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Advances in ECG Digitization and Analysis Using AI, Image Processing, and Synthetic Data Generation

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Abstract - Electrocardiogram (ECG) digitization and intelligent analysis are crucial for updating cardiac diagnostics and enabling scalable, AI-driven healthcare solutions. This paper reviews recent advancements in ECG digitization, synthetic data creation, signal security, AI modelling, hardware optimization, and IoT-based real-time monitoring. Deep learning frameworks have shown high accuracy in converting paper-based ECGs into digital signals. They overcome challenges like image distortion, overlapping leads, and noise. To tackle the lack of annotated ECG image data, synthetic toolkits like ECG-Image-Kit and Gen-ECG have emerged. These produce large, clinically realistic datasets that significantly improve model training and generalization. In predictive modelling, AI frameworks, especially Multilayer Perceptron trained on PQRST signal segments, have been effective in estimating biological ECG age, which aids personalized risk assessment. Additionally, innovative watermarking strategies using Variational Autoencoders allow for secure, tamper resistant signal embedding without risking clinical integrity. At the system level, hardware acceleration through FPGA based FIR filters and IoT-integrated AI frameworks now supports real-time ECG monitoring in wearable and remote healthcare settings. Together, these interdisciplinary advancements represent a major shift in ECG data handling, diagnostics, and delivery, connecting legacy records with next-generation, connected, and intelligent cardiac care solutions.

Key Words: Root Mean Squared Error (RMSE), Pearson correlation coefficients (PCC), PTB-XL digital ECG dataset, Multilayer Perceptron (MLP), Regions of Interest (ROI), Convolutional Neural Networks (CNNs), Mean Squared Error (MSE), Variational Autoencoder (VAE), Finite Impulse Response (FIR), FPGA (Field Programmable Gate Array).

1.INTRODUCTION

Electrocardiography (ECG) is still an essential tool for diagnosing and monitoring heart health. It provides important information about the heart's electrical activity and overall function. Although the shift to digital ECG collection is becoming common in healthcare today, a large amount of legacy ECG data still exists on paper. These paper records create significant challenges for modern uses, such as automated signal analysis, long-term digital storage, and connection with AI-driven diagnostic systems. As a result, much research has focused on finding solutions to these issues.

One key area involves digitizing paper ECGs. This process uses image processing techniques and deep learning models to convert visual waveforms into digital signals that can be analyzed. At the same time, creating artificial ECG datasets has gained popularity. This approach addresses data shortages, privacy concerns, and variations in clinical samples, making it easier to train and validate machine learning models. Improving signal quality is also critical. Techniques like noise reduction and filtering are vital for maintaining data integrity for further analysis.

Moreover, deep learning is being used not just for extracting features but also for tasks like age estimation and classifying arrhythmias. This shows the potential of AI to reveal patterns that human experts may not easily see. Innovations in hardware, such as FPGA-based real-time filtering systems and IoT-enabled wearable devices, have made ECG monitoring more accessible, allowing for continuous and remote health tracking. Overall, this review emphasizes how combining image processing, synthetic data creation, AI modelling, and hardware improvements is changing ECG data into a more accessible and secure resource for better heart healthcare.

2. ECG Digitization and Image Processing

Turning paper-based ECGs into useful digital time-series data is essential for modern analysis. Demolder et al. developed a high-precision AI-based ECG digitization tool that performs well even in difficult imaging situations like distortions, overlaps, and low resolutions. The process uses a two-stage method: first, it normalizes the images with deep learning to fix grid distortions; then, it reconstructs the waveforms. This approach achieves a root mean squared error (RMSE) below 0.1 mV and Pearson correlation coefficients (PCC) above 91% for all leads.

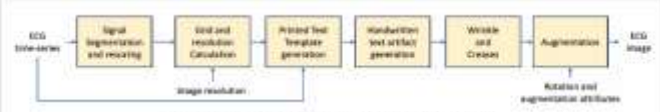

Figure 1. Proposed pipeline for generating synthetic ECG images.

