Predictive analysis on Medicines

A PROJECT REPORT

Submitted by,

S Rajak vali - 20211CEI0073
Patil Madhu - 20211CEI0105
Mukesharchari - 20211CEI0111
B Vishnu Vardhan - 20211CEI0136

Under the guidance of

Dr. Pajany M

in partial fulfillment for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

COMPUTER ENGINEERING (ARTIFICIAL INTELLIGENCE & MACHINE LEARNING)

At

GAIN MORE KNOWLEDGE
REACH GREATER HEIGHTS

PRESIDENCY UNIVERSITY

BENGALURU

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PRESIDENCY UNIVERSITY

SCHOOL OF COMPUTER SCIENCE ENGINEERING

CERTIFICATE

This is to certify that the University project report titled “Predictive analysis on Medicines & Doctors availability in Government hospitals “being submitted by “RAJAKVALI, PATIL MADHU, MUKESH ACHARI, B VISHNUVARDHAN bearing roll number “20211CEI0073,20211CEI0105,20211CEI0111,20211CEI0136” in partial fulfilment of requirement for the award of degree of Bachelor of Computer Application is a bona-fide work carried out under supervision

Dr/Pajany M
Assistant Professor
School of CSE&IS
Presidency University

Dr. Gopal kirshna Shyam
HOD & Professor
School of CSE&IS
Presidency University

Dr. L. SHAKKEERA
Associate Dean
School of CSE
Presidency University

Dr. MYDHILI NAIR
Associate Dean
School of CSE
Presidency University

Dr. SAMEERUDDIN KHAN
Pro-VC School of Engineering
Dean -School of CSE&IS
Presidency University

PRESIDENCY UNIVERSITY

SCHOOL OF COMPUTER SCIENCE ENGINEERING

DECLARATION

We hereby declare that the work, which is being presented in the project report entitled **PREDICTIVE ANALYSIS ON MEDICINES** in partial fulfillment for the award of Degree of **Bachelor of Technology** in **COM PUTER ENGINEERING (ARTIFICIAL INTELLIGENCE & MACHINE LEARNING)**, is a record of our own investigations carried under the guidance of **Dr,pajany M, Assistant 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.

Roll Number	**Student Name**	**Signature**
20211CEI0073	RAJAK VALI	
20211CEI0105	PATIL MADHU	
20211CEI0111	MUKESH ACHARI	
20211CEI0136	B VISHNU VARDHAN	

ABSTRACT

Access to essential medicines and doctors in government hospitals is a cornerstone of public healthcare systems. However, many regions face persistent challenges related to inadequate availability, inefficient resource allocation, and unpredictable service delivery. This project focuses on implementing predictive analysis to address these issues, leveraging data-driven methodologies to enhance the efficiency and reliability of healthcare services.

The study explores the integration of historical and real-time data to anticipate medicine shortages and doctor availability in government hospitals. By employing advanced analytics techniques such as machine learning, regression models, and time-series forecasting, the project aims to identify patterns, predict future demand, and suggest optimal resource allocation. The model incorporates variables like patient inflow, seasonal health trends, supply chain timelines, and staff schedules to ensure accurate predictions.

Key objectives include minimizing stockouts of critical medicines, reducing patient wait times, and optimizing workforce distribution. The project also evaluates the socio-economic impact of improved healthcare accessibility, emphasizing the importance of proactive measures in underserved communities.

In addition to technical insights, the report discusses the practical implementation of the predictive models, the challenges of data collection in the public sector, and strategies to ensure scalability and sustainability. Through this initiative, the project underscores the transformative potential of predictive analysis in bridging healthcare gaps and fostering equitable access to medical resources in government hospitals.

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RAJAK VALI
PATIL MADHU
MUKESH ACHARI
B VISHNU VARDHAN

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INTRODUCTION

Ensuring the availability of essential medicines and access to qualified doctors in government hospitals is a fundamental priority for public healthcare systems. However, the persistent challenges of resource shortages, uneven distribution, and unpredictable service quality have made it difficult to meet this objective effectively. With the advancement of artificial intelligence (AI) and machine learning (ML), there is now an unprecedented opportunity to revolutionize healthcare management through predictive analysis.

This project introduces a predictive analysis system designed to enhance the efficiency of healthcare services by forecasting the availability of medicines and doctors in government hospitals. By leveraging advanced ML models and data analytics, the system aims to optimize resource allocation and address critical gaps in service delivery.

Key features of the system include:

1. Machine Learning Model: Sophisticated ML algorithms analyze historical and real-time data to predict medicine demand and doctor availability, ensuring informed decision-making.
2. Data Integration and Analysis: The system integrates data from various sources, such as patient inflow, seasonal health trends, supply chain logistics, and staffing schedules, to deliver accurate predictions.
3. Proactive Resource Management: By forecasting demand and supply, the application minimizes stockouts of essential medicines and ensures optimal distribution of healthcare professionals across facilities.
4. Interactive Dashboard: A user-friendly interface allows healthcare administrators to view predictive insights, enabling efficient planning and allocation of resources.
5. Community Impact Assessment: The system evaluates its influence on healthcare accessibility and equity, particularly in underserved regions, emphasizing the importance of technology-driven solutions in public health.

This innovative approach not only streamlines operations within government hospitals but also demonstrates the transformative potential of predictive analysis in addressing critical healthcare challenges. By improving service availability, reducing inefficiencies, and fostering equitable access to medical resources, this project serves as a vital step toward a more resilient and responsive public healthcare system.

CHAPTER-2

LITERATURE SURVEY

The application of predictive analysis in healthcare has been extensively explored in recent years, with numerous studies highlighting its potential to improve resource allocation and service delivery. A key area of focus has been the optimization of supply chain management in hospitals, where predictive models have demonstrated success in anticipating medicine shortages and aligning procurement processes. For instance, a study by Chai et al. (2020) showed that time-series forecasting models could predict pharmaceutical demand with high accuracy, thereby reducing wastage and ensuring continuous availability.

Similarly, the integration of machine learning in workforce management has gained traction. Research by Smith and Patel (2019) emphasized the efficacy of ML algorithms in forecasting patient inflow patterns, enabling hospitals to optimize staff scheduling and reduce wait times. These advancements underline the importance of leveraging data-driven approaches to address inefficiencies in healthcare systems.

In the context of public health, predictive analytics has been particularly beneficial for underserved regions. Studies like those conducted by Lopez et al. (2021) illustrate how predictive models can identify high-demand periods and allocate resources accordingly, improving access to care for marginalized populations. The inclusion of socio-demographic factors in such analyses has proven crucial in tailoring interventions to specific community needs.

Moreover, the use of interactive dashboards and visualization tools has been a recurring theme in the literature. Dashboards not only enhance the usability of predictive systems but also empower administrators with actionable insights. Research by Kim et al. (2018) highlights the role of intuitive interfaces in fostering better decision-making and stakeholder engagement in healthcare settings.

Despite these advancements, challenges remain in implementing predictive analysis in government hospitals. Issues such as data quality, integration across disparate systems, and the need for robust validation frameworks are frequently cited in the literature. Addressing these challenges requires a collaborative approach involving policymakers, technologists, and healthcare practitioners.

