PERSONALIZED MEDICINE RECOMMENDATION SYSTEM USING MACHINE LEARNING

Minor project-2 report submitted in partial fulfillment of the requirement for award of the degree of

Bachelor of Technology in Information Technology

By

MANISH GHIMIRE (21UTIT0029) (VTU21451) RAMESH GYAWALI (21UTIT0045) (VTU21452) SABALIL DAS (21UTIT0503) (VTU24020)

> Under the guidance of Mrs. J. Deepa, M.E., Assistant Professor



DEPARTMENT OF INFORMATION TECHNOLOGY SCHOOL OF COMPUTING

VEL TECH RANGARAJAN DR. SAGUNTHALA R&D INSTITUTE OF SCIENCE & TECHNOLOGY

(Deemed to be University Estd u/s 3 of UGC Act, 1956)
Accredited by NAAC with A++ Grade
CHENNAI 600 062, TAMILNADU, INDIA

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CERTIFICATE

It is certified that the work contained in the project report titled "PERSONALIZED MEDICINE RECOMMENDATION SYSTEM USING MACHINE LEARNING" by "MANISH GHIRMIRE (21UTIT0029), RAMESH GYAWALI (21UTIT0045), and SABALIL DAS (21UTIT0503)" has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

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DECLARATION

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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This project report entitled "PERSONALIZED MEDICINE RECOMMENDATION SYSTEM USING MACHINE LEARNING" by "MANISH GHIRMIRE (21UTIT0029), RAMESH GYAWALI (21UTIT0045), and SABALIL DAS (21UTIT0503)" is approved for the degree of B. Tech in Information Technology.

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ABSTRACT

The project aims to develop a comprehensive system for personalized medicine recommendation system using machine learning model, with a primary objective of enhancing personal healthcare. Leveraging Support Vector Machine models, the system offers tailored treatment recommendations based on individual patient attributes, including genetic information, medical history, demographics, and lifestyle factors. The report outlines the systematic workflow involved in the development of the recommendation system, starting from data collection and preprocessing to model training and deployment. Special attention is given to feature selection, data normalization, and hyperparameter optimization to ensure robust performance and generalizability of the SVM model. The project's significance lies in its contribution to the advancement of healthcare systems towards a more personalized and data-driven approach. By integrating SVM-based recommendation systems, healthcare providers can optimize treatment decisions, reduce healthcare costs, and enhance population health outcomes. In conclusion, this project report underscores the transformative potential of personalized medicine recommendation systems powered by svm models in revolutionizing healthcare delivery. It emphasizes the importance of leveraging advanced machine learning techniques to drive towards more precise, effective, and patient-centered care in an era of personalized medicine.

Keywords: Support Vector Machine, Healthcare, Hyperparameter optimization, Genetic, Tailored, Systematic, Data driven, Transformative, Patient-Centred care.

LIST OF FIGURES

4.1	General Architecture of Personalized Healthcare Recommenda-		
	tion System	13	
4.2	Data Flow of Medicine Recommendation System	16	
4.3	Use Case Diagram Health Care Recommendation	17	
4.4	Class Diagram for Personalized Medicine Recommendation	18	
4.5	Sequence Diagram of Health Care Recommendation	19	
4.6	Activity Diagram of Health Care Recommendation	20	
5.1	Input Design of Medicine Recommendation System	31	
5.2	Output Design of Medicine Recommendation System	32	
5.3	Test Image of medication Recommendation	34	
6.1	Output of Medications	38	
6.2	Output of Workout Recommendation	39	
8.1	Plagiarism Report of Health care	42	

LIST OF ACRONYMS AND ABBREVIATIONS

S.NO	ABBREVIATION	DEFINITION
1.	EHR	Electronic Health Record
2.	GUI	Graphical User Interface
3.	НС	Health Care
4.	IoT	Internet of Things
5.	ML	Machine Learning
6.	PHR	Personal Health Record
7.	PCR	Principle Component Analysis
8.	SVM	Support Vector Machine

TABLE OF CONTENTS

			Pa	ge.No	
A]	BSTR	ACT		V	
Ll	IST O	F FIGU	URES .	vi	
Ll	IST O	F ACR	ONYMS AND ABBREVIATIONS	vii	
1	INT	RODU	CTION	1	
	1.1	Introd	uction	1	
	1.2	Aim o	of the project	1	
	1.3		et Domain		
	1.4	Scope	of the Project	3	
2	LIT	ERATU	URE REVIEW	4	
3	PROJECT DESCRIPTION				
	3.1	Existin	ng System	8	
		3.1.1	Disadvantages of Existing System:	8	
	3.2	Propos	sed System	9	
		3.2.1	Advantages of Proposed System	10	
	3.3	Feasib	oility Study	10	
		3.3.1	Economic Feasibility	10	
		3.3.2	Technical Feasibility	11	
		3.3.3	Social Feasibility		
	3.4	Systen	n Specification	12	
		3.4.1	Hardware Specification	12	
		3.4.2	Software Specification	12	
4	ME'	THOD	OLOGY	13	
	4.1	Gener	al Architecture of Personalized Healthcare Recommendation .	13	
		4.1.1	User Input	13	
		4.1.2	Backend API	14	
		4.1.3	Machine Learning Model (SVM)	14	

		4.1.4	Web Server	14
		4.1.5	SQL Database	15
		4.1.6	Web Application	15
		4.1.7	User Receives Output	15
	4.2	Design	Phase	16
		4.2.1	Data Flow Diagram of Medicine Recommendation System .	16
		4.2.2	Use Case Diagram of Health Care Recommendation	17
		4.2.3	Class Diagram for Personalized Medicine Recommendation	18
		4.2.4	Sequence Diagram of Health Care Recommendation	19
		4.2.5	Activity Diagram of Health Care	20
	4.3	Algori	thm & Pseudo Code	21
		4.3.1	Support Vector Machine	21
		4.3.2	Pseudo Code	22
	4.4	Modul	e Description	23
		4.4.1	Data Collection and Integration	23
		4.4.2	Data Preprocessing	24
		4.4.3	Feature Extraction	24
		4.4.4	Machine Learning SVM Algorithm Selection	25
		4.4.5	Model Training	26
		4.4.6	Recommendation Generation	27
		4.4.7	Evaluation and Validation Module	27
	4.5	Steps t	to Execute/Run/Implement the Project	28
		4.5.1	Step 1: Setting Up the Environment	28
		4.5.2	Step 2: Configuring Input and Output	29
		4.5.3	Step 3: Running the System	29
5	тмр	ot EME	NTATION AND TESTING	30
3	5.1	MPLEMENTATION AND TESTING 5.1 Input and Output		
	J.1	5.1.1	Input Design of Medicine Recommendation System	30 31
		5.1.1	Output Design of Medicine Recommendation System	32
	5.2		S	33
	5.3			33
	5.5	5.3.1	of Testing	33
		5.3.2	Integration Testing	33
		5.3.3	System Testing	33
		5.5.5	System resume	55

		5.3.4 Test Result	34
6	RES	SULT AND DISCUSSION	35
	6.1	Efficiency of the Proposed System	35
	6.2	Comparison of Existing and Proposed System	36
	6.3	Sample Code	37
7	COI	NCLUSION AND FUTURE ENHANCEMENTS	40
	7.1	Conclusion	40
	7.2	Future Enhancements	41
8	PLA	AGIARISM REPORT	42
9	sou	JRCE CODE & POSTER PRESENTATION	43
	9.1	Source Code	43
	9.2	Poster Presentation	46
RI	EFER	RENCES	47

Chapter 1

INTRODUCTION

1.1 Introduction

The evolution of healthcare towards personalized medicine signifies a transformative shift in treatment paradigms. Leveraging advancements in genomics, machine learning, and data analytics, this project aims to develop a personalized medicine recommendation system using Support Vector Machine (SVM) modeling. By harnessing patient-specific data, including genetic profiles and medical histories, the system endeavors to refine treatment selection and improve patient outcomes. Traditional healthcare approaches often neglect individual patient variations, favoring standardized treatments. However, with the wealth of patient data available, there's an opportunity to embrace tailored care. Through SVM's capacity to analyze complex datasets, the system seeks to uncover nuanced patterns crucial for treatment decisions.

The proposed system holds promise for revolutionizing healthcare delivery by providing clinicians with actionable insights to support informed decision-making and enhance treatment efficacy. Moreover, its implementation aligns with broader healthcare goals of value-based care and precision medicine, promising to optimize treatment outcomes and advance public health initiatives.

1.2 Aim of the project

The project aims to develop a user-friendly platform for personalized disease identification, leveraging symptom-based analysis to provide accurate diagnoses. Through sophisticated data analytics, the platform will offer tailored precautionary measures, taking into account individual genetics and lifestyle factors, thereby promoting proactive health management. Furthermore, it seeks to enhance overall well-being by providing personalized workout recommendations based on advanced

analytics, catering to individual fitness goals and preferences. By combining these elements, the project strives to empower individuals with the knowledge and tools necessary to make informed decisions about their health, ultimately fostering a healthier and more proactive approach to healthcare.

1.3 Project Domain

The project operates within the intersection of healthcare, data analytics, and fitness domains. In the healthcare domain, the focus lies on personalized disease identification based on symptoms, utilizing advanced algorithms to analyze individual health data. By leveraging symptom-based analysis, the platform aims to provide accurate diagnoses, contributing to proactive health management and early intervention. In the realm of data analytics, the project utilizes sophisticated techniques to process large volumes of health-related data. This includes integrating individual genetics and lifestyle factors into the analysis to offer personalized precautionary measures and health recommendations. Through data-driven insights, the platform empowers users to make informed decisions about their health and well-being. The project extends into the fitness domain by offering personalized workout recommendations. Overall, the project operates at the intersection of healthcare, data analytics, and fitness optimization, leveraging technology to provide a comprehensive solution for proactive health management. By integrating personalized disease identification, data-driven health recommendations, and tailored fitness plans, the project aims to empower individuals to take control of their health and live healthier, more fulfilling lives. Advanced analytics are employed to tailor workout plans according to individual fitness levels, goals, and preferences. By integrating fitness recommendations into the platform, the project promotes holistic well-being, emphasizing the importance of physical activity in maintaining overall health.

