# VIVEKANAND EDUCATION SOCIETY'S INSTITUTE OF TECHNOLOGY

# **Department of Computer Engineering**



Project Report on

# Health+: "Your Digital Health Guardian"

In partial fulfillment of the Fourth Year (Semester–VII),

Bachelor of Engineering (B.E.)

Degree in Computer Engineering at the University of Mumbai

Academic Year 2024-2025

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(2024-25)

# VIVEKANAND EDUCATION SOCIETY'S INSTITUTE OF TECHNOLOGY

# **Department of Computer Engineering**



# **CERTIFICATE OF APPROVAL**

This is to certify that Vidisha Jadhwani(D17A/26), Riddhi Labde(D17B/25), Priti Shamnani(D17B/50), Nikhil Makhija(D17B/27) of Fourth Year Computer Engineering studying under the University of Mumbai has satisfactorily presented the project on Health+: "Your Digital Health Guardian" as a part of the coursework of PROJECT-I for Semester-VII under the guidance of Dr. Dashrath Mane in the year 2024-2025.

# Date Internal Examiner External Examiner Assistant Professor Head of the Department Principal Dr. Dashrath Mane Dr. Mrs. Nupur Giri Dr. J. M. Nair

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We wish to express our profound thanks to all those who helped us in gathering information about the project. Our families too have provided moral support and encouragement several times.

# **Department Of Computer Engineering**

# COURSE OUTCOMES FOR B.E PROJECT

# Learners will be to:-

Course	Description of the Course Outcome
Outcome	
CO 1	Do literature survey/industrial visit and identify the problem of the selected project topic.
CO2	Apply basic engineering fundamental in the domain of practical applications FORproblem identification, formulation and solution
CO 3	Attempt & Design a problem solution in a right approach to complex problems
CO 4	Cultivate the habit of working in a team
CO 5	Correlate the theoretical and experimental/simulations results and draw the proper inferences
CO 6	Demonstrate the knowledge, skills and attitudes of a professional engineer & Prepare report as per the standard guidelines.

# **ABSTRACT**

This project presents the development of Health+, an innovative web-based application designed to provide real-time disease prediction using advanced machine learning techniques. The system is built to analyze user-reported symptoms and predict possible diseases through a combination of machine learning algorithms such as k-Nearest Neighbor, Naive Bayes, Decision Tree, and Random Forest. The dataset used for training these models is extensive, covering a broad spectrum of medical conditions, which ensures the reliability and accuracy of predictions.

Health+ is particularly tailored to serve users who might have limited access to traditional healthcare services, making it a valuable tool for individuals in remote or underserved areas. The platform enables users to input their symptoms, and based on the analysis, it delivers a list of probable diseases, thus providing timely insights into health concerns. Additionally, the application includes a feature where users can upload their medical reports for further analysis, using machine learning models to predict potential health issues based on report data.

A key feature of the platform is its interactive user interface, designed to be intuitive and user-friendly, allowing individuals with varying levels of technological proficiency to navigate the system effortlessly. Health+ also includes a chatbot that facilitates smooth communication, answering queries and guiding users through the prediction process.

The project demonstrates the potential of integrating machine learning with healthcare to create a system that assists users in identifying possible diseases early on. Through continuous refinement and user feedback, the platform is designed to evolve, offering improved accuracy and enhanced user experience. Health+ represents a significant step forward in applying technology to bridge the gap between healthcare services and accessibility, empowering users to take control of their health through informed decision-making.

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# 1 Introduction

# 1.1. Introduction to the project

The integration of digital technologies is causing a considerable transformation in the healthcare industry, especially in the areas of patient care and diagnosis. Using artificial intelligence (AI) and machine learning (ML) to improve medical diagnostics and deliver real-time health insights is one of the newest trends in healthcare. Within this framework, the Health+ project presents a web application intended to function as a "Digital Health Guardian."

By predicting diseases based on user-reported symptoms, Health+ seeks to assist people in obtaining initial health assessments without the immediate need to see a doctor. This technology provides customers with precise and timely predictions by utilizing large datasets and cutting-edge machine learning techniques. Reducing the strain on healthcare systems is the goal, particularly when there are mild symptoms that don't call for immediate medical attention. Health+ is a useful resource for patients and medical professionals because it offers a proactive health management tool.

Health+ acts as a link between patients and healthcare providers in light of the growing accessibility of digital tools and the internet. It provides a dependable system that can function at any time and from any location, providing people with actionable health insights when they most need them. Those who live in rural or underdeveloped areas, where access to healthcare may be restricted or delayed, will especially benefit from this approach. It also enables users to save time, effort, and money on medical bills by avoiding needless trips to the hospital for minor issues. The ultimate goal of Health+ is to empower people by enabling them to independently monitor their health and make more informed decisions about when to seek additional medical help.

# 1.2. Motivation for the project

Numerous obstacles, including those related to finances, infrastructure, and location, are making the state of healthcare worse. Due to a lack of doctors or clinics, patients frequently cannot get healthcare in a timely manner in many parts of the world, especially in rural and neglected areas. Long wait times for consultations are a result of the healthcare systems being overburdened with

patients, even in more developed urban regions. The rising incidence of chronic diseases and the increasing complexity of medical situations exacerbate these systemic problems.

Many of these uncertainties are removed by Health+, which provides a dependable, machine learning-driven illness prediction solution. By assessing their symptoms and making recommendations regarding the possibility of specific illnesses, the system helps users take charge of their health and promotes proactive behavior. Digital health technologies are a viable way to address these issues in such a situation. The need for a method to detect and manage health disorders that is affordable, scalable, and accessible is the driving force behind Health+. Health+ seeks to give quick health assessments to people anywhere in the world by providing disease predictions via an intuitive web platform.

The issue of medical ambiguity is another one that the initiative tackles. Many people have symptoms that could be suggestive of a number of illnesses, from minor ailments like the common cold to more serious conditions like pneumonia or COVID-19. Without proper medical advice, individuals may delay seeking treatment or turn to unreliable sources for self-diagnosis, leading to complications in their health outcomes.

This idea was also greatly influenced by the increasing reliance on the internet for quick and easily available information. People are getting more and more used to utilizing digital platforms for commerce, communication, and education these days. By being accessible around-the-clock and creating a platform where people can get instant health insights, Health+ fits nicely with this trend. This always accessible system guarantees that users are never distant from insightful health advice, which is particularly important in areas where access to healthcare is limited.

# 1.3. Drawback of the existing system

Although the existing healthcare system is effective in treating people, it has a number of significant shortcomings, particularly in terms of early diagnosis and minor health issues. Conventional healthcare models place a strong emphasis on in-person consultations, which aren't necessarily required for minor ailments.

