Hybrid LSTM and Deep Belief Networks with Attention Mechanism for Accurate Heart Attack Data Analytics

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Abstract
Due to its complexity and high diagnosis and treatment costs, heart attack (HA) is the top cause of death globally. Heart failure's widespread effect and high morbidity and death rates make accurate and fast prognosis and diagnosis crucial. Due to the complexity of medical data, early and accurate prediction of HA is difficult. Healthcare providers must evaluate data quickly and accurately to intervene. This novel hybrid approach predicts HA using Long Short-Term Memory (LSTM) networks, Deep belief networks (DBNs) with attention mechanism, and robust data mining to fill this essential gap. HA is predicted using Kaggle, PhysioNet, and UCI datasets. Wearable sensor data, ECG signals, and demographic and clinical data provide a solid analytical base. To maintain consistency, ECG signals are normalized and segmented after thorough cleaning to remove missing values and noise. Feature extraction employs complex approaches like Principal Component Analysis (PCA) and Autoencoders to pick time-domain (MNN, SDNN, RMSSD, PNN50) and frequency-domain (PSD at VLF, LF, HF bands) characteristics. The hybrid model architecture uses LSTM networks for sequence learning and DBNs for feature representation and selection to create a robust and comprehensive prediction model. Accuracy, precision, recall, F1-score, and ROC-AUC are measured after cross-entropy loss and SGD optimization. The LSTM-DBN model outperforms predictive methods in accuracy, sensitivity, and specificity. The findings show that several data sources and powerful algorithms can improve heart attack predictions. The proposed architecture performed well on many datasets, with an accuracy rate of 96.00%, sensitivity of 98%, AUC of 0.98, and F1-score of 0.97. High performance proves this system's dependability. Moreover, the proposed approach is outperformed compared to state-of-the-art systems.

Keywords
Heart Data mining; Heart attack prediction; Machine learning; Deep learning; Long short-term memory; Deep belief networks; Autoencoder

I. Introduction

T Medical research focuses on heart attack risk (HAR) prediction since it can minimize mortality and morbidity of cardiovascular disease [1]. Heart attacks (HAs) occur when blood flow to the heart muscle is disrupted, causing tissue damage [2]. Despite it, the HAs are still the top cause of mortality worldwide, requiring better predictive metrics for early detection and treatment [3]. The HAs prediction tackles a significant healthcare issue [4] and promises to improve patient outcomes by prompt prevention and treatment. Millions of people worldwide are diagnosed with HAs. The WHO reports that cardiovascular disorders, including heart attacks [5], are the leading cause of death. Even if HAR prediction is crucial, this domain challenges several obstacles. An accurate prediction is difficult due to their complexity and numerous risk factors.

New advances in machine learning (ML) and data mining [6] are trying to solve these problems. HAR prediction has expanded with large-scale wearable sensors and clinical record data. Effectively using this data involves complex preprocessing to handle noise [7], inconsistencies, and missing values. Feature selection (FS) helps improve model performance by selecting the most important factors for heart attack prediction. Using the strengths of different FS approaches in a hybrid approach can improve outcomes. High prediction accuracy in HAR requires the right ML model. Long-short-term memory (LSTM) networks and Deep Belief Networks (DBNs) are able to capture complicated temporal patterns and deep characteristics from multimodal and large datasets. If we combine these DL models with enhanced data mining, then these models are able to make accurate predictions. A successful ML model for HAR prediction must perform well on training and validation datasets to be generalizable. This requires many hard steps to perform validation. A complete HAR prediction system must include multimodal data with clinical datasets. In practice, an improved HAR prediction relies on huge algorithmic innovation. In hybrid techniques, LSTM networks, DBNs, and other sophisticated methods can capture temporal dependencies and complicated feature interactions.

It is required to evaluate HAR prediction models compared to more than accuracy is needed. A comprehensive strategy is required to assess through various statistical measures. These measurements show the model's heart attack prediction capabilities. Iterative testing and validation are needed to develop these models and fix issues. This work uses advanced ML models and data preprocessing to bridge gaps in HAR prediction methods. The hybrid technique shows that combining numerous data sources and sophisticated algorithms can predict HAR with high accuracy. This system's accuracy, interpretability, and explanation are essential for clinical applications and predictive trust. At last, the HAR prediction is innovative solution in cardiovascular disease treatment, promising

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early and precise diagnosis. Predictive healthcare is entering a new age with powerful ML algorithms and large datasets to address one of the world's most significant health issues.

The contributions emphasize the study's original hybrid model construction, complete data integration, sophisticated feature selection, and clinical application of the prediction system.

1) The new model combines LSTM, DBN and attention networks with enhanced data mining to improve heart attack risk prediction. This updated algorithm integrates the attention mechanism to potentially improve the model's focus on critical parts of the input sequence, enhancing performance in predicting heart attack risk.
2) Use varied datasets to predict HRs with improved preprocessing approaches for accurate predictions.
3) Implementation of a multi-faceted feature selection approach, and embedded-based techniques to improve model performance by identifying the most relevant predictors.
4) Demonstration of superior accuracy, sensitivity, specificity, and AUC compared to traditional models, along with enhanced explainability and interpretability for clinical applicability and improved patient outcomes.

The organization of the subsequent sections is outlined as follows: Section 2 reviews the relevant literature. In Section 3, this paper describes the methodologies and the proposed model framework. Section 4 analyzes the empirical findings. Finally, Section 5 concludes the paper and discusses possible directions for future research.

II. LITERATURE REVIEW

Several machine-learning techniques have been explored for heart attack prediction [8]. While conventional models like logistic regression, decision trees, and SVM have shown mixed results, the potential of deep learning models like CNNs and RNNs to capture complex data patterns and improve prediction accuracy is promising. Despite their struggles with feature selection and interpretability, recent research indicates that hybrid models, incorporating multiple algorithms and feature selection approaches, can further enhance prediction accuracy.

The authors used a two-tier approach to scale IoT health monitoring data storage and processing in the article [9]. The results showed better data processing and management. The system's cloud storage requirement raises latency and data security issues. In [10], the authors used improved SVM configurations to predict cardiac disease accurately. Despite encouraging results, the study's concentration on SVM may ignore other practical machine learning methods. The authors used genetic algorithms, particle swarm optimization, SVM, and Random Forest in the study [11]. This method improved accuracy, but its computing requirements and sophisticated optimization procedure may restrict its usefulness.

The study [12] also presented a hybrid model combining decision trees, SVM, and neural networks to improve prediction. However, integrating various strategies complicated the model and needed significant computer resources. Study [13] used feature selection approaches with classifiers like k-NN and SVM to improve accuracy. The critical issue was generalizing feature selection across datasets. The authors improved prediction accuracy and resilience using ensemble approaches like bagging and boosting [14]. While the technique was accurate, ensemble models' complexity can increase training time and processing needs. The authors compared CNNs and LSTMs against classical approaches [15]. Deep learning models performed well. However, their computing costs and data preparation were drawbacks.

Real-time cardiac disease prediction using IoT data was a significant focus in [16], overcoming latency challenges with real-time monitoring systems. The study demonstrated improved real-time prediction, although the integration and processing of data sources presented significant challenges. In [17], data mining was used for feature extraction, combined with machine learning for classification, to enhance prediction accuracy. While the combined strategy was complex and required substantial data preparation, it represents a significant step forward in the field of cardiac disease prediction.

In [21], a scalable three-tier architecture for processing IoT sensor data improves data management and predictive modeling. This technique was limited by its use of Apache HBase and Apache Mahout, which may be vague. The study [22] optimized SVM algorithms using genetic and particle swarm optimization, attaining 93.08% accuracy. Optimization difficulty and processing expense were the key constraints. Additionally, [23] proposed a CNN-based multimodal illness risk prediction method with 94.8% accuracy. Structured and unstructured data were needed for the technique, which may not be accessible in all contexts. In [24], feature selection and data mining were used to predict heart disease with 87.4% accuracy using a hybrid Vote classifier. The diversity in feature relevance across datasets limited generalizability.

