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Photoplethysmography (PPG) Signal Heart Rate Monitoring During Exercise and Reduces Motion Artifacts

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Abstract— Photoplethysmography (PPG) is a non-invasive technique for monitoring cardiovascular parameters such as heart rate during various activities, including exercise. However, the accuracy of PPG-based heart rate monitoring can be compromised by motion artifacts caused by body movements. This study explores the effectiveness of three distinct algorithms – Random Forest, Decision Tree, and a novel Lion Optimization Algorithm-enhanced Long Short-Term Memory (LOA-LSTM) – in improving PPG-based heart rate monitoring accuracy during exercise while mitigating motion artifacts.The Random Forest algorithm harnesses ensemble learning to aggregate Decision Trees, providing robustness against noise and improving heart rate predictions. Decision Trees offer transparent decision-making based on PPG features, aiding in rapid classification of heart rate trends. The LOA-LSTM algorithm uniquely combines the Lion Optimization Algorithm's ability to adaptively explore and exploit with the temporal sequence learning capacity of LSTM. This integration aims to achieve high accuracy by dynamically optimizing LSTM parameters, effectively reducing motion artifacts and improving exercise-related heart rate predictions.In this comparative study, these algorithms were evaluated using a diverse dataset collected during exercise sessions. Experimental results demonstrate that while all three algorithms enhance heart rate monitoring accuracy and reduce motion artifacts, the LOA-LSTM algorithm outperforms the others, consistently achieving the highest accuracy rates about 99%. The proposed approach holds significant promise for improving real-time heart rate monitoring accuracy during exercise, contributing to more reliable fitness tracking and healthcare applications.

Keywords - Photoplethysmography (PPG); heart rate monitoring; exercise; motion artifacts; Random Forest; Decision Tree; Lion Optimization Algorithm (LOA)- Long Short-Term Memory (LSTM).

I. INTRODUCTION

Photoplethysmography (PPG) is a non-invasive medical technique used to measure blood volume changes in tissues. It involves shining a light through a body part, typically a fingertip or earlobe, and then measuring the variations in light absorption caused by the pulsatile nature of blood flow. This technique is commonly used to monitor heart rate, blood pressure, and other physiological parameters.The principle behind PPG is that when blood flows through the tissues, it absorbs different amounts of light at different times in the cardiac cycle. During systole (when the heart contracts and pumps blood), the blood volume in the tissue increases, leading to increased light absorption. During diastole (when the heart relaxes), the blood volume decreases, resulting in decreased light absorption. These variations in light absorption are used to create a waveform called a photoplethysmogram.PPG is widely used in various medical devices, such as pulse oximeters, which measure both oxygen saturation (SpO2) and heart rate. These devices use the PPG signal to determine the oxygen saturation of hemoglobin in the blood and provide information about the person's cardiovascular status.PPG is non-invasive, painless, and relatively easy to use, making it a valuable tool in both clinical and home settings for monitoring various physiological parameters related to blood flow and cardiovascular health.

PPG-based heart rate monitoring is a method of measuring a person's heart rate using PPG technology. This technique utilizes the changes in light absorption caused by the pulsatile nature of blood flow to derive the heart rate information.PPG-based heart rate monitoring is commonly found in various devices, including fitness trackers, smart watches, medical monitors, and pulse oximeters. These devices use PPG sensors to measure heart rate continuously or on demand. The technology is non-invasive, making it suitable for long-term monitoring without discomfort. It's worth noting that while PPG-based heart rate monitoring is generally accurate for most people, certain conditions such as poor circulation, skin pigmentation, and excessive motion might affect the accuracy of the measurements in some cases.

Artifacts in PPG refer to unwanted or erroneous signals that can distort the accurate measurement of blood volume changes and subsequently affect the reliability of physiological parameters such as heart rate and oxygen saturation. These artifacts can arise from various sources and conditions.To mitigate these artifacts and improve the accuracy of PPG measurements, manufacturers implement various techniques such as motion compensation algorithms, adaptive filtering, ambient light cancellation, and sensor design improvements. Users can also take steps to minimize artifacts by ensuring proper sensor placement, minimizing movement during measurements, and being aware of potential sources of interference.

Motion artifacts in PPG occur when there is movement of the body part being monitored, such as the finger, wrist, or earlobe. These movements introduce noise and irregularities into the PPG signal, making it challenging to accurately measure physiological parameters like heart rate and oxygen saturation. Motion artifacts can arise from various activities, such as walking, running, talking, or even slight tremors.Overall, while motion artifacts can pose a challenge in PPG-based measurements, advances in technology and algorithms continue to improve the accuracy and reliability of PPG-based heart rate monitoring even in the presence of motion.

