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REVIEW ON PREDICTION OF HEART ATTACK USING TRADITIONAL AND ARTIFICIAL INTELLIGENCE APPROACHES

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ABSTRACT: *Heart attack, clinically known as acute myocardial infarction (AMI), remains a leading cause of global mortality, largely due to delayed diagnosis and complex cardiovascular risk factors. Early and accurate prediction is essential for reducing morbidity and improving patient outcomes. Traditional approaches, including risk-score models, biomarker analysis, and imaging techniques, provide useful insights but often lack the precision and adaptability required for real-time clinical decision-making. Recent advances in artificial intelligence (AI), particularly deep learning, have shown strong potential in identifying complex patterns within large medical datasets. This paper presents a systematic review of traditional, machine learning, and deep learning techniques for heart attack prediction. Key models such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Deep Belief Networks (DBN), and Denoising Autoencoders (DAE) are evaluated based on model design, dataset characteristics, performance metrics, interpretability, and clinical applicability. Findings indicate that hybrid deep learning models generally outperform standalone approaches in accuracy and robustness. However, challenges remain in model explainability, dataset diversity, real-world validation, and clinical integration. This review highlights the potential of AI-driven systems to enhance early detection and support personalized cardiovascular care, while emphasizing the need for interpretable, scalable, and deployment-ready solutions.*

KEYWORDS: Acute Myocardial Infarction, Artificial Intelligence in Healthcare, Clinical Decision Support Systems, Heart Attack Prediction.

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INTRODUCTION

A heart attack, medically referred to as acute myocardial infarction (AMI), is among the most serious forms of cardiovascular disease (Pawan et al., 2024). It arises from a disruption in blood flow to the heart muscle, causing damage to the heart tissue. The diagnosis of heart disease also remains a challenging task. Some of the signs of a possible heart attack include: an intense feeling of pressure, tightness, heaviness, or pain in the middle of the chest that may persist for several minutes or recur after easing off. It may also include aching in either arm or both arms, your back, neck, jaw, or stomach. and breathlessness that may or may not be accompanied by chest discomfort, as well as other symptoms like nausea, cold sweat, or lightheadedness (South Texas, 2024). Several factors—such as high cholesterol, inherited heart conditions, hypertension, inadequate physical activity, smoking, and obesity—can contribute to the development of heart disease. Heart attacks primarily take place when blood circulation to the coronary arteries becomes blocked (Neha *et al.,* 2022).

Heart disease stands as the forefront reason for death rate globally, with heart attacks being a prevalent and serious result of this disease. The timely and exact prediction of heart attacks can predominantly lessen death rates by initiating early,, prompt, and exact medical care (Nina, 2025).

Timely interventions, such as angioplasty and coronary artery bypass grafting, can help reestablish blood flow to the heart. Medications such as thrombolytics can break down blood clots that hinder the coronary arteries (Elias and Maria, 2024). However, deep learning has shown significant promise in medical applications due to its ability to uncover intricate patterns in large datasets (Esteva *et al.,* 2019).

The risk factors peculiar to cardiovascular diseases can be determined and can be intensified to develop an efficient predictive model for heart attack risk (Abbas and Javad, 2016).

The prediction of heart attack starts with acquisition and processing of a robust set of medical data, emphasizing critical elements such as gender, age, history, cholesterol, and blood pressure, specific to the family medically. These elements are drawn from raw data to train deep learning models that can detect trends and predict the likelihood of a heart attack (Hussain and Mohammed*,* 2025).

The performance of a deep learning models is assessed using evaluation metrics such as accuracy, recall, precision, F1-score, and the Area Under the Curve (Kumar *et al.,* 2024). There are lots of benefits of deep learning for heart attack prediction. and the models are interpretable and accessible for healthcare professionals.. However, their potential for accurately predicting heart attacks has been underexplored

The findings of this review work can be used as a basis to reduce the financial burden on healthcare systems by minimizing the need for emergency care, hospitalizations, and long-term treatments associated with heart attacks, by employing a hybrid approach to prediction and prevention of heart attacks and to promote prediction accuracy, improve patient outcomes, and facilitate a proactive approach to managing cardiovascular health.

This paper reviews and analyses traditional and artificial intelligence approaches for prediction of heart attacks. Sections 2-5 discuss the Overview of Heart Attack, traditional Methods for Heart Attack Prediction, Overview of Deep Learning, deep learning models used for Heart

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Attack Prediction. Section 6 presents the review of Previous Studies on Heart Attack Prediction Using Artificial Intelligence Approaches and their summary, while Section 7 analyses the reviewed works. Section 8 concludes the review.

