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IoT based psychological and physical stress evaluation in sportsmen using heart rate variability

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ABSTRACT

Sports have become the important and most prominent play for each and every country to indulge their pride to the world. For this reason, countries are eager and interested in protecting the players/sportsmen in many ways such as health related, money, security etc. The life quality of sportsmen is improved by detecting huge potential known to be stress for preventing and managing the diseases. Moreover, low-cost wearable devices are available for monitoring the vital signs which leads to the detection of stress. Furthermore, the stress-levels are determined by using a particular vital sign known as Heart Rate Variability (HRV) that data is collected from a particular wearable device. In this paper, a real-time detection framework is proposed for analysing the level of stress for a particular sports person. The proposed framework consists of a hybrid classification technique named Multi-Output Regression (MOR) with Deep Convolutional Neural Networks (DCNN) to analyse and identify various stress levels and its relationship with data of HRV. Furthermore, 5-min time determination of each sportsman is distinguished based on their psychological and physical stress-levels. The simulation results show that the performance of the proposed framework obtains a high accuracy level when comparing with other models. With a lower error rate and based on efficiency, the proposed model achieves a high accuracy level of more than 96%.

1. Introduction

Stress is a significant concern in our everyday life. The human situations including worksite, home or society can initiate stress on a person in all possible ways. There are numerous ways that our body can respond to stress; these responses are principally ordered to either physiological responses which incorporate the 'battle or fight' reaction by the Autonomous nervous system (ANS) of our body or conduct responses which incorporate guarded behaviour, expressive and dysfunctional behaviour. In the field of psychobiology, stress is characterized as a mind-boggling response consisting of physiological and mental (i.e., subjective, full of feeling and social) parts (Zhang, 2017). It is viewed as an enthusiastic expression of individuals while involving circumstances seen as exceptionally testing or genuinely undermining. The term was first presented by Hans Selye, the "father of stress", who saw that patients with different experiences several diseases also have equivalent side effects that comprise a reaction to a stimulus (Fink, 2010).

Walter Bradford Cannon presented the idea of "battle or fight" to depict the process of how a body's sensory system is actuated when confronted with a stressor, driving the body to discharge stress hormones for its security (Singh et al., 2018). Hypothalamic-pituitary-adrenal (HPA) nodes and nervous systems are two significant frameworks that react to stress as an endeavour to restore homeostasis (a "consistent state") on a psychophysiological level (Boucsein, 2012). This includes changes in heart action, sweat organ action, and skin temperature. Therefore, physiological signs, including galvanic skin reaction and skin temperature, that are identified with such exercises, can give bits of knowledge into nervous system action (Seoane et al., 2014) and are viewed as dependable pointers of stress (Palanisamy et al., 2013). This psychobiological record of stress is especially valuable in taking account of points that intend to find explicit outward stressors at explicit minutes in existence (Kohavi, 1995). The expanding accessibility of modest and advanced estimation frameworks sets up the reason for novel research thoughts to advise key inquiries for feeling and emotion findings (Wilhelm & Grossman, 2010). Different physiological parameters and combinations of parameters can be used to recognize stress

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(Zangróniz et al., 2017). Stress is considered as the main parameter for HRV. This may eventually lead to cardiovascular diseases (Sathishkumar & Cho, 2019).

The stress can be predominantly ordered into two classifications: Acute stress and Chronic stress. Acute stress is the reaction of the body to a stressor for a shorter period and after that the body will accomplish the balance. Chronic stress is the one which relates for a more extended period and can create unsafe impacts on our body. Stress has an essential job in practically all infections which incorporates diabetes, hypertension, headache, cerebral pains, cardiovascular ailments, emotional wellbeing issues, liver cirrhosis, malignant growth and so on (Humphrey, 2003). Understanding the stress levels of the patients, for example, disease patients and cardiac patients can assume an imperative job in their recuperation, as chronic stress can initiate the malignant growth cells and furthermore cause dynamic development of tumor cells in malignant growth patients (Moreno-Smith et al., 2010), while in cardiac patients it increment the possibility of having a hypertension which isn't attractive for them. Along these lines, it is critical to comprehend the stress status of an individual much before the stress begins to cause some adverse consequences for our body.

The complications of stress related diseases paved a path for developing strategies for managing the stress level in patients. For identifying the stress level, various parameters of stress sources should be identified. Past methodologies show that the mix of a few physiological signs doesn't guarantee the most elevated accuracy exactness. Anyhow, most specialists have utilized galvanic skin reaction, chiefly joined with electrocardiogram or Blood volume pulse. Above all, the statistical structure of every algorithm seems to possess a significant job in predicting the stress level. Methodologically, the utilization of Support Vector Machine (SVM) produces high accuracy by past investigations for stress identification. There are likewise examinations that utilizes deep learning methodologies or data mining based calculations (Sathishkumar et al., 2020).

Various methodologies for stress identification that utilize wearable physiological sensors have been depicted; many can be categorized by two classes. The first is that specialists build up a technique utilizing research centre information, however could not explore the effectiveness of the strategy in genuine examinations. This implies the technique has restricted validity outside the requirements of research facility settings. Then again, a few methodologies have been created dependent on true information, however their validity for distinguishing genuine mental stress is hampered by restrictions intrinsic in characterizing the ground truth in the appraisal of stressful occasions (Can et al., 2019) (Varatharajan et al., 2018).

Regularly, the methodology is to correspond physiological signs with the spatial attributes of the physical condition, which is now and again supported by video accounts. As far as anyone is concerned, there are a couple of research findings that have planned for consolidating the two methodologies and characterize and then identify stress in an controlled lab setting and apply and broaden the collected information in genuine settings. One of the techniques for stress investigation incorporate paper strategy (self-report), body liquid levels testing and physiological parameter assessment (Abdel-Basset et al., 2018). Paper technique is performed by giving a different questionnaire poll and requesting the participants to answer it, where every decision will have a specific score. When the participants finished with the poll, the scores of every decision will be summarized to get a last score which demonstrates the stress level of that individual. Body liquid level testing, for example, spit testing or blood testing is accomplished for the recognition of stress hormone, Cortisol. Both these strategies are not compelling for persistent stress checking. Checking and investigation of physiological parameters can give a significant understanding into one's wellbeing status (Pragna et al., 2017). So in this work an IoT based data acquisition technique is proposed for gathering data for sports man stress evaluation using heart rate variability.

The goal of this work is to build up an effective stress monitoring framework and subsequently lessen the antagonistic impacts of stress on psychological well-being as well as physical wellbeing of the sportsman. The physiological parameters, for example, Heart rate (HR) and Electro dermal action (EDA) are considered, since both are legitimately connected to the central nervous system which is being enacted during the stress reaction. An open IoT stage for collecting the information of sportsmen for every 5 min is developed in this work. The developed system needs a validated record for the information gathering and its analytical process. So, the client needs to make a record and a channel to which the information from the microcontroller will be captured. Data investigation on gathered information should be possible by means of two learning algorithms, Multi-Output Regression (MOR) with Deep Convolutional Neural Networks (DCNN) Visualization. In this proposed work, the information sent from the microcontroller is gotten on this channel and later knowledge examination is performed, thus empowering persistent observing of stress. IoT facilitates high level of accuracy to minimize data risk and decreases the expense of visiting assistance, which improves the effectiveness of treatment that fulfils the expectations of patients. Providers will track patients on an ongoing basis to detect any illness until it evolves that becomes dangerous.

