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REVIEW ARTICLE

Computer-Interpreted Electrocardiograms: Impact on Cardiology Practice

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Abstract

In the realm of modern cardiology, the integration of computer-interpreted electrocardiograms (CI-ECGs) has marked the beginning of a new era of diagnostic precision and efficiency. Contemporary electrocardiogram (ECG) integration systems, applying algorithms and artificial intelligence, have modernized the interpretation of heart rhythms and cardiac morphology. Due to their ability to rapidly analyze and interpret ECG recordings CI-ECGs have already profoundly impacted clinical practice.

This review explores the evolution of computer interpreted ECG technology, evaluates the pros and cons of current automatic reporting systems, analyzes the growing role of artificial intelligence on ECG interpretation technologies, and discusses emerging applications that may have transformative effects on patient outcomes. Emphasis is placed on the role of ECGs in the automatic diagnosis of occlusion myocardial infarctions (OMI).

AI models enhance accuracy and efficiency in ECG interpretation, offering insights into cardiac function and aiding timely detection of concerning patterns for accurate clinical diagnoses. The shift to AI-driven diagnostics has emphasized the importance of data in the realm of cardiology by improving patient care. The integration of novel AI models in ECG analysis has created a promising future for ECG diagnostics through a synergistic fusion of feature-based machine learning models, deep learning approaches, and clinical acumen.

Overall, CI-ECGs have transformed cardiology practice, offering rapid, accurate, and standardized analyses. These systems reduce interpretation time significantly, allowing for quick identification of abnormalities. However, sole reliance on automated interpretations may overlook nuanced findings, risking diagnostic errors. Therefore, a balanced approach in integrating automated analysis with clinical judgment is necessary.

Keywords

Electrocardiography; Cardiology; Artificial Intelligence; Machine Learning.

Introduction

The electrocardiogram (ECG) is a cornerstone diagnostic tool in cardiology, which offers clinicians invaluable insights into the electrical activity of the heart. ECGs can detect structural abnormalities, arrhythmias, and ischemic changes, among other conditions. This test plays a crucial role in the screening, diagnosis, treatment, and risk stratification of a wide range of cardiovascular disorders.

In modern cardiology, the integration of computer-interpreted electrocardiograms (CI-ECGs) has marked

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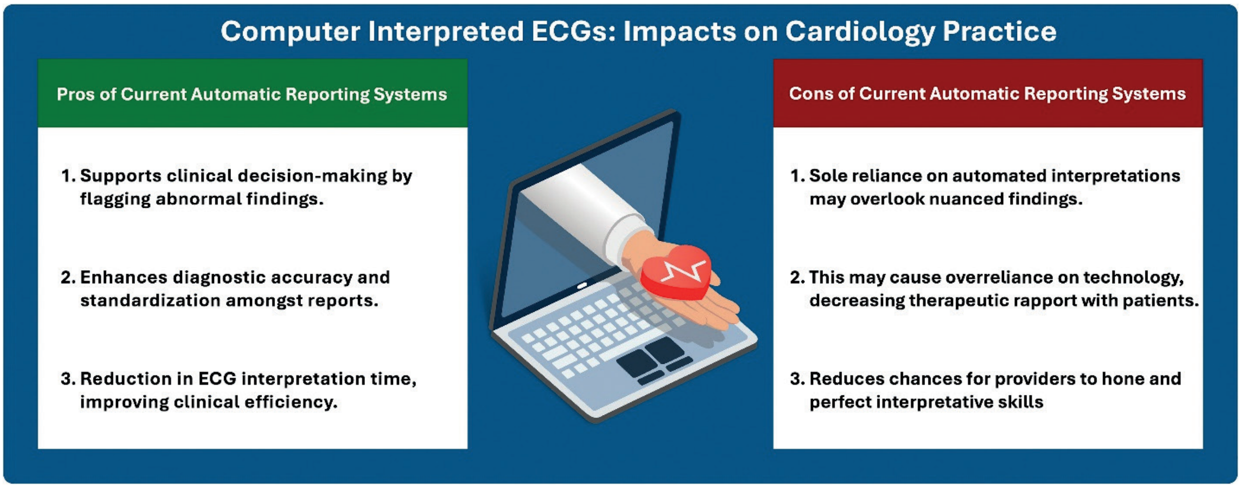

