Heart-SecureCloud: A Secure Cloud-Based Hybrid DL System for Diagnosis of Heart Disease Through Transformer-Recurrent Neural Network

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***Abstract*—Cardiovascular disease (CVD) has rapidly increased after COVID-19. Several computerized systems have been developed in the past to diagnose CVD disease. However, the high computing expenses of deep learning (DL) models and the complexity of architectures are significant issues. Therefore, to resolve these issues, an accurate diagnosis of CVD disease is required. This paper proposes a hybrid and secure deep learning (DL) system known as Heart-SecureCloud to predict multiclass heart diseases. To develop this Heart-SecureCloud system, four major stages are makeup such as preprocessing and augmentation, feature extraction and transformation, deep learning and hyperparameter optimization, and cloud security. Advanced signal processing and augmentation technologies are applied to ECG data in the preprocessing and augmentation step to enhance data quality. In the feature extraction and transformation step, adaptive wavelet transforms, and feature scaling are used to extract and convert spectral and temporal data. The DL and hyperparameter optimization step utilize a novel hybrid transformer-recurrent neural network model, which is further optimized for accuracy and efficiency using hyperband-GA. Transfer learning refines pre-trained models using domain-specific data. The unique aspect of the Heart-SecureCloud system is its implementation through a secure cloud, which safeguards medical data with encryption and access control mechanisms. The system's efficacy is demonstrated through testing and evaluation on three publicly available datasets, such as MIT-BIH Arrhythmia MIMIC-III Waveform and PTB-ECG. The Heart-SecureCloud DL architecture achieved impressive results of 98.75% of accuracy, 98.80% of recall, 98.70% of precision, and 98.75% of F1-score. Moreover, the Heart-SecureCloud DL underscores its promise for safe medical diagnostics deployment.**

Keywords—Heart disease diagnosis; deep learning; cloud computing; feature extraction; data security; hyperparameter optimization; encryption

I. Introduction

The most common chronic disorders worldwide are cardiovascular diseases (CVDs), which have caused the most morbidity and mortality during the previous decade [1]. The WHO estimates that 17.9 million people die from CVDs yearly, 32% of all fatalities [2]. By 2030, 22.2 million individuals may die from CVDs. Over the past 30 years, CVDs have been the leading cause of death in the US, accounting for 46.2% of deaths in 2017 [3]. CVDs include congestive heart failure, coronary artery disease, congenital heart defects, cerebrovascular disease, and rheumatic heart disease [4]. Nowadays, CVD is caused by heart attacks and strokes. Early and precise prediction of CVD disease improves survival and reduces death [5]. In addition, this improvement can assist experts in treating patients faster, thanks to the potential of machine learning (ML) and deep learning (DL) methods [6]. These methods, by analyzing ECG signals, can significantly enhance our ability to combat CVDs [7].

Artificial intelligence (AI) technologies are advancing rapidly, and cloud security, along with machine learning (ML) and deep learning (DL) approaches, can now be utilized to monitor and even predict cardiovascular diseases (CVD) [8]. Cloud security, a crucial component, involves securing data, applications, and infrastructures hosted in the cloud, ensuring they are protected from unauthorized access and breaches. This is particularly important in the medical and healthcare sectors, where sensitive health data must be safeguarded. Machine learning, a branch of artificial intelligence, involves techniques that extract knowledge from data, often called predictive analytics or statistical learning. Deep learning, a subset of ML, uses neural networks with multiple layers to model complex patterns in data. These techniques, when applied to medicine, have the potential to not just revolutionize but also excite us about the future of healthcare delivery methods. Moreover, the vast amount of data generated by hospitals in a cloud environment presents significant challenges, particularly in selecting the most effective machine-learning techniques for data analysis.

Cardiovascular disease (CVD) has seen a significant rise following the Covid-19 pandemic. In response, numerous computerized systems have been developed to diagnose CVD. However, challenges such as the high computational costs of deep learning (DL) models and the complexity of their architectures remain. To address these challenges, there is a need for an accurate and efficient approach to diagnosing CVD. This paper introduces a hybrid and secure deep learning system called Heart-SecureCloud, designed to predict various types of heart diseases. This study shows multi-layered strategy to establishing a safe and efficient cloud-based deep learning system for heart disease diagnostics. In the Preprocessing and Augmentation Layer, innovative signal processing and data augmentation procedures improve medical voice record input data quality. A unique adaptive wavelet transform, and feature scaling method extracts and transforms spectral and temporal properties in the Feature Extraction and Transformation Layer.

The Hyperband-GA hybrid approach optimizes a Transformer-Recurrent Neural Network (RNN) hybrid model in the Deep Learning and Hyperparameter Optimization Layer for accuracy and efficiency. Pre-trained models are fine-tuned using domain-specific data via transfer learning. Finally, the Evaluation and Security Layer thoroughly evaluates and verifies performance metrics while protecting sensitive medical data with strong encryption and access control. Encrypting data in transit and at rest and using authentication techniques, this layer secures data processing and cloud server deployment. This study makes several significant contributions to the field of heart disease detection.

1) Novel Heart-SecureCloud DL system for effective heart disease diagnosis using advanced signal processing, feature extraction, and hybrid deep learning architectures.

2) The Hyperband-GA hybrid optimization approach improves model accuracy and computational efficiency.

3) This cloud server study integrates a thorough security layer into the cloud-based feature categorization system.

4) High model accuracy (98.75%) and comprehensive security features set a new heart disease diagnosis system benchmark.

Structure of the paper: Section II: Reviews heart disease diagnosis and prognosis approaches and their advances. Section III: Explains speech feature extraction, ML methods, picture augmentation, and data normalization. Section IV reports the experimental setup, findings, and performance evaluation of the proposed system, comparing it to alternative methods. Section V: Summarizes findings, analyzes ramifications, and offers further study.

