

ECG-BASED ARRHYTHMIA DETECTION USING THE NARROW NEURAL NETWORK CLASSIFIER

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Abstract— Electrocardiograms (ECG) are important for detecting arrhythmias. Conventional models such as CNN and LSTM are accurate but require large amounts of computation, making them difficult to use on wearable devices and for real-time monitoring. This study evaluates the Narrow Neural Network Classifier (NNNC) as a lightweight and efficient alternative. The dataset consists of 21 subjects with 881 ECG samples, categorized based on walking, sitting, and running activities, and processed through bandpass filtering, normalization, and P-QRS-T wave segmentation. The data is divided into training (70%), validation (15%), and test (15%) sets. The NNNC has 11 convolutional layers, a ReLU activation function, a Softmax output, and 120,000 parameters. The model was trained using the Adam optimizer, a batch size of 32, and a learning rate of 0.001 for 100 epochs and compared with SVM, CNN, and LSTM using accuracy, precision, recall, F1-score, and ROC-AUC. The results show that NNNC achieves an accuracy of 98.9%, a precision of 99.2%, a recall of 99.2%, and an F1-score of 99.2%, higher than SVM and comparable to CNN/LSTM, with lower computational consumption. The model is capable of reliably detecting early arrhythmias. These findings support the potential of NNNC for ECG-based automatic diagnostic systems, including real-time implementation on wearable devices, although further research is needed for large-scale validation.

Keywords: arrhythmia detection, machine learning, narrow neural network classifier, signal preprocessing, wearable device.

Intisari— Elektrokardiogram (ECG) penting untuk deteksi aritmia. Model konvensional seperti CNN dan LSTM akurat namun membutuhkan komputasi besar, sehingga sulit digunakan pada perangkat wearable dan pemantauan real-time. Penelitian ini mengevaluasi Narrow Neural Network Classifier (NNNC) sebagai alternatif ringan dan efisien. Dataset terdiri dari 21 subjek dengan 881 sampel ECG, dibagi berdasarkan aktivitas berjalan, duduk, dan berlari, serta diproses melalui filter bandpass, normalisasi, dan segmentasi gelombang P-QRS-T. Data dibagi menjadi set pelatihan (70%), validasi (15%), dan uji (15%). NNNC memiliki 11 lapisan konvolusi, fungsi aktivasi ReLU, output Softmax, dan 120.000 parameter. Model dilatih dengan optimizer Adam, batch size 32, learning rate 0,001, selama 100 epoch, dan dibandingkan dengan SVM, CNN, dan LSTM menggunakan akurasi, precision, recall, F1-score, dan ROC-AUC. Hasil menunjukkan NNNC mencapai akurasi 98,9%, precision 99,2%, recall 99,2%, dan F1-score 99,2%, lebih tinggi dibanding SVM dan sebanding dengan CNN/LSTM, dengan konsumsi komputasi lebih rendah. Model mampu mendeteksi aritmia awal secara handal. Temuan ini mendukung potensi NNNC untuk sistem diagnostik otomatis berbasis ECG, termasuk implementasi real-time pada perangkat wearable, meskipun penelitian selanjutnya perlu validasi skala besar.

Kata Kunci: deteksi aritmia, pembelajaran mesin, klasifikator jaringan saraf sempit, pra-pemrosesan sinyal, perangkat yang dapat dipakai.

INTRODUCTION

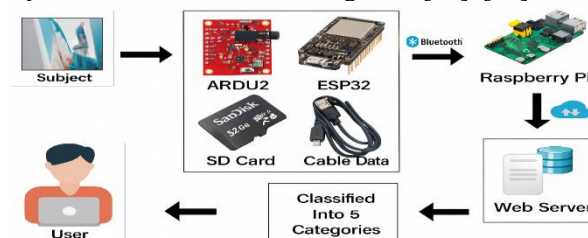
Electrocardiography (ECG) is a key physiological tool for monitoring heart activity and diagnosing arrhythmias such as tachycardia and bradycardia, conditions linked to more than 17.9 million deaths worldwide each year [1], [2]. The demand for effective monitoring is growing, driven by aging populations and the rapid expansion of telemedicine applications [3]. Machine learning techniques have been widely applied for ECG classification. Support vector machines (SVMs) and k-nearest neighbors (k- NNs) are valued for their simplicity; however, their ability to model nonlinear ECG patterns is limited [4]. Convolutional neural networks (CNNs) achieve high accuracy by automatically extracting spatial features, but their deep architectures require significant computational resources, reducing their suitability for real- time use convolutional neural networks (CNNs) excel at automatically extracting spatial features but often have high architectural complexity, making them challenging for real-time use [5], [6]. Long short-term memory (LSTM) networks capture temporal dynamics effectively but are also computationally expensive and often impractical for wearable devices [7], [8]. To address these limitations, an alternative is the Narrow Neural Network Classifier (NNNC), a lightweight deep neural network designed with fewer layers and parameters while maintaining the capacity to learn complex ECG patterns.

