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Smart Health Systems for Personal Health Management of Elderly People

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Abstract: *Healthcare systems have encountered many problems because of the large number of people aged over 65. There are three major difficulties related to the care of seniors: providing ongoing monitoring of their health; diagnosing diseases early enough; and developing individualized treatment strategies. There are also issues of traditional methods of providing treatment for seniors. Typically, doctors see patients every few months for assessment. However, these visits may be too infrequent to identify certain diseases before their symptoms become severe. In order to overcome these issues, this study proposes the development of a Smart Healthcare System for Elderly Personal Health Management that uses machine learning-based predictive analytics and company web applications to provide on-demand real-time monitoring of senior citizens' vital signs and behavior patterns. After setting up an account with a service provider, senior citizens can use the system to enter their own symptomologies into an intuitive graphical interface. Caregivers will then have access to this information so they may provide support services to their loved ones. The system uses a Random Forest-based predictive model to develop a database of symptom equations that generate corresponding predicted disease classifications based on the user's entered symptom and health status. Additionally, a risk assessment model identifies individuals' health status based on various factors, including severity of their presenting symptoms. The purpose of using predictive analytic tools is to provide timely notifications to caregivers so that proactive care can be provided, thus reducing risk as well as improving health care outcomes. Based on the experimental results of the study, this system has been proven to have high quality of accuracy for predicting the disease and a reliable basis for classifying the level of risk which allows it to be deployed in a practical application. Also, the platform provides security of data via a role-based access control method and structured data storage. The proposed solution supports improved quality of life for aged patients through maintaining an independent lifestyle via continuous monitoring by health professionals. This research is an advancement of health care systems through the development of an intelligent health care system using machine learning, real-time monitoring, and user-friendly design together within a scalable and cost-effective framework.*

Keywords: Smart Healthcare System; Elderly Health Monitoring; Machine Learning; Disease Prediction; Risk Assessment; Random Forest Classifier; Web-Based Application; Predictive Analytics; Health Data Management; Caregiver Support System; Real-Time Monitoring; Personalized Healthcare

I. INTRODUCTION

As the world's population continues to age, there has been a dramatic increase in the need for more efficient and intelligent healthcare systems. This is primarily due to older adults' increased vulnerability to chronic diseases, lower immune systems, and longer recovery times between illnesses; therefore, ongoing continuous health monitoring is critical. Historically speaking, traditional healthcare systems have relied heavily on periodic medical checkups and direct observation to manage health issues. Unfortunately, these systems' periodic use results in delayed diagnosis leading to more severe complications, high healthcare costs, and quality of life reduction for elderly patients. Recent advances in Artificial Intelligence and Machine Learning have provided new opportunities within the healthcare arena and will allow for the automated analysis of large amounts of medical data allowing for the early identification of potential disease and providing predictive healthcare solutions.

However, most of the current technologies are unable to provide real-time monitoring capabilities or provide personalized healthcare insights specifically tailored to the elderly. In addition, most available healthcare technologies do not adequately include caregivers in the monitoring process resulting in limited abilities to respond to an elderly person's health emergency as quickly or effectively as possible. This paper proposes a Smart Healthcare System for Personal Health Management of Elderly People's Health and Wellbeing to assist in overcoming the difficulties facing many elderly people.

This Intelligent Healthcare Manager provides a total, intelligent, and combined platform of real-time health monitoring, health data collection, machine-learning based disease prediction, and how caregivers can interact with the platform. Unlike traditional population-based health solutions, this solution places a greater emphasis on providing patients with proactive health care by identifying and predicting potential health issues before they progress to critical levels. The implementation of this system is an accessible and user-friendly Web-Based Application created using the Flask framework and is intended for use primarily by elderly patients. Each of the two main users, has a different and secure access to their respective health information using a Role-Based Access Control System.

