels, such as visual, auditory, environmental, and physiological inputs, characterize multisensory data. As a result, the author offers multimodality and multilocation sensor fusion techniques. Although various articles have been submitted evaluating the state of the art in data fusion and deep learning, each of these works has focused on a different facet of sensor fusion application, leading to a lack of holistic expertise.

Karahan et al. [34] proposed object detection and machine learning for age and gender classification. Using a convolutional neural network (CNN) architecture, age and gender classifications were determined from participants' facial traits in this research. Second, many machine learning techniques were used to recognize objects, and their results were evaluated concerning median average accuracy and inference time. Third, using the Adience dataset, they graphed the results of testing the age and gender classification algorithm. The findings of these experiments demonstrate the efficacy of age and gender classification algorithms. Finally, object identification techniques were evaluated on the COCO dataset, and the results were shown visually. Object detection using machine learning techniques has been shown experimentally.

Zhang et al. [35] discussed the wearable sensing electronic systems (WSES) for analyzing the augmenting sensor performance. The WSES can easily gather biochemical, biopotential, and biophysical signals from living organisms, among other types of physiological data. However, typical data processing approaches, such as feature extractions, recognitions, and classifications, cannot interpret sensory data. With the help of ML algorithms, the WSES has recently improved its sensing performance and the quality of its system-level operations.

Deilami et al. [36] presented machine learning-based models for personality recognition. This work proposes a machine learning-based solution for personality detection from text to use this rich semantic data and avoid the complexity and handmade feature demand of prior approaches. The authors combined CNN with AdaBoost, classical ensemble algorithms, to weigh the likelihood of utilizing the contribution of different filter lengths and exploiting their potential in the last classification by uniting different classifiers with their corresponding filter size. Through a series of tests, the author verified their proposed technique on the Essay datasets, and empirical results showed that the method outperformed machine learning (ML) and deep learning (DL) on the task of personality detection.

Sabry et al. [37] deliberated the on-device dehydration monitoring utilizing ML from wearable device's data. WS such as accelerometers, magnetometers, gyroscopes, galvanic skin response sensors, photoplethysmography sensors, temperature sensors, and barometric pressure sensors may be used for hydration monitoring; the author discussed using machine learning to analyze these data. Personal characteristics such as age, gender, and ethnicity were used with this information to anticipate the last time a person drank and to notify them if that time exceeded a set limit based on their activity level. Models are used, and their results are evaluated so that the best one may be chosen to optimize deployment on the device. While the DNN with a small model size is chosen for wearable devices with restricted memory, the additional trees model earned the lowest error for predicting unknown data with the least training time. Power usage and emphasis on outcomes need more embedded on-device testing.

Ejegwa and Zuakwagh [38] suggested the Fermatean fuzzy-modified composite relation (FFMCR) for pattern recognition. This research uses a soft computing strategy to build an FFMCR based on the max-average rule, which improves the efficacy of FFSs in machine learning. First, the author presents several numerical examples to demonstrate the advantages of the proposed max-average method over the conventional max–min–max calculation. Then, by using the FFMCR and the Fermatean fuzzy max–min–max technique to emphasize comparison analyses, we describe various pattern identification issues in the construction materials and mineral sectors to illustrate the method's applicability.

Boukhennoufa et al. [39] proposed WS and machine learning in poststroke rehabilitation assessment. With wearable devices for data collecting and ML algorithms to assess workouts, this study aims to examine the current achievements achieved in poststroke rehabilitation. This was accomplished by adhering to the PRISMA standards for such systematic reviews. We conducted an electronic search of the databases Scopus, Lens, PubMed, ScienceDirect, and Microsoft Academic. From 2015 to August 2021, the author included peer-reviewed studies on using sensors in stroke rehabilitation.

The main objectives of the article are as follows:

- Designing the spatial data correlation with a support vector machine (SDC-SVM) for sports activity recognition based on sensor data.

- Feature correlation and input size increase the overall classification procedure of WS data correlation using the size and margin of the input and previously stored data.
- The numerical outcomes show that the recommended SDC-SVM technique can improve recognition accuracy, $F1$ score, and computing time compared to existing approaches.

The remainder of this article is prearranged as follows: Section 1 discusses the introduction and related works on sports activity recognition. Section 2 proposes the SDC-SVM model for sports activity recognition. Section 3 deliberates the results and discussion. Finally, Section 4 concludes the research article.

2 Materials and methods

2.1 Data acquisition and workflow

A WS is placed on the sportsman's body to monitor the activity and report the abnormal practice to the rehabilitation center. The rehabilitation center has a list of data regarding the person and gives the necessary feedback to improve the behavior during a workout. Based on the sports, a sensor is placed on the body, and the frequency of the data is sensed by the sensor. The objective is to maximize the accuracy of detection through spatial co-relation of relevant data for the rehabilitation to find the necessary features of the sportsman. WS have expanded the scope of an athlete's performance and movement analysis beyond the subjective evaluations of a coach. As a first step, a system for classifying the physiologic data that may be gathered from a person via sensors attached to strategic areas of the skin or integrated into clothing is presented; these data can provide invaluable insight into the individual's health. Wearable applications for monitoring sports and rehabilitation activities are then compared by explaining the electromechanical transduction methods used by each. This allows for an evaluation of wearable technology, including a thorough comparison of the state of the art of available sensors and systems. In Figure 1, the workflow of the proposed correlation is presented.

