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Hybrid Kolmogorov-Arnold and convolutional neural network model for single-lead electrocardiogram classification

Marlin Ramadhan Baidillah[1], Pratondo Busono[2], I Made Astawa[1], Syaeful Karim[1], Rony Febryarto[1], I Putu Ananta Yogiswara[1], Chaerul Achmad[3], Nashrullah Taufik[1]
[1]Research Center for Electronics, National Research and Innovation Agency, Bandung, Indonesia
[2] Research Center for Smart Mechatronics, National Research and Innovation Agency, Bandung, Indonesia
[3]Department of Cardiology and Vascular Medicine, Faculty of Medicine, Padjadjaran University, Bandung, Indonesia

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ABSTRACT

This study proposes a hybrid Kolmogorov-Arnold networks (KANs) and convolutional neural networks (CNN) to classify electrocardiogram (ECG) signal abnormalities in one lead ECG data of wearable telemedicine. The hybrid model combines CNN to extract hierarchical features from sequential data and KANs to model non-linear relationships with fewer parameters as an efficient classification. The study explores the model's capacity to balance accuracy, computational efficiency, and memory usage as critical factors for real-time health monitoring in resource-constrained environments on the single-lead MIT-Beth Israel hospital (MIT-BIH) Supraventricular Arrhythmia database with five different class labels. For comparison, standalone CNN and KAN models were also trained on the same balanced dataset. The CNN model achieved an accuracy of 96.62%, precision of 96.81%, and recall of 96.53%. The KAN model, while computationally efficient, performed less effectively, with an accuracy of 94.15%, precision of 95.01%, and recall of 92.57%. In contrast, our hybrid KAN-CNN model outperformed both, attaining an accuracy of 97.53%, precision of 97.66%, recall of 97.40%, and a low loss of 0.0840. The study also explores the impact of quantization and compression on model performance, revealing that both CNN and Hybrid KAN-CNN models retained high accuracy post-quantization, whereas the KAN model exhibited a more significant drop in performance.

Corresponding Author:

Marlin Ramadhan Baidillah
Research Center for Electronics, National Research and Innovation Agency
Bandung, 40135, Indonesia.
Email: marlin.ramadhan.baidillah@brin.go.id

1. INTRODUCTION

Cardiovascular diseases remain the leading global cause of death [1], and their early diagnosis relies heavily on electrocardiogram (ECG) interpretation [2]. Traditionally, ECG analysis was done visually by cardiologists, which is time-consuming and susceptible to human bias [3]. The emergence of wearable telemedicine devices has created a demand for automatic, reliable ECG classification methods that are compatible with resource-constrained environments [4], [5]. These devices are typically limited to single-lead ECG due to constraints in power, memory, and size [6]–[8]. Moreover, the use of data compression further degrades signal quality [9], making accurate classification more challenging. Machine learning has gained widespread traction in addressing these limitations due to its flexibility in identifying complex patterns, even from reduced input data [10]. However, the challenge remains in designing models that achieve a balance between classification accuracy and computational efficiency.

A growing body of work has focused on single-lead ECG classification. Mitchell *et al.* [10] and Kim *et al.* [11] demonstrated high performance in arrhythmia and atrial fibrillation (AF) detection using hybrid and deep learning models, while Gadaleta *et al.* [12] showed that combining morphology with demographic features improves near-term AF prediction. Additional efforts have addressed practical deployment. Athif *et al.* [13] and Fan *et al.* [14] developed accurate models for AF detection, though limited in robustness across arrhythmias. Wasimuddin *et al.* [15] proposed a lightweight convolutional neural networks (CNN) for myocardial infarction detection with strong performance and low complexity. Kuznetsova *et al.* [16] used spectral analysis with artificial intelligence (AI) to assess left ventricular diastolic dysfunction (LVDD) but lacked real-time benchmarks. He *et al.* [17] used support vector machines (SVMs) for postoperative AF prediction but didn't explore scalable architectures. Kim *et al.* [18] introduced Tiny convolutional ECG-based system (TinyCES), a memory-efficient CNN validated on MIT-Beth Israel Hospital (MIT-BIH), yet did not evaluate inference time. These studies affirm the feasibility of single-lead ECG classification on constrained platforms, but most focus narrowly on accuracy while underreporting key deployment concerns like quantization, latency, and profiling issues vital for real-time, embedded health monitoring [19].

