

A Deep Reinforcement Learning Approach for Proactive Cardiovascular Risk Prediction in IoT-Enabled Cloud Systems

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Abstract

In recent years, cardiovascular diseases (CVDs) have emerged as a leading cause of mortality worldwide, necessitating advanced and proactive health monitoring systems. This paper presents the design and implementation of an IoT-based cardiovascular health monitoring system that leverages cloud computing and artificial intelligence for real-time analysis. The system integrates IoT-enabled wearable sensors to continuously capture vital signs, such as heart rate, blood pressure, transmitting the data to a cloud-based infrastructure for processing. A novel Deep Deterministic Policy Gradient (DDPG)-enabled model is employed to predict potential cardiovascular anomalies, providing personalized insights and early warnings to patients. The DDPG model enhances the system's decision-making by enabling continuous learning and adaptation to individual health patterns, leading to more accurate predictions and recommendations. The cloud architecture ensures scalability, data security, and real-time access to health data, that leads to low-latency responses for critical alerts. The proposed system's performance is evaluated through simulations and real-world testing, demonstrating its efficacy in early detection of cardiovascular events, reduced false alarms, and improved patient outcomes. This proactive monitoring solution represents a significant step forward in leveraging IoT, AI, and cloud computing for personalized healthcare and disease prevention.

Keywords: *IoT, Cloud Computing, DDPG models, Cardiovascular Diseases*

I. Introduction

Heart disease is a prevalent and life-threatening condition that affects millions of people worldwide. Early detection and proactive management of cardiovascular health can significantly improve outcomes and reduce the impact of heart-related illnesses. In recent years, the convergence of Internet of Things (IoT) technology and Artificial Intelligence (AI) with Machine Learning (ML) algorithms has opened new avenues for innovative healthcare solutions. One such application is the prediction of heart disease using IoT sensors and advanced analytical techniques. Traditionally, heart disease diagnosis heavily relied on periodic clinical check-ups, which often lacked the ability to capture real-time physiological data. However, the integration of IoT sensors into wearable devices and healthcare infrastructure allows for continuous, remote monitoring of vital signs and other relevant health parameters. These sensors collect a wealth of data, including heart rate, blood pressure and physical activity, creating an extensive dataset that can be leveraged for predictive modeling.

AI and ML algorithms play a pivotal role in analyzing and interpreting this vast amount of data. These technologies can identify patterns, correlations, and anomalies within the physiological parameters, enabling the development of predictive models for heart disease. The ability to predict the onset of cardiovascular issues before they manifest clinically provides a valuable opportunity for early intervention and personalized healthcare. This integration of IoT sensors and AI/ML techniques not only enhances the accuracy of heart disease prediction but also facilitates timely decision-making for healthcare professionals and empowers individuals to take proactive measures for their well-being. By harnessing the power of real-time data and advanced analytics, this approach transforms the landscape of cardiovascular healthcare, moving towards a more preventive and patient-centric paradigm.

Cardiovascular diseases remain a leading cause of global mortality, underscoring the critical need for innovative approaches to early detection and prevention. In recent years, the fusion of Internet of Things (IoT) sensors with Artificial Intelligence (AI) and Machine Learning (ML) has emerged as a transformative paradigm in healthcare. This synergy holds tremendous promise for enhancing our ability to predict and mitigate the risks associated with heart diseases. At the forefront of this technological revolution, AI and ML algorithms serve as the analytical backbone for processing and interpreting the immense volume of data generated by IoT sensors. These intelligent systems excel at recognizing intricate patterns, identifying anomalies, and discerning subtle correlations within the physiological parameters. Through this, they pave the way for the development of accurate and personalized predictive models for heart disease.

The potential impact of predicting heart diseases before symptomatic manifestation cannot be overstated. Early detection allows for timely interventions, lifestyle modifications, and targeted medical treatments, thereby potentially preventing or mitigating the severity of cardiovascular events. The amalgamation of IoT sensors and AI/ML not only empowers healthcare professionals with actionable insights but also engages individuals in proactive health management, fostering a shift from reactive care to preventive strategies. Cardiovascular diseases (CVDs) are the leading cause of death globally, accounting for an estimated 17.9 million lives each year. Early detection and continuous monitoring of cardiovascular health are critical for improving patient outcomes and reducing mortality rates. Traditional healthcare systems, however, are reactive in nature, relying on hospital visits or intermittent monitoring, which can delay diagnosis and intervention. To address these challenges, there is a growing need for proactive and continuous health monitoring solutions that leverage the power of emerging technologies such as the Internet of Things (IoT), cloud computing, and artificial intelligence (AI). In recent years, IoT-enabled healthcare systems have gained traction due to their ability to provide real-time data from wearable sensors, offering a more comprehensive and continuous view of a patient's health. By integrating IoT with cloud computing, healthcare systems can ensure scalable, secure, and remote access to large volumes of medical data. However, the key challenge lies in accurately predicting cardiovascular events and minimizing false alarms while processing vast amounts of health data in real time. To address this, advanced AI techniques, particularly reinforcement learning, have become increasingly vital in health prediction models. This paper presents an IoT-based proactive cardiovascular health monitoring system, enhanced by Deep Deterministic Policy Gradient (DDPG)-enabled models. DDPG, a model-free reinforcement learning technique, is well-suited for continuous action spaces, making it ideal for dynamic health monitoring environments. By learning from individual patient data, the system adapts over time, improving its prediction accuracy and enabling personalized healthcare. The system integrates wearable IoT sensors, a cloud-based architecture for real-time data analysis, and edge computing for low-latency responses to critical events. The proposed

