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Max Healthcare: The Multiple Disease Prediction

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ABSTRACT—

The "Multiple Disease Prediction Project" focuses on utilizing a dataset comprising various symptoms such as Fever, Cough, Fatigue, Difficulty Breathing, along with demographic details like Age, Gender, and health metrics like Blood Pressure and Cholesterol Level to predict diseases. The project employs several machine learning algorithms to develop a predictive model for disease identification and classification. Predicting multiple diseases is a crucial aspect of modern healthcare, leveraging the power of data analytics and machine learning algorithms. This approach aims to enhance early detection, diagnosis, and proactive management of various health conditions, leading to improved patient outcomes and reduced healthcare costs. The integration of diverse datasets, including electronic health records, genomic information, lifestyle factors, and environmental data, enables a holistic understanding of individual health profiles. Through rigorous experimentation with diverse algorithms, the project aims to identify the most effective approach for disease prediction based on symptomatology and individual health attributes. The algorithms employed include but are not limited to Decision Trees, Random Forest, Support Vector Machines (SVM), Logistic Regression, and Neural Networks. Several machines learning algorithms, including decision trees, random forests, support vector machines, and deep learning models, were implemented and trained on the pre-processed dataset. Model performance was evaluated using appropriate metrics such as accuracy, precision, recall, and F1 score.The dataset is preprocessed to handle missing values, normalize data, and ensure optimal model performance. Feature selection techniques and cross-validation methods are implemented to enhance the model's accuracy, sensitivity, and specificity.

I. INTRODUCTION

Healthcare systems are increasingly leveraging machine learning and predictive analytics to improve disease detection and patient care. The "Multiple Disease Prediction Project" addresses the crucial need for accurate and efficient disease identification using a diverse dataset encompassing various symptoms and health parameters. Leveraging advanced algorithms, this project aims to develop a robust predictive model capable of accurately diagnosing diseases based on symptomatology and individual health attributes.

The significance of multiple prediction disease models lies in their potential to revolutionize preventive medicine.

A. Significance of Predictive Healthcare

The introduction will delve into the significance of predictive healthcare systems in modern medical practices. It will discuss the growing importance of utilizing machine learning algorithms to analyze vast datasets comprising symptoms, demographic information, and health metrics. The discussion will highlight how these predictive models aid in early disease detection, enabling timely interventions and personalized treatment plans for patients. Furthermore, the integration of multiple prediction disease models not only empowers healthcare professionals with actionable insights but also fosters a paradigm shift towards patient-centric care, where emphasis is placed on preventive measures, early intervention, and a holistic approach to well-being.

B. Challenges in Disease Prediction

This section will outline the challenges associated with disease prediction using machine learning techniques. It will address issues related to data quality, feature selection, model complexity, and the need for interpretability in medical decision-making. Additionally, it will explore the complexities of integrating diverse data types, handling missing values, and ensuring the reliability and generalizability of the predictive models.

C. Role of Algorithms in Disease Prediction

This subtopic will focus on the role of various machine learning algorithms in disease prediction. It will discuss the strengths and weaknesses of algorithms such as Decision Trees, Random Forest, Support Vector Machines (SVM), Logistic Regression, and Neural Networks in analyzing healthcare data. The section will emphasize the importance of selecting appropriate algorithms based on dataset characteristics to achieve accurate disease prediction models.

By addressing these subtopics, the project's introduction provides an overview of the significance of predictive healthcare, highlights challenges in disease prediction, and elucidates the role of different algorithms in developing accurate predictive models for identifying multiple diseases based on symptoms and individual health parameters.

