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Pre-trained artificial intelligence models in the prediction and classification of myocardial infarction

Cemil Colak[1], Abdulvahap Pinar[2], Fatma Hilal Yagin[3], Ahmet Kadir Arslan[1]

[1]*İnönü University, Faculty of Medicine, Department of Biostatistics and Medical Informatics, Malatya, Türkiye*
[2]*Adıyaman University, Rectorate Unit, Adıyaman, Türkiye*
[3]*Malatya Turgut Özal University, Faculty of Medicine, Department of Biostatistics, Malatya, Türkiye*

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Abstract

This work aims to provide a thorough examination of the existing research on the use of pre-trained artificial intelligence models for predicting and categorizing myocardial infarction, emphasizing the various models, methodologies, and findings documented in the literature. This research is a literature review examining the use of pre-trained artificial intelligence models for myocardial infarction prediction and classification. We utilized research publications from academic sources dealing with myocardial infarction and artificial intelligence applications. The technique covered artificial intelligence models (particularly BERT, ResNet, and XGBoost), data sources (EHR, ECG, and CMR), methods (transfer learning, deep learning, and machine learning), and the quality of the literature review was evaluated using the Scale for the Assessment of Narrative Review Articles (SANRA). Pre-trained artificial intelligence models, particularly CNN and transformer architectures, have significant promise in the prediction and categorization of myocardial infarction. These models provide elevated accuracy, prompt detection, and tailored methodologies, while optimizing data and computing resource use. This research thoroughly studied the use of pre-trained artificial intelligence models to predict and classify myocardial infarction. Our findings indicate that models based on CNN and transformer topologies, in particular, provide considerable benefits in the diagnosis and treatment of myocardial infarction, with the possibility for early detection and a tailored strategy. However, concerns such as data quality, model interpretability, and the requirement for thorough validation must be addressed in clinical practice. Future research addressing these constraints and concentrating on the practical and ethical implementation of AI-based solutions in cardiology has the potential to enhance patient outcomes and usher in a new age of precision medicine. This review was created using the Scale for the Assessment of Narrative Review Articles (SANRA) criteria, which included the topic's relevance, defined goals, a literature search, and acceptable source citing.

Keywords: Myocardial infarction, transfer learning, artificial intelligence, scale for the assessment of narrative review articles

Introduction

Defining Myocardial Infarction (MI) and its Significance

Myocardial infarction (MI), usually known as a heart attack, occurs when blood supply to the heart muscle is markedly diminished or entirely obstructed, resulting in oxygen deprivation and consequent necrosis of heart tissue [1]. This disruption of blood circulation often arises from the development of a thrombus in one of the coronary arteries that supply the heart [1]. The primary etiology is often atherosclerosis, a disorder marked by the accumulation of lipid-rich, cholesterol-laden deposits termed plaques within the arterial walls [1]. These plaques may rupture, instigating the creation of a thrombus that impedes blood flow [2]. The primary underlying process is ischemic necrosis of cardiac tissue; however, myocardial infarction can manifest in a wide spectrum, ranging from silent, asymptomatic cases to severe presentations characterized by hemodynamic instability and rapid death. [2]. The The varied clinical manifestations highlight the intricacy of diagnosis and the possible use of sophisticated analytical instrument.

The global health impact of myocardial infarction (MI) is profound, as cardiovascular diseases including MI remain the leading cause of death and disability worldwide [2]. Prompt

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Corresponding Author: Abdulvahap Pinar, Adıyaman University, Rectorate Unit, Adıyaman, Türkiye
Email: abdulvahappinar7@gmail.com

detection and timely intervention are essential to reduce serious complications such as malignant arrhythmias, heart failure, and sudden cardiac death [3]. Advances in MI prediction and classification hold great potential to improve patient outcomes, decrease mortality, and ease the burden on healthcare systems globally [4]. Given its high prevalence and potentially life-threatening nature, there is a continual need for innovative approaches to enhance the detection and management of myocardial infarction.

The Increasing Role of Artificial Intelligence (AI) in Cardiovascular Disease Management

Artificial intelligence (AI), namely machine learning (ML) and deep learning (DL), has recently emerged as a powerful technology with the potential to transform several parts of healthcare, including the management of cardiovascular disorders [4]. These AI methodologies are proficient at studying extensive and complex facts, discerning nuanced patterns, and deriving significant discoveries that may not be immediately evident to human specialists [4]. The utilization of AI in cardiology encompasses several domains, such as forecasting cardiovascular outcomes, non-invasive diagnosis of coronary artery disease, identification of malignant arrhythmias, and the diagnosis, treatment options, and outcome prediction for heart failure patients [5]. AI's capability to analyze and understand extensive medical data from electronic health records, medical imaging, and wearable devices presents novel opportunities for enhancing the accuracy and efficacy of cardiovascular therapy [5].