2. Related works

Uday et al. (2018) designed an IoT framework which can proficiently recognize the stress level of an individual and give an input which can help the individual to adapt to the stressors. The framework comprises an intelligent band module and a chest lash module which can be worn around the wrist and chest individually. The framework screens the parameters, for example, Electro dermal action and Heart rate progressively and sends the information to a cloud-based ThingSpeak server filling in as an online IoT stage. Stress monitoring systems not only developed in humans but also in animals. Cui et al. (2019) proposed a non-intrusive Wearable Stress Monitoring System (WSMS) with Inertial Measurement Units (IMU), PhotoPlethysmoGram (PPG) and Infrared Temperature Measurement (ITM) that expected to constantly and remotely screen the stress indications of animals during transportation.

Kyriakou et al. (2019) proposed a standard rule-based calculation based on galvanic skin reaction and skin temperature, brushing empirical discoveries with master information to guarantee transferability between research facility settings and genuine field researches. A lab trial was done to make a "highest quality level" of physiological reactions to stressors. The calculation in certifiable fields considers utilizing a blended strategy approach by spatially relating the member's apparent stress, geo-found surveys, and comparing true circumstances from the video. Results show that the algorithm distinguishes measurement of stress with 84% precision, demonstrating high connections between deliberate (by wearable sensors), announced (by surveys and eDiary passages), and recorded (by video) stress occasions.

Kyriakou and Resch (2019) proposed a system for the spatial examination of snapshots of stress. In an initial step, moments of stress are recognized through a standard based calculation breaking down galvanic skin reaction and skin temperature estimated by minimal effort wearable physiological sensors. For the spatial investigation, a MOS proportion for the geo-found distinguished moment of stress is presented. This proportion standardizes the recognized moments of stress in close by territories through the accessible records for the region. At that point, the moment proportion is taken care of into a problem area examination to recognize hot and cold spots. Murugan and Devi (2018a, 2018b, 2019) have proposed a hybrid model for analysing the big data to two class classification and proved to be better performance when making a combination of algorithms. Authors have chosen optimization techniques with machine learning algorithms to improve the performance and increase the accuracy.

Affann (2020) portrays the design of a two channels electrodermal action (EDA) sensor and channels electrocardiogram (ECG) sensor. The EDA sensors secure information on all four sensors to the ECG sensor

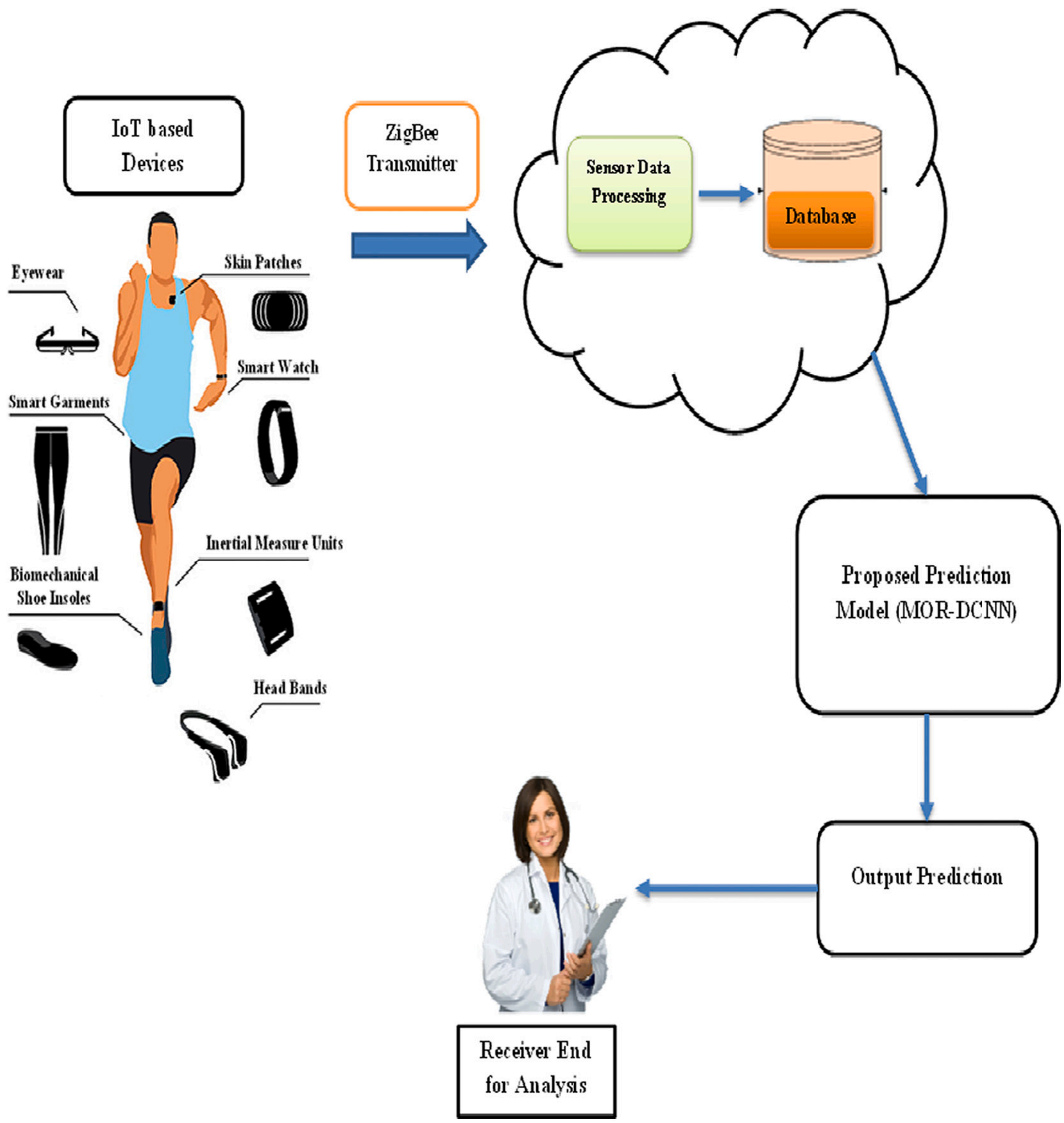

Fig. 1. Proposed framework for stress detection.

with remote WiFi correspondence for expanded wearability. The sensor framework secures two EDA channels to improve the expulsion of movement relics that happen if EDA is estimated on people who need to move their hands in their exercises. The ECG channels are obtained on the chest and the ECG sensor is liable for adjusting the two ECG follows with the packets received from EDA sensors; the ECG sensor sends by means of WiFi adjusted packets to a PC for ongoing plot and information stockpiling. Yoo and Chung (2018) proposed a technique that gathers an assortment of data in double physical situations, (for example, temperature, brightness, and humidity) from IoT gadgets, and examines it continuously. The inconvenience list and wind chill temperature list offered by the Korea Meteorological Administration, and the temperature, brightness and humidity gathered from a biosensor are gathered to digitize the physical conditions of pressure. Likewise, a shrewd healthy stage investigates distinctive pulses relying upon singular conditions, and screens current status. For a pulse, the recurrence of the R-R worth and low frequency (LF) are broken down. For R-R esteem, a most extreme worth location calculation is applied. For LF investigation, Fourier change is utilized.