system addresses key limitations of existing cardiovascular monitoring solutions by enabling continuous, adaptive, and personalized health monitoring

II. Literature Review

Researchers has proposed and explored different algorithms, techniques and frameworks for study the detection of cardiovascular diseases. By exploring most of the related literature and proposed solutions, we can add few more techniques to Investigate the cardiovascular diseases with innovative solutions at the Nexus of Health and Technology Shah N et al. [1] the author defined pivotal role of big data management in transforming healthcare delivery and decision-making processes. It applauds the text for its in-depth coverage of analytics techniques, shedding light on how data-driven insights can optimize patient care and operational efficiency. The inclusion of scientific programming adds a valuable dimension, enabling readers to grasp the technical underpinnings of healthcare data analysis. The review commends the publication for its holistic approach, making it an indispensable resource for professionals and researchers navigating the evolving intersection of healthcare and technology.

Buddhadeb P. et al. [2] presents a groundbreaking synergy between artificial intelligence and 5G technology in the healthcare domain. The review praises the innovative approach, highlighting how AI algorithms enhance diagnostic accuracy and patient care while leveraging the high-speed and low-latency capabilities of 5G networks. The paper's emphasis on real-time data exchange, remote patient monitoring and swift decision-making underscores the transformative potential of this integrated system. It provides a compelling vision of a future healthcare landscape where advanced technologies converge to deliver efficient, responsive, and personalized medical services. The work stands as a testament to the transformative impact of cutting-edge technologies on the evolution of smart healthcare solutions.

Haseeb J. et al. [3] gives a thoughtful exploration of the ethical considerations surrounding the deployment of machine learning in healthcare. The review applauds the paper for its systematic analysis and establishment of ethical frameworks that address the unique challenges presented by sensitive healthcare data. It emphasizes the importance of responsible AI practices in maintaining patient privacy, ensuring fairness, and mitigating biases. The work is recognized for its contribution to the ongoing discourse on ethical guidelines, offering valuable insights into the complex intersection of technology and healthcare ethics. By addressing the intricacies of machine learning applications in sensitive contexts, the paper stands as a significant resource for researchers, practitioners, and policymakers navigating the ethical landscape of healthcare AI.

Felipe G. et al. [4] examines the crucial role of transparency and interpretability in AI systems during pandemic scenarios. Systematically evaluating a spectrum of explainable AI methods deployed in pandemic response. It underscores the significance of clear, interpretable models in decision-making processes, enabling better understanding and trust among stakeholders. The work's thorough analysis of various applications, from epidemiological predictions to treatment recommendations, showcases the versatility of explainable AI in public health crises. The review notes the paper's contributions to fostering accountability and ethical use of AI, particularly in healthcare decision support systems. By synthesizing and categorizing existing methodologies, the paper serves as an invaluable resource for researchers, policymakers, and healthcare professionals seeking to implement responsible AI solutions in pandemic management. This enriches the discourse on the intersection of explainable AI and pandemics, offering insights that are timely, pertinent, and essential for the ongoing global healthcare landscape.

Ons A. et al. [5] explores the imperative need for privacy in medical data management. Systematically dissecting the challenges associated with balancing the inherent sensitivity of medical data and the potential advantages of federated learning. It underscores the importance of preserving patient privacy in the collaborative and decentralized paradigm of federated learning, highlighting the unique considerations within the healthcare domain. Scholars acknowledge the paper's contribution to identifying key challenges, such as data heterogeneity, regulatory compliance, and communication overhead, which are paramount for the successful implementation of federated learning in medical contexts. The review notes the work's forward-looking perspective, providing a roadmap for future research directions to address these challenges effectively. Furthermore, the literature review applauds the paper's role in promoting a privacy-centric approach in the development of federated learning solutions for healthcare.