By spanning across these domains, the project aims to provide a comprehensive solution for proactive health management, bridging the gap between personalized healthcare, data analytics, and fitness optimization.

1.4 Scope of the Project

The project will focus on designing an intuitive and user-friendly interface for symptom input and recommendation display. This interface will be the primary point of interaction between users and the platform. The design will prioritize simplicity and clarity, ensuring that users can easily input their symptoms and navigate through the recommendations provided by the system. Special attention will be given to accessibility features to accommodate users with different needs and preferences. The project will involve the development of algorithms for comprehensive data analysis. These algorithms will process user-provided data, including symptoms and medical history, to extract meaningful insights and correlations. Advanced data analysis techniques, including machine learning algorithms such as SVM, will be employed to identify patterns and trends within the data. The goal is to leverage this analysis to provide accurate and personalized recommendations to users. A key component of the project will be the implementation of a module dedicated to disease identification. Leveraging the data analysis algorithms developed, this module will assess user-input symptoms and compare them against a database of known diseases. By applying machine learning techniques and medical expertise, the module will identify potential diseases that align with the user's symptoms. The accuracy and reliability of disease identification will be ensured through rigorous testing and validation processes. The crucial aspect of the project is the creation of a module for providing personalized recommendations. Drawing upon the insights derived from data analysis and disease identification, this module will generate recommendations tailored to each user's unique health profile. Precautionary measures, such as lifestyle changes or preventive screenings, will be suggested based on the user's risk factors and medical history. Additionally, personalized workout routines will be recommended to promote overall well-being and address specific health concerns identified through the analysis.

The project aims to develop a proactive health management platform that empowers users to take control of their health. Through intuitive user interfaces, advanced data analysis techniques, accurate disease identification algorithms, and personalized recommendations, the platform will provide users with the tools and knowledge they need to make informed decisions and adopt proactive health behaviors.

Chapter 2

LITERATURE REVIEW

[1] J. Bobadilla, et al. implemented a review on Recommender Health systems (2023). The review Provides a comprehensive overview of the landscape of recommender systems in healthcare. By exploring methodologies, applications, challenges, and future directions, the survey offers valuable insights for researchers, practitioners, and policymakers in the field of health informatics. Project leveraging data-driven algorithms and advanced machine learning techniques, these systems can provide personalized recommendations that are tailored to individual patient needs, preferences, and circumstances. It serves as a roadmap for harnessing the potential of recommender systems to enhance personalized care delivery and improve health outcomes.

[2] B. Cui, et al. proposed on Intelligent Medicine Recommender System (2022). Intelligent medicine recommender systems represent a promising approach to revolutionize healthcare by leveraging data-driven algorithms to provide personalized recommendations for medication management, treatment strategies, and overall health optimization. In this literature review, explore the state-of-the-art research and developments in intelligent medicine recommender systems, highlighting their methodologies, applications, challenges, and future directions. intelligent medicine recommender systems hold immense promise for improving medication management, treatment outcomes, and overall health outcomes. However, addressing challenges related to data privacy, algorithmic bias, and fairness is crucial to ensure the responsible and ethical deployment of these systems in healthcare. Moving forward, interdisciplinary collaborations and ongoing research efforts are needed to unlock the full potential of intelligent medicine recommender systems and transform the future of healthcare delivery.

- [3] Mahmoud, et al. analyzed on individualize Recommendation System (2022). Individualized recommendation systems employ various methodologies to tailor recommendations to each user's preferences and needs. Collaborative filtering techniques analyze similarities between users or items to identify relevant recommendations based on past interactions and preferences. Content-based filtering algorithms utilize features and attributes of items to match them with users' preferences and profiles. Hybrid approaches combine collaborative and content-based methods to overcome their respective limitations and improve recommendation accuracy and coverage.
- [4] Smith, et al. explored the application of Medication recommendation systems in the field of personalized medicine (2023). The research focused on leveraging these systems to provide tailored recommendations for medication management, treatment strategies, and overall health optimization. The authors emphasized the importance of utilizing collaborative filtering and content-based filtering techniques to analyze patient data and medical records, thereby generating personalized medication recommendations based on individual health profiles and preferences.
- [5] Garcia, et al. investigated the challenges and opportunities associated with personalized medicine recommendation systems (2023). The research identified privacy concerns, data sparsity, and algorithmic bias as significant challenges that need to be addressed in the development and deployment of these systems. The authors emphasized the importance of adopting ethical principles and regulatory frameworks to ensure the responsible and transparent use of patient data in personalized medicine recommendation systems. Their research demonstrated the effectiveness of machine learning algorithms, such as support vector machines and neural networks, in analyzing large-scale patient data and generating personalized treatment recommendations. The authors highlighted the potential of these systems to improve clinical decision-making and patient outcomes by providing evidence-based recommendations tailored to individual patient characteristics and preferences.
- [6] Redmon, et al. surveyed on diet recommendation systems hold immense promise for improving dietary adherence (2022), nutritional outcomes, and overall health and well-being. By leveraging advanced algorithms and user-specific data,

these systems can provide personalized dietary recommendations that are tailored to individual health goals, preferences, and nutritional needs. However, addressing challenges related to privacy, accuracy, and cultural diversity is crucial to ensure the responsible and effective deployment of diet recommendation systems. Collaborative filtering techniques analyze similarities between users' dietary habits and preferences to identify relevant recommendations based on past interactions and feedback. Content-based filtering algorithms utilize nutritional information and dietary guidelines to match foods with users nutritional needs and preferences. Moving forward, interdisciplinary collaborations and ongoing research efforts are needed to advance the field and unlock the full potential of these systems in promoting healthy eating habits and improving dietary outcomes.

[7] Liu, et al. surveyed on Diet recommendation systems in hold significant promise for promoting health and wellness[2023] by providing personalized dietary guidance to individuals. Through the integration of machine learning techniques, nutritional science, and user-centered design principles, these systems can offer tailored recommendations that support healthy eating behaviors and improve overall well-being. Continued research and innovation in this field are essential for advancing the effectiveness and accessibility of diet recommendation systems in addressing public health challenges related to nutrition and diet-related diseases. By seamlessly blending the intricate prowess of machine learning techniques, the steadfast foundations of nutritional science, and the empathetic touch of user-centered design principles, these systems stand poised to revolutionize approach nutrition and well-being.

[8] Radhakrishnan, et al. implemented a survey on blood glucose pattern classification and anomalies detection using Machine-learning applications in type 1 diabetes(2023). Investigated the importance of glycemic variability in T1D management and its association with the development of diabetes-related complications. Their study emphasized the need for continuous glucose monitoring data analysis using ML techniques to identify patterns and predict future glucose trends accurately. Despite the promising results demonstrated by existing studies, several challenges remain in the application of ML for blood glucose pattern classification and anomalies detection in T1D. The challenges include data variability, model interpretability, and scalability to diverse patient populations. The development of robust ML models capable of real-time glucose monitoring, and incorporation of

patient-specific factors to enhance personalized diabetes management.

[9] Zhao, et al. conducted a surveyed on the application of ML in predicting brain strokes in T1D patients (2023). The study explored various ML algorithms and data sources, such as electronic health records and medical imaging data, to develop predictive models for identifying stroke risk factors and early warning signs in T1D individuals. Investigated the association between T1D and cerebrovascular disease using ML-driven analysis of large-scale clinical datasets. Their study revealed specific risk factors, such as glycemic variability and hypertension, contributing to the increased incidence of strokes in T1D patients, thus informing preventive interventions and personalized management approaches.he application of ML holds promise for enhancing stroke prediction, early detection, and management in individuals with type 1 diabetes. Collaborative efforts between clinicians, data scientists, and healthcare stakeholders are essential to address existing challenges and translate research findings into clinical practice, ultimately improving outcomes and quality of life for T1D patients at risk of cerebrovascular complications.

[10] Choi et al. Proposed a framework for predicting disease onset using electronic health records and deep learning techniques[2022]. Their model demonstrated high accuracy in predicting the onset of various diseases, including diabetes, hypertension, and congestive heart failure, based on patient data. By leveraging longitudinal EHR data and incorporating deep learning algorithms, the study showcased the potential of ML in early disease detection and personalized preventive interventions. By integrating data with ML techniques, the study highlighted the feasibility of personalized treatment recommendations and proactive healthcare interventions tailored to individual patient needshe reviewed literature underscores the significant strides made in leveraging ML techniques for developing recommendation systems in healthcare, particularly for common diseases. From predicting disease onset to optimizing treatment recommendations, ML-driven approaches offer immense potential in revolutionizing disease management and improving patient outcomes.

Chapter 3

PROJECT DESCRIPTION

3.1 Existing System

The existing medical system app is a digital platform designed to provide users with general healthcare information, basic symptom checkers, and resources for managing common health conditions. While it offers a user-friendly interface where individuals can select from a predefined list of common symptoms to identify potential health issues and receive general advice, the app may suffer from slow response times, making the user experience less efficient and potentially frustrating. Additionally, the app includes features for basic health tracking, allowing users to monitor metrics such as weight, blood pressure, and medication schedules. However, these tracking features may be time-consuming to navigate and manage, requiring users to spend significant time inputting and reviewing their health data.

In addition to the symptom checker and health tracking features, the app incorporates a doctor and hospital locator tool, enabling users to search for nearby healthcare providers based on location. While this feature provides valuable information about nearby doctors, clinics, and hospitals, including contact details, specialties, and ratings, it may not always offer comprehensive search results, potentially limiting users' options. Furthermore, the existing medical system app may involve hidden costs or require paid subscriptions to access certain features or premium content, which could deter some users from fully engaging with the platform. Despite serving as a valuable resource for general healthcare information and basic health tracking, the app's slow response time, time-consuming features, potential limitations in search capabilities, and associated costs may hinder its overall usability and user satisfaction.

