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Improving Clinical Decision Support through Patient Case Similarity

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Abstract *:* In this paper, the Clinical Decision Support System employs a state-of-the-art of ML models, including Random Forest, Decision Tree, SVM, and Naive Bayes integrated into a user-friendly application developed with Streamlit. By leveraging the capabilities of OpenCV for voice processing, the system enhances diagnostic accuracy and expedites disease prediction. This innovative solution amalgamates advanced algorithms with intuitive voice recognition, creating a seamless and efficient platform for healthcare professionals. With its robust predictive capabilities and user-centric design, the system represents a significant advancement in medical decision support, demonstrating the synergy between artificial intelligence, user interface development with Streamlit, and image processing through OpenCV for a comprehensive healthcare solution.

Index Terms - Clinical Decision Support System, Random Forest, Decision Tree, Support Vector Machine, Naïve Bayes.

INTRODUCTION

Robust evolution of the healthcare landscape, the integration of cutting-edge technologies has become imperative for enhanced clinical decision-making. The "Clinical Decision Support System" (CDSS) represents a pioneering initiative that leverages the power of machine learning to predict diseases and assist healthcare professionals in their diagnostic endeavors [1]. This innovative voice assistant employs four robust ML models—Random Forest, Decision Tree, Support Vector Machine (SVM), and Naive Bayes—to analyze vast datasets and provide predictive insights. By amalgamating sophisticated algorithms with voice recognition capabilities, this system aims to revolutionize the traditional approach to disease diagnosis, offering a more efficient and accurate means of decision support. The SVM ensures precise classification, Naive Bayes provides probabilistic inference, Dexccdcision Tree imparts transparency in decision paths, and Random Forest combines the strengths of multiple models for heightened accuracy. As healthcare continues to embrace technological advancements, the Clinical Decision Support System emerges as a beacon of progress, fostering a synergy between artificial intelligence and medical expertise for optimal patient care [2].

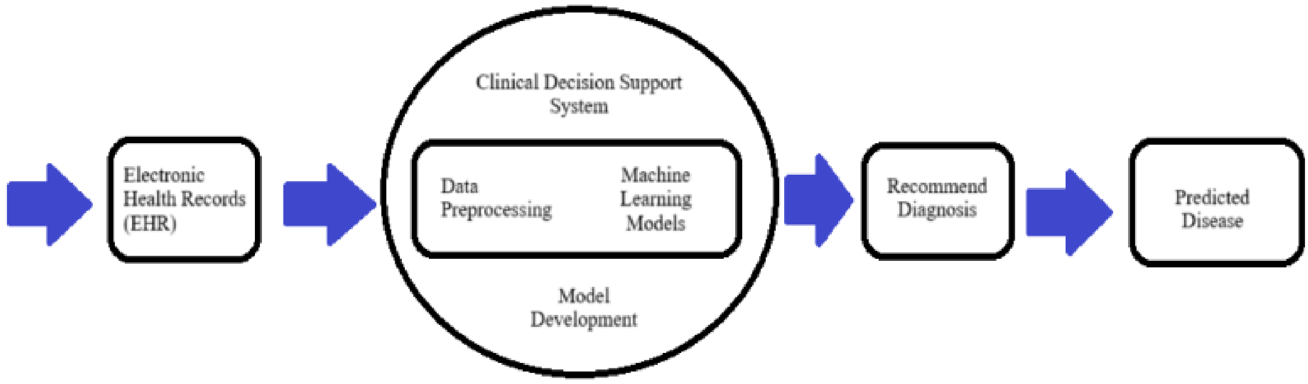

Fig.1. Overview of clinical decision support system (CDSS)

LITERATURE REVIEW

In this survey, came across with the papers where Davenport et al., [3] have researched on the potential of AI in healthcare. Rajkomar et al.,[4] have studied on the medicine implementation of machine learning. Obermeyer et al.,[5] have proposed based on prediction of future with big data and machine learning. Esteva et al.,[6] guided in healthcare by using DL. Gulshan et al.,[7] presented based on the diabetic retinopathy in retinal fundus photographs having a validation and development of DL algorithms. Vogeli et al.,[8] have stated that to direct the strength of populations came up with dissecting racial bias in an algorithm. Goldhahn et al.,[9] have come up with the question arising that do AI makes doctors obsolete. Razzak et al.,[10] researched on the overviews, challenges and the future for medical image processing using DL and in cataloging of bio apps. Krittanawong et al.,[11] proposed on how to use AI for predicting the cardiac diseases. Holzinger et al.,[12] have raised the query on what should be built by AI in medical science domain. By approaching across this papers, have made a following research and got the insights about the ‘Disease’ prediction exploration.