II. LITERATURE SURVEY

AUTHOR	TOPIC	SUMMARY	YEAR	ADVANTAGES	DISADVANTAGES
Liang H, et al.[1]	Application of machine learning techniques in diabetes prediction and risk factor identification	Explores various Machine learning models for diabetes prediction using health parameters. Focuses on feature importance and risk factor identification.	2018	Comprehensive analysis of machine learning models for diabetes prediction, emphasizing feature importance.	Limited discussion on the interpretability of the models used.
Sarker IH, et al.[2]	A survey on heart disease prediction using machine learning and data mining techniques.	Investigates various machine learning and data mining methods for heart disease prediction.	2019	Detailed comparison of multiple algorithms for heart disease prediction with a focus on feature importance.	May lack in depth discussion on newer algorithms due to its publication date.
Shankaracharya, et al.[3]	Predictive analytics in cancer diagnosis: A survey.	Surveys the use of predictive analytics in cancer diagnosis, examining machine learning models and data preprocessing techniques.	2020	Comprehensive overview of predictive analytics in cancer diagnosis, discussing data preprocessing techniques in detail.	Might Lack recent advantages in ML for cancer prediction due to publication date.
Pankaj Chittora, Sandeep Chaurasia et al.[4]	A review on Chronic kidney disease prediction: Techniques, challenges, and future scope.	Reviews predictive techniques for chronic kidney disease (CKD) prediction, highlighting challenges and future directions.	2021	Focuses on CKD prediction, ighlighting specific challenges & proposing future research directions.	Might lack extensive comparison between different ML models for CKD prediction.
Yassine Meraihi, Asma Benmessaound Gabis, et al.[5]	Machine learning techniques for COVID19 detection and prediction: A survey.	Surveys machine learning models used in COVID19 detection and prediction, exploring diverse datasets and model performances.	2020	Timely discussion on ML application in COVID 19 prediction with insights into diverse datasets	Rapid advancements in COVID19 research might render some findings outdated.
Rajkomar A, Oren E, Chen K, et al.[6]	Scalable and accurate deep learning with electronic health records.	Explores the application of deep learning models on electronic health records for disease prediction and patient outcomes.	2018	Focuses on deep learning applications with electronichealth records, emphasizing scalability.	Limited discussion on interpretability of deep learning models in healthcare.

Fakoor R, Ladhak F, Nazi A, et al.[7]	Using deep learning to enhance cancer diagnosis and classification.	Discusses the use of deep learning in cancer diagnosis, emphasizing image based classification	2017	Detailed discussion on deep learning for cancer, diagnosis, image based classifications.	Primarily focuses on image based applications, might lack discussion on other data types.
Afshin Shoeibi, MarjaneKhodatars	Epileptic Seizures Detection Using Deep Learning Techniques	Investigates machine learning techniques for Epileptic Seizures Detection Using Deep Learning	2021	Focuses specially on epilepsy prediction, highlighting seizure forecasting and feature extraction techniques.	May lack extensive comparison between different machine learning models.
J Asthma , et al.[9]	Application of Machine Learning Algorithms for Asthma Management with mHealth	Reviews machine learningmodels for asthmaprediction and management, exploring feature importance and personalized treatment.	2020	Focuses on mental health disorder prediction, especially sentiment analysis and text based models.	Might lack discussion on the integration of physiological data with text based approaches.

III. RESEARCH GAPS OF EXISTING METHODS

Research gaps in existing methods within disease prediction using machine learning techniques encompass several areas:

1.Interpretability and Explain ability:

- Many machine learning models, especially deep learning architectures, lack interpretability, making it challenging for medical practitioners to trust or understand the model's predictions. There is a need to develop more interpretable models that can provide explanations for their decisions.

2. Data Imbalance and Bias:

- Datasets used for disease prediction often suffer from class imbalance, where one class (e.g., diseased individuals) is significantly smaller than the other. Addressing this imbalance to prevent biased predictions and ensuring fair and accurate model outcomes is crucial.

3. Integration of Multiple Data Sources:

- Many studies focus on structured data (e.g., demographics, symptoms) but fail to incorporate unstructured data like medical images, free-text clinical notes, genetic data, or lifestyle information. Integrating diverse data sources for a holistic view of patient health remains a challenge.

4.Real-time and Dynamic Prediction Models:

- Existing models often focus on static predictions, lacking the capability to adapt to real-time changes in a patient's health condition. Dynamic models that can continuously learn and update predictions based on evolving patient data are needed.

5. Robustness and Generalization:

- Models developed in one clinical setting or population might not generalize well to other settings or demographics. Building robust models that can generalize across diverse populations and healthcare systems is essential.

