Review of Hybrid Deep Learning Techniques For Robust ECG Signal Classification by Addressing Noise and Class Imbalance

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This review paper presents a comprehensive analysis of recent advancements in hybrid deep learning techniques for automated electrocardiogram (ECG) signal classification, with a central focus on overcoming challenges such as signal noise and class imbalance. Given the pivotal role of ECG analysis in the early detection of cardiovascular diseases, there is a growing demand for intelligent, robust, and clinically deployable systems. The paper examines hybrid model architectures that integrate Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and attention mechanisms to effectively capture both spatial and temporal features of ECG signals. Key studies are reviewed in terms of their preprocessing strategies, feature optimization methods, and noise mitigation techniques. In addition to architectural insights, the paper outlines a structured taxonomy of hybrid approaches based on model composition, preprocessing methods, imbalance handling techniques, evaluation metrics, and deployment environments. It also explores emerging application areas, including real-time monitoring systems, telecardiology platforms, and clinical decision support tools. Common research limitations—such as computational complexity, limited interpretability, and real-world generalizability—are critically discussed. The review concludes with recommendations to guide future work toward scalable, explainable, and clinically relevant deep learning frameworks, ultimately aiming to support the next generation of intelligent cardiovascular healthcare systems.

Keywords: *ECG Signal Classification, Hybrid Deep Learning, Noise Resilience Class Imbalance*

INTRODUCTION

Electrocardiography (ECG) is a common and non-invasive way to check the heart's electrical activity. It is an important tool for finding and diagnosing cardiovascular disorders, which are one of the main causes of death around

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the world. An ECG signal represents the heart's rhythm and electrical conduction patterns, revealing insights into various cardiac diseases such as arrhythmias, myocardial infarction, and ischemia. Traditionally, educated doctors read ECGs by hand, but because there is so much patient data and the need for quick and accurate diagnoses, there has been a big drive to make automated ECG signal classification systems. These technologies are meant to help doctors find problems quickly and reliably, especially in healthcare settings when resources are limited or demand is high. Automatic ECG classification still has a number of major problems that make it hard for it to be widely used in clinical settings, even if machine learning and deep learning have come a long way.

One of the main problems is signal noise, which can come from many places, such as the patient moving, the electrodes being in the wrong spot, electrical interference, and muscle problems. (Maheb, A.S.B, 2025) These sounds often modify the contour of the ECG waveform, such as the P-wave, QRS complicated, and T-wave. This makes it challenging for algorithms to determine the difference between normal and unusual patterns. Regular filtering methods can get rid of some noise, but they could also change important signal properties without purpose to, which could cause misclassification. (Anu, H. et.al. (2025))

