Available online at: http://www.advancedscientificjournal.com
http://www.krishmapublication.com
IJMASRI, Vol. 1, issue 1, pp. 109 - 115, Apr. -2025
https://doi.org/10.53633/ijmasri

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY ADVANCED SCIENTIFIC RESEARCH AND INNOVATION (IJMASRI)

ISSN: 2582-9130 **IBI IMPACTFACTOR 1.5** **DOI: 10.53633/IJMASRI**

RESEARCH ARTICLE

ELEVATE THE PREDICTIVE PERFORMANCE OF HEART DISEASE DETECTION USING DEEP SUPPORT LEARNING SYSTEM (DSLS)

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Abstract

Heart disease remain sale adding cause of mortality worldwide, underscoring the critical need for early and accurate detection methods. While traditional machine learning models such as Multilayer Perceptron (MLP) and Support Vector Machine (SVM) have demonstrated promise in heart disease prediction, their standalone application faces limitations in precision and sensitivity. This research introduces the Deep Support Learning System (DSLS), a combine model that synergizes MLP's feature learning and dimensionality reduction capabilities with SVM's robust classification performance. The DSLS model is evaluated using the Cleveland Heart Disease Dataset and Cardio vascular Disease Dataset, with preprocessing steps that include normalization, feature selection, and handling missing values. The proposed model provides a novel, efficient, and clinically applicable framework for heart disease prediction, offering significant potential to enhance preventive healthcare and patient outcomes.

Keywords: Heart Disease Prediction, Machine Learning, Deep Support Learning System (DSLS), Multilayer Perceptron (MLP), Support Vector Machine (SVM), Cleveland Heart Disease Dataset, Cardiovascular Disease Dataset, Early Detection, Healthcare Analytics.

Introduction

Heart disease is one of them ost prevalent causes of mortality world wide, accounting for approximately 17.9 million deaths annually, according to the World Health Organization (WHO). It encompasses a range of cardiovascular conditions, such as coronaryartery disease, heart attacks, and heart failure. While machine learning models like Multilayer Perceptron (MLP) and Support Vector Machine (SVM) have shown promise in predicting heart disease, each has limitations when used independently— MLP struggles with generalization,

and SVM lacks feature extraction capabilities. Advanced models like Bidirectional LSTM (BiLSTM) and Random Forest (RF) also face challenges, including high computational costs and sensitivity to class imbalance [4]. To address these limitations, this study proposes the Deep Support Learning System (DSLS), a hybrid model that combines MLP's feature learning strengths with SVM's robust classification capabilities. By leveraging the Cleveland Heart Disease and Cardiovascular Disease datasets, DSLS aims to enhance predictive performance, providing a novel approach to improving early heart disease detection.

There search utilizes the C level and Heart Disease Data set and Cardio vascular Disease Data set, two widely recognized sources of clinical and demographic data for heart disease research. The data sets a repreprocessed to address missing values, normalize features, and optimize the input for the hybrid architecture. The proposed DSLS model is compared against stand alone MLP, SVM, and existing state – of – the – art models such a Bidirectional LSTM (BiLSTM) and R and Forest (RF). The key objectives of this researchare to develop bust hybrid model (DSLS) for early heart disease prediction, To evaluate and compare the performance of with existing models and To assess predictive capabilities across comprehensive metrics, including Accuracy, Precision, Recall, Specificity, F1 Score, AUC-ROC, and AUC-PR.

This paper is organized as follows: Section 2 provides a comprehensive review of existing machine learning models and their limitations. Section 3 presents the Deep Support Learning System (DSLS) and its feature extraction and dimensionality reduction, classification layer for robust decision-making. Section 4 outlines the evaluation metrics and experimental setup, discusses the results and performance analysis. Finally, Sections 5 offer insights into the conclusions, and future research directions.

METHODOLOGY

Data sets

Thisstudyutilizestwowidelyrecognizeddatasetsforheartdiseaseprediction:the**ClevelandHeartDisease Dataset** and the **Cardiovascular Disease Dataset**.

These datasets provide a robust foundation for training and evaluating the proposed Deep Support Learning System (DSLS).

2.2.2FeatureSelectionMethods

Feature selection reduces dimensionality by identifying the most relevant predictors of heart disease, improving the performance and interpretability of models.