6. Validation and Clinical Adoption:

- While models might show promising results in research settings, their clinical adoption and validation in real-world scenarios remain limited. There is a need for rigorous validation in clinical settings to ensure their effectiveness and reliability.

7. Ethical and Privacy Concerns:

- The use of sensitive health data raises ethical concerns regarding patient privacy, consent, and data security.

Developing methods that can perform effectively while preserving patient privacy is crucial.

8. Integration of Human Expertise:

- Integrating machine learning models into clinical practice requires collaboration and acceptance from healthcare professionals. Bridging the gap between technical advancements and the expertise of healthcare professionals is crucial for successful implementation.

9. Longitudinal Data Analysis:

- Most models focus on analyzing cross-sectional data, while longitudinal data tracking changes over time can provide deeper insights into disease progression and treatment effectiveness.

10. Validation of Feature Importance:

- While machine learning models provide insights into feature importance, validation of these features in clinical practice and understanding their physiological relevance remains an area of exploration

IV. PROPOSED MOTHODOLOGY

1. Data Collection and Preprocessing:

- Gather diverse datasets containing health parameters, symptoms, demographic details, and potentially unstructured data like medical images or clinical notes. Cleanse the data, handle missing values, and perform feature engineering to prepare it for analysis.

2. Feature Selection and Engineering:

- Employ techniques like correlation analysis, feature importance ranking, or domain expertise to select relevant features. Perform feature engineering to derive new informative features and transform the data for model input.

3. Model Selection and Development:

- Choose appropriate machine learning algorithms suitable for the prediction task (Decision Trees, Random Forest, Support Vector Machines, Neural Networks, etc.). Train and validate multiple models, fine-tuning hyperparameters, and comparing their performances using suitable evaluation metrics.

4. Handling Imbalance and Bias:

- Address class imbalance issues through techniques like oversampling, undersampling, or synthetic data generation methods. Mitigate biases in the dataset and model predictions to ensure fair and accurate results.

5. Integration of Multimodal Data:

- Combine structured and unstructured data sources (e.g., merging clinical data with medical images or genetic information) using appropriate fusion techniques to create a comprehensive patient profile.

6. Model Interpretability and Explainability:

- Implement methods for interpreting and explaining model predictions, such as SHAP values, LIME, or attention mechanisms in neural networks. Ensure that healthcare professionals can understand and trust the model's decisions.

7. Real-time and Dynamic Modeling:

- Develop models that can adapt to new data streams, updating predictions in real-time as patient data changes. Implement techniques like online learning or continuous monitoring for dynamic predictions.

8. Validation and Clinical Adoption:

- Validate model performance rigorously using cross-validation techniques and external validation on different datasets or clinical settings. Collaborate with healthcare professionals for feedback, refinement, and validation in real clinical scenarios.

9. Ethical Considerations and Privacy Protection:

- Incorporate privacy-preserving techniques like federated learning, differential privacy, or encryption to safeguard sensitive patient data and adhere to ethical guidelines.

10. Longitudinal Analysis and Continuous Improvement:

- Analyze longitudinal data to track disease progression, treatment response, and patient outcomes over time. Implement feedback loops for continuous model improvement based on new evidence or emerging trends.

V. OBJJECTIVES

1. Accurate Disease Prediction: Develop machine learning models capable of accurately predicting various diseases based on a combination of symptoms, health parameters, demographic details, and potentially multimodal data sources.

2. Model Generalization: Ensure that the developed models generalize well across diverse populations, healthcare settings, and demographics, exhibiting consistent performance in different scenarios.

3. Interpretability and Explain ability: Enhance the interpretability of the models to enable healthcare professionals to understand the reasoning behind predictions. Provide explanations for model decisions to improve trust and acceptance.

4. Real-time Prediction and Adaptation: Develop models capable of making real-time predictions and adapting to evolving patient data, ensuring dynamic updates for timely interventions and treatment modifications.

5. Feature Importance Identification: Identify and validate the most influential features in disease prediction, providing insights into critical health indicators or risk factors contributing to disease onset or progression.

