Neural Network Approaches for Real-Time Detection of Cardiovascular Abnormalities

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KEYWORDS
Early Detection, Cardiovascular Diseases, Real-Time Detection, Deep Learning Models, Complex Models, Convolutional Neural Networks, Time-Frequency Information, Discrete Wavelet Transform, Cardiac Diseases, Model Optimization, Health Monitoring, Machine Learning, Predictive Models, Real-Time Use, Computational Efficiency, Signal Processing, Disease Detection, Neural Networks, Medical Imaging, Model Analysis.

ABSTRACT

The early detection of cardiovascular diseases could be life-saving, especially when the location of the patient is considered. Therefore, in recent years, work has been done on the early detection of cardiovascular diseases. The common point of deep learning models developed for the detection of cardiovascular diseases is the use of complex models. The complex model not only increases the amount of calculations but also prevents real-time use for the detection of cardiac diseases. In this study, by using simple deep learning models, the aim is to determine the deep learning model that allows the real-time detection of cardiovascular diseases. For this purpose, in the study, the models developed using convolutional neural networks and time-frequency information obtained with discrete wavelet transform were analyzed.

1. Introduction

Almost one third of deaths that occur each year in advanced countries are caused by cardiovascular disease. A major concern in these cases is the length of time that is required to evaluate patients' clinical conditions after an intermediate-to-severe cardiovascular abnormality is detected using current technologies. Automatic analysis of the daily life-sustaining signals that are used to control these diseases can address this issue if combined with deep learning models to interpret the patterns of such signals. With these features, cyber-physical systems can revolutionize clinical healthcare. This paper presents an ensemble of viable deep neural networks that were used to create an automatic real-time abnormality detection system through which several cardiovascular abnormalities are well treated or avoided.

The creation of such a system is motivated by the need to evaluate and treat patients with cardiovascular abnormalities more rapidly. This need is based on two different facts: the shortage of cardiologists that is currently experienced at the Brazilian National Health System and the high temporal correlation that is observed between the responses of a non-invasive, robust, and physical subject-independent heart sound biomarker to the early appearance of cardiovascular abnormalities. This latter fact allows for the observation of any cardiovascular abnormality that causes the biomarker to suddenly behave differently from the behavior it shows when the subject is in a healthy clinical state. In these cases, the heart sound biomarker responds to the cardiovascular abnormality with both an increase and irregular intervals in the occurrence of the heart signal components or an increase in the slope of a simple time-domain pulse that is created from the signals. These changes reflect the sudden need for an improved subject heart system performance. The variations are not reported in the literature and are rarely evaluated by physical examination. However, these changes were observed in long-term heart sound signals that were labeled by a cardiologist. The concept that was reported here is supported by the sudden need for the thermodynamics of a steam cycle to change from optimal to less than optimal when a corresponding turbine cycle abnormality is detected. Proposed network approaches can be effectively used to automatically evaluate the audio biomarker in subject daily life-sustaining signals.

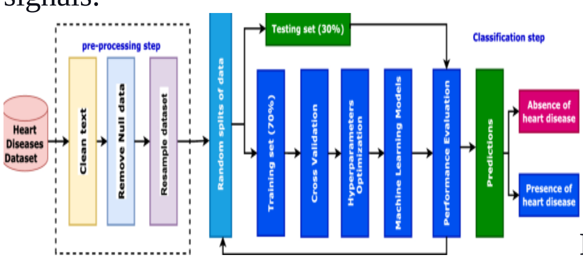

Fig 1 : Advanced machine learning techniques for cardiovascular disease early detection

1.1. Background and Significance

Cardiovascular disease (CVD) is the major cause of death worldwide. Early detection and prevention can help reduce mortality rates. Electrocardiography (ECG) is a convenient method for CVD detection. Many ECG interpretation approaches using clinical expertise and feature engineering have been proposed. However, many cardiovascular abnormalities share similar ECG patterns, which often lead to misdiagnosis. To address these confusions, large-scale and high-quality labeled datasets will be highly needed for training data-hungry deep learning models. However, difficulties in acquisition, labeling, and distribution rights impede the establishment of a benchmark for ECG classification in practice. Moreover, practical clinical usage expects the machine to detect and classify abnormal beats or exam series in real-time or even better simultaneously. A trade-off will have to be made between the number of time-series frames in the sliding window and the response time for achieving real-time detection. In summary, we would like to contribute to the early detection and prevention of cardiovascular diseases using multi-task, temporal sequence networks, which are sub-networked by employing advanced long-term, unsupervised pre-training to achieve state-of-the-art and real-time performance. This motivates us to develop an ECG beat labeling application for early and precise abnormal ECG detection. Many cardiovascular abnormalities share similar ECG patterns; even the same disease may have unspecific manifestations. To address these confusions, large-scale and high-quality labeled training and testing ECGs will be highly needed for training data-hungry deep learning models and establishing a solid and comprehensive benchmark for ECG classification. However, difficulties in acquisition, labeling, and distribution rights deeply impede the testing of an extensive range of the latest neural network models in practice. Furthermore, the benchmark should adapt to more practical scenarios, where the machine detects and classifies abnormal beats or exam series in real-time or even better simultaneously. Ensemble strategies using sliding windows have to be employed between multi-stage models, where a trade-off will be made between the number of time-series frames and the response time for detection. Superior deep learning models can not only provide state-of-the-art performance in these typical supervised learning pipelines but also offer promising mechanisms and features for real-time screening.