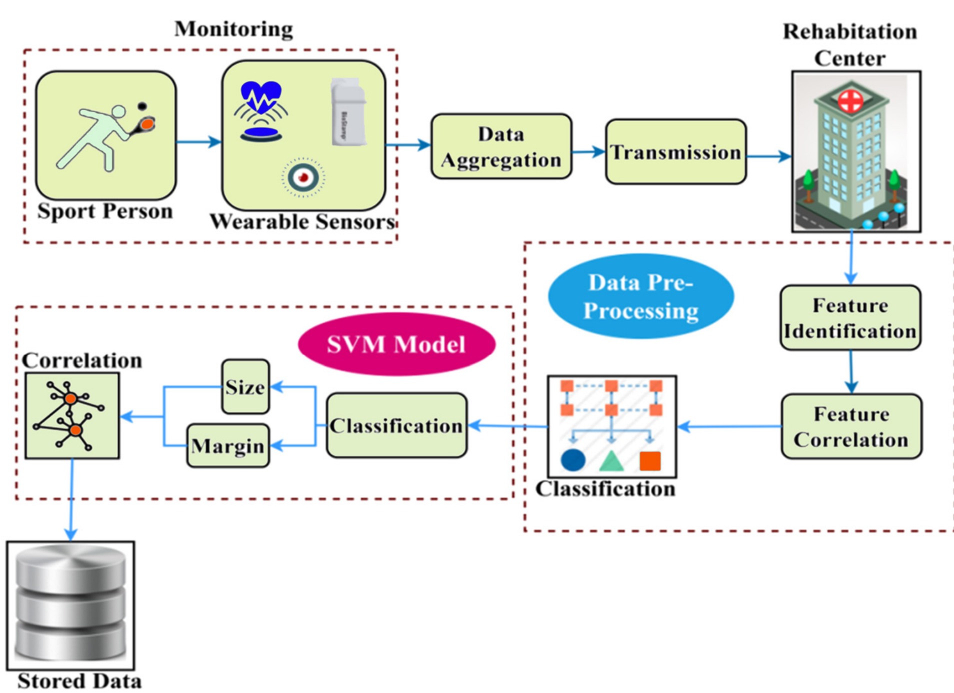

Figure 1: Workflow of the proposed method.

The present work aims to provide a better correlation using the conditional SVM classifier. The classification uses a hyperplane that indicates a positive and negative value. If the value achieves a better correlation, the data tend to be positive; in other cases, if the correlated data are not done properly, it relies on the negative value. SVM is applied to preprocess the activity data in high-dimensional feature space. The purpose and advantage of using the multiclass SVM classifier are that our data set includes multiple activities done by different actors. The classification is then processed using multiclass SVM to determine long-term human sports activity recognition. The SVM consists of two margins, hard and soft; the smooth margin is used herein. The SVM is used to attain the boundary-based classification on vector margin; it is evaluated by finding the nearest data in the margin. The category is done by obtaining both positive and negative data correlation. The rehabilitation gives the maximum data correlation based on the allocated time interval and increases efficient communication. A lack of communication among medicinal providers, conditioning and strength specialists, and sports coaches can slow or avert sportspersons from returning to peak capacity and raise the risk of new injuries and even more demoralizing re-injuries. To meet the higher detection accuracy and system reliability necessities, the data fusion for multiple WS systems is a growing concern based on the spatial correlation of pertinent data for effective sportsman activity recognition. The primary benefit of containing spatial features over completely spatial correlation is that this does not need a direct change of the novel approaches.

By addressing the data co-relation, the communication cost is minimized. For this, the initial step is to aggregate the data from the sensor, and apart from integration, correlation is done for the rehabilitation. Then, the correlation is used to identify the better feature of data; equation (1) is used for the data aggregation process from the sensor. Filter-based feature selection approaches utilize statistical measures to score the dependence or correlation between input parameters that may be filtered to select the most appropriate features. Data aggregation typically includes the fusion of data from multiple sensors at middle nodes and transmitting the aggregated data to base stations (sink).

$$s_0(g) = d' + \frac{v}{r'} \times \prod_{t_a}^{t_a}(p_e - r'). \tag{1}$$

In equation (1), the data aggregation is obtained from the sensor $s_0(g)$, the input data are denoted as d' and v referred to as the sportsman's activity, and r' represents the resting state. The practice speed is also defined as p_e, training time is referred to as t_a, and allotted time is termed as t_a. Therefore, the sensor data give the data about the sportsperson; only the necessary data are obtained and analyzed to define the correlation.

The correlation is based on the prediction of data from the sensor, e.g., if the person who will get some injuries or falls is already registered in the database. If the motion states the chance of falls is made a similarity and results, the output is the feedback and controls certain moves. The subsequent expression (2) is derived to determine the correlation between the present and preceding data in the database.

$$\rho = \begin{cases} \prod_{t_a}^{v} p_e + v \times \dfrac{d'}{d_0' - i_d} < \mathrm{ch}' \\ \prod_{t_a}^{v} p_e + v \times \dfrac{d'}{d_0' - i_d} > \mathrm{ch}'. \end{cases} \tag{2}$$

The sensor data from equation (1) are obtained based on the activity; in equation (2), the movement is monitored to find the chance of risk. The decision is made on two categories; the first category is $\prod_{t_a}^{v} p_e + v \times \frac{d'}{d_0' - i_d} < \mathrm{ch}'$, where the training time of the activity is performed in more speed means, and the present data are subtracted from the preceding data. By doing this, there is a chance of injury and sickness. In equation (2), d_0' is denoted as input data to be analyzed, and the preceding data are represented as i_d. The chance of risk is termed as ch′, and the second category is $\prod_{t_a}^{v} p_e + v \times \frac{d'}{d_0' - i_d} > \mathrm{ch}'$, and in this equation, the processing of the sportsman's activity is determined and evaluates that there is no chance of risk.

