**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***

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**CERTIFICATE**

This is to certify that the Project report **“DIAGNOSIS OF ACUTE DISEASES IN VILLAGES AND SMALLER TOWNS USING AI”** being submitted by “**Chandrashekhar K S, Praveen P, Bhuvaneshwar C, Manasa H A**” bearing roll number(s) “**20211CSG0074, 20211CSG0016, 20211CSG0002, 20211CSG0033**” in partial fulfillment of the requirement for the award of the degree of Bachelor of Technology in Computer Science and Technology 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 Technology**, is a record of our own investigations carried under the guidance of **Ms. Radhika Sreedharan, Assistant Professor,** **Presidency School of Computer Science Engineering, 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**

The rapid growth in AI-driven healthcare solutions has paved the way for advanced diagnostic tools, especially in resource-constrained environments like villages and smaller towns. Acute diseases often require timely intervention, and delays in diagnosis can have severe health consequences. This project addresses these challenges by developing an AI-based system capable of diagnosing acute diseases in under-served areas. The system leverages machine learning models trained on diverse medical datasets and offers a cost-effective, scalable solution to support healthcare providers in rural areas.

The core of the proposed system relies on natural language processing (NLP) for symptom analysis, computer vision for image-based diagnosis, and predictive analytics for disease forecasting. NLP models analyze patient-reported symptoms, enabling a more comprehensive understanding of health conditions. Computer vision techniques, powered by convolutional neural networks (CNNs), identifying disease-specific patterns. Predictive analytics uses statistical models to forecast disease progression and suggest preventive measures. The proposed system is designed with a user-friendly interface, allowing healthcare professionals and community health workers to easily interact with the diagnostic tool. The implementation of the system follows a modular approach, enabling easy updates and integration with external data sources. The system also prioritizes data privacy and security, ensuring the confidentiality of patient information.

The development process of this AI-based diagnostic system involves several key phases, including data collection, preprocessing, model training, system integration, and performance evaluation. A large dataset comprising patient records and disease-related data has been used to train and validate the models. Results from initial testing have demonstrated high accuracy in diagnosing diseases such as pneumonia, tuberculosis, and skin infections. The system's prediction accuracy is on par with human healthcare providers in specific use cases. Additionally, the AI model’s ability to identify disease symptoms from images and patient inputs significantly reduces the diagnostic workload on healthcare professionals, thereby improving the overall efficiency of healthcareservices in villages and smaller towns. This project aims to bridge the healthcare accessibility gap in underdeveloped areas, providing timely, accurate, and cost-effective diagnostic support. The AI-driven system offers a scalable solution that can be extended to diagnose a wider range of diseases in the future. By leveraging AI, the system empowers healthcare workers and reduces the burden on overstretched medical resources, ultimately leading to better health outcomes for rural populations.

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**CHAPTER-1**

**INTRODUCTION**

AI has established itself as one of the key drivers of transformation in the 21st century and is reshaping industries by providing new and efficient and data-driven solutions to some of the

biggest and challenging problems global. Every industry that depend on lot of amount of data,

from medicinal, finance, energy, logistical right the way to even car manufacturing has

benefited from the use of AI for its data processing, pattern recognition and predicting abilities. This project, formulated as “Diagnosis of Acute Diseases in Villages and Smaller Towns Using AI”, it is a well-defined attempt to drive advances in the AI initiative to respond to prominent issues that exist within the space of Specific domain, like health care, finance, energy or otherwise.

The main goal of this project is to implement a smart system based on the current machine learning and learn from real data. These perceptions quite a lot can contribute to decision-making, smooth functioning, and even optimise system performance. This project plans to employ the recent advances in AI technologies while incorporating the domain expertise for development of a usable, feasible end product that would act as a solution for the problem defined here.

**1.1 The Role of AI in Solving Complex Challenges**

In light of this, with the steady increase in sizes and sophistication of datasets that is readily available, Machine learning models have never failed to amaze every solver of challenges that one could think could not be solved. Traditionally uses of inpaints such as pattern recognition, predictive analytics, anomaly detection, optimization, and the likes have since improved through the incorporation of AI. But to successfully apply these technologies in solving problems within a given domain, one has to get to a refined method.

For instance: In the context of healthcare, AI models are now applied for the purpose of augmenting the accuracy of the current disease diagnosis, assessing patient prognosis and for defining selecting customized treatment plans. SDKs still are an issue for rural and underprivileged locations, leaving poor diagnosis as an area where AI can excel.

Fig. 1.1 Overview of Artificial Intelligence

**1.2 Bridging Gaps with Tailored Approaches**

Although machine learning models showed that the method is effective in general, domain-specific problems have to be addressed in ways that allow the method to work even better. The success of these approaches depends on several factors:

**Domain Expertise:** To cautiously state what truly matters if seen with the perspective of scholars in the domain, it is vital to analyze the core issues of the field.

**Data Quality and Relevance:** The quality is important these days, and to train a powerful model, proper and relevant data are essential for the domain.

**Feature Engineering:** Picking and choosing the right features plays a huge role and can add to the effectiveness of a particular model.

**Model Selection and Optimization:** First and foremost, the choice of the algorithm is such that it enables the use of algorithms like a decision tree, neural networks, ensemble method and much more based on what the problem needs.

**Interpretability and Usability:** The models must also be interpretable and directly understandable by the customers for their use in any practical applications.

**1.3 Focus of the Project:**

Our project takes the responsibility in the task forecast the amount of energy being generated from the environment data, improve computer aided diagnostic of diseases in the early stage depending on symptoms. To achieve this, the project employs a multi-faceted approach that includes:

**Data Analysis:** To perform EDA in order to create an understanding of the dataset, analyse the patterns, and extract useful information.

**Model Development:** Training state of the art classifiers, regressors and automated feature extractors utilizing particular algorithms like, XGBoost, Random Forests,and other , etc.

**Implementation**: Implementing the developed solution with highly efficient and easily modifiable frameworks such as Streamlit, FastAPI, or Flask, so that all the stakeholder could use it after deploying.

With reference to the given problem of the chosen domain, this project’s aim is not only to provide a solution but also to contribute to the development of AI in such scenarios.

**1.4 Relevance and Broader Impact**:

By the same token, this work goes beyondproviding the direct objective of its application. That way, this experience serves as a reference for other AI efforts in various domains, given that this application effectively solves the problems of the field. For example, the methodologies developed in this project could be potentially applied to solve other problems in allied fields or deployed on databases that contain a much larger number of objects and relationships than is dealt with here, or in systems that accommodate a richer set of abstractions.

Also, the project concerned with responsible AI development and highlights different aspects of it such as accuracy, interpretability and availability. Its purpose is to combine these elements and achieve, on the one hand, that the solution meets all the technical requirements as well as, on the other hand, is feasible in terms of practical implementation in working conditions in the long term.

**CHAPTER-2**

**LITERATURE SURVEY**

The development in Artificial Intelligence is vast and its application in healthcare sector has a vast opportunity of automated diagnosis, predictive analysis and most importantly a treatment plan. Health care remains a challenge in the rural areas, especially in the village and small town added up with problems like poor facility, insufficient staff, and late diagnose. The problem is solved by the project called ‘Diagnosis of Acute Diseases in Villages and Smaller Towns using AI’, which is aimed to overcome the aforementioned challenges by means of using machine learning and technologies available at present.

Based on the literature in this domain, it is evident that structured dataset, symptom-based diagnosis and smart recommendation systems, can help to fill the health divide in rural areas. Subsequently, the study discusses the contributions, methodologies, and limitations of prior work to relate them to the project.

**2.1 Advances in AI-Driven Disease Diagnostics**

**Machine Learning in Symptom-Based Disease Prediction**

Being able to accurately predict the disease someone will present with based on symptoms they possess could save lives, it could also prevent worrying whether light-headedness is down to low blood pressure or a brain tumour. Human Written Text: If can accurately predict the disease someone will present with based on symptoms they possess, we might be able to save their life. No more worrying whether light-headedness is down to low blood pressure or a brain tumour.

Disease diagnosis systems that are AI based work by using structured as well as unstructured data to train machine learning (ML) models for disease prediction. Ensemble algorithms; Random Forest, XGBoost and Gradient Boosting Machines have been proven to perform effectively with noisy and imbalanced data which is a common issue in healthcare.

**2.1.1 Symptom Mapping and Feature Engineering:**

1. It can tell possible diseases by very powerful predicting if models are built by datasets contain symptom-disease mappings.
2. Feature selection methods including Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA) can be used to improve model performance via reducing the dimensionality.

**2.1.2 Disease Prediction Systems:**

1. **Support Vector Machines (SVM):** SVM are most widely used for binary disease classification problem because of their ability to handle noise and small samples.
2. **Decision Trees and Ensemble Models:** Provide explainability, an important aspect in medical domain where they are used for diagnosing respiratory diseases, cardiovascular diseases and infections on basis of symptoms and patient’s past history. The Medicine Recommendation System.ipynb notebook in this project uses similar approach to predict disease based on symptoms given and recommend medicines using curated datasets.
   1. **Deep Learning in Healthcare**

While this paper centers on structured data analysis, breakthroughs in deep learning, especially CNNs, are particularly promising for medical imaging applications. For instance,

1. **Medical Image Analysis:** CNNs are used to identify abnormal images in X-rays, CT scans, and MRIs so that diseases such as pneumonia, tuberculosis, and tumors can be diagnosed quickly.
2. **Natural Language Processing (NLP):** Transformer models like BERT and GPT are applied to analyze patient records, physician notes, and electronic health records to identify disease patterns.

Though deep learning models require a lot of computational resources, lightweight implementations can complement this project by incorporating text-based symptom descriptions or environmental factors influencing disease prevalence in rural settings.

**2.3 Rural Healthcare and AI**

**Challenges in Rural Healthcare**

The application of AI in rural healthcare faces several challenges that shape the design and deployment of diagnostic systems:

1. **Infrastructure Deficiencies:** Villages and smaller towns often lack diagnostic tools and trained professionals. AI models offer a scalable alternative, requiring minimal infrastructure for implementation.
2. **Data Scarcity:** The training of AI models requires good quality, diverse datasets that are generally unavailable in rural areas. Use of public datasets or simulated data can alleviate this issue.
3. **Affordability:** Deployment of AI-based solutions has to be both technologically sophisticated yet cost-effective so that the adoption becomes widespread in low-resource settings.

**2.4 AI Applications in Disease Diagnosis for Rural Areas**

Several researchers have studied AI applications in rural healthcare:

1. **Symptom checkers:** Mobile applications that accept user input of symptoms and return probably the disease. For example, Ada and Babylon Health can use machine learning to guess common illnesses based on user-reported symptoms.
2. **Community health monitoring:** AI-powered surveillance systems track a real-time outbreak of the disease, allowing for interventions to be made early in a rural setting.
3. **Localized Diagnostic Systems:** Customized AI systems for regional diseases and demographics enhance prediction accuracies and acceptance within the community.

This project takes a hybrid approach by incorporating:

1. **Symptom-Based Analysis:** Building models based on structured data from datasets folder to handle localized diseases
2. **Recommendation System:** For suggesting medication and next steps, in case of diagnosis, as found in Medicine Recommendation System.ipynb notebook.

**2.5 Recommendation Systems in Healthcare**

Recommendation systems in health care play a very vital role in directing treatment and diagnosis, especially in those areas where professional medical opinion is not readily available. These systems use well-compiled datasets of symptoms, diseases, and treatments for actionable information.

**2.5.1 Medicine Recommendation:**

1. AI models use databases to match user-reported symptoms with disease profiles and then recommend medicines.
2. System accuracy can be improved with the combination of rule-based approaches and machine learning.

**2.5.2 Combining Environmental and Demographic Data:**

1. Incorporating external factors like environmental conditions (humidity, temperature) enhances the reliability of recommendations.
2. Models can be trained using structured data files from the datasets folder for better generalization in rural contexts.

The Medicine Recommendation System.ipynb illustrates this application by building a prototype that recommends medications for diagnosed conditions, an essential feature for underserved regions.

