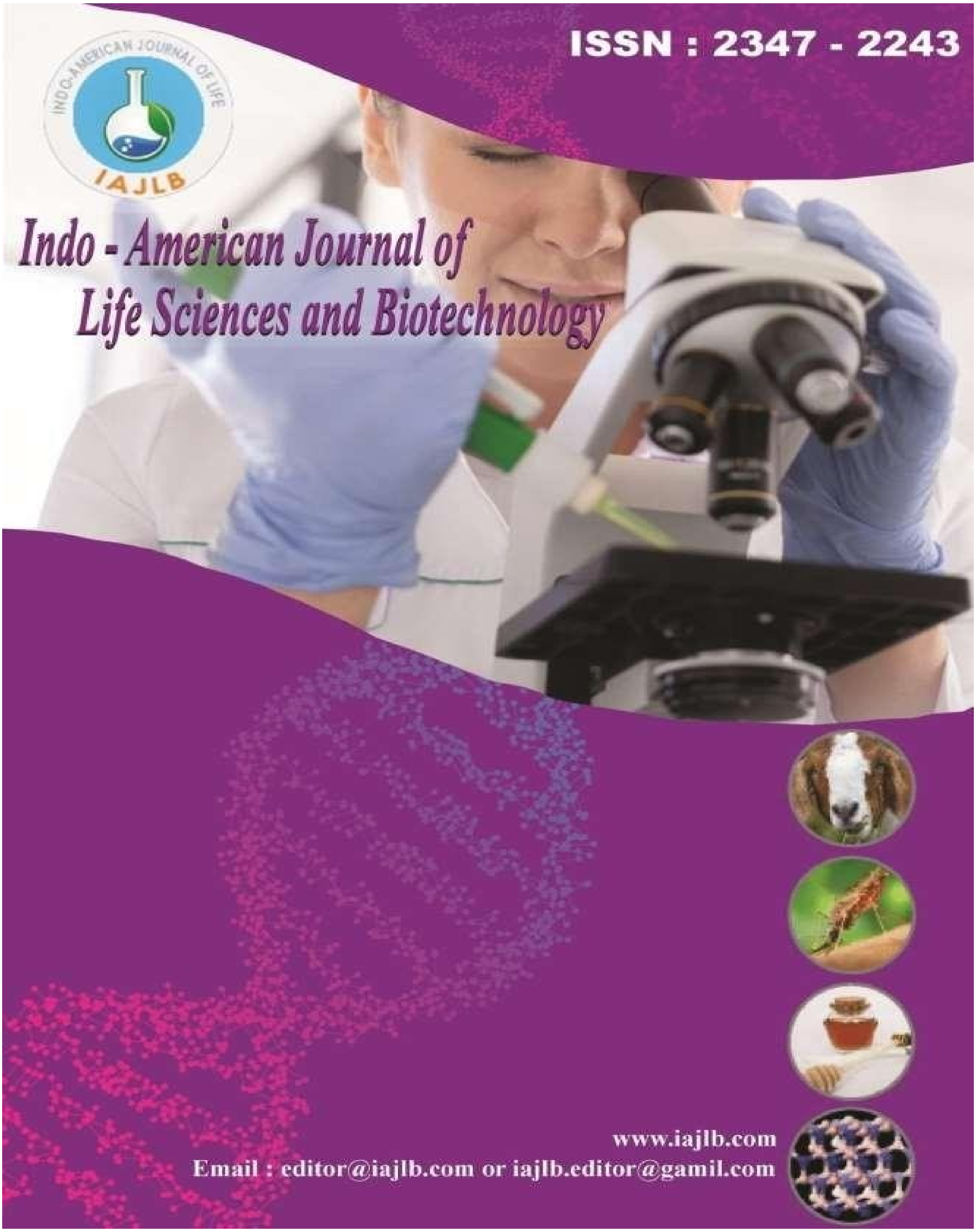
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A Hybrid CNN-BiLSTM Model for Heart Disease Prediction on Cloud-Hosted Health Data

