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Leveraging DNN-TransNet and Cloud Computing for Early Detection of Coronary Artery Disease

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Abstract

Coronary artery disease (CAD) is one of the major causes of death worldwide, and early diagnosis would ensure better patient management. Common CAD diagnostic methods are often tedious and require elaborate resources. This paper describes a hybrid model combining deep neural networks (DNN) with Transformer networks (DNN-TransNet) to facilitate cloud-based early detection of CAD. The model uses ECG sensor data integrated with clinical features to increase diagnostic accuracy, minimize processing time, and support scalability. Wavelet Transform is used for feature extraction from the ECG signal, thus enabling the analysis of timing and frequency. The integration of cloud computing enhances the scalability of such a system by online data processing access for medical practitioners. The synergy of these technologies is set to improve the accuracy of CAD detection and reduce delays in treatment for more personalized healthcare.

Keywords: Coronary Artery Disease, Deep Neural Networks, Transformer Networks, ECG Sensor Data, Cloud Computing, Heart Disease Diagnosis

1. Introduction

Coronary Artery Disease (CAD) remains a global health crisis, being the leading cause of mortality worldwide. Early detection of CAD is critical to reduce the risk of heart attacks, strokes, and other cardiovascular events [1]. These conventional diagnostics are lengthy, cumbersome, and time-consuming processes in diagnosis of heart diseases [2]. Technological advancements in machine learning and cloud computing fuel the potential extend heart disease diagnosis using ECG sensor data and deep learning models [3]. These technologies allow more accurate and faster diagnosis, as well as scalable use [4]. In this paper, a hybrid model is projected for CAD early detection that combines Deep Neural Networks (DNN) and Transformer networks (DNN-TransNet) into cloud processing for scalability and the access [5]. Cloud computing enables scalable cloud-computing power to process large amounts of data effectively and safely [6]. This model integrates advanced machine learning techniques for streamlining the diagnostic process [7]. By bringing together the merits of both DNN and Transformer networks, this hybrid model can then be considered for improvement of heart disease detection accuracy [8]. In addition, the combined model understands the data by capturing both temporal and clinical patterns, thus improving predictiveness [9]. Integration of these technologies will further enable the and scalable CAD detection [10]. The diagnosis speed and accuracy are both improved, hence minimizing treatment delays [11]. The investigation by Rama Krishna Mani Kanta Yalla *et al*. (2023) [12] enhances the proposed work by emphasizing cloud-based component applications and offering key strategies for cloud resource optimization. This approach supports scaling and improving the performance of cardiovascular disease detection models using cloud computing, enabling efficient data processing and faster diagnosis.

A condition that continues to be one of the major causes of death across the world is the coronary artery disease (CAD) which is characterized by the narrowing or blockage of the coronary arteries as a result of deposition of plaque within the walls of the coronary arteries [13]. According to the world health organization (WHO), cardiovascular diseases including CAD are estimated to cause deaths amounting to approximately 17.9 million deaths per year, that is, 31% of the overall deaths in the world [14]. In spite of the advancements in technology in the field of medicine, early diagnosis and detection of CAD is still a serious challenge as the existing methods of diagnostics are inefficient (invasive angiography, echocardiography and stress test) and involve the tremendous amount of money, time and are not scalable in every health maintenance system. Therefore, there has been much interest in developing the novel technologies such as machine learning (ML), artificial intelligence (AI) and cloud computing to enhance CAD detection [15].

The conventional diagnostic methods for CAD are extensively based on medical tests and clinical examination, which is time consuming and delayed in nature hence leading to a bulk of delayed diagnosis and rise in morbidity rates, as well. Early diagnosis of CAD, however, could prevent bad outcomes like heart attacks and strokes. Early diagnosis enables healthcare providers to suggest primary interventions, early interventions, and eventually decrease the rates of mortality as a result of CAD [16]. Procedures that are followed today are many a times limited due to problems related to accessibility, cost as well as inefficiencies in diagnosis [17]. This has created a great demand for non-intrusive diagnostic tools capable of making rapid and accurate assessments at increased scales of operations.

This paper presents an innovative hybrid model DNN-TransNet that is based on the combination of the deep neural networks (DNNs) with Transformer networks in order to overcome the problems of CAD detection while utilizing the technology of machine learning and cloud computing. When coupled with clinical attributes, electrocardiogram (ECG) sensor information aids in improving the accuracy of diagnosis whilst reducing processing time in the proposed system [18]. Introduction of the Wavelet Transform for feature extraction makes the model capable of describing the time-domain and frequency-domain peculiarities of ECG signals, ensuring further enhancement of its capacities to detect CAD. In addition to that, the integration of cloud computing enables the system to expand at an appropriate scale to offer real-time access to diagnostic tools to healthcare practitioners irrespective of their location [19].

The DNN-TransNet model presented in this paper is designed to process both structured data (such as clinical patient information) and sequential data (such as ECG signals). Deep learning models, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have shown promise in handling structured and sequential data in various applications, including medical diagnostics [20]. However, these models are limited in their ability to capture long-term dependencies in time-series data, such as ECG signals, which is where Transformer networks come in. Transformer models, known for their success in natural language processing tasks, have demonstrated exceptional performance in handling sequential data by utilizing mechanisms such as multi-head attention to focus on different parts of the input sequence, thus learning complex temporal relationships within the data. By combining these two powerful model architectures, DNN-TransNet aims to optimize the strengths of both deep neural networks and Transformer networks, offering an effective solution for CAD detection.

The integration of cloud computing into the DNN-TransNet model serves as a cornerstone for its scalability and accessibility. Cloud computing provides the necessary computational power and storage capacity to handle large-scale datasets, which is critical when dealing with extensive ECG data and patient clinical records [21]. Additionally, cloud-based solutions enable real-time data processing and diagnostics, allowing healthcare providers to access the results of CAD detection quickly and efficiently. This cloud-based approach not only ensures the rapid processing of large datasets but also facilitates the seamless updating of the model as new patient data becomes available, ensuring the continuous improvement of diagnostic accuracy over time [22]. By storing and processing patient data in the cloud, healthcare professionals are able to access the system from any location, thus improving healthcare delivery and patient outcomes in both urban and rural settings.