To address this, the present study evaluates Kolmogorov-Arnold networks (KANs), which approximate complex functions with fewer parameters by leveraging learnable univariate activations [20]. KANs have demonstrated compactness and potential for ECG classification [21], but their performance remains limited. In contrast, CNNs extract rich hierarchical features [11], [22] but are often too computationally intensive for wearables [23]. A hybrid KAN-CNN model is proposed to combine the compact efficiency of KANs with the robust feature extraction of CNNs, offering a potential solution for accurate and efficient single-lead ECG classification in wearable devices [24]. This model has not been previously explored in literature. We will benchmark KAN, CNN, and the hybrid model using the MIT-BIH Supraventricular Arrhythmia database, with detailed evaluation of classification performance, memory usage, inference latency, and quantization effects to assess their feasibility for real-time, embedded deployment.

2. METHOD

2.1. Problem formulation and objective

This study addresses the classification of heartbeats from single-lead ECG signals, a common format in wearable devices. The task is framed as a multi-class classification problem, where each input ECG segment is assigned to one of five classes: normal (N), supraventricular (S), ventricular (V), fusion (F), and unclassifiable (Q), as illustrated by the ECG signal morphologies. Given a dataset of m ECG segments, each example consists of a signal $x^i \in \mathbb{R}^n$ and a label $y^i \epsilon \{0,1,2,3,4\}$. The model aims to learn a function $F(\cdot)$ with parameters θ, such that the output is $z^{(i)} = F(x^i; \theta)$.

To interpret the model's output, a SoftMax function is applied to compute class probabilities as$p\left(z_j^i\right) = \frac{\exp\left(z_j^i\right)}{\sum_k exp\left(z_k^i\right)}$. The model is trained using the cross-entropy loss:

$$L(X) = -\frac{1}{m}\sum_{i=1}^{m}\sum_{j=0}^{4} 1\{y^i = j\}\log p\left(z_j^i\right) \tag{1}$$

which penalizes incorrect predictions and encourages the model to assign higher probabilities to the correct class.

2.2. Model training strategy

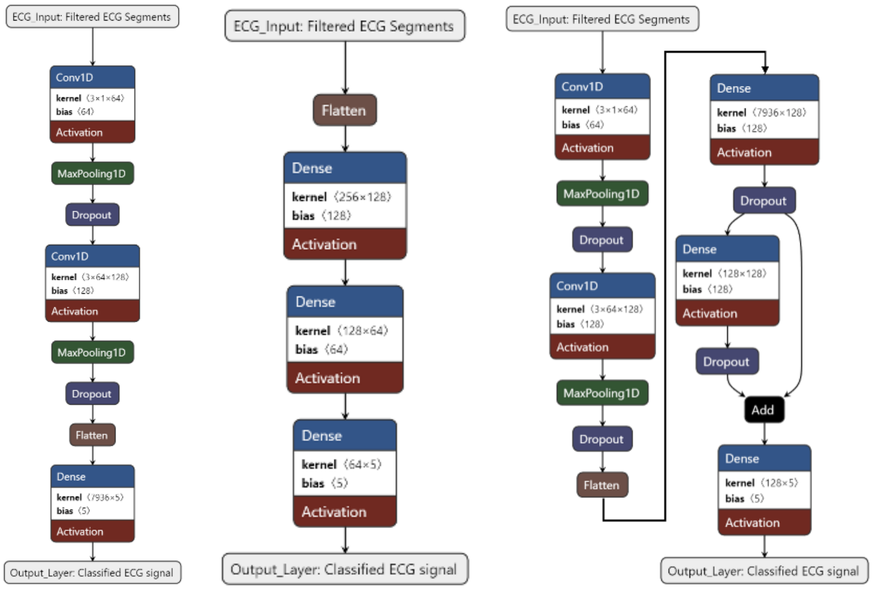
All models are trained using the Adam optimizer [25], which automatically adjusts the learning rate for each parameter and works well with sparse data and noisy gradients. Both are common in ECG classification tasks. An initial learning rate of 0.0005 is used. Training is halted early if the model does not improve for 10 consecutive epochs (early stopping), and categorical cross-entropy is used as the loss function [26].