Using equation (2), the second category is normal and terminated, and the first category is considered for further analysis. Data prediction is made by matching the present and preceding data with the database. The matches satisfy only if the features/data are correlated. The data varies for every instance of time because, for every state, the sensor senses the different data. The data are observed at varying intervals if the person is in movement. In other cases, if the person is in the rest state, similar data are analyzed, and the scope of this proposed method is to attain the correlation data for the rehabilitations. Equation (3) is used to differentiate the movements among the persons.

$$f_0 = \max_{t_a}(d' - d'_0) + \begin{cases} \sqrt{\dfrac{\rho}{t_a}} + (m_0 \times p_e) - r' = 0 \\ \sqrt{\dfrac{\rho}{t_a}} + (m_0 \times p_e) - r' \neq 0. \end{cases} \tag{3}$$

In equation (2), the chance of risk is obtained, and the differentiation is observed by evaluating equation (3). In equation (3), the differentiation is termed as f_0, which also finds the maximum time of training; here, the input data are subtracted from the number of data $d' - d'_0$. It attains two categories, namely, equality and nonequality. Figure 2 presents the process of f_0 derivations as discussed earlier.

In Figure 2, the analysis is preceded using two cases; the first case is $\sqrt{\rho/t_a} + (m_0 \times p_e) - r' = 0$. In this case, the data are monitored by equation (2), and the data are measured by acquiring movement and speed of the workout. Finally, the total activity is subtracted from the resting state, resulting in an accurate status. Therefore, the result for the first condition is equal to 0, meaning that the person is on movement status.

The second case is $\sqrt{\rho/t_a} + (m_0 \times p_e) - r' \neq 0$ means that the person is on rest status because the result is not equal to 0. By differentiating this, the movements and resting period are analyzed, which makes the work easily correlate with the sensor data. The prediction is based on real and predicted values from the sensed data at a particular period interval. Let the data be obtained in the allocated time interval $t = \{d'_1, d'_2, \ldots d'_a\}$, the prediction is made on weighted coefficients, such as $w = \{d'_{w_1}, d'_{w_2}, \ldots d'_{w_n}\}$. The variable n denotes the number of weights assigned to the data for processing. Equation (4) obtains the prediction based on weighted data coefficients. It is used to decrease the error in the network for reliable communication. Network error should be reduced for reliable communication between the sportsperson and the rehabilitation center to avoid data loss.

$$w_{d'} = \sum_{d'=1}^{d'_0} (d'_1(t) + d'_{w_1}) + \frac{s_0}{i_d}. \tag{4}$$

In equation (3), the movements of the sportsman are detected, and the prediction is based on the weighted coefficient. In equation (4), $w_{d'}$ denotes the weight of the data, and the time-based weights are assigned for every input data sensed from the sensor. Then, the present input and the primary data are matched using their associated consequences. Finally, the correlation is used to detect similar data when the spatial correlation model is introduced.

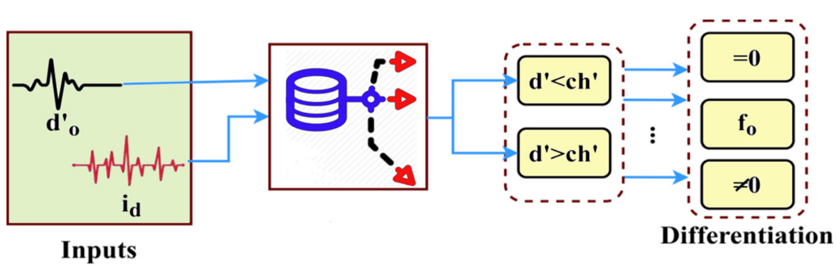

Figure 2: Differentiation of f_0.

2.2 Spatial correlation

The spatial correlation is based on the sensed data, which includes the time between the received data and new data entering. Therefore, it is required to find similar data from the sensor; the initial step is to aggregate the correlation data for reliable communication. This work obtains data and the data size based on a specific time interval. The following equation uses prediction to find the aggregated data correlation based on present and preceding data.

$$\delta(g) = w_{d'} + \left(\prod_{t=0}^{t_a}[m_0 + p_e] - t_a \times [d_0' - f_0]\right) + \frac{1}{\sqrt{\rho/i_d}}. \tag{5}$$

Using equation (4), the prediction data are assigned a weight, and then the correlation is obtained by deriving equation (5) as mentioned earlier. In equation (5), δ represents the correlation, g denotes the aggregation data, and in this, the time-based data are obtained through the sensor and find the similarity. Thus, the present and new data are matched with the relative features, such as doing some activities in the allocated time, and no risk is analyzed. In this way, similarities are obtained based on the prediction. Finally, the data feature correlation is achieved by evaluating equation (6).

$$d'(\delta) = v + \frac{\rho}{t_a} \times \begin{cases} \sum_{f_0}^{j_d}(i_d - j_d) + f_0 < 1 \\ \sum_{f_0}^{j_d}(i_d - j_d) + f_0 > 1. \end{cases} \tag{6}$$

