

A Dual-Framework Approach for Improved Heart Disease Detection: CGAN-Based Data Augmentation and DAE Driven Feature Extraction

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ABSTRACT

This study proposes two different frameworks that incorporate Deep Learning (DL) and Machine Learning (ML) for enhancing heart disease detection across Cleveland, Erbil, and Comprehensive datasets. The first framework integrated Conditional Generative Adversarial Networks (CGANs) with a Random Forest (RF) classifier optimized using the Categorical and Continuous Covariance Matrix Adaptation (CatCMA) algorithm, while the second one utilized a Denoising Autoencoder (DAE) with a Voting Ensemble composed of three classifiers: Support Vector Machine (SVM), Multilayer Perceptron (MLP), and RF. The results showed that both frameworks achieved a higher level of performance compared to traditional methods, with an accuracy of up to 97.01% and 100% recall. Overall, the integration of data augmentation and feature enhancement with optimized classification models seems to be a potential technique for heart disease prediction. Future studies should explore the real-time implementation of various data integration methods to enhance the connection between research and clinical practice.

Keywords-heart disease prediction; machine learning; deep learning; CGAN; denoising autoencoder

I. INTRODUCTION

In 2019, 32% of global deaths were due to cardiovascular disease [1]. The early detection of heart disease remains demanding due to the nature of diagnostic parameters and the subjective elements used in conventional clinical evaluation [2]. The transformative potential of Artificial Intelligence (AI), particularly DL and ML, has been demonstrated across diverse fields, from student performance prediction and social media analysis to advanced medical applications like chest radiograph image retrieval [3-7]. Recent studies have investigated the benefits of AI in heart disease detection, employing techniques, like Artificial Neural Networks (ANNs) [8], ensemble learning [9], feature selection methods [10], and Automated ML (AutoML) [11]. However, numerous models struggle with generalizability, noisy data, feature, and sample limitations [12,

13]. These limitations can lead to overfitting or low tolerance models, increasing the need for more robust and adaptable solutions.

To tackle these persistent issues, this study introduces a dual-framework strategy that incorporates the power of data augmentation, enhanced feature engineering, and ensemble modeling. The first frame employed CGANs to generate class-specific synthetic samples, while the second one utilized a DAE to extract features that were resilient to noise and irrelevant variability.

II. RELATED WORK

The detection of heart disease using both ML and DL has been explored through different algorithms [14]. For instance, authors in [15] utilized a Sparse Autoencoder (SAE) on a

dataset that combined records from five independent sources in order to increase the number of features from 11 to 200 for better results. Their method with Convolutional Neural Network (CNN) exhibited a high accuracy of 90.08%. Additionally, authors in [16], aimed to predict the probability of heart disease utilizing accurate ML models on large real datasets. To achieve this, they utilized k-modes clustering and feature engineering with traditional ML algorithms, such as RF, Decision Tree (DT), MLP, and XGBoost (XGB). MLP achieved the highest accuracy of 87.28%. In [17], eleven independent ML algorithms (e.g., DT, SVM, and Logistic Regression) and 4 Stacking ensemble models with hyperparameter optimization (using GridSearch CV) were employed to detect heart disease. The development of a web interface was also involved using the Ada-Boost-SVM model with hyperparameters that achieved the highest accuracy (88.24%) and ROC Curve (92.00%) to make the detection easier. Authors in [18] integrated their method with optimized ML algorithms for the detection of heart disease. Specifically, they utilized various wearable sensors to collect data and transmit them to the cloud, where the RF classifier outperformed the other proposed classifiers. The Moth Flame Optimization (MFO) algorithm was utilized to select the most significant features. Authors in [19] proposed a system by utilizing a CNN-based denoise autoencoder followed by DL models for automated Atrial Fibrillation (AFib) classification. Denoising Stacked Autoencoders (DAE) were employed to enhance the Electrocardiogram (ECG) signal quality, then passed to an optimized deep classifier, particularly CNN and Bidirectional Long Short-Term Memory (BiLSTM), which demonstrated strong performance. In [20], a Fully-Gated Denoising Auto-Encoder (FGDAE) was developed, which integrated gated convolutions, self-organized Operational Neural Networks (self-ONNs), and U-Net architecture to reduce noise in ECG signals. FGDAE showed better performance in noise reduction, especially in noise and ambulatory environments, which is important for accurate heart disease detection. In [21, 22], authors used autoencoders for classification on tabular data on telecommunications, which exhibit similar aspects with heart disease. The findings indicated that autoencoders outperformed the traditional methods in capturing nonlinear relationships. In [23], CGANs were used to reconstruct a 12-lead ECG signal from a single input signal to narrow the gap between the wearable devices and clinical-grade systems. This raised the accuracy from 71% to 74%. In another application, a proposed CGAN simulated cardiac aging in MRI scans by training it on over 14,000 heart images from the UK Biobank [24]. In [25], an Improved DAE (IDAE) was developed with residual connections for Hepatitis C diagnosis. Compared to standard classifiers and other autoencoder variants, IDAE achieved 99% accuracy. Similarly, in [26] authors used DAEs to extract features from lung cancer transcriptomic data. They analyzed 1900 samples for 13 studies to extract the most compact genes and predict patients better than traditional biomarkers.

