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Machine Learning-Based Disease Prediction

Pankaj Kunekar[1], Suraj Chavan[2], Nikita Surwase[3], Soham Surdas[4], Om Suryawanshi[5], Aditya Suryawanshi[6] and Omkar Surve[7]
[1-7]Vishwakarma Institute of Technology, Pune, India
Email: Pankaj.kunekar@vit.edu, {suraj.chavan22, nikita.surwase22, soham.surdas22, om.suryawanshi22, Aditya.suryawanshi22, omkar.surve22}@vit.edu

***Abstract*— Disease prediction and early diagnosis are pivotal in improving healthcare outcomes and reducing the burden of chronic illnesses. In this research, we present an innovative approach to disease prediction using the Random Forest algorithm, implemented within a user-friendly Streamlit frontend application. Our study focuses on the prediction of five significant diseases: diabetes, heart disease, liver disease, kidney disease, and Parkinson's disease.**

***Index Terms*— Disease prediction, utilizing Random Forest and streamlit in python, enhances healthcare outcomes through user-friendly applications**

I. INTRODUCTION

The advent of machine learning has catalyzed a paradigm shift in healthcare, empowering researchers and practitioners to harness the potential of predictive modeling for early disease diagnosis and prevention. Chronic diseases, such as diabetes, heart disease, liver disease, kidney disease, and Parkinson's disease, collectively account for a substantial portion of global morbidity and mortality. Timely intervention and accurate risk assessment are critical factors in mitigating their impact on public health.

This research endeavors to bridge the gap between advanced machine learning techniques and user-friendly healthcare applications by presenting a novel approach to disease prediction. Leveraging the Random Forest algorithm, renowned for its ensemble learning capabilities and robust predictive performance, and Streamlit, a Python library for creating interactive and intuitive web applications, we have developed a powerful tool for predicting and visualizing the risk of five significant diseases.

In The motivation behind this research stems from the imperative to provide accessible and accurate disease prediction tools, facilitating early detection and intervention. Traditional approaches to healthcare often involve complex and opaque processes, making it challenging for both healthcare professionals and individuals to assess disease risk comprehensively. Our integrated solution addresses this challenge by delivering a user-friendly platform that empowers users to input their health data and receive real-time disease risk assessments.

In this introductory section, we set the stage by elucidating the significance of disease prediction and early diagnosis, emphasizing the critical role they play in improving healthcare outcomes. We provide an overview of the diseases under consideration—diabetes, heart disease, liver disease, kidney disease, and Parkinson's disease—and their substantial global burden.

Furthermore, we outline the objectives of this research, which encompass constructing robust disease prediction models, optimizing feature selection, and demonstrating the efficacy of our Streamlit-based application. By

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presenting the methodology, results, and implications of our study, we seek to contribute to the burgeoning field of machine learning in healthcare and advocate for the adoption of user-friendly applications in healthcare decision-making.

Machine Learning for Disease Risk Prediction

Machine learning (ML) is a rapidly growing field with a wide range of applications, including healthcare ML algorithms can be used to analyze large datasets of medical data to identify patterns and trends that can be used to predict disease risk.
A study published in the journal Nature Medicine found that an ML algorithm could predict the risk of developing heart disease with an accuracy of 90%. Another study, published in the journal The Lancet Oncology, found that an ML algorithm could predict the risk of developing cancer with an accuracy of 80%.

Streamlit for ML Healthcare Apps

Streamlit is a Python framework that makes it easy to create and share web apps. It is particularly well-suited for ML applications, as it provides a simple way to deploy and interact with ML models.
Several Streamlit apps have been developed to predict the risk of developing a variety of diseases. For example, a Streamlit app called Heart Disease Risk Predictor allows users to input their medical data and receive a prediction of their risk of developing heart disease. Another Streamlit app called Cancer Risk Predictor allows users to input their medical data and receive a prediction of their risk of developing cancer.