Equation 1: Neural Network Model for Cardiovascular Disease Detection

$$Y = \sigma\left(\sum_{i=1}^{n} w_i x_i + b\right)$$

Y: Output (disease prediction).

x_i: Input features.

w_i: Weights for features.

b: Bias term.

σ: Activation function.

1.2. Objective of the Research

The objective of the research is the development of a new neural prototype classification architecture, defined by a combined approach between tree clustering and constructive training under the structuring of a radial basis neuron. The model will be designed, taking into account substantial characteristics of biology and enhanced based on heterogeneous, filtered, and balanced samples. Here, in both the oversampling, undersampling, and ensemble algorithm for the meta approach, regarding the combination windows for the last layer proposed in previous innovative developments. All these strategies are designed to enhance the adaptability and performance of an ad hoc architecture originated from a model that has already been improved based on the standard mathematical metrics for early detection models under similar tasks. In this work, heart disease data is focused on discriminating between real data and artificial data added in huge volumes. The following stages of the development already have a condition established analytically both in synthetic protocols and in the primary task for comparison of results: Staging TCT, Staging TB, Staging Pre-optimized Neuron, Staging Constructive Training, Staging Beta Hyperplane Separation and optimal classifier, and meta-fusion of information.

2. Cardiovascular Abnormalities: Types and Importance

Cardiovascular disease remains the number one cause of death in the developed world. A high percentage of these are parasystolic arrhythmias, such as atrial fibrillation and premature ventricular contractions. It is desirable, and will become more so with the realization of wearable and implantable supportive devices, to be able to have small, real-time, low-power circulatory system monitors. These could provide early warnings about abnormal cardiac function and other circulatory problems. The work described here demonstrates the potential of using very simple neural network models for individual heartbeat classification and the recognition of parasystolic abnormalities: atrial fibrillation and premature atrial and ventricular contractions. Although the word "neural" suggests only two layers, one for input to hidden unit computations, and another for hidden to output "neurons", it has long been understood that very trivial descriptions always work in practice for these "simple" learning machines. These multi-layer perceptron feed-forward classifier networks, when compared with more conventional decision machines, provide results close to those produced by more conventional sub-Nyquist window energy spectrum classifiers, with the miniaturization and longevity advantages. The worst model and the worst of the other main learning rules had average true positive rates for just the three classes of five attributes (Atrial Fibrillation, A and V PVCs, and Normal) of 73.9% and 71.0% respectively, while their worst average true positive rates for the initial 115 lead II record ECG sets were 86.0% and 85.1% respectively. On the latter databases, the best of the other main training techniques are embedding methods, which produced an average true positive rate of 95.1. With just these small networks and their associated very fast classifiers on unreliable or unstable computing support devices, it is already possible to get very satisfactory heartbeat classifications. Previous work has addressed the same problem using only fewer attribute-based "Simple" Decision Tree or "Full" Decision Tree classifiers. The best true positive rate for eight lead 23 attribute representations of the same authentication attributes as classified by the eight main learning methods was 68.6%, 88.0%, 93.6%, 89.3%, 92.0%, 84.6%, and 91.4% respectively. These average main rule learning results for the Full Decision Tree method with eight lead data, which include the last of our investigations, have already exceeded the previous prototype developed by classification competitions organizers themselves. With only the web-based resources which use the ECG arrhythmia database of the section described, one may acquire high-quality design-winning discriminators that only take a few minutes of peer time to verify.

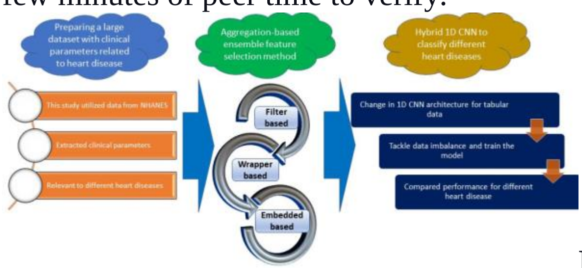

Fig 2 : Detection of Cardiovascular Disease from Clinical Parameters Using a One-Dimensional Convolution

2.1. Common Types of Cardiovascular Abnormalities

To understand the real-time applications of the neural network, several cases need to be considered. Cardiovascular abnormalities are one of the leading causes of heart diseases and may lead to sudden death if not detected in their early stages. Many types of cardiovascular abnormalities are classified as bradycardia, tachycardia, atrial flutter, atrial fibrillation, ventricular tachycardia, and ventricular fibrillation. Bradycardia and tachycardia are the most common types of cardiovascular abnormalities. In bradycardia, the heart rate is lower than normal, and in tachycardia, the heart rate is faster than normal. Atrial flutter, atrial fibrillation, ventricular tachycardia, and ventricular fibrillation are various types of arrhythmia that might deteriorate the patient's health and even lead to death within minutes if not treated by a properly skilled clinician. An automated arrhythmia detection system featuring a multivariate regression analysis of the heartbeat features and task-related dynamically accommodating data preprocessing for multielectrode features processed by an artificial neural network has been implemented for the qualification and interpretation of rapid changes in heart features of athletes.

