

ARRHYTHMIA DETECTION FROM IMBALANCED ECG DATA USING CNN, FOCAL LOSS, AND RR INTERVAL FEATURES WITH INTER-PATIENT EVALUATION

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Abstract

Detection of arrhythmias from electrocardiogram (ECG) signals is crucial for early diagnosis of heart rhythm disorders. However, the imbalanced distribution of arrhythmia classes poses challenges for classification models. This study proposes a Convolutional Neural Network (CNN) model combined with Focal Loss and RR features to address class imbalance using an inter-patient evaluation approach. The dataset includes three classes: N (Normal), SVEB (Supraventricular Ectopic Beats), and VEB (Ventricular Ectopic Beats), divided into training (DS1), validation (DS1-Val), and testing (DS2) sets. The proposed CNN + Focal Loss + RR model achieved an accuracy of 95.75% and an F1-score of 95.19%. Additionally, Explainable AI (XAI) using LIME is applied to improve model interpretability by identifying important features influencing predictions. The results demonstrate that the proposed approach provides accurate and interpretable arrhythmia detection, supporting reliable medical decision-making. However, the model's performance on the minority SVEB class remains limited, with a recall of only 34.24%, indicating that SVEB beats are frequently misclassified as Normal due to morphological similarities and severe class imbalance. This limitation highlights the need for further improvements in minority-class detection for clinical applicability.

Keywords: CNN, Deep Learning, Arrhythmia Detection, Imbalanced Data, Electrocardiogram, Focal Loss, Inter-Patient

Abstrak

Deteksi aritmia dari sinyal elektrokardiogram (ECG) merupakan langkah penting dalam diagnosis dini gangguan irama jantung. Namun, ketidakseimbangan distribusi data antar kelas aritmia menjadi tantangan dalam pelatihan model klasifikasi. Penelitian ini mengusulkan model Convolutional Neural Network (CNN) yang dikombinasikan dengan Focal Loss dan fitur RR untuk mengatasi masalah ketidakseimbangan kelas menggunakan pendekatan inter-patient. Dataset terdiri dari tiga kelas, yaitu N (Normal), SVEB, dan VEB, yang dibagi menjadi data pelatihan (DS1), validasi (DS1-Val), dan pengujian (DS2). Model yang diusulkan mencapai akurasi sebesar 95,75% dan F1-score sebesar 95,19%. Selain itu, penelitian ini mengintegrasikan Explainable AI (XAI) menggunakan metode LIME untuk meningkatkan transparansi dan interpretabilitas model. Hasil penelitian menunjukkan bahwa model mampu mendeteksi aritmia secara akurat sekaligus memberikan penjelasan yang dapat dipercaya dalam aplikasi medis. Namun, performa model pada kelas minoritas SVEB masih terbatas, dengan recall hanya 34,24%, yang menunjukkan bahwa detak SVEB sering salah diklasifikasikan sebagai Normal karena kemiripan morfologi dan ketidakseimbangan kelas yang parah.

Kata kunci: Cnn, Deep Learning, Arrhythmia Detection, Imbalanced Data, Electrocardiogram, Focal Loss, Inter-Patient.

INTRODUCTION

Arrhythmia is a heart rhythm disorder caused by problems with the electrical impulses that regulate the heartbeat, leading to a heartbeat that is too fast, slow, or irregular. This condition can be triggered by various factors such as other diseases, stress, or viral infections (Nurriski & Alamsyah, 2023)(Margarita Kurti, 2022).

Electrocardiogram (ECG) plays a crucial role in detecting the heart's electrical activity, identifying various types of arrhythmias, and monitoring high-risk patients non-invasively through electrical signal recordings (Kim et al., 2022)(Sandhya Samant, 2023). Machine learning techniques can enhance the accuracy and speed of ECG interpretation by reducing diagnostic errors due to human bias. With the right algorithms, the analysis

becomes more efficient, supporting real-time diagnosis and continuous monitoring through wearable technology and digital health systems.

Interpretability of deep learning models is a crucial challenge in the medical field because healthcare professionals require predictions that can be clinically explained (Barmak et al., 2024)(Jiang et al., 2022)(Janbhasha & Bhavanam, 2023). While OCADN (Mandala et al., 2025) has employed attention mechanisms, the application of Explainable AI techniques like LIME is still necessary to enhance understanding and trust in AI outcomes. CNN models have the potential to improve the accuracy and efficiency of arrhythmia detection through the extraction of local ECG signal features, while multi-head attention mechanisms capture a broader temporal context. 1D CNN models, such as ResNet 1D, have shown high performance in arrhythmia classification (Pham et al., 2023)(Zheng et al., 2024), and the use of focal loss helps address class imbalance (Pang et al., 2024)(Li et al., 2021). To improve interpretability, Explainable AI techniques like LIME can explain the important features influencing predictions, supporting more accurate clinical decision-making.