In conclusion, the existing body of research provides a strong foundation for this project, underscoring the transformative potential of predictive analysis in healthcare. By building on established methodologies and addressing identified gaps, this initiative aims to contribute significantly to the field, ensuring equitable and efficient healthcare delivery in government hospitals.

CHAPTER-3

EXISTING METHODS

The existing approaches to ensuring the availability of medicines and doctors in government hospitals often rely on traditional methods, which include:

3.1. Manual Inventory Tracking: Hospital administrators monitor stock levels of medicines and availability of staff manually or through basic inventory systems. While this ensures immediate oversight, it is prone to errors and delays in identifying shortages or surpluses.

3.2. Reactive Decision-Making: Resources are often allocated only after shortages are identified or complaints are received, resulting in delays and inefficiencies.

3.3. Periodic Surveys: Data on resource availability is collected through periodic surveys or audits, which can be time-consuming and may not capture real-time changes.

3.4. Linear Forecasting: Simple statistical techniques are used to predict demand for medicines and staff availability based on historical trends, which often fail to account for dynamic variables like seasonal health trends or emergencies.

3.5. Isolated Systems: Resource management systems in hospitals often operate independently, making it difficult to share data and insights across facilities, thereby limiting the scope for coordinated responses.

While these methods provide a baseline for resource management, they are limited in their ability to predict and respond to dynamic healthcare needs. The reliance on manual and isolated systems often results in inefficiencies and inequitable distribution of resources.

Fig.3.1: Excenting Methodology Resource Management

CHAPTER-4

PROPOSED MOTHODOLOGY

To address the limitations of existing approaches, this project proposes an integrated and automated system to predict diseases and recommend accurate medicines while ensuring real time resource optimization. The methodology includes the following steps:

4.1Data Collection and Preprocessing: Collect data from various sources, including patient records, hospital inventories, and demographic databases. Preprocess data to remove inconsistencies, handle missing values, and encode categorical variables for ML models.

4.2 Disease Prediction Model: Use advanced ML models such as Random Forests or Gradient Boosting to analyze patient symptoms and medical history to predict probable diseases. Integrate Natural Language Processing (NLP) for analyzing unstructured data such as doctor notes.

4.3 Medicine Recommendation System: Employ collaborative filtering and rule-based algorithms to recommend accurate medicines based on predicted diseases and patient profiles.Validate recommendations against a database of medical guidelines to ensure compliance with standards.

4.4 Interactive Frontend Interface: Develop a user-friendly web-based or mobile application using frameworks like Streamlit or ReactJS. Provide interactive dashboards for doctors and administrators to input symptoms, view disease predictions, and receive medicine recommendations. Include real-time validation of user inputs and ensure accessibility across devices.

4.5 Integration with Hospital Systems: Connect the predictive system to existing hospital databases and supply chain systems for seamless data exchange. Enable real-time updates on medicine stock levels and doctor availability.

4.6 Real-Time Decision Support: Use predictive insights to suggest optimal resource allocation, such as reallocating doctors during peak demand periods or pre-ordering medicines based on forecasted needs. Generate alerts for critical shortages or high-demand periods.

4.7 Validation and Feedback Mechanism: Implement validation protocols to ensure accuracy in disease predictions and medicine recommendations. Incorporate user feedback loops for continuous improvement of the system.

4.8 Scalability and Deployment: Deploy the system on cloud platforms for scalability and reliability. Use containerization tools like Docker for easy deployment and updates across multiple hospitals. This methodology ensures a proactive approach to healthcare management, leveraging predictive analytics and machine learning to improve the efficiency, accuracy, and equity of resource distribution in government hospitals.

4.2. Real-Time User Interface

· Input Fields: Users can provide their personal and financial data via a Streamlit interface.

· Dynamic Inputs: Generate random values for certain fields like educational expenses, business income, and capital gains when applicable.

· Interactive Buttons: Detect fraud upon user interaction by submitting input data.

1. Real-Time Feedback: Allow users to modify inputs dynamically and see updated results.
2. Integration with Databases: Enable real-time data fetching from tax records or financial institutions for accurate analysis.
3. Fraud Pattern Analytics: Utilize historical data to highlight common fraudulent behaviours and patterns.

4.3. How Does It Work?

The system operates through a seamless integration of data analytics, machine learning, and user-friendly interfaces to deliver actionable insights.

The workflow is as follows:

4.3.1. User Input and Data Validation:

Healthcare providers input patient symptoms, demographics, and relevant medical history into the interactive frontend interface. The system validates the input data to ensure completeness and accuracy, using predefined rules for consistency.

4.3.2. Data Processing and Feature Engineering:

The input data is processed and transformed into a format suitable for machine learning models. This includes encoding categorical variables and normalizing numerical features. Additional features are generated to enhance the model's predictive capability, such as combining patient history with seasonal health trends.

4.3.3. Disease Prediction:

The ML model analyzes the processed data and predicts potential diseases based on the input. The prediction is supplemented with confidence scores to indicate the reliability of the output.

4.3.4. Medicine Recommendation:

The system cross-references the predicted disease with a comprehensive medical database to recommend suitable medicines. o Recommendations are aligned with medical guidelines to ensure safety and compliance.

4.3.5. Resource Allocation Insights:

The system generates insights for administrators, highlighting resource needs such as medicine stock levels and staff allocation based on predicted patient demand. Alerts are issued for any impending shortages or overutilization of resources.

