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OPTIMIZATION OF SUPPORT VECTOR MACHINE WITH SMOTE AND BAYESIAN METHOD FOR HEART FAILURE CLASSIFICATION

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Abstract: This study applies an integrated approach to optimize heart failure classification. The main objective is to address the challenge of class imbalance in medical datasets and to improve the accuracy, sensitivity, and generalization of the classification model. The urgency of this issue is emphasized by statistics showing that cardiovascular diseases cause approximately 17.9 million deaths worldwide each year. Using a quantitative experimental approach, this study analyzes the "Heart Failure Prediction Dataset" from Kaggle, which consists of 918 records. The data were processed through normalization and encoding, followed by the application of SMOTE on the training set to balance class distribution. This step successfully increased model accuracy from 88.41% to 90.22% and minority class recall from 0.82 to 0.88. Furthermore, Bayesian Optimization was employed to refine the hyperparameters of SVM, resulting in a final model with an accuracy of 89.13% that demonstrated better generalization. This integrated approach significantly enhances the stability, sensitivity, and generalization of the model, making it a reliable tool for clinical decision support systems in predicting heart failure.

Keywords: bayesian optimization; heart failure; machine learning; SMOTE; SVM.

Abstrak: Penelitian ini menerapkan pendekatan terintegrasi untuk mengoptimalkan klasifikasi gagal jantung. Tujuan utama studi ini adalah untuk mengatasi tantangan ketidakseimbangan kelas dalam dataset medis dan meningkatkan akurasi, sensitivitas, serta generalisasi model klasifikasi. Urgensi ini ditegaskan oleh statistik yang menunjukkan bahwa penyakit kardiovaskular menyebabkan sekitar 17,9 juta kematian setiap tahun secara global. Menggunakan pendekatan eksperimental kuantitatif, penelitian ini menganalisis "Heart Failure Prediction Dataset" dari Kaggle, yang terdiri dari 918 catatan. Data diproses dengan normalisasi dan *encoding*, lalu SMOTE diterapkan pada data pelatihan untuk menyeimbangkan distribusi kelas. Langkah ini berhasil meningkatkan akurasi dari 88,41% menjadi 90,22% dan *recall* kelas minoritas dari 0,82 menjadi 0,88. Selanjutnya, Bayesian Optimization menyempurnakan *hyperparameter* SVM, menghasilkan model akhir dengan akurasi 89,13% yang menunjukkan generalisasi lebih baik. Pendekatan terintegrasi ini secara signifikan meningkatkan stabilitas, sensitivitas, dan generalisasi model. Hasil penelitian ini menjadikannya alat yang andal untuk sistem pendukung keputusan klinis dalam prediksi gagal jantung.

Kata kunci: bayesian optimization; gagal jantung; machine learning; SMOTE; SVM

INTRODUCTION

The heart is a primary organ in the circulatory system, responsible for delivering oxygen and nutrients to body tissues and supporting optimal metabolic function [1]. This vital organ also plays a key role in maintaining stable blood pressure through regular contractions and relaxations of the heart muscle, which helps prevent chronic diseases like hypertension and stroke [2]. However, despite its crucial functions, the heart remains vulnerable to various diseases, one of which is heart failure.

Heart failure is a chronic condition in which the heart is unable to pump blood effectively to meet the body's metabolic needs. It can be caused by structural or functional abnormalities of the heart, such as left ventricular dysfunction, coronary artery disease, or heart valve disorders [3],[4]. Common symptoms include shortness of breath, fatigue, edema, reduced physical activity, and psychological impacts like anxiety and depression [5]. Heart failure does not just affect the heart's function; it also impacts other organs like the lungs and kidneys due to complex hemodynamic changes [6].

According to the World Health Organization (2019), cardiovascular diseases, including heart failure, are responsible for approximately 17.9 million deaths annually, with one-third occurring in individuals under the age of 70. In Indonesia, the prevalence of heart disease is 1.5% of the national population or about 2.78 million people (Kemenkes, 2024). Heart disease is also the leading cause of death in the country, with increasing mortality trends each year [7]. These alarming statistics highlight the importance of early detection to reduce complications and lower mortality rates.

Early detection of heart failure can be performed through clinical examinations and the use of technology such as heart rate sensors and oxygen saturation monitors. However, challenges often arise due to the complexity of medical data and class imbalance within datasets [8]. Class imbalance occurs when the majority class significantly outnumbers the minority class, leading machine learning models to perform poorly in identifying critical patterns within the minority class [9].

Several studies have applied SVM in medical classification due to its robustness in handling complex data. Farida and Bahri [10] showed that SVM with linear, RBF, and polynomial kernels achieved accuracies above 84% for heart failure classification, with the linear kernel performing best. Hussain et al. [11] demonstrated that applying SMOTE improved SVM performance in congestive heart failure detection, raising accuracy to 97.14%. Utari [12] also integrated SMOTE-NC with SVM, which improved accuracy and F1-score compared to conventional SVM.

