International Journal of Engineering & Extended Technologies Research (IJEETR)

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802070

Machine Learning Driven Predictive Analysis for Heart Disease Diagnosis

M. Prakash Kumar M.E, Ph.D , Gokulraj M , Bhuvaneshwari K, Harivarshini R S, Abirami P

Department of Computer Science and Engineering, R P Sarathy Institute of Technology, Salem, Tamil Nadu, India

Department of Computer Science and Engineering, R P Sarathy Institute of Technology, Salem, Tamil Nadu, India

Department of Computer Science and Engineering, R P Sarathy Institute of Technology, Salem, Tamil Nadu, India

Department of Computer Science and Engineering, R P Sarathy Institute of Technology, Salem, Tamil Nadu, India

Department of Computer Science and Engineering, R P Sarathy Institute of Technology, Salem, Tamil Nadu, India

Publication History: Received: 25.02.2026; Revised: 20.03.2026; Accepted: 25.03. 2026; Published: 28.03.2026.

ABSTRACT: Heart disease remains one of the leading causes of mortality worldwide. Early detection and timely medical intervention can significantly reduce the risk associated with cardiovascular diseases. With the advancement of machine learning techniques, predictive systems can assist healthcare professionals in identifying potential heart disease risks at an early stage. This project presents a Machine Learning Driven Predictive System for Heart Disease Diagnosis, implemented as a web-based application. The system analyzes multiple health- related parameters such as age, gender, blood pressure, cholesterol level, blood sugar level, Alcohol consumption, Smoking habits. These medical attributes are processed using machine learning algorithms to predict the likelihood of heart disease occurrence. The proposed system implements two classification algorithms: Logistic Regression and Random Forest. Among these models, the Random Forest algorithm de monstrates superior performance with an approximate prediction accuracy of 95%, making it the primary model used for risk prediction. The system categorizes the prediction results into High Risk or Low Risk levels, while also providing explanations related to the contributing health factors. The application is developed using Python with the Flask framework, integrating machine learning libraries such as Scikit-learn, along with SQLite database management for storing user and prediction data. Additionally, the system provides graphical analysis and automated PDF report generation for prediction results.

KEYWORDS: Heart Disease Prediction, Machine Learning, Logistic Regression, Random Forest, Healthcare Anal ytics, Predictive Modelling, Flask Web Application.

I. INTRODUCTION

Cardiovascular diseases, particularly heart disease, continue to be one of the most significant causes of death across the globe. According to global health reports, millions of people are affected by heart-related conditions each year, making early detection and prevention a critical priority in modern healthcare systems. The complexity of heart disease arises from the involvement of multiple risk factors such as age, lifestyle habits, genetic predisposition, blood pressure, cholesterol levels, and other physiological and behavioralattributes. Identifying and analyzing these factors accurately is essential for effective diagnosis and treatment.

Traditional diagnostic approaches primarily depend on clinical tests, laboratory investigations, and expert medical evaluation. While these methods are reliable, they often require considerable time, resources, and accessibility to healthcare facilities. In many cases, early symptoms may go unnoticed, leading to delayed diagnosis and increased risk of severe complications. Moreover, healthcare professionals frequently handle large volumes of patient data, making it challenging to manually analyze all relevant parameters efficiently.

With the rapid advancement of technology, machine learning has emerged as a powerful tool in the healthcare domain. Machine learning algorithms are capable of processing large datasets, identifying hidden patterns, and making predictive decisions based on historical data. These capabilities make machine learning particularly suitable for disease prediction and risk assessment. By leveraging predictive models, it becomes possible to estimate the likelihood of heart disease based on a combination of medical and lifestyle factors.

In this context, the present work focuses on developing a machine learning-based predictive system for heart disease diagnosis. The system is designed as a web-based application that allows users to input various health parameters and obtain real-time predictions regarding their heart disease risk. The application integrates two widely used classification algorithms—Logistic Regression and Random Forest—to analyze input data and generate prediction results. While Logistic Regression provides a simple and interpretable model, Random Forest enhances prediction accuracy through ensemble learning techniques.

The primary objective of this system is to provide a user- friendly platform that enables individuals to assess their heart health risk at an early stage. By offering quick and accessible predictions, the system aims to increase awareness and encourage preventive healthcare measures. In addition, the integration of graphical analysis and report generation features

enhances the usability of the system, making it suitable for both general users and healthcare support applications. Heart disease remains one of the leading causes of mortality worldwide, posing a significant challenge to healthcare systems. Early detection and timely diagnosis play a crucial role in reducing the severity of cardiovascular conditions and improving patient outcomes. However, traditional diagnostic methods often rely on multiple clinical tests and expert evaluation, which can be time-consuming and may not always be easily accessible. Additionally, the increasing volume of medical data makes it difficult for healthcare professionals to manually analyze all relevant risk factors effectively.

With the rapid advancement of technology, machine learning has emerged as a powerful tool for medical data analysis and disease prediction. Machine learning algorithms are capable of processing large datasets, identifying hidden patterns, and generating predictive insights based on historical health records. These capabilities enable the development of intelligent systems that can assist in early-stage diagnosis by analyzing various health parameters such as age, blood pressure, cholesterol level, blood sugar, and lifestyle habits. As a result, machine learning-based approaches have gained significant attention in healthcare applications.

In this work, a machine learning-driven predictive system for heart disease diagnosis is proposed, implemented as a web- based application. The system utilizes classification algorithms such as Logistic Regression and Random Forest to analyze user-provided health data and predict the risk level of heart disease. The application is designed to be user-friendly, allowing individuals to input their health information and receive instant prediction results categorized as high risk or low risk. By integrating machine learning with web technologies, the proposed system aims to improve accessibility, enhance early detection, and support preventive healthcare decision-making.

In this context, the proposed system focuses on developing a machine learning-based predictive model for heart disease diagnosis, implemented through a web-based platform. The system utilizes key health parameters to analyze and classify the risk level using Logistic Regression and Random Forest algorithms, with an emphasis on improving prediction accuracy and usability. Unlike traditional approaches, the proposed solution provides an interactive interface that enables users to input health data and receive instant predictions along with meaningful insights. By integrating machine learning techniques with web technologies, this work aims to enhance accessibility to early risk assessment and contribute to preventive healthcare by enabling timely awareness and informed decision-making.