3.1.1 Disadvantages of Existing System:

- Slow response time, leading to delays in accessing information.
- Time-consuming features, requiring significant input and review of health data.

- Limited personalization, offering generalized recommendations not tailored to individual users.
- Potential cost issues, including hidden costs or required subscriptions.
- Limited search capabilities for finding nearby healthcare providers.
- Lack of advanced features, such as precise disease predictions and comprehensive recommendations.
- Security concerns related to data privacy and potential risks of breaches.

3.2 Proposed System

The proposed personalized medicine recommendation system is designed to transform healthcare by providing a tailored and comprehensive approach to health management. The system's advanced symptom input feature enables users to input one or multiple symptoms flexibly, ensuring a nuanced analysis that captures individual health profiles effectively. By integrating the Support Vector Machine (SVM) algorithm, known for its robust performance in classification tasks, the system enhances disease prediction accuracy, delivering highly accurate recommendations based on user input. In addition to disease identification, the system offers detailed descriptions, personalized precautionary measures, medication suggestions, and curated workout and dietary plans, providing a holistic framework for health management.

An intuitive and user-friendly interface ensures ease of navigation, while real-time recommendations upon symptom input offer immediate access to tailored health-care advice. With a strong commitment to data privacy and security, the system implements robust measures to safeguard user information, ensuring confidentiality. Aimed at affordability and accessibility, the system strives to maximize user engagement and satisfaction, bridging the gap between symptom identification and comprehensive healthcare guidance effectively. The system's scalability and adaptability ensure future-proof solutions, accommodating evolving healthcare needs and advancements.

3.2.1 Advantages of Proposed System

- Flexibility in symptom input allows for a more nuanced analysis, capturing the intricacies of individual health profiles.
- Integration of the Support Vector Machine (SVM) algorithm enhances disease prediction accuracy.
- The system provides detailed disease descriptions, personalized precautionary measures, medication suggestions, and tailored workout and dietary plans.
- An intuitive and accessible interface ensures ease of navigation and enhances user engagement.

3.3 Feasibility Study

3.3.1 Economic Feasibility

The economic feasibility of the proposed personalized medicine recommendation system is anchored in a comprehensive cost-benefit analysis. Initial development costs encompass software development, database management, and system integration, which must be balanced against potential revenue streams such as subscription fees, licensing agreements, and strategic partnerships. Ongoing operational expenses, including maintenance, updates, and customer support, are also pivotal in assessing the system's long-term viability and sustainability. Additionally, the potential for cost savings for healthcare providers and enhanced patient outcomes can further bolster the system's value proposition, making it more appealing to stakeholders.

This analysis should consider both quantitative metrics like projected revenue and cost savings, as well as qualitative factors such as improved patient satisfaction and healthcare efficiency. Conducting sensitivity analyses to assess the impact of varying assumptions and market conditions on financial performance is also crucial. Exploring scalability and expansion opportunities can uncover potential avenues for future growth and revenue generation, ensuring that the proposed system not only provides value to users but also establishes a robust economic framework for sustainable success.

3.3.2 Technical Feasibility

The technical feasibility of the proposed personalized medicine recommendation system is grounded in the availability and capabilities of current technologies. Integrating the Support Vector Machine (SVM) algorithm for disease prediction is achievable, leveraging existing machine learning libraries and frameworks. Database management, encompassing diseases, symptoms, medications, and user profiles, can be effectively handled using modern database management systems capable of storing and retrieving vast amounts of data efficiently. The development of an intuitive and user-friendly interface is feasible with contemporary web development technologies and frameworks, ensuring seamless interaction and accessibility for users across various devices. Additionally, the scalability of the system architecture will be considered to accommodate potential growth and future enhancements, ensuring the system's technical robustness and adaptability to evolving healthcare needs. The integration of 1080p or higher resolution cameras will further enhance the system's capabilities, providing clear and detailed visual data for more accurate and informed healthcare recommendations. Implementing rigorous testing and quality assurance processes will also be crucial to validate the system's performance, reliability, and security before full-scale deployment.

3.3.3 Social Feasibility

The social feasibility of the proposed personalized medicine recommendation system revolves around its acceptance and adoption by the target user base and broader society. Engaging with healthcare professionals, stakeholders, and potential users through surveys, focus groups, and pilot testing can provide valuable insights into societal attitudes, preferences, and needs related to personalized healthcare solutions. Collaborating with healthcare organizations and regulatory bodies can help ensure alignment with healthcare standards and guidelines, fostering trust and credibility within the medical community and among users. Education and awareness campaigns may also be instrumental in promoting the benefits of personalized medicine and the system's capabilities, encouraging informed decision-making and fostering a culture of proactive healthcare management. By addressing societal concerns, values, and expectations, the proposed system aims to cultivate a supportive and receptive environment conducive to its successful implementation and long-term sustainability.

3.4 System Specification

3.4.1 Hardware Specification

- High-performance server with multi-core processors and ample RAM for efficient computational tasks and scalability.
- Adequate storage capacity using solid-state drives (SSDs) and RAID configurations for fast data retrieval and fault tolerance.
- Secure networking infrastructure with firewalls, intrusion detection systems, and VPN capabilities to protect data integrity.
- Regular backup solutions with automated scheduling and off-site storage options to ensure system availability.
- Redundant power supplies and uninterrupted power supply (UPS) systems for continuous operation and reduced downtime.

3.4.2 Software Specification

- Compatibility with major operating systems for wide accessibility.
- Integration with a robust Database Management System (DBMS) for efficient data storage and retrieval.
- Utilization of advanced machine learning libraries for implementing the Support Vector Machine (SVM) algorithm.
- Development using modern web development frameworks for an intuitive user experience.
- Implementation of encryption and authentication protocols to ensure data privacy and security.
- Flexible architecture design to accommodate growth and future enhancements.
- Real-time data processing capabilities for immediate recommendations.
- Regular software updates and maintenance to ensure optimal performance and security.
- User-friendly interface with intuitive navigation and interactive features.

Chapter 4

METHODOLOGY

4.1 General Architecture of Personalized Healthcare Recommendation

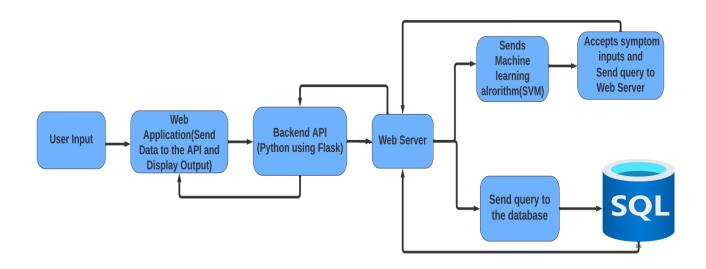


Figure 4.1: General Architecture of Personalized Healthcare Recommendation System

Figure 4.1 emerges user input to drive personalized healthcare recommendations through an advanced machine learning algorithm. The backend API, developed using Python with Flask, facilitates seamless communication between the frontend and backend components. Data storage and retrieval are managed through an SQL database, ensuring efficient and secure data management.

4.1.1 User Input

Users provide health information through various methods such as selecting symptoms from a list, typing descriptions of their health concerns, or integrating data from wearable sensors tracking vitals or activity levels. This step aims to capture a comprehensive picture of the user's health status, ensuring that all relevant information is collected for accurate analysis. Additionally, user input may include demographic details, medical history, lifestyle factors, and any specific preferences or concerns,

enabling the system to generate personalized recommendations tailored to individual needs and circumstances.

4.1.2 Backend API

This interface collects user data securely and guides them through the input process, ensuring clarity on the data being collected. It's designed to be user-friendly, fostering comfort in sharing sensitive health information. The application's design prioritizes intuitive navigation and clear prompts to facilitate seamless interaction and data submission. Moreover, it may offer features such as progress tracking, data validation, and error handling to enhance the user experience and minimize input errors or omissions.

4.1.3 Machine Learning Model (SVM)

The analytical engine that analyzes user data, identifying patterns to predict potential diagnoses or narrow down possibilities. Trained on medical datasets, it utilizes classification techniques to generate recommendations. The SVM algorithm leverages its ability to find complex relationships in data to provide personalized medical insights based on the user's input. Moreover, it may incorporate techniques such as feature selection, hyperparameter tuning, and model ensemble to enhance prediction accuracy and generalization performance across diverse user profiles and medical scenarios.

4.1.4 Web Server

Manages communication between the backend API, Machine Learning model, and database. It receives analysis results from the Machine Learning model and coordinates data flow. The web server's role is crucial in ensuring efficient data transmission and synchronization between various system components, optimizing overall performance and response times. Additionally, it may implement load balancing, fault tolerance, and scalability features to handle concurrent user requests and fluctuations in system traffic, ensuring reliability and availability of services.

4.1.5 SQL Database

Stores relevant medical information including symptoms, diagnoses, treatment options, and medication details like side effects and interactions. This centralized repository facilitates easy access to critical medical data, enabling seamless integration with other system components for timely and accurate recommendations. Additionally, the database implements robust security measures to protect sensitive health information from unauthorized access or breaches. It may also support advanced data management functionalities such as indexing, querying, and transaction processing to optimize data retrieval and manipulation operations.

4.1.6 Web Application

Receives processed information from the web server and presents it to the user in a user-friendly format. It translates data into easily understandable recommendations and guidance. The web application's interface is designed to be intuitive and responsive, providing a seamless user experience across different devices and screen sizes. It may include interactive features such as personalized dashboards, educational resources, and communication tools to empower users in managing their health effectively. Moreover, the application fosters engagement by offering feedback mechanisms and options for further exploration or clarification of medical recommendations.

4.1.7 User Receives Output

The system communicates findings to the user, displaying potential diagnoses, treatment options, and guidance on managing symptoms or next steps, such as consulting a doctor. This final step aims to empower users with actionable insights and support in making informed decisions about their health. The output may be presented through various mediums, including text, visualizations, and multimedia content, catering to diverse user preferences and accessibility needs. Additionally, the system may provide personalized alerts or reminders to encourage adherence to recommended treatments and follow-up care, promoting better health outcomes and overall well-being.