III. METHODOLOGY

This study proposed two novel frameworks for heart disease detection by integrating DL methods for data

augmentation and feature extraction with ML techniques for classification. Figure 1 illustrates an overview of the current approach.

A. Framework 1: CGAN for Data Augmentation

The first framework utilized a CGAN to generate synthetic samples. CGAN is a variant of GAN that conditions the data generation process on class labels, enabling the production of class-specific synthetic instances. CGAN was trained only on the training part of the dataset, as shown in Figure 2, to avoid data leakage. In this setup, the generator learned the real data distribution, while the discriminator network was designed to differentiate between real and synthetic samples. The synthetic samples were combined with the original dataset to boost data variety and improve model generalization. Both the generator and discriminator were implemented as MLPs. The generator consisted of two hidden layers with 256 neurons each and an embedding dimension of 128, trained with a learning rate of 0.0002 and weight decay of $1e-6$. The discriminator also had two hidden layers with 256 neurons each, trained with the same learning rate and weight decay. The model was trained for 100 epochs with a batch size of 500, updating the discriminator once per generator step. A PAC of 10 was used to group samples in the discriminator. Conditional sampling was applied to preserve the distributions of categorical features, enabling the CGAN to generate high-quality synthetic tabular data that maintain correlations between continuous and categorical features, thereby enhancing classifier performance.

An RF classifier was selected due to its robustness, flexibility, and ability to learn complex patterns in datasets, as well as dealing with mixed input features, including continuous and categorical variables. To enhance RF performance, the CatCMA optimizer was utilized, as depicted in Figure 3.

CatCMA is useful for optimizing mixed hyperparameter types (categorical and continuous) [27]. The hyperparameter search space was selected based on common recommendations in the literature and preliminary experiments. The optimized RF hyperparameters included number of trees ($n_{estimators}$): [10, 50, 100, 200], maximum depth (max_{depth}): [None, 10, 20, 30], minimum samples per split ($min_{samples_split}$): [2, 5, 10], and minimum samples per leaf ($min_{samples_leaf}$): [1, 2, 4].

B. Framework 2: DAE for Feature Extraction

The second framework utilized a DAE for feature extraction in order to enhance the quality of the feature that will feed into the classifier (Figure 4). A DAE is a specialized neural network trained to reconstruct clean input data from a corrupted (noisy) version. This process helped the model to learn robust feature representations.

In the current implementation, DAE was trained on a noisy version of the training part of the data until the difference between the original input and the decoder output was minimized. A transformer-based body network was used with 3 hidden layers, with a size of 1024 neurons to encode and decode input features. A small amount of input corruption was applied with a swap noise probability of 0.01 to improve the model's robustness.

