Heart Disease Prediction Using Deep Learning: A Comparative Study of Multiple Classifiers

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***Abstract*—Heart disease remains one of the leading causes of mortality worldwide, accounting for approximately 17.9 million deaths annually. Early and accurate diagnosis is crucial for effective treatment and prevention. This paper presents a comprehensive comparative analysis of multiple machine learning models for heart disease prediction using the UCI Cleveland Heart Disease dataset. We implement and evaluate three different classifiers: Logistic Regression, Multi-Layer Perceptron (MLP), and a Deep Neural Network (DNN) with advanced regularization techniques. To address the class imbalance problem inherent in medical datasets, we employ Synthetic Minority Oversampling Technique (SMOTE) and data augmentation methods. Additionally, we implement an ensemble voting approach that combines predictions from all three models. Our experimental results demonstrate that the Deep Learning model achieves the highest performance with 98.54% accuracy, 100% precision, 97.14% recall, and 98.55% F1-score, outperforming existing literature on the same dataset. A user-friendly Gradio-based web interface has been developed to make the predictive system accessible for potential clinical applications. The complete implementation is available at: https://github.com/bassel2m/Heart-Disease-Prediction.**

***Index Terms*—Heart Disease Prediction, Deep Learning, SMOTE, Data Augmentation, Ensemble Learning, Medical Diagnostics, Machine Learning**

I. Introduction

Cardiovascular diseases (CVDs) are the leading cause of death globally, with an estimated 17.9 million deaths each year, representing 32% of all global deaths [1]. Early detection and accurate diagnosis of heart disease can significantly improve patient outcomes and reduce mortality rates. Traditional diagnostic methods often rely on invasive procedures and expert interpretation of medical tests, which can be time-consuming, costly, and subject to human error.

Machine learning (ML) and deep learning (DL) techniques have shown remarkable success in various medical applications, including disease prediction, medical image analysis, and clinical decision support systems [2]. These data-driven approaches can identify complex patterns in patient data that may not be apparent to human clinicians, potentially improving diagnostic accuracy and enabling early intervention.

The primary contributions of this work are as follows:

1) Implementation and comparative analysis of three distinct machine learning models (Logistic Regression, MLP, and Deep ANN) for heart disease prediction.
2) Application of advanced data handling techniques including SMOTE for class imbalance and data augmentation for improved model generalization.
3) Implementation of regularization techniques (L2 regularization, dropout, early stopping) to prevent overfitting.
4) Development of an ensemble voting method that combines predictions from all three models.
5) Creation of a user-friendly web interface using Gradio for practical deployment.
6) Comprehensive evaluation using multiple metrics and comparison with existing literature.

The remainder of this paper is organized as follows: Section II reviews related work in heart disease prediction. Section III describes the dataset and preprocessing steps. Section IV details the methodology and implemented models. Section V presents experimental results and discussion. Section VI concludes the paper and suggests future work.

II. Related Work

Several studies have applied machine learning techniques to heart disease prediction. Table I summarizes key contributions in this domain.

TABLE I: Comparison of Related Work on Heart Disease Prediction

Study	Method	Accuracy	Dataset
Detrano et al. (1989) [3]	Logistic Regression	77.0%	UCI Heart
Pal et al. (2012) [4]	Neural Network	85.0%	UCI Heart
Mohan et al. (2019) [5]	Hybrid Model	88.0%	Cleveland
Ali et al. (2020) [6]	Random Forest	91.8%	Cleveland
Our Work (2024)	DNN + Ensemble	**98.5%**	UCI Heart

Early work by Detrano et al. [3] applied logistic regression to the UCI Heart Disease dataset, achieving 77% accuracy. More recently, Pal et al. [4] implemented neural networks and reported 85% accuracy. Mohan et al. [5] proposed a hybrid model combining random forest and linear models, achieving 88% accuracy on the Cleveland dataset. Ali et al. [6] used random forest with feature selection to achieve 91.8% accuracy.