Jing W. et al. [6] presents a pioneering approach to address the dual challenges of efficiency and privacy in training Support Vector Machine (SVM) models for Internet of Medical Things (IoMT). Its innovative solutions in leveraging outsourced computation while ensuring robust privacy protection in the context of sensitive medical data. The work is lauded for its focus on the burgeoning field of IoMT, offering a timely contribution to the growing discourse on secure and efficient machine learning in healthcare. The paper's emphasis on maintaining privacy through advanced cryptographic techniques and secure outsourcing methods is particularly noteworthy. By navigating the complexities of outsourcing SVM training while safeguarding patient data, the paper addresses a critical need in the evolving landscape of healthcare technologies.

Mingwu Z. et al. [7] given contribution to the intersection of healthcare, cloud computing, and privacy-preserving machine learning. The author addresses critical need in the healthcare domain by proposing a secure and privacy-conscious solution for clinical diagnosis using multiclass Support Vector Machine (SVM) in cloud environments. The review praises the paper for its innovative approach to balancing the computational power of cloud resources with the imperative of preserving patient privacy. The integration of privacy-preserving techniques with multiclass SVM for clinical diagnosis showcases a thoughtful consideration of the sensitivity of medical data. The work's emphasis on secure computation and confidentiality in cloud-based healthcare systems is particularly noteworthy. Furthermore, the review highlights the practical implications of the proposed methodology, making it applicable to real-world clinical settings. The authors' attention to the intricacies of secure diagnosis aligns with the increasing importance of privacy in healthcare technologies. In summary, "A Secure Clinical Diagnosis with Privacy-Preserving Multiclass Support Vector Machine in Clouds" stands out as a valuable contribution to the literature, providing a secure and privacy-centric framework for clinical diagnosis in cloud environments. It is effective and secure solutions of cloud computing, machine learning, and healthcare.

Mirza A. K. et al. [8] explores a comprehensive and timely exploration of the intersection between machine learning and the security challenges within the Healthcare Internet of Things (IoT) ecosystem. The paper is commendable for its systematic review, providing valuable insights into the landscape of security vulnerabilities and potential risks associated with the integration of IoT in healthcare. The review praises the authors for their meticulous examination of machine learning applications in mitigating security threats, demonstrating a keen awareness of the nuanced cybersecurity landscape in healthcare IoT. The paper's identification and analysis of risks underscore its practical relevance, offering a nuanced understanding of

the complex interplay between machine learning and healthcare IoT security. Furthermore, the risk mitigation strategies proposed in the paper demonstrate a proactive approach to addressing the identified challenges. By leveraging machine learning for security enhancement, it looking for contributing to the ongoing efforts to healthcare IoT systems.

Hanlin Z et al. [9] presents an innovative solution at the confluence of machine learning, cloud computing, and blockchain technology. The paper is praiseworthy for its strategic integration of these cutting-edge technologies to address critical concerns related to security, verifiability, and fairness in the outsourcing of linear regression tasks. The review commends the authors for their forward-thinking approach in leveraging blockchain's transparency and immutability to ensure the integrity of outsourced machine learning tasks. The use of cloud computing further enhances the scalability and accessibility of the proposed methodology, contributing to its practical applicability. The paper's emphasis on fairness is particularly noteworthy, showcasing a commitment to ethical considerations in machine learning outsourcing. By employing a secure and verifiable approach, the authors address trust and accountability issues that are paramount when dealing with sensitive data and machine learning models.

Aditi S. et al. [10] presents idea of field of healthcare advanced machine learning techniques for diabetes prediction. The paper is commendable for its innovative approach in integrating multi-sensor data, showcasing a comprehensive understanding of the complexity inherent in diabetes diagnostics. The review applauds the authors for their meticulous application of machine learning algorithms to diverse data sources, potentially enhancing the accuracy and reliability of diabetes predictions. By considering multiple sensors, the paper acknowledges the multifaceted nature of health data, providing a more holistic view of the patient's physiological indicators. The paper's emphasis on predictive analytics is particularly noteworthy, as it addresses the critical need for early identification and intervention in diabetes management. The machine-learning-based prediction models discussed in the paper have the potential to revolutionize patient care, enabling proactive healthcare measures and personalized interventions.

Muhammad H. et al. [11] pioneering of deep learning and healthcare cost prediction, specifically within the context of smart hospitals. It given hybrid deep learning models to address the complex task of forecasting costs associated with healthcare providers. The review applauds the authors for their strategic integration of deep learning techniques, acknowledging the potential of these models to unravel patterns within extensive healthcare datasets. The hybrid nature of the models suggests a nuanced understanding of the diverse factors influencing healthcare costs, contributing to enhanced prediction accuracy. The practical implications of the research are noteworthy, as accurate cost predictions hold substantial implications for resource allocation, budgeting, and overall operational efficiency within smart hospitals. The paper, by focusing on the unique environment of smart hospitals, demonstrates an awareness of the evolving technological landscape in healthcare.