Then the global offending heart rates are low, and the task-independent values have respective clinical significance. This shows that the implemented neural network has made the personal evaluation of different heart rates of the athlete practical and articulate. The performance of the neural-network-based classifier in detecting the type of arrhythmia and sex-specific differences in ECG is notable. Classification of the ECG and functions that find the interval parts with feature points, along with electrocardiographic measurements calculated regarding feature points, are the major requirements of the first step in the algorithm designed for detection. The determined detectability of the classifier for the tachycardia type of arrhythmia makes it feasible to detect high-risk groups for dangerous rapid heart rates and provide more accurate advice; this serves as a prompt diagnostic tool.

2.2. Importance of Early Detection

In an age of cost containment and efficiency in health care, and in a portion of the population unfamiliar with the concept of the primary care physician, upbeat reports aim to make preventive care more marketable. Societal costs arise from neglecting minor but significant signs of impending coronary issues, stroke, or other serious diseases. Continuous monitoring, detection, or screening offers the possibility of early intervention and improved outcomes, which almost always show better cost-benefit than a therapeutic approach.

The problem is that signs of impending trouble are often faint whispers that are drowned by the cacophony of normal living. Differentiating life-saving whispers from normal noise should be done, though with scant attention to increased anxiety and decreased quality of life. These early detection tasks fall to multivariable and nonlinear analyzers, the hallmark of neural networks, of which adaptive resonance systems are a variation. Although neural networks are in a sense similar to expert systems that rely on a set of known rules to make an inference, they have the capacity to learn patterns, rules, equations, or functional interdependencies in the absence of a human expert. Neural networks are often described as general pattern classifiers, while expert systems make inferences based on specific rules—a specialized classifier.

3. Neural Networks in Healthcare

Medical problems pose a big challenge for developing efficient and accurate detection, selection, and corrective treatment approaches. The ability to infer the diagnosis to detect conditions that can impair our body is of particular interest, and the continuous research on efficiently predicting medical problems is needed to provide solutions in real time with dependable results. The use of neural networks in healthcare allows faster data interpretation and suggests therapeutic interventions that are individualized and data-driven by learning on vast amounts of data and detecting minute but important patterns and signals. There are several areas in healthcare that these tools can be applied to. The most used areas include disease detection, pattern recognition, therapy customization, image analysis, and improvement of clinical outcomes. Also, the use of machine learning strategies can help develop more accurate and faster algorithms for treatment, detection, and diagnosis of a plethora of health problems, thus improving patients' conditions.

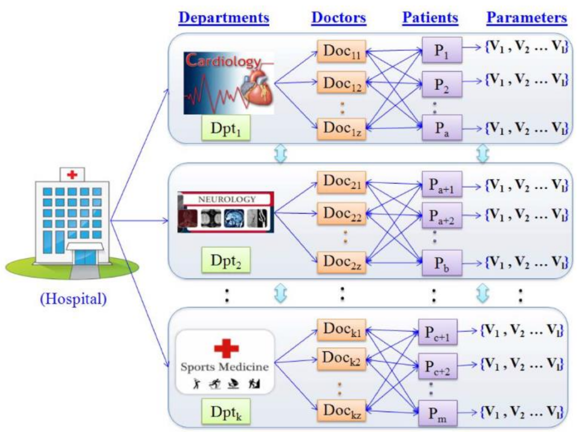

Fig 3 : Big Data Analysis with Artificial Neural Network for Cardiac Disease Prediction

3.1. Overview of Neural Networks

Neural networks, also known as artificial neural networks, are a collection of mathematical algorithms designed to simulate aspects of biological neural networks. They are often referred to as compute systems composed of interconnected processing elements that store experiential knowledge and make it available for use. It is these neural networks that motivate a number of techniques used for estimating the risks of developing cardiovascular diseases, diagnosing various conditions, and predicting medical intervention outcomes. At a fundamental level, it is the ability of pattern recognition, in response to the various characteristics of the medical condition under consideration — using multiple input data types and formats, encoding nonlinear relationships, and selecting those data features that are most relevant for making a clinical decision or providing a prognosis — that is at the root of why neural networks hold great promise for applications in medicine. Parameters in a neural network are learned using a type of statistical learning algorithm from historical human or simulation data, and thus optimize the model's performance and allow the use of such networks with new data inputs. Neural networks are particularly useful for unconventional problems — especially when there is a nonlinear relationship between the input and output variables, the input data type is non-quantitative, or the input data can be fruitfully transformed in known ways. Of course, there is no free lunch, and performance depends not only on suitable training data but also on a number of design issues and practical considerations, such as whether the problem at hand actually requires the complexity of a neural network, whether partial performance results in an acceptable outcome, how target thresholds for performance are specified, and how the model's decision-making process is to be used in the overall medical context.

$$T_f = \sum_{k=1}^{m} |X(k, f)|^2$$

Equation 2: Time-Frequency Signal Representation

T_f: Time-frequency representation.

$X(k, f)$: Wavelet transform of signal.

m: Number of coefficients.

