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IoT-Enabled Prediction Model for Health Monitoring of College Students in Sports Using Big Data Analytics and Convolutional Neural Network

ZhaoHuai Chao[1] · Li Yi[2] · Li Min[1] · Yu Ya Long[1]

Abstract

In recent years, the development of wearable devices and health applications has influenced the technical development of SHM in sports-related activities. These technologies can be invoked to improve the health management of college students who practice certain physical activities. This paper proposed and developed a novel IoT framework for sports health monitoring using prediction models based on big data analytics and convolutional neural networks (CNN). The proposed framework combines IoT technology with state-of-the-art deep learning techniques to analyze extensive data collected from wearable devices, optimizing sports performance and mitigating injury risks. The study outlines a complete methodology, including data collection from multiple sources, preprocessing for CNN models, and constructing and comparing CNN-based predictive models. Experimental results reveal the effectiveness of the proposed technique in predicting injuries and optimizing performance results. Ethical considerations, such as data privacy, model interpretability, and fairness, are also discussed to ensure responsible implementation. The findings highlight the potential of CNN and big data analytics in enhancing sports health management, offering personalized recommendations, and promoting overall well-being among college students. The experiment results outperformed the performance of the different evaluation metrics such as accuracy, sensitivity, specificity, F1 score, and MCC, with the proposed model achieving 0.9342%, 0.8500%, 0.9415%, 0.8803%, and 0.8232%, respectively. The error losses achieved less than those of the other methods, such as MSE, MASE, MAE, and RMSE, which achieved 0.0654%, 0.0758%, 0.2356%, and 0.2537%, respectively. Future research should focus on refining the models, expanding the dataset, and addressing ethical concerns to improve the framework's applicability and effectiveness further.

Keywords Sports health · Internet of things · Predictive analytics · College students · Injury prevention · Big data analytics · Convolutional neural network

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1 Introduction

In recent years, the proliferation of wearable devices and health monitoring applications has revolutionized sports health monitoring, significantly impacting health and performance management. These cutting-edge technologies facilitate continuous data collection, providing an unparalleled opportunity to improve health management, particularly among college students who engage in regular physical activities [1, 2]. It differs from questionnaires and periodic checks, where the persons being monitored must present their health status. Wearable devices and health apps give feedback in real-time and forecast. The traditional strategies are helpful, although they require modifications to serve

quick, targeted signals to audiences whose lives are fast-paced, physically active, and diverse demographics. As college students, balancing coursework, social life, and sports necessitates well-developed systems for providing timely and personalized information for decision-making [3]. Such technology-individualized biomonitoring systems are developed to consider the needs of this group, providing relevant and proper consultation to avoid or at least minimize the risks of such incidents, helping the athletes improve their performance and general health. Smartwatches and activity trackers can assess athletes' heart rate, sleep, and daily steps. This feedback is real-time, and those parameters affect performance and recovery [4]. This could be used by health monitoring applications to forecast possible diseases that are likely to occur, recommend the best workout regimens to undertake, and recommend changes that should be made in the diet. Such personalized health tips are essential for college athletes and other physically active students who must meet their instructors' and coaches' expectations and demands on their sports performance and face numerous challenges and pressures of college life [5]. In addition, advancing artificial intelligence and machine learning in such gadgets afford the ability to predict trends in health and ascertain risks. Unlike the traditional way of diagnosing a disease and providing health care services, this advancement helps in short-term and long-term health care planning and preventive measures [6, 7]. Therefore, the ongoing development of wearable technology and health monitoring applications is expected to be of greater importance to college students' health and performance, thus fostering a better and more active student society.

The technology used to carry out sports health monitoring has significantly impacted the modes of health management among college students. Several people wear professional health trackers, innovative smartwatches, and heart rate monitors that measure physiological parameters in real-time, including heart rate, sleep quality, physical activity, and energy consumption [8]. These devices are gentler and more holistic means of getting an accurate image of one's health and fitness than conventional approaches, which entail once-a-year check-ups and mostly self-reports. Further, it collaborates with wearable technologies by providing applications for recording all consumed food products, exercise plans, and other health-related tips [9]. These applications can facilitate the compilation of various data from different departments, thereby merging data points to provide a comprehensive health profile of a particular student. Such repetitive monitoring is essential since the more frequent monitoring is, the better the chance is to identify small shifts in the health status. For instance, training over-training and under-recovery patterns are noticed initially, minimizing the onset of injuries and enhancing the athlete's performance

[10]. Internet of Things technology also improves the mechanisms used in sports health monitoring systems. Connected things are easily linked, can be programmed, and work in unison, generating a hub of connected things that collects and shares information at a given time. This connectivity facilitates building an elaborate health monitoring structure capable of capturing large amounts of data and not misleading [11]. This is important given that additional factors like temperature, humidity, etc., can be measured together with physiological data to offer a more comprehensive picture of the conditions likely to impact a student's performance and health.

College students engage in sporting activities; monitoring their health, especially concerning injuries, regularly becomes paramount. This risk evaluation technique enables the institute to prevent potential risks, significantly reducing accidents that may hamper the learner's academics and sporting activities. Regular examination is needed to identify early signs of stress or strain in a way that is crucial to the health of a train in the long [12]. The generation of technology is significant in monitoring the health of college students that involves sporting activities. Smartwatches and other health monitoring applications enable data generation in real time regarding different parameters, including heart rate, physical activity, and sleep patterns [13]. These technologies gear real-time feedback and analytics; this enhances the decision-making of students and their trainers concerning training and regenerative periods. Another aspect is modern algorithms, and AI's possibilities in making the devices predict future health issues, which may result in serious complications [14]. This approach makes training schedules less of a problem because they are made depending on the other that requires them. Incorporating these technologies in sports health monitoring is a significant step in promoting and optimizing health management. Engaging in healthy lifestyle practices is highly encouraged, considering the potential detrimental effects of stress on human health [15]. College students are among the country's most stressed demographics because of academic, social, and other pressures; deciding to exercise is an excellent way to reduce pressure. It enhances commitment to exercise, proper diet taking, balanced nourishment, and provision of rest, all leading to improved health standards [16–17]. Besides providing a sound body, all these habits also lead to a sound mind and soul, promoting holistic wellness in colleges.

As for sports health monitoring, this paper presents an enhanced methodology of comprehensive scholarships for college students based on IoT wearable devices, big data analysis, and health Apps using Convolutional Neural Networks (CNN). Wearable technology, where students wear fit trackers and heart rate monitors and incorporate them into

health applications, allows for real-time data collection of the health status of students as well as their level of physical activity. Big data analytics analyze this tremendous amount of data to reveal patterns that help in the accurate monitoring of health and enable predictions to be made. The integration of CNN helps improve the proposed framework in considering sequence training characteristics and growing in the recommendation process. Thus, applying the recommendations would be flexible depending on the individual's varying physiological capacity, minimizing the probability of incurring injuries. The suggested framework is meant to revolutionize college students' sports health management in terms of enhanced timely information delivery, encouragement of proper health practices, and the general well-being of the students under consideration; all these are to be achieved through advanced technological support and state-of-the-art analytics. Firstly, the proposed framework utilizes wearable IoT devices to continuously monitor patients' physiological and environmental parameters in real-time as part of the data acquisition. Secondly, business intelligence stores organize and manage the collected data and perform big data analytics to weave the information from various sources into one unified health picture. Thirdly, the proposed framework employs CNN to generate training and recovery prescriptions and the training and recovery optimization depending on the current state of the trained subject. Finally, concerns about the ethical use of reductionist technologies and summed-up data for portraying college student sports health monitoring are introduced to include data privacy, informed consent, and bias-sensitivity. Also, it supports developing a proper diet plan that will lead to sustainable healthy behaviors in the future and a decreased probability of developing chronic disorders. This paper describes the technological foundation and the advantages expected from good college health management. These implementations have to be made for the successful management of health in college with the primary goal of revolutionizing the present unhealthy condition of college athletes.

The main goals of this paper are the following:

- Firstly, to establish an IoT-based framework for incessant sports health monitoring, using wearable devices and health applications for real-time data collection.
- Secondly, big data analytics and CNN should be integrated to process and analyze the extensive data collected, enhance predictive capabilities, and provide personalized health recommendations.
- Thirdly, the proposed framework optimizes sports performance and reduces injury risks among college students by offering timely insights and adaptive training recommendations based on real-time data.

- Finally, ethical considerations such as data privacy, informed consent, and fairness in using technology and data should be addressed, ensuring the responsible and practical application of the proposed health monitoring system.

The remaining sections of the paper are organized by the order as follows: Sect. 2 of the paper illustrates the state-of-the-art literature review; Sect. 3 of the paper represents the material and methods of sports health monitoring; Sect. 4 of the paper shows components of the assisted physical activity sports health monitoring system; Sect. 5 is representing the experimental results and analysis of the paper. Finally, Sect. 6 of the paper concludes the research work.

