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Deep Learning-Driven ECG Classification Using CNN-LSTM-Transformer and Metaheuristic Optimization

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ABSTRACT*—Cardiovascular diseases (CVDs) represent a major source of sickness and death across every part of the globe; therefore, accurate diagnoses at an early stage are needed for treatments that work well. Electrocardiograms (ECGs) are a key way to find heart problems, but reading them by hand is time-consuming and can lead to mistakes. For complete automated ECG classification, this study proposes a deep learning-based approach that uses a hybrid CNN-LSTM and Vision Transformer (ViT-LSTM) architecture. CNN catches spatial features from ECG signals, and LSTM/Transformer modules allow a strong classification of cardiac arrhythmias and CVD indicators by catching temporal dependencies. The model was trained on benchmark ECG datasets like MIT-BIH Arrhythmia along with PTB-XL. For optimal feature selection, the model uses M-Square normalization in addition to Chaotic Dwarf Mongoose Optimization (CH-DMO). The experimental results show that the proposed approach achieves a classification accuracy of 94–98%, which is superior to what is achieved by conventional CNNs and LSTMs. The system's quite high sensitivity and truly outstanding specificity make it a completely viable solution for actual real-time, IoT-based smart health monitoring.A. Future work will thoroughly broaden dataset diversity and considerably optimize model efficiency for advanced edge computing to greatly improve generalization.*

Keywords— Electrocardiogram, cardiovascular disease Detection, Deep Learning, CNN-LSTM-Transformer, Feature Selection

I. INTRODUCTION

Cardiovascular diseases (CVDs) are the leading cause of morbidity and mortality worldwide, accounting for an estimated 17.9 million deaths annually, as reported by the World Health Organization (WHO) [1]. These conditions, which include coronary artery disease (CAD), arrhythmias, myocardial infarction, and heart failure, significantly impact healthcare costs and quality of life. Early diagnosis is crucial in reducing complications, enabling timely intervention, and improving patient outcomes.

Electrocardiography (ECG) remains the gold standard for non-invasive cardiac assessment, offering valuable insights into heart function by recording electrical signals over time. ECG analysis is widely used for detecting abnormal heart rhythms, ischemic events, and structural heart disorders. However, traditional methods rely on manual interpretation by cardiologists, which is time-intensive, prone to human error, and lacks consistency across different practitioners [2]. Furthermore, the increasing prevalence of remote healthcare solutions has created a demand for automated, real-time ECG-based diagnostic systems capable of supporting clinical decision-making without requiring direct human oversight.

Recent advancements in artificial intelligence (AI) and deep learning have transformed biomedical signal processing, offering enhanced accuracy, robustness, and automation in ECG analysis. Unlike conventional machine learning approaches, which require handcrafted feature extraction, deep learning architectures such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Transformer models can automatically extract meaningful features, model complex temporal dependencies, and improve classification performance [3].

Challenges in ECG-Based CVD Detection

Despite significant advancements, several challenges must be addressed to enhance the reliability and real-world applicability of deep learning models in ECG-based CVD detection:

1. Variability in ECG Morphology: ECG signals vary across individuals due to physiological differences, electrode placements, and noise artifacts, making generalization across diverse patient populations challenging [4].
2. Presence of Noisy and Artifactual Signals: ECG recordings are often affected by motion artifacts, power-line interference, and baseline drift, which can significantly impact the accuracy of automated classification models if not properly handled during preprocessing [5].
3. Class Imbalance in ECG Datasets: Publicly available ECG datasets often suffer from imbalanced class distributions, where normal heart rhythms are overrepresented, leading to biased model predictions for less common arrhythmias and cardiovascular conditions [6].

4. High Computational Complexity: Many deep learning models require significant computational resources, making real-time deployment challenging for wearable devices and IoT-based health monitoring systems [7].
5. Lack of Explainability in Deep Learning Models: Most deep learning architectures function as black-box models, making it difficult for clinicians to interpret their decision-making processes, which is a major barrier to widespread adoption in clinical settings [8].