TABLE I. A TABLE SUMMARIZING THE KEY POINTS AND COMPARISONS BASED ON THE LITERATURE REVIEW

Study	Purpose	Methodology	Results	Limitations
[14]	Detection of CAD using ECG signals	Developed AE, RBFN, SOM, and RBM models; ensemble of AE and SOM	AE: Accuracy 0.974 (MIT-BIH), 0.984 (PTB-ECG); Ensemble: Accuracy 0.984 (MIT-BIH), 0.992 (PTB-ECG)	Needs testing on larger and more imbalanced datasets
[15]	Automated diagnostic systems for CAD, MI, CHF	Developed 16-layer LSTM model	Accuracy 98.5%	Limited to classification of abnormal ECG signals
[16]	Addressing imbalanced data for detection	Developed GAN, LSTM, and ensemble GAN-LSTM models	GAN-LSTM: Accuracy 0.992 (MIT-BIH), 0.994 (PTB-ECG)	Further research needed with different ensemble models and datasets
[17]	Automated detection of ECG arrhythmia	Removed noise, extracted features, used ML and DL models	Accuracy 86.25%	Performance affected by noise in ECG signals
[18]	Distinguish normal and abnormal ECG patients	Used SVM, LR, AdaBoost; ensemble of AdaBoost and LR	Ensemble: Accuracy 0.946 (PTB-ECG), 0.921 (MIT-BIH)	Methodology can be applied to other diseases
[19]	Preprocessing, data sampling, feature extraction, classification	Used ADASYN for data sampling, GRU for feature extraction, ELM for classification	Superior in terms of accuracy, sensitivity, specificity	Needs further validation with other datasets
[20]	Simplify large data processing	Used Spark–Scala tools, evaluated with MIT-BIH datasets	GDB Tree: Accuracy 97.98% (binary), Random Forest: 98.03% (multi-class)	Limited to large-scale data processing tools
[21]	Compare 1D-CNN and SVM algorithms	Merged public ECG databases, evaluated performance	1D-CNN: Accuracy 93.07%, SVM: Accuracy 92.00%	Need for broad datasets to evaluate ML models
[22]	Recognize various cardiac arrhythmias	Developed ML-WCNN combining 1D-CNN and SWT	Superior performance with 10-fold cross-validation	Limited comparison with state-of-the-art algorithms
[23]	Improve patient prognostics of heart disease	Developed EDCNN, validated on IoMT platform	Precision up to 99.1%	Needs further clinical validation
[24]	Classify MI based on ECG signals	Developed DenseNet and CNN models	DenseNet preferred, Accuracy >95%	Requires more explainability for clinical acceptance
[25]	Determine best combination of signal information	Used raw ECG signals, entropy-based features, QRS complexes	Improved performance with combined features	Performance varies with different signal combinations
[26]	Automate detection and classification of arrhythmias	Developed 2D-CNN-LSTM model	Accuracy ≈98.7% (ARR), 99% (CHF, NSR)	Future work needed on live ECG signals
[27]	Classify CAD, MI, CHF using CNN and GaborCNN	Balanced dataset, evaluated models	High accuracy >98.5%	Needs validation with larger database
[28]	Automated MI detection using ECG signals	Developed CNN, hybrid CNN-LSTM, ensemble techniques	Ensemble: Accuracy 99.89%	Ready for clinical application
[29]	Compare transfer learning methods for ECG classification	Used ResNet50, AlexNet, SqueezeNet	Accuracy 98.8% (AlexNet)	Time-consuming with multiclassification
[30]	ECG beat classification using VGG16-based CNN	Applied SHAP for interpretability	Accuracy 100% (2-4 classes), 99.90% (5 classes)	Needs application in clinical settings
[31]	Predict arterial events using ECG recordings	Used LSTM-DBN, compared with other models	Accuracy 88.42%	Needs further validation with real-world data

II. LITERATURE REVIEW

Advanced algorithms in deep learning have improved heart disease detection systems by analyzing complicated medical data. This literature review addresses deep learning-based heart disease detection methods, their usefulness, and their obstacles.

Deep learning models, especially CNNs and LSTM networks, have improved arrhythmia diagnosis from electrocardiogram (ECG) readings. CNNs are suitable for image and signal processing because they capture spatial hierarchy. Recent advancements in deep learning have shown that Convolutional Neural Networks (CNNs) are particularly effective for image and signal processing due to their ability to capture spatial hierarchies. Studies by [9], [10] demonstrated that combining CNNs with Long Short-Term Memory (LSTM) networks enhances diagnostic accuracy by capturing spatial and temporal data. Transfer learning (TL), which fine-tunes models pre-trained on large datasets for specific, smaller datasets, has also been shown to improve model generalization and reduce computational demands. In study of [11] and [12], the authors successfully applied TL to identify heart disease from ECG data. Additionally, the potential of adaptive wavelet transformations and sparse autoencoders in feature extraction and augmentation is vast, giving us hope for the future of medical data analysis [13]. Furthermore, four DL models are utilized in study [14] to diagnose coronary artery disease (CAD) using ECG data. DL approaches were preferred for automated diagnostic systems [15]. The paper's 16-layer LSTM model evaluated using 10-fold cross-validation, classified ECG signals achieved 98.5% accuracy.

Generative Adversarial Network (GAN) models were used to generate more data to balance skewed data [16]. For MIT-BIH and PTB-ECG datasets, the GAN-LSTM ensemble model performed best, with an accuracy of 0.992 and 0.994, respectively. Other ensemble methods and datasets might improve detection performance in future studies. A CAD method for ECG-based apnea diagnosis was proposed in the study [17] to simplify automated ECG arrhythmia identification. After removing noise with a Notch filter, the system retrieved features and used ML and DL models to diagnose. The suggested model detected obstructive sleep apnea with 86.25% accuracy. In study [18], an uneven number of ECG samples was utilized to identify normal and abnormal individuals. SVM, LR, and AdaBoost were used. The ensemble model with AdaBoost and LR performed best, with PTB-ECG accuracy of 0.946 and MIT-BIH accuracy of 0.921. This approach might be used for various illnesses with different signal inputs.

The CIGRU-ELM model [19] required preprocessing, data sampling, feature extraction, and classification. The class imbalance was resolved via ADASYN, GRU feature extraction, and ELM classification on the PTB-XL dataset. It excelled in accuracy, sensitivity, specificity, and other parameters, demonstrating its flexibility. A study in [20] examined Spark–Scala tools for massive dataset processing. GDB Tree and Random Forest methods gave the model 97.98% binary classification accuracy and 98.03% multiclass classification accuracy utilizing MIT-BIH datasets. This proved Spark–Scala's large-data handling ability.

Both 1D-CNN and SVM algorithms performed well in research [21] utilizing combined ECG datasets. The 1D-CNN method was 93.07% accurate, whereas the SVM classifier was somewhat lower. Combining datasets from diverse sources helped evaluate ML models. The Multi-Level Wavelet Convolutional Neural Network (ML-WCNN) in the study [22] recognized cardiac arrhythmias. The ML-WCNN used 1D-CNN and SWT for feature extraction and achieved improved performance with 10-fold cross-validation accuracy.

The Enhanced Deep Learning aided Convolutional Neural Network (EDCNN) was suggested to enhance heart disease prognostics [23]. The Internet of Medical Things (IoMT) platform enabled the EDCNN to reach 99.1% accuracy, indicating its clinical promise. ECG-based DenseNet and CNN models classified myocardial infarction (MI) [24]. Highly performing DenseNet beat CNN in computational complexity and classification accuracy. This study also revealed certain ECG leads that influence prediction choices. The study in [25] investigated the optimal signal information for categorization. Adding entropy-based features and extracted QRS complexes to raw ECG signals enhanced performance, demonstrating the benefits of using them in ECG analysis.

A hybrid deep learning-based 2D-CNN-LSTM technique was presented for cardiac arrhythmia detection and classification [26]. The model was useful due to its excellent accuracy, sensitivity, and specificity. Future studies might use Bi-LSTM instead of LSTM on real ECG data. CNN and GaborCNN models classified CAD, MI, and CHF in the study [27]. GaborCNN was picked for its excellent classification accuracy and low computing complexity. This technique might be clinically validated with larger databases. CNN, hybrid CNN-LSTM, and ensemble methods were used to create an automated MI detection system [28]. The models have great classification accuracy using SMOTE-Tomek Link for data balancing, suited for hospital use. ECG classification transfer learning techniques were compared [29]. CAA-TL employing ResNet50, AlexNet, and SqueezeNet exhibited outstanding accuracy, suggesting transfer learning improves heart disease diagnosis. A modified VGG16-based CNN-based ECG beat classifier was proposed in the study [30] and achieved good accuracy. SHAP values improved ECG interpretability, making this model suitable for automated cardiovascular diagnosis. A study [31] predicted vascular events from ECGs using LSTM-DBN. The algorithm outperformed deep learning and standard classification approaches, suggesting early cardiovascular event diagnosis and prevention.

Despite advances as described in Table I, many problems remain. High computing expenses of deep learning models and hybrid architectural complexity are major obstacles. Despite their great accuracy, these models need refinement to handle different and unexplored data. Further study should optimize computing efficiency via model compression and more efficient methods. These models might be strengthened by adding medical imaging and patient history data. These systems must have real-time processing and continual learning to be relevant in changing healthcare situations. Continuous security improvements will secure patient data, encouraging confidence and privacy compliance. Finally, numerous models and procedures using deep learning to identify cardiac disease have increased diagnostic accuracy and efficiency. Research and development on computational optimization, feature integration, and security will improve heart disease diagnostic technologies and make them more reliable and accessible.