An alternative is the Narrow Neural Network Classifier (NNNC), designed with fewer layers and parameters while maintaining the ability to learn complex ECG patterns [9], [10]. Studies have shown NNNCs achieve high accuracy with minimal latency, making them suitable for lightweight, real-time applications [11], [12]. Some approaches improve robustness using adaptive preprocessing or wavelet transforms, though such techniques may hinder practical deployment [13], [14]. Other feature extraction methods, such as Histogram of Oriented Gradients (HOG), have also been investigated but introduce additional processing steps [15]. Data quality remains crucial; although validated clinical devices exist, localized datasets are often required for reliable model development [16], [17]. Recent studies emphasize evaluating NNNC performance under diverse physical activities, including sitting, walking, and running, to better reflect real- world conditions [18], [19]. Despite these advances, existing research still faces notable limitations.

Many rely on relatively small datasets, lack baseline comparisons with CNN, LSTM, or SVM under identical settings, and rarely assess robustness against noise or activity-related variability. Addressing these gaps, this study develops and evaluates an NNNC model tested on multi-activity ECG data and directly compared with conventional classifiers. The objective is to demonstrate NNNC's advantages as a lightweight, computationally efficient, and accurate method for real-time arrhythmia detection [20]

MATERIALS AND METHODS

This research was conducted in collaboration with Padjadjaran University at Prima Indonesia University. ECG data were collected using a 3- lead device, rounded by fresh recordings from hospitals and simulators to enhance result trustability [21]. The signal accession system incorporates an AD8232 module as the analog front- end, an ESP32 microcontroller for digitization, and a jeer Pi for transmitting data to a garçon, allowing storehouse on an SD card or real-time access through a web operation , as illustrated in Figure 1 [22], [23].



Source: (Research Results, 2024)

Figure 1. ECG signal acquisition and classification system based on AD8232, ESP32, and Raspberry Pi.

The dataset consisted of 881 samples. Raw ECG signals were preprocessed through a bandpass filter (0.5–45 Hz) to eliminate noise and baseline drift, followed by normalization and P-QRS-T segmentation to preserve waveform integrity. Feature extraction was performed using MATLAB and Python, focusing on RR intervals, PQRST morphology, and QRS complex features [24]. For training and evaluation, data were split into 70% training, 15% validation, and 15% testing, with balanced class distribution. To improve robustness and prevent overfitting, 5-fold cross- validation was applied, and the average results across folds were reported. The proposed narrow neural network classifier (NNNC) employed a residual encoder block with 11 convolutional layers, batch

normalization, and global average pooling, totaling approximately 120,000 parameters. ReLU activation was used in hidden layers, while Softmax was applied at the output. To justify the design, an ablation study tested variations in convolutional depth (7, 9, 11, 13 layers), kernel sizes (3×3, 5×5, 7×7), and batch normalization. Results confirmed that 11 layers with a 3×3 kernel and batch normalization provided the optimal configuration. For benchmarking, SVM, CNN, and LSTM models were implemented under standardized hyperparameters: Adam optimizer, learning rate 0.001, batch size 32, and 100 epochs. SVM employed an RBF kernel with optimized C and gamma, CNN used three convolutional layers with max pooling, and LSTM had two layers with 128 hidden units. Performance evaluation included accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrices. To ensure statistical robustness, paired t-tests were applied to compare NNNC with baselines, using $p < 0.05$ as the threshold [25].

