DIAGNOSIS OF ACUTE DISEASES IN VILLAGES AND SMALLER TOWNS USING AI

A PROJECT REPORT

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Under the guidance of,

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in partial fulfillment for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING, COMPUTER ENGINEERING

At

GAIN MORE KNOWLEDGE
REACH GREATER HEIGHTS

PRESIDENCY UNIVERSITY

BENGALURU

JANUARY 2025

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SCHOOL OF COMPUTER SCIENCE ENGINEERING

CERTIFICATE

This is to certify that the Project report **"DIAGNOSIS OF ACUTE DISEASES IN VILLAGES AND SMALLER TOWNS USING AI"** being submitted by "Ms. Shreya Ravi Kumar, Ms. Sneha R, Ms. Neha R" bearing roll number(s) "20211CSE0229, 20211CSE0223, 20211CSE0224" in partial fulfillment of the requirement for the award of the degree of Bachelor of Technology in Computer Science and Engineering is a bonafide work carried out under my supervision.

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DECLARATION

We hereby declare that the work, which is being presented in the project report entitled **DIAGNOSIS OF ACUTE DISEASES IN VILLAGES AND SMALLER TOWNS USING AI** in partial fulfillment for the award of Degree of **Bachelor of Technology** in **Computer Science and Engineering,** is a record of our own investigations carried under the guidance of **Dr. Ramesh Sengodan, Professor, School of Computer Science Engineering & Information Science, Presidency University, Bengaluru.**

We have not submitted the matter presented in this report anywhere for the award of any other Degree.

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ABSTRACT

Artificial intelligence in medical diagnosis is transforming the world of healthcare, providing remarkable precision and efficiency. Artificial intelligence (AI) is a technology that allows computers and machines to replicate human learning, comprehension, problem solving, decision making, creativity, and autonomy. AI-enabled applications and devices can perceive and identify elements. They can comprehend and respond to human words. AI technologies, particularly in medical diagnostics, are changing the way diseases are identified, analyzed, and treated. AI can interpret large volumes of data quickly and effectively using machine learning and deep learning algorithms, providing healthcare providers with useful insights. These innovations not only improve diagnostic precision, but they also allow for early detection and individualized treatment methods. The advancement of AI in healthcare has proven transformational, particularly in the realm of medical diagnosis. AI was initially utilized mostly for tasks in administration, but its scope has grown enormously. AI and machine learning systems now evaluate large volumes of data rapidly and correctly, allowing healthcare providers to make better judgments. These technologies can process medical images, identify trends, and even forecast disease outcomes, transforming medical practice.

In neglected and rural regions, access to high-quality healthcare is frequently confined, which often results in delayed diagnosis and suboptimal health outcomes. Existing ways of resolving this issue, such as telemedicine, have struggled to grow in parallel with growing demands for healthcare. This approach envisions an AI-powered system that can understand a vast amount of medical data, diagnose symptoms, and engage in discussions with patients to seek out about their concerns with their health. With the emergence of cutting-edge AI-driven technologies and the rising appeal of smart assistants like Google and Alexa, innovation in healthcare is entering an age of change.

Consider a software that assesses symptoms, suggests diagnoses and treatment options. It may enable you to exercise self-care and track your progress. This seems like an ideal concept, particularly to

those areas with little healthcare access. While AI applications can help with initial health assessments, they shouldn't be used in place of expert medical guidance. In order to receive the best care, seek the advice of a doctor if symptoms intensify or continue. AI tools can serve as helpful reminders to put your health first and get help when you need it.

ACKNOWLEDGEMENT

First of all, we indebted to the **GOD ALMIGHTY** for giving me an opportunity to excel in our efforts to complete this project on time.

We express our sincere thanks to our respected dean **Dr. Md. Sameeruddin Khan**, Pro-VC, School of Engineering and Dean, School of Computer Science Engineering & Information Science, Presidency University for getting us permission to undergo the project.

We express our heartfelt gratitude to our beloved Associate Deans **Dr. Shakkeera L and Dr. Mydhili Nair,** School of Computer Science Engineering & Information Science, Presidency University, and Dr.Asif Mohammed, Head of the Department, School of Computer Science Engineering & Information Science, Presidency University, for rendering timely help in completing this project successfully.

We are greatly indebted to our guide **Dr Ramesh Sengodan , Professor** and Reviewer **Dr.Pamela Vinitha , Professor**, School of Computer Science Engineering & Information Science, Presidency University for his/her inspirational guidance, and valuable suggestions and for providing us a chance to express our technical capabilities in every respect for the completion of the project work.

We would like to convey our gratitude and heartfelt thanks to the PIP2001 Capstone Project Coordinators **Dr. Sampath A K, Dr. Abdul Khadar A and Mr. Md Zia Ur Rahman,** department Project Coordinators “Dr.Ramesh Sengodan” and Git hub coordinator **Mr. Muthuraj.**

We thank our family and friends for the strong support and inspiration they have provided us in bringing out this project.

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CHAPTER-1

INTRODUCTION

1.1 AI and healthcare

Artificial Intelligence (AI) technology allows computers and robots to mimic human learning, understanding, creativity, problem-solving, autonomy, and decision-making. It is revolutionizing healthcare by facilitating more rapid and precise diagnosis, individualized treatment procedures, and better patient outcomes. Artificial intelligence (AI)-powered solutions will assess enormous volumes of medical information, identify patterns, and forecast potential issues, assisting in the early diagnosis of conditions like diabetes and Parkinson's. Additionally, AI renders healthcare more efficient and accessible by boosting developments in telemedicine, remote monitoring, and drug discovery.

1.1.1 Use cases of AI in healthcare:

The use of AI in healthcare is widespread and significant, improving many facets of patient care and medical procedures. Medical imaging is one of the primary use cases, where AI algorithms evaluate scans to increase the precision of diagnosis for diseases like cancer and pneumonia. Another major area is personalized treatment, where AI assesses patient data to suggest customized treatments based on medical and genetic histories. Furthermore, AI is essential for managing Electronic Health Records (EHRs), identifying healthcare fraud, and enabling remote patient care via chatbots and virtual assistants. These tools facilitate proactive monitoring of chronic illnesses, increase patient engagement, and accelerate administrative procedures. By examining enormous datasets to find patterns and forecast results, AI also advances medical research, clinical decision-making, and pandemic preparedness. In the end, it improves the effectiveness of healthcare delivery by supporting medicines discovery, early disease identification, and clinical trial optimization. Healthcare professionals may concentrate more on patient care thanks to AI's ability to automate documentation, solve staffing issues, and improve mental health monitoring. The healthcare sector is utilizing AI to provide better, quicker, and individualized care, which is increasing patient outcomes and overall operational efficiencies.[11]

2.1 AI in disease diagnosis

Artificial intelligence (AI) has shown itself to be a useful tool for diagnosing illnesses, helping doctors analyze medical imaging such as CT, MRI, and X-rays for quicker and more precise results. Through the processing of patient information, symptoms, and medical history, AI can help with future diagnosis. As this field develops, artificial intelligence (AI) is anticipated to find patterns in massive datasets, allowing for the combining of genetic, lifestyle, and environmental data to diagnose complicated illnesses and the prediction and prevention of disease before symptoms appear. Although AI improves diagnostic procedures, it should be used in conjunction with medical practitioners' knowledge to improve patient care rather than taking their place. For AI to be developed and used in healthcare responsibly, ethical issues, data protection, and ongoing validation are crucial.

2.1.1 Applications used for providing diagnosis

With developments such as Quantum AI (QAI) and General AI (GAI), which provide increased processing capacity and real-time analysis of large medical datasets for more accurate and effective diagnoses, the future of AI-based medical diagnostics appears bright. While GAI, through programs like DeepQA, Watson, and DeepMind, enables pattern identification and data correlation to enhance medical outcomes, quantum optimization algorithms may help determine the best course of therapy. [12]

3.1 AI in the detection of rare diseases

AI assists in the integration and analysis of diverse data. These systems have been utilized successfully over the years for a variety of well-known application cases.The use of these methods to rare diseases (RDs) is also valuable. Faster and more accurate diagnosis would be helpful for the RDs, which are referred to as orphan illnesses. In order to find new instances, algorithms have been developed and are currently being utilized to develop networks and store data from people with uncommon diseases. AI is a crucial diagnostic instrument for RDs as it could assist in genetic analysis, picture recognition, and clinical decision-making.

A mere five percent of the more than 7000 RDs that have been reported globally have a medical treatment. The difficulties faced by RDs can be addressed by utilizing AI technology' capacity to combine and evaluate data from many sources.

CHAPTER-2

LITERATURE SURVEY

2.1 Using AI, Diagnosis of Acute Diseases in Villages and Smaller Towns [3]

Proposed Scheme: There are a number of important steps in the systematic process of developing an AI-powered healthcare system. The system's objectives and scope must first be established, with an emphasis on certain issues such as disease detection, enhancing accessibility, or aiding medical professionals. Data collection, which includes compiling medical datasets while maintaining data privacy and regulatory compliance, is then essential. It is also necessary to describe the technological requirements, including scalability and AI model design. After choosing pertinent features from the data, the AI model is created, trained, and improved continuously. Essential elements like chat, login, and user pages are all part of a simple user interface that is made to make it easier for patients, healthcare providers, and the system to communicate. The system is then put through a rigorous testing and validation process to guarantee its accuracy in practical settings. System performance, user input, and data quality must all be constantly tracked for continuous improvements. Following continuous iterations to improve the AI model based on actual usage and performance data, the system's effect on patient outcomes and healthcare efficiency is finally evaluated.

A system's components, processes, and user interactions are all described in detail in the system design phase, which is a crucial stage in the development process. By covering both functional and technical elements, such as architecture, data structures, algorithms, and interfaces, it closes the gap between abstract concepts and implementation. System design provides a thorough roadmap that prioritizes work, maximizes resource allocation, and promotes effective development. This phase makes it possible for developers to plan ahead, predict problems, and come up with solutions, which guarantees a seamless transition from idea to reality and opens the door for a successful system or application.

Implementation details:

Intuitive Interface: Provide a user-friendly layout with intuitive navigation, eye-catching graphics, and thorough instructions.

Personalization: For user convenience, provide response regeneration, conversation management, and customized suggestions.

Medical care Suggestion: Offer the best available options for treatments while taking patient-specific characteristics, medication interactions, and best practices into account.

Easy access: Make sure it works with assistive technology and allows voice and text-based communication.

Patient Autonomy: Honor the rights and desires of the user without forcing judgments.

The outcomes of the research include increased productivity for healthcare providers by handling routine situations, reducing administrative work and data processing, improving diagnosis accuracy with accurate AI-driven insights, and improving time management.

Increased accessibility through remote help, financial savings through virtual consultations, patient empowerment through tailored health information, and timely resolution of common issues reduce wait times and exposure in medical facilities.

2.2 Diagnosis Of Acute Diseases In Villages And Smaller Towns Using AI [2]

Rural and underserved areas continue to face major barriers to accessing high-quality healthcare, which frequently leads to delayed diagnosis and worse health outcomes. The purpose of this research article is to examine how artificial intelligence (AI) can help address these inequities. In villages and small towns, it investigates how AI can improve the detection of acute diseases by analyzing previous research and literature. The results demonstrate how AI can revolutionize the delivery of accurate and easily accessible diagnostics to marginalized areas.

Methodology: A large dataset gathered from health information surveys was used to train the Support Vector Machines (SVM) and Decision Tree models used in the research technique. With a remarkable 91% accuracy rate, these models prove to be useful in the diagnosis of many illnesses. The system has a chatbot interface to enhance user engagement and guarantee accessibility in remote regions. The system's backend architecture uses the Flask framework to effortlessly combine chatbots and machine learning models, making it efficient and flexible. While the SVM model provides secondary analysis by combining other data, such as symptom duration, to produce severity scores, the Decision Tree Classifier delivers initial symptom-based predictions. In order to facilitate informed responses, information is loaded from CSV files during initialization, including symptom descriptions, severity rankings, and preventative measures. API endpoints that process user inputs, such as /predict and /svm1, provide comprehensive projections for the future descriptions of diseases, and suggestions. By allowing conversational symptom input and health assessments, the chatbot interface improves accessibility and makes the system easy to use, particularly for users in rural areas. The predictive disease analysis, severity evaluation, thorough disease information, and physician consultation assistance are some of the system's primary features. When the app is first launched, the machine learning models are loaded to guarantee prompt and precise predictions. Predictions are enhanced by aggregated data from CSV files, and user inputs are processed smoothly through POST requests. Prediction findings and additional data are included in the structured JSON answers that the system produces. The SVM and Decision Tree models work well together for initial health evaluations, with an accuracy rate of 91%. Enhancing user engagement and establishing the system as a trustworthy, easily accessible resource for directing users toward the right healthcare steps are two benefits of integrating the chatbot interface.