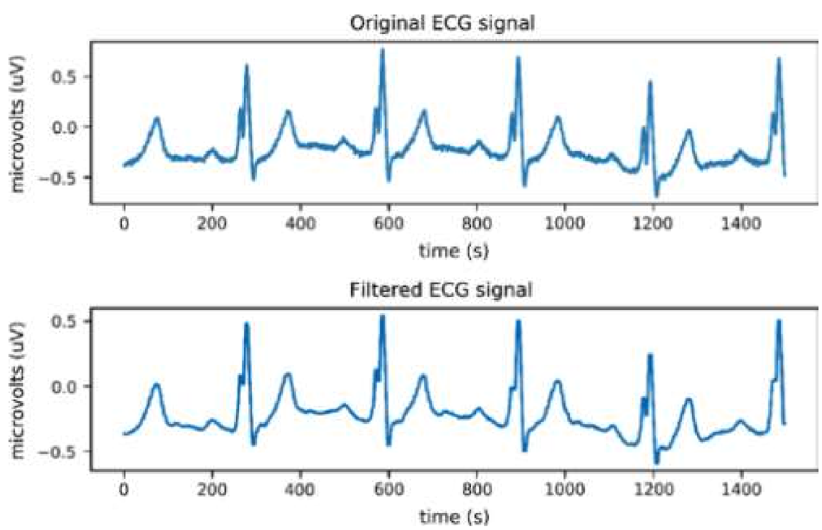

Fig. 1. **ECG Signal based on Deep learning [3]**

Another big problem with ECG datasets is that the classes aren't balanced[4]–[8]. In real-life clinical situations, irregular heartbeats such ventricular fibrillation or atrial flutter happen much less often than normal sinus rhythms. This imbalance makes models that are too focused on the majority classes, which means they can't find rare but clinically important arrhythmias. Overall accuracy and other traditional evaluation metrics may look good, but they often hide the fact that they don't work well for minority courses. To solve this problem, you need to employ advanced data re-sampling methods, weighted loss functions, or customized architectures that can focus learning on categories that aren't well represented without over fitting[9]. A third problem is that ECG classification models may not be very good at making predictions that are true in general. Many models work great on certain datasets but don't work as well when applied to data from other sources or populations because of differences in sample frequency, signal quality, or patient demographics. These models can't be used in the real world since they don't generalize. Most of the studies that are out there only look at performance measures like accuracy, precision, and recall. They often forget about other essential things, such how easy it is to grasp the model, the challenge it is to compute, or how easy it is to use, especially on portable or smart watches. Researchers have been working on hybrid neural networks that combine the best aspects of several model architectures to solve these hard issues. For example, convolutional neural networks (CNNs) are good at figuring out the spatial components of ECG waveforms, but recurrent neural networks (RNNs), especially long short-term memory (LSTM) the facilities, are good at figuring out how things alter over time. When the data is noisy or uneven, hybrid models that combine CNNs with LSTMs or other attention-based algorithms reveal more features or do a better job of classifying it. These designs are also more flexible and can add preprocessing procedures like normalizing signals or denoising auto encoders, which make the model even better. This review article talks about the most recent advances in hybrid deep learning methods for sorting ECG data, with emphasis on how well they deal with noise and class imbalance. First, it will talk about the most fundamental ways to sort and filter ECG data. Then it will explain more about the hybrid deep learning systems that combine different parts of neural networks. A lot of attention will be paid to a paper called "A Hybrid Deep Learning Take for Strong ECG Signal It with Noise Resilience and Class A imbalance Handling." It offers a new technique to combine several deeper learning modules to deal with these problems. In light of recent research, this review is going to take at the study's methods, performance indicators, and contributions. It will also talk about the pros and cons of using these kinds of mixtures in real-life clinical situations. This involves examining how well the computer works, how easy it is to understand, how well it can handle data in real time, and how well it can grow. The evaluation also looks for gaps in current research and offers additional topics to examine, such as validating several datasets that include patient-specific attributes and putting the technology on edge devices. This work seeks to give researchers, doctors, and developers a complete understanding of the current state of hybrid deep learning in ECG classification so that they can make better, more generalisable, more therapeutically effective solutions for monitoring and diagnosing cardiac diseases[10].

RELATED WORK

Panigrahi et al., 2025 This research describes a deep learning-based design that uses ECG data to identify cardiovascular disease (CVD) by combining the Internet of Things (IoT) with predictive health management systems. The model employs deep transfer learning to acquire features using the PTB-XL dataset, then it combines those characteristics to get rid of duplicates. We employ the African Vulture Improvement Algorithm (AVOA) to pick the optimal features. We employ a lot of machine learning classification algorithms to sort things. The ensemble model has the highest reliability, which is 96.31%. By dealing with signal fluctuations and improving automated CVD diagnosis in hospitals, the method makes ECG categorisation more reliable and accurate.[4].

Saranya et al., 2025 gives us a new hybrid deep learning system called DenseNet-ABiLSTM that can use photoplethysmography (PPG) signals to tell different forms of arrhythmia apart. The model employs Attention-based directional LSD to detect temporal correlations and improve the accuracy of classification, together with densely coupled convolutional networks to pull out features. Sinus Rhythm, Early Ventricular Shrinkage, or Atrial Fibrillation are three examples of arrhythmias. The model's capacity is proven by a mean F1 score of 87.74% or an accuracy of 89.14% when compared to ECG data. The method works rather well, and it shows that signals from the PPG can be utilised with more advanced models to locate arrhythmias.[11].

