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PSO-Enhanced LSTM for ECG-Based Medical Time-Series Prediction

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Abstract. Medical time-series data prediction requires exact methods that enable doctors to track patient health and detect medical issues early. The heart's electrical signals, which the electrocardiogram (ECG) records, show intricate time-based patterns because they contain nonlinear elements and include brief intense changes. The ECG time-series modeling process often use LSTM networks because these networks effectively track extended temporal patterns which exist in the signal data. The performance of LSTM models heavily depends on hyperparameter selection, and researchers who manually choose parameters often end up with oversmoothed predictions which fail to include vital clinical waveform characteristics. This research proposes Particle Swarm Optimization–enhanced LSTM (PSO-LSTM) framework as a new solution for ECG time-series prediction. The PSO algorithm conducts automatic hyperparameter optimization through its process of optimizing hidden layer sizes and network depth and learning rate values while maintaining the core LSTM structure. The MIT-BIH Arrhythmia Database provides ECG signals for experiments which undergo identical preprocessing operations and evaluation procedures throughout all testing runs. The proposed PSO-LSTM model is compared with a baseline LSTM under identical training conditions. The research evaluates prediction accuracy by using three performance metrics which consist of mean squared error (MSE) and root mean squared error (RMSE) and mean absolute error (MAE). Results show that the PSO-LSTM model achieves lower prediction errors across all metrics compared to the baseline LSTM. The research shows that metaheuristic-based hyperparameter optimization techniques boost LSTM prediction accuracy for medical time-series data through optimization methods which do not require additional model components.

Keywords: Electrocardiogram, Medical time-series prediction, LSTM, Particle Swarm Optimization, Hyperparameter optimization, Physiological signal analysis

1. Introduction

The non-invasive electrocardiography (ECG) method enables medical professionals to monitor heart electrical signals while helping them identify various cardiovascular diseases [1]. The signals which include P-waves and QRS complexes and T-waves [2] present challenges for modeling because they exhibit nonlinear behavior and non-stationary patterns. The ECG sequence analysis benefits from LSTM networks which effectively detect temporal patterns [3], yet these models perform better than

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conventional machine learning approaches because they learn signal patterns directly [4]. Standard LSTMs show sensitivity to hyperparameter selection because they produce oversmoothed results which fail to detect important clinical waveform variations. The process of uniting deep learning systems with metaheuristic optimization methods becomes necessary to achieve better prediction results and more stable model performance.

2. Methodology

2.1. PSO

PSO is a commonly used metaheuristic optimization method motivated by the collective motion patterns seen in natural swarms (e.g., flocks of birds and schools of fish), where individuals in a group adjust their movements in response to both personal experience and collective knowledge to achieve a common goal [5]. The optimization process of PSO operates through a specific method which distinguishes it from conventional deterministic optimization methods because it performs calculations without needing gradient data or complete solution space evaluation. The system operates with a population of candidate solutions which the authors call particles that move through the search area by following basic mathematical rules which control the balance between searching new areas and finding improved solutions [6].

In PSO, each particle represents a potential solution vector in an n-dimensional search space and maintains its own personal best position encountered so far, as well as a global best position shared among the entire swarm. The algorithm performs each iteration by letting particles update their positions through three elements which include their previous velocity and their personal best positions and the swarm's global best position.

Formally, if $X_i(t)$ and $V_i(t)$ denote the position and velocity of particle i at iteration t, the update rules can be expressed as:

$$V_i(t+1) = w \bullet V_i(t) + c_1 \bullet r_1 \bullet (pbest_i - X_i(t)) + c_2 \bullet r_2 \bullet (gbest - X_i(t)) \tag{1}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{2}$$

where w is the inertia weight, c_1 and c_2 are cognitive and social acceleration coefficients, r_1 and r_2 are uniformly distributed random numbers, and $pbest_i$ and $gbest$ are the personal and global best positions, respectively.

The algorithm operates as a metaheuristic because it uses problem-independent heuristic rules to find near-optimal solutions although it does not ensure global optimality. The optimization of complex problems with high-dimensional nonlinear or multimodal search spaces becomes more efficient through the use of metaheuristics because traditional deterministic methods prove ineffective [7].

Due to its simplicity, relatively few tunable hyperparameters, with its straightforward mechanism and strong global search capability, PSO has been applied to numerous optimization tasks, including hyperparameter search for machine learning and deep learning models. PSO operates as a system which searches for optimal hyperparameters in neural network training to find the best network size and learning rate and layer depth which results in better model performance than manual optimization or time-consuming grid search methods.