2 Literature Review

In the past, sports health monitoring has involved sporadic check-ups with a physician, questionnaires, and coach observations. Although worthwhile, they require constant, timely feedback for timely and effective health promotion. The examinations enabled athletes to be checked occasionally, providing a view of their health status at a particular time; this does not detect changes daily. The study's subjective nature involves using self-reported questionnaires that lead to recall bias while coaches' observations are considered. While self-generated reports have known limitations, such as recall bias, observations by the coaches in this study are prone to subjectivity. Technological development in sports health monitoring has advanced due to wearable technology and IoT inactivity monitoring devices that allow the continual assessment of sports physiological and activity data [18]. Cover wearable devices, including fitness trackers and heart rate monitors, and measure real-time variables, including heart rate, steps, calories burnt, and sleep quality. Sensors for the environmental context are IoT devices that help add such context as temperature, humidity, and so on – a vital option for understanding the effects on performance. It also enables enhanced health tracking frameworks, allowing immediate response and individual adjustments. Such data collection enables early detection and understanding of patterns or trends, avoiding overtraining or injuries and improving the accuracy of overall health care for athletes.

The transfer learning method to create new summaries is the sports videos based on the classification of parts. This study focused on fine-scene categorization within these contexts, which brings practical strategies into action [19]. The study classified scenes into five categories: ABI comes in five types: batting, bowling, bordering, crowding, and close-up, which are analyzed for tagging using the AlexNet pre-trained model. In the approach, new fully connected layers

compared to an encoder were used, which improved data by 99%, with a lower percentage of over 26% on smaller datasets to obtain high accuracy. The test proved its effectiveness in contrast with traditional methods, where Facebook's AlexNet model takes more advantage than other professional models such as Inception V3 and VGGNet16. This study utilized neutrosophy theory to visualize sportsfests selected with significant sporting events. There, Excel data statistics, mechanics, and dynamic functionalities are used to categorize and recognize sports media events. In these aspects, their analysis showed the sequential development of the sports media through the 'beginning period,' the 'high tide,' the 'decent,' and the related ideological values, stochasticity, and fractality of these events proved the positive externalities of media sporting events on the range of sporting activities [20]. This study enhanced the convolutional innovative approach by implementing a real-time violence detection system in football stadiums employing the Histogram of Oriented Gradients and Bidirectional Long Short-Term Memory (HOG-BDLSTM). Real-time video feeds are processed through the Spark; the HOG algorithm is applied to the frames. They are labelled with models of violent and non-violent actions, human aspects, and violent behaviour to educate BDLSTM on the occurrence of violent incidents [21]. Therefore, the system can likely generate the required outputs once past and future data have been included. They are introducing NLP-CI in match analysis and scouting through artificial intelligence. They described how sports professionals can apply NLP-CI and how it can help them more efficiently explore data sets and develop valuable big data AI tools for domain scientists and specialists. This could affect elite and popular sports with limited access to specific resources. It helps badminton specialists examine trajectory information in immersive environments like virtual reality. This system offers an analysis of the raw data, such as the movements of the players and the shuttlecocks, in a way that guides the player's behavior and may be used to improve the player's performance [22].

Based on previous research, this paper aims to investigate the synergy between deep learning and big data analytics, particularly in monitoring sports health. It has been used broadly in the medical field, including Disease prediction, medical image analysis, and Personalized treatment mapping. The study's findings also highlight that it is valuable for activity recognition, performance analysis, and prevention of injuries in sports science, summarizing its ability to offer accurate and real-time evaluations for sports health monitoring. Big data analytics is a critical capability in this area, which aims to process and analyze big data to find insights. In the context of sports health research, big data can be compiled from multiple platforms containing data such as data generated by wearable devices, the

medical history of the person, and the environment sensors surrounding any particular person. The knowledge discovery process includes data mining, machine learning, and predictive modeling variables often used to analyze this data. Coupled with reinforcement learning, Convolutional Neural Networks CNNs have been applied to solve diverse decision-making issues across disciplines such as robotics, finance, and healthcare. These methods can learn optimal policies as the system's behavior is tried and tested. In sports health monitoring, CNNs can map the chronological order of training and recovery and suggest more effective health management according to the subject's physiology compared to existing approaches benefiting from the previous day's training records only.

3 Materials and Methods

3.1 IoT Framework for Sports Health Monitoring Among College Students

The framework of using advanced IoT for sports health monitoring among college students is implemented with wearable devices, a mobile application, environmental sensors, and Health records for the overall health assessment data acquisition. These are provided and transformed through state-of-the-art deep and transfer learning methods so that real-time decision-support feedback and tailored suggestions are given. These measures make the model highly effective and safe from injuries by constantly monitoring and adjusting its performance, offering the patient a highly effective and adaptive health monitoring model. Data collection in this more advanced IoT framework is holistic and triangulates various sources to capture health and activity data from college students [11–23]. Smart devices and wearable gadgets like the fitness tracker and the heart rate monitor provide unending data such as heart rate, steps made, and calories expended. Mobile health applications support this by recording the consumption and calories, forms of exercise, and sleeping schedule. Contextual data include temperature, dust and carbon monoxide levels, and humidity collected by environmental sensors; clinical data include EHRs, which summarize the patient's medical history and current state. Such data collection from multiple sources helps get a comprehensive picture of the student's health and daily activities. Preprocessing methods are critical approaches to dealing with large and varied data characteristics. Data cleaning means that there is always an identification of and dealing with missing/inaccurate/on the wrong units' data. Normalization scales all the data to equate scale, which will enable comparisons to be made. It separates the dataset into time intervals suitable for refined

analysis of the continuity of data received over some time. Feature engineering further derives features from pre-sensed data, such as activity rigour and sleep quality. Algorithms then reduce the size of the dataset by removing the most minor significant features; this enhances operational efficiency during the subsequent steps [24]. That may be why combining data from different sources remains one of the critical elements of the big data analytics approach. Data fusion continues information from sensors and applications as a unified data set. Abnormality detection is a process that seeks to identify nutrient patterns that could herald ill-health in the body. Conceptual grouping of repeated structures in the data is similar to pattern recognition, while forecasting predicts future states of health and performance. Operate to bring identical data points together, which helps in pattern or group analysis for different students' datasets.

The framework uses various supple techniques based on state-of-the-art machine learning algorithms to analyze the preprocessed data. Adopt CNNs and LSTM because of their high-dimensional patterns and temporal characteristics in large-scale data learning [25, 26]. In transfer learning, the learned information from the previous tasks is used to train the new models and boost the efficiency of the models with limited training data. Bags of models integrate several models to generate solutions in analyzing data to facilitate accurate and reliable predictions. A real-time decision support system uses decision support models that make immediate decisions and responses. Finally, it keeps changing the training schedule and the session intensities according to the individual's current condition to get the best out of the person and simultaneously avoid any impacts on the improvement process. It also has warning signals to prevent injuries, poking, overheating, and any other signs that may be picked to show that an athlete or a particular team is overtraining. There is always a need to check and ensure these models are still good to go to prevent jeopardizing the overall business. Flags, commonly used measures of performance, are accuracy, precision, recall, and F1-score, and they are used to measure the outputs of models. The models are updated frequently from the new data set and user feedback; CNN has also been implemented for better learning and adaptation. Other methods make the decisions and predictions easily understandable and interpretable by the current decision-makers. Finally, it seeks optimal performance in assessing sports health and utilizing cutting-edge technologies and methods. The competency-based and feedback loop models entail constant and timely checks on the states of health and performance of college students to guarantee the provision of an optimal monitoring system that is health- and performance-focused, as shown in Fig. 1.

3.2 Data Collection

This dataset will include Physiological and activity data obtained from wearable devices, such as heart rate, step count, sleep duration, and physical activity intensity. Other parameters include environmental parameters that may affect the unit's performance, such as temperature (T) and humidity (H). Because of this, the collection of data for this framework includes gathering information about the student's overt situation and the covert situation within the physiological system of the student. Accordingly, combining these measures makes it possible to construct a solid dataset to determine college students' health and performance and provide recommendations [27]. This complete information collection enables a holistic view of college students' health, considering both internal physiological states and external environmental conditions; the dataset is described as follows:

$$D = \{(HR_i, SC_i, SD_i, PAI_i, T_i, H_i) \mid i = 1, 2, .., N\} \qquad (1)$$

Where N is the variety of data points collected, then each HR_i, SC_i, SD_i, PAI_i, T_i, and H_i gives the information point at time i, which provides an extensive database of health and environmental records in all dimensions wanted for an individual's health recommendations.

3.3 Data Cleaning

The cleaning steps are part of the initial degree of data evaluation, which aims to eliminate any inaccuracies in the data. This entails checking for consistencies within the data sets and eliminating all the consistencies to avoid a distortion of the actual data sets. Deletion and imputation enable completeness on missing data points simply because the whole set may be complete with these data points. Finally, bringing consistency in data formats and eradicating any provenances increase the uniformity of a specific dataset. This approach is thorough, ensuring the data's consistency and validity for further testing. Hence, dealing with duplicate records is an important step that should be taken to avoid a whole bunch of erroneous conclusions made during analysis. If left unattended, such entries will distort certain aspects and give the wrong impression of interpreting the results. Removing the duplicated records from the data is a good idea to handle this.

