Harnessing Deep Learning for Early Detection of Cardiac Abnormalities

Authors:

Ms Prutha Annadate [1]	Dr. Mangesh Bedekar [2]	Dr. Mrunal Annadate [3]
School of Computer Science Engineering Artificial Intelligence and Data Science	School of Computer Science Engineering	School of Electronics and Telecommunications Engineering
Dr. Vishwanath Karad MIT World Peace University, Kothrud, Pune 411038, India		
prutha1411@gmail.com	*mangesh.bedekar@mitwpu.edu.in*	*mrunal.annadate@mitwpu.edu.in*
City and country where study is conducted: Pune, India		

Abstract

Background:

Sudden Cardiac Arrests (SCAs) are potentially fatal situations that strike suddenly, frequently without warning, and can have dire repercussions if left untreated. These incidents result in an abrupt loss of heart function caused by an electrical malfunction in the heart. For the purpose of increasing survival rates and reducing long-term damage, early detection and intervention are essential. In this context, there is great potential to improve response mechanisms and deepen our understanding of SCA by utilizing fog computing and Deep Learning (DL) for Internet of Things (IoT) devices.

Aim:

This study's main goal is to investigate how DL algorithms and fog computing can be used with IoT devices to better understand and anticipate sudden cardiac arrests. The goal is to create a reliable, real-time system that can recognize possible SCA events, examine pertinent data, and enable prompt intervention.

Methods:

The study uses a multidisciplinary methodology, combining fog computing for Internet of Things devices with machine learning techniques. With fog computing, real-time data from wearables—like smartwatches and health monitors—is gathered and processed at the edge. After that, patterns and anomalies in the data are analyzed using DL, this work utilizes the Multilayer Perceptron with ReLu as activation function for faster convergence, to find possible signs of an approaching SCA.

Results: The model achieved an average accuracy of 98.65%, out-performing previous models and converging faster. Another novel feature is the alert system which sends out an alert message whenever there is a predicted SCA.

Observations:
The study's findings show that the comprehension of SCA is greatly improved when DL and fog computing are combined with IoT devices. Real-time data processing and analysis capabilities of the system enable prompt and focused interventions that may even save lives. Additionally, the system can adjust and increase its predictive accuracy over time thanks to the DL algorithms' continuous learning capabilities, which makes it an invaluable tool for cardiovascular health monitoring. To sum up, this study demonstrates how ML ,particularly DL and fog computing can transform our understanding of and response to sudden cardiac arrests, opening the door to new developments in emergency response systemsand healthcare.

Introduction

Sudden Cardiac Arrests (SCA) are a critical medical emergency requiring immediate and precise intervention for the best outcomes. They are often unpredictable and can be fatal if not treated promptly. Given their significant impact on public health, advancing our understanding of SCA and improving response mechanisms is paramount. Recent years have seen a convergence of cutting-edge technologies, such as fog computing and Machine Learning (ML) and Deep Learning (DL), offering new possibilities for addressing the complexities of SCA. Fog computing, which extends cloud computing to the edge of the network, and DL, which enables systems to learn from data, are particularly promising in this regard. Sudden Cardiac Arrests occur when the heart unexpectedly stops beating, disrupting blood flow to the brain and other vital organs. This event is distinct from a heart attack, which is caused by a blockage that stops blood flow to the heart. SCA can be triggered by various conditions, including coronary artery disease, arrhythmias, and structural heart abnormalities. The immediate cause is usually an electrical malfunction that causes an irregular heartbeat (arrhythmia). Without rapid intervention, such as defibrillation or CPR, SCA can lead to death within minutes.

The unpredictable nature of SCA poses significant challenges for timely intervention. Traditional healthcare systems often rely on centralized processing and delayed data transmission, which can be insufficient in emergency situations where every second counts. The latency involved in sending data to centralized cloud servers for analysis can result in delayed responses, which may be detrimental in the case of SCA. Moreover, the lack of continuous monitoring and real-time data analysis limits the ability to predict and prevent such events. Fog computing offers a solution to these challenges by extending cloud computing capabilities to the edge of the network. It enables data processing closer to the source of data generation, reducing latency and improving response times. In the context of healthcare, fog computing allows for real-time data analysis and decision-making at the edge, which is critical for managing emergencies like SCA. Devices equipped with fog computing capabilities can process and analyze data locally, making it possible to detect anomalies and trigger alerts instantaneously.

Deep Learning, a subset of ML, has shown remarkable success in various domains due to its ability to learn from vast amounts of data and identify complex patterns. In healthcare, DL can be used to analyze ECG data and other vital signs to predict the likelihood of SCA. By training DL models on historical data, these systems can learn to recognize early warning signs and risk factors associated with SCA. The ability to continuously learn and adapt from new data makes DL particularly powerful for predictive analytics in healthcare.

The integration of fog computing and DL within the IoT framework represents a significant advancement in cardiovascular health monitoring and emergency medical care. IoT devices equipped with sensors can continuously monitor patients' vital signs, including heart rate, ECG, and other relevant metrics. The data collected by these sensors can be processed locally using fog computing, enabling real-time analysis and immediate response. For instance, consider a wearable device that monitors a patient's ECG. When integrated with fog computing and DL, this device can analyze the ECG data in real-time to detect irregular heart rhythms indicative of an impending SCA. Upon detecting such anomalies, the system can immediately alert the patient and healthcare providers, enabling prompt intervention. This early warning system can significantly enhance the chances of survival and reduce the severity of outcomes. The combination of fog computing and DL also facilitates personalized treatment strategies. By analyzing individual patient data, DL models can tailor recommendations and interventions to each person's unique health profile. This personalized approach ensures that patients receive the most effective treatments based on their specific risk factors and medical history. Additionally, continuous monitoring and real-time data analysis enable healthcare providers to adjust treatments dynamically, improving patient outcomes.

In emergency scenarios, the ability to process and analyze data at the edge can make a critical difference. Fog computing ensures that alerts and notifications are sent without delay, while DL models provide accurate and timely predictions of SCA risks. This integrated approach can also support automated emergency response systems, such as triggering defibrillators or contacting emergency services immediately upon detecting a life-threatening event. One of the key challenges in implementing these technologies is ensuring data privacy and security. Healthcare data is highly sensitive, and protecting it from unauthorized access and breaches is crucial. Fog computing can enhance data security by reducing the amount of data transmitted to centralized servers. Local data processing minimizes the exposure of sensitive information, and advanced encryption techniques can be used to secure data at rest and in transit. Optimizing resource allocation in edge and fog environments is essential for the efficient operation of these systems. Proper resource management ensures that computational power, memory, and network bandwidth are utilized effectively. Techniques such as load balancing and dynamic resource allocation can help maintain the performance and scalability of AI models used in healthcare applications. Validating the effectiveness of DL models in real-world scenarios is critical for their adoption in clinical settings. Collaborative efforts between healthcare providers, technology developers, and regulatory bodies are needed to establish standards and guidelines for the deployment of AI-based solutions. Clinical trials and pilot studies can provide the necessary evidence to demonstrate the reliability and efficacy of these technologies.