Iakovakis and Hadjileontiadis (2016) conducted a novel investigation that intends to utilize a smartwatch, free from other equipment, to predict the Blood Pressure (BP) brought about by postural changes. In cases that the drop is because of orthostatic hypotension (OH) which can cause stroke or even black out elements, which increment the danger of fall in the older at the same time in more younger generation individuals. A numerical model is proposed which can decrease the danger of fall because of OH by detecting pulse fluctuation (information and drops in systolic BP in the wake of remaining in a solid gathering of 10 subjects). Chiu and Ko (2017) set up a wise music determination framework for clients to improve their performance of learning. A passionate music database utilizing information examination groupings was designed. During testing, creative wearable detecting gadgets were utilized to distinguish pulse fluctuation in tests, which correspondingly guided music determination. Individual feelings were then investigated, and fitting tunes were chosen by utilizing the proposed application programming. Data Mining methodologies were utilized to record client inclination, guaranteeing exact characterization. Accurate outcomes created through trial approval demonstrate that this framework produces high fulfilment levels, doesn't increment mental burden, and improves individuals learning performance.

Hernández-Ruiz et al. (2018) showed the structure, execution and investigation of a Machine Learning (ML) model for the estimation of Heart Rate Variability (HRV). Through the coordination of gadgets and innovations of the Internet of Things, a help device is proposed for

Table 1
Characteristics of IoT wearable device.

S. No.	Sensor type	Signal type	Characteristics
1	Chest or skin electrodes	Electrocardiogram	Heart's electrical activity monitoring
2	Pulse oximeter	Saturation of oxygen	Oxygen amount placed in blood for sportsmen
3	Phonocardiograph	Sound of heart	Recording the heart sound
4	Accelerometer	Movement of body	Acceleration force is measured
5	Skin patch	Skin temperature	Measurement of body heat
6	Skin electrodes	Heart rate	Cardiac Cycle frequency measurement
7	FlyRobo	Respiratory sensor	Monitors lungs functions
8	Accelerometer	Speed sensor	Measure velocity

individuals in wellbeing and sports regions who need to know a person's HRV. The heart signs of the subjects were caught through pectoral groups, later they were arranged by a Support Vector Machine calculation that decided whether the HRV is increased or decreased. Rodríguez-Molina et al. (2013) proposes a framework to screen an athlete during an exercise meeting or playing out a game related indoor action. Sensors have been conveyed by methods for a few nodes going about as the nodes of a WSN, alongside a semantic middleware advancement utilized for equipment intricacy reflection purposes (Manogaran et al., 2020). The information detected from the environment, joined with the data obtained from the client, will make the basis of the administrations that can be acquired.

Mateusz et al. (2019) proposed a method for carefully detecting internal heat level and pulse utilizing arduino and simultaneously following children through the IoT method. LM35 is utilized for the sensing internal heat level. Internal heat level is an essential parameter for observing and diagnosing human level of health (Muthu et al., 2020). Heart beat sensor was utilized for detecting pulse. This gadget will permit one to quantify their mean blood vessel pressure in one moment and the exact internal heat level will be shown on the Android through cloud services (Aldhaheri and Lee, 2017). The framework can be utilized to gauge physiological parameters, for example, Heart rate (Systolic and Diastolic), Pulse rate. Elumalai and Ramakrishnan (2020) focused on javelin throw, which is one of the Olympic style events. Because of poor preparing and absence of best mentors, competitors could not give best performance in the Olympics. Competitors need to adjust both physiological and development parameters to accomplish most extreme separation while tossing the lance (Sivaparthipan et al., 2019). An equipment was designed utilizing sensors and an Arduino controller to screen physiological parameters, for example, circulatory strain, pulse and electrocardiogram. Utilizing SQL database and IoT, the deliberate parameters are stored in a web server for additional examination and giving input to competitors.

Table 2
Overview of collected dataset.

HRV	BVP	EDA	Temp	ACC-X	ACC-Y	ACC-Z	Label
60	64	4	4	32	32	32	No stress
60	0	0	382.21	−15	−20	58	Mental stress
62.67	0	0.193	382.21	−14	−20	57	Mental stress
64	0	0.250	382.21	−14	−20	58	No stress
65.6	0	0.254	382.21	−15	−20	58	No stress
67.17	0	0.2546	28.47	−14	−20	58	No stress
68.43	0	0.2546	28.47	−14	−20	58	No stress
69.25	0	0.25581	28.47	−15	−20	58	No stress

3. Proposed methodology

In this section, the proposed model named Multi-Output Regression (MOR) with Deep Convolutional Neural Networks (DCNN) is used for analysing the stress levels of sports persons on different aspects of playing based on the Heart Rate Variability (HRV). The relation between

Table 3
Data labelling preparation results.

Class/label	Total records	Overall percentage
No_stress	1687	8.79%
Mental_stress	3890	20.27%
Physical_stress	8941	46.59%
Combined physical_mental stress	4674	24.35%

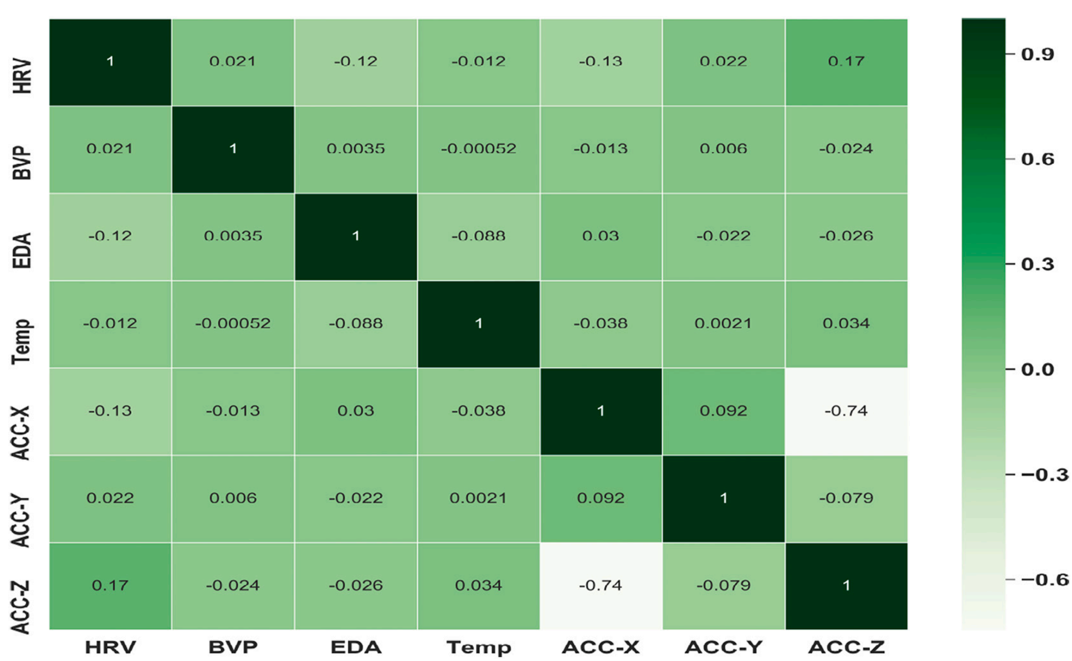

Fig. 2. Heat map of collected dataset.