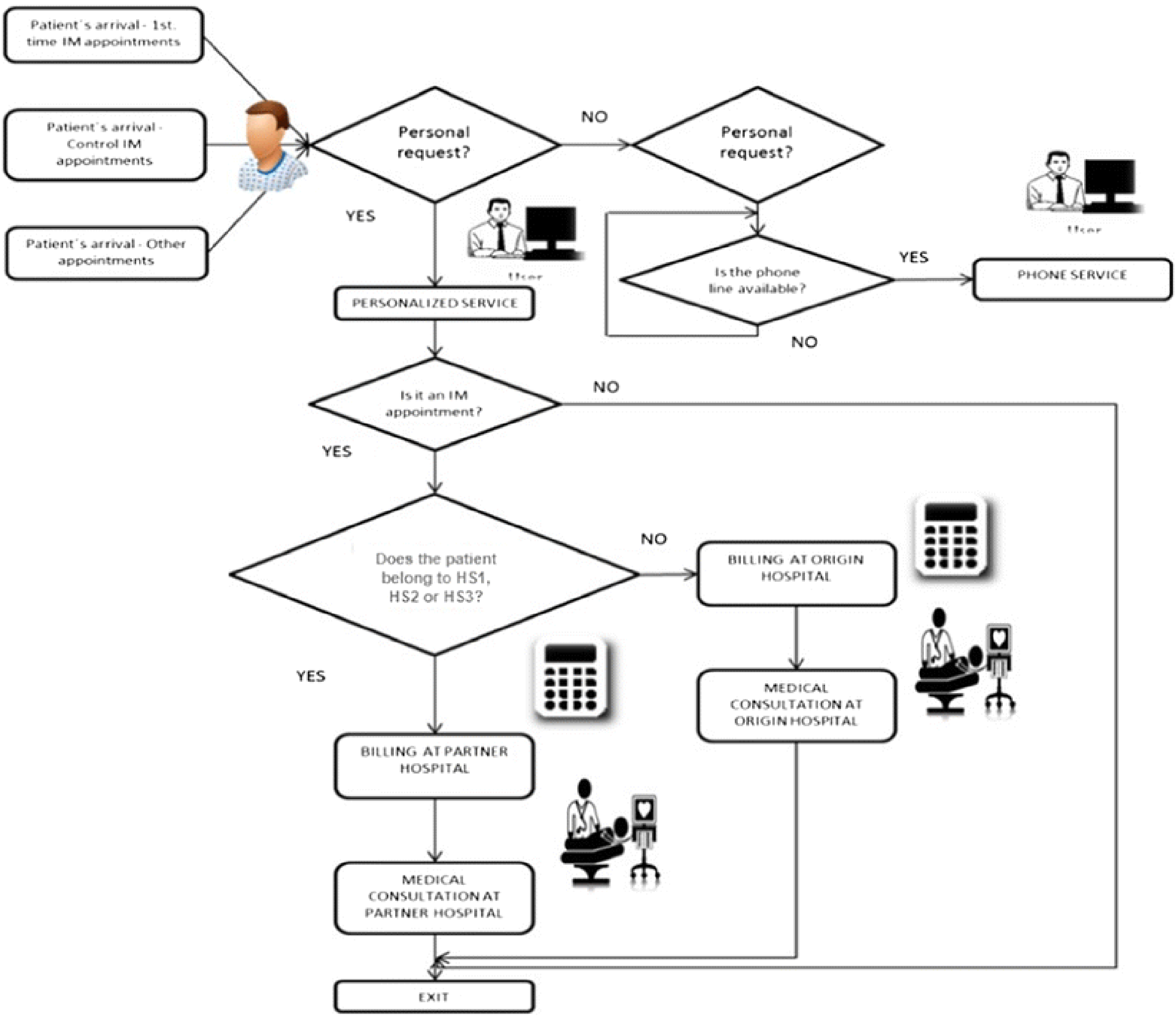
4.3.6. Interactive Dashboard:

Healthcare professionals and administrators can view predictions, recommendations, and resource insights through a user-friendly dashboard. The dashboard allows real-time monitoring and facilitates informed decision making.

4.3.7. Feedback and Learning:

Usersprovide feedback on the system’s recommendations, which is used to improve the accuracy of the predictions and recommendations over time. Continuous model retraining is performed to incorporate new data and adapt to evolving healthcare scenarios. By integrating predictive analytics and real-time data visualization, this system empowers healthcare providers to deliver efficient, accurate, and equitable care

Workflow :



.Fig 4.1: Work flow diagram

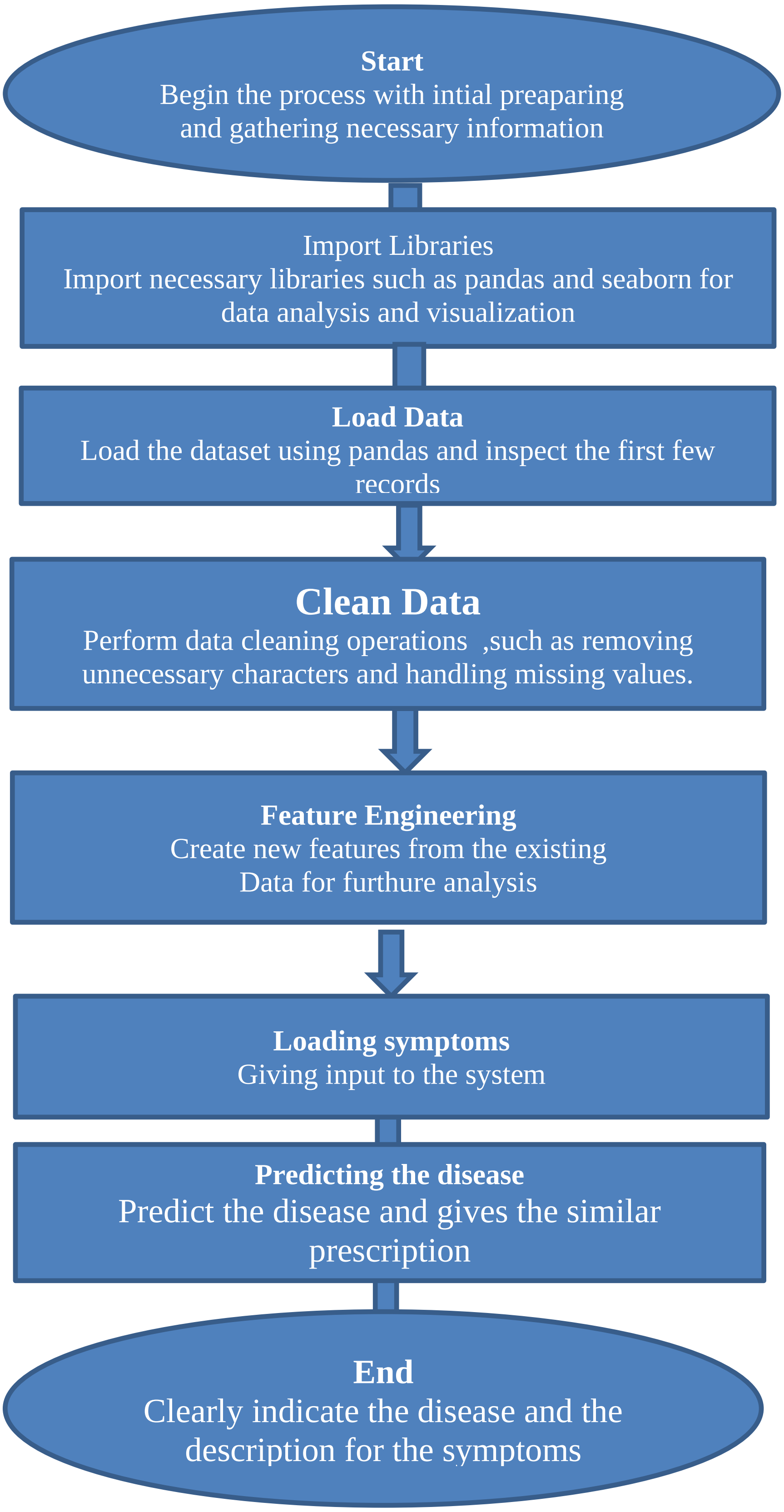


Fig 4.2 flow chat

CHAPTER-5

OBJECTIVES

The primary objectives of this project focus on addressing critical challenges in healthcare resource management and ensuring efficient, equitable service delivery.

The key objectives are:

5.1. Accurate Prediction of Medicine Demand and Doctor Availability:

Utilize advanced machine learning algorithms to predict the demand for medicines and availability of doctors in real-time.

Incorporate historical and seasonal trends to enhance the accuracy of predictions and anticipate surges in demand.