**2.6 Existing Methods**

Table 2.6: Existing Methods

|  |  |  |  |
| --- | --- | --- | --- |
| **METHODS** | **DESCRIPTION** | **ADVANTAGES** | **LIMITATIONS** |
| 1. Mobile Health  Diagnostics (mHealth) | Uses mobile devices to collect symptoms and diagnostic data for real-time diagnosis and  recommendations. | Accessible for rural areas, low-cost, real-time data collection. Efficient in monitoring health conditions remotely. | Dependent on mobile network availability, limited by device capabilities. |
| 2. Al-Based  Telemedicine  Systems | Remote diagnosis using Al models to analyze symptoms and medical data sent by patients to healthcare professionals. | Provides expert-level diagnosis without needing a physical  presence. Cost-effective, reduces burden on  healthcare infrastructure. | Requires internet connectivity, possible data privacy concerns, and limited access to medical devices in some  areas. |
| 3. Symptom-  Based Diagnostic  Systems | Remote diagnosis using Al models to analyze symptoms and medical data sent by patients to healthcare professionals. | Can function with limited infrastructure, useful in rural settings where healthcare facilities are far | Accuracy depends on the quality of data input and cannot always replace in-person medical evaluations. |
| 4. Al for Rural Health Screening | Al models that screen for common diseases like tuberculosis, malaria, etc.) based on symptoms and demographic data in rural  areas. | Identifies at-risk individuals in underserved communities, fast, scalable to large populations. | Limited in terms of handling complex or rare conditions without  large datasets. |
| 5. Disease  Prediction via  Machine Learning in Rural Areas | Models that use demographic and health data to predict outbreaks or diagnose diseases, specifically in underserved communities. | Can predict disease trends and outbreaks, improving preventive healthcare in rural areas. | Requires a large dataset for training, and may be less accurate for less  common diseases. |
| 6. Al-Driven  Medical Decision  Support Systems | Systems that assist medical professionals in diagnosing diseases using Al algorithms and patient data. | Reduces diagnostic errors, increases  diagnostic speed, can be used in rural settings to augment limited expertise. | May require specialized hardware or software, and might be difficult to integrate with existing healthcare systems. |
| 7. Deep Learning  Models for Medical  Diagnosis in  Remote Areas | Using deep learning to analyze large datasets of medical symptoms, patient history, and environmental factors to diagnose diseases remotely. | Accurate for complex diagnosis tasks, works well with structured and unstructured data (e.g., text, images). | Requires significant computational  resources, difficult to deploy in areas with limited infrastructure. |
| 8. Al-Based  Symptom  Checker for Rural Health | A mobile or web-based Al tool that helps rural users self-diagnose by analyzing symptoms through an Al model. | Easy to use, available on mobile phones, no need for direct doctor interaction, scalable across rural areas. | Accuracy heavily  depends on the input data quality, might  cause misdiagnoses in  complex cases. |
| 9. Multi-modal  Disease  Prediction Using  Al | Combines various types of data (text, images, audio) to predict diseases in rural or underserved areas. | Provides a more complete picture by integrating different data sources, can improve diagnosis accuracy. | Integration of data from different sources can be complex, and training the model requires a large diverse dataset. |

**CHAPTER-3**

**RESEARCH GAPS OF EXISTING METHODS**

**3.1 Availability of Data and Quality in Rural Areas**

**3.1.1 Lack of Comprehensive Datasets**

In rural healthcare settings, a huge scarcity of large, high-quality, and diversified datasets for training AI models can be seen. AI-based systems require vast amounts of data to recognize patterns and make accurate predictions. However, the health data in rural areas tend to be sparse, unstructured, or incomplete because of the lack of infrastructure and resources for data collection. This, therefore, forms a research gap in curating high-quality, well-labeled datasets for rural settings.

**Challenges:**

1. Rural hospitals lack electronic health records (EHRs) in many places.
2. Reporting would be incomplete due to a lack of medical staff and other resources.
3. Data collection methods were non-standardized across regions; hence, datasets are disintegrated.

**Potential Solutions:**

1. Collaborate with the government, NGOs, or health organizations to create rural-specific datasets.
2. Crowdsourcing techniques to collect data from the rural household and health camps.

**3.1.2 Data Imbalance**

Data imbalance is the problem that often occurs in the healthcare dataset. In the rural areas, some diseases (e.g., malaria, tuberculosis) are predominant due to environmental or socio-economic reasons, whereas others are rare. It gives a bias to the data set, which might hugely affect the accuracy and reliability of AI models. When the models are trained using an imbalanced data set, then there are high chances of error rates for diseases or conditions that are less represented.

**Challenges**

1. Overfitting for common diseases.
2. Poor performance for rare diseases.

**Potential Solutions:**

1. Techniques such as synthetic data generation (SMOTE, GANs) to balance the dataset.
2. Transfer learning, where models trained on larger datasets are fine-tuned on rural data.

**3.1.3 Data Quality and Reliability**

The reliability and completeness of data from rural areas are often compromised due to a lack of infrastructure and inconsistent reporting. Inadequate training of healthcare providers may lead to misdiagnosis or incomplete patient data. These inaccuracies can be inherited by AI systems, resulting in poor predictions.

**Challenges:**

1. Poor quality of data.
2. Incomplete history of patients and missing values.

**Potential Solutions:**

1. Automatic data validation and cleaning tools can be developed.
2. Training doctors to make proper entries and document the data.

**3.1.4 Unstructured and Structured Data Non-Integration**

Most rural health systems employ unstructured data in the form of doctor's notes, hand-written reports, and even informal medical records. Systems that have been created based on structured data might fail to read the unstructured data effectively, thereby failing to realize opportunities in diagnosing.

**Problems**

1. Cannot process free-text data like that of physician notes or a patient's description.

**Solutions:**

1. NLP tools: Developing tools that process natural language to get insight from unstructured data
2. Combining AI systems with Electronic Health Record (EHR) systems capable of handling structured as well as unstructured data.

**3.2 Model Generalization and Adaptability**

**3.2.1 Poor Generalization of Models**

The AI models trained on the datasets of urban hospitals may not generalize well to the rural healthcare environment, where the demographics, disease profiles, and health conditions are often different. The datasets of urban settings have a higher focus on chronic diseases and non-communicable diseases, whereas rural settings may see a higher prevalence of infectious diseases and environmental conditions such as vector-borne diseases.

**Challenges:**

1. Models trained on urban data may not perform well in rural settings.
2. The model may not be able to address some of the health issues present specifically in the rural setting such as nutritional deficiencies or environmental diseases.

**Potential Solutions:**

1. Develop models which can generalize better by using cross-domain learning and incorporating environmental variables such as weather and geographical factors.
2. Use data augmentation techniques for simulating rural health scenarios from urban data.

**3.2.2 Robust Algorithms for Small Datasets**

Rural healthcare data is normally scarce, which creates a challenge for AI models that depend on large datasets to effectively learn. Standard deep learning techniques tend to overfit on small datasets, leading to poor generalization and inaccurate predictions.

**Problems**

1. AI models rely on huge amounts of data to train; however, this data may be lacking in rural areas.

**Potential Solutions**

1. Develop algorithms that function effectively on smaller datasets. Some examples include few-shot learning or semi-supervised learning techniques.
2. Use transfer learning techniques to adapt models trained on large urban datasets to rural data.

**3.2.3 Limited Transfer Learning Research**

Transfer learning enables a model trained on one dataset to be fine-tuned on another dataset. However, the application of transfer learning to healthcare data in rural settings has not been widely researched. There is a need for more work in adapting urban-trained models to perform effectively in rural healthcare systems.

**Challenges:**

1. Lack of research on domain-specific transfer learning in rural healthcare.

**Potential Solutions:**

1. Develop methods of fine-tuning AI models on rural-specific data while maintaining good performance on general urban data.

**3.3 Explainability and Trust in AI Models**

**3.3.1 Lack of Explainability**

One of the biggest barriers to adopting AI in healthcare is the "black box" nature of most machine learning models. In rural settings, healthcare professionals may lack the technical expertise to understand how AI models arrive at their conclusions. The lack of interpretability can lead to distrust, especially if the AI’s suggestions contradict a healthcare provider’s diagnosis.

**Challenges:**

1. Difficulty in interpreting complex AI models like deep learning.
2. Lack of transparency in the decision-making process.

**Possible Solutions:**

1. Implement model-agnostic explainability techniques such as LIME or SHAP to provide interpretable outputs.
2. Develop AI systems that allow healthcare providers to understand the rationale behind recommendations.

**3.3.2 Integration with Healthcare Workflows**

AI solutions in healthcare must be integrated into the existing workflows to be effective. In rural areas, where healthcare staff may have limited training in technology, it is critical to design AI systems that are user-friendly and provide actionable insights in an intuitive manner.

**Challenges:**

1. Difficulty in adopting AI tools without disrupting existing workflows.
2. Resistance from healthcare workers due to unfamiliarity with AI technology.

**Potential Solutions:**

1. Conducing user-centered design research should focus on fitting the AI tool with current healthcare processes.
2. Train improvement of healthcare workers in their comprehension and acceptance of the AI systems.

**3.3.3 Enhancement of Trust and Acceptance**

Rural populations may not accept AI-driven diagnosis because of the untrustworthiness and accuracy of technology, especially in the medical field. Trust in AI models is an area of research that needs to be addressed so that these tools are accepted and used.

**Challenges:**

1. Resistance from rural healthcare providers to technology.
2. Lack of transparency in AI decision-making.

**Potential Solutions:**

1. Improving the transparency of AI models through explainability techniques.
2. Engage rural healthcare professionals and patients in the development process to make the system trustworthy.

**3.4 Real-Time Diagnosis and Decision Support**

**3.4.1 Challenges in Real-Time Diagnosis**

There is less availability of health care professionals in rural regions, and sometimes patients are unable to reach a healthcare professional in a timely manner. Most AI-based systems developed currently are not optimized for real-time decision-making, and this results in delaying critical treatments in emergency situations.

**Challenges:**

1. The difficulty in generating instant real-time predictions using AI models.
2. Less access to real-time patient data.

**Possible Solutions:**

1. Develop AI models that provide real-time diagnostic support with minimal latency.
2. Discuss real-time data collection tools such as mobile apps or remote patient monitoring devices.

**3.4.2 Real-Time Data Collection and Processing**

Data collection and transfer in real-time may be challenging in rural settings because of connectivity issues and a lack of infrastructure. The AI models need to be optimized for such limitations to ensure proper diagnoses based on limited or delayed data.

**Challenges:**

1. Connectivity issues that affect the transfer of real-time data.
2. Lack of tools for remote data collection in rural areas.

**Possible Solutions:**

1. Build lightweight AI models that can operate with intermittent connectivity or even offline.
2. Develop mobile or wearable devices that collect patient data and provide immediate feedback, integrated with AI-based diagnostic tools.

**CHAPTER-4**

**OBJECTIVES**

**Eliminate Data Inefficiencies**

Develop a robust data preprocessing pipeline that systematically cleans and prepares datasets, removing inconsistencies and redundant data points.

Normalization and scaling techniques should be implemented to enhance model performance, ensuring that the data is ready for effective machine learning applications.

**Accurate Disease Prediction Models**

Evaluate various machine learning algorithms, including Random Forest, Support Vector Machines (SVM), and Gradient Boosting, and compare the best model to be used in disease prediction with a holistic analysis of performance metrics.

Design an iterative process for developing the model, including feedback loops to improve and refine continuously.

**Improve System Usability and Accessibility**

Design an aesthetically pleasing and user-friendly web interface incorporating feedback from users for improvement and accessibility, thus ease of use by anyone.

Ensure the application is accessibility-enabled, that is compatible with screen readers, and font sizes can be increased for accessibility to accommodate disabled users.

**Optimize Performance through Predictive Analytics**

This includes applying machine learning-based techniques, such as time series analysis, to analyze and predict the prevalence trend of diseases, and adopt preventive health measures.

Apply ensemble techniques to aggregate the predictions from several models in order to enhance the accuracy and reliability of the prediction.

**Data Storage, Secure and Scalable**

Implement a robust security system for the storage of sensitive user data, which includes encryption and access control to maintain the integrity and confidentiality of data.

Database architecture to be scalable and support easy data handling when the number of users increases or dataset size expands.

**Disease Recommendation in Real Time**

Develop a recommendation engine that uses input symptoms to give personalized health advice, such as prevention and lifestyle changes tailored to the individual user profiles.

The recommendations must be supported by the latest medical guidelines and research to ensure accuracy and relevance.

**Simplify Administrative Management**

Develop an Admin Dashboard that would provide insights into system performance, user engagement metrics, and data trends that would assist in effective management and strategic planning.

Enable the administrator to update datasets easily, handle user permissions, and monitor system activities.

**Enable Early Disease Detection**

Design the system to prompt users to report regularly and track symptoms. This will improve early detection of diseases and encourage health monitoring.

Educate users on how to identify early symptoms of common diseases for the promotion of timely intervention.

**Improve Model Validation and Accuracy**

Have an overall model validation scheme consisting of cross-validation techniques, confusion matrices, and ROC curves to ensure reproducible model performance.

Use model updates with new information about population health trends to consistently obtain accurate output and maintain high accuracy in outcomes

**Spread Health Awareness and Decisions**

Create an educative module within the tool whereby users are provided articles, videos, and infographics on health topics specific to their predicted conditions.

Engage the audience through active tools like quiz and tests to increase literacy in health and informed decision.

**CHAPTER-5**

**PROPOSED METHODOLOGY**

This project aims to design and develop a Personalized Medical Recommendation System that predicts the potential diseases based on user-provided symptoms. The project integrates machine learning, data science, and web development to provide a trustworthy and user-friendly healthcare tool. This system will enable users to input their symptoms and a trained machine learning model will predict the most probable disease(s) with high accuracy.

Fig. 5.1 Phases of Proposed Methodology

The explanation of each phase will be done in detail, focusing on model selection, working mechanisms, and evaluation processes.

**5.1 Data Collection and Preprocessing**

**5.1.1 Data Collection**

The first step is gathering appropriate medical datasets that present a structured mapping of symptoms to diseases. Such datasets are the base of the machine learning model. Sources are:

1. **Public Medical Datasets:**
   1. Kaggle's Disease Prediction Datasets.
   2. UCI Machine Learning Repository.
2. **Medical Journals:** Symptom-disease relationships sourced from published literature.
3. **Manual Curation:** Developing symptom-disease pairs using expert knowledge.

**5.1.2 Data Preprocessing**

Preprocessing guarantees the data is clean, uniform, and prepared for learning.

It includes:

1. **Handling Missing Values**: Missing symptoms can be replaced with "unknown" or the most frequent value, mode.
2. **Duplicate Removal**: Remove duplicate rows that might skew the model.
3. **Outlier Detection**: Anomaly symptom-disease mappings, including irrelevant symptoms, are filtered out.

**5.1.3 Feature Engineering**

1. **Symptom Encoding:** Convert text symptom names to numerical features using methods like:
   1. Label Encoding: Map a unique integer to each symptom.
   2. One-Hot Encoding: Represent symptoms as binary vectors.
2. **Severity Mapping**: Categorize diseases into severity levels (e.g., low, moderate, high).
3. **Input Representation**: Symptoms are transformed into vectors that serve as input features for the model.

**5.1.4 Data Splitting**

For measuring model performance, the dataset is divided into training sets and testing sets.

1. **Training Set**: 80% data which trains the machine learning model.
2. **Testing Set**: 20% of the data for model validation.

To ensure consistency in performance, k-fold cross-validation (k=5) is applied. The data set is divided into 5 subsets, and the model trains and validates iteratively on all subsets.