Anu et al., 2025 A hybrid model for identifying ECGs that combines Convolutional Neural Network (CNN), future quick recall (LSTM), or Aquila Optimisation (AQO) to fix the difficulties with prior methods. By optimising key parameters, the recommended AQO-CNN-LSTM model provides the system stronger and more efficient. This is different from typical classifiers like SVM or KNN, which are vulnerable to noise and take a long time to analyse. The hybrid model makes things preciser, takes less time to process, and renders things more exact. These results suggest that it might be used to sort ECGs in real time, which would make it a valuable and scalable tool to discover heart issues in healthcare monitoring systems.[2].

Najia & Faouzi, 2025 offers a deep learning system that uses CNN, the Convolutional Block Focus Module (CBAM), as well BiLSTM to make ECG classification more accurate. The model divides heartbeats in five groups based on AAMI EC57 guidelines. The Fake Minority The oversampling method (SMOTE) is implemented to fix the problem of class imbalance. The approach is tested on the MIT-BIH ventricular fibrillation dataset or yields an accuracy of 99.20%, a precision of 97.50%, a specificity of 99.81%, or an average F1 score of 98.29%. The approach illustrates that using techniques for concentration with complicated patterns can make automatic ECG classification substantially more dependable and valuable.[8].

Selvapriya & Kavitha, 2024 suggests a better technique to sort ECGs by employing a hybrid model that combines a CNN-RNN building with Signal Dependent Classify Order Mean (SD-ROM) to cut down on noise. SD-ROM preprocessing makes the ECG signal better by getting rid of noise and bringing out the key parts. The CNN half looks for patterns in space, whereas the RNN part looks for trends in time. This new strategy performs better than older ones and improves the accuracy of classification. The model's capacity to track ECGs in real time and discover heart abnormalities early makes it a viable tool for both clinical and remote medical care, since it delivers reliable and effective diagnostic support. [12].

Table - 1

Author & Year	Method	Findings	Research Gap
Alldughayfiq et al., 2023 [13]	Hybrid Deep Learning model using 1D CNN and BiLSTM on PPG and ECG signals for atrial fibrillation (AF) classification	Achieved 95% accuracy in AF classification using transmissive PPG signals; Precision 0.88, Recall 0.85, F1 Score 0.84. Demonstrated strong performance in identifying AF vs. non-AF cases.	Limited research exists on deep learning applications using transmissive PPG signals; further validation across broader datasets and device settings is needed.
Mahmud et al., 2023 [14]	2D-CNN with transfer learning (ResNet50, VGG16/19) and ensemble models; trained on both 1D ECG signals and 2D image representations	Achieved 94% accuracy for ECG signal classification and 93% for ECG images; showed improved arrhythmia detection by combining ensemble and transfer learning techniques.	Requires investigation of real-time applicability, model interpretability, and deployment challenges in clinical settings.
Islam et al., 2022 [15]	Bidirectional RNN (BiGRU/BiLSTM) with Dilated CNN; uses wavelet transform, normalization, and GAN for signal enhancement and class balancing	Achieved 99.90% accuracy and recall on MIT-BIH dataset; significantly reduced training time and improved performance with hybrid BiRNN and dilated CNN-based fusion features.	Model performance on real-time/live ECG signals and scalability across diverse patient demographics remains untested; lacks cloud-based deployment integration.
Madan et al., 2022[16]	1D ECG converted to 2D scalogram images; Hybrid model combining 2D CNN and LSTM for arrhythmia classification	Achieved 98.7% accuracy for ARR, 99% for CHF and NSR, with average sensitivity 98.33% and specificity 98.35%; outperformed existing techniques in arrhythmia classification.	Future work suggested on applying Bi-LSTM instead of LSTM and extending the method to real-time/live ECG signal analysis and deployment in practical healthcare environments.