If D represents the original dataset and $D\prime$ represents the cleaned dataset without duplicates, the relationship can be expressed as:

$$D' = D - \{x \in D \mid count\,(x) > 1\} \qquad (2)$$

Fig. 1 The IoT framework for sports health monitoring for college students
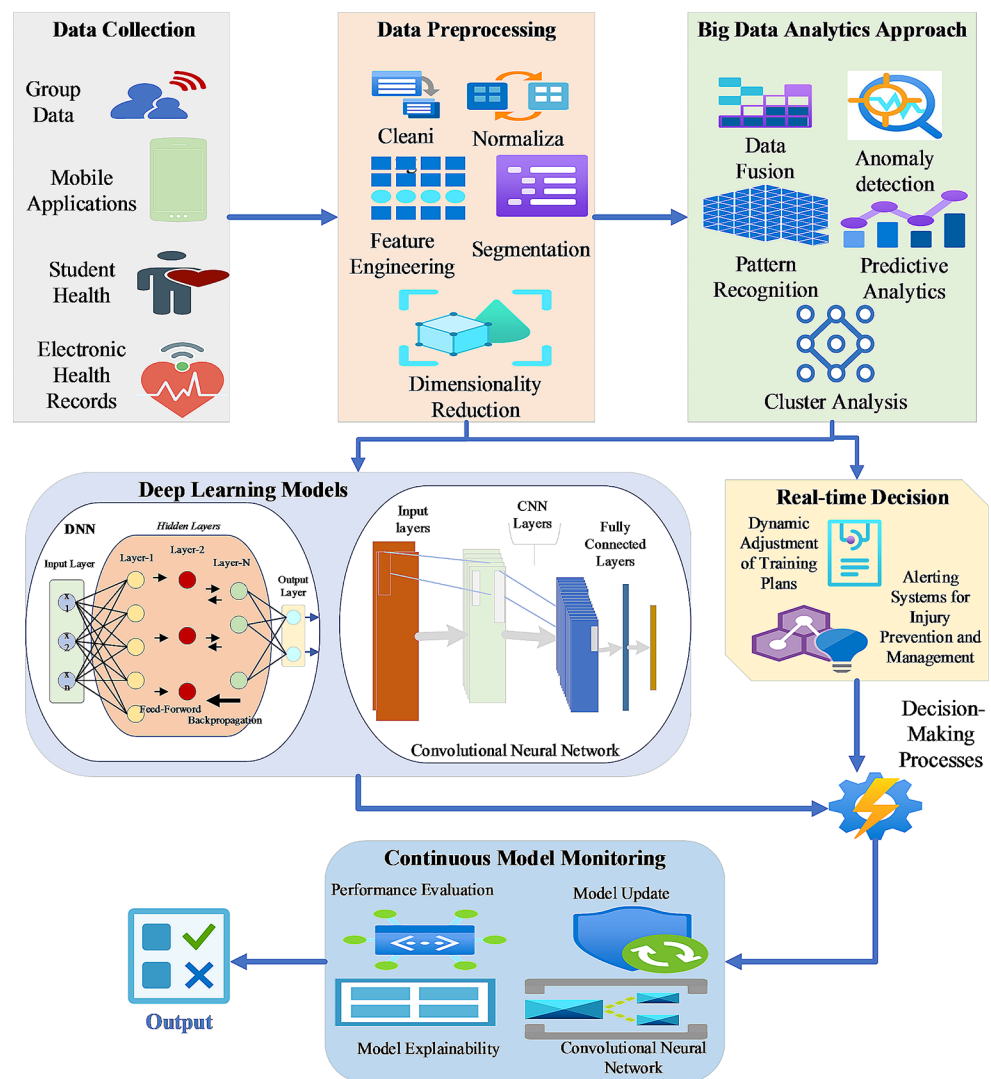
The above equation means that D prime is accomplished by eradicating all the repetitive elements from the original dataset in the form of x. This process eliminates similar and duplicated instances, so the cleaned dataset D' includes no repeated entries, and further analysis and data processing will be more precise and accurate.

To that extent, methods of dealing with missing data are essential steps to take to adjust for any data gaps when conducting analysis. There are two standard approaches to handling such data points: imputation, where missing values are substituted with other possible values, and deletion, where total records with missing values are deleted. For mean imputation, the missing value is replaced by the average of the observed values, as expressed in the following equation:

$$x_{imputed} = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad (3)$$

Here, $x_{imputed}$, refers to the imputed value, x_i refers to the available values, and n represents the actual number of recorded values. This strategy helps to maintain the availability of the necessary data to provide extensive coverage, which is instrumental in generating accurate analysis.

In other words, keeping data consistent in a larger context is suitable for pulling out consistent information from the dataset. Standardizing data formats and correcting inconsistencies are key steps in achieving this.

$$C = standardize(D_{clean}) \qquad (4)$$

Where C is the corrected dataset, achieved through normalization of the cleaned dataset, which D_{clean} denotes the function standardizes controls standardizing all data within D_{clean}, so there aren't any odd-shaped entries. It also refines the dataset, making the information collected complete and more consistent, which makes for better analysis and improved interpretation.

3.4 Preprocessing Steps

Data cleaning preprocessing will prepare the analysis for normalization methodologies, including separate min-max scaling or z-score normalization, to guarantee all data is on the same scale. For a feature x in the dataset, the normalized value x′ is calculated as:

$$x' = \frac{x = x_{\min}}{x_{\max} - x_{\min}} \tag{5}$$

Alternatively, z-score normalization:

$$x'' = \frac{x - \mu}{\sigma} \tag{6}$$

Where μ is the mean, and sigma is the standard value of x. $x_{\min}$, is the minimum and maximum value of the dataset for x. This transformation ensures that all the values of x are taken and scaled in the same proportion within an assigned barrier, preparing each feature for fair comparison.

3.5 Feature Extraction

Feature extraction is central in turning raw sensor data into usable insights into college students' health and physical activity. This process entails extracting key business performance indicators from the collected data through wellness tracking gadgets, including smartwatches and fitness trackers, among other sensors. These features provide a complete picture of their physical activity, physiological parameters, general health, and the various statistics, frequencies, and numerous other features that can be derived from raw data. Quantitative characteristics are essential for summarizing the data acquired in SHM through wearable devices and analyzing the collected information [28]. Such features are the arithmetic average heart rate during an interval mean heart rate, μ_{HR}, and the indicator of the dispersion of the distribution of heart rates σ_{HR}. Activity intensity (AI) is another parameter, the mean value of the vector of the acceleration rate obtained from the accelerometer, averaging all the observed activity data and representing the general level of physical activity. These statistical features provide information on college students' physiological state and activity patterns toward objective health assessment and monitoring. The following statistical descriptors constitute essential aspects of conceptualizing and quantifying sports health monitoring data from wearable devices. Mean heart rate μ_{HR}, is used to determine the average of the various variability over a given time, thus giving us a primary reference point in checking cardiovascular health. The coefficient of variation in heart rate represents the standard deviation of

heart rate σ_{HR}, reflecting the physiological stress or activity level.

The mean is determined to obtain a reference value that can be used to analyze heart rate values in the dataset. All the heart rates are calculated by getting the mean of the entire set of measurements. The formula for the mean heart rate is:

$$\mu_{HR} = \frac{1}{N} \sum_{i=1}^{N} HR_i \tag{7}$$

In this equation, HR_i, is each heart rate reading, and N is the sample size, which is the number of readings taken. To derive the average heart rate for the entire dataset, all the obtained heart rates are then divided by the number of measurements, which will depict the mean or average heart rate of the totality of the dataset.

The standard deviation of heart rate calculates the amount of spread or dispersion from the mean concerning heart rates within a given dataset. It shows the degree to which the measurements are far from the average heart rate. The formula for the standard deviation of heart rate is provided in Eq. 8:

$$\sigma_{HR} \sqrt{\frac{1}{N} \sum_{i=1}^{N} (HR_i - \mu_{HR})^2} \tag{8}$$

HR_i represents each heart rate measurement, μ_{HR} is the mean heart rate, and N is the total number of measurements. By calculating the squared differences between each heart rate value and the mean, summing these differences, and then taking the square root of the average, we obtain the standard deviation. This measures how spread out the heart rate values are around the mean.

Activity Intensity measures the overall intensity of physical activity, calculated using the accelerometer data from three axes x, y, and z. The formula for AI is:

$$AI = \frac{1}{N} \sum_{i=1}^{N} \sqrt{a_{x,i}^2 + a_{y,i}^2 + a_{z,i}^2} \tag{9}$$

Here, $a_{x,i}, a_{y,i}$, and $a_{z,i}$ represent the accelerometer readings along the x, y, and z axes for the ith measurement, respectively, and N is the total number of measurements. Obtain the activity intensity by squaring the readings from each axis, summing them, taking the square root of the sum, and averaging these values across all measurements. This measure provides an overall assessment of physical activity intensity based on the accelerometer data.

The Fourier transform of heart rate is used to convert the time-domain heart rate signal into its frequency-domain representation. This helps in analyzing the frequency components present in the heart rate data. The formula for the Fourier transforms of heart rate is:

$$FT_{HR}(f) = \sum_{i=1}^{N} HR_i . e^{-j2\pi f t_i} \tag{10}$$

HR_i is the heart rate assessment at the specified time t_i, at the same time, f is the frequency, N represents the number of heart rate assessments, and finally, j symbolizes the imaginary number. This transformation lets us analyze the segment of the ECG, which has a frequency nature and reveals periodic and other frequency characteristics of the heart rate signal.