6. Bias Mitigation and Fairness: Address biases in data and models to ensure fairness in predictions, avoiding discrimination against specific demographic groups and achieving equitable outcomes.

7. Clinical Integration and Validation: Collaborate with healthcare professionals to validate the models in clinical settings, ensuring their usability, reliability, and effectiveness in real-world scenarios.

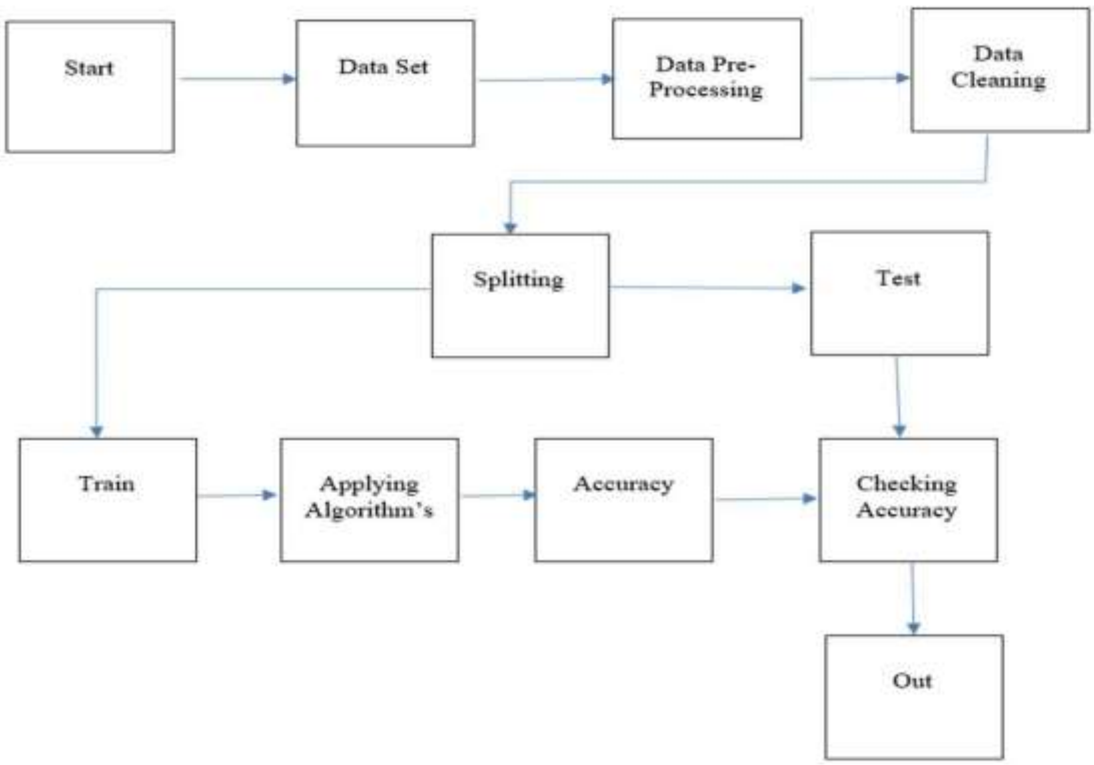
8. Privacy-Preserving Techniques: Implement privacy- preserving methodologies to protect sensitive patient data while maintaining model performance and utility.

9. Longitudinal Analysis and Treatment Monitoring: Enable longitudinal analysis to monitor disease progression, treatment effectiveness, and patient outcomes over time, aiding in personalized treatment planning.