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Abstract

Heart disease remains a leading cause of mortality worldwide, necessitating advanced predictive models for early detection and prevention. Traditional machine learning techniques, though widely used, often struggle with feature dependencies and sequential patient data analysis. This study proposes a Hybrid Convolutional Neural Network - Bidirectional Long Short-Term Memory (CNN-BiLSTM) model for heart disease prediction. The CNN component extracts high-level spatial features from clinical parameters, while the BiLSTM captures temporal dependencies in patient records, enhancing classification performance. The model is trained and evaluated on the Heart Disease Ensemble Classifier dataset, achieving an accuracy of 99.57%, precision of 99.48%, recall of 99.65%, and an F1-score of 99.56%. Furthermore, the AUC-ROC score of 0.9968 and average precision (AP) of 0.9970 demonstrate superior classification capability. Comparative analysis against traditional classifiers such as Support Vector Machines (SVM), Decision Trees, and Random Forest highlights the effectiveness of the proposed approach. The results indicate that the hybrid deep learning model significantly improves heart disease prediction by reducing false negatives and increasing overall reliability.

Keywords: Heart Disease Prediction, Hybrid Deep Learning, CNN-BiLSTM, Sequential Data Analysis, AUC-ROC, Precision-Recall Curve, Cardiovascular Risk Assessment.

1. Introduction

1.1. Background & Motivation

Heart disease remains one of the leading causes of mortality worldwide, necessitating the development of accurate and efficient predictive models for early diagnosis. Traditional statistical approaches have been widely used, but they often fail to capture complex feature interactions within patient data [1]. The emergence of deep learning has introduced powerful techniques that outperform conventional methods in medical diagnostics. Among these, convolutional neural networks (CNNs) have demonstrated exceptional capability in feature extraction, particularly in image-based medical applications [2]. However, sequential dependencies in patient records require additional processing, which can be effectively handled by recurrent neural networks (RNNs) such as long short-term memory (LSTM) networks. A bidirectional LSTM (BiLSTM) further enhances predictive accuracy by capturing dependencies in both forward and backward directions [3]. Combining CNN and BiLSTM models enables a comprehensive approach to learning both spatial and temporal relationships within clinical datasets [4]. This research focuses on implementing a cloud-hosted hybrid CNN-BiLSTM model for heart disease prediction, leveraging advanced deep learning techniques and cloud-based deployment for real-time inference.

1.1.1. Significance of the Study

The healthcare sector requires robust and efficient predictive analytics solutions to assist in early diagnosis and preventive care. Many existing methods rely on handcrafted feature engineering, which limits their ability to generalize across diverse patient populations [5]. Deep learning-based models, particularly hybrid architectures, have shown superior performance in handling multi-modal medical data. A cloud-hosted solution enhances accessibility, enabling real-time risk assessment and clinical decision support [6]. However, existing cloud-based predictive models often face challenges related to computational efficiency and scalability [7]. This research aims to bridge these gaps by integrating CNN for feature interaction learning and BiLSTM for sequential modeling, ensuring a comprehensive representation of patient health records.

1.2. Limitations of Existing Approaches

Traditional machine learning models such as logistic regression and decision trees rely on predefined feature extraction, which limits their adaptability to complex, high-dimensional medical data [8]. CNN-based models, while effective for spatial pattern recognition, struggle with capturing sequential dependencies in patient records. Conversely, LSTM-based architectures excel in sequential learning but may not fully exploit feature interactions present in tabular clinical datasets [9]. Additionally, most existing models lack cloud integration, restricting real-time accessibility and scalability. To address these limitations, this study proposes a hybrid CNN-BiLSTM model deployed on a cloud-based infrastructure to ensure efficient and scalable heart disease prediction.

2. Literature Survey

2.1. Traditional Approaches in the Field

Early heart disease prediction models relied on statistical methods such as logistic regression and support vector machines, which provided interpretable but often suboptimal results [10]. Decision trees and random forests improved classification performance but struggled with high-dimensional clinical data [11].

