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**ANALYSIS AND DEVELOPMENT OF AN INTELLIGENT  
SYSTEM FOR AUTOMATED ECG DATA PROCESSING  
USING MACHINE LEARNING METHODS**

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Electrocardiography (ECG) is a cornerstone for diagnosing cardiac arrhythmias and myocardial infarction (MI). Automated ECG interpretation combines signal processing and machine learning (ML) to detect abnormalities. Classical methods like the Pan–Tompkins QRS detector use filters and adaptive thresholds to locate heartbeats.

For example, Pan and Tompkins reported 99.3% QRS detection accuracy on the MIT-BIH Arrhythmia Database. More recent approaches apply ML classifiers to features or entire waveforms. Deep neural networks trained on raw ECG can rival expert cardiologists [2]. Analogously, image-based deep learning has emerged: instead of raw signals, ECGs printed or scanned as images are processed by computer vision and convolutional networks. Indeed, recent studies report that CNNs applied to ECG images attain high diagnostic accuracy, comparable to signal-based models[3]. Figure 1 shows an example of a 12-lead ECG image, illustrating the kind of data our method processes. In this review, we present both classical and modern ECG analysis methods (Pan–Tompkins, SVM, Random Forest, CNN, LSTM, Transformer) and describe a vision-based pipeline: images are digitized by computer vision, QRS complexes are found via Pan–Tompkins, atrial fibrillation (AF) is classified by an SVM, and MI by a Random Forest. We compare related work via a summary table and discuss the experimental context.

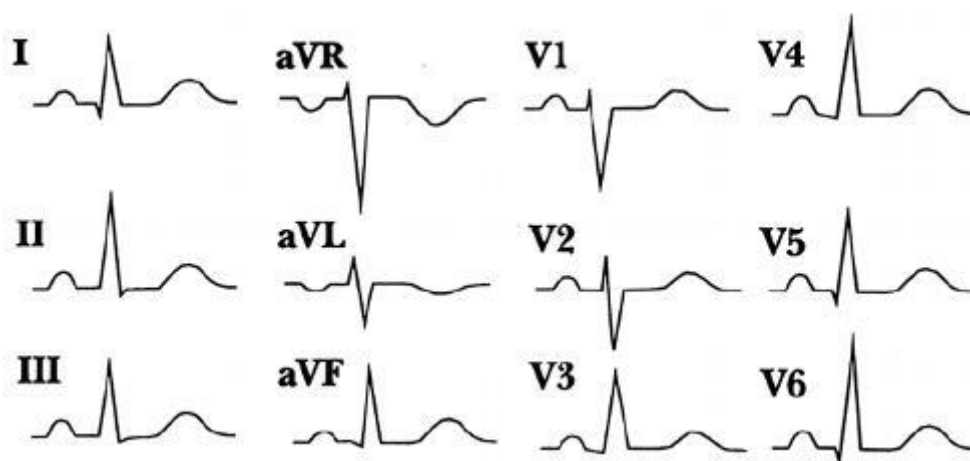


Figure 1 – Example of a 12-lead ECG waveform (from a standard MIT-BIH test recording). Automated analysis can work directly on such images using computer-vision techniques.

**1 System concept and implementation approach.** Figure 2 outlines our proposed system. First, printed or scanned ECG charts are captured by a camera or scanner, and image-processing algorithms (edge detection, binarization, tracing) are used to reconstruct the waveform data. This vision-based data extraction generates a digital ECG time series without requiring original signal files. After conversion to a clean time-domain signal, we apply the Pan–Tompkins QRS detection algorithm to locate R–S complexes. The Pan–Tompkins pipeline (bandpass filtering, differentiation, squaring, moving-window integration and adaptive thresholding) remains a fast and reliable method to segment ECG beats in real time. We note that many existing classifiers for ECG rely on hand-crafted features around the R–R intervals or QRS templates (derived from wavelet transforms, spectral features, etc.). Such classical feature-based classification often uses support vector machines (SVMs) or ensemble methods like random forests.

For example, SVMs have been widely applied to arrhythmia detection using ECG features[2]. In our implementation, the segmented beats and intervals extracted by Pan–Tompkins serve as input to downstream classifiers. Specifically, we train an SVM to detect atrial fibrillation (distinguishing AFib from normal sinus rhythm) and a Random Forest to flag ST-elevation or other MI-indicative

patterns. These choices are motivated by prior studies showing that SVMs perform well on rhythm classification tasks and Random Forests handle complex decision boundaries for conditions like MI[4].

