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Article

Research on the influence of health fitness and mental health analyzed by image processing technology

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Abstract: Sports offer numerous benefits for physical and mental health, and current research focuses on a comprehensive evaluation of an athlete's well-being to enhance performance. Thermal imaging techniques are employed to observe athletes' activities in both psychological and physiological aspects. During competitive pursuits and exercise, thermal imaging records the athlete's temperature fluctuations. These temperature data, combined with other biometric information like heart rate, provide a more in-depth understanding of the athlete's state. To establish a connection with biomechanical performance, we consider muscle activation patterns and motion dynamics. Muscle activation during intense competition leads to increased metabolic heat, which is detectable via thermal imaging. For example, highly activated muscle groups may exhibit distinct temperature elevations. Motion dynamics, such as the speed and range of limb movements, also impact heat dissipation and distribution. Faster movements may cause more rapid heat convection, altering the thermal patterns captured. The collected thermal images undergo processing to reduce noise and enhance contrast. Specific regions are identified to extract relevant features, which are then analyzed for temperature patterns. Abnormal temperature distributions are detected using Gradient Optimized Recurrent Neural Networks (GO-RNN) to assess the athlete's physical and mental health. This analysis not only predicts potential injuries but also links thermal data with biomechanical performance. By correlating thermal imaging results with muscle activation and motion dynamics, we can develop more accurate performance evaluation models. This integration allows for a more precise understanding of an athlete's condition, enabling personalized training programs and better injury prevention strategies, ultimately leading to improved athletic performance and well-being.

Keywords: sportsperson; mental health; thermal images; biomechanical performance; muscle activation patterns; temperature patterns; Gradient Optimized Recurrent Neural Networks (GO-RNN)

1. Introduction

The sports organizational [1] structure provides specific demands and opportunities for athletes to improve their physical activities in varied durations, intensity, and mode. The National Health Service (NHS) [2] stated that people who participated in physical activities had a 30% lower risk of depression. In addition, exercise also minimizes illness and anxiety and maximizes the energy level. Most of the time, the athlete's mental health is associated with physical activities [3,4]. Therefore, mental health is more important in sports. Several athletes have difficulties and concerns about their wellness and mental health. Athletes invest thousands of hours into physical training, and there has been a recent shift in the focus of athletes, instructors, and trainers to include mental preparation [5,6].

Receiving mental toughness means keeping your mind on task, overcoming obstacles, and accepting aid when needed. Therefore, the Sports Medicine Society of America recognizes 14 mental health issues [7,8] in sports, which consist of gender issues, bullying, hazing, sexuality, illness, injuries, sports transitioning, eating disorders, anxiety, depression, Attention deficit hyperactivity disorder, sleep, and overtraining. Therefore, the sports sector requires automatic systems to assess athletes' well-being and general health.

The automatic systems frequently monitor physiological responses [9], such as respiration, temperature, heart rate, and skin response. The observed physiological information determines the athlete's mental and physical state. Every athlete has unique physiological characteristics that respond to the external factors that identify the person's psychological states, such as stress level, mood, emotions, dishonesty, and distractions [10,11]. The sports sector's automatic monitoring system involves observing the athlete's blood pressure, sugar, glucose level, electrocardiograph, and pulse rate. The skin is an important organ that obtains signals from brain control units to manage the body temperature [12,13]. The heat and sweat are released through the skin, called the thermoregulation. This concept is applied to the thermal imaging process to detect the skin thermal radiation emission because it interprets the physiological changes. The thermal images [14] identify skin temperatures from the various physiological signals in the human body. The gathered thermal images are processed using various image processing and machine learning techniques that identify the human body changes. The images are frequently explored to predict the ROI region, which is used to determine the features [15]. The extracted features are analyzed using learning techniques such as neural models and classifiers to predict the athlete's abnormal pattern. However, the traditional monitoring system has challenges because of the nature of thermal images and the complexity of human physiology. Thermal cameras [16,17] are expensive and less feasible; therefore, the quality of the images is very poor. The low-quality images cause minimum accuracy while predicting athletes' health status. In addition, thermal image interpretation [18] is affected by different factors, such as skin colour and environmental conditions. Thermographic images of athletes are private and may reveal intimate details about their health and well-being. Data gathering is complicated by the need to protect subjects' anonymity and gain their informed consent. Determining a person's health, fitness, or mental wellness is difficult using only thermal photos. Due to the complexity of these factors, it is necessary to have a more global view that incorporates additional data and expert opinion. The thermal imaging [19] results can be affected by the conditions in which athletes practice and compete. It can be challenging to account for these kinds of real-world deviations. Therefore, effective automatic systems must examine the sportsperson's physical and mental health to improve their achievements. The challenges are overcome by applying the Gradient Optimized Recurrent Neural Networks (GO-RNN). The automatic systems use image processing techniques to remove the noise from the image, reduce the image quality, and interpret related issues. The noise-removed images are further enhanced according to the histogram features that maximize the image quality. The high-quality images are directly linked with the accuracy factor. In addition, the recurrent neural model predicts the athlete's health factors sequentially, reducing the complexity. The neural network uses the thermal region features that predict the person's temperature and activity changes. The extracted information explores the influencing factors of the sportsperson. The experimental study uses the captured thermal images to analyze the influencing factors of the athlete's physical and mental factors. Then the overall objective of this study is listed below.

- To predict athletes' health outcomes such as illness risk, likelihood achieving, and illness susceptibility using GO-RNN with maximum accuracy.
- Optimize athletes' training and recovery strategies to enhance their physiological response.
- To assess the sportsperson's mental health and stress level by examining the thermal patterns to reduce excessive stress.

Then, the rest of the paper is organized as follows: Section 2 investigates the various researcher's opinions regarding the sportsperson's mental and physical health impacts; Section 3 discusses the GO-RNN approach's working process to assess the athlete's mental and physical health; Section 4 discusses the efficiency of the GO-RNN-based mental health assessment process and a conclusion is described in section 5.

2. Related works

This section describes the various researcher's opinions, frameworks, ideas, and thoughts to explore the sportsperson's well-being. Fu and Fu [20] created distributed simulation systems to monitor Athletes mental health using IoT devices. This study aims to analyze the psychological quality of education and the factors that influence sports performance. The analysis explores scientific literacy, training, and competition atmosphere via psychological quality education. In addition, IoT sensors are embedded in athlete's bodies to collect information. The gathered details are processed using particle swarm optimization with a back propagation neural model (PSO-BPNN). The model trains the features used to predict the athlete's mental health with maximum accuracy.

Xu et al. [21] developed an athlete's psychological regulation prediction system using Radial Neural Networks (RNN). This work intends to manage the minimum training and learning speed while classifying the large volume of data. The RNN is applied to solve the training issues because it can process unpredictable and known intrusions. The network has several layers that can process the inputs, recognize the athlete's mental health by up to 20% improvement, and manage their privacy by up to 99% compared to other methods like back propagation neural networks.

Chen et al. [22] established cognitive evaluation systems to assess the athlete's injuries using Radial Basis Networks (RBF) [22]. The system aims to minimize the risk factors while examining the risk factors involved with athletes. The model uses the Gaussian distribution and the radial basis networks to identify the injuries with a high prediction rate. In addition, learned network parameters are generated using neural learning that minimizes the risk factors. The network-based learning process uses the 25 athletes' information to predict their health condition and risk factors. The developed model identifies 38.7% of single injury degree and 40.5% of composite injuries. The results are compared with the Bayesian and Lagrange models in which the radial basis network attains maximum accuracy.