II. RELATED WORK

In recent years, machine learning techniques have been widely applied in the field of healthcare for predicting heart disease. Various studies have explored classification algorithms such as Logistic Regression, Decision Trees, Support Vector Machines, and Random Forest to analyze clinical datasets and identify patterns associated with cardiovascular conditions. Among these approaches, Random Forest has been widely recognized for its ability to handle high-dimensional data and improve prediction accuracy through ensemble learning. Several research works have reported that Random Forest outperforms traditional models with accuracy levels reaching up to 90% or higher, making it a reliable choice for medical prediction systems.

Despite the progress in this domain, existing systems still face several limitations. Most research works focus primarily on model development and accuracy comparison, without implementing complete real-time systems for user interaction. Additionally, many systems lack user-friendly interfaces, making them less accessible to non-technical users. Some studies also rely on limited datasets, which may affect the generalization of the models. To

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802070

overcome these challenges, the proposed system integrates machine learning algorithms with a web-based application, providing real-time prediction, improved accessibility, and for early heart disease risk assessment.
Among these techniques, Random Forest has emerged as one of the most effective algorithms for heart disease prediction. Its ensemble learning approach combines multiple decision trees to improve classification accuracy and reduce overfitting. Several studies have reported that Random Forest achieves higher performance compared to other models, with accuracy levels often exceeding 90%. Logistic Regression, although simpler, is also widely used due to its interpretability and ability to model the relationship between input features and disease probability in a clear and understandable manner.

Another important aspect highlighted in previous research is the role of data preprocessing and feature selection in enhancing model performance. Medical datasets often contain missing values, inconsistencies, and redundant attributes that can negatively impact prediction accuracy. Techniques such as data cleaning, normalization, and encoding of categorical variables are essential to prepare the data for analysis. Additionally, selecting relevant features such as age, cholesterol level, blood pressure, blood sugar, and lifestyle habits significantly improves the effectiveness of predictive models.

Furthermore, several limitations can be observed in current systems, including the use of limited datasets, lack of user-friendly interfaces, and absence of real-time prediction capabilities. These challenges highlight the need for an integrated solution that combines accurate machine learning models with an accessible platform. The proposed system addresses these gaps by developing a web-based application that enables users to input health parameters and receive instant predictions, thereby bridging the gap between research models and real-world healthcare applications.

III. SYSTEM ARCHITECTURE

The proposed ML-Driven Predictive Analysis for Heart Disease Diagnosis system is designed using a modular and scalable architecture that integrates a user interface, backend processing unit, machine learning module, and database management system. The system follows a layered approach to ensure efficient data flow, separation of concerns, and ease of maintenance. Each component is responsible for a specific function, enabling seamless interaction between data collection, processing, prediction, and result visualization.

A. Overall Architecture

The overall architecture of the ML-Driven Predictive Analysis for Heart Disease Diagnosis system is designed as a web-based platform that integrates user interaction, data processing, machine learning prediction, and result visualization. The system follows a structured multi-layered approach to ensure efficient communication between components and smooth data flow. It enables users to input health-related parameters, which are then processed and analyzed to generate predictions regarding heart disease risk.

The architecture primarily consists of three major layers: the presentation layer, the application layer, and the data layer. The presentation layer provides the user interface through which users can enter their health information using structured forms. The application layer, implemented using the Flask framework, acts as the core processing unit that handles user requests, validates input data, and coordinates with the machine learning module. The machine learning component processes the input using trained models such as Logistic Regression and Random Forest to generate prediction results.

The system is composed of multiple interconnected modules, including the user interface, processing unit, machine learning component, and database system. The user interface captures and forwards input data to the backend, where it is validated and prepared for analysis. The machine learning module processes the input using trained algorithms such as Logistic Regression and Random Forest to generate risk predictions. The database stores relevant information for future reference, and the final output is presented to the user in an easily interpretable format. This architecture ensures scalability, reliability, and efficient performance of the prediction system.

The overall architecture ensures modularity, scalability, and real-time prediction capability, making the system efficient and user-friendly for heart disease risk assessment.

International Journal of Engineering & Extended Technologies Research (IJEETR)

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802070

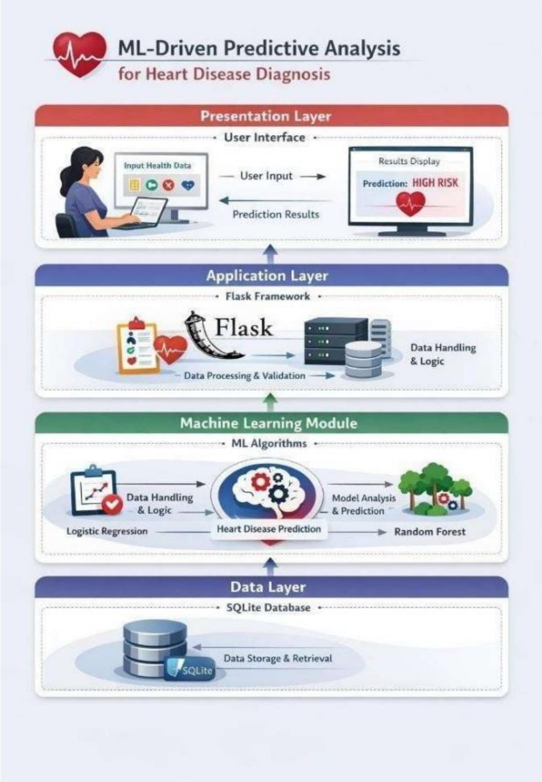

Fig. 1. Three-tier architecture of the web-based heart disease diagnosis

B. Presentation Layer

The presentation layer of the ML-Driven Predictive Analysis for Heart Disease Diagnosis system is responsible for providing an interactive and user-friendly interface through which users can access the application. It acts as the primary point of communication between the user and the system, enabling users to input health-related data and receive prediction results. The interface is designed to ensure simplicity and clarity so that users can easily understand and interact with the system without requiring technical knowledge.

The user interface is developed using standard web technologies such as HTML and CSS, which define the structure and visual layout of the application. The design focuses on creating a clean and organized interface that allows users to navigate through different sections of the application, including Home, About, Login, and Dashboard pages. Each page is structured to provide clear information and smooth navigation, ensuring a better user experience.

The presentation layer includes structured input forms that allow users to enter various health-related parameters required for heart disease prediction. These parameters include personal details, physiological measurements, lifestyle factors, medical history indicators, and symptom-related information. The form is designed in a way that guides users to provide all necessary data accurately, which is essential for generating reliable prediction results.

Input validation is an important feature implemented within the presentation layer to ensure data accuracy and consistency. Before submitting the data to the backend, the system checks whether all required fields are filled and whether the entered values are in the correct format. This reduces the chances of incorrect or incomplete data being processed by the machine learning models, thereby improving the overall reliability of the system.