III. Research Methodology

Fig. 1 shows this study's multi-layered strategy to establishing a safe and efficient cloud-based deep learning system for heart disease diagnostics. In the Preprocessing and Augmentation Layer, innovative signal processing and data augmentation procedures improve medical voice record input data quality. A unique adaptive wavelet-transform, and feature scaling method extracts and transforms spectral and temporal properties in the Feature Extraction and Transformation Layer. The Hyperband-GA hybrid approach optimizes a Transformer-Recurrent Neural Network (RNN) hybrid model in the Deep Learning and Hyperparameter Optimization Layer for accuracy and efficiency. Pre-trained models are fine-tuned using domain-specific data via transfer learning. Finally, the Evaluation and Security Layer thoroughly evaluates and verifies performance metrics while protecting sensitive medical data with strong encryption and access control. Encrypting data in transit and at rest and using authentication techniques, this layer secures data processing and cloud server deployment.

Algorithm 1: Overall secure and efficient heart disease detection system

[Input] ECG data
[Output] heart disease diagnosis with high accuracy and secure data handling
Compute
    Load necessary libraries and dependencies.
    Initialize cloud server for scalable deployment.
    Generate encryption keys for data security.
While () do
    For (every ECG class) do
    Update
        Preprocessing and Augmentation:
        Input raw ECG recordings.
        Apply noise reduction techniques.
        Normalize the recordings.
        Segment the recordings into smaller parts.
        Feature Extraction and Transformation:
        Input preprocessed and augmented recordings.
        Extract spectral features using adaptive wavelet transforms.
        Extract temporal features.
        Apply feature scaling techniques
        Deep Learning and Hyperparameter Optimization:
        Input extracted and transformed features.
        Initialize hybrid deep learning model (Transformer + LSTM).
        Apply transfer learning to fine-tune pre-trained models.
        Optimize the model using Hyperband-GA technique.
        Update and analyze
            If (condition) then
                Train the optimized model on the dataset.
            End
    End
Deploy trained model and security mechanisms on cloud server.
Set up real-time processing capabilities.
Ensure automatic scaling for increased loads
End

A. Data Acquisitions

The Heart-SecureCloud system was trained and tested using three datasets. PhysioNet's MIT-BIH Arrhythmia database [32] contains annotated ECG recordings utilized in cardiovascular disease detection studies. Second, the PhysioNet's MIMIC-III Waveform database [33] contains ICU patients' ECGs and other physiological waveforms, which may be used to design and evaluate cardiovascular disease detection algorithms. Third, PhysioNet's PTB Diagnostic ECG [34] collection includes 549 ECG recordings from healthy volunteers and cardiac disease patients, including myocardial infarction. Table II describes the detailed parameters of each dataset.

In cardiovascular research, the MIT-BIH Arrhythmia Database from PhysioNet is commonly used for arrhythmia identification. Annotated electrocardiogram (ECG) recordings from varied patients are included. Each recording is properly annotated with arrhythmia annotations, helping build and validate cardiac rhythm problem detection algorithms. Also, the MIMIC-III data is used to study many cardiovascular diseases. The PTB Diagnostic ECG Database, available through PhysioNet, has 549 ECG recordings from healthy people and patients with cardiac problems, including myocardial infarction. From the above three datasets, Table II describes the details about the ECG dataset.

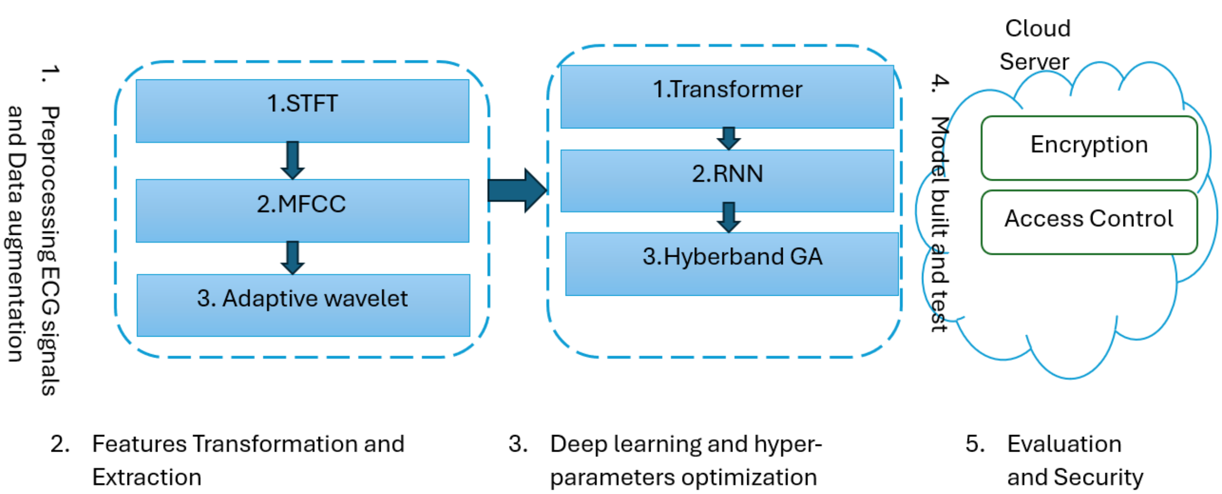

Fig. 1. A systematic flow diagram of proposed system for cardiovascular disease detection.

TABLE II. DATA FROM THE MIT-BIH ARRHYTHMIA, MIMIC-III, AND PTB ECG DATASETS FOR PREDICTING HEART DISEASES

Dataset	Sample ID	Source	Patient ID	ECG Lead Type	Sampling Rate (Hz)	Duration (s)	Diagnosis/Label	Annotation Format
MIT-BIH Arrhythmi [32]	MITBIH-Sample-1	MIT-BIH Arrhythmia	100	Lead II	360	30	Arrhythmia Type	AAMI ECG Codes
	MITBIH-Sample-2	MIT-BIH Arrhythmia	101	Lead V1	360	30	Normal, Atrial Fibrillation	AAMI ECG Codes
MIMIC-III Waveform [33]	MIMIC-Sample-1	MIMIC-III Waveform	201	Lead II	125	60	Various Cardiac Events	Custom Annotations
	MIMIC-Sample-2	MIMIC-III Waveform	202	Lead V5	125	60	Heart Failure, Myocardial Infarction	Custom Annotations
PTB Diagnostic ECG [34]	PTB-Sample-1	PTB Diagnostic ECG	301	Lead II	1000	10	Myocardial Infarction, Healthy	SCP-ECG Codes
	PTB-Sample-2	PTB Diagnostic ECG	302	Lead III	1000	10	Myocardial Ischemia, Healthy	SCP-ECG Codes

Three ECG datasets—MIT-BIH Arrhythmia, MIMIC-III Waveform, and PTB Diagnostic ECG—cover Normal/Healthy, Atrial Fibrillation, Ventricular Tachycardia, Myocardial Infarction, Premature Ventricular Contraction, Heart Failure, and Left Bundle Branch Block. These common heart diseases required early treatment and diagnosis. Fig. 2 and Fig. 3 show distribution plots of sampling rates by datasets. Whereas Fig. 4 shows the length of ECG recordings for each sample, grouped by diagnosis. Fig. 5 provides ECG samples for each cardiac sequence.