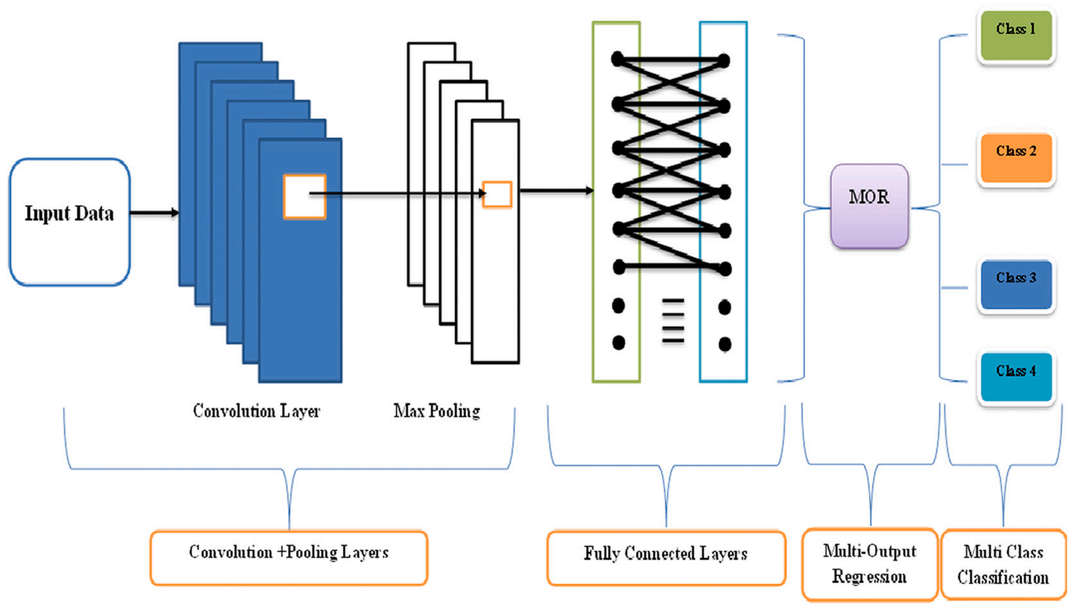

Fig. 3. Framework of proposed MOR-DCNN.

various individual or predictor variables and one dependent or observed variables is generally explained by multiple regression. It can be used to predict the consequences or impacts of modifications. Regression analysis predicts trends and potential values in order to obtain estimates of points. Furthermore, the proposed method classifies the stress levels based on four classes and these are Physical Stress, Mental Stress, No stress and combination of Physical-Mental Stress for detecting whether the person playing is having stress or not. Fig. 1 shows the proposed MOR-DCNN framework for detection of physical stress. Furthermore, the IoT sensor devices help in collecting the data from the sports people and transmit the data using zigbee technology to the cloud storage. The cloud server will process the data and store it for future analysis, the data which is stored in the server can be accessed by the doctors for analysing the stress level. Before the data accessed by doctors the machine model can predict and classify the stress level obtained by the sports person and sent to the doctor for verification and easily find the sportsmen who are having more stress. By analysing this proposed technique, several countries can make up their athletes and players for several games to be ready in a calm state for achieving more prizes. Moreover, the framework shown in Fig. 1 abruptly makes the general collection of data, storage, processing, and classification. Each process has been explained below regarding the detection and classification of stress levels.

Zigbee Technology is an emerging connectivity model that defines a series of protocols such as sensors and communication channels for use in low bit rate, short to mid-range mobile communication protocols. It is used in wireless management and surveillance, where in such applications the quantity of knowledge and the quality of communication is much smaller. Zigbee Technology enables many applications in which application is the monitoring that the inpatient, where a patient wears a Zigbee machine that gathers information such as blood pressure and heart rate regularly.

IoT integrated devices like eyewear, smart costumes, smart insoles, watches, bangles, head bands, etc., were unified into the physique elements and allowed to collect and propagate data using a zigbee

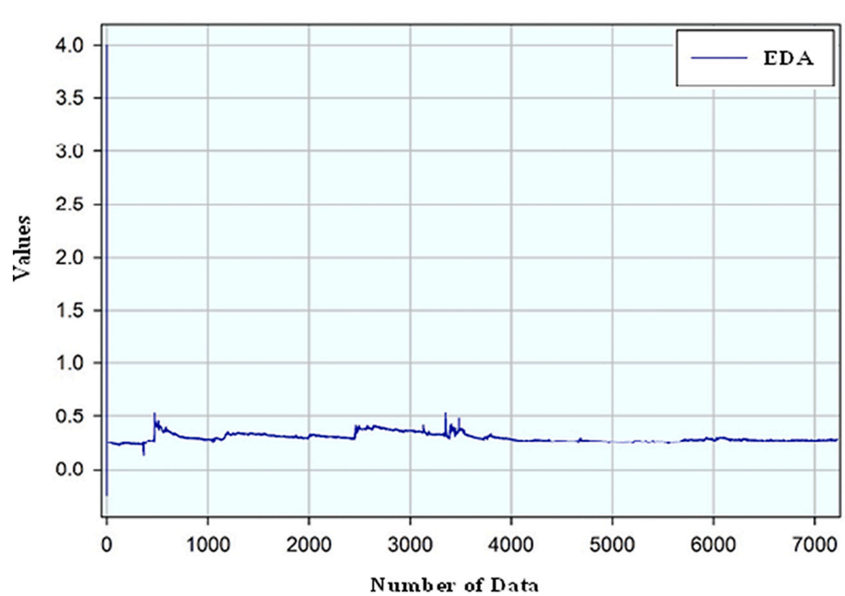

Fig. 4. Statistics of collected EDA data.