The integration of fog computing and Deep Learning within the IoT framework offers a comprehensive and innovative approach to understanding, predicting, and managing sudden cardiac arrests. By leveraging real-time data analytics at the edge of the network, this approach has the potential to revolutionize cardiovascular health monitoring and emergency medical care. The ability to detect early signs of SCA, provide timely interventions, and deliver personalized treatment strategies can significantly improve patient outcomes and reduce mortality rates associated with SCA. While the potential benefits are substantial, several challenges must be addressed to ensure the successful implementation of these technologies. Ensuring data privacy and security, optimizing resource allocation, and validating the effectiveness of AI models in real-world scenarios are critical steps. Collaborative efforts among stakeholders, including healthcare providers, technology developers, and regulatory bodies, are essential to establish standards and guidelines for deployment. Overall, the convergence of fog computing, DL, and IoT represents a promising frontier in healthcare technology. Continued research and development in this area will pave the way for innovative solutions that enhance patient care and save lives. The future of cardiovascular health monitoring lies in the seamless integration of these advanced technologies, enabling a proactive and responsive healthcare system that can effectively manage and mitigate the risks associated with sudden cardiac arrests.

Related Works

In [1] during ECG patch monitoring, the PPG-based algorithm showed a high positive predictive value for concurrent AF detection. Numerous participants were successfully enrolled in the study, yielding a diverse dataset for analysis. Fitbits in particular are wearable technology that could be useful in identifying people who have undiagnosed AF. The objective of the study in [2] was to evaluate four distinct approaches to data reduction for continuous electrocardiogram (ECG) data obtained in cynomolgus monkeys during a validation study. Jacketed telemetry was used to collect the data. On various dosing days, the animals were given ascending doses of moxifloxacin after either a vehicle or vehicle treatment. On each dosing day, continuous ECG recordings were made for 25 hours. Four data reduction techniques were then applied: large duration averages (0.5-4 hours), super-intervals (3.5-9 hours averages), 1-min average snapshots, and 15-min average snapshots. In [3] according to the study, compared to MPP followed by a 12-lead ECG, single-time point lead-I ECG devices in primary care may be a more economical use of NHS resources for detecting AF in patients with signs or symptoms and an irregular pulse. In [4] the study's objectives are to examine and assess unsupervised electrocardiogram (ECG) clustering methods, most of which have been created in the previous ten years. Recent advances in machine learning and deep learning algorithms, along with their useful applications, are the main focus. In [5] according to the study, smartphones are expanding the use of ECG and arrhythmia detection, enabling a larger population to have access to the technology. The conversation focuses on how smartphone-based solutions, such as Kardia Mobile and ECG Check, are better at detecting arrhythmias than more conventional wearable monitors that are primarily intended for activity tracking. In [6] with training and application on 3D VCG, the DL architecture showed improved precision with high F1-scores of 99.80% and 99.64% in leave-one-out cross-validation and cross-database validation protocols, respectively. In [7] the purpose of the study is to evaluate and compare various transfer learning techniques for electrocardiogram (ECG) classification in the context of ECG arrhythmia detection. An ECG dataset from Kaggle is multi-classified using the proposed model, CAA-TL, which is enhanced with real-time and other datasets (healthy and unhealthy). In [8] the standard 12-lead ECG is frequently used to diagnose heart disease, but it may not always be the best method, according to the study. Investigation into other techniques, like the examination of high-frequency QRS components, may yield more diagnostic data. In [9] the study found that a useful technique for detecting the QRS complex in the 12-lead ECG was the combination of signal entropy and SVM. In [10] the study found that the idea for creating a cloud-based health care system came from recent developments in cloud computing and mobile technology. These systems have the potential to improve accessibility and convenience for medical professionals and patients by enabling the automated gathering and sharing of medical data. [11] The purpose of the study was to describe and assess a novel automated technique for identifying reversals in the precordial and peripheral leads of electrocardiograms (ECGs). The method was designed to analyze cable reversals using basic criteria that took into account correlation dependencies between leads. [12] The research noted that while various attempts have been made to quantify diagnostic distortion brought about by low-dimensional ECG representation techniques, no widely recognized quantitative measure has been developed specifically for this purpose.The purpose of the suggested framework was to address the need for an effective and dependable way to evaluate diagnostic distortion brought on by ECG processing methods. In [13] the goal of the project was to create a toolbox for Electrocardiography (ECG) analysis with a graphical user interface that is easy to use. The toolkit was made to cover every stage of ECG analysis, from statistical research to the recording device. Furthermore, a novel feature computation approach was put out for ECG analysis with the goal of offering unique information that goes beyond the primary wave amplitudes and durations. [14] It was shown that automated ECG interpretation software excluded AF with the highest accuracy. It was discovered that, nonetheless, its diagnostic capacity for AF was comparable to that of all medical specialists. In primary care, general practitioners (GPs) were shown to have a higher specificity of AF diagnosis from ECG than nurses. [15] The study takes a broad approach, integrating knowledge from the supervised AI algorithms' mathematical foundation with an emphasis on their use in electrocardiogram (ECG) analysis. The techniques entail explaining how AI has transformed physicians' ability to diagnose patients by analyzing ECGs. The mentioned algorithms are trained on large datasets by finding underlying patterns without the need for hard-coded rules. A few AI ECG cardiac screening algorithms are also reviewed, with a focus on those that identify several structural and valvular disorders, episodic atrial fibrillation, and left ventricular dysfunction. [16] The assessment indicates that even with the significant advancements in artificial intelligence and the technology applications in cardiac electrophysiology, there can still be unanswered questions that need to be answered. Validation studies to guarantee the accuracy and dependability of AI-assisted illness signature recognition in electrocardiography may be one area where research is still lacking. The review may also suggest that more research is needed to determine whether AI can be used in population-based atrial fibrillation detection, taking into account ethical, economical, and accessibility issues. The promise of extended realities, non-invasive ablation therapy, and robots in EP care may point to the necessity for more investigation into the practical difficulties and therapeutic efficacy of these innovations. [17] The review suggests that even with these encouraging improvements, there might still remain unanswered research questions. Among these would be the requirement for validation studies to evaluate the effectiveness and dependability of AI models in the real world for identifying different phenotypic features and cardiovascular diseases. [18] The study included 180,922 patients with 649,931 normal sinus rhythm ECGs. The AI-enabled ECG identified atrial fibrillation with an AUC of 0.87 (95% CI 0.86-0.88), sensitivity of 79.0%, specificity of 79.5%, F1 score of 39.2%, and overall accuracy of 79.4%. When including all ECGs acquired during the first month of each patient's window of interest, the AUC increased to 0.90 (95% CI 0.90-0.91), sensitivity to 82.3%, specificity to 83.4%, F1 score to 45.4%, and overall accuracy to 83.3%. [19] The findings demonstrate that, despite its lengthy history, electrocardiography is still relevant today. The growing interest in ECG is ascribed to advances in artificial intelligence (AI), namely in the areas of machine learning and deep learning, which are predicted to open up new avenues for the assessment and interpretation of ECG data. The reference to overcoming shortcomings in traditional computer-assisted ECG examination points to a positive assessment of AI's potential to solve problems in this field. [20] Several research gaps in the field of AI-based electrocardiography are identified by the review. First of all, it points out that the majority of research are proof-of-concept investigations, and it's frequently unclear what level of private data was used in these studies. This implies that more extensive and standardized datasets are required, and the authors stress the significance of clinical validation in various contexts and collectives. Artificial intelligence (AI) solutions are often perceived as being opaque, which highlights the necessity for AI algorithms to be transparent and comprehensible. [21] The article's observations highlight how AI is revolutionizing ECG analysis. The conversation is on the enthusiasm that machine learning and computer techniques have brought about, which has resulted in the revival of the ECG, one of the most important diagnostic instruments.