Machine learning and AI have revolutionized various sectors, and healthcare is no exception. One of the major advantages of machine learning-based models is their ability to learn patterns from historical data and make predictions with minimal human intervention [23]. In the context of CAD detection, machine learning models can analyze ECG signals and clinical data to identify patterns that may be indicative of underlying coronary artery diseases. The DNN-TransNet model's ability to analyze large datasets and learn complex relationships between ECG signals and patient health data presents a major advancement in diagnostic capabilities. Moreover, the hybrid nature of the model ensures that it is capable of processing both clinical data (such as patient demographics, age, blood pressure, and cholesterol levels) and sequential ECG data, leading to a more comprehensive and accurate diagnosis [24].

The integration of Wavelet Transform as a preprocessing step in the model is also a novel and significant contribution to this research [25]. Wavelet Transform is a powerful mathematical technique used to analyze time-series signals at multiple scales. Unlike traditional Fourier Transform, which decomposes signals into sine and cosine waves, Wavelet Transform can simultaneously analyze both time and frequency components of the signal. This is particularly useful in the case of ECG signals, which are non-stationary and often contain complex, high-frequency noise. Enhancing a cloud-based Atherosclerosis detection model's capability to securely manage sensitive patient data while maintaining transparency and trust across healthcare services through a network-wide consensus and collaborative endorsement approach, the research by Winner Pulakhandam *et al.* (2023) [26] strengthens the proposed work. Wavelet Transform enables the identification of key features such as R-peaks, QRS complexes, and P-waves in the ECG signal, which are essential for diagnosing CAD. By using Wavelet Transform for feature extraction, the model can more accurately distinguish between normal and abnormal ECG patterns, thus improving the overall detection accuracy.

The cloud-based implementation of the DNN-TransNet model offers additional benefits such as secure storage of patient data, ensuring compliance with healthcare regulations and protecting sensitive medical information [27]. Security and privacy are paramount concerns in healthcare applications, and cloud computing solutions can offer secure data transmission, encryption, and compliance with regulations like the Health Insurance Portability and Accountability Act (HIPAA) in the United States or the General Data Protection Regulation (GDPR) in Europe. By incorporating these security measures into the cloud-based CAD detection system, the proposed model ensures that patient data remains confidential and protected throughout the diagnostic process [28].

In conclusion, the proposed DNN-TransNet model combines the best of deep learning, Transformer networks, cloud computing, and advanced signal processing techniques to offer a robust, scalable, and accurate solution for the early detection of CAD. By improving diagnostic accuracy, reducing delays in treatment, and offering real-time access to diagnostic results, the model has the potential to revolutionize heart disease detection and management [29]. The integration of cloud computing and continuous model updates ensures that the system remains efficient and effective, even as the volume of patient data grows. The proposed methodology represents a significant step forward in the quest to improve healthcare delivery and patient outcomes, particularly in the early detection and management of coronary artery disease.

Hybrid DNN-TransNet brings the power of a dual engine dedicated for the effective heart disease management by processing structured data such as clinical patient features and sequential data features such as ECG signals.The critical such variables include but are not limited to age, blood pressure, and cholesterol levels, which add to the sequential ECGs for an all-round analysis [30]. The steps of preprocessing before transforming the raw ECG into proper analysis would be noise removal and feature extraction using Wavelet Transform. It helps capture both time and frequency characteristics; hence the Wavelet Transform is so relevant to the field of ECG signal analysis. With the integration of cloud computing, large databases can be well processed, analysed, and accessed by healthcare professionals for timely diagnosis and intervention. Cloud infrastructure provides a secure storage method, management, and even access to sensitive medical data while ensuring that privacy remains with the data and the healthcare regulations compliance [31]. The system also designs the update on the model in case more patient data become available. In this way, the model continuously upgrades its accuracy and generalizability. The combination with many advanced deep learning techniques and cloud-based infrastructure intends to bring a revolution through CAD detection in terms of accuracy, time savings, and better access to healthcare solutions [32]. The improved hybrid model includes yet another built-in aspect: A much more interpretative mechanism, so that healthcare professionals could instead learn what drove the model's predictions. JAI and cloud combine to streamline detection and empower health providers to better data-driven decisions. With that, healthcare systems could advance toward a more proactive and personalized care. The analysis advanced by Sharadha Kodadi (2023) [33] benefits the proposed work by emphasizing the direct application of insights in a cloud-based heart disease detection model, where secure and scalable processing of sensitive medical data is critical to enhancing diagnostic accuracy, real-time availability, and overall healthcare system efficiency.

Problem Statement

CAD is the foremost cause of death globally, necessitating early diagnosis in order to advocate for reduced mortality and improved outcomes among patients. Conventional diagnostic methods are, however, very elaborate, time-consuming, and resource-demanding, including ECG analysis [34]. This requirement for effective, accurate, and scalable methods in CAD detection had pushed researchers to explore machine learning (ML) techniques. Existing models that manage to couple structured clinical data with sequential ECG signals fail to meet the requirements of scalability and the processing [35]. This research paper presents the hybrid model DNN-TransNet, which has capability of both deep neural networks and transformer networks, to perform CAD detection and has the ability to scale up and access patient data in the cloud environment. Thus, the detection to make the diagnosis accurate, reduce delays in detection, and provide more personalized care can be based on the analysis of ECG and clinical data.