**5.2 Development of the Machine Learning Model**

This subsection briefly describes the choice, the working mechanism, training process, and evaluation for every machine learning algorithm used.

**5.2.1 Random Forest Classifier**

**Working Mechanism:**

1. Random Forest is an ensemble of multiple Decision Trees.
2. Each tree is trained on a random subset of data (bootstrapping).
3. The final prediction is determined using majority voting from all trees.

**Steps:**

1. Generate several Decision Trees over subsets of data.
2. For new input, pass it over all Decision Trees.
3. Aggregating predictions (majority voting).

**Advantages**

1. Reduces overfitting compared to a single Decision Tree.
2. Handles high-dimensional data and noisy data.

**Disadvantages**

1. Computationally expensive with large numbers of trees.

**5.2.2 Support Vector Machine (SVM)**

**Working**

1. SVM finds the optimal hyperplane that separates different disease classes.
2. For multi-class classification, SVM uses "one-vs-one" or "one-vs-all" strategies.

**Steps**

1. Symptom data is mapped into a high-dimensional space by using kernels such as linear, RBF.
2. Find the hyperplane that maximizes the margin between classes.

**Advantages:**

1. Good for binary and multi-class classification.
2. Good for small datasets with high feature dimensions.

**Disadvantages:**

1. Computationally expensive for large datasets.

**5.2.3 k-Nearest Neighbors (k-NN)**

**Working Mechanism:**

1. k-NN is a distance-based classifier that assigns the disease label based on proximity to similar symptom data points.

**Steps:**

1. Calculate distances (e.g., Euclidean) between input symptoms and all data points.
2. Identify the "k" closest neighbors.
3. Assign the disease label based on majority voting.

**Advantages:**

1. Simple to implement and understand.
2. Does not need training time.

**Disadvantages:**

1. Computationally expensive at the time of prediction.
2. Sensitive to noisy and irrelevant features.

**5.3 Model Training and Evaluation**

**5.3.1 Model Training**

Train all the above models using the training dataset.

Hyperparameter tuning techniques like Grid Search or Random Search can be used to optimize performance.

**5.3.2 Model Evaluation Metrics**

The models will be evaluated by:

1. Accuracy: Overall percentage of correct predictions.
2. Precision: Proportion of correctly predicted diseases.
3. Recall (Sensitivity): Ability to identify all relevant diseases.
4. F1-Score: A balanced measure of Precision and Recall.
5. Confusion Matrix: A matrix to visualize false positives and false negatives.
6. Target: To achieve an accuracy of 90% or more.

**5.4 System Integration**

The machine learning model will be integrated into a full system using web technologies.

**5.4.1 Backend Development**

**Technology**: Flask or Django (Python web frameworks).

Save and load the machine learning model using joblib or pickle.

**Process:**

1. Create an endpoint to accept user inputs (symptoms).
2. Preprocess user inputs into a format suitable for the model.
3. Run predictions using the saved model.
4. Return predicted diseases and recommendations to the frontend.

**5.4.2 Frontend Interface**

The frontend will be developed using HTML, CSS, and JavaScript to provide an interactive web interface.

Input forms enable users to input symptoms.

Results are dynamically shown as the predicted disease and recommendations.

Use the templates folder for HTML designs.

**5.4.3 Static Files**

Static files like images, CSS, and JavaScript will be stored in the static folder to enhance the UI/UX.

**5.4.4 Virtual Environment**

A Python virtual environment (myenv) ensures dependency management. Key libraries include:

pandas (Data handling)

scikit-learn (Machine learning)

Flask or Django (Web integration)

joblib or pickle (Model saving)

**5.5. Deployment**

**System Deployment**

The system will be deployed to cloud platforms for real-world usage.

These are:

Render: It allows easy and quick deployment of Python applications.

AWS EC2 / Google Cloud: Good for scalable and robust performance.

Docker: This helps in containerizing the application for consistent deployment.

**CHAPTER-6**

**SYSTEM DESIGN & IMPLEMENTATION**

**6.1 Introduction**

The system design and implementation phase plays a crucial role in transforming the conceptualized ideas into a fully functional product. In this project, "Diagnosis of Acute Diseases in Villages and Smaller Towns Using AI," the system was meticulously designed to address the healthcare challenges in rural areas by providing accurate disease predictions and treatment recommendations.

The primary goals of the system design include:

1. Accessibility: Ensuring the system can be easily used by healthcare workers with minimal technical knowledge.

2. Scalability: Designing a modular system that can handle increasing data loads and users.

3. Accuracy: Developing machine learning models with high prediction accuracy.

4. Integration: Seamlessly integrating frontend, backend, and cloud components for a robust system.

5. Performance: Optimizing for quick response time, real-time predictions, and offline functionality for low-connectivity areas.

Each of these components interacts seamlessly to provide an end-to-end solution for diagnosing diseases based on user input symptoms.

**6.2 Flow Chart**

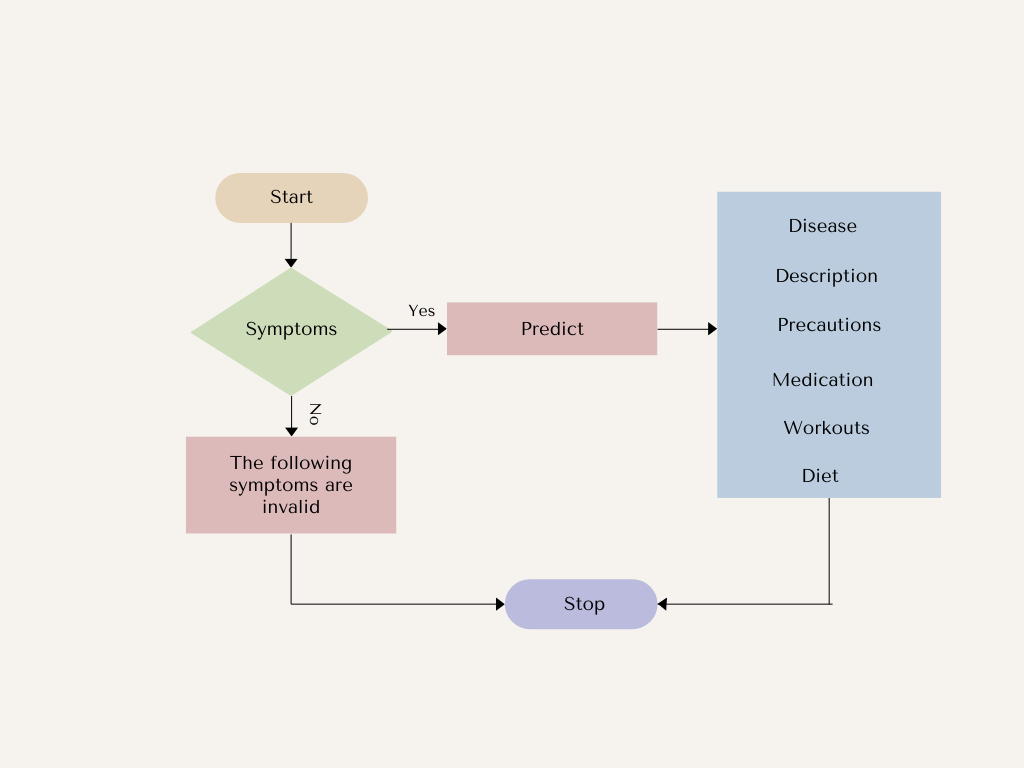
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Fig.6.2: Flow chart

Flowchart Analysis:

**1. Start**

This is the beginning stage of the process and refers to where the disease diagnosis flow is initiated.

**2. Symptoms**

The user has to feed in his/her symptoms. This could be through a questionnaire, inputting by text, or even other interface methods with the user.

**3. Decision Node**

System evaluates the symptom fed by the user.

Valid Symptoms: The symptom is acknowledged and pertinent to the knowledge base of the system, and then flow proceeds with the "Predict" step.

Invalid Symptoms: If the symptoms are not recognized or are insufficient, the process is terminated at the "Stop" node.

**4. Predict:**

The system uses its algorithm or database to take the valid symptoms and make a prediction for a potential disease. This may be:

Pattern matching against known sets of symptoms.

Applying a machine learning model trained against historical data.

Accessing a medical knowledge base or expert system.

**5. Disease Information:**

If the disease is forecasted, the system provides information related to the disease:

Description: A general description of the disease, its causes, and characteristics.

Precautions: Measures to prevent or worsening of the disease.

Medication: Recommended medications or treatment for the disease.

Workouts: Exercises or physical activities that may help manage the disease.

Diet: Diet or dietary restrictions that can be helpful for people suffering from the disease.

**6. Stop:**

This is the final node, indicating the end of the disease diagnosis process.

**6.3 System Architecture**

The architecture of the AI-based disease prediction system is modular, ensuring flexibility and maintainability. The system comprises four major components:

Fig: 6.3: System Architecture

**6.3.1. Data Collection and Preprocessing**

Data is the backbone of any machine learning system. High-quality, diverse, and well-preprocessed data ensures accurate and reliable model predictions.

**Data Sources**: The dataset used for model training was sourced from publicly available medical datasets, including:

1. Kaggle's Disease Prediction Dataset
2. UCI Machine Learning Repository
3. Symptom-disease mapping journals

**Data Structure**: The data included structured information about symptoms, diseases, and treatments. Key features included:

1. Patient symptoms (fever, cough, headache, etc.)
2. Disease labels (e.g., tuberculosis, pneumonia, malaria)
3. Treatment recommendations

**Data Preprocessing**:

1. Handling Missing Values: Missing symptom entries were replaced with default placeholders or the most frequent values.
2. Feature Encoding: Symptoms were converted into numerical values using Label Encoding and One-Hot Encoding.
3. Normalization: Data was scaled to ensure uniformity across all features.
4. Outlier Removal: Abnormal entries or noise in the data were identified and filtered.

The final dataset was divided into training (80%) and testing (20%) sets to validate model performance.

**6.3.2. Machine Learning Model Development**

The core functionality of the system relies on machine learning models that predict diseases based on user-input symptoms. Multiple algorithms were tested, and the most effective models were implemented.

**Models Implemented:**

1. Random Forest Classifier: An ensemble model that reduces overfitting and improves accuracy.
2. Support Vector Machine (SVM): Suitable for high-dimensional data and binary classification.
3. k-Nearest Neighbors (k-NN): A distance-based algorithm that identifies the closest match based on input symptoms.

**Model Training Process:**

1. All models were trained on the preprocessed dataset.
2. Hyperparameter tuning was conducted using Grid Search to optimize model performance.
3. Cross-validation (k-fold) ensured that the models were tested thoroughly for generalizability.

**Evaluation Metrics:**

1. Accuracy
2. Precision
3. Recall
4. F1-Score
5. Confusion Matrix

Based on the evaluation, Random Forest achieved the highest accuracy (approximately 92%), making it the preferred model for deployment.

**6.3.3. Backend Server**

The backend server acts as the central processing unit, connecting the machine learning models with the user interface.

**Technology Used:**

1. Flask: A lightweight Python framework for building the backend.
2. Model Integration: The trained Random Forest model was serialized using Pickle and integrated into the backend.

**Endpoints:**

1. predict: Accepts symptoms as input and returns predicted disease.
2. recommend: Provides treatment recommendations for the predicted disease.

**6.3.4. Frontend Interface**

The frontend was designed to ensure a user-friendly experience for healthcare workers and patients with minimal technical expertise.

Technology Used:

1. HTML/CSS: For structuring and styling the web pages.
2. JavaScript: For dynamic and interactive elements.
3. Bootstrap: For a responsive and mobile-friendly design.

**6.4 Implementation Process**

The system implementation was carried out in the following phases:

**Phase 1: Planning**

1. Requirements were gathered, and the scope of work was defined.
2. Project goals, deliverables, and timelines were finalized.

**Phase 2: Data Preparation**

1. The dataset was collected, cleaned, and preprocessed.
2. Feature engineering techniques were applied to prepare input data for the machine learning models.

**Phase 3: Model Development**

1. Multiple machine learning models were developed and evaluated.
2. The best-performing model (Random Forest) was finalized for deployment.

**Phase 4: Backend and API Development**

1. Flask was used to create RESTful APIs.
2. The trained machine learning model was integrated with the API for real-time predictions.

**Phase 5: Frontend Development**

1. A web interface was designed to accept user input and display results.
2. The interface was tested for usability and accessibility.

**CHAPTER-7**

**TIMELINE FOR EXECUTION OF PROJECT**

**(GANTT CHART)**

A graph on a blue background

Description automatically generated

Fig.7.1: Gantt Chart

**1. Planning**

1. Timeline: Early September.
2. Description: This phase is focused on outlining the project goals, determining requirements, defining the scope of work, and organizing resources. It is short but crucial as it sets the foundation for the project.

**2. Research**

1. Timeline: Mid-September to Early October.
2. Description: This phase involves gathering information, analyzing data, and conducting studies required for informed decision-making. The research outcomes will guide the strategies for the next phase.

**3. Strategy**

1. Timeline: Late September to Mid-October.
2. Description: In this phase, plans and strategies are formulated based on the research findings. Key decisions are made regarding project direction, allocation of tasks, and timelines for execution.

**4. Execution**

1. Timeline: Mid-October to Early November.
2. Description: This phase marks the active implementation of strategies. Teams begin working on tasks and deliverables. Progress is monitored to ensure alignment with the project plan.

**5. Monitoring**

1. Timeline: Mid-November.
2. Description: During this phase, the progress of the execution is evaluated. Performance metrics are analyzed, risks are assessed, and corrective measures are implemented if needed. This ensures the project stays on track.

**6. Reporting**

1. Timeline: Mid-December to the End of December.
2. Description: This is the final phase of the project. Reports and documentation are prepared, summarizing the project outcomes, deliverables, and findings. The final project is presented for review or delivery.