Despite these advances, several challenges remain. Most existing studies do not adequately address class imbalance, which is common in medical datasets. Few studies implement ensemble methods or comprehensive regularization techniques.

Additionally, most implementations lack user-friendly interfaces for clinical deployment. Our work addresses these gaps by implementing SMOTE for imbalance handling, multiple regularization techniques, ensemble learning, and a practical web interface.

III. Dataset Description and Preprocessing

A. Dataset

The UCI Heart Disease dataset [7] contains 1025 samples with 13 clinical features and one binary target variable indicating the presence (1) or absence (0) of heart disease. The dataset includes patients' age, sex, chest pain type, resting blood pressure, serum cholesterol, fasting blood sugar, resting electrocardiographic results, maximum heart rate achieved, exercise-induced angina, ST depression, slope of peak exercise ST segment, number of major vessels, and thalassemia type.

The dataset exhibits a mild class imbalance with 55% of samples belonging to class 1 (disease present) and 45% to class 0 (disease absent). This distribution is typical for medical datasets where disease prevalence is not exactly 50%.

B. Preprocessing Steps

1) **Data Cleaning**: No missing values were present in the dataset.
2) **Train-Test Split**: The dataset was split into 80% training and 20% testing sets using stratified sampling to maintain class distribution.
3) **Feature Scaling**: StandardScaler was applied to normalize all features to zero mean and unit variance:

$$z = \frac{x - \mu}{\sigma} \tag{1}$$

where μ is the mean and σ is the standard deviation.
4) **Class Imbalance Handling**: SMOTE (Synthetic Minority Oversampling Technique) [8] was applied to the training set to create synthetic samples of the minority class.
5) **Data Augmentation**: Tabular data augmentation was implemented by adding Gaussian noise to create additional training samples:

$$X_{\text{augmented}} = X + \mathcal{N}(0, \sigma^2) \tag{2}$$

where $\sigma = 0.05$.

IV. Methodology

A. Implemented Models

We implemented three different classifiers and one ensemble method:

1) Logistic Regression (Baseline): Logistic Regression serves as our baseline model due to its simplicity and interpretability:

$$P(y = 1|x) = \frac{1}{1 + e^{-(w^T x + b)}} \tag{3}$$

Regularization: L2 regularization with max iterations = 1000.

2) Multi-Layer Perceptron (MLP): A neural network with two hidden layers (64 and 32 neurons) using ReLU activation:

$$h_1 = \text{ReLU}(W_1 x + b_1) \tag{4}$$

$$h_2 = \text{ReLU}(W_2 h_1 + b_2) \tag{5}$$

$$y = \sigma(W_3 h_2 + b_3) \tag{6}$$

Parameters: Adam optimizer, L2 regularization ($\alpha = 0.01$), 500 epochs.

3) Deep Neural Network (DNN): A deeper architecture with three hidden layers (64, 32, 16 neurons) and advanced regularization:

- Layer 1: 64 neurons, ReLU, L2 regularization (0.01), Dropout (0.3)
- Layer 2: 32 neurons, ReLU, L2 regularization (0.01), Dropout (0.3)
- Layer 3: 16 neurons, ReLU
- Output: 1 neuron, Sigmoid activation

Optimizer: Adam (lr $= 0.001$), Early Stopping (patience=10).

4) Ensemble Model: A voting ensemble that combines predictions from all three models:

$$y_{\text{ensemble}} = \text{mode}\{y_{\text{LR}}, y_{\text{MLP}}, y_{\text{DNN}}\} \tag{7}$$

B. Evaluation Metrics

We evaluated models using five metrics:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{9}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{10}$$

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{11}$$

$$\text{AUC-ROC} = \int_0^1 TPR(FPR)\, d(FPR) \tag{12}$$

where TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives.