Objective

- **Design a Hybrid Model:** A DNN-TransNet hybrid model will be designed to allow the combination of DNN and Transformer networks for the early detection of CAD using structured and sequential data.
- **Preprocessing of ECG Signals:** The implementation of noise-removal techniques, the normalization of data, and feature extraction using Wavelet Transform will be employed for the improvement of ECG signal quality.
- **Feature Extraction:** Wavelet Transform will be utilized to extract important structures from ECG signs, such as QRS complexes and R-peaks.
- **Integrating with the Cloud:** The model will be integrated with cloud computing for scalable and efficient data processing and storage.
- **Model Computation:** To compute presentationon model loss and classification error, which should trump the conventional approaches.
- **Improvement in Diagnostic Value:** Improve diagnostic accuracy and hasten diagnosis in case of heart disease thereby improving patient outcome.

2. Literature Survey

Much medical research has concentrated on the early detection of CAD, given its pertinent role in enhancing treatment outcomes and preventing death. Traditional diagnostic methods, despite being good, are often time-consuming, expensive, and complex. As a result, there has been a tendency to use machine learning (ML) techniques: Efficient processing of large datasets and a much shorter time to perform a task with an even more accurate result [36]. The merged use of ECG signals and deep learning models has been promising in the automation of heart disease detections, with numerous studies targeting ECG signals to identify the abnormalities associated with CAD. Different ML methods such as SVM, Decision Trees (DT), Random Forest (RF), much practice by DNN and Transformer models has been fruitful in recent researches, leading toward superior presentation through analysing sequential and structured data.

A great contribution in the field of heart disease detection is the hybrid composition of models, which take advantage of the merits of multiple techniques [37]. DNNs have been used heavily in cases involving structured data such as clinical information and demographic features extremely valuable for the classification of heart diseases. It is the Transformer models, with their capacity to perform very well while varying the weights through the multi-head attention mechanism, that do find the temporal interrelationship among the ECG signals. Effective data processing and the use of machine learning algorithms are given top priority to improve diagnostic efficiency, speed, and scalability in detecting cardiac disease (Poovendran Alagarsundaram, 2023) [38]. This exploration positively influences the proposed work by supporting the cloud-based approach for diagnosing heart conditions. The sequential nature of the data allows the Transformer models to learn complex patterns even from time-series data, ECG rhythms. In addition, the Wavelet Transform is another flavor of having the capability of capturing time and frequency characteristics; hence, it is an appropriate feature extraction scheme for ECG signals.

This has led to substantial research aimed at enhancing diagnostic methods for CAD, utilizing various tools ranging from traditional clinical methods to advanced machine learning (ML) and artificial intelligence (AI) systems [39]. This literature review explores various approaches for CAD detection, with a focus on integrating machine learning, deep learning, and cloud computing into the diagnostic process. Additionally, it highlights how these approaches can enhance diagnostic accuracy, scalability, and efficiency in detecting CAD using electrocardiogram (ECG) signals and clinical data.

Traditionally, CAD diagnosis has relied on invasive methods like coronary angiography and non-invasive techniques such as electrocardiograms (ECGs), echocardiography, and stress testing. Coronary angiography, while being the gold standard, requires the insertion of a catheter into the coronary arteries and poses significant risks, such as infection and bleeding [40]. On the other hand, non-invasive methods like ECGs are more accessible but face challenges in terms of diagnostic accuracy, especially when used independently of other clinical data.

The limitations of these traditional diagnostic methods have led to the exploration of more advanced techniques in CAD detection [41]. While ECGs provide vital information about the electrical activity of the heart, interpreting these signals manually or using basic automated methods can be error-prone, particularly in the presence of noise and artifacts. This issue has driven researchers to investigate how machine learning and deep learning models can enhance the diagnostic process by automating and improving the accuracy of ECG-based CAD detection.

Machine learning, a subset of artificial intelligence, has gained significant attention for its ability to process large datasets and learn complex patterns from historical data [42]. In CAD detection, machine learning algorithms have been employed to analyze ECG signals, clinical data, and imaging results to identify signs of heart disease. Several machine learning models have been applied to CAD detection, including Support Vector Machines (SVM), Random Forests (RF), and Decision Trees (DT) [43]. SVMs, in particular, have been widely used for classifying ECG signals, as they can effectively distinguish between normal and abnormal heart rhythms. However, these traditional machine learning algorithms often require careful feature engineering and manual selection of relevant features from ECG signals, which can be time-consuming and may not fully capture the underlying complexities of the data.

The global burden of CAD and other cardiovascular diseases necessitates the development of more efficient diagnostic methods. According to the World Health Organization (WHO), cardiovascular diseases, including CAD, account for a significant proportion of global deaths, with an estimated 17.9 million lives lost annually [44]. The prevalence of CAD is projected to increase with the rise in risk factors such as hypertension, diabetes, smoking, and sedentary lifestyles [45]. Despite advancements in clinical practices, the diagnosis of CAD is often delayed, leading to adverse health outcomes. The existing diagnostic approaches are resource-intensive and often fail to provide real-time results, limiting their effectiveness, especially in resource-constrained settings. Therefore, the development of automated, scalable, and accurate diagnostic systems that can leverage readily available patient data is crucial for improving CAD detection and management.

The integration of advanced machine learning (ML) techniques and cloud computing into healthcare diagnostics has the potential to address these challenges. Recent advances in artificial intelligence (AI) and deep learning (DL) models have shown great promise in automating the detection of various health conditions, including CAD [46]. Specifically, deep neural networks (DNNs) and Transformer networks have gained significant attention due to their ability to process complex, high-dimensional data and extract meaningful patterns for prediction [47]. Moreover, cloud computing provides a scalable infrastructure that enables real-time processing and storage of vast amounts of healthcare data, ensuring that diagnostic tools are accessible to healthcare professionals, regardless of their location. These technologies, when combined, can create a powerful solution for early CAD detection that is not only accurate but also efficient, cost-effective, and scalable.