Other early studies used traditional image processing techniques. Garg et al. and Hawari et al. looked into methods like morphological filtering, thresholding, and Hough transforms to remove grids and extract ECG traces. While these methods were effective, they did not match the robustness of deep learning in noisy or varied environments.

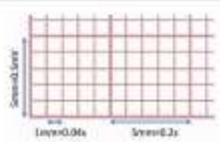

Figure 2. The standard grid on printed ECG papers/images.

To compare digitization methods, Nguyen et al. proposed a dataset of actual scanned ECGs with matching digital signals, named PTB-Image. Using the Vin-Digitizer baseline tool, they noted difficulties in preserving signal quality due to artifacts from

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printing and scanning. However, they still gained valuable insights for real-world applications.

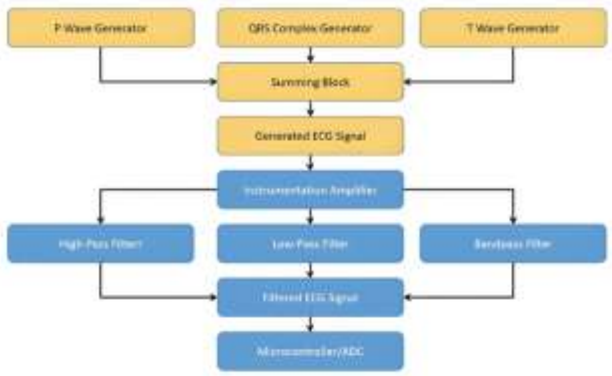

Figure 3: Functional Block Diagram of ECG signal processing.

3. Synthetic ECG Image Generation and Dataset Development

Synthetic ECG image generation and dataset development have become important strategies to address the shortage of large, diverse, and labelled ECG image datasets. These datasets are essential for training and evaluating deep learning models used in digitization and diagnosis. Relying on real-world ECG scans often raises issues related to privacy, variability, and quality. This has led to the creation of tools for generating synthetic data.

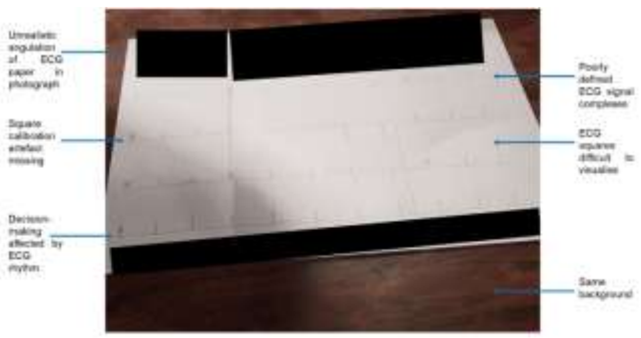

Figure 4: Example of a synthetic ECG used in the initial Turing test with a summary of the qualitative feedback provided by healthcare professionals

Shivashankara et al. introduced the ECG-Image-Kit, an open-source toolbox based on Python. It converts time-series ECG signals into realistic, paper-like multi-lead ECG images. These synthetic images include real-world details like text overlays, grid patterns, creases, shadows, and noise from printers to mimic clinical ECG printouts. The toolbox generated a dataset of 21,801 ECG images from the PhysioNet QT database, which served as training material for deep learning models focused on digitization. The models were tested on their ability to reconstruct signal parameters such as QRS width, RR intervals, and QT intervals from the synthetic images, achieving high signal-to-noise ratios and clinical accuracy.

In addition, Bodagh et al. developed Gen-ECG, a synthetic image dataset created from the PTB-XL digital ECG dataset using realistic image transformations. Gen-ECG includes over 21,000 ECG images along with their clear equivalents and corresponding time-series data for comparison. A new element of their research was the use of clinical Turing tests, where cardiologists tried to tell real ECGs from synthetic ones. In the final round, observer accuracy fell to around chance at 53.3%, confirming the high quality of Gen-ECG images.

