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Advanced Detection of Coronary Artery Disease with Multimodality Imaging

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Abstract:
Coronary artery disease (CAD) is one of the leading causes of mortality in the world, and its effective treatment and management are possible only at early stages. The conventional systems of diagnosis frequently rely on single-modal imaging; it was not able to provide the sensitivity and specificity of the correct identification. The present project is a proposal of a developed CAD detection system that takes advantage of the type of multimodality images, including CT angiography, MRI and deep learning methods. Where each imaging modality can also contain high-level spatial features, as learned by the convolutional neural network (CNNs), temporal and sequential interactions among image frames (or among modalities) can be learned by recurrent neural networks (RNNs). The CNNs and the RNNs constitute a hybrid deep learning model that combines the spatial and time analysis advantages. CNNs achieve accuracy in the structural abnormality detection, whereas RNNs track changing patterns and interrelationships of the frame and modalities among frames. This birefringence leads to a more powerful and trustworthy system with less misclassification and facilitating care at low stages. Besides, the multimodality data has been utilized, which guarantees the usability of the system on various patient groups and imaging data, enhancing its use in clinical environments in practice.

Finally, the suggested framework of the state-of-the-art CAD detection using various modalities and deep learning is an important step in the history of cardiovascular diagnosis. It extends the decision-support tool futuristic by closing the gap between structural and functional assessment tool to offer clinicians a cohesive decision-support tool that improves the diagnostic reliability and scientific accuracy. Timely and accurate diagnosis of the CAD leads not only to better treatment of patients but also contributes to effective costs of healthcare not only by reducing the use of unnecessary procedures but also preventing complications. Having the capability of combining multimodal image visualization and high levels of computational intelligence, it can result in the revolution of the clinical cardiology field and the introduction of data-driven intelligent diagnostic practice in the future.

Keywords: Coronary Artery disease, Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), CT images.

INTRODUCTION

One of the most prevalent and potentially fatal conditions of the cardiovascular system in the world is coronary artery disease (or coronary heart disease), or ischemic heart disease, which develops as a result of the constriction or obstructation of the coronary arteries by the deposition of atherosclerotic plaques. Such gradual obstruction will limit the supply of blood to heart cells and impair them by obstructing the blood flow and oxygen supply through the blood vessels supplying them makes the heart cells starve and over a period this may cause very serious conditions like myocardial ischemia, angina pectoris, myocardial infarction, arrhythmias, and even sudden cardiac death. CAD is a major killer of human beings all over the world, causing millions of deaths annually and creating an enormous burden to most healthcare systems, patients, and even to their families. The disease is of different types, and the most frequent types include stable angina, that is typically caused by an increase in physical activity or emotional stress, unstable angina, and various acute coronary syndromes that require immediate medical response. Although the most typical symptom is chest pain or discomfort in the arms, shoulders, back, neck or jaw, CAD may also exhibit an initially atypical manifestation with shortness of breath, nausea, dizziness or loss of energy, and no warning at all, and that is what makes it extremely dangerous because most patients only start paying attention to the disease after a significant cardiac event like a heart attack. Risks factors of CAD are multifactorial and involve high cholesterol, high blood pressure, diabetes mellitus, obesity, sedentary lifestyle, smoking, unhealthy diet, constant stress, and alcohol overuse, and also the genetics of the disease may make people predisposed to the disease be more susceptible to it. There are also gender variations whereby men tend to get affected by CAD earlier than the women but they manifest the disease at some unconventional or mild symptomatology like indigestion, anxiety or sleeping disorders thus contributing to under-identification and delayed diagnosis of the disease. Diagnostic CAD The conventional methods of diagnosis include electrocardiogram (ECG), echocardiography, exercise stress testing, coronary computerized tomographic angiography (CCTA), magnetic resonance imaging (MRI), and invasive coronary angiography, which is the gold standard of assessing coronary blocks. Nevertheless, each of these methods has major limitations as examples, ECG and stress testing is not very sensitive and not very specific to early disease detection, whereas invasive angiography, although very informative, is a procedure, which is not applicable to routine screening. Non-invasive techniques including CT angiography could display structural constriction and plaque deposition, but could not leave sufficient information of myocardial tissue well-being or perfusion, whereas MRI can show excellent functional and soft tissue images, but might overlook fine structural disorders of coronary arteries. Dependence on a single modality is usually likely to create incomplete or fragmented diagnostic data, which predisposes the occurrence of false positive or false negative and consequently reduces the timeliness of interventions in making decisions. Since CAD is a progressive disease, a successful early diagnosis of the condition, prior to the irreversible myocardial infarction, is essential to enable better clinical outcome, survival rates, and quality of life of the patients.