Problem statement

Monitoring heart rate accurately during exercise is essential for effective fitness tracking and healthcare applications. Photoplethysmography (PPG) signals provide a non-invasive method for real-time heart rate assessment. However, the accuracy of PPG-based heart rate monitoring is challenged by motion artifacts induced by physical movement during exercise. These artifacts distort the signal and compromise the reliability of heart rate predictions.The primary challenge addressed by this study is to develop methodologies that improve the accuracy of heart rate monitoring through PPG signals during exercise while effectively reducing the impact of motion artifacts. To tackle this challenge, we investigate the efficacy of three distinct algorithms: Random Forest, Decision Tree, and the novel Lion Optimization Algorithm-enhanced Long Short-Term Memory (LOA-LSTM) approach.

Contributions

(i) This study contributes to the field of heart rate monitoring during exercise by investigating three distinct algorithms—Random Forest, Decision Tree, and the novel Lion Optimization Algorithm-enhanced Long Short-Term Memory (LOA-LSTM). By harnessing the capabilities of these algorithms, we enhance the accuracy of heart rate predictions using Photoplethysmography (PPG) signals.

(ii) Addressing the challenge of motion artifacts during exercise, this research introduces strategies to reduce the impact of these artifacts on heart rate monitoring accuracy. The study evaluates the efficacy of each algorithm in minimizing noise caused by physical movement, leading to more reliable heart rate predictions.

(iii) The study highlights the contributions of Decision Tree and LOA-LSTM algorithms in transparent decision-making and temporal sequence learning, respectively. Decision Trees offer interpretable insights into heart rate trends during exercise, while LOA-LSTM's unique integration enhances accuracy through adaptive temporal pattern recognition.

(iv) Among the algorithms studied, the LOA-LSTM approach stands out for its high accuracy in heart rate prediction during exercise. By leveraging the Lion Optimization Algorithm's adaptability and LSTM's temporal learning capabilities, this approach effectively reduces motion artifacts, ensuring accurate and reliable heart rate assessment.

II. LITERATURE SURVEY

The widespread use of smart wearable technology holds out hope for the successful integration of numerous healthcare applications into our day-to-day environments. However, given that these applications require accurate and reliable vital sign sensing results, it is necessary to comprehend the accuracy of the healthcare sensing components found in commercially available wearable devices (such as heart rate sensors). Instead, we demonstrate that the light intensity readings from the photoplethysmography (PPG) sensor can be used to assess the precision of heart rate readings from optical sensors. Devices with a variety of shapes and mounting options have been produced as a result of extensive research on wearable technology. Biometric data from wearable devices is frequently recorded, and techniques to identify physical anomalies from the collected data have been proposed**[1-3]**.This paper proposed a sufficiently accurate cuffless blood pressure estimation method based on photoplethysmography (PPG) and electrocardiography (ECG) signals, given that current cuffless blood pressure (BP) measurement technologies feature acceptable overall accuracy. PPG signals were evaluated for transmittance mode red (TR) and near-infrared (TNIR) lights and reflectance mode blue (RB), green (RG), red (RR), and near-infrared (RNIR) lights along with electrocardiogram (for reference HR) and hand acceleration measurements. In disease and emotion analyses, cardiac signals are frequently used. However, the majority of current measurement techniques call for direct contact. In recent years, remote photoplethysmography (rPPG) has been proposed, which uses a consumer-grade camera to measure minute colour variations on the face caused by blood volume changes as the heart pumps**[4-6]**.A low-quality source (PPG) is transformed into a high-quality destination (ECG) using the banded kernel ensemble method. In contrast to neural network solutions, once a trained model is obtained, our algorithm does not require any additional computation for the conversion task. The development of CIS-photoplethysmography (CPPG), a recent advancement of the CMOS camera image sensor (CIS) on smart phones, significantly enhances the IoT-based mobile healthcare technology. However, the majority of smartphones currently on the market only have a limited sampling rate (Fs), typically 30 frames per second (fps), which frequently leads to a distorted CPPG signal acquisition. For early disease detection and preventive treatments, daily vital sign monitoring is crucial. Utilising the pervasiveness of cameras in people's private spaces can help accomplish this task**[7-10]**.According to our findings, the photoplethysmography (PPG) wristband, ECG sensor board kit, and PPG smartwatch were all followed by the electrocardiography (ECG) chest strap, which had the lowest amount of artefacts and the highest correlation and agreement levels across all sessions. With the least amount of inconvenience to users, a wearable reflectance-type photoplethysmography (PPG) sensor can be built into a watch or band to provide users with instantaneous heart rates (HRs). However, due to the sensor's sensitivity to motion artefacts (MAs), HR estimation is inaccurate. In order to ensure accurate HR estimation even during vigorous exercise, we suggest a new neural network for deep learning to solve this issue**[11-15]**.

