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A Hybrid CNN-LSTM Framework for ECG Classification with Genetic Algorithm-Based Feature Optimization

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Abstract

Objective: The aim is to improve the accuracy and effectiveness of ECG signal classification, which is crucial for the premature detection of cardiovascular diseases. Our primary aim was to develop a robust, lightweight hybrid model that achieves a high classification rate while maintaining low computational complexity, making it suitable for real-time clinical applications. **Methods:** A deep learning hybrid model, consisting of a Convolutional Neural Network (CNN) with Long Short–Term Memory (LSTM), is introduced. For feature selection, a Genetic Algorithm (GA) is employed, utilizing a Support Vector Machine (SVM) as the fitness function of the GA. Principal Component Analysis (PCA) is used for dimensionality reduction. Denoising, normalization, and segmentation of ECG signals from the PTB-XL dataset. CNN layers detect spatial features, while LSTM layers capture temporal relationships. The Adam optimizer is used to enhance training convergence. **Findings:** The proposed CNN-LSTM + GA-SVM-PCA model achieved precision, classification accuracy, recall, specificity, and F1-score levels of 97.83%, 98.12%, 97.46%, 98.72%, and 97.65%, respectively, outperforming the existing alternative models, including CNN, FSL, and ATCNN. It can reduce the volume of input data and accelerate the learning process by approximately 30%, resulting in improved efficiency and performance. The model's performance in classifying normal and abnormal ECGs is satisfactory. **Novelty:** The uniqueness of this work lies in the integration of three feature selection methods —GA, SVM, and PCA —into a CNN-LSTM network for ECG analysis. Unlike existing models, the proposed method can strike a good balance between classification ability and complexity. It has great potential for real-time ECG monitoring, AI-aided medical check-ups, and clinical decision support systems for cardiovascular medical care.

Keywords: Genetic Algorithm; Electrocardiogram; CNN; LSTM; Feature Selection

1 Introduction

Electrocardiogram (ECG) signals are essential for diagnosing heart diseases and identifying various heart problems, including rhythm disorders (arrhythmias), coronary artery disease, myocardial infarctions (heart attacks), and heart failure. Accurate and automated ECG signal classification supports clinical intervention, reducing severe complications and mortality rates. Cardiovascular diseases (CVDs) remain the leading cause of death worldwide, highlighting the necessity for precise diagnostics. Traditionally, ECG analysis relied on manual interpretation by clinicians, which often resulted in subjective, inconsistent, and time-consuming outcomes. Therefore, there has been increasing interest in computer-aided classification methods in recent literature.[1] WaveECG distributions were created by stacking ECG recordings to form an amplitude contour map, and PathECG distributions by converting resampled ECG traces into vector cardiograms.

The PTB-XL database is an open-access ECG database offered by the Physikalisch-Technische Bundesanstalt (PTB) in Germany. From 18,885 patients, nearly 21,000 clinical 12-lead electrocardiogram recordings were collected as the dataset. Each recording lasted for 10 seconds and was recorded at either 500 Hz or 100 Hz. The dataset is labelled with diagnostic statements according to the standard SCP-ECG and other possible conditions, including Myocardial Infarction, conduction delays, and rhythm abnormalities. The dataset comprises a substantial amount of metadata, including age, sex, and diagnostic classifications of the subjects, making it highly useful for supervised machine learning (ML) and deep learning (DL) based research in medical signal processing. With its large-scale, high-quality labels and clinical diversity, PTB-XL serves as a strong benchmark for the development and evaluation of ECG classification.[2] The dataset PTB-XL presents a rich foundation for evaluating and training ECG analysis processes, supporting a wide range of predictive tasks. One key application involves inferring specific subsets of ECG statements directly from recorded signals.[3] The PTB-XL database enabled the application of different feature extraction methods due to the availability of an extensive, annotated, and standardized set of ECG recordings spanning various diagnostic categories. Its rich set of annotations and high-fidelity signals facilitated rigid diagnostic algorithm testing, and it offered a diverse set of clinical cases for training and evaluating ECG classification models that are powerful and interpretable. The use of standardized ontologies, such as SNOMED CT, also improves interoperability with other clinical databases and systems.

