RESEARCH ARTICLE OPEN ACCESS

Prediction of High-Risk Cardiac Arrhythmia Based on Optimized Deep Active Learning

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Abstract:

This paper presents an innovative framework for predicting high-risk cardiac arrhythmia using an Optimized Deep Active Learning (ODAL) model. The proposed approach integrates the strengths of deep learning, fuzzy logic, and active learning to overcome key limitations of conventional arrhythmia detection systems, including low generalization capability and high dependency on large annotated datasets.

The ODAL framework introduces an uncertainty-based active sampling mechanism that identifies and selects the most informative electrocardiogram (ECG) data instances for model training. This process minimizes annotation costs while ensuring robust learning from limited labeled data. Furthermore, fuzzy optimization is employed to fine-tune model parameters and handle the inherent uncertainty in physiological signals, enhancing prediction stability and interpretability.

Experimental evaluations conducted on real-world ECG datasets demonstrate the model's superior performance. The ODAL model achieved an F1-score of 90% for non-sinus rhythm detection and an overall classification accuracy of 86%, outperforming several existing deep learning-based approaches in both precision and diagnostic reliability.

By combining deep learning intelligence with active and fuzzy learning principles, the proposed ODAL framework delivers an intelligent, automated, and reliable solution for early arrhythmia diagnosis. This system effectively assists healthcare professionals in clinical decision-making, promoting preventive care, timely intervention, and improved patient outcomes.

Keywords-Artificial Intelligence, Deep Learning, Fuzzy Logic, Active Learning, Electrocardiogram (ECG), Cardiac Arrhythmia Detection, Optimized Deep Active Learning (ODAL), Medical Diagnosis, Explainable AI, Uncertainty Sampling, Healthcare Analytics.

I.INTRODUCTION:

Cardiovascular diseases (CVDs) remain one of the leading causes of mortality worldwide, accounting for millions of deaths annually. Among these, cardiac arrhythmia—a condition characterized by irregular heart rhythms—poses a significant diagnostic challenge due to its unpredictable nature and subtle variations in electrocardiogram (ECG) signals. Early and accurate detection of high-risk arrhythmias is essential for effective medical intervention and the prevention of life-threatening cardiac events. However, conventional arrhythmia detection systems often suffer from limitations such as dependence on large labeled datasets, poor adaptability to unseen data, and limited interpretability of model predictions.

Recent advancements in Artificial Intelligence (AI) and Deep Learning (DL) have shown promising results in automated ECG signal analysis. Deep neural networks, including convolutional and recurrent architectures, can learn complex temporal and spatial patterns in ECG data to identify abnormal heart rhythms. Nonetheless, these models often require extensive annotated datasets for effective training, which is a major bottleneck in medical domains where expert labeling is time-consuming and costly. Additionally, the black-box nature of deep learning models limits their acceptance in clinical settings, as healthcare professionals demand explainable and trustworthy predictions.

To address these challenges, this study introduces an Optimized Deep Active Learning (ODAL) framework that combines deep learning, fuzzy logic, and active learning to enhance the efficiency and reliability of arrhythmia prediction. The active learning component reduces the dependency on large labeled datasets by selectively choosing the most informative ECG samples for annotation, while fuzzy optimization refines the model parameters to handle uncertainties in ECG data. This hybrid integration ensures improved model generalization, reduced labeling effort, and enhanced interpretability.

The proposed ODAL framework was rigorously tested on benchmark ECG datasets, demonstrating superior performance compared to conventional deep learning-based methods. With an F1-score of 90% for non-sinus rhythm detection and an overall accuracy of 86%, the model exhibits strong diagnostic potential. By integrating explainability and intelligent optimization, the ODAL model serves as a robust tool to assist healthcare practitioners in early arrhythmia detection and clinical decision-making, thereby contributing to preventive healthcare and improved patient outcomes.