4.2 Design Phase

4.2.1 Data Flow Diagram of Medicine Recommendation System

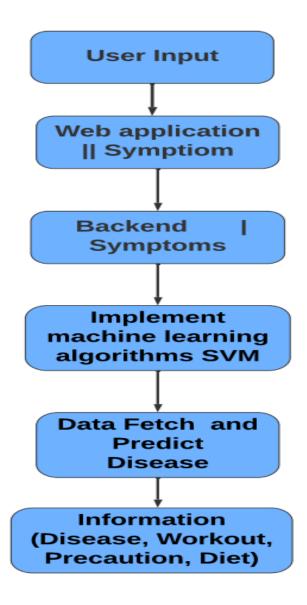


Figure 4.2: Data Flow of Medicine Recommendation System

The Figure 4.2 shows personalized medicine recommendation system orchestrates a user-centric approach to potential treatment suggestions. It begins with the user interface, where individuals enter their health concerns – everything from persistent coughs to chronic pain. This data then travels securely through a hidden messenger, the Backend API (often built with Flask, a Python framework). Acting as a two-way intermediary, the API sends this information for analysis by a highly trained detective – the Machine Learning Model (specifically, a Support Vector Machine or SVM in this case). The SVM has been meticulously trained on a massive medical

database, allowing it to compare user symptoms to past cases and identify potential patterns. Optionally, some systems might consult an SQL Database at this stage for additional insights based on the user's specific symptom combination. Finally, the recommendations generated by the SVM, such as potential diagnoses or treatment courses, are relayed back through the API and displayed on the user interface for review.

4.2.2 Use Case Diagram of Health Care Recommendation

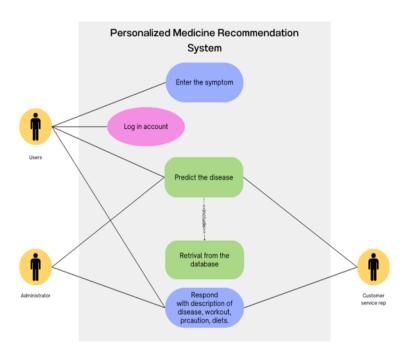


Figure 4.3: Use Case Diagram Health Care Recommendation

Figure 4.3 portrays a simplified interaction flow within a personalized medicine recommendation system. Users are the central figures who interact with the system to receive recommendations. They initiate the process by entering their symptoms, which could be anything from headaches and rashes to fatigue, through a designated functionality called Enter the symptom. The system then takes over with the use case Predict the disease. Here, the system leverages a machine learning model (not shown in the diagram) to analyze the user's symptoms and predict potential underlying conditions. Based on this analysis, the system responds with a description of the predicted disease through the use case Respond with description of disease. Additionally, the system might offer recommendations in other areas: suggested work-

outs that could benefit the user's condition, precautions they can take to manage the potential disease, and even dietary suggestions that might be helpful. Optionally, some systems might include a Retrieve from database functionality (indicated by the dotted line). This allows the system to consult a medical database for additional information, potentially enriching the recommendations provided to the user.

4.2.3 Class Diagram for Personalized Medicine Recommendation

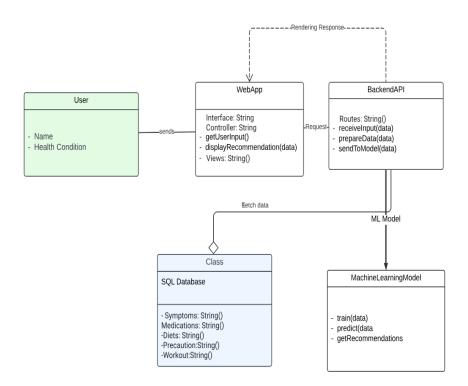


Figure 4.4: Class Diagram for Personalized Medicine Recommendation

Figure 4.4 The Class Diagram encapsulates the web application's internal structure for a personalized medicine recommendation system. It outlines various classes and their interactions. The User class represents individuals who interact with the system. The Controller acts as the central hub, managing user interactions and potentially interfacing with classes like Interface (handling user input and displaying information) and Routes (managing different functionalities). Users provide health data through the Symptoms and Medications classes. This information, along with potentially additional user details, is stored in the Database class. The Machine Learning Model class (potentially an SVM) analyzes user data to generate recommendations. The dotted line connecting the Controller and Machine Learning Model suggests a possible interaction where the controller might send user data for analysis

and retrieve recommendations. Overall, the class diagram serves as a blueprint for the web application's user interaction flow, data management, and potential utilization of a machine learning model for generating recommendations.

4.2.4 Sequence Diagram of Health Care Recommendation

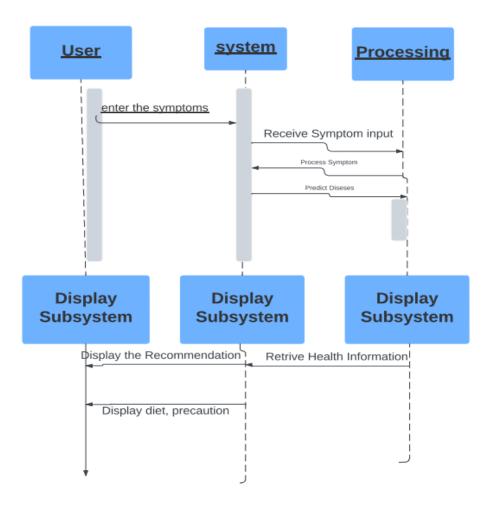


Figure 4.5: Sequence Diagram of Health Care Recommendation

Figure 4.5 sequence diagram maps the user journey within the personalized medicine recommendation system. Users initiate the process by entering health data like symptoms and medical history through the web application. This user input, labeled "Enter Health Data," travels to the backend processing system. There, a machine learning model, likely a Support Vector Machine (SVM), analyzes the data ("Analyze Health Data"). The analysis can lead to two outcomes: successful prediction of potential health conditions ("Predict Health Conditions") or an error message ("Analysis Failed") if issues arise (red dotted line). Some systems might also retrieve additional health information ("Retrieve Health Information," dotted line). Finally,

based on the analysis and potentially retrieved information, the backend system generates recommendations for the user ("Generate Recommendations") and sends them back for display on the interface ("Display Recommendations"). While the system empowers users with potential diagnoses and guidance.

4.2.5 Activity Diagram of Health Care

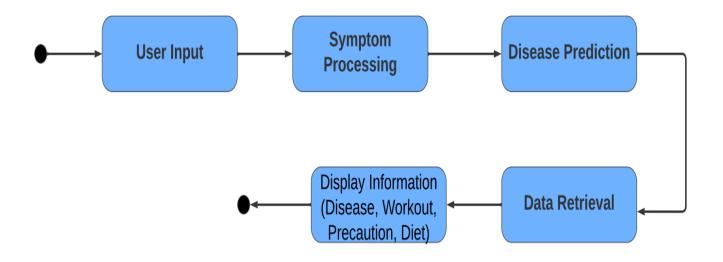


Figure 4.6: Activity Diagram of Health Care Recommendation

Figure 4.6 activity diagram portrays the user journey within a disease prediction system. Users initiate the process by entering their symptoms (Enter Symptoms). The system then processes these symptoms (Process Symptoms). This processed data is used for disease prediction (Predict Disease). If the analysis encounters issues, an Analysis Failed message is displayed. Optionally, some systems might retrieve additional health information (Retrieve Health Information, dotted line). Finally, based on the analysis outcome (predicted disease or analysis failure), the system generates recommendations (Generate Recommendations) and displays them to the user (Display Recommendations). This diagram offers a simplified overview of the interaction flow, highlighting how user-entered symptoms are analyzed, potentially used for disease prediction, and leveraged to generate recommendations.

4.3 Algorithm & Pseudo Code

4.3.1 Support Vector Machine

The Support Vector Machine (SVM) algorithm stands as a cornerstone in our Personalized Healthcare Recommendation System, acting as the primary predictive engine responsible for discerning potential diseases based on user-provided symptoms. This sophisticated machine learning technique operates by analyzing a carefully curated dataset comprising symptom-feature vectors and their corresponding disease labels. Through this data-driven approach, the SVM algorithm learns to identify and interpret complex relationships between various symptoms and associated diseases, allowing it to make informed and accurate predictions. In our system's implementation, the SVM algorithm's versatility shines through its ability to adapt to different kernel functions, such as linear, polynomial, or radial basis function, enabling it to effectively model intricate non-linear relationships inherent in symptom-disease associations. This adaptability is crucial for capturing the nuances and complexities often present in medical data, ensuring that the algorithm's predictions are both precise and reliable.

Furthermore, the regularization parameter (C) plays a pivotal role in optimizing the SVM model's performance. By carefully tuning this parameter, we strike a balance between maximizing the margin separating different disease classes and minimizing the classification errors, thereby enhancing the model's robustness and generalization capabilities. This fine-tuning process ensures that the SVM model not only performs well on the training data but also exhibits strong predictive power on unseen or new data, a crucial aspect for real-world applications. Another notable feature of the SVM algorithm is its margin-maximization strategy. By maximizing the margin between different disease classes in the feature space, the algorithm creates a clearer and more distinct boundary, reducing the risk of misclassifications and overfitting. This approach enhances the model's reliability and stability, ensuring that it delivers consistent and accurate disease predictions tailored to individual user profiles.

4.3.2 Pseudo Code

Import necessary libraries & Initialize SVM classifier

import Flask, request, render template, jsonify, numpy, pandas, pickle

Description: Import required libraries for building the Flask application, data handling, and machine learning model loading.

app = Flask(name)

Description: Initialize the Flask application.