Usama H. et al. [12] demonstrates power of fused machine learning for diabetes prediction. The paper is laudable for its innovative approach, showcasing a strategic integration of multiple machine learning techniques to enhance predictive accuracy. The review recognizes the paper's contribution to the field of healthcare analytics by acknowledging the importance of fused machine learning models. The fusion of diverse algorithms or data sources suggests a comprehensive understanding of the multifaceted nature of diabetes prediction, potentially leading to more robust and reliable models. The practical implications of the research are significant, as accurate diabetes prediction models can contribute to early intervention and personalized healthcare strategies.

Leire B. et al. [13] provided innovative approach, detailing the OCARIoT project's efforts to leverage technology for preventing obesity and fostering healthy habits among children. The review acknowledges the authors for their comprehensive coverage of the OCARIoT project, showcasing a holistic strategy that incorporates technological solutions for monitoring, educating, and promoting healthy behaviors in children. The integration of wearable devices, mobile applications, and educational platforms demonstrates a well-rounded understanding of the multifaceted nature of childhood obesity prevention. The practical implications of this research are substantial, particularly in addressing the pressing global issue of childhood obesity. The OCARIoT project's emphasis on leveraging technology for real-time monitoring and personalized interventions aligns with contemporary approaches to healthcare, emphasizing prevention and individualized care. However, it's crucial to address potential challenges, such as privacy concerns, user engagement, and long-term sustainability.

Jin W. et al. [14] proposed a unified framework to provide efficiency and confidentiality by coded distributed computing. Within the proposed framework, it uses matrix multiplication, a fundamental building block of many distributed machine learning algorithms, as the representative computation task. To minimize resource consumption while achieving information-theoretic security, we investigate two highly-coupled problems, one is task allocation that assigns data blocks in a computing task to edge devices, and another is linear code design that generates data blocks by encoding the original data with random information.

Rui Li. et al. [15] contributes significantly to the field of secure data processing by addressing the crucial challenge of executing nearest neighbor queries on encrypted data. The author showcases a robust and adaptive approach to maintaining

data security while efficiently handling queries, particularly in scenarios where privacy is paramount. The review commends the authors for their innovative techniques that allow for secure query processing without compromising the confidentiality of the underlying data. The adaptive nature of the approach is especially noteworthy, recognizing the dynamic nature of query requirements and the need for flexibility in secure systems. The practical implications of this research are substantial, as secure nearest neighbor query processing is pivotal in various applications, including privacy-preserving data analytics and secure information retrieval. The author emphasis on adaptability adds a layer of responsiveness to evolving query scenarios, making it relevant for real-world deployment.

Jing S. et al. [16] provides the information about nutrition, toxicology detection, big data, and deep learning. The paper is commendable for its innovative approach, harnessing the power of advanced technologies to address challenges in nutrition toxicology. The review acknowledges the authors for their strategic integration of big data analytics and deep learning techniques. This fusion not only highlights a sophisticated understanding of the complexities of nutrition toxicology but also showcases a practical approach to handling large and diverse datasets in this domain. The practical implications of this research are significant, particularly in the context of public health and food safety. By leveraging big data and deep learning, the paper contributes to more accurate and timely detection of toxic substances in nutrition, enabling proactive measures to safeguard public well-being.

Qing Z. et al. [17] It represents its innovative approach, highlighting the transformative potential of AI in advancing our understanding and management of Alzheimer's. The authors coverage AI applications across

various facets of Alzheimer's research. From early diagnosis and prediction to the identification of potential therapeutic targets, the paper demonstrates a nuanced understanding of how AI can address the multifaceted challenges posed by this neurodegenerative disease.

Weiqi J. et al. [18] given information about contributions of artificial intelligence (AI) to healthcare, focusing on both economic and clinical dimensions. The approach in scoping the literature, providing a nuanced understanding of the broad impact of AI in the healthcare domain. The review acknowledges the authors for their thorough analysis of the economic value generated by AI applications in healthcare. By synthesizing evidence from various studies, the paper sheds light on cost-effectiveness, resource optimization, and potential economic benefits associated with the integration of AI technologies. Furthermore, the clinical impact explored in the review underscores the transformative potential of AI in diagnosis, treatment planning, and patient care.