Equation (5) is used to attain the correlation for aggregated data; after that, the data are correlated using equation (6), where $d'(\delta)$ represents the data correlation. The sportsman's activity is obtained, tracks the movements, and checks for risk; if not, the process is continued to find the correlation for the data. Equation (6) uses two levels to achieve the correlation between sports data; the first level is $\sum_{f_0}^{j_d}(i_d - j_d) + f_0 < 1$, j_d represents the arriving data; here, the differentiation of data is obtained in equation (3). The arriving data and the input data are matched based on equation (3); if they are lesser than 1 means, the process is not identifying the correct data. The second level is $\sum_{f_0}^{j_d}(i_d - j_d) + f_0 > 1$; here, the arriving data are matched with the preceding data in the database and finds the desired output greater than 1. It denotes that the correlation is matched in this second level after obtaining it in equation (6). The size-based data are attained for timely data arriving at the rehabilitation. The subsequent expression (7) is used to achieve the size-based data correlation from the aggregated data,

$$Z_0(\delta) = \frac{d_0'}{p_e} \times (t - t_a) + \begin{cases} \sqrt{\frac{w_{d'}}{j_d}} + \sum(f_0 - d_0') = 0 \\ \sqrt{\frac{w_{d'}}{j_d}} + \sum(f_0 - d_0') \neq 0. \end{cases} \tag{7}$$

The data correlation is obtained in equation (6); the data size is analyzed using equation (7). The data size is termed as $Z(\delta)$, here; the input data verify the speed at the allocated time. This indicates that the training is performed in the specified time interval; the time is noted for every movement. In Figure 3, the output extraction of $Z_0(\delta)$ from the differentiation of f_0 is illustrated.

The measurement of the movements of the sportsman is obtained by the weight used in equation (4). Then, in equation (7), two stages are used to find the size correlation. The first stage is $\sqrt{w_{d'}/j_d} + \sum(f_0 - d_0') = 0$, where the data weight is defined for the arriving data, then the similarity is achieved by $(f_0 - d_0')$. The resultant equals 0, where the data size is achieved in the first stage. The second stage is $\sqrt{w_{d'}/j_d} + \sum(f_0 - d_0') \neq 0$, where the data

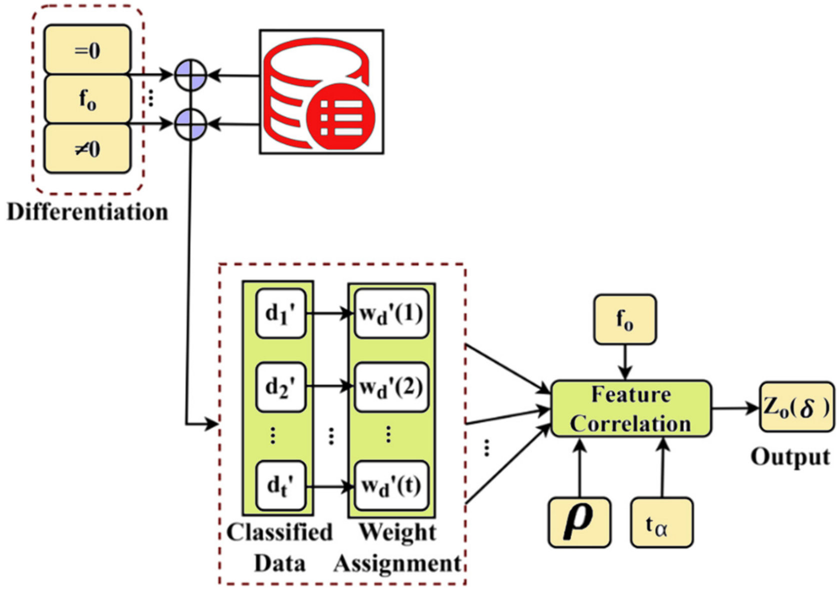

Figure 3: $z_0(\delta)$ Output process.

weights are not equal to 0, which includes the size that is not correlated with the arriving data. Equations (6) and (7) are rewritten in equation (8) as follows:

$$\delta(d', z_0) = \left[\left(\frac{\rho}{t_\alpha} + \frac{d_0'}{p_e}\right) \times \left(\frac{\sqrt{\frac{w_{d'}}{j_d}} + \sum(f_0 - d_0')}{\sum_{f_0}^{j_d}(i_d - j_d) + f_0}\right)\right] + (t - t_\alpha). \tag{8}$$

The correlation is measured for the data size based on the weights. Then, the time-based data size is evaluated by obtaining equation (8). Here, the spatial correlation is measured for the time-based data size for rehabilitation. Finally, better communication is achieved by using an efficient machine learning approach, SVM. It is used to classify the correlation data for reliable communication between the sportsperson and rehabilitation.

2.3 SVM – Spatial correlation

The SVM is used to find the correlation from the aggregated data based on classification. The data are classified by analyzing the sensor's input and arrival data. It has the decision boundary used to maximize the margin of the data. The boundary separates the correlation accurately classified and noncorrelation, which are not organized. The best hyperplane denotes if more correlated data appear in the limit. The SVM algorithm aims to determine the optimal line or decision boundary that splits the m-dimensional space into classes, making it simple to allocate the new data point to the correct class in the future. A hyperplane describes the optimal boundaries for making a decision regarding maximizing the sensor data and accurately separating the correlation and noncorrelation.