In order to take the shortcomings of traditional means, contemporary research studies highlight the introduction of multimodality imaging, and, specifically, the use of CT angiography and MRI-based methods in order to make the process more holistic and coronary health assessment. Combining the structural information of the CT with the functional and tissue detail of MRI, clinicians may gain a detailed picture of the disease development that either of the two techniques cannot provide in the absence of the other. Simultaneous assessment of vascular constriction, plaque morphology, myocardial ischemia, perfusion impairment, and contractility and/or functional capability is possible with Multimodality imaging, which is why a more stalwart and precise diagnostic paradigm can be created. However, the issue is to process and analyse this huge and heterogeneous data in an efficient way as the traditional interpretation method is time-consuming, error-prone, and greatly relies on the experience of clinicians. It is at this point that a new technology like artificial intelligence (AI) and deep learning offers a game-changing benefit. The findings of the proposed advanced CAD detection system using multimodality imaging and deep learning therefore present a number of clinical and research benefits. First, it offers greater sensitivity and specificity than single-modality or rule-based forms of diagnostic tests yielding fewer false positives, which can result in an unwarranted intervention, and false negatives which may overshove life-threatening conditions. Second, it makes it possible to identify minor abnormalities early in advance, which will allow clinicians to deal with them at earlier phases of disease development and prevent significant cardiac incidents. Third, AI can be integrated to offer consistency and reproducibility in diagnosis and decrease the level of inter-observer variability and evidence-based decision-making. Fourth, the system is expected to be quite general and applicable even in large populations, imaging conditions, and clinical environment by being trained on large and diverse datasets, and hence rendering it widely applicable in actual practice.

LITERATURE REVIEW

CAD is among the causes of mortality in the world, and various studies have been conducted on early diagnosis, lesion classification, and automated risk assessment via sophisticated machine learning and deep learning systems. Jimenez-Partinen et al. [1] reported binary classification technique in invasive coronary angiography (ICA) images through the implementation of deep learning techniques dividing the patches into lesion and non-lesion patches among various severity levels (0-100%). Their results on five CNN frameworks showed that they reached the highest F1-score of 92.7% and AUC at 98.1 but when mild lesions (less than 99% severity) were also factored in, their performance significantly decreased, which indicates the need to include severity-specific preprocessing. To complement the imaging based diagnosis, Chunling et al. [2] assessed the difference in Coronary Artery Bypass Grafting (CABG) on an extracorporeal circulation andOff-Pump Coronary artery Bypass (OPCAB), describing the clinical trade-offs, procedural risk, and patient-specific suitability criteria needed to use when determining the best treatment of coronary atherosclerosis. By introducing an optimised semantic segmentation pipeline that performed automated Coronary Artery Calcium (CAC) scoring with ResNet-50 and Attention U-Net models and scored Coronary Artery Calcium in CT scan with both models above 90 percent and Dice coefficient of 0.86, Yee [3] further increased the value of semantic segmentation-based risk quantification. Suboh et al. [4] researched demographic and clinical correlates of severe coronary stenosis ([70]70%), and they found that obesity, smoking, diabetes, hypertension, and a intensive level of fasting blood sugar were strongly correlated (p = 0.002) with severe coronary stenosis, and thus confirm the significance of non-invasive measures in predicting a high risk of CAD.