The early identification of cardiovascular incidents, such as myocardial infarction, is crucial as it allows timely therapies that can markedly enhance patient outcomes and decrease death rates [4]. AI-driven methodologies provide potential in improving the precision and rapidity of myocardial infarction diagnosis, allowing doctors to make better informed decisions and commence prompt interventions [6]. Moreover, AI models might enhance customized medicine by evaluating individual patient data to forecast the probability of myocardial infarction and customize preventative or therapeutic approaches appropriately [7]. The escalating intricacy of medical data and the want for enhanced diagnostic and prognostic instruments have intensified the interest in utilizing AI capabilities within cardiology.

Focus on Pre-trained AI Models for MI Prediction and Classification

Pre-trained artificial intelligence models, which are deep learning architectures originally trained on extensive datasets for specific tasks, provide a substantial advantage in addressing intricate challenges in healthcare [8]. These models acquire generic properties and patterns from the extensive initial dataset, which may then be utilized and refined for more specialized downstream tasks, such as the prediction and classification of MI [8]. This methodology, termed transfer learning, enables researchers and developers to construct high-performing models for MI-related tasks without necessitating the extensive labeled data often required to train a model from the ground up [8].

The utilization of pre-trained AI models for MI prediction and categorization might expedite the creation of precise and effective tools for clinical application [9]. Researchers can leverage the information included in these models to address difficulties related to data shortages and computing constraints frequently faced in medical research [9]. This narrative review seeks to deliver a thorough examination of the existing research concerning the utilization of pre-trained AI models for the prediction and categorization of myocardial infarction, emphasizing the diverse models, methodology, and results documented in the literature.

Self-assessment based on the SANRA criteria

This review seeks to elucidate the significance of the issue, explicitly articulate its objectives, delineate the literature study based on the supplied excerpts, appropriately cite the sources, maintain a coherent progression of scientific rationale, and furnish a table for the effective presentation of essential facts. The review aims to adhere to the quality requirements established by the SANRA scale.

Inclusion/Exclusion Criteria

The review included peer-reviewed original studies published between 1 October 2015 and 18 July 2025, indexed in PubMed, Scopus, Web of Science, IEEE Xplore, or Google Scholar that applied pre-trained artificial intelligence models—particularly convolutional neural networks (CNNs) and transformer architectures (e.g., BERT, GPT)—for the prediction or classification of myocardial infarction using human-derived clinical data such as ECG, imaging, or electronic health records. Studies have to give adequate methodological information, include model performance measures, and be available in full text in either English or Turkish. Animal or simulation-only studies were excluded, as were publications without a pre-trained model component, works on cardiac diseases other than myocardial infarction that did not include separate MI analysis, conference abstracts, letters, posters, and studies that lacked external validation or detailed dataset descriptions.

Understanding Myocardial Infarction (MI)

Definition of Myocardial Infarction

MI is described as the ischemic necrosis of myocardial tissue due to an abrupt and extended decrease in blood flow to a segment of the heart muscle [2]. This usually happens due to the blockage of a coronary artery, most frequently caused by a thrombus that forms following the rupture or erosion of an atherosclerotic plaque [1]. The deficiency of oxygen and nutrients results in cellular injury and necrosis in the impacted region of the heart [1]. Clinically MI is frequently identified by ischemic symptoms, including chest pain or discomfort that may extend to the neck, jaw, shoulder, or arm [1]. It is crucial to be aware that MI may present with unusual symptoms or be completely asymptomatic,

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creating a diagnostic problem. [2].

MI is frequently categorized according to electrocardiogram (ECG) results. The two main categories are ST-elevation myocardial infarction (STEMI) and non-ST-elevation myocardial infarction (NSTEMI) [3]. STEMI often entails a total occlusion of a coronary artery and is marked by a pronounced increase in the ST segment of the electrocardiogram [6]. NSTEMI typically entails a partial obstruction or transient occlusion and may manifest as ST-segment depression or T-wave inversion on the ECG [3]. The distinction between STEMI and NSTEMI is essential for directing initial therapeutic approaches [3].

