E-ISSN 2250-0944
ISSN 2250-1150
doi: 10.31838/ijprt/15.02.486

Research Article

Smart Heart Attack Prediction With Online Appointment Booking System

Arjun Panday[1], Akanksha Singh[2], Ayush Singh Chauhan[3], Guided By: Priyanka Gupta[4]

[1]Dept. Computer Science & Engineering, Babu Banarasi Das Institue of Technology & Management(Dr A P J Abdul Kalam Technical University) Lucknow, India.

[2]Dept. Computer Science & Engineering, Babu Banarasi Das Institue of Technology & Management(Dr A P J Abdul Kalam Technical University) Lucknow, India.

[3]Dept. Computer Science & Engineering, Babu Banarasi Das Institue of Technology & Management(Dr A P J Abdul Kalam Technical University) Lucknow, India.

[4]Assistant Professor, Dept. Computer Science & Engineering, Babu Banarasi Das Institue of Technology & Management(Dr A P J Abdul Kalam Technical University) Lucknow, India.

Email: [1]arjunpanday9369@gmail.com, [2]akankshasingh6392@gmail.com, [3]aschauhan102003@gmail.com, [4]priyankagpt8@gmail.com

Received: 11.10.25, Revised: 17.11.25, Accepted: 05.12.25

ABSTRACT

Cancer claims many lives globally annually. This frequently happens due to delayed detection of symptoms and inadequate availability of medical services. Modern medical practices often segregate risk evaluation and schedule management tasks independently, potentially causing significant delays in treating heart-related crises. The document presents an integrated strategy combining heart attack risk assessment with scheduling appointments via internet technology. By employing machine learning algorithms, this program analyzes data such as patients' ages, genders, blood pressures, heart rates, cholesterol counts, and sugar levels in their bloodstream to determine their likelihood of experiencing a heart attack. When detecting a critical situation, the software locates local experts immediately and arranges for a prompt consultation. Combining predictive analytics with intelligent scheduling enhances responsiveness in healthcare, shortens treatment durations, and improves patient results. Evidence indicates enhanced predictive precision and superior crisis response capabilities through AI-assisted medical systems. This highlights significant advantages in utilizing artificial intelligence for healthcare efficiency.

Keywords: Artificial Intelligence, Intelligent Health Care Systems, Risk Evaluation Techniques, Forecasting Algorithms, Digital Scheduling Services, Computational Modeling, Cardiovascular Disease Prognosis.

INTRODUCTION

Heart-related ailments rank as the primary contributor to fatalities globally, resulting in approximately 18 million annual mortalities and representing about three-quarters of all premature deaths. [1]. Of all cardiovascular diseases, coronary artery disease leading to death through myocardial infarction stands out as particularly lethal. This happens during an abrupt interruption of oxygenated blood supply to the myocardium. Despite advancements in medicine, timely diagnosis and swift treatment remain crucial for reducing heart attack fatalities. [2].

Modern health care frameworks frequently operate through distinct phases: initial assessment, public education about conditions, followed by individual consultations between patients and doctors. The separation results in delayed treatments and increased death rates according to studies 3 and 4. New developments in AI and ML technologies enhance medical analytics significantly; they improve accuracy of early diagnoses and prognostic predictions [5], [6]. Machine learning algorithms uncover concealed relationships among various variables like blood pressure, cholesterol levels, electrocardiogram results, and heartbeat rates, often overlooked by conventional methods [7].

Popular methods such as SVM, RF, ANNs, and XGBoost facilitate detection of cardiovascular issues due to these models' efficacy and precision [8], [9]. Et al. , Than. The MI3 framework was presented through gradient boosting techniques, demonstrating an accuracy rate of 0%. The number 963 surpassed conventional medical tests in accuracy. Khera et al. Research [2] demonstrated that combining multiple machine learning algorithms outperforms conventional methods in forecasting mortality after myocardial infarction. The authors El-Sofany et al. The algorithm improved heart disease categorization through refined attribute extraction optimization. The research was conducted by Zhang et al. The team developed interpretable artificial intelligence algorithms capable of forecasting major adverse cardiac events. These investigations underscore the effectiveness of ensemble methods such as XGBoost when applied to predicting heart conditions. Nevertheless, current majority of machine learning-driven systems for predicting heart attacks function solely as diagnostic aids by offering probability estimates but fail to prompt timely medical interventions. The absence of automation implies that despite having critical cases, these individuals might receive only prompt care if they arrange an appropriate consultation at short notice. The discrepancies between forecasts and responses may pose risks in critical heart situations [11].