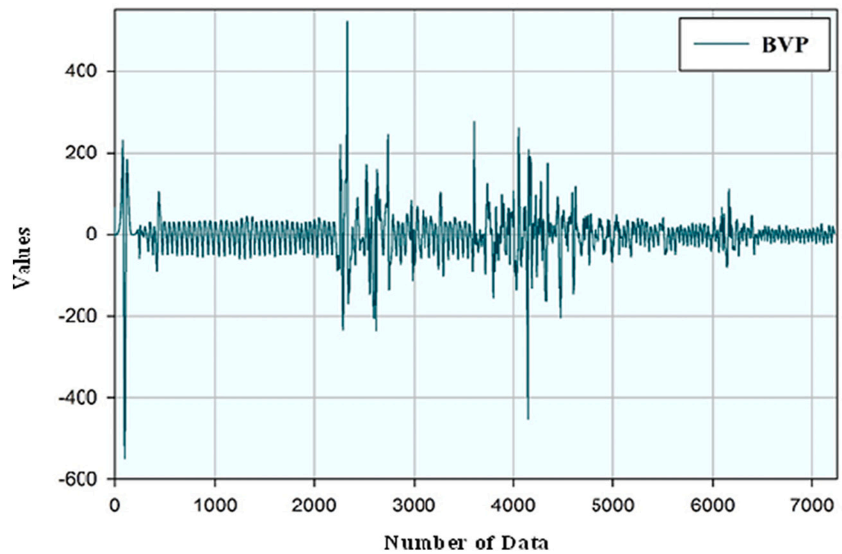

Fig. 5. Statistics of collected BVP data.

transmitter which acts as a suite of high-level communication for wireless control and monitoring system. They are integrated with radios and micro controllers for data exchange to and fro in a challenged distributed environment. The data about an individual or a sports man are monitored on the basis of blood pressure, stress level, heart rate, neural data, veins, etc., were aggregated as per any one of data aggregation mechanism and stores it a sustained database. Data which was aggregated is allowed for dynamic training and modelling process which segregates the result of an accuracy.

3.1. IoT sensor wearable devices

Table 1 shows some of the wearable IoT sensor devices and its characteristics with the company product name. Also, Table 1 gives the validation of devices that are processed or not with reliability testing and checked if calibration is required. The IoT devices help in collecting the data from the sports people in order to analyse the stress level of each player. The sensors collect information regarding the person's details with heart variability rate, temperature, electro thermal activity, photoplethysmograph, and accelerometer.

3.2. ZigBee protocol

It is one type of high-level protocol which is based on the specification of IEEE 802.15 that helps in creating a personal network for transmitting the data collected from the source IoT devices and sent to the cloud server for storage. It will be a better option that suits low power digital-radios, medical device data collection, and also for small projects. Most of the wireless technologies are using ZigBee to transmit the information or data from other networks to the receiver end.

3.3. Cloud storage

The sensor data collected from the IoT devices are processed and stored for future reference as well as for further process to predict the stress level based on the proposed classification model. The raw dataset is analysed and stored and pre-processed the data for better classification performance. Fig. 2 shows the heat matrix for the collected dataset.

3.4. Dataset description

Table 2 shows the overview of the collected dataset in which a total

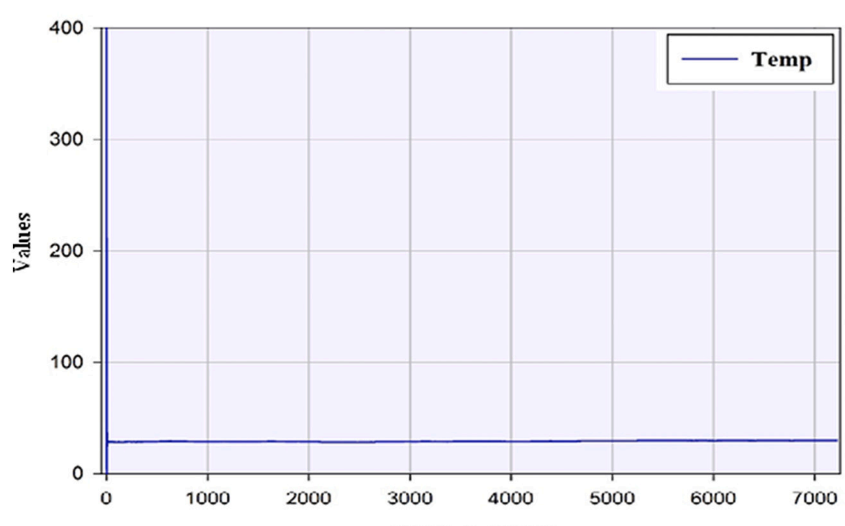

Fig. 6. Statistics of collected temp data.

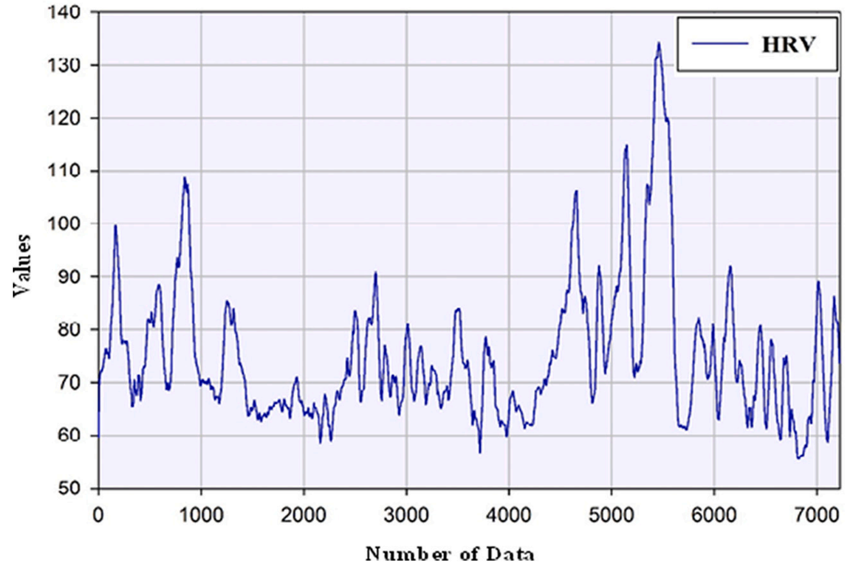

Fig. 7. Statistics of collected HRV data.

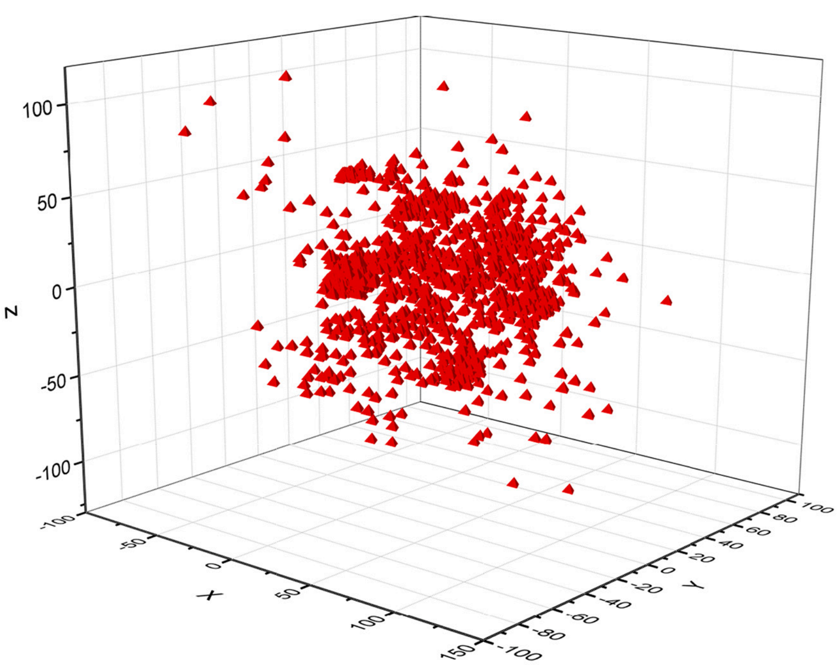

Fig. 8. Statistics of collected ACC data for x, y, and z axis.