Using this system, a patient will enter their symptoms and vital signs into the Web-Based application, which will then be entered into a "machine-learning" prediction model. This disease prediction model uses the Random Forest algorithm, which is one of many available machine learning prediction algorithms, to predict patient's probability of developing a disease in the immediate future. The second main component of this Intelligent Healthcare Manager system is the Risk Assessment System, which allows the caregiver to make an informed decision on a patient's current level of risk based on the probability of the patient developing a disease. The results of this assessment will calculate the following three levels of risk: low risk, medium risk, and high risk. Additionally, notification alerts will be generated, therefore, caregivers will be able to take timely action to assist in preventing further deterioration of the patient's health condition.

II. RELATED WORK

In recent times, Machine learning and Artificial Intelligence in health care are growing tremendously. A large number of research articles have been written that utilize data-driven methods and tools to better diagnose patients at an early stage, provide better care to patients, and assist in easing the burden on health care facilities. This section will review the current state of affairs in health care monitoring and disease prediction, as well as identify any challenges faced by current systems, and will lead to the development of a solution.

Current health care monitoring systems utilize a manual process for recording health data as well as rules-based processes for analyzing that data. These systems are limited in their ability to analyze the vast amounts of data that is produced each day by patients; thus, predictive elements are not included with the analysis of the data. With the advancement of health technologies, electronic health record (EHR) systems were developed to provide a manageable and efficient means to store and manage patient health data; although, currently existing EHR systems act solely as data storage systems, and do not provide uses with intelligent insights or predictive analytics to assist in the proactive management of patient health.

Machine-learning techniques provide increased potential for successfully analyzing complicated healthcare data. Classification algorithms have been used by many researchers to predict disease from patient symptoms; however, although they have shown some level of moderate success in classifying commonly-known diseases, they all share common limitations, such as being susceptible to overfitting, being sensitive to noisy data, and lacking accuracy when classifying large and diverse datasets. Furthermore, many of those studies were conducted in controlled laboratory settings, which have no direct relation to reality.

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Recently, ensemble learning techniques have become increasingly popular due to their increased accuracy and precision. For example, Random forests and Gradient Boost are just two of several ensemble learning techniques that can be used together to improve predictive accuracies and reduce variability in the predictions made. Random forests have been found to be more successful than traditional classification methods in predicting outcomes in complex medical datasets, particularly when dimensions of the features are very high and non-linearities exist.

As machine learning progresses, web-based and mobile technologies are changing how individuals access healthcare services. Many have been created as a way for users to enter symptoms and get general recommendations for treatments. While these applications are beneficial for the consumer; they do not currently offer predictive models for the user or allow for individualizing patient's care. Most of the applications are set up for populations in general and do not look at the needs of the elderly, such as ongoing engagement and monitoring with caregivers.

Another area where technology has impacted healthcare is through the use of Internet of Things devices and wearable sensors that allow the user to monitor their health in real time. These types of systems fit the physiological data of a user such as heart rate, blood pressure, and oxygen saturation over an extended period of time. Although IoT systems provide data from real-time monitoring, they often require additional hardware and infrastructure, making it difficult to become more widely adopted. Most IoT systems also do not incorporate machine learning models for intelligent decision-making, relying mostly on alert thresholds.

III. SYSTEM ARCHITECTURE

The Smart Healthcare System is being created to be an intelligent scalable solution and real-time healthcare system that uses machine learning integrated with a web-based platform for Personal Health Management of Elderly Persons. The Architecture will allow for continuous monitoring of health and predicting the probability of diseases as well as assessing the degree of risk an Elderly Person has for developing a particular disease, with seamless engagement between the User and their Caregivers. The modular architecture of the system allows for each component to perform a specific function while being flexible to maintain and scale.