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The impacts of CI-ECGs on cardiology practice

the beginning of a new era of diagnostic precision and efficiency. Contemporary ECG integration systems, applying algorithms and artificial intelligence, have modernized the interpretation of heart rhythms and cardiac morphology.[1] Due to their ability to rapidly analyze and interpret ECG recordings, CI-ECGs have already profoundly impacted clinical practice.[1] However, older available automated ECG interpretation systems have not demonstrated the ability to be solely relied upon.[1] They sometimes fall short in noticing subtle changes and correctly specifying abnormal rhythms. Moreover, they are generally lacking in clinical decision-making support.[2]

While new ECG interpretation algorithms have displayed promising outcomes across diverse pathologies, refining ECG interpretation in patients presenting with chest pain emerges as a paramount clinical imperative. This stems from the direct impact of early reperfusion on the morbidity and mortality of myocardial infarction patients.

Consequently, in this review, we will (i) explore the evolution of CI-ECG technology throughout history, (ii) evaluate the pros and cons of current automatic reporting systems, (iii) investigate the increasing influence of artificial intelligence on ECG interpretation technologies, and (iv) discuss existing and emerging applications that may have transformative effects on patient outcomes. Emphasis will be placed on the role of ECGs in the automatic diagnosis of occlusion myocardial infarctions (OMI).

Methods

An electronic review of published data was conducted in PubMed, EMBASE and MEDLINE databases. The selection of articles of interest was made according to the following criteria: 1) case series, case reports, systematic reviews, observational studies, retrospective and prospective studies, cross-sectional studies and pronouncements of professional associations and scientific societies; 2) published within the last 10 years, 3) English language; and 4) papers referring to the history of automatic reporting ECG systems, pros and cons of current automatic reporting systems, AI & ECGs, value of machine learning process, value of AI in detecting OMI, ECG interpretation, and the impact of automated ECGs on cardiology practice. Studies were excluded if the full text was not accessible.

Several investigators (S.G., A.K., S.S., R. H., A.B. and A.M.) conducted the research independently. First, relevance based on title and abstract was determined. Selected publications were further reviewed for relevance using the full text. Disagreement was solved by consensus. A secondary search was conducted by reviewing the reference lists of included papers.

History of Automatic Reporting ECG Systems

The history of automatic reporting ECG systems traces back to the mid-20th century when advancements in technology laid the foundation for automated analysis of ECGs.[3] Early work focused on developing systems capable of detecting and interpreting cardiac rhythms and abnormalities with minimal human help.

However, in the 1960s, experts in biomedical engineering and computer science began exploring the usefulness of digital signal processing techniques for ECG analysis.[4] One of the earliest automatic ECG interpretation systems was developed by Frank Sanborn and his colleagues at the Massachusetts Institute of Technology (MIT) in the late 1960s.[4] Their work used pattern recognition algorithms to identify specific waveforms that indicated various cardiac diagnoses.

After that, throughout the 1970s and 1980s, researchers made further improvements by modernizing automatic ECG reporting systems.[5] Improvements drove these advancements to computing power and the development of sophisticated algorithms for signal processing and pattern recognition. In concert with these developments, industry stakeholders expanded the distribution of automatic ECG analysis software in commercial products for clinical use.[5]

By the 1990s, automatic reporting ECG systems had become universally utilized in healthcare environments.[3] These systems are now an integral part of clinical practice, enabling rapid acquisition and interpretation of ECG recordings, leading to more efficient clinical diagnoses and treatments. Furthermore, ECG machines became integrated with hospital information systems, allowing for automatic generation of electronic reports, further streamlining clinical settings.

In the 21st century, automatic reporting of ECG systems continued to evolve with advancements in artificial intelligence and machine learning.[3] Modern systems use deep learning algorithms trained from large datasets to improve the accuracy of ECG analysis. These systems can detect subtle abnormalities, predict adverse cardiac events, and provide personalized risk assessments.

Overall, the history of automatic reporting ECG systems represents an impressive journey of technological innovation, from early experimental prototypes to sophisticated AI-powered platforms.

Pros of Current Automatic Reporting Systems

CI-ECGs have revolutionized cardiology practice by providing rapid, accurate, and standardized analyses of cardiac rhythm and morphology (Central Illustration).