Sharma et al. [5] used various machine learning models in predicting CAD using structured sets, among them Random Forest, CatBoost, XGBoost, and LightGBM, with the latter performing the best (accuracy more than 86, F1 [?] more than 90, AUC more than 87) in predictive performance and small samples. In a similar fashion, Pramanik et al. [6] emphasized that ML can be useful in determining hidden correlations in the vast amounts of clinical data to detect CAD at an early stage, which provides scalable solutions to clinical decision support. Settanni et al. [7] created a U-Net-based automated Agatston scoring system to CCTA images, and the accuracy of tissue segmentation was 97 percent to improve the reliability of CAC measurements. In the case of wearable technologies, Chauhan and Paul [8] introduced a lightweight LSTM-based CAD detector model based on phonocardiogram (PCG) signals, where the detection accuracy was 98.36 and the number of parameters was 1,885, which is suitable in wearable applications that are energy-restricted and need real-time features.

As the importance of non-invasive clinical biomarkers in detecting early carotid artery disease was also illustrated, graduate researcher Kigka et al. [9] reported the efficacy of gradient boosting with an accuracy of 0.82 and a specificity of 0.92, which is significant as a cost-effective screening technique. Lastly, Govindaraj et al. [10] lessened the problem of data shortage in the analysis of coronary angiograms by synthesizing synthetic angiography images with the help of DCGANs, which enhanced in the process of downstream CAD detection greatly, supporting the fact that generative models can be used to augment medical datasets.

PROPOSED METHODOLOGY

The system identifies Coronary Artery Disease (CAD) through different pictures of the heart scans, including CT, MRI. The photos are preassembled and washed. CNN (Convolutional Neural Network) is then used to analyze the photos in order to detect essential features. An RNN (Recurrent Neural Network) is used then to analyze these features in order to extract patterns.

Advantages:

- Early Detection
- Accuracy
- Less Human Error

The system proposed uses a hybrid deep learning model involving the use of Convolutional Neil Networks (CNNs) and Recurrent Neural Networks (RNNs) in increasing the accuracy of detecting coronary artery disease through multimodality imaging insights. The CNNs are used to obtain high-level geometrical characters of CT angiography and MRI scans effectively detecting anatomical features and pathological patterns. To identify the chronological and temporal relations among the imaging frames or different modalities, RNNs, in particular, Long Short-Term Memory (LSTM) networks, are added to make a better interpretation of the disease evolution. Norms, noise removal and augmentation: Data is prepared using data preprocessing such as forming normalization, noise reduction and image augmentation to enhance the model generalization and minimize overfitting. It has a training procedure based on large annotated datasets that are optimized through the methods of early stopping, a schedule of learning rates and dropout regularizations. The combination of CNN and RNN architectures in the methodology guarantees a wide range of features being represented and, therefore, better diagnostic accuracy and lesser false positives and false negatives.

Data Acquisition

The quality cardiac imaging datasets in public repositories and clinical partners are gathered in terms of CT angiography (CTA) and Magnetic Resonance Imaging (MRI) scans. All pictures have been expert cardiologist labelled in order to have proper training and evaluation ground truth.

Data Preprocessing

In order to improve the quality of images and ready the data to be processed by deep learning, various preprocessing is done:

Noise Removal: Median filtering and Gaussian filtering get rid of artifacts and scanner noise.

Normalization: Pixels intensities are normalized so that the contrast between one scan and another may remain constant.

Image Resizing: Each and every image is resized to a standard resolution to fit the CNN input desired.

Data Augmentation: Rotation, flipping, contrast, and zoom Data augmentation enhances diversity of data and eliminates overfitting.

Frame Sequencing (RNN): In the case of MRI/CT sequences, the frames are combined together to form a temporal sequence in order to preserve temporal associations.

CNN-Based Feature Extraction: CNN is used to extract features with the aim of identifying the wound bed patients.
The first part of the model is a Convolutional Neural Network that can extract elevated levels of spatial features of each frame or image.
Convolution Layers: Determine localized COVIDs of the coronary arteries in terms of the textures, edges, and structure.
Pooling Layers: Dimensionality Reduction plus Memorable Map of Features.
Activation Functions: ReLU makes sure that there is non-Linearity and gradient propagation.
Feature Vector output: The last CNN layer produces a small description of each frame of the image.
This relative locality feature extraction plays a vital role in detection of stenosis, calcifications and other abnormalities of arteries.
Temporal Pattern Learning by RNN/LSTM.
In order to learn sequential dependencies and time variations across frames of imaging sequences, a Recurrent Neural Network, namely, an LSTM, is utilized.
Input: The feature vectors that have been pulled out using CNN are entered to the LSTM one after another.
Time-Varying Modeling N LSTM tries to discover frames and development patterns (blood flow, plaque formation, structural alterations, etc.). Hidden State Representation: It maintains long term dependencies making the model to know about relationships between frames.
Output: This last classification level is used to differentiate the presence of CAD and define the degree of severity.