[22] The study's findings highlight the distinctions between the two AI-ECG techniques, ML and DL. With a focus on particular ECG variables for focused tasks such wide QRS complex tachycardia discrimination, the machine learning approach makes use of expert domain knowledge. On the other hand, for more general tasks like a thorough 12-lead ECG interpretation, the DL technique depends on a more extensive and independent recognition of several ECG parameters. The study highlights how crucial it is for researchers working on AI-ECG solutions to comprehend these distinctions. [23] The study's findings highlight the clinical significance of minute variations in QRS when evaluating diastolic dysfunction, decreased EF, the onset of HF, and the responsiveness of therapy. The study acknowledges that precise physical measurements are necessary to detect these minute variations, but it also proposes

that using artificial intelligence (AI) to analyze ECG data may result in a faster and more thorough evaluation, particularly when working with big populations.

In conclusion, there are a number of research gaps that need to be filled even though ML and DL have the potential to completely transform cardiac arrhythmia diagnosis and ECG analysis. These include the requirement for research on the clinical applications of AI-based ECG analysis, standardized datasets, and validation studies. Closing these gaps will make it more likely that AI will be successfully incorporated into clinical practice to improve cardiac care. This paper fills a research vacuum by examining the need for studies on the practical applications of AI-based ECG analysis with the help of the alerting system and edge based analysis for accessing the health of an individual in short cycles, to find a potential for SCA, and alert them. This prompts an individual at risk to facilitate interaction with their nearest physician and potentially avoid a SCA.

Methodology

The aim of any medical detection system is to send alerts and/ or detect a potential problem, in our case, a chance of a SCA. The process commences with the acquisition of data from edge sources, with the data predominantly being numeric in nature. The initial phase of data processing involves preliminary data analytics, which encompasses fundamental data cleaning and preparation procedures to render the data suitable for subsequent analysis. These data cleaning steps encompass the elimination of duplicates, rectification of errors, and ensuring consistent formatting of the data. Subsequently, the data is modeled using a Multi-Layer Perceptron (MLP), the architectural details of which are elaborated upon below. The primary objective of the preliminary analytics phase is to ascertain whether an alert should be triggered, while more advanced analytics can be conducted at the cloud level on the processed data. We used the 2-lead recordings from the open-source dataset 'INCART 2-lead Arrhythmia Database' for our investigation. A lengthy recording from one lead is used to create a rhythm strip in order to guarantee accurate evaluation of the heart rhythm. Lead II is the recommended option for recording the rhythm strip because of its ability to clearly display the P wave.

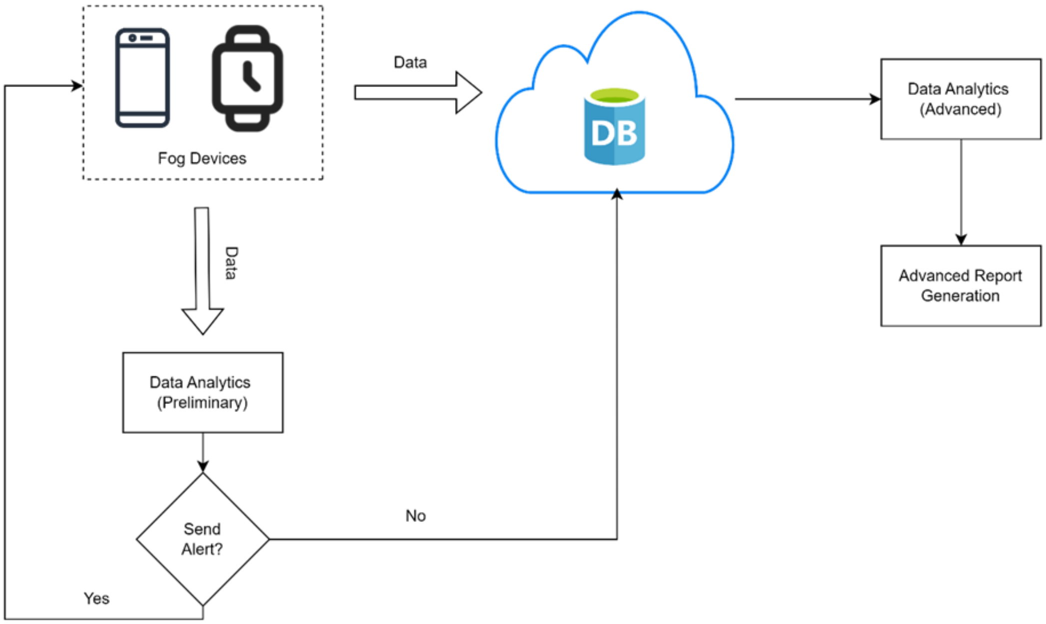

Fig 1. Proposed methodology

Our model employs a MLP architecture with five hidden layers, as shown in Fig. 2, each utilizing the Rectified Linear Unit (ReLU) activation function defined as;

$f(x)$=max(0,x) …Equation 1

which means that it returns the input value if it is positive, and zero otherwise. This choice of activation function is known for its ability to facilitate faster convergence during training. Each hidden layer is composed of 100 neurons, allowing the model to effectively capture the complexities inherent in the dataset. Furthermore, the output layer of the MLP employs the sigmoid activation function, defined as;

$$f(x) = \frac{1}{1+e^{-x}}$$ …Equation 2

where e is the base of the natural logarithm. The sigmoid function maps any real value to the range (0,1) The sigmoid activation function is particularly suitable for binary classification tasks, as it outputs probabilities, providing a measure of confidence for the prediction of Sudden Cardiac Arrest (SCA) occurrence.