Furthermore, a lot of the self-diagnosis resources that are already on the internet are imprecise and not customized for each user. Age, symptom intensity, or past medical history are not taken into account by these tools. For instance, fever and exhaustion can be symptoms shared by both minor infections and more serious illnesses, making it challenging for people to distinguish between the two without the assistance of a qualified medical practitioner. For users who depend on these tools for guidance, the overlap in symptoms frequently results in misdiagnosis or inappropriate counsel, further complicating health consequences.

In addition, most internet tools don't offer useful advice, so consumers are left unsure of what to do next in their healthcare journey. Personalized forecasts based on unique health characteristics are not available in current systems, and the likelihood of co-occurring illnesses is frequently overlooked. Patients may consequently feel perplexed or uncertain about whether they require medical assistance. Another major worry is the breach in data privacy, since a lot of self-diagnosis apps do not sufficiently secure user data. This may damage people's trust and make them less likely to use these kinds of tools. The necessity of a system such as Health+ is underscored by the absence of a complete, accurate, and secure digital solution. The initiative addresses concerns about user privacy, data security, and accessibility while attempting to provide accurate disease predictions.

#### 1.4. Problem Definition

Accurate and timely diagnosis is vital for effective healthcare, but many individuals face barriers to accessing medical help when symptoms first arise. Factors like uncertainty about the severity of symptoms, geographical limitations, and financial constraints can delay professional consultation. This delay often leads to the progression of diseases, making treatment more complicated and costly.

A significant issue is that symptoms of many illnesses, such as fever, fatigue, and cough, can overlap across a wide range of conditions, from minor infections to serious diseases like pneumonia or COVID-19. This overlap makes it challenging for people to self-diagnose, which can either cause unnecessary alarm or result in a failure to seek timely care. Current self-diagnosis tools are generally inadequate, as they do not account for individual differences in health, medical history, or the unique presentation of symptoms.

The core problem is the need for an accessible, accurate, and user-friendly system that helps individuals assess their health based on initial symptoms. Health+ aims to bridge this gap by offering a machine-learning-powered platform that provides reliable, personalized health predictions. By doing so, it encourages users to seek medical help when necessary, while ensuring their data privacy and security.

# 1.5 Relevance of the Project

The relevance of Health+ lies in its ability to address current healthcare challenges by offering a solution that improves accessibility and efficiency. As healthcare demands increase globally, particularly in remote and underserved areas, there is a growing need for digital tools that allow individuals to proactively manage their health. Many people face obstacles such as long waiting times and high medical costs for minor health concerns, while others in rural areas may struggle with limited access to healthcare services. Health+ offers a practical and scalable solution by providing users with 24/7 access to health predictions based on their symptoms, reducing the reliance on physical consultations for non-urgent issues.

With the rising use of the internet and digital tools in everyday life, people are increasingly turning to online resources for quick and convenient health information. Health+ takes advantage of this trend by offering a platform that delivers immediate, data-driven health insights. The project aligns with global efforts to integrate artificial intelligence and machine learning into healthcare, helping individuals make informed decisions about their health. This is especially important in areas where healthcare infrastructure is strained, allowing for early detection of potential illnesses and preventing the escalation of health conditions.

Moreover, the system promotes better health outcomes by providing personalized recommendations, which encourages users to seek professional medical advice when necessary. By doing so, Health+ not only enhances individual health management but also alleviates pressure on healthcare providers, making the system a valuable contribution to the evolving landscape of digital health.

# 1.6 Methodology used

Health+ utilizes a machine learning-based approach to provide accurate disease predictions based on user-reported symptoms. The methodology involves several key steps:

- Data Collection: Large datasets linking symptoms to diseases are gathered from credible sources such as medical records, scientific databases, and health publications. This data forms the foundation for the machine learning model, allowing it to make predictions across a wide range of conditions.
- **Model Training**: Using supervised learning, the model is trained to identify patterns and relationships between symptoms and diseases. As it learns from the data, the model improves its ability to make accurate predictions based on user input.
- User Input: A simple, user-friendly interface allows individuals to enter their symptoms, along with relevant personal details such as age, gender, and medical history. This personalized information ensures that the model provides predictions tailored to each user's specific health context.
- Prediction Process: The model analyzes the user's input, comparing it to the dataset to generate a list of potential diseases. Each disease is ranked based on the likelihood of occurrence, giving users a clear understanding of their possible conditions and guiding them toward appropriate actions.
- Feedback Loop: After users receive a professional diagnosis or further treatment, they
  can provide feedback on the accuracy of the predictions. This feedback is used to
  continually refine the model, ensuring that it remains up-to-date and accurate as medical
  knowledge evolves.

This systematic approach allows Health+ to provide reliable, personalized health predictions, improving the accessibility and accuracy of healthcare information for users.

# 2 Literature Survey

# 2.1 Research Paper

# 1. Multi Disease Prediction Using Machine Learning

#### **Abstract:**

The study presents a comprehensive approach to multi-disease prediction utilizing machine learning techniques. It begins with data collection from diverse sources, particularly electronic health records and medical databases, focusing on conditions like diabetes, heart disease, and Parkinson's disease. The methodology incorporates data preprocessing, including cleaning and transformation, to prepare the dataset for machine learning applications. During model selection, various algorithms were carefully chosen, trained on the preprocessed data, and evaluated based on performance metrics like accuracy and precision. The dataset was divided into training and testing sets to assess the models' effectiveness rigorously. Ultimately, the trained models were deployed within an interactive web application, enabling users to input symptoms and receive real-time predictions.

#### **Inference:**

The study identifies a significant gap in the current literature regarding the application of machine learning models for multi-disease prediction. While demonstrating the effectiveness of Support Vector Machines (SVM) and logistic regression for specific diseases, the authors point out the need for improved accuracy and reliability across a broader spectrum of health conditions. Future research should focus on integrating and comparing multiple algorithms to enhance overall performance and utilizing extensive datasets to improve model robustness. Additionally, incorporating advanced methodologies like deep learning and ensemble techniques could refine predictive capabilities and extend the applicability of these models.

# 2. A Collaborative Empirical Analysis on Machine Learning-Based Disease Prediction in the Healthcare System

#### **Abstract:**

This paper outlines a systematic methodology for classifying medical data through various machine learning algorithms. The process initiates with data preprocessing, which includes

essential steps like cleaning, feature encoding, and correlation analysis. The dataset is then divided into training and testing subsets. The employed algorithms—k-Nearest Neighbor (kNN), Naive Bayes (NB), Decision Tree (DT), and Random Forest (RF)—are strategically chosen for their unique strengths in disease prediction. The kNN algorithm focuses on identifying disease categories by analyzing symptom data and implementing majority voting, while NB calculates disease probabilities based on symptom presence. DT recursively divides data to optimize information gain, and RF aggregates results from multiple trees to enhance accuracy and minimize overfitting. The models are evaluated using metrics like accuracy, F1 score, and cross-validation, with deployment facilitated through a Flask API and user-friendly frontend for real-time predictions.