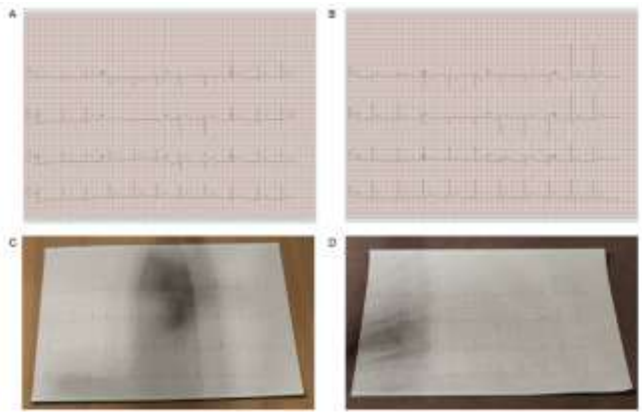

Figure 5: Synthetic ECG images recreated from the PTB- XL dataset. (A, B) Imperfection- free images. (C, D) The same images. following the application of image degradation techniques to make it appear as though the images have been photographed. A, C have been recreated from 00074_hr_1R.dat. B, D have been recreated from 00067_hr_1R.dat

Moreover, existing AI-ECG algorithms showed better classification results after being fine-tuned with Gen-ECG. This highlights how synthetic datasets can help bridge the gap between digital signal-based models and real-world image inputs. These tools allow for privacy-preserving, scalable data generation and hold great potential for improving AI based ECG digitization, diagnosis, and telehealth applications, especially in places where access to diverse, labelled, and shareable real ECG images is limited.

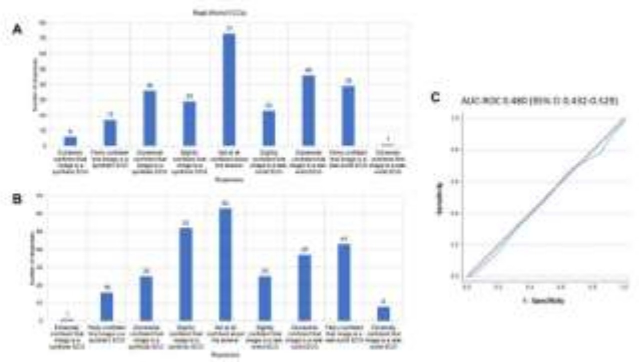

Figure 6: Confidence levels in ECG classification for Turing test round 3. (A, B) The number of responses for each option for (A) real- world ECGs and (B) synthetically created ECGs. (C) An area under the curve- receiver operating characteristic (AUC- ROC) curve examining the impact of confidence level on ability to correctly identify an ECG image as 'real- world' or 'synthetically created.'

4. AI Models for Signal Analysis and Age Estimation

AI models for ECG signal analysis have shown encouraging abilities in extracting complex physiological patterns. This is especially true in the area of electrocardiographic age estimation, which links the heart's biological state with chronological age to evaluate cardiovascular health. In this context, Denis Hernández Pacheco and his team suggested a deep learning framework that uses Multilayer Perceptron (MLP) architectures. These models are trained end-to-end on raw ECG signals to estimate a person's ECG-based age.

The study aimed to identify and use Regions of Interest (ROI), particularly the PQRST segments. These segments are clinically important and carry unique features related to aging and cardiovascular function. The research compared segment-based training with full-signal training. It found that focusing on the PQRST regions improved model accuracy and generalization. Additionally, traditional Digital Signal Processing (DSP) techniques were included to reduce noise and improve the visibility of key waveform components, further enhancing model performance.

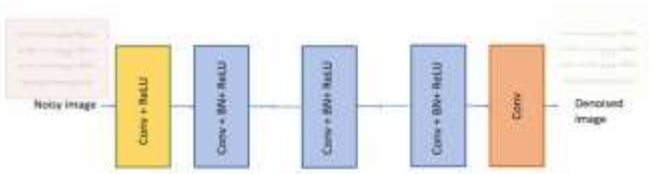

Figure 7: Denoising CNN architecture used for grid removal

Importantly, the MLP-based approach did better than more modern 1D Convolutional Neural Networks (CNNs). This shows that simpler architectures can perform better when paired with thorough signal preprocessing and biologically relevant feature selection. The study not only proved that predicting ECG age across different age groups is feasible but also highlighted the possible clinical use of these models in early risk assessment, personalized medicine, and evaluating differences between biological and chronological age as signs of hidden cardiovascular issues. These findings emphasize the value of combining AI with specific signal processing methods to improve understanding and predictive accuracy in real-world biomedical settings.