2.3 Artificial Intelligence (AI) in Rare Diseases: Is the Future Brighter? [10]

This review was conducted using PubMed's Entrez Programming Utilities (API) to search the Medline database using a mix of keywords associated with rare diseases (RDs), congenital disorders of glycosylation (CDG), artificial intelligence (AI), machine learning (ML), and neural networks. Using Biopython libraries, a Python script made the search easier. The results were narrowed down to the top twenty pertinent papers using MeSH terms, titles, and abstracts. Three rounds of screening were used in the selection process: (1) four researchers screened the articles based on their titles and abstracts, (2) the full-text reviews of the articles that met the selection criteria took place in the second round, and (3) two independent researchers performed a final round of full-text analysis to guarantee consistent selection criteria for the included manuscripts. The following criteria were used for inclusion and exclusion: We only took into consideration English-language manuscripts that included the full title, abstract, and MeSH terms. Articles that addressed the use of certain AI algorithms (or sets of algorithms) to solve RD-related issues were included.

Reviews, although some were presented for context, were not included; only RDs with Orpha codes from the Orphanet categorization were taken into consideration. The included reviews' references were additionally checked to make sure no pertinent papers were missed. Table 1 lists the AI- and ML-based techniques that were used in the chosen articles.

Table 1. List of available artificial intelligence (AI)- and machine learning (ML)-based methods used in rare diseases (RDs) organized by function.

General Function	Specific Function	Reference	Software/Platform/Algorithm	AI/ML Method	Disease(s)
Mutation Detection and Prediction	Predicts the pathogenicity/disease relevance of genetic variants	Alirezaie et al.	CADD **https://cadd.gs.washington.edu/**	SVM	Several RDs
			ClinPred **https://sites.google.com/site/clinpred/**	Ensemble classifier (RF and gradient boosting models)	
		Yan et al.	CNVdigest **https://github.com/yangxi1016/CNVdigest)**	DNorm (conditional random fields, stochastic gradient descent, pairwise learning to rank)	Digeorge syndrome
		Alirezaie et al.	Fathmm-MKL **http://fathmm.biocompute.org.uk/fathmmMKL.htm**	SVM based on multiple kernel learning	Several RDs
			GenoCanyon **http://genocanyon.med.yale.edu/**	Unsupervised statistical learning	
			M-CAP **http://bejerano.stanford.edu/mcap/**	Gradient boosting trees	
			MetaLR	Ensemble classifier	
			Meta-SVM	Meta-analytic SVM	
		Browne et al.	Meta-SNP **http://snps.biofold.org/meta-snp/**	RF	Mevalonic kinase deficiency
			nsSNP Analyzer **http://snpanalyzer.uthsc.edu/**	RF	
			PhD-SNP **http://snps.biofold.org/phd-snp/phd-snp.html**	SVM	

The diagnosis and prognosis of rare diseases (RDs) are being transformed by artificial intelligence (AI) and machine learning (ML) techniques that improve biochemical fingerprinting, phenotypic analysis, and mutation discovery. While SpliceAI and other deep learning frameworks evaluate cryptic splice mutations and noncoding variants, VEST and CliniPred employ machine learning (ML) to predict mutations that cause disease. Clinical data integration and phenotype-driven systems such as HANRD and eDiVA enhance variant prediction and disease gene prioritization. DeepGestalt and other imaging-based tools use facial recognition and neuroimaging to help diagnose RD, while biochemical techniques like infrared spectroscopy in conjunction with neural networks provide more affordable diagnostic options. AI is also improving prognostic modeling for diseases like synovial sarcoma, improving survival forecasts, and providing therapeutic advice for rare cancers and RDs.

2.4 Review of Artificial Intelligence Techniques in Imaging Data Acquisition, Segmentation, and Diagnosis for COVID-19 [4]

There are three primary steps in the imaging-based diagnosis workflow for COVID-19 using thoracic CT scans: image capture, pre-scan preparation, and disease diagnosis. As part of the pre-scan phase, technicians help patients position themselves in a certain way. The region from the apex to the base of the lung is covered by a single breath-hold CT scan during image collection. Following the optimization of parameters according to the patient's body shape, the raw data is converted into pictures and sent to Picture Archiving and Communication Systems (PACS) for diagnosis. By making imaging procedures safer, more precise, and more effective, artificial intelligence (AI) has completely transformed this conventional workflow. Specialized imaging platforms, lung and infection zone segmentation, clinical evaluations, and diagnostic tools are among the AI uses in COVID-19 imaging. Numerous commercial systems effectively incorporate AI to improve these procedures. During the COVID-19 pandemic, AI had a revolutionary effect on medical imaging, as evidenced by events like China's Medical Imaging Computing Seminar (MICS), which brought together academics and companies to exchange breakthroughs. This study tries to direct future research and applications while highlighting the vital role AI-powered medical imaging plays in the fight against COVID-19. It offers publicly accessible datasets to facilitate future developments and discusses intelligent imaging platforms and machine learning techniques for segmentation, diagnosis, and prognosis. The paper also discusses the difficulties and unresolved issues in the sector, providing useful information for radiologists and researchers to improve AI applications in medical imaging, especially when it comes to controlling pandemics like COVID-19.

Traditional imaging procedures have been revolutionized by AI-powered contactless imaging workflows, especially during the COVID-19 epidemic, as they minimize technician-patient contact and lower the danger of viral exposure. The intimate contact required for patient positioning in traditional procedures, including chest X-rays and CT scans, presents a serious risk of infection. With the use of sophisticated visual sensors like RGB, thermal cameras, and depth sensors, AI has made it possible to automate and contactless imaging procedures. These systems are capable of generating precise 3D patient models, identifying the anatomy of the patient, and estimating scanning parameters like scan range and ISO-centering. Access, efficiency, and safety have been further enhanced by mobile CT platforms with AI-based pre-scan and diagnosis tools, which separate personnel from patients and automate crucial processes like alignment and scanning. Furthermore, U-Net and its variations are examples of AI-powered segmentation approaches that have proven essential in locating lung regions and lesions in imaging data, enabling accurate diagnosis and therapy planning for COVID-19 and related illnesses. These developments show how AI is essential for improving imaging workflows and solving public health issues.

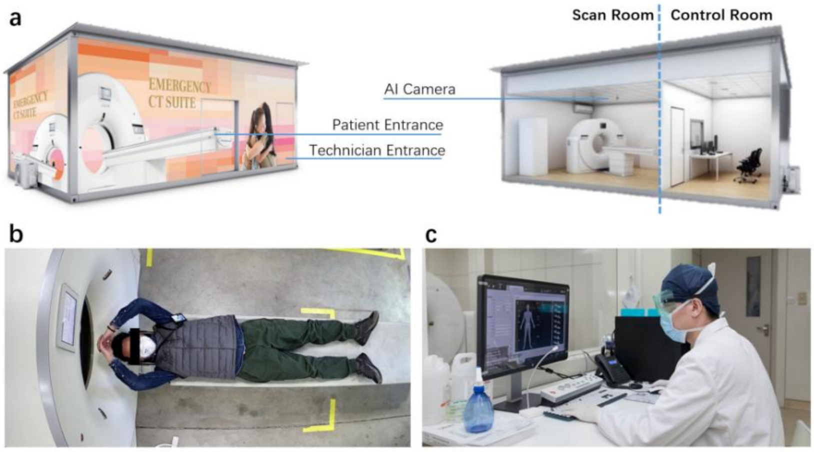


Fig. 1. (a) A mobile CT platform equipped with AI-empowered automated image acquisition workflow; (b) An example image captured by patient monitoring camera of CT system; (c) Positioning and scanning of patient operated remotely by a technician.

The patient is prompted to situate themselves on the patient bed both visually and audibly as soon as they enter the scan room. The patient can be observed through a window or through a live video feed from an AI camera positioned on the ceiling, and technicians can change the patient's posture as necessary. Using camera-captured photos, the patient positioning system creates a 3D posture and a completely reconstructed digital mesh of the patient after the technician or an AI-driven motion analysis algorithm has verified the patient's positioning. In order to provide control signals and optimum scanning settings for technician assessment, this 3D mesh is utilized to ascertain the scan range and the 3D centerline of the target body area. The patient bed is automatically positioned in the ISO center and transferred into the CT scanner after approval. After that, the CT scans are processed and examined for screening and diagnosis.

2.5 AI and Big Data: A New Paradigm for Decision Making in Healthcare

The responsibilities of doctors and nurses could be drastically changed by the introduction of artificial intelligence (AI) into healthcare. Medical professionals will keep an eye on AI-driven choices and processes in the future to protect patients and reduce hazards like statistical inaccuracies and uneven treatment results. Acute care AI systems need to give thorough information about the variables affecting their choices in order to do this. Medical education must move from traditional decision-making to contemporary time-pattern recognition in order to prepare doctors for AI oversight. Large amounts of varied and fast-moving data are produced by the healthcare industry from sources such as lab tests, biological pictures, medical records, and real-time health monitoring. Big data approaches have enormous promise to improve disease identification and treatment as well as healthcare efficiency. The use of big data in health informatics is being investigated by researchers more and more, especially in the areas of complex disease management and diagnosis. [5]

2.6 Harnessing AI for Early Detection of Cardiovascular Diseases: Insights from Predictive Models Using Patient Data

Introduction: Every year, cardiovascular diseases (CVDs) claim around 18 million lives, making them a major global health concern. Early detection of these "silent killers" can often be prevented by current diagnostic techniques, which postpones essential therapies. Nonetheless, developments in machine learning (ML) and artificial intelligence (AI) offer chances for early diagnosis, which could revolutionize healthcare by accurately forecasting cardiovascular events.

Background and Motivation: A substantial amount of death worldwide is caused by CVDs, which are made worse by variables including aging populations and bad lifestyles. Conventional diagnostic techniques frequently only identify illnesses when they are somewhat advanced. Through the integration of many data sources, AI can improve risk assessment and aid in the early detection and management of CVDs.

Methodology: Wearable technology, medical histories, and ECG readings were used to gather data. To increase predictive capability, key features were designed, and a number of machine learning models (ML) were created and verified, including random forests, support vector machines, and neural networks. Strong model performance was guaranteed by cross-validation and hyperparameter adjustment.

Data source	**Number of Records**	**Number of Features**	**Feature Types**
ECG Signal	50,000	15	Numerical (e.g. peak intervals)
Wearable Devices	60,000	10	Numerical (e.g. heart rate, activity levels)
Medical History	40,000	20	Categorical (e.g. family history, lifestyle factors)

Table 1: Summary of Data Characteristics for CVD Prediction Models

Data Type	Engineered Feature	Description
ECG Signal	Heart Rate Variability	Standard deviation of RR intervals
Wearable Devices	Activity Level Variance	Variance in step count over time
Medical History	Age-cholesterol Interaction	Interaction term between age and cholesterol

Table 2: Engineered Features for Predictive Modeling

Results: With a 92% accuracy rate, Gradient Boosting was the most successful model, followed by Support Vector Machines and Decision Trees. Age, blood pressure fluctuations, and cholesterol levels were identified as important predictors via feature significance analysis.

Model	Accuracy	Precision	Recall	F1 score
Support Vector Machine	86%	84%	85%	84.5%
Decision Tree	89%	87%	88%	87.5%
Gradient Boosting	92%	91%	90%	90.5%

Table 3: Performance metrics of Machine Learning models for CVD Prediction

By integrating a variety of data, AI has the potential to significantly improve early CVD prediction. In order to address ethical issues, test these models in practical situations, and broaden data sources for better healthcare outcomes, the findings support the need for more study. In order to lessen the burden of CVDs worldwide, proactive, tailored interventions powered by AI technology may be a part of the future of cardiovascular care. [6]

2.7 The Use of AI in Detecting Rare Diseases

This article examines how artificial intelligence (AI) can help with rare disease detection and treatment, which impact less than 1 in 2,000 people.

Difficulties with Diagnosis: Because rare diseases have a wide range of symptoms and a diagnostic process that might take five to thirty years, they frequently go undiagnosed. The lack of approved medicines for many diseases results in poor medical treatment.

AI's Role: Through the analysis of extensive datasets, symptoms, and genetic data, AI can improve diagnostic accuracy. The development of symptom-disease models with the aid of machine learning algorithms could speed up the diagnostic process.

Ethical challenges: The application of AI brings up ethical challenges, such as privacy concerns and biases in training datasets. AI has the potential to revolutionize the diagnosis of uncommon diseases, but its responsible and equitable application in healthcare requires addressing ethical issues.