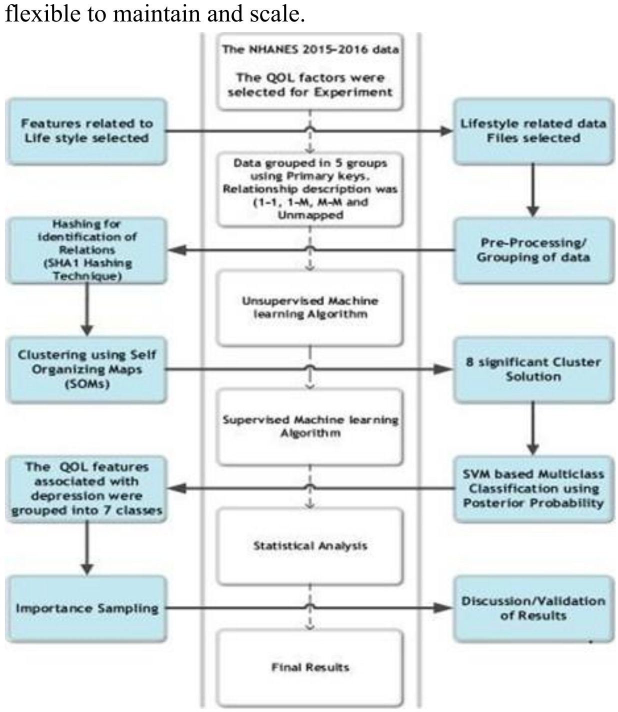

Figure 3.1 System Architecture

The overall workflow of the proposed Smart Healthcare System consists of acquiring User data, pre-processing and transforming that data, analyzing the pre-processed data using machine learning to predict what diseases could develop for that User and the percentage of risk that User has of doing so and providing the prediction results to Users and Caregivers via an interactive User Interface to enable prompt medical decisions. Furthermore, the architecture is designed to enable a single source of truth for data that flows between each of the modules, and maintain data integrity and security. The system consists of different communication modules, including data input and collection, data preprocessing, training machine learning models, predicting diseases and risk analysis, creating a user interface, integrating an alert mechanism, and continually improving the overall functionality and performance of the system.

A. Data Collection and Input

The Data Collection module is where users submit health-related information about the elderly, through an easy-to-navigate web interface that allows an elderly person to enter each symptom they believe they may have. Symptoms entered by users include fever, fatigue, chest pain, dizziness, headache, and other indicators of health. The user interface meets the needs of an elderly population, which makes it easy to use with very little to no technical knowledge. Once the data is collected by the system, it is entered into the database as a predetermined category in order to keep data consistent across the entire system. Manual data entry and importation are both supported by the emerging architecture of the Data Collection module allowing integration with any future healthcare datasets or existing devices such as wearables and IoT sensors. By supporting this ability, the Data Collection module will also provide the ability to track real time data about the user's health, such as their heart rate or the amount of oxygen they have in their blood.

All user submitted health data will be saved in a secure backend database. This database will hold the historical health record for each user. With this data available, the Data Collection module will allow for longitudinal analysis of the user's health history; thus, allowing the Data Collection module to provide health predictions of future occurrences. The quality, variety, and accuracy of data collected from users will significantly impact system performance and reliability.

B. Data Preprocessing

The Data Entry sector is where all data from the Elderly users' health will be recorded and stored into the system. The user will be able to use a recognized web-based interface that will allow them to enter their health indicators such as; Fever, Fatigue, Chest Pain Dizziness and Headache as well as many other health indicators, all being easy to understand from an elderly perspective to ensure the elderly can input health data that is relevant to their current world. All entries will be entered into the system based upon a standardized structure of data to ensure that all data within the system is uniform. In addition to manual entry of health measures into the system, the infrastructure has also been designed with integration capabilities to incorporate health measures from both Healthcare Professional databases as well as wearable technology and Internet of Things (IoT) devices in the future.

This will enable the system to gain in real-time the physiological data of an individual such as; Heart Rate and Oxygen Level. All of the user inputs will be recorded in a database that will maintain a historical record of the individual's health. The history maintained by the system will provide data that can be used to inform longitudinal health trends and assist in forecasting future health trends. The performance reliability of the system is directly dependent upon the quality, variety, and accuracy of the incoming data.