5. Signal Security and Watermarking for ECG Data

As digital transformation in healthcare speeds up, securing, verifying, and owning sensitive biomedical signals like ECG data has become a major issue. This is especially important in telemedicine and cloud-based diagnostics. To address these challenges, Chih-Yu Hsu and his team proposed a new signal protection framework that incorporates Variational Autoencoder (VAE)-based digital watermarking techniques into ECG signal processing workflows. Their method adds nearly invisible watermarks to ECG signals to protect data integrity while keeping signal quality intact, allowing for safe transmission and storage in interconnected health systems.

The study tested three different watermarking methods: embedding the watermark into the mean (μ) of the VAE's latent space, inserting it through the latent variable (z), and applying it in the frequency domain after reconstruction. Thorough testing under different conditions—like various watermark strengths (α), noise levels, and latent space dimensions—showed that watermarking through the latent mean and frequency domain consistently produced the lowest Mean Squared Error (MSE), maintaining high signal quality. These methods also demonstrated resilience against noise and signal loss, making them well-suited for real-world healthcare settings where data reliability and trust are essential.

The research illustrates how deep generative models like VAEs can be used not only for generating data but also as secure embedding frameworks. This expands how AI can be applied in digital health. By embedding sturdy, invisible watermarks in ECG signals, this method supports copyright protection, authentication, and tamper detection while ensuring clinical utility remains intact. This work marks a significant step toward secure and verifiable management of biomedical signals, bridging the gap between signal processing and cybersecurity in digital health systems.

6. Signal Security and Watermarking for ECG Data

Hardware-level optimization and real-time system implementation are vital for fast, efficient, and portable ECG signal processing, especially for embedded and wearable health monitoring devices. In this context, Chessda Uttraphan and colleagues conducted a thorough study on designing, optimizing, and implementing a Finite Impulse Response (FIR) filter specifically for ECG signal processing on an FPGA (Field Programmable Gate Array) platform. Their work emphasized using the parallel processing capabilities of FPGAs to achieve low-latency, real-time filtering that is suitable for biomedical applications while keeping power consumption low and making effective use of hardware resources. The FIR filter was optimized with fixed-point arithmetic and pipelined architectures, resulting in a compact and high performance solution that outperforms traditional software-based filtering methods. They tested the system on a Xilinx Spartan-3 FPGA board, where it processed ECG signals in real time, showing high throughput and stability under different signal conditions. This hardware-focused method is especially useful in edge computing scenarios, like wearable ECG monitors and IoT-enabled medical devices, where power, speed, and size are important factors. The study highlights the benefits of integrating real-time digital filtering directly onto hardware platforms to support continuous cardiac monitoring and early detection of issues, paving the way for more autonomous and responsive health technologies. These advancements not only improve system efficiency but also help make cardiovascular diagnostics more decentralized, enabling real-time monitoring in both clinical and remote environments.