2.3. Neural network architectures

Three machine learning models are evaluated and shown in Figure 1, a CNN, a KAN, and a hybrid KAN–CNN model. Each is designed for single-lead ECG signals and optimized for low-resource environments such as wearable health monitors. CNN architecture Figure 1(a), CNNs are designed to automatically detect patterns from raw input signals, making them highly effective for ECG feature extraction. This architecture uses two layers of one-dimensional (1D) convolution followed by max-pooling, dropout, and activation layers (ReLU) to capture low- and high-level features such as QRS complexes and P-waves. A flatten layer prepares the data for a fully connected (dense) layer, which outputs class probabilities using SoftMax activation. CNNs are known for their speed and simplicity, making them a strong baseline.

KAN architecture Figure 1(b), KAN are a new class of machine learning models that aim to approximate complex functions using fewer parameters by combining univariate functions. This makes them well-suited for environments with limited memory. The ECG signal is first flattened and passed through two dense layers with learnable univariate activations based on the Kolmogorov–Arnold representation theorem [20]. These dense layers focus on modeling nonlinear relationships within the ECG signal. A final SoftMax layer outputs the class probabilities.

Hybrid KAN–CNN architecture Figure 1(c), the proposed hybrid model combines the advantages of both CNNs and KANs. It begins with the CNN component, which extracts structured and hierarchical features from the raw ECG signal using convolution and pooling layers. After flattening the CNN output, the resulting feature vector is fed into the KAN component. Here, dense layers with learnable activation functions refine the extracted features by modeling complex, non-linear relationships. Additionally, residual connections are used between layers to improve training stability and enable deeper learning by allowing easier gradient flow, following the approach of Huang *et al.* [27]. This architecture is designed to maintain CNN's powerful pattern recognition while leveraging KAN's efficiency for more accurate classification with fewer computational resources.



(a) (b) (c)

Figure 1. The architecture machine learning models: (a) CNN model, (b) KAN model, and (c) hybrid KAN-CNN

3. EXPERIMENT

3.1. Datasets

The dataset used for training and evaluating the hybrid KAN-CNN model is the MIT-BIH supraventricular arrhythmia database [28]. This database is a widely used standard in ECG classification research and provides a diverse set of arrhythmia recordings. The dataset includes annotated single-lead ECG signals, with a focus on supraventricular arrhythmias and contains recordings of ECG signals from 48 patients, each with two-channel recordings (V1 and V2) collected over a period of 24 hours. Each recording is sampled at 128 Hz, and annotations are provided for various types of arrhythmias, see Figure 2. In this classification study, the graphs of each signal type in Figure 2 are considered, with five labels from the dataset: N, S, V, F, and Q. Signal N, normal beat, has symmetrical waveform with clear P, QRS, and T waves. Signal S, supraventricular premature beat, is similar to signal N, but might have slight variations in amplitude or duration. Signal V, ventricular premature beat, is a wide, bizarre QRS complex, often preceded by a compensatory pause. Signal F, fusion of ventricular and normal beat, is a hybrid of signals N and V, with a wider QRS complex than N but not as wide as V. Meanwhile, signal Q, unclassifiable beat, is a waveform that doesn't fit the typical patterns of N, S, V, or F.

For this study, the dataset is splitted into training and test sets. The training set is used to train the model, while the test set is reserved for evaluating the model's performance. The training set is further balanced using Synthetic minority over-sampling technique (SMOTE) to address class imbalance issues by generating synthetic samples for minority classes [29], see Figure 3(a). All the data were balanced into 10000 data.