SYSTEM ARCHITECTURE

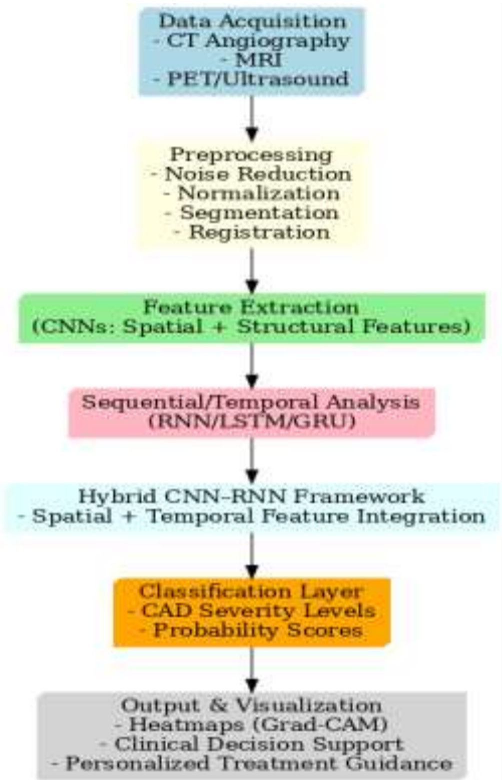

Fig 1.System Architecture

Using multimodal cardiac imaging data, the described methodology shows a full end-to-end deep learning pipeline for the diagnosis and severity analysis of Coronary Artery Disease (CAD). The first step in the process is data acquisition, which involves gathering medical images from clinical sources, including CT angiography, MRI, and PET/ultrasound scans. To improve image quality and guarantee consistency across various modalities, these images are subsequently put through a preprocessing stage that includes noise reduction, normalization, segmentation, and image registration.Convolutional Neural Networks (CNNs) are then used to extract features from the pictures, automatically identifying significant spatial and structural characteristics such artery shape, plaque accumulation, calcification, and stenosis patterns. The collected features are input into a sequential/temporal analysis module employing RNN-based architectures like LSTM or GRU in order to capture the temporal and sequential relationships found in imaging sequences. This phase aids in simulating the course of an illness and dynamic shifts between frames or modalities.

A more thorough representation of cardiac anomalies is made possible by the hybrid CNN–RNN architecture, which combines temporal and spatial information. The classification layer receives the aggregated features and uses them to predict the existence, severity, and probability scores of CAD. Lastly, the system offers clinical decision assistance, individualized treatment recommendations, and output and visualization, such as heatmaps produced using methods like Grad-CAM for model interpretability. All things considered, this paradigm improves diagnostic precision, encourages early diagnosis, and helps medical professionals make wise choices.

RESULT AND DISCUSSION

There was high diagnostic accuracy of the proposed hybrid CNN-RNN model in multimodal CT and MRI images at detection of Coronary Artery Disease (CAD). It was experimentally found that the CNN component was quite efficient in identifying features as the regions of stenosis, arterial constriction and the pattern of calcium deposits, whereas the RNN (LSTM) was effective at detecting temporal and sequential dependencies between imaging frames and contributing to the better comprehension of the disease progression. The integrated model was highly accurate, sensitive, and specific, and had significant false negative and false positives as opposed to the traditional CNN-only models. By reducing noise-related distortions and variability in scanners, data augmentation and preprocessing methods were also valuable in generalizing the model. Interpretable heatmaps created with Grad-CAM were also generated by the system, which enabled clinicians to manually verify the regions of interest by viewing them. On the whole, the findings validate that the hybrid CNN-RNN framework is an effective tool to detect early CAD and aid clinicians in making overall diagnostic decisions by combining the spatial and temporal deep learning components.