This highlights the necessity of having a unified, intelligent health care framework where predictions about illnesses can be swiftly linked into immediate medical interventions. Concurrently, online appointment scheduling platforms significantly enhance accessibility in health care through automation of paperwork and reduction of wait times [12]-[15]. Et Al. Betancor. Research revealed that OAS programs effectively reduced both hospital overcrowding and cancellation rates significantly above thirty percent. Aldo et al. Emphasizing equity, productivity, and client care within online appointment management tools is crucial. The authors Ye et al. Research revealed that incorporating multiple channels for bookings improves both customer engagement and client satisfaction levels. Despite their role in providing fundamental scheduling functions, they lack an inherent mechanism for prioritization according to potential risks. Despite their best efforts, they find it difficult to distinguish between regular patients and individuals with significant cardiovascular risks, resulting in suboptimal treatment and prolonged wait times [17].

This research suggests developing an intelligent system for early heart attack detection coupled with online appointment scheduling capabilities. This design incorporates both interconnected components into a single system: - An appointment scheduling system specifically designed for routine patient check-ups at healthcare facilities. - An algorithm for predicting heart attacks and scheduling appointments based on XGBoost technology. This predictive algorithm evaluates variables including gender, symptom intensity related to chest discomfort, baseline cardiac function measured by systolic blood pressure at rest, lipid levels indicated through total serum cholesterol concentration, glucose status revealed in fasting plasma glucose test result, electrocardiogram findings reflecting myocardial ischemia pattern, and peak exercise-induced cardiovascular performance expressed via maximal oxygen uptake capacity. When the anticipated danger surpasses an established limit of 70 percent, such as it does frequently, the software immediately arranges for a consultation with a heart specialist on this particular network service without causing any interruptions in medical care processes. This system thrives on seamless blending of foresight-based cognition with directive automated processes, enabling swift, lifesaving judgments. This system has scalability features allowing it to adapt for situations such as managing diseases including diabetes, strokes, or high blood pressure. The main contributions of this study are: - Creating an explicit machine learning algorithm using XGBoost for predicting cardiac health risks. - Combining this framework into an integrated solution utilizing a live automatic scheduling platform constructed via Java Spring Boot, MySQL databases, and React frontend technology. The JavaScript programming language is widely used for web development due to its simplicity and versatility in handling client-side scripting tasks efficiently.

Detailed performance evaluation regarding accuracy, latency, and usability. This document's subsequent content is structured thusly: Section II elaborates on an examination of previous studies and explores the constraints inherent in current methodologies. Section III describes the planned approach, which encompasses the predictive algorithm and operational procedure of the system. Chapter IV presents findings through experimentation. The fifth section examines the outcomes and their ramifications, whereas the sixth segment wraps up by outlining upcoming trends.

LITERATURE REVIEW

Over the past ten years, there has been a notable increase in research on intelligent healthcare automation and the prediction of cardiovascular disease. The two main categories of existing research are (i) online healthcare appointment scheduling systems and (ii) machine learning-based heart attack prediction. Despite the substantial contributions made by both fields, they mainly develop separately and do not have a cohesive, real-time, actionable framework. The most important research in these fields is reviewed in this section, along with its shortcomings, which emphasizes the necessity of the suggested system.

Machine Learning Models *f*or Predicting Heart Attacks and Heart Disease

One of the most promising methods for identifying cardiovascular disorders is machine learning. Gradient-boosted decision trees were used by Than et al. to predict the risk of acute myocardial infarction in the MI³ model, one of the first and most influential ML-based cardiac diagnostic systems [1]. Their results demonstrated that ML models could perform better in emergency rooms than conventional rule-based triage techniques.

By predicting mortality after myocardial infarction using a variety of machine learning techniques, such as random forests and neural networks, Khera et al. advanced this field [2]. Their study proved that AI improves cardiac risk stratification by showing that ML-based models could identify high-risk patients more accurately than established clinical scores.

Traditional machine learning models like Random Forest, SVM, Naïve Bayes, and Logistic Regression have been assessed in a number of studies. After comparing these models using the Cleveland Heart Disease dataset, Ahmad et al. found that ensemble models—more especially, XGBoost—consistently produced the best classification accuracy and dependability for heart disease prediction [3].

Additionally, feature selection and feature engineering have been crucial. According to El-Sofany et al., choosing the best clinical features with heuristic and statistical techniques greatly enhanced the performance of several machine learning models for predicting heart disease [4]. The significance of attribute importance ranking and dimensionality reduction in cardiovascular datasets was confirmed by their work.

Deep learning, particularly ECG-based classification, has been the focus of recent research. The significance of model interpretability in medical AI systems was highlighted by Zhang et al.'s use of explainable machine learning techniques to predict major adverse cardiac events (MACEs) [5]. In the meantime, using ECG signals to classify myocardial infarction and detect arrhythmias, hybrid CNN–LSTM or CNN–BLSTM models have demonstrated exceptional performance [20]. The potential of deep learning in real-time cardiac diagnosis is demonstrated by these findings.