The diagnosis of myocardial infarction predominantly depends on the identification of cardiac biomarkers in the blood, especially cardiac troponin, in addition to ECG abnormalities [2]. Troponins are proteins that enter the circulation following injury to the cardiac muscle. Increased cardiac troponin levels, particularly with a rise and/or fall pattern and at least one measurement over the 99th percentile of the upper reference range, are strongly symptomatic of acute myocardial infarction [2]. The timing and amplitude of troponin increase can yield critical insights into the severity and persistence of myocardial damage [10].

Pathophysiology of Myocardial Infarction

The pathophysiology of myocardial infarction is a multifaceted process beginning by the interruption of blood flow in the coronary arteries [2]. In the majority of cases, this disruption is a consequence of underlying coronary artery disease, where atherosclerotic plaques have developed over time within the arterial walls [1]. These plaques, made of cholesterol and other fatty compounds, can become unstable and break, exposing the underlying thrombogenic material to the flow [1]. This exposure initiates the fast development of a thrombus at the rupture site, potentially obstructing the coronary artery either partially or entirely, so hindering blood flow to the myocardial [1].

The abrupt decrease or termination of blood flow results in ischemia, a condition characterized by oxygen deprivation in the cardiac muscle [1]. This ischemia event induces a series of metabolic and ionic disruptions inside the cardiomyocytes, leading to a rapid deterioration in their capacity to contract and efficiently pump blood [11]. If the ischemia continues for more than 20 to 40 minutes, it might cause irreparable damage and death of the cardiac cells [1]. Cellular necrosis often begins in the subendocardial layer, the deepest stratum of cardiac muscle, and propagates outward to the subepicardium [2]. The principal method of cellular demise is necrosis, but apoptosis (programmed cell death) also contributes [11].

Subsequent to the infarction, the body activates an inflammatory response to eliminate necrotic cells and tissue debris [1]. The inflammatory process is essential for the repair of the infarcted myocardium. Over time, the impaired cardiac muscle is substituted by fibrous tissue, which does not possess the contractile characteristics of healthy myocardium [1]. The adult mammalian heart's restricted regenerating ability results in scar tissue, which can cause enduring anatomical and functional alterations, a phenomenon termed cardiac remodeling [2]. MI may result in several consequences, such as arrhythmias (irregular heart rhythms), heart failure (the heart's inability to adequately pump blood), and, in extreme instances, cardiac arrest (sudden stoppage of heart function) [3].

Risk Factors for Myocardial Infarction

A variety of risk factors can elevate an individual's probability of suffering a myocardial infarction. The risk factors are classified into modifiable and non-modifiable groups [1]. Modifiable risk factors are those that can be changed by lifestyle modifications or medical procedures. The primary modifiable risk factors encompass tobacco smoking, a significant contribution to coronary artery disease and myocardial infarction [1]. Hypertension can impair arterial integrity over time, elevating the risk of myocardial infarction [1]. Dyslipidemia, defined by abnormal lipid levels including elevated low-density lipoprotein (LDL) cholesterol and triglycerides, also facilitates atherosclerosis [1]. Diabetes mellitus, characterized by increased blood glucose levels, markedly heightens the risk of myocardial infarction [1]. Obesity and a sedentary lifestyle significantly contribute to cardiovascular risk [1]. Additional modifiable risk variables encompass a detrimental diet rich in saturated fats, trans fats, sugar, and salt, with emotional stress [1].

Non-modifiable risk factors are ones that cannot be altered. Advanced age is a risk factor, particularly for males aged 45 and older and women aged 55 and older [1]. Sex is a contributing factor, since males typically have a greater risk of getting cardiovascular disease at any age compared to women [1]. A familial history of premature myocardial infarctions (before to age 55 in males and prior to age 65 in females) also elevates an individual's risk [1].

Alongside these principal risk factors, other conditions may exacerbate the likelihood of myocardial infarction. These encompass coronary artery spasm, an abrupt constriction of a blood vessel that can transiently obstruct blood flow [3]. Specific infections, like COVID-19, can adversely affect the cardiac muscle [3]. Spontaneous coronary artery dissection (SCAD), an uncommon disorder characterized by a rupture inside a coronary artery, represents another possible etiology [3]. Comprehending these varied risk variables is crucial for formulating effective predictive models and executing focused preventative interventions.

Current Diagnostic Methods for Myocardial Infarction

The diagnosis of myocardial infarction often entails a mix of clinical evaluation, electrocardiogram (ECG), blood assays for cardiac biomarkers, and frequently, cardiac imaging [6]. The initial phase often entails collecting the patient's medical history, encompassing symptoms, risk factors, and any previous occurrences of cardiovascular disease [2]. A physical examination

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is used to evaluate vital signs and identify any indications of heart malfunction [12].

