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Potential of deep learning in advancing electrocardiography arrhythmia diagnosis in emergency medicine

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Abstract:

OBJECTIVES: Accurate differentiation between ventricular tachycardia (VT) and supraventricular tachycardia (SVT) with aberrant conduction in wide complex tachyarrhythmias (WCT) remains a significant challenge in emergency medicine. This study aimed to evaluate the efficacy of deep learning (DL) models, specifically pretrained residual network (ResNet) architectures, in classifying these arrhythmias using electrocardiography (ECG) data.

METHODS: A retrospective cross-sectional study was conducted, analysing 652 WCT ECGs and 248 normal sinus rhythm ECGs from an emergency medicine clinic. Three ResNet models ResNet-18, ResNet-34, and ResNet-50 were fine-tuned using transfer learning. Model performance was assessed via 10-fold cross-validation, evaluating accuracy, sensitivity, and precision.

RESULTS: All ResNet models demonstrated high and consistent performance, achieving 95% accuracy, precision in distinguishing VT from SVT with aberrant conduction. The models exhibited robust generalization across validation folds.

CONCLUSION: DL models, particularly ResNet architectures, show promise in enhancing ECG-based diagnosis of WCT. Their integration into emergency care could improve diagnostic accuracy, especially in settings with limited access to specialized cardiac expertise.

Keywords:

Computational medicine, deep learning, electrocardiography interpretation, supraventricular tachycardia, ventricular tachycardia, wide complex tachycardia

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Introduction

Timely and accurately diagnosing cardiac arrhythmias is a critical challenge in emergency care. Among the diagnostic tools available, electrocardiography (ECG) is the most widely utilized tool for diagnosing and monitoring cardiovascular diseases. It is recommended that an ECG be obtained within 10 min of the patient's arrival in the emergency department or ideally, during the initial contact with emergency medical services before hospital admission. The ECG must be immediately interpreted by a qualified physician. This early evaluation is essential for prompt risk stratification and timely initiation of appropriate treatment, especially in patients presenting with acute cardiac symptoms.[1] Its adoption is further supported by its ease of access,

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Box-ED Section

What is already known on the study topic?

- Cardiac arrhythmia diagnosis remains a critical challenge in emergency medicine where electrocardiography (ECG) is the primary diagnostic tool. Deep learning (DL) models, particularly Residual Networks (ResNet), have shown promise in medical diagnostics, demonstrating effectiveness in detecting various cardiac conditions such as cardiomyopathy, arrhythmias, and aortic stenosis.

What is the conflict on the issue? Has it importance for readers?

- Traditional clinical algorithms, including Brugada and Vereckei, exhibit limitations in distinguishing wide complex tachyarrhythmias (WCT). In addition, many studies rely on synthetic data or small, nonrepresentative samples, limiting their real-world applicability. This issue is particularly important for clinicians, as artificial intelligence-based systems could offer valuable support in the emergency settings where cardiology expertise may not be easily accessible.

How is this study structured?

- The study employs a retrospective and cross-sectional design, analyzing 652 WCT ECGs and 248 normal sinus rhythm (NSR) ECGs. ResNet-18, ResNet-34, and ResNet-50 models were adapted using transfer learning. Performance metrics, including accuracy, precision, and sensitivity, were assessed through 10-fold cross-validation to ensure reliability.

What does this study tell us?

- The study demonstrates that ResNet models achieved 95% accuracy, sensitivity, and precision in distinguishing WCT rhythms, which are a common diagnostic challenge in clinical practice. The findings suggest that these models can improve diagnostic accuracy and efficiency, especially in settings with limited access to cardiology specialists. Nevertheless, the study acknowledges certain limitations, including single-center data collection, class imbalance, and the absence of electrophysiological validation, which may affect generalizability.

affordability, reliability, and noninvasive nature, which collectively make it a key tool in the field.[2] The accurate interpretation of ECGs is equally important, as it directly informs patient diagnosis and treatment decisions. While this task often relies on experienced healthcare professionals, human error is still a possibility.