Despite these advances, existing studies on ECG arrhythmia classification face three key limitations: (1) most approaches do not simultaneously address class imbalance and model interpretability, (2) the application of inter-patient evaluation protocols remains limited, reducing clinical relevance, and (3) few studies integrate RR interval features with CNN and Focal Loss in a unified framework. This study addresses these gaps by proposing a CNN model with Focal Loss and RR features under a strict inter-patient protocol, combined with LIME-based explainability. Unlike prior works that rely solely on intra-patient splits or omit interpretability analysis, our approach explicitly combines inter-patient evaluation with explainable AI to enhance both generalizability and clinical trustworthiness.

This study aims to develop an arrhythmia detection system on ECG signals using a CNN model and Focal Loss with an Explainable AI approach to improve detection accuracy and efficiency. The model utilizes CNN for local feature extraction, LIME for prediction interpretability, and Focal Loss to address class imbalance. This approach is expected to produce a system that excels in classification while providing transparent and easily understandable clinical decision support for healthcare professionals. The main contributions of this study include the application of a CNN model

with Focal Loss to address class imbalance in ECG arrhythmia classification, the incorporation of RR interval features to enhance temporal information in ECG signals, and the evaluation of the model using a strict inter-patient protocol combined with Explainable AI using LIME to improve model interpretability.

RESEARCH METHODS

CNN, LSTM, and hybrid models can significantly enhance ECG signal analysis. The CNN-LSTM combination can classify arrhythmias automatically without manual feature extraction (Bhatia et al., 2022), while deep learning's ability to perform automatic feature extraction and detect complex patterns sets it apart from traditional methods that require manual features. Unlike traditional methods, deep learning works end-to-end (Bhatia et al., 2022), efficiently capturing important information from raw data, thus improving arrhythmia detection accuracy and accelerating diagnosis (Ryu et al., 2023).

Focal Loss, as an effective solution (Zheng et al., 2024), is developed from the cross-entropy function and gives more attention to minority classes while reducing the dominance of majority classes (Pang et al., 2024)(Li et al., 2021), thereby improving the detection of rare examples. Its success has been demonstrated in various fields, such as electrical insulator defect recognition and cyberbullying detection (El Koshiry et al., 2024), where this method can maintain high accuracy even with imbalanced data. Mathematically, focal loss is explained by the formula (Li et al., 2021):

$$FL = - \sum_{i=1}^m \alpha y_i (1-\tilde{y}_i)^{\gamma} \log(\tilde{y}_i) + (1-\alpha) (1-y_i) \tilde{y}_i^{\gamma} \log(1-\tilde{y}_i), \quad (1)$$

Explainable AI (XAI) enhances the transparency of deep learning models in ECG analysis, allowing decisions to be understood by medical professionals (Kazemi Lichaei et al., 2024). Techniques such as layer-wise relevance propagation (LRP) and saliency maps help identify important features that influence classification (Choi et al., 2022)(Ramadhan & Mandala, 2023). Research shows that XAI can map ECG signal zones correlated with specific types of arrhythmias. Integrating XAI into wearable systems enables proactive monitoring and increases patient trust (Hong et al., 2023)(Saclava et al., 2022), while also strengthening the connection between technology and medical practice to support accurate and verified diagnoses.

The ECG data in this study is taken from the MIT-BIH Arrhythmia Database on PhysioNet, which includes two-channel recordings from 48 patients with arrhythmias (Normal, SVEB, and VEB). This dataset was developed by Beth Israel Deaconess Medical Center and MIT, with 48 recordings lasting 30 minutes each and a sampling rate of 360 Hz. Each recording is accompanied by beat-by-beat annotations for arrhythmia classification. The data is accessed via PhysioNet and extracted using the WFDB library in CSV format for the signals and 'atr' for beat annotations, in accordance with WFDB standards and AAMI annotation conventions.