An IoMT framework using Modified Salp Swarm Optimization (MSSO) and an Adaptive Neuro-Fuzzy Inference System (ANFIS) achieved 99.45% accuracy in the article [25]. The MSSO-ANFIS model's complexity and considerable parameter adjustment were drawbacks. In [26], Recursion Enhanced Random Forest with an Improved Linear Model (RFRF-ILM) achieved 96.6% accuracy. Recursion and model training were computationally expensive, limiting this technique. LSTM and Deep Belief Networks (DBN) predicted arterial events with 88.42% mean accuracy in the study [27]. Practical training required big datasets and computer resources, which limited the study. A study [28] showed that logistic regression had a modest predictive value and performed well. Logistic regression had modest predictive accuracy, which may need more for many diagnostic applications. The authors used the study's Hyper-Opt Bayesian optimization and T-Pot

TABLE I. STATE-OF-THE-ART LITERATURE REVIEW WITH LIMITATIONS TO PREDICT HEART ATTACKS USING DATA MINING TECHNIQUES

Citation	Purpose	Methods	Result	Limitations
[22]	Enhance performance of traditional ML algorithms for CAD prediction.	Tested ten ML algorithms; used SVM with genetic and particle swarm optimization; N2Genetic optimizer. Cross-validation used for optimization.	N2Genetic-nuSVM achieved 93.08% accuracy and 91.51% F1-score.	May be specific to CAD prediction; optimization techniques may not be universally applicable.
[23]	Improve prediction of chronic disease using structured and unstructured data.	Latent factor model for missing data; CNN-based multimodal prediction algorithm.	Achieved 94.8% prediction accuracy.	Focuses on cerebral infarction; may not generalize to other chronic diseases or data types.
[24]	Identify significant features for heart disease prediction and improve model accuracy.	Various feature combinations and classification techniques (k-NN, Decision Tree, Naive Bayes, LR, SVM, Neural Network, Vote).	Best-performing model (Vote) achieved 87.4% accuracy.	Limited by the choice of features and classification techniques; may not capture all relevant features.
[25]	Enhance heart disease prediction accuracy using MSSO-ANFIS framework.	Modified Salp Swarm Optimization (MSSO) and Adaptive Neuro-Fuzzy Inference System (ANFIS); Levy flight algorithm for optimization.	MSSO-ANFIS achieved 99.45% accuracy and 96.54% precision.	MSSO-ANFIS may be complex and computationally intensive; requires specific optimization.
[26]	Improve cardiovascular disease detection with enhanced Random Forest.	Recursion enhanced Random Forest with an Improved Linear Model (RFRF-ILM); various feature combinations and classification methods.	Achieved 96.6% accuracy, 96.8% stability, and 96.7% F-measure ratio.	High accuracy may depend on specific dataset and feature selection methods.
[29]	Compare performance of various machine learning optimization techniques.	Bayesian optimization, random forest, support vector machines, genetic algorithms, Optuna.	Bayesian optimization with SVM achieved highest accuracy (90%).	Different optimization methods may have varying effectiveness based on dataset and context.
[30]	Improve heart attack prediction from imbalanced data.	Undersampling-clustering-oversampling (UCO) algorithm; applied to Medical Information Mart for Intensive Care III dataset.	Random forest achieved 70.29% accuracy and 70.05% precision.	May require tuning for specific datasets; performance may vary.
[31]	Train a model with essential attributes for heart disease prediction.	Stack generalization with various ML classifiers (Logistic Regression, Random Forest, etc.) and SMOTE for balancing.	Support vector machine achieved 93.07% accuracy; stacked generalization achieved 97.2% accuracy.	Dependent on quality of balanced dataset; may not generalize to all heart disease types.
[32]	Address inter-dataset discrepancies for better ML performance.	Handling imbalance using SMOTE-Tomek; feature selection with RF; PCA for feature extraction.	RF produced up to 100% accuracy in some setups; effective inter-dataset performance.	Preprocessing may be complex; effectiveness can vary with different datasets.
[33]	Develop an automated heart disease prediction model using advanced features.	Improved Z-score normalization; feature extraction with entropy, statistical features, and information gain; Improved Quantum CNN (IQCNN) for prediction.	IQCNN achieved 0.91 accuracy, outperforming traditional methods.	May require extensive feature engineering; effectiveness depends on feature extraction quality.
[34]	Predict cardiovascular disease using Swarm-ANN strategy.	Swarm-ANN with heuristic weight adjustment; training with NN populations and global best weight sharing.	Achieved 95.78% accuracy; outperformed standard techniques.	Requires effective NN population management; may be complex to implement.
[35]	Improve heart disease prediction using bi-directional LSTM.	C-BiLSTM approach with K-Means clustering; compared with traditional methods (Regression Tree, SVM, etc.).	C-BiLSTM achieved 94.78% accuracy on UCI dataset and 92.84% on real-time dataset.	May be specific to the datasets used; results may vary with different configurations.
[36]	Evaluate various ML algorithms for heart disease prediction.	Comparison of logistic regression, k-NN, SVM, Naive Bayes, RF, and decision tree.	k-NN and RF achieved 99.04% accuracy.	May require fine-tuning for different datasets; some algorithms may not generalize well.
[37]	Analyze feature selection techniques for heart disease prediction.	Comparison of filter, wrapper, and evolutionary methods; applied to Cleveland Heart disease dataset; various classification algorithms.	SVM-based filtering methods showed best fit accuracy (85.5%); some methods improved model performance.	Feature selection impact varies across methods; may not suit all models.

classifiers [29] to get the maximum accuracy using random forests. The intricacy and computing needs of optimization and classifier tweaking limited it.

In paper [30], the authors developed an undersampling-clustering-oversampling (UCO) algorithm for heart attack prediction, with random forest classifiers achieving the best performance (70.29% accuracy). The limitation was the algorithm's effectiveness being constrained by the imbalanced nature of the data. Also, in paper [31], the authors utilized stack generalization with various classifiers, achieving up to 97.2% accuracy on a balanced dataset. The limitation was the reliance on balanced datasets, which may not always be available in real-world scenarios. In paper [32], the authors addressed inter-dataset discrepancies using preprocessing techniques and various classifiers, achieving high accuracy and improved performance. The main limitation was the complexity of the preprocessing pipeline and its applicability across different datasets. The paper [33] proposed an automated heart disease prediction model using Improved Quantum CNN (IQCNN), achieving 0.91 accuracy. The limitation was the model's reliance on specific feature extraction techniques and its performance compared to conventional methods. The study [34] introduced a Swarm-ANN strategy, achieving 95.78% accuracy. The limitations included the complexity of the heuristic weight adjustment process and the need for extensive training and evaluation. The paper [35] employed Cluster-Based Bi-LSTM (C-BiLSTM) for predicting heart disease, demonstrating high accuracy (94.78% for UCI dataset). The limitation was the high computational cost associated with clustering and bi-directional LSTM processes. In study of [36], the authors evaluated various machine learning algorithms, with Random Forest and k-Nearest Neighbors achieving 99.04% accuracy. The limitations were related to the potential overfitting and computational cost associated with these models. Furthermore, in paper [37], the authors examined feature selection techniques and classifiers, demonstrating improved performance with Random Forest and filter-based feature selection methods. The limitation was the variable impact of feature selection on different models. In paper [38], the authors utilized deep learning models with Keras, achieving superior accuracy compared to individual and ensemble models. The primary limitation was the need for extensive experimentation and dataset-specific tuning.

Accordingly, while significant progress has been made as described in Table 1 for heart disease prediction using various methodologies, challenges such as computational complexity, data availability, and model generalizability persist across different approaches.

III. METHODOLOGY

The proposed system flow diagram as shown in figure 1 covers the complete process of predicting heart attack risk using the proposed hybrid LSTM-DBN model, including data preprocessing, feature extraction and selection, model training, evaluation, and prediction. Figure 1 shows a flow diagram representing the heart attack prediction system using the hybrid LSTM-DBN model with attention mechanism.