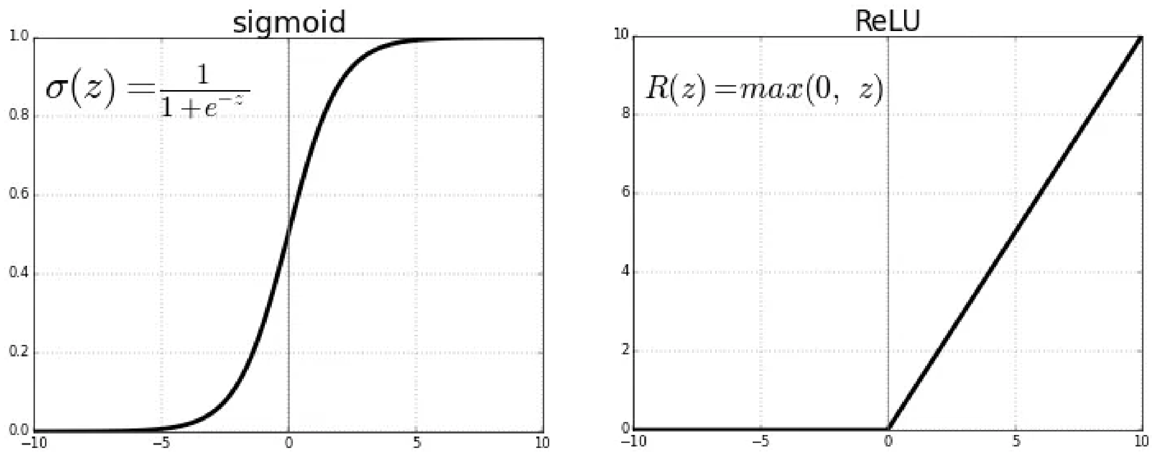

Fig. 2 ReLu v/s Logistic Sigmoid cited from source [24]

The input layer of our model consists of 34 inputs, representing the features used for prediction. It is important to note that the architectural representation provided above focuses solely on the hidden layers and does not accurately portray the scale of the entire network.

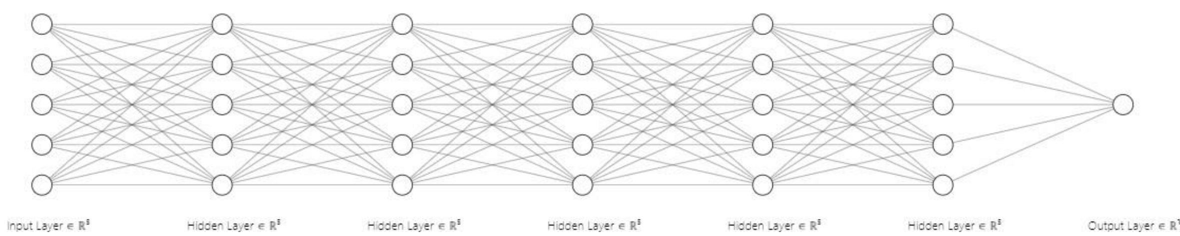

Fig. 3 Architecture of Multilayer Perceptron

Expanding on the architectural details as demonstrated in Fig 3 (not to scale), the use of multiple hidden layers allows the model to learn intricate patterns and relationships within the data. Each hidden layer processes the input data, extracting higher-level features that contribute to the final prediction. The ReLU activation function is chosen for its ability to mitigate the vanishing gradient problem, which can hinder the training of deep neural networks. The choice of 100 neurons per hidden layer strikes a balance between model complexity and computational efficiency, ensuring that the model can effectively learn from the data without overfitting.

Results

In order to make precise predictions, the proposed methodology runs each epoch with a batch size of 60. To model 60 readings a minute. The data is processed in batches of 60 rows, with accuracy measured for each batch. Accuracy is defined as the proportion of correct classifications or predictions in each batch.

The graph illustrates how model accuracy evolves with increasing training data. Overall, the graph in Fig. 4 reveals that accuracy of the data batches fluctuates between 0.6 and 1.0, with no discernible trend over time. Average accuracy of the proposed model is 98.65%.