Overall, the study highlights how AI has the ability to transform the detection and treatment of uncommon diseases while urging careful evaluation of the ethical ramifications.

CHAPTER-3

RESEARCH GAPS OF EXISTING METHODS

- Lower accuracy performance of the Support Vector Machine highlighted inverse complexity.
- The use of retrospective data and the biases present in electronic health records (EHRs) could affect how well these results generalize.
- AI models may inherit biases from training data, potentially leading to unequal treatment across different demographic groups. This makes ensuring fairness and transparency a challenge.
- Clinical deployment requires rigorous testing and validation in real-world settings to ensure reliability.
- Predictive models like Gradient Boosting can struggle with real-world accuracy due to overfitting or biased data.
- AI models in imaging require large, high-quality datasets, which can be challenging to obtain due to privacy and regulatory constraints.
- Reliance on AI can reduce physicians' independent decision-making, potentially leading to overdependence on technology.
- AI technologies can enhance efficiency and accuracy, they may lack the human touch and emotional understanding necessary for effective patient care. Human oversight ensures that patients receive compassionate care and have a trusted healthcare provider who can address their concerns and provide emotional support.

CHAPTER-4
PROPOSED METHODOLOGY

With the help of AI and machine learning techniques, a basic user interface (UI) made with HTML and CSS can be created that enables users to quickly submit their symptoms and obtain a medical diagnosis. Usually, this user interface consists of text fields for users to enter their symptoms, a button to submit the data, and a results section that shows the projected illness. To assess input symptoms and determine the most likely ailment, the system's backend utilizes machine learning algorithms like Random Forest Classifier and XGBoost. The Random Forest method builds multiple decision trees during training and averages their predictions. It categorizes patients as at risk or not for heart disease after dividing the dataset into training and testing groups. The model's performance is evaluated using accuracy, supporting early identification and preventive healthcare practices. For diabetes prediction, a dataset with features like age, BMI, and blood pressure, apart from many others, is used. After preprocessing, the data is split into training and testing sets. Random Forest constructs decision trees from various data subsets and combines their predictions. Model evaluation through accuracy helps medical professionals identify diabetes early and treat it effectively. XG Boost begins by loading and analyzing the parkinsons dataset, separating the labels (which indicate the condition of the disease) from the input data (which are features). It partitions the data into training (85%) and testing (15%) sets and scales the features for consistency. Using the training data, the model is trained to find patterns that may indicate Parkinson's disease. While accuracy is the program's primary statistic, it may also assess precision and recall for a more thorough performance study.

Because the interface is so simple, even people with little technological expertise can readily interact with the system. It is critical to address equity and reduce biases in AI algorithms and data as AI becomes more incorporated into healthcare. Particularly when it comes to underprivileged groups or uncommon diseases, bias in training data or algorithmic decision-making might produce discriminatory results. The objective is to make sure that training data is representative and varied, and that algorithms are routinely examined and tested to find and fix biases. Establishing moral guidelines and international laws is also necessary to guarantee the ethical and fair application of AI in healthcare. By focusing on data protection, patient permission, openness, and accountability, these policies should guarantee that AI tools serve physicians, benefit patients, and foster healthcare innovation without sacrificing safety or equity.

Dataset used for heart disease prediction: heart.csv

This dataset, which includes demographic data and a variety of health metrics, is associated with heart disease. The number of rows and columns is broken down below, along with a synopsis of each column.

Dataset Dimensions: Number of Rows: 303, Number of Columns: 14.

Columns Overview

Age: The individual's age, expressed in years. This is an ongoing variable that may affect the risk of heart disease.Sex: The individual's gender (1 = male, 0 = female). Understanding gender-related variations in the prevalence of heart disease is made easier by this categorical variable.Chest pain type, or CP, is a classification of the following types of chest pain:

0: Conventional angina

1. atypical angina
2. Pain that is not angina
3. No symptoms

Trestbps: The person's blood pressure at rest (measured in millimeter-Hg). An essential component of evaluating cardiovascular health is this continuous variable.

Chol: The amount of serum cholesterol (in milligrams per deciliter). One important heart disease risk factor is high cholesterol.

The fasting blood sugar level, or Fbs, is as follows: 1 = true if > 120 mg/dL, 0 = false. The existence of diabetes risk is indicated by this binary variable.

Results of a resting electrocardiogram, or "restecg," are divided into the following categories:

0: Normal

First, exhibiting aberrant ST-T waves

2. Exhibiting either clear or likely left ventricular hypertrophy Thalach (attained maximal heart rate): bpm, or the highest heart rate attained during activity. Greater values may be a sign of improved cardiovascular fitness. Exang, or exercise-induced angina, is a metric that indicates whether or not angina occurred during exercise (1 = yes, 0 = no). It is crucial to consider this binary variable when evaluating exercise tolerance.

Oldpeak: Exercise-induced ST depression compared to rest (a cardiac function metric). This constant may be a sign of ischemic heart disease.

Slope: The peak workout ST segment's slope, divided into the following categories: Upsloping (0), flat (1), and downsloping (2).

Ca, or the number of major vessels colored by fluoroscopy, is the total number of major vessels (0–3) that have undergone fluoroscopy coloring. This variable aids in determining how severe coronary artery disease is.

Thal (thalassemia): classification of thalassemia state, including:

1. Typical
2. Repaired flaw
3: Reversible flaw

The goal variable that indicates whether heart disease is present (1 = presence, 0 = absence) is the target variable. This dataset's main objective is to use the features offered to determine if a patient has heart disease or not. Numerous machine learning methods, including logistic regression, decision trees, Random Forest, and support vector machines, are commonly used to do this.

Dataset used for diabetes disease prediction: diabetes.csv

Predicting diabetes, particularly Type 2 diabetes, is a frequent use for this dataset. It includes a number of characteristics that are important for diabetes diagnosis and treatment, as well as an outcome variable that shows whether diabetes is present or not. There are 768 rows in the dataset, and each row represents a distinct patient. The dataset has eight columns, or characteristics, which are listed below:

Pregnancy: The number of pregnancies the patient has encountered. This characteristic can reveal hormonal shifts that impact glucose metabolism and serve in determining the risk for gestational diabetes.

Glucose: In an oral glucose tolerance test, measure the plasma glucose levels after two hours. Diabetes is mostly indicated by elevated glucose levels. The diagnosis of the illness depends on this measurement.

Blood Pressure: Diastolic blood pressure (mm Hg) is the blood pressure measurement.Diabetes is frequently linked to hypertension, which can raise the probability of complications.

SkinThickness: Skin fold thickness of the triceps (mm). Insulin resistance and body fat may be indirectly indicated by this parameter.

Serum insulin: 2-hour (mu U/ml). Insulin resistance and body fat may be indirectly indicated by this parameter.

BMI: Weight in kg/(height in m)^2 is the body mass index, or BMI. Body mass index is a key health factor for diabetes. Higher BMI values indicates obesity, which is directly correlated to the development of diabetes.

DiabetesPedigreeFunction: A function which utilizes family history to rate a person's risk of acquiring diabetes. This characteristic is crucial for comprehending familial risk factors since it measures the hereditary potential to develop diabetes.

Age: The patient's age in years.

With the use of the dataset, a Random Forest Classifier may be used to create a promising diabetes prediction model. A technique for ensemble learning called Random Forest builds many decision trees during training and outputs the individual trees' mode of categorization.

Dataset used for Parkinson’s disease prediction: parksinsons.data

The dataset you provide uses a variety of voice characteristics to identify Parkinson's illness. A participant's voice recording is represented by each row, and different metrics pertinent to voice and speech analysis are included in the columns.

Overview Columns for the Dataset Described

Column Name Description Name Recording identifier (phon_R01_S01_1, for example).

MDVP:Fo (Hz)Hertz is the unit of measurement for fundamental frequency (Fo).

The maximum frequency (Fhi) expressed in Hertz is MDVP:Fhi(Hz).

MDVP: Flo (Hz)Hertz for the minimum frequency (Flo).

MDVP: Jitter (%)A metric used to quantify frequency variability is jitter %.

MDVP: Abs jitterAbsolute jitter is a frequency stability metric.

MDVP: RAPAnother jitter metric is Relative Average Perturbation.

MDVP: PPQPerturbation of Pitch variability is measured by the quotient.

Jitter: DDPPitch perturbation differences to differences.

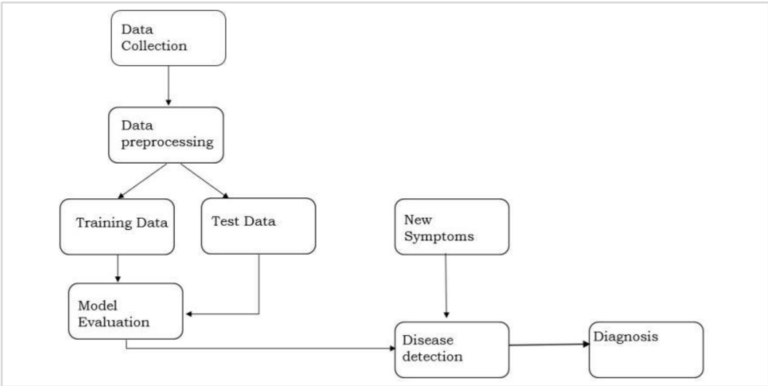
MDVP: ShineAmplitude variation in voice, indicating loudness stability.

MDVP:Shimmer(dB) Shimmer measured in decibels.

Shimmer:APQ3 Amplitude perturbation

MDVP:APQ (overall amplitude perturbation quotient); SHIMMER:DDA (difference of differences of amplitude perturbation); NHR (noise-to-harmonics ratio), HNR (harmonics-to-noise ratio), status label (presence (1) or absence (0) of Parkinson's disease); RPDE (recurrence period density entropy), a measure of signal complexity; DFA (detrended fluctuation analysis), a measure of signal variability; spread1 (spread of the first set of features); D2 (correlation dimension), a measure of fractal dimension; PPE (pitch period entropy), which indicates irregularity in pitch.

Architecture:



The initial phase of gathering relevant information is called data collection.The collected data is cleaned and prepared for analysis at the Data Preprocessing phase.Two preprocessed data sets exist: To train the model, training data is used and Test Data is used to evaluate how well the model performs. In the Model Evaluation phase,the model is assessed to determine its predictive accuracy after training. The New Symptom branch demonstrates the ability to add more symptoms for analysis to the system.By examining the input symptoms, the model determines potential illnesses in the Disease detection phase .The system's final output, "Generate Diagnosis," is a diagnosis based on the user-inputted symptoms and the condition that was found. A simplistic HTML and CSS user interface (UI) that allows users to rapidly input their symptoms and receive a medical diagnosis may be developed with the use of AI and machine learning algorithms.Flask is a web framework designed to be minimalistic. To make use of its characteristics, which include render_template for controlling HTML templates, the flask module must be manually imported. At the core of the Flask application is the doctor_app module, within which the app object is assembled. In a nutshell, Flask functions as this web application's foundation, handling HTTP requests, routing, and dynamically obtaining HTML templates. Considering this structure is scalable and adaptable implementing new routes or templates as the program broadens is effortless. Heart Disease Prediction: Based on the input dataset, the Python software makes predictions about heart disease using a machine learning model.The steps followed by the program are as follows:

1. Data Collection: The application uses `pd.read_csv('/content/heart.csv')` to read the heart disease dataset from a CSV file. The dataset is explored and understood using the

`hdata.head()`, `hdata.tail()`, `hdata.shape`, `hdata.info()`, `hdata.isnull().sum()`, and `hdata.describe()` methods.

2. Data Preprocessing: Using the formulas `X = hdata.drop(columns='target', axis=1)` and `Y = hdata['target']`, the software divides the dataset into features (X) and target variable (Y).

3. Training Data: `train_test_split(X, Y, test_size=0.2, random_state=42)` is used by the software to divide the dataset into training and testing sets.The machine learning model is trained using the training data (X_train, Y_train).

4. Test Data: The performance of the trained model is assessed using the testing data (X_test, Y_test).

5. Model Evaluation: The program creates a Random Forest Classifier model using `RandomForestClassifier(n_estimators=100, random_state=42)`.
   - The model is trained on the training data using `model.fit(X_train, Y_train)`.
   - The model's predictions on the test data are obtained using `Y_pred = model.predict(X_test)`.
   - The accuracy of the model is calculated using `accuracy_score(Y_test, Y_pred)`.

6. New Symptoms: The program creates a new input data point using `inputData = (75, 0, 2, 145, 233, 1, 0, 150, 0, 2.3, 0, 0, 1)`.The input data is converted to a numpy array and reshaped using `input_array_data = np.asarray(inputData)` and `input_data_reshaped = input_array_data.reshape(1, -1)`.