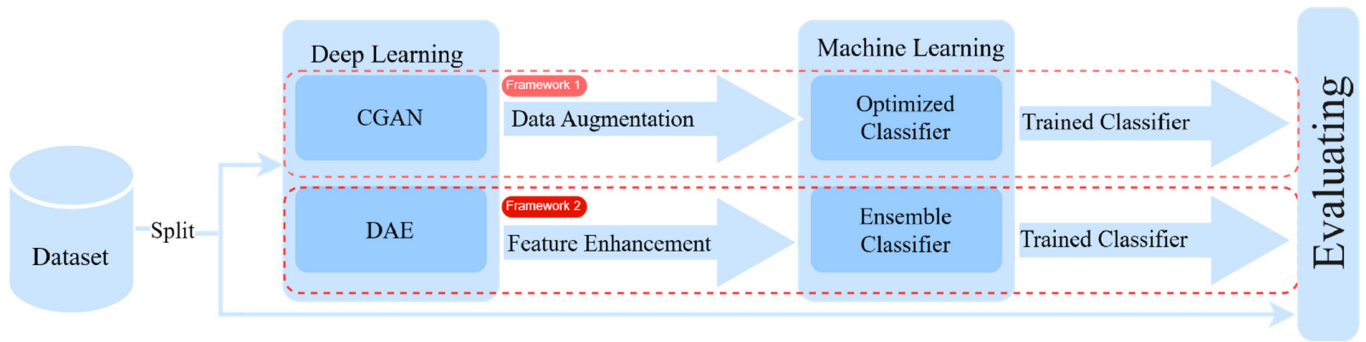


Fig. 1. Proposed dual-framework design for heart disease classification using CGAN, DAE.

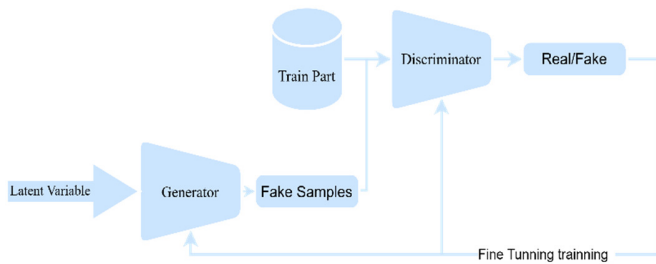


Fig. 2. Framework 1-Part 1: CGAN training workflow.

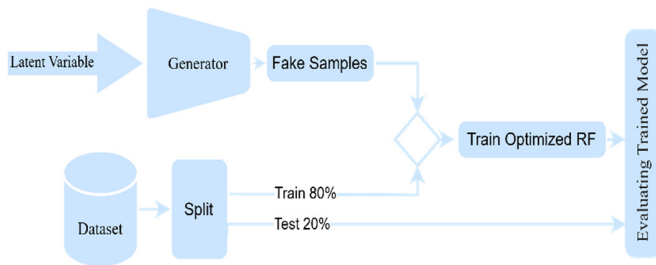


Fig. 3. Framework 1-Part 2: synthetic data augmentation and RF pipeline.

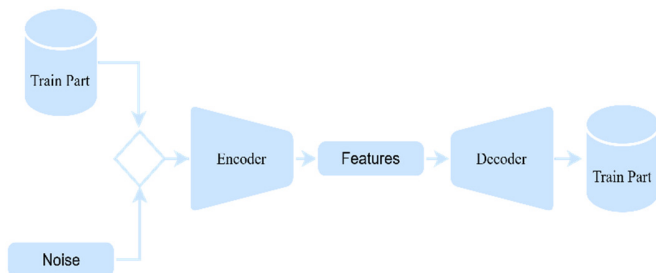


Fig. 4. Framework 2-Part 1: DAE training process.

Once training was completed, the encoder part was retained and used as a feature extractor to transform the original dataset into a more informative representation (Figure 5). After feature extraction, a voting ensemble classifier was employed by combining three models: SVM, MLP, and RF. Each model was selected carefully based on classifier characteristics. Specifically, SVM was chosen due to its highly effectiveness in high-dimensional spaces and workability even when the number of features is greater than the number of samples. MLP is a type of ANN that excels at capturing complex patterns and non-linear relationships in data, while RF is an ensemble-based

DT method that provides high accuracy and robustness to noise.