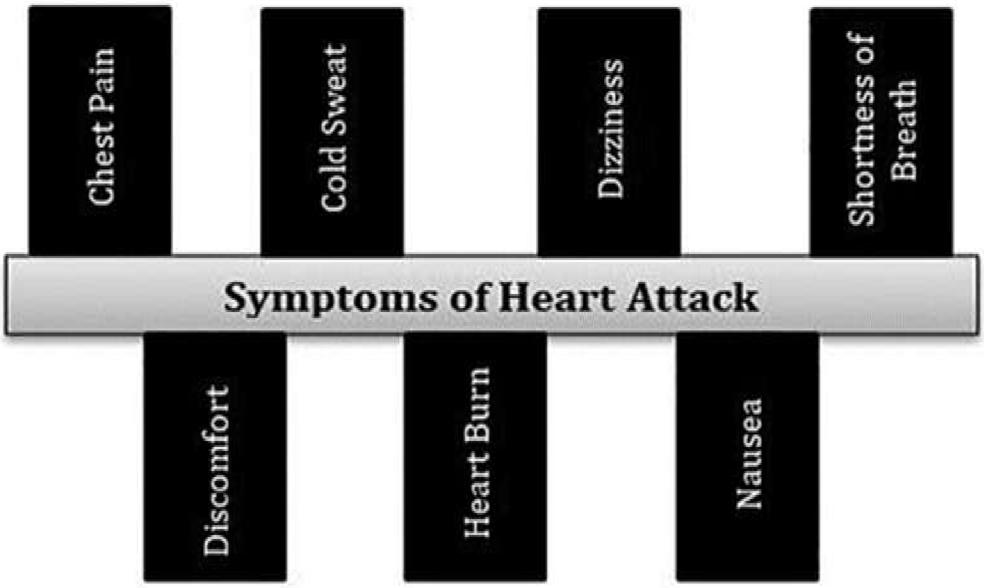
Overview of Heart Attack

Heart attack is a prominent cardiovascular disease that has killed a lot of people globally owing to many reasons. It happens when the blood supply to a section of the heart is obstructed long enough to cause damage to the heart muscle. And this is called myocardial infarction. The sudden stop of blood flow to a part of the heart muscle causes a heart attack and seldom arises without chest pain resulting to shortness of breath, pressure, or pain in the upper abdomen. The increasing heart attack incidence among younger populations, along with the constraints of current medical tools, financial burdens, and diagnostic predicaments, stressed the need for proactive measures (Mohammad *et al.,* 2024).

Symptoms of a Heart Attack

The symptoms of a heart attack can vary among individuals but commonly include: (a) A sensation of pressure, fullness, pain in the middle of the chest or squeezing (b) Discomfort or pain that may extend to one or both arms, as well as the back, jaw, neck, or abdomen (c) Shortness of breath, which may occur with or without chest discomfort. (d) Additional symptoms, such as cold sweats, nausea, or dizziness, which may indicate autonomic nervous system involvement. Figure 1 presents symptoms of a heart attack.

Figure 1: Symptoms of Heart Attack (Mohammad *et al.,* 2024).



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Causes of Heart Attack

Most heart attacks, or myocardial infarctions, occur due to the formation of a blood clot that blocks one of the coronary arteries that deliver oxygen-rich blood to the heart muscle. When blood flow becomes obstructed, oxygen deprivation leads to the death of myocardial cells . The occurrence of heart attacks is not always predictable, as they can happen during rest, sleep, sudden physical exertion, exposure to cold weather, or significant emotional or physical stress. These stressors may increase myocardial oxygen demand or cause hemodynamic changes that trigger a cardiac event. Atherosclerosis is the primary underlying cause of heart attacks. It involves the accumulation of plaque, composed of cholesterol and other cellular components, within the walls of the coronary arteries (TGH, 2025). When a plaque breaks open, it can trigger the development of a blood clot, which may obstruct blood flow even further and potentially cause a heart attack. Figure 2 shows one of the causes of a heart attack.

Figure 2: One of the Causes of Heart Attack, NIH (2022)

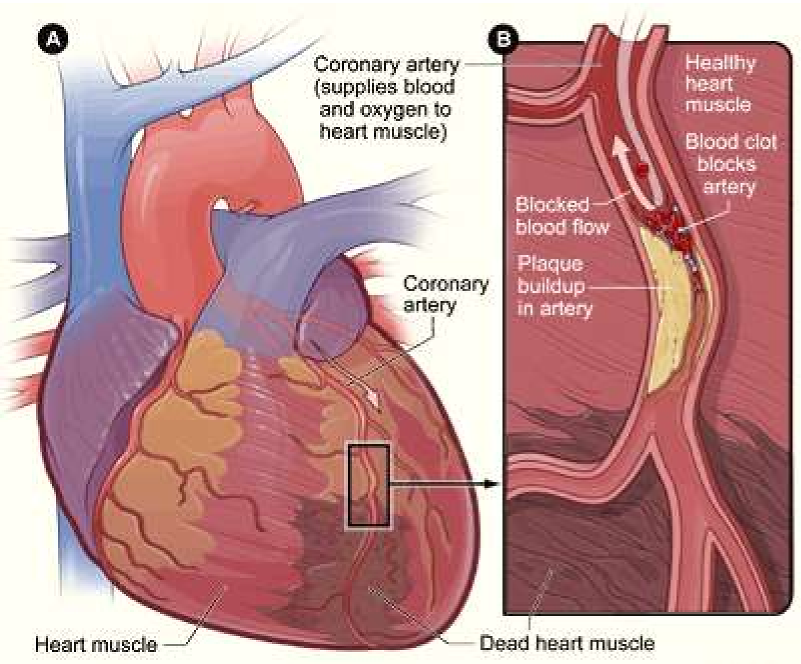

Figure 2A illustrates the area of damage (dead heart tissue) resulting from a heart attack, while Figure 2B depicts a coronary artery containing plaque deposits and a blood clot.