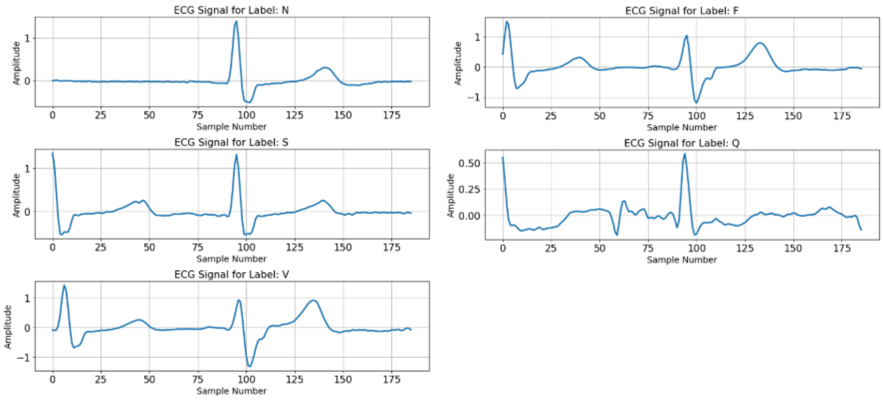
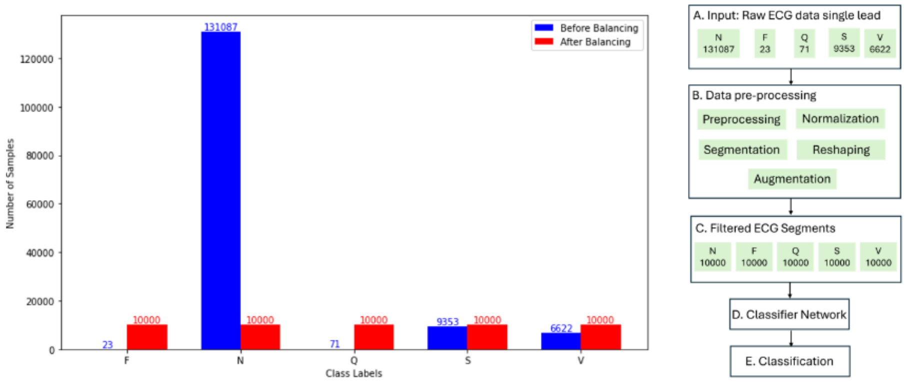


Figure 2. The different morphology of ECG signals classed in the MIT-BIH dataset

3.2. Data preprocessing

Data preprocessing, as shown in Figure 3(b), is a critical step to ensure that the ECG signals are suitable for input into the model. The preprocessing steps are applied, such as segmentation, reshaping, and data augmentation. To simulate real-world wearable scenarios, data compression is applied by down sampling the ECG signals. The impact of compression on model performance is evaluated alongside the effects of quantization, particularly when deploying models on resource-constrained devices.



(a) (b)

Figure 3. Data preprocessing: (a) the balancing data and (b) overall data flow

3.3. Time profiling and computational efficiency analysis

Time profiling evaluates the computational efficiency of each model by measuring both training and inference durations, which are essential for real-time applications on wearable devices with limited processing capacity [9]. While training is usually performed offline, fast training remains important for use cases requiring frequent updates, such as personalized ECG monitoring systems [30]. In such contexts, reduced training time enables quicker model adaptation with minimal service interruption. Inference time, the duration required to make predictions on new data, is especially critical for continuous, real-time monitoring. Wearable ECG devices must operate within tight latency constraints to detect cardiac abnormalities promptly [31]. Delays in inference could compromise timely feedback and reduce clinical effectiveness [9].

3.4. Quantization, compression, and different dataset size analysis

To make the models suitable for embedded systems, quantization was applied using TensorFlow lite. Quantization reduces the precision of model weights from 32-bit floating-point to 8-bit integers, significantly reducing model size and inference times [32]. Additionally, compression analysis was conducted by applying signal down sampling, simulating data compression typically used in wearable ECG monitors to reduce storage and transmission requirements [33]. Meanwhile, we also conducted the different dataset sizes (500, 5000, and

10000 samples) in order to evaluate the robustness in real situations in which the number of data could be limited [34].

3.5. Evaluation metrics

The performance of the models is evaluated using several key metrics [35], such as accuracy, precision, recall, and confusion matrix. These metrics are calculated for both the training and test datasets to assess the model's ability to generalize to new, unseen data. The results are compared with those of traditional CNNs and standalone KANs to demonstrate the effectiveness of the hybrid KAN-CNN approach.

4. RESULTS AND DISCUSSION

4.1. Model performance comparison (accuracy, precision, recall)

Figure 4 presents the comparative performance of CNN, KAN, and hybrid KAN-CNN models in terms of accuracy, precision, recall, and loss. The hybrid KAN-CNN consistently outperforms the other models, making it particularly suitable for real-time single-lead ECG classification.