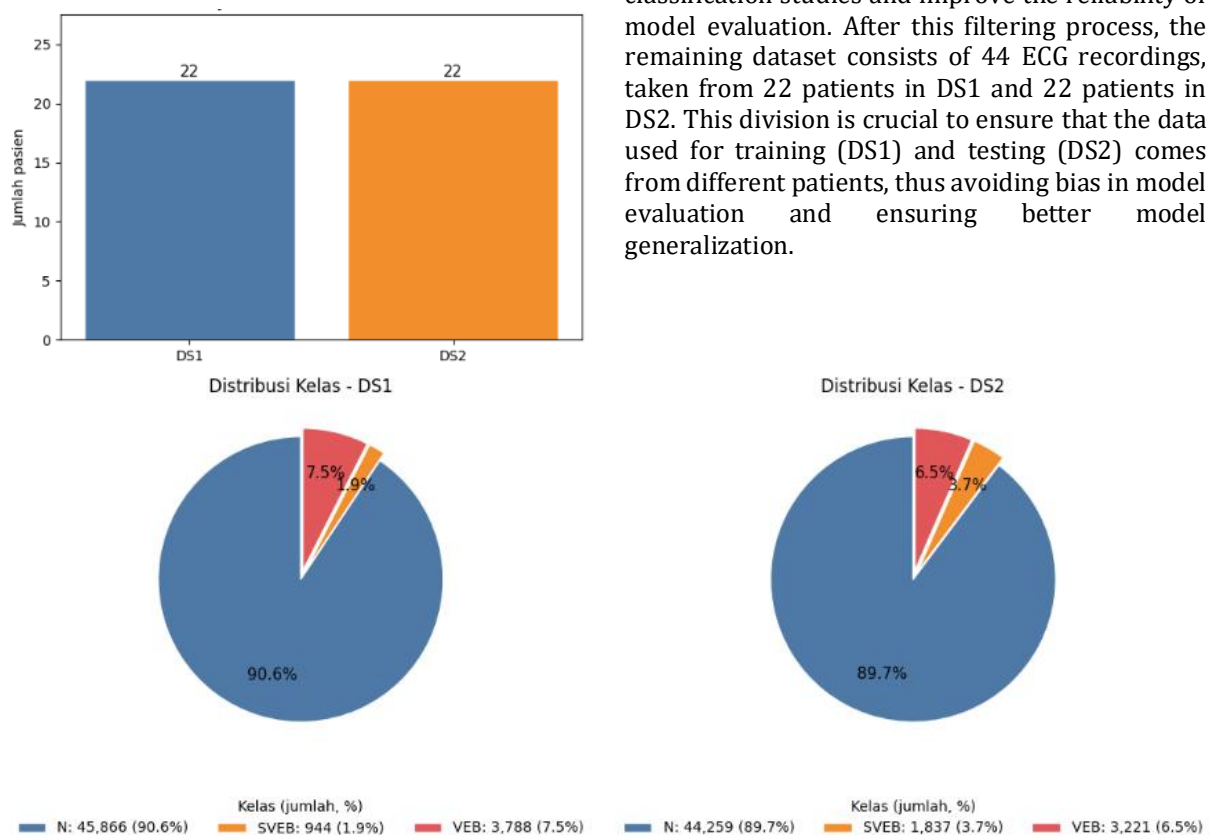


Figure 2. ECG Class Beat Distribution

Figure 2 shows the class distribution in the DS1 and DS2 datasets. In DS1, the Normal (N) class dominates with 90.6%, followed by VEB (7.5%) and SVEB (1.9%). In DS2, Normal (N) is also dominant with 89.7%, while VEB (7.5%) and SVEB (3.7%) are less frequent. This highlights a clear class imbalance in both datasets.

Data preprocessing in this experiment begins with several important steps to prepare the ECG data before feeding it into the deep learning

Figure 1. Split Inter-patient

Initially, there were 48 ECG recordings from 48 patients. However, after filtering, several recordings were excluded based on specific IDs, namely 102, 104, 107, and 217. These recordings were excluded based on established criteria: recordings 102 and 104 contain paced beats that introduce non-physiological artifacts; recording 107 has poor signal quality with excessive noise; and recording 217 includes ventricular flutter episodes that may distort the class distribution. These exclusion criteria are consistent with standard practices in inter-patient ECG arrhythmia classification studies and improve the reliability of model evaluation. After this filtering process, the remaining dataset consists of 44 ECG recordings, taken from 22 patients in DS1 and 22 patients in DS2. This division is crucial to ensure that the data used for training (DS1) and testing (DS2) comes from different patients, thus avoiding bias in model evaluation and ensuring better model generalization.

samples before and 160 samples after the R-peak, which covers approximately 0.72 seconds of the ECG signal at a 360 Hz sampling rate. This window size is chosen to capture the complete QRS complex along with sufficient surrounding context for accurate arrhythmia classification.