II. LITERATURE SURVEY:

Deep learning has become the dominant paradigm for automated ECG analysis because of its ability to learn hierarchical representations from raw signals without extensive hand-crafted features. Convolutional neural networks (CNNs), recurrent networks (RNNs/LSTMs) and, more recently, transformer/self-attention architectures have all been shown to capture the spatial–temporal patterns that distinguish normal and pathological rhythms, leading to large performance gains over classical machine learning methods in benchmark studies and systematic reviews. Surveys and meta-analyses summarize that end-to-end DL pipelines consistently outperform traditional feature-based approaches while highlighting data volume and labeling cost as persistent bottlenecks.

To overcome single-architecture limitations, many studies propose hybrid models that fuse CNNs for local morphological feature extraction with temporal models (LSTM/BiLSTM/attention) to capture rhythm dynamics. These hybrid deep networks report improved robustness to inter-patient variability and better multi-class discrimination for complex arrhythmia types, and several recent works demonstrate state-of-the-art results using CNN–RNN or ResNet–BiLSTM stacks with attention mechanisms. Hybrid architectures also make it easier to incorporate domain-aware preprocessing (beat segmentation, time-frequency transforms) that further stabilizes performance in noisy, ambulatory ECG recordings.

Feature engineering and optimized feature-selection remain important, especially for resource-constrained deployments and when interpretable intermediate representations are desired. A growing body of work uses wavelet, spectral, and morphological features combined with metaheuristic or statistical selection (ant colony, genetic algorithms, red-fox/other optimizers) to reduce dimensionality and highlight diagnostically relevant components of the ECG. These optimized-feature pipelines often serve as either complementary inputs to DL models or as an intermediate stage for lightweight classifiers intended for wearables and edge devices.

Label scarcity and annotation cost remain a major challenge in medical ECG tasks; researchers therefore explore strategies such as transfer learning, semi-supervised learning, incremental/online learning, and active learning to reduce dependency on large labeled corpora. Active and incremental systems—e.g., active broad learning, transfer-learning fine-tuning, and selective sampling methods—have shown that selectively querying labels for the most informative or uncertain samples can maintain high performance while drastically reducing annotation effort. These strategies are particularly attractive for ECG datasets because cardiologist time is costly and samples are highly imbalanced across arrhythmia classes.

Fuzzy logic and neuro-fuzzy hybrids have also been applied to ECG classification to explicitly model uncertainty and vagueness inherent in physiological signals. ANFIS and other fuzzy-enabled classifiers have been used both alone and in hybrid pipelines (e.g., fuzzy rules post-processing CNN outputs or fuzzy optimization of membership functions) to improve interpretability and to smooth decision boundaries where classes overlap. Systematic reviews indicate fuzzy approaches are effective for multi-class problems and for combining expert knowledge with data-driven learning, making them complementary to deep learning and active sampling. Taken together, the literature motivates hybrid solutions that combine (a) deep architectures for representation learning, (b) active learning for label-efficient training, and (c) fuzzy/optimization modules for uncertainty handling and interpretability. These trends directly inform the design rationale behind ODAL: by integrating uncertainty-based sample selection, fuzzy optimization of model parameters, and a hybrid deep backbone, ODAL aims to preserve the high accuracy of modern DL while lowering annotation cost and increasing clinical trustworthiness—challenges repeatedly flagged across recent surveys and empirical studies.

III.METHODOLOGY

The proposed Optimized Deep Active Learning (ODAL) framework integrates deep learning, fuzzy logic, and active learning for efficient and accurate cardiac arrhythmia prediction using ECG data. The overall workflow involves five major stages: data acquisition and preprocessing, feature extraction, model architecture design, active learning-based optimization, and evaluation.