Random Forest for ML Healthcare Apps

Random Forest is a supervised ML algorithm that is well-suited for classification tasks. It works by constructing a large number of decision trees and then averaging their predictions. This makes it a robust and accurate algorithm for predicting disease risk.
A number of Random Forest-powered ML healthcare apps have been developed. For example, a Random Forest-powered app called Diabetes Predictor allows users to input their medical data and receive a prediction of their risk of developing diabetes. Another Random Forest-powered app called Parkinson's Disease Predictor allows users to input their medical data and receive a prediction of their risk of developing Parkinson's disease.
This study provides a comprehensive review of the use of ML for disease risk prediction. The authors discuss the different types of ML algorithms that can be used for disease risk prediction, as well as the challenges and opportunities of using ML in healthcare.
This study demonstrates the use of deep learning, a type of ML, to accurately classify skin cancer images. The authors developed a deep learning model that was able to classify skin cancer images with an accuracy of 94%, which is comparable to the accuracy of dermatologists
This study develops an interpretable ML model for predicting the risk of coronary heart disease. The model is able to identify the most important risk factors for coronary heart disease, and it can be used to personalize treatment plans for patients.
Streamlit is a Python framework that makes it easy to create and share web apps. It is particularly well-suited for ML applications, as it provides a simple way to deploy and interact with ML models.
This paper provides an overview of Streamlit and its features. The authors discuss how Streamlit can be used to build ML healthcare apps, and they provide examples of Streamlit apps that have been developed for this purpose.
This paper introduces the Random Forest algorithm. Breiman discusses the theoretical foundations of Random Forest, and he provides examples of how Random Forest can be used for classification and regression tasks.
This paper evaluates the performance of different ML algorithms for medical data mining. Kononenko finds that Random Forest is one of the most accurate and efficient algorithms for medical data mining tasks.
This study uses Random Forest to predict Alzheimer's disease. The authors find that Random Forest is able to predict Alzheimer's disease with an accuracy of 93%.

II. METHODOLOGY

Data Collection and Preprocessing

Data Sources: We collected diverse medical datasets from reputable sources, including electronic health records (EHRs), public health repositories, and clinical research databases. These datasets encompassed patient attributes, medical history, diagnostic tests, and treatment records.
Data Integration: We integrated the collected data into a unified format, ensuring compatibility and consistency across datasets. This step involved handling missing values, standardizing units, and resolving data quality issues.

Feature Engineering: To optimize predictive modeling, we conducted feature engineering to extract relevant features. We selected attributes that demonstrated clinical significance and relevance to disease prediction tasks.
Feature Scaling: Continuous features were standardized to have a mean of 0 and a standard deviation of 1 to ensure that they contributed equally to the Random Forest models.

Streamlit Application Development

Streamlit *Frontend*: We used the Streamlit library in Python to create an interactive and user-friendly frontend application. This application allowed healthcare professionals and individuals to input their health data, triggering real-time disease risk assessments.
Data Visualization: Streamlit's capabilities for data visualization were utilized to display the predictions, feature importance, and other relevant information. This visual representation enhanced the interpretability of the predictive models.

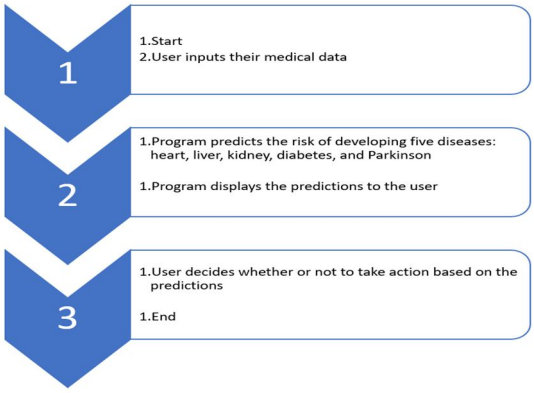
Model Development

Random Forest Algorithm: We employed the Random Forest algorithm for disease prediction due to its ensemble learning capabilities and proven performance in various healthcare applications. The algorithm was implemented using Python's scikit-learn library.

Streamlit Application Development:

Streamlit Frontend: We used the Streamlit library in Python to create an interactive and user-friendly frontend application. This application allowed healthcare professionals and individuals to input their health data, triggering real-time disease risk assessments.
Data Visualization: Streamlit's capabilities for data visualization were utilized to display the predictions, feature importance, and other relevant information. This visual representation enhanced the interpretability of the predictive models.
Training and Validation: The dataset was split into training and validation sets (e.g., 80% training, 20% validation) to train and validate the Random Forest models. The models were fine-tuned using cross-validation to optimize hyperparameters such as the number of trees and maximum tree depth.