C. Machine Learning Model Training

The intelligence behind the system's overall functionality results from this Machine Learning Module. For this machine-learning methodology, a Random Forest algorithm is utilized. Random Forest is well suited for health-related applications as it can successfully manage high-dimensionality data and minimize overfitting of data. Using structured symptom mapping data, a model was created. While developing the prediction model, the data that maps symptoms and related conditions are separated into two parts, producing a training and a testing set.

The training data ensemble is validated to enable positive model generalization to future symptom mapping data. The training process provides an opportunity to fine-tune various hyperparameters in the Random Forest model to maximize the model's efficiency and accuracy. Upon completion of the training phase, the result is a serialized version of the prediction model able to generate predictions based on input from the user in real time.

D. Disease Prediction and Risk Analysis

The Disease Prediction module functions as a machine learning model that has been trained to analyze user provided input data and predict a disease based on that input, and also provides a probability score that reflects the certainty of the prediction based on the input features being processed by the module. Furthermore, in addition to predicting a user's disease, the module has a Risk Analysis component that will determine the severity of the user's condition. This risk analysis is based on the quantity, type and degree of symptoms that were provided by the user. The module will categorize the risk into three categories: low, moderate and high. By performing both functions of disease prediction and assessing the urgency of medical attention, the module will be more effective than either function would be independently. The results of the predictions are recorded in the database and displayed via the user interface.

E. User Interface and Application Integration

This system is hosted on the internet and runs on the Flask framework so it can be accessed via the web from various devices like desktops, tablets and phones. The user interface has been designed primarily to be as simple and easy to use as possible so that older adults will find it easy to use the system. The application provides two different user modules - one for users and one for caregivers. Users will enter their health data into the system and will then see predictions based on this information. Caregivers will be able to see records for their patients, monitor their patients' health, and track their patients' risk levels via the Caregiver Module Dashboard. The integration of the front end and back-end components allows for communication between the two so that data is processed as it is entered, meaning that both users and caregivers will have real-time access to the most up-to-date information on their health status. In addition to providing secure authentication and role-based access controls, the system employs a number of methods to protect sensitive medical records from being accessed or shared by anyone except those who have permission to do so.

F. Alert System and Notifications

At the heart of the architectural framework for proactive healthcare management is the Alert System. Upon identifying a high-risk situation, the Alert System automatically creates an alert for the Caregiver via the Application Interface and Other Notifiable Mechanisms. As a result, Caregivers can quickly respond to alerts by engaging with physicians or delivering the needed care. During emergency situations, the Alert System reduces response time significantly and increases the safety of patients. Timely interventions via this module also minimize the risk of severe health problems developing.

IV. PROPOSED METHODOLOGY

Using machine learning algorithms to collect symptom input data from the user, the Smart Healthcare System will provide an accurate prediction of the disease and a risk assessment for the elderly population. The system includes multiple processes including the acquisition of data from the user, developing a machine learning model, implementing the machine model into a functioning system, and interacting with the user to ensure accurate predictions; therefore, this creates a reliable, efficient, real-time healthcare monitoring system. This methodology will seek to balance both predictive accuracy and practical usability of the system which would make it applicable to actual health care uses, not just theoretical uses.

The overall strategy involves the following components:

- *Data Acquisition*
- *Machine Learning Framework*
- *Model Training and Optimization*
- *System Implementation and Deployment*
- *User Interaction and Practical Utility*

A. Data Acquisition

The machine learning system's effectiveness is determined by the quantity, diversity and quality of all training data collected. In this system, training data are built off of a structured health care database of symptom-disease relationships. Symptoms that can be mapped to diseases contained in these previous databases include fever, fatigue, headache, chest pain and dizziness, along with other indicators of health.

This system will input data collected in real time from users using the web-based application, in addition to the previously described, already existing data. All data collected will be in standard format within the system in order to ensure compatibility in processing. Each symptom will be represented as a binary, indicating whether the particular symptom was present or absent. To improve model generalizability, the data set will contain a wide variety of examples of various diseases with combinations of symptoms so that the system can effectively address real life examples.