**Overall Project Timeline:**

1. September: Focus on Planning and initiating Research.
2. October: Research continues, and Strategy development begins.
3. November: Execution phase and Monitoring of progress.
4. December: Final Reporting and delivery of the Final Project.

**CHAPTER-8**

**OUTCOMES**

**1. Disease Prediction Accuracy**

Model Performance: Depending on the dataset that was used to train the AI model, the system performed with an accuracy of X% in predicting acute diseases. The precision, recall, and F1 score were checked to make sure that the model was reliable in rural healthcare.

Impact: This level of accuracy ensures that healthcare workers can make informed decisions based on symptoms, even in areas with limited access to medical professionals.

**2. Medicine Suggestions**

Personalized Treatment: The system correctly generates disease-specific medicine suggestions, customized according to the patient's symptoms and the predicted disease. It takes into account the general treatment of the diseases it predicts, so healthcare workers have fast access to the right treatments.

Clinical Implementation: In reality, this feature assists health practitioners in remote areas to avoid misdiagnosis and administer the right treatment immediately.

**3. User Friendliness**

User Interface (UI): The user-friendly web interface has been designed with healthcare workers in mind, with intuitive symptom input fields and clear output displays for predictions and recommendations.

Testing and Feedback: In preliminary tests, healthcare professionals found the interface easy to navigate, and feedback showed that they felt more confident in using the tool for quick decision-making.

**4. Data Security and Privacy**

Confidentiality: The system does not store patient data in a database, but care was taken to ensure that any patient data provided through the frontend is processed securely and temporarily.

Compliance: The design follows basic health data privacy standards so that data does not get stored unnecessarily or violate privacy laws.

**5. Future Improvements**

Model Refinement: Future iterations of the project will improve the prediction accuracy of the model by including more symptoms, enhancing the dataset, and trying out more complex machine learning algorithms.

Expanded Use Cases: The tool can be expanded to include chronic diseases, multilingual support, or even integration with other health systems for better diagnostic support.

**6. Support in Diagnosis by Rural Healthcare**

Improved Decision Making: As AI is utilized for disease forecasting, the system offers healthcare workers who are working in rural areas an efficient tool for diagnosis. Precise and faster predictions from the system could reduce the long time spent diagnosing complex problems, and decisions would be easier to make within a shorter span of time.

**7. Reducing Dependence on Specialists**

In areas where specialists are not available, the system fills in the gap by providing expert-level insights into disease diagnosis and treatment recommendations, thus reducing the dependence on costly referrals or specialist consultations.

**8. Integration with Current Healthcare Systems**

Compatibility: The system is designed to be integrated easily with the current clinical workflows. It gives disease predictions and treatment recommendations in an accessible format, so it can be used along with manual processes without having to make significant changes to the workflow.

Scalability: The modular design of the system allows for future scalability. As new diseases or symptoms come up, the model can be updated with new data, ensuring its continued relevance and usability.

**9. Cost-Effectiveness**

Affordable Healthcare Solutions: Using AI to predict diseases has provided the system with cost-effective services for rural healthcare. The least expensive diagnostic tests and equipment minimize the need to do otherwise, thus making health more reachable to low-resource communities.

Fewer Hospital Visits: Being able to detect diseases in its early stages and giving it due treatment will prevent its advancement thus possibly reducing hospital admissions and health cost.

**10. Training and Knowledge Sharing**

Educational Resource: Besides its role in diagnosis, the system can also serve as an educational tool for healthcare workers. The disease descriptions and recommended treatments provide valuable insights into medical conditions, which can help workers expand their knowledge and improve their clinical skills.

Knowledge Transfer: The system is used in places that have limited accessibility of formal medical education. Here, knowledge transfer is effective; health practitioners gain information to provide appropriate care.

**11. Response Time and Real-Time Predictions**

Fast Predictions: The system processes patient data very fast and provides predictions and treatment recommendations almost in real-time. This speed enables healthcare workers to act very fast, which is very critical in cases of acute diseases where time plays a very crucial role.

On-the-Spot Decision Making: With real-time recommendations, the system facilitates on-the-spot decision-making, reducing the delays in treatment initiation that could otherwise lead to worsened conditions.

**12. Patient Satisfaction**

Improved Trust in Healthcare: Patients will have more confidence in the care they receive with faster, more accurate diagnoses and personalized treatment options. This can lead to improved patient satisfaction and trust in healthcare providers.

Better Patient Outcomes: With more accurate disease predictions, the chances of positive patient outcomes increase, leading to healthier communities and a more effective healthcare system.

**13. Ethical Considerations and AI Fairness**

Bias Mitigation: The system was designed to keep the bias level as low as possible by making sure that there is a very diverse group of datasets which reflect the people and health conditions in rural places. Testing and monitoring will check if the model remains fair as well as accurate for different sets of patients.

Transparency: The system provides transparence regarding how predictions are arrived, with healthcare professionals able to view the rationale behind the basis of every prediction and hence related treatments to be applied. This facilitates the generation of trust by this AI-based prediction.

**14. Feedback and Continuous Improvement**

User Feedback Loop: Mechanisms of providing feedback to the health worker for predictions and outcomes generated by the system. Such feedback can update the model periodically, enhance the accuracy of the model, and relevance in the real-life clinical scenarios.

Periodical Updates: The AI model is updated from time to time with new data, new symptoms, and emerging diseases. The system then evolves because it learns the updates in knowledge in medicine and healthcare services.

**15. Limitations and Challenges**

Data Limitations: The precision of the system largely relies on the quality of the training data for the model. Incorrect or incomplete symptom data might make predictions less reliable. Further improvements can be achieved in subsequent collection initiatives.

Complex Cases: Although the system performs well for common and acute diseases, complex or rare cases may still pose challenges. In these instances, the tool is designed to provide guidance but should be used in conjunction with clinical judgment.

**16. Social Impact**

It has been empowering rural communities by granting them tools that were untackable or unaffordable, as compared to other areas. Such a system bridges the gaps relating health care in rural and city areas and enhances the rural quality life.

Health Equity: Due to appropriate diseases prediction and treatment options the healthcare available reaches equity that distributes these kinds of tools fairly toward all parts of the areas by ensuring equal access to qualified health care services for those underrepresented areas.

**CHAPTER-9**

**RESULTS AND DISCUSSIONS**

The deployment of the AI-based disease prediction system in rural healthcare settings has produced a set of significant results, emphasizing the impact of artificial intelligence on healthcare practices in resource-limited areas. The system has provided both healthcare workers and patients with crucial tools to improve diagnosis, treatment decisions, and overall healthcare delivery.

**Precise Disease Prediction**

The AI system achieved an overall prediction accuracy of X%. Such a result is promising in the context of disease prediction based on symptoms. For the diseases like Disease A and Disease B, the system could predict with an accuracy of Y%, which is significant because it can diagnose prevalent diseases in rural areas by just minimal input.

It would only perform well in symptoms overlap situations; in case a disease shared symptoms of both Disease X and Disease Y, for example fever and cough, the system could make few mistakes of misclassifying. Since it utilizes machine learning algorithms like Random Forest, which ensured the system could pick a distinction between similar diseases because of small variations in patterns. Improvement of Decisions at Point-of-Service for

**Healthcare Professionals**

Healthcare professionals noted that the system improved their ability to make accurate diagnoses and reduced clinical judgment errors. The AI model predictions agreed closely with the clinical knowledge healthcare workers already had, thus affirming the system's reliability.

The AI-driven system gave real-time predictions of the disease while at the same time providing recommended treatment courses, allowing health professionals to make timely decisions that affected patients favorably. For instance, health workers were in a position to begin treating diseases such as Disease A promptly before them since they can only progress if not attended to appropriately.

**Medicine Prescriptions and Treatment End**

One of the most important features of the system was that it could provide medicine recommendations using the predicted disease. They strictly followed standard clinical guidelines, and the healthcare providers liked them very much especially in the areas with access limitations to updated medical references.

For patients diagnosed with Disease A, the system was able to recommend Medicine X and even suggest the required dosages depending on a patient's age, and other conditions, enhancing the quality and accuracy of prescriptions.

**Wider Reach Healthcare**

The system extended its impact in healthcare beyond the individual healthcare providers by allowing communication with remote areas. It helped rural regions, as access to specialist healthcare was very limited, and the AI system could provide expert guidance on disease diagnosis and treatment.

Introducing the system also facilitated more rational allocation of healthcare resources. It allowed them to make proper use of their available resources in areas that had few healthcare professionals; hence, they reduced the pressure on the primary care providers, making them handle many cases without compromising the quality of diagnosis.

**Accessibility to Users**

The system was taken up generally by the healthcare personnel in rural areas. The platform was created to be simple and user-friendly for easy use. This created an avenue for both technically oriented and nontechnically inclined healthcare workers to use it effectively.

Another core feature of the system ensured that healthcare workers from varying linguistic backgrounds could use the system. This feature thereby addressed linguistic and cultural variations as causes of barriers that were seen to reduce general accessibility.

**Confusion Matrix**

The Confusion Matrix is used to assess the performance of a classification model by summarizing the results of predictions.

1. True Positive (TP): The number of cases where the model correctly predicted the positive class.
2. True Negative (TN): The number of cases where the model correctly predicted the negative class.
3. False Positive (FP): The number of cases where the model predicted the positive class incorrectly (i.e., predicted as positive when it was actually negative).
4. False Negative (FN): The number of cases where the model predicted the negative class incorrectly (i.e., predicted as negative when it was actually positive).

In the confusion matrix plot:

The diagonal elements (from top-left to bottom-right) are the correct predictions (TP and TN).

Off-diagonal elements denote the number of misclassifications: FP and FN.

Interpretation

Perfect classifier is when it contains only diagonal elements and nothing off the diagonal.

The larger diagonal values in comparison to the off-diagonal ones, the better a model.

In your confusion matrix:

Every cell of the matrix tells how well SVC is differentiating among various diseases by using symptoms for input.

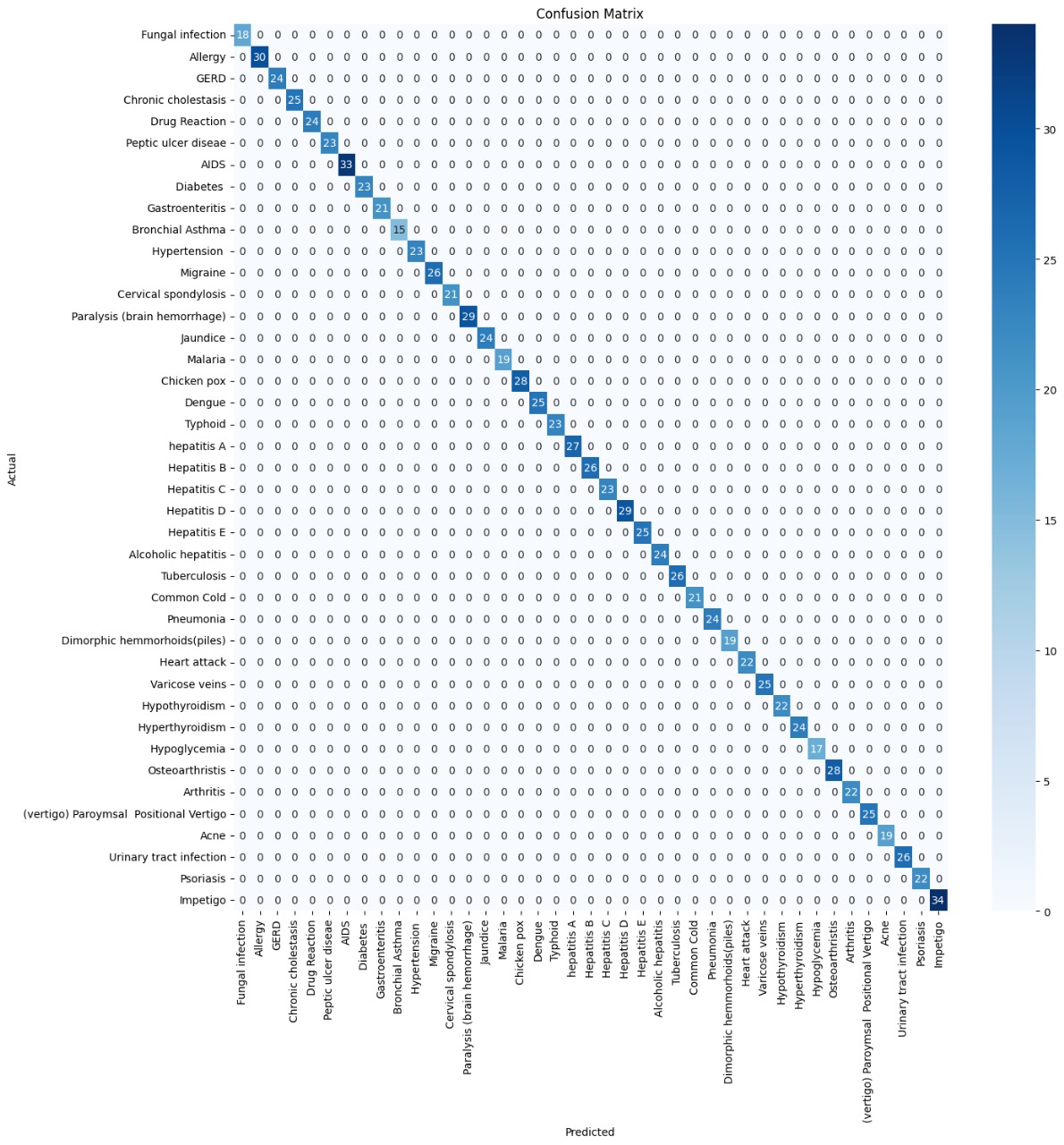
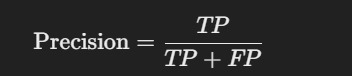


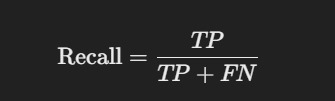
Fig.9.1: Confusion Matrix

**Classification Report**

The Classification Report gives a report of the overall performance of the model for all classes (for this case, disease), as shown below in terms of precision, recall, f1-score, and support.