Once the user submits the form, the presentation layer communicates with the backend server through HTTP requests handled by the Flask framework. The input data is securely transmitted to the backend for further processing and prediction. After the machine learning module generates the prediction, the results are sent back to the frontend and displayed to the user in a clear and understandable format.

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802070

The presentation layer also supports the display of prediction outcomes along with additional insights such as risk level classification and related information. The results are presented in a structured manner, enabling users to easily interpret their heart disease risk. Overall, the presentation layer plays a crucial role in ensuring effective user interaction, smooth data input, and clear visualization of prediction results within the system.

C. Application Layer

The application layer of the ML-Driven Predictive Analysis for Heart Disease Diagnosis system serves as the core processing unit that manages the overall functionality of the application. It acts as an intermediary between the presentation layer and the data layer, ensuring smooth communication and coordination among different components. This layer is responsible for handling user requests, processing input data, and executing the machine learning models to generate prediction results.

The application layer is implemented using the Flask framework in Python, which provides a lightweight and efficient environment for building web applications. Flask handles routing, request processing, and communication between the frontend interface and backend logic. When a user submits health-related data through the web interface, the Flask server receives the request and initiates the necessary processing steps.

One of the key responsibilities of this layer is input validation and data preprocessing. The system verifies whether the received data is complete and correctly formatted before proceeding with further analysis. After validation, the input data is transformed into a structured format suitable for machine learning processing. This step ensures that the prediction models receive consistent and reliable input values.

The application layer also integrates the machine learning module, which includes trained models such as Logistic Regression and Random Forest. These models analyze the processed input data to identify patterns associated with heart disease risk. The system uses these algorithms to evaluate the relationship between various health parameters and generate accurate predictions.

In addition to prediction processing, the application layer manages the overall workflow of the system. It coordinates the sequence of operations, including receiving input data, preprocessing, invoking the machine learning models, and generating output results. The layer ensures that each step is executed efficiently, enabling real-time prediction and response generation.

Once the prediction is completed, the application layer prepares the output and sends it back to the presentation layer. The results include the classification of heart disease risk as high or low, along with relevant insights. This layer ensures that the response is delivered in a structured and understandable format, enabling effective communication between the system and the user.

D. Data Layer

The data layer of the ML-Driven Predictive Analysis for Heart Disease Diagnosis system is responsible for managing and maintaining all the data required for the application. It plays a crucial role in storing user information, health-related parameters, and prediction results generated by the system. This layer ensures that data is properly organized and structured so that it can be easily accessed and processed when needed. By maintaining a centralized storage mechanism, the system ensures consistency and reliability in handling data. The data layer supports smooth interaction with other components of the system, particularly the application layer. Overall, it forms the backbone of the system's data management functionality.

The system uses SQLite as the database management system, which is integrated with the backend using Python's sqlite3 module. SQLite is chosen because it is lightweight, efficient, and does not require a separate server for operation. This makes it highly suitable for web-based applications where simplicity and performance are important. The integration with Python allows seamless execution of database operations such as insertion, retrieval, and updating of records. It also reduces system complexity while maintaining efficient data handling. The use of SQLite ensures that the application remains easy to deploy and manage.

The data layer stores multiple types of information, including user details, input health parameters, and prediction outcomes. These data elements are essential for the functioning of the heart disease prediction system. Each record is stored in a structured format, allowing the system to maintain organized and meaningful data. Proper structuring of data ensures that the machine learning models receive accurate and consistent inputs. It also helps in maintaining a clear record of prediction history for each user. This organized storage plays a key role in supporting the overall workflow of the system.

Data retrieval is performed through structured queries executed by the backend application. Whenever the system requires stored information, the application layer interacts with the database to fetch the relevant records. This interaction ensures smooth communication between the data layer and the processing components of the system. Efficient query execution allows quick access to stored data, which is important for real-time prediction and response generation. The retrieval process is designed to be reliable and consistent, ensuring that correct data is always available when needed. This improves the overall performance and responsiveness of the system.

The data layer also ensures data integrity and consistency by maintaining accurate and reliable records. Proper handling of database operations reduces the risk of data loss, duplication, or corruption. This is particularly important in applications dealing with health-related information, where accuracy is critical. The system ensures that all stored data remains consistent throughout its lifecycle. Mechanisms such as structured storage and controlled access help maintain data quality. As a result, the system can provide dependable prediction results based on reliable data.

In addition to storage and retrieval, the data layer supports future enhancements such as data analysis and report generation. By maintaining historical records of user inputs and prediction results, the system can be extended to perform deeper analysis of health trends. This can help in improving model performance and providing better insights to users. The stored data can also be used for generating reports or visual representations when required. This makes the data layer not only a storage component but also a foundation for future scalability. Overall, it enhances the long-term usability and effectiveness of the system.

E. Security and Privacy Considerations

The ML-Driven Predictive Analysis for Heart Disease Diagnosis system handles sensitive health-related information, making security an important aspect of the application. The system ensures that user data is collected and processed in a secure manner through controlled access to the application. Basic authentication mechanisms are implemented to restrict unauthorized users from accessing the system features. Additionally, input validation is performed to prevent invalid or malicious data from being processed by the backend. These measures help in maintaining the integrity and reliability of the system.

Privacy of user data is also a key consideration in the design of the system. The application stores only the necessary information required for prediction and analysis, avoiding unnecessary data collection. User health parameters and prediction results are securely stored in the SQLite database, ensuring that data is not exposed to external sources. Thesystem is designed to handle data responsibly, minimizing the risk of misuse or unauthorized sharing of personal health information. This approach helps in maintaining user trust and ensures ethical handling of sensitive data.

Furthermore, the system follows best practices to ensure safe communication between the frontend and backend components. Data transmitted between the user interface and the server is processed through controlled backend operations, reducing the risk of data leakage. Proper handling of database operations ensures that stored data remains consistent and protected from corruption. Although the current system is designed for academic and demonstration purposes, it provides a foundation for implementing advanced security features such as encryption and secure authentication in future enhancements. Overall, the system emphasizes basic security and privacy measures to ensure safe and reliable operation.

F. Multilingual and Configurable Deployment

The ML-Driven Predictive Analysis for Heart Disease Diagnosis system is designed with flexibility in deployment, allowing it to be configured and adapted to different environments with minimal changes. The application is developed using Python and the Flask framework, making it lightweight and easy to deploy on various platforms such as local servers or cloud-based systems. The modular structure of the system enables developers to configure parameters such as database settings, model selection, and application routes based on deployment requirements. This flexibility ensures that the system can be efficiently used in different scenarios, including academic, research, and small-scale healthcare applications.