One significant impact of CI-ECGs is the reduction in interpretation time.[6] Traditionally, manual interpretation of ECGs required clinical expertise and time, often leading to delays in treatment. With computerized interpretation, ECGs can be analyzed within seconds, allowing for quick identification of abnormalities and timely intervention. This rapid turnaround time is crucial in emergencies such as myocardial infarctions, where rapid treatment is necessary. Moreover, CI-ECGs enhance diagnostic accuracy and consistency. While experienced cardiologists are highly skilled in ECG interpretation, human error can still affect results, particularly when fatigue sets in. Automated algorithms minimize these errors by providing standardized analyses based on a set of criteria.[1] This ensures that interpretations are objective, leading to more reliable diagnoses.

Additionally, computerized ECG interpretation allows for remote monitoring and telemedicine. With the rise of digital health, patients at home can record ECGs using mobile devices and send the rhythms to practitioners.[7] Computer algorithms quickly analyze recordings and alert clinicians to abnormal findings remotely. Remote monitoring is especially valuable for patients with chronic disease or those at risk of arrhythmias, allowing for proactive management and a reduction in regular in-person appointments.

Furthermore, CI-ECGs support decision-making in clinical practice by providing clinicians with actionable insights. Algorithms can flag abnormal findings and highlight subtle changes. This helps physicians formulate efficient treatment plans and reduces the chances of overlooking critical information. Furthermore, there may be a potential decrease in healthcare costs through the avoidance of unnecessary sophisticated testing. For example, if ECG-AI tools could predict aortic stenosis early, complex testing might be reduced as physicians would only have to order tests based on the predictions of such ECG tools. This could also improve the management of conditions that are treatable by providing early diagnoses.

Cons of Current Automatic Reporting Systems

While CI-ECGs offer significant advantages, there are potential drawbacks to consider (Central Illustration).

First, relying solely on automated interpretations may lend itself to overlooking nuanced findings that a trained clinician would identify, potentially leading to errors in diagnosis.[1] For example, older automatic reporting systems have demonstrated a lack of sensitivity and specificity in noticing subtle changes, detecting abnormal rhythms, and supporting clinical decision-making.[1] Additionally, the speed of computerized interpretation may prioritize efficiency over thoroughness, failing to capture clinically significant changes on an ECG.[2]

Moreover, while remote monitoring provides patients with both accessibility and convenience, there are potential drawbacks to consider. One concern is the risk of overreliance on technology, which may lead to decreases in establishing therapeutic rapports between patients and clinicians and a loss of detailed clinical assessments, including subjective factors such as personal histories.[6] Additionally, ECGs recorded outside of controlled clinical settings may be variable, depending on a myriad of factors such as the patient's environment. This raises questions about the validity of the data and the potential for misinterpretation.

In addition, the transition to remote monitoring may exacerbate healthcare disparities, as patients with limited technology access or digital literacy may face barriers to participating. Therefore, while remote ECG monitoring does have undeniable benefits in improving patient care, careful appraisal of limitations and appropriate safety measures would be essential to implement equitable care.

Finally, complete reliance on technology can limit opportunities for healthcare providers to hone and perfect their interpretative skills. This may diminish diagnostic proficiency over the years. Therefore, while rapid interpretation is essential in emergent situations, a balanced approach that synergizes automated analysis with clinical judgment is necessary to ensure comprehensive ECG interpretation.[1]

Overall, while computerized ECG interpretation offers undeniable advantages, clinicians must maintain a cautious and discerning approach, recognizing its limitations and integrating automated analyses with clinical judgment. The hope is that new machine learning and artificial intelligence will also modernize current automatic reporting systems, thus improving sensitivity and specificity for clinical practice.[8]

The Role of Artificial Intelligence in ECG Analysis

Introduction to Artificial Intelligence in ECG Analysis

The advent of artificial intelligence-augmented ECG (AI-ECG) models has revitalized the field of electrocardiology. These models extend beyond conventional machine learning to include a diverse array of deep learning approaches. Through their development and implementation, clinicians might gain access to sophisticated analytical tools that provide profound insights into cardiac function, facilitate the timely detection of intricate patterns, and enhance the delivery of accurate clinical diagnoses.[8]

This shift towards AI-driven diagnostics is propelling cardiology into a data-centric era, setting the stage for profound advancements in patient care.[9] The ability of AI models to process and analyze large datasets greatly surpasses human capabilities and can facilitate the identification of predictive patterns that were once elusive.[10] Enhancement not only improves the precision of cardiac evaluations but also broadens the scope for personalized preventive medicine, allowing for treatment strategies that are uniquely tailored to the nuances of individual cardiac profiles.