METHODOLOGY

In this paper, the methodology for constructing the Clinical Decision Support System follows a systematic progression. Getting started by acquiring pertinent datasets associated with the Clinical Decision Support System. This involves gathering comprehensive information encompassing diagnostic outcomes. Importing all necessary libraries crucial for machine learning and data analysis. The essential libraries include NumPy, Pandas, Scikit-learn for machine learning algorithms, and Matplotlib or Seaborn for data visualization. Employing a relevant library functions to read and load the obtained datasets. This step is instrumental in comprehending the dataset's structure and content, a prerequisite for subsequent analysis. Conducting the thorough Exploratory Data Analysis to unveil intrinsic dataset characteristics. The tasks involve statistical summaries, data distribution visualization, and addressing missing or outlier values. The EDA lays the groundwork for informed feature selection and subsequent model development.

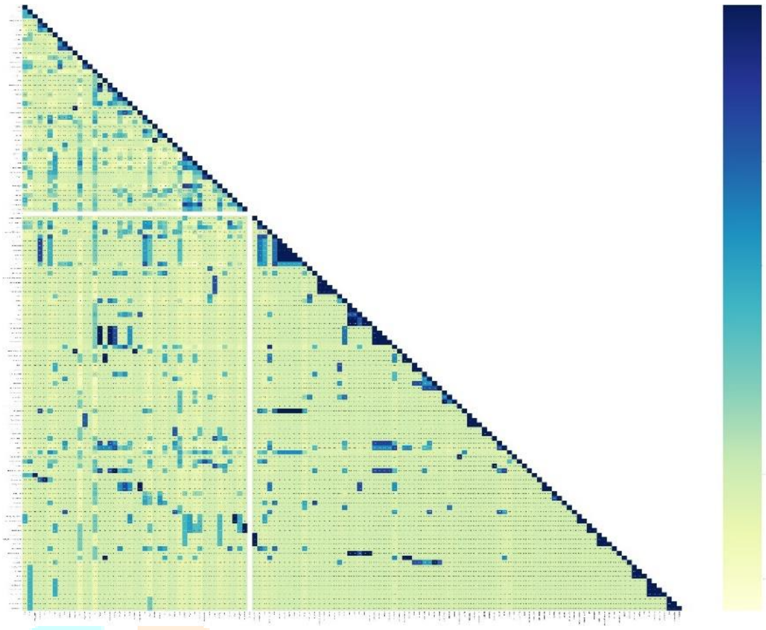

Fig.2a. Performed exploratory data analysis on the features

These methodical steps constitute a foundational framework, paving the way for subsequent stages like feature engineering, model training, and seamless integration into the Clinical Decision Support System. Dividing the collected data into testing and training sets to ease model training and unbiased evaluation. This step ensures the model's generalization to unseen data, a crucial aspect of robust performance. Fitting the selected ML models (Random Forest, Decision Tree, SVM, and Naive Bayes) using the training data. Evaluate each model's performance using appropriate metrics, such as accuracy. This iterative process aids in selecting the most effective model for disease prediction. Utilization of OpenCV for text-to-speech functionality, converting textual information into audible output. Integrating this feature into the application built with Streamlit, ensuring a user-friendly interface. Streamlit simplifies the development process, allowing for easy customization and deployment of the Clinical Decision Support System. The incorporation of OpenCV enhances the system's accessibility and user interaction. These subsequent steps propel the Clinical Decision Support System towards completion, enhancing its functionality with evaluation metrics and integrating user-centric features through OpenCV for text-to-speech and Streamlit for application development.