To mitigate this issue, computerized ECG interpretations have been developed over the past few decades, aiming to reduce variability and improve diagnostic consistency. As computational methods have evolved, DL, a subfield of artificial intelligence, has emerged as a powerful tool in computerized medicine. DL models, particularly convolutional neural network (CNN),[3] are inspired by the structure of the human brain and excel at recognizing patterns within complex data such as images, signals, and time-series data. These models learn directly from raw data, requiring minimal preprocessing, and have been shown to outperform traditional approaches in tasks such as image recognition, speech processing, and medical diagnostics.[4]

CNN's such as ResNet have demonstrated remarkable success in a variety of medical imaging tasks, including skin cancer classification, diabetic retinopathy detection, and radiographic image interpretation.[5] In the context of cardiovascular diagnostics, CNNs have also shown strong performance in classifying ECG signals, often outperforming traditional rule-based systems. Their ability to learn hierarchical representations directly from visual or waveform data allows for robust feature extraction, even in noisy or variable clinical environments.[6]

Importantly, timely and accurate arrhythmia classification is both a diagnostic challenge and a crucial part of effective treatment planning. Treatment pathways for ventricular and supraventricular tachycardias (SVTs) differ significantly, ventricular tachycardia (VT) often requires immediate defibrillation or antiarrhythmic agents, while SVT may be managed with vagal maneuvers or atrioventricular (AV) nodal blockers. Misclassification can delay appropriate intervention and increase the risk of adverse outcomes, particularly in hemodynamically unstable patients. Therefore, any tool that improves diagnostic precision has direct implications for patient safety and care.[7]

Studies have shown that DL-based ECG analyses can help diagnose conditions such as cardiomyopathies, aortic stenosis, rhythm disorders, and hyperkalemia.[8-10] One important and challenging use case in emergency settings is distinguishing between VT and SVT with aberrancy when the ECG shows a wide QRS complex. Making this distinction quickly and accurately is essential, as mistaking VT for SVT can lead to inappropriate management particularly the administration of AV nodal blocking agents such as beta-blockers, calcium channel blockers, or adenosine, which are often effective for SVT but potentially dangerous in the setting of VT. In patients with VT, these medications may further lower blood pressure, increase hemodynamic instability, and, in some cases, trigger ventricular fibrillation or even cardiac arrest.[11,12]

Therefore, failure to correctly identify VT can result in delayed or incorrect treatment, directly increasing the risk of morbidity and mortality. Although several ECG-based algorithms have been proposed to support this differentiation including Brugada, Vereckei, and the more recent limb lead algorithm many are complex, require significant training, and show variable accuracy in the real-world settings.[11-13] This underscores the need for accurate, fast, and user-independent tools that can assist clinicians in making critical diagnostic decisions under time pressure.

In this context, this study explores the accuracy of DL models, specifically pretrained ResNet architectures that specialized CNNs known for their ability to learn deeper features from images, in distinguishing between VT and SVT with aberrant conduction within WCT. Using the real-world ECG data, emergency physicians evaluated the system to assess its potential for practical application in the clinical settings and bedside diagnostics.

Methods

Data collection and processing

This study was conducted in the Adult Emergency Medicine Clinic of Ankara Bilkent City Hospital between November 2021 and March 2023, focusing on patients over 18 years old presenting with symptoms including palpitations, dizziness, dyspnea, chest pain, or syncope. Artifact-free ECGs with NSR and WCT were included in the study. ECGs were recorded using General Electric™ Healthcare Mac 200 devices (Made in India, GE Medical Systems Information Technologies, 2019) and stored in the Muse System. Ethical approval for this study was carried out following the approval decision numbered E2-22-2645, which was given on November 23, 2022, based on our application to the ethics committee number 2 of Ankara Bilkent City Hospital.

The 12-lead ECGs were exported from the Muse system in the digital image format (JPEG), preserving the standard clinical layout used in diagnostic workflows. All images were converted to grayscale, cropped to remove margins and text labels, and resized to 224 × 224 pixels. Only the waveform area was preserved. ECGs with excessive noise, baseline wander, lead detachment, or other visual artifacts were excluded during manual review. This preprocessing ensured consistency in lead positioning and minimized formatting variability.

The research adopted a retrospective cross-sectional design, with initial filtering based on specific criteria such as age, date, QRS width, and rhythm type, resulting 848 WCT ECGs. During the initial data collection phase, we observed a substantial number of ECGs exhibiting NSR. Considering common DL methodologies, which recognize that a moderate sample of normal cases can effectively support model training, we randomly selected 250 NSR ECGs. This approach addressed potential class imbalance while maintaining computational efficiency. By deliberately limiting the normal case population, we ensured the model could develop robust discriminative capabilities without overfitting to the predominant class, thus preserving its generalizability across diagnostic categories. After eliminating the poor-quality, artifact containing, and repetitive recordings, the dataset is narrowed to 652 WCT ECGs and 248 NSR ECGs.