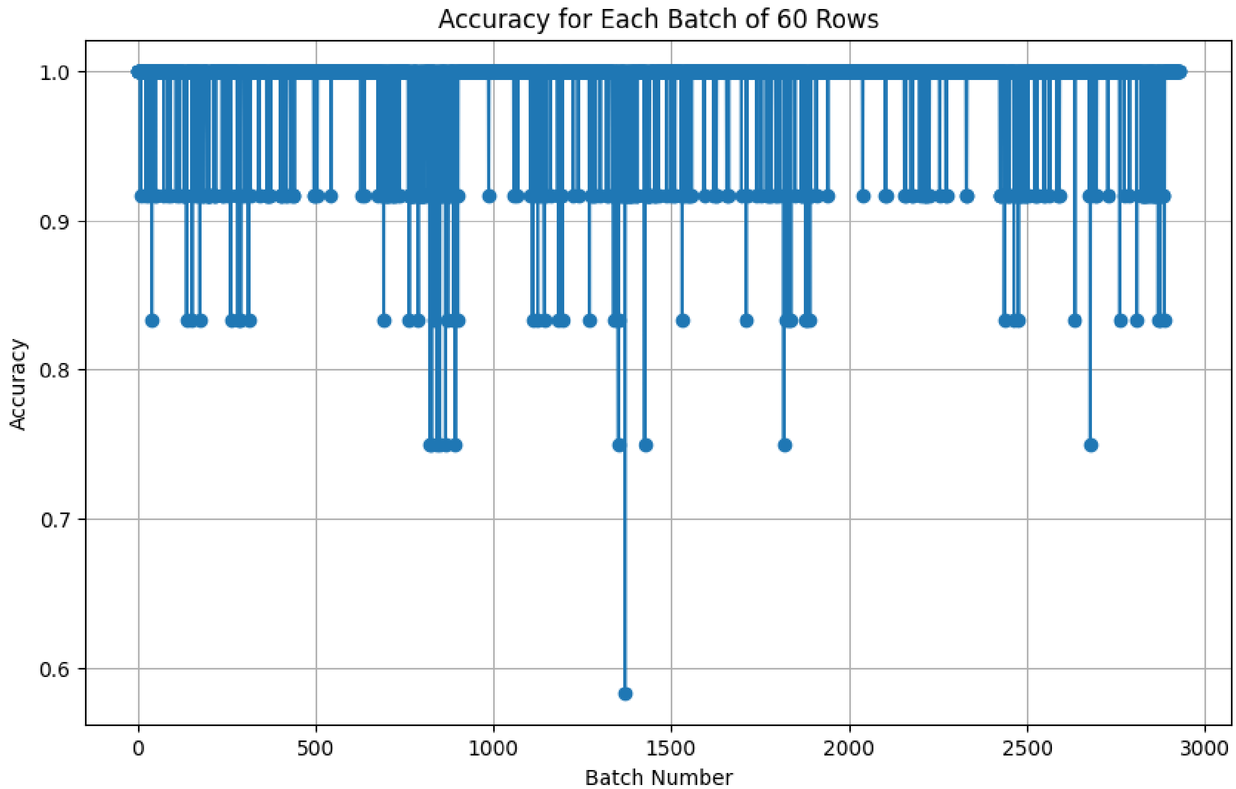

Fig. 4 Accuracy v/s batch number

The output of the MLP gives the probability of a SCA occurring in the range of 0 to 1, with 1 being the 100% probability of it occurring. Quantifying these occurrences gives us a peek into the possibilities of a SCA as shown in Fig. 5.

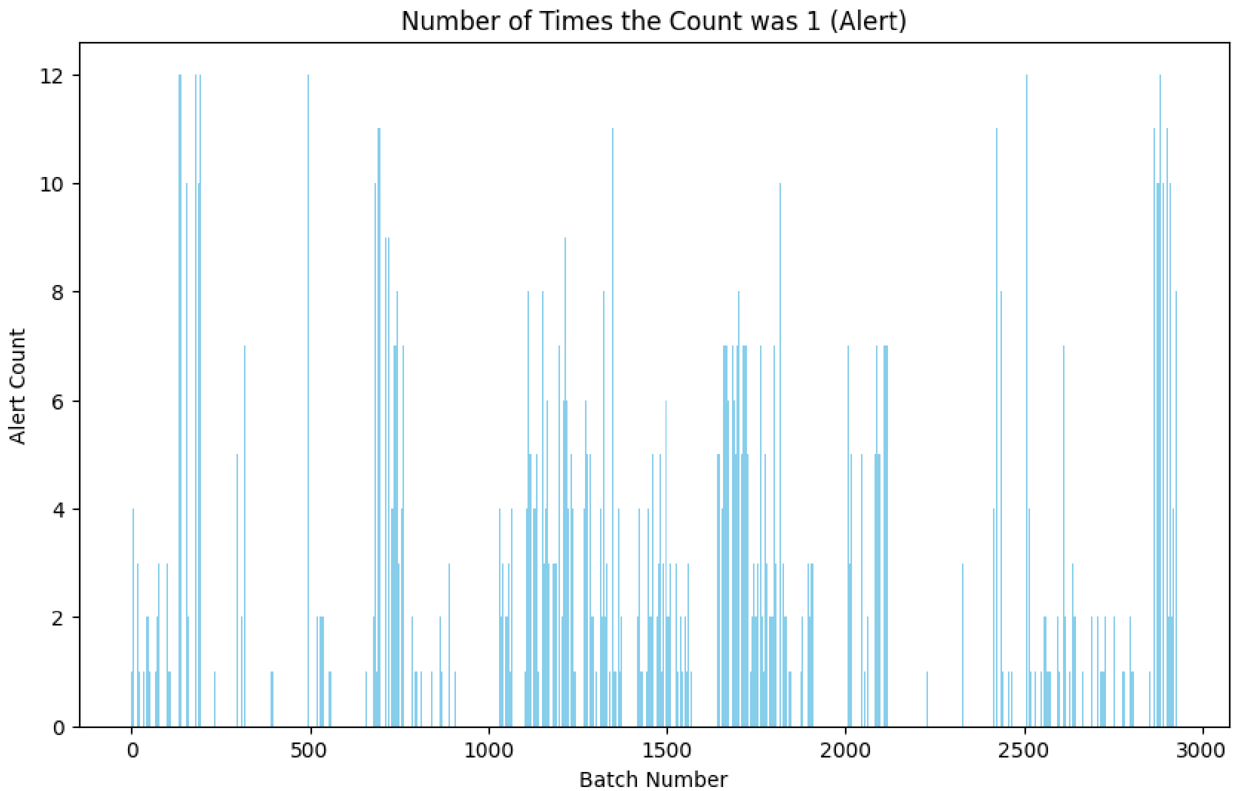

Fig. 5 Count of 100% probability of SCA occurrence.

And to ascertain how many individual chances of SCA are predicted Fig. 6 helps with betterunderstanding of the rarity of the occasion. We can safely presume that a SCA is a rare occurrence.