Diagnosis of Heart Attack

The diagnosis of a heart attack involves several key factors, and confirming it may take time, often requiring a few days to be certain. The primary diagnostic elements include the following: (a) Chest pain, Cleveland Clinic (2025) characteristics: The intensity, duration, and nature of chest pain—typically described as pressure, tightness, or discomfort—are significant indicators. Persistent or recurring chest pain raises suspicion of a heart attack. (b) Electrocardiogram (ECG): An ECG is a fundamental diagnostic tool, providing information about the heart's electrical activity. Key abnormalities, such as ST-segment elevation, are critical in diagnosing a heart attack. (c) Blood tests: Blood tests are essential for confirming a

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heart attack. Elevated levels of cardiac biomarkers, especially troponins, indicate heart muscle damage and help in confirming the diagnosis.

Treatment of Heart Attack

Prompt medical intervention is essential in reducing myocardial damage during a heart attack, as early treatment significantly improves patient outcomes. Immediate medical care is administered even before a definitive diagnosis to stabilize the patient and prevent further cardiac injury. These initial interventions include aspirin, which acts as an antiplatelet agent to prevent further clot formation, oxygen therapy to enhance oxygen delivery to ischemic myocardial tissue, nitroglycerin to reduce the heart's oxygen demand and improve blood circulation through the coronary arteries, and analgesics to relieve chest pain. Once a heart attack is confirmed, treatment strategies focus on rapidly restoring blood flow to the affected coronary arteries. The two primary approaches are thrombolytic therapy and percutaneous coronary intervention, commonly referred to as coronary angioplasty. Thrombolytic therapy involves administering fibrinolytic agents to dissolve occlusive thrombi, whereas PCI is a catheter-based procedure that mechanically reopens blocked arteries, often with stent placement, to restore normal blood flow. Both treatments have been shown to significantly reduce mortality and improve long-term cardiac function in patients with acute myocardial infarction.

Preventing Recurrent Heart Attacks

Preventing recurrent heart attacks is essential for reducing long-term mortality and improving the quality of life for individuals with cardiovascular diseases (CVDs). Several strategies, including lifestyle changes, pharmacological treatments, revascularization procedures, and ongoing medical monitoring, have been shown to effectively lower the risk of subsequent heart attacks (AHA, 2025). These approaches are vital in preventing further cardiac events and improving patient outcomes.

(a) Lifestyle Modifications: A heart-healthy lifestyle is fundamental in reducing the risk of recurrent heart attacks. A diet rich in whole grains, lean proteins, fruits, and vegetables; regular physical activity, alongside maintaining a healthy weight, helps manage risk factors such as diabetes, high blood pressure, and hyperlipidemia. Smoking cessation is particularly important, as tobacco use significantly contributes to the onset of coronary artery disease and increases the risk of further heart attacks. In addition, reducing alcohol consumption, managing stress, and prioritizing sleep hygiene have been shown to contribute to heart disease prevention.

(b) Pharmacological Interventions: Pharmacological therapies play a pivotal role in preventing recurrent heart attacks. Antiplatelet agents, such as aspirin, are routinely prescribed to reduce the formation of blood clots, lowering the chances of another heart attack. Statins, which help reduce cholesterol levels, are essential in preventing the progression of atherosclerosis, thereby lowering the risk of a future heart attack.

(c) Revascularization Procedures: For individuals with advanced coronary artery disease, revascularization procedures such as coronary angioplasty with stent placement are effective in restoring blood flow to the heart, significantly reducing the risk of recurrent heart attacks. These interventions are often combined with medical therapy to optimize patient outcomes. In more advanced cases, coronary artery bypass grafting (CABG) may be necessary to improve circulation and prevent further cardiac events.

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(d) Consistent monitoring and timely identification are essential. to managing patients at high risk for recurrent heart attacks. Routine check-ups to assess heart function, adjust medications, and monitor other risk factors, such as diabetes and hypertension, are critical for preventing complications. Furthermore, wearable health devices and telemedicine are becoming invaluable tools for monitoring heart health (real-time), allowing for timely interventions when necessary.

Traditional Methods for Heart Attack Prediction

Conventional approaches for predicting heart attacks depend on evaluating well-established cardiovascular risk factors, clinical assessments, and diagnostic tests. These methods help estimate the risk of having a heart attack based on medical history, lifestyle choices, and physiological parameters.

Risk Factor-Based Prediction Models

Several scoring systems have been developed to quantify an individual's heart attack risk:

(a) Framingham Risk Score (FRS): This is among the most commonly employed tools for estimating an individual's 10-year risk of cardiovascular disease. It considers variables such as age and gender, systolic and diastolic blood pressure, total and HDL cholesterol levels, smoking status, and history of diabetes. Although FRS is widely applied, it has limitations in certain ethnic groups and younger populations

(b) Reynolds Risk Score (RRS): This is an enhancement of FRS; the Reynolds Risk Score uses High-sensitivity C-reactive protein (hs-CRP). Family history of cardiovascular disease. Studies have suggested that RRS improves risk prediction, particularly in women.

(c) Systematic Coronary Risk Evaluation (SCORE): The SCORE model, commonly used in Europe, estimates an individual's long-term cardiovascular disease (CVD) risk. It focuses on mortality risk over a 10–30 years period, making it useful for long-term prevention strategies.

Clinical Evaluations and Diagnostic Tests

Traditional heart attack prediction also involves various diagnostic tests:

(a) Electrocardiogram (ECG/EKG): This measures electrical activity of the heart and detects abnormal rhythms, signs of ischemia (insufficient blood supply), and previous silent heart attacks. While ECGs are crucial for diagnosing existing cardiac conditions, they may not always predict heart attacks in asymptomatic individuals.