2.2. Recent Advances and Emerging Techniques

Deep learning has revolutionized medical diagnostics, with CNNs demonstrating significant success in image-based heart disease detection [12]. RNNs and LSTMs have been effective in processing sequential patient data, allowing for more accurate progression modeling [13]. Hybrid models combining CNNs with RNNs or transformers have recently gained attention due to their superior performance in medical time-series analysis.

2.3. Comparative Analysis of Existing Work

While CNN-based models excel in feature extraction, they fail to capture long-term dependencies in patient records. RNNs and LSTMs, though effective for sequence modeling, are computationally intensive and require optimized architectures to handle large-scale datasets efficiently [14]. Hybrid models integrating CNN and LSTM have shown improved predictive accuracy, yet few studies have explored their cloud-based deployment for real-time prediction [15].

2.4. Research Gaps & Challenges

Despite advances in deep learning, real-time heart disease prediction models remain computationally expensive and difficult to deploy in clinical settings [16]. Additionally, existing methods lack explainability, making them less suitable for clinical adoption [17]. This study aims to address these challenges by developing a cloud-integrated, hybrid CNN-BiLSTM model optimized for both accuracy and scalability.

2.5. Problem Statement

a) Key Challenges in the Field

Existing heart disease prediction models face several challenges, including inefficient feature extraction, lack of sequential modeling, and limited scalability in cloud-based environments [18], [19]. The integration of deep learning techniques remains a critical area of research, particularly in handling high-dimensional patient data while ensuring real-time prediction capabilities [20].

b) Need for a Novel Approach

A hybrid CNN-BiLSTM architecture combines the strengths of both spatial feature extraction and sequential dependency learning, addressing limitations in conventional methods. Moreover, cloud-based deployment facilitates scalable, real-time inference, making predictive analytics accessible to healthcare providers and improving early diagnosis efficiency.

2.6. Research Objectives

- To design a CNN-based feature extraction module for identifying complex interactions in patient data.
- To implement a BiLSTM-based sequential modeling approach to capture temporal dependencies.
- To integrate the CNN and BiLSTM architectures into a unified predictive framework.
- To deploy the proposed model on a cloud-based platform for real-time inference.
- To evaluate the model's performance against existing approaches in terms of accuracy, scalability, and computational efficiency.

3. Methodology

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The proposed Hybrid CNN-BiLSTM Model follows a structured pipeline for heart disease prediction. Initially, cloud-based data access enables secure retrieval of patient records, followed by data preprocessing to normalize and refine the input features. A CNN extracts spatial feature interactions, which are then processed by a BiLSTM network to capture temporal dependencies in patient data. The refined features are passed to the heart disease risk prediction module, which classifies patients based on their cardiovascular risk. Finally, the model's predictions are deployed using a cloud-based risk scoring system, with results stored for auditing and further analysis. (Figure 1: Architecture Diagram).