of 7 features are taken and one separate feature is added with a name label for the stress classes. The seven features mainly used for the classification of stress levels are HRV which analyse the heart-rate, Blood Volume Pulse (BVP) is the data taken from photo-plethysmograph where it Monitors fluctuations in blood flow corresponding to physiological changes and blood circulation in the pulmonary veins, Temp is the temperature of the body, Electrodermal activity (EDA) is an emotional euphoria neurobehavioral measure recording continual variation in the electrical patterns of the skin. EDA is the data of electrodermal activity, ACC is the data from accelerometer of x, y, and z axis, and finally label is the feature for denoting the class for stress levels. Fig. 2 shows the heat matrix of the collected dataset to prove that the features used for this research is well enough for the classification and performance improvement of the model. It is a visualization map for the tracking of a consumer or athletes by global networks. The heatmap illustrates a number of deployment-related problems. It monitors the physical information of the users, records performance metrics such as rate, speed, and length which analyzes the performance of users and compares performance indicators with several other users.

3.5. Proposed MOR-DCNN prediction model

The proposed Multi-Output Regression with Deep Convolution neural network is used for classification and prediction of stress level obtained by the sportsmen. The proposed model is having more advantages in preparing the sports person for better outcome of result. A total of 32 men and 24 women participants were chosen who are all in playing status and collected the data based on their health and physical fitness for the sports they play. Based on the features and data collected (Rajakumari, Punitha, Lakshmanakumar, & Suresh, 2020) from IoT

Table 4
Confusion matrix of predicted stress levels.

Classes/labels	No_stress	Physical_stress	Mental_stress	Combination of physical and mental
No_stress	1596	69	22	0
Physical_stress	28	8876	29	8
Mental_stress	64	16	3798	15
Combination of physical and mental	32	45	0	4597

Table 5
Performance comparison of proposed MOR-DCNN vs existing models.

Algorithms	TPR (%)	FPR (%)	Accuracy (%)
Proposed MOR-DCNN	97.3	0.65	98.2
DCNN	94.5	0.74	95.2
MO-SVR	94.9	0.72	95.8
SVM	93.6	0.67	94.2
RF	92.8	0.86	93.4

devices the classification of stress levels are predicted by four classes and these are ‘Physical_Stress’, ‘No_Stress’, ‘Mental_Stress’, and ‘combination of Physical-Mental Stress’. The parameters labelled here are calculated in terms of several metrics such as HRV, BVP, EDA, Temp, Acceleration data, etc. Table 3 shows the test data prepared for the four classes and number of records obtained for each class.

3.5.1. Model training

The model training of stress detection using the collected data having the parameters such as heart variability rate, temperature, electro thermal activity, photo-plethysmograph, and accelerometer with added feature named label which includes four classes. The stress detection model is trained and evaluated using the proposed MOR-DCNN. The data splits into a training and testing phase which includes a total of 19,192 records. Furthermore, 70% of the records used for training and 30% is for testing purposes. Overall, the records separated as per the label in which No_Stress contains 1687, Mental_Stress with 3890, Physical_Stress includes 8941, and Combined Physical_Mental Stress contains 4674.

3.6. Proposed MOR-DCNN framework

The multiple output regression technique with deep convolutional neural network is used for analysing the stress levels which improves performance of the classifier when classifying more classes. Fig. 3 shows the proposed MOR-DCNN framework for the detection and classification of stress levels. The multiple output support vector regression model is used with DCNN to classify the four classes of stress levels in order to obtain better accuracy.

From Fig. 2, the overall workflow for the classification of stress levels is shown by sending the input to the convolution layer and max pooling is obtained, the data then processed to fully connected layers to analyse the class and using the multi-output regression technique further classification is done. It is used to apply a filter to an data which was aggregated by collection to get a resulting need. It make to look as a good sense with its types and orientation. It also allows to recollect about gentle kind of information. The resolution of feature maps of previous is reduced by the down-sampling or pooling layer. The invariance is produced for distortion or small transformation by pooling later. The input data is separated into disjoints regions by the pooling layer having a size of ($N \times N$) for producing one output for each region (Manogaran et al., 2020). The pooling layer given in the Fig. 2 can be average or maximum. However, the input data given with a size of ($R \times$

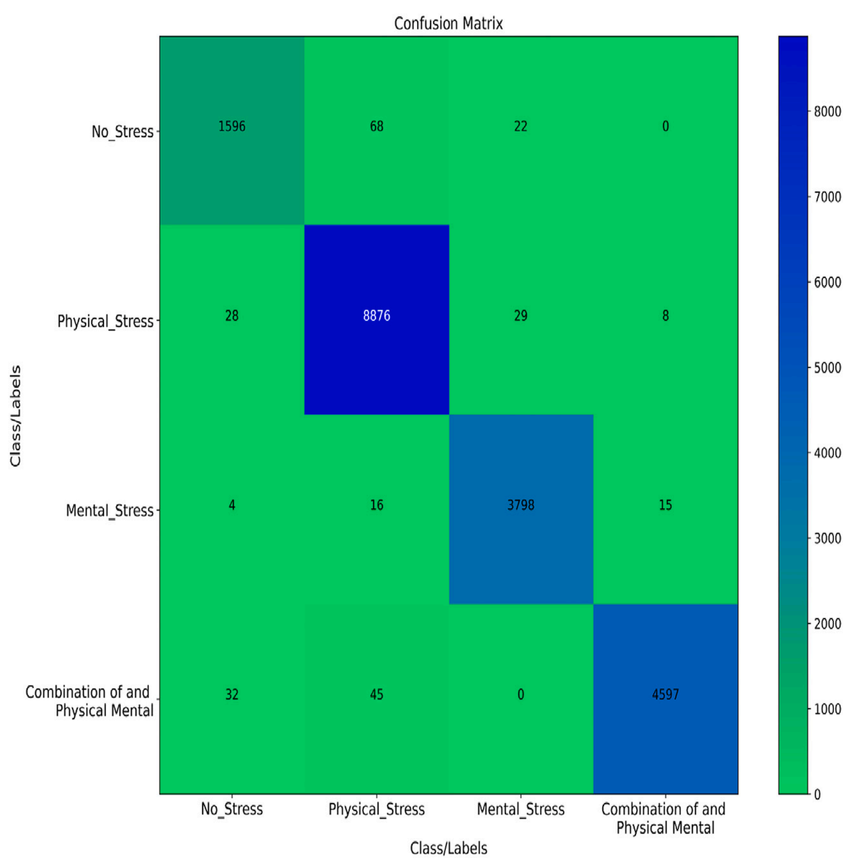

Fig. 9. Confusion matrix analysis for proposed MOR-DCNN.