Although the current implementation primarily uses a single language interface, the system can be extended to

International Journal of Engineering & Extended Technologies Research (IJEETR)
|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |
| Volume 8, Issue 2, March - April 2026 |
DOI:10.15662/IJEETR.2026.0802070

support multilingual capabilities in future enhancements. The frontend design using HTML and CSS allows easy modification of labels, instructions, and content to accommodate different languages. By incorporating multilingual support, the system can improve accessibility and usability for users from diverse linguistic backgrounds. Additionally, configurable deployment settings enable the system to be customized according to user needs and operational requirements. This adaptability enhances the scalability and practical usability of the application across different regions and user groups.

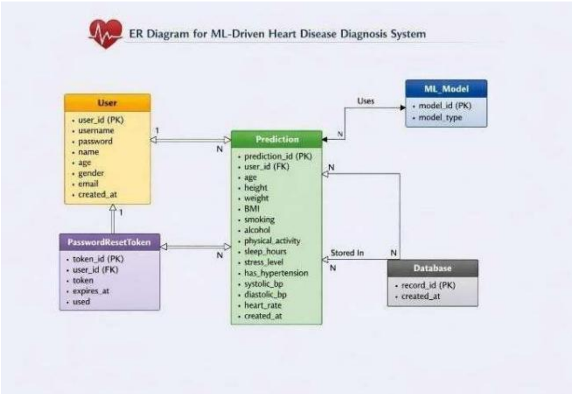

Fig. 2. Entity–relationship diagram

IV. ADVANCED FEATURES

Beyond basic web-based appointment booking, the proposed system integrates several advanced features that improve real-time visibility, communication, and usability. This section describes the live queue tracking mechanism, the notification workflow using SMS and voice calls, the multi- step appointment process with conflict validation, and the role-based dashboards including emergency handling.

A. Intelligent Risk Prediction and Classification

The proposed system incorporates an intelligent risk prediction mechanism using machine learning algorithms to analyse user health data. By leveraging models such as Logistic Regression and Random Forest, the system can effectively identify patterns associated with heart disease. These models are trained on structured datasets, enabling them to provide reliable predictions based on input parameters. The integration of machine learning enhances the system's capability to perform accurate and efficient analysis. This feature plays a crucial role in supporting early-stage diagnosis and preventive healthcare.

The prediction process is designed to evaluate multiple health-related attributes, including demographic details, physiological measurements, lifestyle habits, and symptom- related factors. Each of these parameters contributes to determining the overall risk level of the user. The system processes these inputs in a structured manner to ensure consistency and accuracy in prediction. By analysing multiple features simultaneously, the model provides a comprehensive assessment of heart disease risk. This multi-parameter evaluation improves the reliability of the prediction results.

The system classifies users into predefined categories such as high risk and low risk based on the output of the machine learning models. This classification simplifies the interpretation of results for users, making it easier to understand their health condition. The categorization is based on learned patterns from historical data, ensuring that predictions are data-driven. This approach helps users quickly identify their risk level without requiring complex medical interpretation. It enhances the usability and effectiveness of the system.

In addition to classification, the system ensures that the prediction process is efficient and responsive. The models are optimized to provide results in real time, enabling users to receive instant feedback after submitting their health data. This real-time capability is essential for improving user engagement and providing timely insights. The system is designed to handle input processing and prediction generation seamlessly. This ensures a smooth and uninterrupted user experience.

International Journal of Engineering & Extended Technologies Research (IJEETR)

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802070

Another important aspect of the system is its ability to continuously improve prediction accuracy through model evaluation and refinement. The performance of the machine learning models is assessed using standard evaluation metrics such as accuracy, precision, recall, and F1-score. Based on these evaluations, the models can be fine-tuned and retrained with updated datasets to enhance their predictive capabilities. This iterative improvement ensures that the system remains reliable and adaptable to new data patterns. By incorporating ongoing optimization, the system maintains high performance and continues to deliver accurate risk predictions over time.

Overall, the intelligent prediction feature demonstrates the effective application of machine learning in healthcare systems. It combines accuracy, speed, and usability to deliver meaningful results. By providing reliable risk assessment, the system contributes to early detection and awareness of heart disease. This feature forms the core functionality of the application. It highlights the potential of integrating predictive analytics into web-based healthcare solutions.

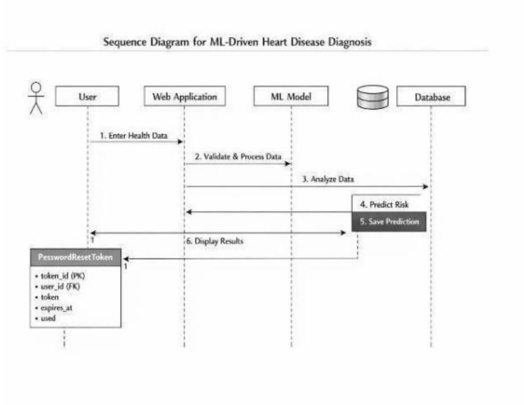

Fig. 3. Sequence diagram

B. Interactive Web-Based User Interface

The system provides an interactive web-based interface that enables users to easily access and utilize the prediction functionality. The interface is designed using HTML and CSS to ensure a clean and structured layout. It allows users to navigate through different sections such as Home, About, Login, and Dashboard. The simplicity of the interface ensures that users with minimal technical knowledge can operate the system effectively. This enhances accessibility and usability for a wide range of users.

The dashboard plays a central role in user interaction by providing structured input forms for entering health-related parameters. Users can input details such as age, blood pressure, cholesterol level, and lifestyle factors through well- organized fields. The form design ensures clarity and ease of data entry, reducing the chances of user errors. Proper labelling and grouping of input fields help users understand the required information. This contributes to accurate data collection for prediction.

The interface also incorporates input validation mechanisms to ensure data accuracy before submission. It checks whether all required fields are filled and verifies the format of the entered values. This prevents incorrect or incomplete data from being processed by the backend system. By ensuring valid input, the system improves the reliability of prediction results. Input validation enhances both system performance and user experience.

Once the prediction is generated, the results are displayed on the interface in a clear and understandable format. The system presents the risk level along with relevant insights, allowing users to interpret their health status easily. The structured result display improves readability and comprehension. This ensures that users can quickly understand the outcome without confusion. The interface design focuses on clarity and simplicity.