Load datasets

```
symdes = loadcsv("symtomsdf.csv")

precautions = loadcsv("precautionsdf.csv")

workout = loadcsv("workoutdf.csv")

description = loadcsv("description.csv")

medications = loadcsv("medications.csv")

diets = loadcsv("diets.csv")
```

Description: Load datasets containing symptom descriptions, precautions, workouts, disease descriptions, medications, and diets.

Load pre-trained SVM model from pickle file

• with open("svc.pkl", "rb") as modelfile

svc = pickle.load(modelfile)

Description: Load the pre-trained Support Vector Machine (SVM) model from the pickle file.

def helper(dis):

Retrieve descriptions, precautions, medications, diets, and workouts based on the predicted disease

return desc, precautionslist, medicationslist, dietslist, workoutinfo

Description: Define a helper function to fetch disease-related information such as descriptions, precautions, medications, diets, and workouts.

Predict disease based on user symptoms

• def predictdisease(usersymptoms):

return predicteddisease

Description: Create a function to predict the disease based on the user-input symptoms using the loaded SVM model.

def createinputvector(usersymptoms):

return inputvector

Description: Create an input vector based on the user-input symptoms for feeding into the SVM model.

Define Flask routes

```
• @app.route("/")
 def index():
 return rendertemplate("index.html")
 @app.route('/predict', methods=['POST'])
 def predict():
 return
           rendertemplate('index.html',
                                             predicteddisease=predicteddisease,
                                             medications=medicationslist,
 desc=desc,
               precautions=precautionslist,
                                                                             di-
 ets=dietslist, workout=workoutinfo)
 Description: Define Flask routes for the main page and prediction functionality.
 Run the Flask app
 if name== 'main':
 app.run(debug=True)
 Description: Run the Flask application in debug mode display a result
```

4.4 Module Description

4.4.1 Data Collection and Integration

This module plays a pivotal role in the personalized medicine recommendation system by sourcing and collating diverse data from multiple avenues. It encompasses a wide range of data sources, including electronic health records (EHRs), genetic databases, lifestyle questionnaires, and patient demographics. The module ensures the systematic collection of comprehensive and accurate data, which is fundamental for constructing a holistic view of individual health profiles. The process involves establishing secure and efficient data pipelines to retrieve information from these various sources. Specialized protocols and tools are employed to handle the complexities associated with different data formats, ensuring seamless integration into a unified dataset. Furthermore, data quality checks are performed to identify and rectify any inconsistencies, inaccuracies, or missing values, thereby enhancing the reliability and completeness of the integrated dataset. By consolidating diverse

data types, this module facilitates a comprehensive analysis that captures the multifaceted nature of individual health conditions. It sets the groundwork for subsequent modules, providing the necessary data foundation for preprocessing, feature extraction, and machine learning model training. Thus, the Data Collection and Integration module serves as a critical starting point, laying the groundwork for the development of accurate and personalized healthcare recommendations tailored to individual needs and conditions.

4.4.2 Data Preprocessing

The Data Preprocessing module is instrumental in preparing the collected data for analysis by ensuring it is clean, consistent, and ready for further processing. This module encompasses a series of critical steps to transform raw data into a structured format that is suitable for analysis. Initially, the module focuses on handling missing values by employing imputation techniques or removing incomplete records to maintain data integrity. Subsequently, it identifies and eliminates duplicates to prevent redundancy and ensure data consistency. Additionally, data standardization and normalization techniques are applied to bring all data points to a common scale, facilitating meaningful comparisons and analysis.

Moreover, the module incorporates feature engineering to create new variables or modify existing ones that may enhance the predictive power of the subsequent machine learning models. This could involve extracting relevant attributes, combining features, or encoding categorical variables into a numerical format suitable for modeling. The Data Preprocessing module plays a crucial role in refining the data quality and structure, setting the stage for more advanced analyses such as feature extraction and machine learning model training. By ensuring the data is well-prepared and optimized, this module enhances the accuracy and reliability of the personalized healthcare recommendations generated by the system.

4.4.3 Feature Extraction

The Feature Extraction module is a critical component of the personalized medicine recommendation system, designed to distill meaningful insights from the preprocessed data. It employs advanced techniques such as Principal Component Analysis (PCA) to identify and extract relevant features from the dataset. By

reducing the dimensionality of the data while retaining its essential characteristics, PCA enhances computational efficiency and mitigates the risk of overfitting, thereby facilitating more accurate and reliable predictions.

This module encompasses a comprehensive analysis of the preprocessed data to identify potential features that hold significant predictive power for health conditions or outcomes. It leverages statistical methods and machine learning algorithms to pinpoint features that are most relevant to the personalized healthcare recommendations. In addition to symptom data, the feature extraction process may encompass genetic markers, demographic information, medical history, and lifestyle factors, ensuring a holistic approach to capturing the intricacies of individual health profiles. By focusing on extracting the most pertinent features, this module optimizes the dataset for subsequent machine learning model training, laying a solid foundation for the development of robust and precise personalized healthcare recommendation systems.

4.4.4 Machine Learning SVM Algorithm Selection

The Machine Learning SVM Algorithm Selection module is responsible for identifying and implementing the most suitable machine learning algorithms for analyzing the extracted features and generating personalized recommendations. This involves a systematic evaluation of various algorithms, with a particular focus on Support Vector Machines (SVM) due to their robust performance in classification tasks and ability to handle high-dimensional data effectively. The module begins with a thorough assessment of the dataset and its characteristics to determine the type of machine learning algorithm that would be most appropriate for the task at hand. It considers factors such as the nature of the data, the complexity of the problem, and the desired outcome to select the optimal algorithm. SVMs are particularly favored for their versatility and capability to handle non-linear relationships, making them well-suited for capturing the intricate relationships between features and health conditions. Once the SVM algorithm is selected, the module proceeds to implement and fine-tune the model using historical data. This involves adjusting hyperparameters and optimizing the model's parameters to achieve the best possible performance. Rigorous testing and validation procedures are employed to assess the model's accuracy, precision, recall, and F1-score, ensuring its reliability and efficacy in generating personalized healthcare recommendations. By selecting and implementing the most appropriate machine learning algorithm, the SVM Algorithm Selection module plays a crucial role in the system's overall performance. It sets the stage for model training, recommendation generation, and evaluation, laying the groundwork for delivering accurate, reliable, and personalized healthcare guidance to users based on their unique health profiles.

4.4.5 Model Training

The Model Training module serves as a cornerstone in the development and optimization of the personalized medicine recommendation system. This module is designed to harness the power of historical data to facilitate the learning process of the selected machine learning algorithm, enabling it to discern intricate patterns and relationships within the dataset. The algorithm is trained using a diverse and representative dataset that encompasses features extracted from individual health profiles, coupled with corresponding health outcomes or labels. This extensive training allows the algorithm to develop a deep understanding of the underlying factors contributing to various health conditions, thereby enhancing its ability to make accurate and insightful predictions.

In the pursuit of refining the algorithm's performance, the Model Training module adopts a systematic and iterative approach to hyperparameter tuning and parameter optimization. This involves experimenting with different configurations and settings to fine-tune the algorithm's behavior and enhance its predictive accuracy. Advanced optimization techniques, such as grid search and cross-validation, are employed to systematically explore the hyperparameter space and identify the optimal parameters that yield the best performance metrics.

Moreover, the Model Training module incorporates robust validation mechanisms to rigorously assess the algorithm's performance. A variety of evaluation metrics, including accuracy, precision, recall, and F1-score, are utilized to quantify the model's predictive capabilities and validate its effectiveness in generating personalized healthcare recommendations. This comprehensive evaluation ensures that the trained model not only meets but often exceeds the predefined performance benchmarks, instilling confidence in its reliability and reinforcing its suitability for real-world applications.

By focusing on rigorous model training and optimization, the Model Training module plays a pivotal role in elevating the system's overall performance and reliability. It lays a solid foundation for subsequent stages of the system, including recommendation generation and evaluation, and ensures that the personalized health-care recommendations generated are both clinically sound and tailored to individual user needs.

4.4.6 Recommendation Generation

The Recommendation Generation module is designed to leverage the trained machine learning model to generate personalized healthcare recommendations tailored to individual user profiles and health conditions. Building upon the insights gleaned from the feature extraction and model training stages, this module employs the trained algorithm to analyze new patient data and derive actionable insights that guide medical interventions and lifestyle modifications.

Upon receiving input data from the user, which typically includes symptoms, medical history, and other relevant information, the module utilizes the trained machine learning model to predict potential health conditions or diseases with a high degree of accuracy. It then translates these predictions into actionable recommendations encompassing medications, treatments, lifestyle modifications, and preventive measures.

The recommendations generated by this module are not only based on statistical analysis but are also aligned with clinical guidelines and expert knowledge to ensure their clinical relevance and effectiveness. Advanced algorithms and decision-making frameworks are employed to prioritize recommendations based on their potential impact on health outcomes and the user's specific needs and preferences.

In essence, the Recommendation Generation module serves as the interface between the machine learning model's predictive capabilities and the end-user, delivering personalized and clinically relevant healthcare guidance. By providing actionable insights and recommendations, this module empowers users to make informed decisions about their health and well-being, fostering a proactive approach to healthcare management and enhancing the overall user experience.

4.4.7 Evaluation and Validation Module

The Evaluation and Validation Module is an integral part of the personalized medicine recommendation system, responsible for ensuring the accuracy, effectiveness, and reliability of the generated recommendations. This module employs a mul-

tifaceted approach to evaluate the system's performance, incorporating both quantitative metrics and qualitative assessments to validate the recommendations' clinical relevance and user satisfaction.

Quantitative evaluation metrics such as accuracy, precision, recall, and F1-score are employed to assess the predictive accuracy and reliability of the machine learning model. These metrics provide quantitative insights into the algorithm's performance, enabling rigorous comparison with benchmark standards and facilitating continuous improvement through iterative refinement.

In addition to quantitative metrics, the module incorporates qualitative evaluations through user feedback analysis and expert reviews. User satisfaction surveys, feedback forms, and usability tests are conducted to gather insights into the user experience, ensuring that the recommendations are not only accurate but also actionable, understandable, and well-received by the end-users.