Theoretical Framework of AI-ECG Algorithms

Ideally, modern ECG interpretation analysis will be supported by a robust suite of sophisticated AI algorithms, which offer substantial enhancements in pattern recognition and decision-making capabilities.[11] Unlike conventional automated ECG interpretation software used in clinical settings, which often depends on rule-based algorithms and decision trees, modern AI-ECG algorithms offer distinct advantages. While traditional algorithms identify specific waveforms, intervals, or segments in ECG interpretation and compare them against clinical criteria, their rigidity may fail to fully capture the complexity of certain cardiac pathologies, limiting adaptability and depth of analysis.[12] In contrast, newly developed AI-ECG algorithms harness a broader range of machine learning and deep learning techniques, each with unique capabilities in processing, analyzing, and adapting to ECG data.

AI-ECG Learning Frameworks

Novel AI-ECG approaches may be more broadly categorized according to the manner in which algorithms process and "learn" the data.

- **Supervised Learning:** Predominantly used in classification tasks, supervised learning algorithms are trained on a labeled dataset where specific patterns are associated with various cardiac conditions.[13] These models excel at mapping input data (e.g., ECG signals and measurements) to accurate outputs (ECG and clinical diagnoses), becoming highly proficient in recognizing similar patterns in new, unseen data. In contrast to rule-based algorithms, this method can adapt to a wider range of data variations and learn complex ECG patterns.

- **Unsupervised Learning:** This method proves invaluable in detecting unusual or atypical patterns in ECG data without prior labeling, which is important for identifying new or rare cardiac conditions that may not conform to the traditional rule-based framework.[14] By analyzing data without predefined labels, unsupervised learning can unveil hidden structures or anomalies in ECG signals and offer insights into previously unrecognized phenomena.
- **Reinforcement Learning:** An emerging technique in ECG analysis, reinforcement learning algorithms improve their accuracy over time by optimizing their decisions through a process of trial and error, adjusting actions based on continuous feedback.[15] This type of learning is particularly advantageous in environments where the algorithm needs to adapt quickly to new information or changing conditions, providing a dynamic contrast to the static nature of rule-based algorithms.

Feature-Based Machine Learning Approaches

Feature-based machine learning algorithms make use of prespecified features from ECG signal data, which are incorporated into a machine learning model architecture (e.g., logistic regression, random forest, naïve Bayes, support vector machine, etc.) to enable accurate diagnostic classifications. This approach offers a notable advantage in terms of model explainability, as it allows for clearer tracing of model outputs back to the influence of the model inputs used in the modeling process.[16] However, this approach may require extensive expert domain knowledge, as it may be imperative to understand the clinical relevance of each measurable feature in the context of cardiac physiology.[17] In one sense, such an approach may mirror the decision-making process of a physician, taking into account multiple explainable features with a physiologic basis that have been historically proven to be indicators of specific cardiac conditions.

However, despite the effectiveness that may be achieved with feature-based approaches in specific scenarios, they can be limited by their dependence on the pre-defined features.[18] This limitation may lead to omitted or yet-to-be-defined features that may be quite useful for diagnostic classification, especially patterns that are not fully encompassed by predefined features. Additionally, depending on specific, identified features can reduce the adaptability of these algorithms to data subtleties, yet-to-be-recognized relationships, or unique nuances present in individual patient cases. This rigidity can be a significant drawback, especially in complex clinical cases where subtle aberrations in the ECG could indicate critical developments in a patient's condition.

Deep Learning Approaches

Unlike feature-based methods, deep neural network architectures represent an alternative approach that is primarily data-driven and does not heavily depend on expert domain knowledge.[18] Deep learning approaches enable the exploration and identification of complex hierarchal patterns that may not have been previously recognized or clearly defined in the medical literature.

- **Convolutional Neural Networks (CNNs):** CNNs are a sub-category of deep learning and have demonstrated exceptional capabilities in processing spatial relationships within data, making them particularly effective for interpreting the structured patterns of ECG signals.[19] Their architecture is adept at recognizing complex patterns with high precision, accommodating variations in signal presentation such as slight shifts or distortions. For instance, CNN models have been shown to predict low left ventricular ejection fraction and the likelihood of developing atrial fibrillation from a sinus rhythm ECG, representing predictive findings that are not typical of the diagnostic findings in traditional, rule-based approaches.[20-24]
- **Recurrent Neural Networks (RNNs):** Excelling in the analysis of sequential or time-series data, RNNs are another subcategory of deep learning that is invaluable for diagnosing conditions that manifest over time, such as atrial fibrillation or progressive conduction defects.[25] These networks manage the temporal dynamics of the ECG signal by maintaining a memory of previous inputs. This enables a continuous and dynamic analysis that adapts to new data in real time. This feature is particularly helpful for accurately capturing

and interpreting the evolving nature of cardiac conditions that may vary significantly between different readings and over time.