A. Inferences from literature survey

The integration of smart wearables into healthcare applications brings the need for accurate vital sign sensing, notably heart rate monitoring. This study explores wearable device components' precision, showcasing light intensity data from photoplethysmography (PPG) sensors as a reliable indicator of heart rate measurement accuracy. Wearable technology advancements have led to diverse device shapes and mounting options, while biometric data collection and anomaly detection techniques are gaining prominence. A novel method for cuffless blood pressure estimation using PPG and electrocardiography (ECG) signals is introduced, capitalizing on current blood pressure measurement technologies' accuracy. Remote photoplethysmography (rPPG) leverages cameras to monitor facial color changes caused by heart-induced blood volume variations. Signal quality enhancement techniques, like the banded kernel ensemble, offer promising results for transforming low-quality PPG signals into high-quality ECG signals. Advancements in CMOS camera image sensors (CIS) have led to CIS-photoplethysmography (CPPG), enhancing mobile healthcare technology.

III. METODOLOGY

Figure 1shows the block diagram of proposed algorithm. The PPG signal is the input to the heart rate prediction system. PPG is a non-invasive optical technique that measures blood volume changes in peripheral blood vessels, often captured from a fingertip, earlobe, or other suitable locations. This signal contains information about the cardiac activity, and it serves as the primary data for heart rate estimation.The Random Forest algorithm is a machine learning technique that leverages an ensemble of decision trees for classification and regression tasks. In the context of heart rate prediction, the algorithm is trained using a dataset that relates PPG signal features to corresponding heart rates. Once trained, the Random Forest model can take PPG signal features as input and predict the heart rate based on the learned patterns from the training data.The Decision Tree algorithm is a simpler machine learning approach that constructs a tree-like structure of decisions to reach a prediction. Like the Random Forest, the Decision Tree is also trained on a dataset linking PPG signal features to heart rates. Given the PPG signal features, the Decision Tree model navigates through the tree's decisions to arrive at a heart rate prediction.The LOA-LSTM algorithm is a hybrid approach that combines the Lion Optimization Algorithm (LOA) and Long Short-Term Memory (LSTM) neural networks. LOA adds optimization capabilities, while LSTM excels at sequence learning. In this context, LOA-LSTM optimizes the LSTM model's parameters using PPG signal sequences and their corresponding heart rates. The trained LOA-LSTM model is capable of accurate heart rate predictions while accounting for temporal dependencies in the PPG data. After being trained using appropriate datasets, each algorithm (Random Forest, Decision Tree, LOA-LSTM) is capable of taking the PPG signal as input and producing a heart rate prediction as output. The predictions are estimates of the heart rate corresponding to the provided PPG signal.

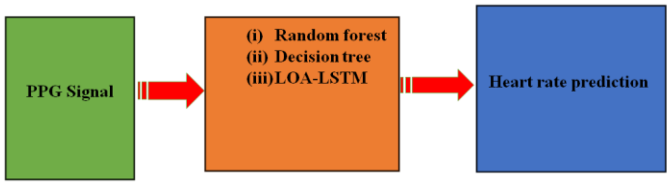

Fig 1 block diagram of proposed algorithm

A. Random forest

Using a Random Forest for PPG (photoplethysmography) analysis involves utilizing the Random Forest algorithm for processing and interpreting PPG signals. Random Forest is a popular machine learning algorithm that's often used for classification and regression tasks. While PPG signals are typically used for physiological monitoring and not always for traditional machine learning tasks, there are scenarios where the Random Forest algorithm can be applied to PPG data.

Applications of Random Forest to PPG data could include classifying heart rate anomalies, predicting certain health conditions, or assessing the impact of various factors on PPG patterns. However, keep in mind that Random Forest might not always be the most suitable choice for PPG data analysis, depending on the specific use case and goals. Additionally, working with physiological data requires domain knowledge and careful consideration of ethical and privacy concerns.