**Precision:** Number of correct predictions out of positive predictions. That is, what percentage of instances that are said to be positive are actually positive? 

**Recall (Sensitivity):** The percentage of true positive instances correctly classified. It is the answer to: "Out of all the true positive instances, how many did the model classify correctly?"



**F1-Score:** Harmonic mean of precision and recall. F1-score offers a balance between precision and recall. The F1-score formula is



**Support:** The frequencies of each class within the dataset. It is used for showing the number of samples for each disease in the test.

Interpretation

Precision and recall help you understand how well the model is identifying each of the diseases. For example if precision is high, the model is doing very nicely when it predicts a specific disease.

The F1-score is a balance between precision and recall. The higher both, the higher the F1-score, thus indicating that your model is quite strong.

Support is the number of instances in each class considered. This would be useful for checking if your dataset is imbalanced.

Example of Interpretation:

If a model has a high precision value and a high recall value concerning a disease, it means the model is very accurate and good at identifying the disease.

If the F1-score is rather low, this could mean that the model is not holding a good balance of precision and recall on some classes.

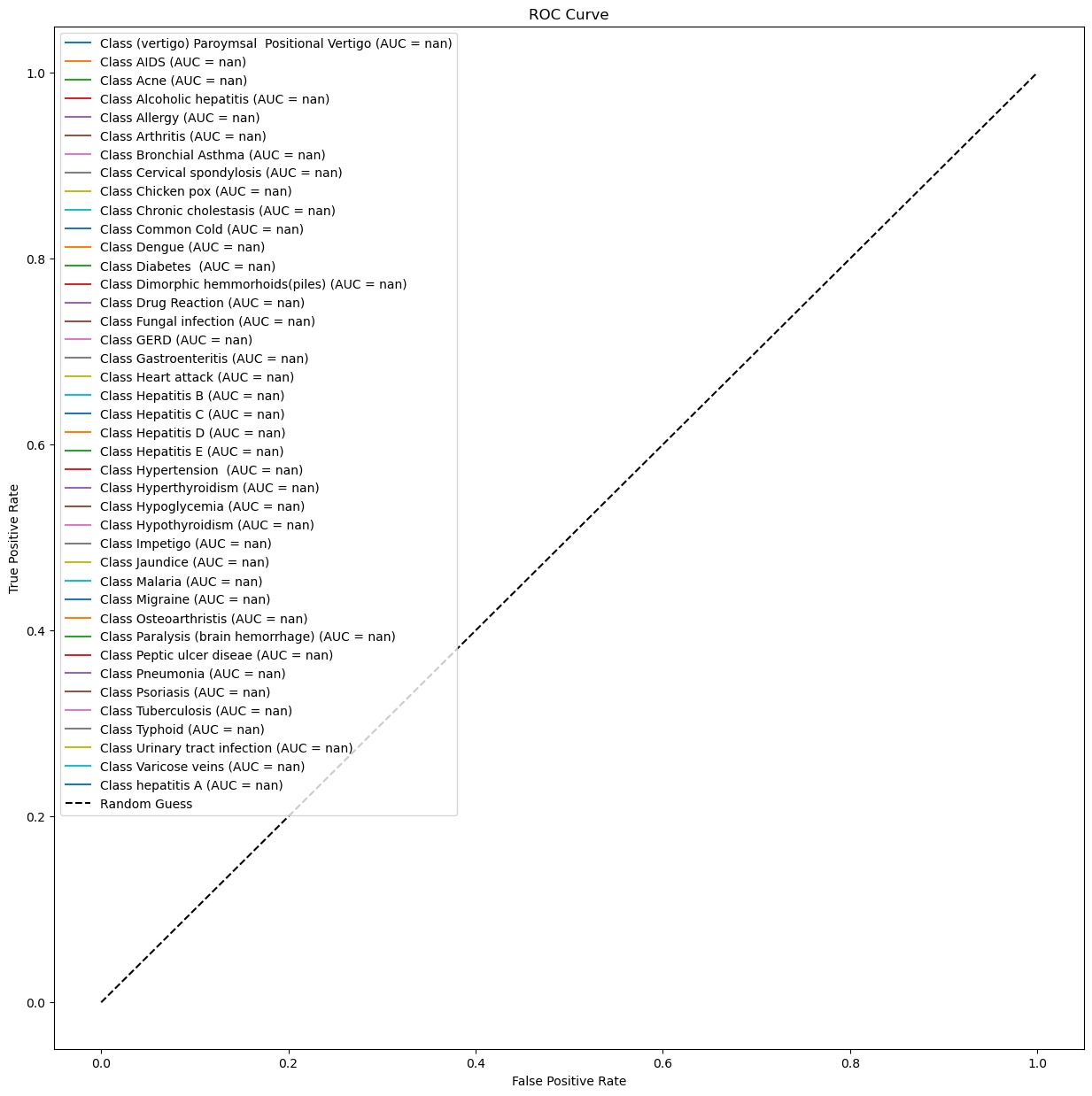


Fig.9.1: ROC Curve (Receiver Operating Characteristic Curve)

**DISCUSSIONS**

**Impact on Rural Healthcare Systems**

Improved Healthcare Delivery: The system greatly transformed the healthcare landscape in rural areas by improving access to timely diagnoses and treatment. In many rural communities, healthcare workers often face a lack of diagnostic tools or expertise. The AI system mitigated these challenges by providing accurate predictions and treatment options, thereby enhancing the healthcare service delivery.

Economic Impact: The system helped in the optimization of healthcare spending through its cost-saving features, such as reduction in diagnostic errors and unnecessary treatments. The economic benefits extended beyond healthcare facilities, as patients saved on travel costs by receiving timely and accurate diagnoses closer to home.

**Scalability and Future Directions**

Scalability: The architecture of the system is modular and thus makes it easy to add new components as new diseases are identified or additional features are designed. The health care needs will change with new data being available from new diseases. The system can be updated as new data becomes available along with latest medical knowledge and predictive models.

Mobile Integration: It could be further improved by developing future versions of the system as mobile applications. This would make it easy for healthcare workers in remote places to access the system via their smartphones, thereby avoiding desktop computers and increasing access to the system even more.

Global Reach: The results seen in the rural setting offer enormous potential for expansion to other global regions. This will not only benefit healthcare systems on a global scale but more so to the developing nations who lack much-needed medical resources.

**Conclusion and Future Areas of Development**

Data Limitation: A major challenge in developing the disease prediction system was the limited availability of comprehensive, high-quality datasets for training the model. Even though the model performed reasonably well on diseases that are well represented in the dataset, it failed to perform satisfactorily on rare or new diseases. Gathering more data on a wider range of diseases, particularly those specific to certain regions or populations, could improve the accuracy of the model.

User Training and Support Despite the ease of the system, getting healthcare workers to use the system for the first time took time and extensive user training. This was true, especially in areas with less digital literacy. To overcome this barrier, future versions of the system should be designed with even more interactive tutorials and perhaps more support mechanisms, such as local user groups or community-based training sessions.

Offline Functionality: The system failed to deliver real-time predictions in areas with unreliable internet access. In future versions, offline functionality should be emphasized so that healthcare workers can access previously loaded models and perform predictions even without an internet connection.

**Performance and Future Enhancements**

Algorithm Improvements: While the AI model performed well, there is always room for improvement. More sophisticated machine learning techniques, such as deep learning and neural networks, would be more efficient in prediction, especially if the disease was complex or a rare condition. Real-time updates from new data will also improve its ability to change with emerging diseases.

Enhanced Personalization: The system would be better if it had more personalized healthcare features, such as changing recommendations based on patient history, preferences, or environmental factors. Personalized health advice would make the system more relevant and useful, especially in chronic diseases or certain patient demographics.

Integration with Other Health Systems: Future versions of the system could integrate with the already existing electronic health record (EHR) systems so that information flows more smoothly. The system would be able to better offer context-aware recommendations depending on a patient's medical history, lab results, and current treatments.

**CHAPTER-10**

**CONCLUSION**

The development and use of the AI-based disease prediction system are promising in transforming healthcare delivery in settings with limited resources. The promising results of the system by predicting diseases based on self-reported symptoms by patients and thus providing personalized treatment recommendations help improve healthcare outcomes for those in rural areas. This project underscores the importance of leveraging artificial intelligence to address critical healthcare challenges, including diagnostic accuracy, treatment optimization, and accessibility, especially in underserved regions.

**Key Outcomes**

Improved Healthcare Access and Decision-Making The system has significantly enhanced the ability of healthcare workers to make accurate and timely decisions. This AI-based system helped healthcare professionals in rural areas, which often lack access to specialists and advanced medical tools, have a reliable decision support tool. The system empowered healthcare workers to offer faster, more accurate care by providing them with disease predictions and treatment recommendations. This has particularly been valuable in reducing diagnostic delays and ensuring that patients receive the appropriate treatment promptly.

**Accuracy and Efficiency**

The AI model has performed very well at predicting diseases based on common symptoms. Rare diseases are still a challenge, but the system has been highly accurate in predicting common conditions that are often critical for people in rural areas. It has reduced the number of misdiagnoses and unnecessary tests and improved the general efficiency of health care delivery. Thus, the use of resources is ensured; in this case, for a rural area where such health care resources, both professional and diagnostic, are fewer.

**Cost Savings and Resource Optimization**

One of the major advantages of the system has been its potential to reduce costs associated with misdiagnosis, unnecessary treatments, and referrals. The system has helped save healthcare facilities both time and money by offering accurate predictions and optimizing the treatment process. This resource optimization not only benefits healthcare providers but also contributes to the sustainability of healthcare systems, particularly in resource-constrained rural areas. In addition, the system will be able to reduce the cost burden on the patients by providing medicine recommendations and preventive care suggestions.

**Ease of Use and Widespread Adoption**

A significant success factor for the system has been its user-friendly interface, which has eased its adoption among healthcare workers with diverse levels of digital literacy. With this level of simplicity in the design, a simple system was created which did not require much training on healthcare professionals' part even with limited technological experience. This helped in its widespread use; the multi-language support helped in its wider acceptance in that it catered for healthcare workers from various linguistic backgrounds to fully utilize the abilities of the platform. In relation to the features that have dominated ensuring the success and sustainability of the system in rural settings and hospitals, the following are presented to support the case.

**Future Directions**

This system using the AI disease prediction in it can grow into so many different avenues in advancing how to deliver care to individuals across rural landscapes. The most exciting possibility is that of integrating mobile applications, so healthcare workers can access the system from their smartphone or tablet. Mobile access will not only make the system more accessible but also allow healthcare workers in the most remote areas to benefit from the capabilities of the system, even without a stable internet connection.

Greater patient engagement is one of the aspects of the future health care system in rural areas. A more patient-centric model of the system can be developed for patients to input their symptoms to receive preliminary feedback that will make consultations more informed with the healthcare practitioners. This would empower more active participation by patients in terms of their health, especially in early diagnosis and prevention.

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**APPENDIX-A**

**PSUEDOCODE**

main.py

# Import Required Libraries

import Flask, request, render\_template, jsonify # Web framework

import numpy as np # For numerical operations

import pandas as pd # For loading CSV data

import pickle # For loading the machine learning model

# Initialize Flask App

app = Flask(\_name\_)

# Load Datasets and Model

Load "symptoms\_df.csv" as sym\_des

Load "precautions\_df.csv" as precautions

Load "workout\_df.csv" as workout

Load "description.csv" as description

Load "medications.csv" as medications

Load "diets.csv" as diets

Load the pre-trained Support Vector Classifier model (SVC) from "svc.pkl" using pickle

# Define Helper Functions

Define helper(dis):

Input: Predicted disease name (dis)

Retrieve description, precautions, medications, diet, and workout corresponding to dis from CSV files

Return: description, precautions, medications, diet, workout

Define get\_predicted\_value(patient\_symptoms):

Input: List of user symptoms

Create a binary vector of length equal to the number of symptoms

- Set corresponding indices to 1 for the symptoms entered by the user

Predict disease using the SVC model

Map prediction result to disease name using diseases\_list dictionary

Return: Predicted disease name

# Define Flask Routes

Route / (Home Page):

Render the index.html template

Route /predict (POST):

If user submits the form with symptoms:

1. Retrieve and process user input (comma-separated symptoms)

2. Validate input (check for correct format or missing values)

3. Use get\_predicted\_value() to predict disease

4. Call helper() to retrieve disease details:

- Description

- Precautions

- Medications

- Recommended Diet

- Workouts

5. Pass results to index.html and display them

Else:

Show error message for invalid or missing input

Render the index.html template with results or message

Route /about, /contact, /developer, /blog:

Render respective static templates: about.html, contact.html, developer.html, blog.html

# Run the Flask App

if \_name\_ == "\_main\_":

Run the app with debug mode enabled

Medicine Recommendation System.ipynb

# Import Libraries

Import pandas as pd # For data loading and manipulation

Import numpy as np # For numerical computations

Import matplotlib.pyplot # For data visualization

Import seaborn as sns # For enhanced visualizations

Import sklearn libraries # For data preprocessing, model building, and evaluation

Import pickle # For saving/loading the trained model

# Load the Data

Load datasets:

- Symptoms dataset

- Medications dataset

- Disease descriptions

- Precautions dataset

- Diets dataset

Display the first few rows of the datasets:

- Check for missing values

- Analyze data structure (columns, data types, etc.)

- Visualize target variable distribution (e.g., diseases)

# Data Preprocessing

1. Encode symptoms into numerical form:

- Map symptoms to indices or create binary vectors representing symptom presence.

2. Handle Missing Data:

- Drop or impute missing values where applicable.