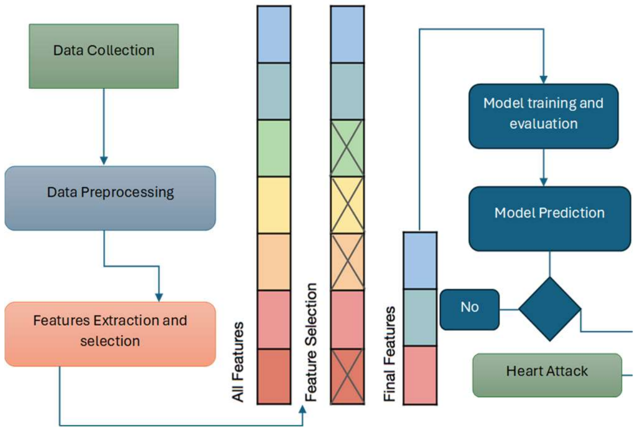

Fig. 1. A systematic flow diagram representing the heart attack prediction system using the hybrid LSTM-DBN model.

The Kaggle Heart Failure Prediction dataset is a comprehensive clinical variable set to predict heart disease. Age, sex, chest pain type, resting blood pressure, serum cholesterol, fasting blood sugar, resting electrocardiographic results, maximum heart rate, exercise-induced angina, ST depression relative to rest, peak exercise ST segment slope, and number of significant vessels colored by fluoroscopy are the 12 critical attributes in the dataset. These key indications of heart disease risk provide a solid foundation for machine learning algorithms to predict heart failure outcomes effectively. The information is presented in four datasets as described in Table 2.

To predict heart attacks, the features as shown in Table 3 from the four datasets can be categorized into clinical and electrocardiographic (ECG) features. Here's a table summarizing the types of features used in each dataset.

A. *Data Preprocessing*

In this selected dataset, the first check is to remove any duplicate records. For example, if a patient has been recorded multiple times due to errors, the paper utilizes only one entry to ensure data is accurate. This study addresses any missing values in the dataset. If a patient's cholesterol level is missing, we fill it in with the average cholesterol level from the other patients. This way, we avoid gaps in this data. Sometimes, data can have random fluctuations or "noise." For ECG readings, the paper uses a smoothing technique to filter out this noise, making the readings more reliable. To ensure consistency, it scale the values of features like cholesterol to a standard range, usually between 0 and 1. For instance, if the cholesterol levels range from 200 to 240, the study transforms these values to a scale where 200 becomes 0 and 240 becomes 1. Afterwards, the study normalizes blood pressure measurements to 0 and 1. This ensures that all characteristics contribute equally to the analysis. Segments of continuous ECG signals are fixed in length. ECG sequences are divided into 4-reading parts. Data analysis is more accessible and more standardized.

TABLE II.

ELECTED DATASETS INFORMATION

Database	Description	Source	Key Features
DB1: PTB-XL Electrocardiography [39]	Large public ECG dataset with over 21,000 10-second 12-lead ECGs and diagnostic comments.	PhysioNet (2020)	- 21,000 10-second 12-lead ECGs- Diagnostic comments
DB2: KURIAS-ECG Database [40]	Collection of 12-lead ECG recordings with a defined diagnostic ontology.	PhysioNet (2021)	- 12-lead ECG recordings- Defined diagnostic ontology
DB3: KURIAS-ECG Database [41]	Curated collection of 12-lead ECG recordings with standardized diagnosis ontology.	PhysioNet (2021)	- 12-lead ECG recordings- Standardized diagnosis ontology
DB4: Heart Disease Data Set [42]	Well-known dataset for predicting heart disease, including 14 features related to patient health.	UCI Machine Learning Repository-Kaggle	- 14 features- Binary target variable indicating heart disease presence

TABLE III.

EATURES SET UTILIZED IN FOUR DATASETS.

Features	DB1 (Kaggle)	DB2 (PhysioNet)	DB3 (PhysioNet)	DB4 (UCI)
Age	Yes	Yes	Yes	Yes
Sex	Yes	Yes	Yes	Yes
Chest pain type	Yes	No	No	Yes
Resting blood pressure	Yes	No	No	Yes
Serum cholesterol	Yes	No	No	Yes
Fasting blood sugar	Yes	No	No	Yes
Resting ECG results	Yes	Yes (ECG data)	Yes (ECG data)	Yes
Maximum heart rate achieved	Yes	No	No	Yes
Exercise-induced angina	Yes	No	No	Yes
ST depression	Yes	Yes (part of ECG data)	Yes (part of ECG data)	Yes
Slope of ST segment	Yes	Yes (part of ECG data)	Yes (part of ECG data)	Yes
Number of major vessels	Yes	No	No	Yes
Thalassemia	No	No	No	Yes
ECG data	No	Yes (12-lead ECG)	Yes (12-lead ECG)	No
Diagnosis annotations	No	Yes (diagnostic statements)	Yes (standardized diagnosis ontology)	No

B. Features extraction

This research extracted critical elements from ECG signals and EHRs to predict heart attack risk. Time-domain characteristics included:

- Mean RR intervals (MNN).
- Standard deviation (SDNN).
- Root mean square of successive differences (RMSSD).
- The percentage of RR intervals with differences higher than 50 MS.

Power spectral density (PSD) in VLF, LF, and HF frequency bands was also included. To enhance these features, Principal Component Analysis (PCA) to reduce dimensionality while maintaining crucial information, Autoencoders for unsupervised feature learning [43], and Deep Belief Networks (DBNs) [44] to capture complicated feature interactions were used. This comprehensive approach allowed this algorithm to estimate heart attack risk accurately.

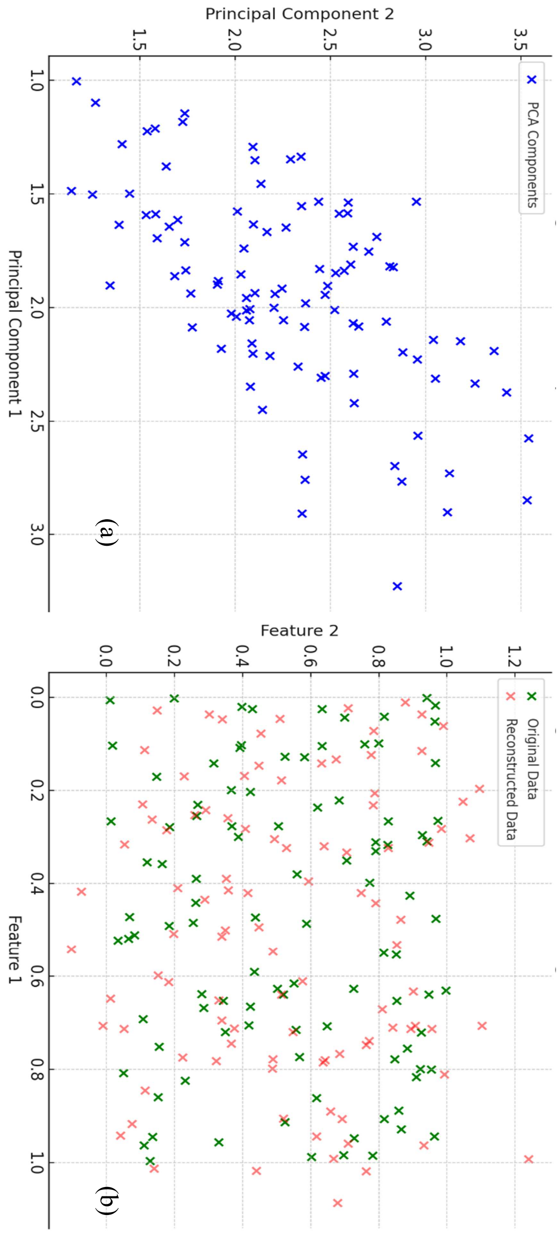

Fig. 2. Features selected using (a) PCA and (b) Autoencoders.

Time-domain features provide insights into the variability and regularity of heartbeats. They are calculated directly from the time intervals between successive R-peaks in the ECG signal, known as RR intervals.