(b) Stress Testing: Stress tests evaluate the heart's performance under exertion using exercise treadmill tests, and pharmacological stress testing. These tests help identify ischemic changes but have moderate sensitivity in predicting future cardiac events.

(c) Coronary Angiography: A more invasive approach, this is typically reserved for high-risk individuals and those already experiencing symptoms of coronary artery disease.

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Biomarker Analysis

Certain blood-based biomarkers have been linked to heart attack risk:

(a) Troponin (cTnI and cTnT): Elevated levels indicate myocardial damage and are crucial for diagnosing ongoing heart attacks. (b) High-Sensitivity C-Reactive Protein (hs-CRP): A marker of inflammation, hs-CRP is associated with increased cardiovascular risk. (c) Lipoprotein(a) [Lp(a)]: High Lp(a) levels are linked to a higher likelihood of atherosclerosis and coronary events.

While these biomarkers are useful, they are usually used in conjunction with other assessments rather than as standalone predictors.

Imaging Techniques

Advanced imaging techniques improve risk assessment beyond traditional methods:

(a) Carotid Intima-Media Thickness (CIMT) Measurement: Measures artery wall thickness via ultrasound, providing insight into early atherosclerosis

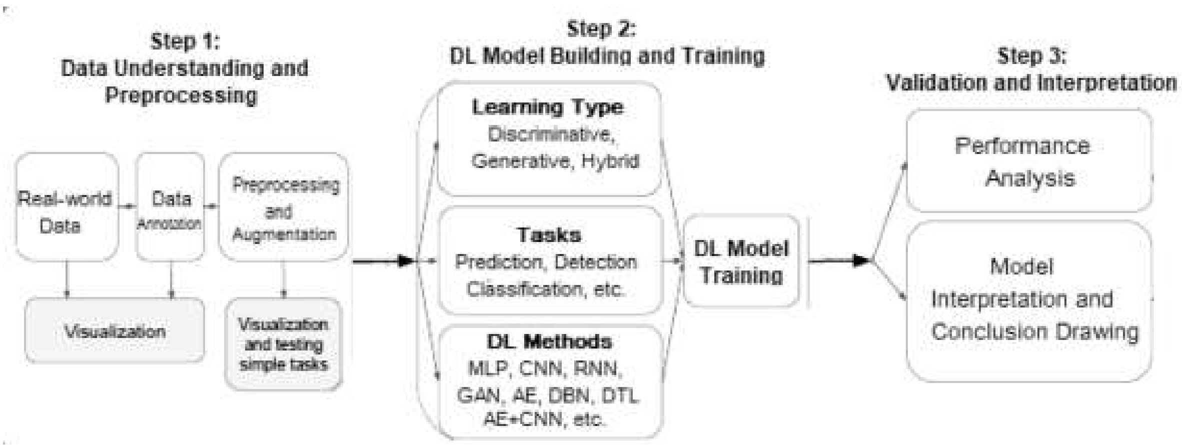
(b) Coronary Artery Calcium (CAC) Scoring: A CT imaging test used to identify calcium buildup in the coronary arteries, which correlates with increased cardiovascular risk.

These methods offer a more precise risk evaluation but are not always used in routine clinical assessments due to cost and accessibility.

Overview of Deep Learning

Deep learning (DL) algorithms have recently evolved from machine learning and soft computing methods. Currently, DL has gained prominence due to its intelligence, efficient learning capabilities, accuracy, and robustness in model development. A DL model typically undergoes processing steps similar to those used in machine learning modeling. Figure 3 shows the workflow of DL.

Figure 3: A typical DL. A three-stage workflow is adopted to tackle real-world problems (Taye, 2023).



However, there are important elements that are peculiar and are considered important prior to working on DL modeling to address practical, real-world challenges. They are (i) data

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dependencies: DL is specifically dependent on a robust volume of data to develop a model driven by data for a specific problem application. This is to enhance model accuracy. The more the data, the better the improved model performance to solve the problem at hand. (ii) Hardware Dependencies: The Deep Learning algorithms need vast calculation processes involved in training a model with robust datasets. As vast as the computations, the more the advantage of a Graphical Processing Unit (GPU) over a Central Processing Unit (CPU); the GPU is predominantly applied for optimizing the operations efficiently. (iii) Feature Engineering Process: This involves deriving meaningful features—such as attributes—from unprocessed data through the application of domain expertise (Deng & Dong, 2014). (iv) Model Training and Execution Time: Overall, training a deep learning model is time-consuming because these algorithms contain a large number of parameters, resulting in longer training durations. (v) Black-box view and Interpretability: Interpretability is a major concern when contrasting deep learning with conventional machine learning. It is often difficult to clarify how a deep learning model arrives at its results, making it operate like a "black box."