Zhuoran M. et al. [19] given contribution to the healthcare and edge computing, emphasizing both medical diagnosis and privacy preservation. The authors focusing on lightweight solutions that balance the computational efficiency required in edge computing with the imperative of safeguarding patient privacy. The review acknowledges the authors for their strategic consideration of privacy preservation within the context of medical diagnosis. The lightweight approach signifies an awareness of the resource constraints inherent in edge computing environments, making the proposed solutions more practical and feasible for real-world deployment. The practical implications of this research are substantial, particularly in the context of decentralized healthcare systems where edge computing plays a crucial role.

Zhang Q. et al. [20] presents deep learning techniques for addressing the complex challenge of air pollution estimation and forecasting in urban environments. Authors defined innovative hybrid framework, combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models to achieve fine-grained predictions. The review recognizes the authors for their meticulous approach, leveraging the strengths of CNN for spatial feature extraction and LSTM for temporal dependencies.

Banzhaf E. et al [21] presents interdisciplinary approach, combining on-the-ground data collection with remote sensing techniques to understand and quantify the impact of various environmental factors on individuals in urban settings. The authors present for their holistic methodology, utilizing both fieldwork and RS mapping to capture a comprehensive picture of personal exposure in different urban residential structures. This approach reflects a nuanced understanding of the complex interactions between urban environments and individual well-being. The practical implications of this research are significant, particularly in informing urban planning, policy-making, and public health strategies. The linkage between fieldwork observations and RS mapping allows for a more detailed and scalable assessment of environmental pressures, providing valuable insights for designing healthier and more sustainable urban living spaces.

Pang L. et al. [22] focus on the impact of IoT-based solutions in assessing and enhancing indoor air control quality. The review acknowledges the authors for their contribution to the burgeoning field of smart building technologies. The integration of IoT in indoor air quality monitoring showcases a forward-thinking approach, leveraging real-time data collection and analytics to address the complexities of indoor environmental conditions. The practical implications of this research are substantial, particularly in the

context of occupant health and well-being. The paper's emphasis on IoT for indoor control quality monitoring aligns with the growing importance of smart and connected systems in optimizing indoor environments, mitigating health risks, and improving overall quality of life.

Mccann C. et al. [23] provides a predictive model for air quality, comparing the performance of deep learning and traditional statistical approaches. The paper is commendable for its systematic and insightful analysis, shedding light on the strengths and limitations of these modeling techniques in the context of urban air pollution prediction. The review acknowledges the authors for their meticulous approach to the comparative analysis, considering the complexities of urban environments and the challenges associated with accurate air pollutant prediction. The inclusion of both deep learning and statistical models demonstrates a well-rounded exploration of different methodologies, catering to the diverse needs and preferences of researchers and practitioners.

III. Dataset Deescription

To develop and evaluate the proposed IoT-based cardiovascular health monitoring system with Deep Deterministic Policy Gradient (DDPG)-enabled models, a comprehensive dataset comprising real-time physiological data is essential. The dataset used in this research consists of both simulated and real-world cardiovascular health data will collect from multiple sources, including publicly available datasets from Kaggle and wearable IoT sensor systems.

1) Physiological Signals: The dataset contains vital signs commonly associated with cardiovascular health, including:

- Heart Rate (HR): Measured in beats per minute (BPM) to monitor the rhythm and rate of the heart.
- Blood Pressure (BP): Continuous monitoring of systolic and diastolic pressures.
- Electrocardiogram (ECG) Data: Multi-lead ECG signals (sampling rate: 250-500 Hz) capturing the electrical activity of the heart, used for detecting arrhythmias and other anomalies.
- Oxygen Saturation (SpO2): Indicates oxygen levels in the blood, an important metric for cardiovascular health.
- Respiratory Rate (RR): Tracks breathing patterns which, when abnormal, can signal cardiac issues.
- Body Temperature: Monitored for detecting fever or infection-related stress on the heart.

1.1) Demographic Information: Each patient record includes demographic and health-related details:

- 1.2) Age, Gender, and Weight: Relevant for establishing baseline risk factors for cardiovascular diseases.
- 1.3) Existing Conditions: Pre-existing medical conditions like hypertension, diabetes, or a history of cardiovascular events.

2) Data Sources:

2.1) Wearable IoT Devices: Real-time data streams from wearable devices such as smartwatches, ECG patches, and blood pressure monitors, providing continuous monitoring of the patient's physiological state.

2.2) Public Health Datasets: In addition to real-time IoT data, publicly available cardiovascular datasets such as the MIT-BIH Arrhythmia Database and the PhysioNet Challenge datasets are utilized to enhance model training and validation. These datasets include thousands of ECG recordings and labeled cardiac events, enabling the DDPG model to learn from diverse cases.