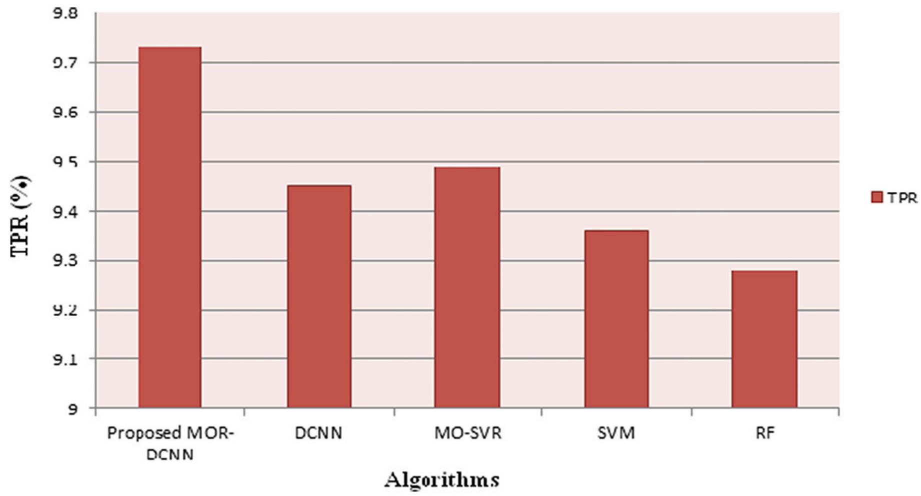

Fig. 10. Comparison of TPR for proposed vs existing models.

R) for the pooling layer then Eq. (1) can be obtained.

$$PL = \frac{R}{N} \tag{1}$$

The one or full connected layers given in the deep convolutional neural network (DCNN) is somewhat similar to the feed-forward neural networks and this layer is used for extracting the global features from the given input data. The hidden layers are connected with these fully-connected layers (Rodríguez-Molina et al., 2013) which explains the methods of accuracy approximation and comparison of cross validation and number of bootstrap samples through the study of artificial data datasets.

The posterior probability is estimated by the last softmax layer for classifying the labels as per given Eq. (2).

$$x_n = \frac{exp(-w_n)}{\sum_{v=1}^{C} exp(-w_v)} \tag{2}$$

where, x_n is the outcome posterior probability, w is the hidden layer, C is the class label, n and v is denoted as number of terms.

The multi-output regression will have input from the output of DCNN data which can be denoted as D of X number of instances which will contain the values that are assigned for each of the features F_1, ………. , $F_y and M_1$, ………, M_x. The final equation for the process of MOR is given in Eq. (3).

$$D = \left\{ \left(f^{(1)}, m^{(1)}\right), ……………., \left(f^{(X)}, m^{(X)}\right) \right\} \tag{3}$$

The input vector of y is used for characterizing each instance of data with predictive or descriptive variables as such given in Eq. (4).

$$f^{(l)} = \left(f_1^{(l)}, ……., f_j^{(l)}, ……., f_y^{(l)}\right) \tag{4}$$

The target variable for the output vector x is given in Eq. (5).

$$m^{(l)} = \left(m_1^{(l)}, ……., m_i^{(l)}, ……., m_x^{(l)}\right) \text{ Where}, j \in \{1, ….y\}, i \in \{1, ….x\} \tag{5}$$

For each control parameter to be expected, the strategy to multi-output regression requires segmenting the regression problem into a different matter. This implies the outputs are separate from each other. A variety of problems can provide remarkably accurate predictions. The main target of this multi-output regression is finding the class from D which consists of function H where each instance is assigned to it and the given vector is **f**, and the vector **m** of the target values of d is given in Eq. (6).

$$H : \Omega_{F_1} \times …….. \times \Omega_{F_y} \rightarrow \Omega_{M_1} \times …….. \times \Omega_{M_x} \tag{6}$$

$$f = (f_1, ……., f_y) \mapsto m = (m_1, …….., m_x)$$

where,

The sample space is denoted as Ω_{F_i} and Ω_{M_j} for each predicted variable F_i, for all $i \in \{1, …. ., y\}$, and each target variable M_j, for all $j \in \{1, …. ., x\}$.

The simultaneous prediction of values for the learned Multi-Output Regression (MOR) model can be predicted as per the given Eq. (7) and the new unlabelled instances for all target variables is given in Eq. (8).

$$Target\ variable = \left\{\widehat{f}^{(N+1)}, ……, \widehat{f}^{(N')}\right\} \tag{7}$$

$$For\ unlabelled\ instance = \left\{m^{(N+1)}, ……, m^{(N')}\right\} \tag{8}$$

Therefore, the classification of stress levels based on the four labels such as 'Physical_Stress', 'No_Stress', 'Mental_Stress', and 'combination of Physical-Mental Stress' can be predicted by the proposed model as per the mathematical model of the DCNN with MOR. The target variable can be the outcome of the DCCN model with the input to the MOR technique to multi class classification under new circumstances when incoming new unlabelled data.

4. Results and discussion

In this section, the experimental results are shown for the proposed MOR-DCNN model with each feature statistics based on their values. The proposed model obtains a high accuracy level more that 96% with having less error rate and based on the performance metrics given the accuracy, true positive rate, and false positive rate are performed.

4.1. Performance metrics

The performance of the classifier is analysed based on these three metrics such as, accuracy, true positive rate (TPR), and false positive rate (FPR). These performance metrics help in classifying the stress levels of sportsmen as per the equations given below.

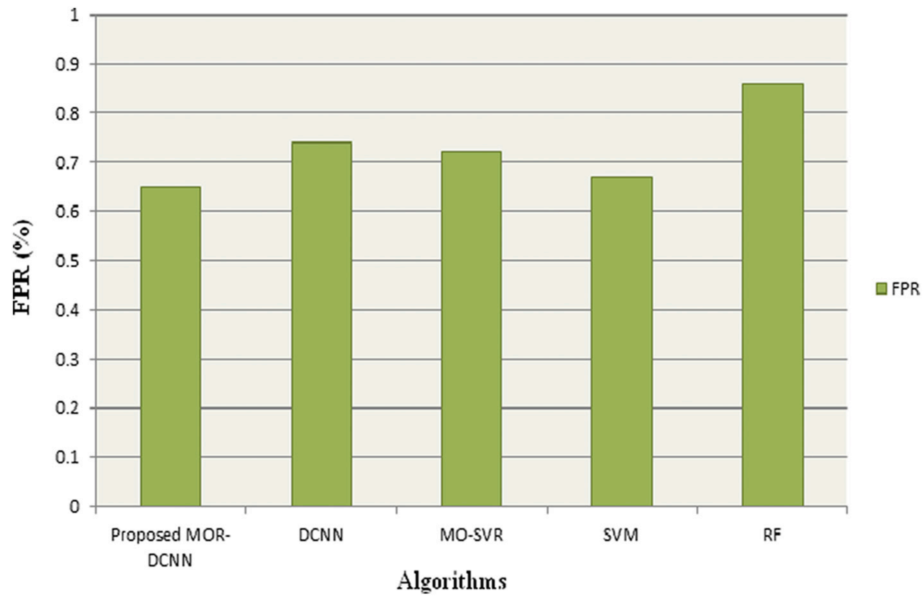

Fig. 11. Comparison of FPR for proposed vs existing models.