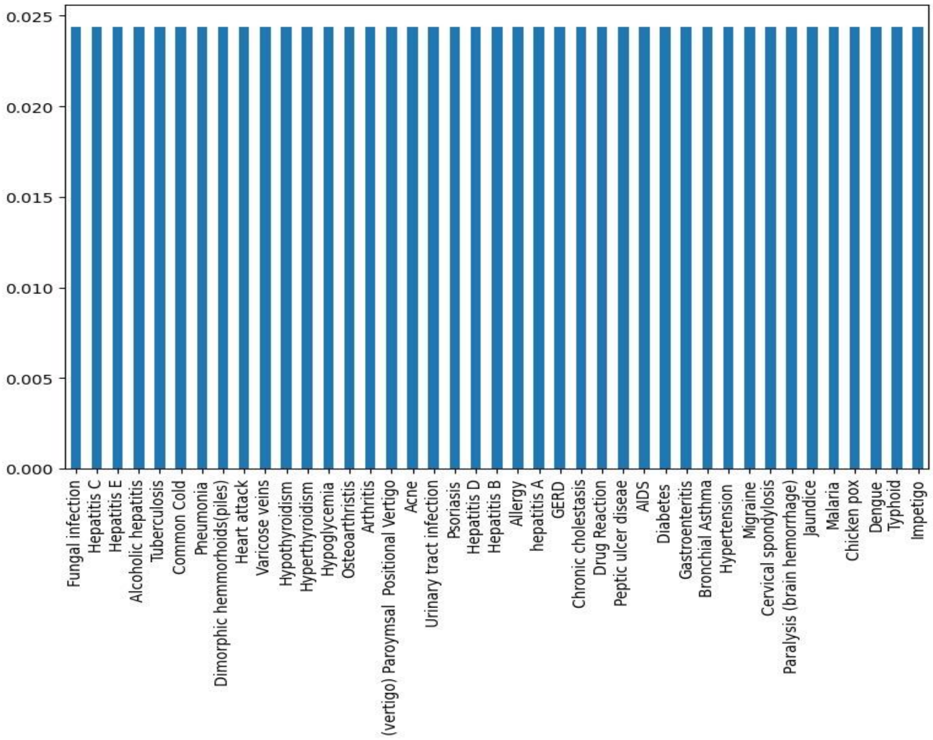

Fig.2b. Performed exploratory data analysis on the features

OUTCOMES

The outcomes of the developed Clinical Decision Support System are highly promising, showcasing substantial accuracy across various machine learning models. The predictive performance of the system, as measured by accuracy metrics, demonstrates the efficacy of the implemented models: [a] Naive Bayes: 95%, [b] Decision Tree: 92%, [c] Support Vector Machine: 95%, [d] Random Forest: 95%.

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Random Forest
Acurracy:  0.9513546798029556
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Fig.3a. Random Forest

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DecisionTree
Acurracy:  0.9267241379310345
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Fig.3b. Decision Tree

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Support Vector Machine
Acurracy:  0.9513546798029556
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Fig.3c.Support Vector Machine

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Naive Bayes
Acurracy:  0.9513546798029556
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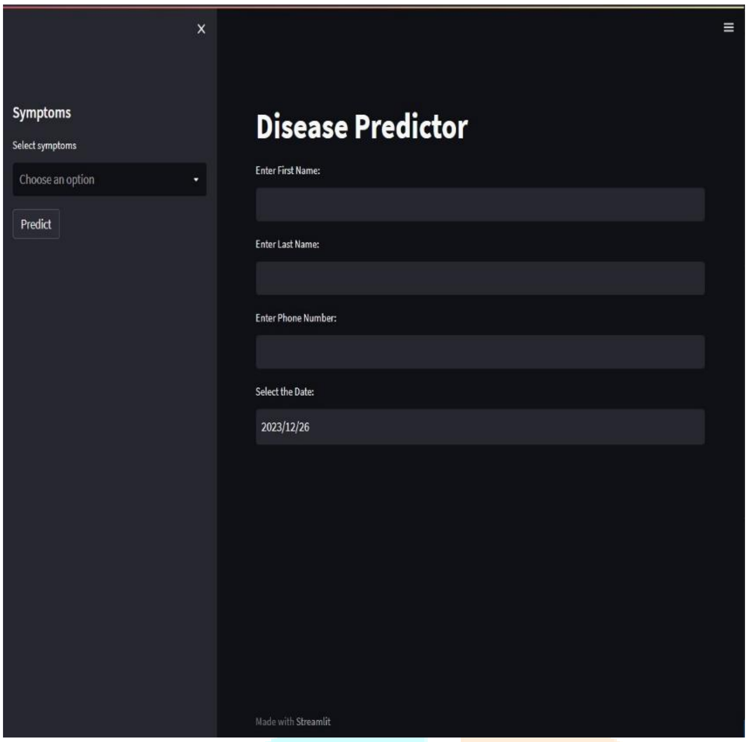
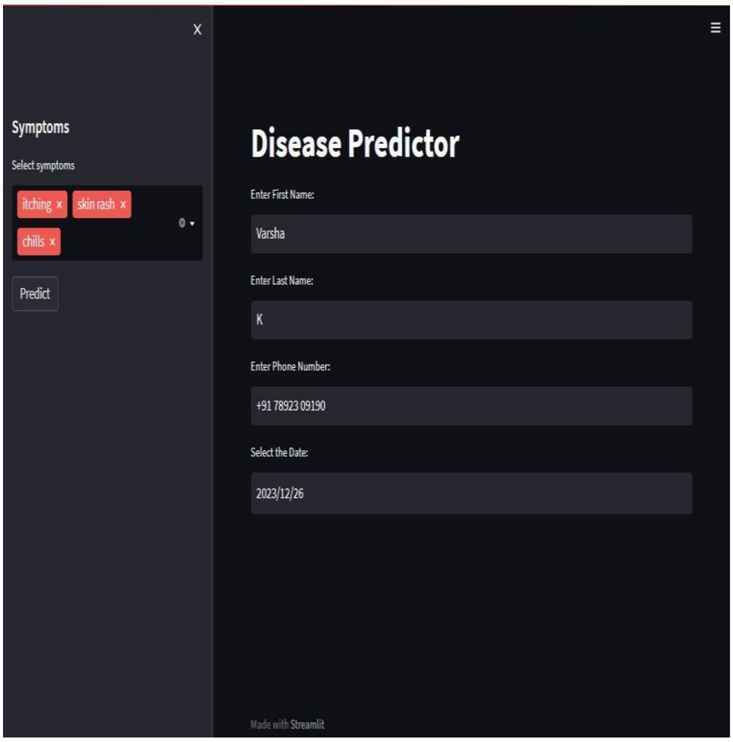
Fig.3d.Naive Bayes