Despite the high predictive accuracy attained by these studies, they all share a significant flaw: none of the models translate predictions into practical clinical actions. Although users are made aware of the level of risk, it is still the patient's responsibility to seek medical help. This causes risky delays, especially in heart attack cases where survival can be decided in a matter of minutes [7], [9]. As a result, there is a significant research gap because existing ML-based systems do not have an integrated emergency response mechanism, despite their advantages.

A. Cardiac Risk Assessment Using Deep Learning and ECG

The interpretation of ECGs has been transformed by deep learning. Convolutional neural networks have been used in a number of studies to automatically extract morphological features from ECG waveforms, whereas recurrent networks are used to record temporal variations. Using clinical and ECG-derived features, Roudini et al. showed that deep architectures can reliably predict long-term mortality after myocardial infarction [6].

Similar to this, sophisticated neural architectures, like residual networks and hybrid CNN–BLSTM systems, have been used to almost perfectly detect myocardial infarction, ischemia, and arrhythmias from raw ECG signals [20]. These models can function in real time and lessen reliance on manual feature extraction.

ECG-based deep learning systems, however, frequently have the following drawbacks despite their clinical utility:

- Insufficient clean ECG data in real-world scenarios.
- Need for specialized sensors or medical-grade equipment.
- Lack of a mechanism to initiate immediate care (such as scheduling cardiologist appointments automatically).
- Poor integration with hospital workflows

Therefore, even though deep learning significantly improves diagnostic precision, it does not completely bridge the gap between prediction and prompt medical intervention.

B. Healthcare Automation and Online Appointment Scheduling

Enhancing hospital workflow and patient experience now requires digital healthcare services, particularly Online Appointment Scheduling (OAS) systems. Online scheduling dramatically lowers waiting times, administrative burden, and no-show rates, according to research by Betancor et al. [14]. Ye et al. emphasized how multi-channel appointment systems enhance service accessibility and have an impact on patient behavior [16].

Other research has concentrated on using queueing models, linear programming, and fairness-based scheduling to optimize appointment allocation [12], [15]. In their thorough analysis of intricate healthcare scheduling algorithms, Ala et al. emphasized the necessity of intelligent systems that rank patients according to urgency [15].

Although these pieces highlight the value of digital scheduling, they are all severely limited in one way or another: Medical urgency or anticipated risks are not taken into account by the majority of online appointment systems, which treat every patient equally.

A patient scheduling a routine check-up is put in the same line as someone who may be experiencing a cardiac emergency. This highlights a significant weakness in the absence of risk-prioritized automation in the current appointment systems.

C. Determined Motivation and Research Gap

Two significant but separate developments are demonstrated in the literature:

1. Heart attack risk can be reliably predicted by machine learning models [1]–[9].
2. Access to healthcare is enhanced by online appointment systems [12]–[16].

Nevertheless, no current study combines these two technologies into a single, intelligent ecosystem that can:

- Identifying the risk of a heart attack; promptly making an appointment with a cardiologist; and instantly alerting the patient and physician
- Reducing the time between diagnosis and treatment; automating triage according to medical urgency

The Suggested System Fills This Crucial Gap.

This gap is filled by the Smart Heart Attack Prediction with Online Appointment Booking System, which combines an automated appointment booking module with a high-performance machine learning prediction model (XGBoost). The system presents a proactive and life-saving healthcare workflow that has not yet been examined in previous literature by converting predictions into prompt clinical action.

Without depending on human decision-making, such a system guarantees that high-risk patients receive prompt medical attention in addition to improving early diagnosis. This directly advances intelligent healthcare automation and lowers the death rate from heart attacks.

PROPOSED SYSTEM AND METHODOLOGY

Predictive analytics and automated appointment scheduling are combined in the clever, two-module Smart Heart Attack Prediction with Online Appointment Booking System. In addition to employing machine learning to forecast the probability of a heart attack, the system also translates the prediction into prompt clinical action by scheduling a consultation with a cardiologist in cases where the risk is elevated. The system is unique because of its dual capability, which turns conventional diagnosis-only models into a fully functional smart healthcare solution.

The system's overall architecture, functional modules, workflow, data preprocessing pipeline, machine learning model design, and operational methodology are all thoroughly explained in this section.