#### **Inference:**

The study highlights a critical gap in the efficiency of existing algorithms, particularly concerning the high computational demands of the Random Forest method. Future improvements should include expanding the dataset to encompass a broader range of diseases and symptoms, as well as exploring advanced deep learning techniques to enhance prediction capabilities. Additionally, establishing a comprehensive user management system could significantly improve the practical application of the model in both clinical and public health environments by efficiently managing patient records and facilitating model updates.

### 3. Multiple Disease Prediction Using Machine Learning Algorithms

#### **Abstract:**

This research discusses the application of Bayesian classifiers and Support Vector Machines (SVM) for disease prediction, leveraging their ability to calculate prior probabilities and establish optimal decision boundaries. The study emphasizes the use of Naive Bayes classifiers for efficient predictions, particularly in determining stages of kidney disease. Furthermore, Fuzzy KNN techniques address data uncertainties, enhancing predictions for cardiac diseases. The research also integrates Artificial Neural Networks (ANN) to model complex patterns, achieving an accuracy of 80% in predicting heart disease. Additionally, hybrid models that combine K-means clustering with the C4.5 classification method are utilized to improve diabetes

prediction accuracy. The Decision Tree method, notably the C4.5 algorithm, is acknowledged for its interpretability and effectiveness across various data types.

#### **Inference:**

The paper identifies a notable gap in predicting heart disease among diabetic patients, as current models primarily target general populations. This indicates a need for more focused research that examines the interplay between diabetes and cardiovascular conditions. To enhance the clinical relevance of predictive models, it is crucial to integrate longitudinal data, assess additional performance metrics beyond mere accuracy, and consider interdisciplinary approaches that could improve prediction strategies and their applicability in real-world healthcare settings.

# 4. Multiple Disease Prediction Using Machine Learning and Deep Learning with the Implementation of Web Technology

#### Abstract:

This paper describes a comprehensive methodology for predicting multiple diseases using various machine learning algorithms and web technologies. Data is collected from reliable sources, including Kaggle, the Pima Indian Dataset, and the UCI Machine Learning Repository, covering diseases such as diabetes, heart disease, lung cancer, Parkinson's disease, and brain stroke. A wide array of algorithms—such as Quadratic Discriminant Analysis (QDA), k-Nearest Neighbors (KNN), SVM, Linear Discriminant Analysis (LDA), Naive Bayes, Decision Trees, Random Forest, AdaBoost, K-means clustering, XGBoost, Gradient Boosting, Neural Networks, and Long Short-Term Memory (LSTM)—are implemented and evaluated based on metrics including RMSE, MAE, recall, precision, F1 score, R², and overall accuracy. The architecture consists of a web application, a local server, and a database, featuring user-specific input pages and a management system to enhance real-time model retraining.

#### **Inference:**

The authors recognize critical gaps in their research, particularly the limited scope of diseases analyzed, potentially neglecting a wider range of medical conditions. Furthermore, the absence of advanced feature selection techniques could impair model performance. The integration of machine learning models into practical clinical settings remains underexplored, as do strategies for managing class imbalance and continuously updating models with new data. Future studies

should aim to address these limitations by incorporating more comprehensive datasets and advanced methodologies to enhance predictive accuracy and clinical utility.

## 5. Identifying Multiple Diseases in the Human Body Using Machine Learning

#### **Abstract:**

This paper outlines a robust methodology for predicting various diseases, specifically heart disease, diabetes, and Parkinson's disease, by employing tailored machine learning algorithms. The initial phase involves comprehensive data preprocessing to address null values and prepare the dataset for analysis. For heart disease prediction, the research utilizes a Support Vector Machine (SVM) to establish an optimal decision boundary. In diabetes prediction, a Random Forest classifier is employed to enhance accuracy through aggregation of multiple decision trees, effectively handling the complexity of the dataset. Additionally, Logistic Regression is utilized for predicting Parkinson's disease, providing probabilistic outcomes that facilitate early detection and intervention based on symptom assessment.

#### **Inference:**

The study highlights methodological limitations, particularly in its focus on a restricted set of diseases and reliance on conventional machine learning algorithms. While the employed algorithms are effective, they may not capitalize on the advancements offered by more sophisticated or hybrid techniques. Furthermore, the integration of diverse data sources and real-time prediction capabilities remains unaddressed. Future research could benefit from exploring advanced methodologies and utilizing broader datasets to enhance prediction performance and applicability across varied health conditions.

### 6. Streamlit-Powered Comprehensive Health Analysis and Disease Prediction System

#### **Abstract:**

This research presents a comprehensive health analysis and disease prediction system powered by Streamlit. The study gathers datasets pertaining to diabetes, heart disease, and Parkinson's disease from credible sources such as Kaggle. Data preprocessing involves rigorous cleaning, noise reduction, and symptom relevance assessment, narrowing down from 132 available symptoms to the most pertinent. The model employs various machine learning algorithms,

including Random Forest Classifier, Logistic Regression, SVM, and Extra Tree Classifier, trained on an 80-20 split of the data. Performance evaluation focuses on identifying the model with the highest accuracy for deployment in a user-friendly environment.

#### **Inference:**

The paper identifies key gaps in existing research tools for disease prediction, such as narrow disease coverage, lack of personalization, and absence of feedback mechanisms for continuous improvement. Many models tend to overlook individual health factors, which can lead to less accurate predictions over time. Additionally, the overlap of symptoms across different conditions is a challenge, particularly for users in remote areas. The proposed solution, Health+: Your Digital Health Guardian, aims to address these limitations by providing a more comprehensive, personalized, and user-friendly platform that incorporates user feedback to enhance prediction accuracy and reliability.

#### 7. Prediction of Multiple Diseases Using Machine Learning Techniques

#### **Abstract:**

This research investigates the application of machine learning techniques for predicting multiple diseases, focusing on diabetes, heart disease, and chronic kidney disease. The study emphasizes the importance of comprehensive data collection, preprocessing, and feature selection to enhance model performance. It utilizes algorithms such as Decision Trees, SVM, and Random Forest to train the models on a robust dataset. The evaluation metrics include accuracy, sensitivity, specificity, and F1 score, providing a holistic view of each algorithm's performance. The results reveal that the Random Forest algorithm achieved the highest accuracy, followed by Decision Trees and SVM.