RECENT ADVANCES IN HYBRID DEEP LEARNING MODELS

There have been a lot of changes to how automatic heart rhythm signal classification works. It used to use normal machine learning techniques, but now it uses models from deep learning, notably hybrid architectures. The purpose of these mixed models is to combine the best aspects of several deep learning components so that ECG signals may be interpreted more precisely and reliably. When the data is noisy or there are not enough examples of each class, hybrid deep learning frameworks can make categorisation work much better. People commonly utilize both Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to sort ECGs. A lot of people enjoy LSTM networks, which are a type of RNN.[11], [17]–[20].

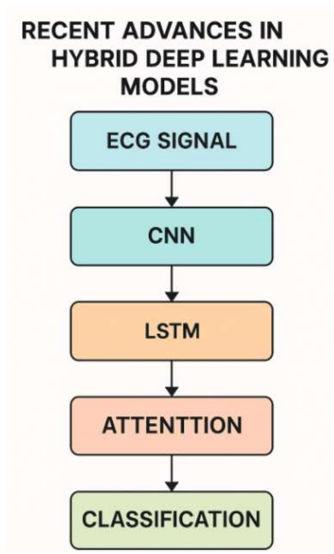

Fig. 2. **Recent Advances in Hybrid Deep Learning Models**

CNNs are very good at figuring out the size and structure of P-waves, QRS complexes, or T-waves from ECG waves. These traits are very important for figuring out what makes a cardiac rhythm normal or abnormal. CNNs alone, on the other conjunction, cannot fully show how time-series information evolves over time. Adding LSTM layers fixes this problem. These layers are meant to store and comprehend long-term temporal information, which helps the model find patterns and relationships in ECG data that happens over time. Along with the LSTM or CNN integration, several new models also use attention techniques. Attention modules modify the weights of different time steps or features during instruction to make the model focus more on the most important parts of the signal. This feature causes the model easier to understand and works a lot better, especially when there are complicated arrhythmias or the waveform patterns that overlap. Some more advanced hybrid models use Transformer-based arrangement or bidirectional LSTMs (BiLSTM) to assist the model understand the signals it gets from the past and the future better. The work that is being examined at is a good example of this kind of mixed architecture.[21]–[23]. The suggested model uses CNN layers to collect spatial information and LSTM layers to get time-related data. The model also has an attention mechanism that focuses on the parts of the signal that are predicted to show certain types of arrhythmia. This method with multiple layers lets the machine process signals in an ECG in a way that considers their hierarchy and context. Putting them in the proper class is now easier. The study it looked at included a very precise way of dealing with loud ECG data, which is a new and interesting idea. Before the data is sent to the hybrid model, the authors utilize a preprocessing pipeline that comprises denoising filters or signals normalization to make sure that any signal parts that have no value or are distorted are as small as possible. This stage is very important to make sure that the categorization is still correct in the real world, where things like baseline drift, motion noise, or electrode movements might modify ECG data. The work also makes a big difference by showing how to deal with differences between classes, which is something that often happens when trying to find arrhythmias. The study makes sure that there are enough examples of minority classes, such ventricular fibrillation, in the training by using a number of methods, including as weighted losses, data enrichment, and re-sampling. This balanced training technique makes a model that is fairer or works well on both common and unusual but important classes. The suggested hybrid model does well on a number of performance parameters, such as accuracy, F1-score, precision, and recall. The hybrid architecture is better at sorting data than models that only use CNNs or LSTMs. This is especially true when the inputs are noisy or the datasets are very unequal. The model can be utilized in real-time ECG monitoring systems, such wearable health gadgets or platforms that allow you follow patients from a distance, because it can use what it learns on new test data. To put it simply, the research we studied indicated that hybrid deep learning architectures have gotten better in the past few years. This shows that AI models are becoming stronger and more useful for figuring out biological signals. By integrating the spatial efficiency of CNNs, the temporal memory of LSTMs, and the adaptive focus of attention processes, these models set a new benchmark for ECG classification systems that are strong, accurate, and helpful in a clinical situation. Future research will surely build on this study by looking at even better architectures, real-time deployment tactics, and explainable AI methodologies to help close the gap between making algorithms and using them in clinical practice.