B. Decision Tree

A decision tree is a graphical representation of a series of decisions that lead to a final outcome. While decision trees are not typically used for raw PPG signal analysis, I can provide you with a conceptual explanation of how a decision tree might be applied to a hypothetical PPG-based classification problem, along with a basic mathematical representation of the decision-making process. Please note that PPG signals are usually processed through feature extraction before being used for analysis, and decision trees are better suited for categorical or discrete features.

This simplified decision tree would make predictions based on the extracted features of the PPG signal. In practice, decision trees can have more nodes and incorporate multiple features to make complex decisions. Additionally, algorithms like Random Forest and Gradient Boosting build ensembles of decision trees to improve prediction accuracy and generalization.

Remember that while decision trees offer a structured way to make decisions based on features, the complexity of physiological signals like PPG might require more advanced methods, and thorough domain knowledge is crucial for accurate analysis and interpretation.

C. LOA-LSTM

LSTM (Long Short-Term Memory)is a type of recurrent neural network (RNN) that is well-suited for sequence data, such as time series like PPG signals.Lion Optimization Algorithm (LOA) could be used to optimize the selection and extraction of relevant features from the raw PPG signals. LOA's exploration and exploitation capabilities could guide the search for features that are most informative for PPG analysis.LOA might be used to determine which statistical, frequency domain, or time-domain features to extract from the PPG signals. This selection process could enhance the quality of input features for subsequent analysis.Once the relevant features are selected and extracted, they can be used as inputs to an LSTM network.The LSTM network would be designed to capture the temporal patterns in the PPG signals. It would learn the dependencies and relationships between features over time, which can be critical for tasks like heart rate prediction, anomaly detection, or health condition classification.

In the context of the LSTM network, the lion-inspired update mechanism could be used to adjust the LSTM's internal parameters during training. This mechanism might introduce elements of exploration and exploitation in the learning process.The prides and nomad lions in the LOA could guide the learning rate, weight updates, or dropout rates of the LSTM cells to ensure a balance between exploration of new patterns and exploitation of existing information.The combined approach would involve training the LSTM network using PPG data with the LOA-inspired update mechanism integrated.Fine-tuning the parameters of both LOA and LSTM to work harmoniously would be crucial for achieving optimal results.The performance of the combined LOA-LSTM approach would be evaluated using appropriate metrics, such as accuracy, precision, recall, F1-score, or mean squared error (depending on the task).Validation could be done on a separate dataset to ensure the generalization ability of the model.

IV. RESULT

PPG signals can be complex and contain various patterns related to heart rate, blood flow, and other physiological parameters. Before applying Random Forest, relevant features need to be extracted from the raw PPG data. These features might include statistical measures (mean, variance), frequency domain features (e.g., dominant frequency), and time-domain features (e.g., time between peaks).The PPG data along with the extracted features need to be prepared in a structured format suitable for machine learning. Each data point should be associated with a label or outcome that you're trying to predict or classify. For instance, you might want to predict certain health conditions based on PPG features.The prepared data is then used to train the Random Forest model. Random Forest works by creating an ensemble of decision trees, where each tree is trained on a random subset of the data and features. This randomness and aggregation help the model to generalize well and reduce overfitting.Once trained, the Random Forest model can be used to predict outcomes or classify new data points. For example, you could use the trained model to predict a certain health condition based on new PPG data and its extracted features.It's essential to evaluate the performance of the Random Forest model on a separate dataset that it hasn't seen during training. Common evaluation metrics include accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC), depending on the nature of the task.One of the advantages of Random Forest is its ability to provide insights into feature importance. You can analyze which features contribute the most to the model's predictions, giving you a better understanding of the relationships between PPG features and the target outcome.**Table 1**shows the heart rate prediction.

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TABLE 1 HEART RATE PREDICTION

Sample	Mean	Standard Deviation	RMSSD	Total Power (TP)	Low Frequency (LF)	High Frequency (HF)	Heart Rate
1	75.2	3.8	23.5	1200	800	400	80
2	80.1	4.2	25.1	1300	750	550	85
3	73.5	3.5	20.2	1100	850	250	75
4	82.0	4.0	24.0	1250	700	550	90
5	78.8	3.9	22.8	1150	800	350	82