Challenges of Implementing New AI Models

Despite its significant advantages, integrating novel AI models into ECG analysis presents several challenges that must be addressed to ensure their effective implementation in clinical settings.

Among these challenges is ensuring that AI-ECG models are provided with high-quality data. The efficacy of AI models is dependent on the quality and diversity of the data used for training.[26] Inadequate or poor-quality data will result in model inaccuracies that ultimately degrade performance in clinical applications. Additionally, biased data sets can skew AI predictions, leading to algorithmic bias where models inadvertently develop biases based on the demographic characteristics of the training data, potentially causing disparities in diagnostic accuracy across different patient groups.[27-29]

Overfitting represents another significant challenge, characterized by models that perform exceptionally well on training data but fail to generalize to new and unseen datasets.[30] This can limit the utility of AI models in real-world settings, where they must be able to accurately interpret data from a broad spectrum of individuals and conditions not represented in the initial training phase.

Another challenge lies in ensuring that the data used for developing an AI-ECG model is representative of its intended application, as variations in disease prevalence within different populations can greatly impact the performance and applicability of AI-ECG models.[31] For example, AI-ECG algorithms trained populations with a high prevalence of certain cardiac conditions may not perform as expected in a population where such conditions are rare. Therefore, rigorous evaluation of these models within the intended populations where they are expected to be used may be needed to understand the expected performance of AI-ECG models fully.

Understanding the interaction between human clinicians and emerging predictive AI-ECG models is growing in importance. Although AI can augment decision-making and diagnostics, comprehending its impact on physician behaviors, clinical decisions, and patient outcomes is crucial. Prospective studies offer a means to gain insight into these dynamics.[32] Furthermore, effort should be made to ensure that clinicians are trained to interpret AI predictions within the broader context of patient care, understanding both the strengths and limitations of AI-assisted diagnostics. This includes recognizing when to rely on AI guidance and when to question or override automated recommendations based on human insight or additional clinical evidence.

Lastly, another important challenge will be the integration of these tools into clinical settings. This integration must be thoughtfully managed to maintain trust in AI systems, ensure adherence to medical standards, and ultimately enhance patient outcomes through more accurate and timely diagnoses. Moreover, another scenario where artificial intelligence will undoubtedly reshape the course of medicine is its potential applications in medical education. However, delving further into this topic exceeds the scope of the present discussion.

Clinical Utilities of ECG-AI Tools

There are several clinical applications of ECG-AI tools, including the diagnosis of aortic stenosis, cardiac amyloidosis, valvular heart disease, contractile dysfunction and more.[33-36] The use of AI in improving ECG utility is vast and undeniable in the field of cardiology.

For this review, an example of the value of AI in detecting acute myocardial infarction and coronary artery disease will be used. In the current landscape of automatic reporting, the development of a system to diagnose acute coronary occlusion myocardial infarction (ACOMI, shortened to OMI) has contributed to revolutionary advances in the cardiology community. Clinical decision making for OMI is heavily based on the ECG, making it a valuable example to exemplify the usefulness of AI.

Value of AI in Detecting OMI

The 12-lead ECG plays an essential role in the rapid identification of patients with persistent OMI without collateral circulation who are at risk for irreversible infarction of the involved myocardial territory. Detecting and measuring ST Elevation (STE) millimeter criteria on the ECG has long been the standard method for diagnosing OMI, even though STE was neither developed nor subsequently correlated as an accurate measure of angiographic occlusion. In fact, STE is very insensitive and non-specific for acute coronary occlusion.[37-45] Not surprisingly, then, 25%-33% of NSTEMI are found to have an occluded infarct artery at next day angiography, and these patients have far higher mortality than NSTEMI with an open artery.[46,47]

Thus, it has been proposed that the STEMI/NonSTEMI paradigm should be replaced with the name of the actual underlying pathology, which is acute coronary occlusion. Accordingly, the term Occlusion MI/Non-Occlusion MI (OMI/NOMI) can be used as its replacement.[37,48] Expert ECG interpretation using other features of the ECG, including hyperacute T-waves, any ST depression (STD) maximal in leads V1-V4, terminal QRS distortion, subtle STE with other features such as any reciprocal STD, or associated Q-waves, can diagnose OMI with double the sensitivity of the STEMI criteria while maintaining equal, or better, specificity.[49,50] While assessing blinded ECGs, the presence or absence of OMI has been validated using a more robust angiographic reference standard, including the presence of culprit lesion, vessel flow, intervention, and peak troponin as a surrogate for infarct size in arteries that were open but with a culprit.[49,50-54]