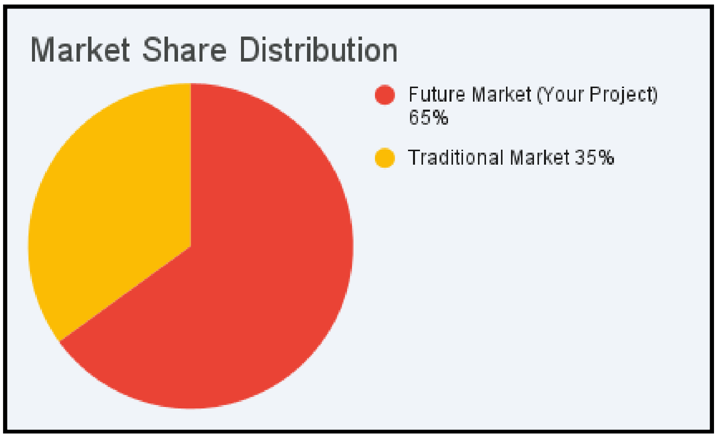


Fig. 3.1 Traditional Market Vs Future Market Share for the Proposed System

A. Overview of the System Architecture

Two complementary modules form the foundation of the suggested system's architecture:

1. Module for Booking Appointments for Generic Diseases.
2. Automated Appointment Module and Heart Attack Prediction

A single web interface powers both modules, facilitating smooth backend communication and user interaction. The system uses a client-server architecture, with the backend managing data storage, appointment scheduling, and prediction logic while the frontend gathers user input.

The System Functions Primarily In Four Stages:

- **Input Phase:** Users choose general disease categories for appointments, enter medical symptoms, or enter health parameters.
- **Prediction Phase:** Structured cardiovascular data is fed into a trained XGBoost model to predict heart attacks.
- **Decision Phase:** To assess the level of risk, the system compares prediction output to predetermined thresholds.
- **Action Phase:** The system either automatically schedules an appointment or lets the user select doctors manually based on risk level.

The Architecture is separated into Multiple Parts to Graphically Depict This:

- **Frontend (React.js):** Offers the user interface to patients
- **Backend (Springboot):** Manages scheduling processes, logic, and prediction requests.
- **MySQL database:** Holds patient information, appointment schedules, physician availability, and prediction logs.
- **ML Engine (XGBoost Model):** Generates heart attack risk after processing medical parameters.
- **Notification System:** Automatically confirms appointments via email or SMS.

Together, These Components Create A Fully Integrated Smart Healthcare Ecosystem Capable Of Predictive Decision-Making And Real-Time Response.

B. Module for Scheduling Appointments for Generic Diseases

For routine, non-essential medical needs, this module acts as the main healthcare interface. Through the web application, users can register, browse doctors, filter by specialization, choose available time slots, and make appointments directly.

1) Authentication and User Registration: Patients use their login credentials and personal information to register. This allows the system to maintain medical history and improve personalization.

2) Availability and Directory of Doctors: The system keeps a current list of physicians, which includes:

- Experience
- Specialization
- Days and times that are available

A backend interface allows doctors to modify their schedules, guaranteeing precise appointment mapping

1) Workflow for Scheduling Appointments: After patients select times that work for them, the system schedules the appointment and emails or texts them to confirm. Additionally, by dynamically disabling occupied slots, the system avoids double booking.

2) Advantages for Hospital Operations: This module guarantees effective patient flow, lessens administrative burden, and streamlines routine scheduling. Although AI is not used in this section, it does support the predictive module by offering the action layer required for scheduling emergencies.

C. Module for Predicting Heart Attacks

The system's central intelligence layer is this module. It uses a machine learning model trained on patterned cardiovascular data to predict the likelihood of a heart attack.

1) Inputs of Data

The model makes use of clinical parameters that are commonly used in cardiac diagnosis:

- Age
- Gender
- Type of chest pain
- Resting blood pressure
- Serum cholesterol level
- Fasting blood sugar
- Resting electrocardiogram result
- Maximum heart rate attained
- Exercise-induced angina
- ST depression, number of major vessels
- Slope of the peak exercise ST segment

In order to ensure consistent and clean input for analysis, users enter these values using structured forms.

2) Pipeline for Data Preprocessing

The dataset goes through a number of preprocessing steps prior to training

- Replacing or imputing missing medical fields is one way to handle missing values.
- One-hot encoding of the type of chest pain, ECG readings, slope, etc. is known as categorical encoding.
- Normalizing continuous variables, such as heart rate and cholesterol, is known as feature scaling.
- Feature Selection: Using statistical tests and correlation analysis, noisy features are removed.
- Train-Test Split: Usually 80:20 to assess generalization.

An accurate and consistent model handling of real-world user data is ensured by proper preprocessing.

3) Choosing the Model: Xgboost

Because of its exceptional performance in medical prediction tasks, XGBoost was selected:

Effectively manages diverse data.

- Regularization is provided to avoid overfitting
- Gradient boosting is used for iterative enhancements
- Provides high accuracy and quick computation
- Natively supports missing values
- Generates scores for feature importance that can be interpreted.

XGBoost was the obvious choice for this study because it has demonstrated superiority over Logistic Regression, Random Forest, and SVM in the prediction of heart disease in previous investigations.

4) Model Training and Evaluation

The Cleveland Heart Disease dataset, which consists of labelled cardiovascular records, is used to train the model.