The hybrid KAN-CNN achieves the best results with an accuracy of 0.9753, precision of 0.9766, recall of 0.9740, and a low loss of 0.0840. Its superior performance stems from combining CNN's hierarchical feature extraction with KAN's efficient function approximation, enhanced further by residual connections that mitigate vanishing gradient issues. The CNN model follows closely with an accuracy of 0.9662, precision of 0.9681, recall of 0.9653, and a loss of 0.1163. Its strength lies in automatic feature learning from sequential data, which is essential for identifying diverse cardiac patterns. The KAN model, while offering the fastest training and inference times, shows lower accuracy (0.9415), precision (0.9501), and recall (0.9257), with a higher loss of 0.3464. Its reduced performance reflects limited feature extraction capability, though its low computational cost may benefit embedded, low-power devices. Overall, the hybrid architecture effectively integrates the advantages of CNN and KAN, delivering high precision and low error rates crucial for minimizing misdiagnoses in wearable ECG systems.

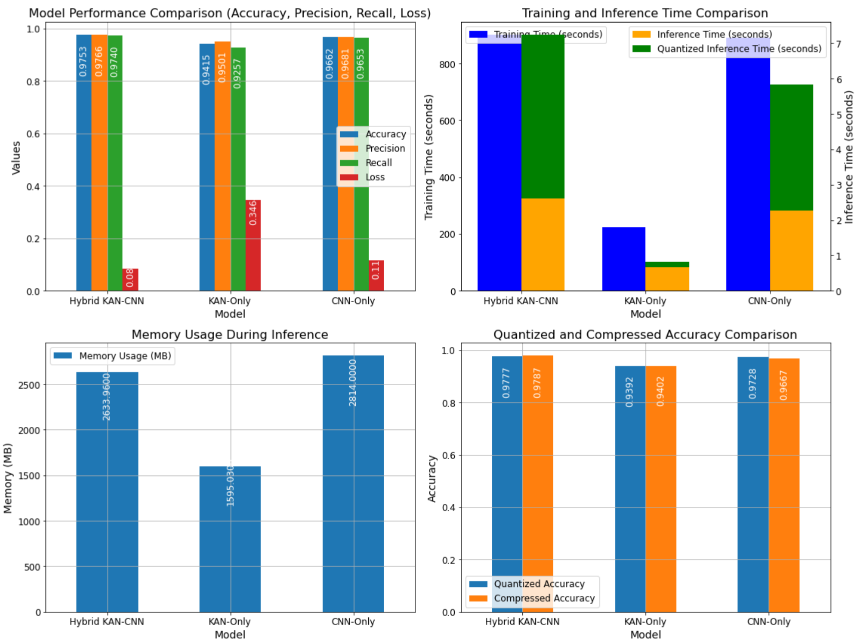


Figure 4. Model performance comparison: training and inference time comparison, memory usage during inference comparison, and quantized and compressed accuracy comparison

4.2. Training and inference time comparison

As shown in Figure 4 (upper right), computational efficiency is crucial for real-time ECG analysis on wearable devices. CNN achieves a balanced performance with 889.79 seconds training and 2.27 seconds inference time; quantization slightly increases inference to 3.56 seconds per 10,000 samples. KAN offers the fastest processing—224.10 seconds training and 0.67 seconds inference—but with lower classification accuracy, limiting its suitability for high-stakes monitoring. Hybrid KAN-CNN takes 902.27 seconds to train and 2.61 seconds for inference, rising to 4.64 seconds post-quantization. This trade-off delivers a strong gain in accuracy, remaining practical for mid-tier embedded systems. Overall, hybrid KAN-CNN provides the most effective balance of speed and accuracy for wearable ECG applications.

4.3. Memory usage during inference

The memory usage comparison is shown in Figure 4 (bottom left). KAN is the most memory-efficient model, requiring 1595.03 MB during inference. This is advantageous for systems where memory is a constraint, though the model's reduced classification performance must be considered. Hybrid KAN-CNN consumes 2633.96 MB during inference, which is slightly lower than the CNN model at 2814.00 MB. This shows that despite the additional residual connections, the hybrid model manages memory efficiently, making it suitable for devices with higher memory availability. Therefore, hybrid KAN-CNN strikes a good balance between memory usage and performance, which is beneficial for wearable ECG classification systems that operate in resource-constrained environments.