HRV describes a range of time intervals between consecutive beats, commonly called the NN intervals. They are important in measuring the activity of one of the significant components of the peripheral nervous system, the autonomic nervous system. The formula for HRV is:

$$HRV = \frac{1}{N-1} \sum_{i=1}^{N} (NN_1 - \mu_{NN})^2 \tag{11}$$

Here, NN_i refers to a specific NN interval, μ_{NN} refers to the mean of all the intervals, and N represents the total number of intervals of NN. The variance of the intervals is calculated by directly adding after squaring the differences between each interval and the average interval, NN_1. This variance is the HRV, a measure of the fluctuation in the heartbeat rate, and is the characterization of cardiac and autonomic prognostics.

Energy expenditure defines total energy throughout time and requires a more significant number of calories to perform than the resting metabolic rate (RMR). It is usually done using MET values, body weight, and exercise or physical activity time. The formula for EE is:

$$EE = \sum_{i=1}^{N} (MET_i \times W \times \Delta t_i) \tag{12}$$

MET_i, is the metabolic rate of the ith activity, W is the body weight, and Δt_i, is the duration. The below adds all the MET values for the total time spent undertaking each activity to give the total energy expenditure throughout the period. Physical activity can be defined as the total amount of energy an individual expends in activity; thus, this measure aids in evaluating.

# 4 Evaluation of Physical Activity Sports Health Monitoring

Measurement of Physical Activity in SM in sports concerning health involves monitoring systems that can successfully capture aspects of physical activity with those involved in sporting activities. This evaluation often involves reviewing data acquired by wearing a device and comparing it to standards and norms. The benchmark comprises activity step count precision, heart rate, sleep cycle monitoring, and activity intensity. The purpose is to keep monitoring the chosen metric so that people can get trustworthy reports on how active they are in body and mind and use this information to improve their health.

4.1 Components of the Assisted Physical Activity Sports Health Monitoring System

Assisted physical activity sports health monitoring enables innovative IoT technologies to give college athletes real-time physical health status information. It covers wearable devices, access points, routers, cloud storage, and servers that form the system's infrastructure. Fitness trackers, heart rate monitors, sleep tracking, and GPS trackers measure the amount of physical activity, the number of heartbeats per minute, the hours of sleep, and the extent of effort. They employ Wi-Fi and Bluetooth technology to transfer this data to other corresponding Access Points, strengthening the connection. These devices are managed by an IoT Gateway router, which connects them to the internet through cellular WAN connections. The data collected is then stored in IoT cloud storage and processed within the personal and medical servers for real-time analysis [29]. This setup enables the healthcare provider to have constant and proximity access to the patient's information for real-time chronic care and urgent treatment whenever the need arises. Figure 2 shows this system makes it possible to develop individual approaches to their clients, identify health issues early, and respond to emergencies as best as possible, thus improving college students' health when they are involved in different sports activities.

These data are stored in IoT cloud storage systems acquired by the transmission procedure. Individuals and medical servers perform this duty, making it easier and quicker to sort and analyze them. Cloud storage services for big data mean that data storage can be expanded, and personal and medical servers will remain near the data; it will perform computations on them or access them as necessary. The monitoring system generates massive data, which must be stored in the data center. This data can then be made available remotely for usage by health care providers, thus not only allowing for frequently continuing remote care. It

Fig. 2 IoT framework for sports health monitoring
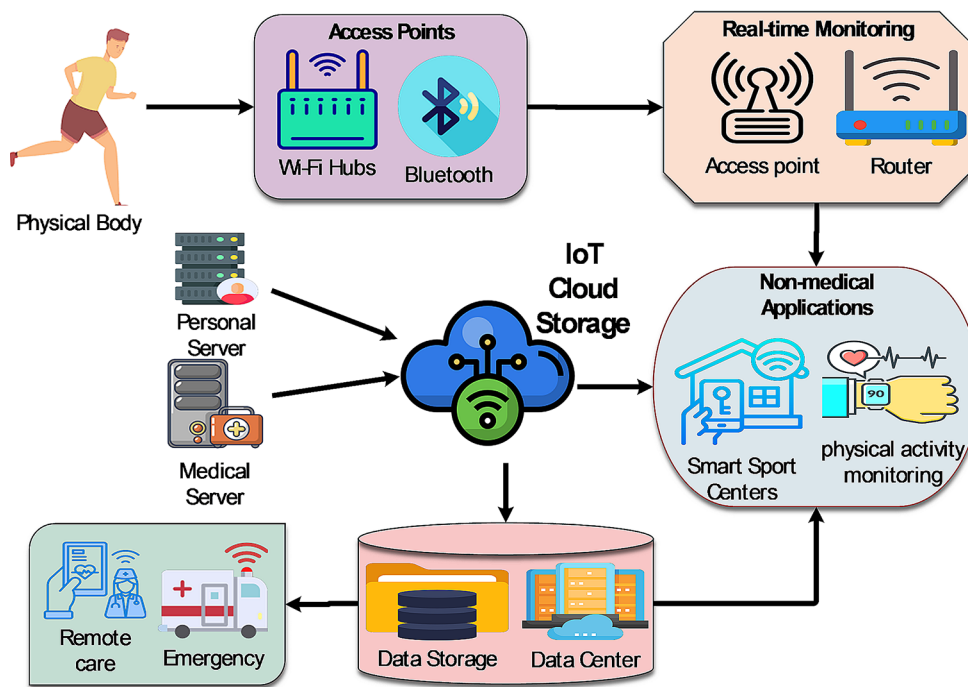
can also aid in notifying the physician or any medical personnel in the event of health complications to enable early treatment. Physical Activity Intensity (PAI) measures the intensity of physical activity over a period T. It is calculated by integrating the squared rates of change of position along the x, y, and z concerning time in the formula for PAI:

$$PAI = \frac{1}{T} \int_0^T \left(\sqrt{\left(\frac{dX(t)}{dt}\right)^2 + \left(\frac{dY(t)}{dt}\right)^2 \left(\frac{dZ(t)}{dt}\right)^2} \right) dt \quad (13)$$

Here $\frac{dX(t)}{dt}$, $\frac{dY(t)}{dt}$ and $\frac{dZ(t)}{dt}$ is the angular velocities affecting the objects along the x, y, and z at time t respectively.

Caloric Burn Rate refers to the rate at which total calories are burnt throughout the day and as a result of completing different physical activities according to intensity, duration, MET value, and performance weight. The formula for CBR is:

$$CBR = \left(\sum_{i=1}^N (Activity\ Intensity_i \times Duration_i \times MET_i) \right) \times Weight \quad (14)$$

Here, Activity intensity represents the intensity of the ith activity, $Duration_i$, is the duration of the ith activity, MET_i, is the metabolic equivalent of the activity, and weight is defined as body weight. To derive the CBR, we add the products of the activity intensity, duration, and MET values of each activity and then multiply the outcome by body weight. Thus, CBR is the total level of calories expended during the activities. Health-conscious people, athletes, and those who seek to shape their bodies can invest adequate time in several activities to maximize their CBR and achieve their fitness goals.

4.2 The Role of Wearable Technology in Modern Sports Health Monitoring

Mobile devices, smart watches, body sensors, smart shoes, smart shirts, smart glasses, and smartphones have become essential tools for monitoring the health of athletes in contemporary sports. It monitors the user's heart rate, body temperature, blood pressure, and physical activity. Vital signs and physical activity are captured from the wrist or regular clothing through smartwatches and body sensors, while smart shoes capture movement, steps, and gait. Smart shirts and glasses also collect more physiological and environmental information [30]. This data is transmitted through Bluetooth and the GPRS to the IoT Gateway Router, which acts as the central provider, ensuring proper connection to IoT Cloud Storage. This cloud infrastructure helps establish an analytical view of the collected data as and when it is gathered. Physical activity: healthcare professionals use software to follow students' physical activity, record abnormalities or illogical behavior, and give health advice accordingly. Real-time monitoring makes it possible to provide feedback instantly and modify training plans in the training process, as well as general health and performance benefits. Such integration presents the cohesive system between wearable technology, IoT systems, and the healthcare sector

aimed at enhancing the health of sporting individuals and optimizing college students' athletic output, as presented in Fig. 3.

Electrical apparel, Smartwatches, Body sensors, Smart shoes, Smart shirts, and Smart glasses are important aspects of modern-day sports health monitoring. It is now possible to hold small devices that constantly monitor patients' heart rates, body temperatures, blood pressures, and activity levels. Smartwatches and body sensors are small, portable, and placed around the garment. It monitors vital signs and physical activity using the following equations:

The core temperature at a given time t can be predicted as a base temperature BT0 + weighted sum of temperature measurement. The formula for BT is:

$$BT(t) = BT_0 + \frac{\sum_{i=1}^{N}(T_i . w_i)}{\sum_{i=1}^{N} w_i} \tag{15}$$

Here, BT_0 represents the base body temperature, T_i represents the ith temperature measurement, and w_i represents the weight assigned to the ith temperature measurement.

A feedback loop can be represented as a control system that adjusts its output based on the difference between the desired and actual values. The formula for a Proportional-Integral-Derivative (PID) feedback loop is:

$$FL(t) = K_p e(t) + K_i \int_0^t e(\tau)d\tau + K_d \frac{de(t)}{dt} \tag{16}$$

Here, $e(t)$ is the error at time t, K_p is the proportional gain, K_i is the integral gain and K_d is the derivative gain.