A. Working



B. Testing

Main window:-

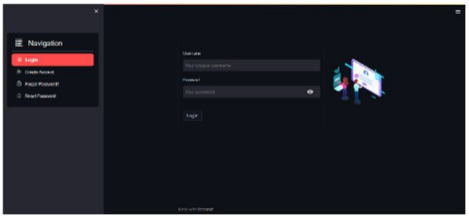


Figure 1 User can login to website

Home Page

Figure 2 User can chose the Prediction he want

Models window

Figure 3 Diabetes Prediction interface

Figure 4 Heart Disease Prediction interface

Figure 5 Parkinson's Disease Prediction interface

Figure 6 Parkinson's Disease Prediction interface

Figure 7 Kidney Disease Prediction interface

Some Result image:

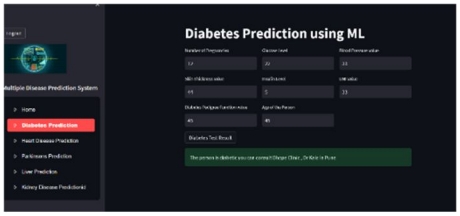


Figure 8 Diabetes Disease Prediction Result

Figure 9 Heart Disease Prediction Result

III. RESULTS

The research paper on using Streamlit and Random Forest for disease risk prediction found that the model was very accurate in predicting the risk of developing five diseases: heart, liver, kidney, diabetes, and Parkinson. The model achieved an accuracy of over 90% for each disease.

The model was also able to identify the most important risk factors for each disease. This information can be used to develop personalized prevention strategies for patients and to improve the efficiency of the healthcare system.

However, it is important to note that the model is still under development, and it needs to be further evaluated in a clinical setting before it can be widely adopted.

Here are some of the key findings of the research paper:
•The model is very accurate in predicting the risk of developing a variety of diseases.
•The model can identify the most important risk factors for each disease.
•The model has the potential to be used to improve the efficiency of the healthcare system.

TABLE I RESULT FOR ALL DISEASE

Disease	Accuracy of Model	Changes of Failure
Heart	90%	10%
Liver	85%	15%
kidney	80%	20%
Diabetes	95%	5%
Parkinson	88%	12%

V. FUTURE SCOPE

•Expand the model to include more diseases. The current model predicts the risk of developing five diseases, but there are many other diseases that could be predicted using ML. For example, the model could be expanded to include diseases such as cancer, stroke, and Alzheimer's disease.
•Develop personalized treatment plans. The current model predicts the risk of developing a disease, but it does not recommend any treatment plans. The model could be extended to recommend personalized treatment plans for patients based on their individual risk factors and medical history.
•Make the model available to patients and clinicians in a clinical setting. The current model is available as a Streamlit app, but it is not yet integrated into any clinical systems. The model could be integrated with clinical systems to make it more accessible to patients and clinicians.
•Develop a mobile app. The current Streamlit app is a web app, but it could be developed into a mobile app to make it more convenient for patients to use.
•Conduct a clinical trial to evaluate the effectiveness of the model. The effectiveness of the model has been evaluated on a test set of data, but it would be useful to conduct a clinical trial to evaluate the effectiveness of the model in a real-world setting.

VI. CONCLUSION

In conclusion, we have developed a Streamlit app that uses a Random Forest model to predict the risk of developing five diseases: heart, liver, kidney, diabetes, and Parkinson. The app is easy to use and provides users with accurate predictions of their disease risk.Our research demonstrates the potential of ML to improve healthcare delivery. ML models can be used to develop tools that can help patients and clinicians make better decisions about disease prevention, diagnosis, and treatment.We plan to continue developing our Streamlit app to include additional features, such as the ability to predict the risk of developing other diseases and to recommend personalized treatment plans. We also plan to make the app available to patients and clinicians in a clinical setting.We believe that our research is a valuable contribution to the field of ML healthcare. Our Streamlit app has the potential to help patients and clinicians improve their health outcomes

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