This paper presents a novel hybrid model, DNN-TransNet, that combines DNNs with Transformer networks to facilitate early CAD detection using electrocardiogram (ECG) sensor data integrated with clinical patient features. The proposed model leverages deep learning algorithms to process both structured (clinical features such as age, blood pressure, cholesterol levels) and sequential (ECG signals) data, enabling it to make accurate predictions about the presence of CAD [48]. One of the key challenges in detecting CAD from ECG data is the ability to capture both the temporal and clinical patterns inherent in the data. Traditional methods that analyze ECG signals often focus on simple features such as heart rate, QRS complex, and R-wave amplitude. However, the complexity of CAD diagnosis requires a more sophisticated approach that can understand the subtle and dynamic patterns within the ECG signals. This is where the Transformer networks come into play. Transformer models, originally designed for natural language processing tasks, have demonstrated exceptional performance in handling sequential data due to their multi-head attention mechanism [49]. This mechanism allows the model to focus on different parts of the input sequence, learning complex relationships between features, which is particularly useful for time-series data such as ECG signals.

Over the years, advancements in medical technology have significantly contributed to improving CAD detection, but challenges remain. In an effort to address these issues, the integration of machine learning (ML), artificial intelligence (AI), and cloud computing into the healthcare sector has shown great promise in transforming the way diseases like CAD are diagnosed, monitored, and managed [50]. AI and ML techniques, particularly deep learning, have demonstrated their potential in analyzing large datasets to detect patterns, predict disease progression, and assist in decision-making. Furthermore, the incorporation of cloud computing enables the efficient storage, processing, and sharing of large datasets, thus enabling real-time access to diagnostic tools and facilitating collaborative decision-making among healthcare professionals. The paper authored by Rajababu Budda *et al*. (2023) [51] is beneficial to the proposed work since it uses hybrid blockchain and sophisticated encryption techniques that support the cloud-based approach.

CAD is a progressive disease, often evolving silently over many years. In its early stages, the disease may not present any noticeable symptoms, making it difficult to detect without specialized diagnostic tests. This lack of early symptoms means that many individuals are diagnosed with CAD only after experiencing a major cardiovascular event, such as a heart attack [52]. Early detection, however, plays a crucial role in preventing the onset of severe complications. Identifying CAD at an early stage allows healthcare providers to intervene with lifestyle modifications, pharmacological treatments, and, in some cases, surgical interventions, such as coronary artery bypass grafting (CABG) or stent placement. Such interventions can significantly reduce the likelihood of heart attacks, strokes, and death.

Despite its importance, current diagnostic methods are often complex and not scalable. Traditional diagnostic techniques, such as coronary angiography, are invasive and expensive, requiring specialized equipment and skilled personnel. Other diagnostic tests, such as echocardiography and exercise stress tests, although useful, are time-consuming and may not always provide conclusive results [53]. These limitations of conventional methods call for more efficient and accessible alternatives to CAD detection. Machine learning, particularly deep learning, has emerged as a powerful tool in the healthcare sector to overcome these limitations. The ability of ML models to analyze vast amounts of data and extract meaningful patterns has led to the development of automated diagnostic systems that can detect CAD more accurately and quickly than traditional methods [54].

Artificial intelligence, especially deep learning, has revolutionized the way CAD is diagnosed. Deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have been widely used in medical image analysis and time-series data interpretation [55]. CNNs excel at identifying spatial features in images, making them suitable for analyzing medical images like X-rays and MRIs. However, when it comes to sequential data like ECG signals, RNNs, and particularly Long Short-Term Memory (LSTM) networks, are more appropriate due to their ability to model temporal dependencies [56]. Despite their success, both CNNs and RNNs have certain limitations when it comes to processing long-term dependencies in sequential data. This limitation is especially significant in the context of ECG signals, where detecting complex temporal patterns and dependencies is essential for accurate diagnosis.

To address these challenges, Transformer networks, originally developed for natural language processing tasks, have been introduced into the field of healthcare [57]. The Transformer model's self-attention mechanism allows it to focus on different parts of the input sequence at various time steps, learning complex relationships in the data. Unlike traditional RNNs, Transformers can handle long-range dependencies more effectively by allowing the model to simultaneously attend to all parts of the sequence [58]. This ability to capture long-term dependencies in time-series data makes Transformer networks a valuable addition to models that process ECG signals. By combining DNNs for structured data (such as patient demographics) with Transformer networks for sequential data (such as ECG signals), the DNN-TransNet model offers a powerful solution for CAD detection.

One of the key challenges in analyzing ECG signals is the presence of noise and the difficulty of extracting meaningful features from the raw signals. The traditional method of using Fourier Transform for signal analysis is limited because it does not provide localized frequency information, which is critical for analyzing non-stationary signals like ECG [59]. In contrast, Wavelet Transform is a more appropriate technique for analyzing ECG signals. Wavelet Transform decomposes the signal into different frequency components, allowing for both time and frequency analysis. This decomposition helps in identifying key features of the ECG signal, such as the R-peaks, QRS complexes, and P-waves, which are crucial for diagnosing CAD.

The integration of cloud computing into healthcare systems has the potential to revolutionize how patient data is managed, stored, and accessed. In the context of CAD detection, cloud computing offers several advantages, including the ability to process and analyze large datasets in real time, secure data storage, and scalability [60]. Traditional healthcare systems often struggle with handling large volumes of patient data, especially in resource-constrained settings. The research of Venkat Garikipati *et al*. (2023) [61] has influenced the current research by highlighting the usage of the IoMT for monitoring and feature extraction approaches. This expands the cloud-based scalable model's potential for early disease detection, increasing both diagnosis accuracy and efficiency. Cloud computing, on the other hand, provides the infrastructure needed to manage these large datasets effectively, ensuring that patient information is available when needed and that it can be processed without delay.