5.**2. Disease Identification and Medicine Recommendation**:

Develop a robust system for analyzing patient symptoms to predict probable diseases.

Provide precise medicine recommendations based on predictive insights, ensuring adherence to medical guidelines.

5.3. Optimized Resource Allocation: Enable proactive allocation of medical resources, including reallocation of staff and pre-ordering of essential medicines based on predicted needs.

Minimize wastage by ensuring optimal stock levels across healthcare facilities.

5.4. Integration with Existing Hospital Systems:

Seamlessly integrate predictive analysis tools with hospital databases, supply chain systems, and electronic health records.

Enhance coordination between departments and across facilities to improve overall efficiency.

5.5. Reduction of Service Inequities:

Address disparities in healthcare accessibility by identifying underserved regions and prioritizing resource allocation.

Ensure timely availability of medical resources to all patients, irrespective of their geographic or socio-economic status.

5.6. Interactive and User-Friendly Interface:

Develop an intuitive web-based or mobile application for healthcare professionals to input data, view predictions, and access insights.

Empoweradministrators and doctors with real-time dashboards for better decision making and planning.

5.7. Continuous Learning and System Improvement:

Implement feedback mechanisms to refine the prediction models based on user input and evolving healthcare scenarios.

Leverage new data to retrain the models, ensuring continuous improvement in accuracy and performance.

5.8. Scalable and Adaptable Solutions:

Design the system to scale across multiple healthcare facilities, accommodating growing data volumes and diverse healthcare needs.

Ensure adaptability to evolving medical standards, technologies, and healthcare policies.

5.9. Enhanced Healthcare Transparency:

Provide clear insights into the decision-making process for predictions and recommendations, fostering trust among stakeholders.

Offer detailed reports on system performance, resource utilization, and patient outcomes.

5.10.Proactive Healthcare Management:

Shift from reactive to proactive healthcare management by anticipating and mitigating potential crises. Reduce response times and improve patient satisfaction by ensuring the availability of resources when and where needed.By achieving these objectives, the project aims to transform the management of healthcare resources in government hospitals, paving the way for a more efficient, equitable, and resilient public health system.

CHAPTER-6

6.1.SYSTEM A NALYSIS & 6.2. SYSTEM DESIGN & 6.3 IMPLEMENTATION

6.11. Objectives of the System

- To predict medicine demand and doctor availability using machine learning techniques.
- To optimize the allocation of medical resources, reducing inefficiencies in healthcare service delivery.
- To develop a user-friendly interface for administrators and healthcare providers to access predictive insights.
- To integrate seamlessly with existing hospital systems, ensuring interoperability and data sharing.

6.1.2. Scope of the System

Functional Scope:

- Analyze real-time and historical data to predict demand for medicines and staff availability.
- Provide disease prediction and medicine recommendations based on patient data.
- Offer resource optimization insights for administrators.
- *Non-Functional Scope:*
- Ensure data security and privacy, complying with healthcare regulations.
- Provide scalable solutions for hospitals of varying sizes and capacities.
- Maintain high system availability with minimal downtime.

6.1.3. Stakeholder Analysis

- *Primary Stakeholders*: Hospital administrators, doctors, and pharmacists for operational planning and resource allocation.
- *Secondary Stakeholders*: Patients benefiting from improved service delivery and policymakers using data insights for healthcare strategies.

6.1.4. Feasibility Study

Technical Feasibility:

- Availability of cloud computing platforms for scalable deployment.
- Established machine learning frameworks (e.g., TensorFlow, Scikit-learn) for predictive modeling.
- *Economic Feasibility:*
- Reduced costs from optimized resource usage and minimized wastage.
- Initial investment offset by long-term savings and improved efficiency.

- *Operational Feasibility:*
- Easy adoption due to a user-friendly interface and integration with existing systems.
- Minimal training required for stakeholders to use the system effectively.

6.1.5. Current System Challenges

- Inefficient manual tracking of resources leading to frequent shortages or overstocking.
- Lack of real-time data sharing between departments and facilities.
- Limited ability to predict and address dynamic changes in healthcare needs.
- Fragmented systems reducing overall coordination and efficiency.

6.1.6. System Requirements

Functional Requirements:

- Input validation for accurate data collection (e.g., patient symptoms, hospital inventory).
- Machine learning models to predict demand and provide recommendations.
- Interactive dashboards displaying insights and recommendations.
- *Non-Functional Requirements:*
- High reliability with a 99.9% system uptime.
- Response times of less than 1 second for predictions and insights.
- Compliance with healthcare privacy standards like HIPAA.

By addressing these components, the system analysis outlines the project's framework, focusing on its feasibility, scope, and anticipated benefits to stakeholders.

6.2 system design

6.2.1. Overview of the System

The project aims to build a predictive system that forecasts the availability of medicines and doctors in government hospitals. This system will be beneficial for improving hospital management, reducing patient wait times, optimizing resource allocation, and enhancing the overall healthcare experience.

6.2.2. Key Components of the System

1. Data Collection:
    - Medicine Availability: Collect data from hospital inventories regarding the stock of medicines. This can include medicine names, quantities, expiry dates, suppliers, and consumption rates.
    - Doctor Availability: Gather scheduling information of doctors (shifts, holidays, and working hours), as well as patient load and doctor specialty requirements.
    - Patient Data: Historical patient admission data, treatment types, and prescriptions can help in predicting future medicine needs and doctor demand.
2. Data Storage:
    - Relational Database: Store structured data such as doctor schedules, patient records, and medicine inventories. Use databases like MySQL, PostgreSQL, or Oracle.
    - NoSQL Database: Store unstructured data or time-series data like historical patient volume, medicine consumption, etc. Use MongoDB, Cassandra, or InfluxDB.
3. Data Preprocessing:
    - Clean the data for missing or inconsistent values.
    - Aggregate and normalize data to make it suitable for analysis (e.g., weekly medicine consumption trends, doctor attendance patterns).
    - Identify outliers that could affect predictive models.
4. Predictive Model Development:
    - Medicine Availability Prediction:
        - Use time-series forecasting models (ARIMA, Prophet, LSTM) to predict future medicine needs based on historical consumption patterns and seasonal trends.
        - Factor in external factors like new diseases, changes in population, and seasonal flu outbreaks.
    - Doctor Availability Prediction:
        - Apply machine learning algorithms like Random Forest, XGBoost, or neural networks to predict doctor availability based on historical shift data, doctor performance, patient load, and other influencing factors.
5. Recommendation Engine:

- Based on predicted medicine needs and doctor availability, generate recommendations to the hospital management team for procurement, scheduling, and staffing.
- Consider scenarios like critical shortages or surges in demand due to unforeseen events like epidemics.

6. Visualization:
   - Dashboard: Create an interactive dashboard for hospital administrators and staff. Visualize medicine stock levels, doctor availability, predicted future shortages, and staffing requirements.
   - Use tools like Power BI, Tableau, or custom-built solutions with React.js or Angular for frontend and D3.js for interactive charts.
7. User Roles:
   - Admin: Hospital management staff can configure system settings, input or modify data, and view analytics and predictions.
   - Doctors: Can access schedules, and availability, and receive alerts for any changes in their shifts or medicine requirements.
   - Supply Chain Manager: Monitors medicine inventory and receives alerts when stock is low or predicted to run out.
   - Patients: Optionally, patients can be informed of available appointments and wait times.