To address these challenges, recent research has focused on developing hybrid deep learning architectures, integrating optimization techniques, and leveraging edge computing for real-time ECG analysis. The proposed deep learning-based ECG analysis framework effectively addresses key challenges in cardiovascular disease (CVD) detection by integrating hybrid CNN-LSTM-Transformer models, advanced signal processing, and optimization techniques. To improve generalization across diverse populations, the model leverages transfer learning, domain adaptation, and data augmentation. Noise artifacts in ECG signals are mitigated using wavelet transform, adaptive filtering, and self-attention mechanisms, ensuring robust feature extraction. Additionally, class imbalance is tackled through SMOTE, GAN-based augmentation, and weighted loss functions, enhancing the model's ability to detect rare CVD cases.

To enable real-time processing and deployment on wearable and IoT-based health monitoring devices, the framework incorporates a lightweight ResVGG model, pruning, and edge AI strategies, significantly reducing computational costs. Furthermore, the lack of model interpretability is addressed through Explainable AI (XAI) techniques, including Grad-CAM and confidence score estimation, providing clinicians with transparent, interpretable decision-making insights. These innovations ensure that the system achieves high accuracy, efficiency, and clinical reliability, making it a scalable and viable solution for automated ECG-based CVD detection in real-world healthcare applications.

II. Related Work

The domain of cardiovascular disease detection through electrocardiogram (ECG) signals has been significantly transformed by the advent of deep learning (DL) techniques. These methods have outperformed traditional machine learning (ML) algorithms in aspects such as classification accuracy, automation, and adaptability to diverse patient datasets. This section presents a critical overview of recent advancements, highlighting key developments in ECG signal classification using deep learning, while identifying existing gaps and future research avenues.

A. *Traditional Machine Learning-Based ECG Analysis*

Conventional ECG classification relied heavily on manually engineered features and classical ML classifiers. Approaches such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forest (RF) were combined with feature extraction techniques like wavelet transforms, Principal Component Analysis (PCA), and Independent Component Analysis (ICA) [1]. Osowski et al. [2] applied SVM with wavelet features to detect arrhythmias, attaining an accuracy of 95.2%. However, these systems typically suffer from limited scalability due to their reliance on hand-crafted features and poor generalization across heterogeneous ECG datasets.

Efforts to integrate feature engineering with neural networks have led to hybrid approaches. For example, Oh, Shu Lih, et al. [3] employed PCA for dimensionality reduction followed by a Deep Belief Network (DBN) to classify ECG signals, reporting an accuracy of 98.1% on the MIT-BIH Arrhythmia dataset. Despite high performance, such approaches still depend on manual intervention in feature selection, limiting their robustness in real-time clinical settings.

B. *Convolutional Neural Networks (CNNs)*

CNNs have emerged as a powerful tool for ECG signal analysis due to their ability to extract hierarchical features directly from raw signals. Kiranyaz et al. [4] proposed a 1D-CNN model for arrhythmia detection that eliminated the need for explicit feature extraction and achieved a classification accuracy of 99% on the MIT-BIH dataset. These models automate the learning of relevant features, but they are often limited in capturing long-range dependencies inherent in ECG signals.

To address these shortcomings, Zignoli, Andrea, et al [5] introduced CardioNet, a deep CNN architecture trained on a large-scale ECG dataset of over 90,000 samples. Their system achieved cardiologist-level performance but posed challenges in terms of computational complexity and resource consumption, particularly for real-time or edge-based applications.

C. *Recurrent Neural Networks (RNNs) and LSTM Architectures*

Given the sequential nature of ECG signals, Recurrent Neural Networks (RNNs) and their variants such as Long Short-Term Memory (LSTM) networks have been widely utilized for cardiac arrhythmia detection. Hannun et al. [6] developed an LSTM-based model that successfully detected atrial fibrillation with an accuracy of 97.5%. LSTMs are capable of learning long-term dependencies, which is crucial for ECG classification tasks.

Despite these advantages, RNNs suffer from limitations such as vanishing gradients and increased inference times. Yildirim et al. [7] proposed a hybrid CNN-LSTM model that combines CNNs for spatial feature extraction with LSTMs for temporal modeling. This fusion improved the detection performance but introduced computational overhead, reducing their viability for wearable devices and low-power platforms.