The data are represented in the two pairs of features such as (x, y); based on this, only the data are placed. Boundary ranges between $(-1, 1)$, if the data rely on the positive value, are labeled data. In another case, if the data lie in the negative value, they are denoted as unlabeled data. The distance between the hyperplane is derived by its vector point and characterized as $2/u$, where u is the vector for the margin. Expression (9) is utilized to obtain the data margin. The optimal hyperplane splits the negative and positive values. The location of the hyperplane is identified by the closest training set pairs, termed the support vectors.

$$\beta = \begin{cases} l - (u \times x) = 1 \\ l - (u \times x) = -1, \end{cases} \tag{9}$$

$$\beta_0 = \begin{cases} l - (u \times x) \geq 1, & \text{if } y_{d'} = 1 \\ l - (u \times x) \leq -1, & \text{if } y_{d'} = -1. \end{cases} \tag{10}$$

By using equation (8), the correlation for data size is derived, and from that, SVM margins are evaluated by using equations (9) and (10). In equation (9), β denotes the margin boundary, and the first level indicates that a positive value lies on the margin, where l referred to as the data vector value for the hyperplane. In Figure 4, the conventional SVM classification for $s_0(g)$ is represented for both the conditions of ch′.

In the classification represented earlier, the margin is defined for both the solutions of Z_0. The variable u is termed a vector for the margin; in this level 1, the vector margin and hyperplane are estimated to be positive values. The second level in equation (9) denotes the negative value for the vector margin that indicates no correlation occurs for the sensed data. In equation (10), β_0 represents the condition for positive and negative values. The first stage indicates the need for positive data if the processing occurrence is greater than or equal to 1. The second condition represents the negative data for the sportsperson if lesser than or equal to 1. The margin for both equations (9) and (10) is rewritten by using equation (11).

$$\delta(x,y)_{d'} = \frac{d_0'}{m_0} \times l - (u \times x) > 1, \forall 1, x > d. \tag{11}$$

Equations (9) and (10) are used to detect the positive values for the input data; by using equation (11), the correlation is achieved by deriving the margin vector. In this, the hyperplane separates the positive and negative data. Equation (12) represents the co-relation data by using the SVM classifier.

$$\delta(\Delta) = \max_{\rho} f_0 \begin{cases} \dfrac{1}{d_0'} + \sum\limits_{t}^{w(p_e)} \beta + [v \times m_0] + j_d = 1 \\ \dfrac{1}{d_0'} + \sum\limits_{t}^{w(p_e)} \beta + [v \times m_0] + j_d = -1. \end{cases} \tag{12}$$

In equation (11), the correlation is obtained by deriving the margin (x, y), and equation (12) is used to find the correlation based on SVM. The variable Δ represents SVM classification to achieve maximum correlation from the sensed data. Equation (12) represents two stages: the first stage is $1/d_0' + \sum_t^{w(p_e)}\beta + [v \times m_0] + j_d = 1$, where the margin vector indicates the positive data under the hyperplane boundary. So, in this stage, the possessed data are positive, which means the correlation improves. The second stage is $1/d_0' + \sum_t^{w(p_e)}\beta + [v \times m_0] + j_d = -1$, where the negative indicates no correlation for the sensed data. In Figures 5 and 6, the SVM output of $(f_0 - d_0')$ for the β is assessed. As represented in these figures, the proposed method satisfies the correlation data for the

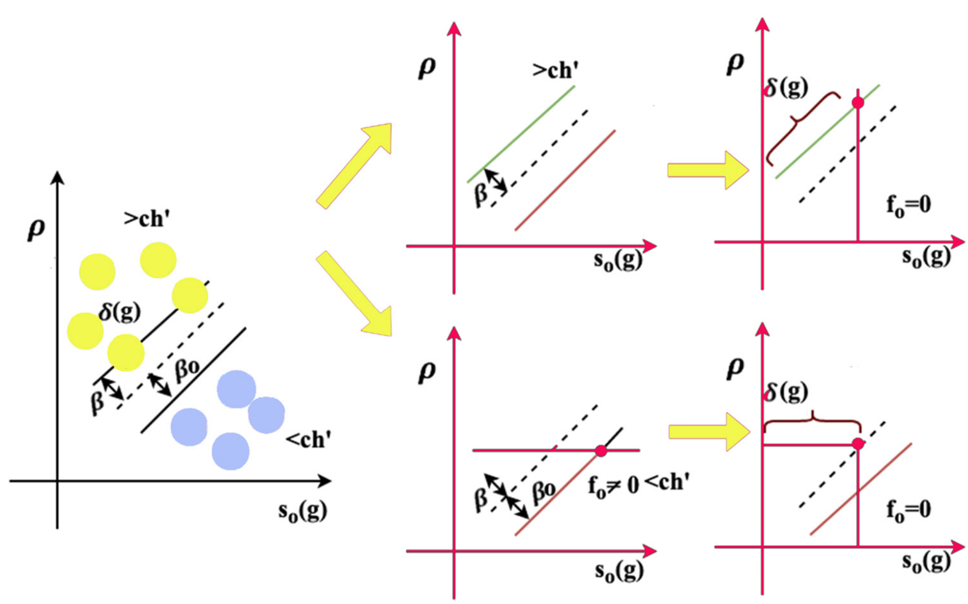

Figure 4: SVM Classifications for $s_0(g)$ based on ch′ conditions.

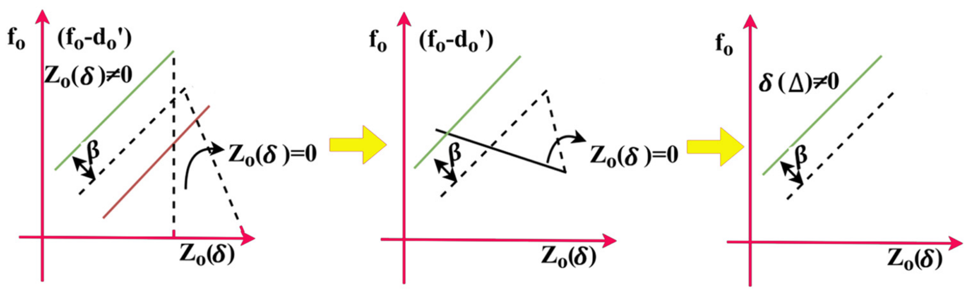

Figure 5: SVM solutions for Z_0 based on β.