1. **Filter-BasedMethods:**
   - **Correlation Analysis:** Pearsonor Spearman correlation coefficients will be used to assess the relationship between features and the target variable. Highly correlated features (with r>0.7r > 0.7r>0.7) will be prioritized.

Correlation Analysis (Pearson Coefficient):

For two features X **and** Y**:**

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

Compute Pearson correlation coefficients to measure linear relationships between features and the target variable.

Chi-SquareTest:

Categorical predictors will be evaluated using the Chi-Square test to identify statistically significant associations with the target variable.
For categorical predictors:

$$x^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

Where, Oi and Ei are observed and expected frequencies, respectively.

2. **WrapperMethods**
3. **EmbeddedMethods**

- **LASSO (Least Absolute Shrinkage and Selection Operator):**

LASSO regularization will be applied to automatically select features by shrinking the

coefficients of less important predictors to zero. LASSO introduces a penalty to shrink coefficients:

$$min_w \left(\frac{1}{2n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 + \lambda \sum_{j=1}^{p} |w_j| \right)$$

Where w_j is the weight of the jth feature, λ is the regularization parameter, y_i is the observed output,

Apply LASSO regression to shrink coefficient sofless relevant predictors to zero. Example,

- Retained features: Age, BMI, and cholesterol levels with significant non-zero co efficients. The selected features will capture critical health indicators (e.g.,cholesterol, blood pressure, BMI) and demographic factors (e.g.,age,gender), ensuring a compact and relevant data set for training DSLS. By addressing missing values, scaling features, and selecting the most in formative predictors, the preprocessing pipeline ensures that the input data is clean, consistent, and optimized for the hybrid DSLS model, enhancing its ability to predict heart disease accurately.

Deep Support Learning System (DSLS): Model Architecture

The proposed Deep Support Learning System (DSLS) integrates a Multi-Layer Perceptron (MLP) for feature extraction and dimensionality reduction with a Support Vector Machine (SVM) for bust classification. This hybrid architecture leverages the strengths of both components to enhance predictive accuracy in heart disease diagnosis. Below is the detailed algorithm:

Step1: Data Input and Preprocessing

- **Input:**

X={x1,x2,…,xn} where xi is a feature vector with d dimensions, and y={y1,y2,…,yn} are the corresponding labels.

- **Preprocessing:**
  - Handle missing values, outliers, and normalize the dataset (refer to previous preprocessing steps).
  - Normalize feature x_i: Min – Max Scaling,

Where, Xjis the j-th feature across all samples.

Step2: MLP for Feature Extraction and Dimensionality Reduction

- **InputLayer:** The normalized data set X′. Each feature vector x_i' is fed into the input layer of the MLP.
- **Hidden Layers:** For each layer l:
  - Calculate the weighted sum:

$$x_j' = \frac{x_j - \min(X_j)}{\max(X_j) - \min(X_j)}$$

Where,

- $W^{(l)}$ is the weight matrix of layer.
- $b^{(l)}$is the bias vector flayer l.
- $a^{(l-1)}$is the activation output from the previous layer.
- Apply an activation function f:

$$a^{(l)} = f(z^{(l)})$$

Common activation functions:

- ReLU:f(z)=max(0,z)

- **Output Layer:** Output are duced feature vector X″ with dimensionality d′(d′<d).

Step3: SVM for Classification

1. **Input:**

The reduced feature set $X'' = \{x_1'', x_2'', \ldots, x_n''\}$

2. **Hyper plane Optimization:** The SVM finds a hyperplaneh (x) = w·x+b that separates the classes with the maximum margin.

Objective Function:

$$min_{w,b}\frac{1}{2}||w||^2$$

$$K(x_i, x_j) = exp(-\gamma||x_i - x_j||^2$$

Kernel Trick (if non linear): Use a kernel function K(xi,xj) to map input features to a higher-dimensional space.