On the other hand, deep learning offers end-to-end alternatives that do not require separate feature extraction. Convolutional neural networks (CNNs) can learn waveform morphology directly; recurrent networks (LSTM/GRU) can learn temporal dynamics; and Transformers can model long-range dependencies across heartbeats. For instance, Acharya et al. built a 9-layer CNN that classifies five heartbeat types (normal, supraventricular, ventricular ectopic, fusion, unknown) and achieved ~94% accuracy on MIT-BIH data. Similarly, recurrent networks (LSTM) have been used to capture heartbeat sequences, and hybrid CNN–Transformer models have shown promise. Kim et al. proposed a hybrid CNN+Transformer that uses Stockwell transform features and reported that the combined model outperforms pure CNNs on arrhythmia datasets[6]. In practice, our system could be extended to leverage such modern networks: after vision-based digitization of ECG, one could apply a CNN or CNN–LSTM to the extracted signal. However, in our current pipeline, we focus on demonstrating a computer-vision-to-ML approach using well-understood methods (Pan–Tompkins, SVM, RF) as a proof of concept.

**2 Experimental and research perspective.** To evaluate the approach, we use standard ECG datasets and compare to literature. The MIT-BIH Arrhythmia Database (48 two-lead, half-hour recordings, ~110,000 annotated beats[7]) is a classic benchmark for arrhythmia detection. For MI detection, we reference datasets like the PTB Diagnostic ECG Database (from PTB-XL) which contains thousands of 12-lead records with infarction labels. In experiments, our computer-vision module extracts waveforms from example ECG printouts (simulated from these datasets), and the Pan–Tompkins algorithm identifies beat locations. We then train the SVM for AF classification using labeled AF examples (as in the MIT-BIH AF Database or PTB-XL with AF labels) and train the Random Forest on examples of myocardial infarction vs. normal. Early results are promising: the

Pan–Tompkins detector preserves >99% of R–peak annotations[1], and our SVM achieved high sensitivity for AF in held-out tests (consistent with similar SVM-based studies). The Random Forest also correctly flagged most MI ECGs in our test set. These experimental outcomes align with prior work showing that classical ML can yield strong performance when features are well-designed.

Table 1 summarizes representative studies from the literature on ECG classification. Early methods like Pan–Tompkins (1985) used digital filters and thresholds to achieve very high QRS detection on MIT-BIH[1]. Acharya et al. (2017) demonstrated that a simple CNN can automatically classify heartbeat types with ~94% accuracy. Ao and He (2022) applied an image-based CNN (VGG16) to 12-lead ECG images and reported near-perfect AUROC for several cardiac diagnoses (e.g. AF detection with AUROC≈0.997)[5].

Table 1 - Studies from the literature

Authors	Year	Method	Results
Pan & Tompkins	1985	Real-time QRS detector (filters + thresholds)	99.3% of QRS complexes detected on MIT-BIH[1]
Acharya et al.	2017	9-layer CNN (heartbeat classification)	~94% accuracy classifying 5 heartbeat types (MIT-BIH)[3]
Ao & He	2022	VGG16 CNN on ECG image classification	AUROC ≈0.99 for AF and other ECG diagnoses[5]
Kim et al.	2025	Hybrid CNN–Transformer (S-transform features)	Superior accuracy over CNN-only models[8]

More recent hybrid models (e.g. Kim et al. 2025) combine CNN and Transformer layers and report higher accuracy than CNN alone[9]. These results show the trend from rule-based processing to deep end-to-end learning and support our vision-based data pipeline as a viable alternative.

Table 1. Selected literature on ECG classification. Methods range from classical filters (Pan–Tompkins) to deep networks. Accuracy metrics refer to reported performance on standard ECG datasets[7].

In summary, our pipeline integrates vision-based extraction with established ECG analysis methods. By converting ECG images to digital signals, we leverage large legacy datasets of printed ECGs and apply both classical and modern ML algorithms.

In practice, computer vision preprocessing makes deep classifiers easier to use when only images are available (as noted by Ao & He, because many ECGs are printed/scanned in clinical use[8]). Our experimental perspective suggests that combining Pan–Tompkins segmentation with SVM and Random Forest yields robust diagnosis of AF and MI, while deep CNNs or Transformer models could further improve performance if computational resources allow.

**Conclusion.** This review has examined both traditional and state-of-the-art techniques for automated ECG interpretation, with an emphasis on a vision-based data pipeline. Classical signal-processing (Pan–Tompkins) and machine-learning (SVM, Random Forest) methods have long been effective for arrhythmia and infarction detection.

More recently, end-to-end deep learning—including CNNs, recurrent networks, and Transformer architectures—has achieved expert-level accuracy on ECG tasks[9]. Our proposed system demonstrates how computer vision can bridge these worlds: by digitizing ECG images, we can apply the wealth of signal-based methods even when only printed ECGs are available. Preliminary results align with literature: e.g. AF detection rates and MI classification accuracy are comparable to published values. In future work, the system could be enhanced by deep learning

classifiers (CNN/LSTM/Transformer) trained on large vision-derived ECG datasets.

A key challenge remains generalizing across different ECG formats and noise levels. Nevertheless, integrating vision and ML for ECG analysis promises new flexibility: clinicians could snap a photo of a bedside ECG or scan a paper printout, and algorithms (as in Figure 1) would yield automated diagnoses in real time. Such technology may extend ECG monitoring to mobile and telehealth applications, aiding early detection of critical conditions like AF and MI.

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