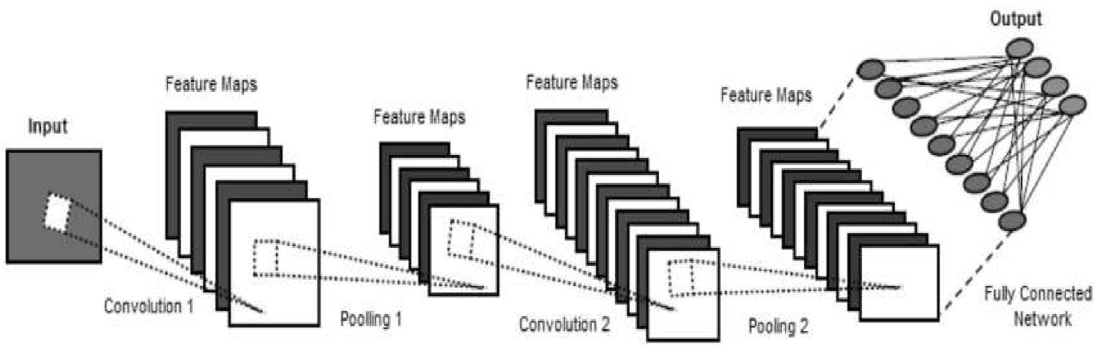
Deep Learning Models Used for Heart Attack Prediction

The following are some of the neural network and deep learning models employed for the prediction of heart attacks in literature by researchers. These include Convolutional neural network (CNN), Long Short-Term Memory (LSTM), Recurrent neural network (RNN), Denoising autoencoder (DAE), and Deep belief networks (DBNs), which are the most predominantly used methods globally. Meanwhile, some of the researchers have also employed Machine learning approaches for prediction of heart attacks.

Convolutional Neural Network

This is one of the most familiar structures of Deep Learning methods globally used for image processing applications. It has three (3) types of layers with various convolutional, pooling, and fully connected layers (Mosavi *et al.,* 2019) (Figure 4). Each convolutional neural network (CNN) Bezdan and Džakula (2019). is trained through two main phases: the feed-forward phase and the back-propagation phase. Some of the most widely used CNN architectures include AlexNet (Krizhevsky et al., 2012), ZFNet (Zeiler and Fergus, 2014), VGGNet (Simonyan and Zisserman, 2014), GoogLeNet (Szegedy et al., 2015), and ResNet (He et al., 2016). Although CNN is mainly utilized for image processing applications but has also found applications in energy, electronics systems, computational mechanics and remote sensing.

Figure 4: Typical Convolutional Neural Network Structure. Mosavi *et al.* (2019)



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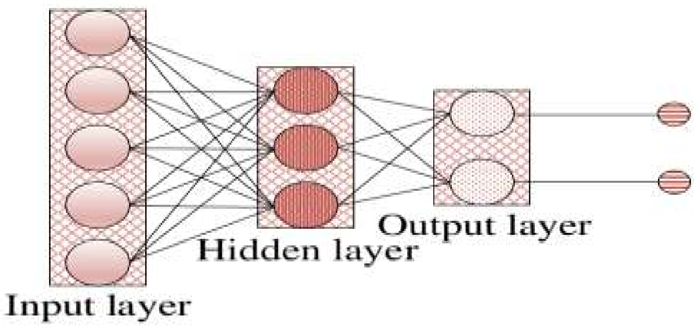
Recurrent Neural Networks

It is specifically intended to identify ordered patterns in data, including speech and textual data and handwriting, and it supports feedback (loop) connections that enable recurrent computations to process input data sequentially. Essentially, it is a conventional neural network extended across time, where connections are passed to subsequent time steps rather than to different layers within the same step. The hidden units retain previous inputs in a state vector, which is then used to compute the network's outputs. A typical RNN structure is shown in Figure 5.

Figure 5: A Typical RNN Structure Min *et al.*(2017)

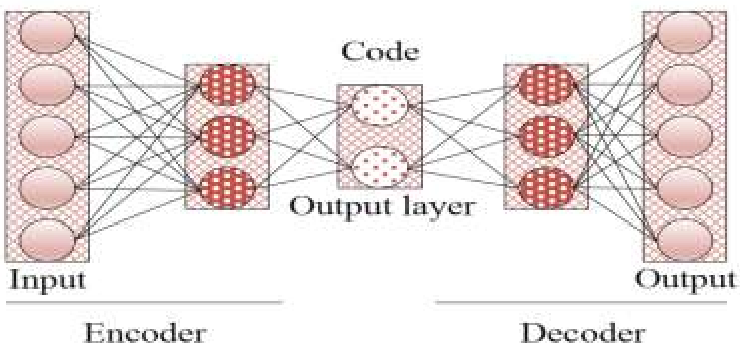


RNN is a predominantly newer deep learning method, and that is all the more reason the domain of applications is still infant. However, hydrological prediction, energy, expert systems, economics, and navigation are recent domains of applications.

Denoising AutoEncoder

A denoising autoencoder is a modified form of the standard autoencoder designed to enhance feature representation by adjusting the reconstruction objective, thereby minimizing the chances of the model simply learning an identity mapping. It is an extension of AutoEncoder as an asymmetrical neural network for learning features used for noisy datasets. It consists of three primary layers—the input, encoding, and decoding layers. A DAE can also be combined or stacked to capture higher-level features. It is widely used in cybersecurity, energy forecasting, banking, image classification, fraud detection, and speaker verification domains. A typical structure of a Denoising AutoEncoder method is shown in Figure 6.