CRITICAL EVALUATION AND DISCUSSION

Hybrid deep learning models are getting a lot of attention in the field of ECG signal categorisation since they can combine several types of feature learning into one framework. Their main strength is the way they combine different types of neural networks, like Convolutional Neural Networks (CNNs) for recognising spatial patterns and Recurrent Neural Networks (RNNs), especially Long Short-Term Memory (LSTM) units, for capturing temporal dependencies in sequential data like ECG signals. This layered and hierarchical processing system makes the model far better at finding both short-term and long-term heart problems. This is what makes hybrid models different from various forms of machine learning along with deep learning that can work on their own. One of the best things about hybrid designs is that they can handle the problems that come up in real-world data, including noise in commands or class imbalance. These models have become better at dealing with artefacts that are common in ambulatory ECG recordings by employing denoising filters, autoencoders, and preparation methods including baseline correction and signal normalisation. Attention processes can assist models continually focus on important parts of the ECG waves, such as arrhythmic tendencies that noise or poor signal-to-noise ratios might hide. These methods make diagnosis much more accurate, especially in places where there is lots of noise, like when utilising wearable ECG monitoring equipment. Hybrid models also help in classifying minority classes, which is another important thing they do. A prevalent problem in biological datasets is class imbalance, which is when you see a lot fewer beating hearts than normal rhythms. To remedy this, hybrid deep learning frameworks often use things like focal loss functions, fake oversampling methods like SMOTE, and class weighting algorithms while training. These strategies make it more probable that types of arrhythmia that are clinically relevant but not well-known will be detected. This makes the system better at diagnosing problems in general.[24]–[28]. However, hybrid models still have some problems. One of the biggest problems is that they are hard to compute. When you add CNN, LSTM, and attention layers together, you typically get big networks with many parameters that need a lot of processing power and memory. This makes it hard to use in places with limited resources, including mobile health apps, low-power embedded systems, or devices that monitor things in real time. The trade-off between how complicated a model is and how well it works in real time is still a big problem for therapeutic use. Another problem is that hybrid deep learning models are hard to understand. These models do a great job of predicting things, but they often act like “black boxes,” making it hard to see how they make decisions. This lack of clarity might hurt trust in the medical field, especially when it comes to critical diagnostic situations. Attention processes can help us understand which sections of the ECG the model is focussing on, but they don't fully explain why it makes categorisation conclusions. This problem needs to be looked at more in future study since regulatory authorities and healthcare professionals want AI that can be explained. Another worry is that the data is dependent. Most hybrid models are trained and tested on publically available datasets that are well-structured, like MIT-BIH Arrhythmia or PTB-XL. These datasets are useful for benchmarking, but they don't always show the complete range of real-world patient data, such as differences in age, gender, comorbidities, and recording conditions. Models that are only trained on certain datasets may not work as well when they are given new data from different populations or devices. Cross-dataset validation and domain adaption techniques aren't used enough and are an important topic that needs more research. The paper that was evaluated shows encouraging results when it comes to dealing with noisy data and class imbalance, thanks to a well-defined preprocessing pipeline and training improvements. But we don't know how well these tactics work in uncontrolled, real-time situations. Some types of signal noise may not work well with denoising methods, while oversampling methods may add fake patterns that make it harder for the model to generalise. Also, not much study has been done on how well hybrid models hold up against attacks or when there are overlapping waveform patterns. A big gap in the existing research is that it doesn't focus enough on how well they work in real life and in clinical settings. Most studies focus on how well algorithms work, but they don't talk about how easy it would be to use them, how to design the user interface, what the rules are, or how to connect them to existing healthcare systems like electronic health records (EHRs). Also, not many studies use feedback from cardiologists or end users in the evaluation process, which is important for making systems that are not only technically sound but also clinically relevant and easy to use. Hybrid deep learning models are a big step forward in automated ECG classification because they give you powerful tools for dealing with noise and class imbalance. But to go from research to practice, future work needs to focus on making models easier to understand, less computationally intensive, more accurate across different datasets, and more useful in the real world. These measures will be very important to make sure that these kinds of models can really change how heart disease is diagnosed in both clinical and distant healthcare settings.