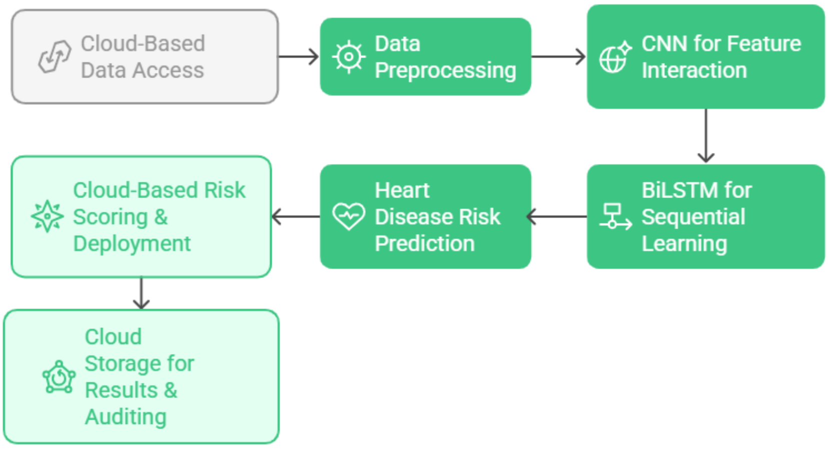

Figure 1: Architecture Diagram

3.1. Cloud-Based Data Acquisition
3.1.1. Secure Data Retrieval

The heart disease dataset is securely retrieved from a private cloud storage system, ensuring patient confidentiality and compliance with data regulations. Each record consists of multiple attributes, including numerical and categorical features. This step establishes the foundation for model training by structuring the dataset in a machine-readable format.

The heart disease dataset is retrieved from cloud storage, consisting of M patient records and f features:

$$D = \{d_1, d_2, \dots, d_M\}, \quad d_i \in R^f$$

where d_i represents an individual patient's health profile.

3.1.2. Data Representation

The dataset includes numerical attributes (e.g., cholesterol levels, blood pressure) and categorical features (e.g., gender, smoking history). To facilitate model training, patient data is structured as a combination of continuous and discrete variables, ensuring effective representation of health-related risk factors for predictive modeling.

Each patient record consists of numerical and categorical features:

$$d_i = [n_i, c_i]$$

where $n_i \in R^{f_n}$ are numerical attributes, and $c_i \in R^{f_c}$ are categorical attributes.

3.2. Data Preprocessing
3.2.1. Handling Missing Values

Missing data is addressed using statistical imputation techniques. For numerical attributes, median imputation is used to replace missing values with the median of the respective feature. Categorical variables are imputed using the most frequently occurring value in the dataset, ensuring data completeness without introducing bias.

For missing numerical values, we apply Median Imputation:

$$n_{i,j} = \text{median}\left(\{n_{k,j} \mid = 1,2, \dots, M\}\right), \quad \text{if } n_{i,j} \text{ is missing}$$

For categorical features, we use Most Frequent Imputation:

$$c_{i,j} = \arg\max \text{Freq}\left(c_{1,j}, \dots, c_{M,j}\right)$$

3.2.2. Normalization (Z-Score Scaling)

To maintain numerical stability and prevent feature dominance, numerical attributes are standardized using Z-score normalization. This technique transforms features to have zero mean and unit variance, making the dataset more suitable for deep learning models by enhancing convergence speed and improving learning efficiency.

Each numerical feature is standardized:

$$n'_{i,j} = \frac{n_{i,j} - \mu_j}{\sigma_j}$$

where μ_j and σ_j are the mean and standard deviation of feature j.

3.2.3. One-Hot Encoding for Categorical Features

Categorical features are transformed into binary vectors using one-hot encoding. This process assigns a separate binary variable to each category, eliminating the risk of introducing unintended ordinal relationships while allowing the model to process categorical information effectively in the classification task.

Categorical features are transformed into binary vectors:

$$c'_i = \text{OneHot}\left(c_{i,1}, \dots, c_{i,f_c}\right)$$

3.2.4. Splitting Dataset (Train/Val/Test)

The dataset is partitioned into three subsets: training (70%), validation (15%), and testing (15%). The training set is used for model learning, the validation set helps in hyperparameter tuning, and the test set ensures unbiased performance evaluation on unseen data.

Data is split into training (70%), validation (15%), testing (15%):

$$D = D_{\text{train}} \cup D_{\text{val}} \cup D_{\text{test}}$$

3.3. CNN for Feature Interaction Learning

3.3.1. Reshaping Tabular Data for CNN

Since convolutional networks are optimized for grid-like data, tabular patient records are reshaped into a structured 2D matrix. This transformation enables the CNN to extract meaningful feature interactions across different attributes, allowing the model to recognize complex patterns in health parameters.