- Radial Basis Function (RBF):

3. **Decision Function:** For a new samplex,

$$y = sign\left(\sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b\right)$$

Where, α_i are the Lagrange multipliers

Step 4: Training the DSLS Model

1. **TrainMLP:**OptimizeweightsWandbiasesbusing backpropagationandgradientdescent.

$$L_{MLP} = \frac{1}{n}\sum_{i=1}^{n}||y_i - \hat{y}_i||^2$$

- Lossfunction:

2. **Extract Features:** Pass input data through the trained MLP to obtain reduced features X″.
3. **Train SVM:** Use the extracted features X' 'to train the SVM.

Step 5: Model Evaluation

1. **Metrics:** Evaluate the DSLS using accuracy, precision, recall, F1-score, AUC-ROC and AUC-PR.
2. **Output:** The trained DSLS model for heart disease prediction.

The Deep Support Learning System (DSLS)

Integrates the strength so deep learning and machine learning to creat earobust system
for. The model is designed to leverage the feature extraction cap abilities of a Multi- Layer Perceptron (MLP) and the classification accuracy of a Support Vector Machine (SVM) [17] [18]. Each step in the DSLS algorithm is crucial for achieving high performance in prediction tasks.
The MLP acts as the feature extract or in the DSLS. It comprises an input layer, multiple hidden layers, and an output layer that produces a reduced feature setoutput layer that produces a reduced feature set.

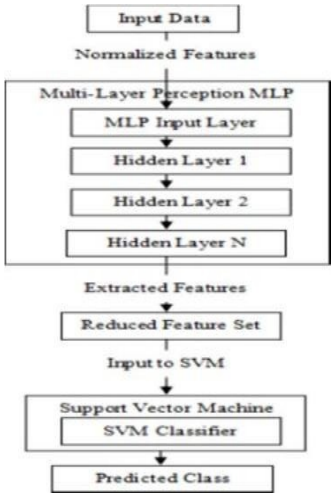

Figure1: Work flow of Deep Support Learning System (DSLS)

The reduced feature set generated by the MLP is passed as input to the SVM.

- **SVMK ernel**: A radial basis function (RBF) or linear kernel isused depending on the data's complexity. The kernel function transforms the input data into a higher dimensional space to achieve better class separability.
- **Decision Boundary**: The SVM identifies the optimal hyper plane that separates the data points of different classes.
- **Regularization**: SVM employs regularization parameters to control the trade-off between achieving low error on the training data and maintaining generalization. The DSLS algorithm offers several advantages over stand alone models:
- **MLP** efficiently handles high-dimensional data, extracts complex features, and reduces noise.
- **SVM** provides robust classification, especially incases of imbalanced data or overlapping classes.

The hybrid nature of DSLS combines the best of both approaches, leading to improved generalization and prediction accuracy.

By integrating MLP for feature extraction and dimensionality reduction with SVM for classification, DSLS addresses the limitations of standalone models and offers a powerful solution for heart disease prediction tasks.

Experimental result and disscussions

The experiments were conducted in a controlled computing environment with the following specifications:

The operating system used was Windows 7**,** and the system was equipped with **4GB RAM** and a **1T Bhard disk**. The processor was an **Intel Core i5** (or equivalent), and the programming language used for model development was **Python**. For implementing machine learning algorithms, the following libraries were employed: **Tensor Flow**, **Keras**, **Scikit-Learn**, **NumPy**, **Pandas**, and **Matplotlib**.

The hyper parameters for both the **Recurrent Neural Network (RNN)** and **Long Short-Term Memory (LSTM)** models were carefully tuned to ensure optimal performance. The settings for both models are as follows:

- **Learning Rate:** 0.001for both RNN and LSTM.
- **BatchSize:** 32 for both models.
- **Optimizer:** The **Adamoptimizer** was used for both RNN and LSTM.
- **DropoutRate:** 0.2 for both models to reduce over fitting.
- **Number of Layers:** Both models used 3 layers.
- **Number of Neurons per Layer:** 128, 64, and 32 neuronsin each layer for both RNN and LSTM.
- **Activation Function: ReLU** was used for the hidden layers, and **Sigmoid** was used for the output layer in both models.
- **Loss Function:** Both models used **Binary Cross-Entropy**.
- **Number of Epochs:** Both models were trained for100 epochs.
- **ValidationSplit:** 15% of the data was reserved for validation in both models.