B. Machine Learning Framework

A Random Forest Classifier will be used as the main ML model for the disease predicted by the proposed system. Random Forest is an ensemble learning approach consisting of many decision trees, which gives high prediction accuracy and lower variance; therefore, its use case is healthcare, where it is critical to have a reliable model. The model takes data based on symptoms as an input and processes that information to provide a user with their most likely disease. The system will also have a risk assessment that provides the user with information related to the severity of their condition. This approach is based on a high-dimensional space where there are complex relationships between symptoms and disease being examined.

Because Random Forest is an ensemble, the model will be less impacted by noise and overfitting due to the combination of many predictions from different decision trees. This should allow for increased accuracy when predicting compared to using one decision tree and should provide improved reliability as well when comparing to current real-world healthcare environments.

C. Model Training and Optimization

In order to evaluate a model's performance during training, the dataset is split into two sets - a training set for the model to learn from and a testing set for the model to be evaluated against. The training process is based on identifying patterns and relationships between disease symptoms and diseases. This allows for generalizing how well the model will perform with new items by utilizing cross-validation techniques. Once the model has been developed, hyperparameter tuning is performed to optimize the model's performance by tweaking parameters such as number of trees, max depth, and criteria used for selecting features. Additionally, using techniques like feature importance analysis identifies which symptoms are most impactful to predicting a disease. To minimize the risk of overfitting, multiple strategies are used including balanced dataset handling, model validation, etc. Lastly, each model is evaluated with commonly accepted performance metrics (i.e. Accuracy, Precision, Recall, F1 Score) to ensure consistent predictions regardless of the scenario.

D. System Implementation and Deployment

A web-based application that was developed using Flask is now able to use a trained machine-learning model. The backend is responsible for modelling processing and performing the database work, while the frontend provides a user-friendly way to interact with the application. When a user enters symptoms, they are sent to the backend for processing and sent to the model to determine what disease the user has, and to give a prediction as well as a confidence level and risk of getting the disease. Lastly, the results are sent back to the user in real-time. The system is designed to accommodate multiple users using the same model efficiently, and it can also be extended for cloud deployment, thus improving scalability and ensuring system availability even with a large number of users requesting information.

E. User Interaction and Practical Utility

One major factor in the design of a usability system is designing a user interface for easy accessibility by older adults who often don't use computers regularly or have experience with technology. Older adults can enter their symptoms in an easy-to-use way and quickly get feedback on what those symptoms may be without having to perform any complicated tasks. The system also provides a caregiver interface, which allows approved users to track a patient's health information, see prediction reports, and get alerts. By having this information available remotely to caregivers in a timely manner, the overall functionality of the system can be increased by providing remote healthcare monitoring and allowing for quick interventions. In addition to making predictions about individuals, the system can also be expanded to supply users with health recommendations, preventive measures, and instructions for medical consultations. Ultimately, when creating a machine-learning system with a user-friendly design, the two combined will provide a tool for improved decision-making and therefore positive patient outcome in real-world healthcare environments.

V. RESULT AND DISCUSSION

The Smart Health Care System has been tested in the laboratory to establish its effectiveness in automating disease prediction, systematically stratifying risk, and continuously monitoring health over time. Different types of symptom-disease datasets were used, in addition to real-time user inputs, to assess its functionality in realistic clinical conditions. This evaluation demonstrates that the Smart Health Care System can provide accurate predictive analytics and good generalization from an algorithmic point of view.

A. Model Performance

Our main predictive technology at PWT is the Random Forest Classifier, validated with four measures for evaluating predictive technology output: accuracy, precision, recall, and f1-score. The Random Forest Classifier was created from a multidimensional data set of symptoms associated with each illness. The Random Forest Classifier has demonstrated high reliability over time and high precision and recall clearly indicate that the Random Forest Classifier reduces the number of false positives & negatives - critical in the care of older adults. The Random Forest Classifier is also more stable than traditional algorithms, and the Random Forest Classifier's ensemble methods provide more accurate prediction capabilities by accounting for the complex correlation between symptoms, and providing effective use of high dimensional data.