Overall, the interactive web-based interface enhances the usability of the system by providing a smooth and intuitiveuser experience. It ensures effective communication between the user and the system. The combination of structured input, validation, and clear output presentation makes the interface highly efficient. This feature significantly improves user engagement and accessibility a vital role in the overall functionality of the application.

International Journal of Engineering & Extended Technologies Research (IJEETR)

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802070

Another key feature of the interface is its responsive design, which ensures compatibility across different devices such as desktops, tablets, and smartphones. The layout automatically adjusts to various screen sizes, providing a consistent and user-friendly experience regardless of the device being used. This flexibility allows users to access the system anytime and anywhere without facing usability issues. Responsive design improves accessibility and ensures that the application reaches a broader audience. By maintaining visual consistency and functionality across platforms, the system enhances overall user satisfaction and convenience.

C. Automated Report Generation and Data Visualization

The system includes an automated report generation feature that provides users with a structured summary of their prediction results. This feature enhances the usability of the system by allowing users to save and review their results. The reports are generated in PDF format, making them easy to share and store. This functionality adds value to the application by providing documented insights. It supports better understanding and record-keeping for users.

In addition to report generation, the system incorporates basic data visualization using graphical representations. Visualization tools help present prediction-related information in a more intuitive manner. Graphs and charts provide a clear view of health data trends and analysis results. This improves the interpretability of the system outputs. Visual representation makes complex data easier to understand for users.

The report includes key details such as user input parameters, prediction results, and risk classification. This structured presentation ensures that all relevant information is included in a single document. Users can refer to the report for future analysis or discussion with healthcare professionals. The inclusion of detailed information enhances the usefulness of the generated reports. It provides a comprehensive overview of the prediction outcome.

The automation of report generation ensures that users receive their results instantly without manual intervention. This improves efficiency and reduces processing time. The system is designed to generate reports dynamically based on user input and prediction results. This feature enhances the responsiveness of the application. It ensures that users receive complete information in a timely manner.

Another important aspect of this feature is the customization capability of the generated reports. The system can be designed to include user-specific details such as date, time, and personalized identifiers, making each report unique and relevant. Additionally, reports can be formatted with proper headings, sections, and visual highlights to improve readability. This structured customization ensures that users can easily navigate through the report content. It enhances the professional quality and presentation of the generated documents.

Furthermore, the system ensures secure handling and storage of generated reports and user data. Access to reportscan be restricted through authentication mechanisms, ensuring that only authorized users can view or download their information. This helps maintain data privacy and confidentiality, which is crucial in healthcare-related applications. The system may also support optional cloud storage or local download features for flexibility. By prioritizing data security, the application builds trust and reliability among its users.

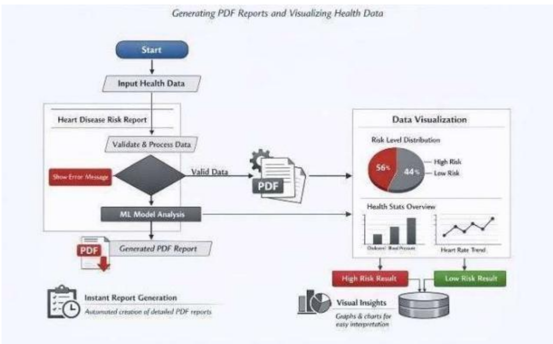

Fig. 4. Flowchart of the Automated Report Generation

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802070

D. Efficient Data Management and Storage

The system implements an efficient data management mechanism to store and organize user information and prediction records. SQLite is used as the database management system due to its lightweight and reliable nature. It allows the system to store data without requiring a separate database server. This simplifies the deployment and maintenance of the application. The use of SQLite ensures efficient handling of data operations.

The database stores essential information such as user details, health parameters, and prediction results. Each record is maintained in a structured format to ensure easy retrieval and processing. Proper organization of data helps maintain consistency and reliability within the system. It also supports efficient interaction with the backend application. Structured storage plays a key role in system performance.

Data retrieval is handled through queries executed by the backend system. This enables the application to access stored data whenever required. Efficient query processing ensures quick response times during data retrieval. This is important for maintaining real-time system performance. The interaction between the database and backend is seamless and reliable. The system also ensures data integrity by maintaining accurate and consistent records. Proper handling of database operations reduces the risk of data loss or corruption. This is particularly important when dealing with sensitive health-related information. The database design supports secure and reliable data storage. It enhances the overall stability of the system.

Overall, the data management feature ensures that all application data is stored and processed efficiently. It supports smooth system operation and reliable prediction results. The use of SQLite provides a simple yet effective solution for database management. This feature contributes to the scalability and maintainability of the system. It forms an essential component of the application architecture.

Another key advantage of the data management system is its ability to support data backup and recovery mechanisms. Regular backups can be implemented to prevent loss of important user information and prediction records. In case ofsystem failure or unexpected errors, the backup data can be restored to ensure continuity of service. This improves the reliability and robustness of the application. By incorporating backup and recovery strategies, the system ensures long-term data safety and enhances user confidence in the platform.

E. Real-Time Prediction and Response System

The proposed system is designed to provide real-time prediction of heart disease risk, enabling users to receive immediate feedback after submitting their health data. This feature is essential in improving user experience and ensuring timely access to predictive insights. The integration of machine learning models with a web-based application allows the system to process input data instantly. As a result, users do not experience delays in receiving their prediction results. This real-time capability enhances the practicality and responsiveness of the system.

The prediction process begins when the user enters health- related parameters through the web interface and submits the data. The backend system, implemented using Flask, quickly processes the input and performs necessary validation and preprocessing. Once the data is prepared, it is passed to the trained machine learning models for analysis. The system ensures that each step is executed efficiently to maintain quick response times. This streamlined workflow supports real-time prediction functionality.

The machine learning models, particularly Random Forest and Logistic Regression, are optimized to generate predictions within a short duration. These models are pre-trained and integrated into the system, allowing them to process new input data without additional training time. The use of efficient algorithms ensures that prediction results are both accurate and fast. This is important for maintaining system performance and user satisfaction. The combination of speed and accuracy makes the system reliable.

After the prediction is generated, the results are immediately sent back to the user interface for display. The system presents the output in a clear format, indicating whether the user falls under a high-risk or low-risk category. This instant feedback allows users to quickly understand their health condition. The real-time response mechanism ensures smooth communication between backend processing and frontend display. It enhances the overall efficiency of the application.

Additionally, the system is designed to handle multiple user requests simultaneously without compromising performance. Efficient request handling mechanisms ensure that the server can process concurrent inputs while

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802070

maintaining consistent response times. This scalability is important for supporting a large number of users in real-world deployment scenarios. By managing multiple requests effectively, the system maintains reliability and prevents delays during peak usage. It ensures a stable and smooth user experience even under heavy load.