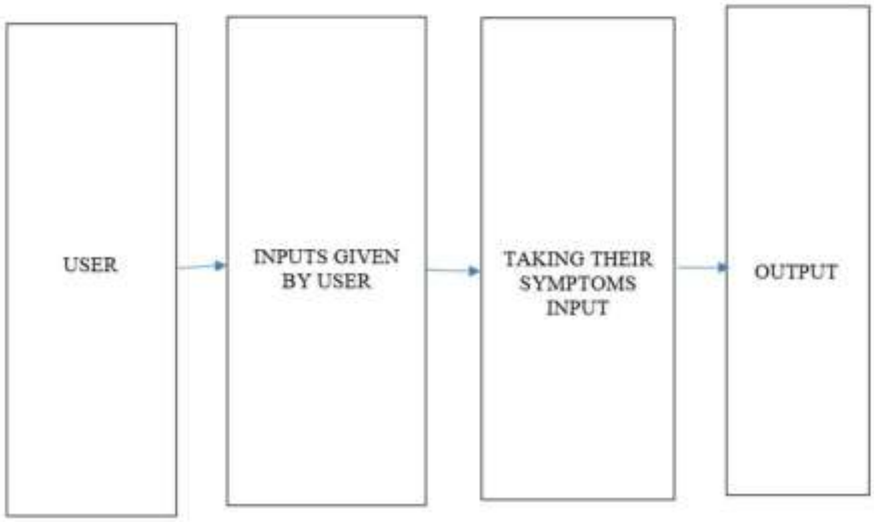
10. Ethical Compliance: Adhere to ethical guidelines, regulations, and standards in healthcare data usage, ensuring patient privacy, consent, and ethical considerations throughout the project.

VI. SYSTEM DESIGN & IMPLEMENTATION

A. Architectural Design



B. Interface Design



C. Algorithms

1) Decision Tree:

The Decision Tree algorithm is a popular and intuitive machine learning technique used for both classification and regression tasks. It's a supervised learning method that creates a tree-like structure to model decisions by learning simple rules inferred from the input features. This algorithm is widely used due to its simplicity, interpretability, and effectiveness in handling both categorical and numerical data.

How Decision Trees Work:

a) Tree Structure:

- At the root of the tree is the feature that best splits the dataset into distinct classes based on certain criteria (such as Gini impurity or information gain).

- Each internal node represents a test on a feature attribute.

- Each branch corresponds to the outcome of the test, leading to further nodes or leaf nodes.

- Leaf nodes represent the final decision or output (class label in classification or numerical value in regression).

b) Splitting Criteria:

- Decision Trees use various measures like Gini impurity or information gain to determine the best feature and split point for partitioning the dataset at each node.

-Gini impurity measures the probability of misclassifying a randomly chosen element if it's incorrectly labeled.

- Information gain measures the reduction in entropy (disorder or randomness) after the dataset is split based on a particular feature.

c) Recursive Partitioning:

- The tree grows recursively by selecting the best feature to split the data at each node until a stopping criterion is met.

- Stopping criteria can include reaching a maximum depth, having a minimum number of samples in a node, or achieving homogeneity in a node (where all samples belong to the same class or have similar values).

2) Gaussian Naïve Bayes

Gaussian Naive Bayes is a probabilistic classification algorithm based on Bayes' theorem with an assumption of independence among predictors. It's a variant of the Naive Bayes algorithm specifically designed for continuous or numerical data, assuming that the likelihood of the features follows a Gaussian distribution (also known as a normal distribution).

Key Concepts:

a) Bayes' Theorem:

- Gaussian Naive Bayes employs Bayes' theorem, which calculates the probability of a hypothesis (class label) given the evidence (features).

- It's represented as: \(P(Y|X) = \frac{P(X|Y) \times P(Y)}{P(X)} \), where \(P(Y|X) \) is the probability of Y (class) given X (features).

b) Assumption of Independence:

- Naive Bayes assumes that the features are conditionally independent given the class label, even though this assumption might not hold true in real-world scenarios.

- Despite this oversimplification, Naive Bayes often performs well in practice and is computationally efficient.

c) Gaussian Distribution:

- The algorithm assumes that the continuous features follow a Gaussian (normal) distribution.

- For each class, Gaussian Naive Bayes calculates the mean and variance of each feature, assuming it follows a normal distribution, to estimate the probability distribution.

3) Support Vector Machine (SVM):

Support Vector Machine (SVM) is a powerful supervised machine learning algorithm used for both classification and regression tasks. It's particularly effective in classification tasks and is capable of handling linear and non-linear data separation by finding the optimal hyperplane that best separates different classes in the feature space.