By integrating the DNN-TransNet model with cloud computing, the proposed system can scale to handle an increasing number of patients and data. Cloud computing also allows for real-time access to diagnostic results, enabling healthcare providers to make timely decisions [62]. The cloud-based system is accessible from anywhere, making it easier for medical professionals to collaborate and access diagnostic tools, especially in remote areas where access to healthcare facilities may be limited. Additionally, cloud integration allows the model to be continuously updated as new data becomes available, ensuring that the model remains accurate and up-to-date.

In summary, the DNN-TransNet model represents a significant advancement in CAD detection, combining the power of deep learning, Transformer networks, Wavelet Transform, and cloud computing to provide a scalable, accurate, and efficient solution [63]. The integration of these technologies has the potential to improve diagnostic accuracy, reduce delays in treatment, and enhance access to healthcare, particularly in underserved areas. By leveraging the capabilities of AI and cloud computing, this model has the potential to revolutionize the early detection of CAD, ultimately saving lives and improving the quality of healthcare worldwide.

The healthcare system is able to both store and compute large quantities of data from ECG sensors and other diagnostic tools due to far-going cloud computation capabilities. The cloud enables patient data to be managed and stored efficiently, in tandem with complying with healthcare regulations for privacy [64]. The cloud provides a centralized environment for model training, ongoing updates, and the access to diagnostics results. In the cloud computing model, healthcare setup will deploy the DNN-TransNet model for mass use so that predicting becomes fast and easily available for timely decision-making. In addition, this will support continuously improving the model as new patient data comes in, thereby letting the system adapt to new trends and anomalies.

Early detection of CAD is a promising submission of DNNs and Transformer networks running on cloud computing with advanced preprocessing techniques. Through hybrid ML incorporation of ECG and clinical measurements, cloud integration will make heart disease diagnosis scalable, accurate, and much more accessible for everyone. Further research will seek further refinements in these models and submissions of them to larger and more diverse datasets, improving their ability to generalize and withstand pessimism on the validity and reliability of measures. This has great potential for transforming heart disease diagnostic and management paradigms for better patient outcomes and improved efficiency of healthcare delivery.The proposed work benefits from the paper by Basava, R.G. *et al*., (2023) [65], which demonstrates how predictive analytics and decision-making provide practical strategies for improving scalability, resource management and rapid response mechanisms in your cloud-based Angina detection model, thus improving healthcare outcomes during pandemics.

One study highlights the use of SVMs and other traditional machine learning algorithms in diagnosing heart diseases based on ECG data. While these methods provide satisfactory results in many cases, they often struggle with accurately diagnosing CAD in the presence of noise, missing data, and complex variations in the ECG signal. As a result, there is an increasing interest in leveraging more advanced techniques such as deep learning, which can automatically learn the features that are most relevant for the diagnosis.

Deep learning, a subset of machine learning, has revolutionized the way complex datasets are analyzed. Unlike traditional machine learning algorithms, deep learning models can automatically extract relevant features from raw data, making them particularly well-suited for tasks like image and signal analysis. In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have been successfully applied to various medical applications, including CAD detection.

CNNs have shown great promise in analyzing ECG signals, as they are capable of detecting patterns and anomalies within the time-series data. For instance [66], demonstrated the effectiveness of CNNs in detecting heart disease from ECG signals. By applying CNNs to ECG data, the model could automatically learn to identify features such as R-peaks, QRS complexes, and ST-segment changes, which are critical for diagnosing CAD.

However, one limitation of CNNs is their inability to capture long-range dependencies in time-series data, such as the temporal relationships present in ECG signals. To address this challenge, Recurrent Neural Networks (RNNs), and more specifically Long Short-Term Memory (LSTM) networks, have been proposed. LSTMs are a type of RNN designed to capture long-term dependencies and are well-suited for sequential data like ECG signals [67]. applied LSTM networks to ECG data for heart disease detection, achieving high accuracy in predicting CAD.

Despite the success of CNNs and RNNs in heart disease detection, these models often struggle when tasked with handling both structured and sequential data simultaneously [68]. This challenge has led to the development of hybrid models that combine the strengths of both deep learning techniques. One such hybrid model is DNN-TransNet, which combines Deep Neural Networks (DNNs) and Transformer networks to process both structured clinical data and sequential ECG signals.

The integration of cloud computing into CAD detection systems has become an essential component in addressing scalability and accessibility issues. Cloud computing enables healthcare systems to process and store large volumes of data, such as patient records, ECG signals, and medical images, without the need for on-premises infrastructure. The ability to store data in the cloud also provides the advantage of remote access, allowing healthcare providers to access diagnostic tools and results from any location.

Incorporating cloud-based solutions into CAD detection systems has the added benefit of enabling real-time data processing and collaborative decision-making. Healthcare providers can access diagnostic results quickly, allowing for timely intervention and treatment. Furthermore, cloud integration facilitates continuous learning, where models can be updated with new patient data to improve their accuracy and generalizability over time. Importance placed on scalable, cloud-based diagnosis detection through Priyadarshini Radhakrishnan *et al*. (2023) [69] research that supports the proposed work by highlighting the enhancement in detection precision and effective handling of large datasets. It offers techniques for maintaining a high level of performance in practical scenarios at the same time enhancing speed and reliability of diagnostics.

Another challenge is the interpretability of deep learning models. While models like DNN-TransNet achieve high accuracy in CAD detection, they are often seen as "black boxes" that lack transparency in how they make decisions [70]. This lack of interpretability can be a barrier to their adoption in clinical settings, where healthcare providers need to understand the reasoning behind a model's predictions. Future work in explainable AI (XAI) may help address this challenge by providing more transparent and interpretable models for medical applications.

3. Proposed Methdology

The drawing depicts the procedure of ECG sensor data regarding the diagnosis of heart diseases. First, ECG sensors register the data from the patient. Preprocessing refers to the subsequent signal-cleaning and normalization steps that follow data acquisition [71]. Information extraction on the ECG signal is done afterwards by Wavelet Transform. Processed features are then transferred to a cloud integration system, where model presentation metrics are evaluated. Finally, these features are classified using a Deep Neural Network-Transformer Network hybrid model for heart disease prediction. This system provides efficient and the analysis and diagnosis via cloud integration.