Non-OMI or acute MI that does not have ongoing ischemia is very difficult to diagnose with the ECG. Many researchers have attempted to diagnose all MI (Non-OMI in addition to OMI) with machine learning methods, but without success because the subset of non-OMI is so difficult to diagnose.[55-58] Others have trained and tested their systems on STEMI ECGs from STEMI databases and have excellent performance. Still, by the nature of STEMI databases, these studies exclude NSTEMI that are OMI because NSTEMI is not included in STEMI databases.[59,60] A previous study developed an AI system that was trained with 74 hand-crafted items (not a DNN) and turned their attention to OMI instead of all acute MI; their accuracy was excellent, with an AUC of 0.87.[61] Reliance on hand-crafted features, however, has its limitations, since there are few validated finite rules for detecting subtle OMI patterns.

An example of the value of automatic reporting is the development of a system, Powerful Medical, where any ECG can be digitized and converted into a usable waveform. This system was used to collect thousands of 12-lead ECG waveforms with expert ECG interpretation and angiographic outcomes. Then, a DNN-based AI model named PMcardio OMI AI ECG Model ("Queen of Hearts" for short) was developed to understand the complex parameter space of acute coronary occlusion regardless of the presence of typical STE. This DNN was tested on a large database of known outcomes, with clinical symptoms and a troponin elevation consistent with the fourth universal definition of MI and angiographic evidence of acute culprit coronary stenosis with either (i) a thrombolysis in myocardial infarction (TIMI) flow grade of 0–1 or (ii) a TIMI flow grade of 2–3 with emergent or urgent percutaneous revascularization. In an international evaluation of more than 3000 ECGs, the DNN-based AI model detected an angiographically confirmed diagnosis of OMI with favorable performance (AUC 0.94, Sensitivity 81% and Specificity 94%), which was non-inferior to expert ECG interpreters.[62]

The QoH translator is a proof-of-concept AI visualization tool for the Queen of Hearts (OMI AI ECG Model v1). Four aspects of this AI system have been designed to analyze ECG data and are circled in red (Figure 1, Panel B).

1. **ECG-wide AI prediction (OMI/not-OMI)**:
   - This refers to the AI's ability to make predictions or classifications based on the entire ECG signal.
   - The AI is predicting whether the ECG indicates the presence of OMI or not.
2. **Per-lead AI prediction**:
   - ECGs typically consist of multiple leads, each providing a different perspective on the heart's electrical activity.
   - "Per-lead AI prediction" refers to the AI's ability to analyze each lead individually and make predictions or assessments based on each one.
3. **Lead relevancy (percentage & color intensity of the rectangular box)**:
   - In the context of ECG analysis, different leads may carry different levels of diagnostic significance.
   - "Lead relevancy" indicates the importance or usefulness of each lead in making a diagnosis or prediction.
   - The percentage and color intensity of a rectangular box represent the degree of relevancy assigned to each lead, helping clinicians understand which leads are more crucial in the analysis.
4. **Time-point relevancy (intensity of blue vertical lines)**:
   - ECGs are plotted over time, with each vertical line representing a specific moment in time.
   - "Time-point relevancy" refers to the importance or significance of certain time points within the ECG signal.