Table - 2

Summary of Strengths and Limitations of Hybrid Deep Learning Models in ECG Classification

Aspect	Strengths	Limitations
Model Architecture	Combines CNN and LSTM for spatial-temporal feature learning	High computational complexity and memory demand
Noise Resilience	Uses denoising layers, filters, and attention to handle signal artifacts	May fail under extreme or unpredictable real-world noise conditions
Class Imbalance Handling	Incorporates focal loss, SMOTE, and class weighting for minority classes	Oversampling may introduce artificial patterns and affect generalization
Classification Performance	High accuracy, precision, and recall across diverse ECG categories	Performance may degrade with unseen or out-of-distribution data
Interpretability	Attention mechanisms offer some insight into signal focus	Overall remains a “black box” with limited transparency
Clinical Usability	Potential for real-time arrhythmia detection and remote monitoring	Few studies consider deployment feasibility or user feedback in design

To provide a concise and comparative overview of the key points discussed in this section, Table summarizes the major strengths and limitations of hybrid deep learning models for ECG signal classification. This table serves as a quick reference for readers to understand the trade-offs involved in using such models in both research and clinical settings. Each row highlights a specific aspect—ranging from architectural design to clinical usability—along with corresponding advantages and challenges. By presenting this information in tabular form, the review enables clearer comparison across technical and practical dimensions, helping researchers, developers, and clinicians identify not only the innovations brought by hybrid models but also the barriers that must be overcome for real-world implementation. The table reinforces the critical analysis provided in the discussion and supports the argument that while hybrid models hold great potential, further refinements are needed to enhance their interpretability, efficiency, and clinical readiness.

APPLICATION AREAS OF HYBRID DEEP LEARNING IN ECG ANALYSIS

Hybrid deep learning models are not only ideas; they are also being used more and more in real life in healthcare[29]–[34]. These examples show how combining CNNs, LSTMs, and attention processes in ECG analysis can make a big difference in the real world:

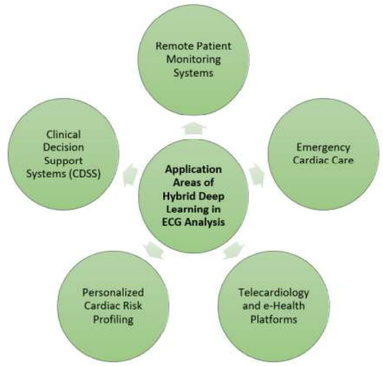

Fig. 3. Application Areas of Hybrid Deep Learning in ECG Analysis

5.1 Remote Patient Monitoring Systems

Hybrid models are being integrated into wearable devices and mobile health platforms to monitor ECG signals in real time. This helps in early detection of anomalies like atrial fibrillation and arrhythmia, allowing timely medical intervention.

5.2 Emergency Cardiac Care

Portable ECG devices powered by blended deep learning can quickly classify heart events in ambulances or emergency situations, which helps doctors make decisions and triage faster.

5.3 Telecardiology and e-Health Platforms

Cloud-based solutions that use combined approaches let experts look at ECG signals from a distance. This is quite useful in rural or resource-limited areas.

5.4 Personalized Cardiac Risk Profiling

Hybrid systems can be used to improve models for individual patients, which helps clinicians make better diagnoses by looking at an individual's health past or signal patterns.

5.5 Clinical Decision Support Systems (CDSS)

Hybrid ECG classification is a part of CDSS, assisting doctors decide based on data by correctly detecting heart issues.