Lu et al. [23] detected sports psychological factors from mobile sensor data using Deep Neural Networks (DNN). This study uses long- and short-term neural networks to analyze and predict psychological fatigue detection. The sensors are utilized to collect the information processed with the help of a neural model that identifies the changes in athlete's activities and fatigue conditions. Nazarov, A. M. [24] analyzes the psychological mechanism for improving athletes's psychological protection. This research aims to maximize the personal development of athletes based on their mental and physical health. An analytical and theoretical framework is examined during the analysis to maximize the athlete's psychological thinking and protect their information.

Cao et al. [25] applied machine learning techniques to create the football players strength training process. This work intends to examine the functional strength training of football players. During the analysis, the player's physical fitness level is continuously observed, and their posture is recognized using machine learning. This study uses the 116 adolescents' information collected, which is processed using the backpropagation neural model. The neural network analyzes the patient's movements, kicks, and standard movements to enhance training.

The emotional and physical health effects of burnout in athletes are examined in a systematic review and meta-analysis by Glandorf et al. [26]. They use a systematic approach, using several studies to investigate burnout's effects in depth. Mental health issues like despair and anxiety and physical health hazards like greater injury susceptibility are also highlighted in the study. This study performs a meta-analysis that ensures the system's reliability. In addition, the study examines the athlete population to explore the various factors of sportsperson stress which helps to remove the difficulties in data analysis.

Bentez-Sillero et al. [27] analyzed psychological elements and changes in the development of football players. The study uses self-report questionnaires to understand the player's mindset, motivation factors, confidence and self-control. The collected information is further explored with a statistical study to identify the psychological factors and influences on their football performance, which is also examined. Future studies may benefit from including qualitative views to further understand these mental facets of sports. Adolescent female athletes' stories are explored in Eke et al.'s [28] study, emphasizing the athletes' perspectives on self-compassion, performance, and mental health. The study thoroughly examines these factors in the context of young female athletes using qualitative research. The study aims to shed light on the complex interplay of adolescents' self-compassion, athletic success, and emotional health and well-being. This research aids in clarifying the mental and emotional benefits of sports for this population, providing crucial information for designing interventions that promote athlete's health condition.

Liu and Qiao [29] analyze and design a dual-feature fusion neural network for estimating sports injuries. The research looks into how neural networks might be used to provide an innovative assessment of sports-related injuries. It examines previous research on injury forecasting in sports and draws attention to the value of utilizing dual-feature fusion techniques to improve injury estimation models' precision. This study builds on existing literature by laying the groundwork for a novel neural network model to estimate sports injuries that use the fusion of numerous data. Athlete, human behavior recognition, using continuous picture deep learning and sensor technologies is his research's foundation [30]. The paper explores the emerging topic of human behavior recognition in sports by analyzing visual data and sensor data. The forthcoming review analyzes prior work in athlete behaviour recognition, emphasizing the value of deep learning methods and sensor technologies in gaining a more precise and timely understanding of athletes' actions and performances. This research covers the way for future work on sophisticated systems to improve sports training and performance analysis by monitoring and analyzing athlete behaviour in real-time across wireless networks. According to various researcher's opinions, athletes use numerous image processing and machine learning techniques to investigate physical and mental health conditions. The existing methods use different learning techniques to identify the sportsperson's mental health. However, the existing systems require an effective training model to reduce the overall computation complexity. In addition, the well-being system receives diverse data that require an optimized system to maximize the prediction rate.

In contrast to conventional techniques, which depend on human judgement and data collection intervals, the ML-DRTTSI model offers real-time thermal imaging to monitor physiological changes and athletes' temperatures continually [31]. It is more difficult to detect urgent or subtle health hazards using traditional approaches due to bias, delays, and a lack of real-time data. On the other hand, the ML-DRTTSI model and GO-RNN work together to automate data analysis, spot anomalies, forecast injuries, and provide a thorough, objective evaluation of mental and physical well-being. This approach reduces the room for human mistakes and enhances performance insights.

3. Analyzing health fitness and mental health using Gradient Optimized Recurrent Neural Networks (GO-RNN)

This study aims to analyze and predict the sportsperson's fitness and mental health from thermal images using Gradient Optimized Recurrent Neural Networks (GO-RNN). Thermal images determine the temperature variations used to predict the potential injuries in athletes. During practice and competition, an athlete's core temperature can be monitored via thermal imaging. Thermal images identify the athlete's temperature variations used to determine the injuries and strains in a particular area. In addition, temperature variations are examined in every physical activity to help predict the athlete's mental health and stress level. However, thermal images are diverse and complex, which consumes high computation time and requires a high training process to improve the performance. Therefore, this study uses image processing with intelligent learning techniques to maximize the sportsperson's physical and mental health analysis process. Then, the overall working process of this study is illustrated in **Figure 1**.

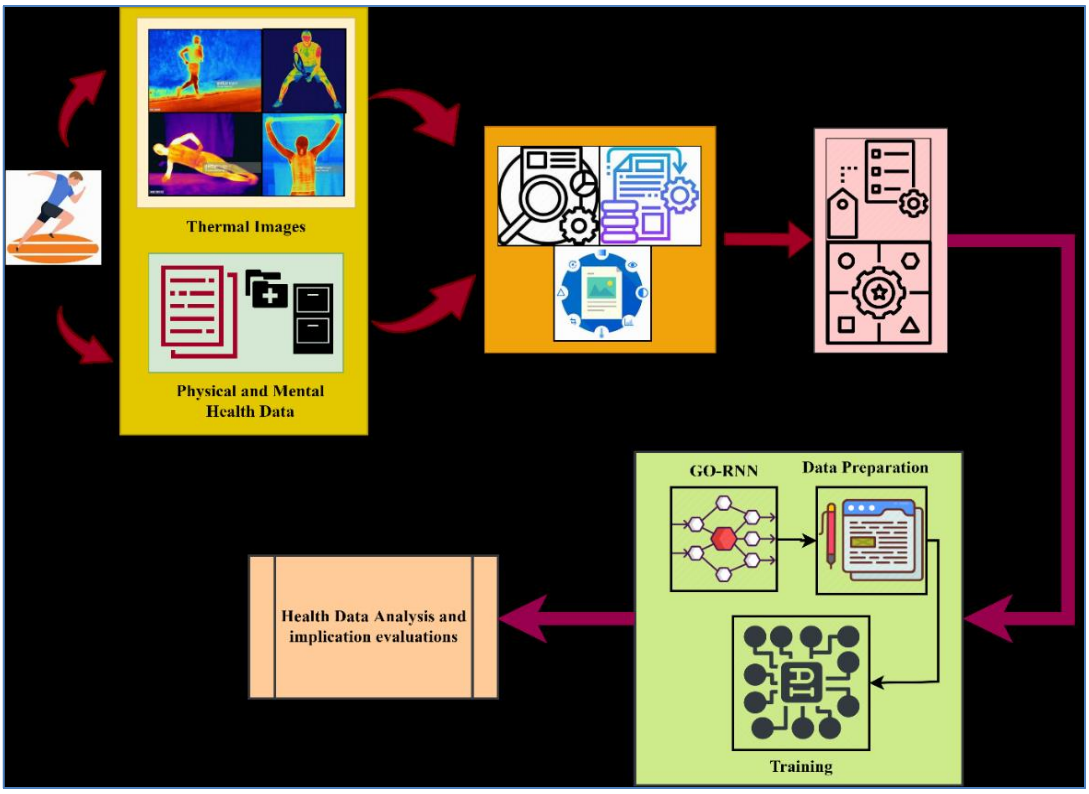


Figure 1. Working structure of GO-RNN-based athlete physical and mental health analysis.