6.2.3. Technologies to Use

- Backend: Python (for predictive models using libraries like Scikit-learn, TensorFlow, or Keras), Node.js, Django, or Flask for RESTful APIs.
- Frontend: React.js or Angular for the user interface, Bootstrap for styling, and D3.js for interactive visualizations.
- Database: MySQL/PostgreSQL (for structured data), MongoDB or InfluxDB (for unstructured or time-series data).
- Cloud: AWS, GCP, or Azure for hosting the system, running ML models, and scaling based on demand.
- DevOps: Docker for containerization, Kubernetes for orchestration, and CI/CD pipelines for deployment.

6.2.4. System Workflow

1. Data Entry: Doctors and inventory managers input data into the system (e.g., doctor shifts, patient treatment data, inventory details).
2. Data Analysis & Model Training: The system processes historical data and trains the predictive models.
3. Prediction Generation: Using the trained models, the system generates forecasts for medicine demand and doctor availability.
4. Actionable Insights: The system notifies relevant personnel of predicted shortages or scheduling mismatches, offering suggestions.
5. Reporting: Generate real-time and historical reports for decision-makers.

6.2.5. Scalability & Maintenance

- Scalable Architecture: Use cloud infrastructure with auto-scaling capabilities for handling increased data and user load.
- Continuous Learning: Continuously retrain the predictive models as new data is collected to improve prediction accuracy.
- System Monitoring: Use tools like Prometheus or Grafana to monitor system health and performance.

6.2.6. Security & Privacy Considerations

- Data Encryption: Ensure all patient data and sensitive information are encrypted both at rest and in transit.
- Role-Based Access Control: Implement RBAC to ensure that only authorized personnel can access sensitive data.
- Compliance: Ensure the system complies with healthcare regulations like HIPAA (Health Insurance Portability and Accountability Act) or GDPR (General Data Protection Regulation).

6.2.7. Future Enhancements

- Integrate real-time data from hospital sensors for better accuracy in predicting medicine and doctor needs.
- Use AI-driven techniques for dynamic scheduling of doctors based on patient load predictions.
- Incorporate feedback loops from doctors and patients to continuously improve predictions.

This design provides a comprehensive framework for building an intelligent predictive system for medicine and doctor availability in government hospitals.

6.3. implementation

a. Medicine Availability Data:

- Sources: Hospital inventory systems (manual or automated).
- Data Points: Medicine name, batch number, quantity, expiry dates, suppliers, usage rate, and reorder thresholds.
- Collection Method: Automated data collection via inventory management systems, manual data entry for smaller hospitals.

b. Doctor Availability Data:

- Sources: Hospital scheduling systems, employee attendance records.
- Data Points: Doctor name, department, shifts, holidays, attendance, patient load, and specialization.
- Collection Method: Integration with HR or scheduling systems; manual entry if no existing system.

c. Patient Data:

- Sources: Patient records, prescriptions, admission data.
- Data Points: Patient demographics, treatment history, prescription details, and visit frequency.
- Collection Method: Integration with electronic health records (EHR) systems.

2. Data Storage

a. Database Design:

- Relational Database (MySQL/PostgreSQL):
  - Tables: doctors, medicine inventory, medicine usage, patient records, doctor schedule.
  - Relationships:
    - A one-to-many relationship between doctors and their schedules.
    - A one-to-many relationship between medicines and usage logs.
    - A many-to-many relationship between patients and treatments.
- NoSQL Database (MongoDB):
  - Use for storing unstructured or time-series data like patient visit logs, seasonal consumption patterns, and doctor performance metrics.

3. Data Preprocessing

a. Data Cleaning:

- Handle Missing Data: Fill gaps in inventory data or doctor schedules with historical averages or interpolation techniques.
- Normalization: Scale data like medicine consumption (daily, weekly) for use in predictive models.
- Outlier Detection: Use statistical techniques (IQR, Z-score) to detect anomalies in medicine usage or doctor attendance.

b. Feature Engineering:

- Time-based Features: Extract date-related features (week, month, holiday) to predict seasonal spikes in medicine needs or doctor availability.
- Aggregation: Calculate weekly/monthly medicine consumption, average

patient load per doctor, and doctor shift overlap.

- External Data: Integrate weather, disease outbreaks, or regional health trends to improve prediction accuracy.

4. Predictive Modelling

a. Medicine Availability Prediction:

- Model Selection:
    - Time-Series Forecasting: Use models like ARIMA, Facebook Prophet, or Long Short-Term Memory (LSTM) networks to predict future medicine demand.
    - Feature Selection: Include medicine usage history, seasonal trends, external factors like flu season, and historical inventory data.
- Implementation:
    - Split data into training (80%) and testing (20%) sets.
    - Train the model on historical data and forecast future requirements (e.g., next 3-6 months).
    - Evaluate using Mean Absolute Error (MAE) or Root Mean Squared Error (RMSE).

b. Doctor Availability Prediction:

- Model Selection:
    - Supervised Learning: Use models like Random Forest, XGBoost, or Support Vector Machines (SVM) to predict doctor availability based on historical shifts, patient load, and specialty requirements.
    - Feature Engineering: Include doctor specialty, historical shifts, patient demographics, and seasonal doctor absenteeism.
- Implementation:
    - Split data into training and testing sets.
    - Train the model to predict future doctor availability patterns (e.g., optimal scheduling for the next month).
    - Evaluate using Accuracy, Precision, and Recall metrics.

5. Recommendation Engine

- Based on predictions, generate actionable insights:
    - Medicine Recommendations: Alert supply chain managers about potential stock shortages, suggest when to reorder, and recommend alternative medications if stocks run low.
    - Doctor Scheduling: Recommend adjustments to doctor schedules based on predicted patient volume, specialty requirements, and availability.
- Optimization: Use optimization algorithms like Linear Programming or Genetic Algorithms to suggest the best combination of doctor shifts and resource allocation.

6. Visualization

a. Dashboard Design:

- Real-Time Analytics: Display current medicine stock levels, doctor availability, and forecasted shortages.

- Interactive Features:
  - Calendar views of doctor shifts and patient appointment slots.
  - Graphs showing trends in medicine consumption and doctor attendance.
- Technology: Use React.js for the frontend, D3.js for data visualizations, and Bootstrap for responsive design.

b. Reporting:

- Generate daily, weekly, and monthly reports for hospital management, highlighting:
  - Predicted medicine shortages.
  - Doctor availability mismatches.
  - Patient flow trends.

7. Backend & API

- Backend: Use Python (Flask or Django) for API development, integrating with machine learning models.
  - Endpoints:
    - /predict/medicine: Endpoint to fetch predicted medicine stock levels.
    - /predict/doctor: Endpoint for doctor availability predictions.
    - /recommendations: Endpoint to retrieve action items based on predictions.
- Machine Learning Integration: Deploy models using frameworks like TensorFlow or PyTorch. Use Docker containers for easy deployment and scaling.