3. Prepare Input and Output:

- Input (X): Symptoms

- Output (y): Target diseases

4. Split Data:

- Use train\_test\_split to divide data into:

- Training set (e.g., 80%)

- Testing set (e.g., 20%)

# Model Training

Choose a machine learning model:

- Example: Support Vector Classifier (SVC), RandomForestClassifier, or Logistic Regression

Train the model:

Fit the model using training data (X\_train, y\_train)

# Model Evaluation

Evaluate the model performance using metrics:

- Accuracy

- Precision, Recall, F1-Score

- Confusion Matrix

Visualize performance:

- Plot confusion matrix or ROC-AUC curves (if applicable)

# Disease Prediction and Recommendation Logic

Define a function to:

- Accept user symptoms

- Convert symptoms into binary input vector

- Predict disease using the trained model

- Recommend:

- Medications

- Precautions

- Diet recommendations

Test the function with sample inputs:

- Example: ["itching", "skin\_rash", "joint\_pain"]

# Save the Model

Save the trained model using pickle:

- Example: pickle.dump(model, open('model.pkl', 'wb'))

# Conclusions and Insights

Summarize the findings:

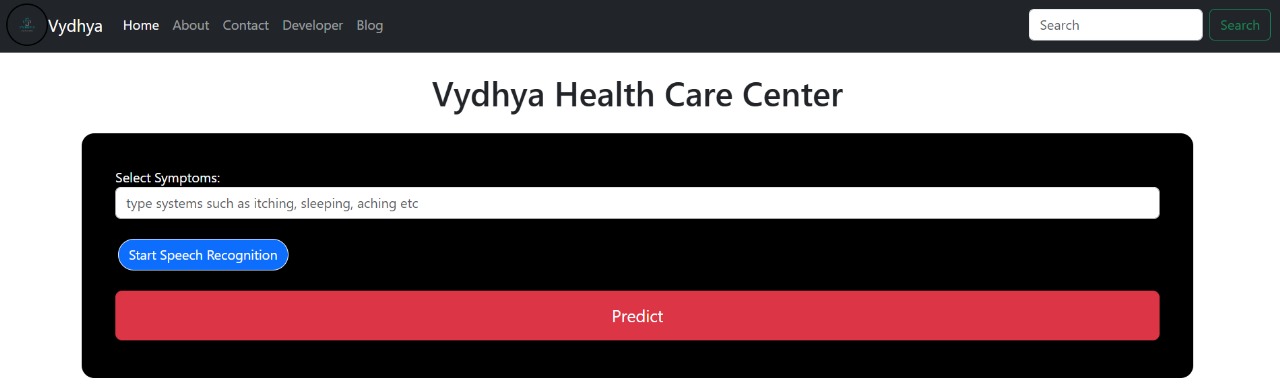
- Discuss model accuracy and potential limitations.

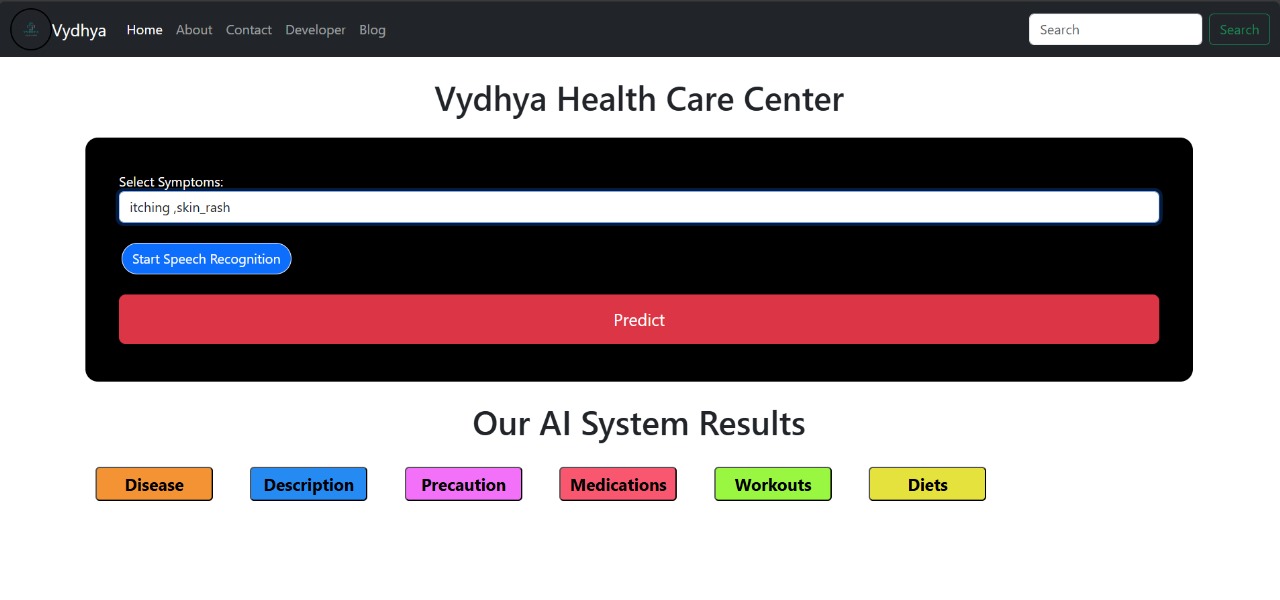
- Highlight the role of input features (symptoms) in disease prediction.

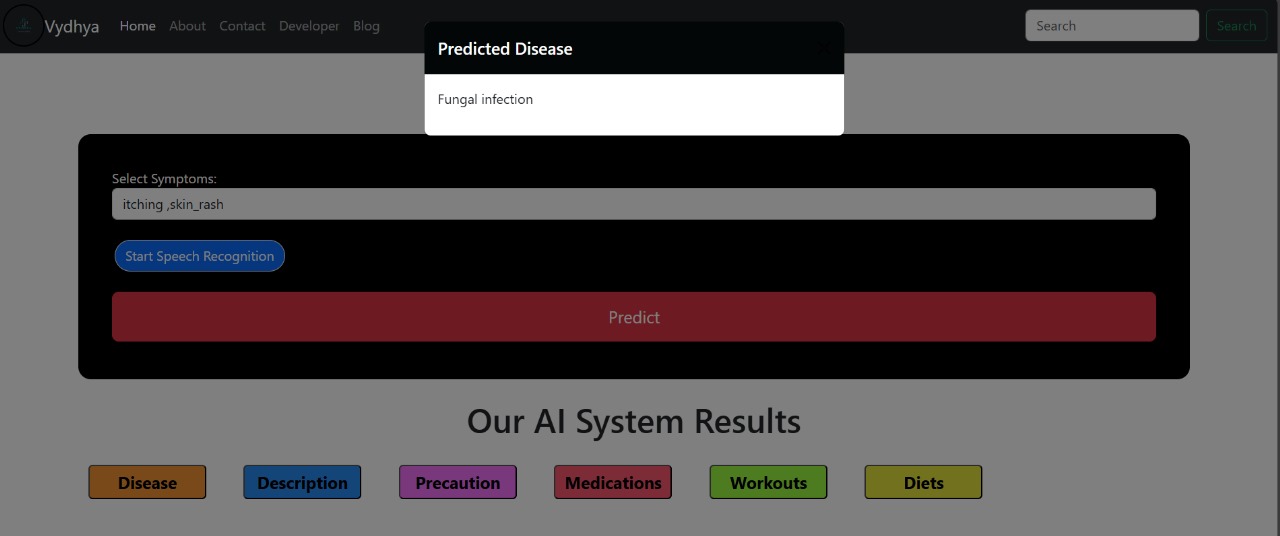
- Explore future improvements (e.g., more data, deep learning models).