4.3 Deep Learning Architectures

The Convolutional Neural Networks (CNNs) model will incorporate features using deep learning techniques, such as the convolutional neural network for the convolutional layers and the recurrent neural network for the recurrent layers. The merged architecture will allow the model to analyze the data sequences and patterns in space and time, boosting the predictions.
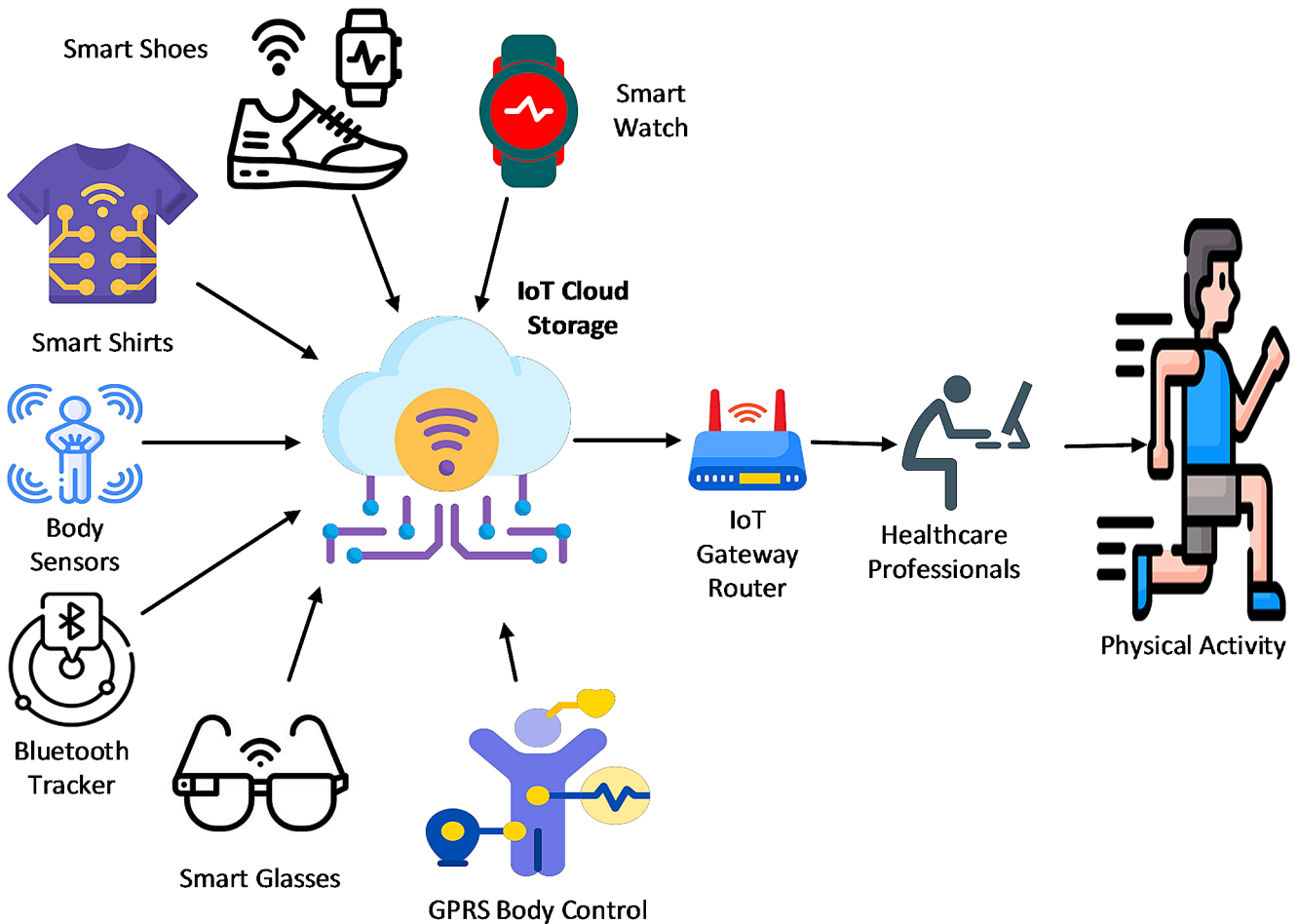

Fig. 3 IoT-based wearable technology system for sports health monitoring

4.3.1 Convolutional Neural Networks

Sports health monitoring with the help of convolutional neural networks starts with input sports health data containing a list of physiological parameters. This data passes through feature extraction by several convolution layers, where filters are applied to recognize certain appearances [31]. Then, it goes through pooling layers to downsample the data to lower dimensions and reduce computational complexity. Stacking multiple Convolution and Pooling Layers helps identify the relevant features from the input data. Hence, fully connected layers are used for feature classification, depending on the features extracted from the input. Figure 4 is given in the Output layer according to the problem's needs, whether health-related problems or performance parameters.

4.3.2 Recurrent Neural Networks

Recurrent neural networks, exceptionally long short-term memory (LSTM) networks, are suitable for sports health monitoring since they are designed to address sequential data. In simple terms, it starts with a Sports Health Dataset comprising multiple physiological parameters. After performing feature extraction, raw data involves the convolution layer of 32 filter sizes to identify the first level of features and the pooling layer to minimize data dimensions [3]. A second layer of the Convolutional Layer with a filter size of 64 enhances the feature extraction process. In contrast, the second layer of the Pooling Layer reduces the amount of data involved even more. It then goes into the RNN LSTM Layer, and an input vector representing the extracted feature is passed through it. The LSTM network deals with the temporal properties and sequences, and the feature vector represents the extracted information at the final step of time. Lastly, the Output Layer employs this information; it generates assessed and unassessed health indices for usable information on sports health checks, as illustrated in Fig. 5.
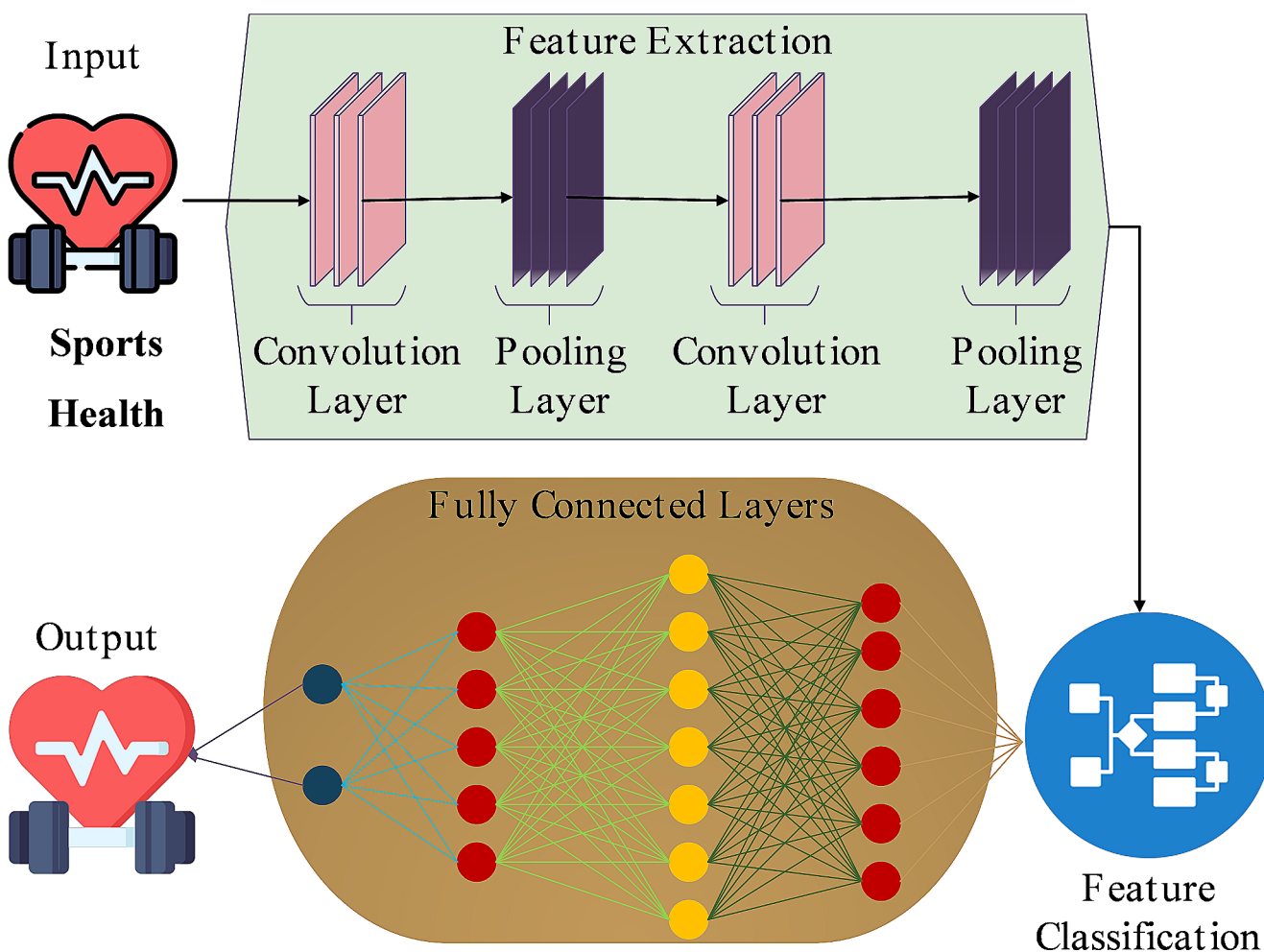