Due to new advancements in Artificial Intelligence (AI), ML, and DL-based methods have emerged as powerful techniques for ECG classification. In contrast to traditional ML models that use hand-engineered features, deep learning structures shape the ECG waveforms hierarchically and automatically, leading to an enhancement in classification performance.[4] Automated ECG analysis and diagnosis have drawn considerable attention for assisting physicians and enhancing the efficiency and accuracy of ECG interpretation.[5] A multi-domain framework was proposed, in which complementary features were extracted from the time, frequency, and time-frequency domains, providing a more comprehensive illustration of ECG signals and thereby achieving improved classification performance.[6],[7] LSTMs are highly effective at modelling temporal tasks. They are particularly well-suited for dealing with problems that involve inputs of varying lengths, making them very useful in scientific and technical domains.

CNNs are highly effective for modelling spatial patterns (e.g., morphological changes in ECG). In contrast, Recurrent Neural Networks or their variants, such as LSTM models, excel at capturing temporal dependency information in time-sequence data. However, deep learning models struggle with the high dimensionality and redundancy of ECG features, which can result in excessive computational costs, overfitting, and reduced interpretability. Feature selection methods are essential tools for addressing these issues, as they aid in identifying the most relevant features, thereby improving the model's generalization and efficiency. GAs inspired by natural selection provide a powerful and effective optimization technique for feature selection, where feature subsets are iteratively chosen based on their classification performance.

To address this problem, this study presents a novel hybrid technique that enhances ECG classification performance by combining GA-based feature selection with the CNN-LSTM DL model. A large-scale clinical ECG dataset, PTB-XL, was used in the experiments. ECG signals are thoroughly pre-processed for noise filtering, normalization, and segmentation to guarantee good input. CNN can capture spatial features, and LSTM can capture temporal dependencies for pattern recognition. The Adam optimizer effectively trains the model, allowing it to converge stably.

Experimental results demonstrate that the proposed method exceeds baseline DL methods in terms of accuracy, precision, sensitivity, specificity, and F1 Score. Using the selected features by GA, the model improves computational efficiency and reliability although maintaining high classification accuracy. The outcomes of this study may provide valuable insights for developing AI-based intelligent healthcare applications for ECG analysis for real-time monitoring and automatic diagnosis of cardiovascular diseases.

2 Related Works

Recent studies have investigated a wide range of deep learning frameworks and optimization algorithms for ECG classification, including both CNN-based and RNN-based approaches, as well as other components such as attention-based mechanisms and evolutionary-based methods to improve diagnostic performance and efficiency further.

2.1 DL ECG Classification

Since CNNs can capture spatial features well, some researchers have focused on CNN-based ECG categorization models.[(8)] showed that a convolutional network, with augmented entropy features, was better than the other two in terms of accuracy for all tasks.[(9)] trained and tested AlexNet and LeNet for ECG signal classification and reported that AlexNet outperformed LeNet in all evaluation measurements.[(10)] The FSL strategy improves the classification performance while preserving the network weights at the same time such that the model can be continuously updated as long as new samples are added.[(11)] Used the DenseNet model with input modified for 1D ECG data, showing that it is capable of ECG event classification. It also underscores the potential of using pre-trained models as foundation architectures for transfer learning, particularly in scenarios with limited labelled data.[(12)] The recommended model modifies the LENET architecture by integrating a 1D convolutional layer with the LeakyReLU activation and three dense layers. The inclusion of max-pooling and optimized kernel sizes reduces computational complexity while preserving high classification accuracy.

2.2 Optimization Methods for Feature Selection

Feature selection is crucial for enhancing the accuracy of ECG classification by reducing the model's dimensionality and improving its interpretability.[(13)]A Sobel operator-based approach was used for edge detection to convert ECG images into a graph-structured format, enabling more effective feature selection by highlighting important structural features within the signal images. This enables the model to capture key patterns in the data more effectively, resulting in improved overall performance.[(14)],[(15)] By combining feature selection and an inter-patient, cross-validation strategy, the investigation makes validation more practicable and clinically applicable. This approach provides a more accurate estimate of actual performance by evaluating model generalizability in unseen patients.[(16)] The ATCNN model was employed, which fuses temporal-level CNN layers with different dilation rates as well as both temporal and spatial attention mechanisms to learn the multi-scale dynamics of pathological features from ECGs comprehensively.[(17)] In Adam, the velocity is combined with adaptive learning rates to facilitate fast convergence; however, overly aggressive weight updates can cause overfitting.

In this study, we used GA + SVM to select the finest features from ECG signals to improve the classification accuracy. The GA reduces the dimension of the feature space and selects the most discriminant features. It works through evolution, utilizing mechanisms such as natural selection, genetic crossover, and genetic mutation. Combining GA with the CNN-LSTM model enhances the efficiency and classification performance of the model in ECG signal classification.