TAXONOMY OF HYBRID DEEP LEARNING APPROACHES FOR ECG

This part presents a structured taxonomy that will help us understand and compare the different kinds of hybrid algorithms utilising deep learning that are used to identify ECG signals. This taxonomy shows the full area by putting techniques into groups based on their model architecture, signal processing, educating strategy, or tactical scope. It also helps folks make better models that are novel.[35]–[41].

Table - 3
Taxonomy Of Hybrid Deep Learning Approaches In ECG Signal Classification

Category	Examples/Techniques	Description
Model Composition	CNN-LSTM, CNN-BiLSTM-Attention, Transformer-CNN hybrids	These architectures combine spatial (CNN) and temporal (LSTM/BiLSTM) learning, often enhanced with attention modules or transformer blocks for context.
Signal Preprocessing	Denoising filters, SD-ROM, signal normalization	Preprocessing enhances signal quality by reducing artifacts like baseline drift or motion noise, ensuring relevant ECG features are preserved.
Noise Handling Mechanism	Autoencoders, Wavelet Transforms, frequency-aware filters	Techniques aimed at suppressing background noise while retaining critical information for rhythm classification.
Class Imbalance Strategy	SMOTE, Weighted/Focal Loss, Data Augmentation	These methods mitigate skewed class distributions in ECG datasets, improving model sensitivity to rare arrhythmic events.
Evaluation Metrics	Accuracy, F1-score, Specificity, Sensitivity	Standardized metrics for assessing model performance across both common and minority classes, ensuring comprehensive validation.
Deployment Scope	Real-time systems, embedded devices, cloud-based platforms	Hybrid models are increasingly being tailored for deployment on wearable health monitors, edge devices, or cloud-integrated telehealth solutions.

This table presents a list of a hybrid deep learning approaches that are used to categorise ECGs in a systematic way. It puts significant aspects into groupings, such as model architecture, processing methods, reducing noise methods, dealing with class imbalance, measurement metrics, and deployment settings. To highlight how crucial each category is for building powerful and clinically relevant ECG system classifications, it is combined with a few common methods and a short explanation.

This taxonomy not only sorts the most significant methodological components of hybrid systems, but it also demonstrates the design trade-offs researchers have to make, including establishing a balance between accuracy and comprehension or generalisation and restricted resources. It shows you how to develop new ECG classification approaches that work properly in the clinic and are straightforward for computers to utilise.

CONCLUSION

This study reveals that hybrid models of deep learning that include neural network models (CNNs), LSTM (long-short-term memory) networks, and focus processes have made ECG signal categorisation significantly better. When it comes to navigating noisy ECG data and addressing class imbalance, these models operate better than ordinary machine learning and deep learning methods that work on their own. Hybrid frameworks are even more powerful now that they can incorporate transformer-based designs, attention modules, and domain adaption approaches. Also, researchers are looking towards explainable AI ways to make models more transparent and trustworthy, especially in healthcare settings. Even with these improvements, there are still problems. High computational complexity, limited interpretability, and problems with deploying in real time on devices with few resources are still major obstacles to clinical translation. The paper makes a big deal out of the fact that hybrid models are having real-world effects in more and more application areas, like remote patient monitoring, emergency cardiac care, telecardiology, and clinical decision support systems. These examples show how hybrid designs can be useful in real-world healthcare settings and how they could change the way things are done. The review gives a systematic view by introducing a "taxonomy of hybrid deep learning approaches," which sorts the different methods into groups based on their model architecture, preprocessing, noise handling, class balance, evaluation metrics, and deployment scope. This taxonomy not only organises the research that has already been done, but it also helps with planning and doing new research. In the future, research should focus on building hybrid models that are both lightweight and accurate, and that can work in real time and with limited resources. It is also very important to do validations on a variety of real-world datasets and to include comments from doctors who use the system. Also, making these models easier to understand and more ethically sound will be important for building trust and getting regulatory approval for clinical use.

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