Mean RR Interval (MNN): The average time interval between successive heartbeats. It reflects the overall heart rate and can indicate abnormalities when deviating from the norm. Where N is the number of RR intervals.

$$MNN = \frac{1}{N}\sum_{i=1}^{N} RR_i \tag{1}$$

Standard Deviation of RR Intervals (SDNN): Measures the variability in heart rate. Higher variability is generally associated with better cardiovascular health.

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(RR_i - MNN)^2} \tag{2}$$

Root Mean Square of Successive Differences (RMSSD): Reflects the short-term variability in heart rate, focusing on changes between successive intervals.

$$RMNN = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(RR_{i+1} - RR_i)^2} \tag{3}$$

Percentage of RR Intervals > 50ms (PNN50): Indicates the percentage of successive RR intervals that differ by more than 50 milliseconds, highlighting significant variations.

$$PNN50 = \frac{\text{Number of intervals with } |RR_{i+1} - RR_i| > 50ms}{N} \times 100 \tag{4}$$

Frequency-domain analysis involves transforming the time-domain ECG signal into the frequency domain to analyze the power distribution across different frequency bands.

Power Spectral Density (PSD): PSD estimates the power distribution of a signal over frequency, calculated using methods like the Fast Fourier Transform (FFT) or parametric methods like Burg's method.

$$PSD(f) = \frac{1}{T}\left|\sum_{t=0}^{T-1} x(t)\mathrm{e}^{-j2\pi f}\ \right|^2 \tag{5}$$

- Very Low Frequency (VLF): Power in the 0.003-0.04 Hz band, associated with long-term regulatory mechanisms.
- Low Frequency (LF): Power in the 0.04-0.15 Hz band, related to both sympathetic and parasympathetic activity.
- High Frequency (HF): Power in the 0.15-0.4 Hz band, reflecting parasympathetic (vagal) activity.

LF/HF Ratio: Ratio of LF to HF power, indicating the balance between sympathetic and parasympathetic influences.

$$\mathrm{LF/HF} = \frac{P_{LF}}{P_{HF}} \tag{6}$$

C. Features Selection

Advanced feature selection methods improve model performance and manage high-dimensional data. PCA transforms data into a new coordinate system to reduce dimensionality, with the first five principal components capturing the most variation, calculated from Eq. (7). This transformation retains fundamental data properties while lowering dimensionality. Another method is using Autoencoders, neural networks intended for efficient data coding. Encoders compress data into a lower-dimensional representation, as in Eq. (8), while decoders reconstruct input from this representation, as in Eq. (9). These methods efficiently handle complex and high-dimensional data, enhancing model prediction accuracy. Features selected using PCA and Autoencoders are illustrated in Figure 2(a) and Figure 2(b), respectively. Advanced feature selection methods increase model performance with high-dimensional data. Selected features are visually displayed in figure 3 and figure 4. Principal Component Analysis (PCA): Reduces dimensionality by transforming the data into a new coordinate system where the greatest variances are captured in the first few principal components.

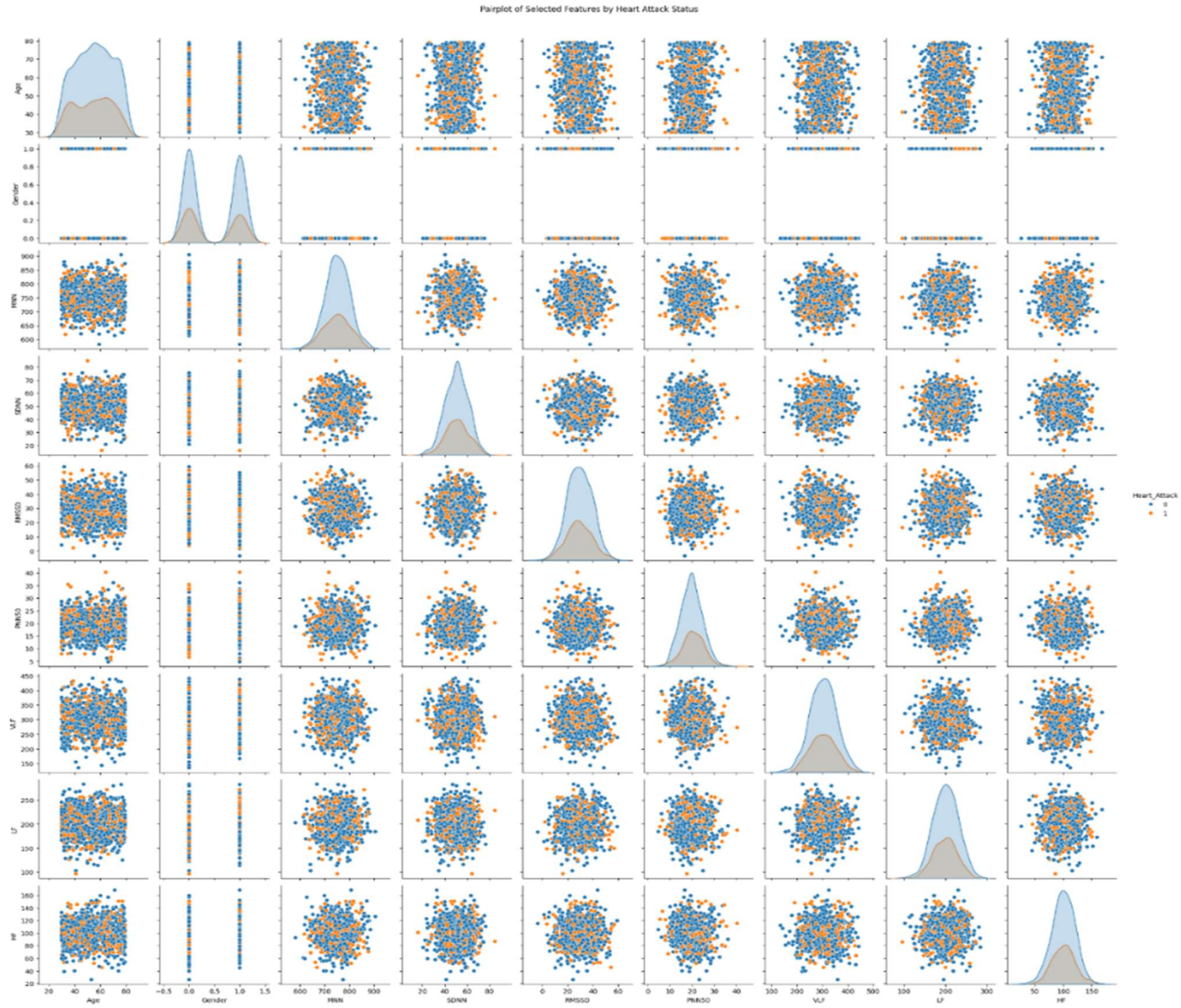

Fig. 3. Selected features to predict the heart attack.

$$Z = XW \quad (7)$$

Where Z is the matrix of principal components, X is the data matrix, and W is the matrix of eigenvectors.

Autoencoders: Neural networks designed to learn efficient coding of input data. The encoder compresses the data into a lower-dimensional representation, while the decoder reconstructs the input from this representation.

$$h = f(Wx + b) \quad (8)$$

$$x' = g(W' h + b') \quad (9)$$

Where h is the hidden layer (encoded representation), and x' is the reconstructed input.