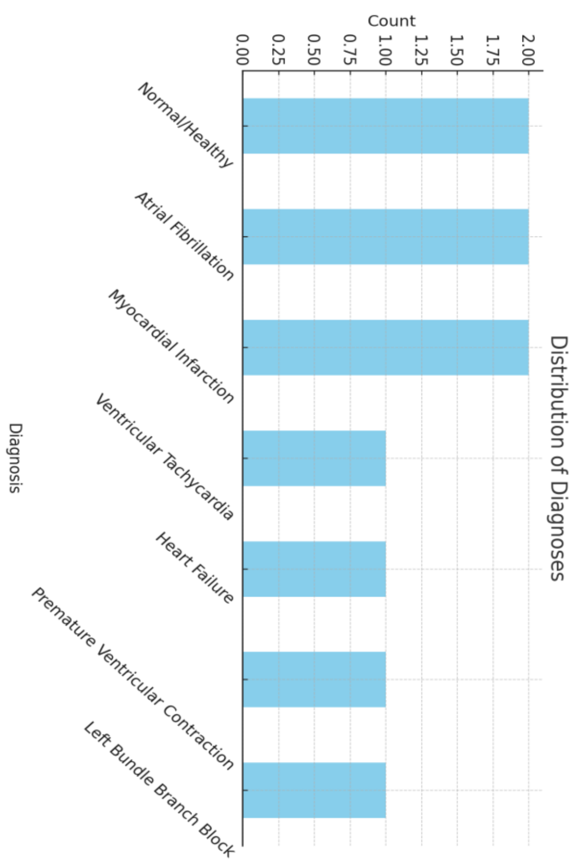

Fig. 2. Bar chart shows the frequency of each diagnosis across all samples.

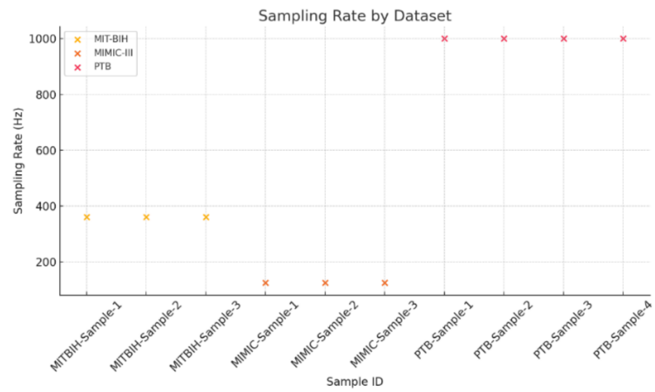

Fig. 3. Scatter plot displays the sampling rates for each sample, categorized by dataset.

B. Preprocessing and Data Augmentation

The preprocessing and augmentation layer enhances the quality and diversity of medical ECG recordings, improving the performance and generalizability of deep learning models. Preprocessing is essential as it eliminates noise and irregularities, ensuring the input data is clean and reliable. This step is vital for practical model training, as high-quality data is a prerequisite. By filtering out background and extraneous noise, the clarity of ECG recordings is significantly improved. Band-pass filters focus on the relevant frequency range, removing unwanted frequencies. Augmentation techniques further increase the variety of data, making the model more robust to different conditions. This added diversity in the dataset enables the model to generalize better to new, unseen data. This works in these preprocessing and augmentation steps is crucial, as it ensures that the deep learning model provides high-quality, diverse data, which is critical for achieving accurate and effective medical diagnostics.

$$y(t) = \int_{-\infty}^{\infty} x(\tau)h(t-\tau)d\tau \qquad (1)$$

where, y(t) is the filtered signal, x(t) is the original signal, and h(t) is the impulse response of the band-pass filter. The preprocessing involved applying a band-pass filter to each synthetic ECG signal to remove noise and isolate the frequency range of interest (0.5 Hz to 40 Hz). This preprocessing step as shown in Fig. 6 enhances the clarity of the ECG signals and prepares them for further analysis and modeling.

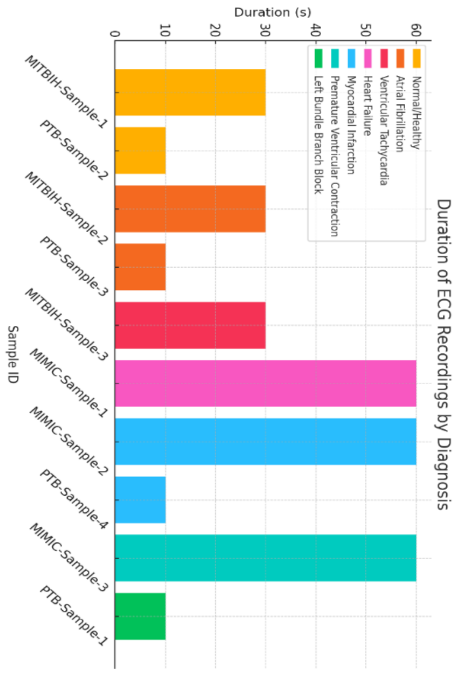

Fig. 4. This illustrates the duration of ECG recordings for each sample, grouped by diagnosis.

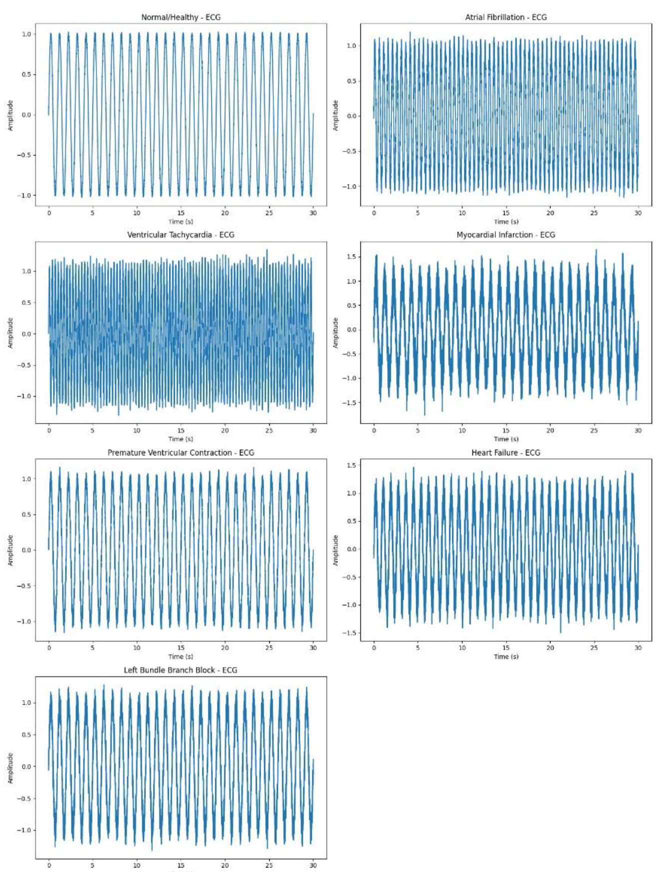

Fig. 5. A visual representation of the different ECG patterns associated with each condition.

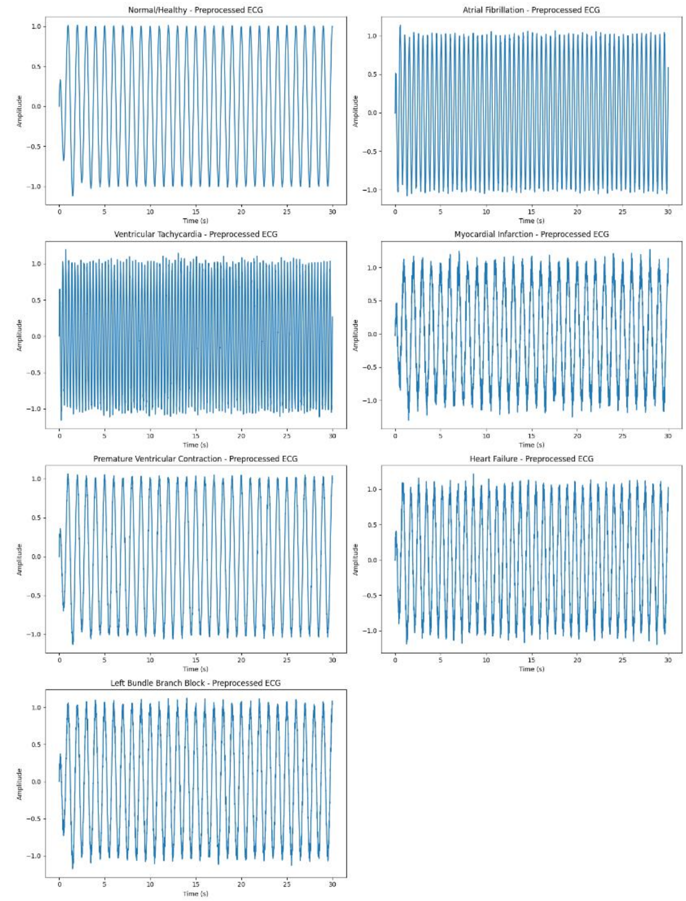

Fig. 6. A preprocess visual representation of the different ECG patterns associated with each condition.