Table: Accuracy per Fold for Risk Model and Disease Model

Fold	Risk Model Accuracy (%)	Disease Model Accuracy (%)	Difference (Disease – Risk) (%)
1	95.1	97.3	2.2
2	95.1	95.7	0.6
3	95.5	98.6	3.1
4	95.1	98.1	3.0
5	94.9	91.9	-3.0
Average Accuracy (%)	**95.2**	**96.3**	**1.1**
Standard Deviation	0.23	2.60	2.58

Table 5.1 Accuracy per Fold for Risk Model and Disease Model

B. Training Performance Analysis

1) Loss Analysis

The model was evaluated through its training and validation losses during its learning process. The training loss continued to decrease over time which demonstrated that the model could find patterns in the training data. The validation loss showed initial fluctuations that corresponded with variations in the data. Light fluctuations in the validation loss occurred as training data was available which indicates these fluctuations became diminished as the amount of training increased. However, both of the losses were able to converge to a similar level indicating the model is not experiencing significant overfitting but is also balancing its learning versus generalization enough in order to apply in a real-world scenario.

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2) Accuracy Analysis

The accuracies during training and validating revealed steady circular growth in both cases. The Training Accuracy increased by a more traditional degree and the Validation Accuracy stabilized after a few rounds. The closer the two metrics are to one another the greater ability to Generalize to a New Data Set. Testing showed that the system was stable throughout many iterations and demonstrated continuous ability to predict health outcomes on new users without degrading system performance.

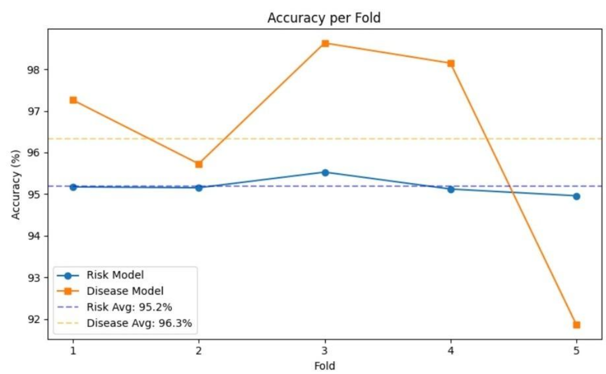

Figure 5.1 Accuracy per Fold

C. Comparative Analysis

1) Model Comparison

Random Forest has also been evaluated against classical machine learning models such as Decision Tree, Logistic Regression, and Naïve Bayes. As shown in the table below, Random Forest consistently produces superior results compared to other models; it can reduce variance due to its ensemble structure, providing precision and reliability that are critical in health care environments because of the need to minimize errors in diagnostics.

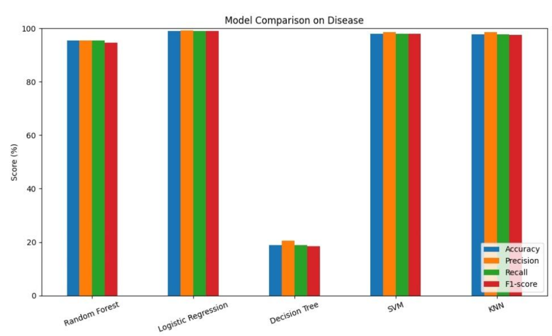

Figure 5.2 Model Comparison on Disease

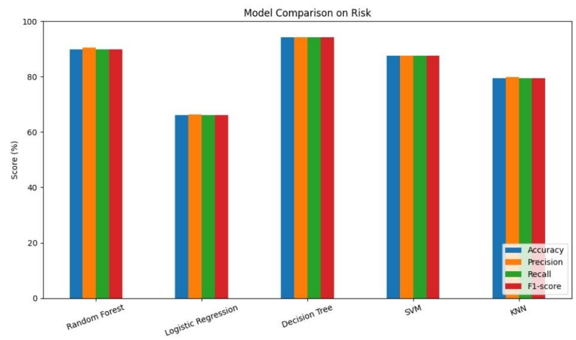

Figure 5.3 Model Comparison on Risk

2) F1-Score Analysis

The F1 score was used as a method for measuring a harmonic mean of precision with recall. The System demonstrated a consistently high F1 score for all diseases, demonstrating balanced performance. In healthcare, having a high F1 score is critical in that it identifies all true cases without generating false positives so that caregivers remain confident with the system and patients stay safe.