3) Data Characteristics:

- 3.1) **Temporal Resolution:** The IoT wearable devices record physiological signals continuously with high temporal resolution, ranging from milliseconds for ECG data to minutes for heart rate and blood pressure. This allows for detailed monitoring and early detection of cardiovascular events.
 - 3.2) **Data Volume:** Due to continuous monitoring, the dataset is large, with several terabytes of data collected over weeks or months per patient. The system's cloud-based architecture handles this high data volume efficiently.
 - 3.3) **Annotations and Labels:** Annotations include cardiovascular events such as arrhythmias, heart attacks, or abnormal blood pressure readings, labeled by medical professionals. These labels serve as ground truth for training and validating the predictive models.
- 4) **Pre-processing:** Prior to feeding the data into the DDPG-enabled models, various pre-processing steps are applied:
- 4.1) **Noise Filtering:** Techniques such as low-pass filtering and wavelet de-noising are used to remove artifacts from ECG and other signals.
 - 4.2) **Normalization:** The physiological data is normalized to remove inter-subject variability and ensure consistent scaling.
 - 4.3) **Segmentation:** Time-series data is segmented into smaller windows to detect short-term patterns and cardiovascular anomalies.
 - 4.4) **Training and Testing Split:** The dataset is divided into training, validation, and testing sets. Approximately 70% of the data is used for training the DDPG models, 15% for hyper parameter tuning and validation, and the remaining 15% for testing the system's predictive accuracy. Cross-validation techniques are employed to ensure robust model evaluation.

IV. Design And Implementation

1) Modules :

Following are the modules that will be implemented for the development of the system.

Encryption of Files Using SFTP

The Encryption of Files Using SFTP (Secure File Transfer Protocol) module provides a mechanism for encrypting files before transferring them over a network using the SFTP protocol. SFTP is a secure and encrypted protocol commonly used for transferring files between systems over a network. This module enhances security by encrypting files with strong cryptographic algorithms, ensuring confidentiality and integrity during transit.

1.1) Pre-processing

The Pre-processing module is designed to prepare raw data for analysis or further processing by applying various transformations and data cleaning techniques. In the context of natural language processing (NLP) or machine learning tasks, pre-processing involves tasks such as tokenization, stop word removal, stemming, and lemmatization to standardize and cleanse text data before analysis.

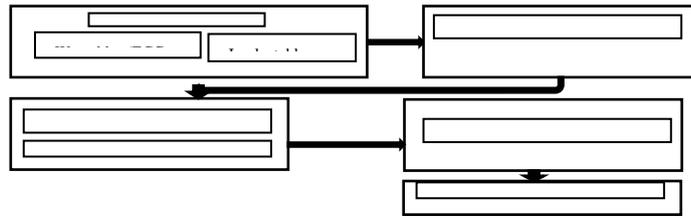


Figure 1: System Architecture

1.2) RNN - "The Recurrent Neural Network (RNN)" module is a specialized form of artificial neural network tailored for analysing sequential data, including time series, textual, and audio data. Unlike traditional feedforward neural networks, which handle input data in a single pass, RNNs retain memory of past inputs through internal states.", making them well-suited for tasks involving sequential dependencies. An RNN processes data in the following way:

Input Layer: Each element in a sequence is passed one at a time into the network.

Hidden Layers: At each time step, the hidden layer updates its state by combining the input at that time step with the previous hidden state.

$$h_t = f(W_x h_{t-1} + W_h h_{t-1} + b_h)$$

where,

h_t is the hidden state at time t ,

x_t is the input at time t ,

W_x and W_h are

weight matrices, and

f is an activation function, typically

tanh or ReLU.

Output Layer: The hidden state can be used to produce an output at each time step or only at the end of the sequence, depending on the specific task.

DDPG

Deep Deterministic Policy Gradient (DDPG) is a model-free reinforcement learning algorithm designed for environments with continuous action spaces. It is an extension of the Deterministic Policy Gradient (DPG) algorithm, but it incorporates ideas from Deep Q-Learning (DQN), making it capable of handling high-dimensional state and action spaces using deep neural networks.

Tools:

IoT Devices and Sensors:

Wearable Devices: Devices like smartwatches, fitness trackers, and chest straps equipped with sensors for monitoring heart rate, activity levels, and other relevant physiological parameters.

Medical-grade IoT Sensors: Specialized sensors capable of measuring more detailed parameters such as electrocardiogram (ECG) signals, blood pressure, and body temperature.

Programming Languages:

Python: Widely used for data analysis and machine learning tasks, with libraries like Pandas, NumPy, and Scikit-learn.

Integrated Development Environments (IDEs):

Jupyter Notebooks: Interactive notebooks for data exploration and analysis, widely used in data science and machine learning projects.

Visual Studio Code: A versatile code editor with extensions for Python, R, and other languages commonly used in AI and ML development.