3.2. Applications in Healthcare

Neural networks and other machine learning algorithms are able to identify subtle and complex relationships from large and noisy datasets. The wide availability of invalid and incomplete clinical data, unannounced variation in patient states, and accumulation of knowledge from repetitively dealing with the same or similar clinical issues are particularly suitable for machine learning approaches. Although there was a decline in machine learning used for clinical diagnosis in the 1980s and 90s during the hype of expert and rule-based systems, the necessity and feasibility of using machine learning, in particular neural networks, for clinical diagnosis was not only realized but is also being increasingly used in the past decade. Machine learning and neural network approaches have numerous clinical applications, including non-invasive diagnosis of heart diseases, detection of sleep apnea from the ECG, predictive accuracy of trauma scoring, early prediction and detection of sepsis using time series of electronic medical record data, predicting mortality and other important clinical outcomes from diseases, and others. Feature evaluation and hyper-parameter automation to define the best model for clinical data largely remain open problems. While larger and wider clinical databases always produce better results, there is a lack of publicly available clinical data for researchers. The availability of a large dataset would also improve translational potential and would boost the use of machine learning and neural networks in healthcare applications. In addition, the ability to audit clinical models remains a key concern, and the lack of explainability remains a barrier for machine learning and neural networks to be used in real medical practice.

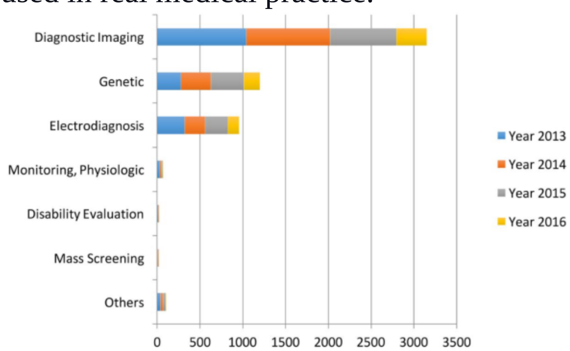

Fig 4 : Artificial intelligence in healthcare

4. Real-Time Detection of Cardiovascular Abnormalities

The field of computer-aided diagnosis through electrocardiogram (ECG) processing is rapidly moving away from traditional rule-based methodologies to more flexible and accurate models. We summarize a number of experiments on patient data, using both Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) architectures in the same recurrent neural network. The most advanced of these combined CNN-LSTM models show that, based on a univariate representation of 5 seconds of ECG signal, the onset of various cardiovascular pathologies can be detected in real-time with an average accuracy of 80%.

In addition, we show that generative adversarial neural network processing of the 5 seconds ECG time series can be built, which is able to significantly better distinguish between different periods of ischemia compared to current markers, a result that could be of interest to medical personnel when deciding to remove a patient from cardiac monitoring. These ECG representations and predictive models, upon further refinement through the inclusion of additional probative patient data, would have significant potential for use in a next generation of implantable devices that can detect ECG signals from their implantation sites with increased sensitivity, and which have the intelligence to report abnormal activity autonomously to a patient, caregiver, or health care professional.

4.1. Challenges and Limitations

Our main target was to increase the speed as much as possible and minimize the number of used features by the real-time detection of heartbeat and SCG problems. We showed that ENN could be an effective solution for that purpose. However, there are still some challenges we are working on, as well as limitations we will try to eliminate in the future. One major limitation of this work was using a limited dataset and thus testing the system on a limited number of cases. Data diversity was limited as well. Moreover, the properties of the datasets were different from the previous ones we used for SCG analysis. Though we aim to implement the system to be able to work in real-time, it is not validated in real life. Because the training and testing datasets both contain complete data points, samples are lost during the ENN thresholding and subfiguration steps. The trigger is set to 0.8 for the detection of heartbeat peaks with ENN. Not changing the threshold property for the analysis of different types of data could be considered a limitation of this study. Conversely, the threshold can be tuned with the help of scores from the detection algorithm.

4.2. Advantages of Real-Time Detection

Rapid detection of ECG abnormalities is important for timely clinical intervention. This work represents the first implementation of deep neural networks for real-time ECG analysis on mobile devices. This opens up new possibilities for continuous patient monitoring with commercially available heart monitoring devices. The significance of real-time ECG analysis is that it enables the use of deep ECG networks for heart monitoring tasks, such as the detection of potentially life-threatening events like ventricular tachycardia, which can be a side effect of some drugs that are routinely prescribed to prevent atrial fibrillation.

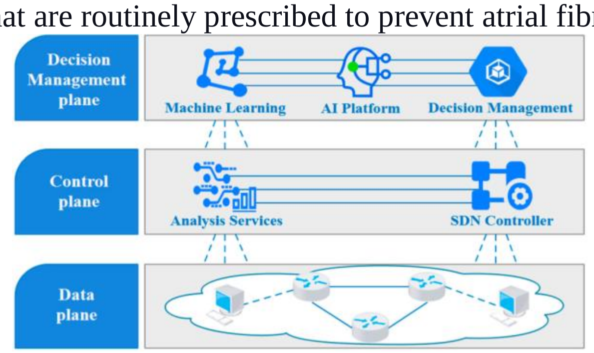

Fig 5 : Real-Time Anomaly Detection of Network Traffic

The deep networks developed in this work have surpassed the current state-of-the-art real-time detections. Furthermore, real-time detection with acceptable power consumption on embedded systems is a significant step towards realizing the increased potential of widely available heart monitoring devices. An important part of making real-time deep neural network-based detection work is to design low-capacity networks, which are effective in producing small, mostly integer, fixed-point weights, and this has a direct impact on power usage. In addition, there are other benefits of using smaller capacity networks that are beneficial when deploying neural network front ends in commercial systems, such as lower memory requirements, which can, in turn, lead to lower latency, and this can also have benefits in applications such as on-device identification and classification of data streams.