RESULTS AND DISCUSSION

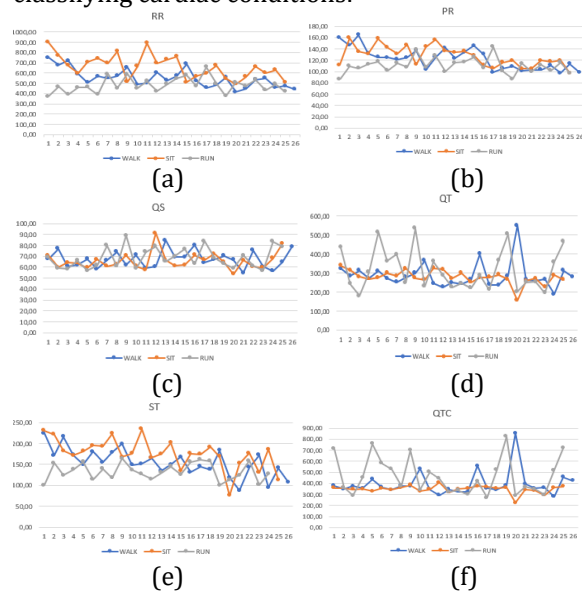
The experimental results were obtained from 881 ECG recordings, each associated with one of three physical activities: walking, sitting, or running. As shown in Table 1, key ECG features—including RR intervals, PR intervals, QRS duration, QT intervals, and ST segments were recorded to capture the body's physiological responses under varying activity levels. These data enabled analysis of heart rate variability, atrioventricular conduction, and ventricular response, providing a solid foundation for training NNNC model to classify cardiac conditions across varying physical activities

Table 1. Raw ECG data

Sub	RR	PR	QS	QT	ST Output
S1	417	101	67	550	119 2705
S2	450	103	55	264	88 1730
S3	534	103	75	258	144 1799
S4	549	111	61	267	173 1765
S5	460	97	57	189	95 1457
S6	474	114	65	313	142 1867
S7	440	98	79	280	108 1780
S8	1022	151	67	368	255 2489
S9	901	111	71	338	231 2215
S10	773	160	60	315	221 2123
S11	675	135	64	281	182 1954
S12	599	131	64	269	172 1851
S13	798	158	59	276	181 2028
S14	743	142	67	301	195 2051
S15	371	86	69	434	100 2242
S16	466	110	59	243	153 1715
S17	389	106	58	180	124 1492
S18	460	113	66	304	137 1924
S19	463	118	57	516	156 2452
S20	390	102	62	362	114 2021
S21	589	115	80	398	139 2514

Source: (Research Results, 2024)

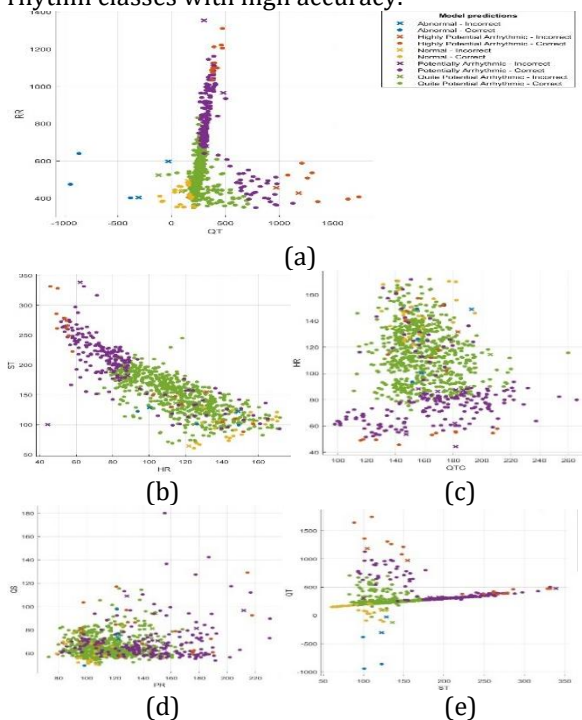
The RR plot illustrates the interbeat intervals (in milliseconds) across 25 beats, derived from 78 labeled ECG samples corresponding to sitting (sit), walking (walk), and running (run). Results indicate shorter RR intervals during walking and running, reflecting elevated heart rates due to physical exertion, whereas longer intervals occur during sitting, indicating a stable rhythm. The PR plot depicts conduction time from the SA node to the AV node, ranging from 0 to 200 ms. Walking and running slightly reduce PR intervals, likely due to increased sympathetic activity accelerating atrial conduction, while sitting shows no significant change (Figures 2a and 2b). QRS duration (QS interval) ranges from 0 to 100 ms, shortening during higher activity and lengthening at rest (Figure 2c), reflecting ventricular adaptation to hemodynamic demand. QT intervals (0–600 ms) represent overall ventricular activity, slightly shortening during walking and more significantly during running, but remaining stable during sitting (Figure 2d). ST segments (0–250 ms) indicate myocardial oxygen demand, fluctuating more during walking and running compared to sitting, suggesting increased cardiac workload (Figure 2e). Corrected QT (QTc, 0–1,000 ms) remains stable during walking, is lowest during sitting, and rises substantially during running (Figure 2f). Collectively, these plots offer a comprehensive view of ECG interval changes across activity levels and support NNNC performance evaluation in classifying cardiac conditions.