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The research uses PSO to optimize vital LSTM parameters which results in quick identification of best configurations for ECG time-series forecasting without requiring full or gradient-based optimization methods.

2.2. LSTM

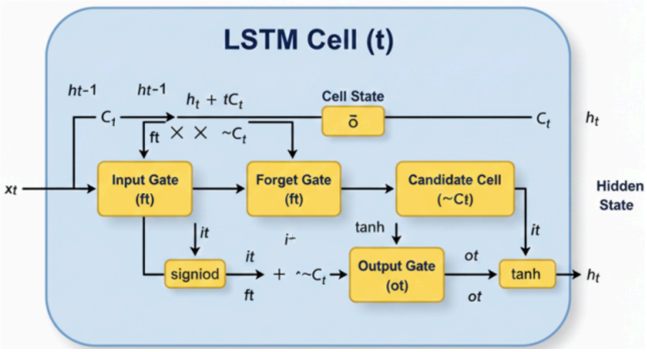

Figure 1. LSTM architecture diagram

LSTM are specialized RNNs that facilitate learning long-term dependencies in sequence data. Traditional RNNs have the theoretical capability to maintain information throughout time yet their training process results in vanishing or exploding gradients which restricts their capacity to detect extended sequence dependencies. LSTM networks overcome this limitation through a carefully designed memory cell structure and gating mechanisms that control the flow of information across time steps, enabling the network to retain or forget information as needed for effective sequence learning [3].

As shown in Fig. 1, the three main gating systems of each LSTM cell function to control data transmission between cells. The cell operates these gates to decide when new data should access its internal state and when to discard present information and perform a read operation. Specifically, the input gate determines how much new information should enter the memory cell, the forget gate controls how much of the existing information should be retained or forgotten, and the output gate decides what information should be exported to the next time step.

The LSTM network architecture enables it to store and update memory information across extended time periods which makes it an ideal choice for time-series prediction because future predictions require information from distant past observations. The ability of LSTM models in physiological signal modeling enables them to detect both long-term patterns and short-term changes within ECG signals through direct analysis of unprocessed or processed signal data without needing human-made features.

Research has introduced two separate models which use LSTM architecture as standalone systems and hybrid models that combine different approaches to achieve better results. Research shows that models which unite CNN with LSTM layers can extract local spatial information through their convolutional operations and simultaneously analyze sequence order using LSTM layers.

The models based on LSTMs achieve good results but their performance depends heavily on the selection of hidden layer dimensions and the number of hidden layers and the learning rate value. The wrong configuration settings will cause training to produce either overfitting or underfitting results or unstable training behavior when working with complex noisy real-world time-series data such as ECG signals.

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Therefore, the process of hyperparameter optimization for LSTM models serves as a critical necessity to achieve the best possible predictive results. The process of manual tuning or grid search works for small problems with low-dimensional spaces but it leads to computational challenges when working with big models and complicated signal patterns. The current restriction forces researchers to use automated metaheuristic optimization methods like PSO because these methods perform better than exhaustive search techniques when they need to explore large hyperparameter spaces.

2.3. ECG signal preprocessing

The clinical recordings produce raw ECG signals which contain different types of noise and artifacts including baseline wander and power-line interference and muscle artifacts and motion noise. The unwanted elements in ECG signals will create distortions which affect the normal patterns of P-waves and QRS complexes and T-waves and this will negatively impact the accuracy of modeling and learning algorithms which need to be handled before their execution. The process of ECG data preparation stands as a vital requirement which must occur before both model training and feature extraction operations [8].

The standard ECG time-series preprocessing sequence consists of four stages which start with filtering followed by noise reduction and then normalization and finish with window segmentation. The signal acquisition process produces two types of noise which band-pass filtering and Butterworth filters use to eliminate. Following filtering, techniques like z-score normalization or min–max scaling are typically used to transform ECG amplitudes into a uniform range, reducing the influence of inter-participant variability and facilitating stable learning across deep models. The optimization process during model training becomes controlled by large amplitude differences when normalization techniques are applied.

In addition to filtering and normalization, segmentation of ECG into fixed-length windows or heart beat cycles is another common step, particularly for machine learning applications. The method of sliding window segmentation transforms the endless signal stream into training-ready data samples which maintain their natural time-based relationships with essential medical events including the QRS complex.

The literature also presents several advanced preprocessing methods which include adaptive filter-based noise removal and statistical and frequency-domain transform-based feature extraction and beat alignment to improve both signal quality and feature discrimination. For deep learning based approaches, some studies also perform differencing or detrending to reduce baseline fluctuations and focus the model on dynamic components of the ECG signal that are most relevant for prediction tasks.

