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Predicting Player's Healthiness Using Machine Learning

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***Abstract* - This research paper introduces the PHD (Player Health Detection) system as a solution to address the issue of inadequate health checking of players prior to sports events. The PHD system, utilize real-time image and video processing technology, to detect players' health conditions and prioritize their safety and well-being. The system incorporates analysis of body balance, injury detection, exercise video analysis, and heart rate measurement to evaluate player eligibility for sports events. For this specific purpose, we have created a mobile application by integrating computer vision technology and employing specialized image processing software. The anticipated outcomes of this solution include injury prevention, enhanced player safety, and informed decision-making for coaches regarding player participation. The implementation of the PHD system contributes to the advancement of the sports industry by creating a safer environment and actively supporting the health and well-being of players.**

Keywords: PHD, sports events, real-time system, image processing, injury prevention, body balance analysis, heart rate measurement, video analysis.

I. INTRODUCTION

Evaluating the health status of players before engaging in sporting activities is crucial, and recent technological advancements offer comprehensive health analysis options. This research paper proposes a multidimensional approach that incorporates four key components—heart rate, injury detection, body balance assessment, and fitness levels—to analyze players' health before attending a sport event. Heart rate serves as a physiological parameter reflecting cardiovascular health and overall fitness. Computer vision techniques, such as facial recognition algorithms, detect changes indicative of heart rate fluctuations. This non-invasive method allows health professionals to assess heart rate conveniently, providing valuable insights into athletes' physiological state. Advanced imaging technologies and machine learning algorithms enhance injury detection with a promising accuracy and efficiency. By training models on a large dataset of injury images, impressive accuracy has been achieved in identifying neck, hand, and leg injuries. This automated approach reduces assessment time and subjectivity, enabling swift injury detection and evaluation.

Recent advancements in motion capture technologies and computer vision algorithms enable accurate body balance assessment through posture analysis. Systems utilizing skeletal tracking and machine learning techniques to analyze postures, identify unbalanced areas. Objective assessment of body balance helps develop targeted interventions and training programs, improving performance and reducing injury risk. Fitness levels directly impact athletes' ability to meet physical demands. Traditional assessments were time-consuming, but technology streamlines the process. Analyzing warm-up exercise count rates quantifies performance in various aspects of fitness. Machine learning algorithms enhance the assessment, providing quick and reliable evaluations. This data-driven approach eliminates subjectivity, enabling effective monitoring and tailored training programs.

The goal of the proposed study is to integrate heart rate detection, injury detection, body balance assessment, and fitness level estimation for comprehensive pre-event health analysis. By combining these elements, a holistic picture of athlete health and readiness is obtained, facilitating informed decisions about their eligibility. This paper proposes an approach using computer vision algorithms, and machine learning models to analyze multiple facets of player health simultaneously.

II. LITERATURE REVIEW

Heart rate monitoring is crucial for assessing cardiovascular fitness and performance, and non-contact systems have gained popularity for their convenience and affordability. Florian Michahelles, Ramon Wicki, and Bernt Schiele developed a micro-impulse radar (MIR) technology, which employs filtering, local maxima detection, and separation calculations to assess heart rate[1]. Several research

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papers propose innovative non-contact methods for heart rate monitoring[2][3][4].MIR is adaptable and affordable, making it a promising wearable heart rate sensor. H. Rahman, M.U. Ahmed, S. Begum, and P. Funk proposed an image processing-based method using a webcam to analyze facial skin color variations caused by blood circulation[5]. Fast Fourier Transform (FFT), Independent Component Analysis (ICA), and Principal Component Analysis (PCA) enable real-time heart rate estimation. Verkruyse et al. utilized a digital camera with an appropriate light source to measure heart rate and respiratory rate over short periods[6]. Jensen and Hannemose proposed a system that combines face detection techniques and ICA to extract the heart rate signal[5]. Lee, Tseng, and Huang developed an image-based method using a laptop's embedded video camera to detect heartbeats based on light absorption by human faces[7]. Image processing and ICA were used for relevant information extraction. These innovative approaches offer contactless heart rate monitoring solutions with various benefits for athletes and healthcare professionals[8][9].