Figure 1 illustrates the working process of GO-RNN-related sportsperson physical and mental health assessment. There, athlete health information and activities are frequently collected via thermal imaging and data collection. The collected data and images are processed to remove noise from images. The images are fine-tuned to enhance the image contrast. Then, features are extracted to identify the temperature variation from the athlete's body. The temperature identifies the athlete's stress and depression level, which is performed with the help of the RNN classifier. The network analyzes the patient's health information sequentially to identify the athlete's abnormal activities. From the activities, there are changes in physical exercise and other activities in sports. Then, the influence of mental and physical health is analyzed to examine the implications in the sports sector.

The following is how the suggested approach to data preparation, noise reduction, and feature extraction functions:

The collected thermal pictures are subjected to image processing algorithms for data preprocessing and noise reduction, which cleans the data by enhancing contrast and reducing noise. This is crucial to get accurate temperature readings all over the athlete's body while exercising and to get good pictures.

Feature Extraction: Following the improvement of picture quality, certain areas within thermal images are located to extract important characteristics, including temperature changes, associated with mental and physiological processes. The following temperature study and performance evaluation rely heavily on these characteristics.

Probably what this strategy entails for GO-RNN model training and validation is: During training, the GO-RNN model is given the processed thermal data and the features that have been extracted. Through supervised learning, the model is taught to identify patterns associated with typical and non-standard temperature fluctuations and situations pertaining to the mind and body.

Validation: To ensure the model can properly forecast the athlete's health state and injury risks, it is validated using a subset of the thermal data not utilised for training. This reduces the likelihood of overfitting and improves the model's accuracy.

3.1. Thermal image preprocessing

Initially, the athlete's thermal images are collected and processed with the help of a Hierarchical Thermal Noise Reduction (HTNR) approach. The HTNR approach aims to eliminate the noise from thermal images and improve image quality by preserving the image temperature information and brightness. The infrared camera captures the athlete's thermal images that capture temperature differences in the scene. In the image, each pixel is related to the temperature value. During the preprocessing, bad pixel correction, radiometric calibrations, and flat field corrections are performed to attain the image's exact temperature value. Then, noise information is analyzed regarding various factors such as atmospheric conditions, sensor noise, and motion artifacts. The HTNR approach divides the images into multiple scales according to the frequency components. The low-frequency components have important temperature details, and the high components contain noise details. The mean filtering process is applied to preserve the image brightness values and manage the sensitive details. At last, the denoised thermal images are reconstructed by considering the processed high-frequency components with low-frequency components. Then, the overall preprocessing working process is illustrated in **Figure 2**.

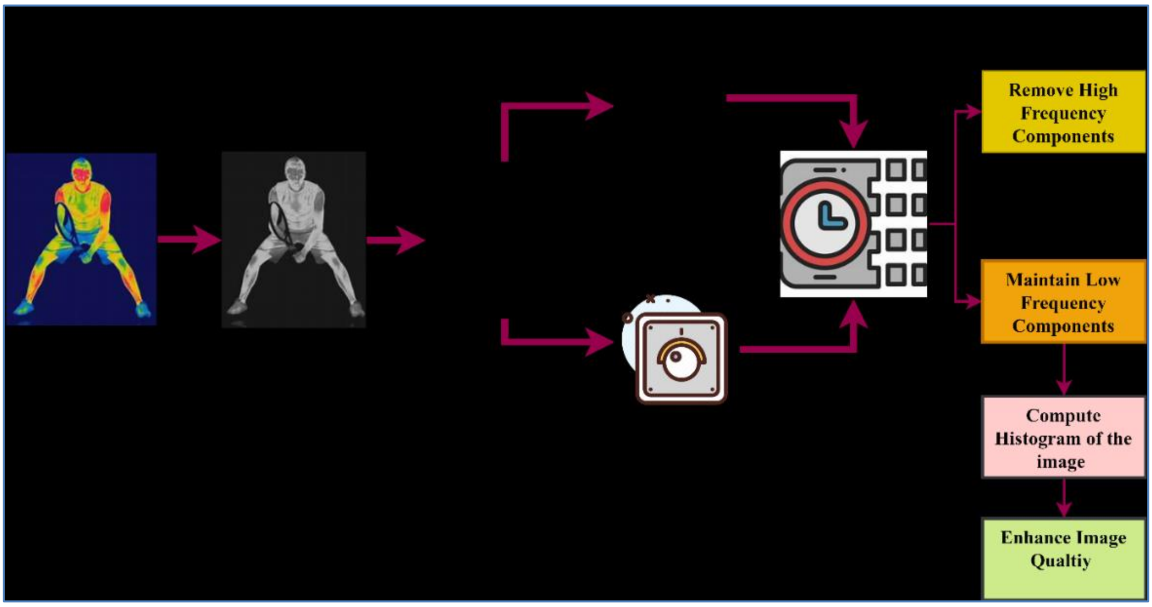


Figure 2. Process of HTNR-based image noise removal.

The thermal image is analyzed to enhance the image intensity, which is done by computing the median value of the pixels in the image. Every pixel in the image is compared with the threshold value and neighbouring pixels. If the pixel brightness value is minimum, then the particular pixel is changed using the median value. After enhancing the image intensity value, decomposition increases the brightness value. Considered, the thermal image is denoted as TI and is decomposed into multiple sub-images based on the brightness value μ_{TI}. During the decomposition, TI is split into a foreground image TI_f and background image TI_b. Hence, the image is defined using Equation (1)

$$TI = TI_b \cup TI_f \tag{1}$$

In Equation (1) thermal image is represented as (m, n) pixel and the background image is expanded according to Equation (2).

$$TI_b(m,n) = \{TI((m,n)|TI(m,n)) < \mu_{TI}, \forall \mathrm{T}I(m,n) \in \mathrm{T}I\} \tag{2}$$

In Equation (2), $TI_b(m,n)$ is denoted as the thermal image at (m,n) coordinate locations and TI_b is the background version of the thermal images, and the μ_{TI} is denoted as the brightness value of the thermal images. Likewise, the foreground of the thermal images is represented using Equation (3)

$$TI_f(m,n) = \{TI((m,n)|TI(m,n)) \geq \mu_{TI}, \forall \mathrm{T}I(m,n) \in \mathrm{T}I\} \tag{3}$$

Equation (3) is used to derive the foreground information from the thermal image TI. After dividing the images, the pixels are frequently examined using pixel intensity values. The pixel intensity is collated with the threshold value during the computation to remove the noise. The image pixel probability density value is computed to identify the distribution of the pixel. This process enhances the thermal image contrast, which is directly linked with the accuracy of the abnormal identification process. Then, Equation (4) is utilized to estimate the pixel probability density values.

$$p(TI_k) = \frac{n^k}{n} \tag{4}$$

In Equation (4), n^k is the total times of a particular level in the image TI, and n is the amount of athlete's sample thermal images. Along with $p(TI_k)$ cumulative density value $C(TI) = \sum_{j=0}^{k} p(I_j)$ is computed, which helps predict the thermal image histogram representation. Then, the histogram computation is represented using Equation (5)

$$f(TI) = TI_0 + (TI_{L-1} - L_0)C(\mathrm{T}I) \tag{5}$$

In Equation (5), the input image transformation function is represented as $f(TI)$, image cumulative function is denoted as $C(\mathrm{T}I)$. According to the above process, image noise is removed, the histogram is estimated to enhance the image quality, and the original image is reconstructed using Equation (6)

$$Y = f(TI) = \{(f(\mathrm{T}I(m,n)|\forall \mathrm{T}I(m,n) \in \mathrm{T}I)\} \tag{6}$$

According to the hierarchical image analysis process, intensity and histogram analysis effectively remove the image's noise. This stage helps to reduce the difficulties and complexity of thermal image analysis because each pixel is examined completely to improve the overall health data analysis rate. In addition, the sensor-based collected information is handled by the median filter to eliminate the noise and inconsistent information. Then min-max normalization process is performed to normalize the health data. Effective utilization of hierarchical approaches reduces image and data analysis difficulties.