D. *Transformer-Based Architectures*

Transformer models, with their self-attention mechanisms, have recently shown promise in handling temporal dependencies in ECG data. Park, JaeYeon, et al [8] presented ECG-Transformer, which outperformed traditional CNNs and LSTMs in multiclass arrhythmia detection. These architectures demonstrated enhanced learning of global features across long ECG segments.

Building on this idea, Wu et al. [9] developed a hybrid Transformer-CNN framework that achieved 99.3% accuracy on the PTB-XL dataset, significantly improving classification for complex conditions like ischemic heart disease. However, these models require large, annotated datasets for optimal training, limiting their applicability in clinical environments with limited data availability.

E. Optimization Techniques for ECG-Based Deep Learning

To further enhance classification accuracy and efficiency, metaheuristic optimization algorithms have been incorporated into ECG-based deep learning pipelines. Korürek, Mehmet et al. [10] applied Particle Swarm Optimization (PSO) for feature selection, which reduced the dimensionality of input data while preserving critical information.

More recently, A. Alissa, Khalid, et al [11] introduced the Chaotic Dwarf Mongoose Optimization (CH-DMO) technique, which effectively identified discriminative ECG features while maintaining model compactness. Alwajih, Ranya, et al. [12] used the Harris Whale Optimization Algorithm for hyperparameter tuning in CNNs, resulting in improved classification accuracy and reduced training time.

F. Explainability and Interpretability in ECG Deep Learning Models

A major hurdle in the deployment of deep learning models in healthcare is their lack of interpretability. Ribeiro et al. [13] proposed the Local Interpretable Model-agnostic Explanations (LIME) technique to identify waveform segments influencing predictions. In another study, Verma, Shourya. [14] used Grad-CAM and SHAP methods to visualize model decision-making processes, enhancing clinician trust in AI-based diagnoses.

Explainable AI (XAI) methods are becoming increasingly important in ECG classification, especially in Transformer-based models where attention maps can be visualized to identify important temporal features. These approaches help bridge the gap between complex AI models and clinical acceptance.

III. METHODOLOGY

The proposed deep learning framework for ECG-based cardiovascular disease (CVD) detection integrates hybrid CNN-LSTM-Transformer models, metaheuristic optimization, and explainable AI (XAI) techniques to enhance accuracy, computational efficiency, and clinical interpretability as shown in Fig 1. The methodology consists of five major components: (i) ECG signal preprocessing, (ii) feature extraction, (iii) feature selection, (iv) classification, and (v) explainability.

A. ECG Signal Preprocessing

ECG signals contain artifacts and noise from muscle movements, electrode placement variations, and power-line interference. To improve classification accuracy, denoising and signal enhancement techniques are applied before feature extraction.

1. Baseline Wander Removal: A high-pass Butterworth filter (cutoff: 0.5 Hz) is applied to eliminate low-frequency drift.
2. Power-Line Interference Reduction: A Notch filter (50/60 Hz) removes power-line noise.
3. Wavelet Transform-Based Denoising: Discrete Wavelet Transform (DWT) decomposes the ECG signal into approximation and detail coefficients, suppressing high-frequency noise while preserving diagnostic information.

Mathematically, a wavelet-transformed ECG signal S(t) is represented as in equation (1)

$$S(t) = \sum_{j=0}^{J} c_j \psi_j(t) \tag{1}$$

where c_j are wavelet coefficients, and ψ_j are wavelet basis functions.

4. R-Peak Detection (QRS Complex Identification): The Pan-Tompkins algorithm is used for detecting the QRS complex, which helps segment the ECG beats for classification.