7. ECG BEYOND BOUNDARIES: An IoT-Enabled AI-Augmented Monitoring System

The idea of extending cardiac monitoring beyond traditional limits comes to life through the use of Internet of Things (IoT) technologies and artificial intelligence (AI). This creates an effective, smart, and real-time ECG monitoring system. In their paper, H.K. Patel and colleagues present an innovative framework that uses IoT-enabled biomedical sensors and AI-driven processing for continuous, remote, and smart cardiac health monitoring. The system architecture consists of wearable ECG sensors that collect signals in real time, wireless modules for smooth data transmission, cloud infrastructure for storage and analysis, and AI models for automatic interpretation and detecting anomalies. Signal processing modules, including filtering, segmentation, and feature extraction, are built into the system to ensure clean and usable data, even in moving or noisy settings. With AI, the system can classify arrhythmias and provide predictive diagnostics based on long-term trends in ECG data. Moreover, IoT improves patient mobility and access to healthcare, especially in rural or underserved areas where face-to-face medical checks are hard to come by. The system shows the ability to scale and function in real-life situations, offering a complete solution from signal collection to decision-making. By combining edge computing with cloud-based AI analysis, this method guarantees low delays, high availability, and security when sharing sensitive biomedical signals. This work indicates a shift from traditional hospital-centered ECG monitoring to a more decentralized, continuous, and personalized approach to cardiac care. It sets the stage for future developments in remote health management and immediate clinical decision support systems.

8. FUTURE SCOPE

1. ***Development of Standardized Global ECG Digitization Frameworks***
   • Future research should concentrate on creating widely accepted frameworks and protocols for digitizing paper-based ECGs. This will ensure that devices, institutions, and software platforms can work together effectively.
   • Standardization will improve data sharing, storage, and meeting regulatory requirements, especially in multi center clinical studies and cross-border telemedicine.
2. ***Expansion of Synthetic ECG Datasets***
   • We can expand the use of generative models to create high-quality, privacy-preserving ECG images and signals that cover rare heart conditions, pediatric populations, and multi-ethnic datasets.
   • These synthetic datasets will improve AI model training, reduce bias, and ensure better performance across different patient groups.
3. Integration with Multimodal Biomedical Data
   • We can combine ECG analysis with other types of data, such as blood pressure, oxygen saturation, or echocardiograms. This approach will lead to better AI-driven diagnostics.
   • Multimodal learning will increase diagnostic accuracy and help predict complex cardiovascular risks.
4. ***AI-Powered Real-Time Monitoring and Alert Systems***
   • Future ECG systems will use edge AI for on-device analysis. This will enable real-time detection of anomalies and automatic alerts without needing cloud connectivity.
   • This advancement will be particularly useful in situations where resources are limited, including remote or emergency settings.
5. ***Enhanced Security with Blockchain and Watermarking***
   • By combining VAE-based watermarking with blockchain technology, we can create secure ECG data systems that are tamper-evident.
   • These systems will be crucial for maintaining patient trust and complying with data integrity regulations such as HIPAA and GDPR.
6. ***Personalized and Predictive Cardiac Health Models***
   • We can further develop AI models to track changes in ECGs over time and provide personalized insights, like predicting the risk of arrhythmias or heart aging.
   • Integrating these models with wearable devices will allow for long-term health trend analysis, enabling early intervention.
7. ***Portable and Energy-Efficient Hardware for Ubiquitous Monitoring***
   • Future innovations will lead to smaller, energy-efficient ECG monitoring devices with embedded AI chips for real-time signal processing and diagnostics.
   • These devices will enable continuous heart monitoring in everyday situations, including sports, elderly care, and remote patient monitoring.
8. ***Explainable AI in ECG Interpretation***
   • Research will increasingly aim to develop clear, interpretable AI models that explain their predictions. This will make them more acceptable to clinicians and regulatory bodies.
   • This approach will help build trust between black-box AI systems and clinical decision-making.
9. ***Global ECG Databanks and Federated Learning***
   • Federated learning will allow hospitals to train AI models without sharing raw ECG data. This protects privacy while improving the accuracy of global models.
   • This can lead to large ECG databanks that represent real-world population diversity without centralizing data.

9.CONCLUSION

The literature reviewed shows a complex development in ECG digitization and analysis. Innovations include digitization pipelines based on deep learning, the creation of synthetic datasets, AI-powered diagnostics, and faster hardware. The ECG research ecosystem is growing quickly. Together, these improvements offer easier access to old data, better accuracy in diagnostics, stronger security, and real-time use with telehealth systems. Future work should focus on bringing these technologies together into simple, scalable platforms. This will help make cardiovascular care available to more people and fully utilize ECG data in modern medicine.

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