Fig. 4 The architecture of the CNN-based predictive model

4.3.3 Performance Evaluation Metrics for CNN-Based Predictive Models

Hyperparameters and optimization techniques must be fine-tuned for efficient model usage depending on the level of performance required. Their work includes choosing the correct combination/ tuning of hyperparameters, which include the learning rate, the strength of the regularization, and the kind of networks needed to fuel the model. Conventional methods are grid search, random search, and other auto-tuning hyperparameters methods such as CNN algorithms and RNN also exist. Nevertheless, cross-validation and early-stopping techniques help avoid overfitting and increase the model's generalization capabilities. The hyperparameter optimization results in better skilled, resistant, and competent models more suitable for real-life situations [32–33]. Several performance measures are invariable when evaluating CNN-based predictive models because a thorough analysis requires these aspects. There are primary epidemiological indices such as accuracy, sensitivity, specificity, MCC, precision, recall, F1 score, Mean squared error (MSE), Mean absolute scaled error (MASE), Mean absolute error (MAE), and Root mean squared error (RMSE). Applying these metrics allows for the evaluation of the model's ability to predict the outcomes given the input data, and the results can be enhanced and compared to one another effectively, especially in different data sets and in other settings of the same model.

5 Experimental Results

The paper's experimental results show the performance of CNN models given to the validation dataset. It includes basic techniques of various measurements such as accuracy, sensitivity, specificity, F1 score, Matthews correlation coefficient, Mean Squared error, Mean Absolute Scaled error, Mean Absolute error, and Root Mean squared error. It provides a comprehensive method for evaluating how well the

model will work since all aspects have been tested. Moreover, the proposed CNN-based approach is compared to conventional techniques and algorithms to assess the efficacy of sports health monitoring and check the proposed approach's optimal performance. Understanding how different methodologies may be more or less beneficial depending on their various functionalities is important. Moreover, the analysis in the paper guides the usage of the model's forecast and advice as derived from the classification, which adds depth to the discussion of the applicability of these findings in practice. The experimental results are significant in ascertaining the effectiveness and suitability of CNN models in supporting the progress of this research field.

The requirements for the system configuration also guarantee that the interconnections at the moment of its implementation and during experimentation are suitable. This includes requirements for the operating system, Windows 10; programming language, Python 3.7.0; PyTorch 1.2 or later for Python 3.5 or later; and TensorFlow 1 for Keras 2.7.0. It also specifies the prerequisite software environment Anaconda 3 & Jupyter Notebook. At the same time, from the hardware point of view, it includes details regarding the CPU, RAM & GPU specifications of the computer used, namely Intel Core i7, 16 GB RAM, and NVIDIA GeForce GTX 1060, respectively. Table 1 summarizes the systems that should be in place to put the relative configurations.

An optimal learning rate enhances the model's accuracy and highlights the importance of selecting and effectiveness in sports health monitoring. As proposed, a learning rate of 0.01 achieved the highest accuracy of 93.42%, along with notable sensitivity, specificity, F1 score, and MCC values. Lower learning rates, such as 0.001 and 0.05, resulted in slightly lower accuracy, while higher rates, like 0.1 and 0.5, decreased performance across all metrics. Figure 6 presents the impact of different learning rates on the performance metrics of the CNN model.

Figure 7 presents performance metrics like Mean Squared Error (MSE), Mean Absolute Scaled Error (MASE), Mean Absolute Error (MAE), and Root Mean Squared Error

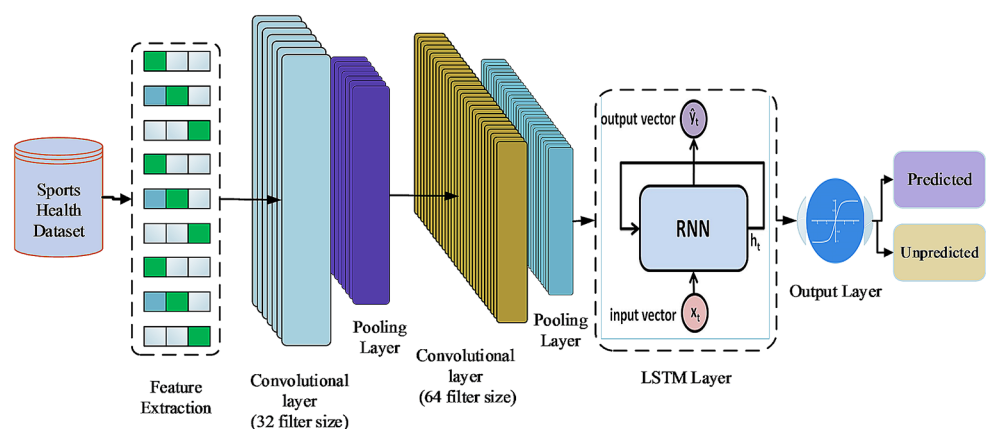**Fig. 5** The architecture of the LSTM-based RNN predictive model in sports health monitoring

Table 1 System requirements for configurations

Component	Requirement and Version
Operating System	Windows 10
Program language	Python 3.10
Libraries	TensorFlow 2.7.0
	PyTorch 1.4 or later
	Keras 2.7.0
	NumPy
	Pandas
	Scikit-learn
Framework	Anaconda3
	Jupyter Notebook
CPU	Intel Core i7
RAM	16GB
GPU	NVIDIA GeForce GTX 1060)
Storage	500GB
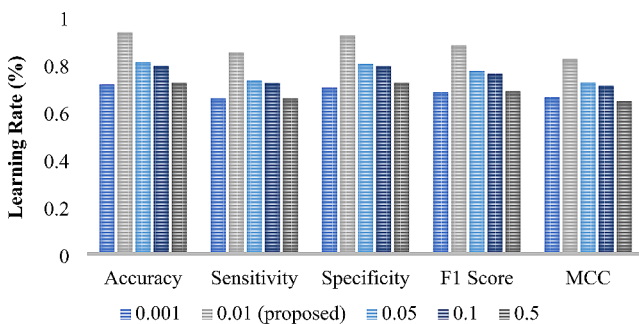
Fig. 6 Performance of learning rate on CNN model
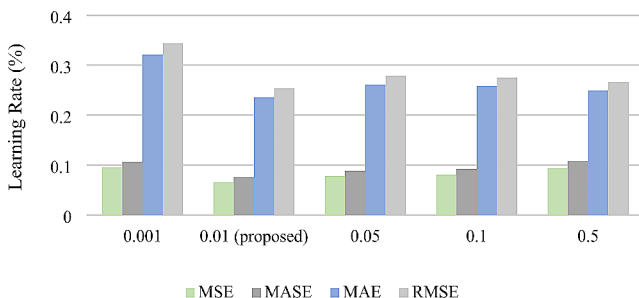
Fig. 7 Performance of learning rate on error loss of the CNN model

(RMSE) for different learning rates. MSE gauges the average squared error, MASE evaluates forecast accuracy, MAE measures absolute differences, and RMSE computes the square root of average squared differences. Lower values signify improved model accuracy and effectiveness, aiding in learning rate selection for optimal performance.

The CNN model's performance metrics for sports health monitoring were analyzed using different batch sizes. The suggested batch size 64 produced the highest accuracy at 93.42%, alongside notable sensitivity, specificity, F1 score, and MCC values. Smaller batch sizes, such as 16 and 32, led to lower accuracy and overall performance. Batch size 64 yielded less sensitivity, specificity, and F1 score, though the
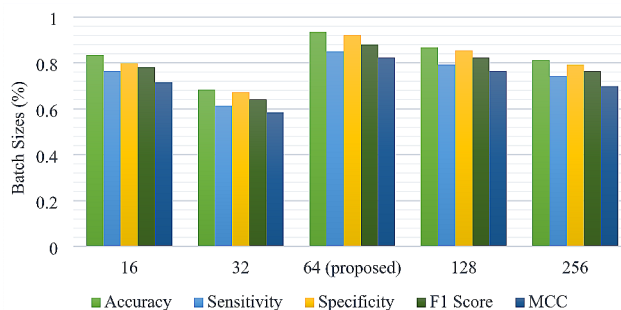

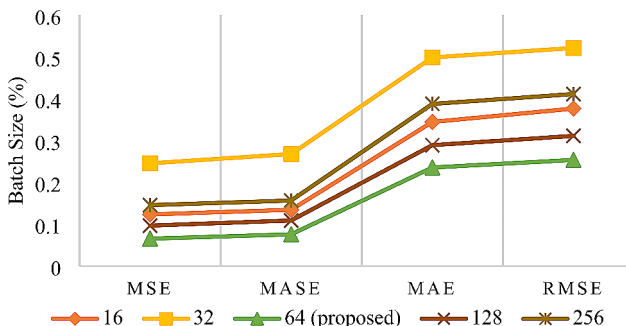**Fig. 8** Performance of CNN model with different batch sizes

Fig. 9 Performance of the error loss metrics of the CNN model with varying batch size

model had higher accuracy. Performance with larger batch sizes 128 and 256 was better, with slightly higher accuracy than the recommended batch size. Figure 8 depicts the accuracy, loss, and time of training the CNN model with different batch sizes.