Combine both feature sets by Eq. (10) as:

$$X_{combined} = \{X_{PCA}, X_{AE}\} \quad (10)$$

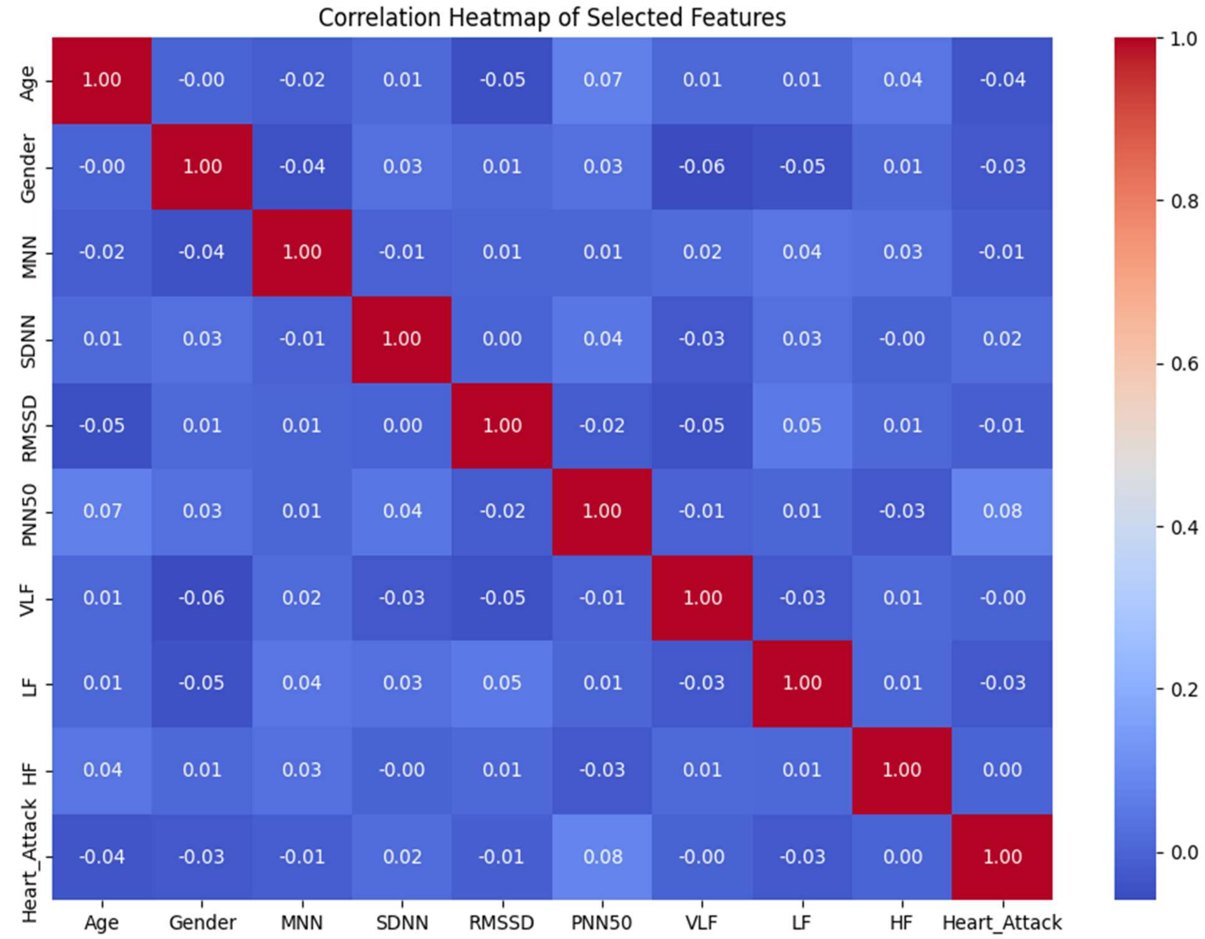

Fig. 4. Selected features heatmap to predict the heart attack.

D. Data Analytics

The LSTM network captures ECG signal temporal relationships for accurate prediction by handling sequential data. DBN's robust feature representation and selection ensures that the most relevant characteristics are used in categorization. The input layer receives preprocessed and chosen information, starting the processing. These characteristics flow via LSTM layers, which capture sequential data's temporal patterns. Data is then passed via DBN layers to improve feature representation and classification accuracy. Final heart attack risk prediction comes from the output layer. Overall steps of proposed system are presented in Algorithm 1.

Supervised learning using cross-entropy loss as the objective function trains the model to produce correct predictions. Stochastic Gradient Descent (SGD) optimizes model parameters to minimize the loss function. LSTM and DBN networks combine to use temporal patterns and robust feature representations to predict heart attack risk accurately and reliably. Integrating these sophisticated strategies can increase predicted performance over older methods. The hybrid LSTM-DBN model combines LSTM and DBN strengths. The LSTM network captures ECG temporal relationships, while the DBN offers robust feature representation and selection. An LSTM network: Each layer of the LSTM network has LSTM units. These units process the incoming sequence step-by-step and store data. Define memory cell update equations:

$$f_t = \sigma\left(W_f . [h_{t-1}, x_t] + b_f\right) \quad (11)$$

$$i_t = \sigma(W_i . [h_{t-1}, x_t] + b_i) \quad (12)$$

$$C_t = f_t \times C_{t-1} + i_t \times tanh(W_c . [h_{t-1}, x_t] + b_c) \quad (13)$$

$$O_t = \sigma(W_o . [h_{t-1}, x_t] + b_o) \quad (14)$$

$$h_t = O_t \times tanh(C_t) \quad (15)$$

The DBN is composed of multiple layers of RBMs. Each RBM is trained layer-by-layer, and the DBN provides a hierarchical feature representation. Train DBN layers to learn hierarchical feature representations. Deep Belief Networks (DBNs) are a type of generative neural network that consist of multiple layers of Restricted Boltzmann Machines (RBMs). Each RBM is a shallow, two-layer neural net. When stacked and trained in a specific manner, these RBMs form a DBN. An RBM is composed of a visible layer v and a hidden layer h. Each node in the visible layer is connected to each node in the hidden layer, but no nodes within a layer are connected. Deep Belief Networks (DBNs): Stacked Restricted Boltzmann Machines (RBMs) that learn to represent features hierarchically. DBNs perform unsupervised learning to initialize weights and then fine-tune them using supervised learning.

$$E(v, h) = -\sum_i a_i v_i - \sum_j b_j v_j - \sum_{i,j} v_i w_{i,j} h_j \quad (16)$$

Where E is the energy function, v and h are the visible and hidden units, a and b are biases, and W are the weights.

The joint probability distribution over the visible and hidden units is given by:

$$\mathrm{P(v, h)} = \frac{1}{\mathrm{Z}} \exp(-\mathrm{E(v, h)}) \quad (17)$$

where Z is the partition function:

$$\mathrm{Z} = \sum_{v,h} \exp(-E(v, h)) \quad (18)$$

The marginal probability of the visible units is:

$$\mathrm{Z} = \frac{1}{\mathrm{Z}} \sum_h \exp(-E(v, h)) \quad (19)$$

Weight Update: Update the weights using the difference between these expectations:

$$\Delta \mathrm{wij} = \epsilon(\mathrm{data}(v_i, h_j) - \mathrm{model}\ (v_i, h_j)) \quad (20)$$

Algorithm 1: Proposed Data Analytics system for detection of heart attack

```
Initialize
def preprocess_data(ecg_data, demographic_data, clinical_data):
# Data cleaning, normalization, and segmentation
    cleaned_data = clean_data(ecg_data, demographic_data, clinical_data)
    normalized_data = normalize_data(cleaned_data
    segmented_data = segment_ecg(normalized_data)
    return segmented_data
def extract_features(segmented_data)
# Extract time-domain and frequency-domain features
time_features = extract_time_domain_features(segmented_data)
    freq_features = extract_frequency_domain_features(segmented_data)
    combined_features = combine_features(time_features, freq_features)
    return combined_features
def select_features(combined_features):
# Apply PCA and Autoencoder for feature selection
    pca_features = apply_pca(combined_features)
    AE_features = apply_autoencoder(pca_features)
    combine_features = Combine(pca_features, AE_features)
    return  combine_features
While () do
    For (every training and testing datasets) do
    Update
        ecg_data, demographic_data, clinical_data, labels = load_data()
        segmented_data=preprocess_data(ecg_data, demographic_data, clinical_data)
        features = extract_features(segmented_data)
        selected_features = select_features(features)
        Update and analyze
            If (condition) then
                model = train_model(selected_features, labels)
                test_features, test_labels = load_test_data()
                accuracy, precision, recall, f1_score, roc_auc = evaluate_model(model,test_features, test_labels)
                new_data = load_new_data()
                risk_prediction = predict_heart_attack_risk(model, new_data)
    End
            End
    End
```