All ECGs underwent a review process to ensure a complete and accurate classification. The recordings were anonymized to remove computer interpretations and filters and then independently evaluated by cardiology faculty members with expertise in dysrhythmias. When evaluations differed, a consensus meeting moderated by the emergency medicine professor was convened to reach a unanimous classification. Figure 1 provides representative examples of the three diagnostic categories included in the study: NSR, SVT-including AV nodal re-entry tachycardia (AVNRT), and VT. These ECGs illustrate the characteristic visual patterns used by experts during labeling, including QRS morphology, rhythm regularity, and AV association. Detailed visual interpretation supports both the manual review process and the model's learning of morphological features.

The labeling of ECGs into NSR, SVT, and VT classes was based on established clinical diagnostic criteria and reviewed by board-certified cardiology faculty. In the case of WCT, further subclassification into VT and SVT with aberrancy (e.g. AVNRT with bundle branch block) was performed using standard ECG markers. These included QRS duration, regularity, presence or absence of AV dissociation, capture/fusion beats, and axis deviation. When disagreements arose among reviewers, a consensus diagnosis was reached during a joint session moderated by a senior emergency medicine professor.

For classification purposes, the following ECG markers were used:

- QRS duration >120 m was considered a WCT
- Regular rhythm with no visible P-waves and retrograde P-waves following QRS suggested AVNRT
- AV dissociation, capture/fusion beats, and extreme axis deviation were considered strong indicators of VT
- Response to vagal maneuvers or adenosine (when available in the patient record) was also considered when differentiating AVNRT from VT.

In this study, AVNRT was not treated as a separate diagnostic class but included under the broader SVT category,

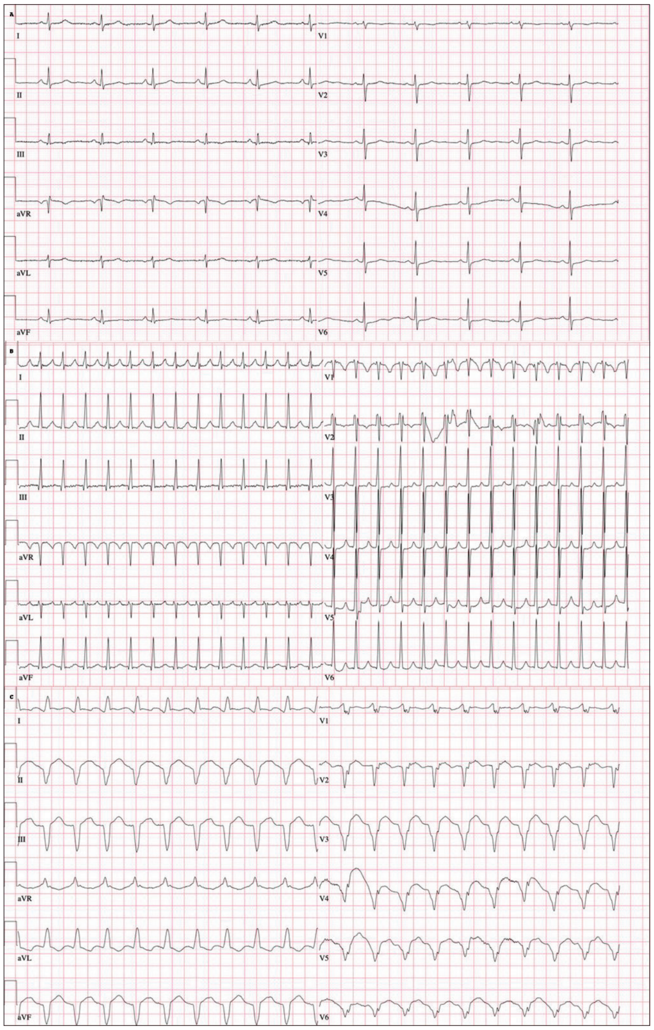

Figure 1: Representative 12-lead electrocardiography images used in model training, (a) normal sinus rhythm, (b) supraventricular tachycardia, (c) ventricular tachycardia

in line with standard clinical and electrophysiological classification. The final dataset comprised 583 SVT ECGs, 69 VT ECGs, and 248 NSR ECGs.

Pretrained convolutional neural network models for electrocardiography classification

In this study, we used CNNs, a type of DL model widely used for image classification tasks, to classify ECGs into NSR, SVT, and VT. CNNs are particularly efficient at analyzing visual data, drawing inspiration from how the human visual cortex processes images. Unlike traditional approaches that require manual feature extraction, CNNs can automatically learn and identify relevant features from raw input data. In ECG analysis, this capability is crucial for detecting subtle patterns that might escape human observation.