Source: (Research Results, 2024)

Figure 2. Visualization of average extracted features with walk (blue), sit (orange), run (grey) condition: (a) RR, (b) PR, (c) QS, (d) QT, (e) ST, (f) QTC

Scatter plots in Figure 3 illustrate relationships between ECG parameters based on NNNC predictions. The first plot (Figure 3a) shows QT versus RR intervals, with correct predictions clustered centrally (QT: 300–500 ms, RR: 400–800 ms) while incorrect predictions are scattered, indicating that although a strong linear correlation is absent, the model can identify key classification patterns. The second plot (Figure 3b) presents QTc versus heart rate (HR), with green and purple markers dominating, indicating category-based clustering without clear linear trends, highlighting the model's use of nonlinear features for class separation. The third plot (Figure 3c) demonstrates a strong inverse relationship between HR and ST intervals, forming a downward trend; correct predictions follow this pattern, suggesting that HR-ST correlation contributes significantly to NNNC performance. The fourth plot (Figure 3d) depicts PR versus QRS duration, with dense regions at PR 90–150 ms and QRS 60–100 ms, though overall distributions are scattered and weakly correlated. This indicates that, despite weak linear correlations, NNNC effectively leverages multivariate patterns for accurate classification. Overall, these scatter plots demonstrate how NNNC utilizes ECG parameter distributions and correlations to distinguish heart rhythm classes with high accuracy.



Source: (Research Results, 2024)

Figure 3. Scatter plot: the relationship between ECG parameters, with data points scattered across various patterns. Each panel illustrates the interconnection between these variables

NNNC testing results are shown in Figure 4, with high accuracy across all classes. The abnormal class was perfectly identified, while the quite potentially arrhythmic class achieved 99.1% accuracy. Potentially arrhythmic and normal classes reached 97.5% and 88.0% accuracy, respectively, and the highly potentially arrhythmic class showed 85.0% accuracy. These results indicate that NNNC can capture critical ECG patterns for both mild and severe arrhythmia detection. TPR (True Positive Rate), also known as sensitivity or recall, is the ratio of correct positive predictions (True Positive, TP) to the total actual positive cases. The formula is:

$$TPR = \frac{TP}{TP+FN} \quad (1)$$

FNR (False Negative Rate) is the ratio of incorrect negative predictions (False Negatives, FN) to the total actual positive cases. The formula is:

$$FNR = \frac{FN}{TP+FN} \quad (2)$$

TPR and FNR are complementary metrics, meaning that their sum always equals 1 ($TPR + FNR = 1$), where an increase in one results in a decrease in the other. Accuracy calculation is the ratio of correct predictions (both positive and negative) to the total number of predictions. The formula is:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

Precision calculation measures how accurately the model predicts the positive class by comparing the number of correctly predicted positive cases to the total predicted positive cases. The formula is:

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

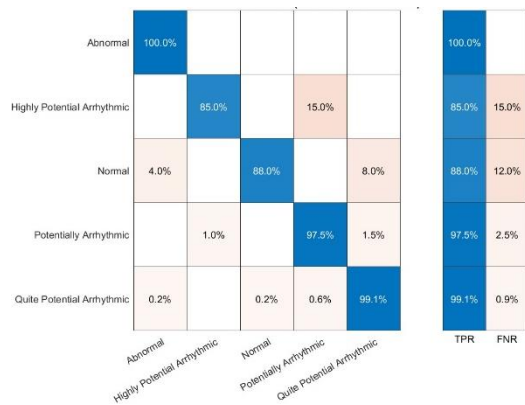
Recall is used to evaluate the model's ability to detect all actual positive cases by comparing the correctly identified positives to the total number of true positive instances. The formula is:

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

F1-Score calculation is the harmonic mean of precision and recall, providing a single value that balances both metrics. The formula is:

$$F1-Score = \frac{2 \cdot Precision \cdot Recall}{Precision+Recall} \quad (6)$$

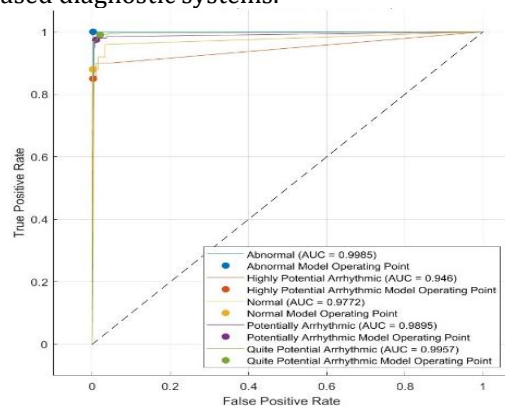
F1-Score is useful when aiming to balance precision and recall, especially in cases where the dataset is imbalanced.