2.3 Reflection: Existing Studies—Challenges and Gaps

Even though ECG classification has been enhanced dramatically based on deep learning, there still exist several unresolved challenges in the literature. Many current methods rely on high-dimensional input features, which create feature redundancy and increase computational costs, making them less suitable for real-time deployment. Furthermore, most models are uninterpretable, an important consideration for clinical confidence and decision support. Feature representation and dimensionality reduction are empirically less considered or inefficiently tuned, thus adding unnecessary complexity and slowing down convergence. There haven't been many studies on how to improve model efficiency and understanding by using evolutionary feature selection and statistical methods like Principal Component Analysis (PCA). Moreover, most models fail to simultaneously exploit the spatial and temporal dependencies in ECG, leading to suboptimal diagnostic performance.

This work addresses these gaps by using a CNN-LSTM hybrid model in conjunction with GA feature selection and PCA.GA identifies these ECG features as the most important, and then PCA simplifies the data by removing related components. This joint learning strategy not only avoids repetitive information and cuts down training time but also enhances the generalization ability of the trained model. The CNN-LSTM model also can capture spatial and temporal properties of ECG signals. When combined, these improvements result in an efficient and interpretable ECG classification model that performs well and is suitable for real-time clinical use cases.

3 Methodology

3.1 PTB-XL Dataset and Data Loading

The dataset PTB-XL (https://physionet.org/content/ptb-xl/1.0.1/) is an open, large-scale dataset comprising 10-second recordings from clinical settings. It contains ECG signals in .dat files, along with .csv files that record patient information, diagnosis labels, and signal details. Here, we load the data and address common readtable problems to allow proper parsing and processing of the data.

3.2 Extraction and pre-processing of ECG signal

The raw ECG signal was taken from .dat files available in the PTB-XL database. These data are 12 lead ECG recordings of duration 10 seconds and covered at 500 Hz. The corresponding .hea files were employed to parse header information and map the data correctly. Preprocessing of the signals was performed to prepare them for classification:

- **Filtering:** The cut-off frequencies used for band-pass Butterworth filter were 0.5 Hz and 40 Hz to get rid of unwanted parts of the signal. In particular, this step removed baseline wander (low-frequency drift), high-frequency noise and power-line interference (50/60 Hz), which are often found to be sources of distortion in ECG records. This enhances the quality of P, Q, R, S and T waveforms which is essential for accurate feature detection.
- **Scaling:** Normalized with min-max operation from filtering, thus all ECG signals were scaled to interval [0, 1] in **Equation (1)**

$$x_{scaled} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

This makes the input values consistent in a scale and improves the convergence rate of the learning algorithm and reduces instability of the training due to outlier values of amplitude.

- **Segmentation:** For CNN-LSTM model input, each signal was divided to fixed size windows of 5 seconds (2500 samples in each segment). Segments were aligned to the R-peaks of the ECG waveforms to ensure that the significant cardiac cycles are within each segment. It also augments training samples and enables the model to concentrate on entire cardiac events, thus improving the temporal learning capability of the model.

3.3 Feature Selection by the Combination of GA, SVM and PCA

In order to enhance the efficiency of ECG classification, the method is formulated with the concept of PCA for dimensionality reduction along with GA–based feature selection assessed by SVM classifier.

(i) PCA for Initial Reduction:

PCA is performed for the preprocessed ECG recordings to reduce and retain the most significant parts of the feature set that cover most of the signal's variance and reducing redundancy.

(ii) GA for Selecting Relevant Features:

Genetic Algorithm is then employed to find out the optimum subset of PCA- reduced features. Each sub features set is represented by the binary chromosome. The fitness of each subset is the result of training an SVM and evaluating its performance on a validation set with classification measures, such as accuracy or F1-score.

Feature selection is crucial for enhancing the efficiency and simplification of models. The feature selection using a Genetic Algorithm (GA) was used to decrease the redundancy and enhance the classification accuracy. The GA was composed of the following parameters:

- **Population Size:** 50

  A moderate size of population is adopted to compromise between exploration and computational complexity.

- **Number of Generations:** 100

  The population was evolved through 100 generations of the algorithm to ensure convergence toward optimal feature subsets.

- **Selection:** Choosing the best-performing feature subsets for the next generation.
- **Type of Crossover and Its Rate:** Single-point crossover, 0.8 probability.

  This permits efficient blending of genes while retaining high performance characteristics.

- **Mutation Rate:** 0.01

  A small mutation rate value was adopted to bring in diversity and avoid premature convergence.