Overall, the preprocessing step improves signal quality by removing noise which enables data-driven models including LSTM networks to process clean and meaningful input sequences. The learning process of models becomes ineffective because they detect random noise patterns instead of actual physiological data which leads to poor generalization performance and limited clinical applications.

2.4. PSO-enhanced LSTM framework

The main contribution of this research is uniting PSO with a LSTM network. The ability of LSTM networks to detect patterns in sequential data depends on their hyperparameter settings which include hidden state dimensions and learning rate values and the number of stacked layers. The

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process of manual parameter adjustment through heuristic methods becomes both time-consuming and produces suboptimal results when dealing with complex high-dimensional medical time-series prediction tasks. Therefore, an automatic and systematic strategy for hyperparameter selection is desirable to improve predictive performance and model generalization.

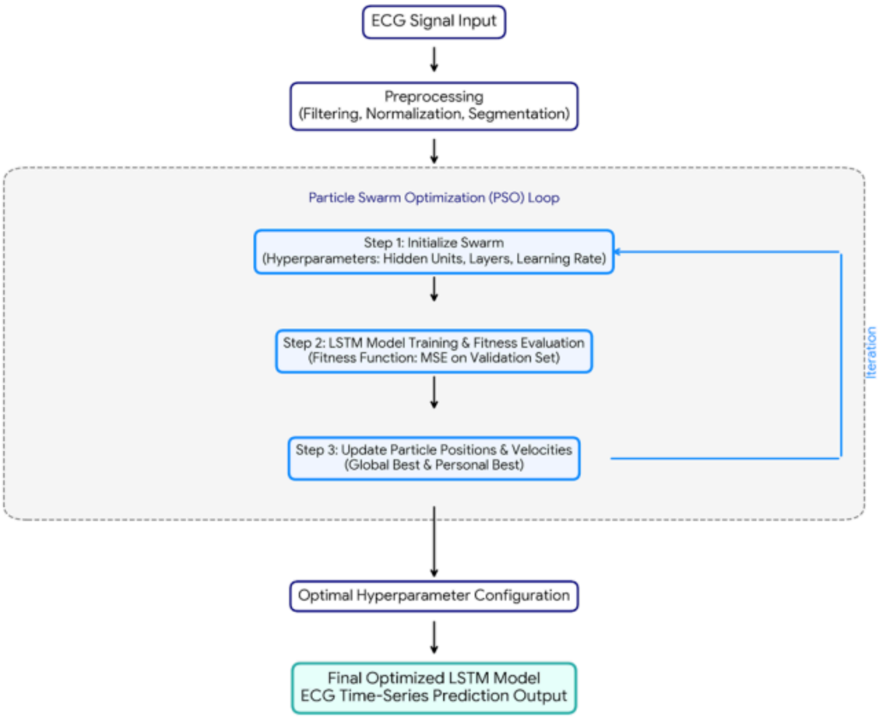

Figure 2. PSO-enhanced LSTM for ECG-based medical time-series prediction

PSO is a swarm-intelligence metaheuristic in which a population of agents cooperatively searches the solution space, inspired by flocking and schooling phenomena. The method solves complex optimization problems through gradient-free and exhaustive search-free operations in [5] and [6]. The neural network optimization process uses PSO to search through extensive hyperparameter combinations which results in finding optimal settings that improve model training performance and prediction results. PSO-tuned LSTM models have proven superior to basic LSTM models in various fields according to research studies which include environmental forecasting and time-series regression tasks [9].

The workflow of the PSO-enhanced LSTM framework consists of the following major steps:

1. Initialize Swarm: The defined search space for hyperparameter optimization includes three LSTM hyperparameters which are hidden layer size and learning rate and number of LSTM layers. This search space encapsulates the possible configurations to be evaluated by PSO.

2. LSTM Model Training & Fitness Evaluation: The model is instantiated with a random distribution of particles which exist inside the established hyperparameter range. Each particle represents a candidate hyperparameter configuration. The evaluation metric, such as mean squared error (MSE), serves as the fitness function that PSO seeks to minimize.

3. Update Particle Positions & Velocities: Particle positions (hyperparameter values) and velocities are updated iteratively based on each particle’s personal best and the global best solutions found so far. The system uses this update method to search new hyperparameter areas while using known successful parameter values.