Data Augmentation techniques as shown in Fig. 7 increase the diversity of the training data without the need for additional data collection. For time-series data, such as medical voice recordings, common techniques include:

Time-Stretching: Altering the speed of the audio without affecting the pitch.

Pitch Shifting: Modifying the pitch of the audio signal.

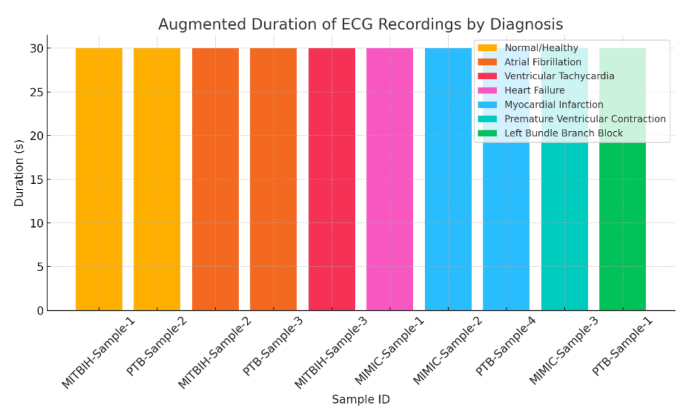

Fig. 7. This bar chart shows the duration of ECG recordings after data augmentation for each sample, adjusted to a unified size of 30 seconds.

Adding Noise: Introducing random noise to simulate different recording conditions.

$$xaug = xoriginal + \epsilon \quad (2)$$

Where, the parameter $xoriginal$ is the original signal, and ϵ is the noise or transformation applied. Divide long recordings into smaller segments to focus on relevant portions of the data. Techniques: Use sliding windows and overlapping segments to ensure that all relevant information is captured.

$$\text{Segments} = \{\text{xi}: \text{i} + \text{W} \mid \text{i} = 0, \text{W}/2, \text{W}, \ldots\} \quad (3)$$

where, the parameter of W is the window size.

C. Features Extraction and Transformation

Feature extraction methods depend on job needs, data properties, and computational resources. Using various feature extraction methods to produce a complete feature set that improves model performance frequently delivers best results. Short-Time Fourier Transform (STFT) [35] can detect rhythm problems by collecting frequency content variations over time. Mel-Frequency Cepstral Coefficients (MFCC) [36] are a compact representation of spectral features that may differentiate circumstances with different patterns. Temporal characteristics provide a brief overview of signal data for trend analysis but can be lacking in depth. Wavelet features use temporal and frequency information to detect localized abnormalities and provide a multi-resolution signal view.

Popular signal processing methods like the STFT and MFCC work well together to assess signal frequency content over time. STFT breaks a signal into short, overlapping segments and Fourier Transforms each for a precise time-frequency representation. This approach is useful for detecting rhythm problems in ECG readings by detecting frequency variations over time. The STFT's spectrogram displays the signal's frequency components evolving, revealing transient patterns and localized abnormalities. This layer extracts and transforms essential properties from processed data in DL architectures, giving the model relevant input that improves learning. Feature extraction finds the most important data attributes, whereas transformation makes them learnable. Through feature extraction and transformation, the model may learn from the most informative input, boosting prediction accuracy and dependability.

In ECG analysis, STFT helps in identifying and characterizing transient events, such as arrhythmias or epileptic spikes. Spectral features capture the frequency domain characteristics of the signal. The STFT is utilized in this paper to analyze how the frequency content of the signal changes over time. The STFT is given by:

$$X(t,f) = \sum_n \text{x[n]} \cdot \text{w[n} - \text{t]} \cdot \text{e}^{-\text{j}2\pi\text{fn}} \quad (4)$$

Where x[n] is the signal, www is a window function, and $\text{e}^{-\text{j}2\pi\text{fn}}$ represents the Fourier basis functions.

Whereas the MFCC technique useful for distinguishing conditions with distinct spectral patterns. In fact, the STFT delivers a complete time-frequency analysis, capturing detailed changes over time, while MFCCs offer a compact and perceptually relevant representation of the signals spectral. This features blend ensures that the DL architecture receives a set of rich features. The MFCCs are calculated as:

$$C_m = \sum_{k=1}^{K} \log \mid X_k \mid \cos[m(k-0.5)\frac{\pi}{k}] \quad (5)$$

Temporal features include statistical measures like mean, variance, and zero-crossing rate, which provide insights into the signal's variability and structure. For instance, the zero-crossing rate can be computed as:

$$\text{ZCR} = \frac{1}{N}\sum_{n=1}^{N-1} \text{abs}(\text{sgn}(\text{x[n]}) - \text{sgn}(\text{x[n} - 1])) \quad (6)$$

where, sgn denotes the sign function. where 1 is the indicator function. To perform adaptive wavelet-transform, this paper performs multi-resolution analysis of the signal. Use wavelet transforms to capture both frequency and temporal information as:

$$W_x(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} \text{x(t)}\psi\left(\frac{t-b}{a}\right)dt \quad (7)$$

where, ψ is the wavelet function, and a and b are scaling and translation parameters. Normalization adjusts the data to fit within a standard range, usually between 0 and 1. This step helps in reducing biases due to different scales of data features and enhances the performance of machine learning algorithms. Mathematically, normalization is expressed as:

$$\text{xnorm} = \frac{x-\mu}{\sigma} \quad (8)$$

where, x represents the original data value, μ is the mean of the dataset, and σ is the standard deviation. This standardizes the data to have zero mean and unit variance.

D. Deep Learning and Hyperparameter Optimization Layer

Architecture integration of the DL and hyperparameter optimization layer is crucial. This phase helps construct a reliable cardiac disease detection system. Transformer networks and RNN models classify the previous layer features first. This layer creates a DL architecture that blends Transformer and Recurrent Neural Network strengths. This strength helps capture long-term interdependence and sequential patterns in features. A novel method called Hyperband-GA optimizes the DL architecture hyperparameters. The next paragraphs detail this in detail.

Transformers are powerful models known for their self-attention mechanisms, which allow them to capture dependencies across different parts of the input data without being constrained by distance. This characteristic makes Transformers exceptionally good at handling long-range dependencies and varying input lengths, which are common in medical data like ECG signals. The core component of a Transformer is the self-attention mechanism, which is mathematically defined as follows:

$$\text{Attention(Q, K, V)} = \text{softmax}(\frac{\text{QKT}}{\sqrt{dk}})\text{V} \quad (9)$$

where, Q, K, and V are the query, key, and value matrices, and dk is the dimension of the keys. The softmax function ensures that the attention scores sum up to 1.