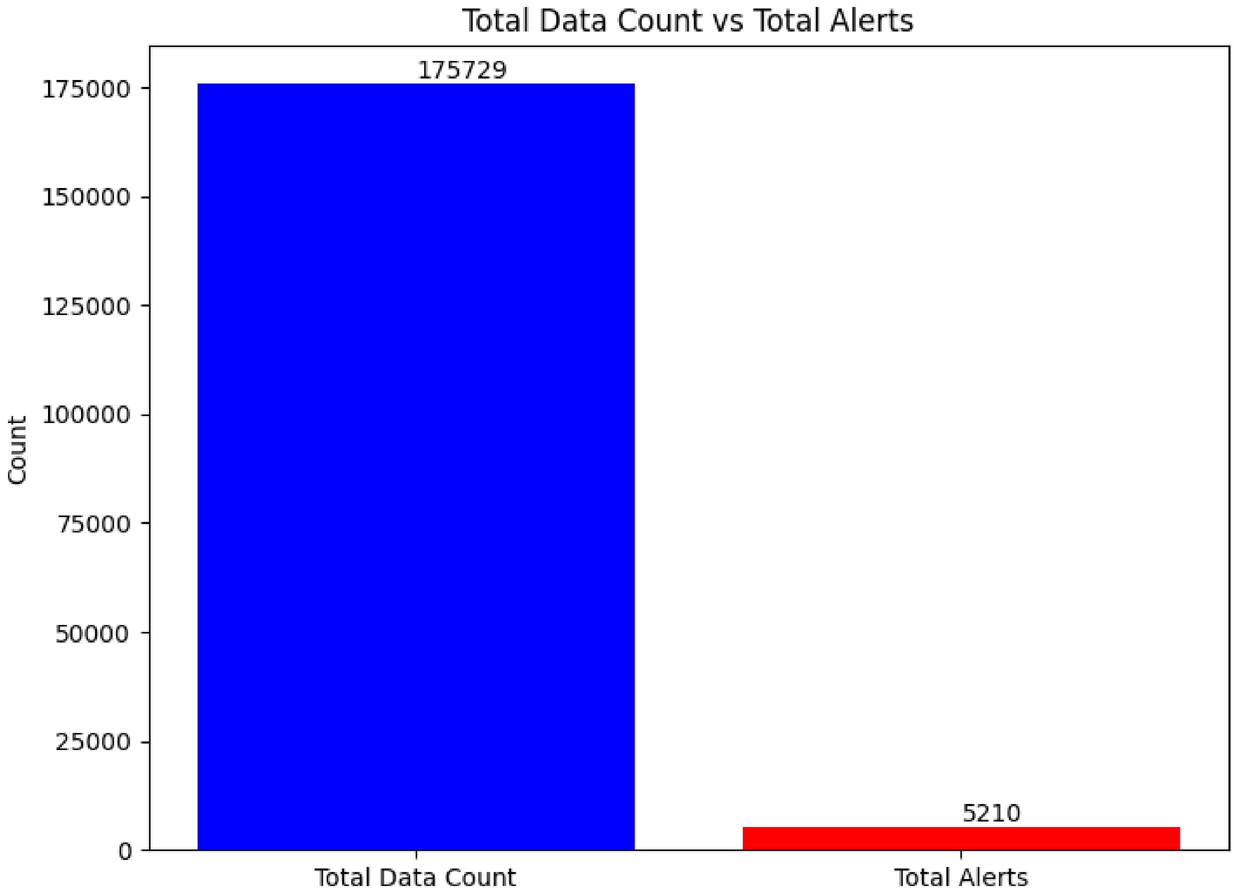

Fig. 6 Total Alerts

Discussion

This work addresses a significant research gap by focusing on the practical applications of AI-based ECG analysis, specifically in the context of edge-based analysis and warning systems for short-term health assessment. The primary objective is to identify individuals at risk for Atrial Fibrillation (AF) and promptly notify them to seek medical attention, potentially preventing a Sudden Cardiac Arrest (SCA). The methodology employed in this study involves processing data in batches of 60 rows, calculating accuracy for each batch, and progressively training the model with more data to observe changes in accuracy. The model architecture utilized is a Multilayer Perceptron (MLP) with five hidden layers, ReLU activation functions, and a sigmoid activation function in the output layer. This architecture enables the model to effectively capture complex relationships and patterns within the data, resulting in an impressive average accuracy of 98.65%.

The study's findings illustrate the potential of AI, particularly Deep Learning (DL), in forecasting the likelihood of SCA occurrence, as the model generates probabilities ranging from 0 to 1. Despite fluctuations in accuracy between 0.6 and 1.0 for different data batches, the analysis reveals no discernible pattern over time. Furthermore, the study highlights the rarity of SCA incidents, underscoring the importance of accurate and timely detection methods. Overall, this research provides valuable insights into the practical applications of AI-based ECG analysis for predicting SCA and identifying individuals at risk for AF. The findings contribute to the growing body of knowledge in this field and emphasize the potential of AI to enhance cardiovascular health monitoring and emergency medical care.

Ensuring data privacy and security is paramount, as these technologies deal with sensitive health information. Robust security measures must be established to protect patient data from unauthorized access or breaches. This involves implementing advanced encryption techniques, secure data storage solutions, and strict access controls. Additionally, compliance with healthcare regulations such as HIPAA (Health Insurance Portability and Accountability Act) is essential to maintain the confidentiality and integrity of patient data.

Optimizing resource allocation in edge and fog environments is another significant challenge. These technologies rely on efficient utilization of computational resources to process data in real-time. Proper resource allocation can enhance the performance and scalability of AI models, ensuring timely and accurate analysis of ECG data. Strategies such as load balancing, resource scheduling, and dynamic resource management can be employed to optimize resource usage in edge and fog computing environments. This will ensure that the computational demands of AI models are met without overburdening the infrastructure.

Validating the effectiveness of ML models in real-world scenarios is essential to ensure their reliability and efficacy in clinical settings. Collaborative efforts between healthcare providers, technology developers, and regulatory bodies are crucial to establish standards and guidelines for the deployment of AI-based ECG analysis technologies. These collaborations can facilitate the development of comprehensive validation frameworks that include clinical trials, pilot studies, and performance benchmarks. By working together, stakeholders can address these challenges and pave the way for the successful implementation of these transformative technologies in healthcare.

Furthermore, addressing the challenge of interpretability in AI models is critical for their adoption in clinical practice. Clinicians need to understand the decision-making process of AI models to trust and effectively use these tools. Developing explainable AI techniques that provide insights into the model's reasoning can bridge this gap and enhance the acceptance of AI-based solutions in healthcare.

The potential integration of AI-based ECG analysis with existing healthcare systems also poses a challenge. Seamless integration requires interoperability between different healthcare systems and AI platforms. Standardizing data formats, communication protocols, and interfaces can facilitate the integration process and ensure that AI-based solutions work harmoniously with existing healthcare infrastructure.

Additionally, continuous monitoring and updating of AI models are necessary to maintain their accuracy and relevance. As new data becomes available and medical knowledge evolves, AI models need to be retrained and fine-tuned to reflect these changes. Establishing mechanisms for ongoing model maintenance and updates will ensure that AI-based ECG analysis remains effective and up-to-date.

Conclusion

To sum up, this study adds to the expanding corpus of research on AI-based ECG analysis and emphasizes how AI may enhance emergency medical care and cardiovascular health monitoring. The proposed methodology of using a Multilayer Perceptron (MLP) with edge-based analysis and warning systems shows promise in identifying individuals at risk for AF and potentially preventing SCAs. By processing data in batches of 60 rows and employing advanced AI techniques, the model achieves an impressive average accuracy of 98.65%, demonstrating the potential of AI in predicting SCA occurrences.