- **Fitness Evaluation:** An SVM classifier was trained on each chromosome and validated on a validation set, for which the F1-score served as fitness.
- **Termination Condition:** The GA was stopped when the maximum number of generations was obtained or when the fitness improvement tended to zero relative to one generation back.

The best subset with highest fitness is selected as the final input to train the CNN-LSTM model.

3.4 Hybrid CNN-LSTM Model

The proposed hybrid deep-learning model uses a CNN and an LSTM model structure for ECG classification.

- **CNN Convolutional Layer:** Convolutional layers capture spatial patterns and morphological characteristics for ECG signal processing and contribute to improved feature learning.
- **LSTM layer:** The LSTM network is employed to capture the sequential requirements and sequential patterns in ECG signals, which are applied to the time-series data.
- **Fully Connected Layer:** Pooled spatial and temporal features are fed through a fully connected layer, which ultimately makes the decision.
- **Softmax Layer:** This layer outputs a probability distribution over the target classes and is used for multi-class classification tasks, such as arrhythmia detection in ECG signals.

The deep learning structure combines CNN and LSTM networks for accurate ECG signal classification. The model begins with the input layer, which takes raw 1D ECG signals and processes them through a series of four convolutional blocks. Each block consists of a 1D convolutional layer, ReLU activation, batch normalization, and a dropout layer. These convolutional blocks are designed to learn increasingly abstract and discriminative features in the ECG signal. The first layer learns low-level features, such as sharp transitions and wave boundaries. The second layer discovers mid-level waveform structures. The third layer identifies complex morphological patterns, and the fourth captures high-level features for more accurate temporal modelling. This progressive feature extraction can help the model learn fine-grained spatial features of the ECG signals. After the last convolution, we vectorize the features and feed them to a single LSTM, allowing it to capture the multi-timescale and time-dependent properties over the processed signal. A dropout layer was added after the LSTM to prevent overfitting. Finally, a softmax layer and a fully connected dense layer are used for classification. The proposed hybrid CNN-LSTM approach benefits from spatial feature learning and temporal sequence modelling; therefore, it is particularly effective for ECG signal analysis and abnormality detection. This is illustrated in Figure 1.

4 Implementation

The proposed method was developed based on several steps, such as data preparation and feature selection, which is carried out through GA, and finally, training the hybrid CNN-LSTM model. These steps are described in detail in the following subsections.

Figure 2 presents an overview of the top-down process for ECG classification, focusing on the end-to-end pipeline using the PTB-XL dataset, with an emphasis on feature selection and deep learning model training. First, metadata is generated from PTB-XL records, where low-variance features are first filtered to remove redundant and non-informative data. PCA was further applied to the entire dataset to improve computational efficiency. Because feature selection based on GA is computationally expensive, we reduced the dataset size to 3000 data samples. A hybrid of GA and SVM is used for feature selection, which attempts to explore the search space with GA and evaluate each selected set of extracted outcomes using SVM. The best set of attributes was then chosen to train the DL model. The dataset was separated into training and testing data in an 80:20 proportion, and a hybrid CNN-LSTM model was developed using the selected features. Following training, the model makes predictions for the test data. Finally, performance was measured using classic evaluation metrics, such as accuracy, precision, sensitivity, specificity, and F1-score. Thus, we can determine the most appropriate features for learning the proper ECG classification model.