4.4. Quantized and compressed accuracy comparison

Quantization and compression, as shown in Figure 4 (bottom right), are critical for deploying machine learning models on embedded systems. CNN follows a similar pattern, with a quantized accuracy of 0.9728 and compressed accuracy of 0.9667, making it suitable for systems where moderate computational resources are available. KAN model, while efficient in terms of memory and computation, suffers from a larger drop in accuracy, with quantized accuracy of 0.9392 and compressed accuracy of 0.9402. This shows that KAN alone is not as robust in real-time, compressed environments, limiting its applicability in high-performance wearable devices. Hybrid KAN-CNN shows resilience to both quantization and compression, with only a slight drop in accuracy after quantization (0.9777) and compression (0.9717). This ensures that the model maintains its high classification performance even on resource-constrained devices.

4.5. Dataset size variation

Considering the real practice, the number of datasets could be limited and not always available. Thus, evaluating the model performances with different dataset sizes should be conducted. Here, we evaluated three different dataset sizes which are 500, 5,000, and 10,000 samples. As shown in Figure 5, model performance comparison across different dataset sizes shows a significant effect on accuracy, precision, and recall among the models.

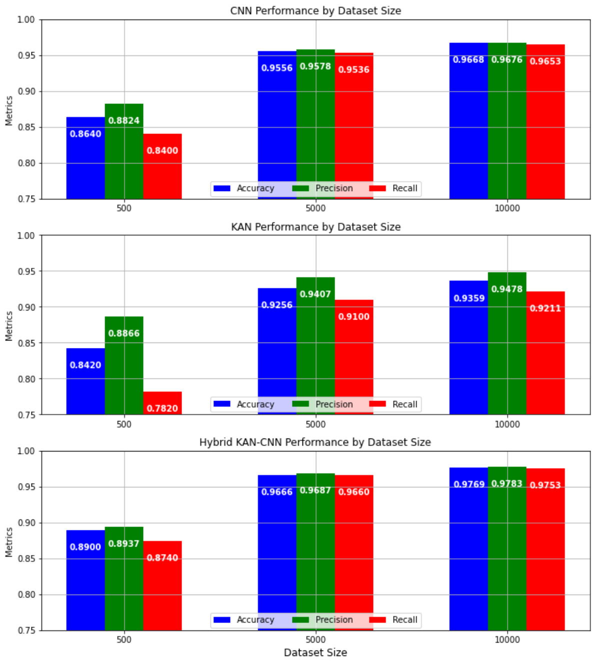
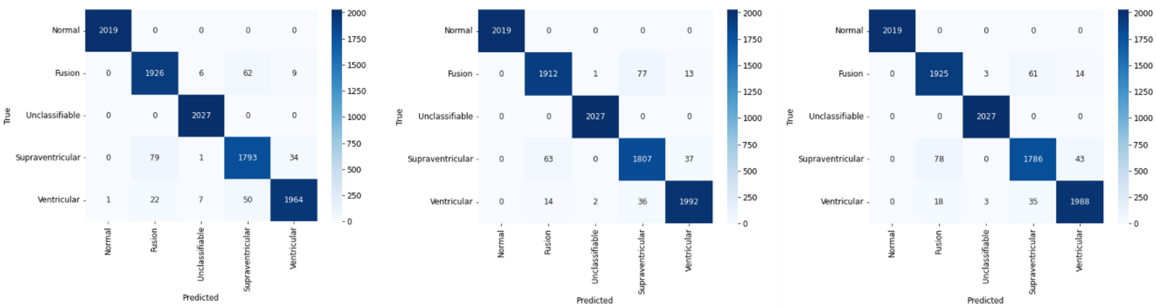


Figure 5. Model performance comparison across different dataset sizes

When trained on the largest dataset of 10,000 samples, the hybrid KAN-CNN with residual connections achieved the highest performance. The CNN model follows closely, while the KAN-only model underperforms. At a dataset size of 5000 samples, a similar trend is observed. The hybrid KAN-CNN with residual connections maintains its superior performance. For the smallest dataset (500 samples), performance drops across all models, yet the hybrid KAN-CNN maintains the highest accuracy, precision, and recall. The results suggest that larger datasets amplify the feature extraction capabilities of the hybrid KAN-CNN model which helps preserve crucial features across layers.