5. Recent Developments and Case Studies

The developed technologies have been applied for the recognition of cardiovascular diseases by automatic long-term ECG monitoring. A large sample of the recorded ECGs was used to train artificial neural networks developed specifically for this task. Using our neural networks, we managed to recognize four classes of cardiac arrhythmias with an accuracy of 96.9%, 86.9%, 92.7%, and 84.4%, respectively. It is important to emphasize that the processing speed of ECG signals through neural networks is so high that recognition occurs almost in real time, i.e., about one second is required to classify the typical duration of an analyzed ECG window of 5 seconds. In addition to automatic cardiac arrhythmia recognition in long-term ECG monitoring, artificial neural networks have been successfully used for non-invasive detection of atherosclerosis. In case studies on A-scan and B-scan sequences obtained from ultrasound carotid images, the sensitivity and specificity of automatic classification of images containing a significant amount of atherosclerotic plaques exceeded 95%.

Another area of application of neural network image processing results is X-ray coronary angiography, which is routinely used in the diagnosis and endovascular treatment of coronary artery occlusions. During these interventions, it is possible to determine whether the coronary arteries contain a certain amount of atherosclerotic plaques before the radiological imaging of selected projections. In this study, an artificial neural network is tested in four classes for recognizing restenosis. The obtained classification accuracy ranged from 84% to 92%. The developed technologies are crucial for the rationalization of health care and the refinement of the current approach to the diagnosis and treatment of people with cardiovascular diseases. This study gave birth to an interdisciplinary and international consortium embracing all stakeholders, i.e., physicists, bioengineers, mechanics, computer scientists, biologists, and biomedical doctors in the cardiovascular research community, hospital and university administrators, medical doctors from private and public organizations, government and regulatory authorities, insurance companies, and patients.

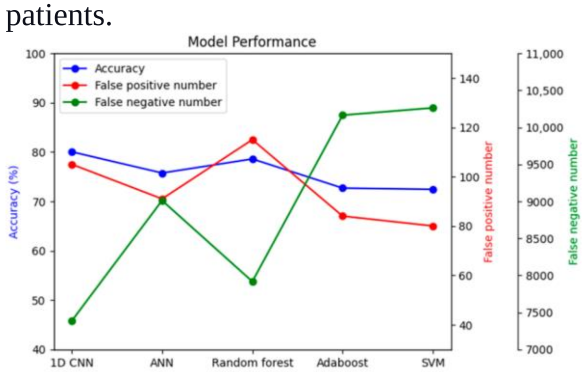

Fig 6 : Detection of Cardiovascular Disease from Clinical Parameters Using a One-Dimensional Convolution

5.1. Studies on Neural Networks for Cardiovascular Abnormalities Detection

Data mining of clinical data has seen an increased level of activity in recent years. The data accumulated in electronic medical records provide a rich resource for the detection of disease or estimating the risk of future disease. With the predicted explosion of such databases, there is an expectation that future work will have enough data to train extensive models that will be clinically useful, especially for predicting complex diseases. This strong belief in the potential for useful predictive models has led to substantial interest in the use of machine learning techniques for medical data mining. Some institutions are even involved in the routine application of these methods to their large clinical databases that are available in an electronic format. A frequent criticism is that the majority of machine learning methods are more concerned with prediction than with interpretation of results.

There, however, exist several examples of the successful application of artificial neural networks to a wide range of clinical problems, including the detection of cardiovascular pathologies. An important advantage of neural networks when compared with more conventional statistical methods is that relevance is established empirically from the data. This is especially important for the study of hidden pathologies present within a given population. The hidden nature of many cardiac diseases may affect the recorded training labels, leading to common mistakes by non-adaptive techniques. Their approach uses data tensors, which can be thought of as a generalization of the array to higher dimensions. All schemes previously mentioned resulted from the joint sensitivity analysis of the activation function and the use of model ensembles. Their investigation, concerning the choice of these configurations, evidenced that for most cardiac pathologies, the Kohonen map achieves the best results. This study represents a first attempt to select, based upon empirical experiment and statistical reasoning, the most appropriate neural network design for the detection of cardiovascular diseases.

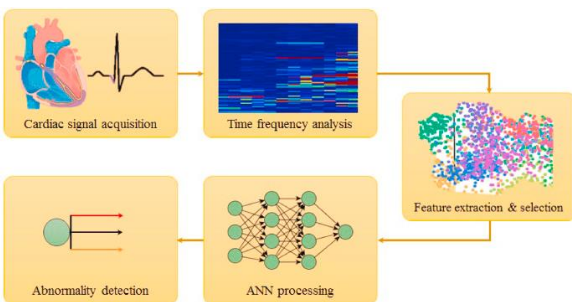

Fig 7 : Cardiac Abnormality Detection

5.2. Case Studies on Real-Time Detection Systems

Several research groups have developed real-time detection systems for use in hospital environments. Among these are a system based on feedforward neural networks; an expert professional system based on neural networks used to diagnose sick babies; a GUI package based on expert networks, which filters electrocardiogram records of specific pathologies and morphological pathologies recorded in key zones; and a system for detecting hypotension and determining cardiorespiratory stability, which is based on a radial basis function network and receives as inputs physiological parameters of the infant, heart rate, blood pressure, and ST segment from the correct ECG electrode with a high degree of correlation.