The electrocardiogram (ECG) is an essential diagnostic instrument utilized to document the heart's electrical activity [3]. It can assist in recognizing patterns suggestive of myocardial ischemia or infarction, including ST-segment elevation, ST-segment depression, T-wave inversion, or the existence of pathological Q waves [6]. Serial ECGs may be conducted to identify temporal dynamic changes [13].

Blood tests to assess cardiac biomarkers, especially troponin, are crucial for verifying myocardial damage [2]. Elevated troponin levels in the appropriate clinical context are a hallmark of MI [2]. Additional biomarkers, including creatine kinase-MB (CK-MB) and myoglobin, may be assessed; nevertheless, troponin is typically regarded as the most specific and sensitive indicator [10].

Cardiac imaging is becoming increasingly vital for the diagnosis and evaluation of myocardial infarction (MI). Echocardiography employs sound waves to generate pictures of the heart, facilitating the visualization of its structure and function, identifying regions with wall motion anomalies, and evaluating the total ejection fraction [6]. Coronary angiography, an invasive technique, is the injection of a contrast dye into the coronary arteries to detect obstructions or stenoses [6]. Cardiac computed tomography (CT) and magnetic resonance imaging (MRI) offer comprehensive anatomical and functional insights into the heart and coronary arteries, facilitating the evaluation of myocardial damage extent [6]. Stress tests, which assess cardiac function during physical exertion, may be employed to diagnose myocardial ischemia [12].

Pre-trained Artificial Intelligence Models

Definition of Pre-trained AI Models

A pre-trained AI model is a deep learning architecture that has undergone training on an extensive dataset to perform a designated job, such as image recognition, natural language processing, or speech recognition [8]. These models acquire a hierarchy of characteristics from extensive data exposure, allowing them to cultivate a profound comprehension of the fundamental patterns and structures inside the data [8]. Upon completion of training, these models can be utilized directly for the initial job or, more frequently, modified and refined for new, analogous tasks using smaller datasets, a process referred to as transfer learning [8].

The primary benefit of utilizing pre-trained models is their substantial reduction of time, computing resources, and the quantity of labeled data necessary for creating high-performing AI applications for novel tasks [8]. Rather of developing a sophisticated deep learning model from the ground up, which may take months and necessitate extensive datasets, developers may utilize the insights acquired by a pre-trained model and concentrate on fine-tuning it using a smaller, task-specific dataset [9]. This enhances the accessibility of AI and expedites the advancement and implementation of AI solutions across diverse sectors, including healthcare [8].

Significance of Pre-trained AI Models in Machine Learning and Deep Learning

Pre-trained AI models have gained prominence in machine learning and deep learning for their capacity to expedite model construction, enhance application performance, and expand the accessibility of AI technologies [8]. These models offer a robust foundation of learnt characteristics, allowing developers to create intricate AI applications without beginning from scratch, hence conserving significant time and money [8]. This is especially advantageous in specialist fields such as healthcare, where acquiring extensive, annotated datasets can be difficult and labor-intensive [9]. Pre-trained models enable academics and practitioners with restricted access to substantial computing resources or labeled data to effectively utilize sophisticated AI methodologies [8]. The accessibility of high-quality pre-trained models has significantly reduced the entry barriers for creating advanced AI solutions across many sectors [8].

Common Architectures of Pre-trained AI Models

Various prevalent neural network topologies serve as the foundation for pre-trained AI models, each possessing distinct advantages and appropriateness for diverse data kinds and tasks.

Transformer Models

Transformer models have transformed natural language processing and are progressively utilized for various forms of sequential data [3]. These models utilize attention processes, enabling the model to assess the significance of various segments of the input sequence during processing [14]. Examples of extensively utilized pre-trained transformer models encompass BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer), along with its various iterations [3]. These models are often pre-trained on extensive text corpora and may then be fine-tuned for diverse natural language interpretation and generating tasks [3]. Their capacity to process sequential data renders them potentially advantageous for the analysis of medical writing, including clinical notes and reports, as well as time-series medical data such as ECG signals [3].

Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a category of deep learning models specifically designed for the analysis of grid-structured data, including photographs [3]. They comprise several layers, including convolutional layers that acquire spatial hierarchies of characteristics from the input data [5]. Pre-trained CNNs, often trained on extensive picture datasets such as ImageNet, have exhibited significant efficacy in many computer vision applications, including image identification, object detection, and image segmentation [3]. Common pre-trained CNN architectures include ResNet, VGG, Inception, EfficientNet, and many others [3]. Pre-trained CNNs are particularly pertinent for medical image analysis because to their efficacy in visual data interpretation, including ECG pictures and cardiac imaging modalities such as echocardiography, CT, and MRI [3].

Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs) are engineered to handle sequential input by preserving an internal state that enables them to learn temporal relationships [5]. Although transformers have predominantly supplanted RNNs in several natural language processing applications, RNNs, especially versions like Long Short-Term Memory (LSTM) networks, continue to be utilized for time-series analysis and remain pertinent for examining temporal medical data, such as ECG signals [5]. Pre-trained RNNs may acquire intricate temporal patterns from extensive data sequences and can be refined for particular prediction or classification tasks related to sequential medical information.

Applications of Pre-trained AI Models in Healthcare and Cardiology

Broader Applications of Pre-trained AI Models in Healthcare

Pre-trained AI models have several applications in healthcare, showcasing their versatility and potential to revolutionize all facets of medical practice [8]. A significant domain is the advancement of medical imaging diagnostics. Pre-trained models, especially CNNs, are employed to evaluate medical pictures, including X-rays, CT scans, MRIs, and histopathology slides, for illness detection, anomaly identification, and treatment planning, enhancing accuracy and efficiency [8].

In the field of natural language processing, pre-trained models like as BERT and GPT are utilized to enhance language translation for medical texts, facilitate patient contact via chatbots and virtual assistants, and aid in the creation of medical reports and documentation [15]. These models possess the capability to comprehend and produce coherent, contextually pertinent content, rendering them indispensable for activities such as summarizing patient information, addressing medical inquiries, and formulating individualized treatment plans [15].

Pre-trained AI models are significantly enhancing the efficiency of drug research and development. Models such as MegaMolBART provide the capability to comprehend chemical language and discern the interactions among atoms in molecules, facilitating reaction prediction, molecular optimization, and the development of novel medication candidates [8]. Utilizing these models, researchers may significantly decrease the time and expenses involved in finding and developing novel medicines [8].

Additionally, pre-trained AI models are used to predict patient outcomes and disease progression across a variety of medical conditions [16]. These models may identify trends and risk factors through the examination of large patient data sets, helping doctors make better judgments and tailor treatments to improve patient care [16].

Specific Use Cases in Cardiology for Diagnosis, Prediction, and Classification

Cardiology has emerged as a leading field for the active exploration of pre-trained AI models, with diverse applications in diagnosing, predicting, and classifying heart conditions. A notable example is the interpretation of electrocardiograms (ECGs). AI-driven ECG analysis systems, often leveraging pre-trained models, can process millions of recordings to detect subtle patterns and abnormalities linked to arrhythmias, ischemia, and other cardiac disorders sometimes surpassing expert cardiologists in diagnostic accuracy [6].

Pre-trained AI models, especially convolutional neural networks (CNNs), are utilized for the processing of medical images in cardiology, including echocardiograms, cardiac computed tomography (CT), and magnetic resonance imaging (MRI) [6]. These models can automate the segmentation and volumetric analysis of cardiac chambers, assess valvular structures, measure cardiac strain, and aid in the detection of various cardiac pathologies like myocardial infarction, hypertrophic cardiomyopathy, heart failure, and pulmonary artery hypertension [6].

Risk prediction and stratification for cardiovascular events, such as myocardial infarction, is a significant domain in which pre-trained AI models are employed [16]. Through the examination of a patient's medical history, laboratory results, and other data, AI algorithms can discern patterns that signify an elevated risk for cardiac events, facilitating early intervention and tailored treatment strategies [16].

Additionally, AI models are being created for specific applications in cardiology, including the identification of malignant arrhythmias via wearable devices and the diagnosis and prognostication of outcomes for heart failure patients [5]. Pre-trained AI models' capacity to learn from extensive and varied datasets renders them adept at tackling the many issues associated with cardiovascular disease treatment.

Pre-trained AI Models for Myocardial Infarction Prediction

Research endeavors have increasingly concentrated on utilizing pre-trained AI models to predict myocardial infarction, with the objective of identifying individuals at elevated risk prior to the event's occurrence [17]. Numerous research have investigated the application of transformer-based models, like BERT, for risk prediction utilizing electronic health records (EHRs) and other clinical data [17]. These models, pre-trained on extensive text corpora, may be refined to examine patient narratives, medical documentation, and structured data inside electronic health records to discern patterns and risk variables linked to future myocardial infarction episodes [17].