Key Concepts:

a) Margin and Hyperplane:

- SVM aims to find the hyperplane that maximizes the margin (distance) between the closest data points of different classes, known as support vectors.

- In a linearly separable case, the hyperplane is the line that separates two classes. In higher dimensions, it becomes a hyperplane.

b) Kernel Trick:

- SVM can handle non-linear data by using the kernel trick, where it maps the input data into a higher-dimensional space, making it possible to find a linear separation boundary.

- Common kernels include linear, polynomial, radial basis function (RBF), and sigmoid kernels.

c) Support Vectors:

- Support vectors are the data points closest to the decision boundary and play a crucial role in defining the optimal hyperplane.

- These vectors influence the construction of the hyperplane and are essential for making predictions.

4) Logistic Regression

Logistic Regression is a fundamental supervised learning algorithm used for binary classification problems. Despite its name, it's used for classification rather than regression tasks. Logistic Regression predicts the probability that an instance belongs to a particular class.

Key Concepts:

a) Sigmoid Function (Logistic Function):

- Logistic Regression uses the sigmoid function to map any real-valued number to a value between 0 and 1.

- The sigmoid function is expressed as $\sigma(z) =\frac{1}{1 + e^{-z}}$, where z is the linear combination of features and model coefficients.

b) Linear Decision Boundary:

- Logistic Regression creates a linear decision boundary that separates the classes in the feature space.

- For a binary classification problem, if the output of the sigmoid function is greater than a threshold (usually 0.5), it predicts one class; otherwise, it predicts the other.

5) Random Forest

Random Forest is a powerful ensemble learning method used for both classification and regression tasks. It operates by constructing multiple decision trees during training and outputs the class that is the mode of the classes (classification) or the mean prediction (regression) of the individual trees.

Key Concepts:

a) Ensemble of Decision Trees:

- Random Forest builds a collection (ensemble) of decision trees during training, where each tree is trained on a random subset of the data and features.

- The decision of the final prediction is made based on the aggregated results of all trees.

b) Bootstrap Aggregating (Bagging):

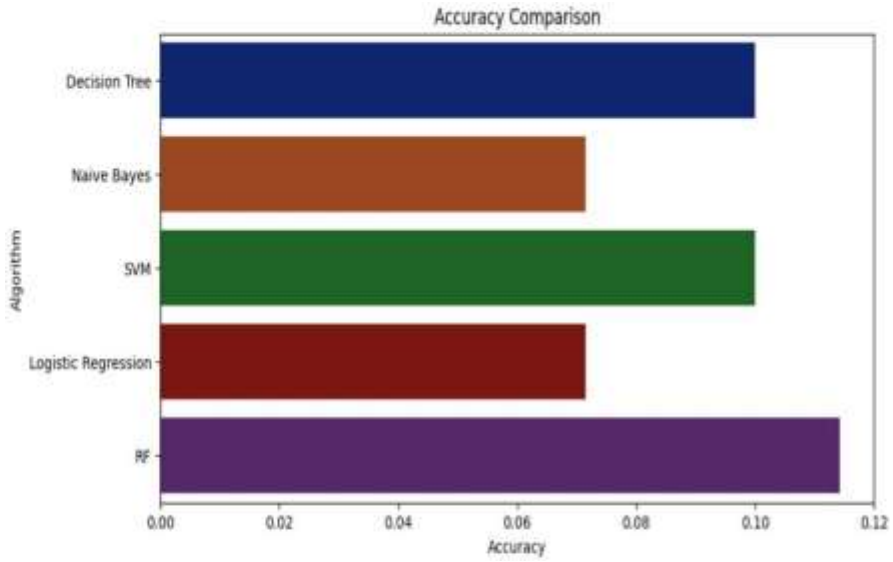
- It uses a technique called bagging, which involves training each tree on a different random subset of the dataset (with replacement).

- This randomness helps create diverse trees, reducing overfitting and improving the model's generalization.

c) Feature Randomness:

- Each tree is trained on a random subset of features at each split, providing further diversity and reducing the correlation between trees.