4.6. Confusion matrix analysis

Figure 6 illustrates how each model classifies ECG beats across predefined classes. CNN, Figure 6(a), shows strong performance, particularly for normal, unclassifiable, and ventricular classes. However, it has noticeable misclassifications in the fusion (62 beats misclassified as supraventricular) and supraventricular classes (79 beats misclassified as fusion). KAN, Figure 6(b), exhibits higher misclassification, especially for fusion beats (77 misclassified as supraventricular) and supraventricular beats (63 misclassified as fusion, 37 as ventricular), reflecting its limitations in handling complex patterns. Hybrid KAN-CNN, Figure 6(c), significantly reduces misclassification across all classes, improving generalizability. The confusion matrix shows reduced off-diagonal values, particularly for fusion, supraventricular, and ventricular classes, indicating fewer misclassifications. for example, supraventricular beats are better distinguished (only 43 misclassified compared to 63 and 79 in the other models), and ventricular misclassifications are the lowest among the three models. The hybrid model retains CNN's high fidelity in feature extraction while leveraging KAN's compact and efficient function approximation, leading to improved generalization and accuracy. Its ability to capture subtle distinctions enhances its reliability for real-time ECG analysis in wearable telemedicine.



(a) (b) (c)

Figure 6. Comparison of confusion matrix: (a) CNN, (b) KAN, and (c) hybrid KAN-CNN

4.7. Comparison with existing study and perspective for future studies

Compared to the work by Huang *et al.* [21], who used KAN for efficient ECG classification on single-lead data (F1: 0.75 in-sample, 0.62 out-of-sample), our study demonstrates that while KAN alone offers speed and compactness, it lacks the robustness required for complex signal interpretation. The hybrid KAN-CNN model introduced here outperforms both our KAN-only baseline and Huang's KAN approach, achieving 0.9753 accuracy, 0.9766 precision, and 0.9740 recall on the MIT-BIH dataset—at the cost of increased architectural complexity.

While Huang's model favors edge deployment with fewer parameters and learnable edge activations, its lower generalizability and lack of reported inference times limit direct comparison. In contrast, our hybrid KAN-CNN balances accuracy and computational load (902.27s training, 2.61s inference), benefiting from residual learning and CNN-based feature extraction—crucial for wearable ECG applications.

Future research can extend this work by: scaling to multi-lead ECGs for better detection of complex arrhythmias, expanding from classification to real-time anomaly detection and prediction, exploring advanced CNN-KAN integration with attention or deeper residual paths, testing generalizability across diverse datasets and patient populations, enhancing KAN's adaptability on small datasets via better regularization and architectural tuning for deployment in a wearable device.

4.8. Discussion

The hybrid KAN-CNN outperforms both standalone KAN and CNN models due to its ability to integrate their complementary strengths. While CNN excels at hierarchical feature extraction from raw ECG signals and KAN offers fast, memory-efficient approximation, their combination in the hybrid model enables both rich representation and efficient learning. This synergy is evident in its superior accuracy (0.9753), precision (0.9766), and recall (0.9740), alongside a low loss (0.0840). The addition of residual connections in the hybrid model further enhances training stability and mitigates vanishing gradient issues, particularly in deeper architectures. Compared to CNN, the hybrid maintains comparable inference time and slightly lower memory usage, while significantly outperforming KAN in classification robustness. Notably, under dataset size variation, the hybrid consistently maintains top performance, especially when data is limited—suggesting better generalization. Its resilience to quantization and compression also makes it suitable for deployment in real-time, resource-constrained wearable systems. The hybrid model strikes a superior balance between performance, efficiency, and adaptability, making it the most viable architecture for accurate and scalable ECG signal classification.

5. CONCLUSION

In this study, we evaluated the performance of KAN, CNN, and a hybrid KAN-CNN model for ECG classification in the context of wearable telemedicine systems, particularly focusing on single-lead ECG signals. The hybrid KAN-CNN model is the most viable solution for single-lead ECG classification in wearable telemedicine, offering the best trade-off between classification performance, computational efficiency, and memory usage. Its robustness and adaptability to embedded systems make it ideal for real-time health monitoring applications.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Marlin Ramadhan Baidillah	✓	✓	✓		✓	✓			✓	✓	✓		✓	✓
Pratondo Busono		✓								✓		✓	✓	
I Made Astawa	✓	✓	✓							✓				
Syaeful Karim	✓		✓							✓				
Rony Febryarto	✓		✓							✓				
I Putu Ananta Yogiswara	✓		✓							✓				
Chaerul Achmad	✓			✓						✓				
Nashrullah Taufik	✓		✓							✓				

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state that there is no conflict of interest.