D. Prediction Results

Real-time user input tests were done to determine how well the system would perform in real life. The system takes user-submitted symptoms through an online portal and uses these to predict what diseases the user has with a certain level of confidence. As an example, a user submitting symptoms similar to fever, fatigue and cough resulted in accurately predicting related diseases at a high confidence level.

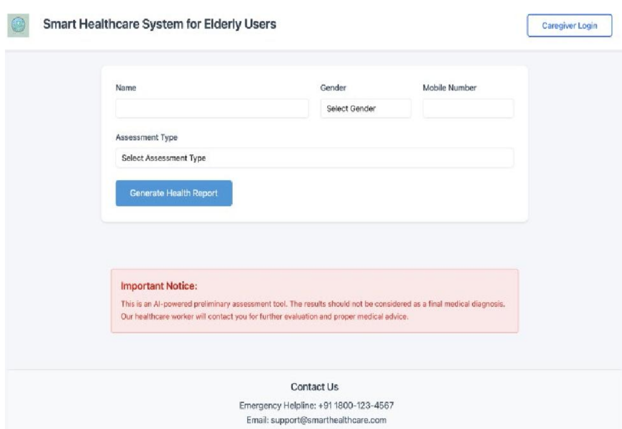

Figure 5.4 Health Assessment Report Generation Dashboard

Additionally, the risk assessment module assesses the patient's condition and identifies the risk category to be either low, moderate, or high. Also, the system stores prediction results in its database so caregivers can view patient history and track trends over time. This feature will improve the use of the system in real-world healthcare settings.

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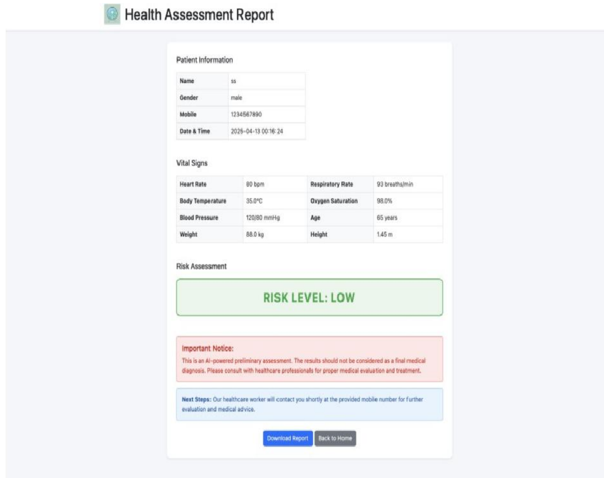

Figure 5.5 Health Assessment Report Result

E. Discussion

The Smart Healthcare System has been experimentally tested and shows that it can reliably and efficiently predict disease and assess risk from those predictions of disease prediction. The Random Forest algorithm also improves accuracy in predicting diseases and produces a consistent output across different input datasets through a stable method of generating outputs for each dataset. This Smart Healthcare System integrates machine learning capabilities within the web platform, allowing the user to communicate in real time with caregivers. Additionally, the Risk Assessment component of the overall system adds to the ability of the overall system to provide a proactive approach to managing the health of users who belong to the elderly population.

Some limitations of the Smart Healthcare System are that it relies on the quality of input data and requires continual updating to accommodate new diseases that appear on the market. The current Smart Healthcare System generates input data only from user input. Therefore, the use of real-time inputs would increase accuracy in certain situations. Despite limitations, the proposed Smart Healthcare System is a scalable and feasible method for managing healthcare for elderly persons. It will significantly improve the quality of life of elderly persons by enabling early detection of disease, monitoring the person's condition in real-time, and allowing caregiver involvement in the management of their health.