Figure 6: A Typical Structure of a Denoising AutoEncoder Method Al Rahhal *et al.* (2016)



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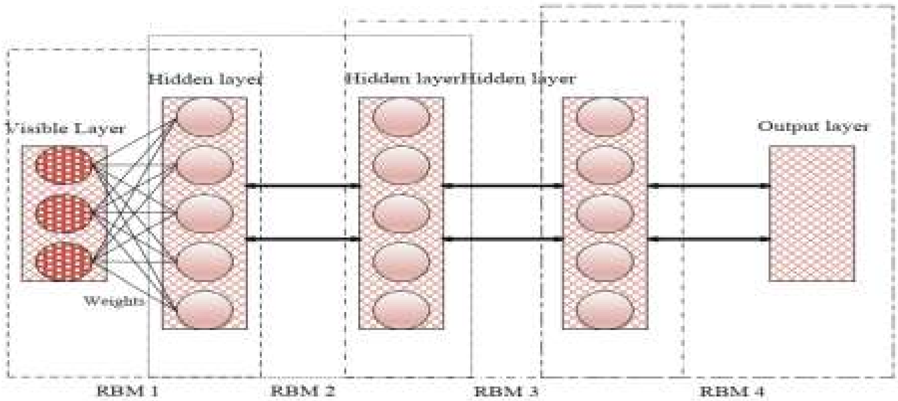
Deep Belief Networks (DBNs)

It is a method of deep learning (Taye, 2023) that is utilized for highly configured sphere learning of data and consists of more than one layer, with connections linking different layers but no connections among units within the same layer. It is regarded as a hybrid multilayered neural network, including directed and undirected connections. A DBN is capable of learning hierarchical representations of input data due to its deep architecture.The core concept of a DBN is to first train feed-forward neural networks in an unsupervised manner using unlabeled data, and then fine-tune the network with labeled data (Zhu and Zhang, 2020). DBNs are composed of Restricted Boltzmann Machines (RBMs), which are trained sequentially in a greedy manner. Each RBM layer interacts with both the preceding and succeeding layers, and the overall model consists of a feed-forward network stacked with multiple RBM layers. An RBM itself comprises only two layers: a visible layer and a hidden layer. Figure 7 shows a prototype deep belief network architecture.

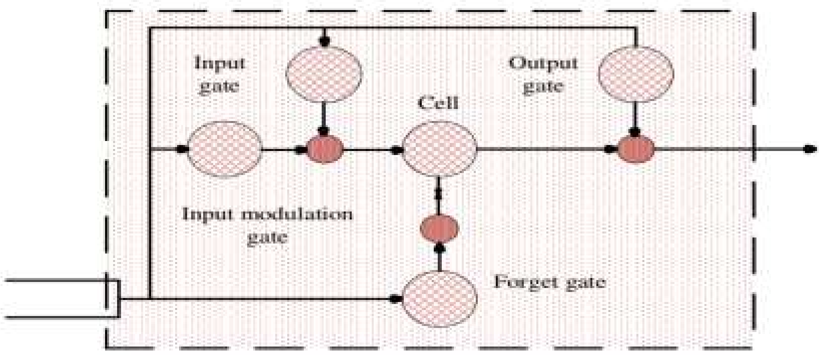
Figure 7: A Prototype Deep Belief Network Architecture Vieira *et al.*(2017)



Long Short-Term Memory (LSTM)

This type of RNN employs feedback links to support general computation, making it effective for recognizing sequences and patterns and for handling image processing tasks. Generally, an LSTM (Figure 8) is composed of three main components: the input gate, output gate, and forget gate (Waqas and Humphries, 2024). The LSTM regulates when new information is allowed into the cell and determines how information from previous time steps is retained.

Figure 8: A Prototype of LSTM Structure Mosavi et al. (2019)



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Review of Previous Studies on Heart Attack Prediction Using Artificial Intelligence Approaches

This section reviews related works that have been done relevant to the present study globally. Several researchers have worked on heart attacks using deep learning models.

Harpreet and Gnaneswar (2024) conducted research on Prediction of Heart Attacks Based on Data Analysis with Deep Leaning Approach. Preprocessing of interchanged patient data, consisting of medical perspectives and clinical measurements, coupled with the use of deep learning models such as Naïve Bayes and Decision Trees, was used. The results show that deep learning can accurately predict heart events, with strong performance metrics, and also highlight its clinical potential and suggest future improvements for heart risk prediction.

Elias and Maria (2024) researched the application of Deep Learning for Heart Attack Prediction with explainable artificial Intelligence. The study used and compared the performance of CNN, RNN, MLP, GRU,and LSTM, as well as a hybrid model, to predict heart attacks. The study concluded that the hybrid model has the highest performance as compared to the other models, with an accuracy of 91%, a precision of 89%, a recall of 90%, and an F1-score of 89%.

Pokkuluri and Usha (2023) worked on Deep Learning for Heart Attack Prediction. The study used a robust dataset from demographic details, medical background, lifestyle characteristics, and clinical indicators. The model's effectiveness was evaluated on an independent test dataset using metrics such as accuracy, precision, recall, and AUC-ROC, with an accuracy of 80%, specificity of 0.78%, sensitivity and F1 Score of 82%.

Neha *et al*. (2022) researched machine learning–based heart attack prediction: a study was carried out on heart attack prediction using an ML-based framework (ML-HAP), where heart attack risk factors were analyzed, and predictions were made employing machine learning techniques such as Support Vector Machines, Logistic Regression, Naïve Bayes, and XGBoost. XGBoost achieved an AUC of 0.94, while Logistic Regression scored 0.92. These ML models, especially boosting algorithms, were very effective in predicting heart attack symptoms.