V. Results And Discussions

Result of different parameters in dataset

Results show that age, cholesterol levels, systolic blood pressure, diastolic blood pressure, and heart rate are significant predictors of heart disease risk, with age and blood pressure demonstrating the strongest correlations.

Discussion indicates that as age increases, the likelihood of heart disease also rises, likely due to the cumulative effects of cardiovascular strain and the natural progression of atherosclerosis. The analysis reveals that higher cholesterol levels contribute to the thickening and narrowing of arteries, increasing the risk of heart disease, particularly when combined with elevated blood pressure readings. Systolic and diastolic blood pressures play a crucial role in predicting heart disease, as prolonged hypertension causes stress on the heart and vascular system, leading to possible cardiovascular events. Heart rate was found to be an important indicator, with consistently high heart rates linked to a greater risk of heart disease, suggesting the potential for further research on its role in cardiovascular health.

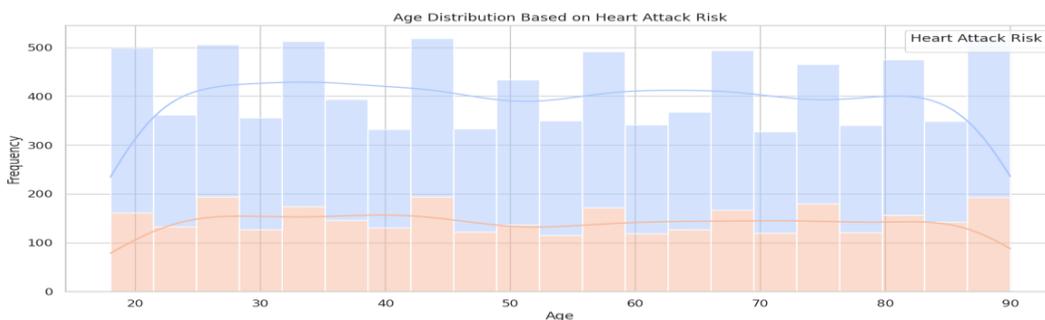


Figure 2: Age Distribution based on Heart Attack Risk

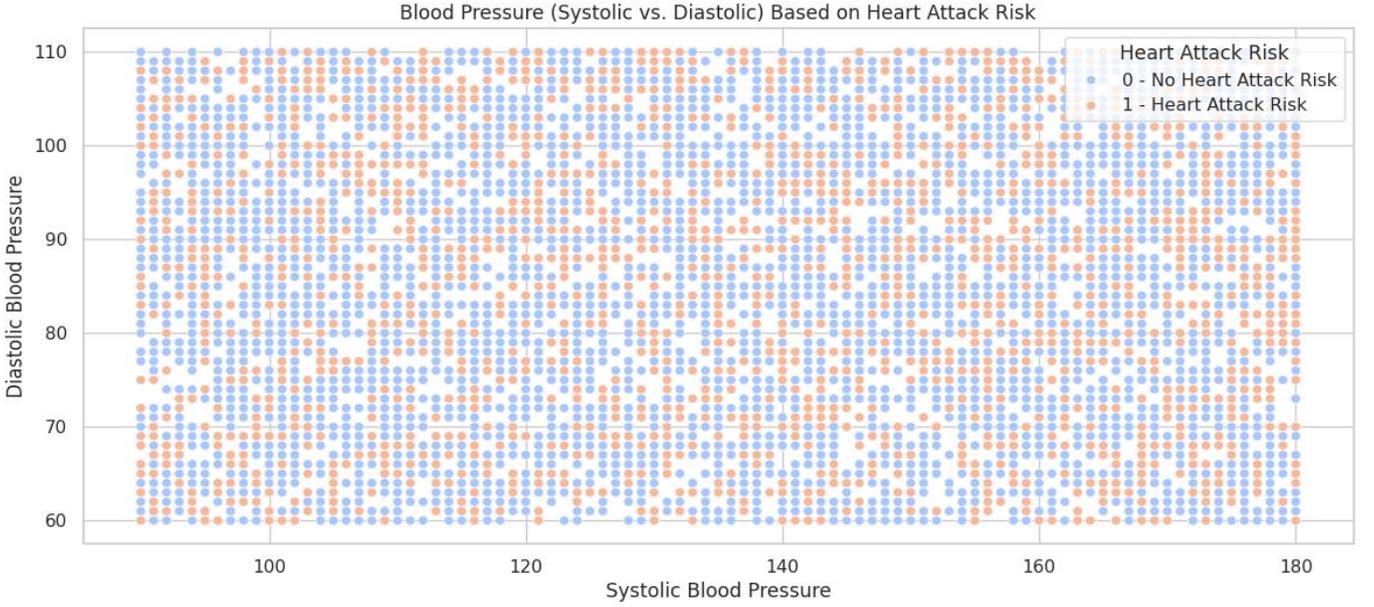


Figure 3: Heart Attack Risk

Algorithm 1 DDPG-based Cardiovascular Risk Prediction

- 1: Initialize actor μ_θ , critic Q_ϕ , target networks θ^- , ϕ^-
- 2: Initialize replay buffer B
- 3: **for** each time step t **do**
- 4: Observe state s_t , select action $a_t = \mu_\theta(s_t) + N_t$