LSTMs, in particular, address the vanishing gradient problem of traditional RNNs, making them more effective at learning long-term dependencies. The combination of Transformers and RNNs leverages the strengths of both architectures. Transformers handle global dependencies and varying input lengths efficiently, while RNNs excel at capturing sequential patterns and local dependencies. Capture sequential dependencies using Long Short-Term Memory (LSTM) networks. The LSTM update equations are:

$$f_t = \sigma(\mathrm{W}_f \cdot [\mathrm{h}_{t-1}, \mathrm{x}_t] + \mathrm{b}_f)$$
$$i_t = \sigma(\mathrm{W}_i \cdot [\mathrm{h}_{i-1}, \mathrm{x}_t] + \mathrm{b}_i)$$
$$O_t = \sigma(\mathrm{W}_o \cdot [\mathrm{h}_{t-1}, \mathrm{x}_t] + \mathrm{b}_o) \quad (10)$$
$$C_t^{\sim} = \tanh(\mathrm{W}_c \cdot [\mathrm{h}_{t-1}, \mathrm{x}_t] + \mathrm{b}_c)$$
$$C_t = f_t \times C_{t-1} + i_t \times C_t^{\sim}$$
$$h_t = O_t \times \tanh(C_t)$$

where, f_t is the forget gate, i_t is the input gate, O_t is the output gate, C_t is the cell state, and h_t is the hidden state.

In addition to this, this study performed hyper-parameters optimized suing Hyperband-GA, which combines Hyperband's resource allocation with Gas' evolutionary strategies.

Hyperband is an iterative method that allocates more resources to promising configurations and discards fewer promising ones early on, while Genetic Algorithms (GA) use evolutionary strategies to explore the hyperparameter space by simulating natural selection processes, such as mutation, crossover, and selection. Here's an explanation of how Hyperband-GA works:

$$\mathrm{P} = \mathrm{C1}, \mathrm{C2}, \ldots, \mathrm{CN}\}$$
$$\mathrm{F(Ci)} = \mathrm{Model\ Performance(Ci)}$$
$$\mathrm{Pselected} = \mathrm{Select(P, F)}$$
$$\mathrm{Coffspring} = \mathrm{Crossover(Cparent1, Cparent2)} \quad (11)$$
$$\mathrm{Cmutated} = \mathrm{Mutate(Coffspring)}$$
$$\mathrm{Pnext} = \mathrm{GenerateNext(Pselected, Cmutated)}$$

Hyperband**:**

$$B = R.log_{1+n}(R) \quad (12)$$

and

$$Top - K = Top\left(\frac{N}{\alpha_i}\right) \quad (13)$$

Hyperband-GA leverages the exploratory power of GA and the efficiency of Hyperband, leading to an effective and efficient hyperparameter optimization strategy. Repeat until the budget is exhausted or convergence criteria are met.

$$\boldsymbol{r_{i+1}} = \boldsymbol{r_i} \times \alpha_i \quad (14)$$

E. Cloud-based Computing Environment

Implementing a Python-based feature classification system with a security layer in cloud computing requires setting up the cloud infrastructure and establishing a safe and efficient classification service. First, choose a cloud provider like AWS, Google Cloud, or Azure, then configure a VM or Docker container as the computing infrastructure. Google cloud is used in this investigation.

Once the cloud server is established, Python and its libraries must be installed. Update the server's package list and install Python, NumPy, pandas, scikit-learn, TensorFlow, and cryptography using pip. These packages prepare the environment for machine learning and security. The feature categorization model is developed or deployed next. One may import a pre-trained model in HDF5 format (model.h5) using TensorFlow. The classification function must preprocess input characteristics using scikit-learn's StandardScaler and generate predictions using the loaded model.

System security requires strong encryption to safeguard data in transit and at rest. Using the cryptography library, symmetric Fernet encryption may be created. Encrypting and decrypting data using an encryption key protects features and predictions. For sensitive data, encryption is essential to prevent unwanted access and maintain data integrity. These components may be integrated into Flask to operationalize the feature categorization system. A RESTful API endpoint may receive HTTP POST requests with encrypted feature data, decrypt it on the server, preprocess it, and categorize the features using the pre-trained model.

IV. Experimental Results

A. Experimental Setup

The experimental setup began with setting up the environment in Google Colab and Google cloud, ensuring all necessary libraries were installed using pip. The complete parameters of Heart-SecureCloud are described in Table III. Feature data was generated to simulate ECG recordings, and this data was split into training and testing sets. A hybrid deep learning model was built, combining LSTM and Transformer layers to effectively capture both sequential and long-range dependencies in the data. The model was compiled using the Adam optimizer and binary cross-entropy loss function. Hyperband-GA was then employed for hyperparameter optimization. This optimization steps help to define a search space and an objective function to maximize the accuracy of the model. Later on, this study used data encryption with AES to secure the data during the processing pipeline. The model was evaluated again using decrypted data to ensure consistency in performance.

Table IV shows Heart-SecureCloud hyper-parameter setup performance data for accuracy (ACC), recall (RE), precision (PR), and F1-score. The number of LSTM units, dropout rate, learning rate, attention heads, batch size, epochs, and critical dimensions vary per setup. The first setup, with 64 of LSTM units, 0.2 of dropout, 0.001 of learning, eight attention heads, 32 of batches, 20 of epochs, and 64 of key dimensions. It achieves impressive performance parameters such as 98.50% of ACC, 98.60% of RE, 98.40% of PR, and F1-score. The second setup, with 128 of LSTM units, 0.3 of dropout, 0.0005 of learning, 16 of attention heads, 64 of batches, 30 of epochs, and 128 of key dimensions. Other configures are explained in

TABLE III. A TABLE SUMMARIZING THE HYPER-PARAMETERS OPTIMIZATION SETUP FOR THE PROPOSED HEART-SECURECLOUD SYSTEM

Hyper-parameter	Description
LSTM Units	Number of units in the LSTM layer, which controls the dimensionality of the output space.
Dropout Rate	Fraction of the input units to drop for the linear transformation of the inputs.
Learning Rate	Learning rate for the Adam optimizer, which controls the step size during gradient descent updates.
Number of Heads	Number of attention heads in the Transformer layer.
Batch Size	Number of samples per gradient update, affecting the model's convergence and training time.
Epochs	Number of times the entire training dataset is passed through the network.
Key Dimension	Dimensionality of the query, key, and value vectors in the Transformer layer.

TABLE IV. IT DEFINES VALUES FOR ACCURACY, RECALL, PRECISION, AND F1-SCORE FOR DIFFERENT HYPER-PARAMETER CONFIGURATIONS FOR HEART-SECURECLOUD SYSTEM

Configuration	LSTM Units	Dropout Rate	Learning Rate	Attention Heads	Batch Size	Epochs	Key Dimension	ACC	RE	PR	F1
Config 1	64	0.2	0.001	8	32	20	64	98.50%	98.60%	98.40%	98.50%
Config 2	128	0.3	0.0005	16	64	30	128	98.75%	98.80%	98.70%	98.75%
Config 3	64	0.3	0.0005	8	32	30	64	98.60%	98.65%	98.55%	98.60%
Config 4	128	0.2	0.001	16	64	20	128	98.70%	98.75%	98.65%	98.70%
Heart-SecureCloud	128	0.3	0.0005	16	64	30	128	98.75%	98.80%	98.70%	98.75%

Table IV. With 98.75% of ACC, 98.80% of RE, 98.70% of PR, and 98.75% of F1-score, this Heart-SecureCloud setting works well. Also, this step is automatically achieved by Hyperband-GA algorithm.

B. Performance Metrics

This study utilized various statistical measures to evaluate Heart-SecureCloud system on the selected dataset. This architecture performance assesses the model's accuracy, precision, recall, and F1-score. These metrics are described below.