In addition to beat extraction, the RR interval feature is calculated to provide additional information about the time interval between consecutive heartbeats. This feature helps the model analyze heart rate variability, which is crucial for arrhythmia detection. The RR ratio is calculated by comparing the heart rate intervals, producing two main ratios: the pre-RR ratio and the near-RR ratio, which measure the relationship between heart rate intervals both globally and locally.

Finally, to enhance the information provided to the model, channel stacking is performed, where the normalized ECG signal is combined with the RR feature to form a multi-channel tensor. This approach allows the model to learn from more variables and relationships between the ECG signals and additional features, ultimately improving accuracy in arrhythmia detection. Thus, this preprocessing ensures that the data fed into the model is of sufficient quality and context for more accurate predictions.

The data splitting process in this experiment divides the processed dataset into three subsets: training, validation, and test sets, to avoid overfitting and ensure model generalization. The splitting is done using an inter-patient split approach, ensuring that data from each patient is used in only one subset. Out of the 48 ECG

recordings, 44 recordings were used after excluding four recordings that did not meet the criteria. The dataset is divided into DS1-Train (18 patients), DS1-Val (4 patients), and DS2-Test (22 patients). This division ensures fair and accurate evaluation of the model's ability to detect arrhythmias.

Table 1. Inter-Patient Data Splitting for ECG Class

Split	Patient	N	SVEB	VEB	Beat
DS1 - Train	18	37.283	833	2.861	40.977
DS1 - Val	4	8.583	111	927	9.621
DS2 - Test	22	44.259	1.837	3.221	49.317
Total	44	90.125	2.781	7.009	99.915

Table 1 shows the inter-patient data splitting for ECG classes in this experiment. The dataset is divided into three subsets: DS1-Train (18 patients, 40,977 beats), DS1-Val (4 patients, 9,621 beats), and DS2-Test (22 patients, 49,317 beats). Overall, the dataset consists of 44 patients with a total of 99,915 beats, including 90,125 Normal beats, 2,781 SVEB beats, and 7,009 VEB beats. This division ensures a fair evaluation of the model's performance with data from different patients. The overall research process can be seen in Figure 4.