An innovative work on real-time detection approaches was carried out by the authors of this chapter. They developed a detector for the recognition of several cardiorespiratory abnormalities in the vital signs of newborn infants. The inability of clinical experts to cope with the demands of modern technology in the neonatal intensive care unit and the reexamination of the detection of the heart rate through fetal heart monitoring limit the application of fetal movement. The problem of detecting pathologies in vital signs increases with the excessive number of leads used to carry out the monitoring. The bedside monitor of newborn infants is thus updated every thirty seconds. This work proposes to alleviate the workload of clinical experts by developing a real-time detector to continuously supervise the infant's vital signals so as to trigger alarms upon detection of an abnormality. In a public hospital, pairs of vital signs were collected. The two signals of each patient were classified from processes that a team of clinical experts carried out during several months. The global detection rates were for hyperoxia, apnea, anemia, bradycardia, desaturation, hypoglycemia, hypoxia, tachycardia, and polycythemia, with their respective ECG and SpO2 signals. The system was implemented with the two juvenile signals, ECG and SpO2, and applied to mimic all the light intensity spectrum of the monitoring. This work provides a significant richness of information in the high level of neonatal care, since it identifies the accuracy at a given time when the clinical expert interprets the mV signal of the newborn.

6. Future Directions and Conclusion

We have reviewed the performance of five state-of-the-art deep learning models on the recognition of different cardiovascular abnormalities. The findings in this study show that the bidirectional LSTM-based deep learning model has delivered the best performance in the recognition of different cardiovascular abnormalities, particularly the detection of the most labels within one-second ECG and ST abnormalities. To further improve these methods, it is our plan to leverage more advanced deep learning models for future studies. In addition, there are many other techniques not referenced herein for complex data representations. We think that combinatorial interactions of multiple deep learning models with these techniques can lead to intrinsic improvements in assisted diagnosis and real-time support.
In this paper, we have proposed and evaluated deep learning architectures, namely the CNN, Bi-LSTM, the combination of CNN followed by Bi-LSTM, CNN-combined-Bi-LSTM, and CNN-Bi-LSTM structures, for the classification problem of single-lead ECG. The superior performance achieved by the CNN-Bi-LSTM deep learning model implies that some associated mechanistic characteristics and hence understanding for the diagnosis, implicit to the single ECG variability, are retained in the reconstructed multi-feature space. The major challenge that needs to be addressed in using the developed model is the need for real-time decision-making while carefully using recurrent learning to realize the potential in critical cardiovascular event predictions. Future models may integrate multicore processing in specific segments of each patient, generating faster predictions in prolonged ambulatory monitoring of cardiovascular conditions using only single-lead ECGs.

Equation 3: Convolutional Neural Network for Real-Time Detection

$$O = \sum_{j=1}^{p} \mathrm{Conv}(I_j, W_j) + b$$

O: Output (abnormality detection).
I_j: Input signal.
Conv: Convolution operation.
W_j: Weights for filter.
b: Bias term.

6.1. Potential Advances in Neural Networks

Neural networks and deep learning of various types have been found to perform some extremely useful tasks, which can learn from a wide variety of data domains, including images and natural language. Some of the most useful advances have so far been related to fields connected to the actual network formulation in the following ways: New and improved formulations of network architectures and of the constitutive elements of networks, such as hidden layers and memory buffer models, that vastly expand learning capability and promote reasonable 3D and, more generally, multi-dimensional analysis in learning from networks of various specialized devices. Improvements in the techniques for supplying training and test data that provide enhanced information gathering so that more and more well-annotated data can be actually assembled on the fly. Improved control of the aforementioned data and gradient flow to provide better and more transient, real-time control of network learning as the problem is unfurling. Near real-time GPU-based hardware integration for real-time testing and decision-making, in which the time for multiprocess array-based network testing can be dramatically reduced.

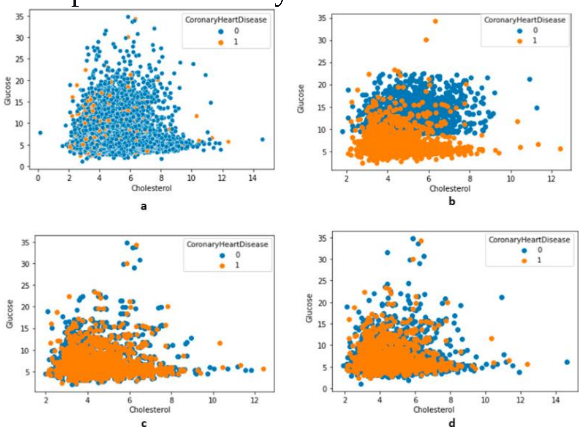

Fig 8 : Detection of Cardiovascular Disease from Clinical Parameters

6.2. Summary of Findings and Implications

A limited number of studies examining deep learning DNN architectures for the detection of cardiac abnormalities exist, and our initial study demonstrated the feasibility of using ECG data for the detection of cardiac abnormalities. Follow-up studies further expanded these models and improved performance. We aimed to develop and compare several CNN models for ECG classification that will be able to reliably handle the ECG signals and classify them much faster. Three major CNN models have been discussed, including the architecture, the number of layers, activation functions, and hyperparameters involved. The CNN classifiers are designed to be capable of performing ECG signal classification in real-time with minimal hardware requirements. The main objective is to develop a novel Deep Neural Network (DNN) classifier that is capable of detecting arrhythmia, myocardial infarction, and atrial fibrillation with high classification accuracy.