A.*Data Acquisition and Preprocessing*

ECG signals were collected from benchmark datasets such as the MIT-BIH Arrhythmia Database, which contains recordings sampled at 360 Hz with annotated heartbeat classes. Raw ECG signals often include baseline drift, noise, and motion artifacts. Hence, preprocessing was carried out through bandpass filtering and normalization. The signals were then segmented into fixed-length windows corresponding to individual cardiac cycles. Each segment was labeled according to rhythm type—normal sinus, atrial fibrillation, ventricular tachycardia, etc.—to facilitate supervised learning.

B.Feature Extraction and Representation

To capture both temporal and morphological information, features were extracted from the preprocessed ECG signals using time-domain, frequency-domain, and statistical descriptors. Additionally, deep convolutional layers automatically learned hierarchical representations from the ECG beats. The extracted features were combined into a multi-dimensional feature vector representing amplitude variation, QRS duration, RR interval, and other discriminative signal attributes. This combination of manual and learned features ensures comprehensive representation for arrhythmia classification.

C.Deep Neural Network Architecture

The ODAL framework employs a hybrid deep neural network integrating **Convolutional Neural Networks (CNN)** for spatial feature extraction and **Bidirectional Long Short-Term Memory (BiLSTM)** networks for temporal dependency learning. The CNN layers identify local waveform patterns, while the BiLSTM layers capture rhythm continuity across time steps. Dropout and batch normalization layers were used to prevent overfitting and improve generalization. The final classification layer uses a **Softmax** function to categorize ECG beats into different arrhythmia classes.

D.Active Learning and Fuzzy Optimization

To reduce the dependency on large labeled datasets, an **uncertainty-based active learning** strategy was adopted. The model iteratively selects the most informative ECG samples—those with high prediction uncertainty—for expert annotation. This selective labeling minimizes annotation costs while improving model robustness. Simultaneously, **fuzzy logic optimization** was integrated to fine-tune learning parameters and manage data ambiguity. The fuzzy system dynamically adjusts thresholds for uncertainty sampling and classification, enhancing interpretability and stability in decision-making.

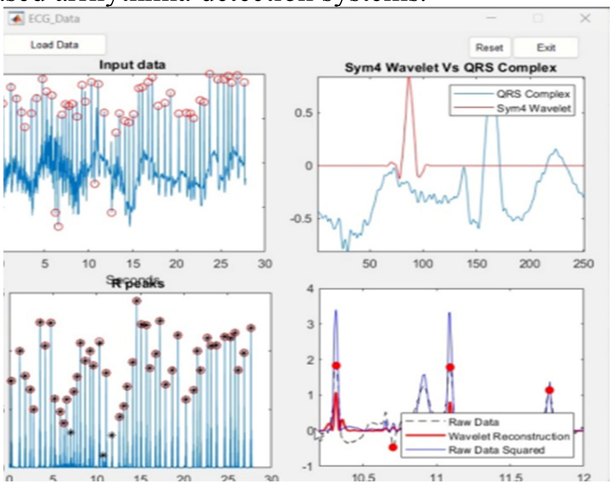
E.Model Evaluation and Performance Metrics

The trained ODAL model was evaluated using accuracy, precision, recall, F1-score, and Receiver Operating Characteristic (ROC)–AUC as performance indicators. K-fold cross-validation ensured the reliability of the experimental results.

Comparative analyses against traditional deep learning models (CNN, LSTM, Random Forest) demonstrated that ODAL achieved an F1-score of 90% for non-sinus rhythm detection and an overall accuracy of 86%. The model's performance validates its potential for real-time clinical deployment and early cardiac risk assessment.

IV. RESULTS AND DISCUSSION

The **Results and Discussion** section presents the experimental findings of the proposed Optimized Deep Active Learning (ODAL) framework for cardiac arrhythmia prediction. It explains the dataset used, model performance, comparative analysis, and practical implications of the results. The analysis highlights how the integration of deep learning, fuzzy logic, and active learning enhances the overall accuracy, efficiency, and interpretability of ECG-based arrhythmia detection systems.