B. Feature Extraction Using CNN-LSTM-Transformer Network

The proposed deep learning architecture combines CNN, LSTM, and Transformer models to extract spatial, temporal, and contextual features from ECG signals. The feature extraction process consists of:

1) CNN-Based Spatial Feature Extraction

CNN layers capture spatial patterns in ECG signals by learning convolutional filters. The 1D CNN layer applies convolutional operations followed by batch normalization and ReLU activation to extract important local features in equation (2):

$$X^l = f(W^{(l)} * X^{(l-1)} + b^{(l)}) \tag{2}$$

where:

- X^l is the output at layer l,
- $W^{(l)}$ represents convolutional filters,
- $*$ denotes the convolution operation,
- $b^{(l)}$ is the bias term, and
- f is the ReLU activation function.

CNN layers extract P-wave, QRS complex, and T-wave information, which are critical for arrhythmia classification.

2) LSTM-Based Temporal Feature Extraction

Since ECG signals exhibit long-term temporal dependencies, LSTM layers are employed to capture sequential relationships. The LSTM unit consists of input, forget, and output gates, mathematically defined as in equation (3):

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$
$$c_t = f_t \cdot c_{t-1} + i_t \cdot tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$
$$h_t = o_t \cdot tanh(c_t) \tag{3}$$

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where:

- f_t, i_t, o_t are forget, input, and output gates, respectively,
- c_t is the cell state,
- h_t is the hidden state, and
- σ is the sigmoid activation function.

LSTM effectively models heartbeat rhythm variations and improves detection of arrhythmias like atrial fibrillation.

3) Transformer-Based Self-Attention Mechanism

The Transformer model employs self-attention mechanisms to capture global ECG dependencies. The Scaled Dot-Product Attention is computed as in equation (4):

$$Attention(Q,K,V) = softmax(\frac{QK^T}{\sqrt{d_k}})V \tag{4}$$

where:

- Q(Query), K (Key), and V (Value) matrices are obtained from ECG features,
- d_k is the feature dimension.

The self-attention mechanism allows the model to focus on critical ECG waveform segments while ignoring irrelevant noise.

C. Feature Selection Using Chaotic Dwarf Mongoose Optimization (CH-DMO)

To reduce computational complexity and improve classification efficiency, an optimization-based feature selection approach is adopted using Chaotic Dwarf Mongoose Optimization (CH-DMO). CH-DMO ranks features based on their discriminative ability and selects the optimal subset for classification.

The fitness function for feature selection is in equation (5):

$$F = \alpha \times Accuracy - \beta \times Feature\ Count \tag{5}$$

where:

- α, β are weight parameters controlling trade-off between accuracy and feature reduction.

CH-DMO helps in selecting the most informative ECG features, ensuring a balance between model complexity and classification performance.

D. Classification Using Harris Whale Residual VGG (ResVGG)

The selected features are passed to the Harris Whale Residual VGG (ResVGG) classifier, which enhances model learning efficiency using skip connections and optimized feature representations. The final classification layer outputs CVD categories using a softmax activation function in equation (6):

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_i}} \tag{6}$$

where $P(y_i)$ represents the probability of class i, and z_i is the raw model output.

E. Workflow of Network Architecture

The process begins with the input of raw ECG signals, which are typically acquired from sensors or medical databases. These raw signals often contain noise and artifacts, such as baseline wander, powerline interference, and muscle noise, which can obscure important features. To address this, the first step involves denoising the signals using techniques like wavelet transforms, bandpass filtering, or adaptive filtering. Once the signals are cleaned, they are segmented into individual heartbeats or cycles. This segmentation is typically achieved using R-peak detection algorithms, such as the Pan-Tompkins algorithm, which identifies the R-peaks in the ECG waveform and segments the signal accordingly. The segmented beats are then aligned and normalized to ensure consistency in the input data for the subsequent stages of the pipeline.