#### **Inference:**

The authors recognize significant limitations in their research, notably the restricted variety of diseases considered and the lack of real-time predictive capabilities. There is also an opportunity to improve feature selection methods to optimize model performance. The integration of multi-source data, including demographic information and lifestyle factors, could lead to more personalized predictions. Future research should explore hybrid models and deep learning

techniques to address these gaps and enhance the robustness and applicability of disease prediction systems in clinical settings.

## 8. A Machine Learning Framework for Multiple Disease Prediction

#### **Abstract:**

This study presents a machine learning framework designed to predict multiple diseases based on user-input symptoms. The research employs a variety of machine learning algorithms, including k-Nearest Neighbors (kNN), Naive Bayes, and Random Forest, evaluated against various performance metrics such as accuracy, precision, recall, and F1 score. The study emphasizes the importance of dataset diversity, encompassing various demographic factors to improve prediction reliability. The framework integrates a web-based interface for user interaction, enabling easy symptom input and immediate feedback on potential diseases.

#### **Inference:**

The paper identifies gaps in existing research concerning the breadth of diseases analyzed and the adequacy of datasets used. While machine learning provides robust prediction capabilities, the reliance on static datasets limits the model's adaptability to new conditions and evolving medical knowledge. Future studies should aim to incorporate real-time data processing and user feedback mechanisms to enhance the predictive capabilities and relevance of the framework in addressing the dynamic nature of healthcare.

# 9. Enhancing Disease Prediction Accuracy with Machine Learning Techniques

#### **Abstract:**

This research discusses the enhancement of disease prediction accuracy through advanced machine learning techniques, focusing on chronic diseases such as diabetes, heart disease, and asthma. The study employs various algorithms, including Random Forest, SVM, and Gradient Boosting, each selected for its distinct predictive capabilities. The methodology emphasizes data preprocessing, including feature engineering and normalization, to improve model accuracy. The performance evaluation highlights the strengths and weaknesses of each algorithm, providing a comparative analysis based on accuracy, F1 score, and computational efficiency.

#### **Inference:**

The authors note critical gaps in predictive modeling, particularly concerning the scalability of models and the integration of multi-modal data sources. Current models often lack adaptability to changing healthcare landscapes and evolving patient demographics. Future work should focus on developing adaptive algorithms that can learn from new data continuously and explore the potential of ensemble methods to combine the strengths of various algorithms for improved predictive performance.

# 10. Comprehensive Health Diagnosis and Prediction Framework Utilizing Machine Learning

#### **Abstract:**

This paper outlines a comprehensive health diagnosis and prediction framework leveraging machine learning techniques for multiple diseases, including diabetes, cardiovascular diseases, and respiratory conditions. The research integrates a user-friendly web application that allows individuals to input their symptoms and receive predictive insights. The framework employs machine learning models such as SVM, kNN, and Random Forest, evaluated on metrics like accuracy, sensitivity, and specificity. The results indicate a high level of accuracy, highlighting the effectiveness of machine learning in disease prediction.

#### **Inference:**

The research identifies significant gaps in the existing literature regarding the integration of user feedback in refining predictive models. While the accuracy of predictions is promising, there remains a need for more comprehensive datasets that reflect a broader range of demographic factors. Future studies should explore incorporating user experiences and ongoing data collection to improve the relevance and effectiveness of predictive models in real-world healthcare applications.

# 2.2. Books / Articles referred / news paper referred

The research draws from various journal articles and papers discussing the application of machine learning in disease prediction. Below are key references used:

#### 1. K. Reshma et al. (2024)

"Multi Disease Prediction System Using Machine Learning". The paper focuses on the use of machine learning algorithms like Random Forest and SVM for predicting diseases such as diabetes, heart disease, and Parkinson's. It highlights the importance of accurate data preprocessing and model selection for improving prediction accuracy.

# 2. A. Das et al. (2023)

"A Collaborative Empirical Analysis on Machine Learning Based Disease Prediction in Health Care System". This paper explores the use of multiple machine learning models such as k-NN, Decision Trees, and Naive Bayes for disease prediction, discussing the importance of robust data cleaning and model evaluation.

### 3. K. Arumugam et al. (2023)

"Multiple Disease Prediction Using Machine Learning Algorithms". The authors utilize a combination of Naive Bayes, Logistic Regression, and k-NN to predict various diseases, with a particular focus on hybrid approaches for more accurate predictions.

#### 4. Mostafizur Rahman et al. (2023)

"Multiple Disease Prediction using Machine Learning and Deep Learning with the Implementation of Web Technology". This article focuses on using deep learning techniques such as Neural Networks and LSTM for disease prediction, with the system built as a web application.

These papers provide foundational insights into data preprocessing techniques, the use of hybrid models, and the comparison of different algorithms to improve disease prediction accuracy.

# 2.3. Interaction with Domain Experts

Interviews with healthcare professionals and data scientists played a crucial role in shaping the project. Medical experts emphasized the importance of clinical relevance in the models, guiding decisions about which symptoms and diseases to focus on. This input helped align the disease

prediction system with real-world healthcare needs, ensuring that the algorithms provided

actionable insights that healthcare providers could easily interpret and use.

Data scientists provided technical guidance on optimizing machine learning models, offering

strategies for improving data preprocessing, feature selection, and algorithm performance. Their

expertise helped in enhancing model accuracy and ensuring the scalability of the system,

particularly in terms of handling large datasets efficiently.

2.4. Patent Search

Patent 1

• Title: Multi Disease Prediction System Using Random Forest Algorithm in Healthcare

System

• Year: 2022

• Summary: This patent outlines a system that utilizes the Random Forest algorithm for

the prediction of multiple diseases based on user symptoms. It features a web application

that processes real-time symptom data and provides health predictions for various

conditions like diabetes and heart disease. The model integrates large datasets and

handles data preprocessing efficiently, ensuring high accuracy in its predictions.

Patent 2

**Title**: A Stable AI-Based Binary and Multiple Class Heart Disease Prediction Model for

**IoMT** 

• Year: 2022

• Summary: This patent presents an AI-based model that combines machine learning with

the Internet of Medical Things (IoMT) for heart disease prediction. It uses advanced

algorithms like Gradient Boosted Decision Trees (GBDT) and fuzzy logic to enhance the

stability and accuracy of predictions. The system continuously monitors patient data

through IoMT devices, providing real-time health monitoring and early warning for heart

conditions.

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Patent 3

Title: Symptoms-Based Multiple Disease Prediction Model Using Machine Learning

Approach

• Year: 2021

**Summary**: This patent describes a machine learning system that predicts multiple

diseases by analyzing symptoms provided by users. The algorithms employed include

Naive Bayes, Decision Trees, and Random Forest, with a focus on delivering fast and

accurate predictions. It is designed for easy integration into healthcare systems,

particularly in rural areas where access to medical professionals may be limited.