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4. Convergence and Selection: The iteration process continues until a stopping criterion is met (e.g., maximum iterations or minimal improvement). The global best particle represents the optimized hyperparameter configuration, which is then used to train the final LSTM model.

The proposed framework uses PSO to explore different solutions while LSTM networks provide modeling capabilities to discover hyperparameters which result in better ECG time-series prediction. The new model design maintains ECG signal stability in areas which show no changes but it identifies short-lived biological fluctuations more effectively than models with manually selected parameters.

3. Experiments

3.1. Dataset description

This study evaluated the proposed PSO-enhanced LSTM model on publicly available electrocardiogram (ECG) recordings from the MIT-BIH Arrhythmia Database. The MIT-BIH Arrhythmia Database is a widely used benchmark for ECG analysis, comprising 48 two-channel ambulatory recordings, each approximately 30 minutes long, collected from 47 during clinical monitoring at the Beth Israel Hospital Arrhythmia Laboratory. The dataset contains ECG signals which were recorded at 360 Hz sampling rate with 11-bit resolution between -10 mV and +10 mV while cardiologists annotated heartbeats for evaluation [10].

The ECG waveforms contain normal sinus rhythms together with different arrhythmias which makes the dataset suitable for classification tasks and time-series prediction and modeling research. The signals need to undergo preprocessing to obtain a single lead signal (MLII) which researchers use for modeling purposes and this research uses a single-lead representation because it follows previous forecasting studies.

3.2. Experimental setup

The proposed PSO-enhanced LSTM model received evaluation through testing against a standard LSTM model which operated under identical experimental parameters. The dataset required partitioning into three sets for all experiments which used 70% for training and 15% for validation and 15% for testing.

The research evaluates an unchanging reference point against an improved system design. The baseline model depends on a basic LSTM structure with pre-defined default parameters but the PSO-LSTM model searches for best hyperparameter values from a specified range. Hyperparameter configurations and parameter settings are shown in Table 1 and Table 2.

Table 1. Comparison of hyperparameter configurations for baseline LSTM and PSO-LSTM

Parameter	Baseline LSTM	PSO-LSTM Search Space
Hidden Layer Size	64	$\in [32,128]$
LSTM Layers	1	$\in \{1,2,3\}$
Learning Rate	0.001	$\in [0.0005,0.005]$
Optimizer	Adam	Adam
Loss Function	MSE	MSE
Training Epochs	20	20

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Table 2. Parameter settings for PSO

PSO Parameter	Value
Population Size	8
Maximum Iterations	10
w	0.5
c1\c2	1.5

The prediction performance is measured through three metrics which include mean squared error (MSE) and root mean squared error (RMSE) and mean absolute error (MAE). The metrics function as main indicators which measure how well predictions match actual ECG values through their assessment of prediction accuracy. MAE is their most important measurement because it resists outliers effectively, especially with ECG signals, which contain fast physiological changes and sharp transient events.

3.3. Experimental results

3.3.1. Baseline LSTM results

As shown in Fig. 3, the baseline LSTM captures the general trend of ECG waveforms. Overall, the model exhibits good stability in smooth regions, but it struggles to precisely follow sharp transient features such as abrupt peaks corresponding to R-peaks in the ECG signal.

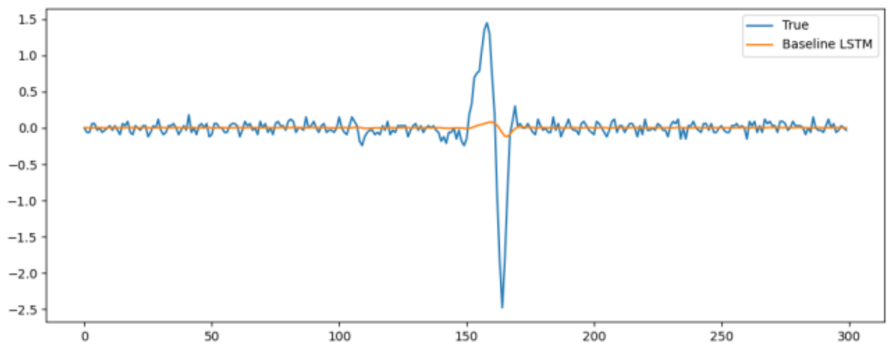

Figure 3. Prediction results of the baseline LSTM model

The quantitative performance of the baseline model on the test set is summarized in Table 3:

Table 3. Performance metrics the baseline LSTM model

Metric	Value
MSE	0.06681522
RMSE	0.2584864
MAE	0.09977298

Baseline performance shows that while the model is reasonable for general trend prediction, it is limited in capturing physiologically significant transient events.