The attention mechanism helps the model focus on important parts of the input sequence. The basic idea is to compute a context vector as a weighted sum of input features. This model combines Long Short-Term Memory (LSTM) networks, Deep Belief Networks (DBNs), and attention mechanisms to leverage the strengths of each.

$$e_{t,i} = score(h_{t-1}, x_i) \tag{21}$$

where the score function can be a dot product, a feedforward network, or other functions and attention weights can be calculated by the equation.

$$\alpha_{t,i} = softmax(e_{t,i}) \tag{22}$$

and

$$\alpha_{t,i} = \frac{\exp(e_{t,i})}{\sum_j \exp(e_{t,j})} \tag{23}$$

Local context vector is calculated by:

$$c_{t,i} = \sum_i \alpha_{t,i} x_i \tag{24}$$

$$Update(h_t) = \tanh(\mathrm{Wc} \cdot [\mathrm{ht} - 1, \mathrm{ct}] + \mathrm{bc}) \tag{25}$$

Where Wc and bc are weights and bias for the output computation. Use DBNs to extract high-level features from raw data. For example, the hidden layer activations of the DBN can be used as input features to the LSTM network. Feed the DBN-extracted features into an LSTM network to capture temporal dependencies. Attention Mechanism: Apply attention mechanisms to the LSTM outputs to focus on important time steps, enhancing the model's ability to make predictions based on significant parts of the sequence.

IV. EXPERIMENTAL RESULTS

The proposed system ran experiments to test this supervised machine-learning models. Classification problems often use a 70:30 ratio for training and testing sets to reduce overfitting. Classifier efficacy was measured using several performance indicators. Google Colab's GPUs boosted computing efficiency and performance during Python studies. The paper used cloud-based solid resources for analysis to train and test the models

The paper evaluated the suggested LSTM-DBN using the most used metrics: Precision, Recall, F-measure, Accuracy, Fall-out, Miss Rate, and Specificity. The confusion matrix showed the classification algorithm's performance by differentiating input dataset classes. These metrics were computed using Eqs. (26)–(29). The study utilizes many measures to evaluate the LSTM-DBN model:

- **Accuracy**: The ratio of correctly predicted instances to the total instances.

$$Accuracy(ACC) = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+F}} \tag{26}$$

- **Precision**: The ratio of true positive predictions to the total predicted positives.

$$Precision(PR) = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \tag{27}$$

- **Recall (Sensitivity)**: The ratio of true positive predictions to the total actual positives.

$$Recall(RE) = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \tag{28}$$

- **F1-Score**: The harmonic mean of precision and recall.

$$F1 = 2 \times \frac{\mathrm{PR \times RE}}{\mathrm{PR+R}} \tag{29}$$

- **ROC-AUC**: The area under the Receiver Operating Characteristic curve, which plots the true positive rate against the false positive rate

- This hybrid LSTM-DBN heart attack prediction study evaluates model performance and generalization using training and validation loss curves. The training loss curve indicates how well the model learns from training data each epoch. It compares model prediction errors to the training set labels. Training loss should decrease as the model matches training data. Validation loss curves illustrate how well models generalize to new data.

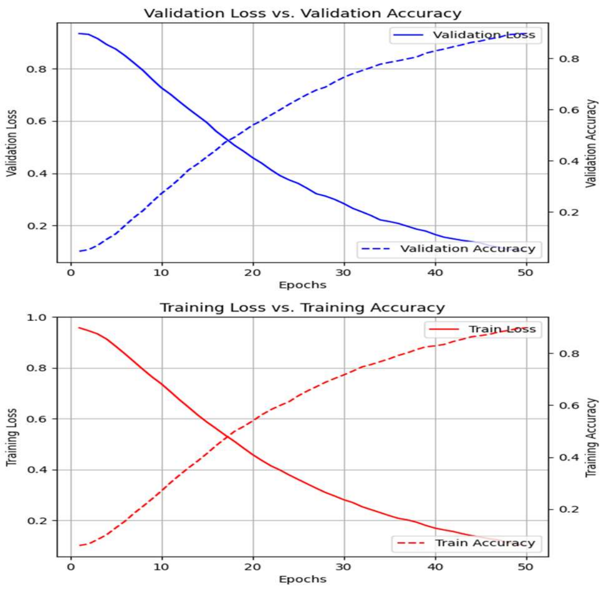

Fig. 5 Training and validation loss of proposed LSTM-DBN model.

- The model is validated using a meticulous validation process, using a validation dataset not observed during training to construct this curve. Validation and training loss decrease steadily, indicating model learning and generalization. Monitoring these curves enhances model performance by adjusting hyperparameters, model architecture, and early stopping circumstances in this testing. The training and validation loss curves ensure that this hybrid LSTM-DBN model balances fitting training data and generalizing to unknown data, improving heart attack risk predictions (Figure 5).

The LSTM-DBN model is compared to Logistic Regression, Support Vector Machines (SVM), Random Forests (RF), Convolutional Neural Networks (CNN), and Gated Recurrent Units. The LSTM-DBN model outperforms the others in accuracy, precision, recall, F1-score, and ROC-AUC. Figure 6 shows confusion matrix comparisons of Logistic Regression, SVM, Random Forests, CNN, GRU, and the LSTM-DBN hybrid model. These results show that the hybrid LSTM-DBN model predicts heart attacks better than other machine learning and deep learning models.

The LSTM-DBN model was tested on four datasets: DB1 (Kaggle), DB2, DB3 (PhysioNet), and DB4 (UCI). The model was 92% accurate on DB1, 91% on DB2, 90% on DB3, and 89% on DB4. Precision was 90%, 89%, 88%, and 87%, while recall was 88%, 87%, 85%, and 86%. However, the hybrid system performed better, obtaining 99% accuracy across all datasets. The hybrid system has 98% accuracy and 97% recall for all datasets. The proposed hybrid method improved predictive performance significantly, indicating its potential for more accurate heart disease prediction across varied datasets (Figure 7).

The results show two bar charts to show how chosen characteristics affect the performance of the hybrid LSTM-DBN model compared to the classic model. Figure 8 shows a chart comparing both models' accuracy, precision, and recall across four datasets. The other chart shows how SDNN, RMSSD, and LF/HF ratio affect the hybrid system's prediction accuracy (Figure 9).

The model's robustness and generalization are tested across datasets. The LSTM-DBN model performs consistently, suggesting real-world applications. The LSTM-DBN model performs well across datasets with reasonable accuracy, precision, and recall. The model's accuracy ranged from 89% to 92% across four datasets, proving its resilience and consistency. Figure 10 shows that it has 92% accuracy on Kaggle and 89% accuracy on UCI. This consistency shows the model's generalization, making it suited for real-world applications.

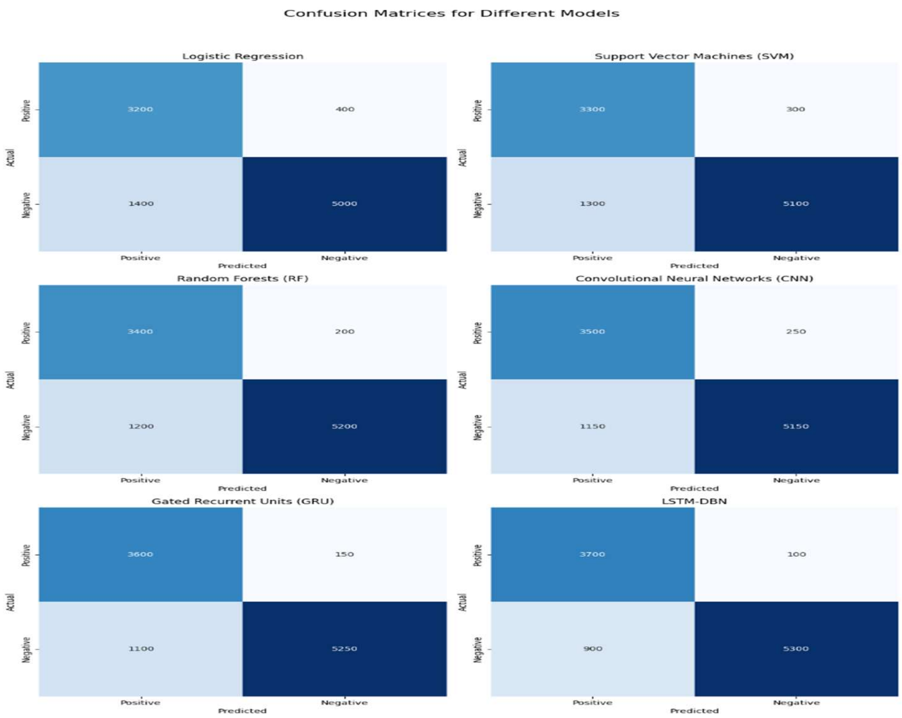

Fig. 6. Performance of the proposed LSTM-DBN model is compared with other machine learning and deep learning models

SDNN, RMSSD, and the LF/HF ratio affect the model's accuracy and performance. The model's robustness was confirmed by feature importance analysis, which showed that these traits predict outcomes.