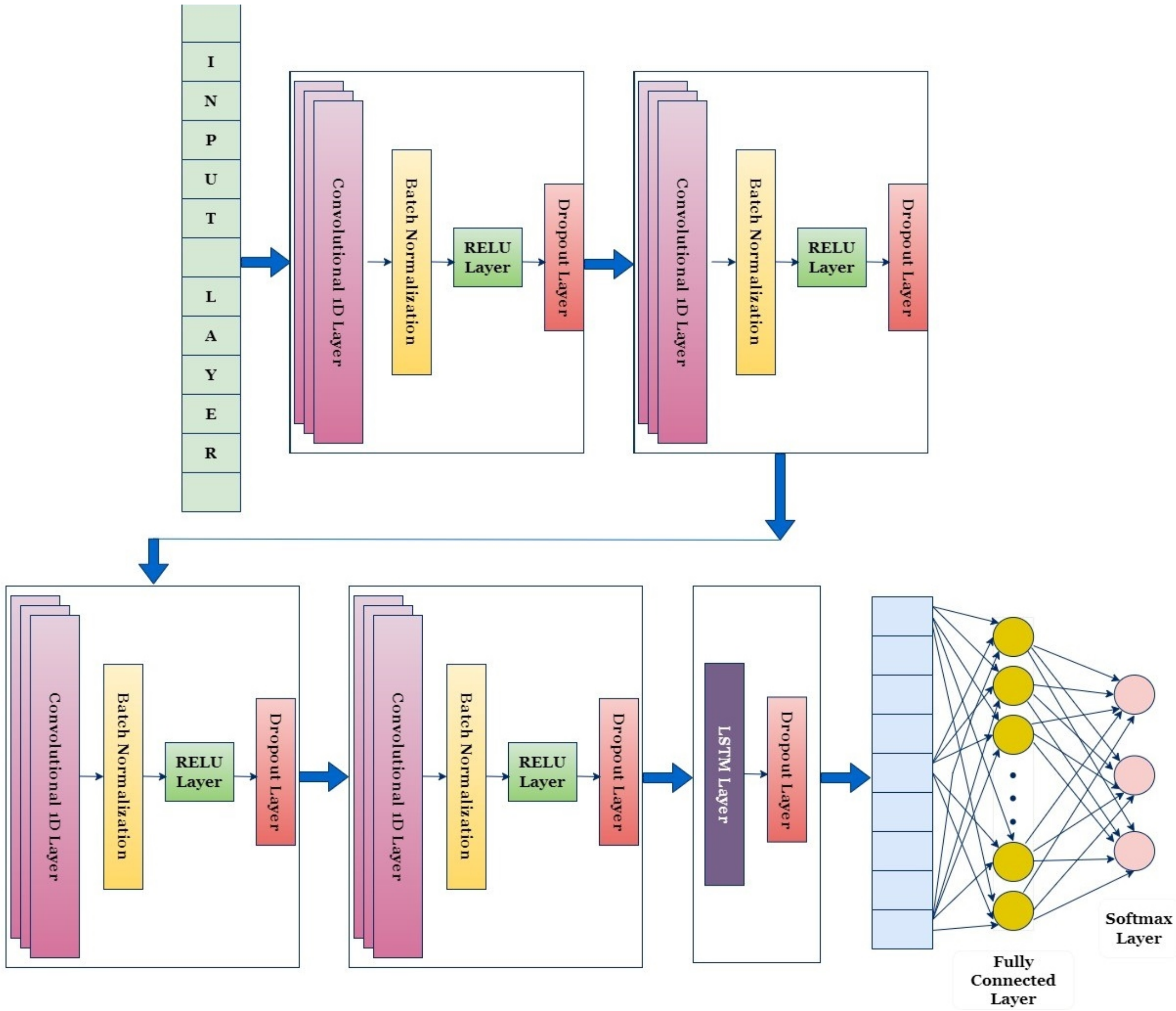

Fig 1. Architecture Design for ECG Classification

4.1 Data Preparation

The PTB-XL dataset was read and pre-processed to obtain good input data for training. The key steps include:

- **Data Loading:** The submitted dataset consisted of ECG signals in .dat format, parsed in a particular way via a method to eliminate the problems encountered with a generic readtable.
- **Filtering:** A band-pass filter is used to reject baseline wander, high-frequency noise, and power-line interference.
- **Data Normalization:** Min-max normalization was applied to normalize the ECG signals over a particular range.
- **Segmentation:** The ECG was divided into fixed-length windows to convert samples of varying lengths to a uniform length.

4.2 Feature selection using GA

The most salient features are selected first by PCA reduction of the dimensionality of the original ECG features. PCA converts the unique correlated features into an innovative set of uncorrelated principal components that capture the majority of the variance within the data. GA operates on the transformed set to select the best subset of components. An SVM model is trained and tested to assess the quality of the subsets by treating it as a fitness value.