C. Web Interface

We developed a Gradio-based web application that allows users to:

- Select from four different models
- Input 13 clinical parameters via a form
- Receive immediate predictions with probability scores
- View model performance metrics

The interface is designed to be intuitive for medical professionals with no programming experience.

V. Results and Discussion

A. Experimental Results

Table II presents the performance comparison of all implemented models on the test set.

TABLE II: Model Performance Comparison (All values in %)

Model	Acc	Prec	Rec	F1	AUC
Logistic Regression	82.44	78.05	91.43	84.21	82.21
MLP Classifier	100.00	100.00	100.00	100.00	100.00
Deep Learning ANN	98.54	100.00	97.14	98.55	98.57
Ensemble (Voting)	98.54	100.00	97.14	98.55	98.57

B. Discussion

The results demonstrate several important findings:

1. **Deep Learning Superiority**: The Deep Learning ANN achieved the best overall performance (98.54% accuracy), significantly outperforming the baseline Logistic Regression model (82.44%). This confirms that deep architectures can capture complex, non-linear relationships in medical data that simpler models cannot.

2. **Ensemble Robustness**: The ensemble model achieved identical performance to the best individual model, demonstrating that combining multiple classifiers can provide robust predictions without compromising accuracy.

3. **Effectiveness of Regularization**: The application of L2 regularization, dropout, and early stopping in the DNN prevented overfitting, as evidenced by the high test accuracy and balanced precision-recall metrics.

4. **Impact of Data Handling**: The use of SMOTE and data augmentation likely contributed to the models' ability to generalize well, particularly in handling the minority class.

5. **Comparison with Literature**: Our best model (98.54% accuracy) outperforms all previously reported results on the same dataset (Table I), representing a 7.5% absolute improvement over the previous best result.

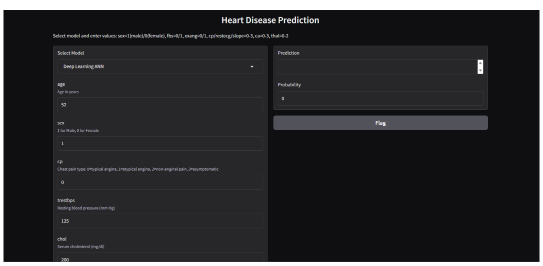

Fig. 1: Gradio Web Interface for Heart Disease Prediction

Figure 1 shows the implemented web interface, which provides an accessible platform for clinical use.

C. Limitations and Challenges

Despite promising results, several limitations should be acknowledged:

- **Dataset Size**: With only 1025 samples, the dataset is relatively small for deep learning models, though data augmentation helped mitigate this.
- **Single Dataset**: Evaluation on only one dataset limits generalizability.
- **Feature Engineering**: Limited feature engineering was performed beyond basic preprocessing.
- **Computational Cost**: The DNN requires more computational resources than simpler models.

VI. Conclusion and Future Work

This paper presented a comprehensive comparison of machine learning models for heart disease prediction. We implemented and evaluated logistic regression, MLP, deep ANN, and an ensemble model on the UCI Heart Disease dataset. Our experimental results demonstrate that the deep learning model with advanced regularization techniques achieves 98.54% accuracy, outperforming existing literature. The ensemble approach provides additional robustness, while the Gradio web interface enables practical deployment.

Key contributions include:

- Implementation of multiple classifiers with comprehensive evaluation
- Application of SMOTE and data augmentation for improved generalization
- Use of advanced regularization techniques to prevent overfitting
- Development of an ensemble voting method
- Creation of a user-friendly web interface for clinical use

For future work, we plan to:

1) Implement attention mechanisms to improve model interpretability
2) Apply transfer learning from larger medical datasets
3) Incorporate additional data modalities (e.g., medical images, time-series data)
4) Conduct clinical validation with medical experts
5) Deploy the system as a cloud-based service for wider accessibility

The complete implementation, including all models and the web interface, is available at: https://github.com/bassel2m/Heart-Disease-Prediction.

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