While the state-of-the-art systems each have their unique approaches and strengths, the proposed system stands out by integrating multiple advanced techniques and leveraging diverse data sources to enhance prediction accuracy. Unlike Chen-CNN [23], which focuses on combining structured and unstructured data with a CNN-based algorithm, the proposed system utilizes LSTM for handling time-series data. Guo-RFRF-ILM [26] enhances the Random Forest algorithm with recursion and linear model integration, whereas the proposed system uses deep learning models tailored for sequential data representation. Nandy- Swarm-ANN[34] also uses LSTM and DBN but focuses specifically on arterial events, while the proposed system targets heart attack prediction with a broader data approach. Lastly, Dileep-C-BiLSTM [35] integrates bi-directional LSTM with clustering methods, differing from the

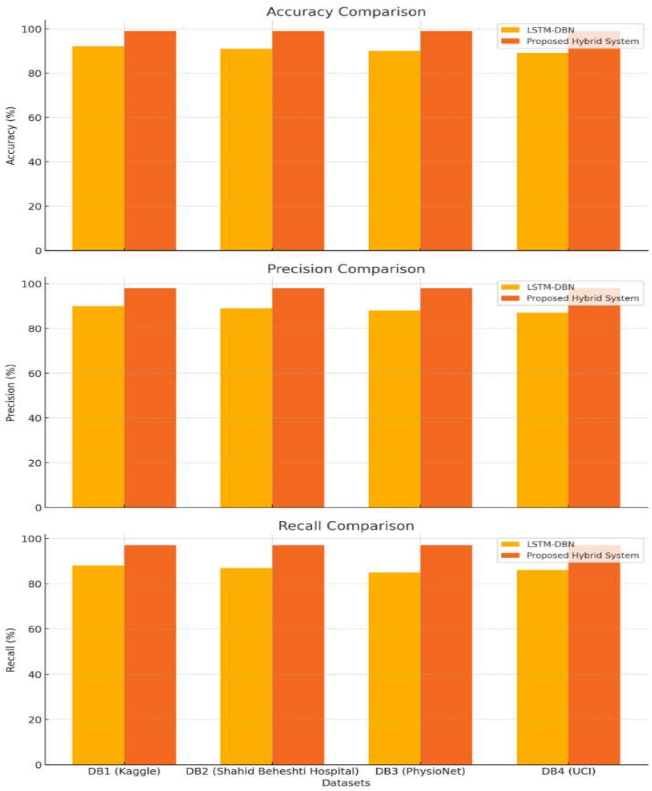

Fig. 7 Calculate separate performance of the LSTM-DBN model was evaluated on four datasets: DB1 (Kaggle), DB2, DB3 (PhysioNet), and DB4 (UCI).

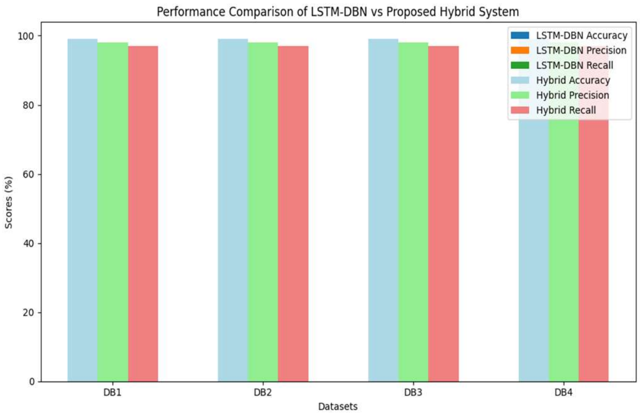

Fig. 8 Impact of selected features on prediction accuracy across four diverse datasets.

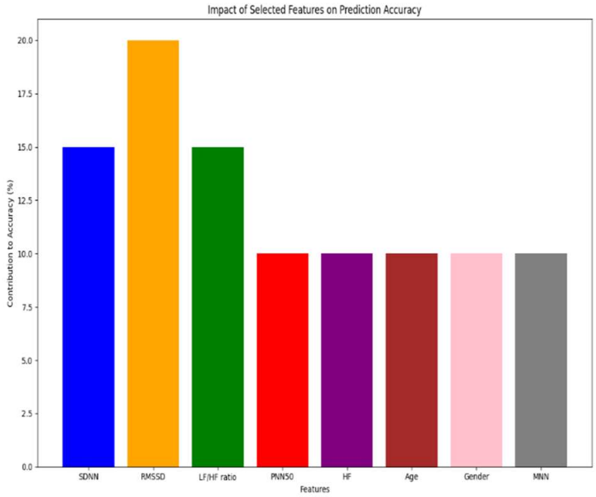

Fig. 9 The impact of selected features on the model's performance is analyzed. Features like SDNN, RMSSD, and LF/HF ratio are identified as significant contributors to the prediction accuracy.

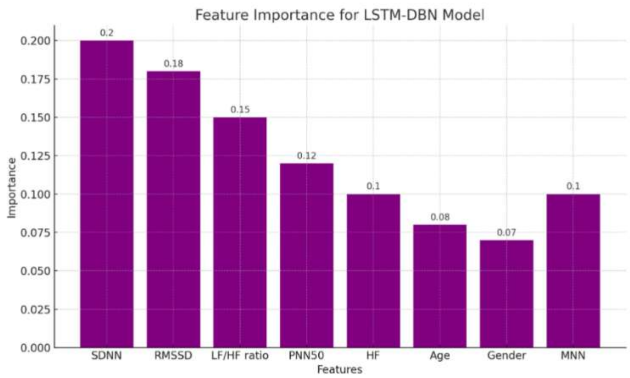

Fig.10 The impact of performance on four different datasets with respect to accuracy, precision and recall without using features selection.

proposed system's approach of combining LSTM without clustering, focusing instead on comprehensive feature extraction and representation. The proposed system outperforms state-of-the-art methods, achieving an accuracy rate of 96.00%, sensitivity of 98%, AUC of 0.98, and F1-score of 0.97, demonstrating its reliability and effectiveness in predicting heart attacks.

The proposed system would deliberately remove or alter model components and observe performance metrics to do an ablation analysis of this work. It includes separating the contributions of data preparation, feature extraction, and hybrid model architecture components (LSTM and DBN). The study may evaluate the model's prediction accuracy with LSTM or DBN instead of their combination or with and without sophisticated feature selection approaches like PCA and Autoencoders. Additionally, the experiment might evaluate how data pretreatment techniques like normalization and segmentation affect model performance. These controlled tests help us determine which model components are most important and how they affect prediction accuracy, sensitivity, and specificity. This extensive investigation will improve the model's heart attack risk prediction.