These commendable accuracy scores underscore the system's proficiency in disease prediction, affirming its potential as a reliable clinical decision support tool. Additionally, the successful integration of Streamlit and OpenCV into the application enhances user experience and accessibility. The combination of a user friendly interface with advanced text-to-speech capabilities through OpenCV signifies a significant stride in making the Clinical Decision Support System not only accurate but also user-centric and inclusive. This project represents a valuable contribution to the realm of healthcare technology, promising improved diagnostic support for healthcare professionals.

OUTPUTS:





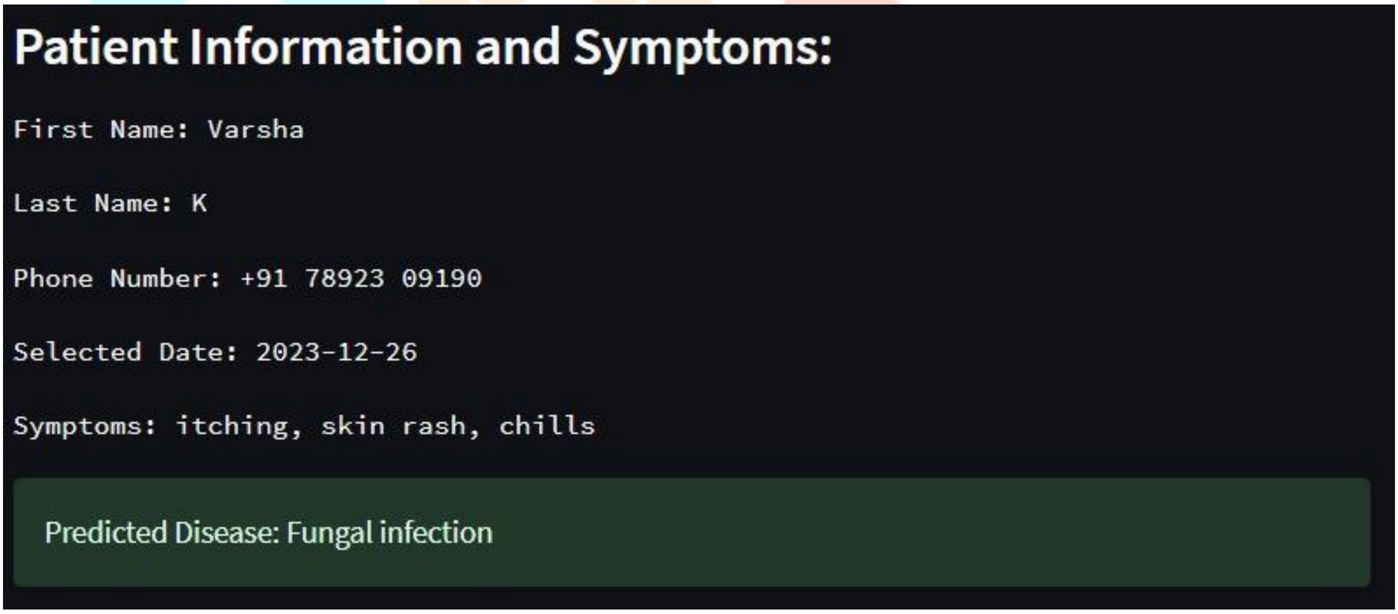


Fig.3e. Voice assistant developed by Streamlit and OpenCV

CONCLUSION

In conclusion, the development of the Clinical Decision Support System represents a significant advancement in healthcare technology. The high accuracy achieved by ML models, Random Forest, Decision Tree, SVM, and Naive Bayes—validates the system's efficacy in disease prediction. These outcomes underscore the potential of leveraging artificial intelligence for enhanced clinical decisionmaking. The successful integration of Streamlit and OpenCV further elevates the system, providing a user-friendly interface and incorporating text-to-speech functionality for improved accessibility. The project not only demonstrates the capabilities of advanced machine learning techniques in medical diagnostics but also emphasizes the importance of user-centric design for practical implementation. As the healthcare industry continues to embrace technological innovations, the Clinical Decision Support System stands as a testament to the synergy between artificial intelligence and user interface development.
This project holds the promise of contributing significantly to the field, offering a robust and accessible tool for healthcare professionals in their diagnostic endeavors.

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