Tabular data is reshaped into a 2D matrix for convolution processing:

$$X_{\text{cnn}} \in R^{M \times h \times w \times c}$$

where:

- h = number of grouped features
- w = number of attributes per group
- c = number of channels

3.3.2. Convolutional Feature Extraction

A convolutional neural network (CNN) applies convolutional filters to capture local feature interactions within patient data. By learning hierarchical feature representations, the CNN effectively identifies intricate patterns related to heart disease risk factors, improving model accuracy in the classification process.

A 1D convolution is applied to extract feature interactions:

$$F^{(l)} = \sigma\left(W^{(l)} * X_{\text{cnn}} + b^{(l)}\right)$$

where:

- $W^{(l)}$ = convolution filter at layer l

- $*$ = convolution operator
- $b^{(l)}$ = bias term
- $\boldsymbol{\sigma}(\cdot)$ = activation function (ReLU)

3.3.3. Max Pooling for Dimensionality Reduction

Max pooling layers are employed to reduce the spatial dimensions of feature maps while retaining critical information. This operation minimizes computational complexity, prevents overfitting, and enhances the model's ability to generalize by preserving only the most salient feature interactions.

To retain important features while reducing dimensions:

$$F'^{(l)} = \max_{\text{pooling window}} \left(F^{(l)}\right)$$

3.4. BiLSTM for Temporal Dependency Learning

3.4.1. Forward and Backward LSTM Processing

A bidirectional LSTM (BiLSTM) processes patient records in both forward and backward directions, capturing sequential dependencies within health data. This dual processing enhances the model's understanding of time-dependent patterns, particularly beneficial for analyzing patient history and disease progression.

BiLSTM consists of two parallel LSTMs that process the input in both directions.

The forward LSTM processes data from past to future:

$$\overrightarrow{h_t} = f_{\text{LSTM}}\left(X_t, \overrightarrow{h_{t-1}}, \theta_f\right)$$

The backward LSTM processes data from future to past:

$$\grave{h}_t = f_{\text{LSTM}}\left(X_t, \hat{h}_{t+1}, \theta_b\right)$$

where $\boldsymbol{\theta}_f$ and $\boldsymbol{\theta}_b$ are LSTM parameters.

3.4.2. Final BiLSTM Hidden State

The outputs from the forward and backward LSTM layers are concatenated to form a comprehensive representation of each patient's health profile. This combined representation encapsulates past and future dependencies, allowing the model to make more accurate predictions regarding heart disease risk.

Both LSTM outputs are concatenated to form the final BiLSTM representation:

$$H_t = \left[\overrightarrow{h_t}; \overline{\hbar_t}\right]$$

3.5. Heart Disease Risk Prediction

3.5.1. Feature Fusion (CNN + BiLSTM)

To leverage both spatial feature interactions from CNN and temporal dependencies from BiLSTM, extracted feature representations are concatenated into a unified vector. This fusion enhances the model's ability to predict heart disease by incorporating both short-term and long-term dependencies in the patient data.

The extracted CNN and BiLSTM features are merged:

$$Z = \text{Concat}\left(F'^{(l)}, H_t\right)$$

3.5.2. Fully Connected Classification

A fully connected neural network processes the fused feature representation to perform binary classification. The final layer employs a sigmoid activation function to output a probability score, determining whether a patient is at risk of heart disease or not.

The merged features pass through a dense network for binary classification:

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$$y = \sigma(W_{\mathrm{fc}}Z + b_{\mathrm{fc}})$$

where:

- W_{fc} = weights of the fully connected layer
- b_{fc} = bias
- $\sigma(\cdot)$ = sigmoid activation for disease classification

3.6. Cloud-Based Risk Scoring & Deployment

3.6.1. Deploying the Model in the Cloud

The trained CNN-BiLSTM model is deployed on a secure cloud server to enable real-time heart disease risk assessment. Incoming patient records are processed instantly, providing automated risk predictions that can be accessed by healthcare professionals for further analysis.