3.2. Athlete's thermal feature extraction

Feature extraction is important to identify the relationship between physical and mental health. The influence of mental health affects the athlete's performance. This process transfers the gathered thermal information into meaningful and statistical features. The extracted features are more useful for predicting temperature patterns. The thermal images are collected from various parts of the body; therefore, the context information of each region should be analyzed effectively. This study uses segmentation to identify and predict the particular ROR region in the thermal images. During this process, images are divided into different segments, and the particular contour or boundary is identified to extract the features. The temperature threshold value is set to identify the high sweat or temperature region. The clustering is done by applying the Advanced Generous Clustering Method (AGCM). The segmentation is performed based on thermal image pixel similarity. According to the similarity, images are decomposed into several sub-images to determine the high-temperature region in the human body. Clustering is performed regarding pixel examination and super similar pixels' formation. Each pixel eigenvalue value is computed to determine the pixel similarities. A quantitative assessment is also performed to form the cluster based on an undirected graph. Let's assume the undirected graph is G with V data point and E edges between data points $G(V, E)$. Every edge has a particular weight value as w_{ij} $(i, j) \in E$. Then segmentation process is applied to the images to eliminate the graph partitioning problems. The partitioning problem is solved by splitting into the low-similarity and high-similarity vertex. Then, the normalization of the input thermal images is defined using Equation (7)

$$w(A, B) = \sum_{i \in A, j \in B} w_{i,j} \tag{7}$$

According to the weight values, the n-cut process is applied, which is defined as $ncut(A, B) = \frac{w(A,B)}{w(A,V)} + \frac{w(A,B)}{w(B,V)}$. Here, A and B are defined as the vertex subset of images. After performing the $ncut$ process, pixel similarities are computed to identify the association between each pixel.

$$nassoc(A, B) = \frac{w(A, A)}{w(A, V)} + \frac{w(B, B)}{w(B, V)} \tag{8}$$

As said, during the segmentation, the NP-hard problem is addressed by estimating the minimum cut value that is identified as $d(i) = \sum_j w_{ij}$. Here, d is the diagonal matrix $n * n$, and the minimum cut value of the vertex is defined in Equation (9)

$$\min ncut(A,B) = min_y \frac{y^T(D-W)y}{y^T Dy} \tag{9}$$

In Equation (9), the $y_i \in \{1, -\mathrm{b}\}$ where –b is constant and $y^T D1 = 0$. This process identifies the relationship between each pixel, and similar pixels are grouped to form the cluster. The clustering process addresses the k-means problems by using an effective k-means cluster function that is defined in Equation (10)

$$k(x_i, x_j) = \varphi^T(x_i)\varphi(x_j) \tag{10}$$

The kernel function is mentioned as $k(x_i, x_j)$ and the kernel problem is addressed by taking the cluster elements reciprocal. The frequent estimation of pixel similarity is used to identify the high temperature-related region. The identified regions are analyzed further to extract the measurements from thermal images. Several measurements, such as mean temperature, temperature variability, spatial patterns, temporal patterns, and frequency domain features, are derived to investigate the athlete's health and mental conditions.

First, the average temperature value is calculated for the thermal region. The mean value is estimated by computing the summation of the entire temperature values in the region and divided by the number of temperature pixels (data points) in the region. The average temperature value is calculated using Equation (11)

$$\tau = \frac{1}{N}\sum_{i=1}^{N} T_i \tag{11}$$

In the Equation, average temperature τ is computed from the count of the temperature points in region N and the temperature value at pixel *i*. After that, temperature variability is estimated based on how temperature values differ in the region. The temperature fluctuation is calculated using Equation (12)

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(T_i - \tau)^2} \tag{12}$$

In Equation (12), temperature variability is defined as σ, the total number of temperature points is N, the temperature value at the pixel is T, and the average temperature value is τ. Spatial analysis examines thermal images in terms of patterns and fluctuations in temperature over multiple locations or places. Changes in regional temperatures related to physical and mental well-being can be more easily detected. Then, the spatial mean temperature $\tau_{spatial}$ is computed as $\tau_{spatial} = \frac{1}{N}\sum_{i=1}^{N} T_i$; spatial value is estimated within the region. During the computation. The temperature value at the pixel is chosen within the region. Then, temporal temperature is computed to identify the particular patterns in the thermal images. Temperature fluctuations and trends throughout time are the focus of temporal analysis. This becomes especially important if you have a series of thermal images taken at various intervals in time. The temporal mean temperature is estimated as $\tau_{temporal} = \frac{1}{M}\sum_{j=1}^{M} T_j$. The $\tau_{temporal}$ is estimated based on the total number of thermal images in the sequence. The extracted features are normalized to scale the values. The normalization process fine-tunes the value from 0 to 1, simplifying the overall data analysis process. Each thermal image then has a feature vector constructed from the extracted features. This feature vector is then used as the raw material for other types of analysis, including but not limited to machine learning models and statistical tests. Once features have been extracted, they go through a correlation analysis to determine if there is a connection between those variables and some measure of physical or mental well-being. This is useful for determining which temperature characteristics most predict the outcomes of interest.

3.3. Abnormal temperature pattern prediction

The last step of this work is identifying the abnormal temperature patterns to predict the stress level of athletes. This study uses Recurrent Neural Networks (RNN) to classify the temperature features because it handles the sequential data easily. The gathered thermal images are processed to extract the temperature information. Then, data has to be split into training, testing, and validation to maintain the temporal order of the sequence. Then, the data sequence is prepared to generate the training model that recognizes abnormal patterns with maximum accuracy. During the training process, optimization is applied iteratively to maximize the recognition rate and minimize the error rate. The optimization function is used to predict the maximum and minimum values. The global maximum and minimum function identify the minimum and maximum values from the entire domain function. The local minimum and maximum values are used to determine the minimum and maximum value of the function within the range. These two values are more useful for predicting the optimized value that reduces the deviation between the output values. As said, the input thermal images are processed by noise removal, eliminating the noise from images, and the segmentation approach identifies the region from thermal images. Then, the stress temperature pattern classification process is described in **Figure 3**.