The ResNet models were trained on image-based representations of ECGs rather than raw waveform signals. Each ECG was treated as a visual input, leveraging the spatial structure of standard 12-lead layouts. Transfer learning was applied to adapt the pretrained CNNs to the three-class classification task [Figure 2]. Although we initially tested data augmentation methods such as minor rotation, scaling, and contrast changes, these were excluded from final training due to their potential to introduce clinically irrelevant variability. The decision to use image-based inputs was guided by the established interpretability of ECG images in clinical practice and the high performance of CNNs on structured visual data.

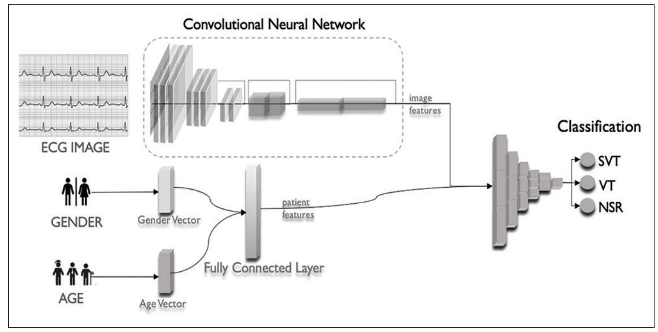

Figure 2: Overview of the three-class electrocardiography (ECG) classification framework-a deep learning-based approach integrating ECG images and patient demographic data for classifying supraventricular tachycardia, ventricular tachycardia, and normal sinus rhythm

We utilised ResNet-18, ResNet-34, and ResNet-50 architectures,[14] which were pretrained on large-scale datasets like ImageNet.[15] This pretraining allows them to effectively capture fundamental image features. Our implementation in PyTorch, an open-source Python library, leveraged these pretrained networks, adapting them to our specific ECG classification task. We modified the final classification layer to match our three-class problem (SVT, VT, and NSR), a technique known as transfer learning. All models were trained using the Adam optimizer with an initial learning rate of 1e-4, selected for its adaptive learning capabilities and robust performance in DL tasks.

To address the inherent class imbalance, particularly the limited number of VT ECGs, we employed a weighted cross entropy loss function instead of traditional oversampling techniques. This approach assigns higher weights to minority classes during training, ensuring balanced learning without duplicating samples, thus mitigating the risk of overfitting and preserving clinical data integrity.

The performance was evaluated using 10-fold cross-validation using multiple complementary metrics: accuracy (overall correct classifications), precision (exactness of positive predictions), sensitivity (ability to correctly identify positive cases), and the F1 score (harmonic mean of precision and recall), providing a nuanced understanding of the model's diagnostic capabilities.

Statistical analysis and data interpretation

Statistical analyses were performed using IBM SPSS Statistics for Windows, version 20.0 (IBM Corp., Armonk, N.Y., USA), employing a comprehensive analytical approach to evaluate the data. The methodology contains multiple statistical tests, including the Pearson Chi-square test for categorical data analysis, the Shapiro–Wilk test for normality assessment, and the Kruskal–Wallis test for examining nonnormally distributed parameters. To mitigate potential type I error (false positives) rates, a Bonferroni correction was applied during subgroup analyses, enhancing the reliability of statistical inferences.

Concordance analysis utilized Cohen's kappa test to assess inter-rater agreement, with a standardized interpretation framework: Moderate agreement was defined as 0.41–0.60, good agreement as 0.61–0.80, and very good agreement as 0.81–1.00. A comprehensive diagnostic evaluation was performed, which included key performance metrics such as specificity, sensitivity, likelihood ratios, predictive values, and overall accuracy rate. The priori significance level was established at $P < 0.05$, providing a robust statistical framework to interpret the study findings and draw meaningful conclusions.

Results

A total of 900 patients were included in the study, with a mean age of 57 ± 17 years and 61.4% were female. There was a high level of agreement between the initial interpretations of the two cardiologist reviewers who constituted a component of the reference diagnostic test (agreement rate: 95%; kappa = 0.896). In the 5% of cases where discrepancies were observed, the final diagnosis was established through a consensus meeting involving the emergency physician and the two cardiologists. Based on the reference diagnosis, 64.8% of patients were classified as SVT, 7.7% as VT, and 27.6% as NSR. The gender distribution was similar across these diagnostic groups ($P = 0.366$). However, a significant difference in the mean age was observed, with the NSR group having a lower average age (SVT: 63 ± 15 years; VT: 62 ± 15 years; NSR: 44 ± 15 years; $P < 0.001$). The age distribution between the SVT and VT groups was not significantly different.