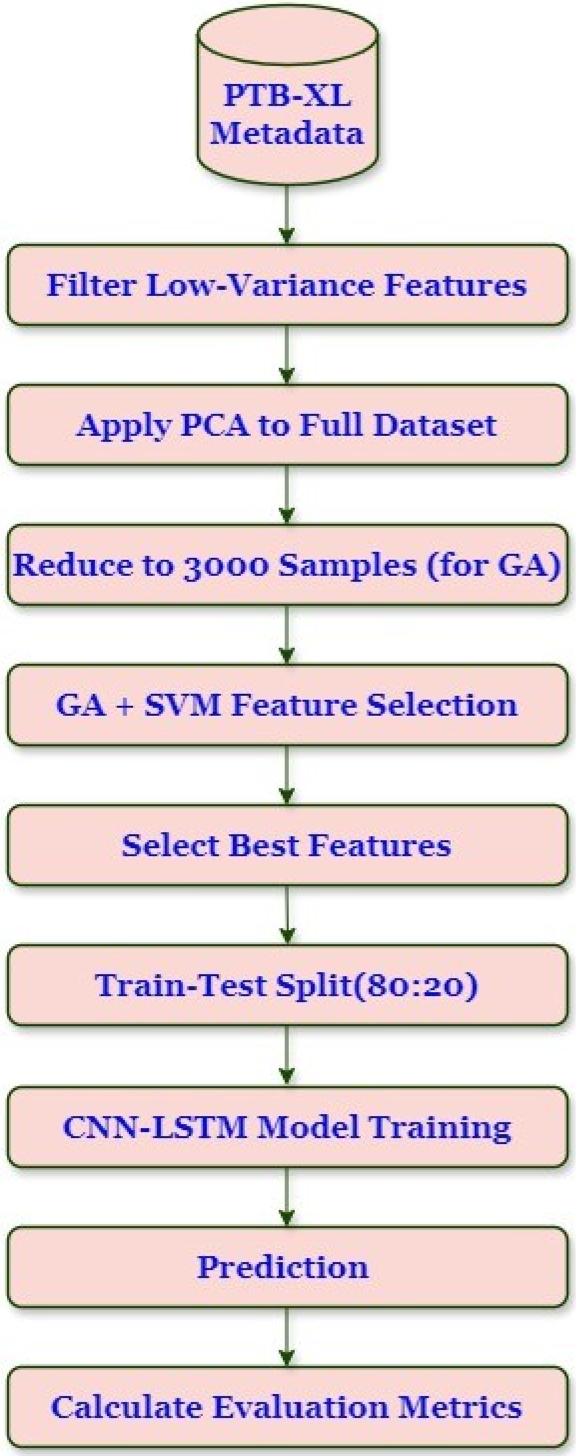

Fig 2. Workflow of ECG Signal Classification

A GA was employed for feature selection to obtain an optimal input feature set, thereby enhancing the model's efficiency. The steps involved are:

- **Initialization:** Randomly initialize feature subsets.
- **Fitness Function:** The fitness of each subset is evaluated in terms of the classification performance.
- **Selection, Crossover, and Mutation:** The best-performing subsets are subjected to genetic operations to identify the new feature subsets.
- **Convergence:** A good subset is obtained, and the dimensionality is reduced without losing classification information.

4.3 CNN-LSTM Model Training

The model used here is the CNN-LSTM model, which is built using batch normalization, a RELU, and a Dropout layer.

- **CNN Layers:** The convolutional layers capture the spatial features from ECG signals.
- **Batch Normalization:** Normalizes the activations to accelerate training and enhance stability.
- **ReLU Activation Layer:** It is used to introduce non-linearity into the system model, enabling it to learn complex and deep patterns.
- **Dropout Layer:** To avoid overfitting, a portion of the neurons is removed during training.
- **LSTM Layers:** The LSTM networks capture the time dependencies and sequential nature.
- **Adam Optimizer:** The Adam optimization process is adopted to update weights efficiently.
- **Performance Measure:** Categorical cross-entropy loss measures classification accuracy.
- **Training:** This is conducted using the optimal feature subset and is validated by k-fold cross-validation to ensure robustness.

After training the CNN-LSTM model based on the best features, we start the testing phase by applying the unseen ECG signals. Denoising, normalizing, and segmenting is performed on inputs to guarantee the consistency. Then PCA is carried out in an attempt to map the signal into a lower feature space, where the most significant components are kept based on the selection performed by the GA. These features are passed to the pre-trained CNN-LSTM model, which provides probability scores for all possible classes. The class with the greatest probability is the model's prediction. (normal or abnormal, for instance). In terms of prediction accuracy, performance measures (accuracy, precision, recall, F1-score, and specificity) are evaluated on the test dataset to demonstrate the model's effectiveness in real-world ECG classification problems.

4.4 Performance Metrics

We estimate the trained model with state-of-the-art performance metrics:

Accuracy:

The number of classes correctly predicted out of all classes was referred to as the accuracy in **Equation (2)**.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{2}$$

Precision:

The proportion of values in a given class that are accurately predicted, relative to the total number of values, is known as the precision, as shown in **Equation (3)**.

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

Recall

Recall or sensitivity is the percentage of predicted values in a given class that are present in the observed data, as provided in **Equation (4)**.