This literature review also explores the existing research on utilizing image processing methods to detect athletes' injuries and assess their healthiness. Previous research has primarily focused on specific sports or injury sites. Notably, studies on knee injuries achieved high accuracy (98.32%) using infrared thermography and convolutional neural networks [10]. Another investigation centred on head injuries during the Beijing 2022 Winter Olympics, proposing automated identification methods and treatment strategies [11]. Cross-Sport Injury Analysis: Some studies have examined injuries across different sports. Image processing and machine learning techniques have been employed to analyze injuries in football players, yielding an accuracy of 81.2% [12][13]. Additionally, injuries in dance and gymnastics have been explored, showcasing the versatility of imaging technology in diverse athletic disciplines[8][14]. In 2017, 77 Chinese national basketball players were analyzed using X-ray and ultrasound technology to identify injuries in football competitors[7]. The literature review emphasizes the need for a comprehensive approach for athletes, The proposed research aims to the objective is to develop accurate assessments of injury severity, detect injuries, and determine athletes' fitness for future participation.

Posture recognition and analysis in computer vision and healthcare have received considerable attention. This review examines pertinent research papers that contribute to the advancement of posture recognition. The Iran Conference on Machine Vision and Image Processing (MVIP) proposed a deep learning-based posture recognition system that combines CNNs and RNNs for real-time posture classification [15]. Chen and Yang introduced a system based on pose estimation algorithms and deep learning for detecting and correcting postural abnormalities in stroke rehabilitation, providing real-time feedback and aiding in rehabilitation [16]. Liao, Miaou, and Li developed a markerless walking posture analysis system using computer vision techniques, achieving accurate recognition without external markers or sensors [17]. Lefebvre and Makni focused on posture detection in eHealth services, employing sensor fusion techniques to enhance accuracy, particularly in healthcare applications [18]. Wang, Chang, Haung, and Wang explored human posture recognition using the Kinect sensor, improving detection accuracy through the utilization of 3D skeletal information and depth data [19]. These studies demonstrate the potential of deep learning, computer vision, and sensor fusion for real-time posture detection in healthcare, rehabilitation, and eHealth services. Further research is warranted to refine these approaches, address specific posture-related challenges, and develop effective tools for promoting correct posture and preventing musculoskeletal disorders.

Various systems worldwide are utilized to analyse human body motion, encompassing the tracking of specific body parts and patterns over time to evaluate physical fitness. Arm exercises can be examined through video recording, although processing large files can be time-consuming. To expedite the process, algorithms such as Map Reduce and Haar-like-feature-based detection can be employed to detect body parts [20]. Motion capture systems tend to be expensive, leading to the use of simple rulers for measuring joint angles, albeit with lower accuracy. Kinect, capable of detecting kinematic data in 3D, enables the assessment of range of motion under the guidance of specialists [21][22]. In sports, the analysis of human motion holds great significance. Professional golfers' movements, for instance, can be identified using the Lucas-Kanade algorithm [23]. Diving actions can be analysed by tracking knee and hip joint angles with video analysis tools [24]. Human Activity Recognition (HAR) plays a crucial role in coaching and athlete performance evaluation. The MMDOS dataset combines data from various sensors, including Kinect V2 and RGB cameras, focusing on exercises such as squats and push-ups [25]. To address the limitations posed by costly equipment, a proposed PHD system aims to enhance the physical fitness and confidence of players through affordable solutions and innovative features.

III. METHODOLOGY

A) User Detection of Heart Rate using Facial Emotions: Unveiling the Correlation with Convolutional Neural Networks

The detection of heart rate using facial emotions involved several key steps. First, emotions were mapped to specific

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heart rate ranges based on established research findings and reputable sources in the field. Emotions such as happiness, sadness, anger, fear, and relaxation were associated with distinct heart rate ranges, reflecting their respective physiological responses. The training of the heart rate detection model utilized a data set sourced from online. This data set consisted of 48x48 pixel grayscale images of faces, with emotion labels including Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral. The faces have been automatically registered so that the face is more or less centered and occupies about the same amount of space in each image. Preprocessing steps were applied to ensure data quality and uniformity, including data cleaning and normalization.