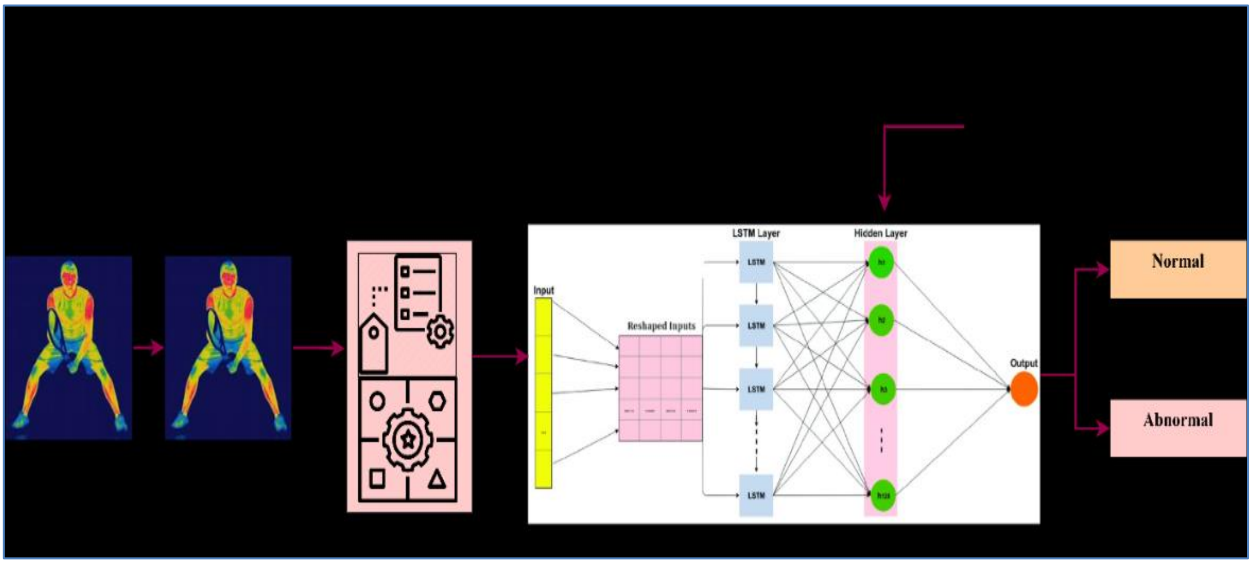


Figure 3. Working Process of Go-RNN Temperature Pattern Prediction.

Thermal imaging cameras capture the temperature changes of athletes and provide valuable data, but their prohibitive cost puts them out of reach for many persons and sports groups. Find less expensive alternatives, including portable thermal devices or less expensive sensors, as a potential option. It is also possible to reduce costs using cloud-based processing or collaborating with IT companies to move computing tasks off-site. Businesses and governments might also invest in open-source image processing software and subsidise its costs to make the technology more accessible and affordable. The input thermal images have the sequence length, height, width, and channels as shape attributes. Considered (10, 128, 128,1) is the sequence of 10 frame images with 128 × 128 pixel resolution with one gray channel. Then, the region of interest is derived from the image, which is further examined to extract the temperature features. The input images are processed, and the reshaped images are obtained to fit the sequence length, estimated as (sequence length, image height × image width × number of channels). The recurrent layers use the additional layer to determine the temporal dependencies; each layer has hyperparameters. The multiple layers compute the more complex patterns from the temperature features. After initializing the multiple layers, the training process is performed for input sequences, and the model provides the labels (0-normal and 1-abnormal). The training process uses the batch size and epochs to create the model, and the validation data is utilized to validate the dataset. The recurrent network identifies the abnormal temperature patterns from the thermal images.

The abnormal patterns occur because of the stress and other depressive state of the sportsperson. Section 3 explains that GO-RNN is a strong tool for analysing temperature trends but that non-expert coaches and athletes may find it difficult to grasp due to the model's intricacy and the "black box" aspect of deep learning. To tackle this problem, it would be wise to include easy and understandable dashboards. These dashboards should provide information straightforwardly and practically, with measurements and visualisations that are easy to comprehend. Further, making the findings more understandable and making the technology more accessible for practical application in sports training and performance monitoring may be achieved by including model interpretability elements, such as explicit descriptions of significant patterns or alarms. The network consists of a cell with several key gates and components that play a crucial role in output computation. The input gate i_t controls the flow of information into the cells that are defined using Equation (13).

$$i_t = \sigma(W_i.[h_{t-1}.x_t] + b_i) \tag{13}$$

The forget gate evaluates information from the previous cell state to see if it should be forgotten, as defined in Equation (14).

$$f_t = \sigma\left(W_f.[h_{t-1}.x_t] + b_f\right) \tag{14}$$

The computed input gate and forget gate are utilized to update the cell state C_t which is described in Equation (15).

$$C_t = f_t.C_{t-1} + i_t.\tanh(W_c.[h_{t-1}.x_t] + b_c) \tag{15}$$

The part of the cell state that is revealed as the output is controlled by the output gate, which is mentioned in Equation (16).

$$O_t = \sigma(W_o.[h_{t-1}.x_t] + b_o) \tag{16}$$

During the output computation, the hidden state h_t is updated depending on the output gate and cell gate that is defined in Equation (17).

$$h_t = O_t.\tanh(C_t) \tag{17}$$

In the above computations, input at the time step is defined as x_t, previous hidden state is represented as h_{t-1}, bias values are presented as b, and the sigmoid function is denoted as σ. The output gives the output values as normal or abnormal temperature features. If the network gives 0 as output, then the sportsperson is facing stress issues and if it has one, then the person is normal in their activities. Network output is compared with the trained label during the computation to minimize the error rate. Then, the network performance is improved by optimizing and fine-tuning the network parameters. The network optimization process is described in **Figure 4**.

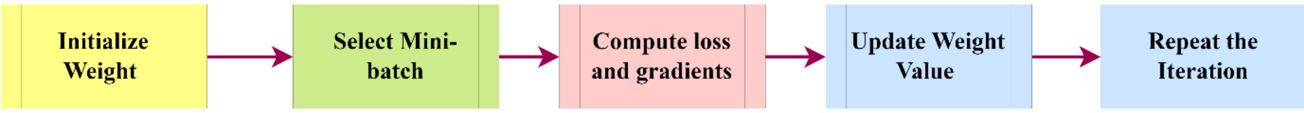


Figure 4. Flow of network parameter optimization.

This work uses the stochastic gradient descent optimizer to fine-tune the parameters. The optimization algorithm updates the network parameters, such as weight and bias values. The updating process is performed according to the gradient value of the loss function randomly chosen from the mini-batch data points. In addition, the optimization process helps to escape the local minima and converge solutions effectively. Then, the weight updating process is defined using Equation (18).

$$\theta \leftarrow \theta - \eta.\nabla L(\theta, x_i, y_i) \tag{18}$$

In Equation (18), updated parameters are denoted as θ, which is computed with the help of learning rate η, loss function $L(\theta, x_i, y_i)$ of data points (x_i, y_i) and gradient loss function $\nabla L(\theta, x_i, y_i)$ concerning θ. This process reduces the deviations between the output values and maximizes the prediction accuracy. From the predicted temperature pattern stress level, the athlete's health and mental status are examined and used to maximize the sportsperson's performance.

3.4. Influence of physical and mental health on sports performance

The dynamic and crucial force influencing an athlete's performance in sports is the interplay between their physical ability and mental resilience. Technological advances have opened up promising paths for research into this intricate connection in recent years. Among these developments, thermal imaging has emerged as a potent technique for investigating how stress affects the thermal patterns of athletes. This paper uses the powerful capabilities of recurrent neural networks (RNNs) optimized with gradient descent to investigate the interplay between physical and mental health and its significant impact on athletic performance. This study explores the human body's physiological changes in response to stress, explains how thermal imaging detects these shifts and then discusses the implications for athletes, coaches, and other sports professionals who strive to maximize physical and mental performance.

Athletic success requires more than physical strength. It links mental toughness, emotional fortitude, and psychological health to athlete performance. Stress cannot be overlooked in this intricate network of contributors. Stress is constant for athletes. Stress might originate from strict physical activity, competition anxiety, or environmental influences. It can inspire greatness or hinder it. The intricate relationship between physical and mental health and sports performance must be examined. Stress causes hormonal changes, autonomic nervous system activation, and temperature regulation, among other complex physiological responses. Stress hormones are potent regulators of blood flow and body temperature. Thermal imaging can record these fine-grained yet crucial variations because physiological reactions leave distinct fingerprints on the body's thermal environment. Thermal imaging, or infrared thermography, detects and displays surface temperature variations without damage. Thermal imaging lets athletes monitor skin temperature. Thermal imaging is useful for examining the complex link between stress and sports performance because stress increases localised temperature in the head, neck, and hands.