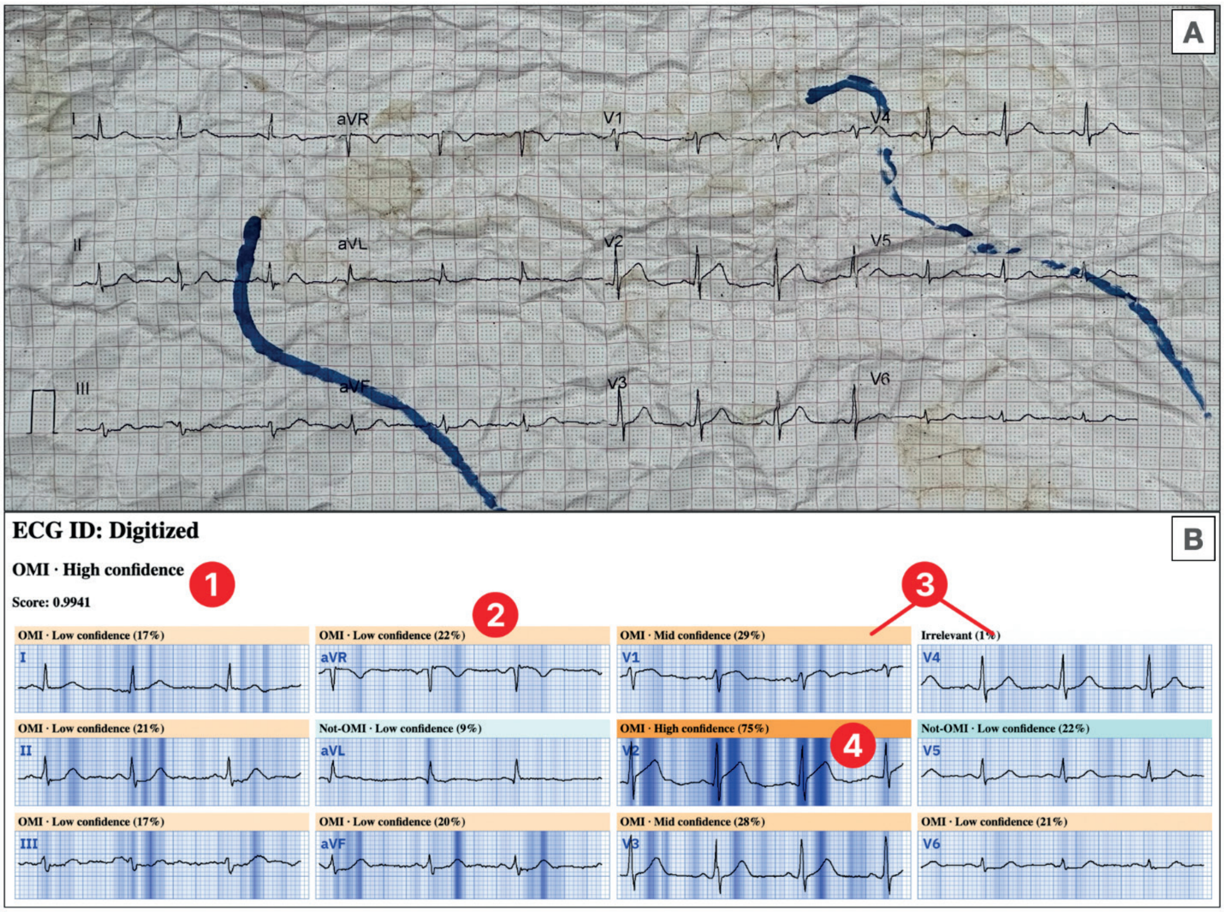

Figure 1 – A) Original manual ECG used to create digitized ECG image; B) Digitized ECG Image (using QoH translator), consisting of four elements (circled in red):
1) ECG-wide AI prediction (presence of OMI or not): AI's ability to make predictions or classifications based on the entire ECG signal.
2) Per-lead AI prediction: AI's ability to analyze each lead individually and make predictions based on each lead separately.
3) Lead relevancy (percentage & color intensity of the rectangular box): the percentage and color intensity of a rectangular box represent the degree of relevancy assigned to each lead, helping clinicians understand which leads are more crucial in the analysis.
4) Time-point relevancy (intensity of blue vertical lines): refers to the importance of certain time points in the ECG signal, highlighting key events that help in diagnosis.
**Further detail on these four components is in the text*
This OMI AI ECG Model detects acute coronary occlusion on a digitized ECG image with High confidence. The most relevant feature for the AI model in this case is hyper-acute T-waves in lead V2. This patient had a proximal LAD occlusion, which was confirmed angiographically.

- The intensity of blue vertical lines indicates the relevance or significance of moments in the ECG data, highlighting key events or patterns that aid in diagnosis or prediction.

In summary, these four aspects outline how this AI system analyzes ECG data comprehensively, considering the entire signal as well as individual leads and specific time points, to make predictions or assessments related to cardiac health regarding the presence of OMI.

To demonstrate this, Figure 1, Panel A shows the before and Figure 1, Panel B shows the after of an automated ECG report. Alongside existing automated ECG analysis software, innovative systems such as this continue to be engineered to enhance the accuracy of ECG interpretation significantly.