Muhammad *et al. (2021)* worked on research titled " An Efficient SMOTE-Based Deep Learning Model for Heart Attack Prediction. The study presents a cost-effective way forward to predict heart attack with high accuracy and reliability, and the use of UCI dataset using different machine learning algorithms was used. The findings indicate that, among all the machine learning algorithms, the SMOTE-based artificial neural network performed best performed better than other models.

Abbas and Javad (2016) researched on prediction of heart attacks in patients using AI (Artificial Intelligence). The result identifies that artificial intelligence algorithms—such as self-adaptive neural networks from fuzzy clustering, clustering combined with SVM classification, and fuzzy rule discovery—have shown successful results in analyzing heart patient data.

Mustafa Al-Asadi et al (2024) carried out research on heart attack analysis and prediction using machine learning on heart-related data that includes genetics, lifestyle, medical history, and body measurements, gathered from different medical sources. The result shows that after testing several machine learning models to predict heart attacks, Random Forest performed best with 90% accuracy, showing its strength in handling complex data. Logistic Regression

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and SVM both achieved 85%, proving effective despite being simpler models. Decision Trees had the lowest accuracy at 77%, but they offered clear insights into which features matter most.

Manish et al. (2025) conducted a research work on Hybrid Machine Learning and Deep Learning Approach for Heart Attack Prediction using IoT Sensors, Gradient Boosting. The results demonstrate that the hybrid approach integrating Random Forest and LSTM outperforms all standalone models across accuracy, precision, recall, F1-score, and AUC. Notably, the hybrid model attained an accuracy of 96.5%, exceeding that of the LSTM model (95.4%) and Gradient Boosting Machines (GBM) (93.2%).

Nooka et al (2024) conducted research using a deep learning (The system smoothly combines data from Google Fit, health records, wearable devices, and user inputs). The results indicate that the model exceeds traditional methods, showing remarkable performance in evaluating heart attack risk.

Madhu and Ramesh (2021) researched on prediction of heart attack using SVM. This survey explores the use of the SVM binary classifier model implemented in Python, along with various predictive models aimed at achieving high accuracy and low computational complexity. A quadratic kernel function is applied in the SVM to create a hyperplane for a two-class classifier. However, the expected accuracy was not achieved.

Prakash et al. (2023) worked on Unveiling Key Predictors for Early Heart Attack Detection using Machine learning, and XAI with LIME was used to improve accuracy. The "Attack" and "Normal" data were labeled as 1 and 0, then standardized. Four algorithms—ABC, RF, GBC, and LGBM—were applied to predict whether a sample was "Attacked" or "Normal." LGBM slightly outperformed the others with a training accuracy of 99.33%. When comparing the performance of the four algorithms, RF, GBC, and LGBM showed similar results in precision (around 97.03%), recall (96.04%), and F1-score (0.97). The use of stratified sampling ensured that both the training and testing datasets preserved the same proportional distribution of classes, positive and negative cases, to prevent bias.

The summary of reviewed literature (Table 1) on heart attack prediction using both traditional and AI-based methods is organized based on the source, main focus, models or systems used, dataset sources, key findings, and identified research gaps.

Table 1: Summary of Related Works

Author	Focus	Models/Systems Used	Sources of Data Set	Result	Gap
Harpreet and Gnaneswar (2024)	Heart attack prediction using DL	Naïve Bayes, Decision Trees	Interchanged patient data	Strong performance metrics	Dataset source not standardized; limited detail on dataset size; possible generalization issues.
Elias and Maria (2024)	Explainable AI for heart	MLP, CNN, RNN, LSTM, GRU, Hybrid	Not specified	Hybrid: Acc=91%, Prec=89%,	Dataset details missing;

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	prediction			Rec=90%, F1=89%	unclear on external validation; limited clinical trial evidence.
Biao et al. (2024)	Cardiovascular disease diagnosis	Deep learning + Ant colony optimization	Big medical data	Intelligent diagnosis model	No performance metrics reported; unclear scalability in real-time settings.
Mansoor et al. (2023)	CVD prediction	LSTM	UCI dataset (14 variables)	LSTM gave higher accuracy, less time	Small dataset with limited features; lacks multi-center validation.
Pokkuluri and Usha (2023)	Heart attack prediction	Deep Learning	Demographic + medical data	Acc=80%, Sens=82%, F1=82%, Spec=78%	Accuracy moderate; may underperform in high-risk cases; unclear handling of imbalanced data.
Saravanan et al. (2023)	Active ML for CVD prediction	LVQ + 8 classifiers	UCI-repository	LVQ: Acc=98.7%	Possible overfitting on small UCI dataset; generalizability uncertain.
Omankwu and Ubah. (2023)	Hybrid DL model	RNN, DNN	UCI (303 angiography patients)	RNN=98.23%, DNN=98.5%	High accuracy on small dataset; real-world robustness untested.
Neha et al. (2022)	ML-based heart attack prediction	SVM, LR, Naïve Bayes, XGBoost	Not specified	XGBoost AUC=0.94, LR=0.92	Dataset details missing; feature selection