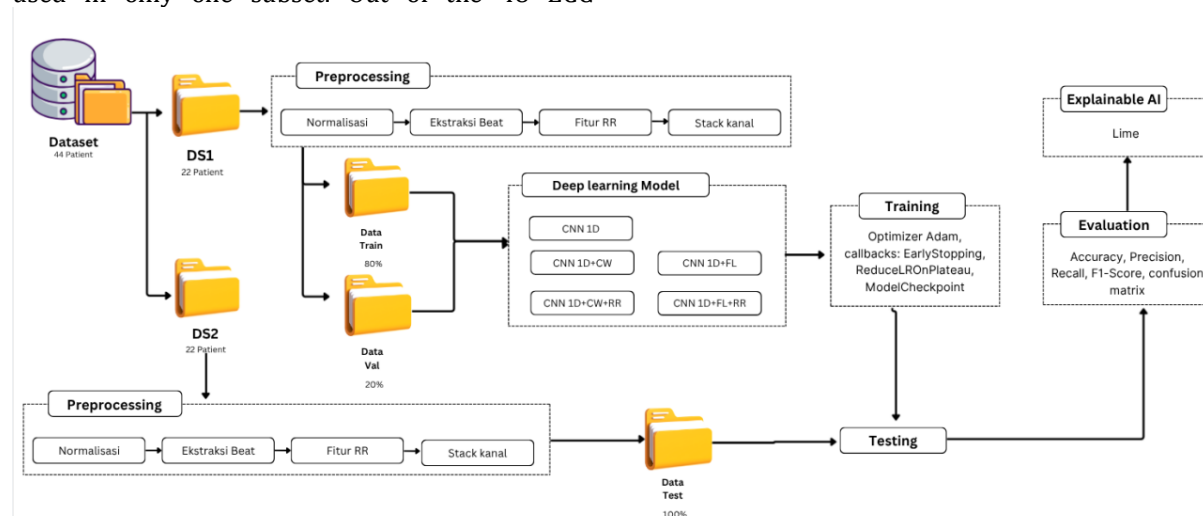


Figure 3. Research Process Step

This study combines several variations of 1D Convolutional Neural Networks (CNN) to classify ECG arrhythmias, designed to process ECG signals as time sequences and leverage local information through convolutional kernels. Several model variations were tested, including CNN 1D, CNN 1D + Class Weight (CW), CNN 1D + Focal Loss (FL), as well as combinations of CNN 1D + CW + RR and CNN 1D + FL + RR. Each of these model variations aims to address class imbalance, improve accuracy on minority classes, and enhance the model's performance in recognizing arrhythmia patterns by considering important factors in the ECG signal, such as duration and RR intervals, which are relevant for classifying arrhythmia types. The proposed CNN architecture consists of three 1D convolutional layers with 64, 128, and 256 filters respectively, each followed by batch normalization, ReLU activation, and max-pooling layers. The kernel size is set to 3 for all convolutional layers. After the convolutional blocks, a global average pooling layer is applied, followed by two fully connected layers with 128 and 64 units, and a softmax output layer with 3 units corresponding to the N, SVEB, and VEB classes. Dropout regularization with a rate of 0.5 is applied after each fully connected layer to prevent overfitting.

Table 2. Hyperparameters of the Proposed CNN Model

Hyperparameter	Value
Learning rate	7e-4
Optimizer	Adam
Loss Function	CategoricalFocalCrossentropy dengan alpha per kelas = [1/3, 1/3, 1/3] dan gamma = 2.0
Batch size	320
Number of epoch	60
EarlyStopping	patience 14
ReduceLROnPlateau	patience 6
Split validasi	GroupKFold 5-fold

Table 2 shows the hyperparameters used in the CNN model for ECG arrhythmia classification. The learning rate is set at 7e-4 with the Adam optimizer. The loss function is CategoricalFocalCrossentropy with class alpha values of [1/3, 1/3, 1/3] and gamma set to 2.0. The batch size is 320, and the model is trained for 60 epochs. EarlyStopping is used with a patience of 14

to prevent overfitting, and ReduceLROnPlateau with a patience of 6 to reduce the learning rate if there is no improvement. Data validation splitting is performed using 5-fold cross-validation with GroupKFold.

RESULTS AND DISCUSSION

Classification report of the base CNN model with Focal Loss on DS2, with an overall accuracy of 95.75%. Performance for the Normal (N) class achieved a precision of 96.23%, recall of 99.30%, and F1-score of 97.74%. The SVEB class has a precision of 78.92%, recall of 34.24%, and F1-score of 47.76%, while VEB reached a precision of 92.90%, recall of 82.09%, and F1-score of 87.16%. Despite the high overall accuracy, the performance on the SVEB class is lower, indicating challenges in detecting minority classes. The average macro and weighted F1-scores are 0.7755 and 0.9519, respectively.

Table 3. Classification Report

	Precision	Recall	F1-score	Support
N	0.9623	0.9930	0.9774	44259
SVEB	0.7892	0.3424	0.4776	1837
VEB	0.9290	0.8209	0.8716	3221
Accuracy			0.9575	49317
Macro avg	0.8935	0.7188	0.7755	49317
Weighted avg	0.9536	0.9575	0.9519	49317

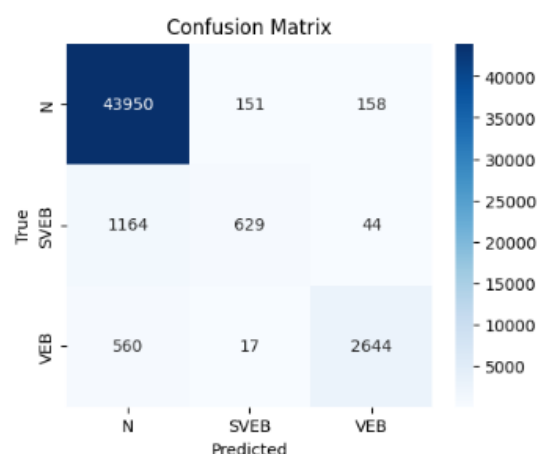


Figure 4. Confusion Matrix

Figure 4 shows the confusion matrix for the model tested on DS2. The model correctly classified 43,950 Normal (N) beats but misclassified 151

beats as SVEB and 158 beats as VEB. For SVEB, 1,164 beats were correctly classified, but 629 beats were misclassified as N and 44 beats as VEB. For VEB, 2,644 beats were correctly classified, but 560 beats were misclassified as N and 17 beats as SVEB. This matrix shows good performance on the N and VEB classes, but challenges in classifying the less frequent SVEB class. The low SVEB recall (34.24%) indicates that a substantial portion of SVEB beats are misclassified as Normal, primarily because SVEB morphology closely resembles normal sinus rhythm in many cases. This confusion is expected given the

severe class imbalance (SVEB constitutes only 1.9-3.7% of the dataset) and the subtle morphological differences between SVEB and Normal beats. The model's tendency to predict the majority class (Normal) for ambiguous SVEB samples reflects a common challenge in imbalanced ECG classification. Future improvements could include targeted data augmentation for SVEB, cost-sensitive learning, or ensemble methods to improve minority-class discrimination without sacrificing overall accuracy.