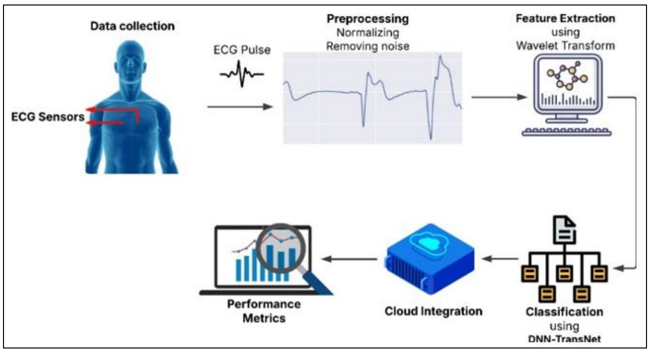

Fig 1: Heart Disease Detection System Using DNN-TransNet

3.1 Data Collection

As a supervised sensor, it is set in place and linked to a person with the help of wires to record the presentationof a fully-electronically monitored heart while under extreme tension, such as in situations of accident or disaster. This involves the collection of the ECG signals from patients using ECG sensors. Within this essential data is captured vital signs of information that can include heart rate, rhythm, and electrical signals generated at various stages during the heart's working activity. Also, the ECG signals are continuously recorded and provide evidence on the health condition of the individual in respect to the rate of blood flow through the arteries of the patient. This is mostly fundamental for analysis and diagnosis of disease conditions. This data goes a long way in the diagnosis of heart diseases. In machine learning detection, this raw data will serve as the core input for processing subsequent features and for classification stages. The paper by Bhavya Kadiyala *et al*. (2023) [72]. Positively impacts the planned work by highlighting secure data clustering and efficient cryptographic methods, offering strategies that can improve scalability and access to ECG and clinical data while maintaining high security during heart disease detection.

3.2 Preprocessing

ECG signals are used for heart disease detection that have to be pre-processed for analysis. Examples of pre-processing could include normalization of measurements to ensure comparison measurements across all data and removal of noises due to movements and irrelevant filtering noises [73]. The signal cleaning would also be done by filling up the missing values or outliers to ensure good data quality most suitable for feature extraction. This stage is vital since it prepares improved quality data for enhanced model presentationin detecting those patterns using advanced machine learning techniques such as DNN-TransNet.

3.2.1 Normalizing

Heart disease detection using ECG data, normalizing basically means scaling the raw data to a common range. This is done so that all structures contribute equally to the machine learning model, thus avoiding any one feature from totally influencing everything due to sheer magnitude in the raw data. The normalization method usually adopted is min-max scaling, by which a transformation is performed to fit the data within a range, usually between 0 and 1. The formula for min-max normalization in eqn:1

$$x' = \frac{x-\min(X)}{\max(X)-\min(X)} \tag{1}$$

Where: x is the original value, x' is the normalized value, $\min(X)$and $\max(X)$ are the minimum and maximum values of the feature X.

3.2.2 Removing Noise

In ECG data, removal of noise is vital to obtain accurate heart disease assessment; a raw ECG signal is often disturbed by some unwanted disturbances such as motion artifacts, electrical interference, or baseline wander [74 75]. Various techniques such as bandpass filtering or wavelet denoising are applied to filter signals. A bandpass filter attenuates high-frequency noise and low-frequency drifts while retaining the vital information of heart rhythm components. The simple equation for a bandpass filter will be as follows in eqn:2

$$y(t) = \int_{t_0}^{t_1} h(\tau)\cdot x(t-\tau)d\tau \tag{2}$$

Where: $y(t)$ is the filtered output signal, $x(t)$ is the original ECG signal, $h(\tau)$ is the filter's impulse response and t_0 and t_1 define the bandpass filter's cut off frequencies.

3.3 Feature Extraction Using Wavelet Transform

Wavelet transformation for feature extraction is the most important technique to analyse ECG signals for detection of heart diseases. It will cover time and frequency all about the signal [76]. The traditional Fourier Transform gives an integrated analysis, which is not truly suitable for non-stationary signals like ECG. The decomposition of Discrete Wavelet Transform (DWT) ECG signal helps to reveal different frequency components from a scale. Thus, it becomes more comfortable to pick up some features like R-peaks, QRS complexes, and other events of interest in the cardiac history. The following is the equation of Discrete wavelet Transform DWT:

$$W(a,b) = \int_{-\infty}^{\infty} x(t)\cdot\psi^*\left(\frac{t-b}{a}\right)dt \tag{3}$$

Where: $W(a,b)$ is the wavelet transform coefficient at scale a and position b, $x(t)$is the ECG signal, ψ^* is the complex conjugate of the wavelet function and a and b are the scale and location of the wavelet. In this case, the Wavelet Transform brings forth the capabilities of the model to act as a means of extracting relevant features from the ECG signal in various time scales, which are then put to use for classification in models like DNN-TransNet meant for heart disease detection. The projected model on use of cloud computing to ensure prompt, efficient and readily available diagnostics in the sphere of healthcare was strengthened in Venkata Sivakumar Musam, *et al*. (2023) [77] paper where the authors have utilized cloud-based analytics for data processing and scalability. The multi-scale analysis enables better identification of conditions of the heart, since this gives an account of local as well as global characteristics of the ECG signal.