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					process not discussed.
Muhammad et al. (2021)	SMOTE-based DL	ANN + SMOTE	UCI dataset	Performed better than others	Dependent on synthetic oversampling; may not reflect real patient variation.
Abbas & Javad (2016)	AI for patient prediction	Fuzzy Clustering + SVM	Patient data	Effective AI-based prediction	No accuracy metrics; applicability to large datasets untested.
Mustafa Al-Asadi (2024)	ML on heart data	RF, LR, SVM, DT	Mixed medical data	RF=90%, LR/SVM=85%, DT=77%	No mention of external validation; possible data source heterogeneity.
Alexander and Wang (2017)	Big Data & mining for heart attack	Big Data, Data Mining	Not specified	Scalable and high-quality system	No accuracy values provided; lacks model performance benchmarking.
Manish et al. (2025)	Hybrid ML/DL with IoT	RF + LSTM + GBM	IoT sensor-based	Hybrid=96.5%, LSTM=95.4%, GBM=93.2%	Reliance on IoT sensors may limit application in low-resource settings.
Nooka et al. (2024)	Wearables & DL	Deep Learning	Google Fit, EHR, wearables	Outperformed traditional methods	Privacy and data integration challenges; device dependency.
Madhu and Ramesh (2021)	SVM for prediction	SVM	Python model	Low accuracy	Model choice may be suboptimal; requires more advanced algorithms.

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Prakash et al. (2023)	XAI for early heart detection	ABC, RF, GBC, LGBM	Labeled "Attack/Normal"	LGBM=99.33 %, F1=0.97	Potential overfitting; needs testing on unseen real-world data.

Analysis of the Reviewed Literature

The reviewed studies collectively demonstrate significant progress in applying machine learning (ML), deep learning (DL), and hybrid computational models for heart attack and cardiovascular disease (CVD) prediction. A consistent trend across the literature is the widespread use of classical ML models such as Logistic Regression, SVM, Decision Trees, Random Forests, and Naïve Bayes, as well as advanced architectures like LSTM, CNNs, RNNs, GRUs, and hybrid IoT-enabled systems. These techniques generally report high accuracy, sensitivity, and F1 scores—often exceeding 90% in many deep learning and hybrid approaches. For instance, hybrid architectures or deep learning models proposed by Elias and Maria (2024), Omankwu et al. (2023), and Prakash et al. (2023) consistently report accuracies above 95%, suggesting the potential of advanced neural networks for early detection.

However, several important methodological issues recur across the works. A major concern is the heavy reliance on small and homogeneous datasets, particularly the UCI Cleveland dataset, used in studies by Mansoor et al. (2023), Saravanan et al. (2023), Muhammad et al. (2021), and Omankwu et al. (2023). This dataset has only 303 records and limited feature diversity, raising concerns about overfitting and poor generalization to real-world health settings. Additionally, many studies omit critical dataset details—such as sample size, demographic distribution, or data acquisition procedures—making it difficult to assess reliability, replicability, and clinical relevance. Authors such as Neha et al. (2022),, and Biao et al. (2024) fail to specify dataset characteristics or performance metrics, limiting the credibility of their findings.

Another recurring pattern is the lack of external validation and multi-center evaluation. Most models, despite reporting high accuracy, are only tested on single-source or synthetic datasets (e.g., SMOTE-based augmentation in Muhammad et al., 2021). This raises concerns about whether their performance would remain consistent on diverse populations, noisy clinical data, or real-time monitoring environments. Similarly, IoT- and wearable-driven systems (Manish et al., 2025; Nooka et al., 2024) show promise due to continuous monitoring capabilities but face constraints related to device dependency, connectivity stability, privacy risks, and accessibility in low-resource regions.

Interpretability also remains a significant gap. Although explainable AI (XAI) approaches are emerging, such as those discussed by Elias and Maria (2024) and Prakash et al. (2023), interpretability is still limited in most deep learning studies. Clinicians need transparent and trustworthy models, yet many high-performing CNN/LSTM models lack mechanisms for explaining diagnostic decisions.

Overall, the literature reveals strong model performance but exposes persistent issues regarding dataset quality, transparency, clinical applicability, interpretability, and generalization. These

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limitations highlight the need for robust, real-time, and externally validated AI-based heart attack prediction systems—particularly those deployable on edge devices, scalable across diverse populations, and aligned with clinical decision-making processes.

CONCLUSION

This review demonstrates that both traditional clinical methods and modern artificial intelligence techniques play important roles in predicting heart attacks, but AI—particularly deep learning—offers clear advantages in handling complex, high-dimensional medical data. Traditional approaches, such as risk-factor scoring systems, diagnostic testing, and biomarker analysis, remain valuable for clinical decision-making but are limited by their reliance on predefined risk structures and moderate predictive power. In contrast, deep learning models—including CNN, RNN, LSTM, DBN, and DAE—show strong capability to uncover hidden patterns, integrate diverse patient features, and deliver superior predictive accuracy.

The reviewed studies consistently confirm that AI-based models outperform traditional models in prediction precision, recall, and overall diagnostic reliability. Hybrid deep learning architectures, in particular, demonstrate the highest performance, indicating that combining multiple networks can better capture the nonlinear dependencies associated with cardiovascular risks. Despite these strengths, interpretability and data dependence remain key challenges that must be addressed for broader clinical adoption.

Overall, this review emphasizes that integrating traditional medical expertise with advanced AI approaches provides a more robust pathway for early detection and prevention of heart attacks. The insights from this work can support the development of cost-effective prediction systems, reduce the burden on healthcare resources, improve patient outcomes, and strengthen proactive cardiovascular disease management. Continued research into explainable, scalable, and clinically validated AI models is essential for the next phase of innovation in heart attack prediction.

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