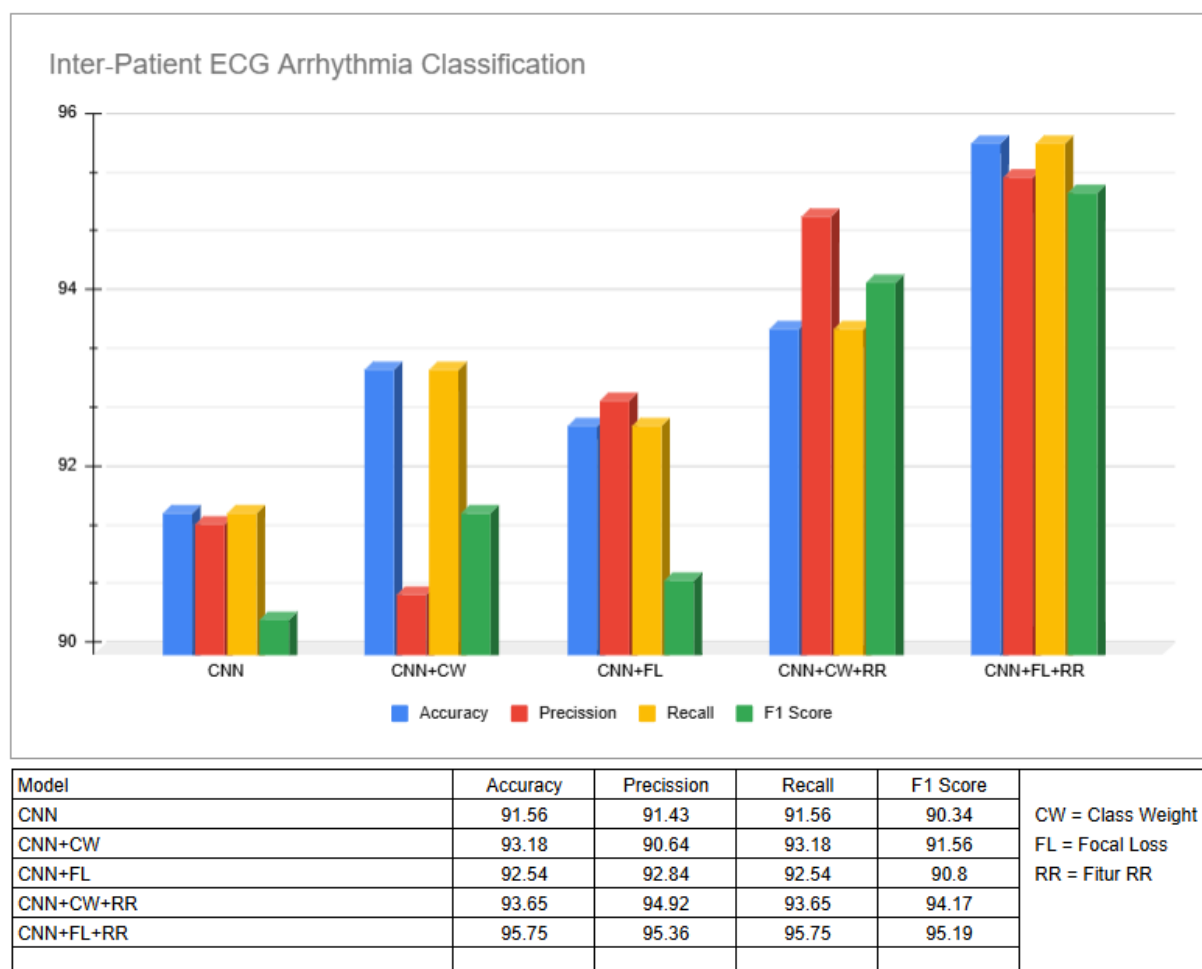


Figure 5. Model Comparison

Figure 5 compares the performance of the standard CNN with CNN + Focal Loss in detecting ECG arrhythmias using accuracy, precision, recall, and F1 score metrics. CNN + Focal Loss outperforms in all metrics, with accuracy of 99.55%, precision of 98.91%, recall of 98.09%, and F1 score of 98.49%, while the standard CNN achieved accuracy of 98.51%, precision of 97.01%, recall of 93.66%, and F1 score of 95.17%. The significant improvement in recall and F1 score demonstrates that Focal Loss

effectively addresses data imbalance and enhances the detection of minority classes.