Patent 4

**Title**: Disease Predictor Based on Symptoms Using Machine Learning

**Year**: 2022

**Summary**: The patent covers a system that uses machine learning techniques such as

SVM and Naive Bayes for predicting diseases based on symptoms reported by users. The

model allows for real-time processing and is designed to be user-friendly, providing

immediate feedback to patients and healthcare professionals. It focuses on increasing the

accessibility of healthcare by enabling early diagnosis and intervention.

Patent 5

**Title**: Method and System for Predicting Health Risks Using Machine Learning

Year: 2021

**Summary**: The system outlined in this patent predicts a variety of health risks using

machine learning algorithms. By analyzing patient data such as medical history,

symptoms, and lifestyle factors, the model identifies patterns and predicts future health

risks. The system uses algorithms like Logistic Regression, Random Forest, and Support

Vector Machines (SVM) to achieve high prediction accuracy, assisting healthcare

providers in making proactive decisions.

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Patent 6

• Title: Automated Healthcare System for Disease Diagnosis Using AI and Machine

Learning

**Year**: 2020

**Summary**: This patent describes an automated system that utilizes AI and machine

learning for disease diagnosis. The system collects patient symptoms and medical history,

using deep learning models such as Convolutional Neural Networks (CNN) to predict

diseases like respiratory illnesses and cardiovascular conditions. Designed for clinical

and non-clinical use, the system offers scalable solutions for diagnosing common and

complex diseases, improving the speed and accuracy of early-stage diagnosis.

Patent 7

Title: Multi-Parameter Disease Prediction System Using Ensemble Machine Learning

Models

**Year**: 2021

**Summary**: The system covered in this patent predicts multiple diseases by incorporating

ensemble machine learning models such as AdaBoost, Gradient Boosting, and Bagging.

The system integrates various health metrics, including biometric and lifestyle data, to

predict conditions like diabetes, hypertension, and cardiovascular diseases. By using

multiple models, the system increases accuracy, particularly in cases with overlapping

symptoms or complex health profiles.

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# 3. Requirement Of Proposed System

# 3.1 Functional Requirements

- **Symptom Input**: Users can input their health details such as symptoms, severity, age, gender, and medical history for analysis.
- **Disease Prediction**: The system provides disease predictions based on symptom data using trained machine learning models.
- **Confidence Scores**: Each prediction is accompanied by a probability score to inform the user of the likelihood of each diagnosis.
- **Severity Evaluation**: The system evaluates the severity of the user's condition and offers recommendations for medical intervention.
- **User Feedback**: Users can report the accuracy of predictions, allowing the system to refine its models over time.
- **Health Information**: The system provides detailed insights into each predicted disease, including causes, symptoms, and treatment recommendations.
- **Profile Management**: Users can create profiles to store medical history and access personalized predictions based on their previous inputs.
- Multi-Platform Access: The system is accessible via web or mobile, making it convenient for users to access health guidance anytime, anywhere.
- **24/7 Availability**: The system offers round-the-clock service, enabling immediate access to predictions without delays.

# 3.2. Non-Functional Requirements

- **Performance**: The system should deliver accurate predictions in a timely manner, with minimal processing delays.
- **Scalability**: The system should efficiently scale to handle an increasing number of users and data without degradation in performance.
- **Security**: User data should be encrypted and stored securely, adhering to data protection laws (e.g., GDPR, HIPAA).
- **Reliability**: The system must be highly available, ensuring uninterrupted access for users at all times.

• Ease of Use: The interface should be intuitive, allowing users to input their symptoms and receive predictions without technical expertise.

• Cross-Platform Compatibility: The system should function on multiple devices and

operating systems, including desktops, smartphones, and tablets.

• **Data Integrity**: The system must ensure the accuracy and consistency of data inputs and

outputs.

## 3.3. Constraints

• Input Accuracy: The system's accuracy depends on the quality and completeness of the

user-reported symptoms. Incorrect inputs could lead to inaccurate predictions.

• Overlapping Symptoms: Many diseases share common symptoms, making it

challenging to differentiate them without in-depth analysis.

• Ethical Concerns: The system must avoid providing misleading or risky advice. It

should clearly indicate that it is not a replacement for professional medical consultation.

• Legal and Privacy Concerns: The system must comply with regulations protecting

sensitive medical information, such as GDPR or HIPAA.

# 3.4. Hardware & Software Requirements

• Hardware requirements

Processor: Core i3/i5/i7

o RAM · 2-4GB

○ HDD: 500 GB

#### **Software Requirements:**

• Platform: Windows Xp/7/8/10

o Coding Language: Python,

Technologies : React

o Database: SQL

o IDE/Editor: VS Code, Colab Notebook

# 3.5. Techniques utilized till date for the proposed system

#### **Machine Learning Algorithms**:

• Random Forest: For interpretability and handling non-linear relationships.

• Support Vector Machines (SVM): For high-dimensional data.

• Naive Bayes: For probabilistic predictions based on symptom occurrence.

**Data Collection**: Data is sourced from reliable public health repositories and user feedback to keep the system's predictions current and relevant.

# 3.6. Tools utilized till date for the proposed system

Programming Language: Python, due to its versatility in handling machine learning tasks and web development.

Machine Learning Frameworks:

- Scikit-learn for basic algorithms and preprocessing tasks.
- TensorFlow/Keras for building and training deep learning models.

Web Development Framework: Flask for lightweight web applications, or Django for larger, more structured web-based platforms.

Cloud Infrastructure: Services like AWS or Google Cloud are used for scaling, ensuring high availability and secure data handling.

Data Processing Tools:

- Pandas/NumPy for managing and manipulating data.
- Matplotlib/Seaborn for visualizing model performance and results.

# 3.7. Project Proposal

The Health+ system aims to revolutionize how users manage their health by providing fast and reliable disease predictions based on symptoms. By integrating machine learning algorithms, the system gives users immediate insights into potential conditions and helps them make informed decisions regarding their health. Health+ is especially beneficial for users in underserved areas where access to healthcare is limited. The system is designed to continuously learn from user feedback and will incorporate new data sources to stay updated with the latest medical information, ensuring the system's predictions remain accurate and useful.

# 4. Proposed Design

# 4.1 Block diagram representation of the proposed system

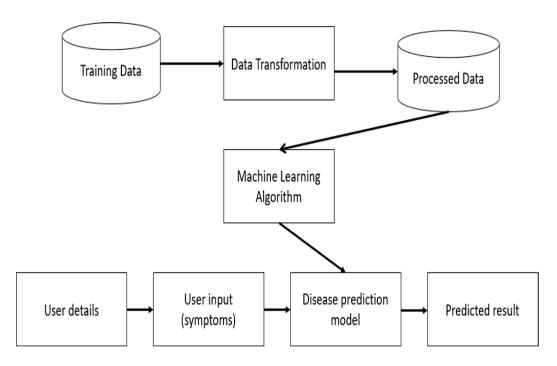


Fig 4.1.i Block Diagram

This diagram shows a process where training data is transformed and used by a machine learning algorithm to predict diseases based on user input of symptoms and personal details.