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

Specificity

One way to examine specificity is through the antithesis of sensitivity. The sensitivity of the negative class, or the quantity of values that were misclassified relative to the total number of values that were incorrectly predicted, as shown in **Equation (5)**.

$$Specificity = \frac{TN}{FP+TN} \tag{5}$$

F1-Score

This measure ensures that the model's capacity serves correctly by balancing recall and precision as specified in **Equation (6)**.

$$F1_{Score} = \frac{2 * Precision * Recall}{Precision + Recall} \tag{6}$$

5 Simulation Results and Discussion

The proposed model used a method called 5-fold cross-validation to test how well the CNN-LSTM model with GA-based feature selection performed and to assess the effectiveness of the final predictors. The model obtained an overall average accuracy of 98.12% (95% CI: 97.93%–98.31%). The precision was 97.83% (CI: 97.70–97.96), the recall was 97.46% (CI: 97.31–97.61), the specificity was 98.72% (CI: 98.61–98.83), and the F1-score was 97.65% (CI: 97.51–97.79). These confidence intervals verify the dominance and statistical validity of the performance of the proposed model over data splits. The results do confirm the fact that the hybrid scheme of the genetic algorithm for feature selection truly improves the classification performance with robustness and generalization. The proposed model not only achieves better performance compared with state-of-the-art methods but also achieves statistically significant (and stable) improvements in the classification of ECG signals. Figure 3 and Figure 4 show the accuracy and loss performance of the proposed model.

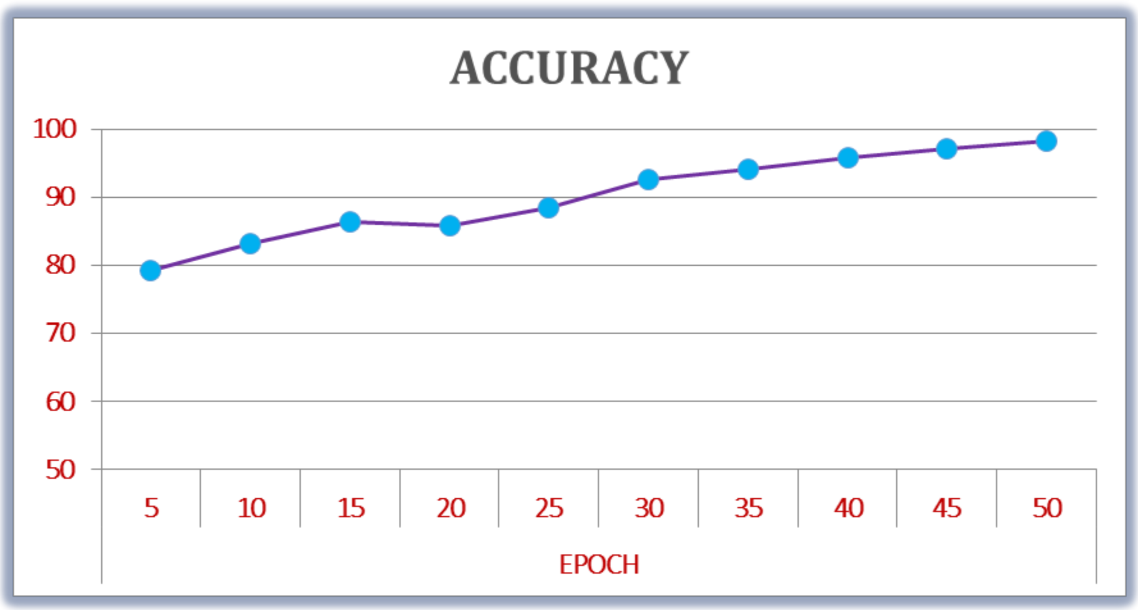

Fig 3. Accuracy Performance

5.1 Comparison with Prior Models

Table 1 presents a comparison of different ECG classification models and the improvement due to the CNN-LSTM model and the GA-based feature selection integration. These traditional CNN-based models presented lower accuracy and recall, suggesting that their generality is restricted. It achieved a compromise between high recall and balanced metrics for the Few-Shot Learning (FSL) approach, as well as moderate improvement for the model ATCNN, which incorporated temporal and attention mechanisms. The new CNN-LSTM + GA model, however, performed significantly better than the group of all