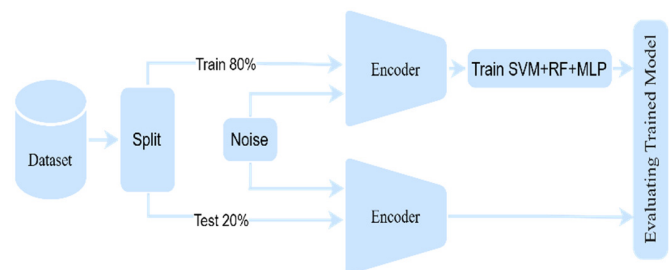


Fig. 5. Framework 2-Part 2: feature extraction and ensemble classification pipeline using SVM, MLP, and RF.

C. Datasets

Three distinct datasets were utilized, each comprising a variety of categorical and continuous features that are indispensable for heart disease detection. These datasets were divided into a 20% testing set and an 80% training set. The random state parameter was fixed at 42 to ensure reproducibility. This was accomplished by employing the train test split function from the scikit-learn library.

1) Heart Disease Cleveland

This dataset consists of 303 samples, with 14 columns (13 features and 1 target). The dataset contains a mix of 8 categorical features and 5 continuous features, such as age, sex, and chest pain type [28]. The features of the Heart Disease Cleveland dataset and their descriptions are presented in Table I.

2) Erbil Heart Disease

This dataset includes 333 samples after dropping the missing values, with 21 columns (20 features and 1 target). The features were divided into five categories: patient demographic, patient medical history, physical and symptomatic examinations, medical lab tests, and diagnostic features [29] (Table II).

3) Heart Disease Dataset (Comprehensive)

This dataset, derived from the amalgamation of data from five sources, consists of 1190 instances, with 12 columns (11 features and 1 target). These features included demographic, clinical, and diagnostic attributes relevant to heart disease prediction [30], and are displayed in Table III.

TABLE I. HEART DISEASE CLEVELAND FEATURES

Feature	Description	Values/range
Age	Patient's age in years	Any positive integer
Sex	Gender	0 (Female), 1 (Male)
Cp	Type of chest pain	0: Typical Angina, 1: Atypical Angina, 2: Non-anginal Pain, 3: asymptomatic
Trestbps	Blood pressure at rest (mm/Hg)	Any positive integer
Chol	Serum cholesterol in mg/dl	Any positive integer
Fbs	Fasting blood sugar level (>120 mg/dl is true, otherwise false)	0 (False), 1 (True)
Restecg	ECG result at rest	0: Normal, 1: ST-T wave abnormality, 2: Left ventricular hypertrophy
Thalach	Maximum heart rate achieved	Any positive integer
Exang	Angina induced by exercise	0 (No), 1 (Yes)
Oldpeak	Exercise induced ST depression relative to rest state	Any real number (could be negative or positive)
Slope	ST segment slope during peak exercise	0: Up sloping, 1: Flat, 2: Down sloping
Ca	Number of major vessels (0-3)	0, 1, 2, 3
Thal	Blood disorder (Thalassemia)	0: NULL, 1: Normal blood flow, 2: Fixed defect, 3: Reversible defect
Target	Target variable (heart disease prediction)	0: Normal, 1: Heart disease

TABLE II. ERBIL HEART DISEASE FEATURES

Feature	Description	Values/range
Age	Age of patients in years	Any positive integer
Sex	Gender of the patient	0: Male, 1: Female
Smoking	If the patient smokes or not	0: No, 1: Yes
Years	Number of years of smoking, if smoker	Positive integer or 0 (if non-smoker)
LDL	LDL-Cholesterol ratio	Any positive float
Chp	Chest pain type	1: Typical angina, 2: Atypical angina, 3: Non-anginal pain, 4: Asymptomatic
Height	Height of the patient in cm	Any positive number
Weight	Weight of the patient in kg	Any positive number
FH	Family history of heart disease	0: No, 1: Yes
Active	If the patient is active	0: No, 1: Yes
Lifestyle	Place of living	1: City, 2: Town, 3: Village
CI	Cardiac intervention history	0: No, 1: Yes
HR	Heart Rate ratio	Any positive number
DM	Diabetes status	0: No, 1: Yes
Bpsys	Systolic blood pressure ratio	Any positive number
Bpdias	Diastolic blood pressure ratio	Any positive number
HTN	Hypertension status	0: No, 1: Yes
IVSD	Interventricular septal diastole measurement (echo parameter)	Any positive number
ECGpatt	ECG test result	1: ST-Elevation, 2: ST-Depression, 3: T-Inversion, 4: Normal
Qwave	Presence of Q wave	0: No, 1: Yes
Target	Heart disease status	0: Without heart disease, 1: With heart disease