# **Explanation for the block diagram:**

- 1. Training Data: The process starts with the acquisition of historical medical data, which includes a collection of symptoms linked to various diseases. This dataset forms the foundation for training the predictive model, providing the essential examples for the machine learning algorithms to identify relevant patterns.
- 2. Data Transformation: The raw training data undergoes several preprocessing steps to prepare it for machine learning applications. This stage includes data cleaning (eliminating inaccuracies), normalization (adjusting data scales), and addressing any missing values. Additionally, relevant features are extracted to improve the model's learning efficacy.

- 3. Processed Data: Once the preprocessing is complete, the data is organized into a structured format, making it ready for subsequent training and evaluation of the model. This structured data ensures that the machine learning algorithms can efficiently learn from it.
- 4. Machine Learning Algorithm: At the heart of the system lies the machine learning algorithm, which utilizes the processed data to discern patterns and connections between symptoms and diseases. The model is continuously updated with new information to enhance its predictive capabilities over time.
- 5. User Details and User Input (Symptoms): The system features an interactive user interface, allowing individuals to input their symptoms along with other relevant details such as age and gender. This information is crucial for tailoring predictions and improving accuracy.
- 6. Disease Prediction Model: Utilizing the trained machine learning model, the system evaluates the user-provided symptoms and details. This evaluation leads to predictions of potential diseases based on recognized patterns.
- 7. Predicted Result: In the final step, the system compiles a list of likely diseases, ranked by the probability of each condition based on the user's input. This output is then presented to the user, assisting them in making informed decisions regarding medical consultation and health management.

# 4.2. Modular diagram representation of the proposed system

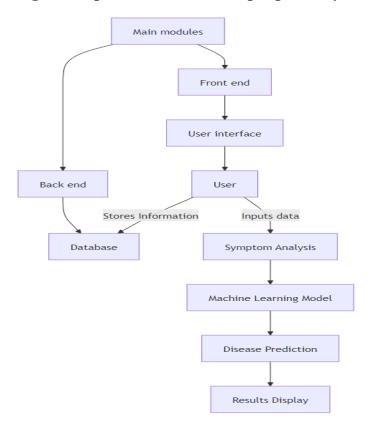


Fig 4.2.i Modular Diagram

The diagram outlines a system where the front-end collects user symptom inputs, which are processed by a machine learning model in the back-end to generate disease predictions.

# Explanation for the modular block diagram:

Disease Prediction System Architecture: The modular diagram outlines the architecture of a potential disease prediction system, breaking down the system into several interconnected modules, each responsible for specific tasks.

## 1. Main Modules

This refers to the key components of the system, which are divided into:

- Front end: Manages the user interaction (UI/UX).
- Back end: Handles data storage, processing, and model predictions.

**2. Front End:** This is the User Interface where the user interacts with the system. The user will input relevant symptoms through this interface.

#### 3. User Interaction

The user provides symptom data through the UI. This step has two flows:

- 1. **Inputting Data**: The user enters symptoms (e.g., fever, cough) for diagnosis.
- 2. **Storing Information**: User data (e.g., personal details, past reports) may also be stored in a Database for future reference.

# 4. Database (Back End)

The Database stores:

- User records and historical data.
- Symptoms and disease datasets, which can improve prediction over time.

The Back end manages communication between the database and the rest of the system, ensuring the data is stored and retrieved efficiently.

#### 5. Symptom Analysis

Once the user submits their symptoms, they are processed in this module. The data will undergo:

- **Pre-processing**: Removing redundant information.
- **Feature extraction**: Identifying key symptoms relevant to specific diseases.

#### 6. Machine Learning Model

The processed symptom data is fed into a trained Machine Learning Model, which predicts the potential disease. This model uses algorithms such as:

- SVM
- Random Forests
- Naive Bayes

The model has been trained on historical data to identify disease patterns accurately.

#### 7. Disease Prediction

Based on the input data, the ML model predicts one or more likely diseases.

# 8. Results Display

The final diagnosis or prediction is presented to the user through the User Interface. The results may include:

- Probability scores for multiple diseases.
- Suggestions for next steps, such as consulting a doctor.

# 4.3 Design of the proposed system with proper explanation of each

# a. Data Flow Diagrams

# DFD(Level 0)

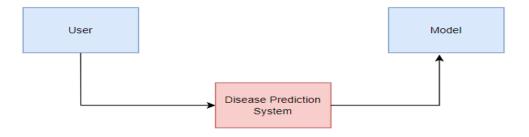


Fig 4.3.a.i Data Flow Diagram (Level 0)

The Level 0 DFD shows the basic interaction between the system and external entities. Here, the User inputs symptoms into the Disease Prediction System. The system sends these symptoms to an ML Model, which processes and returns a predicted disease. Finally, the system displays the prediction to the user. This high-level overview highlights the basic inputs and outputs but does not show any internal workings of the system, making it an abstract view of the overall process.

### **DFD**(Level 1)

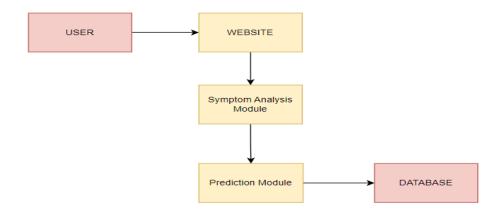


Fig 4.3.a.ii Data Flow Diagram (Level 1)

Level 1 breaks the Disease Prediction System into core components: User Interface (UI), Symptom Analysis Module, and ML Prediction Module. The UI collects symptoms from the user and displays the prediction. The Symptom Analysis Module validates and processes symptoms, preparing them for the ML Prediction Module, which encodes and applies machine learning algorithms to predict the disease. A database can be used to store or retrieve disease-related data. The data flow shows how symptoms move through the system for analysis and the prediction is displayed to the user.

#### DFD(Level 2)

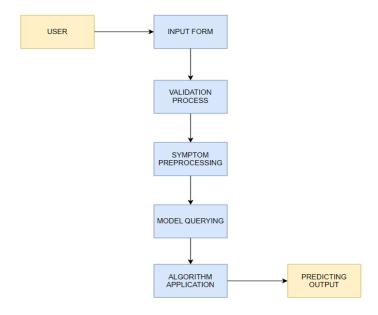


Fig 4.3.a.iii Data Flow Diagram (Level 2)

Level 2 provides detailed processes within each module. The User Interface collects user input via the Input Form and displays predictions. The Symptom Analysis Module involves three sub-processes: Validation to check input, Preprocessing to clean data, and Model Querying to pass data to the ML module. The ML Prediction Module consists of Algorithm Application, and Prediction Output. Data moves through each sub-process to generate an accurate prediction.