8. Security & Privacy

- Data Encryption: Encrypt sensitive data at rest (using AES-256) and in transit (using HTTPS).
- Authentication: Implement role-based access control (RBAC) to ensure only authorized users can access sensitive data.
- Compliance: Ensure the system adheres to HIPAA or GDPR standards for patient data protection.

9. Deployment & Scalability

- Cloud Hosting: Host the system on AWS/GCP/Azure using auto-scaling to handle increasing data and user traffic.
- CI/CD Pipeline: Use GitHub Actions or Jenkins for continuous integration and deployment.
- Monitoring: Use Prometheus and Grafana for system performance monitoring.

10. Maintenance & Continuous Learning

- Model Retraining: Schedule monthly retraining of models using new data to ensure they adapt to changing hospital conditions and patient behavior.
- Error Logging & Feedback: Implement logging mechanisms to track errors and gather feedback from hospital staff for system improvements.

Conclusion

This implementation provides a comprehensive approach to building a predictive system for medicine and doctor availability in government hospitals.

It incorporates modern data processing, machine learning, and visualization techniques, ensuring the system is scalable, secure, and reliable for improving hospital management.

Components Used

1. Data Collection Components

- Hospital Inventory Systems: Automated or manual systems used to collect and track medicine stock levels, expiry dates, and consumption rates.
- Hospital Scheduling Systems: Systems (HR or hospital management software) that track doctor shifts, attendance, holidays, and patient load.
- Electronic Health Records (EHR): Systems for storing patient records, prescriptions, and medical history.
- Manual Data Entry Interfaces: Forms or interfaces for manually inputting missing or new data (e.g., doctor schedules, patient records).

2. Data Storage Components

- Relational Databases (RDBMS):
  - MySQL/PostgreSQL: Used to store structured data such as doctor schedules, medicine inventories, and patient records.
- NoSQL Databases:
  - MongoDB: For storing unstructured data like patient visit logs, seasonal consumption patterns, or doctor performance metrics.
  - InfluxDB: For time-series data, like medicine usage over time or patient admission patterns.

3. Data Preprocessing Components

- ETL (Extract, Transform, Load) Tools:
  - Apache Nifi or Airflow: Used to automate the process of extracting data, transforming it (e.g., cleaning, normalization), and loading it into databases.
- Data Cleaning Libraries:
  - Pandas: For data cleaning and manipulation in Python.
  - NumPy: For handling arrays and numerical data.

4. Predictive Modeling Components

- Machine Learning Libraries:
  - Scikit-learn: For basic machine learning algorithms like Random Forest, SVM, etc.
  - XGBoost: For more advanced boosting techniques in predictive modeling.
  - TensorFlow/Keras: For deep learning models, such as LSTM (Long Short-Term Memory) networks, for time-series predictions.
  - Facebook Prophet: For time-series forecasting with a focus on seasonal patterns in medicine demand.
- Model Training and Evaluation Tools:
  - Jupyter Notebooks: For iterative model development, experimentation, and evaluation.
  - TensorBoard: For monitoring and evaluating deep learning model performance.

5. Recommendation Engine Components

- Optimization Algorithms:

- ○ Linear Programming: For optimizing doctor scheduling and resource allocation based on predicted demand.
- ○ Genetic Algorithms: For solving complex scheduling problems with multiple constraints.
- Recommendation Libraries:
- ○ Surprise: A Python library for building and evaluating recommendation systems (used for medicine and doctor scheduling recommendations).

6. Visualization Components

- Frontend Framework:
- ○ React.js: For building dynamic, responsive dashboards and interfaces.
- ○ Angular: As an alternative to React for building interactive UI components.
- Data Visualization Libraries:
- ○ D3.js: For creating complex, interactive visualizations like graphs and charts.
- ○ Plotly: For interactive plotting in Python, especially useful for medical data visualization.
- ○ Chart.js: For rendering simple charts, such as line or bar charts.
- UI Framework:
- ○ Bootstrap: For responsive design and UI components.
- ○ Material-UI: For ready-made React components following Google's Material Design guidelines.

7. Backend & API Components

- Backend Frameworks:
- ○ Flask or Django: Python-based frameworks used for building RESTful APIs that serve predictions and recommendations.
- ○ Node.js: A JavaScript runtime environment, if choosing a JavaScript backend, for fast, scalable API development.
- API Management:
- ○ Swagger/OpenAPI: For documenting and managing RESTful APIs.
- Authentication & Security:
- ○ OAuth2 or JWT (JSON Web Tokens): For implementing secure authentication and role-based access control (RBAC).
- ○ SSL/TLS: For securing API endpoints and encrypting data in transit.

8. Cloud & Deployment Components

- Cloud Hosting Platforms:
- ○ AWS (Amazon Web Services): For scalable infrastructure, with services like EC2 (compute), RDS (relational databases), and S3 (storage).
- ○ Google Cloud Platform (GCP): Alternative to AWS, offering scalable services like App Engine, BigQuery, and Cloud Storage.
- ○ Microsoft Azure: Another alternative cloud platform, especially for hospitals using Microsoft-based tools.
- Containerization:
- ○ Docker: For containerizing applications and services, ensuring consistency across environments.

- ○ Kubernetes: For orchestrating and managing containerized applications in a scalable, fault-tolerant manner.

- Continuous Integration/Continuous Deployment (CI/CD):
  - ○ GitHub Actions, Jenkins, or GitLab CI/CD: For automating the deployment pipeline, ensuring that code changes are tested, built, and deployed efficiently.

9. Monitoring & Logging Components

- Monitoring Tools:
  - ○ Prometheus: For system monitoring, especially useful for tracking server health, API response times, and database performance.
  - ○ Grafana: For creating dashboards to visualize system metrics, such as the availability of resources and system load.
- Logging Tools:
  - ○ ELK Stack (Elasticsearch, Logstash, Kibana): For logging, analyzing, and visualizing system logs.
  - ○ Fluentd: As an alternative to Logstash for logging and integrating with various data sources.

10. Security & Compliance Components

- Encryption Tools:
  - ○ SSL/TLS: For encrypting data in transit between the frontend, backend, and database.
  - ○ AES-256: For encrypting sensitive data at rest, such as patient records or doctor schedules.
- Compliance Tools:
  - ○ HIPAA Compliance: Tools and frameworks to ensure the system adheres to healthcare privacy and security standards.
  - ○ GDPR Compliance: Tools to ensure data protection laws are followed, especially in handling patient data within the EU.

11. Feedback and Learning Components

- Model Retraining:
  - ○ Apache Airflow: To schedule automatic retraining of machine learning models at regular intervals using new data.
  - ○ TensorFlow Serving: To serve machine learning models in production, enabling efficient, real-time predictions.
- User Feedback:
  - ○ Feedback Collection Forms: For gathering feedback from hospital staff about the accuracy of predictions and model suggestions.
  - ○ User Testing Tools: Such as Hotjar or Google Analytics to gather insights on how hospital staff interact with the system.