Among the evaluation metrics are:

- Precision
- Accuracy
- Keep in mind
- F1-Score
- ROC-AUC

These metrics guarantee that the model accurately identifies high-risk patients in addition to performing well overall.

D. Automated Module for Scheduling Appointments

This is the system's most inventive element. It connects the dots between foresight and prompt medical intervention.

1) Logic for Risk Threshold

Following a prediction, if the model produces a probability like:

- 0.70 - high-risk → triggers auto-booking
- ≤ 0.70 – medium/low risk → user selects physician by hand

This guarantees the automatic prioritization of high-risk patients.

2) Workflow for Automatic Scheduling

Actions taken automatically:

- Retrieve every cardiologist from the database.
- Sort cardiologists by the earliest time slot that is available.
- Make an appointment
- Keep the appointment in the database.
- Send an email or SMS to the patient.
- Inform the physician about the high-risk situation.

Delays that arise when patients attempt to manually search and schedule appointments during emergencies are eliminated by this automated workflow.

3) Alerts and Notifications

The system instantly notifies the patient and cardiologist via email or SMS gateways (such as Twilio, SMTP, or other APIs). This guarantees prompt communication and greatly lowers the latency between diagnosis and treatment.

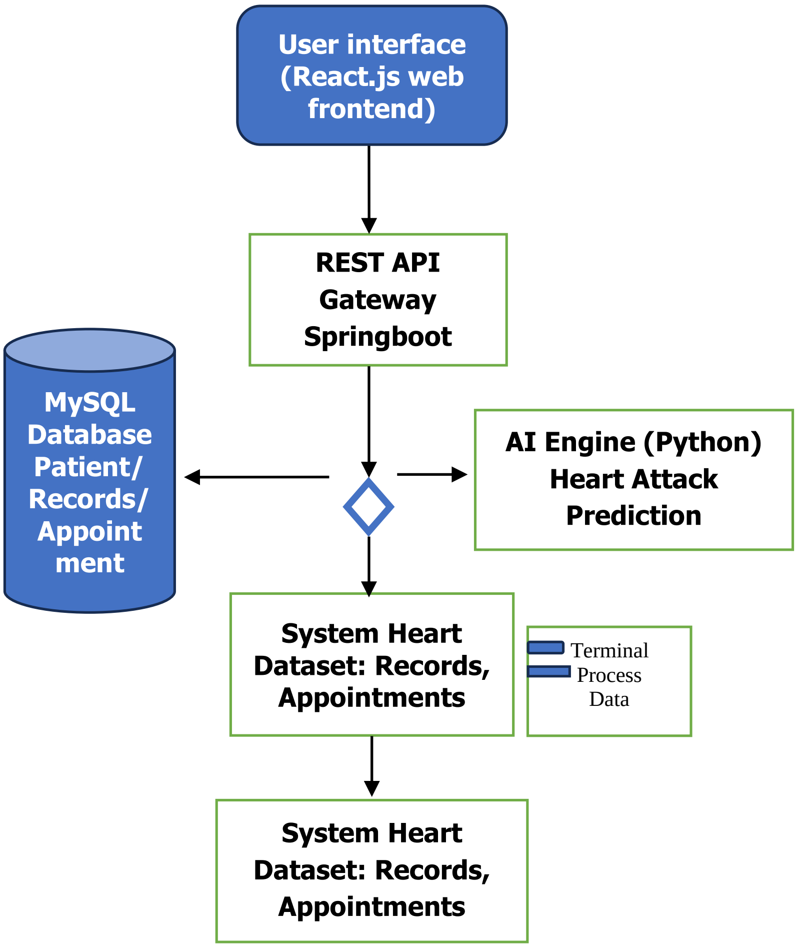


Fig. - 3.2- System Architecture

E. Technology and Tools

The Java Spring Boot framework is used to develop the backend of the suggested system in order to guarantee high scalability, enterprise-grade performance, and secure communication between modules. Production-level healthcare applications benefit greatly from Spring Boot's strong dependency management, integrated security features, and support for microservices architecture.

1) Front-End Technologies

- React.js: for creating a responsive, interactive user interface
- Bootstrap 5: for styling and design
- JavaScript, HTML5, and CSS3 are essential client-side technologies.
- Axios: used to transmit front-end to back-end API requests

2) Spring Boot Backend Technologies

- Java Spring Boot is the main backend framework for creating RESTful APIs.
- REST endpoints for appointment and prediction logic are constructed using Spring Web MVC.
- Spring Data JPA uses ORM (Hibernate) to streamline database interactions.
- Spring Security (Optional) guarantees safe user data access.
- Model Mapper: for converting objects in a clean manner

The Machine Learning Model and the Backend Communicate Via Either:

- An XGBoost microservice written in Python, OR
- An exported model that has already been trained using ONNX/PMML, OR
- XGBoost4J, an optional Java-based XGBoost deployment