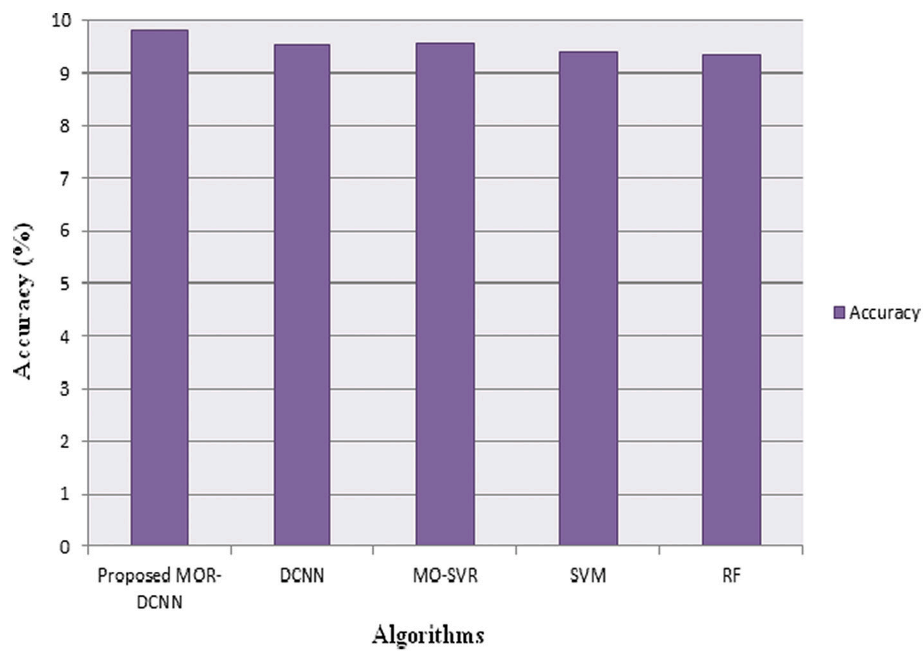

Fig. 12. Comparison of accuracy for proposed vs existing models.

$$True\ Positive\ Rate\ (TPR) = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP) + False\ Negative\ (FN)} \tag{9}$$

$$False\ Positive\ Rate\ (FPR) = \frac{False\ Positive\ (FP)}{False\ Positive\ (FP) + True\ Negative\ (TN)} \tag{10}$$

$$Accuracy = \frac{True\ Positive\ (TP) + True\ Negative\ (TN)}{True\ Positive\ (TP) + True\ Negative\ (TN) + False\ Positive\ (FP) + False\ Negative\ (FN)} \tag{11}$$

4.2. Feature statistics

Figs. 4 and 5 shows the statistics of the features for Electro dermal action (EDA) and Blood volume pulse (BVP) collected data from IoT sensor devices. The EDA in Fig. 4 shows the total number collected with the values included in it and it reads the details of electro dermal activity of the person playing sports. The BVP has certain values most similar for several readings as shown in Fig. 5 that are taken using photoplethysmography.

Figs. 6 and 7 shows the statistics for the collected data for the temperature and heart rate for each sports person and the values of the data are given clearly. The temperature data are taken based on the temperature-sensor device to analyse the certain heat level. The HRV expressed to be the heart beat rate of the sports person at rest and after play.

Fig. 8 shows the statistics of data collected from IoT sensor devices from the 3-axis accelerometer device. The acceleration range is measured from this device based on x-axis, y-axis, and z-axis. The statistics of collected data is shown in which the number of data obtained from the collected sensor with certain values and its ranges can be seen from how the stress levels can be detected based upon these data.

4.3. Confusion matrix

This technique is used for evaluation of the classification accuracy level, in which the correctly classified terms are given and how many classes are wrongly predicted. The actual prediction of certain labels can be easily identified. Table 4 shows the predicted results based on the confusion matrix. Fig. 4 shows the overview of the confusion matrix for the prediction of stress levels based on the class 'Physical_Stress', 'No_Stress', 'Mental_Stress', and 'combination of Physical-Mental Stress'. The confusion matrix helps in analysing the error prediction of classes which are not correctly classified and the overall accuracy of the mode can be obtained.

4.4. Performance analysis

The performance can be analysed based on the classification outcome of the proposed model and comparison with other techniques. Table 5 shows the overall performance of the proposed MOR-DCNN model in terms of accuracy, true positive rate, and false positive rate. The results compared with other existing models like Deep Convolutional Neural Network (DCNN), Multi-Output Support Vector Regression (MO-SVR), Support Vector Model (SVM), and Random Forest (RF) (Fig. 9).

Fig. 10 shows the performance analysis of true positive rate for the proposed model with existing techniques. The proposed model obtains an overall 97.3% of true positive rate when compared with DCNN which has 94.5%, but still MO-SVR proves to better than DCNN by having 94.9% where proposed models overcome by having higher positive rate followed with less value obtained for Random Forest (RF) algorithm. Fig. 11 shows false positive rate in which the RF has high false positive rate of 0.86% and followed with DCNN and MO-SVR having 0.74% and 0.72%. But the SVM has lesser false positive rate when compared with DCNN and MO-SVR and proposed model seems have better error rate of 0.65%. Fig. 12 shows the overall accuracy comparison for the proposed work with other existing models in which MOR-DCNN outperforms by obtaining 98.2% and least accuracy is obtained by RF having 93.4%.

5. Conclusion

In this research, a real-time analysis of physiological and physical stress detection for the sportsperson has been analysed using the proposed MOR-DCNN. The analysis of stress level for the sportsmen could be helpful in obtaining the stability of the person in handling the situation based on which sports they are playing. For this reason, the proposed stress detection model can be used to detect the stress and classify which type of levels the person is going through. The four types of stress levels such as 'Physical_Stress', 'No_Stress', 'Mental_Stress', and 'combination of Physical-Mental Stress' is labelled in the data to identify which level the sports person is having now. The model is trained with the collected data from the IoT sensor devices based on the features it obtained and these are HRV, BVP, EDA, Temp, ACC x,y, and z-axis. The proposed model obtains overall accuracy of 98.2% with having less false positive rate of 0.65% when compared with other techniques like DCNN with 94.5% and the RF has very lesser value of 92.8%. The proposed model proves to be a better classification model when compared to other techniques.

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