For the training of the heart rate detection model, a Convolutional Neural Network (CNN) was employed due to its effectiveness in analyzing visual data, such as facial expressions. The model was trained using 100 epochs, with various hyperparameters chosen to optimize performance. The choice of the number of epochs was based on factors such as achieving convergence, preventing overfitting, and obtaining satisfactory model performance. The learning rate was experimented with values of 0.1, 0.01, and 0.001, while batch sizes of 32, 64, and 128 were utilized to balance training efficiency and memory usage. The ReLU activation function was used for the hidden layers, and softmax activation was employed in the output layer. The maximum heart rate (MHR) can be estimated using the commonly used equation:

$$MHR = 220 - age$$

This equation provides a rough estimate of the maximum number of times your heart can beat per minute during physical exertion[26]. The optimization algorithm selected for training the model was Adam, known for its adaptive learning rate mechanism and effectiveness in deep learning tasks. The Adam algorithm provided the necessary optimization for the heart rate detection model. The experimental setup involved using hardware and software suitable for deep learning tasks. The model was implemented using Python programming language and the TensorFlow deep learning framework. Preprocessing steps were applied to the data set, including data cleaning and normalization, to ensure data quality and uniformity.

Model evaluation was performed using appropriate metrics such as accuracy, precision, recall, or mean absolute error. The performance of the heart rate detection model was assessed using a separate test set or cross-validation. The results obtained from the heart rate detection model were analyzed and discussed, highlighting the achieved performance metrics and their implications in relation to the objective of detecting heart rate using facial emotions.

B) Analyse images to detect injuries of the player's body using image processing to check healthiness of the player

A robust injury detection system requires a comprehensive dataset of neck, knee, and hand injuries. The dataset collection process involves gathering a wide range of images that depict various types of injuries, encompassing different orientations and severity levels. This dataset improves models' generalization to real-world scenarios. In addition to the images themselves, the dataset requires meticulous annotation with labels indicating the presence and precise location of injuries within each body part. This research aims to enhance injury detection system performance and contribute to advancements in sports medicine and athlete health assessment.

The research preprocesses hand, neck, and knee images and injury images using various techniques to improve quality and prepare them for analysis. These include resizing, cropping, normalizing brightness, contrast, and color levels, denoising, and data augmentation to increase diversity and robustness. These steps optimize the dataset for accurate injury detection in the research stages. The dataset is analyzed using exploratory data analysis (EDA) techniques to identify patterns, biases, and potential limitations. This helps determine if certain types of injuries are overrepresented or underrepresented, impacting the system's performance and generalizability. Thorough assessment and preprocessing are essential for accurate and reliable injury detection.

The development of an injury detection system involves the design and training of algorithms and models. One of the key aspects is body part detection, where a convolutional neural network (CNN) model is trained to classify and localize the specific body part present in the input image (neck, knee, or hand). CNN models capture specific features, using multiple layers and optimizing with algorithms like Adam and RMS prop. Fine-tuning hyperparameters enhances performance.

In addition to that, the direction of the body part in the image needs to be determined. This is achieved by training separate CNN models for each body part that predict the direction (e.g., horizontal, vertical) based on the input image. These models are trained on labeled datasets and optimized using appropriate algorithms and hyperparameters, capturing directional information. The final step is to detect injury levels based on injury size or severity, using CNN models to analyze specific body parts and estimate injury size or severity.

C) Analyse Different Body Postures to Identify Incorrect Areas of the Body

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A diverse dataset was collected, consisting of individuals demonstrating three postures: sitting, standing hands-open, and standing hands-down. This dataset included variations in body types, ages, and genders. High-quality images were captured to accurately represent body poses, and ground truth labels were annotated to indicate correct and incorrect postures. PoseNet, a deep learning model, estimated human body poses in real-time using a single camera input. It detected key joint positions like shoulders, wrists, hips, and knees, facilitating posture analysis. The pre-trained PoseNet model accurately recognized and estimated human body poses, obtained from open-source libraries or frameworks.

Sitting posture was detected by analyzing the positions of specific joints, such as the left or right hip and knee. The vertical distance (dy) between these joints played a critical role in sitting posture detection. Comparing this distance to a predefined threshold value of 40 units determined the correctness of the sitting posture. A vertical distance below the threshold indicated a correct posture, while exceeding the threshold classified the posture as incorrect.