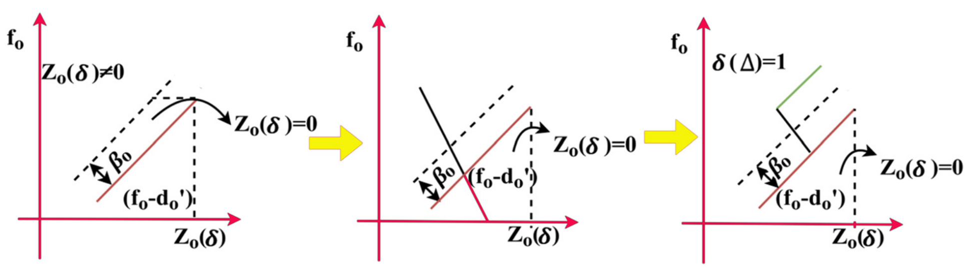

Figure 6: SVM solutions for Z_0 based on β_0.

sportsperson for rehabilitation. The correlation output is based on both β and β_0 through independent SVM classification instances. The high is the classification instance, and the high is the correlation accuracy. By obtaining equation (12), the correlation is achieved by deriving the SVM classifier. Hence, the communication is efficient for the rehabilitation center to improve the data and gives feedback regarding the activity. For every input data, the correlation varies by evaluating $\delta(d', z_0)$. The data size is observed based on aggregating the data from the allocated time t_α.

3 Results

The performance of the proposed correlation method is analyzed using experimental analysis using the data source in “UCI Machine Learning Repository” [40]. The initial purpose of the data gathered for the REALDISP (REAListic sensor DISPlacement) dataset was to study the impact of sensor displacement on activity detection in natural environments. It expands upon the ideas of perfect placement, self-positioning, and displacement by external factors. Boundary conditions for recognition algorithms may be found in the ideal and mutual-displacement conditions, which are the two most extreme displacement versions. Conversely, self-placement illustrates a user's conception of how sensors may be placed, for instance, in a sports or leisure app. The dataset has 17 people with various sensor modalities (rate of turn, acceleration, quaternions, and magnetic field) (warm up, cool down, and fitness workouts). In addition to its usefulness for studying sensor displacement, the dataset may be used as a baseline for testing activity detection methods under ideal circumstances. This data source analyses the WS data from nine sensors placed at different human body parts for its correlation. This data source provides 33 sports activities among which rope jumping, bending, cycling, and trunk twisting are accounted for in this correlation. From the available 120 attributes of the data source, five columns of 67 features for the aforementioned activities are used for recognition. The recognition is performed as a correlation of the 67 characteristics for the 4 exercises labeled in the data source. The proposed method performs 10 classifications through SVM. For the analysis purpose, accuracy, $F1$ score, and detection time are utilized to verify the reliability of the suggested technique. The comparative analysis is performed along with the existing techniques such as BasIS [21], DFF-HAR [20], and SFD-RBM [16].

Table 1: Accuracy of varying WS data

WS Data	BasIS	DFF-HAR	SFD-RBM	SDC-SVM
10	87.08	87.19	89.61	89.97
20	88.09	88.23	90.35	90.06
30	88.15	89.62	89.41	92.78
40	87.49	88.8	91.06	91.94
50	87.67	88.48	91.53	90.09
60	87.6	89.38	89.36	90.7
70	87.3	90.21	91.9	92.6
80	87.11	88.46	90.59	92.54
90	87.17	89.88	89.64	91.59
100	87.37	89.41	90.77	92.94

Table 2: Accuracy of varying classification instances (CI)

CI	BasIS	DFF-HAR	SFD-RBM	SDC-SVM
1	87.81	89.3	91.68	91.32
2	87.58	88.29	90.81	91.15
3	87.5	88.43	90.75	90.07
4	88.16	88.35	90.8	90.77
5	87.99	89.16	89.15	91.47
6	88.06	89.21	90.81	91.36
7	87.9	88.69	89.19	91.79
8	87.63	88.49	89.71	92.05
9	87.02	88.19	90.27	91.53
10	87.93	89.3	91.97	92.48

Table 3: Accuracy of varying subjects

	BasIS	DFF-HAR	SFD-RBM	SDC-SVM
Sub 1	87.63	89.51	91.37	92.33
Sub 2	88.21	88.12	89.2	90.47
Sub 3	87.97	89.06	91.63	90.92
Sub 4	87.14	89.08	90.78	92.45

3.1 Accuracy analysis

In the proposed method, $\delta(\Delta)$ denotes the correlation factor for accuracy. The proposed method first classifies the features for ch′-based conditional verification using d_0 and i_d. The differentiation function is equated to the conditional analysis of four possibilities of $d' <$ ch′ and $d' >$ ch′ for excluding features that do not satisfy $w_d'(t)$. Therefore, the nonlinear conditions of the f_0 and t_a differentiate $Z_0(\delta)$ and $d_t{}'$ for the precise classification. In the SVM classification process, the spatial features of "g" are extracted by differentiating β and β_0 for different differentiation processes. The conditions > ch′ and < ch′ for $\delta(g)$ are granularly differentiated using $\delta(x, y)$ and $s_0(g)$. Theρ -based analysis of the input through a series of classifications by identifying $y_{d'} = 1$ and $y_{d'} = -1$ margins is useful in leveraging the precise feature analysis; hence, Tables 1–3 show that the accuracy of recognizing the activity and its correlation are improved. In addition, the classification of features in the