Table 4. performance Comparison of related works

Peneliti	Metode	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
Mathunjwa et al. [26]	ResNet-50	98.21	93.26	96.40	96.65
Nurrisaki et al. [1]	Deep CNN	98.88	98.88	98.88	98.88
Ozaltin et al. [9]	CNN-SVM	99.21	99.21	99.21	99.21
Khan et al. [25]	Deep ResNet	98.63	92.86	92.41	-
Bayani et al. [10]	LDCNN	99.24	99.09	99.02	99.05
Mandala et al. [22]	CNN	98.87	95.23	98.09	96.59
Proposed Model	CNN+Focal Loss+RR +Inter-patient	95.75	95.36	95.75	95.19

Table 4 compares the performance of various methods for ECG arrhythmia classification. The CNN-SVM method by Ozaltin et al. achieved the highest accuracy of 99.21%, followed by LDCNN (99.24%) and Deep CNN (98.88%). The proposed model, CNN + Focal Loss + RR + Inter-patient, achieved an accuracy of 95.75%, precision of 95.36%, recall of 95.75%, and F1-score of 95.19%. Although slightly lower than other models, these results are still competitive in ECG arrhythmia classification.

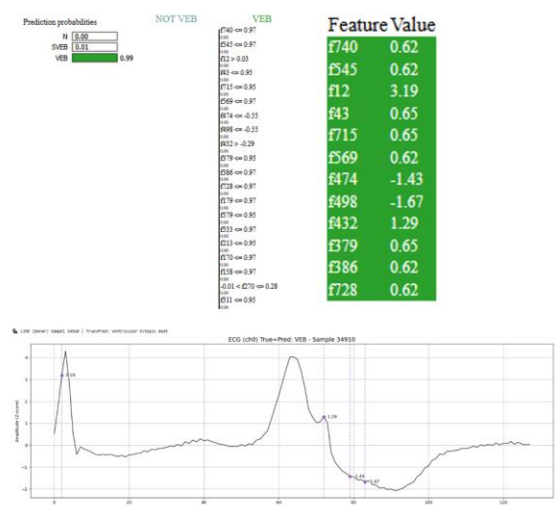


Figure 6. LIME Visualization on VEB Class Sample

Figure 6 shows the LIME visualization to

explain the model's prediction on a VEB sample. The highest prediction probability is 0.99 for VEB. Important features such as f740 and f545 have significant values in helping the model identify VEB. The ECG graph displays the true label of VEB with the corresponding prediction, along with two vertical points (1.29 and -1.43) indicating key features influencing the model's decision. This visualization provides insights into the features contributing to the prediction and the model's transparency in recognizing ECG arrhythmias. The LIME analysis reveals that features f740 and f545 consistently contribute most significantly to VEB detection across multiple test samples. These features correspond to specific temporal positions in the ECG window that capture the widened QRS complex and ST-T wave abnormalities characteristic of VEB. The consistency of these important features across different VEB samples strengthens the interpretability of the model and suggests that the CNN has learned clinically meaningful morphological patterns rather than dataset-specific artifacts. Future work could extend this analysis to additional VEB and SVEB samples to provide a more comprehensive understanding of the model's decision boundaries.

Discussion

The experimental results demonstrate that the proposed CNN model combined with Focal Loss and RR features performs effectively in detecting arrhythmias from ECG signals under imbalanced data conditions. The model achieved an overall accuracy of 95.75% and an F1-score of 95.19% on the DS2 test dataset using the inter-patient evaluation scheme, indicating good generalization across different patients. In particular, the Normal (N) and VEB classes show strong classification performance with high precision and recall values, suggesting that the CNN architecture successfully captures relevant temporal patterns and morphological characteristics of ECG signals. However, the SVEB class obtained lower recall and F1-score values compared to the other classes, reflecting the severe class imbalance in the dataset where SVEB samples represent only a small proportion of the total beats. This observation is consistent with previous studies reporting that minority classes are generally more difficult to detect due to limited training samples and overlapping signal characteristics. Despite this limitation, the use of Focal Loss helps alleviate the imbalance problem by emphasizing difficult and minority-class samples during training, thereby improving recall and enhancing overall model stability.