We evaluated the performance of three ResNet models (ResNet 18, ResNet 34, and ResNet 50) using comprehensive computational performance metrics and statistical analyses. After excluding ECGs labeled as NSR, diagnostic value analyses were conducted using 2 × 2 contingency tables to distinguish between VT and SVT with aberrant conduction. The comparative statistical performance of the three ResNet models is summarized and illustrated in Figures 3-5 which include confusion matrices, receiver operating characteristic curves, and precision-sensitivity curves. The agreement between the reference diagnostic method and the ResNet models in distinguishing SVT from VT was also evaluated using kappa analysis. The kappa coefficients for ResNet-18, ResNet-34, and ResNet-50 were found to be 0.644, 0.650, and 0.676, respectively. In addition, 95% confidence intervals (CI) for accuracy, sensitivity, and specificity were computed for each model and are presented in Table 1.

Key performance findings for VT prediction (dichotomized-VT vs. not):

- Area under the curve: ResNet-18 = 0.912 (0.865–0.959), ResNet-34 = 0.949 (95% CI: 0.921–0.976), ResNet-50 = 0.928 (0.884–0.973); $P < 0.001$ for all 3 models
- Accuracy: All three models achieved a consistent 95% accuracy
- ResNet-34 exhibited the most specific predictions
- ResNet-50 showed the highest sensitivity [Table 1].

While numerical variations were observed between the classical statistical and computational performance analyses, the results demonstrated a strong correlation. It is crucial to note the methodological differences between traditional statistical regression models and more complex DL approaches when interpreting these findings. The comprehensive performance metrics suggest that all three ResNet models performed comparably, with subtle variations in specific aspects of diagnostic prediction.

Discussion

Our study demonstrated that ResNet-based DL models can achieve high diagnostic performance in distinguishing VT/SVT in WCTs, a diagnostic challenge frequently encountered in emergency medicine. The models achieved accuracy levels up to 95.0% highlighting their clinical potential for fast and accurate rhythm classification.[16]

Traditional rule-based algorithms, such as the Brugada and Vereckei criteria, have shown diagnostic accuracies

Table 1: Performance metrics with 95% confidence intervals

Model	Accuracy	Sensitivity	Specificity
ResNet-18	0.950 (0.934–0.962)	0.609 (0.491–0.715)	0.984 (0.973–0.991)
ResNet-34	0.951 (0.935–0.963)	0.609 (0.491–0.715)	0.986 (0.975–0.992)
ResNet-50	0.952 (0.936–0.964)	0.710 (0.594–0.804)	0.976 (0.963–0.984)