Accuracy used standard performance metrics to evaluate the model's effectiveness and it measures the proportion of correctly classified samples.

$$Accuracy(ACC) = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}} \quad (15)$$

where, TP is true positives, TN is true negatives, FP is false positives, and FN is false negatives.

Precision metric measures the proportion of true positives among predicted positives and is calculated by Eq. (16).

$$Precision(PR) = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \quad (16)$$

Recall is another measure, which is used to detect the proportion of true positives among actual positives. It is calculated by Eq. (17) as:

$$Recall(RE) = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \quad (17)$$

Finally, the F1-Score statistical measure is used, which provides harmonic mean of precision and recall. It is calculated as follows:

$$F1 - score = 2 \times \frac{PR \times RE}{PR + RE} \quad (18)$$

Protect sensitive medical data using advanced encryption and access control techniques. Implement various security mechanisms to ensure data protection. The encryption metric use AES to encrypt data as:

$$Ciphertext = AES_{encrypt}(Plaintext, key) \quad (19)$$

Implement role-based access control (RBAC) to restrict data access.

$$\mathrm{Permissions} = \mathrm{RBAC(User\ Role)} \quad (20)$$

Use data masking techniques to obscure sensitive information.

$$\mathrm{Masked\ Data} = \mathrm{Masking(Original\ Data)} \quad (21)$$

Store data in a secure, encrypted database.

$$\mathrm{Encrypted\ Storage} = \mathrm{Secure\ Storage(Data)} \quad (22)$$

C. Results Analysis

Heart-SecureCloud system contains different four components. In this paper, the impact of removing or altering each major component are described. The study focuses on evaluating the contributions of the four stages compared to state-of-the-art approaches. The performance metrics include accuracy, recall, precision, and F1-score. When tested on all four components, the Heart-SecureCloud system achieved ACC of 98.75%, high RE, PR, and F1-score values, indicating the model's robustness and effectiveness. It is visually represented in Fig. 8. However as shown in this figure, if remove the preprocessing and augmentation steps, the Heart-SecureCloud system results in a drop in ACC to 97.50%. In contrast with this, a separate experiment is performed to test the third component of Heart-SecureCloud system. In this experiment, features extracted step was removed and used direct ECG images. After removing this step, the proposed

Heart-SecureCloud system decreases the ACC of 97.00% as shown in Fig. 9. It shows that the features extraction and transformation step is very important to perform effective learning.

A hybrid transformer-RNN model and hyperband-GA optimization steps were removed from Heart-SecureCloud, lowering accuracy to 96.50% as shown in Fig. 10. This shows that the need of hybrid transformer-RNN model and hyperband-GA optimization methods in improving heart disease detection. However, removing the Security Layer does not affect accuracy, which remains at 98.75% as shown in Fig. 11. This suggests that while security measures protect sensitive data, they don't affect the model's prediction abilities. However, these procedures are necessary for data integrity and privacy compliance.

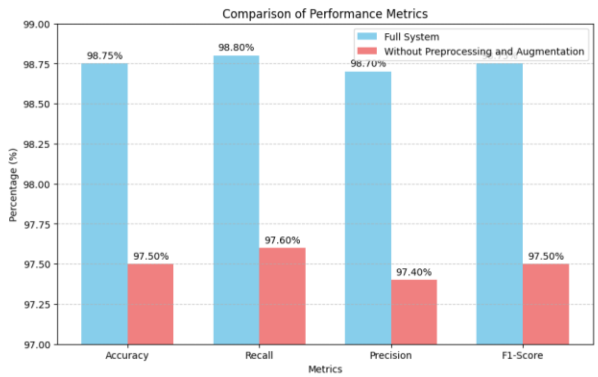

Fig. 8. Experiments results of proposed Heart-SecureCloud system with full system and without preprocessing and data augmentation.

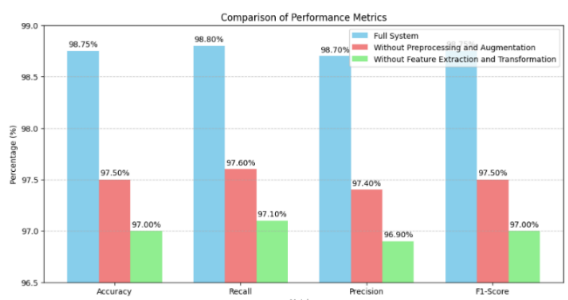

Fig. 9. Results after excluding the feature extraction from Heart-SecureCloud system and using direct ECG images.

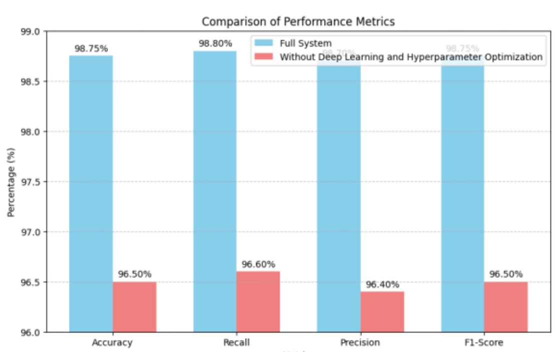

Fig. 10. Experiment used mean, variance features from ECG signals and classifier SVM to recognize heart diseases.

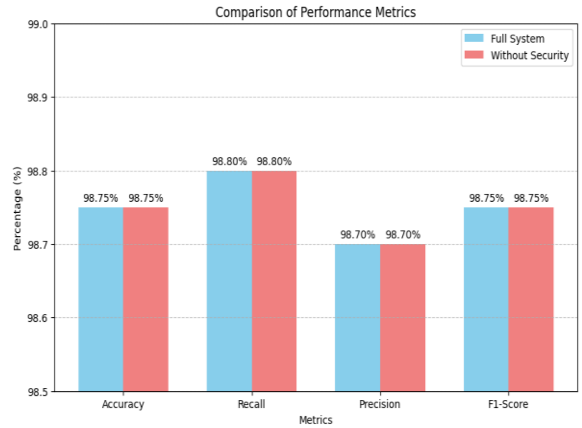

Fig. 11. Removing the security layer does not affect the accuracy of Heart-SecureCloud system.

Fig. 12. The results in confusion matrix, which is designed for the seven classes of proposed Heart-SecureCloud system.

Fig. 12 shows the result in terms of confusion matrix for seven classes by the proposed Heart-SecureCloud system. Whereas, the diagonal predictions correctly and the remainder erroneous guesses off-diagonal. Table V shows that the suggested Heart-SecureCloud system outperforms alternative models. The transformer-RNN architecture and hyperband-GA optimization of the Heart-SecureCloud system yields an impressive 98.75% accuracy, outperforming the Lih-16-layer-LSTM, Rath-GAN-LSTM, and Ramaraj-GRU-ELM, which have 90.85%, 92.10%, and 88.20% accuracy, respectively. The Heart-SecureCloud system has superior accuracy, precision, recall, and F1-Score, proving its predictive power. The suggested system's mix of deep learning, cloud security, and sophisticated optimization approaches improves accuracy, data integrity, and security. Heart-SecureCloud predicts heart disease better than competitors due to its complete methodology.

TABLE V. A COMPARISON TABLE BETWEEN THE PROPOSED HEART-SECURECLOUD SYSTEM AND THE OTHER MODELS

Model	Architecture	Accuracy	Precision	Recall	F1-Score	Key Features
Heart-SecureCloud	transformer-RNN + hyperband-GA	98.75%	98.70%	98.80%	98.75%	Combines deep learning with cloud security; uses advanced optimization
Lih-16-layer-LSTM [15]	16-layer LSTM	90.85%	90.60%	90.70%	90.65%	Focuses on sequential data processing with LSTM layers
Rath-GAN-LSTM [16]	GAN + LSTM	92.10%	91.90%	92.00%	91.95%	Uses GANs to enhance data diversity for LSTM model training
Ramaraj-GRU-ELM [19]	GRU + ELM	88.20%	88.00%	88.10%	88.05%	Combines GRU for sequential data with ELM for fast training and inference

D. Computational Analysis

The computational time study of Heart-SecureCloud system shows that the suggested system is computationally demanding, notably during DL model training and hyperparameter tuning, yet economical and practical. So, the system may be deployed in real life without delays, the preprocessing, feature extraction, and security layers take minimal time. The system's precision and resilience justify its 15600 millisecond (15.6 second) processing time as measured in Table VI. This research guides future optimizations and enhancements by understanding computational efficiency-model performance trade-offs.