TABLE III. HEART DISEASE DATASET (COMPREHENSIVE) DATASET FEATURES

Feature	Description	Values/range
Age	Patient's age in years	Any positive integer
Sex	Patient's gender	0 (Female), 1 (Male)
Chest pain	Types of chest pain experienced	1: Typical Angina, 2: Atypical Angina, 3: Non-anginal Pain, 4: Asymptomatic
Resting bp s	Resting blood pressure in mmHg	Any positive integer
Cholesterol	Serum cholesterol level in mg/dL	Any positive integer
Fasting sugar	Indicates if fasting blood sugar is >120 mg/dL	0 (No), 1 (Yes)
Resting ecg	Results of resting electrocardiogram	0: Normal, 1: Abnormal, 2: Left ventricular hypertrophy (LVH)
Max heart rate	Maximum heart rate achieved during testing	Any positive integer
Exercise angina	Exercise-induced angina (1: Yes, 0: No)	0 (No), 1 (Yes)
Oldpeak	ST depression induced by exercise relative to rest	Any real number (could be negative or positive)
ST slope	Slope of the ST segment during peak exercise	0: Normal, 1: Upsloping, 2: Flat, 3: Downsloping
Target	Target variable indicating heart disease (1: Disease, 0: No Disease)	0 (No Disease), 1 (Disease)

D. Evaluation Metrics

1) Accuracy

The proportion of correct predictions to the total number of predictions is calculated as:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

2) Precision

Precision describes the proportion of true positive predictions to the total number of instances predicted as positive. It is expressed as:

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

3) Recall

Recall measures the number of the actual positives that the model correctly identifies and is calculated as:

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

4) F1 Score

The F1 Score gives a harmonic idea about the Precision and Recall metrics. It reaches its peak value when Precision matches Recall. It is calculated as:

$$\text{F1 score} = 2 \times \left(\frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \right) \quad (4)$$

IV. RESULTS

Tables IV and V present the results of the two frameworks and their comparison with other models. Figure 6 illustrates the confusion matrices of both frameworks. It is important to note that the proposed frameworks incorporated optimization and feature extraction techniques (CatCMA and DAE) that are inherently stochastic, and the experiments were conducted in the Google Colab environment, where variations in hardware allocation and runtime conditions may occur.

TABLE IV. COMPARATIVE PERFORMANCE OF PROPOSED METHODS VERSUS BASELINE MODELS ON THREE DATASETS

Dataset	Method	Accuracy	Precision	Recall	F1
Cleveland	RF	78.68	78.66	78.68	78.65
	LR	83.61	83.84	83.61	83.63
	SVM+LDA	88.85	87.88	90.62	89.23
	RF +PCA	70.49	75.00	65.62	70.00
	LR +MI	86.89	87.50	87.50	87.50
	Framework 1	90.16	81.82	100	90.00
Erbil	Framework 2	91.80	89.66	92.86	91.23
	RF	64.18	41.19	64.18	50.18
	LR	79.10	80.35	79.10	77.44
	LR+PCA	61.19	58.82	34.48	43.48
	RF +MI	91.04	82.86	100	90.62
	Framework 1	97.01	97.67	97.67	97.67
Comprehensive	Framework 2	95.52	97.62	95.35	96.47
	RF	79.41	77.3	86.51	81.65
	LR	74.37	75.19	76.98	76.08
	RF +PCA	82.77	84.09	84.73	84.41
	LR +MI	84.03	83.45	88.55	85.93
	Framework 1	88.66	87.22	92.06	89.58
	Framework 2	91.6	93.44	90.48	91.94