7. Disease Detection: The trained model is used to predict the class (0 or 1) for the new input data using `prediction = model.predict(input_data_reshaped)`

8. Diagnosis: If the prediction is 1, the program prints "The Person has a Heart Disease".If the prediction is 0, the program prints "The Person does not have Heart Disease".

The user interface displays to be an app for doctors called "Doctor App" and is separated into three main sections: Parkinson's Disease, Diabetes, and Heart Disease. The user can enter patient data, including age, cholesterol, resting blood pressure, and maximum heart rate, in the Heart Disease section, and the application will diagnose the patient with heart disease based on the information entered; in the Diabetes section, the user can enter the patient's BMI and glucose level, and the application will diagnose them with diabetes; in the Parkinson's Disease section, the user can enter the patient's MDVP:Fo(Hz) value, and the application will diagnose them with Parkinson's disease.

This Python program, which follows the architecture steps shown in the image, includes data collection, preprocessing, model training and evaluation, and prediction on new data. In summary, it shows how to use a Random Forest Classifier to predict the presence or absence of heart disease based on a given dataset.(Similarly for other diseases such as diabetes and parkinsons). Typically, this user interface includes text areas where users may enter their symptoms, a results section that displays the estimated sickness, and a button to submit the data. The backend of the system uses machine learning methods such as Random Forest Classifier and XGBoost to evaluate input symptoms and identify the most likely condition. During training, the Random Forest technique creates many decision trees and averages their forecasts. After splitting the dataset into training and testing groups, it classifies patients as either at risk or not for heart disease. Accuracy is used to assess the model's performance, which promotes early detection and preventative medical procedures. Among many other variables, a dataset containing blood pressure, age, and BMI is used to predict diabetes. The data is divided into training and testing sets following preprocessing. Using different data subsets, Random Forest builds decision trees and aggregates their forecasts. Accurate model evaluation aids in the early detection and efficient treatment of diabetes by medical experts. The Parkinson's dataset is loaded and analyzed using XG Boost, which then separates the input data (which are features) from the labels (which show the state of the disease). It scales the features for consistency and separates the data into training (85%) and testing (15%) groups. The model is trained to identify patterns that could point to Parkinson's disease using the training data. The program's main metric is accuracy, but for a more complete performance analysis, it may also evaluate precision and recall. Even those with less background in technology may easily engage with the system due to its user-friendly interface.

CHAPTER-5

OBJECTIVES

- **Precise Disease Prediction:** The software ought to accurately estimate the sickness or diseases the patient may have depending on the symptoms entered. Make use of complex models that have been trained on big datasets of patient symptoms and disease diagnoses, such as machine learning or expert systems. Both common and unusual diseases should be supported by the system.
- **Simple to Use Interface:** Patients and healthcare professionals should be able to enter symptoms into the software with ease owing to an intuitive interface. Create a straightforward and easy-to-use interface that either lets users enter free-text (symptom description). It should be possible to access the system from a variety of platforms, including desktop and mobile phones.
- **Constant Learning and Improvements:** Keep the software updated with the most recent medical research and changing disease trends, and make sure it learns from fresh data. Provide a way for the machine learning model to be updated and retrained on a regular basis using user input and freshly collected medical data.
- **Security of Data and Privacy:** In accordance with medical data protection laws, make sure patient data is handled with the utmost privacy and security. Protect sensitive health information by using secure data storage techniques.
- **Assistance in Diagnostics for Medical Professionals:** To give medical practitioners a decision support tool or diagnostic recommendations to help them. Make that the software is able to produce predictions along with supplementary data, like diagnostic standards or possible tests required for validation.
- **Adherence to Medical Standards:** Make that the system complies with national and international health regulations and medical diagnostic standards. Update the system periodically to reflect the most recent diagnostic standards, clinical recommendations, and methods for treatment.

By achieving these goals, the system will give patients and medical professionals a dependable and effective tool to aid in the diagnostic procedure. It is crucial to keep in mind that this software should be used as a supplementary aid in medical decision-making rather than as a substitute for a professional diagnosis.

CHAPTER-6

SYSTEM DESIGN & IMPLEMENTATION

DESIGN PROCEDURE

- Python libraries: numpy, pandas, matplotlib, seaborn, scaler
- Machine learning algorithms: Random Forest Classifier, XG Boost
- Pandas facilitates data analysis and manipulation, whereas NumPy effectively applies numerical operations on medical data.
- Medical data can be better understood by using data visualization tools like Matplotlib and Seaborn.
- Scalers ensure consistent scales for various properties and preprocess data.
- Medical data can be transformed into predictive models with machine learning techniques like decision trees and support vector machines.
- These algorithms are able to identify trends, learn from patient data, and accurately predict the diagnosis of diseases.
- Flask is a web-based tool that may be accessed via a browser instead of being a stand-alone desktop program. The application can be used by users from any web-browsing device, making deployment and accessibility simple.

IMPLEMENTATION

Several crucial phases are involved in the construction of the illness prediction program, which combines data collecting, processing, and prediction features. The system begins by creating an intuitive user interface, like a website, where users may enter their symptoms, specific health factors, and optional health information. The backend has programming that maps diseases patterns to indicators and other risk factors. When making predictions, a machine learning model or rule-based algorithm that has been trained on past medical data analyzes the inputs and suggests potential diagnoses along with probability levels. This project makes use of the Random Forest Classifier and XG Boost models. To assess input symptoms and determine the most likely disease, the system's backend employs machine learning techniques like XGBoost and Random Forest Classifier.The Random Forest method generates a large number of decision trees and averages their predictions. Patients are classified as either at risk or not for heart disease after the dataset has been divided into training and testing groups. In order to evaluate the model's effectiveness and encourage early identification and preventative medical measures, accuracy is utilized. To predict diabetes, a dataset comprising age, BMI, and blood pressure is utilized. Preprocessing is followed by the division of the data into training and testing sets. Random Forest constructs decision trees with various data subsets and aggregates their predictions. Precise model assessment facilitates the early identification and effective management of diabetes by health professionals.The Parkinson's dataset is loaded and analyzed using XG Boost, which then separates the input data (which are features) from the labels (which show the state of the disease). It scales the features for consistency and separates the data into training (85%) and testing (15%) groups. The model is trained to identify patterns that could point to Parkinson's disease using the training data. As a web-based utility that can be used through a browser rather than as a standalone desktop application, Flask makes deployment and accessibility easy because users may use the application from any web-browsing device.

CHAPTER-7
TIMELINE FOR EXECUTION OF PROJECT
(GANTT CHART)

DIAGNOSIS OF ACUTE DISEASES

ID	Task name	Start	Finish	2024				2025
				Sep	Oct	Nov	Dec	Jan
1	Title Selection	5/9/2024	8/9/2024					
2	Review 0	12/9/2024	18/9/2024					
3	Review 1	15/10/2024	21/10/2024					
4	Review 2	19/11/2024	21/11/2024					
5	Review 3	17/12/2024	19/12/2024					
6	Final Viva-Voce	10/1/2025	16/1/2025					

CHAPTER-8
OUTCOMES

A straightforward and simple interface created with HTML, CSS, and JavaScript was the project's end outcome. Through hyperlinks on the main page, users can enter conditions for heart disease, diabetes, and Parkinson's disease, and the results are anticipated based upon the symptoms they provide. The software assists patients get a hold of healthcare services, especially in underprivileged places like small towns or rural villages. By making remote access possible, it assures stable availability and promotes early disease detection, enhancing public health overall by lowering the need for critical, late-stage treatments. Cost-effectiveness is one key result, that keeps healthcare affordable for consumers and families. Early recognition eliminates the need for costly treatment options and inpatient stays by minimizing the progression of the disease. Individuals with minimum technical expertise are able to utilize the application. The interface's simplicity prompts users to actively participate in their health, thereby removing any hesitation or concerns regarding health care processes.

CHAPTER-9
RESULTS AND DISCUSSIONS

Several crucial steps are involved in developing a basic illness prediction program, including gathering user input, analyzing the data, and formulating predictions using a machine learning model or predetermined logic. In order to forecast possible acute illnesses, the created program efficiently collects and analyzes user input. Heart Diseases are predicted using the Random Forest classifier with an accuracy of 98.5%, after analyzing a dataset with 1025 entries. The program predicts diabetes with an accuracy of 87.6% using Random Forest, after analyzing a dataset of 768 entries. The program trained an XGBoost model by analyzing a dataset of 195 entries related to Parkinson's illness. The model produced largely accurate predictions, with an accuracy of 96.67%.

The program has several advantages.Through its straightforward interface, individuals without technical expertise can benefit from it. For critical situations, the prediction process' speed and near-real-time findings are crucial. Additionally, the software might be enhanced to incorporate new symptoms or diseases in order to maintain up with advances in medical science because it is scalable.

However, there are some constraints on the program. In difficult or uncommon situations, its accuracy may be hampered because of its dependence on the caliber of the data utilized for training or developing its prediction logic. Furthermore, it is simply a preliminary screening tool and oversimplifies multi-symptom diseases. It cannot replace a professional medical diagnosis. A few modifications are put forward for the future to deal with these kinds of problems. Using machine learning models might improve the precision and flexibility of predictions. Further, ethical concerns including safeguarding user privacy and minimizing biases in training data are crucial to the system's long-term reliability and trustworthiness.

The illness prediction program shows considerable potential as a leading-edge instrument that will enhance healthcare awareness and accessibility. Its fundamental architecture successfully blends sophisticated algorithms with user-friendly features to provide prompt and precise predictions depending on user inputs. Its capacity to facilitate early illness identification has been one of its biggest achievements. Treatment outcomes and implications can be significantly enhanced through early detection of conditions involving diabetes, heart disease, and Parkinson's. The program serves as a bridge for users who would be reluctant to seek emergency medical treatment because they lack the knowledge, time, or supports to go about so by making predictive insights readily available.

The software's ability to help in initial screening makes it a useful supplement tool in the healthcare ecosystem, even if it cannot replace expert medical guidance. Its contributions to public health research, health awareness, and early detection demonstrate its innovative potential to improve healthcare delivery and results globally. With further development, this instrument may establish itself as a key component in the fusion of technology and medicine, influencing a future in which easily available and customized healthcare is the norm.

CHAPTER-10
CONCLUSION

When creating software that predicts diseases using artificial intelligence (AI) and user-reported symptoms, it is important to understand that this tool should be used as an additional tool to support medical decision-making, not as a substitute for a professional diagnosis. The ability to precisely evaluate and handle vast amounts of data from multiple sources, such as patient histories, medical records, and symptom input, has been shown to be possible with AI technologies, especially those that use machine learning. In order to assist in identifying prevalent illnesses and anticipating future health problems, these technologies can swiftly spot patterns and correlations that human doctors could take longer to see. Although AI has the potential to improve medical diagnosis efficiency and accuracy, it is crucial to make sure that these systems are managed by humans. Furthermore, AI models are sometimes criticized for their lack of transparency, which means that they might not always articulate how they arrive at a specific diagnosis. This lack of clarity might make it difficult to trust and hold people accountable, particularly if a diagnosis or recommended course of treatment has unfavorable effects. Maintaining the explainability of AI decisions is essential for boosting system trust and giving medical professionals the knowledge they need to make wise choices. Furthermore, the ethical issues with AI in healthcare extend beyond issues of responsibility and transparency. The possibility of employment displacement is one problem, especially for medical professionals whose jobs could be automated by AI in the diagnostic process. Although AI can help medical personnel, there is a worry that technology may eliminate the need for human labor in some fields, which would change job trends and need retraining for impacted employees. Given the difficulties and moral dilemmas—such as accountability, transparency, and possible job displacement—AI-powered diagnostic software has a lot to offer the medical field. With its ability to analyze user-reported symptoms and suggest possible diseases, it can improve diagnostic speed and accuracy, especially in underprivileged areas with limited access to medical specialists. This can lessen the workload for healthcare professionals, freeing them up to concentrate on more complicated situations, prioritize care, and prioritize patients. Additionally, AI has the potential to continuously enhance its forecasts over time, improving health outcomes. In order to ensure ethical decision-making, the software should always be used under human supervision. However, it can empower patients to seek early medical attention, optimize resource allocation, and support healthcare professionals, all of which will improve overall healthcare delivery, efficiency, and accessibility.