Stochastic Gradient Descent (SGD) and Recurrent Neural Networks (RNNs) perform well in deep learning and sports science to assess athletes' mental and physical fitness. This approach relies on physiological (heart rate and body temperature), psychological (stress and mood assessments), training, and thermal image data. Data preprocessing is critical in the technical world, including cleansing, feature extraction, and normalization. The RNN architecture is the main attraction since it can process time series and sequential data. The model can efficiently update its weights and biases using a stochastic gradient descent optimisation algorithm. This allows the model to avoid local minima successfully and converge. Sequences in the dataset represent discrete periods and contain data on the athletes' physiological, psychological, and thermal states. The RNN's memory cells and recurrent connections allow it to discern temporal patterns and links between many mental and physical health measures. To optimize the model's convergence, hyperparameters like learning rates and batch sizes typically need to be fine-tuned through technical modification. The predicted performance of the model in terms of an athlete's mental state, physical readiness, and overall performance is measured using evaluation indicators that are particular to the environment. The approach is applicable in real-world sporting environments, where it may be used to keep an eye on players and give them and their coaches immediate feedback. The ability to tailor the model to particular athletes' specific attributes and stress responses is also significant. The model is kept at the cutting edge of performance optimization by constantly updating it with new data and keeping up with deep learning and sports science developments. Combining SGD and RNNs creates a technical framework that allows sports professionals and athletes to understand better the intricate relationship between an individual's mental and physical health, leading to more effective, individualized training plans and better chances of avoiding injuries.

Several important safeguards are put in place to protect athletes' privacy when thermal imaging technology is used. The transmission and storage of data are protected by encryption, and the anonymisation process guarantees that the athletes' identities are not associated with the data. The data is protected by access controls that limit who may access it, and athletes provide their informed permission before any data is collected or used. To guarantee that all data protection criteria are satisfied, it is important to comply with privacy rules. These measures ensure the athletes' privacy and security as they get the advantages of the technology by protecting their sensitive physiological and psychological data.

4. Results and discussions

This section analyzes the efficiency of the Gradient Optimization Recurrent Neural Networks (GO-RNN) based sportsperson mental and physical health analysis. During the analysis, thermal images are collected in various physical activities and exercise directions. The gathered thermal images are explored in different aspects to predict the temperatures and variabilities. The high-quality thermal camera is utilized to capture the temperature variations of the images. The thermal camera is integrated with the smartphones to capture sportspeople's every activity. This study uses the thermal image dataset (https://bbh.create.aau.dk/?page_id=489) [32] to analyze the system efficiency. The dataset consists of 37,423 frames, and each image is 1920 × 480 pixels. The images are captured with the help of AXIS Q1922 thermal sensor, uncooled microbolometer 8–14 µm, 10 mm focal length. The collected images were processed with the help of the HTNR technique that minimizes the noise from the image, and the image quality is enhanced according to the histogram values. Then, temperature regions are segmented by identifying similar pixels, and the regions are grouped accordingly [33,34]. The regions are further examined to derive the temperature variation, average temperature, spatial temperature, and temporal temperature. The derived features are fed into the neural network that forms the training model. The training model uses the gradient optimizer and learning rate to fine-tune the network performance. The system's excellence is evaluated using various metrics such as accuracy, precision, mean square error rate, recall, root mean square error, and Cohen's kappa. The efficiency of the system is compared with Particle Swarm Optimization with A Back Propagation Neural Model (PSO-BPNN) [21], Radial Basis Networks (RBF) [23] and Deep Neural Networks (DNN) [24]. Then, the obtained mean square error rate analysis is illustrated in **Figure 5**.

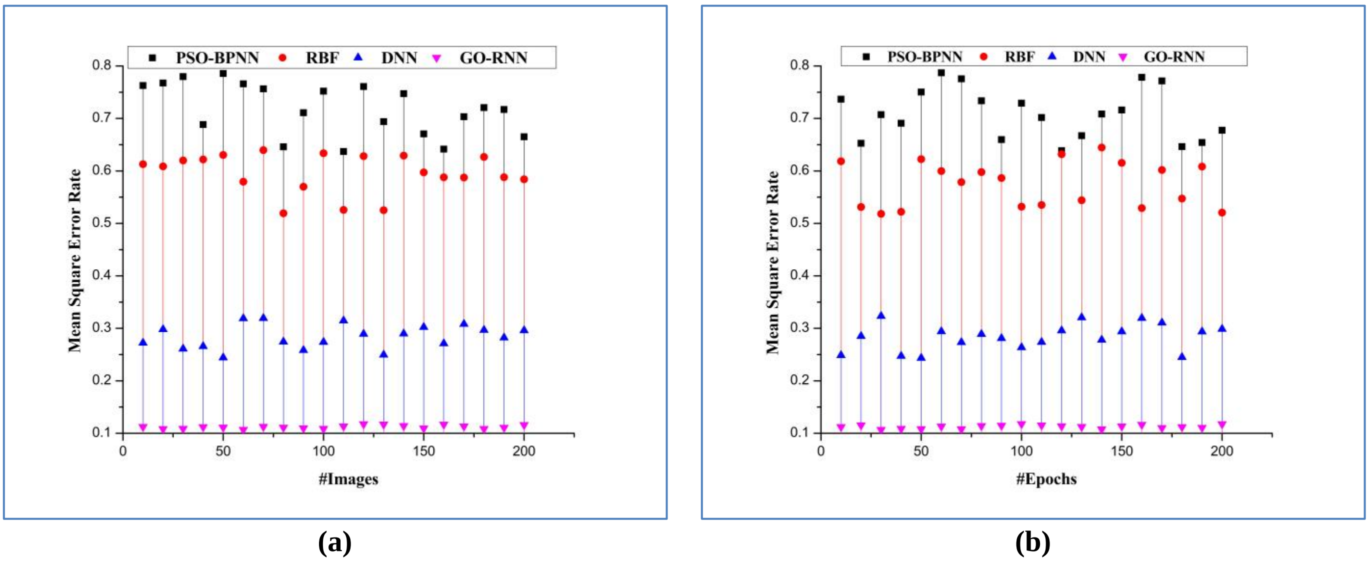


Figure 5. Mean square error rate analysis of GO-RNN, **(a)** images; **(b)** epochs.

Figure 5 illustrates the GO-RNN method mean square error rate value, and the results are compared with existing methods. Here, the collected thermal images are processed by a hierarchical thermal noise reduction technique to remove the noise in foreground and background information. In addition, a median filter is used to replace the noise pixels that eliminate unwanted pixel information. Then, the histogram equalization approach is examined to enhance the image quality. The thermal images are complex, which causes errors when capturing them. The effective utilization of the noise removal process reduces the difficulties and complexities while predicting the stress temperature patterns from thermal images. In addition, the method uses the gradient descent optimization approach to fine-tune the network parameters, reducing the deviation between the output values. Further, the efficiency of the GO-RNN system is evaluated using the root mean square error values, and the result is shown in **Figure 6**.