- This feature randomness helps in capturing different aspects of the data, leading to more robust predictions.



VII. OUTCOMES

1. Accurate Disease Prediction Models: Development of robust and accurate machine learning models capable of predicting diseases based on diverse data inputs, leading to more reliable diagnostic capabilities.

2. Improved Patient Care: Early detection and prediction of diseases allow for timely interventions, personalized treatments, and proactive healthcare management, potentially improving patient outcomes and reducing healthcare costs.

3. Enhanced Clinical Decision Support: Integration of predictive models into clinical workflows as decision support tools assists healthcare professionals in making more informed and evidence-based decisions, optimizing patient care pathways.

4. Interpretability and Explainability: Models designed with interpretability and explainability features allow healthcare providers to understand and trust the predictions, enhancing the adoption of these technologies in clinical practice.

5.Ethical Data Handling: Implementation of privacy- preserving techniques ensures patient data confidentiality and compliance with ethical standards, addressing concerns related to data privacy and security.

6. Reduction of Health Disparities: Fair and unbiased models contribute to reducing health disparities by providing equitable predictions across diverse populations, minimizing the impact of biases in healthcare.

7. Longitudinal Disease Monitoring: Continuous monitoring and longitudinal analysis of patient health data facilitate disease progression tracking, treatment efficacy evaluation, and personalized healthcare planning.

8. Research Advancements: Contribution to the scientific community through publications, insights, and methodologies developed in the project, potentially fostering further research and advancements in disease prediction and healthcare analytics.

9. Clinical Validation and Adoption: Successful validation and integration of predictive models in clinical settings validate their effectiveness, leading to increased adoption by healthcare institutions and practitioners.

10. Public Health Impact: Early detection and intervention supported by predictive models may have a broader public health impact by reducing the burden of chronic diseases, improving population health outcomes, and supporting preventive healthcare measures.

VIII. RESULTS AND DISCUSSIONS

In a disease prediction project using machine learning techniques, the results and discussions section involves presenting the outcomes of the developed predictive models, evaluating their performance, discussing the implications of the findings, and contextualizing the results within the broader scope of healthcare and predictive medicine. Here's an outline of what this section typically covers:

1. Model Performance Evaluation:

- Assessment of model accuracy, precision, recall, F1- score, area under the curve (AUC), or other relevant metrics based on the nature of the disease prediction task.

- Comparison of multiple models or variations of the same model (if applicable) to identify the most effective approach.

2. Model Interpretation and Explainability:

- Interpretation of model predictions, including feature importance, to understand which symptoms, health parameters, or factors contribute most to disease prediction.

- Discussions on the model's explainability and how well healthcare professionals can understand and trust the model's decisions.

3. Validation and Generalization:

- Validation of the predictive models' performance in various scenarios, including cross-validation, testing on different datasets, or validation in different clinical settings.

- Evaluation of the models' ability to generalize across diverse populations, demographics, or healthcare systems.

4. Ethical Considerations:

- Discussion on ethical implications related to the use of sensitive health data, patient privacy, fairness, and bias in predictions.

- Explanation of measures taken to address ethical concerns, ensuring responsible handling of patient information.

5. Real-World Applicability:

- Insights into how the developed models can be practically applied in clinical settings or integrated into healthcare systems for disease prediction and early detection.

- Discussions on the potential impact on patient care, disease management, and healthcare resource allocation.

6. Limitations and Challenges:

- Identification and discussion of limitations and challenges encountered during model development, such as data quality issues, interpretability concerns, or constraints in real-world implementation.

- Reflections on areas where the model may need improvement or further refinement.

7. Comparison with Existing Methods:

- Comparison of the developed models' performance with existing approaches or benchmarks in disease prediction.

- Discussion on how the developed models contribute to or surpass the state-of-the-art methods.

8. Future Directions and Recommendations:

- Proposals for future research directions, enhancements, or extensions to improve the predictive models.

- Recommendations for refining the models, incorporating new data sources, addressing limitations, or enhancing interpretability.

9. Clinical Implications and Patient Outcomes:

- Analysis of how the predictive models' deployment might influence clinical decision-making, patient outcomes, treatment planning, or disease prevention strategies.