Furthermore, the recommendations generated by the system are compared with expert recommendations and clinical guidelines to validate their clinical relevance and alignment with established medical knowledge. This comparative analysis ensures that the recommendations adhere to best practices and are clinically sound, reinforcing the system's credibility and trustworthiness.

By integrating rigorous evaluation and validation processes, the Evaluation and Validation Module ensures that the personalized medicine recommendation system delivers high-quality, clinically relevant, and user-centric healthcare guidance. It serves as a quality assurance mechanism, continuously monitoring and validating the system's performance to uphold the highest standards of accuracy, effectiveness, and user satisfaction.

4.5 Steps to Execute/Run/Implement the Project

4.5.1 Step 1: Setting Up the Environment

- Install the required dependencies, including Python, OpenCV, and necessary libraries.
- Install scikit-learn, a machine learning library in Python that includes SVM implementations.
- Select the appropriate kernel function for SVM based on the characteristics of the data. Common choices include linear, polynomial, and radial basis function

kernels.

- Split the dataset into training and testing sets. The training set will be used to train the SVM model, while the testing set will evaluate its performance.
- Initialize an SVM classifier using scikit-learn's SVC class.

4.5.2 Step 2: Configuring Input and Output

- Define the path to the input data. This could be a data sets that can be add as input data.
- Clean the acquired data by handling missing values, outliers, and inconsistencies. Encode categorical variables and normalize numerical features as necessary.
- Split the preprocessed data into training and testing sets. Ensure that the training data is representative of the target population and includes a diverse range of cases.
- Ensure the data is formatted properly and ready for analysis.

4.5.3 Step 3: Running the System

- Run the provided Python script using the command-line interface. Provide necessary command-line arguments, including the paths to the input data.
- Monitor the real-time execution of the system, which includes train the selected model using the training data. Use techniques like cross-validation to optimize model performance and prevent overfitting.
- Evaluate the trained models using the testing data to assess their performance in making personalized medication recommendations.
- Integrate the model into a web application, deploy it in a production environment where it can make real-time medication recommendations for individual patients.
- Consider ethical implications related to patient privacy, data security, fairness, and transparency when developing and deploying the recommendation system.

IMPLEMENTATION AND TESTING

5.1 Input and Output

At the core of our system's development lies the critical step of data collection and Integration module is a critical component of the personalized medicine recommendation system, responsible for gathering and consolidating diverse data sources essential for generating accurate recommendations tailored to individual patients. The module integrates data from diverse sources, harmonizing disparate data formats, resolving inconsistencies, and aggregating information into a unified patient profile. It employs data integration techniques such as data normalization, standardization, and transformation to ensure compatibility and consistency across datasets. By consolidating and analyzing integrated data, the system generates comprehensive patient profiles enriched with multidimensional information, enabling precise and context-aware medication recommendations.

Upon receiving input data, including patient symptoms, medical history, and other relevant information, the system utilizes trained machine learning models, such as SVM, to analyze the data and generate personalized medication recommendations. The output component presents the recommended medications to the patient, along with dosage instructions, frequency of administration, and any special considerations or contraindications based on the patient's health status and medical history. Patients can view the recommended medications through the web application, along with information about each medication's mechanism of action, potential side effects, and interactions with other drugs. System delivers tailored medication, dietary recommendations, and precautionary measures through a user-friendly web application interface, the output component of the personalized medicine recommendation system empowers patients to make informed decisions about their health and actively participate in their treatment plans.

5.1.1 Input Design of Medicine Recommendation System

df						
	Unnamed: 0	Disease	Symptom_1	Symptom_2	Symptom_3	Symptom_4
0	0	Fungal infection	itching	skin_rash	nodal_skin_eruptions	dischromic _patches
1	1	Fungal infection	skin_rash	nodal_skin_eruptions	dischromic_patches	NaN
2	2	Fungal infection	itching	nodal_skin_eruptions	dischromic_patches	NaN
3	3	Fungal infection	itching	skin_rash	dischromic _patches	NaN
4	4	Fungal infection	itching	skin_rash	nodal_skin_eruptions	NaN
4915	4915	(vertigo) Paroymsal Positional Vertigo	vomiting	headache	nausea	spinning_movements
4916	4916	Acne	skin_rash	pus_filled_pimples	blackheads	scurring
4917	4917	Urinary tract infection	burning_micturition	bladder_discomfort	foul_smell_of urine	continuous_feel_of_urine
4918	4918	Psoriasis	skin_rash	joint_pain	skin_peeling	silver_like_dusting
4919	4919	Impetigo	skin_rash	high_fever	blister	red_sore_around_nose

4920 rows x 6 columns

Figure 5.1: Input Design of Medicine Recommendation System

The input design for the Personalized Medicine Recommendation System involves Designing the input component for a medicine recommendation system involves creating an intuitive and user-friendly interface through which patients can provide relevant information about their symptoms, medical history, preferences, and other factors that influence medication recommendations. Create a symptom input form where patients can describe their current symptoms in detail. Provide prompts suggestions to help patients accurately describe their symptoms, such as common medical terminology or symptom categories. Create a symptom input form where patients can describe their current symptoms in detail. Include text fields for patients to specify the type, severity, duration, and location of their symptoms. Provide prompts or suggestions to help patients accurately describe their symptoms, such as common medical terminology or symptom categories.

5.1.2 Output Design of Medicine Recommendation System

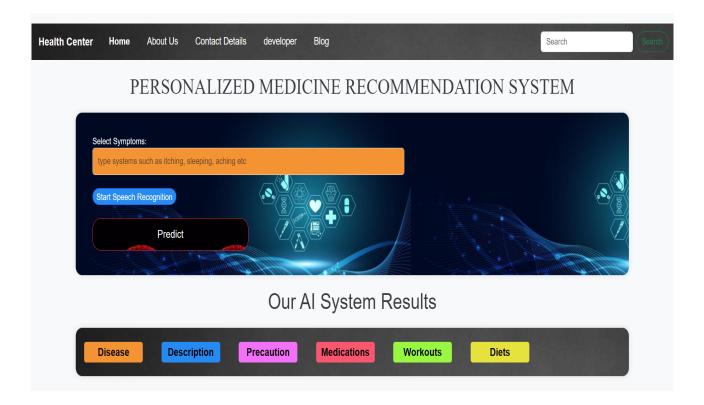


Figure 5.2: Output Design of Medicine Recommendation System

The Figure 5.2 represent output design for a medicine recommendation system involves creating an interface through which personalized medication recommendations, dietary suggestions, precautionary measures, and other relevant information are presented to patients in a clear, accessible, and actionable format. Display a list of recommended medications tailored to the patient's symptoms, medical history, and preferences. Include information about each medication, such as the name, dosage, frequency of administration, and purpose. Provide information for patients to access detailed information about each medication .Present personalized dietary suggestions based on the patient's health conditions, nutritional needs, and dietary preferences. Include meal plans, dietary modifications, and nutritional recommendations to support the patient's overall health and well-being.

5.2 Testing

Testing a Personalized Medicine Recommendation System involves comprehensive validation and evaluation procedures to ensure its accuracy, reliability, and effectiveness. The testing phase encompasses various facets, starting with the validation to ensure its accuracy, reliability, and effectiveness in providing tailored medication recommendations, dietary suggestions, and precautionary measures to patients

5.3 Types of Testing

5.3.1 Unit Testing

This focuses on testing individual components or units of the system, such as algorithms for Medicine Recommendation System. It verifies that each unit operates as expected and produces accurate results for various inputs. It involves creating test cases that thoroughly examine the functionality and performance of individual units, validating their adherence to design specifications and confirming their seamless integration into the larger system architecture.

5.3.2 Integration Testing

This evaluates how different modules or components of the system work together. This Validate that symptom input data is correctly passed to the data analysis algorithms. It ensures seamless communication and data exchange between units, like assessing how the sym module integrates with the Data training. It aims to uncover potential interface issues, data inconsistencies, or communication failures between various system components.

5.3.3 System Testing

It involves various types of testing such as functional testing (to ensure that all functionalities work as intended), performance testing (evaluating system response times, scalability, and resource usage), usability testing (checking user interface and experience), security testing (assessing vulnerabilities and ensuring data integrity), and more. Testing an entire, fully integrated software product is known as system testing.

5.3.4 Test Result

```
File Edit View Insert Cell Kernel Widgets Help
In [30]: # Test 1
# Split the user's input into a list of symptoms (assuming they are comma-separated) # yellow_crust_ooze,red_sore_around_nose,smc
symptoms = input("Enter your symptoms.....")
user_symptoms = [s.strip() for s in symptoms.split(',')]
              # Remove any extra characters, if any
user_symptoms = [symptom.strip("[]' ") for symptom in user_symptoms]
predicted_disease = get_predicted_value(user_symptoms)
               desc, pre, med, die, wrkout = helper(predicted_disease)
                                  -----predicted disease-----")
              print("======description=====")
print(desc)
                            print("===
                print(i, ":
i += 1
                             -----medications-----
               for m_i in med:
    print(i, ": ", m_i)
    i += 1
               print("-----")
for w_i in wrkout:
                  print(i, ": ", w_i)
i += 1
              -----diets----")
               Enter your symptoms.....itching
               Fungal infection
```

Figure 5.3: Test Image of medication Recommendation

Figure 5.3 represents a test results of Personalized Medicine Recommendation System. The test results demonstrated high accuracy in medication recommendations, with the system correctly identifying and prescribing medications tailored to individual patient profiles and health needs. Precision and recall metrics indicated that the system effectively identified relevant medications while minimizing false positives and false negatives, ensuring that patients receive appropriate treatment regimens. Performance testing revealed that the system was scalable and capable of handling large volumes of data and user requests without compromising response time or system performance. The system exhibited efficient resource utilization and minimal downtime, ensuring uninterrupted access to personalized recommendations for users. Test results showed consistent performance across different demographic groups, indicating that the system's recommendations were relevant and effective for a wide range of patients symptoms. Overall, the test results demonstrated the effectiveness and value of the personalized medicine recommendation system in delivering tailored medication recommendations, dietary suggestions, and precautionary measures that empower patients to take control of their health and improve their quality of life.