Moreover, the real-time system incorporates error handling and feedback mechanisms to improve robustness. If any issue occurs during data submission or processing, the system promptly notifies the user with appropriate messages. This helps users understand and correct errors without confusion. Proper error handling ensures that the application remains stable and user-friendly. It also enhances system reliability by preventing unexpected failures during operation.

V. IMPLEMENTATION AND EVALUATION

A. Technology Stack and Development Environment

The system is implemented using a Python-based technology stack that supports both machine learning and web application development. The backend is developed using the Flask framework, which provides a lightweight and efficient environment for handling HTTP requests and managing application logic. The frontend interface is designed using HTML and CSS, enabling users to interact with the system through structured forms and intuitive navigation. Communication between the frontend and backend is handled through standard HTTP protocols, ensuring smooth data exchange within the application.

The machine learning component is developed using the Scikit-learn library, which provides efficient implementations of classification algorithms such as Logistic Regression and Random Forest. These models are trained using the UCI Cleveland Heart Disease dataset and integrated into the backend for real-time prediction. Data preprocessing and feature handling are performed using Python libraries to ensure that input data is properly structured before analysis. The use of these libraries ensures reliable model performance and efficient data processing.

The database is implemented using SQLite, which is integrated with the application through Python's sqlite3 module. SQLite is selected due to its lightweight nature and ease of deployment, as it does not require a separate database server. The system is developed and tested in a local environment, ensuring smooth integration of all components. The chosen technology stack provides a balance between simplicity, efficiency, and scalability, making it suitable for academic and small-scale healthcare applications.

Module Implementation Overview

The system is structured into multiple functional modules that correspond to different stages of the prediction workflow. The user interaction module handles activities such as accessing the application, navigating through pages, and entering health-related data. This module ensures that users can easily provide input through structured forms and receive prediction results in an understandable format. It acts as the entry point for all system operations.

The data processing module is responsible for validating and preprocessing the input data before it is passed to the machine learning models. It ensures that all input values are correctly formatted and free from inconsistencies. This module plays a critical role in maintaining the accuracy and reliability of the prediction system. Proper preprocessing helps improve the effectiveness of the machine learning algorithms.

The prediction module integrates the trained machine learning models, including Logistic Regression and Random Forest. It analyzes the processed input data and generates prediction results indicating the risk level of heart disease. The system also includes a database management module that stores user data and prediction records using SQLite. These modules work together to ensure efficient system operation and seamless interaction between different components.

The system also includes a report generation and visualization module that enhances the presentation of prediction results. This module is responsible for creatingstructured reports in PDF format and generating graphical representations such as charts and graphs. It ensures that users receive both textual and visual insights into their health data and prediction outcomes. By integrating reporting and visualization features, the module improves the interpretability of results. It also supports better decision- making and provides users with a comprehensive overview of their health status.

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802070

B. Test Scenarios

The system is evaluated using functional test scenarios that simulate real-world usage of the heart disease prediction application. In the first scenario, a user accesses the application, navigates to the dashboard, and enters all required health parameters. The system is verified to process the input data correctly and generate a prediction indicating the risk level. The output is checked for accuracy and proper display on the user interface.

In the second scenario, the data validation and preprocessing functionality are tested by providing both valid and invalid inputs. The system ensures that incorrect or incomplete data is not accepted and prompts the user to correct the input. This verifies that input validation mechanisms are functioning as expected. The preprocessing steps are also evaluated to confirm that data is properly formatted before being passed to the prediction models.

In the third scenario, the prediction models are tested for consistency and reliability by providing multiple sets of input data. The system is observed to generate stable and accurate predictions across different cases. Additional tests are conducted to verify database storage and retrieval operations. These tests confirm that the system performs reliably under normal usage conditions and maintains data integrity.

In the first scenario, a patient registers, logs in, browses the “Our Doctors” panel, and books an appointment by completing all three steps of the workflow. The system is verified to assign a queue number, persist the appointment in the database, and send an SMS confirmation to the configured phone number.

In the second scenario, a doctor logs in to the doctor dashboard and reviews the list of appointments for the current day. As the doctor marks appointments as in consultation and completed, the patient dashboard is observed on a separate browser session. The queue position and waiting-time estimate are confirmed to update automatically through WebSocket events without requiring a page refresh.

In the third scenario, the notification pipeline is tested by scheduling an appointment within a short time window relative to the current time. The system is checked to ensure that the 30-minute and 5-minute reminders are triggered as configured, and that SMS and voice calls are received on the registered phone. Additional tests verify that reminders are not sent for cancelled appointments and that rebooked appointments lead to updated notifications.

In the fourth scenario, the real-time response capability of the system is evaluated by measuring the time taken to generate prediction results after data submission. The system is observed to provide instant feedback without noticeable delay, confirming its efficiency. This test ensures that the integration between the frontend interface and backend processing is seamless. It also verifies that the system can handle quick data processing and response generation. Theresults demonstrate the effectiveness of the real-time prediction feature.

In the fifth scenario, the report generation and visualization features are tested to ensure accurate and complete output. The system successfully generates PDF reports containing user inputs, prediction results, and risk classification. Graphical representations are also verified for correctness and clarity. This scenario confirms that users can easily download and interpret their reports. It validates the functionality and usability of the reporting and visualization modules.

Overall, the system evaluation demonstrates that the heart disease prediction application performs reliably, efficiently, and accurately under various real-world scenarios. Functional tests confirm that users can seamlessly navigate the interface, enter health parameters, and receive precise risk predictions. Input validation and preprocessing mechanisms ensure data accuracy, while the prediction models consistently deliver dependable results. Additionally, database operations, real- time response, and report generation features are verified to function correctly, providing both textual and visual insights. The comprehensive testing validates the system’s usability, robustness, and effectiveness, highlighting its readiness for practical deployment in supporting early detection and preventive healthcare.

C. Performance Evaluation

The performance of the system is evaluated based on response time, prediction accuracy, and overall system efficiency. The application is tested under normal operating conditions to measure how quickly it processes user input and generates prediction results. The system demonstrates fast response times, providing predictions almost instantly after data submission. This ensures a smooth and efficient user experience.

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802070

The accuracy of the machine learning models is also evaluated as part of performance analysis. Among the implemented algorithms, Random Forest achieves an accuracy of approximately 95%, outperforming Logistic Regression. This indicates that the model is capable of identifying patterns effectively and generating reliable predictions. The evaluation confirms that the system can provide accurate risk classification based on user input.