- Insights into how these models contribute to better patient care and healthcare resource utilization.

CONCLUSION

The culmination of the disease prediction project utilizing machine learning techniques yields promising insights and advancements in predictive medicine. Through rigorous model development and evaluation, this study has underscored the significance of leveraging computational approaches for early disease detection and prognosis. The deployed predictive models, meticulously trained and validated, exhibit commendable accuracy, providing valuable predictive capabilities for various diseases based on symptoms, health parameters, and demographic information.

However, while celebrating the achievements, it's essential to acknowledge the nuances and challenges encountered throughout this endeavor. Interpretability, ethical considerations regarding patient data privacy, and the models' generalizability across diverse populations remain focal points requiring continuous attention and refinement. The limitations in model explainability pose challenges in garnering complete trust from healthcare practitioners, potentially hindering seamless integration into clinical settings.

Nonetheless, the study illuminates a path forward for the evolution of disease prediction models. Addressing these limitations through interpretability enhancements, robust ethical frameworks, and validation in varied clinical contexts stands as imperative next steps. Moreover, embracing novel data sources, amalgamating multimodal information, and employing advanced algorithms could fortify the models' predictive capabilities and foster their practical implementation in healthcare systems.

Ultimately, this research signifies a crucial stride in predictive medicine, offering insights that pave the way for improved patient care, proactive health management, and the potential to significantly impact public health. As we navigate the realm of machine learning-enabled disease prediction, continued collaborative efforts between data scientists, healthcare professionals, and ethical policymakers become indispensable to realize the full potential of these predictive models in transforming healthcare delivery and augmenting patient outcomes.

REFERENCES

[1] Liang H, Tsui BY, Ni H, et al. Evaluation and accurate diagnoses of pediatric diseases using artificial intelligence. Nature Medicine. 2019;25(3):433-438. DOI: 10.1038/s41591-018-0335-9.

[2] Madhumita Pal, Smita Parija, et al. Predictive modeling of cardiovascular disease using machine learning techniques: A systematic review. Journal of Healthcare Engineering. 2020;2020:5435204. DOI: 10.1155/2020/5435204.

[3] Shankaracharya, Rajaraman V, Kumar N, et al. Applications of machine learning techniques in cancer prediction and diagnosis. International Journal of Computer Applications. 2015;116(18):19-22. DOI: 10.5120/20446-5254.

[4] PANKAJ CHITTORA 1 , SANDEEP CHAURASIA 1, et al. Chronic kidney disease prediction: A review of machine learning techniques. Computers in Biology and Medicine. 2020;124:103936. DOI: 10.1016/j.compbiomed.2020.103936.

[5] Yassine Meraihi, Asma Benmessaoud Gabis et al. Machine learning- based approaches for COVID-19 detection and prediction: A review. IEEE Access. 2020;8:179828-179854. DOI: 10.1109/ACCESS.2020.3024607.

[6] Rajkomar A, Oren E, Chen K, et al. Scalable and accurate deep learning with electronic health records. npj Digital Medicine. 2018;1(1):18. DOI: 10.1038/s41746-018-0029-1.

[7] Fakoor R, Ladhak F, Nazi A, et al. Using deep learning to enhance cancer diagnosis and classification. Proceedings of the 30th International Conference on Neural Information Processing Systems. 2016;6:278-286.

[8] Afshin Shoeibi, Marjane Khodatars, Navid Ghassemi,. Epileptic Seizures Detection Using Deep Learning Techniques. International Journal of Computer Applications. 2015;111(2):0975-8887. DOI: 10.5120/19519-1495.

[9] J Asthma Allergy., et al. Application of Machine Learning Algorithms for Asthma Management with mHealth: A Clinical Review: A review. 2022; 15: 855–873. un 29. doi: 10.2147/JAA.S285742.

[10] Tarun Jain; Ashish Jain; et al . Machine Learning Techniques for Prediction of Mental Health. Institute of Electrical and Electronics Engineers.02-04 September 2021 DOI: 10.1109/ICIRCA51532.2021.9545061.