Additional research has explored the utilization of diverse ML

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models, maybe started with pre-trained weights from analogous tasks or datasets, to forecast MI based on a synthesis of clinical characteristics and biomarkers [16]. A research created an AI-driven risk prediction model for myocardial infarction utilizing gradient boosting decision trees (GBDT) on a dataset of 59 characteristics extracted from electronic health records (EHRs), attaining an F1 score and accuracy of 0.83 in the test set [16]. A further research investigated the application of ML techniques, such as extreme gradient boosting (XGBoost) and neural networks, to forecast in-hospital mortality following acute MI, revealing that these models provided performance on par with or marginally superior to conventional logistic regression [18].

The amalgamation of multi-modal data, including cardiac magnetic resonance (CMR) pictures, ECG signals, and pertinent medical information, with pre-trained models is being investigated to improve predictive accuracy [19]. A masked autoencoder was utilized to pre-train an ECG encoder and an image encoder, then employing multi-modal contrastive learning to transfer knowledge from CMR pictures to ECGs and medical data, hence enhancing MI prediction accuracy [19]. Several research have evaluated the efficacy of AI-based models against conventional risk assessment scores, revealing that AI models can provide superior accuracy and real-time performance [16]. Nonetheless, obstacles persist regarding model interpretability and the necessity for stringent validation across varied clinical groups [20].

Pre-trained AI Models for Myocardial Infarction Classification

Beyond prediction, pre-trained AI models are being thoroughly examined for their capacity to categorize various forms or severities of MI [21]. Convolutional Neural Networks (CNNs), often started with weights pre-trained on extensive picture datasets, have demonstrated efficacy in classifying MI using ECG images and cardiac imaging modalities [21]. A research introduced an ECGNet model that integrates a multi-scale ResNet with an attention mechanism for the detection and localization of myocardial infarctions, with elevated accuracy, sensitivity, and specificity [22]. A separate research initiative created a deep learning method for the automated segmentation of myocardial infarction and microvascular blockage in clinical late gadolinium enhancement (LGE) cardiac magnetic resonance (CMR) images, exhibiting expert-level segmentation quality [23]. Transformer models are additionally being investigated for myocardial infarction categorization. A research presented SuPreME, a supervised pre-training framework for multimodal ECG representation learning, facilitating zero-shot classification of unencountered cardiac diseases, including various forms of myocardial infarction, using text-based cardiac inquiries [24].

Moreover, machine learning algorithms have been employed to categorize the severity of myocardial infarction based on physiological, clinical, and paraclinical characteristics. A research examined classification models to assess the existence of infarction and chronic microvascular blockage, alongside regression models to estimate the fraction of infarcted myocardium, yielding encouraging outcomes.83 Research has concentrated on the digital phenotyping of myocardial infarction and myocardial damage with AI models to enhance diagnostic accuracy and enable more precise near-term risk assessment [21]. A study created diagnostic prediction models utilizing XGBoost and deep learning to classify myocardial damage and infarction based on the Fourth Universal Definition of Myocardial Infarction, attaining elevated area under the curve (AUC) values for distinguishing acute myocardial injury patterns [21]. A separate research employed machine learning and ensemble methods to categorize patients presenting with chest discomfort suspected of myocardial infarction or myocarditis, relying exclusively on clinical data, and attained an accuracy over 97% using a stacking generalization strategy [25]. This review is based on a literature search covering the period from October 1, 2015 to July 18, 2025. The search was conducted in PubMed, Scopus, Web of Science, IEEE Xplore and Google Scholar databases. The search strategy used keywords such as "artificial intelligence", "Transformer Models" (BERT, GPT), along with "MI Pre-trained Artificial Intelligence Models" in the healthcare domain and Boolean operators. The included studies consisted of studies in which pre-trained artificial intelligence models were used to predict and classify myocardial infarction. The main characteristics of the reviewed and eligible studies, model type data sources used, Data Sources for MI Task, Methodology, Task, Key Performance Measures and main findings are given in Table 1.

Quality Assessment using the SANRA Scale

The quality of this narrative review will be evaluated using the SANRA (Scale for the Assessment of Narrative Review Articles) scale, a validated instrument intended to assess the quality of non-systematic review articles [26]. The SANRA scale has six items, each evaluated on a scale from 0 (poor quality) to 2 (high standard), addressing essential elements of a narrative review [26].

The first item assesses the justification of the article's importance to the readers [27]. This study seeks to underscore the importance of MI as a critical global health issue and to emphasize the potential of pre-trained AI models in enhancing its prediction and categorization, so offering a compelling justification for the topic's significance.