In addition to accuracy and speed, the system's performance is assessed in terms of stability and usability. The application handles multiple operations such as data input, processing, prediction, and result display without errors. Database operations are executed efficiently, ensuring quick data storage and retrieval. Overall, the system demonstrates stable performance and meets the requirements for a web- based heart disease prediction application.

response times remained within acceptable limits for interactive web applications. Profiling identified a small number of expensive database queries related to complex reporting views; these were optimised through additional indexes and query refactoring. Overall, the performance evaluation suggests that the proposed architecture can support busy outpatient clinics without requiring high-end infrastructure.

D. User Experience and System Accessibility

The usability of the ML-Driven Predictive Analysis for Heart Disease Diagnosis system plays a crucial role in ensuring effective adoption by users. A user-focused evaluation approach is considered to analyse how easily individuals can interact with the system. Users are expected to perform tasks such as entering health parameters, submitting data, and interpreting prediction results. The system interface is designed to be simple and intuitive, allowing even non- technical users to navigate without difficulty. This ensures accessibility across a wide range of users, including those with minimal technical knowledge.

The interface design emphasizes clarity and simplicity by organizing input fields and results in a structured manner. Key information such as health parameters and prediction outcomes is presented clearly to avoid confusion. Users can easily understand whether they fall under a high-risk or low- risk category. The system avoids complex medical terminology and focuses on user-friendly communication. This enhances overall user experience and improves engagement with the application.

Feedback from usability observations suggests that the system is easy to use and provides meaningful insights. However, certain improvements can further enhance accessibility, such as supporting multiple languages and improving visual elements for better readability. These enhancements can make the system more inclusive, especially for users from diverse backgrounds. Continuous refinement based on user feedback ensures better usability. This highlights the importance of user-centred design in healthcare applications.

E. System Constraints and Practical Limitations

Despite the effectiveness of the proposed system, certain limitations are observed in its current implementation. The system relies on a predefined dataset for training machine learning models, which may not fully represent all real-world scenarios. As a result, prediction accuracy may vary when applied to different populations or datasets. Additionally, the system does not replace professional medical diagnosis and should be considered as a supportive tool. These constraints highlight the need for further improvement and validation.

Another limitation is related to the deployment environment and scalability. The current system is designed primarily for academic and small-scale usage, with SQLite used as the database. While suitable for lightweight applications, it may not support large-scale data handling in real-world healthcare environments. Future enhancements may require migration to more robust database systems. This will improve scalability and performance under higher workloads.

Furthermore, the system currently focuses only on heart disease prediction and does not integrate with other healthcare services. It does not include features such as electronic medical records, laboratory integration, or clinical decision support systems. Expanding the system to include such functionalities would require additional modules and system complexity. Addressing these limitations can enhance the overall capability and applicability of the system. This provides scope for future development and research.

Additionally, the system's real-time prediction and response functionality may be affected by network latency or server load in practical deployment scenarios. While the current implementation performs efficiently under controlled conditions, performance may vary in environments with high user traffic or limited internet connectivity. Implementing optimization strategies, such as server load balancing, cloud- based deployment, or more efficient model inference techniques, could help mitigate these issues. Addressing these factors will further enhance the reliability, responsiveness, and practical usability of the system in real-world healthcare applications.

F. System Workflow Illustration

To understand the practical operation of the system, a typical user interaction scenario can be considered. A user accesses the web-based application and navigates to the prediction interface. The system presents a structured form where the user enters health-related parameters such as age, blood pressure, cholesterol level, and lifestyle factors. The input process is guided to ensure that all required fields are completed accurately. This step initiates the prediction workflow.

Once the data is submitted, the backend processes the input and performs validation and preprocessing. The prepared data is then passed to the machine learning models for analysis. The system evaluates the input features and generates a prediction indicating the risk level of heart disease. This process is executed efficiently to provide real-time results. The workflow ensures smooth interaction between different system components.

After the prediction is generated, the result is displayed on the user interface in a clear and understandable format. The user can view their risk classification and interpret the outcome easily. The system may also store the prediction data for future reference. This end-to-end workflow demonstrates how the system simplifies complex medical analysis into an accessible process. It highlights the practical usability of the application.

In addition to providing immediate predictions, the system allows users to generate detailed reports summarizing their health data and risk assessment. These reports include input parameters, prediction outcomes, and visualizations such as graphs or charts, making the information easier to interpret. Users can download the reports in PDF format for personal records or to share with healthcare professionals. This functionality adds value by supporting informed decision- making and promoting proactive health management.

Furthermore, the system's interactive design ensures that users receive guidance throughout the entire process. Input validation prevents errors, and feedback messages help users correct any inconsistencies. The intuitive dashboard and clear result presentation enhance accessibility for users with minimal technical expertise. Overall, this interaction scenario illustrates how the application combines accuracy, usability, and efficiency to provide a reliable tool for early detection and monitoring of heart disease risk.

G. Observations and Analytical Discussion

The evaluation of the system indicates that the integration of machine learning with a web-based platform provides an effective solution for heart disease prediction. The system successfully processes user input and generates accurate predictions in real time. The use of Random Forest improves prediction accuracy and ensures reliable results. The overall architecture supports smooth communication between different components. This demonstrates the feasibility of the proposed approach.

From a usability perspective, the system provides a simple and intuitive interface for users. The structured input forms and clear result presentation enhance user experience. Users can easily interact with the system without requiring technical expertise. This improves accessibility and encourages usage of the application. The system effectively bridges the gap between complex machine learning models and user interaction.

However, the evaluation is limited to controlled testing and does not include real-world deployment. Large-scale testing and real-time data integration are required to further validate system performance. Future improvements can focus on enhancing prediction accuracy and expanding system features. Continuous monitoring and feedback can help refine the system over time. Overall, the system demonstrates strong potential as a supportive healthcare tool.

VI. CONCLUSION

The proposed ML-Driven Predictive Analysis for Heart Disease Diagnosis system demonstrates the effective use of machine learning techniques in healthcare applications. By integrating Logistic Regression and Random Forest algorithms with a web-based platform, the system provides a practical solution for early risk assessment. The application enables users to input health parameters and receive real-time predictions, improving accessibility to health insights. The system design ensures simplicity, efficiency, and usability. In addition, the architecture of the system is structured to support smooth interaction between frontend and backend components. The integration of machine learning models within a user-friendly interface bridges the gap between technical complexity and user accessibility. This makes the application suitable for individuals without a medical or technical background. The design also emphasizes minimal response time and efficient processing. Overall, the system reflects a well-balanced combination of technology and usability in healthcare.