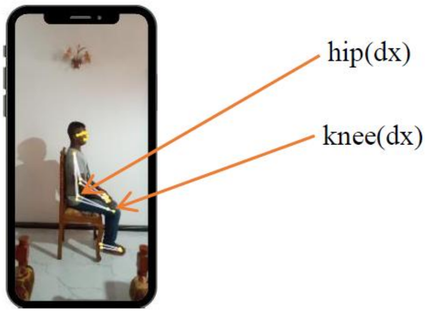

Figure 1: Sitting posture detection

$$(transformX(righthip.position.dx, size) + 40) \leq transformX(rightKnee.position.dx, size)) \,||$$

$$(transformX(righthip.position.dx, size) - 40) >= transformX(rightKnee.position.dx, size)$$

To detect the standing hands-open posture, the positions of the left or right shoulder and wrist joints were examined. The horizontal distance (dx) between these joints served as the key metric for hands open posture detection. Comparing this distance to a threshold value of 50 cm identified the hands open posture. A horizontal distance below the threshold indicated a correct posture, representing an open and relaxed stance.

The hands-down posture was identified by analyzing the positions of the left or right shoulder and wrist joints. In addition to the vertical distance (dy) between these joints, the relative positioning of the shoulder and wrist was considered. A threshold value of 50 units for the vertical distance, along with the shoulder positioned above the wrist, indicated a correct hands-down posture.

Posture Validation

For the standing posture, the correctness of hands-open and hands-down postures was assessed. In the hands-open posture, the vertical distances (dy) between the shoulder, elbow, and wrist points were compared. If the difference was below a threshold of 40 units, the posture was correct. Similarly, in the hands-down posture, the horizontal distances (dx) between the shoulder, elbow, and wrist points were compared, and a difference below the threshold indicated a correct posture.

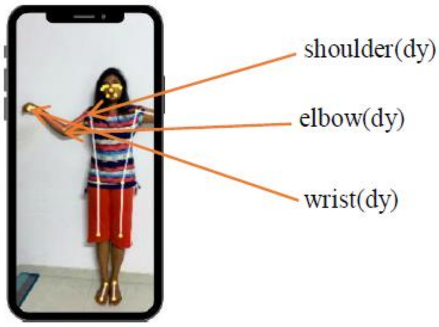

Figure 2: Standing posture validation

$$(min(transformY(leftShoulder.position.dy, size), transformY\ (leftWrist.position.dy, size)) - 10) >= transformY(leftElbow.position.dy, size)$$

The correctness of the leg position was validated by comparing the horizontal distances (dx) between the hip, knee, and ankle points. A difference below the threshold of 40 units indicated a correct leg position. To determine the correctness of the backbone position, the horizontal distances (dx) between the hip and shoulder points were used. A difference below the threshold of 40 units indicated a correct backbone position.

To assess the correctness of the backbone position in the sitting posture, the horizontal distances (dx) between the hip and shoulder points were analyzed. A threshold of 12 units was set, and a difference below this threshold indicated a correct backbone position, while exceeding the threshold classified the posture as incorrect.

D) Analyse different exercises to identify and get the repition counts to calculate the fitness level of the player

The methodology for this research paper involves generating a fitness level for players as a percentage by counting the number of repetitions performed in three selected

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warm-up exercises: Side static lunge, Squat, and Inner thigh and oblique.

The exercise detection process utilizes the PoseNet model: a machine learning model which is used to predict the positions of various body components, such as the hands and fingers, in static images or moving pictures, to estimate joint positions, specifically the hip and pinky positions: the little finger's position is one of the key points that the model tries to predict, in real-time from the input video frame. The relationship between these joint positions is used to identify each exercise. Specific criteria are applied for each exercise:

For the Single-Arm Overhead Side Bend, the x-coordinate of the right hip position is compared to the x-coordinate of the right pinky position with an additional requirement that the x-coordinate of the right hip should be greater than the x-coordinate of the right elbow with an offset of 15 units.