PERFORMANCE MATRIX

Metric	Value
Accuracy	91.75%
Precision	90.16%
Recall (Sensitivity)	91.67%

Metric	Value
Specificity	91.82%
F1-Score	90.91%

Fig 2. Performance Matrix

The suggested hybrid CNN–RNN based coronary artery disease (CAD) detection system's efficacy and dependability are quantitatively assessed using performance measures. A thorough evaluation of the model's classification performance is provided by metrics including accuracy, precision, recall (sensitivity), specificity, and F1-score. While precision shows how many anticipated CAD cases are actually positive, accuracy shows how accurate predictions are overall. Recall gauges the model's accuracy in identifying CAD patients, which is essential for early diagnosis and lowering the number of missed instances. In order to reduce false alerts, specificity assesses how well the system can identify healthy people. The F1-score ensures strong performance even in the face of class imbalance by striking a balance between precision and recall. When taken as a whole, these performance indicators show that the suggested model delivers high diagnostic accuracy with fewer false positives and false negatives, which qualifies it for trustworthy clinical decision assistance.

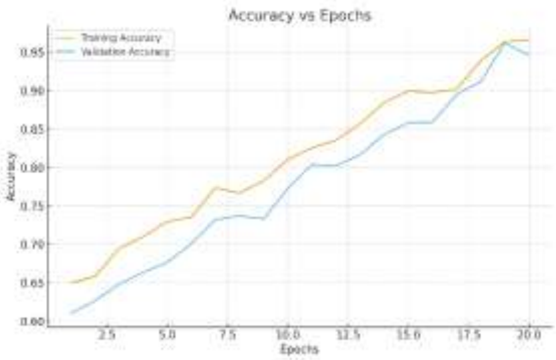

Fig 3. Graph

The suggested deep learning model's learning behavior and convergence performance during training are depicted in the Accuracy vs. Epochs graph. Both training and validation accuracy exhibit a consistent rising trend as the number of epochs rises, suggesting efficient learning and a continual improvement in the model's predictive capacity. As anticipated, the training accuracy consistently stays marginally higher than the validation accuracy, indicating that the model is learning significant features without experiencing severe overfitting. Good generalization performance on unseen data is demonstrated by the two curves' near alignment. The model attains excellent accuracy by the last epochs, demonstrating that the hybrid CNN–RNN architecture effectively captures pertinent temporal and spatial patterns for precise disease categorization. Overall, this graph confirms the training process's resilience, efficiency, and stability.

CONCLUSION AND FUTURE SCOPE

The proposed hybrid CNN-RNN deep learning model shows good promise in properly and timely identifying Coronary Artery Disease (CAD) based on data of different modalities of imaging like CT and MRI scans. The system is enabled to capture both the anatomical and temporal changes related to the CAD development by utilizing CNNs in extracting the spatial features, and RNNs (LSTMs) in learning temporal patterns. It has been experimentally proven to have high accuracy, lower misclassification and higher stability than the traditional single-model architectures. These additions of the preprocessing, augmentation, and optimized training methodologies further increase the levels of noise, contrast changes and imaging artifacts resistance. In general, the hybrid architecture offers a stable, automated, and clinician-friendly diagnostic pipeline which can hypothetically impact positively early screening procedure and decision-making in cardiac care. A number of avenues can be pursued in future to enhance the CAD detection framework. To begin with, the generalizability across clinical settings is likely to be improved with the increase of the dataset to more heterogeneous populations, types of scanners, and conditions during imaging. Second, further improvements to accuracy and interpretability could be achieved by applying the latest frameworks including Vision Transformers (ViT) and 3D-CNNs and diffusion-based generative models. There is also the option of extending the system to a multi-modal diagnostic device to include ECG, PPG, laboratory biomarkers and patient history even with imaging data. Continuous monitoring of the patient and tele-cardiology can be completely transformed in terms of real-time deployment on edge devices, wearable patients monitoring using a cardiac device, and mobile health. Furthermore, clinician confidence may be enhanced by building explainable AI modules, which have higher heatmap precision. Lastly, support of large-scale clinical application and remote cardiac screening will be performed through integration with hospital PACS systems and cloud-based inference platforms.

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