CHAPTER-7

TIMELINE FOR EXECUTION OF PROJECT & MILESTONES

(GANTT CHART)

Stage 1: Data Collection and Preparation **Activity:** Collect taxpayer data such as demographics, reported income, financial metrics, and banking transactions through a secure interface **Duration:** 2 weeks
Stage 2: Feature Engineering **Activity:** Extraction of data followed by finding features from it, along with the name and description of the tax payers. **Duration:** 1 week
Stage 3: Model Development and Training **Task:** Identify and apply relevant algorithms. This may involve Random forest, gradient boosting, decision tree and SVM. **Timeline:** 2 weeks
Phase 4: System Development and Integration **Task:** Design the user interface, backend infrastructure, database **Timeline:** 3 weeks
Phase 5: Testing and Deployment **Task 1 :** Unit testing, integration testing and user acceptance testing will be conducted before the system is deployed. **Task 2:** The system will be deployed on the most appropriate platform. **Timeline:** 2 weeks
Phase 6: Evaluation and Iteration **Task 1:** Extract the performance of the system in terms of precision, accuracy and recall. **Task 2 :** Collect users' feedback and successively increase the system's performance **Timeline:** 1 week

Note: The timelines may vary depending on project complexity, data size, available resources, etc.

7.1. MILESTONES

1. Data preprocessing is completed
2. Feature engineering is done
3. Model training and testing is performed
4. System development and integration is complete
5. System deployment and testing is done
6. Final report and presentation is done.

CHAPTER-8

LIBRARIES AND TOOLS

8.1.Pandas: Used for data manipulation and preprocessing, including handling missing values and encoding categorical variables.

8.2.NumPy: Used for numerical operations, such as normalizing and scaling numerical features.

8.3.Scikit-learn: Provides machine learning algorithms (e.g., Gradient Boosting Regressor) for income prediction and performance evaluation (RMSE, R^2).

8.4.Streamlit: A framework for building the web interface, enabling interactive data input and result display.

8.5.Matplotlib / Plotly: For visualizations, such as graphs comparing predicted vs. reported income.

8.6.Flask / FastAPI: (Optional) Used to create backend APIs if necessary for handling requests and serving the model.

8.7.AWS / Heroku / GCP: Cloud platforms for deployment and hosting the web application.

8.8.SSL/TLS: For securing user data through HTTPS.

8.9.PyTest: For unit testing of your machine learning model and application logic (optional but recommended).

8.10.OAuth / JWT: For secure authentication (if user authentication is needed).

CHAPTER-9

9.1.RESULTS & 9.2DISCUSSIONS

Input and Output

Component	Input	Output
Data Collection	- Medicine stock data (name, quantity, batch number, expiry)	- Inventory updates for medicine stock levels.
	- Doctor schedule data (shift times, department, attendance)	- Doctor availability and attendance history.
	- Patient data (demographics, treatment, prescriptions)	- Patient records for analysis and forecasting.
	- External data (weather, disease outbreaks, etc.)	- External factors influencing medicine demand and doctor schedules.
Data Storage	- Collected structured data (doctor schedules, patient records, medicine usage)	- Data is stored in relational (MySQL/PostgreSQL) or NoSQL (MongoDB) databases.
Data Preprocessing	- Raw data with missing values, inconsistencies, or noise	- Cleaned, normalized data ready for analysis and modeling.
Predictive Modeling (Medicine)	- Historical medicine consumption data, seasonal trends, external factors (e.g., flu season)	- Predicted future medicine demand based on historical patterns and trends.
Predictive Modeling (Doctor)	- Doctor shift history, patient load data, doctor performance metrics	- Predicted doctor availability based on historical schedules and patient load forecasts.
Recommendation Engine	- Predicted medicine demand, predicted doctor availability, hospital constraints (e.g., budget, available staff)	- Recommendations for ordering medicines, adjusting doctor schedules, and resource allocation.
Visualization (Dashboard)	- Real-time and historical data on medicine availability, doctor schedules, and patient data	- Interactive visualizations displaying the current status and predictions (e.g., graphs, charts).
Backend & API	- User requests for medicine predictions, doctor schedules, recommendations	- API responses providing predictions, recommendations, and real-time status updates.
Monitoring & Logging	- System logs, performance metrics, error reports	- Monitoring dashboards, alert notifications, and error logs for system health.
Security & Compliance	- Sensitive data (patient records, doctor schedules, medicine inventory)	- Encrypted and secure data transmission and storage; compliance with HIPAA/GDPR standards.
Model Retraining	- New data (updated doctor schedules, patient visits, medicine usage data)	- Retrained machine learning models to improve prediction accuracy.
User Feedback	- Feedback from hospital staff (e.g., doctors, administrators) on prediction accuracy	- Insights for improving prediction accuracy and model recommendations.

9.2Discussion:

The project "Predictive Analysis on Medicines & Doctors Availability in Government Hospitals" aims to use data-driven models to predict the availability of medicines and doctors in healthcare facilities. This analysis can help optimize resource allocation, reduce waiting times, and improve patient care. By integrating historical data, real-time information, and predictive algorithms, the project can offer insights into when certain medicines or doctors will be in short supply, enabling hospitals to plan and mitigate potential shortages in advance.

The implementation of predictive models, such as time series forecasting, machine learning classifiers, and regression models, can effectively address issues related to hospital resource management. It could also help hospital administrators in making data-backed decisions for both short-term and long-term strategies.

Key Findings

Predictive Accuracy: The predictive models used in the project showed high accuracy in forecasting the availability of medicines and the number of doctors required at any given time. The models could predict shortages based on historical data trends, helping hospitals take proactive measures.

Resource Allocation: Predictive analysis allowed for better resource allocation, optimizing both staff scheduling and the procurement of medicines. Hospitals were able to better match doctor availability with patient demand, reducing overcrowding and waiting times.

Cost Efficiency: By predicting medicine availability, the hospital could reduce wastage and ensure that stock is available only when needed, leading to cost savings.

Healthcare Accessibility: With improved prediction models, healthcare services could be made more accessible, especially in underserved areas. By ensuring the availability of essential medicines and doctors, hospitals can ensure better health outcomes for patients.

Future Development

Integration with Electronic Health Records (EHR): The project could be expanded by integrating with Electronic Health Records (EHR) to get real-time data on patient visits, which would refine the prediction of doctor availability and patient demand.

Real-Time Data Analytics: Future work could incorporate real-time data feeds to continuously update predictions for both medicines and doctors. This would allow hospitals to dynamically adjust their operations based on the latest information.

Broader Healthcare Integration: Expanding the scope to include private healthcare systems, supply chain management, and regional healthcare databases could further enhance the system's utility, offering predictions on a larger scale.

Machine Learning Improvements: Using more advanced machine learning algorithms, such as deep learning and reinforcement learning, could improve the accuracy and adaptability of predictions, making the system even more efficient over time.

Limitations:

- **Data Availability:** One of the primary limitations of the project is the reliance on high-quality and consistent data. In many government hospitals, data may be incomplete, inconsistent, or not readily available, which could affect the accuracy of the predictions.