The performance indicators related to a CNN model used in sports health monitoring were trained and tested with batch sizes 16, 32, 64, 128, or 256. Hence, the evaluation metrics used include Mean Squared Error (MSE), Mean Absolute Scaled Error (MASE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). These metrics were used to assess the fidelity of the model and the degree of health outcome certainty. Figure 9 portrays the variation in the CNN model's compaction against various batch sizes to identify the suitable batch size used in sports health monitoring applications.

This constructed an environment where the performance of the error loss metrics for the CNN model with varying Batch Sizes could be assessed in the subsequent section. Therefore, accuracy expresses to what extent the model's predictions were correct on average. Sensitivity is defined as the power of a test to give a proper verdict for positive cases, while specificity identifies the extent of accurate diagnosis for negative cases. The F1 Score combines precision and recall, balancing them. The MCC assesses the correlation between predicted and actual values. Among the optimizers, Adam achieved the highest accuracy of 93.42%

and MCC of 0.8232, indicating its effectiveness in the task. SGD and RMSprop also performed well, followed by Adagrad and Adadelta. Table 2 presents the performance metrics of different optimizers for sports.

Table 3 compares the performance of different optimizers in sports health monitoring. Adam performs best with the lowest MSE, MASE, MAE, and RMSE values. Adadelta shows the poorest performance across all metrics, indicating higher errors. The results suggest that the choice of optimizer significantly impacts model performance, with Adam being the most effective and Adadelta being the least effective in this context.

Figure 10 compares the performance of different activation functions in a predictive model for sports health monitoring. Softmax proposed ReLU and Sigmoid functions exhibit high accuracy, with Softmax leading slightly. ReLU has the highest specificity, indicating better identifying actual negative cases. The sigmoid function shows balanced performance across sensitivity and specificity. Tanh, Leaky ReLU, and ELU functions have lower accuracy but offer valuable insights into model performance, demonstrating their applicability in specific scenarios.

Figure 11 represents the performance of different activation functions in terms of MSE, MASE, MAE, and RMSE. The experimental results reveal that Softmax and ReLU error rates are lower than other activation functions, indicating a better-performing model. The errors in the next set of activation functions, Sigmoid, Tanh, Leaky ReLU, and ELU, are successively higher, indicating the poor performance of those activation functions for the plugged-in model.

These are crucial techniques used in the cycle to improve model organizations, contributing to enhancing prediction in various application forms. Grid Search achieved the highest accuracy at 93.42%, with a sensitivity of 85.00% and a specificity of 94.15%. Random Search closely followed, reaching 91.65% accuracy, with sensitivity and specificity values of 82.50% and 92.82%, respectively. Bayesian Optimization, Genetic Algorithms, and other techniques showed similar trends, each contributing to refining model parameters for improved performance. Table 4 demonstrates the effectiveness of different search methods in optimizing model performance.

Table 5 shows the performance metrics for different search methods, optimizing models and reducing error loss. The techniques evaluated include Grid Search, Random Search, Bayesian Optimization, Genetic Algorithm, Particle Swarm, Simulated Annealing, Differential Evolution, and Hill Climbing. The evaluation is based on important metrics such as Mean Squared Error (MSE), Mean Absolute Scaled Error (MASE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). Lower values for these

Table 2 Performance metrics of different optimizers for sports health monitoring

Optimizer	Accuracy	Sensitivity	Specificity	F1 Score	MCC
Adam	0.9342	0.8500	0.9415	0.8803	0.8232
SGD	0.8732	0.8305	0.8914	0.8642	0.8013
RMSprop	0.8457	0.8123	0.8652	0.8327	0.7804
Adagrad	0.7835	0.7458	0.8054	0.7736	0.7125
Adadelta	0.7395	0.6982	0.7589	0.7256	0.6678

Table 3 Comparison of errors and loss metrics across optimizers

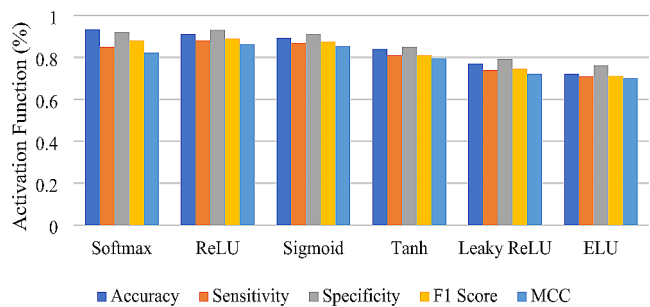| Optimizer	MSE	MASE	MAE	RMSE
Adam	0.0654	0.0758	0.2356	0.2537
SGD	0.0731	0.0824	0.2557	0.2779
RMSprop	0.0842	0.0956	0.2798	0.2981
Adagrad	0.0987	0.1056	0.3045	0.3276
Adadelta	0.1156	0.1267	0.3489	0.3724

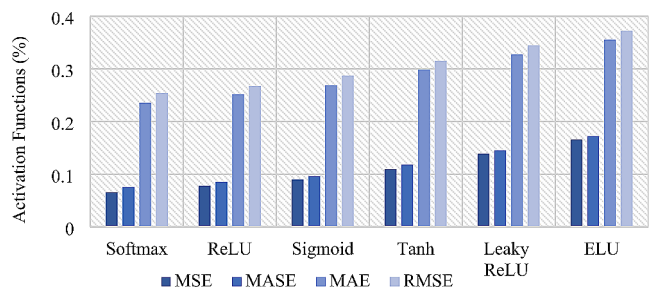**Fig. 10** Activation function performance in sports health monitoring model

Fig. 11 Error loss analysis for various activation functions

metrics indicate better optimization performance, showing how effective the search methods are in refining model parameters for improved accuracy and predictive capability.

The proposed CNN model's error loss showcases significant improvement during training, reducing from 2.0 to 0.0, indicating effective learning. Similarly, the validation loss demonstrates substantial progress, decreasing from 0.66 to 0.0. This decline in loss values signifies enhanced model performance. It suggests that the CNN architecture successfully learns and generalizes patterns from the data, leading to more accurate predictions and improved overall performance, as shown in Fig. 12.

Table 4 Comparison of search methods for model optimization

Search Method	Accuracy	Sensitivity	Specificity	F1 Score	MCC
Grid Search	0.9342	0.8500	0.9415	0.8803	0.8232
Random Search	0.9165	0.8250	0.9282	0.8687	0.7987
Bayesian Optimization	0.9102	0.8150	0.9221	0.8621	0.7887
Genetic Algorithm	0.9034	0.8050	0.9145	0.8563	0.7782
Particle Swarm	0.8971	0.7950	0.9076	0.8485	0.7678
Simulated Annealing	0.8912	0.7850	0.8973	0.8401	0.7586
Differential Evolution	0.8865	0.7800	0.8924	0.8345	0.7485
Hill Climbing	0.8801	0.7750	0.8956	0.8289	0.7378

Table 5 Error loss evaluation across search methods

| Search Method	MSE	MASE	MAE	RMSE
Grid Search	0.0712	0.0795	0.2356	0.2625
Random Search	0.0756	0.0821	0.2456	0.2721
Bayesian Optimization	0.0802	0.0865	0.2556	0.2821
Genetic Algorithm	0.0845	0.0901	0.2654	0.2925
Particle Swarm	0.0891	0.0955	0.2752	0.3021
Simulated Annealing	0.0912	0.0978	0.2851	0.3125
Differential Evolution	0.0935	0.0996	0.2956	0.3221
Hill Climbing	0.0995	0.1064	0.3054	0.332

The confusion matrix of the proposed CNN model shows a strong diagonal, indicating accurate predictions. The top-left and bottom-right cells show true negatives and positives, respectively, demonstrating the model's ability to classify instances correctly. On the other hand, the top-right and bottom-left cells represent false positives and false negatives, illustrating misclassifications. With a high true positive rate (0.91) and true negative rate (0.93), the model exhibits robust performance, as depicted in Fig. 13.

The CNN architecture has demonstrated the highest accuracy at 93.42%, with a specificity of 94.15%, showing its ability to identify true negatives accurately. The Recurrent Neural Net follows closely with an accuracy of 92.15% and a specificity of 93.21%. The Transformer and Capsule Network architectures also exhibit competitive performance, with accuracies of 91.24% and 90.56%, respectively. These models show promising results in sensitivity and specificity, suggesting their effectiveness in correctly identifying true positives and negatives. While Deep Belief Network, Autoencoder, Generative Adversarial, and Graph Neural Network architectures display slightly lower accuracies, they still offer considerable performance in sensitivity and specificity, showcasing their potential in various applications, as shown in Fig. 14.

As for performance measures, Fig. 15 shows the mean squared error (MSE), mean absolute scaled error (MASE), mean absolute errors (MAE), and root mean squared errors (RMSE) for the various architectures of the neural networks. CNN's error metrics are the lowest and can be considered the most accurate and precise among all the models. The error graph shows that the graph neural network has higher error rates for areas with lower accuracy and precision. It is also worth explaining that all these metrics are critical when assessing the performance and efficiency of different neural network architectures in areas such as predictive modeling and classification.