Subsequent investigations ought to concentrate on verifying these results in medical environments and investigating supplementary uses of AI in cardiac treatment. Clinical validation studies are essential to confirm the efficacy and reliability of AI-based ECG analysis in real-world settings. These studies can provide valuable insights into the practical challenges and benefits of implementing AI solutions in healthcare, paving the way for broader adoption.

In conclusion, there are still a number of research gaps that need to be filled even though AI and machine learning have the enormous potential to transform the diagnosis and analysis of cardiac arrhythmias and ECGs. Ensuring data privacy and security, optimizing resource allocation in edge and fog environments,and validating the effectiveness of ML models in real-world scenarios are critical challenges that must be addressed. Collaboration between healthcare providers, technology developers, and regulatory bodies will be essential to establish standards and guidelines for deployment.

Addressing the challenge of interpretability in AI models is also crucial. Developing explainable AI techniques can enhance the trust and acceptance of AI-based solutions among clinicians, facilitating their integration into clinical practice. Additionally, standardizing data formats and communication protocols can enable seamless integration of AI-based ECG analysis with existing healthcare systems, ensuring interoperability and efficient workflow.

Continuous monitoring and updating of AI models are necessary to maintain their accuracy and relevance. Establishing mechanisms for ongoing model maintenance and updates will ensure that AI-based ECG analysis remains effective and up-to-date with the latest medical knowledge and data.

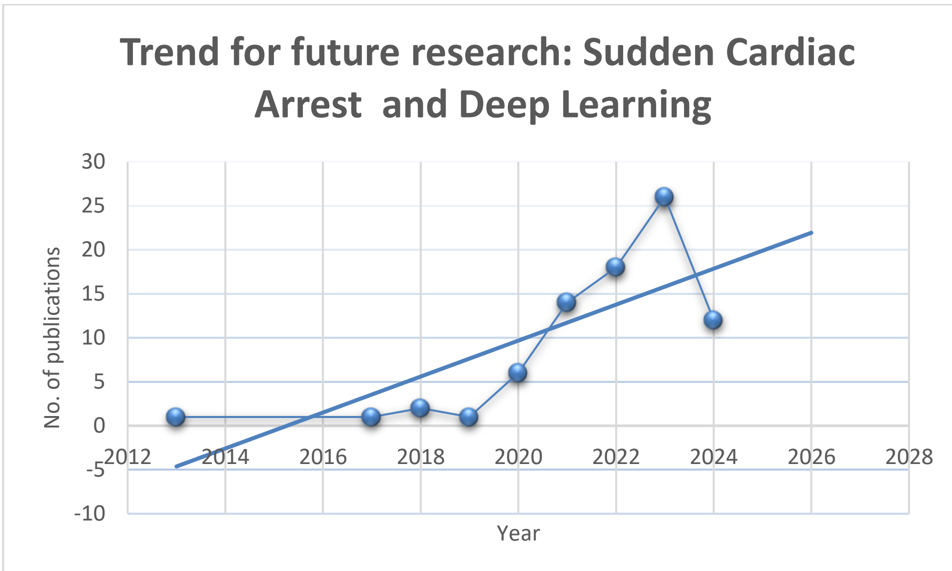

Fig. 7 Future Trends data from PubMed[25]

Overall, this study highlights the potential of AI to revolutionize cardiac health monitoring and emergency medical care. By addressing the key challenges and gaps identified in this research, stakeholders can work towards the successful implementation of AI-based ECG analysis technologies. This will ultimately enhance cardiovascular health monitoring, improve patient outcomes, and reduce the incidence of sudden cardiac arrests. The integration of AI in healthcare holds great promise, and continued research and collaboration will be vital in realizing its full potential.

References

[1] Lubitz SA, Faranesh AZ, Selvaggi C, Atlas SJ, McManus DD, Singer DE, Pagoto S, McConnell MV, Pantelopoulos A, Foulkes AS. Detection of Atrial Fibrillation in a Large Population Using Wearable Devices: The Fitbit Heart Study. Circulation. 2022 Nov 8;146(19):1415-1424. doi: 10.1161/CIRCULATIONAHA.122.060291. Epub 2022 Sep 23. PMID: 36148649; PMCID: PMC9640290.

[2] Skinner M, Xing G, Lu J, Ren J, Oldman K. Detecting drug-induced changes in ECG parameters using jacketed telemetry: Effect of different data reduction techniques. J Pharmacol Toxicol Methods. 2017 May-Jun;85:38-48. doi: 10.1016/j.vascn.2016.12.004. Epub 2017 Jan 5. PMID: 28065822

[3] Duarte R, Stainthorpe A, Mahon J, Greenhalgh J, Richardson M, Nevitt S, Kotas E, Boland A, Thom H, Marshall T, Hall M, Takwoingi Y. Lead-I ECG for detecting atrial fibrillation in patients attending primary care with an irregular pulse using single-time point testing: A systematic review and economic evaluation. PLoS One. 2019 Dec 23;14(12):e0226671. doi: 10.1371/journal.pone.0226671. PMID: 31869370; PMCID: PMC6927656.