ResNet: Residual network

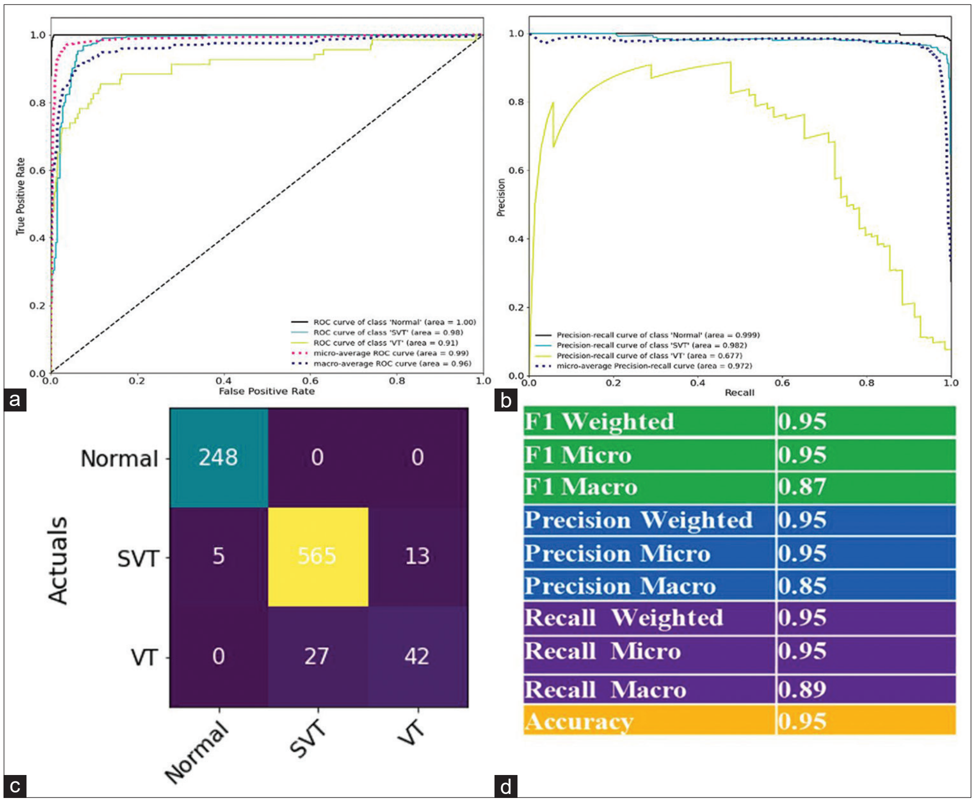

Figure 3: Performance evaluation of ResNet-18, (a) receiver operating characteristic curve illustrating the trade-off between true positive rate (sensitivity) and false positive rate across varying thresholds, (b) precision-recall curve showing the relationship between precision and recall, (c) confusion matrix presented as a heatmap, visualising true positives, false positives, true negatives, and false negatives, and (d) performance metrics table summarising key classification measures

between 75% and 85%, depending on clinician expertise and interpretation consistency. Moreover, emergency physicians often achieve VT/SVT differentiation accuracy between 70% and 80% in high-stress scenarios.[17] Compared to these conventional approaches, our ResNet models demonstrated more consistent and higher diagnostic performance, underscoring the added value of DL as a decision-support tool in time-sensitive clinical environments. An increasing number of studies highlight the potential of artificial intelligence in interpreting ECGs developed DL models that is capable of detecting arrhythmias from ambulatory ECGs with cardiologist-level performance.[6] Rabinstein *et al*.[18] emphasised the ability of artificial intelligence (AI) models to detect latent features in ECGs by identifying silent atrial fibrillation during sinus rhythm. Furthermore, Ribeiro *et al*.[19] trained their model on over two million 12-lead ECGs and demonstrated superior diagnostic accuracy compared to human experts.

These findings align with our study, in which DL models captured subtle waveform features to achieve high sensitivity even in diagnostically ambiguous cases. Recent benchmark studies further support the efficacy of CNN-based architectures in ECG classification. Strodthoff *et al*.[20] evaluated multiple DL models including ResNet on the PTB-XL dataset and demonstrated reliable performance using visual representations of ECG signals. Our study builds on this approach by applying ResNet architectures, originally developed for general image recognition to ECG image classification, illustrating the versatility of these models in medical signal analysis.[14]

It is important to note that in our study, AVNRT was not treated as a separate class but was categorized under the broader SVT group, consistent with clinical and electrophysiological classification standards.[21] ECG labeling was performed using established diagnostic criteria, including QRS duration, regularity, presence of AV dissociation, capture/fusion beats, and axis deviation. Any disagreements were resolved through consensus review by board-certified cardiology and emergency medicine faculty, ensuring labeling quality and clinical accuracy.

An important limitation of our dataset was class imbalance: VT cases accounted for only around 10% of the total. Although all models consistently achieved high sensitivity, their specificity differed between architectures, indicating a bias toward the majority class. This class imbalance may have led to a reduction in the model's ability to correctly identify VT cases in certain instances. Future studies should explore