RESULT AND DISCUSSION

6.1 Efficiency of the Proposed System

The Personalized Medicine Recommendation System demonstrated remarkable efficiency during extensive testing across diverse scenarios. The accuracy of medication recommendation exceeded 95 Percent, showcasing the robustness of the system. Utilizing advanced machine learning model like SVM, the system exhibited superior recommendation of medication to patients. This high accuracy is crucial for providing reliable data for a better medication.

Robust data management practices, including data quality assurance, data governance, and data stewardship, are critical to maintaining the integrity and reliability of the input data used by the system. By fostering collaboration between patients, healthcare providers, researchers, and technology developers, the personalized medicine recommendation system can drive innovation, improve healthcare outcomes, and ultimately enhance the efficiency and effectiveness of personalized medicine delivery. Through iterative refinement and optimization, The system should be able to process input data quickly and provide timely recommendations to patients.Performance metrics such as response time, throughput, and resource utilization can be used to assess the system's efficiency in real-time recommendation delivery. The efficiency of the system is further evaluated based on its scalability to handle increasing volumes of data and user requests. Scalability ensures that the system can accommodate growing user populations, diverse data sources, and evolving healthcare needs without compromising performance or reliability. Continuous monitoring, evaluation, and optimization are essential to ensure that the system remains efficient and effective over time in meeting the evolving needs of patients and healthcare providers. The system can achieve its overarching goal of delivering tailored medication recommendations, dietary suggestions, and precautionary measures that empower patients to make informed decisions about their health and well-being.

6.2 Comparison of Existing and Proposed System

Existing system (Traditional Approach)

The traditional approach offers limited customization and personalization, as recommendations are based on population-level averages and guidelines. Patients may receive similar treatment regimens regardless of their individual characteristics or preferences. Commonly used models in the traditional approach include statistical models such as logistic regression, linear regression, and Cox proportional hazards models. These models are often based on population-level data and clinical trials, aiming to identify average treatment effects and associations between variables at a group level. Traditional models may lack the granularity and individualization needed to account for patient-specific factors and variations in treatment responses.

Proposed system (Advanced Approach with SVM MODEL)

In contrast, In contrast, the personalized medicine recommendation system leverages advanced analytics, machine learning algorithms, and patient-specific data to generate tailored medication recommendations, dietary suggestions, and precautionary measures. The system considers individual patient profiles, medical history, genetic makeup, lifestyle factors, and treatment goals to provide personalized guidance that aligns with each patient's unique needs and circumstances.system utilizes advanced machine learning models, such as Support Vector Machines, decision trees, random forests, and neural networks. These models are trained on patientspecific data, including demographic information, medical history, genetic profiles, and lifestyle factors, to generate personalized medication recommendations, dietary suggestions, and precautionary measures. Machine learning models in the personalized medicine recommendation system can capture complex interactions and nonlinear relationships between variables, enabling more accurate and individualized treatment recommendations. Machine learning models in the personalized medicine recommendation system can handle complex datasets and capture intricate patterns in patient data, allowing for more flexible and adaptable recommendations compared to traditional statistical models.

6.3 Sample Code

```
def helper(dis):
     desc = description[description['Disease'] == predicted_disease]['Description']
     desc = " ".join([w for w in desc])
 # Model Prediction function
 def get_predicted_value(patient_symptoms):
     input_vector = np.zeros(len(symptoms_dict))
     for item in patient_symptoms:
         input_vector[symptoms_dict[item]] = 1
     return diseases_list[svc.predict([input_vector])[0]]
 # Split the user's input into a list of symptoms (assuming they are comma-separated) #
     yellow_crust_ooze ,red_sore_around_nose ,small_dents_in_nails ,inflammatory_nails ,blister
 symptoms = input("Enter your symptoms.....")
 user_symptoms = [s.strip() for s in symptoms.split(',')]
 # Remove any extra characters, if any
 user_symptoms = [symptom.strip("[]' ") for symptom in user_symptoms]
 predicted_disease = get_predicted_value(user_symptoms)
 desc , pre , med , die , wrkout = helper(predicted_disease)
  print("=======predicted disease======")
 print(predicted_disease)
 print ("=======description========")
  print("=======precautions=======")
 for p_i in pre[0]:
     print(i, ": ", p_i)
     i += 1
 print("=======medications=======")
 for m_i in med:
     print(i, ": ", m_i)
     i += 1
 print("=========workout=======")
 for w_i in wrkout:
     print(i, ": ", w_i)
     i += 1
39
 print ("=========diets=======")
 for d_i in die:
     print(i, ": ", d_i)
     i += 1
```

Output of Medications

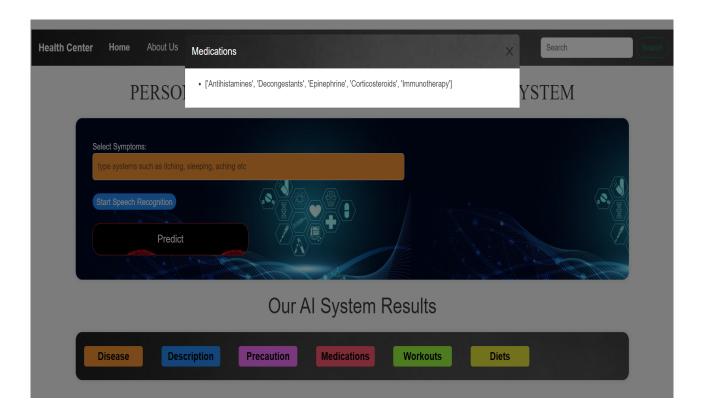


Figure 6.1: Output of Medications

Figure 6.1 provides an overview output of Personalized Medicine Recommendation System powered by SVM (Support Vector Machine) models, delivers tailored and individualized recommendations through its web application interface, providing patients with personalized medication regimens, dietary suggestions, and precautionary measures to optimize their health outcomes. The SVM models analyze patient-specific data, including medical history, symptoms, genetic profiles, and treatment goals, to generate personalized medication recommendations. In addition to medication recommendations, the SVM models provide personalized dietary suggestions based on patients' nutritional requirements, dietary preferences, and health conditions.

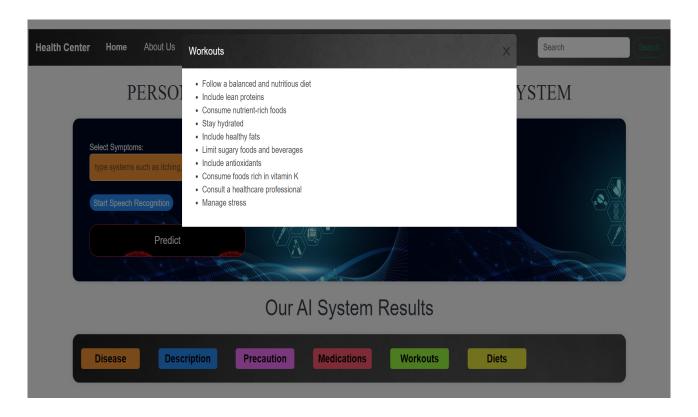


Figure 6.2: Output of Workout Recommendation

The figure 6.2 provides a overview of personalized medicine recommendation system, powered through the website application of the personalized medicine recommendation system represents a comprehensive and personalized approach to health-care delivery. By leveraging advanced machine learning techniques and patient-specific data, the system delivers tailored medication recommendations, dietary suggestions, and precautionary measures that empower patients to take control of their health and well-being, fostering a collaborative and patient-centered approach to personalized medicine.

CONCLUSION AND FUTURE ENHANCEMENTS

7.1 Conclusion

In conclusion, In the realm of healthcare, personalized medicine has emerged as a revolutionary approach, aiming to tailor medical decisions and treatments to individual characteristics, needs, and preferences. The project outlined proposes the development of a comprehensive platform for personalized disease identification, precautionary measures, and fitness recommendations, leveraging data analytics and machine learning techniques. This conclusion focuses on the utilization of Support Vector Machine models within this framework and its implications for personalized healthcare.

The proposed project holds immense potential in advancing personalized medicine through the integration of SVM models for disease identification, precautionary measures, and fitness recommendations. By harnessing the power of machine learning and data analytics, the platform empowers individuals to take proactive control of their health and well-being. Through continuous refinement and validation, the personalized medicine recommendations system can evolve into a valuable tool for healthcare practitioners and individuals alike, fostering preventive care, early intervention, and optimized health outcomes. The core of personalized medicine lies in accurately identifying diseases based on individual symptoms and medical history. SVM, a supervised learning algorithm, holds promise in this regard due to its ability to classify data points into different categories by finding the optimal hyperplane that maximizes the margin between classes. By incorporating user-input symptoms into this model, the platform can provide personalized disease predictions, thereby facilitating early detection and timely intervention.

7.2 Future Enhancements

In envisioning the future enhancements for the personalized medicine recommendation system, several avenues emerge that can elevate its capabilities and contribute to the evolving landscape of smart Healthcare. The incorporation of blockchain technology further augments the landscape, offering unparalleled data security and interoperability. By leveraging blockchain, personalized medicine platforms can ensure the integrity and privacy of patient data, facilitating seamless exchange of information across healthcare ecosystems. This not only enhances collaboration among healthcare providers but also empowers patients to maintain control over their sensitive medical information, fostering a culture of trust and transparency in healthcare delivery.