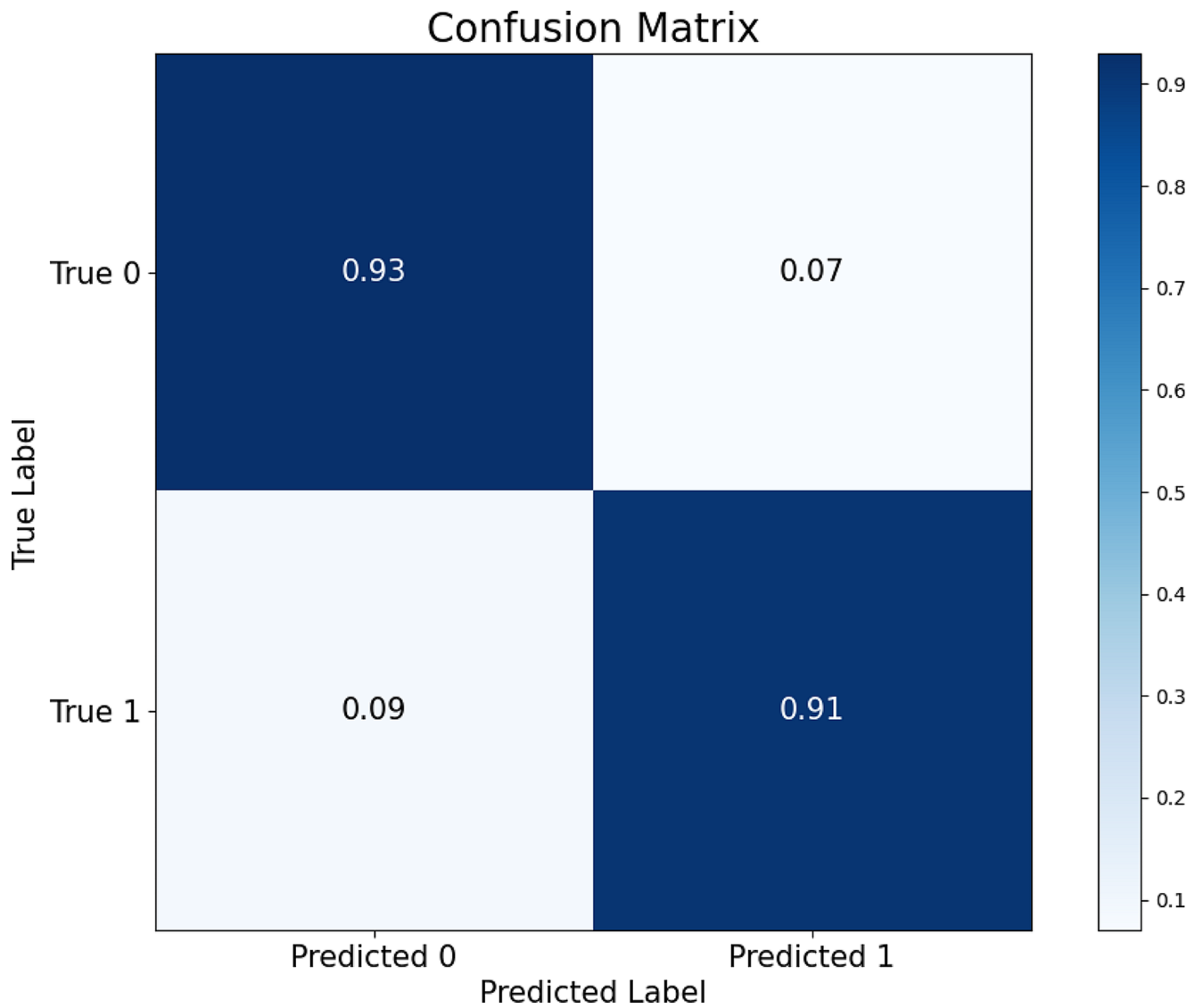**Fig. 12** Error loss reduction in proposed CNN model losses
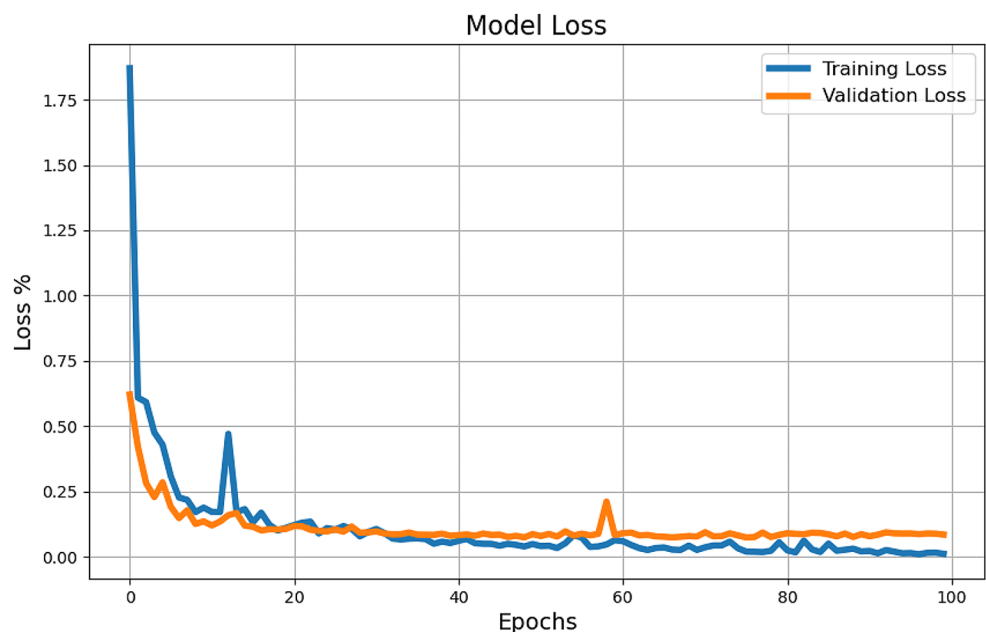
Confusion Matrix

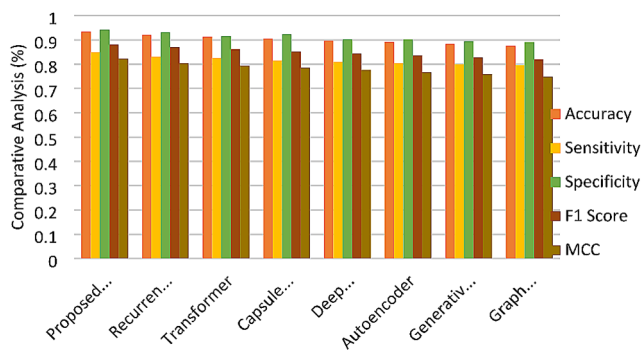**Fig. 13** Confusion matrix for proposed CNN model

Fig. 14 Comparative analysis of different deep learning architectures for classification performance
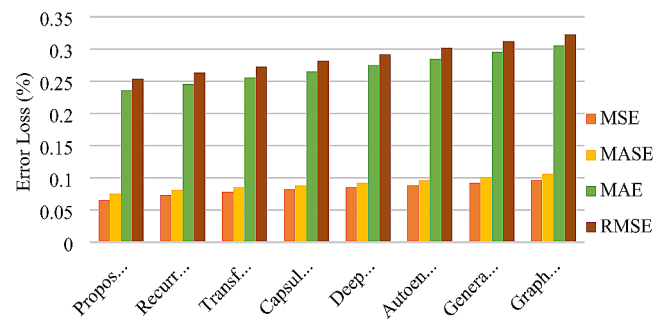

Fig. 15 Performance of the different deep learning architectures on the error loss metrics

6 Conclusion

This paper proposes a novel and enhanced IoT-based system for monitoring the health of college students in sports complexes using wearable gadgets, big data management, and CNNs. Combining real-time health monitoring using wearable devices with advanced analysis techniques, the proposed framework differs from the conventional health monitoring methods, usually done periodically with the help of self-reported files or other basic yet less accurate approaches. The present approach aims at constant tracking and forecasting and provides refined suggestions for avoiding injuries while enhancing results. The utilization of the proposed framework is further supported through experimental assessment, which confirms the accurate identification of melanoma using the CNN model in terms of its accuracy, sensitivity, specificity, F1, and Matthews Correlation Coefficient. Such measures show the model's capability concerning effective and accurate predictions and analyses. Additionally, the study of the results on the mean and standard deviation of the errors derived from the MSE, MASE, MAE, and RMSE shows that the results are lower than those of other methods, thus assessing the effectiveness and accuracy of the framework. Further, the interlinkage between wearable IoT and big data analytics improves short-term chronic condition monitoring and adds to the systematic and innovative well-being proactive construction. The feature of constant supervision of the individual and external conditions guarantees the accurate and prompt delivery of health updates, which college students require for proper health management to cope with the challenges of a strict study and sporting regime. The implementation plan evaluations focus on ethical issues, including data privacy, model interpretability, and considerations of fairness to reduce risks. This paper has also highlighted how these ethical aspects are also focused on ensuring that the framework being developed here aims at establishing a reliable and effective health monitoring network.

Author Contributions All the authors have contributions in each section.

Data Availability No datasets were generated or analysed during the current study.

Declarations

Competing Interests The authors declare no competing interests.

Conflict of Interest The authors affirm the absence of any conflicting interests.

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