[4] Nezamabadi K, Sardaripour N, Haghi B, Forouzanfar M. Unsupervised ECG Analysis: A Review. IEEE Rev Biomed Eng. 2023;16:208-224. doi: 10.1109/RBME.2022.3154893. Epub 2023 Jan 5. PMID: 35226604
[5] Garabelli P, Stavrakis S, Po S. Smartphone-based arrhythmia monitoring. Curr Opin Cardiol. 2017 Jan;32(1):53-57. doi: 10.1097/HCO.0000000000000350. PMID: 27875477.
[6] Mehri M, Calmon G, Odille F, Oster J. A Deep Learning Architecture Using 3D Vectorcardiogram to Detect R-Peaks in ECG with Enhanced Precision. Sensors (Basel). 2023 Feb 18;23(4):2288. doi: 10.3390/s23042288. PMID: 36850889; PMCID: PMC9963088.
[7] Rahman AU, Asif RN, Sultan K, Alsaif SA, Abbas S, Khan MA, Mosavi A. ECG Classification for Detecting ECG Arrhythmia Empowered with Deep Learning Approaches. Comput Intell Neurosci. 2022 Jul 31;2022:6852845. doi: 10.1155/2022/6852845. PMID: 35958748; PMCID: PMC9357747.
[8] Trägårdh E, Schlegel TT. High-frequency QRS electrocardiogram. Clin Physiol Funct Imaging. 2007 Jul;27(4):197-204. doi: 10.1111/j.1475-097X.2007.00738.x. PMID: 17564667.
[9] Mehta SS, Lingayat NS. Combined entropy based method for detection of QRS complexes in 12-lead electrocardiogram using SVM. Comput Biol Med. 2008 Jan;38(1):138-45. doi: 10.1016/j.compbiomed.2007.08.003. Epub 2007 Oct 1. PMID: 17905219
[10] Xia H, Asif I, Zhao X. Cloud-ECG for real time ECG monitoring and analysis. Comput Methods Programs Biomed. 2013 Jun;110(3):253-9. doi: 10.1016/j.cmpb.2012.11.008. Epub 2012 Dec 20. PMID: 23261079.
[11] Jekova I, Krasteva V, Leber R, Schmid R, Twerenbold R, Müller C, Reichlin T, Abächerli R. Inter-lead correlation analysis for automated detection of cable reversals in 12/16-lead ECG. Comput Methods Programs Biomed. 2016 Oct;134:31-41. doi: 10.1016/j.cmpb.2016.06.003. Epub 2016 Jun 23. PMID: 27480730.
[12] Kovács P, Böck C, Tschoellitsch T, Huemer M, Meier J. Diagnostic quality assessment for low-dimensional ECG representations. Comput Biol Med. 2022 Nov;150:106086. doi: 10.1016/j.compbiomed.2022.106086. Epub 2022 Sep 13. PMID: 36191392.
[13] Yanık H, Değirmenci E, Büyükakıllı B, Karpuz D, Kılınç OH, Gürgül S. Electrocardiography (ECG) analysis and a new feature extraction method using wavelet transform with scalogram analysis. Biomed Tech (Berl). 2020 Oct 25;65(5):543-556. doi: 10.1515/bmt-2019-0147. PMID: 32441663.
[14] Taggar JS, Coleman T, Lewis S, Heneghan C, Jones M. Accuracy of methods for diagnosing atrial fibrillation using 12-lead ECG: A systematic review and meta-analysis. Int J Cardiol. 2015 Apr 1;184:175-183. doi: 10.1016/j.ijcard.2015.02.014. Epub 2015 Feb 10. PMID: 25705010.
[15] Attia ZI, Harmon DM, Behr ER, Friedman PA. Application of artificial intelligence to the electrocardiogram. Eur Heart J. 2021 Dec 7;42(46):4717-4730. doi: 10.1093/eurheartj/ehab649. PMID: 34534279; PMCID: PMC8500024.
[16] Nagarajan VD, Lee SL, Robertus JL, Nienaber CA, Trayanova NA, Ernst S. Artificial intelligence in the diagnosis and management of arrhythmias. Eur Heart J. 2021 Oct 7;42(38):3904-3916. doi: 10.1093/eurheartj/ehab544. PMID: 34392353; PMCID: PMC8497074.
[17] Siontis KC, Noseworthy PA, Attia ZI, Friedman PA. Artificial intelligence-enhanced electrocardiography in cardiovascular disease management. Nat Rev Cardiol. 2021 Jul;18(7):465-478. doi: 10.1038/s41569-020-00503-2. Epub 2021 Feb 1. PMID: 33526938; PMCID: PMC7848866.
[18] Attia ZI, Noseworthy PA, Lopez-Jimenez F, Asirvatham SJ, Deshmukh AJ, Gersh BJ, Carter RE, Yao X, Rabinstein AA, Erickson BJ, Kapa S, Friedman PA. An artificial intelligence-enabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: a retrospective

analysis of outcome prediction. Lancet. 2019 Sep 7;394(10201):861-867. doi: 10.1016/S0140-6736(19)31721-0. Epub 2019 Aug 1. PMID: 31378392.
[19] Haverkamp W, Strodthoff N, Israel C. EKG-Diagnostik mithilfe künstlicher Intelligenz: aktueller Stand und zukünftige Perspektiven – Teil 1 : Grundlagen [Artificial intelligence-based ECG analysis: current status and future perspectives-Part 1 : Basic principles]. Herzschrittmacherther Elektrophysiol. 2022 Jun;33(2):232-240. German. doi: 10.1007/s00399-022-00854-y. Epub 2022 May 12. Erratum in: Herzschrittmacherther Elektrophysiol. 2022 May 31;: PMID: 35552486; PMCID: PMC9177483.
[20] Haverkamp W, Strodthoff N, Israel C. EKG-Diagnostik mit Hilfe künstlicher Intelligenz: aktueller Stand und zukünftige Perspektiven – Teil 2 : Aktuelle Studienlage und Ausblick [Artificial intelligence-based ECG analysis: current status and future perspectives-Part 2 : Recent studies and future]. Herzschrittmacherther Elektrophysiol. 2022 Sep;33(3):305-311. German. doi: 10.1007/s00399-022-00855-x. Epub 2022 May 12. Erratum in: Herzschrittmacherther Elektrophysiol. 2022 Jun 2;: PMID: 35552487; PMCID: PMC9411078.
[21] Kashou AH, Adedinsewo DA, Siontis KC, Noseworthy PA. Artificial Intelligence-Enabled ECG: Physiologic and Pathophysiologic Insights and Implications. Compr Physiol. 2022 Jun 29;12(3):3417-3424. doi: 10.1002/cphy.c210001. PMID: 35766831; PMCID: PMC9795459.
[22] Kashou AH, May AM, Noseworthy PA. Comparison of two artificial intelligence-augmented ECG approaches: Machine learning and deep learning. J Electrocardiol. 2023 Jul-Aug;79:75-80. doi: 10.1016/j.jelectrocard.2023.03.009. Epub 2023 Mar 15. PMID: 36989954.
[23] García-Escobar A, Vera-Vera S, Jurado-Román A, Jiménez-Valero S, Galeote G, Moreno R. Subtle QRS changes are associated with reduced ejection fraction, diastolic dysfunction, and heart failure development and therapy responsiveness: Applications for artificial intelligence to ECG. Ann Noninvasive Electrocardiol. 2022 Nov;27(6):e12998. doi: 10.1111/anec.12998. Epub 2022 Jul 29. PMID: 35904538; PMCID: PMC9674781.
[24] https://towardsdatascience.com/activation-functions-neural-networks-1cbd9f8d91d6
[25] https://pubmed.ncbi.nlm.nih.gov/?term=sudden+cardiac+arrest+%2B+deep+learning