Figure 3: Single-Arm Overhead Side Bend

$$(transformX(rightHip.position.dx, size)) > (transformX(rightPinky.position.dx, size)) \&\&$$

$$((transformX(rightHip.position.dx, size) - 15)) > transformX(rightElbow.position.dx, size))$$

For the Inner thigh and oblique, the x-coordinate of the right hip position, with an offset of 15 units added, is compared to the x-coordinate of the right pinky position;

Figure 4: Inner thigh and oblique detection

$$(transformX(rightHip.position.dx, size) + 15) < (transformX(rightPinky.position.dx, size))$$

For the Squat, the y-coordinate of the right hip position, with an offset of 10 units added, is compared to the y-coordinate of the right Pinky position;

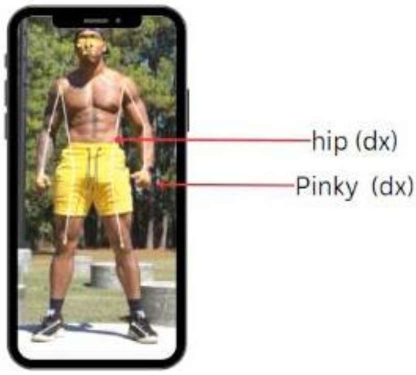

Figure 5: Squat Detection

$$(transformY(rightHip.position.dy, size) + 10) \leq (transformY(rightPinky.position.dy, size))$$

Once an exercise is detected from the above three types of exercises, the next step is to count the repetitions. Rep counting is achieved by analysing joint positions and specific postures relevant to each exercise. Conditions or postures indicating the completion of one repetition are defined for each exercise. By tracking changes in these conditions or postures over time, the repetition count is incremented whenever a full repetition is detected.

For the Squat, changes in the y-coordinate of the right hip position are monitored, incrementing the repetition count when the user goes from the down position to the up position. For the Side Static Lunge, transitions between distinct phases of the exercise are tracked, considering the positions of the nose, left wrist, and right wrist. The repetition count is incremented when the user transitions from one position to another. For the Inner Thigh and Oblique, transitions between distinct phases of the exercise are also tracked, considering the positions of the left knee and right knee. The repetition count is incremented when the user transitions from one side to the other.

The fitness rate for each exercise is calculated by getting the average reps counts in a selected period. The validations have added to get a separate fitness level for each exercise like “Already done”, “Rep count is zero”, “Redo the exercise again”, etc. The final fitness percentage is calculated by getting the average fitness rate of the above three exercises.

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IV. RESULT AND DISCUSSION

A) Evaluation of Heart Rate Detection Model using Facial Emotions: Insights into Accuracy and Heart Rate Estimation

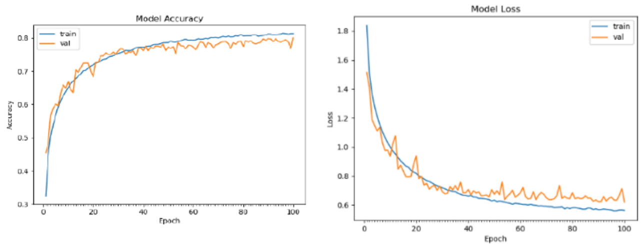

Figure 6: Heart Rate Detection Model Accuracy Chart and loss chart

The heart rate detection model's performance was evaluated using accuracy and loss metrics. Accuracy measured the proportion of correctly predicted emotions, while loss quantified the discrepancy between predicted and actual emotions. Higher accuracy and lower loss indicated successful mapping between facial emotions and heart rate ranges. The accuracy chart (Figure 10) depicted the trend of accuracy values, while the loss chart (Figure 11) illustrated the trend of loss values during evaluation. Continuous 10-second intervals of detected emotions were used to calculate the average heart rate, reflecting the player's physiological state. Preprocessing techniques enhanced the quality of the emotion data. The computed average heart rate within each interval offered insights into the dynamic changes in heart rate corresponding to different facial emotions. This approach provided a comprehensive understanding of the relationship between facial emotions and heart rate, enabling analysis of the temporal dynamics of heart rate fluctuations. The findings demonstrate the effectiveness of facial expression-based heart rate estimation and contribute to applications in real-time emotional and physiological monitoring.