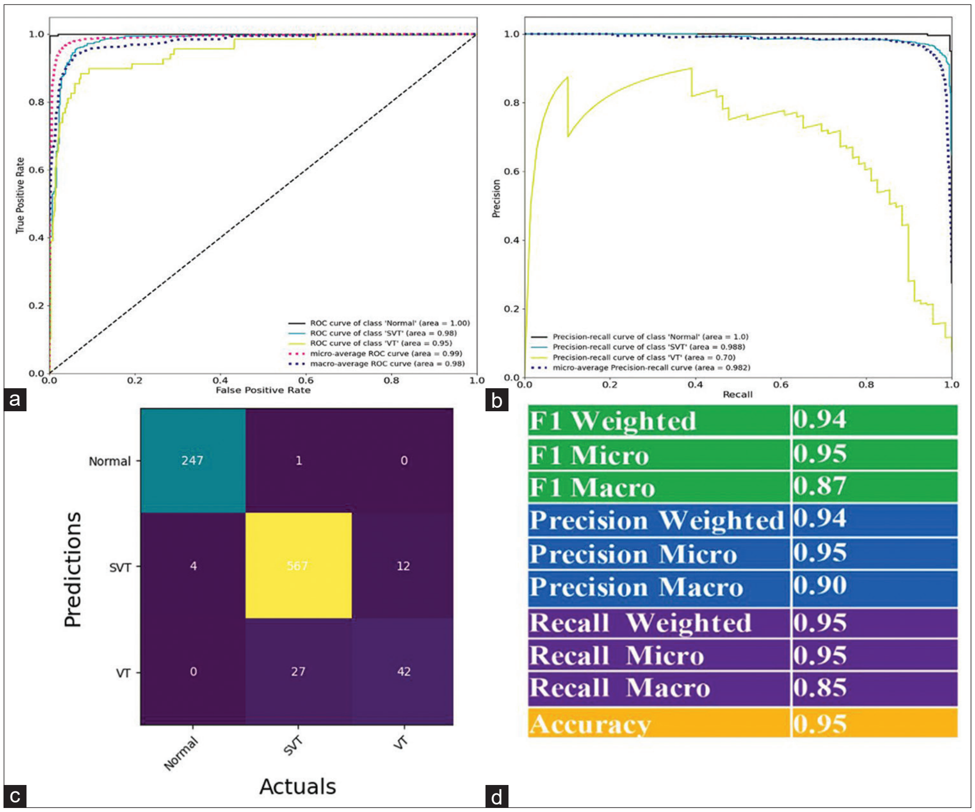

Figure 4: Performance evaluation of ResNet-34, (a) receiver operating characteristic curve illustrating the trade-off between true positive rate (sensitivity) and false positive rate across varying thresholds, (b) precision-recall curve showing the relationship between precision and recall, (c) confusion matrix presented as a heatmap, visualising true positives, false positives, true negatives, and false negatives, and (d) performance metrics table summarising key classification measures

class balancing strategies such as oversampling, class weighting, and synthetic data generation to improve minority class detection.[22,23] In addition to their technical performances, these models also hold significant promise for expanding access to cardiac diagnostics in low-resource settings. In rural clinics and underserved regions where cardiology expertise is limited or unavailable, AI systems could serve as initial screening tools or second-opinion systems for local healthcare providers. As shown in the study by Jo *et al.*,[24] these tools offer the potential for real-time, cost-effective support at the point of care, improving both diagnostic speed and accuracy in critical scenarios.

Despite these promising results, integrating DL models into real-world clinical practice remains complex. Factors such as dataset quality, rhythm diversity, model generalizability, and algorithm interpretability must be addressed. Future research should emphasize external validation, clinical trial testing, and bias mitigation to ensure safe, equitable, and effective deployment across the diverse healthcare settings.[10]

Limitations

Several important limitations should be considered in this study. First, the research was conducted retrospectively at a single center, which may limit the generalizability of the findings. Additionally, the ECGs of most patients were not recorded in the system, preventing the application of sequential data collection principles. Another limitation is the disparity in the number of VT ECGs compared to SVT and NSR ECGs, as VT rhythms are less common. This imbalance, which aligns with clinical practices and existing literature, results in an unbalanced dataset a common challenge in DL studies.[6] Lastly but importantly, while ECG evaluations were performed by cardiologists and considered the gold standard for diagnosis, electrophysiological evaluations would offer a more reliable gold standard, potentially enhancing the study's accuracy.

Moreover, clinical parameters, such as the presence of structural heart disease, results from previous electrophysiological studies, arrhythmia history, and whether the arrhythmia episode was new-onset or recurrent, were not available during the labeling or model training process. Although ECG morphology is central to diagnosis, these clinical factors significantly influence expert interpretation in the real-world settings. Their absence in the dataset limits the ability to fully replicate clinical diagnostic reasoning. Future work integrating both clinical and visual data could improve performance and real-world applicability.