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APPENDIX-A

PSUEDOCODE

1. Import required libraries:
   - Import necessary libraries for data handling, preprocessing, modeling, and evaluation.
2. Load Parkinson's dataset:
   - Load the dataset from the specified path.
3. Data Preprocessing:
   - Drop the 'name' column as it is not a feature.
   - Separate the dataset into features (X) and the target variable (y).
   - Normalize the feature data using MinMaxScaler to scale the values between -1 and 1
4. Split the dataset:
   - Split the data into training and testing sets (85% training, 15% testing).
5. Create and train the XGBoost model:
   - Create an XGBoost classifier model.
   - Fit the model to the training data.
6. Feature Importance Ranking:
   - Calculate the feature importance using the trained model.
   - Create a ranking of features based on importance.
   - Print the sorted feature importance.
7. Select top 4 important features:
   - Identify the top 4 most important features based on the ranking.
   - Create a new dataset using the selected features (including the target variable).
8. Split the dataset again:
   - Split the new dataset into training and testing sets.
9. Normalize selected features:
   - Apply MinMaxScaler to the selected features for normalization.
10. Retrain the model:
    - Fit the XGBoost model to the training data using the selected features.
11. Evaluate the Model:
    - Predict the target variable for the test data.
    - Calculate the accuracy of the model using accuracy_score.
12. User Input for Prediction:
    - Define a function to predict Parkinson's disease based on user input.

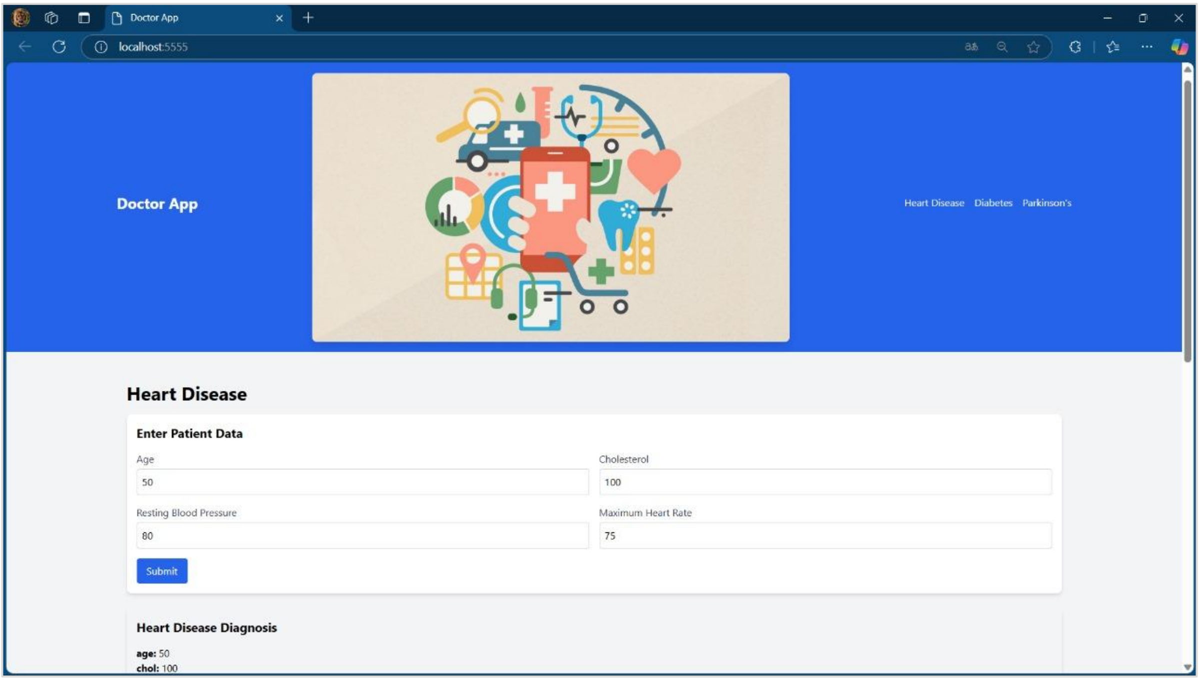
- The function scales the input data using the same scaler and returns a prediction of "Parkinson's" or "No Parkinson's" based on the model.

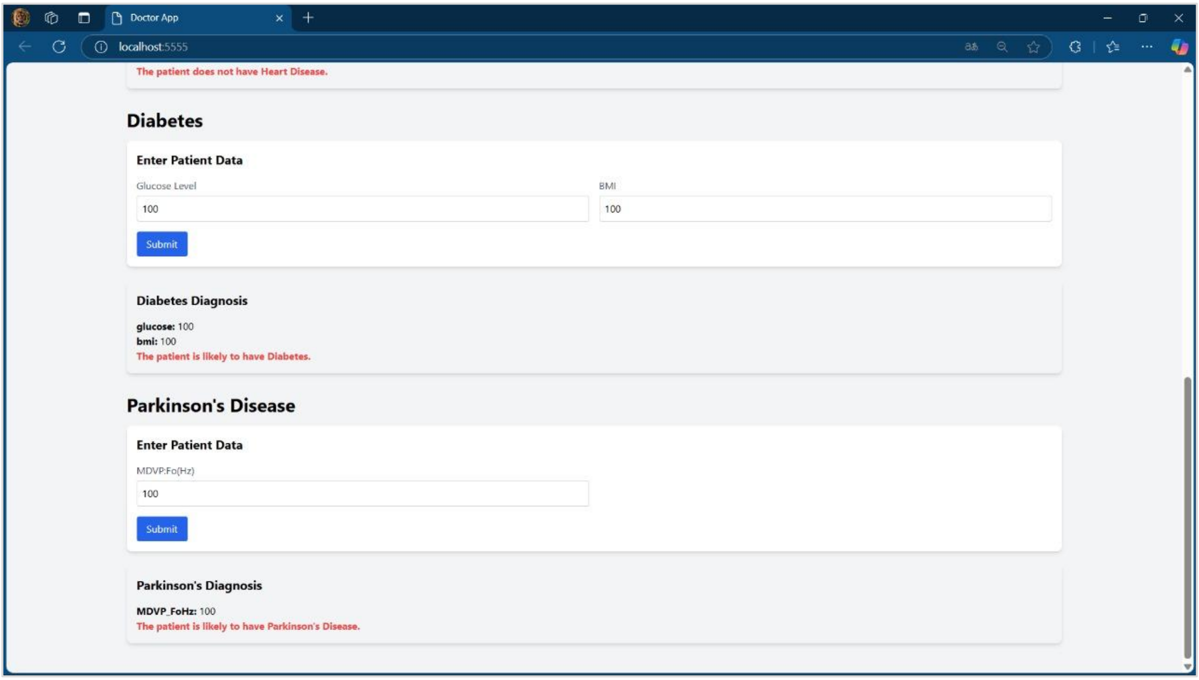
13. Get user input:
    - Prompt the user to input values for the top 4 important features.
14. Make a Prediction:
    - Call the prediction function with the user inputs and print the result.
15. End.

Similarly for other diseases.(Heart disease and Diabetes disease)

APPENDIX-B

SCREENSHOTS





APPENDIX-C

ENCLOSURES

1. International Journal of Innovative Research In Technology (IJIRT) has accepted and published the paper.

Reference number: IJIRT171936/Volume 11/Issue 8/

ISSN: 2349-6002 | ESTD Year: 2014 | Monthly Issue

International Journal of Innovative Research in Technology (IJIRT)

An International Scholarly Open Access, Peer-Reviewed Journal

Ref No: IJIRT171936/Volume 11/Issue 8/

Subject: Publication of paper at International Journal of Innovative Research in Technology

Dear Author,

With Greetings we are informing you that your paper has been successfully published in the International Journal of Innovative Research in Technology (ISSN: 2349-6002)

Following are the details regarding the published paper.

About IJIRT: An International Scholarly Open Access Journal, Peer-Reviewed, Refereed Journal Impact factor Calculated by Google Scholar and Semantic Scholar, AI-Powered Research Tool, Multidisciplinary, Monthly, Multilanguage Journal, Indexing in All Major Databases and Metadata, Citation Generator, Impact Factor 8.01, ISSN: 2349-6002

UGC Approval	: UGC and ISSN Approved - UGC Approved
Journal No	: 47859
Link	: https://www.ugc.ac.in/journallist/subjectwisejurnallist.aspx?tid=MjM0OTUxNjI=&&did=U2VhcmNoIGJ5IElTU04=
Paper ID	: IJIRT171936
Title of the Paper	: DIAGNOSIS OF ACUTE DISEASES IN VILLAGES AND SMALLER TOWNS USING AI
Impact Factor	: 7.367 (Calculated by Google Scholar)
Published In	: Volume 11, Issue 8
Publication Date	: 08-Jan-2025
Page No	: 1396-1405
Published URL	: https://ijirt.org/Article?manuscript=171936
Authors	: Shreya Ravi Kumar, Neha R, Sneha R

Thank you very much for publishing your article with IJIRT. We would appreciate if you continue your support and keep sharing your knowledge by writing for our journal IJIRT.

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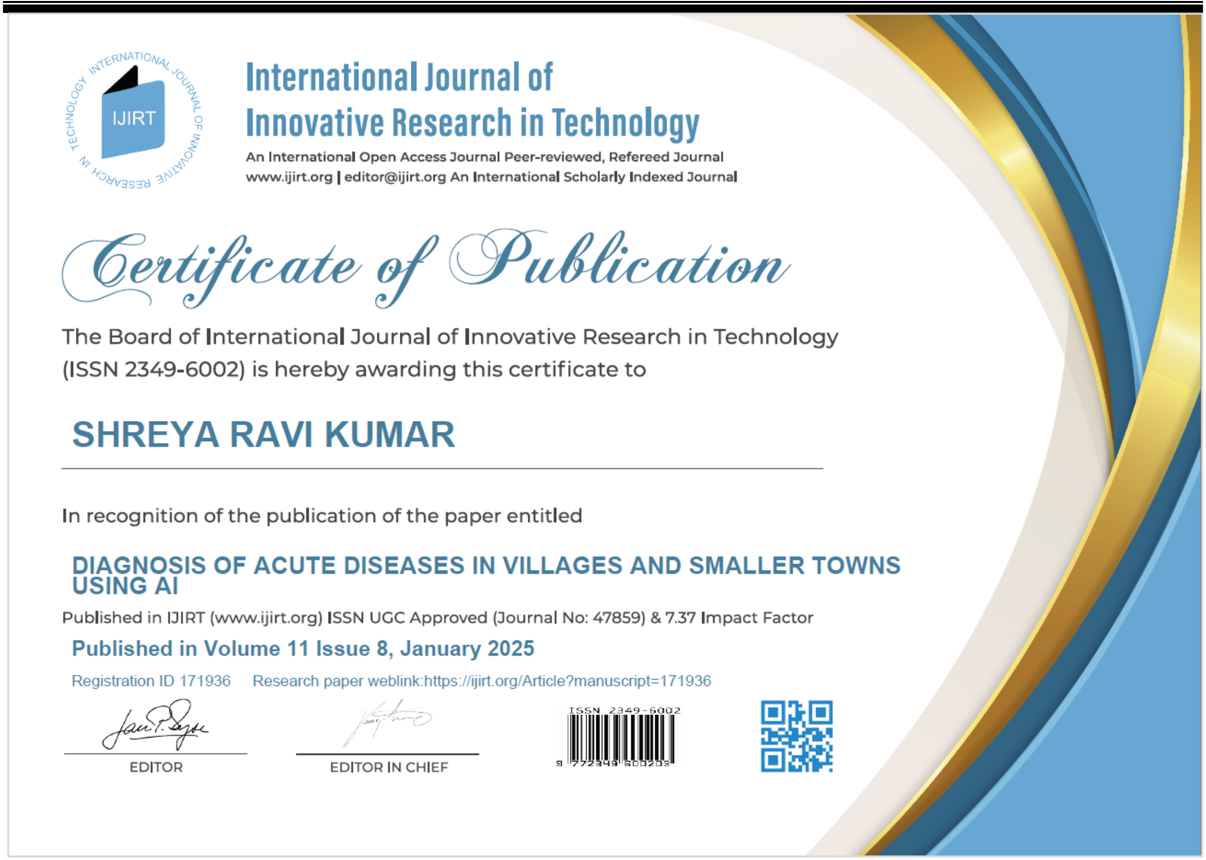

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Published in IJIRT (www.ijirt.org) ISSN UGC Approved (Journal No: 47859) & 7.37 Impact Factor