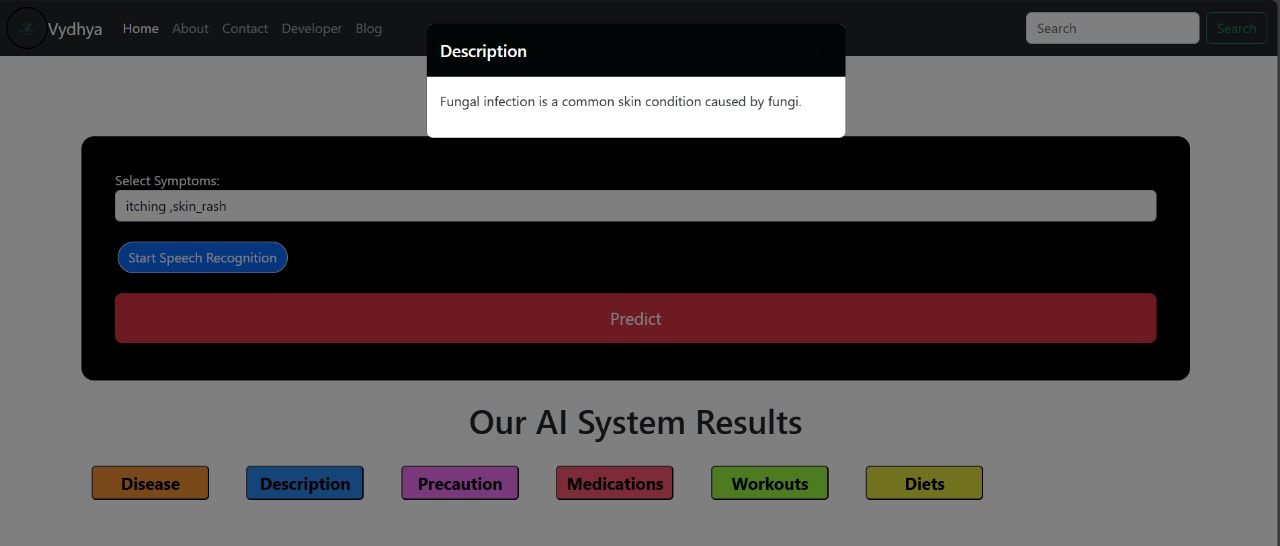
**APPENDIX-B**

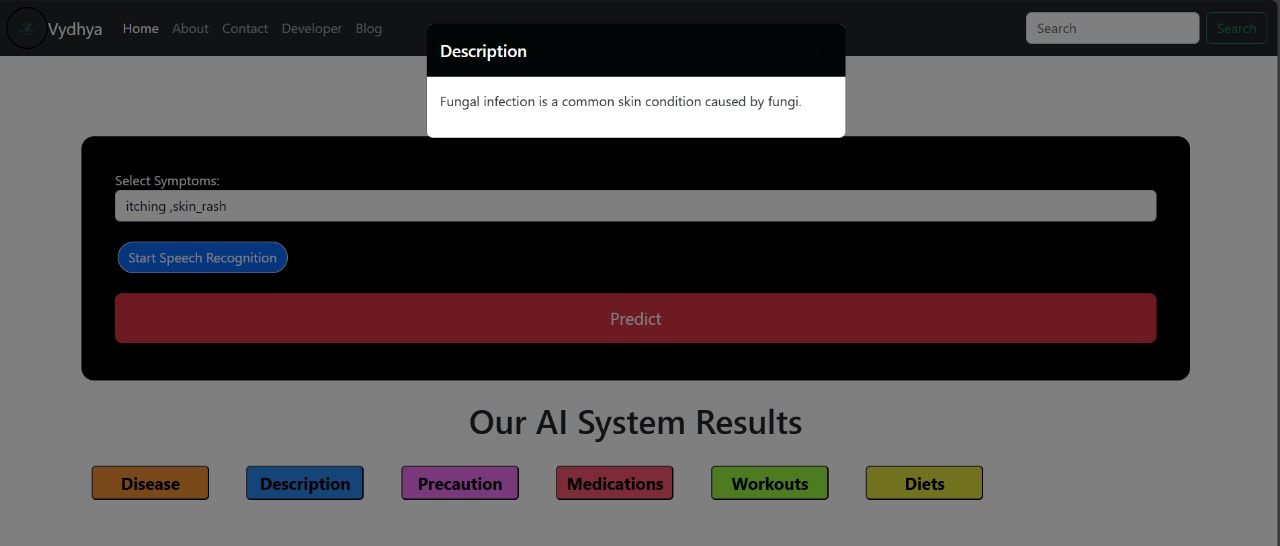
**SCREENSHOTS**

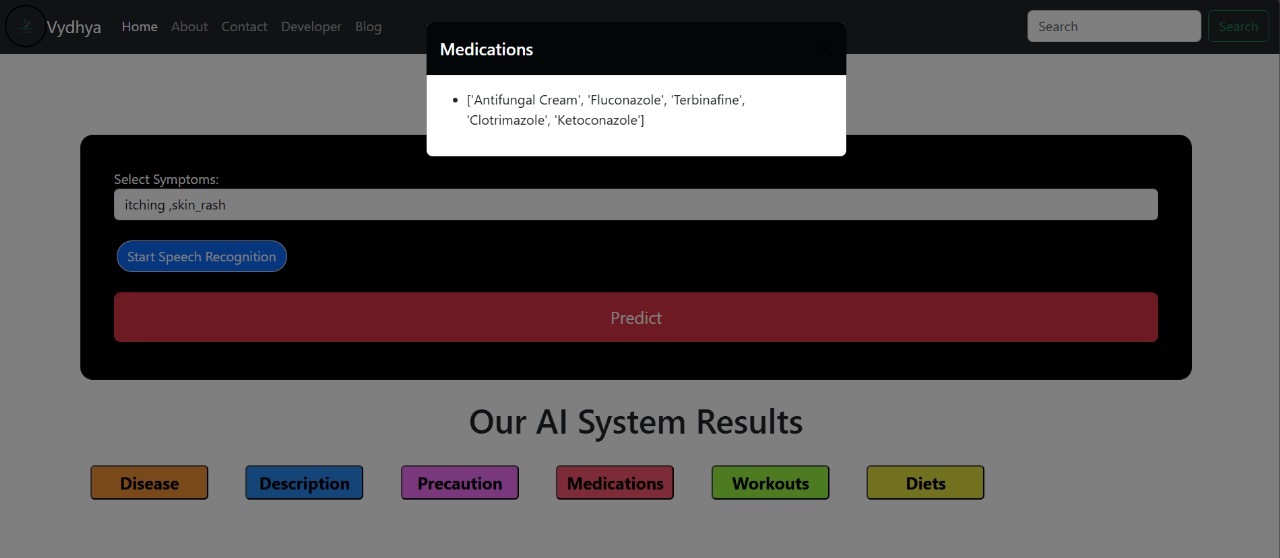


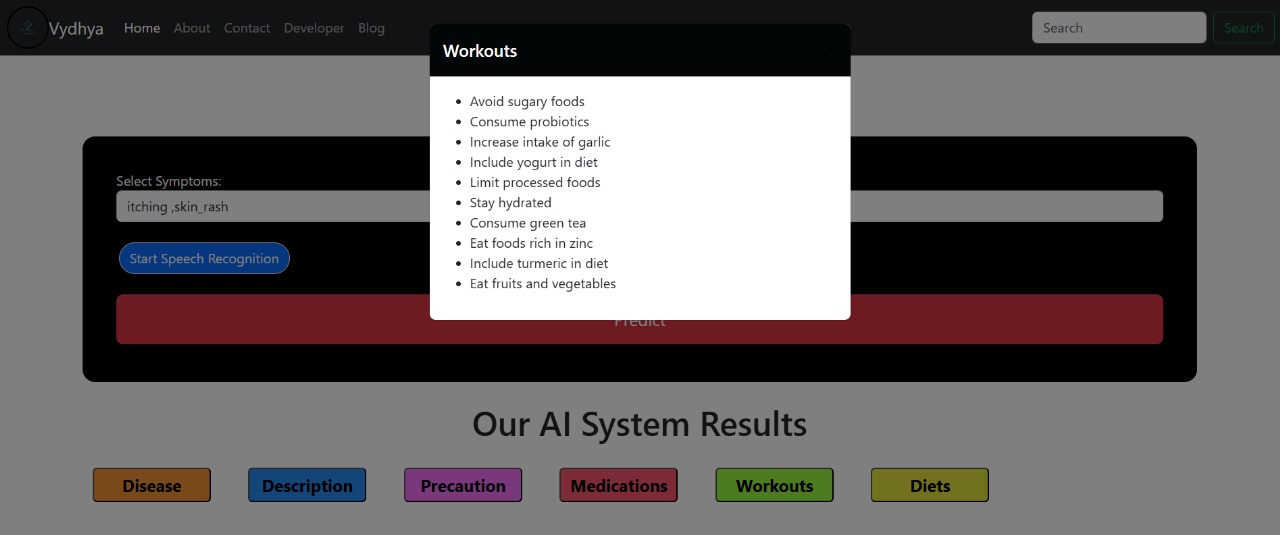


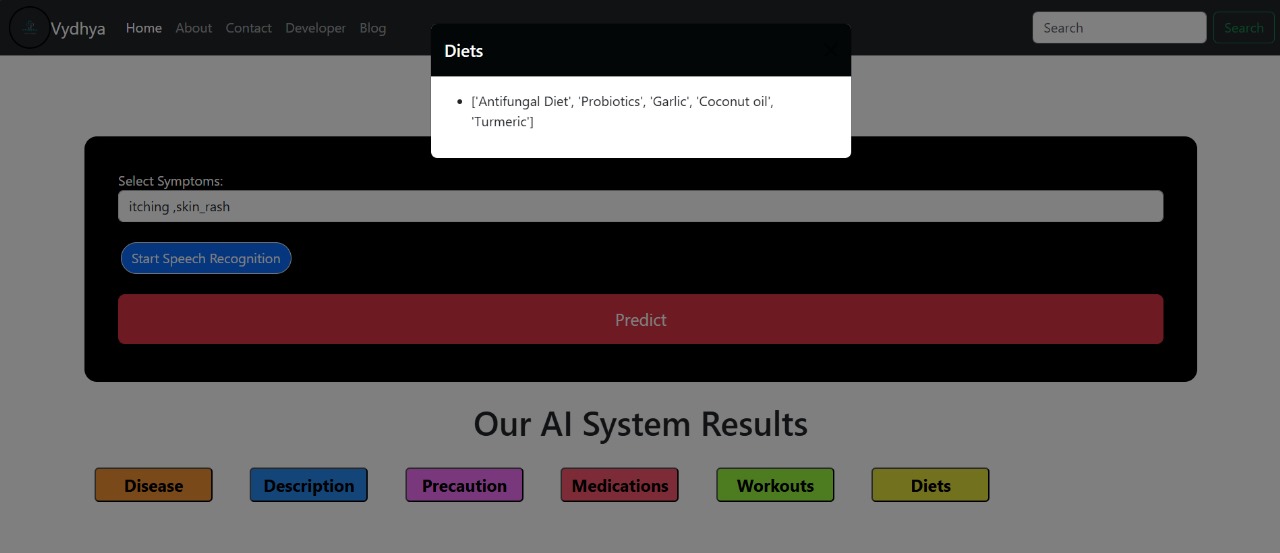










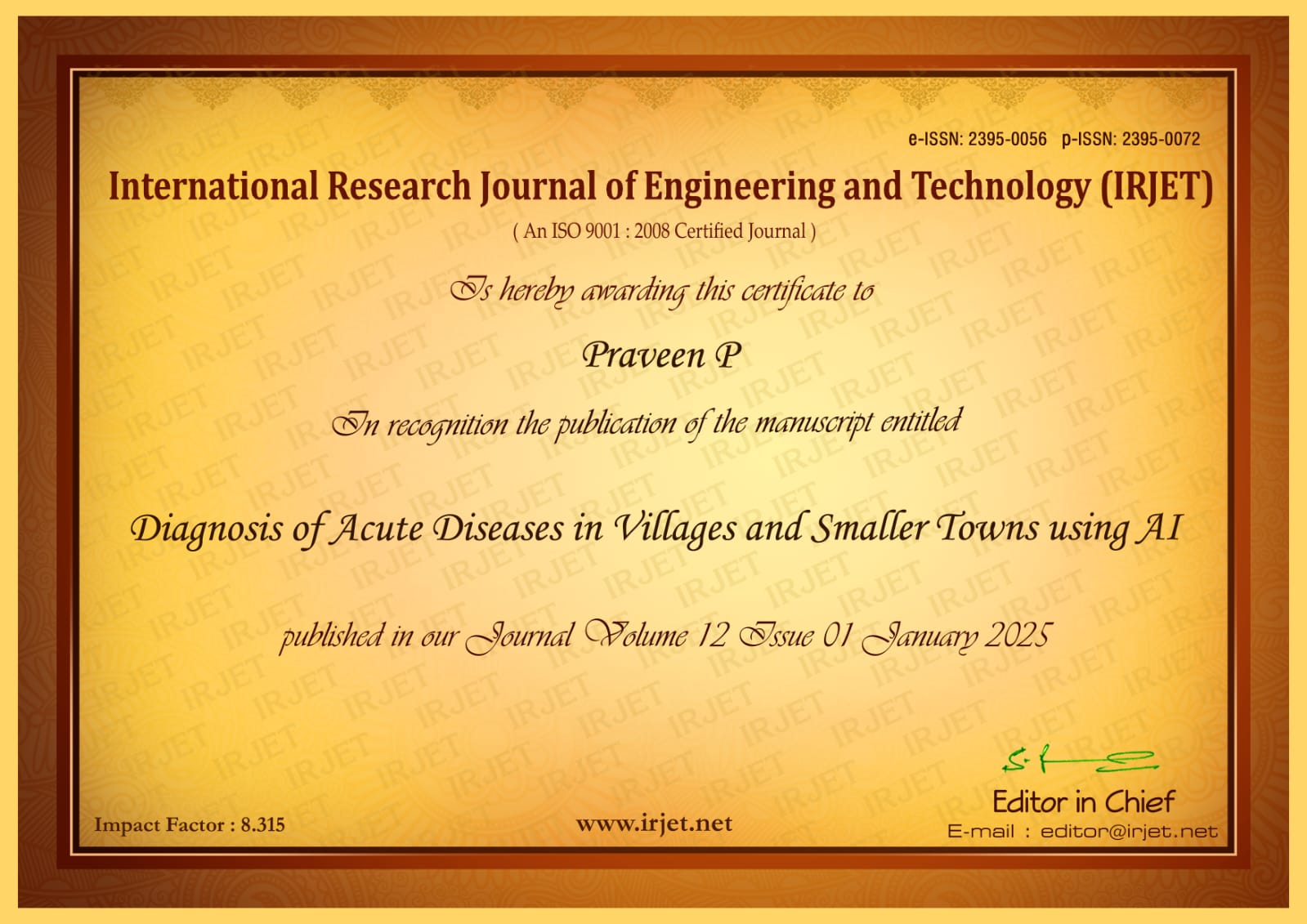


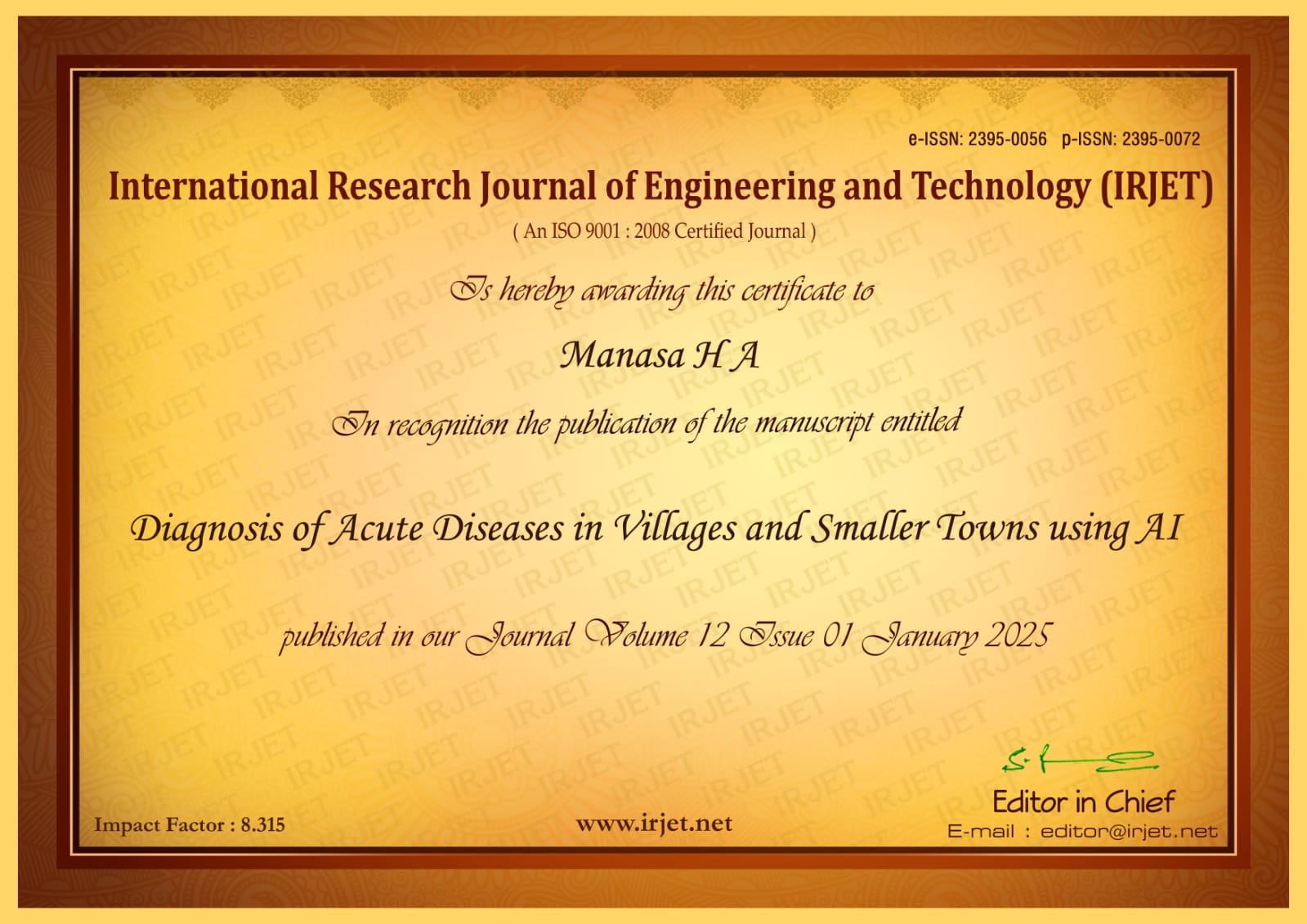
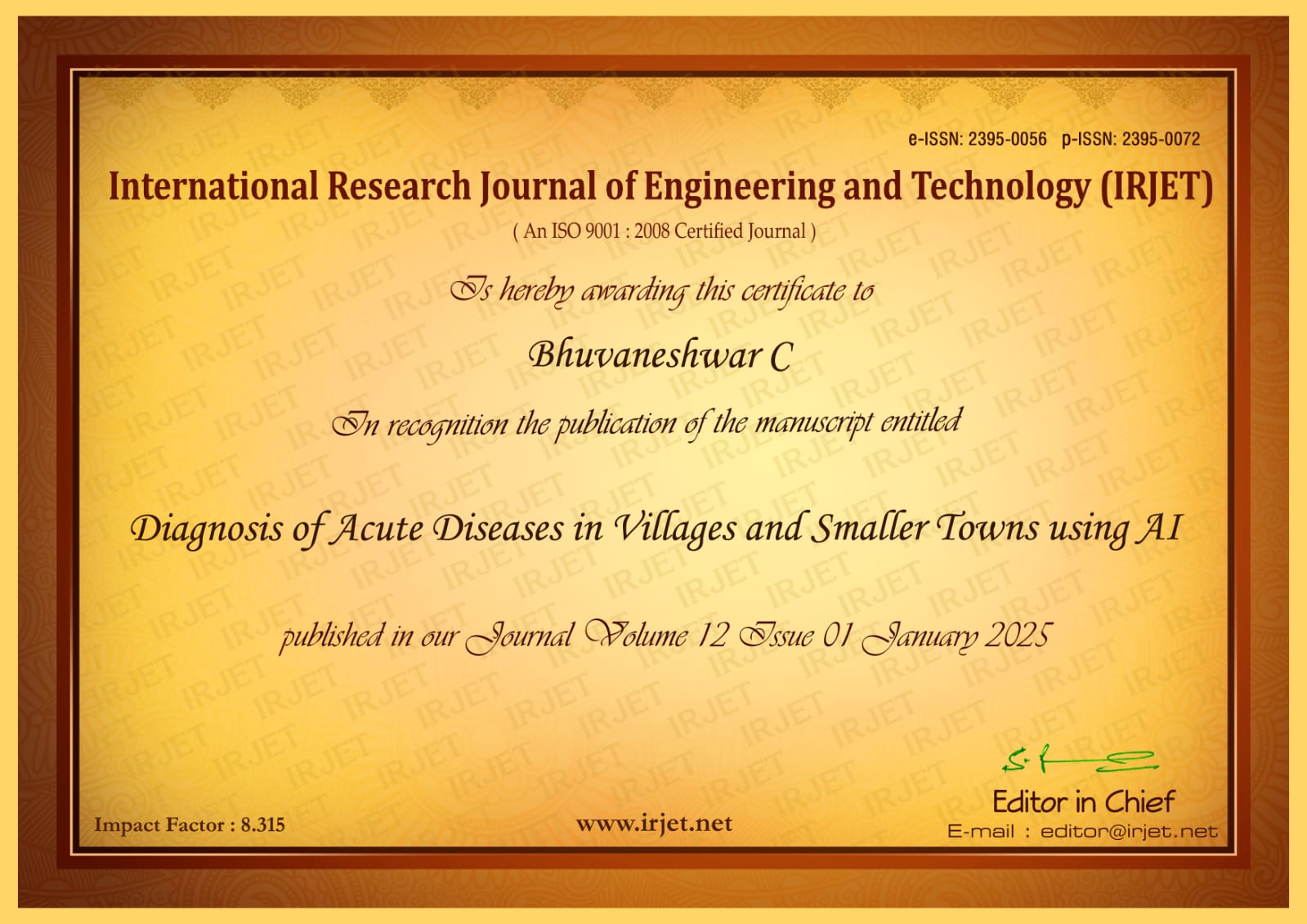
**APPENDIX-C**