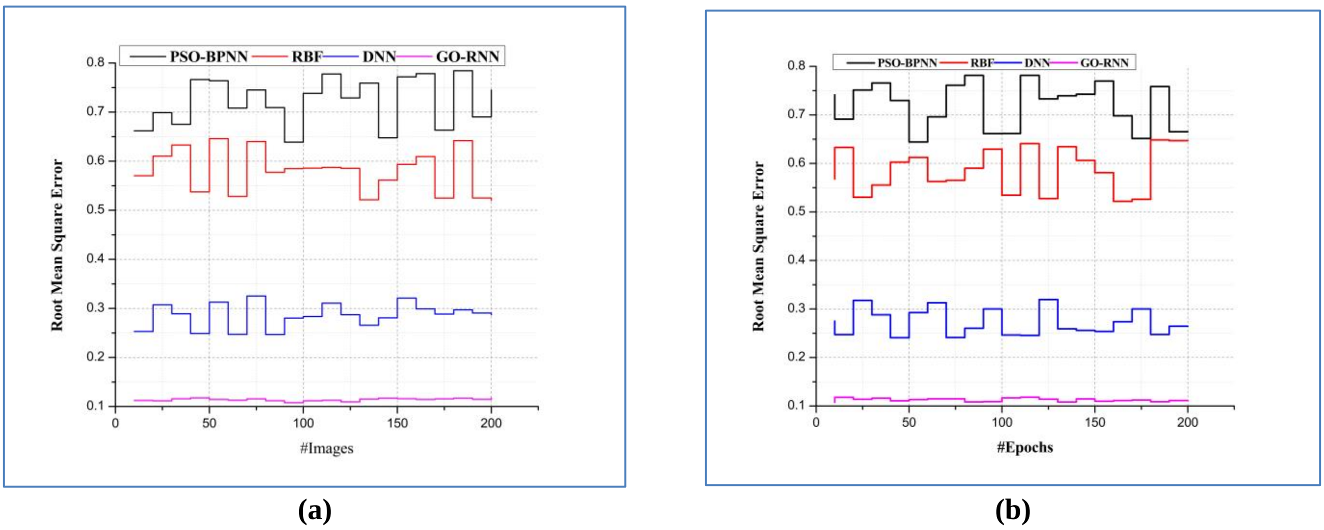
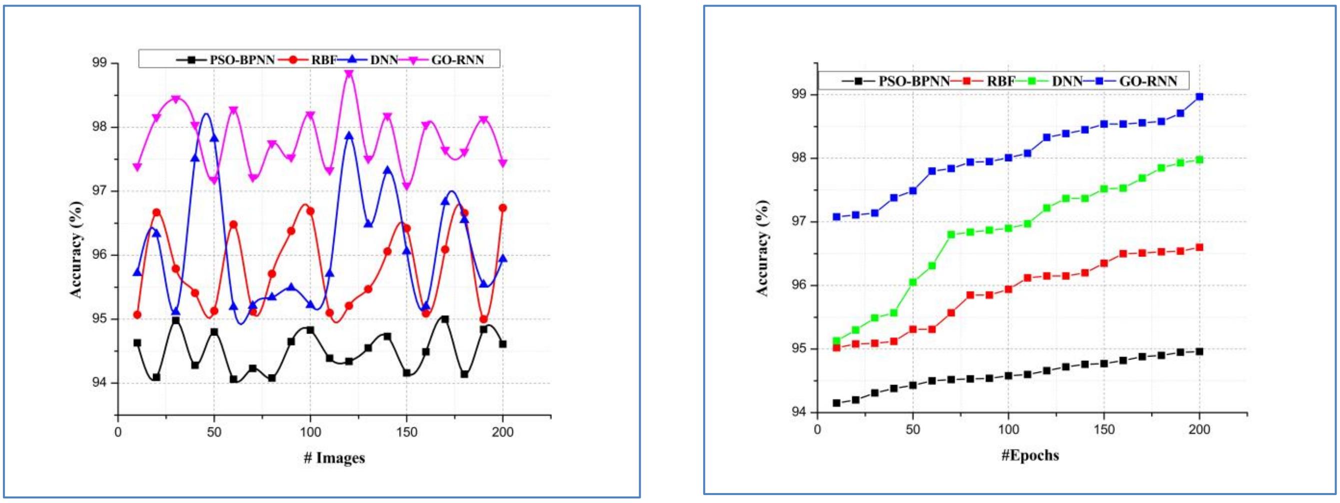


Figure 6. Root mean square error rate analysis of GO-RNN, **(a)** images; **(b)** epochs.

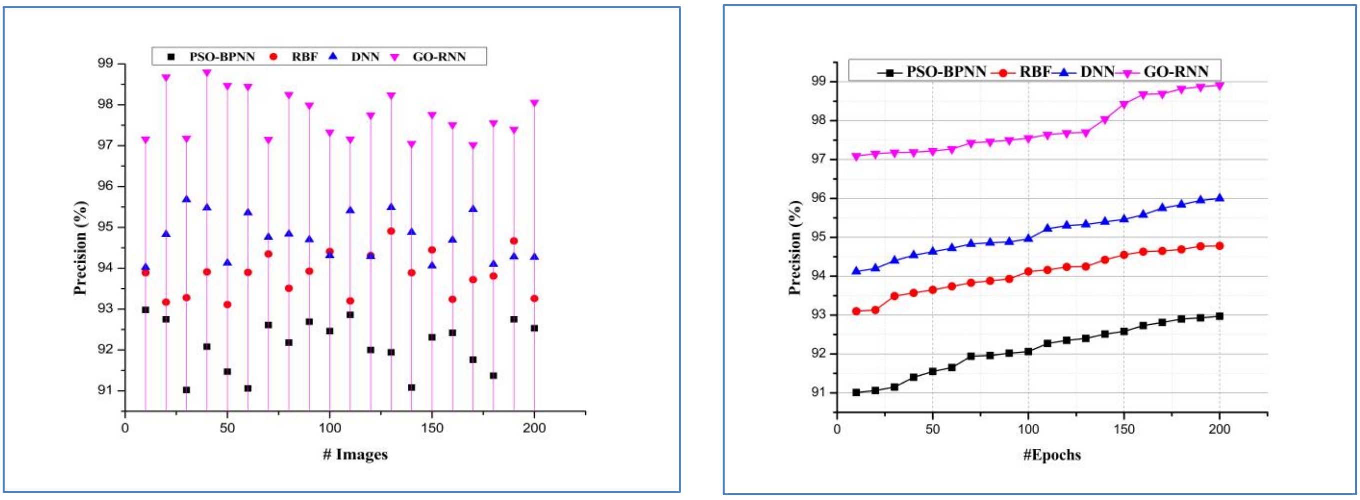
Figure 6 illustrates the root mean square error rate analysis of the GO-RNN approach. If a hierarchical thermal noise reduction strategy achieves the best feasible RMSE value, it minimizes noise and distortion in thermal images. The root-mean-squared error (RMSE) quantifies how off estimates are, on average. In this case, it represents the degree of agreement between the denoised thermal images and the actual temperatures [35-36]. Lower RMSE values indicate that the approach has successfully conserved the essential thermal information while reducing the influence of noise, leading to more precise temperature measurements. This is especially important in sports science, where precise temperature readings are vital to evaluating players' health and performance. The excellent accuracy of the GO-RNN model in predicting mental health states from thermal data is reflected in the low RMSE value obtained in an examination of athletes' mental health based on the model. Root-mean-squared error measures mental health indicator differences between predictions and observations. The GO-RNN model's ability to capture complicated thermal data patterns and correlations suggests it can accurately predict athletes' emotions. This precision is needed to assess athletes' mental health immediately and adopt therapy or training adjustments. In both cases, RMSE values indicate method robustness and reliability. This indicates that the hierarchical thermal noise reduction method has greatly improved thermal picture quality. The GO-RNN model can accurately predict athletes' psychological well-being using thermal data. These findings demonstrate the importance of these methods in thermal imaging and sports science, where accurate data is essential for athlete safety and performance [37,38].