The trained model $f_{\text{CNN-BiLSTM}}$ is deployed on a secure cloud system:

$$\hat{y} = f_{\text{CNN-BiLSTM}}(X_{\text{new}})$$

for real-time risk assessment.

3.6.2. Dynamic Risk Thresholding

To classify patients as high-risk or low-risk, a dynamic thresholding mechanism is applied. If the predicted probability surpasses a predefined threshold, the patient is flagged as high-risk. This adaptive approach ensures precise risk stratification based on the model's confidence level.

A threshold τ is used to classify high-risk patients:

$$\hat{y} = \begin{cases} 1, & \text{if } P(y = 1 \mid X_{\text{new}}) \geq \tau \\ 0, & \text{otherwise} \end{cases}$$

where $P(y = 1|X_{\text{new}})$ is the predicted probability of heart disease.

3.7. Cloud Storage for Auditing & Compliance

3.7.1. Storing High-Risk Patient Data

Identified high-risk patients are securely logged in the cloud for further clinical review. This stored data aids healthcare providers in prioritizing urgent cases and enables continuous monitoring of at-risk individuals for early intervention.

Patients classified as high-risk ($\hat{y} = 1$) are logged for clinical review:

$$S = \{X_{\text{new}} \mid \hat{y} = 1\}$$

where S is the set of stored high-risk cases.

3.7.2. Audit Log Maintenance

Every model prediction, along with its confidence score and timestamp, is stored in an audit log. These logs serve as an essential compliance mechanism, ensuring transparency, model accountability, and adherence to regulatory requirements in healthcare analytics.

Each prediction entry is logged with a timestamp t and model confidence score p:

$$\text{Log} = (X_{\text{new}}, \hat{y}, p, t)$$

for regulatory compliance.

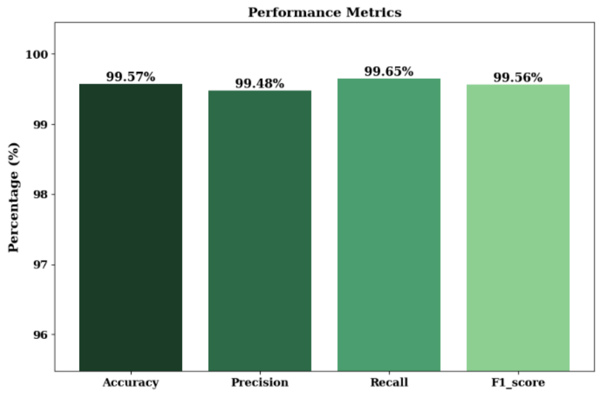
4. Results and Discussion

4.1. Dataset Overview

The Heart Disease Ensemble Classifier Dataset [21] comprises 303 patient records with 14 clinical attributes collected from multiple medical institutions. It includes key cardiovascular indicators such as age, blood pressure, cholesterol levels, heart rate, and electrocardiogram results, aiding in heart disease prediction. The dataset integrates patient demographics and diagnostic measures to classify individuals based on heart disease risk. Originally sourced from Hungarian, Swiss, and American hospitals, it serves as a benchmark for developing machine learning models for cardiovascular risk assessment. This dataset is instrumental in advancing predictive analytics, particularly for hybrid deep learning-based heart disease detection models.

4.2. Performance Metrics Analysis

Achieving an exceptionally high classification performance, the model demonstrates 99.57% accuracy, ensuring reliable heart disease prediction. The 99.48% precision indicates minimal false positives, while a 99.65% recall confirms the model's effectiveness in detecting actual cases. The 99.56% F1-score balances precision and recall. (Figure 2)