Waluyo and Munir [13] reported that SMOTE with XGBoost achieved 88.9% accuracy for heart failure mortality prediction, confirming the effectiveness of data balancing. Beyond SMOTE, Elshewey et al. [14], Lubis et al. [15], and Rani et al. [16] highlighted the role of Bayesian Optimization in enhancing SVM performance in disease detection and prediction tasks.

While these studies highlight the effectiveness of SMOTE and Bayesian Optimization, most applied them separately and rarely in the context of heart failure classification. This research integrates SMOTE for data balancing, SVM as the main classifier, and Bayesian Optimization for hyperparameter tuning into

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a single framework. By combining these methods, the study aims to achieve better accuracy, recall, and generalization simultaneously, offering a more reliable approach for developing clinical decision support systems in heart failure prediction.

METHOD

This study adopted a quantitative experimental approach to examine the effect of combining Support Vector Machine (SVM), Synthetic Minority Oversampling Technique (SMOTE), and Bayesian Optimization (BO) in classifying heart failure. The dataset used was the “Heart Failure Prediction Dataset” from Kaggle, consisting of 918 records with 11 predictor variables and one target variable (HeartDisease).

The predictor variables include Age (age of the patient in years), Sex (gender: M = Male, F = Female), ChestPainType (type of chest pain categorized as Typical Angina/TA, Atypical Angina/ATA, Non-Anginal Pain/NAP, and Asymptomatic/ASY), RestingBP (resting blood pressure in mmHg), Cholesterol (serum cholesterol level in mg/dl), FastingBS (fasting blood sugar, with a value of 1 if >120 mg/dl and 0 otherwise), RestingECG (resting electrocardiogram results categorized as Normal, ST-T wave abnormality/ST and Left Ventricular Hypertrophy/LVH), MaxHR (maximum heart rate achieved, ranging from 60 to 202), ExerciseAngina (exercise-induced angina: Y = Yes, N = No), Oldpeak (numeric value of ST depression), and ST_Slope (slope of the ST segment categorized as Up, Flat, or Down). The target variable, HeartDisease, is labeled as 1 if the patient is diagnosed with heart disease and 0 if the condition is normal.

Table 1. Kaggle Dataset Sample

No	Age	Gender	ChestPainType	RestingBP	…	HeartDisease
0	40	M	ATA	140	…	0
1	49	F	NAP	160	…	1
2	37	M	ATA	130	…	0
…	…	…	…	…	…	…
917	38	M	NAP	138	…	0

Data preprocessing included cleaning missing or duplicate entries, encoding categorical variables using label encoding, and applying normalization with StandardScaler so that each feature had zero mean and unit variance, calculated as:

$$x_{scaled} = \frac{x - \mu}{\sigma} \quad (1)$$

Description:
μ is the feature average
σ is the feature standard deviation

To address class imbalance, SMOTE was applied only to the training data. New synthetic samples were generated for the minority class using the formula:

$$x_{\{new\}} = x_i + \lambda\left(x_{\{nn\}} - x_i\right),\ \lambda \sim U(0,1) \quad (2)$$

Description:
x_i is a minority instance
$x_{\{nn\}}$ is nearest neighbor

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The dataset was split into 80% training and 20% testing using stratified sampling to maintain class proportions.

SVM was chosen as the primary classifier due to its ability to handle high-dimensional data and minimize overfitting. The decision function of SVM is defined as:

$$f(x)= w^T x + b \quad (3)$$

The optimization seeks to maximize the margin while minimizing classification error:

$$\min_{w,b,\xi} \frac{1}{2} \; ||w||^2 + C \sum_{i=1}^{n} \xi_i \quad (4)$$

with condition that

$$y_i \, (w^T x_i + b) \geq 1 - \xi_i, \;\; \xi_i \geq 0 \quad (5)$$

Bayesian Optimization was employed to tune hyperparameters such as the regularization parameter CCC, kernel type, gamma, and polynomial degree. The optimization was implemented with the Optuna framework using 5-fold cross-validation, with classification accuracy as the objective function.

Finally, model performance was evaluated using accuracy, precision, recall, F1-score, and the Area Under the ROC Curve (AUC), where:

Accuracy

$$\text{Accuracy}= \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

Presision

$$\text{Precision}= \frac{TP}{TP+FP} \quad (7)$$

Recall

$$\text{Recall}= \frac{TP}{TP+FN} \quad (8)$$

F1-Score

$$\text{F1-Score}= \frac{2 \text{ x Presision x Recall}}{\text{Presision+Recall}} \quad (9)$$

And AUC represents the area under the ROC curve, reflecting the model's ability to discriminate between classes.