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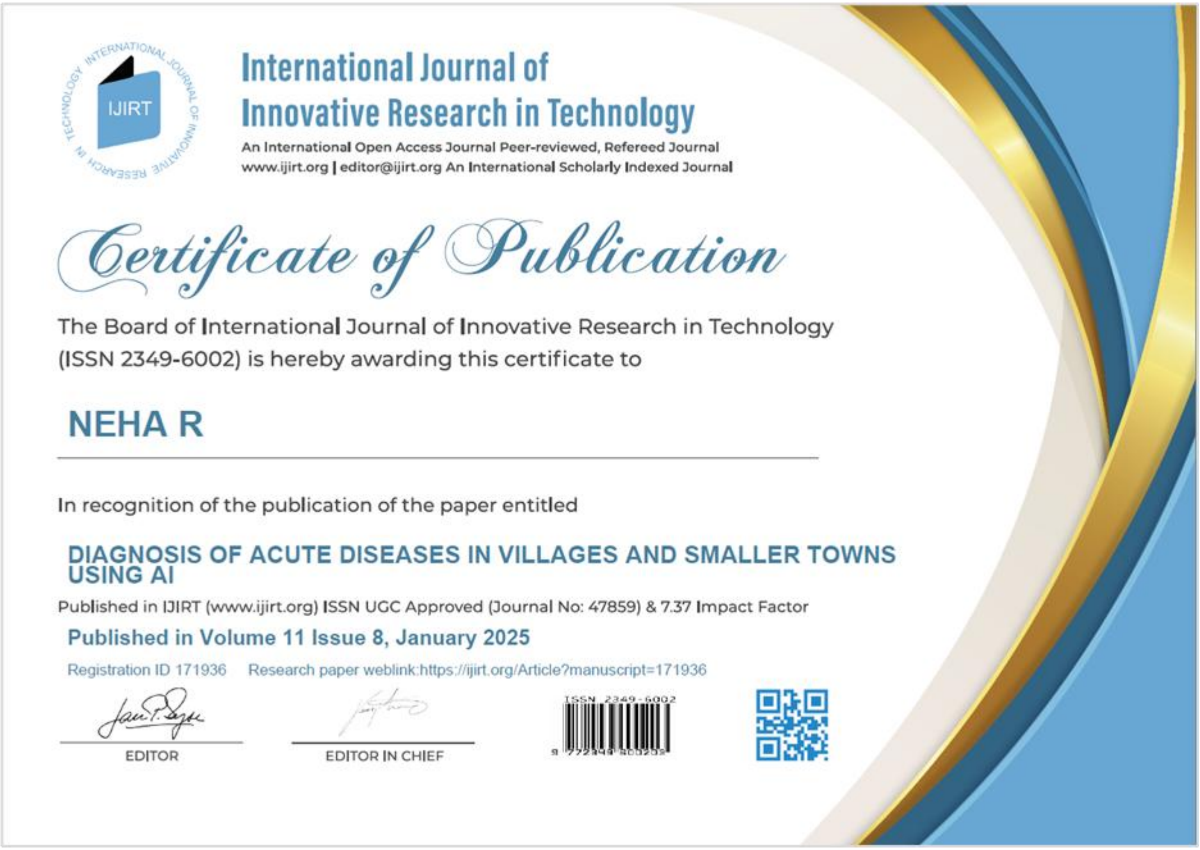

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ISSN 2349-6002

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Diagnosis of Acute Diseases in Villages and Smaller Towns Using AI

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Abstract*— Healthcare has changed as an effect of artificial intelligence's remarkable accuracy and efficiency in medical diagnostics. A technology named artificial intelligence (AI) lets computers along with additional machines to mimic human abilities such as understanding, problem-solving, innovative thinking, autonomy, and the decision-making process Applications and devices with AI capabilities possess the ability to recognize and understand objects. They are able to decode and give response to human speech. AI is transforming the way illnesses are recognized, evaluated, and treated, especially in the field of medical diagnostics. Using machine learning and deep learning algorithms, AI can swiftly and effectively understand enormous quantities of data, offering healthcare professionals insightful information. These developments not only increase the accuracy of diagnoses but also make it possible for early diagnosis and customized treatment plans. In the early days, AI was primarily employed for administrative duties, but its use has risen significantly. Massive quantities of data can now be accurately and quickly evaluated by AI and machine learning systems, which helps healthcare professionals make better decisions. Medical practice can be revolutionised by these technologies, which can interpret medical pictures, discover trends, and even predict the course of diseases. Access to effective healthcare is usually limited in neglected and rural areas, leading to mediocre health outcomes and delayed diagnosis. Existing ways of resolving this issue, such as telemedicine, have struggled to grow in parallel with growing demands for healthcare. According to this method, a system driven by artificial intelligence would be able to comprehend a large volume of medical data, identify symptoms, and converse with patients in order to find out about their medical concerns. The advent of advanced AI-powered technology and the growing popularity of smart assistants like Google and Alexa signal the beginning of an era of change in healthcare innovation.

***Indexed Terms*- Artificial intelligence., Random Forest Classifier, XGBoost,Disease Prediction, healthcare.**

I. INTRODUCTION

Artificial intelligence (AI) is the term used to define how computer systems may simulate human intellect, allowing computers to carry out activities like learning, reasoning, problem-solving, and sensory input interpretation that normally need human cognitive abilities. In a matter of minutes, artificial intelligence (AI) algorithms can sort through millions of patient information and medical photos, finding minute patterns that the human eye could overlook. AI in healthcare uses novel techniques like machine learning and deep learning to evaluate complicated medical data, helping with tasks like identifying anomalies in X-rays and CT scans, forecasting illnesses, and assisting with procedures. In the future, AI could help with diagnosis through analyzing patient data, symptoms, and medical history. Safety of data, moral concerns, and constant validation are vital for the effective development and application of AI in healthcare.

AI-based medical diagnostics seems to have a bright future because to advancements like Quantum AI (QAI) and General AI (GAI), which offer greater processing power and real-time analysis of massive medical datasets for more precise and efficient diagnosis.The optimum course of treatment may be determined by quantum optimization algorithms, even while GAI, through programs like DeepQA, Watson, and DeepMind, provides pattern discovery and data correlation to improve medical outcomes.It is also beneficial to use these techniques to identify rare diseases (RDs). For the RDs, also known as orphan diseases, a quicker and more precise diagnosis would be beneficial.Algorithms have been created and are being used to build networks and preserve data from individuals with rare medical conditions in order to discover new occurrences.Since AI has the potential to support genetic analysis, image identification, and

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clinical decision-making, it is an essential diagnostic tool for RDs.

Consider a piece of software that evaluates symptoms and makes recommendations for diagnosis and solutions.It could make it possible for you to monitor your development and practice self-care. This appears like an appropriate concept, especially in areas with limited access to medical care.Software made with the help of Artificial Intelligence can assist with preliminary health evaluations, but they should not be utilized in place of professional medical advice.It is advised to take the help of the software only as a diagnostic tool and not for further treatment.If the symptoms of a disease persists,it is better to seek the advice of a health professional.AI technologies have the potential to be useful reminders to prioritize your health and seek assistance when necessary.

II. RELATED WORK

2.1 Evaluation of artificial intelligence techniques in disease diagnosis and prediction

This article investigates how Artificial Intelligence specifically, Machine Learning (ML) and Deep Learning (DL can improve medical diagnoses by automatically analyzing medical imagery. It emphasizes how AI lowers medical burden, minimizes mistakes, and increases the precision of disease detection and prognosis.With a target on methods like Support Vector Machines (SVM) and Convolutional Neural Networks (CNN), the paper discusses numerous AI applications across a range of ailments, including cancer and cardiovascular problems.It also discusses issues like model complexity and data requirements, offering possible fixes like model compression and data augmentation.The document concludes that by enhancing patient outcomes and diagnostic precision, AI technologies have the potential to completely transform the healthcare industry. [1]

2.2 Diagnosis Of Acute Diseases In Villages And Smaller Towns Using AI

The research methodology with the use of Decision Tree and Support Vector Machine (SVM) models trained on a dataset gathered through health information questionnaires,achieves a high diagnostic accuracy of 91%.The Flask framework, upon which the system's backend is based, allows for the smooth integration of chatbots and machine learning models for improved user engagement, especially in rural regions.Based on user-entered symptoms, the Decision Tree model produces initial, fast predictions; the SVM model, on the other hand, improves predictions by determining severity scores and providing thorough disease descriptions, advice on precautions, and recommendations for consultation.While models are preloaded using the joblib library for efficiency, prediction data, including severity ratings and symptom descriptions, is dynamically loaded from CSV files.The solution, which can be accessed through API endpoints, makes healthcare advice more obvious and approachable by enabling users to enter symptoms and obtain health evaluations via a simple chatbot interface.[2]

2.3 Using AI, Diagnosis of Acute Diseases in Villages and Smaller Towns

This paper explains the methodology used in the construction of a software with a user friendly interface that allows users to communicate with the system and get updates about health through regular assessments.An AI-powered healthcare system designed methodically, beginning with the establishment of specific objectives, such as enhancing diagnosis, accessibility, or aiding medical professionals, and then detailing the features of the system.The data is collected from various medical datasets while making sure that the privacy laws are followed. Feature selection, training, validation, and repeated accuracy improvements are used to build the AI model. Effective connection between users and the system is ensured by an intuitive user interface that includes chat, sign-up, and login options. This is followed by testing across datasets and real world situations part of the validation process and observation of system performance,user input and data quality takes place.The impact of the system on healthcare outcomes is regularly assessed, and iterative improvements are made in response to insights gathered from practical implementation.[3]

2.4 Review of Artificial Intelligence Techniques in Imaging Data Acquisition, Segmentation and Diagnosis for COVID-19

The article explores whether medical imaging procedures can be enhanced through artificial

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intelligence (AI) with the objective to counter COVID-19. AI has been indispensable in automating imaging methods, ranging from CT and X-ray scans, which has lowered patient-provider interaction during the outbreak of the disease. It enables reliable information collection, segmentation, and diagnosis, which facilitates faster and more thorough lung infection observation and detection. Through the process of persistent and credible processing of imaging data, AI systems also assist in advantageous and clinical decision-making. The prerequisite for large, quality data sets and the chance of biases in algorithms are setbacks. This study underlines the possible uses of AI in boosting efficiency while pointing out the necessity of continuous innovation and extensive testing for practical application.

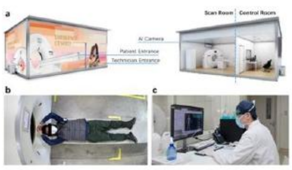

Fig. 1. (a) A mobile CT platform equipped with AI-empowered automated image acquisition workflow; (b) An example image captured by patient monitoring camera of CT system; (c) Positioning and scanning of patient operated remotely by a technician.

As they enter the scan room, patients are directed to lie down on the bed while being monitored over by live video feeds or cameras with artificial intelligence. In order to verify the scan range and body alignment, a 3D digital mesh of the patient is produced using camera images. This makes it possible for accurate bed arrangement and ideal scanning parameters, which the technician may check ahead to the CT scan commencing.[4]

2.5 AI and Big Data: A New Paradigm for Decision Making in Healthcare

The article discusses how new developments in big data and artificial intelligence (AI) have impacted healthcare decision-making, with an accent on the technologies' impact on policy, the require for modifications to medical education, and their incorporation into medical practices. The article discusses how new developments in big data and artificial intelligence (AI) have impacted healthcare decision-making, with an accent on the technologies' impact on policy, the require for modifications to medical education, and their incorporation into medical practices. Despite the challenges, integrating big data analytics is essential when enhancing healthcare delivery given that it offers opportunity for enhanced decision-making and system efficiency. In order to ensure accessibility and effectiveness, clinical decision support systems (CDSS), that implement a variety of AI algorithms for assisting healthcare providers make informed decisions, must be created together with professionals. Implementing AI can be challenging given communication gaps, reliance on AI that might decrease clinical knowledge, and the complicated nature of antibiotic resistance. While AI may be helpful in decision-making, it must be handled carefully to avoid making resistance problems more severe. Finally, while the use of AI in healthcare has a likelihood of substantially alter the tasks of healthcare workers, leveraging its benefits needs educational reforms along with a shift in medical decision-making toward knowledge of context and real-time data analysis.[5]

2.6 Harnessing AI for Early Detection of Cardiovascular Diseases: Insights from Predictive Models Using Patient Data

This study analyzes ways artificial intelligence (AI) could assist in the earlier detection of cardiovascular diseases (CVDs) through the review of patient data, that includes electrocardiograms (ECGs), wearable device data, and medical histories. Medical professionals might be able to give tailored treatments that improve patient outcomes by integrating AI into their field of practice. There are still concerns, though, particularly the mandate for rigorous clinical verification of AI models and tensions surrounding data privacy. The following research should center on developing these models making use of an assortment of datasets and addressing practical problems connected to adopting AI into medical interventions. The recognition and treatment of cardiac conditions could be entirely redesigned with AI, revealing up the possibilities to more assertive yet effective medical procedures.[6]