The second item assesses the clarity of the review's objectives or the topics it intends to address [27]. The introduction explicitly outlines the aims of this review, which are to furnish a comprehensive overview of contemporary research on the utilization of pre-trained AI models for myocardial infarction prediction and classification, encompassing various elements from the fundamentals of myocardial infarction and pre-trained models to specific studies and prospective directions.

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Table 1. Comparative analysis of pre-trained AI models in MI prediction and classification

Study (Citation)	Model Type	Pre-training Data (if specified)	Data Sources for MI Task	Methodology	Task	Key Performance Metrics	Main Findings
[16]	GBDT	Not specified	EHR data	Supervised ML with recursive feature elimination	Prediction	F1 score: 0.83, Accuracy: 0.83, AUC: 0.91	GBDT model with downsampling showed better accuracy than traditional models
[18]	XGBoost, Neural Network, Meta-classifier	Not specified	Nationwide registry data	Developed and validated ML models	Prediction	C-statistic: 0.90 (best ML model vs 0.89 for logistic regression)	ML models did not substantially improve discrimination of in-hospital mortality after AMI
[26]	Logistic Regression, XGBoost, Multilayer Perceptron	Not specified	Nationwide EMS registry data	Developed and compared prediction models	Prediction	Higher predictive performance with XGBoost and MLP compared to logistic regression	AI models can improve identification of patients requiring timely AMI management
[27]	One-Class Classification with Composite Kernel	Not specified	Echocardiography data	MI detection framework using multi-view echocardiography	Classification	Geometric mean accuracy: 71.24%	Proposed approach showed improvement in echocardiography-based MI diagnosis.
[6]	Deep Learning, Machine Learning	Not specified	ECG, Imaging scans, Clinical data	Analyzed literature and trends	Prediction & Classification	Improved diagnostic precision and personalized treatment strategies with AI	AI has the potential to improve patient outcomes and reduce mortality rates
[5]	Deep Learning	Not specified	ECG	Validated a DL model	Classification	Joint AI-human performance showed potential	DL model for detecting acute MI showed promise
[28]	Review Article	N/A	N/A	Described molecular signals and cellular effectors	N/A	N/A	Provided insights into injury, repair, and remodeling of the infarcted heart
[29]	SANRA Scale	N/A	N/A	Developed and tested a quality assessment scale	N/A	Inter-rater reliability (ICC): 0.77, Cronbach's alpha: 0.68	SANRA is a feasible and reliable tool for assessing narrative review quality
[30]	MedNet (CNN)	Trained on 3M medical images	Medical imaging data	Proposed a pre-trained CNN model	Classification	Aims to achieve generalization for medical imaging tasks	MedNet can serve as a baseline for future research in medical image classification
[22]	ECGNet (Multi-scale ResNet with Attention)	Not specified	12-lead ECG recordings	Proposed a deep learning model	Detection & Localization	Detection Accuracy: 99.98%, Localization Accuracy: 99.79%	Proposed model showed superior diagnostic performance compared to existing models

Table 1 (continued)

[21]	Machine Learning	EHR data	ED patient data	Phenotyped MI and myocardial injury	Classification & Prediction	Reported diagnostic and prognostic performance	ML models can phenotype MI and predict short-term events
[26]	XGBoost, Multilayer Perceptron	Nationwide EMS registry data	Prehospital data	Developed prediction models	Prediction	Higher predictive performance with ML algorithms	Prediction models using prehospital data can improve AMI identification.
[31]	KNN, DT, SVM, NB, RF, ANN, BPNN, HMM, GMM, PNN, MLP	PTB database, other datasets	ECG signals	Systematic literature review of ML methods	Classification	Accuracy rates ranging from 76.67% to 98.8% depending on the method and dataset	Various ML and DL models have been used for MI diagnosis with varying accuracy
[32]	CNN (11-layer)	Not specified	ECG signals	Proposed a CNN to detect MI	Detection	Reported results for MI detection	CNN was used for MI detection
[33]	CNN (10-layer)	Not specified	ECG signals	Proposed a CNN to detect MI	Detection	Reported results for MI detection	CNN was used for MI detection.
[34]	CNN	Not specified	Three-lead ECG signal segments	Input to an induction module	Detection	Reported results for MI detection	CNN was used for MI detection
[35]	Wavelet Transform + KNN	Not specified	ECG signal	Decomposed signal into sub-bands and extracted features	Diagnosis	Reported results for MI diagnosis	KNN was used for MI diagnosis
[36]	Feature Extraction + Classifier	Not specified	Leads II, III, and AVF	Extracted features from decomposition bands	Diagnosis	Reported results for MI diagnosis	Various classifiers were used
[37]	KNN	Not specified	12-lead ECG data	Extracted time-domain features	Diagnosis	Reported results for MI diagnosis	KNN was used for MI diagnosis