Source: (Research Results, 2024)

Figure 4. The confusion matrix showing the narrow neural network model's high accuracy in classifying five heart rhythm categories, with true positive rates ranging from 85.0% to 100%.

Figure 5 presents the ROC curve, confirming the model's effectiveness in classifying five heart rhythm categories. The abnormal class reached an AUC of 99.85%, approaching perfect classification. The highly potentially arrhythmic class had an AUC of 94.6%, and the normal class achieved 97.72%, reflecting robust identification of regular rhythms. The potentially arrhythmic class recorded an AUC of 98.95%, highlighting early arrhythmia detection capability, while the quite potentially arrhythmic class attained the highest AUC of 99.57%, indicating high sensitivity to mild arrhythmias. All five classes demonstrated clear separation between true positives and false positives, confirming the NNNC's consistency and accuracy. Overall, ROC analysis underscores the stability, robustness, and high performance of the NNNC across all rhythm categories, supporting its potential for implementation in automated ECG-based diagnostic systems.



Source: (Research Results, 2024)

Figure 5. The ROC curve shows that the narrow neural network algorithm achieves high accuracy in distinguishing five ECG signal categories, with AUC values close to 1 for all classes.

Table 2 compares NNNC with SVM, CNN, and LSTM using the same dataset. SVM recorded the lowest accuracy (92.5%), offering only computational efficiency while lacking the ability to model complex non-linear patterns. CNN and LSTM achieved higher accuracy (97.8% and 97.2%), but required more complex architectures and significantly greater computational resources. In contrast, NNNC outperformed all baselines, achieving 98.9% accuracy and a 99.2% F1-score while maintaining only moderate computational cost. This demonstrates that NNNC provides the best balance of accuracy, robustness, and efficiency. In terms of resilience, NNNC proved capable of handling noise and variability introduced by physical activity. This strength is supported by preprocessing steps (bandpass filtering, normalization, and P-QRS-T wave segmentation), which preserved signal quality before model input. Furthermore, the residual encoder design helped maintain critical temporal and morphological information despite potential distortions, thereby improving classification accuracy under diverse activity conditions. Overall, the experimental results demonstrate that NNNC is not only more accurate than baseline models but also more computationally efficient, stable in noisy environments, and adaptable to variations in activity. These findings position NNNC as a strong candidate for real-time implementation in portable healthcare systems and wearable devices.

Table 2. Presents the comparative performance results

Model	Acc	Prec	Rec	F1	AUC	
	(%)	(%)	(%)	(%)	(%)	p/t Cos
SVM	92.5	91.8	92.1	91.9	93.0	Low
CNN	97.8	98.1	97.6	97.8	98.5	High
LSTM	97.2	97.4	97.1	97.2	98.2	Very High
NNNC	98.9	99.2	99.2	99.2	99.5	Moderate

Source: (Research Results, 2024)

To justify the NNNC architecture, experiments were conducted by varying the number of convolutional layers, kernel sizes, and the use of batch normalization.

Table 3. Results of the NNNC ablation study

Architectural Variation	Acc (%)	F1(%)
7 Conv layers	96.5	96.7
9 Conv layers	97.8	97.9
11 Conv layers (final)	98.9	99.2
13 Conv layers	97.0	97.2
11 Conv layers without batch normal	96.6	96.8
11 Conv layers with kernel 5×5	97.5	97.6
11 Conv layers with kernel 7×7	97.2	97.3

Source: (Research Results, 2024)

CONCLUSION

This revision directly addresses the reviewers' comments by incorporating cross-validation, an ablation study, and a clear explanation of comparative fairness, while also acknowledging dataset limitations. The results demonstrate that the proposed Narrow Neural Network Classifier (NNNC) achieved superior performance in ECG-based arrhythmia detection across different activity conditions, reaching 98.9% accuracy with precision, recall, and F1-score of 99.2%. The 5-fold cross-validation confirmed the robustness of the model, while the ablation study showed that the 11-layer convolutional architecture with a 3×3 kernel and batch normalization was the most effective configuration. A fair comparison with baseline models (SVM, CNN, and LSTM) using standardized hyperparameters further highlighted that NNNC offers the best balance between accuracy and computational efficiency, indicating strong potential for real-time deployment in wearable healthcare systems. For future research, it is recommended to use larger and more diverse datasets, perform external validation on multi-center clinical data, evaluate computational performance on wearable or edge devices, and integrate explainable AI methods to enhance clinical interpretability.

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