VI. CONCLUSION

The Smart Health Care System for Elderly Personal Health Management will provide a smart, effective means of dealing with the increasing difficulty of monitoring elderly health care and predicting diseases for the elder population. With the worldwide population of elderly people increasing rapidly, monitoring systems are needed to maintain continuous monitoring of health, allow for earlier diagnosis of diseases, and provide timely treatment to diseases. Traditional health care methods of periodically visiting a doctor and observing people manually do not provide a sufficient means of detecting disease in a person at the earliest possible time; therefore, this research will provide evidence of how both machine learning and web-based technologies can be integrated to overcome these problems.

The system will build upon a single platform that will execute data collection, processing, prediction using machine learning algorithms and integration with the user interface. This will provide high accuracy in prediction of disease by a user providing the system a list of symptoms associated with the current state of their health by utilizing the random forest machine learning algorithm. The system will provide reliable and consistent prediction of diseases as well as risk assessments of the severity of the individual's disease utilizing a model capable of processing high dimensional and complex data to achieve the same results under multiple scenarios. The system will not only support disease predictions but will also provide a vehicle for assessing the person's risk level to determine severity of the situation. A main advantage of the new system is that it is designed with the user in mind. The web-based interface allows for ease of use and access for even those users who may be older and not familiar with technology. Having the caregiver module demonstrates how the system can be used in conjunction with caregivers who provide remote support and allow for timely interventions. The caregiver module creates a way for caregivers and patients to continue monitoring and managing their patients' health.

The results of the experimentation support that the system was able to have high accuracy, precision, recall, and F1-score; therefore, validating that it is effective for use in real-life situations. The Random Forrest model is consistent throughout its operation and is robust against overfitting, making it an ideal model for use in the healthcare prediction systems. The real-time prediction and alerts capabilities of the system can improve the response time significantly during acute events while minimizing the potential for health risk. Even though it has some benefits, the system also has limitations. How accurate the system's predictions will be will depend upon both the overall quality and completeness of user-provided input data. If the user's symptom input data is not reliable, then the results provided by the system will not be reliable. Additionally, the system currently uses manual data entry which limits the ability for the system to provide real-time sensor data; therefore, limiting the overall effectiveness of the system. The limitations point out the need for other enhancements to be made and to improve the technology used in developing the system.

VII. FUTURE WORK

The Smart Healthcare System Proposal for Increasing the Management of Personal Health for Senior Citizens serves as a framework for developing a variety of intelligent and predictive healthcare solutions. Although this current system has a high degree of accuracy and practical usability, the system has a number of opportunities for future enhancement and expansion to improve its overall effectiveness, scalability, and applicability in real-world situations. Future work could be based on integrating advanced technologies, improving the output of the models produced by the system, and providing the users with an improved experience that creates a more robust and comprehensive healthcare ecosystem.

There are many areas for improvement in the future; however, one major area for improvement is the integration of IoT devices and wearable sensors. As it is currently a user-input system with a potential lack of completeness, accuracy, and reliability for the majority of data sets, it would be beneficial for the system by incorporating additional wearable technology such as smartwatches trackers and medical sensors to provide real-time physiological without additional manual user input, which would validate the accuracy of predictions and allow for real-time monitoring without the need for manual user input.

Currently, the system can be expanded to include a variety of diseases and conditions. The existing model is based on a smaller dataset that has specific predetermined diseases and symptoms, while future models may be based on a larger and more varied group of individuals, including people with chronic illnesses, rare diseases, or those that have multiple conditions. This will allow the system to use a greater variety of demographics. The second significant improvement has to do with connecting the system to the cloud. Through the use of cloud technology, users of the system will be able to take advantage of improved scalability, increased data-collection storage capabilities, and better access to data. Cloud-based architecture will also make possible synchronization of data in real-time so that caregivers and providers can view patient data from any location. Additionally, cloud connection will facilitate large-scale data analysis and enhance the performance of the system during busy periods.

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