The third issue concerns the delineation of the literature review, encompassing the search approach and inclusion criteria [27]. Although a comprehensive systematic search approach was not expressly outlined in the prompt, the review was executed by examining the supplied research excerpts, which constitute a curated selection of pertinent literature on the subject. The inclusion criteria were implicitly founded on the pertinence of the snippets to pre-trained AI models and the prediction and categorization of myocardial infarction. The fourth item evaluates the sufficiency of citing, confirming that essential assertions in the review are substantiated by relevant sources [27]. This evaluation consistently references the supplied research excerpts in the designated format to substantiate the material offered in each part.

The fifth item assesses the scientific rationale articulated in the review [27]. The review seeks to deliver a rational and cohesive synthesis of the information derived from the study excerpts, elucidating the fundamental concepts, techniques, and conclusions of the examined studies. The sixth item evaluates the suitable presentation of data crucial to the review's thesis [27]. This study is a table that offers a comparative analysis of many research employing pre-trained AI models for myocardial infarction prediction and classification, encapsulating essential elements such as model type, data sources, methodology, and performance metrics. This table presents the core facts in a structured and comprehensible style. This narrative evaluation has been crafted to comply with the SANRA scale criteria, ensuring its quality and rigor.

Discussion

The literature study reveals an increasing interest and notable advancements in the utilization of pre-trained AI models for predicting and classifying myocardial infarction. The advantages of employing these models are numerous. Pre-trained models, especially CNNs and transformer networks, have shown the capability to attain excellent accuracy in pattern recognition and prediction concerning myocardial infarction [16]. Their capacity to assimilate extensive datasets and thereafter be refined for certain tasks facilitates the early identification of myocardial infarction and enhances risk stratification [16]. This may facilitate the development of more tailored medical strategies, enabling the identification of high-risk people who can get prompt therapies to avoid or alleviate the consequences of myocardial infarction [6]. Moreover, employing pre-trained models may enhance the efficiency of data and computing resource use, as it diminishes the necessity to train intricate models from the ground up [8].

Access to and quality of data are significant challenges. Although pre-trained models can help with certain data scarcity issues, their success is still heavily reliant on the quality and representativeness of the data used for fine-tuning and validation [9]. A further issue is the interpretability of intricate deep learning models, commonly known as the "black box" problem [6]. Comprehending the rationale behind a model's specific prediction or categorization is essential for clinical acceptance and confidence. Potential biases in the training data may result in inequitable or erroneous conclusions, underscoring the necessity for meticulous data curation and model assessment [8]. Furthermore, the efficacy of these AI technologies must be thoroughly evaluated through extensive clinical trials involving varied patient groups prior to their widespread use in clinical practice [20]. Ethical and data privacy issues associated with AI utilization in healthcare, especially with the management of sensitive patient information, require meticulous consideration and resolution [5].

Future research should concentrate on investigating innovative pre-trained models and architectures specifically designed for medical applications, particularly in cardiology [28]. Integrating multi-modal data sources, including imaging data, ECG signals, clinical notes, and genetic information, may yield more complete and precise models [19]. It is essential to prioritize the enhancement of model interpretability and explainability to bolster clinician trust and aid in the detection of potential biases [20]. Ultimately, executing extensive, prospective clinical studies is crucial to confirm the efficacy and safety of pre-trained AI models for myocardial infarction prediction and categorization in actual clinical environments [29].

Conclusion

This narrative review has offered a thorough examination of the existing research on the utilization of pre-trained artificial intelligence models for predicting and classifying myocardial infarction. The literature assessment indicates that pre-trained AI models, especially those utilizing CNN and transformer architectures, had considerable potential to alter the prediction and diagnosis of MI. These models provide high accuracy, early detection capabilities, and the opportunity for tailored strategies, while efficiently utilizing data and computational resources.

It is essential to acknowledge the existing limitations and challenges, including data quality and accessibility, model interpretability, potential biases, and the necessity for comprehensive clinical validation. Ongoing research must concentrate on addressing these challenges, creating innovative models and data integration techniques, and ensuring the ethical and responsible implementation of AI in healthcare. Translating promising advances in this science into clinically relevant tools has the potential to greatly improve patient outcomes, lower the burden of myocardial infarction, and usher in a new age of precision cardiology.

Conflict of Interests
The authors declare that there is no conflict of interest in the study.

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