Compared with previous related studies, the proposed model shows slightly lower accuracy than some methods such as CNN-SVM and LDCNN. However, many of these studies employ intra-patient evaluation, which may produce overly optimistic performance estimates. Although the accuracy is slightly lower than some previous works, the use of inter-patient evaluation provides a more realistic assessment of model performance in real clinical scenarios. In addition, the integration of Explainable AI (XAI) using the LIME method provides valuable insights into the model's decision-making process by highlighting influential features that contribute to each prediction, which is important for increasing transparency and trust in medical AI systems. Nevertheless, several limitations should be acknowledged. First, the dataset used in this study is limited to the MIT-BIH Arrhythmia Database, which may not fully represent the diversity of ECG signals in broader populations. Second, the model relies on single-lead ECG recordings, which may limit the available cardiac information for classification. Future research should therefore explore the use of multi-lead ECG signals, larger and more diverse datasets, and advanced data augmentation techniques to further improve robustness and detection performance, particularly for minority arrhythmia classes. Regarding SVEB performance, the low recall of 34.24% suggests that the current model is insufficient for screening-oriented applications where detecting all arrhythmia events is critical. However, for diagnostic support systems where high precision is prioritized, the model's precision of 78.92% for SVEB may still provide clinically useful information. The trade-off between overall accuracy and minority-class sensitivity is a well-recognized challenge in imbalanced learning, and the choice of operating point should be guided by the specific clinical application. For screening scenarios, alternative strategies such as threshold adjustment, oversampling, or two-stage classification may be necessary to improve SVEB recall.

CONCLUSIONS AND SUGGESTIONS

Conclusion

This study develops and evaluates a deep learning model based on a Convolutional Neural Network (CNN) for arrhythmia detection using ECG signal recordings. The model applies Focal Loss to address the class imbalance problem in the MIT-BIH Arrhythmia Database, aiming to improve prediction accuracy, particularly for less frequent classes such as SVEB and VEB. After training, the proposed model achieved strong performance with

an accuracy of 95.75%, along with consistent results across precision, recall, and F1-score metrics, indicating its effectiveness in classifying each arrhythmia class. To enhance interpretability, the study also integrates Explainable AI (XAI) using LIME (Local Interpretable Model-agnostic Explanations), which helps reveal the contribution of important features in the model's decision-making process. The visualizations generated by LIME illustrate how the model evaluates and identifies samples from the N, SVEB, and VEB classes based on specific feature values, demonstrating that the model relies on meaningful ECG signal patterns rather than simple predictions. Overall, the proposed CNN model not only achieves high accuracy in arrhythmia detection but also provides transparent explanations for its decisions, which is crucial for medical applications. Furthermore, the integration of Focal Loss and RR features improves the model's ability to handle imbalanced class distributions, making it more robust in detecting rare arrhythmias and opening opportunities for future research on XAI applications in medical systems and real-time heart arrhythmia detection. While the model achieves satisfactory overall performance, the limited SVEB recall underscores the need for future work to address minority-class detection, particularly through data augmentation, advanced sampling strategies, or multi-task learning approaches that can better capture subtle morphological differences between SVEB and Normal beats.

Suggestion

One important recommendation for this research is to further explore data augmentation techniques to enrich the dataset, particularly for underrepresented classes such as SVEB and VEB. Although the model has achieved strong accuracy, data augmentation can enhance the model's generalization ability by introducing additional ECG signal variations that better represent real-world conditions. Techniques such as time-shifting, scaling, and adding noise can provide the model with more diverse training examples, helping reduce the risk of overfitting and improving performance on unseen data. Additionally, future research could incorporate multi-lead ECG signals as model inputs, since the current study uses only a single ECG lead during training. Utilizing information from multiple ECG leads would allow the model to capture a more comprehensive representation of cardiac activity, potentially improving arrhythmia detection accuracy and enabling the model to better understand signal variability across different measurement points.

Further development could also consider integrating real-time processing into the arrhythmia detection system, for example through edge computing or wearable devices that analyze ECG signals directly at the source. This would be particularly valuable in medical applications requiring early detection, such as continuous monitoring of high-risk cardiac patients in hospitals or at home, and could enable timely alerts for both medical professionals and patients. Finally, evaluating the model on larger and more diverse datasets from different sources and populations would be beneficial, as it would help improve the model's robustness and performance in underrepresented cases while supporting broader real-world deployment, considering the physiological variability among individuals that may influence ECG signals and arrhythmia patterns.

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