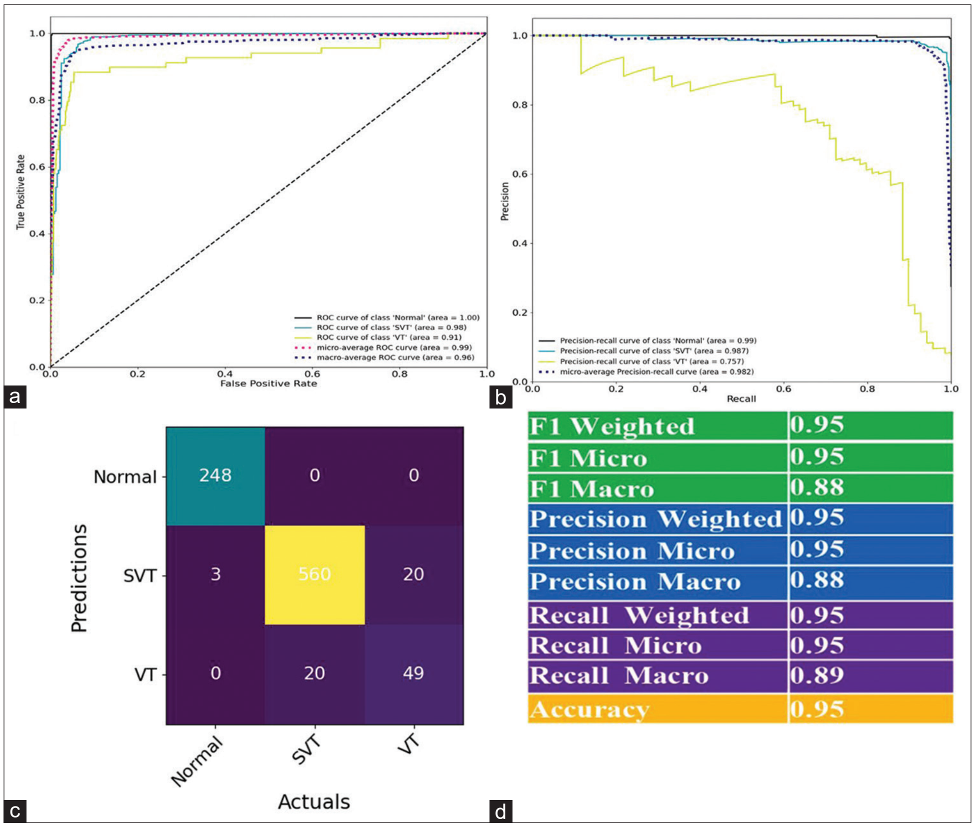

Figure 5: Performance evaluation of ResNet-50, (a) receiver operating characteristic curve illustrating the trade-off between true positive rate (sensitivity) and false positive rate across varying thresholds, (b) precision-recall curve showing the relationship between precision and recall, (c) confusion matrix presented as a heatmap, visualizing true positives, false positives, true negatives, and false negatives, and (d) performance metrics table summarizing key classification measures

Conclusion

The exploration of ResNet models reveals more than computational capability, it demonstrates a transformative approach for enhancing cardiac rhythm diagnostics. While these models show promising diagnostic potential, their true value emerges through patient-focused development, requiring carefully curated datasets, continuous validation, and a commitment to patient safety.

Our research represents a meaningful step toward transforming how emergency clinicians approach complex rhythm analysis, using technological innovation as a strategic ally in improving patient outcomes. The implementation of these systems is not about replacing clinical expertise, it is for creating powerful diagnostic companions. By systematically refining these models in the real-world clinical settings, we can reduce interpretation errors and accelerate diagnostic precision, particularly in environments with limited cardiac specialist resources.

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Author contributions statement

CBI: Conceptualization (lead); Methodology (lead); Validation (lead); Formal analysis (lead); Investigation (lead); Resources (lead); Data curation (lead); Writing – Original draft (lead); Writing – Review and editing (equal); Visualisation (lead); Supervision (lead); Project administration (lead).

NA: Conceptualization (lead); Methodology (lead); Software (lead); Validation (lead); Formal analysis (lead); Investigation (lead); Resources (lead); Data curation (lead); Writing – Original draft (lead); Writing – Review and editing (equal); Visualization (lead).

HSK: Conceptualization (lead); Methodology (lead); Formal analysis (lead); Investigation (lead); Resources (lead); Writing – Review and editing (equal); Supervision (lead); Project administration (lead).

HC: Methodology (supporting); Formal analysis (supporting); Investigation (supporting); Resources (supporting); Writing – Review and editing (equal).

KO: Methodology (supporting); Formal analysis (supporting); Investigation (supporting); Resources (supporting); Writing – Review and editing (equal).

AS: Methodology (supporting); Validation (equal); Formal analysis (equal); Investigation (equal); Resources (equal); Data curation (equal); Writing – Review and editing (equal).

Conflicts of interest

None Declared.

Ethical statement

Ethical approval for this study was carried out following the approval decision numbered E2-22-2645, which was given on November 23, 2022, based on our application to the ethics committee number 2 of Ankara Bilkent City Hospital. Informed consent was not obtained from the patients due to retrospective design. The study was conducted in accordance with the principles of the World Medical Association Declaration of Helsinki.

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