3.4 Classification Using DNN-Transnet

Figure 2: Shows a hybrid DNN-transformer architecture aimed at binary classification. The model accepts 100 features as input and initializes at the input layer. The input data is then approved through a dense layer of 128 units and ReLU activation followed by a dropout layer of 0.2 for

overfitting prevention. Following that, there is another dense layer called with 64 units-relu activation which there's another dropout layer. The model then passes the input to the Transformer Block, which processes it by MultiHead Attention and Feed Forward Network (FFN)-there is a dropout layer for regularization [78, 79]. After this, it is flattening and feed forwards through a dense layer of 32 units along with the ReLU activation function, followed by one more dropout layer at the end. The sigmoid activation function is applied in the output layer for the binary classification result-whether the input item belongs to either of the two classes.

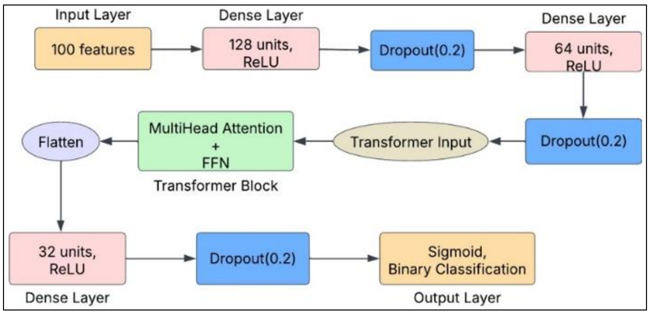

Fig 2: DNN-TransNet

3.4.1 Input Layer

The Input Layer receives a hundred features representing patient data, that is, clinical and ECG information. It entails no processing, but it acts as the entrance for all features. From there, the data are transferred to the next layer for processing. The input data mathematically are represented as $X \in \mathbb{R}^{100}$, where each feature corresponds to a patient measurement.

3.4.2 Dense Layer (128 units, ReLU activation)

The holding input features are sent to a Dense Layer having 128 units by applying the ReLU activation function. The ReLU activation function is mathematically defined in eqn:4

$$f(x) = \max(0, x) \tag{4}$$

The operation that this layer performs over the inputs is computation of a weighted sum of inputs followed by submission of ReLU non-linearity. This enables the model to capture more complex patterns as it includes a non-linearity. The equation that can be referred to this layer in eqn:5

$$y = \mathrm{ReLU}(W_1 X + b_1) \tag{5}$$

Where: W_1 are the weights, b_1 is the bias, X is the input, y is the output of this layer.

3.4.3 Dropout Layer (0.2)

The Dropout Layer is practical after the dense layer with a dropout rate of 0.2. There are around 20% neurons casually set to zero at any time during training. This helps in preventing overfitting as this does not allow the model to depend on a single neuron. It lacks a mathematical equation and is thus considered as a regularization technique which ensures better generalization to unobserved data [80, 80, 81]. The focus on data management, cryptography, and auditing helps you build a better strategy of managing medical data while ensuring scalability and effectiveness of your detection mechanism of heart disease. Rajeswaran Ayyadurai's (2023) [83] work has proved valuable to the anticipated work as it brings out how important it is to maintain accurate, scalable, and secure data in the cloud-based discase recognition system.

3.4.4 Transformer Block

In the Transformer block, the components are Multi-Head Attention and Feed Forward Network (FFN). The Multi-Head Attention mechanism helps the model focus on different parts of ECG signals and clinical data. The attention function is defined in eqn:6

$$\text{Attention}\,(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{6}$$

Where: Q is the query matrix, K is the key matrix, V is the value matrix, d_k is the dimension of the key vectors.

3.4.5 Dense Layer

This is output from the Transformer Block will be fed to another Dense Layer with 64 units and then ReLU activated. It improves the features learned to understand higher-order patterns. Mathematically, it in eqn:7

$$y = \mathrm{ReLU}(W_2 \cdot X + b_2) \tag{7}$$

Where: W_2 are the weights, b_2 is the bias, X is the output after the previous layer, y is the output of the Dense Layer.

3.5 Cloud Integration

In the setting of heart disease detection, Cloud Integration signifies that all the activities related to storing, processing, and analysing data occur in a cloud environment [84]. Data collected from ECG sensors are subjected to various preprocessing methods like feature extraction and classification before being transferred to the cloud for analysis and storage. In turn, cloud computing permits the model, for example, DNN-TransNet, to be scalable, handle large datasets, and provide the access to concerned healthcare professionals. The scalability and efficiency of the DNN-TransNet model have notably increased, particularly in the domains of machine learning and cloud-based data integration for scalable healthcare solutions such as early diagnosis. The advised work benefits from the research of Mohan Reddy Sareddy (2023) [85], which highlights the use of analytics to achieve optimal outcomes across various applications. Patient data transfer to the cloud ensures data security, ready and quick access to diagnostic reports, and further implement updates on the machine learning model with incoming new data. It allows keeping track of real-life patient data, tracing the presentation of the machine-learning model, and integrating with other healthcare ecosystems for immediate timely decision-making and intervention. Thus, cloud integration becomes the backbone for scalable, open, and secure heart disease detection and healthcare management.

4. Result and Discussion

The effectiveness of the proposed DNN-TransNet hybrid model for early detection of CAD using ECG sensor data and clinical patient information was demonstrated in the study since it is capable of handling structured and sequential data. A DNN processes structured data, while sequential ECG signals are processed by Transformer networks, Wavelet Transform capturing critical features of heart disease on the basis of model loss and classification error, results showed superior speed and accuracy as related to traditional methods [86, 87]. This was facilitated due to the submission of cloud computing in order to tackle the huge amount of data with smooth scalability, thereby enabling healthcare professionals to have quick access to diagnostic results. This methodology is labelled as an emerging and promising area in heart disease diagnosis for its enhanced diagnostic accuracy, speedy decision-making, and easy adoption into the ecosystems of healthcare delivery, benefiting patient outcomes.