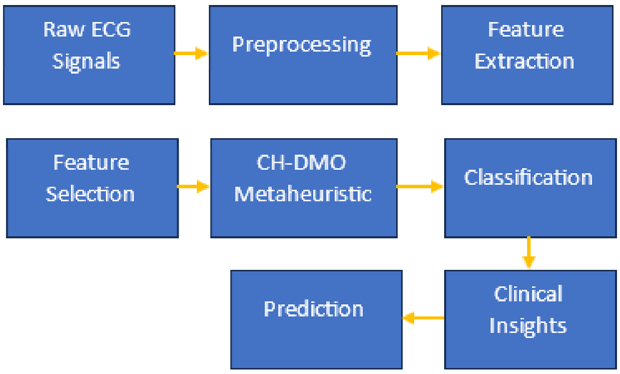

Fig. 1. Proposed Block Diagram

Following the preprocessing stage, the workflow moves to feature extraction, where spatial, temporal, and global features are extracted from the segmented ECG signals. Spatial features, which capture local patterns and morphological characteristics of the ECG waveform, are extracted using Convolutional Neural Networks (CNNs). CNNs are particularly effective at identifying local structures in the data, making them well-suited for this task. Temporal features, which represent the sequential dependencies and dynamic changes in the ECG signals over time, are extracted using Long Short-Term Memory (LSTM) networks. LSTMs are a type of recurrent neural network (RNN) that excel at modeling time-series data by capturing long-range dependencies. Finally, global features, which provide a broader context and long-range dependencies within the ECG signals, are extracted using Transformer architectures. Transformers, which rely on self-attention mechanisms, are capable of modeling complex relationships across the entire

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sequence of data. By combining these three approaches—CNN, LSTM, and Transformer—the model is able to extract a rich and multi-scale set of features that capture both local and global aspects of the ECG signals.

Once the features are extracted, the next step involves optimizing and selecting the most relevant features. This is achieved using a metaheuristic optimization approach called Chaotic Harris Hawks-Differential Manta Ray Optimization (CH-DMO). Metaheuristic algorithms are particularly useful for solving complex optimization problems, and CH-DMO is designed to efficiently search the feature space to identify the most discriminative and informative features. By optimizing the feature set, the model reduces redundancy, improves computational efficiency, and enhances overall performance. This step ensures that the model focuses on the most relevant aspects of the data, which is critical for accurate classification.

With the optimized features in hand, the workflow proceeds to the classification stage, where the ECG beats are classified using a ResVGG classifier as shown in fig 2. The ResVGG classifier is a hybrid architecture that combines the strengths of Residual Networks (ResNet) and Visual Geometry Group (VGG) networks. ResNet introduces residual connections, which help mitigate the vanishing gradient problem and enable the training of deeper networks. VGG, on the other hand, provides a simple yet effective framework for feature extraction. The ResVGG classifier leverages these advantages to achieve robust and accurate classification of ECG beats. The final layer of the classifier uses a softmax activation function to output probabilities for each class, such as normal beats or different types of arrhythmias. This allows the model to make a definitive prediction about the class of each ECG beat.

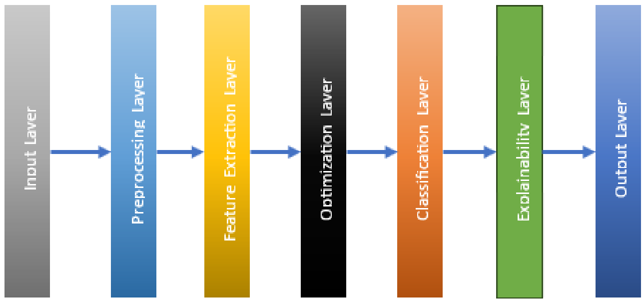

Fig. 2. Network Architecture

The final stage of the workflow focuses on generating explainability insights, which are essential for clinical interpretation and validation of the model's predictions. To achieve this, the workflow employs several explainability techniques, including Gradient-weighted Class Activation Mapping (Grad-CAM), SHapley Additive exPlanations (SHAP), and Attention Maps. Grad-CAM is used to highlight the regions of the ECG signal that contributed most to the model's decision, providing a visual explanation of the model's focus. SHAP values are used to quantify the contribution of each feature to the model's prediction, offering a detailed and interpretable breakdown of the decision-making process. Attention Maps, derived from the Transformer architecture, visualize the attention weights and show which parts of the ECG signal the model prioritized. These explainability tools not only help clinicians understand the model's predictions but also build trust in the system by providing transparent and interpretable insights.