RESULT AND DISCUSSION

The dataset, obtained from Kaggle, contains 918 records with 11 predictor variables and one binary target (HeartDisease). Numerical features include age, blood pressure, cholesterol, maximum heart rate, and ST depression (oldpeak), while categorical features consist of sex, chest pain type, fasting blood sugar, resting ECG, exercise-induced angina, and ST slope.

Before model construction, data cleaning was performed to handle missing values, categorical features were encoded using Label Encoding

Table 2. Dataset After Encoding Categorial

	Gender	ChestPainType	RestingBP	ExerciseAngina	...	HeartDisease
0	1	1	1	0	...	0
1	0	2	1	0	...	1
2	1	1	2	0	...	0
3	0	0	1	1	...	1
4	1	2	1	0	...	0

Normalization ensures that all features are on the same scale, which is crucial because SVM is sensitive to scale differences. This study uses StandardScaler from scikit-learn to standardize data by converting each feature to have a mean of 0 and a standard deviation of 1. This process is applied to all numerical attributes (Age, RestingBP, Cholesterol, MaxHR, Oldpeak) to ensure balanced influence during SVM training.

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[[1.         0.33333333 0.5        ... 0.78873239 0.29545455 0.        ]
 [0.         0.66666667 0.5        ... 0.67605634 0.40909091 1.        ]
 [1.         0.33333333 1.         ... 0.26760563 0.29545455 0.        ]
 ...
 [1.         0.         0.5        ... 0.38732394 0.43181818 1.        ]
 [0.         0.33333333 0.         ... 0.8028169  0.29545455 1.        ]
 [1.         0.66666667 0.5        ... 0.79577465 0.29545455 0.        ]]
```

Image 1. StandardScaller

The dataset is split into training (80%) and testing (20%) sets using stratified sampling to maintain class balance. Training data (333 class 0, 402 class 1) is used for model training and optimization, while testing data (83 class 0, 101 class 1) is for final evaluation.

The training set (734 samples) was imbalanced, with 401 HeartDisease=1 and 333 HeartDisease=0, risking bias toward the majority class, as shown in Image 2.

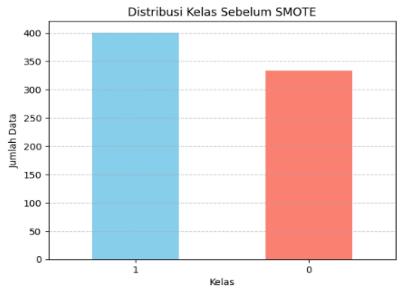

Image 2. Class Distribution Before SMOTE

To address this, SMOTE was applied only to the training data, generating synthetic samples for the minority class. This resulted in a balanced distribution of 401 samples per class (total 802), preventing data leakage and improving model fairness, as shown in Image 3.

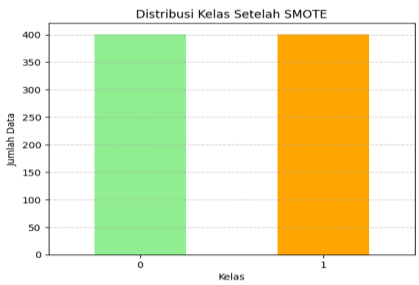

Image 3. Class Distribution After SMOTE

The classification performance was evaluated under three scenarios: SVM before SMOTE, SVM after using SMOTE, and the integrated framework SVM+SMOTE+BO.

The initial SVM model trained on the imbalanced dataset achieved 88.41% accuracy and AUC 0.96, but showed bias toward the majority class.

Table3. Model Evaluation Before SMOTE

Metrics	Class 0	Class 1
Presisi	0.91	0.87
Recall	0.82	0.93
F1-score	0.87	0.90
Support	125	151

Metrics (Table 3) indicate lower recall for class 0 (0.82) compared to class 1 (0.93), meaning non-heart disease cases were harder to detect.

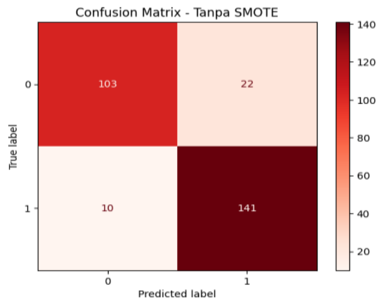

Image 4. Confusion Matrix Before SMOTE

The confusion matrix showed 22 false positives and 10 false negatives, which is critical in medical contexts.

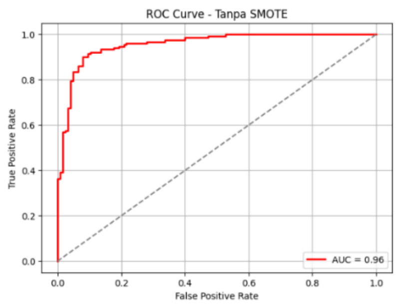

Image 5. ROC Curve Before SMOTE