2.7 The Use of AI in Detecting Rare Diseases

This paper explores the role of Artificial Intelligence (AI) in detecting rare diseases.Rare diseases,also known as 'orphan diseases' impact only a small portion of a population,defined as the one that affects 1 in 2000 people.These diseases are known as orphan

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diseases because there are limited treatment for them in the medical industry.But, by evaluating many data sources to enable precise diagnosis and treatment planning, artificial intelligence (AI) breakthroughs are revolutionizing the identification of uncommon diseases.In addition to helping with drug efficacy studies and identifying genetic abnormalities, AI may improve clinical decision-making through machine learning and decision support systems.Case studies demonstrate the promise of AI by shortening diagnostic timeframes and improving accuracy, such as in diagnosing a kid with seizures or determining the genetic origins of developmental delays.It is interesting to note that an AI-powered pilot research in Israel increased diagnosis success rates from 46% to over 70%.The promise of AI to alleviate the diagnostic bottlenecks frequently found in uncommon diseases is highlighted by its speed, cost-effectiveness, and enhanced results, despite difficulties with staff training and integration with healthcare providers.[7]

2.8 Towards a Chatbot for Medical Diagnosis Based on Patient Symptoms

This study documented the number of crucial stages that were engaged in the process of creating the medical diagnosing chatbot. First, information was gathered from patient consultation records, with an emphasis on physician diagnoses, symptoms, and demographics for twelve disorders.After preprocessing to remove outliers and missing values, the data was divided into training and test sets for the purpose of training and assessing the model.Several machine learning techniques were used to build the prediction model, such as Random Forest, Extra Tree, and Logistic Regression.In order to evaluate the system's functionality, measures including F1 score, recall, accuracy, and precision were used. To create individualized medical reports and medications based on the anticipated ailments, the model was evaluated and then combined with a Llama2 conversational model.[8]

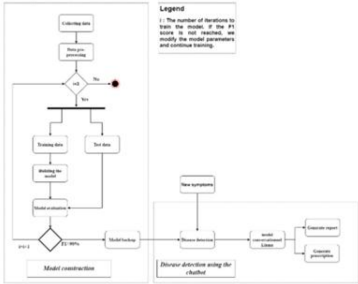

Figure 1. *Methodology flowcard.*

Figure 2. *Conversation between the doctor and the bot*

Figure 3. *Predicted disease and generation of the report*

2.9 Technical Aspects of Developing Chatbots for Medical Applications: Scoping Review

The purpose of this brief study was to investigate the development approaches and technological features of chatbots in the medical domain.The authors found 45 papers that satisfied their inclusion criteria after conducting a thorough search across eight literature databases.The evaluation concentrated on chatbots with text input and output that were made for medical purposes.Text comprehension, dialogue management, database layers, and text production modules were among the technological components that were employed to categorize chatbots using a narrative synthesis.The analysis found that while machine learning techniques were less prevalent, the majority of chatbots (40%) depended on pattern matching techniques to comprehend text.English was the primary medium of communication, and apps related to general and mental health received a lot of attention.The four primary parts of the chatbots were usually a text generating module, a data management layer, a dialogue management module, and a text understanding module.Although chatbots are becoming more and more common in the healthcare industry, the analysis comes to the conclusion that further research is required to improve their efficacy in medical applications and connect development methods with clinical outcomes.[9]

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2.10 Artificial Intelligence (AI) in Rare Diseases: Is the Future Brighter

This paper examines how AI may be used to solve the particular problems presented by rare diseases (RDs), which cumulatively impact millions of people worldwide.Since there are over 7000 RDs known to exist and only 5% of them have medical treatments accessible, creative solutions are desperately needed.Clinical trials, medication development, diagnostics, and other fields are using AI technology, especially deep learning.By improving illness categorization, facilitating medication repurposing, and improving mutation discovery, these techniques eventually seek to accelerate the treatment development process for RDs.The article highlights particular uses of AI in congenital diseases of glycosylation (CDG), including programs such as the Rare Disease Auxiliary Diagnosis (RDAD) system for diagnosis prioritization and Face2Gene for face analysis.The complexity of RDs and the lack of data are major obstacles to the field's adoption of AI, regardless of the encouraging developments.To guarantee that impacted patients have fair access to these technologies, the authors address ethical and practical issues while promoting more research into AI's potential to enhance diagnosis and treatment choices.[10]

2.11 AI in healthcare: Use cases, applications, benefits, solution, AI agents and implementation

The control of large datasets, treatment of patients, and administrative efficiency are only a few of the many issues facing the healthcare sector. A groundbreaking approach that optimizes the caliber, effectiveness, and usability of healthcare services is artificial intelligence (AI). The worldwide AI healthcare industry is predicted to increase from USD 15.1 billion in 2022 to over USD 187.95 billion by 2030. AI delivers assistance in early illness detection, individualized treatment plans, and operational optimization through examination of vast data sets. AI has impacted the healthcare industry with numerous significant applications. The creation of defined goals, preservation of good data quality, which includes all relevant parties, and dealing with ethical problems relating to discrimination and privacy are all worthwhile for the seamless integration of AI in healthcare. [11]

2.12 Perspective of Artificial Intelligence in Disease Diagnosis: A Review of Current and Future Endeavours in the Medical Field

The article speaks of artificial intelligence's (AI) capability to perform ailment diagnosis. Medical visuals such as MRIs and X-rays are currently being evaluated using AI technology, leading to a quicker and more precise diagnosis. In addition, they examine patient data along with symptoms to help professionals reach more informed decisions. As AI evolves, it could be able to detect patterns in vast volumes of medical data and possibly even foresee illnesses before symptoms show up. For dentists, AI-based solutions such as Dragon Ambient Experience (DAX) simplify documentation and alleviate stress. The two primary forms of artificial intelligence (AI) are machine learning (ML) and expert systems. Expert systems have limitations in terms of performance and information accumulation, but they rely on an inference engine and a knowledge base to generate predictions and options. ML, on the contrary hand, is vital to AI and is dependent upon huge datasets for training in order to advance computer intelligence.[12]

III. METHODOLOGY

3.1 Tools and technologies

In medical data analysis and machine learning, Python libraries like NumPy, Pandas, Matplotlib, Seaborn, and Scalers are essential.Pandas makes data analysis and manipulation easier, and NumPy effectively manages numerical operations on medical information.Complex medical data is easier to grasp with the use of data visualization tools like Seaborn and Matplotlib.Scalers are necessary for preparing data and guaranteeing uniform scales for different properties. XGBoost and Random Forest Classifier are two examples of machine learning algorithms that turn medical data into predictive models, recognizing patterns, learning from patient data, and correctly diagnosing illnesses.

Dataset used for heart disease prediction: heart.csv

This dataset, which includes demographic data and a variety of health metrics, is associated with heart disease. The number of rows and columns is broken down below, along with a synopsis of each column.

Dataset Dimensions: Number of Rows: 303, Number of Columns: 14.

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Columns Overview

Age: The individual's age, expressed in years. This is an ongoing variable that may affect the risk of heart disease.Sex: The individual's gender (1 = male, 0 = female). Understanding gender-related variations in the prevalence of heart disease is made easier by this categorical variable.Chest pain type, or CP, is a classification of the following types of chest pain:

0: Conventional angina
1. atypical angina
2. Pain that is not angina
3. No symptoms

Trestbps: The person's blood pressure at rest (measured in millimeter-Hg). An essential component of evaluating cardiovascular health is this continuous variable.

Chol: The amount of serum cholesterol (in milligrams per deciliter). One important heart disease risk factor is high cholesterol.

The fasting blood sugar level, or Fbs, is as follows: 1 = true if > 120 mg/dL, 0 = false. The existence of diabetes risk is indicated by this binary variable.

Results of a resting electrocardiogram, or "restecg," are divided into the following categories:

0: Normal

First, exhibiting aberrant ST-T waves

2. Exhibiting either clear or likely left ventricular hypertrophy Thalach (attained maximal heart rate): bpm, or the highest heart rate attained during activity. Greater values may be a sign of improved cardiovascular fitness. Exang, or exercise-induced angina, is a metric that indicates whether or not angina occurred during exercise (1 = yes, 0 = no). It is crucial to consider this binary variable when evaluating exercise tolerance.

Oldpeak: Exercise-induced ST depression compared to rest (a cardiac function metric). This constant may be a sign of ischemic heart disease.

Slope: The peak workout ST segment's slope, divided into the following categories: Upsloping (0), flat (1), and downsloping (2).

Ca, or the number of major vessels colored by fluoroscopy, is the total number of major vessels (0–3) that have undergone fluoroscopy coloring. This variable aids in determining how severe coronary artery disease is.

Thal (thalassemia): classification of thalassemia state, including:

1. Typical
2. Repaired flaw
3: Reversible flaw

The goal variable that indicates whether heart disease is present (1 = presence, 0 = absence) is the target variable. This dataset's main objective is to use the features offered to determine if a patient has heart disease or not. Numerous machine learning methods, including logistic regression, decision trees, Random Forest, and support vector machines, are commonly used to do this.

Dataset used for diabetes disease prediction: diabetes.csv

Predicting diabetes, particularly Type 2 diabetes, is a frequent use for this dataset. It includes a number of characteristics that are important for diabetes diagnosis and treatment, as well as an outcome variable that shows whether diabetes is present or not. There are 768 rows in the dataset, and each row represents a distinct patient. The dataset has eight columns, or characteristics, which are listed below:

Pregnancy: The number of pregnancies the patient has encountered. This characteristic can reveal hormonal shifts that impact glucose metabolism and serve in determining the risk for gestational diabetes.

Glucose: In an oral glucose tolerance test, measure the plasma glucose levels after two hours. Diabetes is mostly indicated by elevated glucose levels. The diagnosis of the illness depends on this measurement.

Blood Pressure: Diastolic blood pressure (mm Hg) is the blood pressure measurement.Diabetes is frequently linked to hypertension, which can raise the probability of complications.

SkinThickness: Skin fold thickness of the triceps (mm). Insulin resistance and body fat may be indirectly indicated by this parameter.

Serum insulin: 2-hour (mu U/ml). Insulin resistance and body fat may be indirectly indicated by this parameter.

BMI: Weight in kg/(height in m)^2 is the body mass index, or BMI. Body mass index is a key health factor for diabetes. Higher BMI values indicates obesity, which is directly correlated to the development of diabetes.

DiabetesPedigreeFunction: A function which utilizes family history to rate a person's risk of acquiring

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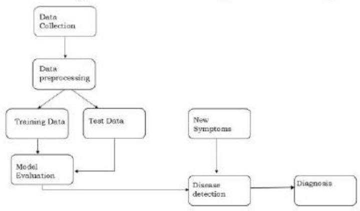
diabetes. This characteristic is crucial for comprehending familial risk factors since it measures the hereditary potential to develop diabetes.
Age: The patient's age in years.
With the use of the dataset, a Random Forest Classifier may be used to create a promising diabetes prediction model. A technique for ensemble learning called Random Forest builds many decision trees during training and outputs the individual trees' mode of categorization.
Dataset used for Parkinson's disease prediction: parksinsons.data
The dataset you provide uses a variety of voice characteristics to identify Parkinson's illness. A participant's voice recording is represented by each row, and different metrics pertinent to voice and speech analysis are included in the columns.

Overview Columns for the Dataset Described Column Name Description Name Recording identifier (phon_R01_S01_1, for example).
MDVP:Fo (Hz)Hertz is the unit of measurement for fundamental frequency (Fo).
The maximum frequency (Fhi) expressed in Hertz is MDVP:Fhi(Hz).
MDVP: Flo (Hz)Hertz for the minimum frequency (Flo).
MDVP: Jitter (%)A metric used to quantify frequency variability is jitter %.
MDVP: Abs jitterAbsolute jitter is a frequency stability metric.
MDVP: RAPAnother jitter metric is Relative Average Perturbation.
MDVP: PPQPerturbation of Pitch variability is measured by the quotient.
Jitter: DDPPitch perturbation differences to differences.
MDVP: ShineAmplitude variation in voice, indicating loudness stability.
MDVP:Shimmer(dB) Shimmer measured in decibels.
Shimmer:APQ3 Amplitude perturbation
MDVP:APQ (overall amplitude perturbation quotient); SHIMMER:DDA (difference of differences of amplitude perturbation); NHR (noise-to-harmonics ratio), HNR (harmonics-to-noise ratio), status label (presence (1) or absence (0) of Parkinson's disease); RPDE (recurrence period density entropy), a measure of signal complexity; DFA (detrended fluctuation analysis), a measure of signal variability; spread1 (spread of the first set of features); D2 (correlation dimension), a measure of fractal dimension; PPE (pitch period entropy), which indicates irregularity in pitch.