Discussion

CI-ECGs have transformed cardiology practice, offering rapid, accurate, and standardized analyses (Central Illustration). These systems reduce interpretation time significantly, allowing for quick identification of abnormalities, crucial in emergency settings. They enhance diagnostic accuracy and consistency, minimizing human error. Furthermore, computerized ECG interpretation allows for the integration of remote monitoring into clinical practice, helping patients with chronic cardiovascular conditions. However, sole reliance on automated interpretations may overlook nuanced findings, risking diagnostic errors. The speed of interpretation could prioritize efficiency over thoroughness, potentially lowering diagnostic proficiency. Remote monitoring may reduce patient-clinician interactions. Therefore, a balanced approach to integrating automated analysis with clinical judgment is necessary.

AI models enhance accuracy and efficiency in ECG interpretation, offering insights into cardiac function and aiding the timely detection of concerning patterns for accurate clinical diagnoses. The shift to AI-driven diagnostics has emphasized the importance of data in the realm of cardiology by improving patient care through advanced analytical tools. AI-ECG algorithms use various learning methods, which enhance pattern recognition and decision-making capabilities. Feature-based machine learning offers model interpretability but may lack adaptability, while deep learning, including CNNs and RNNs, excels in processing complex patterns without heavy reliance on expert knowledge.

The integration of novel AI models in ECG analysis marks a shift in the field of electrocardiology. It provides clinicians with new systems that will impact the diagnostic landscape and overall approach to patient care. There exists a promising future for ECG diagnostics through a synergistic fusion of feature-based machine learning models, deep learning approaches, and clinical acumen.

As these technologies become more sensitive and specific, their integration into clinical practice will require rigorous validation and testing to ensure they perform effectively with different patient demographics such as age, race, sex, and more.[1] This involves not only addressing challenges such as the quality of data and algorithmic bias but also ensuring that these advanced tools are used in a way that enhances the clinician's expertise. Ultimately, the hope is that novel AI-ECG algorithms will never take over human expertise but will enrich the clinical experience by paving the way for personalized patient care.

Furthermore, as mentioned, OMI is a critical cardiac diagnosis that requires the use of information from the 12-lead ECG. Currently, STE criteria for diagnosis lack sensitivity and specificity. The authors advocate for a paradigm shift from STEMI/NonSTEMI to OMI/NOMI, utilizing other ECG features for diagnosis. These manifestations are specific but challenging to teach or algorithmically define. Optimistically, deep convolutional neural networks (DNNs) offer promise in recognizing complex OMI ECG patterns.

The ECG manifestations of ACO are specific but can be subtle and are very difficult to define with algorithms. They can only be reliably discerned by pattern recognition, and artificial intelligence, especially DNN, may be promising. Therefore, in the future, it might be possible to teach a DNN to recognize these complex OMI ECG patterns.

Limitations

Due to the rapid advancement of medicine overall, and particularly of artificial intelligence applications in cardiology, some examples or descriptions may become outdated in a short period after the publication of this manuscript.

Conclusions

Overall, CI-ECGs have revolutionized cardiology by providing clinicians with rapid, accurate, and standardized analyses. With the added advent of AI models to improve ECG systems, a new era of enhanced diagnostic accuracy and consistency has come about. However, reliance solely on automated interpretations may overlook nuanced findings, risking diagnostic errors. Therefore, the automation of ECGs necessitates a balanced approach integrating automated analysis with clinical judgment for accurate interpretation and improved patient care.

Author Contributions

Conception and design of the research, acquisition of data and writing of the manuscript: Gupta S, Kashou AH, Herman R, Smith S, May A, Baranchuk A; analysis and interpretation of the data: Gupta S, Herman R, Smith S, May A; critical revision of the manuscript for intellectual content: Gupta S, Kashou AH, Herman R, Smith S, May A, Echeverri AGM, Del Sueldo M, Berni AC, Farina J, Garcia-Zamora S, Baranchuk A.

Potential Conflict of Interest

The authors Robert Herman and Stephen Smith are shareholders of Powerful Medical, the creator of the Queen of Hearts.

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Study Association

This study is not associated with any thesis or dissertation work.

Ethics Approval and Consent to Participate

This article does not contain any studies with human participants or animals performed by any of the authors.

Erratum

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Correct:

"No potential conflict of interest relevant to this article was reported."

To:

"The authors Robert Herman and Stephen Smith are shareholders of Powerful Medical, the creator of the Queen of Hearts."

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