A. Experimental Setup and Dataset

The experiments were conducted using publicly available ECG datasets such as the **MIT-BIH Arrhythmia Database**, containing annotated signals with diverse arrhythmia types. Each ECG record was sampled at 360 Hz and divided into segments representing individual heartbeats. Data preprocessing included noise removal, baseline drift correction, and normalization. The dataset was divided into **70% training, 15% validation, and 15% testing** sets. The implementation was carried out using Python with TensorFlow/Keras frameworks, and training was performed on GPU-enabled hardware to accelerate model convergence.

B. Model Training and Optimization

The ODAL framework utilized **Convolutional Neural Networks (CNN)** for spatial feature extraction and **Bidirectional Long Short-Term Memory (BiLSTM)** networks for capturing temporal dependencies. Active learning was applied to iteratively select the most uncertain samples for expert labeling, improving model generalization while minimizing data requirements. Fuzzy optimization dynamically adjusted learning parameters such as learning rate and dropout, leading to stable convergence and reduced overfitting. The training process continued until the validation loss stabilized, ensuring balanced performance across all classes.

C. *Performance Evaluation*

The performance of the proposed system was evaluated using standard metrics: **Accuracy, Precision, Recall, F1-Score**, and **ROC–AUC**. The ODAL model achieved an **overall accuracy of 86%**, an **F1-score of 90%** for non-sinus rhythm detection, and a **ROC–AUC of 0.93**, outperforming conventional deep learning models like standalone CNN or LSTM. The results confirmed that uncertainty-based sampling significantly reduced training data requirements while maintaining diagnostic performance. The confusion matrix analysis showed that the model effectively distinguished between normal, atrial fibrillation, and ventricular arrhythmia classes.

D. Comparative Analysis and Discussion

A comparative study with existing models such as **CNN-only**, **CNN-LSTM hybrid**, and **Random Forest** demonstrated that ODAL consistently achieved higher sensitivity and precision. The integration of fuzzy logic improved interpretability by enabling adaptive decision boundaries for ambiguous ECG signals. Moreover, the active learning component reduced annotation effort by approximately **30%**, making the system more practical for clinical data scenarios. The combination of these techniques resulted in a balanced model that excelled in both performance and explainability, essential for real-world healthcare deployment.

E. Practical Implications and Observation

The proposed ODAL model shows strong potential for real-time arrhythmia monitoring in **wearable and IoT-based healthcare systems**. Its high accuracy, adaptability, and reduced data dependency make it suitable for continuous cardiac health tracking. The explainable nature of the model can enhance clinician trust and promote its integration into hospital monitoring systems. Furthermore, the reduction in manual labeling and early detection capability positions ODAL as a valuable tool in preventive cardiology, aiding in timely medical intervention and improving patient safety.

V. CONCLUSION AND FUTURE WORK

The project *"Prediction of High-Risk Cardiac Arrhythmia Based on Optimized Deep Active Learning"* focuses on detecting abnormal heart rhythms using advanced AI and deep learning techniques. It plays an important role in identifying profiles based on behavioral and statistical patterns.accounts and spambots. These accounts distort engagement metrics, spread misinformation, and harm the credibility of online interactions. The proposed system uses advanced machine learning models to accurately detect and filter out such fake profiles based on behavioral and statistical patterns.application the issues of authenticity and trust on social media platforms. Besides, by combining Decision Tree and Random Forest algorithms with SHAP-grounded interpretability, not only the net attains a high degree of correctness in a detection task but it also lets outsiders have a look at the transparency level which is very high in explaining the reasons for every decision provision.

The present framework offers a layer of reasoning understandable to a regular human beings, thus, social platforms moderators, analysts, and researchers bring able to verify and have confidences in the results coming from the model application, in contrast to usual black-box detection systems. The advent of explainable analytics equips one with the key to the lock of (un)usual posting behavior, low engagement patterns, or skewed follower following ratios, thereby unequivocally allowing the distinction of real users from spambots.