DATA AVAILABILITY

The data availability is upon request.

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BIOGRAPHIES OF AUTHORS

Marlin Ramadhan Baidillah received the Ph.D. degree in Mechanical Engineering from the Division of Artificial System of Science, Chiba University, Chiba, Japan, in 2018, under the Japan Society for the Promotion of Science (JSPS) Research Fellowship DC2. He has been a Research Fellow with the Multiphase Flow and Visualization Laboratory, Graduate School of Science and Engineering, Chiba University, since 2018, under the JSPS Post-Doctoral Fellowship and the Chiba University Fellowship. He has also been a Research Coordinator at Ctech Labs Edwar Technology, Tangerang, Indonesia, from 2012 to 2015. He has been with the National Research and Innovation Agency (BRIN), Jakarta, Indonesia, since 2022. His research interests include sensing, imaging, and tomography systems for biomedical and industrial applications. He can be contacted at email: marlin.ramadhan.baidillah@brin.go.id.

Pratondo Busono received his Ph.D. in Mechanical Engineering from the University of New Brunswick, Canada, in 1998, majoring in Nuclear Radiation-Based Imaging Systems. From 1998 to 1999, he was a post-doctoral fellow at the Laboratory of Threat Material Detection in Fredericton, Canada. Over the period from 1988 to 2020, he was with the Agency for the Assessment and Application of Technology (BPPT), heading several research projects in medical technology. Before joining the Research Center for Smart Mechatronics at BRIN, he worked with BRIN's Research Center for Electronics. His research focuses on medical imaging, medical instrumentation, telemedicine, wearable devices, biosensors, and the application of AI in healthcare. He can be contacted at email: prat001@brin.go.id.

I Made Astawa received an engineer degree in electrical engineering majoring in electronics from the Sepuluh Nopember Institute of Technology in 1985 and a masters degree in computer science from the University of Indonesia in 1994. Currently working as a researcher at the National Research and Innovation Agency of Indonesia with research interests and innovation includes ADS-B, software engineering, programming, tsunami detection algorithm, embedded systems, high performance computing and computer vision. He can be contacted at email: imad001@brin.go.id.

Syaeful Karim received the B.Eng. degree in Electrical Engineering from Institute of Technology Bandung, Indonesia, in 1985 and the M.Sc. degree in Computer Science from Monash University, Australia, in 1992. Now, he is a researcher at National Research and Innovation Agency. His research interests include software engineering, software metrics, artificial engineering, machine learning and deep learning, mobile and web application, biomedical electronic and biosensing, telesurgery robotic system, wearable device, and also policy science. He can be contacted at email: syae001@brin.go.id.

Rony Febryarto received the M.Si. degree in Biomedical Engineering from Indonesia University, Indonesia in 2011. He worked as an engineer at BPPT, Indonesia from 2005 to 2021. Since 2021, he has been a researcher in the Group of Biosensing and Bioelectronic Systems at the National Research and Innovation Agency (BRIN) in Jakarta, Indonesia. His research interests include sensing and biomedical engineering systems. He can be contacted at email: rony003@brin.go.id.

I Putu Ananta Yogiswara received the S.Kom. degree in Computer Science from Bina Nusantara University, Indonesia, in 2010 and Master degree (MTI) from the same University in 2012. Currently, he is an Engineer at Electrical Research Center, National Research and Innovation Agency, Indonesia. His interest include microcontroller, RTOS, mobile application, database, deep learning and computer vision. He can be contacted at email: iput005@brin.go.id.

Chaerul Achmad received Medical Science doctoral degree from Padjadjaran University, Indonesia, in 2017 and Master degree from Padjadjaran University, Indonesia, in 1993. Currently, he is a Head of Division of invasive diagnostic, Department of Cardiology and Vascular Medicine, Padjadjaran University. He can be contacted at email: chaerulachmad@gmail.com.

Nashrullah Taufik received the Ir. and M.Sc. degrees in Electrical Engineering from the Delft University of Technology, The Netherlands, in 1994 and 2016, respectively. Currently, he is an Engineer at the Electronics Research Center of the National Research and Innovation Agency. His research interests include simulation and control systems, instrumentation, sensors and the internet of things, navigation electronics systems, surveillance technology of ADS-B, and electromagnetic compatibility. He can be contacted at email: nash001@brin.go.id.