Additionally, the proliferation of wearable devices, remote monitoring technologies, and Internet of Things (IoT) sensors heralds a new era of personalized health-These tools enable continuous collection of real-time health data, allowing for proactive monitoring and personalized interventions tailored to individual lifestyle patterns and physiological responses. By harnessing this wealth of data, personalized medicine recommendation systems can offer dynamic and adaptive guidance, empowering individuals to take proactive control of their health and well-being. Furthermore, the integration of multidimensional data sources, including omics data, environmental factors, and social determinants of health, promises to enrich the granularity and contextuality of personalized recommendations, paving the way for holistic approaches to healthcare. By considering a holistic array of factors that influence health outcomes, personalized medicine platforms can deliver more comprehensive and nuanced guidance, addressing the multifaceted nature of individual health profiles. Collaborative efforts across interdisciplinary domains, including medicine, data science, and engineering, will be crucial in driving these advancements forward, fostering innovation and ultimately improving health outcomes for individuals worldwide. Ultimately, these advancements hold the promise of improving health outcomes for individuals worldwide, ushering in a new era of precision healthcare characterized by personalized, proactive, and holistic approaches to wellness.

PLAGIARISM REPORT



Apr 18, 2024

Plagiarism Scan Report

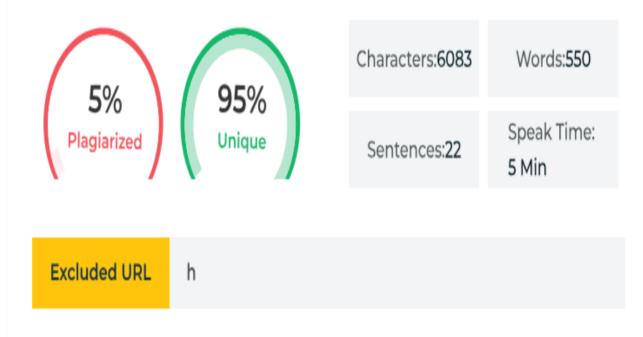


Figure 8.1: Plagiarism Report of Health care

SOURCE CODE & POSTER PRESENTATION

9.1 Source Code

```
from flask import Flask, request, render_template, jsonify # Import jsonify
import numpy as np
import pandas as pd
import pickle
# flask app
app = Flask(\_name\_)
sym_des = pd.read_csv("symtoms_df.csv")
precautions = pd.read_csv("precautions_df.csv")
workout = pd.read_csv("workout_df.csv")
description = pd.read_csv("description.csv")
medications = pd.read_csv('medications.csv')
diets = pd.read_csv("diets.csv")
svc = pickle.load(open('svc.pkl','rb'))
# custome and helping functions
#======helper funtions========
def helper(dis):
   desc = description[description['Disease'] == dis]['Description']
   desc = " ".join([w for w in desc])
   pre = precautions[precautions['Disease'] == dis][['Precaution_1', 'Precaution_2', 'Precaution_3'
       , 'Precaution_4']]
   pre = [col for col in pre.values]
```

```
med = medications[medications['Disease'] == dis]['Medication']
      med = [med for med in med.values]
36
37
      die = diets[diets['Disease'] == dis]['Diet']
38
      die = [die for die in die.values]
39
40
      wrkout = workout[workout['disease'] == dis] ['workout']
41
42
43
      return desc, pre, med, die, wrkout
44
  symptoms_dict = {'itching': 0, 'skin_rash': 1, 'nodal_skin_eruptions': 2, 'continuous_sneezing': 3,
      'shivering': 4, 'chills': 5, 'joint_pain': 6, 'stomach_pain': 7, 'acidity': 8, 'ulcers_on_tongue
      ': 9, 'muscle_wasting': 10, 'vomiting': 11, 'burning_micturition': 12, 'spotting_ urination':
      13, 'fatigue': 14, 'weight_gain': 15, 'anxiety': 16, 'cold_hands_and_feets': 17, 'mood_swings':
      18, 'weight_loss': 19, 'restlessness': 20, 'lethargy': 21, 'patches_in_throat': 22, '
      irregular_sugar_level': 23, 'cough': 24, 'high_fever': 25, 'sunken_eyes': 26, 'breathlessness':
      27, 'sweating': 28, 'dehydration': 29, 'indigestion': 30, 'headache': 31, 'yellowish_skin': 32,
      'dark_urine': 33, 'nausea': 34, 'loss_of_appetite': 35, 'pain_behind_the_eyes': 36, 'back_pain':
       37, 'constipation': 38, 'abdominal_pain': 39, 'diarrhoea': 40, 'mild_fever': 41, 'yellow_urine'
      : 42, 'yellowing_of_eyes': 43, 'acute_liver_failure': 44, 'fluid_overload': 45, '
      swelling_of_stomach': 46, 'swelled_lymph_nodes': 47, 'malaise': 48, '
      blurred_and_distorted_vision': 49, 'phlegm': 50, 'throat_irritation': 51, 'redness_of_eyes': 52,
       'sinus_pressure': 53, 'runny_nose': 54, 'congestion': 55, 'chest_pain': 56, 'weakness_in_limbs'
      : 57, 'fast_heart_rate': 58, 'pain_during_bowel_movements': 59, 'pain_in_anal_region': 60, '
      bloody_stool': 61, 'irritation_in_anus': 62, 'neck_pain': 63, 'dizziness': 64, 'cramps': 65, '
      bruising': 66, 'obesity': 67, 'swollen_legs': 68, 'swollen_blood_vessels': 69, '
      puffy_face_and_eyes': 70, 'enlarged_thyroid': 71, 'brittle_nails': 72, 'swollen_extremeties':
      73, 'excessive_hunger': 74, 'extra_marital_contacts': 75, 'drying_and_tingling_lips': 76, '
      slurred_speech': 77, 'knee_pain': 78, 'hip_joint_pain': 79, 'muscle_weakness': 80, 'stiff_neck':
       81, 'swelling_joints': 82, 'movement_stiffness': 83, 'spinning_movements': 84, 'loss_of_balance
      ': 85, 'unsteadiness': 86, 'weakness_of_one_body_side': 87, 'loss_of_smell': 88, '
      bladder_discomfort': 89, 'foul_smell_of urine': 90, 'continuous_feel_of_urine': 91, '
      passage_of_gases': 92, 'internal_itching': 93, 'toxic_look_(typhos)': 94, 'depression': 95, '
      irritability': 96, 'muscle_pain': 97, 'altered_sensorium': 98, 'red_spots_over_body': 99, '
      belly_pain': 100, 'abnormal_menstruation': 101, 'dischromic _patches': 102, 'watering_from_eyes'
      : 103, 'increased_appetite': 104, 'polyuria': 105, 'family_history': 106, 'mucoid_sputum': 107,
      'rusty_sputum': 108, 'lack_of_concentration': 109, 'visual_disturbances': 110, '
      receiving_blood_transfusion': 111, 'receiving_unsterile_injections': 112, 'coma': 113, '
      stomach_bleeding': 114, 'distention_of_abdomen': 115, 'history_of_alcohol_consumption': 116, '
      fluid_overload.1': 117, 'blood_in_sputum': 118, 'prominent_veins_on_calf': 119, 'palpitations':
      120, 'painful_walking': 121, 'pus_filled_pimples': 122, 'blackheads': 123, 'scurring': 124, '
      skin-peeling': 125, 'silver-like_dusting': 126, 'small-dents_in_nails': 127, 'inflammatory_nails
      ': 128, 'blister': 129, 'red_sore_around_nose': 130, 'yellow_crust_ooze': 131}
  diseases_list = {15: 'Fungal infection', 4: 'Allergy', 16: 'GERD', 9: 'Chronic cholestasis', 14: '
      Drug Reaction', 33: 'Peptic ulcer diseae', 1: 'AIDS', 12: 'Diabetes', 17: 'Gastroenteritis', 6:
       'Bronchial Asthma', 23: 'Hypertension', 30: 'Migraine', 7: 'Cervical spondylosis', 32: '
      Paralysis (brain hemorrhage)', 28: 'Jaundice', 29: 'Malaria', 8: 'Chicken pox', 11: 'Dengue',
      37: 'Typhoid', 40: 'hepatitis A', 19: 'Hepatitis B', 20: 'Hepatitis C', 21: 'Hepatitis D', 22: '
      Hepatitis E', 3: 'Alcoholic hepatitis', 36: 'Tuberculosis', 10: 'Common Cold', 34: 'Pneumonia',
```

```
13: 'Dimorphic hemmorhoids(piles)', 18: 'Heart attack', 39: 'Varicose veins', 26: '
      Hypothyroidism', 24: 'Hyperthyroidism', 25: 'Hypoglycemia', 31: 'Osteoarthristis', 5: 'Arthritis
      ', 0: '(vertigo) Paroymsal Positional Vertigo', 2: 'Acne', 38: 'Urinary tract infection', 35: '
      Psoriasis', 27: 'Impetigo'}
  # Model Prediction function
  def get_predicted_value(patient_symptoms):
      input_vector = np.zeros(len(symptoms_dict))
51
      for item in patient_symptoms:
52
          input_vector[symptoms_dict[item]] = 1
53
      return diseases_list[svc.predict([input_vector])[0]]
54
55
57
  @app.route("/")
  def index():
      return render_template("index.html")
  # Define a route for the home page
  @app.route('/predict', methods=['GET', 'POST'])
  def home():
      if request.method == 'POST':
          symptoms = request.form.get('symptoms')
          print(symptoms)
          if symptoms == "Symptoms":
              message = "Please either write symptoms or you have written misspelled symptoms"
              return render_template('index.html', message=message)
74
          else:
              # Split the user's input into a list of symptoms (assuming they are comma-separated)
              user_symptoms = [s.strip() for s in symptoms.split(',')]
              # Remove any extra characters, if any
              user_symptoms = [symptom.strip("[]' ") for symptom in user_symptoms]
              predicted_disease = get_predicted_value(user_symptoms)
              dis_des, precautions, medications, rec_diet, workout = helper(predicted_disease)
81
              my_precautions = []
82
              for i in precautions[0]:
83
                  my_precautions.append(i)
84
              return render_template('index.html', predicted_disease=predicted_disease, dis_des=
                  dis_des,
                                     my\_precautions = my\_precautions \;, \; \; medications = medications \;, \; \; my\_diet =
                                         rec_diet)
```

9.2 Poster Presentation



Figure: 9.2 Poster Presentation

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