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Although the ROC curve (AUC 0.96) indicates strong overall discrimination, class imbalance reduced sensitivity to the minority class, highlighting the need for data balancing with SMOTE.

Next, the results of applying SMOTE to SVM show a significant improvement in model performance.

Table 4. Model Evaluation After SMOTE

Metrics	Class 0	Class 1
Presisi	0.90	0.90
Recall	0.88	0.92
F1-score	0.89	0.91
Support	125	151

Accuracy increased from 88.41% to 90.22%, with an average precision, recall, and F1-score of 0.90. Recall for Class 0 rose from 0.82 to 0.88, indicating better detection of non-heart disease cases.

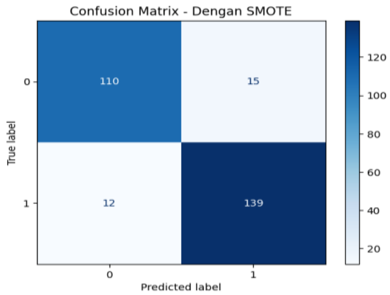

Image 6. Confusion Matrix After SMOTE

The confusion matrix shows a decrease in errors (false positives reduced from 22 to 15, true negatives increased from 103 to 110).

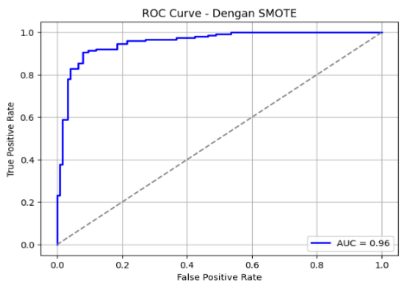

Image 7. ROC Curve After SMOTE

The AUC remained at 0.96, indicating that the discriminative ability did not change, but prediction distribution became more balanced. Overall, SMOTE enhanced the model's generalization, reduced bias toward the majority class, and made the model more reliable for early heart disease detection. After applying SMOTE, Bayesian Optimization (BO) was used to fine-tune SVM hyperparameters with Optuna and 5-fold cross-validation. The best configuration was C = 2.44, Gamma = 0.0068, Kernel = RBF.

Table 5. Model Evaluation After SMOTE and BO

Metrics	Class 0	Class 1
Presisi	0.89	0.90
Recall	0.87	0.91
F1-Score	0.88	0.90
Support	125	151

Accuracy slightly decreased from 90.22% to 89.13%, likely due to better generalization. Despite this, the model remained balanced, with precision, recall, and F1-score averaging 0.89. Recall for class 0 was 0.87 and class 1 0.91, indicating consistent sensitivity.

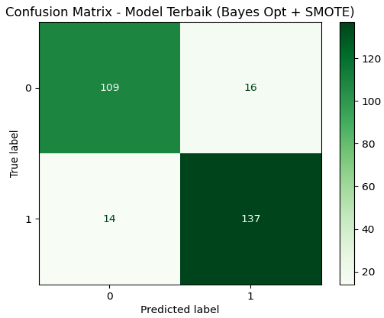

Image 8. Confusion Matrix After SMOTE and Bayesian

The confusion matrix showed 16 false positives and 14 false negatives (slightly higher than after SMOTE), while AUC remained 0.96, confirming strong discriminative ability.

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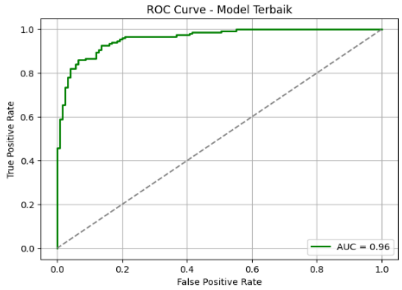

Image 9. ROC Curve After SMOTE and Bayesian

Overall, combining SMOTE and Bayesian Optimization improved stability, sensitivity, and generalization, making it suitable for clinical decision support systems.

CONCLUSION

The integrated approach of SMOTE, SVM, and Bayesian Optimization effectively addressed class imbalance and data complexity in heart failure classification. SMOTE successfully balanced the class distribution, improving recall for class 0 from 0.82 to 0.88 and increasing accuracy from 88.41% to 90.22%. Bayesian Optimization further refined the SVM parameters, resulting in a final model with 89.13% accuracy and improved generalization, despite a slight decrease in nominal accuracy. This combination demonstrates its ability to enhance classification performance and serves as a strong approach for developing reliable clinical decision support systems. For future development, it is recommended to test the model on larger and more diverse datasets to ensure robustness, explore alternative balancing and optimization methods such as genetic algorithms, conduct deeper feature analysis to improve accuracy and sensitivity, and implement Explainable AI (XAI) techniques to increase transparency and trust in clinical practice.

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