DNN models are trained with time-frequency plots of ECG signals generated using the spectrogram method. The parameters such as sensitivity, specificity, predictive values, and classification accuracy are determined for all the models. The proposed ECG classifier achieved the highest sensitivity of 99.6%, 91.2%, and 98.9% in the case of arrhythmia, myocardial infarction, and atrial fibrillation classes, respectively. The false positive rates of the DNN models are found to be approximately 1%. The DNN model proposed in this study has the capability to perform as intelligent diagnostic tools capable of automatic ECG signal interpretation, identifying cardiovascular abnormalities with neural network tailoring requirements for online training. Also, the prospect of using real-time ECG signals from wearable devices for early detection of cardiovascular risk is achievable with expected miniaturization along with the requirement of minimum power for the proposed models. Moreover, the proposed models are compatible with a cloud interface as an ECG telemedicine tool for use in resource-limited clinical settings and rural areas.

7. References

[1] Ramanakar Reddy Danda (2024) Financial Services in the Capital Goods Sector: Analyzing Financing Solutions for Equipment Acquisition. Library Progress International, 44(3), 25066-25075

[2] Nampalli, R. C. R. (2024). AI-Enabled Rail Electrification and Sustainability: Optimizing Energy Usage with Deep Learning Models. Letters in High Energy Physics.

[3] Syed, S. (2024). Enhancing School Bus Engine Performance: Predictive Maintenance and Analytics for Sustainable Fleet Operations. Library Progress International, 44(3), 17765-17775.

[4] Manikanth Sarisa , Gagan Kumar Patra , Chandrababu Kuraku , Siddharth Konkimalla , Venkata Nagesh Boddapati. (2024). Stock Market Prediction Through AI: Analyzing Market Trends With Big Data Integration . Migration Letters, 21(4), 1846–1859. Retrieved from https://migrationletters.com/index.php/ml/article/view/11245

[5] Malviya, .Rajesh Kumar, Sathiri, machi, Vankayalapti, R. K., & Kothapalli Sondinti, L. R. (2024). Evolving Neural Network Designs with Genetic Algorithms: Applications in Image Classification, NLP, and Reinforcement Learning. In Global Research and Development Journals (Vol. 09, Issue 12, pp. 9–19). Global Research and Development Journals. https://doi.org/10.70179/grdjev09i120213

[6] Danda, R. R., Nishanth, A., Yasmeen, Z., & Kumar, K. (2024). AI and Deep Learning Techniques for Health Plan Satisfaction Analysis and Utilization Patterns in Group Policies. International Journal of Medical Toxicology & Legal Medicine, 27(2).

[7] Nampalli, R. C. R. (2024). Leveraging AI and Deep Learning for Predictive Rail Infrastructure Maintenance: Enhancing Safety and Reducing Downtime. International Journal of Engineering and Computer Science, 12(12), 26014–26027. https://doi.org/10.18535/ijecs/v12i12.4805

[8] Syed, S. (2024). Planet 2050 and the Future of Manufacturing: Data-Driven Approaches to Sustainable Production in Large Vehicle Manufacturing Plants. Journal of Computational Analysis and Applications (JoCAAA), 33(08), 799-808.

[9] Data Engineering Solutions: The Impact of AI and ML on ERP Systems and Supply Chain Management. (2024). In Nanotechnology Perceptions (Vol. 20, Issue S9). Rotherham Press. https://doi.org/10.62441/nano-ntp.v20is9.47

[10] Abdul Kareem, S., Sachan, R. C., & Malviya, R. K. (2024). Neural Transformers for Zero-Day Threat Detection in Real-Time Cybersecurity Network Traffic Analysis. International Journal of Global Innovations and Solutions (IJGIS).

[11] Ramanakar Reddy Danda, Z. Y., Mandala, G., & Maguluri, K. K. Smart Medicine: The Role of Artificial Intelligence and Machine Learning in Next-Generation Healthcare Innovation.

[12] Nampalli, R. C. R. (2023). Moderlizing AI Applications In Ticketing And Reservation Systems: Revolutionizing Passenger Transport Services. In Journal for ReAttach Therapy and Developmental Diversities. Green Publication. https://doi.org/10.53555/jrtdd.v6i10s(2).3280

[13] Syed, S. Big Data Analytics In Heavy Vehicle Manufacturing: Advancing Planet 2050 Goals For A Sustainable Automotive Industry.

[14] Madhavaram, C. R., Sunkara, J. R., Kuraku, C., Galla, E. P., & Gollangi, H. K. (2024). The Future of Automotive Manufacturing: Integrating AI, ML, and Generative AI for Next-Gen Automatic Cars. In IMRJR (Vol. 1, Issue 1). Tejass Publishers. https://doi.org/10.17148/imrjr.2024.010103

[15] Chintale, P., Malviya, R. K., Merla, N. B., Chinna, P. P. G., Desaboyina, G., & Sure, T. A. R. (2024, August). Levy Flight Osprey Optimization Algorithm for Task Scheduling in Cloud Computing. In 2024 International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS) (pp. 1-5). IEEE.

[16] Danda, R. R. Decision-Making in Medicare Prescription Drug Plans: A Generative AI Approach to Consumer Behavior Analysis.