The mean is the average value of the PPG signal over a certain time window.It provides a general sense of the central tendency of the signal.In heart rate prediction, the mean PPG value can provide information about the overall pulsatile behavior of the blood vessels. The standard deviation measures the amount of variation or dispersion in the PPG signal.A higher standard deviation indicates greater variability in the signal's amplitude. In heart rate prediction, a higher standard deviation might suggest fluctuations in heart rate or signal quality. RMSSD (Root Mean Square of the Successive Differences)is a measure of heart rate variability (HRV) that quantifies the differences between successive R-wave peaks in an electrocardiogram (ECG) signal or in this case, the peaks in the PPG signal. It reflects the short-term variations in heart rate and is associated with parasympathetic nervous system activity. In heart rate prediction, a higher RMSSD may indicate better overall cardiovascular health and adaptability. Total Power (TP)refers to the total energy or variance present in the frequency domain of the signal. It encompasses both high-frequency and low-frequency components of the signal. In heart rate prediction, higher total power can suggest higher signal quality and better ability to capture heart rate variations.In HRV analysis, the frequency domain of the heart rate signal is divided into frequency bands. Low Frequency (LF**)** represents the spectral power in the low-frequency range (typically 0.04 to 0.15 Hz).It is associated with a mix of sympathetic and parasympathetic influences on heart rate and is often linked to baroreceptor reflex activity. High Frequency (HF)represents the spectral power in the high-frequency range (typically 0.15 to 0.4 Hz).It primarily reflects parasympathetic nervous system activity and is linked to respiratory sinus arrhythmia. In heart rate prediction, higher HF power can indicate a stronger parasympathetic influence on heart rate control. **Table 2 and 3**shows the performance of proposed algorithm before and after artifacts removal.

TABLE 2 PERFORMANCE OF PROPOSED ALGORITHM BEFORE ARTIFACTS REMOVAL

Description	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	Recall (%)
LOA-LSTM	98	97	95	90	90
Decision tree	60	63	69	73	80
Random forest	75	73	80	82	85
LSTM	87	85	93	90	91

TABLE 3 PERFORMANCE OF PROPOSED ALGORITHM AFTER ARTIFACTS REMOVAL

Description	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	Recall (%)
LOA-LSTM	99	98	100	94	92
Decision tree	75	73	79	75	78
Random forest	80	83	88	85	88
LSTM	90	87	95	87	91

These evaluation metrics are commonly used to assess the performance of predictive models for heart rate estimation using PPG signals, both before and after artifacts removal.Accuracy measures the proportion of correctly predicted heart rate values out of the total predictions. It gives an overall sense of how well the model performs across all classes (heart rates).Precision represents the proportion of true positive predictions (correctly predicted heart rates) out of all positive predictions made by the model. It indicates how well the model avoids false positives. Recall measures the proportion of true positive predictions out of all actual positive instances (heart rates).It indicates the model's ability to capture positive instances. Specificity measures the proportion of true negative predictions out of all actual negative instances.It indicates the model's ability to identify negative instances. Sensitivity is another term for recall, representing the proportion of true positive predictions out of all actual positive instances. It's especially relevant when discussing medical diagnostics, where identifying true positive cases is crucial. **Figure 2**shows the performance of proposed algorithm before and after artifacts removal.