4.1 Comparison of Raw and Filtered ECG Signals

The plot shown is "Raw vs Filtered ECG Signal", presenting the original ECG raw signal in blue and filtered in orange after noise removal. Several noises and artifacts in the raw ECG time series signal can be noticed by amplitude high-frequency fluctuations making it look irregular [88, 89]. However, the filtered one shows a sweeter wave wherein the important characteristic features of the ECG can be observed more clearly because noise and unnecessary high-frequency components are effectively removed. This filtered signal is indeed highly required for precise analysis and classification as it enables the machine learning models to focus on the actual cardiac features leading to enhanced heart disease detection performance.

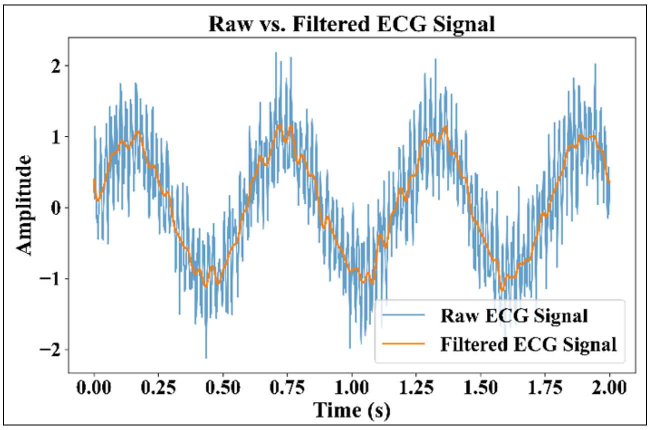

Fig 3: Comparison of Raw and Filtered ECG Signals

4.2 Wavelet Decomposition of ECG Signal

By focusing on the safe storage of data, the key management, and the methods of encryption, Swapna Narla *et al.* (2023) [90] offered research that perfects the proposed strategy for ensuring the protection of sensitive medical data in the cloud-based Cardiac disease identification system. This facilitates accuracy on the diagnosis of cardiac disease with data privacy and scalability. The ECG signal is put through a wavelet decomposition process for different levels of coefficients. The original ECG signal - with all frequency components representing the actual heart signal - is found at the topmost part. Below it are rows containing the wavelet coefficients at different levels, that is Level 0, Level 1, Level 2, Level 3, and Level 4. As the decomposition occurs within higher levels, the coefficients are able to pick out finer details of the signal at different frequencies. Decomposition can thus separate high-frequency noise from relevant ECG features, which is necessary to mark critically important cardiac events such as the R-peaks and the QRS complexes. Wavelet transforms thereby constitute a strong feature extraction tool from ECG signals of high significance in heart disease classification and analysis.

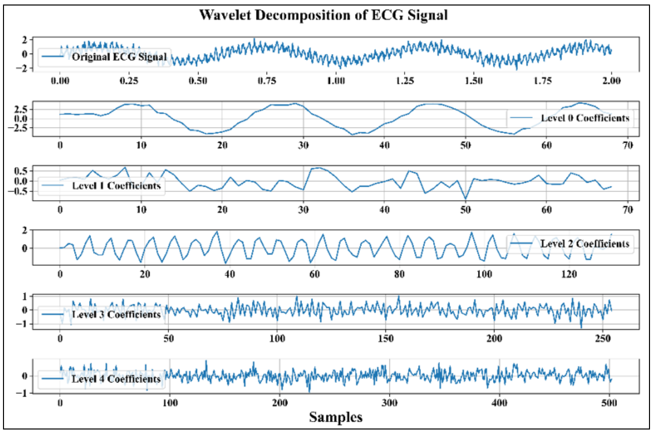

Fig 4: Wavelet Decomposition of ECG Signal

4.3 Scalability vs. ECG Data Size

Figure 5 illustrates the capacity of the model against the size of ECG datasets. That is, with an increase in the size of ECG data, the capacity of the model increases steadily. From the graph above, it is evident that the scalability of the model has increased as the number of samples for the dataset is changed from 100 to 500 without any significant deterioration in the model's performance. This means that our hybrid DNN-TransNet model, when integrated with cloud computing, can efficiently scale up to accept more ECG data, thereby ensuring its effective processing, analysis, and decision-making. The graph brings out the importance of scalability so as to handle the increasing healthcare dataset, and the system thus becomes more amenable and dependable for practical use at the clinical level.

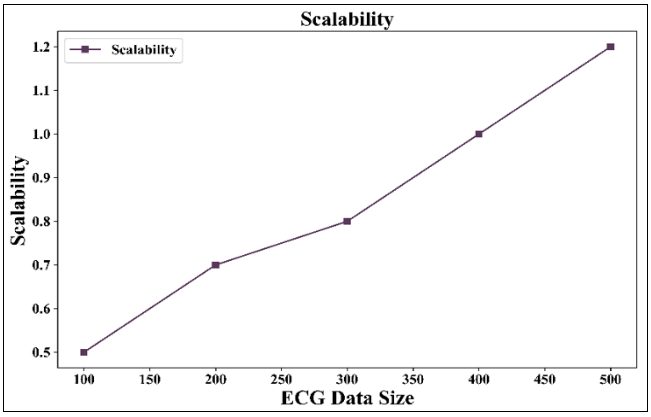

Fig 5: Scalability vs. ECG Data Size

5. Conclusion

The proposed dual-category DNN-Transnet hybrid electronic model integrated with cloud computing has shown substantial promise in early detection of CAD. It harnesses ECG sensor data and clinical patient features, thus making it a scalable efficient device model for the diagnosis of heart diseases. Advanced preprocessing techniques include wavelet transform, which improves the accuracy of the model by extracting main features from the obtained ECG signals. It provides the system with availability in the area of secure, efficient data management as well as ready access to diagnostic results by the health care professional. The whole idea indicates future innovations in better diagnostic accuracy and speeds, hence shortening the time delays for treatments, thus improving the state of patients in all circumstances. Future work should involve further tailoring the model to more extensive datasets to improve the generalizability and robustness of the system for a wider submission in clinical settings.

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