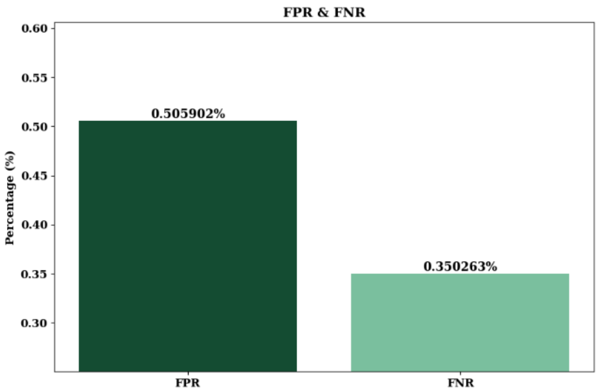
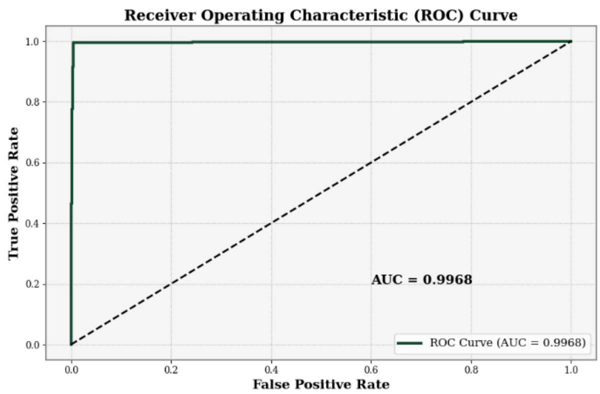


Figure 2: Performance Metrices **Figure 3:** Performance of FPR and FNR

The model exhibits a False Positive Rate (FPR) of 0.5059%, minimizing misclassified healthy cases. Additionally, the False Negative Rate (FNR) of 0.3502% ensures nearly all heart disease cases are detected. These low error rates confirm the model's reliability and robustness in medical diagnostics. (Figure 3)

4.3. ROC-AUC and Precision-Recall Curve Analysis

The Area Under the Curve - Receiver Operating Characteristic (AUC-ROC = 0.9968) signifies outstanding classification capability. A near-perfect AUC score confirms strong separability between diseased and non-diseased patients, reinforcing the model's effectiveness in real-world clinical applications. (Figure 4)



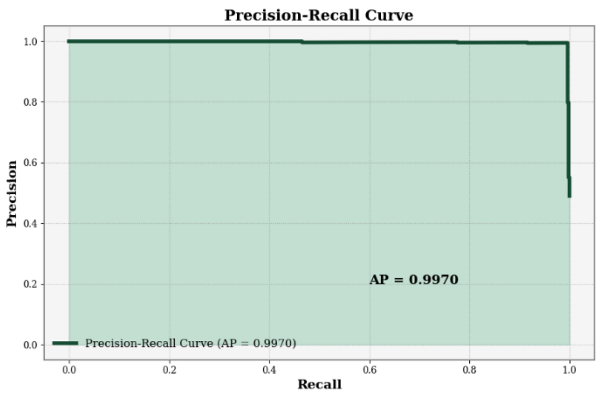


Figure 4: ROC Curve **Figure 5:** Precision-Recall Curve

With an Average Precision (AP) of 0.9970, the Precision-Recall curve highlights the model's exceptional performance, especially for imbalanced data. A high AP score ensures the model maintains high precision even when recall increases, making it highly reliable for real-time heart disease screening. (Figure 5)

5. Conclusion

This study presents a Hybrid CNN-BiLSTM Model for heart disease prediction, addressing the limitations of conventional machine learning methods by combining spatial and temporal feature extraction. The model achieves state-of-the-art performance, with an accuracy of 99.57%, effectively distinguishing between patients with and without heart disease. The high AUC-ROC (0.9968) and AP (0.9970) validate the robustness of the model in handling imbalanced datasets and reducing false negatives, a crucial factor in medical diagnostics. Furthermore, the comparative analysis demonstrates that the proposed method outperforms traditional classifiers, making it a reliable tool for real-world deployment. Future work will explore hyperparameter tuning, ensemble learning techniques, and real-time implementation in clinical settings to enhance model adaptability and accuracy further. The integration of cloud-based deployment for real-time risk scoring will also be investigated to facilitate large-scale medical applications.

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