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3.3.2. PSO-enhanced LSTM results

The PSO-enhanced LSTM model demonstrates clear improvements in both qualitative and quantitative evaluations.

Visually, as shown in Fig. 4, the predicted ECG signal from the PSO-tuned model aligns more closely with ground truth, particularly around rapid amplitude changes and transient physiological events.

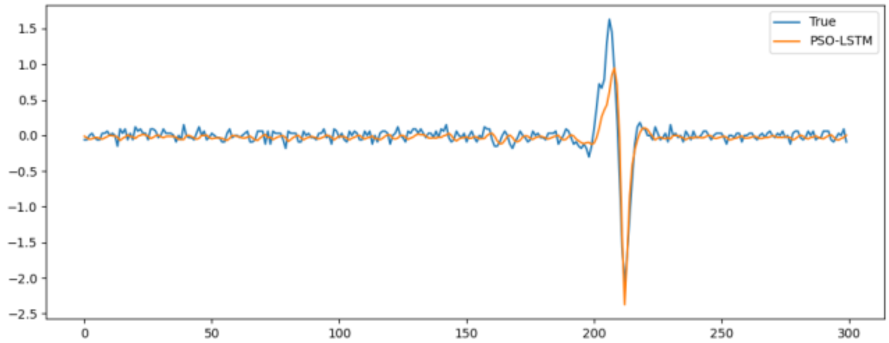

Figure 4. Prediction results of the PSO-enhanced LSTM model

Quantitatively, the PSO-LSTM yields lower errors across all evaluation metrics, as in Table 4:

Table 4. Performance comparison of baseline LSTM and PSO-LSTM

Metric	Baseline	PSO-LSTM
MSE	0.06681522	0.015439934
RMSE	0.2584864	0.124257535
MAE	0.09977298	0.07732696

The improvements indicate that hyperparameter optimization via PSO can significantly enhance model responsiveness to complex ECG dynamics.

3.4. Comparative analysis

The two models show different performance characteristics because the baseline LSTM model tracks general signal patterns yet its set hyperparameters result in “oversmoothing” which produces underestimations of peak values and difficulties with R-peak detection. The PSO-enhanced LSTM model shows better time flexibility because it tracks fast amplitude changes while providing exact measurements of both amplitude and timing.

The quantitative results confirm these findings because the PSO-tuned model produces lower error values for all performance metrics (MSE, RMSE and MAE). The model demonstrates improved performance through its reduced RMSE values which indicate better ability to manage big measurement errors and its lower MAE values which show better accuracy at individual prediction points. The PSO-enhanced model shows better time-based error distribution because it minimizes the specific errors which occur when the baseline model encounters sudden changes in the signal. The PSO optimization method enables the model to achieve better performance by uniting its ability to detect worldwide patterns with its capacity to detect essential temporary biological occurrences.

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4. Conclusion and future work

4.1. Conclusion

In this study, a PSO-enhanced LSTM framework for ECG time-series prediction was proposed and evaluated. The approach unites PSO with a fundamental LSTM network to discover the best hyperparameters which will improve forecasting results through parameter optimization instead of introducing additional model complexity. Experiments were conducted on ECG signals which originated from the MIT-BIH Arrhythmia Database through a standardized signal processing system and testing methodology.

The PSO-LSTM model produces better results than the baseline LSTM model according to experimental data which shows improvements in MSE and RMSE and MAE performance. The PSO-LSTM model achieved superior results in both fast signal change detection and strong ECG signal identification based on the qualitative visual assessment of the results. The research shows that metaheuristic-based hyperparameter optimization methods produce better results which improve LSTM network performance when analyzing biomedical time-series data.

4.2. Limitations and challenges

The research produced positive findings but it is essential to consider multiple restrictions. The study tests its methods through experiments which use individual ECG recordings together with single-lead signals but these conditions restrict how well the results can be applied to other situations. The PSO-based hyperparameter search method needs more computational power which results in performance deterioration when dealing with large datasets or when training models for extended periods. The study investigates short-term time-series prediction but it does not perform clinical tasks including arrhythmia classification or anomaly detection.

4.3. Future work

The research should proceed by using the developed framework to study ECG signals from various leads and by conducting accuracy tests with various patient information sets. Further research needs to study the sequence modeling capabilities of Transformer-based models and hybrid Transformer–LSTM networks which use PSO optimization for their joint operation. The proposed method will become more useful for medical practice through the addition of specific goals for each task and essential assessment standards which doctors use in their work.

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