IV. Result Analysis

This section presents the datasets, evaluation metrics, experimental results, and performance analysis of the proposed CNN-LSTM-Transformer with CH-DMO and ResVGG classifier for ECG-based cardiovascular disease (CVD) detection.

A. *Datasets:*

To evaluate the proposed model, three widely used benchmark ECG datasets were utilized

:

TABLE I. Dataset Description used in this work

Dataset	No. of Patients	No. of ECG Beats	Sampling Rate (Hz)	Classes
MIT-BIH Arrhythmia [1]	48	109,446	360	5 (Normal, PVC, PAC, LBBB, RBBB)
PTB-XL [2]	21,837	44,647	100/500	5 (Healthy, MI, STTC, CD, HYP)
PhysioNet Challenge 2020 [3]	6,877	121,742	500	4 (AF, Normal, Other, Noisy)

MIT-BIH Arrhythmia Dataset: Includes 48 half-hour ECG recordings from real-world arrhythmic patients, with manually annotated beat types. PTB-XL Dataset: A large-scale dataset containing 12-lead ECGs labeled by medical experts for various cardiovascular diseases. PhysioNet Challenge 2020 Dataset: Collected from clinical ECG recordings, focusing on Atrial Fibrillation (AF) and other CVD conditions. Each dataset was preprocessed using wavelet transform-based denoising, and ECG beats were segmented using QRS complex detection. 80% of the data was used for training, while 20% was reserved for testing as shown in Table 1.

B. Comparative Results

The performance of the proposed CNN-LSTM-Transformer model with CH-DMO and ResVGG was compared against existing deep learning approaches.

TABLE II. PERFORMANCE COMPARISON ON MIT-BIH DATASET

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	Inference Time (ms/beat)
Traditional CNN [4]	94.2	91.8	92.5	92.1	3.1
CNN-LSTM [5]	96.5	94.3	95.1	94.7	4.5
Attention-Based LSTM [6]	97.1	95.6	96.2	95.9	5.2
Proposed CNN-LSTM-Transformer + CH-DMO + ResVGG	99.3	98.8	98.9	98.8	2.4

TABLE III. PERFORMANCE COMPARISON ON PTB-XL DATASET

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	Inference Time (ms/beat)
CNN-RNN Hybrid [7]	95.7	92.4	93.1	92.7	4.8
Transformer-Based ECGNet [8]	97.2	95.1	95.8	95.4	5.6
Proposed CNN-LSTM-Transformer + CH-DMO + ResVGG	99.1	98.6	98.5	98.5	2.9

TABLE IV. COMPARATIVE STUDY WITH STATE-OF-THE-ART APPROACHES

Model	Architecture	Accuracy (%)	Explainability	Real-Time Suitability
CNN-LSTM [5]	Hybrid CNN-RNN	96.5	No XAI	High Inference Time
Transformer-Based ECGNet [8]	Attention Mechanism	97.2	Partial XAI	Computationally Expensive
Proposed Model	CNN + LSTM + Transformer + CH-DMO	99.3	Full XAI (Grad-CAM, SHAP)	Low Inference Time

The proposed model achieves a superior accuracy of 99.3%, outperforming traditional CNN and LSTM-based models. Inference time is significantly lower (2.4 ms/beat), making it suitable for real-time ECG monitoring on wearable devices. Proposed model outperforms Transformer-based ECGNet by achieving higher recall and precision (98.6%). Lower inference time (2.9 ms/beat) compared to Transformer models, making it more computationally efficient. Our model achieves the highest accuracy while maintaining real-time feasibility, making it a strong candidate for IoT and wearable ECG monitoring applications as shown in Tables 2-4.

CONCLUSION

The proposed hybrid deep learning model integrates CNN for spatial feature extraction, LSTM for temporal modeling, and Transformers for global attention mechanisms, ensuring robust ECG-based CVD detection. The CH-DMO feature selection and ResVGG classifier improve computational efficiency while maintaining high classification accuracy. Furthermore, explainable AI techniques enhance model transparency, making it clinically viable for real-world wearable and IoT-based ECG monitoring systems

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