3.1 Architecture

The initial phase of gathering relevant information is called data collection.The collected data is cleaned and prepared for analysis at the Data Preprocessing phase.Two preprocessed data sets exist: To train the model, training data is used and Test Data is used to evaluate how well the model performs. In the Model Evaluation phase,the model is assessed to determine its predictive accuracy after training.



The New Symptom branch demonstrates the ability to add more symptoms for analysis to the system.By examining the input symptoms, the model determines potential illnesses in the Disease detection phase .The system's final output, "Generate Diagnosis," is a diagnosis based on the user-inputted symptoms and the condition that was found.

Heart Disease Prediction: Based on the input dataset, the Python software makes predictions about heart disease using a machine learning model.The steps followed by the program are as follows:
1.Data Collection:The application uses `pd.read_csv('/content/heart.csv')` to read the heart disease dataset from a CSV file.The dataset is explored and understood using the `hdata.head()`, `hdata.tail()`, `hdata.shape`, `hdata.info()`, `hdata.isnull().sum()`, and `hdata.describe()` methods.
2.Data Preprocessing:Using the formulas `X = hdata.drop(columns='target', axis=1)` and `Y = hdata['target']`, the software divides the dataset into features (X) and target variable (Y).
3.Training Data:`train_test_split(X, Y, test_size=0.2, random_state=42)` is used by the software to divide the dataset into training and testing sets.The machine

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learning model is trained using the training data (X_train, Y_train).
4.Test Data: The performance of the trained model is assessed using the testing data (X_test, Y_test).
5.Model Evaluation:The program creates a Random Forest Classifiermodelusing `RandomForestClassifier(n_estimators=100, random_state=42)`.
- The model is trained on the training data using `model.fit(X_train, Y_train)`.
- The model's predictions on the test data are obtained using `Y_pred = model.predict(X_test)`.
- The accuracy of the model is calculated using `accuracy_score(Y_test, Y_pred)`.
6.New Symptoms:The program creates a new input data point using `inputData = (75, 0, 2, 145, 233, 1, 0, 150, 0, 2.3, 0, 0, 1)`.The input data is converted to a numpy array and reshaped using `input_array_data = np.asarray(inputData)` and `input_data_reshaped = input_array_data.reshape(1, -1)`.
7.Disease Detection: The trained model is used to predict the class (0 or 1) for the new input data using `prediction = model.predict(input_data_reshaped)`
8.Diagnosis: If the prediction is 1, the program prints "The Person has a Heart Disease".If the prediction is 0, the program prints "The Person does not have Heart Disease".

This Python program, which follows the architecture steps shown in the image, includes data collection, preprocessing, model training and evaluation, and prediction on new data. In summary, it shows how to use a Random Forest Classifier to predict the presence or absence of heart disease based on a given dataset.(Similarly for other diseases such as diabetes and parkinsons).

A simplistic HTML and CSS user interface (UI) that allows users to rapidly input their symptoms and receive a medical diagnosis may be developed with the use of AI and machine learning algorithms.

Typically, this user interface includes text areas where users may enter their symptoms, a results section that displays the estimated sickness, and a button to submit the data. The backend of the system uses machine learning methods such as Random Forest Classifier and XGBoost to evaluate input symptoms and identify the most likely condition. During training, the Random Forest technique creates many decision trees and averages their forecasts. After splitting the dataset into training and testing groups, it classifies patients as either at risk or not for heart disease. Accuracy is used to assess the model's performance, which promotes early detection and preventative medical procedures. Among many other variables, a dataset containing blood pressure, age, and BMI is used to predict diabetes. The data is divided into training and testing sets following preprocessing. Using different data subsets, Random Forest builds decision trees and aggregates their forecasts. Accurate model evaluation aids in the early detection and efficient treatment of diabetes by medical experts. The Parkinson's dataset is loaded and analyzed using XG Boost, which then separates the input data (which are features) from the labels (which show the state of the disease). It scales the features for consistency and separates the data into training (85%) and testing (15%) groups. The model is trained to identify patterns that could point to Parkinson's disease using the training data. The program's main metric is accuracy, but for a more complete performance analysis, it may also evaluate precision and recall.
Even those with less background in technology may easily engage with the system due to its user-friendly interface.

IV. RESULTS

4.1 Model Performance

Creating a simple sickness prediction program involves a number of important tasks, such as collecting user input, evaluating the data, and creating predictions using a machine learning model or preset logic. Effectively gathering and analyzing user input, the developed algorithm predicts potential acute diseases. Using a dataset with 1025 items, the Random Forest classifier predicts heart diseases with a 98.5% accuracy rate. The algorithm analyzes a dataset of 768 items and uses Random Forest to predict diabetes with an accuracy of 87.6%. In order to train an XGBoost model, the computer examined a dataset of 195 items pertaining to Parkinson's disease. The model's 96.67% accuracy rate resulted in predictions that were mostly correct.

The user-friendly interface makes it accessible to those without technical knowledge. The speed and near-real-

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time results of the prediction process are important for critical scenarios. Additionally, because the program is scalable, it may be improved to include new illnesses or symptoms in order to keep up with developments in medical research.

4.2 Limitations

Due to its reliance on the quality of the data used to train or improve its prediction logic, its accuracy may be limited in challenging or unusual scenarios. Moreover, it oversimplifies disorders with many symptoms and is only a preliminary screening tool. A qualified medical diagnosis cannot be substituted by it. To address these kind of issues, a few changes are proposed for the future. Prediction accuracy and adaptability might be increased by using machine learning models. Furthermore, the long-term dependability and credibility of the system depend heavily on ethical considerations including protecting user privacy and reducing biases in training data.

V. DISCUSSION

Using robust machine learning models trained on an extensive set of patient symptoms and diagnoses, the software could smoothly forecast possible diseases based on provided symptoms.The program's intuitive design is what makes it simple for patients and medical practitioners to share symptoms, either as structured inputs or free-text descriptions. It must demonstrate predictions combined with other data, such as diagnostic criteria and advisable tests for confirmation, to assist medical practitioners in making decisions or making diagnostic suggestions.This supports informed dependable medical judgments. Assess that the system corresponds with medical diagnostic standards and national and international health rules and regulations.making choices based on ethics. In order to incorporate the most current clinical advice, diagnostic criteria, and treatment approaches, the model has to be updated on a periodic basis.

CONCLUSION

When implementing software which employs artificial intelligence (AI) and user-reported symptoms to anticipate illnesses, it's essential to remember that this tool should be used as a complement to medical decision-making, not as a replacement for a professional diagnosis. It has been seen that artificial intelligence systems, specifically those incorporating machine learning, can reliably assess and manage massive amounts of data from numerous sources, including patient histories, medical records, and symptom data. These technologies may frantically discover patterns and connections that human doctors might take longer to identify, which can help diagnose widespread illnesses and foretell potential illnesses. Furthermore though AI has the ability to increase the effectiveness and precision of medical diagnostic services it is indispensable that these systems remain managed by other individuals. Additionally, AI models have been criticized for inadequate transparency, which suggests that they could possibly not always articulate how they achieve a certain diagnosis. This dichotomy might make it tricky to trust and hold people responsible, especially if a diagnosis or recommended treatment has side effects. The medical field could really benefit much from artificial intelligence-based diagnostic applications, regardless the challenges and moral questions it brings, including accountability, transparency, and probable job displacement. The possibility to gauge symptoms reported by users and lay out prospective diseases could potentially improve the speed as well as accuracy of diagnosis, especially in financially impoverished regions wherein access to medical personnel is hindered. As this occurs, hospital employees could have less work to attend to, which will allow them to devote their time to more complex cases, prioritize patient care, and adhere to treatment.

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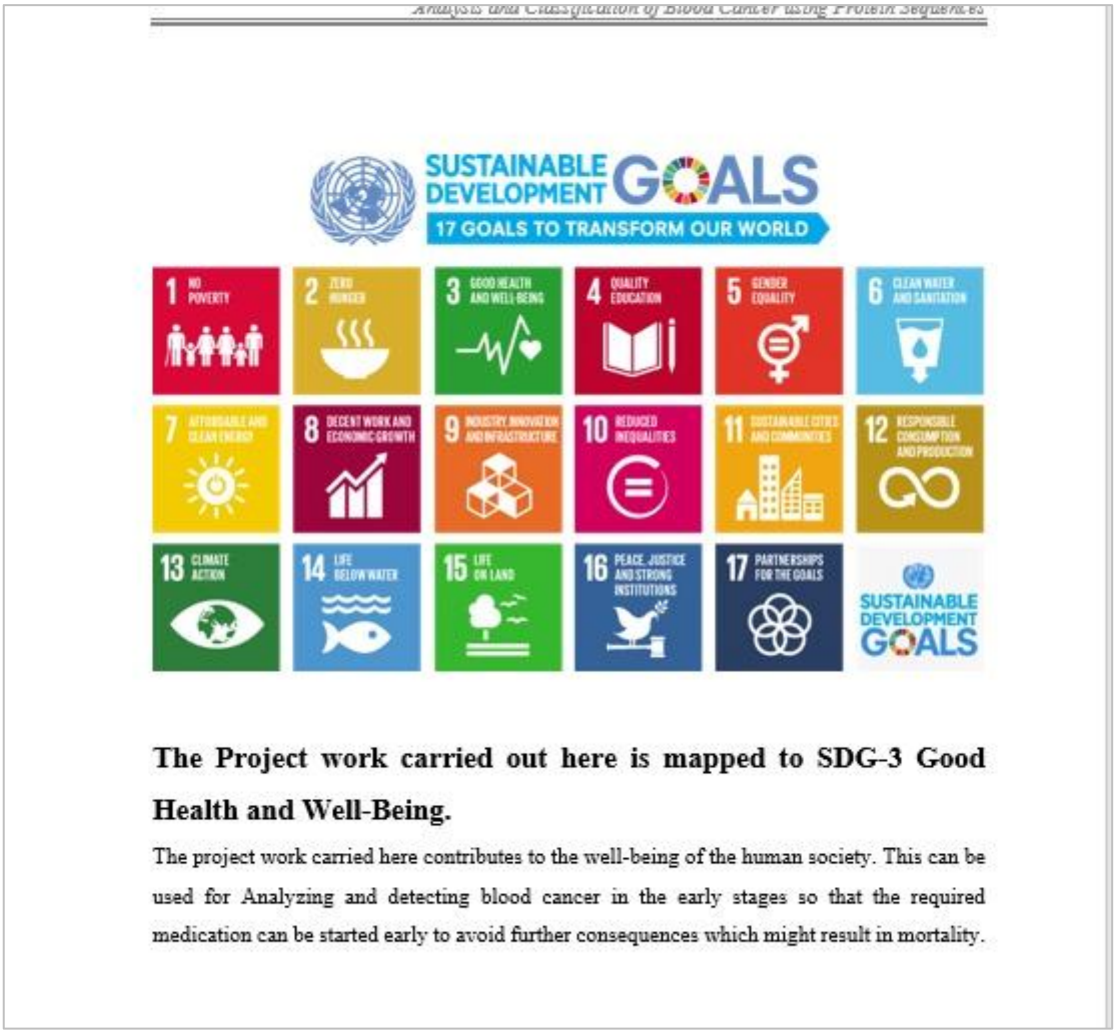
Analysis and Classification of Blood Cancer using Protein Sequences

The Project work carried out here is mapped to SDG-3 Good Health and Well-Being.

The project work carried here contributes to the well-being of the human society. This can be used for Analyzing and detecting blood cancer in the early stages so that the required medication can be started early to avoid further consequences which might result in mortality.

3.

Sustainable Development Goal 3 - Good Health and Well-being:

A major contribution to Goal 3, which is to ensure everyone's health and well-being, is made by this project. The software's straightforward HTML and CSS interface lets users enter disease symptoms, and it uses AI and machine learning algorithms to accurately diagnose the condition. In order to help with early detection and precise treatment planning, this can help medical practitioners by providing possible diagnoses depending on the symptoms entered. The software can improve patient outcomes and the broader healthcare system by increasing the speed and accuracy of diagnosis. This, in turn, helps to improve people's health by giving them fast and accurate health information, which eventually results in better disease and illness management.

Sustainable Development Goal 7 - Affordable and Clean Energy:

This initiative also supports Goal 7, which focuses on clean and economical energy. A large user base from all over the world can access it because it is made to be simple for everyone with an internet connection. The software is compatible with a number of devices, such as laptops, cellphones, and personal computers, and it enables users to receive health diagnostics while they're at home or on the move. The software's internet-based design eliminates the requirement for physical infrastructure and enables users in remote locations or without access to cutting-edge medical facilities to utilize healthcare solutions. By guaranteeing that healthcare solutions are available and cheap for everyone, this promotes the worldwide drive for universal access to high-quality healthcare.