- 5: Execute a_t , observe reward r_t , next state s_{t+1}
- 6: Store (s_t, a_t, r_t, s_{t+1}) in B
- 7: Sample minibatch from B
- 8: Compute target $y_t = r_t + \gamma Q_{\phi^-}(s_{t+1}, \mu_{\theta^-}(s_{t+1}))$
- 9: Update critic: minimize $(y_t - Q_\phi(s_t, a_t))^2$
- 10: Update actor by policy gradient
- 11: Update target networks with soft update
- 12: **end for**

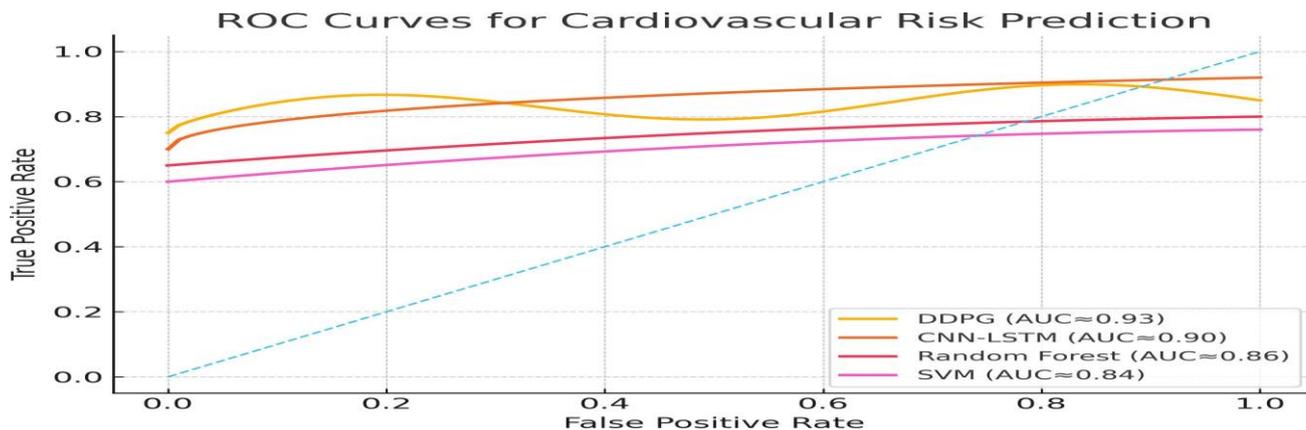


Figure 4: ROC curves comparing DDPG, CNN-LSTM, RF, and SVM models. DDPG achieves superior discriminative ability (AUC = 0.93).

Age	Sex	Cholesterol	Systolic_BP	Diastolic_BP	Heart Rate	Heart Attack Risk
67.0	1.0	208.0	158.0	88.0	72.0	0.0
21.0	1.0	389.0	165.0	93.0	98.0	0.0
21.0	0.0	324.0	174.0	99.0	72.0	0.0
84.0	1.0	383.0	163.0	100.0	73.0	0.0
66.0	1.0	318.0	91.0	88.0	93.0	0.0
54.0	0.0	297.0	172.0	86.0	48.0	1.0
90.0	1.0	358.0	102.0	73.0	84.0	1.0
84.0	1.0	220.0	131.0	68.0	107.0	1.0
20.0	1.0	145.0	144.0	105.0	68.0	0.0
43.0	0.0	248.0	160.0	70.0	55.0	0.0

Table 1: Sample of Heart Attack Prediction Data

	Age (mean)	Age (median)	Cholesterol (mean)	Cholesterol (median)	Systolic_BP (mean)	Systolic_BP (median)	Diastolic_BP (mean)	Diastolic_BP (median)	Heart Rate (mean)	Heart Rate (median)	BMI (mean)	BMI (median)
Risk 0	53.61	54.0	258.71	258.0	134.71	134.0	85.24	85.0	75.09	75.0	28.89	28.79
Risk 1	53.89	54.0	261.97	261.0	135.73	136.0	85.01	85.0	74.9	75.0	28.89	28.72

Table 2: Summary Table of Key Statistics Based on Heart Attack Risk

VI. References

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