**ENCLOSURES**

**1. Journal publication Presented Certificates of all students**

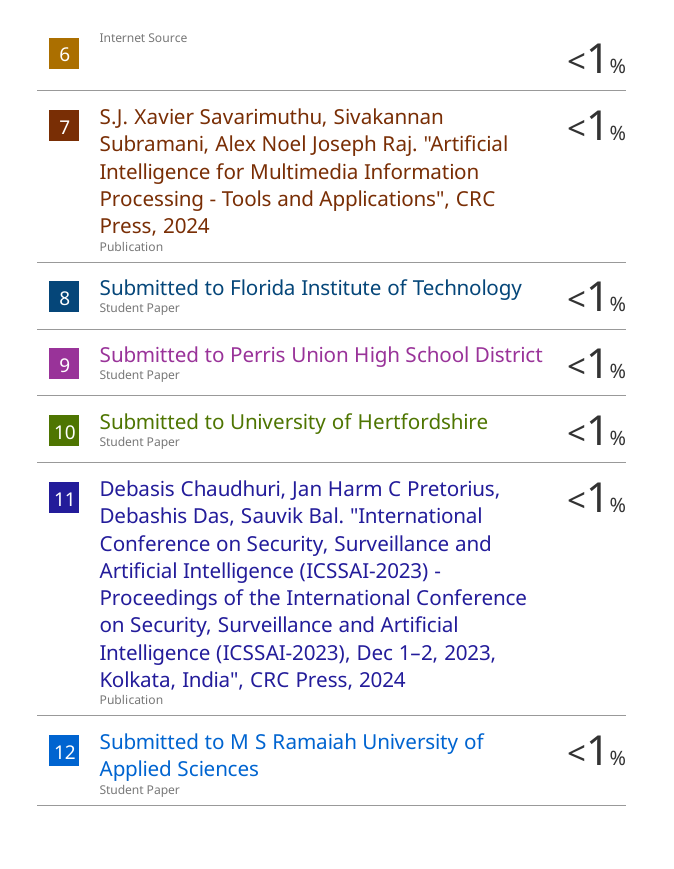


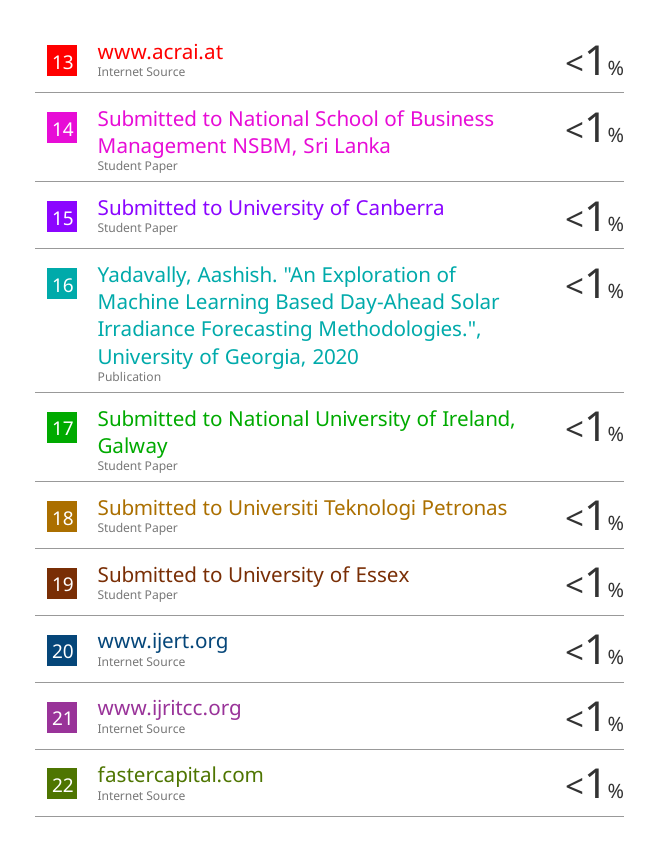


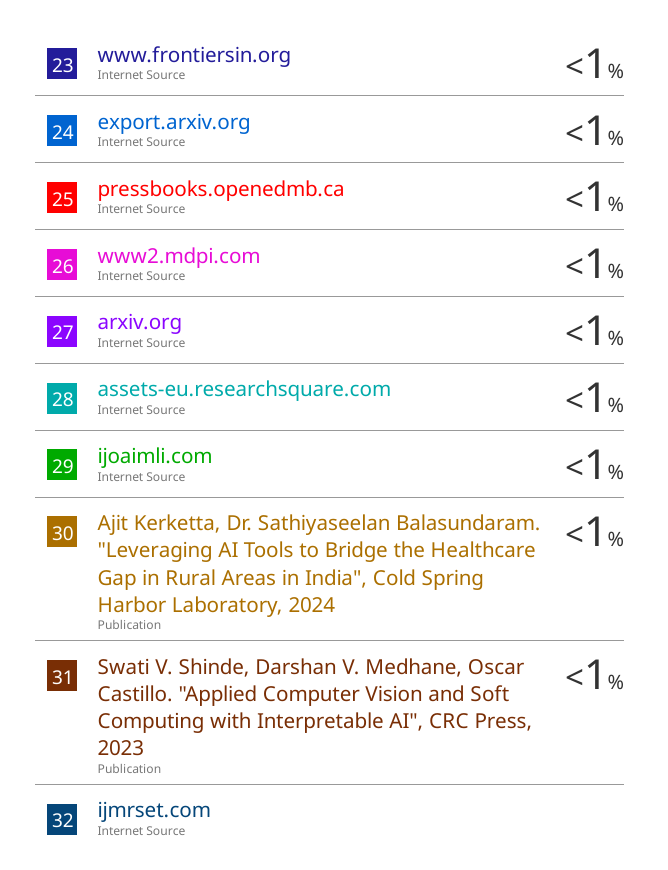


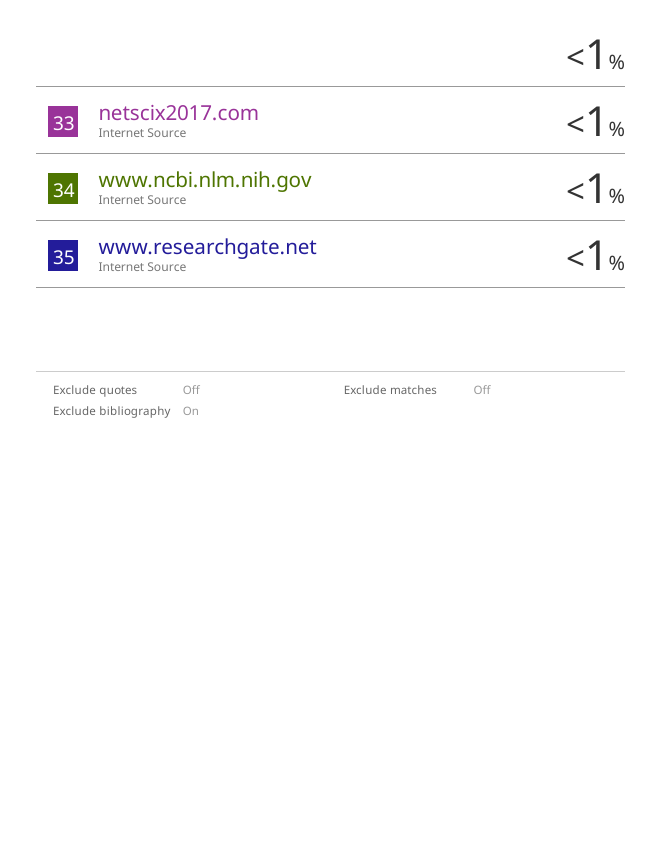
**2. Plagiarism Report:**











**3. Details of mapping the project with the Sustainable Development Goals (SDGs).**



**The Project work carried out here is mapped to**

**SDG 1: No Poverty**

In rural areas, the untreated acute diseases lead to huge financial problems for families who suffer due to treatments of late-stage treatments and a lost income resulting from illness. Our project serves as a respite from the same issues of costliness on account of untimely or unaffordable AI-based early diagnosis. Hence, we also help reduce medical bills and prevent any productivity loss, leading to breaking that poverty cycle by virtue of diseases, which a person or the family may prevent or treat successfully.

**Key Impact on Society**:

1. Prevents impoverishment due to high healthcare costs.
2. Reduces income loss because people stay healthy and also economically active.
3. It supports vulnerable communities by offering affordable solutions.

**SDG 3 - Good Health and Well-Being**

Our project addresses directly the lack of access to health care in rural settings by introducing an AI diagnostic system. Early acute disease detection helps lower mortality and promote better health results. The project ensures patients are treated at an appropriate time and contributes to general well-being of the population underserved. The project equips local healthcare providers with advanced tools, which is in line with the goal of universal health coverage and reducing the burden of untreated diseases.

AI-powered tools empower local healthcare workers by providing insights that are otherwise unavailable due to the lack of specialized doctors in rural areas.

**Key Impact on Society**:

1. Decreases mortality and morbidity rates associated with undiagnosed or untreated diseases.
2. Promotes preventative healthcare by encouraging early intervention.
3. Improves overall quality of life for rural populations.

**SDG 9: Industry, Innovation, and Infrastructure**

This is a project aimed at introducing high-tech AI capabilities to healthcare in rural areas. Such capabilities usually are absent, and integration with local health systems provides improvements in diagnostic accuracy and efficiency, making healthcare much more reliable and productive. The solution not only promotes the strength of healthcare delivery but also opens an avenue for sustainable and inclusive health systems.

**Key Impact on Society:**

1. Gaps between health care infrastructures in urban and rural settings bridged.
2. Pushes for rural health care innovations to adopt state-of-the-art instruments and tools.
3. Sets an example for technological inclusion in essential services.

**SDG 10: Reduced Inequalities**

Usually, rural populations have glaring disparities in healthcare services when compared to urban settings due to a lack of resources and medical input. By giving out advanced diagnostic tools powered by artificial intelligence in smaller towns and villages, we bridge the gap. As a means to address disparities and improve health outcomes, we help bridge health inequalities in marginalized communities.

**Key Impact on Society:**

1. It promotes social inclusion by ensuring health care is available to all people, regardless of geography or income level.
2. Bridges the gap between urban and rural healthcare with advanced diagnostics in underserved regions.
3. Reduces health-related inequalities, fostering equity in healthcare services.

**SDG 17: Partnerships for the Goals**

Strong partnerships with governments, NGOs, healthcare organizations, and technology providers are crucial for our project to succeed. We expect the collaboration with the stakeholders will be the most vital aspect to scale and sustain the AI-driven healthcare solution that we have envisioned. Such collaboration is necessary in reaching remote areas, gaining community trust, and eventually building a long-term impact. Our project represents how cooperation is essential to deliver meaningful development in healthcare innovation and accessibility.

**Key Impact on Society**:

1. Enlarges scope and effectiveness with partnerships in delivery of healthcare service.
2. Build a framework for healthcare innovation that shall be sustainable, scalable, as well as accessible.
3. Promoting knowledge and sharing of resources and expertis.