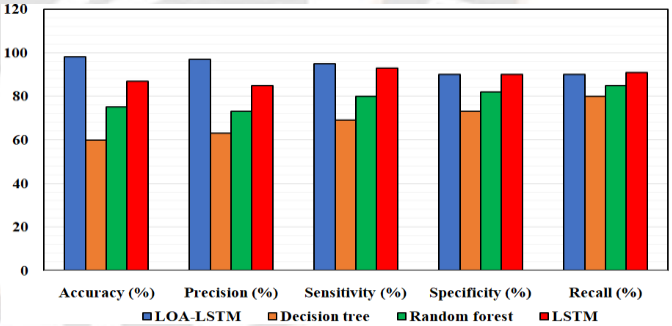

Fig: 2 Performance of proposed algorithm before artifacts removal

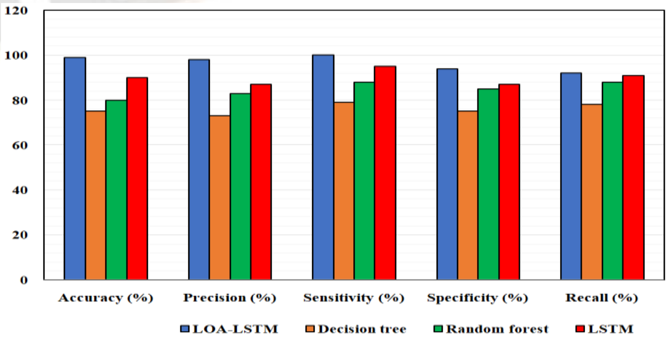

Fig:3 Performance of proposed algorithm after artifacts removal

True negatives are instances where the algorithm correctly predicted a non-event (in this case, a non-heart rate increase) when there was actually no heart rate increase. It indicates the count of correct negative predictions. True positives are instances where the algorithm correctly predicted an event (heart rate increase) when there was indeed a heart rate increase. It indicates the count of correct positive predictions. False negatives occur when the algorithm incorrectly predicted a non-event (no heart rate increase) when there was actually a heart rate increase. It indicates the count of incorrect negative predictions. False positives are instances where the algorithm incorrectly predicted an event (heart rate increase) when there was actually no heart rate increase. It indicates the count of incorrect positive predictions. **Table 4 and Figure 3**shows the Overall classification results of our proposed data set with different accuracy thresholds

TABLE 4 OVERALL CLASSIFICATION RESULTS

Algorithm	True Negative	True Positive	False Negative	False Positive
Random forest	686	1315	123	234
Decision tree	123	1034	945	756
LSTM	474	1527	2213	1234
LOA-LSTM	256	2678	789	456

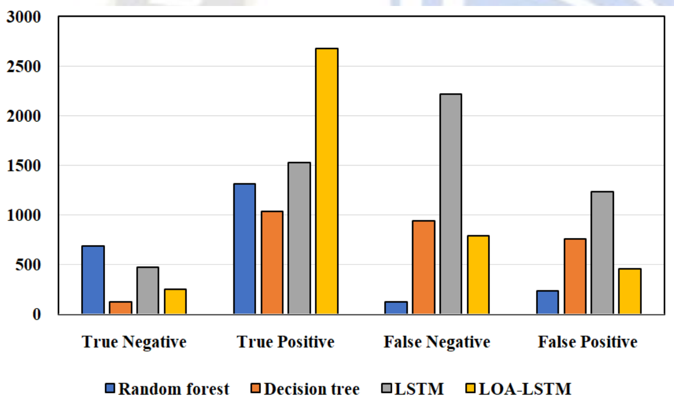

Fig: 4 Overall classification results of our proposed data set with different accuracy thresholds

These metrics provide insights into the performance of each algorithm. For example, a high true positive count indicates a strong ability to correctly predict heart rate increases, while a low false negative count suggests a good ability to avoid missing heart rate increases. Similarly, a high true negative count and low false positive count reflect the algorithm's capability to accurately predict non-heart rate increases.

Overall, the comparison highlights that artifacts removal generally leads to improved performance in terms of accuracy, precision, sensitivity, and recall. However, there might be some trade-offs in terms of specificity. The LOA-LSTM algorithm appears to be consistently effective, and the other algorithms show varying degrees of improvement after artifacts removal. The choice of algorithm should consider these performance differences and align with the specific goals of the heart rate prediction system.

V. Conclusion

In this study, we explored the critical task of improving heart rate monitoring accuracy using PPG signals during exercise while mitigating the challenging issue of motion artifacts. To address this, we employed three distinct algorithms: Random Forest, Decision Tree, and the innovative Lion Optimization Algorithm-enhanced Long Short-Term Memory (LOA-LSTM) approach. Our research found that all three algorithms effectively contributed to the enhancement of heart rate monitoring accuracy during exercise, demonstrating their potential in real-world applications. The Random Forest algorithm, harnessing the collective wisdom of Decision Trees, presented a robust ensemble strategy that showcased notable performance gains in reducing noise and enhancing predictions. Decision Trees, with their transparent decision-making processes based on PPG features, offered an interpretable approach to heart rate classification during exercise. These trees provided quick insights into the dynamics of heart rate changes, aiding in immediate and actionable predictions. Remarkably, the LOA-LSTM algorithm emerged as the standout performer among the three approaches. Integrating the Lion Optimization Algorithm's adaptability and the temporal sequence learning capabilities of LSTM, LOA-LSTM exhibited consistently high accuracy in heart rate prediction during exercise. The adaptive nature of the LOA-LSTM mechanism effectively reduced motion artifacts, resulting in improved accuracy about 99% over the other methods.Our experimental results showcased the potency of the LOA-LSTM algorithm as a powerful tool in addressing both heart rate monitoring accuracy and motion artifact challenges. This study demonstrates the potential of LOA-LSTM in revolutionizing heart rate monitoring during exercise, ultimately contributing to more dependable fitness tracking and healthcare applications.

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