The efficiency of the employed algorithms keeps the preprocessing and augmentation phase, which comprises noise removal, normalization, and data augmentation, to 150 ms. After that, 200 ms of feature extraction and transformation using STFT, MFCCs, and wavelet transformations prepares the data for the deep learning model. Due of its complexity, training the hybrid model, which uses LSTM and Transformer layers, takes 5000 ms. Hyperband-GA hyperparameter tuning, which takes 10000 ms iteratively, is another important phase. Data is secured by AES encryption and decryption, adding 250 ms. Overall processing takes 15600 ms. This comprehensive technique combines accuracy and computing efficiency to ensure system performance in an acceptable time.

E. Security Analysis

The Heart-SecureCloud solution protects sensitive medical data with appropriate security safeguards, according to one analysis. Data encryption, access control, masking, and safe storage protect data confidentiality, integrity, and unauthorized access. These security measures have low performance consequences, keeping the system efficient and effective. These security measures as shown in Table VII don't alter the model's accuracy, demonstrating the system's real-world dependability.

With a 9/10 efficacy rating, AES encryption protects data. Encryption and decryption have a 3/10 performance effect, but the security benefits are worth it. Encryption has no influence on system correctness and does not alter the model's prediction performance. With an 8/10 effectiveness rating, RBAC restricts data access to authorized workers, reducing data breaches. Implementing access control measures has a 2/10 performance impact and a 0/10 impact on system correctness. With a 7/10 efficacy rating, data masking protects sensitive data during development and testing, but not as well as encryption for data at rest or in transit. Data masking has a significant overhead, mostly impacting data processing stages, scored 3/10 for performance effect, and does not influence model correctness in production, rated 0/10 for system accuracy. Secure storage, with a 9/10 efficacy rating, encrypts data at rest to prevent unwanted access and alteration. Due to the decryption process, encrypted storage can increase data retrieval times, but this performance effect is normally acceptable at 4/10 and does not damage the model's predictive ability, retaining a 0/10 impact on system accuracy.

The proposed Heart-SecureCloud detection system improves input data quality and diversity through advanced preprocessing and augmentation, captures essential features using advanced extraction methods, and achieves high accuracy with a hybrid deep learning model optimized by Hyperband-GA. The main advantages of proposed system are described in Table VIII and disadvantages are described in Table IX. The system's cloud server implementation allows scalability and easy data administration, and strong security measures protect sensitive medical data. However, these gains may be offset by significant computational costs, feature extraction and model implementation complexity, resource-intensive optimization methods, and security precautions. Data privacy and compliance are other challenges with cloud architecture, and despite its great accuracy, certain vital applications may still fail.

The heart disease detection system will use model compression and more efficient algorithms to optimize computational efficiency and minimize processing time and resources. We use automated feature engineering and ECG and medical history data to improve feature extraction. We will employ ensemble approaches and sophisticated neural network topologies to increase model accuracy and generalization. Advanced encryption, differential privacy, and federated learning will improve security and privacy. Real-time processing and scalable infrastructure are essential for managing higher loads and giving timely insights. Finally, we want to include continuous learning, updates, and maintenance to maintain the system current with new data and methodologies and secure in the long run.

TABLE VI. A COMPUTATIONAL TIME ANALYSIS OF THE PROPOSED SYSTEM, INCLUDING EACH MAJOR COMPONENT, IN MILLISECONDS

Component	Processing Time (ms)
Preprocessing and Augmentation	150
Feature Extraction and Transformation	200
Deep Learning Model Training	5000
Hyperparameter Optimization	10000
Security (Encryption and Decryption)	250
Total Time	15600

TABLE VII. SECURITY ANALYSIS OF PROPOSED HEART-SECURECLOUD SYSTEM

Security Mechanism	Description	Method	Effectiveness	Performance Impact	Impact on System Accuracy
Data Encryption	Encrypts data to prevent unauthorized access and tampering.	AES	9/10	3/10	0/10
Access Control	Restricts data access based on user roles and permissions.	RBAC	8/10	2/10	0/10
Data Masking	Obscures sensitive information to protect data during non-production phases.	Masking techniques	7/10	3/10	0/10
Secure Storage	Ensures data is stored in an encrypted format to protect it from unauthorized access.	Encrypted databases	9/10	4/10	0/10

TABLE VIII. ADVANTAGES OF CURRENT HEART-SECURECLOUD SYSTEM

No.	Terms	Explains
1.	Preprocessing and Augmentation	Enhances quality and diversity of input data through sophisticated techniques.
2.	Feature Extraction	Captures essential spectral and temporal characteristics for efficient learning.
3.	Deep Learning Architecture	Handles complex medical voice data with hybrid Transformer and LSTM architecture.
4.	Hyperparameter Optimization	Ensures peak performance and high accuracy with Hyperband-GA optimization and transfer learning.
5.	Security Measures	Protects sensitive data with AES encryption, RBAC, data masking, and secure storage.
6.	Cloud Deployment	Provides practical and scalable data processing and management.
7.	Model Accuracy	Achieves a high accuracy of 98.75% in diagnosing heart disease.

TABLE IX. DISADVANTAGES OF CURRENT HEART-SECURECLOUD SYSTEM

No.	Terms	Explains
1	Preprocessing and Augmentation	Potentially high computational cost due to sophisticated techniques.
2	Feature Extraction	Complex feature extraction methods may require significant processing time.
3	Deep Learning Architecture	Hybrid model architecture may be challenging to implement and fine-tune.
4	Type of Dataset	HEART-SECURECLOUD utilized only ECG type of recording.
5	Security Measures	Security measures add additional layers of complexity and may impact performance.
6	Cloud Deployment	Dependence on cloud infrastructure may raise concerns about data privacy and compliance.
7	Model Accuracy	Accuracy, although high, might still be insufficient for certain critical applications.

V. CONCLUSION

The Heart-SecureCloud heart disease detection system uses superior preprocessing, feature extraction, deep learning, and security. Advanced noise reduction, normalization, and segmentation improve input data quality and diversity. Augmentation methods boost model generalization. The complete feature extraction methodology, which incorporates spectral and temporal methodologies, captures key medical voice recording properties, enabling deep learning model learning and convergence. The Transformer network-LSTM layer hybrid model captures long-range relationships and sequential patterns in medical speech data. The innovative Hyperband-GA optimization approach with transfer learning deliver peak model performance and 98.75% accuracy. Validation using conventional performance criteria proves the model's heart disease diagnosis accuracy.

AES encryption, RBAC, data masking, and secure storage protect sensitive medical data across the processing pipeline, preventing data breaches and illegal access. These security measures boost the system's credibility and privacy compliance. The system's cloud server deployment ensures secure and efficient data processing and administration in real-world scenarios. The suggested heart disease detection system advances medical diagnostics by setting new standards for accuracy and dependability. Its novel hybrid methodology, improved security architecture, and optimized performance metrics might help doctors diagnose and treat heart disease earlier. Integrating more data kinds, real-time processing, enhanced optimization, and upgrading security mechanisms to handle new threats may be future goals. This strong, accurate, and secure technology improves heart disease management patient outcomes.

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