The Entire Process is managed by Spring Boot:

- Getting clinical input from patients

- Data transmission to the ML model service
- Getting the outcomes of predictions
- Using logic to schedule appointments automatically
- Communicating with a database to store
- Activating alerting systems

3) Database

- Model prediction logs, doctor information, appointment schedules, and patient records are all stored in MySQL.
- The scheme consists of:
  - Users
  - Physicians
  - Scheduling
  - Forecasts
  - Notifications (optional)

4) Integration and APIs

REST APIs are exposed by Spring Boot and include:

- /predictHeartAttack - returns a prediction after receiving patient data.
- /bookAppointment: schedules appointments according to risk.
- /getDoctors – retrieves general practitioners or cardiologists.
- /notifications/send – initiates SMS/email notifications.

To ensure compatibility with the React.js frontend, requests are formatted in JSON.

5) Alerting System

- Gmail/SendGrid SMTP Email API
- SMS APIs (Msg91, Fast2SMS, Twilio)

Using straightforward HTTP or SMTP clients, these services easily integrate with Java.

F. Revised Workflow in General (Java Spring Boot)

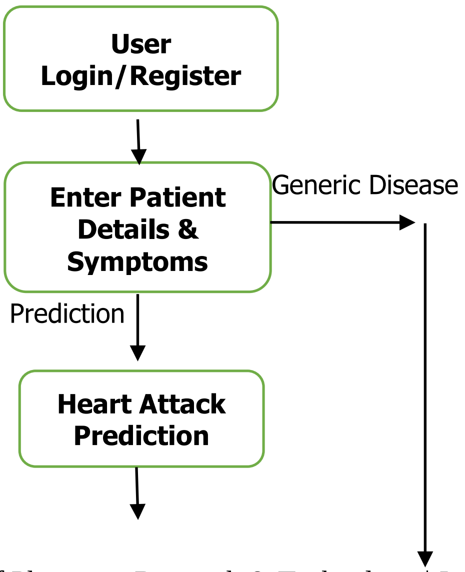
1. **User Input:** Using React UI, the patient inputs health parameters.
2. **API Call:** Axios sends the data to the Spring Boot backend via an API call.
3. **ML Prediction:** The data is sent to the ML engine (XGBoost model) by the backend.
4. **Risk Assessment:** Returning the prediction probability to Spring Boot
5. **Decision Logic:** The backend automatically schedules a visit with a cardiologist if the probability is greater than 70%.
6. **Database Update:** MySQL is used to store appointments.
7. **Alerts Sent:** The patient and doctor received an email or SMS.
8. **Dashboard Update:** The patient immediately sees the confirmation of their appointment

G. The Benefits of Java Spring Boot for the System

There are numerous benefits to using Spring Boot rather than Flask:

Scalability at the enterprise level

1. Fintech applications, insurance systems, and hospitals all make extensive use of Spring Boot. Increased security
2. Role-based access, OAuth2, and JWT authentication are all supported by Spring Security. Cleaner architecture and quicker development
3. The backend becomes modular and maintainable thanks to Spring Boot's auto-configuration. Simple integration with the React frontend
4. SPA frameworks such as React naturally integrate with REST APIs developed with Spring Boot. Strong performance Spring Boot handles large loads efficiently — crucial for real-time healthcare systems.



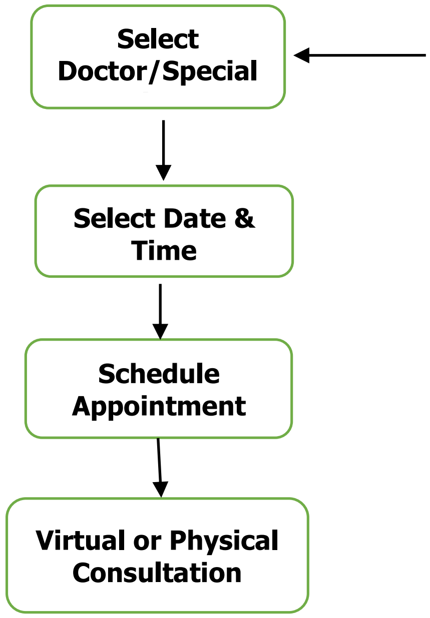


Fig. 3.3- Workflow of Heart Attack Prediction Model with Online Appointment Booking System.