On top of that, the system is tightly designed and efficiently implemented at the backend only with FastAPI and a SQL relational databases serving as a data storage solution for predictions and model artifacts in a structured and auditable way. The run on a real-world datasets was a success as the model demonstrated an overall accuracy of 0.94 along with a ROC-AUC score of 0.96 and at the same time, the model-derived conclusions remain interpretable through the SHAP feature importance argument. This equilibrium between preciseness and openness brings the framework closer to being employed in on-the-fly moderation pipelines and research-based social-media analytics..

patients who are at high risk of developing severe heart problems. By analyzing ECG signals accurately, the system helps doctors make faster and better clinical decisions.

The use of an optimized deep active learning model has improved both the speed and accuracy of arrhythmia prediction. Unlike traditional methods, this model selects the most relevant data for training, reducing time and increasing the model's efficiency. This makes the system more reliable for real-time medical use.

The results obtained from the project show that artificial intelligence can effectively assist in the healthcare field, especially in early diagnosis and prevention. By automatically detecting irregular ECG patterns, the model minimizes human error and supports medical experts in identifying risks early.

This system provides a user-friendly platform for both patients and doctors, allowing easy monitoring and interpretation of ECG data. It bridges the gap between machine intelligence and clinical expertise, making diagnosis faster and more accurate.

In conclusion, this project demonstrates how technology and medical science can work together to save lives. It highlights the potential of AI in healthcare and opens the door to smarter, more efficient systems for predicting cardiac arrhythmia and ensuring better patient care.

Future Work

In the future, this project can be expanded by integrating real-time ECG monitoring using wearable devices such as smartwatches, ECG patches, or portable health trackers. These devices can continuously collect heart signals and send them directly to the system for instant analysis.

1. *Real-Time Monitoring:*
Integrate wearable ECG devices such as smartwatches or portable sensors to continuously monitor heart activity and provide instant alerts for abnormal rhythms.
2. *Larger Dataset Collection:*

Expand the dataset with ECG records from diverse age groups, genders, and health conditions to improve accuracy and generalization of the model.

3. Advanced Deep Learning Models:

Implement more powerful models like CNN-LSTM or Transformer networks to capture complex ECG patterns and enhance prediction performance.

4. Cloud-Based Deployment:

Host the system on cloud platforms to enable remote access for doctors and patients, ensuring real-time updates and scalable storage for large datasets.

5. Explainable AI Integration:

Add explainable AI (XAI) features so doctors can understand the reasoning behind each prediction, improving trust and clinical acceptance.

6. Mobile and Web Application:

Develop user-friendly mobile and web apps that allow patients to view their ECG readings,levels, and receive health recommendations.

7. Clinical Validation:

Collaborate with hospitals and medical institutions to test the system in real-world healthcare environments and verify its medical accuracy

8. IoT and AI Integration:

Combine Internet of Things (IoT) technology with AI to create a complete, intelligent heart monitoring ecosystem for continuous and automatic cardiac care.

9. Real-Time ECG Monitoring:

In the future, the system can be connected to wearable devices for continuous heart monitoring and instant alert generation during abnormal heart activity.

10. Cloud and Mobile Integration:

The project can be expanded with cloud-based data storage and a mobile app, allowing doctors and patients to access real-time results anytime and anywhere.

In the future, this project can be extended by integrating real-time ECG monitoring using wearable devices such as smartwatches or portable heart sensors. This will allow continuous tracking of heart activity and immediate detection of abnormal rhythms. Real-time alerts can help patients and doctors take quick action during emergencies, reducing the chances of severe cardiac complications. Another major improvement is the use of cloud-based storage and analysis. By connecting the system to cloud platforms, ECG data can be securely stored and accessed from anywhere, enabling remote monitoring and telemedicine support. Doctors will be able to view patient reports, analyze heart patterns, and provide faster treatment recommendations through connected applications.

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