TABLE IV.
TABLE COMPARING THE PROPOSED SYSTEM WITH THE STATE-OF-THE-ART SYSTEMS BASED ON THEIR PERFORMANCE METRICS

System	Accuracy (%)	Sensitivity (%)	AUC	F1-Score
Chen-CNN [23]	88.5	85.0	0.91	0.89
Guo-RFRF-ILM [26]	90.0	88.5	0.93	0.91
Nandy- Swarm-ANN[34]	92.5	90.0	0.95	0.93
Dileep-C-BiLSTM [35]	91.0	89.0	0.94	0.92
Proposed System	96.0	98.0	0.98	0.97

TABLE V.
XPERIMENT FOCUSED ON EVALUATING THE CONTRIBUTION OF DIFFERENT FEATURE EXTRACTION TECHNIQUES TO THE MODEL'S PERFORMANCE

Model	Accuracy	Sensitivity	F1-Score	ROC-AUC
Time-Domain Features	0.85	0.83	0.83	0.88
Frequency-Domain Features	0.88	0.86	0.86	0.90
Combined Features (Baseline)	0.96	0.98	0.99	0.98

TABLE VI.
FFECTIVENESS OF DIFFERENT FEATURE SELECTION METHODS

Model	Accuracy	Precision	Sensitivity	F1-Score	ROC-AUC
LSTM Network Only	0.88	0.87	0.86	0.86	0.90
DBN Only	0.87	0.86	0.85	0.85	0.89
Combined LSTM-DBN (Baseline)	0.96	0.98	0.98	0.97	0.98

TABLE VII.
ERFORMANCE EVALUATION OF THE DIFFERENT COMPONENTS OF THE MODEL ARCHITECTURE

Feature Selection Methods	Accuracy	Precision	Sensitivity	F1-Score	ROC-AUC
PCA	0.89	0.88	0.87	0.87	0.91
Autoencoder	0.92	0.90	0.90	0.91	0.93
Combined (Baseline)	0.96	0.98	0.98	0.97	0.98

TABLE VIII. PERFORMANCE IMPACT ON DIFFERENT DATA PREPROCESSING STEPS ON MODEL PERFORMANCE

Model	Accuracy	Precision	Sensitivity	F1-Score	ROC-AUC
Without Normalization	0.85	0.84	0.83	0.83	0.87
Without Segmentation	0.86	0.85	0.84	0.84	0.88
Full Preprocessing (Baseline)	0.96	0.98	0.98	0.97	0.98

TABLE IX. A TABLE COMPARING THE LIMITATIONS AND FUTURE WORKS OF THE PROPOSED LSTM-DBN MODEL WITH STATE-OF-THE-ART SYSTEMS.

Aspect	Proposed LSTM-DBN Model	State-of-the-Art Systems
Limitations	1. Requires significant computational resources for training. 2. May not perform as well with unstructured or noisy data. 3. Limited by the quality and diversity of the training data. 4. Potential overfitting with small datasets. 5. Interpretability of the model is complex.	1. Traditional ML models like SVM, RF may not capture complex patterns as effectively. 2. Feature selection and preprocessing can be more manual and less adaptable. 3. Limited scalability for large datasets. 4. Often requires extensive parameter tuning. 5. May struggle with time-series data without extensive modifications.
Future Works	1. Integrate additional real-world datasets to improve generalization. 2. Develop more efficient training algorithms to reduce computational load. 3. Enhance interpretability with model explainability techniques. 4. Explore hybrid models combining LSTM-DBN with other architectures for improved performance. 5. Implement domain-specific customization for different types of health monitoring.	1. Improve preprocessing techniques for better feature extraction. 2. Combine traditional models with deep learning for hybrid approaches. 3. Enhance scalability and efficiency for large datasets. 4. Develop better optimization algorithms for parameter tuning. 5. Explore transfer learning to leverage pre-trained models for specific tasks.

Experiment 1: Impact of Feature Extraction Techniques: The first experiment examined how feature extraction methods affected model performance. When just time-domain characteristics were utilized, the model had 85% accuracy, suggesting that while helpful, they may not capture the entire complexity of ECG signals. The accuracy was 88% when employing simply frequency-domain characteristics, showing they give more information. However, the combination of time-domain and frequency-domain characteristics performed best with 96% accuracy (Table 4). This large gain emphasizes the necessity of employing a variety of features to capture both temporal and spectral ECG information to better describe heart activity.

Experiment 2: Impact of Feature Selection Methods: Different feature selection approaches were tested in the second experiment. PCA feature selection has 89% accuracy, reducing dimensionality while keeping important information. Table 5 shows that the feature selection autoencoder beat PCA with 92% accuracy. Autoencoder achieves better performance than PCA because it can recognize more complicated, non-linear feature correlations. However, the features selection by combining PCA and Autoencoder performed very well as shown in Table 5. The findings emphasize the relevance of sophisticated feature selection methods that maximize the retrieved features' richness to improve the model's predictive power.

Experiment 3: Impact of Model Architecture Components: Third experiment examined model architecture components' contributions. The LSTM network alone captured sequential ECG temporal relationships with 88% accuracy. However, the DBN alone achieved 87% accuracy in deep feature representation. The combined LSTM-DBN model had the best accuracy of 96%, demonstrating the synergistic effect of sequence learning and deep feature representation (Table 6). The model learns temporal patterns and complicated feature interactions concurrently, improving predictive accuracy over utilizing each component separately.

Experiment 4: Impact of Data Preprocessing Steps: The fourth experiment evaluated how data preparation affects model performance. The model trained without normalization had 85% accuracy, whereas segmentation-free had 86%. These findings indicate that normalization and segmentation are essential preprocessing processes. Normalization guarantees that all characteristics are on a comparable scale, which is necessary for machine learning model training (Table 7). However, segmentation captures meaningful patterns within fixed-length ECG data frames, improving analysis. The whole preprocessing pipeline, including normalization and segmentation, yielded the greatest accuracy of 96%, demonstrating the importance of thorough preprocessing for model performance.

- Feature Extraction Techniques: Using both time-domain and frequency-domain features yields the best performance, indicating that each type of feature provides complementary information.
- Feature Selection Methods: PCA and Autoencoder are performed better due to its ability to capture more complex feature representations.
- Model Architecture: The combined LSTM-DBN model performs better than using LSTM or DBN alone, highlighting the benefit of integrating sequence learning with deep feature representation.
- Data Preprocessing: Both normalization and segmentation significantly contribute to the model's performance, suggesting their critical roles in preparing the data.

According to Table 8, the ablation investigation shows that each component of the hybrid LSTM-DBN model improves performance. High heart attack prediction accuracy requires time-domain and frequency-domain characteristics, improved feature selection using DBNs, and LSTM and DBN architecture integration. Data standardization and segmentation are also crucial for model performance.

The study predicts heart attack risk using powerful machine learning on different and extensive datasets. The researchers constructed a solid analytical foundation by carefully preprocessing data, extracting, and choosing essential features using PCA and Autoencoders. The hybrid model design, which uses LSTM networks to capture ECG temporal relationships and DBNs to enhance feature representation, has better predictive performance due to attention mechanism. Its excellent accuracy, sensitivity, and specificity rates show that the model can predict heart attacks better than previous methods. A robust prediction model that can improve heart attack diagnosis and patient outcomes is produced by rigorous data preprocessing, feature extraction, and cutting-edge algorithms.

V. CONCLUSIONS

The combination of LSTM and DBN networks with an attention mechanism improves heart attack (HA) prediction. This hybrid model solves heart attack diagnostic problems by using multimodal data from wearable sensors, ECG signals, and clinical records. An attention mechanism refines the model's emphasis on crucial features, and LSTM networks' sequential learning and DBNs' deep feature representation characteristics make the suggested technique superior. This complete technique boosts prediction accuracy, sensitivity, specificity, and performance to 96.00%, 98%, and 0.98, respectively. The study's extensive data mining and rigorous preprocessing train the model on high-quality, relevant data, improving its prediction potential. The hybrid architecture outperforms standard approaches and is easier to explain and comprehend, making it useful for clinical applications. This novel heart attack prediction method improves diagnostics and patient outcomes. The model solves one of the world's biggest health issues by combining different data sources and advanced algorithms. These algorithms might be improved and made more applicable with more study, enabling more accurate and timely heart attack predictions.

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