The **Cardiovascular Disease Datase** contains **clinical and life style attributes** that influence heart disease risk. The dataset includes **features such as**:

Feature Name	Description
Age	Patient's Age
Gender	Male (1) / Female (0)
Blood Pressure	Systolican and Diastolic Bp
Cholestrol	Normal, above Normal, High
Glucose level	Normal, above normal, High
Smoking status	Smoker (1) / Non - smoker
Physical Activity	Active (1)/ Inactive (0)
Heart Disease (Target)	Present (1) / Absence (0)

Before training the model, **data preprocessing** was applied:

- **Handling Missing Values:** Imputation with mean / median values
- **Feature Scaling:** Min-max normalization
- **Encoding Categorical Variables:** One-hot encoding

This presents the performance evaluation **Recurrent Neural Networks (RNN)** and **Long Short-Term Memory (LSTM)** for heart disease detection using the **Cardio vascular Disease Dataset**. The models were assessed using key metrics such as **Accuracy**, **Precision**, **Recall**

Table1: Comparative Analysis of RNN vs. LSTM

Metric	RNN(%)	LSTM (%)
Accuracy	85.2	90.3
Precision	82.5	88.6
Recall	80.1	89.4
Specificity	87.6	91.2
F1Score	81.3	89.0

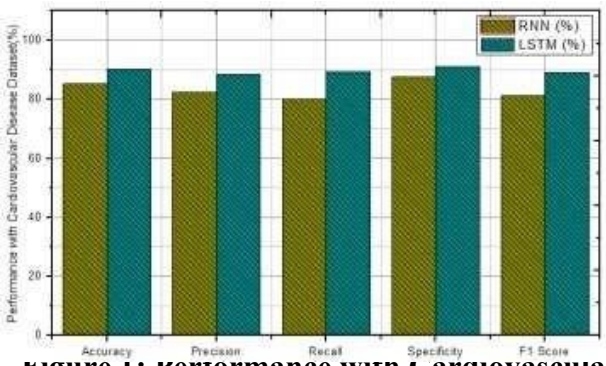

Figure 1: Performance with Cardiovascular Disease Dataset of RNN vs. LSTM

Table1 and Figure1 shown, LST Mout performs RNN across all metrics, achieving higher accuracy, precision, recall, specificity and F1-score. There call of LSTM is significantly higher (89.4%), indicating that it is better at identifying patients with heart disease. Furthermore, LSTM has fewer false negatives (FN), meaning fewer undiagnosed cases compared to RNN. On the other hand, RNN struggles with long-term dependencies, which makes it less effective than LSTM in capturing complex temporal patterns, leading to lower performance.

LSTM is superior due to its ability to handle long-term dependencies and efficiently processs equential medical

- BetterMemoryRetention
- Gradient-DrivenOptimization
- HigherAccuracyinMedical Predictions
- ReducedFalseNegatives
- WorksWellwithLimited Data

Conclusion

In this paper, we investigated the effectiveness of Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) for heart disease detection using the Cardio vascular Disease Dataset. The models were evaluated using key performance metrics, including Accuracy, Precision, Recall (Sensitivity), Specificity, and F1 Score. The results demonstrated that LSTM significantly out performs RNN, achieving higher accuracy (90.3%), indicating better overall predictive performance, improved recall (89.4%), which reduces the risk of false negatives (un diagnosed cases), superior precision (88.6%), ensuring reliable predictions with fewer false positives, and better specificity (91.2%), meaning the model correctly identifies

dropout regularization, prevents vanishing and exploding gradients ,thus improving training stability. Additionally, LSTM's ability to capture complex temporal dependencies in patient records leads to better risk assessment. The proposed LSTM model can serve as are liable tool for early heart disease detection, aiding healthcare professionals in their decision-making process. Although LSTM demonstrated superior performance, there are several areas for improvement and further research:

- Extend the study by integrating Convolutional NeuralNetworks(CNN)withLSTM forenhanced feature extraction and sequence learning.
- Expand the data set to include additional sources like Framingham Heart Study, MIMIC-III, or real-time clinical data. Address potential biases by training models on diverse patient populations.
- Investigate the impact of advanced feature selection methods (e.g., SHAP, PCA) on model performance .Implement Explainable AI (XAI) techniques to provide transparent and interpretable model predictions.

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