[17] Nampalli, R. C. R. (2022). Neural Networks for Enhancing Rail Safety and Security: Real-Time Monitoring and Incident Prediction. In Journal of Artificial Intelligence and Big Data (Vol. 2, Issue 1, pp. 49–63). Science Publications (SCIPUB). https://doi.org/10.31586/jaibd.2022.1155

[18] Syed, S. (2023). Zero Carbon Manufacturing in the Automotive Industry: Integrating Predictive Analytics to Achieve Sustainable Production.

[19] Siddharth K, Gagan Kumar P, Chandrababu K, Janardhana Rao S, Sanjay Ramdas B, et al. (2023) A Comparative Analysis of Network Intrusion Detection Using Different Machine Learning Techniques. J Contemp Edu Theo Artific Intel: JCETAI-102.

[20] Abdul Kareem, S., Sachan, R. C., & Malviya, R. K. (2024). AI-Driven Adaptive Honeypots for Dynamic Cyber Threats. Ram Chandra and Malviya, Rajesh Kumar, AI-Driven Adaptive Honeypots for Dynamic Cyber Threats (September 17, 2024).

[21] Danda, R. R. (2024). Generative AI in Designing Family Health Plans: Balancing Personalized Coverage and Affordability. Utilitas Mathematica, 121, 316-332.

[22] Nampalli, R. C. R., & Adusupalli, B. (2024). Using Machine Learning for Predictive Freight Demand and Route Optimization in Road and Rail Logistics. Library Progress International, 44(3), 17754-17764.

[23] Syed, S. (2024). Sustainable Manufacturing Practices for Zero-Emission Vehicles: Analyzing the Role of Predictive Analytics in Achieving Carbon Neutrality. Utilitas Mathematica, 121, 333-351.

[24] Sunkara, J. R., Bauskar, S. R., Madhavaram, C. R., Galla, E. P., & Gollangi, H. K. (2023). Optimizing Cloud Computing Performance with Advanced DBMS Techniques: A Comparative Study. In Journal for ReAttach Therapy and Developmental Diversities. Green Publication. https://doi.org/10.53555/jrtdd.v6i10s(2).3206

[25] Malviya, R. K. (2024). Leveraging Aiml Ops for Fraud Detection and Prevention in Fintech. Ranjan, P., Dahiya, S., Singh, SK, & Choudhary, sk Enhancing Stock Price Prediction: a Comprehensive Analysis Utilizing Machine Learning and Deep Learning Approaches.

[26] Pandugula, C., Kalisetty, S., & Polineni, T. N. S. (2024). Omni-channel Retail: Leveraging Machine Learning for Personalized Customer Experiences and Transaction Optimization. Utilitas Mathematica, 121, 389-401.

[27] Lekkala, S. (2024). Next-Gen Firewalls: Enhancing Cloud Security with Generative AI. In Journal of Artificial Intelligence & Cloud Computing (Vol. 3, Issue 4, pp. 1–9). Scientific Research and Community Ltd. https://doi.org/10.47363/jaicc/2024(3)404

[28] Vankayalapati, R. K., Sondinti, L. R., Kalisetty, S., & Valiki, S. (2023). Unifying Edge and Cloud Computing: A Framework for Distributed AI and Real-Time Processing. In Journal for ReAttach Therapy and Developmental Diversities. Green Publication. https://doi.org/10.53555/jrtdd.v6i9s(2).3348

[29] Tulasi Naga Subhash Polineni , Kiran Kumar Maguluri , Zakera Yasmeen , Andrew Edward. (2022). AI-Driven Insights Into End-Of-Life Decision-Making: Ethical, Legal, And Clinical Perspectives On Leveraging Machine Learning To Improve Patient Autonomy And Palliative Care Outcomes. Migration Letters, 19(6), 1159–1172. Retrieved from https://migrationletters.com/index.php/ml/article/view/11497

[30] Maguluri, K. K., Pandugula, C., Kalisetty, S., & Mallesham, G. (2022). Advancing Pain Medicine with AI and Neural Networks: Predictive Analytics and Personalized Treatment Plans for Chronic and Acute Pain Managements. In Journal of Artificial Intelligence and Big Data (Vol. 2, Issue 1, pp. 112–126). Science Publications (SCIPUB). https://doi.org/10.31586/jaibd.2022.1201

[31] Kalisetty, S., Pandugula, C., & Mallesham, G. (2023). Leveraging Artificial Intelligence to Enhance Supply Chain Resilience: A Study of Predictive Analytics and Risk

Mitigation Strategies. In Journal of Artificial Intelligence and Big Data (Vol. 3, Issue 1, pp. 29–45). Science Publications (SCIPUB). https://doi.org/10.31586/jaibd.2023.1202

[32] Sondinti, L. R. K., Kalisetty, S., Polineni, T. N. S., & abhireddy, N. (2023). Towards Quantum-Enhanced Cloud Platforms: Bridging Classical and Quantum Computing for Future Workloads. In Journal for ReAttach Therapy and Developmental Diversities. Green Publication. https://doi.org/10.53555/jrtdd.v6i10s(2).3347

[33] Lekkala, S., Avula, R., & Gurijala, P. (2022). Big Data and AI/ML in Threat Detection: A New Era of Cybersecurity. In Journal of Artificial Intelligence and Big Data (Vol. 2, Issue 1, pp. 32–48). Science Publications (SCIPUB). https://doi.org/10.31586/jaibd.2022.1125