TABLE V. ACCURACY COMPARISON BETWEEN PROPOSED METHODS AND EXISTING APPROACHES ACROSS DATASETS

Reference	Dataset	Method	Accuracy
[31]	Cleveland	ANN	88.44
[32]	Cleveland	Ensemble Learning	86.88
[33]	Cleveland	Naïve Bayes	86.60
[34]	Cleveland	SBO Algorithm	90.00
[35]	Cleveland	Q-Learning	87.98
[36]	Cardiovascular Disease	Neural Networks	80.89
Proposed work	Erbil	Framework 1	97.01
Proposed work	Erbil	Framework 2	95.52
Proposed work	Cleveland	Framework 1	90.16
Proposed work	Cleveland	Framework 2	91.80
Proposed work	Comprehensive	Framework 1	88.66
Proposed work	Comprehensive	Framework 2	91.6

A. Performance of Framework 1 (CGAN and RF with CatCMA Optimizer)

Framework 1 achieved high performance across all datasets, outperforming the state-of-the-art methods. On the Cleveland dataset, it exhibited an accuracy of 90.16%, precision of 81.82%, recall of 100%, and F1-score of 90.00%. On the Erbil data, the accuracy was 97.01%, precision 97.67%, recall 97.67%, and F1-score 97.67%. For the Comprehensive

Dataset, the model reached an accuracy of 88.66%, precision of 87.22%, recall of 92.06%, and F1-score of 89.58%.

The integration of CGAN for synthetic data generation and the CatCMA-optimized RF significantly improved generalization, particularly on the Erbil dataset, where it surpassed all baseline methods, as demonstrated in Table IV. The perfect recall (100% on Cleveland) confirms the model's robustness in identifying true positive cases.