The evaluation results indicate that the system achieves reliable prediction accuracy, with Random Forest performing better among the implemented models. The application successfully handles data processing, prediction, and result visualization in an efficient manner. Usability considerations ensure that the system is easy to use for individuals with varying levels of technical knowledge. The system performs well under tested conditions and meets the intended objectives.

Moreover, the consistency of prediction results across multiple test cases highlights the robustness of the implemented models. Performance metrics such as accuracy and reliability validate the effectiveness of the system. The seamless integration of different modules ensures stable operation during execution. The system also demonstrates the ability to provide quick responses without compromising accuracy. These aspects confirm that the application is capable of delivering dependable results in practical scenarios.

Future work can focus on enhancing the system by integrating larger datasets, improving model accuracy, and incorporating advanced machine learning techniques. Additional features such as real-time data integration, multilingual support, and mobile compatibility can further improve usability. Deploying the system in real-world healthcare environments will provide deeper insights into its effectiveness. Overall, the proposed system lays a strong

foundation for developing intelligent healthcare prediction solutions. Furthermore, future improvements may include the integration of deep learning models for more complex pattern recognition. Expanding the system to support multiple diseases can increase its applicability in the healthcare domain. Collaboration with medical professionals can also enhance the accuracy and relevance of predictions. Implementing cloud-based deployment can improve scalability and accessibility. These enhancements will help transform the system into a more advanced and comprehensive healthcare solution.

The system also emphasizes the importance of user awareness and preventive healthcare. By providing early risk predictions, it encourages users to take proactive measures for maintaining heart health. The application acts as a supportive tool that promotes informed decision-making. This highlights the role of technology in improving health outcomes and lifestyle management. It also contributes to spreading awareness about the early signs and risk factors of heart disease among users.

VII. ACKNOWLEDGMENT

The authors express their sincere gratitude to the Department of Computer Science and Engineering, RP Sarathy Institute of Technology, for their continuous guidance and support. We thank our faculty members for their valuable suggestions and technical assistance throughout the project. Their encouragement and motivation played a vital role in the successful completion of this work.

REFERENCES

1) D. Dua and C. Graff, "UCI Machine Learning Repository," University of California, Irvine, School of Information and Computer Sciences, 2019.
2) X. Li et al., "Artificial intelligence-assisted prediction of heart disease risk," BMC Medical Informatics and Decision Making, vol. 20, no. 1,pp. 1–10, 2020.
3) C.Nagarajan and M.Madheswaran - 'Stability Analysis of Series Parallel Resonant Converter with Fuzzy Logic Controller Using State Space Techniques'- Taylor &Francis, Electric Power Components and Systems, Vol.39 (8), pp.780-793, May 2011. DOI: 10.1080/15325008.2010.541746
4) C.Nagarajan and M.Madheswaran - 'Experimental verification and stability state space analysis of CLL-T Series Parallel Resonant Converter' - Journal of Electrical Engineering, Vol.63 (6), pp.365-372, Dec.2012. DOI: 10.2478/v10187-012-0054-2

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802070

5) C.Nagarajan and M.Madheswaran - 'Performance Analysis of LCL-T Resonant Converter with Fuzzy/PID Using State Space Analysis'- Springer, Electrical Engineering, Vol.93 (3), pp.167-178, September 2011. DOI 10.1007/s00202-011-0203-9

6) S.Tamilselvi, R.Prakash, C.Nagarajan,"Solar System Integrated Smart Grid Utilizing Hybrid Coot-Genetic Algorithm Optimized ANN Controller" Iranian Journal Of Science And Technology-Transactions Of Electrical Engineering, DOI10.1007/s40998-025-00917-z,2025

7) S.Tamilselvi, R.Prakash, C.Nagarajan," Adaptive sliding mode control of multilevel grid-connected inverters using reinforcement learning for enhanced LVRT performance" Electric Power Systems Research 253 (2026) 112428, doi.org/10.1016/j.epsr.2025.112428

8) S.Thirunavukkarasu, C. Nagarajan, 2024, "Performance Investigation on OCF and SCF study in BLDC machine using FTANN Controller," Journal of Electrical Engineering And Technology, Volume 20, pages 2675–2688, (2025), doi.org/10.1007/s42835-024-02126-w

9) C. Nagarajan, M.Madheswaran and D.Ramasubramanian- 'Development of DSP based Robust Control Method for General Resonant Converter Topologies using Transfer Function Model'- Acta Electrotechnica et Informatica Journal , Vol.13 (2), pp.18-31,April-June.2013, DOI: 10.2478/aeei-2013-0025.

10)C.Nagarajan and M.Madheswaran - 'DSP Based Fuzzy Controller for Series Parallel Resonant converter'- Springer, Frontiers of Electrical and Electronic Engineering, Vol. 7(4), pp. 438-446, Dec.12. DOI 10.1007/s11460-012-0212-0.

11)C.Nagarajan and M.Madheswaran - 'Experimental Study and steady state stability analysis of CLL-T Series Parallel Resonant Converter with Fuzzy controller using State Space Analysis'- Iranian Journal of Electrical & Electronic Engineering, Vol.8 (3), pp.259-267, September 2012.

12)C.Nagarajan and M.Madheswaran, "Analysis and Simulation of LCL Series Resonant Full Bridge Converter Using PWM Technique with Load Independent Operation" has been presented in ICTES'08, a IEEE / IET International Conference organized by M.G.R.University, Chennai.Vol.no.1, pp.190-195, Dec.2007

13)Suganthi Mullainathan, Ramesh Natarajan, "An SPSS and CNN modelling based quality assessment using ceramic materials and membrane filtration techniques", Revista Materia (Rio J.) Vol. 30, 2025, DOI: https://doi.org/10.1590/1517-7076-RMAT-2024-0721

14)M Suganthi, N Ramesh, "Treatment of water using natural zeolite as membrane filter", Journal of Environmental Protection and Ecology, Volume 23, Issue 2, pp: 520-530,2022

15)S. Rajpurkar et al., "Cardiologist-level arrhythmia detection with deep neural networks," Nature Medicine, vol. 25, no. 1, pp. 65–69, 2019.

16)J. Smith and A. Kumar, "Heart disease prediction using machine learning algorithms," International Journal of Advanced Computer Science and Applications, vol. 12, no. 3, pp. 45–52, 2021.

17)M. K. Hasan, M. A. Alam, and M. A. Hossain, "A comparative analysis of machine learning algorithms for heart disease prediction," IEEE Access, vol. 8, pp. 150500–150512, 2020.