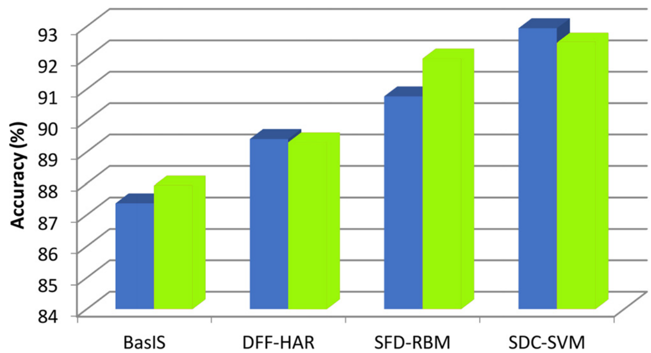

Figure 7: Accuracy comparison.

second level through $\delta(\Delta)$ for $\max f_0$ is recursive in differentiating $\delta(d', z_0)$ for all $s_0(g)$. Therefore, the correlation factor is high for $Z_0(\delta) = 0$ instances by extracting and correlating $(f_0 - d_0')$ features of all the acquired data. This process is common for any WS data and subjects (due to varying physical measurements), achieving better accuracy (Figure 7).

3.2 Computational time

The proposed SVM-based classification requires less time (Figure 8) to detect the activity by preidentifying d_0' and i_d. This helps to differentiate the feature analysis process based on size and margin. The condition based on ch′ identifies f_0 for both the individual and joint d_t' and $w_d'(t)$. This correlation helps to precise the output of $Z_0(\delta)$ without queuing or requiring additional wait time for computation. The mapping of the weights to the classified data eases BVM classification for $\delta(d', Z_0)$ and extracting $\delta(g)$. Following f_0 and ρ, optimal $\delta(g)$ and basis of the ch′ condition are used to identify optimal $Z_0(g)$ for maximizing accuracy (Tables 4–6). Therefore, the time required for the independent data classification is refined using the preprocessing and SVM model, reducing the detection time. Therefore, framed f_0 using ρ, t_α based on $w_{d'}(t)$ filters the occurrence of $Z_0(\delta)$ from which $\delta(\Delta) = 0$ and $\delta(\Delta) = 1$ are analyzed. Different from the conventional process, where $Z_0(\delta)$ is jointly computed, this proposed method differentiates both occurrences, reducing the actual time for computation. Besides, the concurrent process of $\delta(\Delta) = 0$ and $\delta(\Delta) = 1$ helps to reduce the augmented wait time of the computation process.

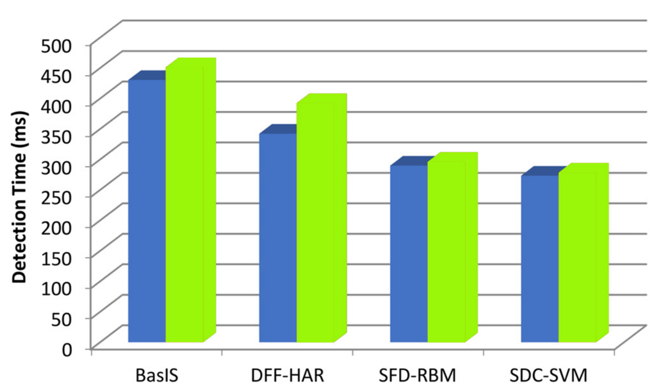

Figure 8: Classification time comparisons.

Table 4: Detection time (ms) of varying WS data

WS Data	BasIS	DFF-HAR	SFD-RBM	SDC-SVM
10	413.92	310.02	259.16	256.45
20	428.76	374.72	319.68	243.05
30	449.36	355.72	266.05	255.72
40	452.81	386.05	338.16	265.25
50	452.75	384.57	336.38	255.54
60	441.06	334.73	348.31	250.18
70	406.69	314.72	293.12	250.26
80	432.97	381.86	328.85	240.78
90	398.01	336.89	309.27	260.02
100	430.33	342.13	289.76	273.3

Table 5: Detection time (ms) of varying classification instances (CI)

CI	BasIS	DFF-HAR	SFD-RBM	SDC-SVM
1	430.52	331.56	308.27	269.37
2	449.17	319.16	310.51	268.43
3	413.24	380.32	321.09	244.98
4	412.7	337.82	336.96	251.66
5	403.49	357.5	276.46	268.86
6	434.36	317.88	277.34	263.09
7	422.92	369.69	296.95	246.36
8	410.16	352.23	320.96	262.2
9	401.95	304.01	315.4	273.61
10	450.98	392.28	295.97	278.11

Table 6: Detection time (ms) of varying subjects

	BasIS	DFF-HAR	SFD-RBM	SDC-SVM
Sub 1	434.27	312.07	284.62	255.23
Sub 2	412.59	357.47	333.36	272.99
Sub 3	394.12	320.79	319.27	264.48
Sub 4	452.68	347.3	295.51	277.98

Table 7: $F1$ score of varying WS data

WS Data	BasIS	DFF-HAR	SFD-RBM	SDV-SVM
10	0.9	0.911	0.934	0.943
20	0.904	0.919	0.939	0.942
30	0.907	0.917	0.935	0.949
40	0.902	0.923	0.933	0.948
50	0.902	0.917	0.933	0.945
60	0.907	0.92	0.94	0.95
70	0.903	0.917	0.939	0.95
80	0.905	0.913	0.94	0.941
90	0.903	0.91	0.93	0.95
100	0.903	0.923	0.933	0.947