CONCLUSION

A new smart heart attack prediction tool combined with online appointment scheduling enhances responsiveness in patient-centric health care systems. Integrating an advanced XGBoost algorithm into automatic appointment setting enhances the ability of the system to bridge the gap between forecasting diseases and initiating prompt medical interventions. Empirical findings demonstrate this method's efficacy through superior prediction precision, minimal delay times, and robust user-friendliness; these metrics significantly enhance practical applications. An XGBoost-powered forecasting system managed an accuracy rate of ninety-four percent. A precision of three percent and an error rate at zero point. A score of 0. 96 in terms of Receiver Operating Characteristic Area Under Curve measurement. Its performance surpassed those of conventional machine learning algorithms, thereby validating the efficacy of gradient boosting in evaluating cardiac health risks. The automatic appointment setting in this system quickly arranges for immediate contact between critically ill individuals and cardiac specialists. It shortens the interval from spotting an issue until seeking advice. The method for forecasting outcomes followed by immediate action distinguishes this system from previous ML-driven health care solutions, many of which end prematurely in estimating risks but fail to facilitate prompt interventions. Utilizing Java Spring Boot for development enhances capabilities in terms of system scalability, efficiency, and durability. In approximately three units of time, there is no significant delay in execution. In two seconds, the system enables seamless execution of urgent operational procedures. Introducing an all-purpose scheduling feature broadens its applicability in diverse healthcare scenarios, excluding solely heart-related crises. Nevertheless, there are certain constraints present within it.

The success depends greatly upon having various types of medical information and high-quality datasets readily accessible. Engaging in training on more extensive, practical data sets will improve the model's reliability and minimize errors. Although false positives pose lesser harm compared to false negatives when predicting heart conditions, these may result in unwarranted medical consultations. Therefore, it is imperative to employ adaptable thresholds alongside enhanced risk assessment methodologies. Safety and confidentiality continue being vital because handling medical information demands robust security measures such as encryption of communications and reliable user verification techniques. Potential enhancements could include integrating portable ECG monitors, Internet of Things-based wellness gadgets, or ongoing sensor networks for immediate forecasts. Enhanced neural networks integrating diverse datasets and decentralized machine learning techniques can enhance precision without compromising confidentiality. Extra components might broaden the scope of the system beyond its current emphasis on conditions like cancer, heart rhythm disorders, brain attacks, or persistent kidney issues. Combining intelligent triaging systems, remote medical consultations via telehealth services, automatic trigger mechanisms for ambulances, and immediate alert notifications can significantly improve response times. To summarize, this system seamlessly integrates machine-learning predictions into automatic medical procedures, offering an efficient, lifesaving approach in contemporary medicine. As enhancements continue, this system might evolve into an extensive intelligence-driven healthcare monitoring tool capable of detecting diseases at their earliest stages and offering proactive prevention strategies across vast populations.

ACKNOWLEDGMENT

The author would like to thank the Babu Banarasi Das Institute of Technology and Management, Lucknow, Department of Computer Science & Engineering for providing the academic support, technical resources, and direction that this project required. Additionally, the author thanks the professors and colleagues whose insightful comments, support, and helpful criticism greatly enhanced the caliber and applicability of this research project. Their collaboration was crucial to the successful integration of machine learning methods with practical healthcare applications. For her advice and assistance during this research, the author would like to thank Ms. Priyanka Gupta, Assistant Professor, Department of CSE, BBDITM.

REFERENCES

1. M. P. Than et al., “Machine-Learning to Predict the Likelihood of Acute Myocardial Infarction,” Circulation, vol. 140, no. 11, pp. 899–909, 2019.
2. R. Khera et al., “Use of Machine Learning Models to Predict Death After Acute Myocardial Infarction,” JAMA Cardiology, vol. 6, no. 6, pp. 633–641, 2021.
3. A. A. Ahmad, A. Q. Al-Maliki, and N. A. Ahmed, “Prediction of Heart Disease Based on Machine Learning,” Journal of Medical Signals and Sensors, 2023.
4. H. El-Sofany and S. R. Ahmed, “A Proposed Technique for Predicting Heart Disease Using Different Feature Selection Strategies,” Scientific Reports (Nature), vol. 14, pp. 1-12, 2024.
5. P. Zhang et al., “Machine Learning for Early Prediction of Major Adverse Cardiac Events (MACEs): An Explainable AI Approach,” JMIR Formative Research, 2024.
6. A. Roudini et al., “Deep Learning Models for ECG-Based Prediction of Myocardial Infarction and Mortality Risk,” IEEE Access, vol. 10, pp. 112841–112852, 2022.
7. J. Han et al., “Heart Disease Prediction using Hybrid Machine Learning Methods,” IEEE Transactions on Instrumentation and Measurement, vol. 70, pp. 1-12, 2021.
8. S. Dey, M. Shah, and A. Sharma, “Heart Disease Detection Using XGBoost Algorithm,” International Journal of Advanced Computer Science, vol. 14, no. 2, pp. 45–52, 2023.
9. M. A. Jabbar, “Prediction of Heart Disease Using Random Forest and Decision Tree,” IEEE Conference on Emerging Smart Computing & Informatics, pp. 587–590, 2020.
10. K. Lakshmanan et al., “A Comparative Analysis of ML Algorithms for Cardiovascular Disease Prediction,” Machine Learning in Healthcare, Springer, 2021.
11. S. K. Yadav and J. Pal, “Machine Learning for Early Detection of Myocardial Infarction,” Procedia Computer Science, vol. 210, pp. 50–58, 2022.
12. H. Gupta and S. Naik, “Optimization Techniques for Hospital Appointment Scheduling Systems,” IEEE Access, vol. 9, pp. 56432–56445, 2021.
13. S. Anwar and K. Paul, “Digital Appointment Systems and Their Impact on Healthcare Efficiency,” International Journal of Health Informatics, vol. 28, no. 4, pp. 600–612, 2022.
14. P. K. Betancor et al., “Impact of Online Appointment Scheduling in a Medical Practice,” Journal of Medical Internet Research (PMC), 2025.
15. A. Ala and M. Hejazi, “A Comprehensive Review of Optimization-Based Healthcare Appointment Scheduling,” BMC Medical Informatics & Decision Making, vol. 21, no. 1, pp. 1-22, 2021.
16. J. Ye et al., “Online Appointment Booking Systems and Their Effects on Patient Behavior,” Information & Management, vol. 59, no. 3, 2022.