#### b. Flowchart for the proposed system

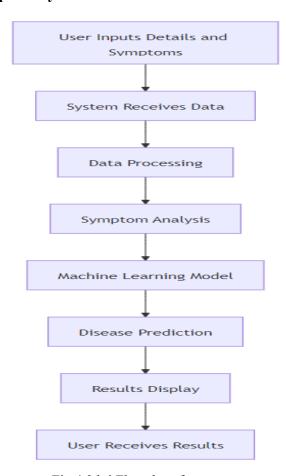


Fig 4.3.b.i Flowchart for system

The flowchart for Health+ outlines the process from user input to disease prediction. It starts with the user inputting symptoms, represented as binary values (0 and 1). The system then pre-processes the data, which is passed into the selected machine learning algorithm, such as k-Nearest Neighbor, Naive Bayes, Decision Tree, or Random Forest. After the algorithm processes the data, a prediction is generated, identifying possible diseases based on the symptoms. The flowchart ends with the system outputting the prediction, which is displayed on the front-end in real-time via the web-based interface.

#### c.Activity Diagram

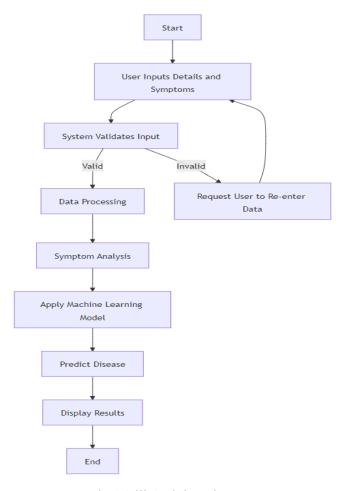


Fig 4.3.iii Activity Diagram

The activity diagram for Health+ captures the sequence of user actions and system responses. It starts when the user accesses the web interface and inputs their symptoms. The system then calls the API to send the data to the backend for processing. Depending on the symptoms and chosen algorithm, the system analyzes the data and returns a prediction to the user. The activity diagram showcases how these processes interact, including decision points, like whether additional input is required or if the recommendation feature is triggered.

#### d. ER diagram

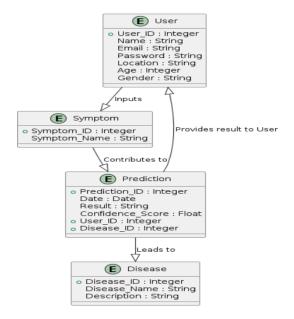


Fig 4.3.d.i ER Diagram

The ER diagram for Health+ shows the relationships between key entities in your system. Entities might include "User," "Symptom Data," "Prediction Result," and "Medical Report." Each user is linked to multiple symptoms they report, and these symptoms are related to a disease prediction. The diagram could also include relationships with external data sources, such as hospitals or doctors, for future recommendation features. Attributes like user ID, symptom ID, prediction result, and medical report data will be defined in the diagram, showing how the data flows and is organized within the system.

#### e. Screenshot of implementation

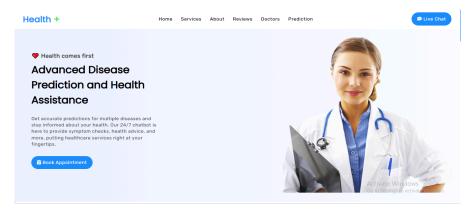


Fig 4.e.i Home Page

This is the home page of our system

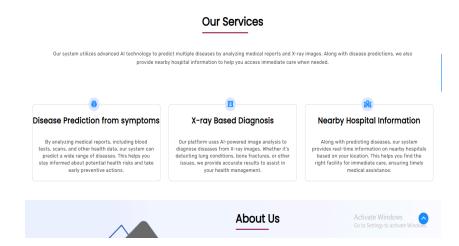


Fig 4.e.ii Services Provided

This page shows the services provided by the system.

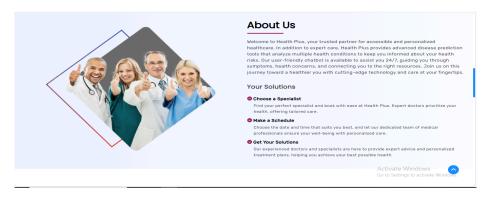


Fig 4.e.iii About Us Page

This page gives us the overall information of the system

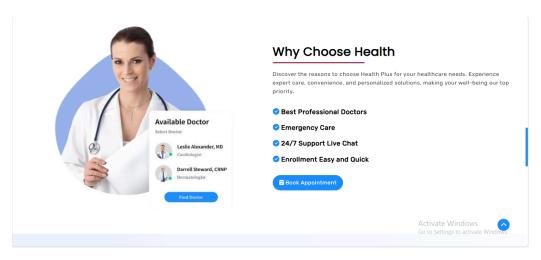


Fig 4.e.iv Professional Guidance

This page shows why we can choose this system for prediction.

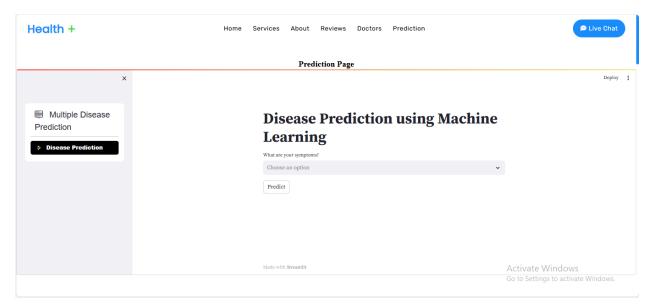


Fig 4.e.v Multiple Disease Prediction

This page contains multiple disease prediction form where based on symptoms the disease will be predicted.

# 4.4 Algorithms utilized in the existing systems

The existing systems for multi-disease prediction leverage a range of machine learning algorithms, each selected for its ability to improve diagnostic accuracy based on the unique dataset and disease context. Some algorithms used are:

- **Support Vector Machines (SVM)**: SVM is widely used for disease prediction due to its ability to handle high-dimensional data and binary classification problems. In the multi-disease prediction system, SVM is employed to classify diseases like heart disease, diabetes, and Parkinson's disease. This approach ensures accurate classification even when the data is non-linearly separable by transforming it into a higher dimension.
- Random Forest: Random Forest is a popular ensemble learning algorithm that aggregates the predictions of multiple decision trees to improve accuracy and prevent overfitting. In the systems studied, Random Forest is used to predict multiple diseases based on patient symptoms, where it performs well due to its ability to manage large datasets with numerous features. Its feature importance mechanism helps in identifying the most relevant symptoms for each disease, making it ideal for medical diagnosis where interpretability is crucial.