Table 8: *F*1 score of varying classification instances (CI)

CI	BasIS	DFF-HAR	SFD-RBM	SDC-SVM
1	0.902	0.912	0.934	0.95
2	0.911	0.923	0.938	0.95
3	0.903	0.921	0.93	0.942
4	0.901	0.919	0.94	0.942
5	0.907	0.913	0.932	0.942
6	0.909	0.921	0.938	0.942
7	0.906	0.922	0.933	0.949
8	0.911	0.916	0.933	0.949
9	0.906	0.92	0.93	0.943
10	0.908	0.92	0.937	0.946

Table 9: *F*1 score of varying subjects

	BasIS	DFF-HAR	SFD-RBM	SDC-SVM
Sub 1	0.909	0.91	0.936	0.943
Sub 2	0.904	0.915	0.934	0.944
Sub 3	0.903	0.923	0.934	0.944
Sub 4	0.912	0.928	0.93	0.942

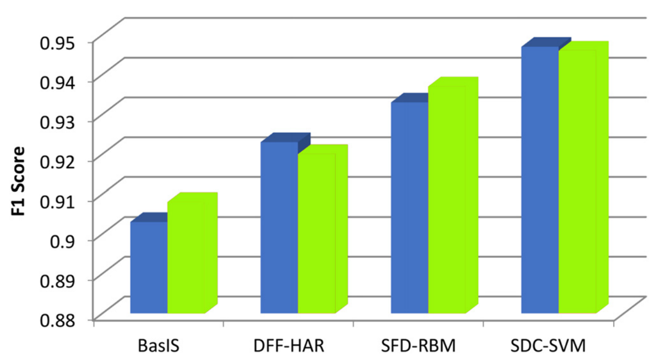

Figure 9: *F*1 score comparisons.

Table 10: Results of the proposed method for different sensor counts

Sensors	Accuracy	Detection time (ms)	*F*1 score
2 + 0	91.13	434.79	0.946
0 + 2	88.91	354.6	0.909
3 + 0	90.39	375.17	0.918
1 + 2	94.95	449.89	0.941
2 + 1	93.84	434.42	0.941
0 + 3	87.96	333.4	0.92
2 + 2	92.01	452.08	0.951

Note that “*x*” + “*x*” in the first column indicates the presence of accelerometer and gyroscope sensors.

3.3 *F*1 score analysis

*F*1 score is computed as follows:

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}},$$
$$\text{Precision} = \frac{\delta(\Delta)}{\delta(\Delta) + Z_0(\delta)}, \tag{13}$$
$$\text{Recall} = \frac{\delta(\Delta)}{\delta(\Delta) + s_0(g)}.$$

In equation (13), $Z_0(\delta)$ and $s_0(g)$ are the false positive and false negative outputs in the intermediate classification state, respectively. The proposed method achieves high $\delta(\Delta)$ by refining $s_0(g)$ in the preclassification step, followed by $Z_0(\delta)$ in the SVM classification. This process is recurrent in the varying WS data and classification instances to maximize accuracy. In Tables 7–9, both instances' precision and recall are retained to achieve a better *F*1 score (Figure 9). The classification is initially condition based, followed by (β, β_0) based differentiation of f_0. Thus, the refinement is optimal in the SVM model to improve the accuracy, precision, and recall.

Table 10 summarizes the results of the accuracy, detection time, and *F*1 score of the proposed method for the varying number of sensors. The observations from the count of sensors providing operational data are accounted for in this tabulation. For the high number of WS data from the active sensors, the accuracy and *F*1 score are high, and the detection time is less. This is because of the maximum data available from different sensors at different intervals. Hence, the classification instances for the data analysis in preclassification and SVM classification are high. This retains the precision and recalls to maximize the *F*1 score.

The numerical outcomes display that the suggested SDC-SVM technique can improve recognition accuracy, *F*1 score, and computing time compared to existing methods such as BasIS, DFF-HAR, and SFD-RBM. For the future studies, the suggested approach can be improved using new fuzzy systems [41–43].

4 Conclusions

This article introduced an SVM-based spatial WS data correlation method for improving the accuracy of activity detection in sports rehabilitation. This method performs two classifications through conditional and differentiation methods for better accuracy. In these classifications, the extreme instances of mediate solution occurrence are mitigated by filtering the mapped features based on the weight factor. The technique employs a hyperplane function that can identify sporting activities and boost the efficiency of activity identification generally. Input margin analysis is applied to the sensor data, after which classification is carried out. Maximizing the total classification method of WS data correlation by considering the size and margin of the input and previously stored data is considered. Spatiotemporal aspects of data are gathered and evaluated using SVMs in both the differentiation and classification examples. Therefore, the differentiation function prevents the unnecessary event of data feature validations, restricting the number of errors. Similarly, the consequent classification increases the number of validating data processes by mapping it with the existing data sources to identify the activity. Unlike conventional SVM models, the margin-based feature validation is performed concurrently for both the upper and lower bounds of the mediate solution. This helps to reduce computation time. The recurrent analysis helps to leverage the *F*1 score ratio of 95.1, maximizing the correlation accuracy of 92% for the varying WS data and classification instances. The main limitation of the suggested SDC-SVM is that a small sample of data was acquired. Potential future research directions include using deep learning neural networks or other similarly advanced nature-inspired algorithms to further optimize the SVM classifier.

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