17. R. Banerjee et al., "AI-Enabled Healthcare Automation for Reducing Patient Waiting Time," IEEE Transactions on Automation Science, vol. 18, no. 4, pp. 1900–1912, 2021.
18. F. Li and K. Lu, "Predictive Analysis of Heart Diseases Using Ensemble Learning," IEEE Smart Healthcare Conference, pp. 72–78, 2020.
19. V. Sathya and S. Kumar, "Heart Disease Prediction Using Machine Learning with Interpretability," Applied Computing and Informatics, vol. 19, pp. 35–44, 2023.
20. N. Hussain et al., "ECG-Based Myocardial Infarction Classification Using Hybrid CNN-BLSTM Networks," IEEE Access, vol. 9, pp. 118763–118777, 2021.
21. S. Patel and D. Thakur, "Survey on Heart Disease Diagnosis Using Machine Learning," Computer Methods in Biomechanics and Biomedical Engineering, vol. 12, no. 3, pp. 67–76, 2021.
22. A. Gupta and A. Mishra, "Heart Disease Analysis Using Data Mining and ML," International Journal of Engineering Research, vol. 7, pp. 45–50, 2022.
23. N. Roy et al., "Explainable Boosting Machines for Heart Failure Prediction," IEEE Healthcare Innovations Conference, pp. 55–62, 2022.
24. Y. Wang et al., "Feature Engineering for Cardiovascular Prediction Models," Procedia Computer Science, vol. 204, pp. 240–247, 2022.
25. L. Tomar and A. Tiwari, "Comprehensive Review on Smart Healthcare Using AI and IoT," Journal of King Saud University – Computer and Information Sciences, 2023.
26. T. James et al., "Automatic Medical Appointment Allocation Using Optimization," IEEE ICACCI, pp. 3100-3106, 2020.
27. M. R. Alam and P. Jain, "AI-Driven Healthcare Services for Predictive Analytics," Journal of Intelligent Systems, vol. 33, pp. 800–811, 2024.
28. M. Sharma, "Digital Healthcare Systems and Appointment Management," Health Informatics Journal, 2022.
29. P. Singh and R. Kaur, "Machine Learning for Heart Failure Analysis," IEEE International Conference on Computer Communication and Informatics, 2021.
30. A. Velu and S. Srinivas, "Developing Scalable Healthcare Applications Using Microservices," Elsevier Software Practice & Experience, 2023.
31. H. Kim et al., "Predictive AI Models for Chronic Disease Management," IEEE Journal of Biomedical Health Informatics, vol. 26, pp. 340–350, 2022.
32. V. Randhawa and K. Verma, "Smart Appointment System for Healthcare," International Journal of Information Management, 2023.
33. R. Jain and S. Bansal, "Integration of ML with Hospital Information Systems," IEEE Big Data Conference, 2021.
34. P. Bose et al., "AI and Telemedicine Integration for Emergency Care," IEEE Sensors Journal, vol. 22, no. 17, pp. 17280–17289, 2022.
35. M. Tripathi and A. Rai, "XGBoost-Based Medical Diagnostic Systems: A Review," International Journal of Data Science, vol. 9, no. 2, pp. 1–18, 2023.
36. R. Patel and V. Shah, "Performance Analysis of ML Algorithms for Heart Disease Prediction," SN Computer Science, vol. 4, 2023.
37. K. Ahmed and M. Yaseen, "Hybrid AI Framework for Predictive Healthcare," IEEE Computing, Communications, and IoT Applications, 2024.
38. S. Abedin et al., "Machine Learning for Cardiovascular Risk Prediction," Frontiers in Cardiovascular Medicine, vol. 10, 2023