- Naive Bayes: The Naive Bayes algorithm is employed for its simplicity and efficiency, especially in handling categorical data and text, such as patient symptoms. It assumes that the features are independent of each other, which may not always be true, but this assumption allows it to work well in practice for medical data. This method is particularly effective for conditions like allergies, where there is a clear probabilistic relationship between symptoms and diseases.
- **Decision Tree Classifier**: Decision trees are used in some systems to model disease predictions by constructing a tree where each node represents a symptom or test, and each branch represents the outcome of the test. This algorithm works well for diagnosing diseases where decisions can be made by answering a series of yes/no questions (i.e., binary splits).

# 4.5 Project Scheduling & Tracking using Timeline / Gantt Chart

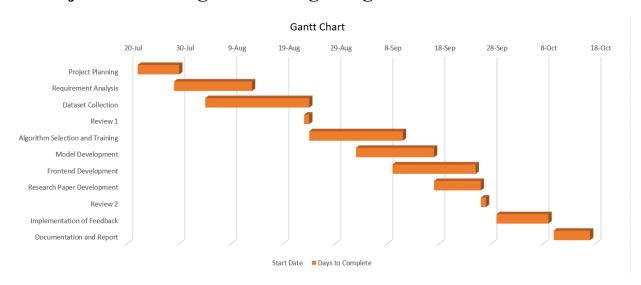


Fig 4.4 Gantt Chart

This chart outlines the timeline and key milestones of the project, illustrating task durations and dependencies for effective project management.

# 5 Proposed Results and Discussions

# **5.1 Determination of Efficiency**

The efficiency of the Health+ system will be evaluated based on its processing speed and resource utilization. We will measure the time taken to analyze user-reported symptoms and generate predictions, aiming for results within a few seconds for optimal user experience. The system's ability to handle multiple concurrent users will also be assessed to ensure scalability and responsiveness.

# 5.2 Determination of Accuracy

To evaluate the accuracy of the disease prediction model, we will analyze the performance metrics outlined in the evaluation measures. The accuracy will be calculated using the formula:

Accuracy = 
$$(TP + TN) / (TP + TN + FP + FN)$$
.

We anticipate achieving an accuracy rate of over 83.2% based on the training dataset. Regular updates and refinements of the machine learning model, using user feedback and the latest medical data, will further enhance accuracy.

# **5.3 Reports on Sensitivity Analysis**

Sensitivity analysis will be conducted to understand how changes in user inputs (e.g., symptom severity, duration, and personal health factors) affect the model's predictions. This analysis will help identify which symptoms and health factors have the most significant impact on the model's outputs. The results will guide further refinements to the model, ensuring that it remains robust and reliable in various scenarios.

# 5.4 Graphs of Accuracy vs. Time

Graphs illustrating the relationship between accuracy and time will be generated to visualize the model's performance over different time intervals. These graphs will plot accuracy percentages against the time taken for predictions, allowing us to analyze trends in model performance as it processes increasing volumes of data. We expect to see a positive correlation between model

updates and accuracy improvements, demonstrating the effectiveness of the feedback loop in enhancing prediction reliability over time.

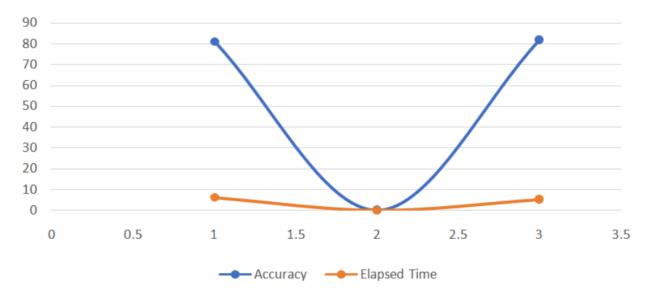


Fig 5.4.i Graphs of Accuracy vs. Time

# **6.Plan Of Action For the Next Semester**

### 6.1 Work Done till Date

So far, significant progress has been made on the Health+ project. We have successfully applied six different machine learning models to predict diseases based on user-reported symptoms. After evaluating the accuracy of each model, we selected the one with the highest performance for our predictions. Additionally, we conducted a correlation matrix visualization to better understand the relationships between various features in our dataset.

Training of the selected model has been completed, and we have implemented a chatbot feature to facilitate user interactions and provide immediate assistance. Furthermore, the frontend of the application has been developed, allowing for an intuitive user experience. The next steps involve integrating this frontend with the backend systems to create a cohesive platform. We are also in the process of building a comprehensive model that includes a doctor appointment system to streamline healthcare access for users.

# 6.2 Plan of Action for Project II

For the upcoming semester, we have outlined the following plan of action to enhance the Health+ project further:

- Integration of Frontend and Backend: Complete the integration of the frontend application with the backend services to ensure seamless data flow and user interaction.
- Enhancement of the Chatbot: Improve the chatbot functionality by incorporating natural language processing capabilities to make interactions more intuitive and user-friendly.
- Expansion of Prediction Models: Explore additional machine learning models and techniques to improve prediction accuracy. This may include deep learning approaches and ensemble methods.
- User Testing and Feedback: Conduct user testing sessions to gather feedback on the application's usability and effectiveness. This will help identify areas for improvement and enhance user satisfaction.

- Implementation of the Doctor Appointment System: Develop the doctor appointment scheduling feature, allowing users to book consultations with healthcare professionals directly through the app.
- Performance Optimization: Focus on optimizing the overall system performance, including reducing response times and ensuring the application can handle multiple users simultaneously without issues.
- Documentation and Reporting: Maintain comprehensive documentation of the project's development process and prepare reports detailing findings, challenges, and solutions.

# 7. Conclusion

Health+ effectively tackles the challenge of providing accessible and affordable healthcare, especially for individuals living in remote areas with limited medical resources. This innovative web-based platform offers automated disease predictions, enabling users to assess their health based on reported symptoms without the need for immediate consultations with healthcare professionals. By leveraging extensive datasets, Health+ analyzes user inputs to deliver critical insights into potential health issues, guiding individuals in determining whether further medical evaluation is necessary.

This system enhances the efficiency and cost-effectiveness of disease diagnosis while empowering users to proactively manage their health. With 24/7 online availability, Health+ ensures that individuals can access essential health information whenever they need it, breaking down barriers to healthcare access. This feature is particularly beneficial for those in underserved regions, where traditional healthcare options may be limited.

# 8. References

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# 9. Appendix

# 9.1 List of Figures

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# 9.2 Review Sheet

# **Review 1**

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# **Review 2**