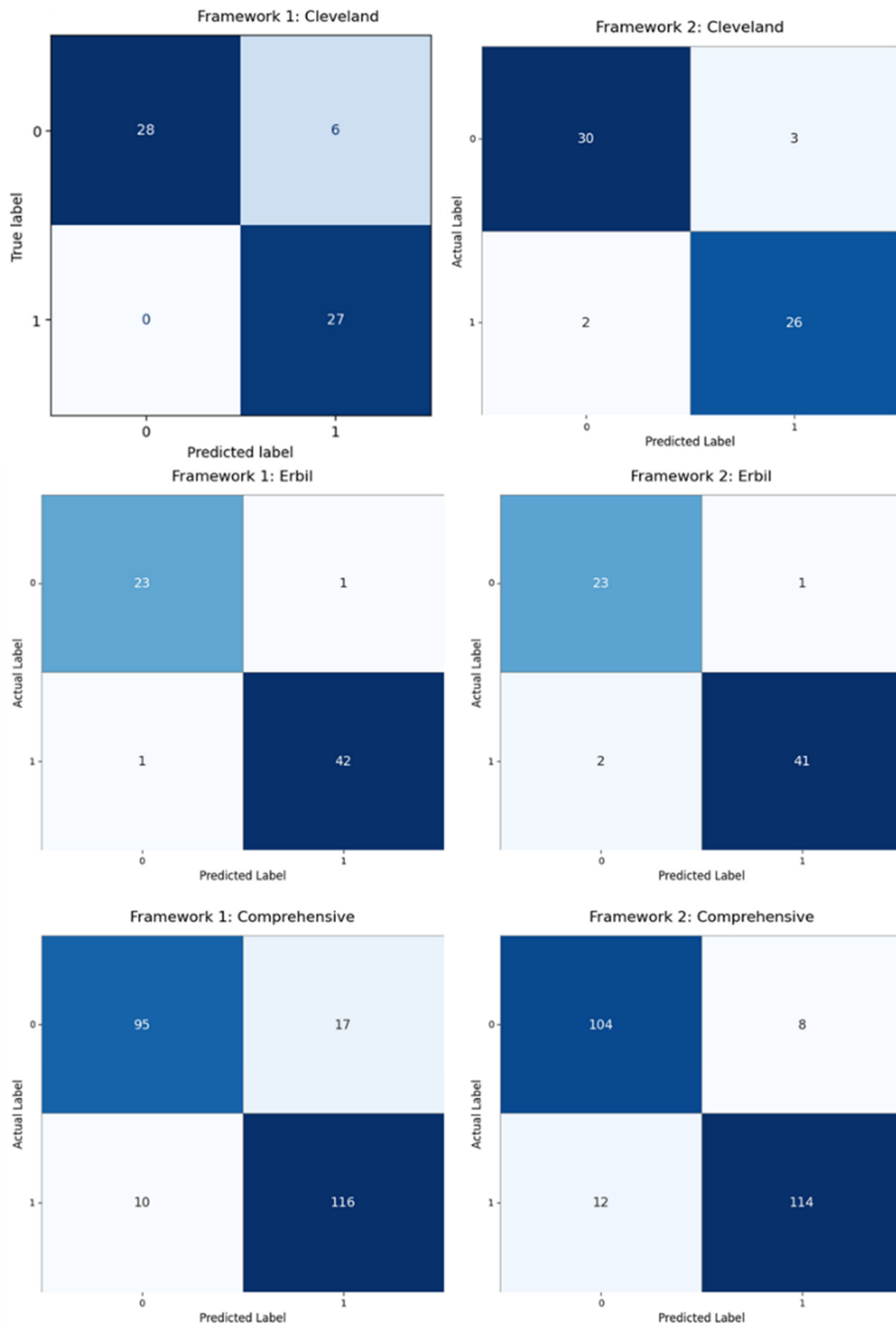


Fig. 6. Confusion matrices for Framework 1 and Framework 2.

B. Performance of Framework 2 (DAE and Voting Ensemble)

Framework 2 also demonstrated superior performance across all datasets. It achieved an accuracy of 91.80%, precision of 89.66%, recall of 92.86%, and F1-score of 91.23% on Cleveland dataset. On Erbil data, the framework obtained an accuracy of 95.52%, precision of 97.62%, recall of 95.35%, and F1-score of 96.47%. For the Comprehensive dataset, it attained an accuracy of 91.60%, precision of 93.44%, recall of 90.48%, and F1-score of 91.94%.

The DAE's feature extraction capability, combined with the Voting Ensemble (SVM, MLP, RF), consistently delivered advanced performance, particularly in balancing precision and recall.

V. DISCUSSION

The experimental results proved that the integration of advanced DL methods for data augmentations and feature extraction with classical ML methods for classifications led to the improvement of both frameworks, which surpassed the existing state-of-the-art methods. Specifically, Framework 1 combined a CGAN with a CatCMA optimized RF classifier, with the results showing superior enhancement, especially in terms of recall. This is important in the medical field because the model can efficiently detect heart disease patterns, minimizing the risk of missed diagnoses. Furthermore, the achieved accuracy on both the Erbil and the Comprehensive datasets reflects the generality of Framework 1 and its applicability in handling various data representations. The second proposed framework, which used DAE and consisted of a Voting Ensemble classifier (SVM, MLP, and RF), also showed very good results on all datasets. The use of DAE for feature extraction enabled the model to detect complex forms within the data, while the Voting Ensemble participated in a balanced decision-making.

Overall, both frameworks have their own specific advantages. Framework 1 is strong at achieving high recall and generalization, while framework 2 provides a balance between precision and recall. However, some limitations remain. For instance, even though the synthetic data generation contributed to the performance improvement, there is always a risk of introducing biases if the generated samples are not carefully validated. Future work should explore further validation strategies for synthetic data.

VI. CONCLUSION

In this study, two different frameworks were proposed that utilized Machine Learning (ML) techniques with data augmentation and optimization strategies to detect heart disease. The first one integrated Conditional Generative Adversarial Networks (CGAN) with a Categorical and Continuous Covariance Matrix Adaptation (CatCMA) optimized Random Forest (RF), while the second one employed a Denoising Autoencoder (DAE) in combination with a Voting Ensemble. Three datasets were used, including Cleveland, Erbil, and Comprehensive sets, and a comparison with conventional methods as well as with previous research was conducted.

The results demonstrated that both frameworks excelled over existing methods. Specifically, Framework 1 achieved the highest recall and generalization performance, while Framework 2 provided a strong balance between precision and recall. The findings suggest that combining synthetic data generation, feature extraction, and advanced optimization techniques could effectively impact heart disease detection systems. Future work includes further improving the performance of the models by exploring hybrid approaches that combine the strengths of both frameworks, incorporating explainable AI techniques to enhance transparency, and validating the models on larger and more diverse datasets.

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