Figure 7 demonstrates the accuracy analysis of the GO-RNN approach while analyzing the athlete's mental and physical health. This study uses clustering techniques that identify the region from the thermal images, increasing the overall mental health analysis process. Maximum accuracy in the context of AGCM means that the available thermal data has been successfully used to categorize athletes into clusters based on their mental health characteristics. These clusters are precise and clear, proving that the approach can identify variations in the emotional states of athletes. While AGCM generates clusters that can be used to forecast athletes' mental health, GO-RNN optimizes these predictions [39]. This means that the GO-RNN model is particularly good at identifying patterns in the clustered data and correctly categorizing athletes according to their mental health status. The model's impressive predictive prowess based on temperature data is reflected in this result. The highest possible result for accuracy indicates that the integrated AGCM and GO-RNN technique is robust for gauging and tracking athletes' psychological states. When it comes to the athletes' mental health, the clustering approach does a great job of grouping them, and the GO-RNN model does a great job of predicting the outcomes for each individual within each cluster. Then, the system's efficiency is further evaluated, and the results obtained are shown in **Figures 8** and **9**.



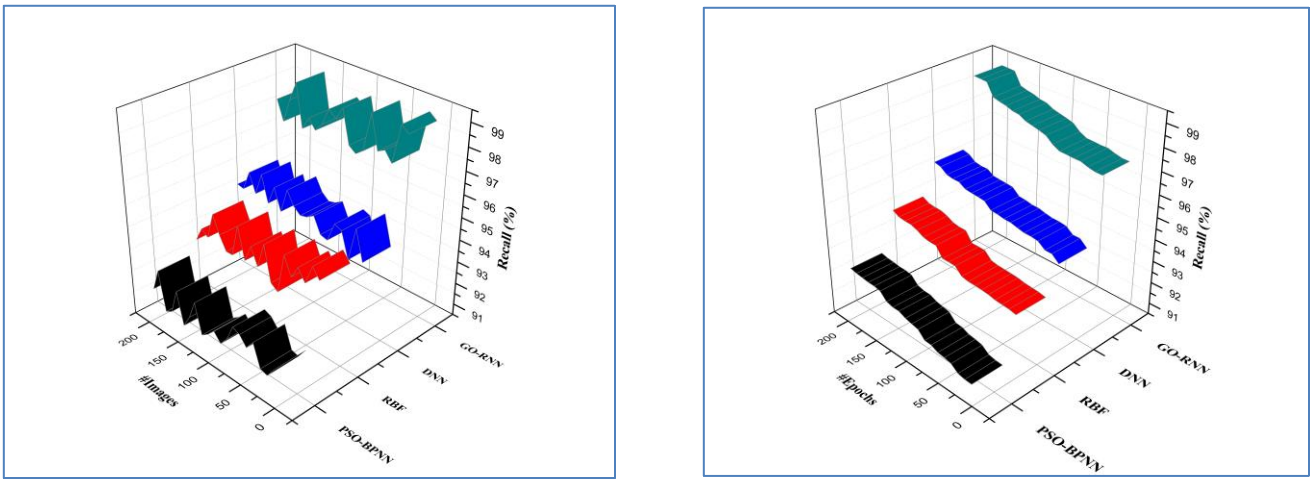
(a) **(b)**

Figure 7. Accuracy analysis of GO-RNN, **(a)** images; **(b)** epochs.



(a) **(b)**

Figure 8. Precision analysis of GO-RNN, **(a)** images; **(b)** epochs.



(a) **(b)**

Figure 9. Recall analysis of GO-RNN, **(a)** images; **(b)** epochs.

Cohen's Kappa values provide valuable insights into the performance and agreement with reference data of various machine learning models, such as the GO-RNN model, Particle Swarm Optimization with Back Propagation Neural Network (PSO-BPNN), Radial Basis Networks (RBF), and Deep Neural Networks (DNN), in the analysis of athletes' mental and physical health. The Cohen's Kappa of 0.95, GO-RNN is the best-performing model in this hypothetical case. This number indicates a high degree of agreement between the model and the ground truth data. This demonstrates that GO-RNN is superior at making accurate predictions to measure athletes' psychological and physiological well-being. Kappa values of 0.81 to 0.87 for additional models, including PSO-BPNN, RBF, and DNN, show that their health assessments are highly consistent. While Kappa results show that GO-RNN performs best, other variables, including model complexity, computational efficiency, interpretability, and alignment with the research's specific aims, should be considered when making the final model selection. Statistical tests should also confirm any discrepancies in Kappa values to ensure their relevance.

In conclusion, Cohen's Kappa values are crucial in quantifying and comparing the agreement levels of different models, and in this hypothetical scenario, GO-RNN shows the highest agreement. However, a thorough model selection in athletes' mental and physical health studies should include statistical analyses and practical criteria. The evaluation criteria and indicators used to gauge success are compared in detail in Section 4, which references other techniques. It would be helpful to discuss the comparative methodologies employed to understand the GO-RNN method's advantages better. Included are the datasets that were analysed, the evaluation metrics used (such as F1 score, accuracy, precision, and recall), and any statistical tests conducted to determine significance. It would be beneficial to clarify how the GO-RNN technique outperforms traditional approaches or machine learning models to bolster its novel and efficient approach to tracking athletes' physiological states. This may manifest as superior prediction ability, quicker convergence, or improved temporal data processing.

5. Discussion

Traditional methods, based on periodic measurements and manual observation, are flawed because they are slow, prone to bias, and miss minor health risks, as is shown by a direct comparison. Neither precise data processing nor real-time monitoring are features of these approaches. By using machine learning and real-time thermal imaging (GO-RNN), the ML-DRTTSI model continuously monitors an athlete's temperature and physiological changes, improving accuracy. By reducing human error, providing rapid insights, and guaranteeing instantaneous anomaly detection, this is light years ahead of traditional methods for injury prediction and performance optimisation.

The ML-DRTTSI model has several benefits, including real-time monitoring, injury prevention, and performance optimisation, but it also has a few drawbacks, as shown in a cost-benefit analysis. Wearable gear and thermal imaging devices aren't cheap but well worth it. Not only is there regular upkeep that athletes must conduct, but some worry that these devices can damage or hinder their performance. Safely handling sensitive medical information also poses a significant threat to data privacy. Regardless of these issues, the concept has great promise for assisting athletes in becoming more precise and injury-free.

6. Conclusion

Thus, the study uses the Gradient optimized recurrent neural model to examine the athlete's mental and physical health. During the analysis, thermal images are utilized to gather the athlete's physical activities that help to explore their mental condition. The gathered images are processed by a hierarchical thermal noise reduction technique that analyzes each pixel and compares it with the threshold value. According to the comparison, the high-frequency components are eliminated from the image, reducing the difficulties of computation complexity. Similar pixels are determined and form a cluster, which helps predict the stress region and the temperature features are extracted. The derived features are processed by a neural model that classifies the normal and abnormal features. The classification clearly states that athletes' mental health problems are directly affected by their physical activities. Therefore, this study requires frequent concentration on sportsperson mental health to improve the overall performance. However, the future system requires optimization techniques to fine-tune the network learning parameters and hyperparameters. In addition, security techniques are required to manage their sensitive information.

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