B) Analyse images to detect injuries of the player's body using image processing to check healthiness of the player

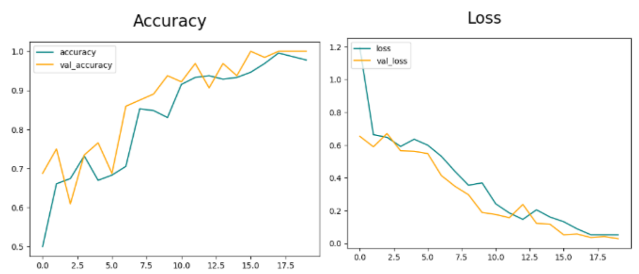

Figure 7: Test accuracy of injury level detection

Adam is used as the optimizer since it gave the best outputs, and it was fit for datasets such as this.

The accuracy of the developed injury detection models was evaluated on a separate test set. The body part detection model achieved 88.02% accuracy, accurately identifying the body part in input images. For direction detection, the models achieved an average accuracy of 79.89%, correctly predicting the orientation. The injury level detection models achieved a classification accuracy of 82.05%, accurately estimating the severity of injuries. Overall, the models showed good accuracy in detecting injuries, identifying body parts, determining direction, and estimating severity.

Figure 8: Injury detection output

C) Analyse Different Body Postures to Identify Incorrect Areas of the Body

The implemented methodology successfully identified correct and incorrect postures in sitting, hands open, and hands down categories. PoseNet, a deep learning model, accurately estimated joint positions using a single camera input for posture analysis. Sitting posture detection involved examining the vertical distances (dy) between hip and knee joints. A threshold of 40 units determined correct or incorrect postures. Similarly, for hands open posture, horizontal distances (dx) between shoulder and wrist joints were analyzed with a threshold of 50 cm. Hands down posture detection considered vertical distance (dy) and relative positioning of shoulder and wrist. A threshold was used to classify correct or incorrect postures. Leg and backbone positions were evaluated using horizontal distances (dx) between specific joint points, with a threshold of 40 units. The methodology effectively distinguished between correct and incorrect postures, highlighting areas of incorrect postures for corrective actions. The research demonstrated reliable posture detection, providing valuable feedback to individuals for improving their posture and alignment.

D) Analyse different exercises to identify and get the rep counts to calculate the fitness level of the player

The study aimed to determine participants' fitness levels by evaluating their performance in three specific exercises: Squat, Inner thigh and oblique, and Single-Arm Overhead

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Side Bend. Fitness levels were determined by counting the number of repetitions completed within a selected period and converting it into a percentage. The results displayed varying fitness levels across the exercises. On average, participants achieved a fitness level of 25% for the Squat exercise, indicating that they completed 25% of the standard rep count in the given time. For the Inner thigh and oblique exercise, the average fitness level was 25%, while for the Single-Arm Overhead Side Bend exercise, it was also 25%. Combining the fitness levels from all three exercises yielded an average overall fitness level and provides the relevant suggestions with the risk level for each player. This comprehensive approach of calculating fitness as a percentage provides a holistic evaluation of an individual's overall fitness. Expanding the methodology to incorporate additional exercises would further enhance the accuracy of determining fitness percentages. This approach is particularly valuable for assessing an individual's fitness level before engaging in sports events, offering a comprehensive overview of their physical capabilities.

V. CONCLUSION

This research paper proposes a multidimensional approach to assess athlete health prior to sports events. The study integrates heart rate analysis through facial expressions, injury detection, body balance assessment, and fitness level estimation to provide a comprehensive evaluation. The research highlights the practicality of using facial expressions for non-invasive heart rate monitoring and employs advanced imaging and machine learning for improved injury detection. Objective body balance assessment aids in identifying unbalanced areas and reducing injury risks. Fitness level estimation using warm-up exercise count rates eliminates subjectivity. The integrated framework aims to revolutionize pre-event health assessments, enhancing athlete well-being and performance. Future directions include incorporating additional parameters in the mobile application, real-time monitoring, expanding the database, and gathering user feedback for continuous improvement. By pursuing these avenues, researchers can advance pre-event health evaluations, benefiting athlete safety, performance, and overall health in sports events.

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