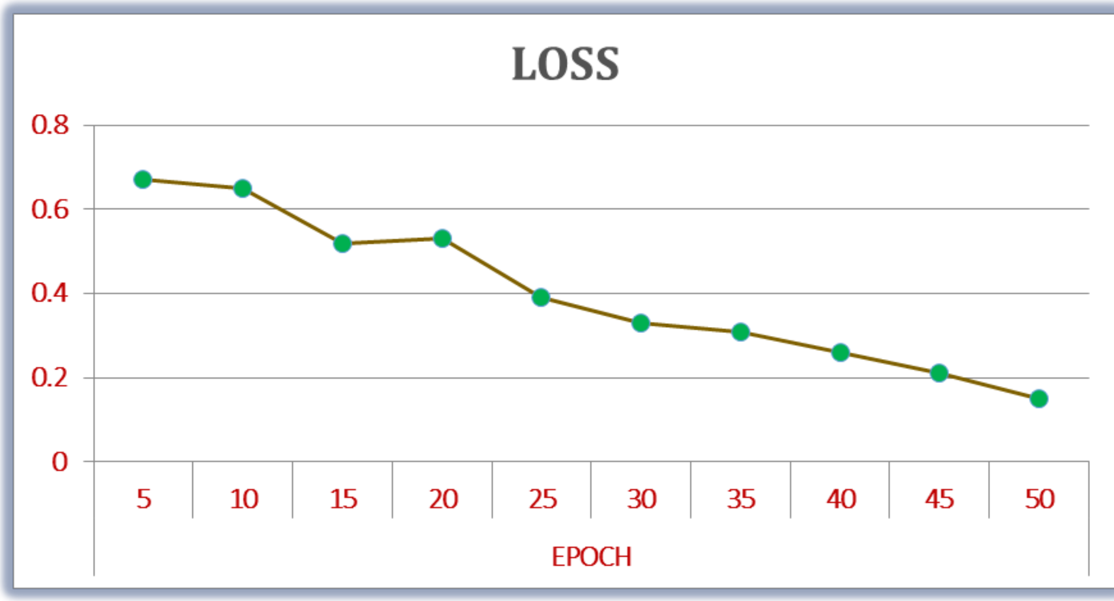

Fig 4. Loss Performance

Table 1. Prior Model Comparison

Reference(s)	Model	Accuracy	Precision	Recall	Specificity	F1-Score
[1]	CNN	72	63	60	-	-
[3]	FSL	90.4	-	89.9	90.4	90.6
[8]	ATCNN	88.05	70.80	83.88	89.01	76.51
Proposed	**CNN-LSTM + GA**	**98.12**	**97.83**	**97.46**	**98.72**	**97.65**

preceding methods, accomplishing the top scores in accuracy, precision, recall, specificity, and F1-score, which demonstrated its capacity to capture complex patterns in the ECG signal, as well as to optimize the relevant features.

6 Conclusion

This study proposes a new DL hybrid model combining CNN and LSTM with GA-based feature selection for ECG classification. The method demonstrated better classification performance with the PTB-XL database compared to traditional approaches. Feature selection was enhanced by the addition of GA, resulting in a decrease in computational time and an improvement in classification accuracy.

6.1 Summary of Key Findings

The proposed ECG classification model first reduces the dimensionality of the extracted features using PCA, followed by taking advantage of the GA to perform the feature selection, where the SVM is used as the fitness function. This joint PCA–GA–SVM model efficiently eliminates redundant and irrelevant features, thereby reducing computational complexity while retaining the most discriminative features for classification. The best feature set was then input into a hybrid CNN-LSTM model to effectively capture spatial features through CNN layers and temporal dynamics through LSTM units. This cooperation yields significant benefits in classification. The sensitivity and specificity were high, confirming the model's ability to recognize both normal and abnormal heart states accurately. Stratified 5-fold cross-validation is also executed to improve the stability and generalization of patient-specific data. In terms of efficiency in real-time high-accuracy ECG analysis tasks, the proposed architecture vastly outperformed the previous CNN, FSL, and ATCNN models.

6.2 Future Enhancements

Future work will explore:

- Real-time ECG Monitoring: The proposed model was embedded in wearable healthcare devices to automatically and regularly monitor the ECG.
- Explainable AI (XAI) methods: Making models more interpretable for clinical decisions, particularly for applications of XAI to deeper network models.
- Integration into Edge Computing: Model deployment in a resource-limited environment for real-time detection.
- Extended Dataset Application: Verify the model performance on more diverse ECG datasets to validate the generalization.
- Attention Mechanisms: Adding self-attention and transformer-based methods to improve classification performance.

In the future, we will investigate real-time ECG monitoring scenarios and attention mechanisms to enhance performance further. This model may have significant implications for automated diagnosis and clinical decision support in AI-based heart health.

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