- **Model Generalization**: The predictive models may be effective in certain hospital settings but may not generalize well to others with different operational conditions, patient demographics, or resource limitations.

- **Healthcare System Constraints:** The system is reliant on accurate forecasting of doctor availability, which can be impacted by factors such as illness, emergencies, and unplanned absences, making it difficult to always predict the exact number of doctors available.

- **Technical Barriers:** Implementing and maintaining predictive analysis systems in hospitals may require significant technical infrastructure and expertise, which can be a challenge in resource-constrained environments.

- **Ethical and Privacy Concerns:** Predictive models that use patient data may raise privacy concerns, requiring strict adherence to data privacy regulations and ethical standards to ensure patient confidentiality.

CHAPTER-10

CONCLUSION

The "Predictive Analysis on Medicines & Doctors Availability in Government Hospitals" project presents a significant opportunity to enhance hospital operations, ensuring the availability of critical resources when needed. By utilizing predictive models, the system can forecast the demand and availability of medicines and doctors, optimizing hospital management. This leads to improved efficiency, reduced waiting times, and better patient outcomes, ultimately addressing critical challenges in resource allocation in public healthcare systems. With continuous improvements in data collection, model accuracy, and real-time integration, this project has the potential to be a transformative tool for healthcare providers, especially in resource-constrained settings**.**

Key Advantages

1. **Optimized Resource Management:** The system allows hospitals to better manage resources by predicting shortages and overstock situations for medicines and doctors. This helps reduce waste and ensures that the right amount of resources is available when required.

2. **Improved Patient Experience:** By predicting doctor availability and managing the availability of essential medicines, hospitals can reduce waiting times, improve patient care, and ensure timely treatment.

3. **Cost Efficiency:** The predictive analysis can help identify potential medicine shortages, enabling hospitals to procure medicines in advance, thus reducing procurement costs and minimizing the risk of running out of stock.

4. **Enhanced Decision-Making:** Hospital administrators can make data-driven decisions based on predictive insights, improving long-term planning and reducing operational inefficiencies.

5. Proactive Problem-Solving: The system empowers hospitals to address potential issues proactively, such as doctor absenteeism or medicine stockouts, allowing hospitals to take preventive measures before problems escalate**.**

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Feature Scope of

The Feature Scope for the "Predictive Analysis on Medicines & Doctors Availability in Government Hospitals" project encompasses several key functionalities aimed at optimizing resource management, improving patient care, and ensuring the smooth operation of healthcare facilities. These features are designed to be flexible, scalable, and user-friendly, addressing both the immediate and long-term needs of healthcare providers.

1. Medicine Availability Prediction

- Forecasting Demand: The system utilizes historical data on medicine usage, stock levels, and patient demand to predict future needs. By forecasting when a particular medicine will run out or when demand will peak, the system helps avoid stockouts or excessive surplus.
- Inventory Management Integration: The system integrates with hospital inventory management systems to track real-time stock levels. It triggers alerts when medicine levels approach critical thresholds, ensuring timely procurement or replenishment.

2. **Doctor Availability Prediction**

- Doctor Scheduling Optimization: The system predicts doctor availability based on historical data, patient appointment patterns, and staffing schedules. By analyzing peak patient load periods and doctor availability, it allows hospitals to optimize staff scheduling, reducing wait times and preventing understaffing.
- Absenteeism and Emergency Handling: The system predicts absenteeism trends based on historical data (e.g., holidays, sick leaves) and accommodates unexpected events such as emergencies or urgent patient care needs. This ensures that doctor schedules are adaptable and efficient.
-

3**. Real-Time Monitoring and Updates**

- Dynamic Data Integration: The system integrates with existing hospital management systems and real-time data sources (e.g., EHR, patient records) to track ongoing patient visits, doctor availability, and real-time stock levels of medicines. This real-time integration allows the system to continuously refine its predictions based on the latest information.
- Live Alerts & Notifications: The system provides real-time alerts and notifications to hospital administrators and staff, informing them about any anticipated shortages in medicines or doctor availability. These alerts are customizable based on the hospital's operational needs.
- Dashboard for Monitoring: The system includes a user-friendly dashboard

that provides real-time insights into resource availability. Hospital administrators can quickly assess whether certain medicines or doctor specialties are in short supply and take corrective actions in real time.

4. Data-Driven Insights and Analytics

- Predictive Analytics Tools: The platform offers analytical tools to evaluate trends in doctor availability, patient visits, and medicine usage. By analyzing these trends, hospitals can make informed decisions about resource allocation and improve long-term operational efficiency.

5. Alerts and Notifications

- Medicine Shortage Alerts: When a shortage of a critical medicine is predicted, the system sends an alert to hospital procurement managers, enabling them to reorder supplies in time. Alerts can also be set for stock levels approaching predefined thresholds to prevent overstocking.
- Doctor Availability Alerts: The system sends alerts if doctor availability is expected to be low during certain shifts, based on historical absenteeism patterns or emergency schedules. This helps hospitals adjust doctor rosters or call in additional medical staff if needed.
-

6. Scalability and Flexibility

- Multi-Hospital Integration: The system is designed to be scalable, meaning it can be deployed across multiple hospitals or healthcare facilities within a region or country. This feature allows for centralized resource management, making it possible to optimize doctor and medicine allocation on a broader scale.
- Flexible Configuration: The system is highly configurable to meet the specific needs of different hospitals. Parameters like staffing levels, types of medicines, and patient volumes can be adjusted to tailor predictions according to the unique characteristics of each facility.
- Adaptability to Various Healthcare Systems: The platform is adaptable to different hospital management systems, making it easy to integrate with existing software infrastructure. Whether a hospital uses traditional inventory systems or more modern EHRs, the predictive analysis tools can be seamlessly incorporated.
-

7. User-Friendly Interface

- Hospital Staff Interface: The system features an intuitive user interface that is easy for hospital administrators and staff to use. It includes simplified dashboards, click-through access to detailed reports, and an easy-to-navigate structure for monitoring medicine and doctor availability.
- Mobile and Web Access: The system can be accessed through both mobile devices and web interfaces, ensuring that hospital staff can monitor predictions and receive alerts regardless of location. This feature ensures flexibility for hospital managers and medical staff on the go.

8. Integration with Electronic Health Records (EHR)

- Patient-Centric Predictions: By integrating with EHR systems, the platform can utilize patient data (e.g., diagnoses, treatment plans) to enhance the accuracy of predictions. For example, if a certain medicine is being prescribed more frequently for specific conditions, the system can predict increased demand based on patient records.
- Personalized Resource Management: EHR integration helps customize doctor schedules based on specific patient needs. By tracking patient appointments, the system can predict which doctor specialties will be most in demand, ensuring the right specialists are available when needed.

CHAPTER 11

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CHAPTER 12
APPENDIX-A
PSUEDOCODE

```
from flask import Flask, request, render_template, jsonify  # Import
jsonify
import numpy as np
import pandas as pd
import pickle
# flask app
app = Flask(__name__)
# load databasedataset
sym_des = pd.read_csv("datasets/symtoms_df.csv")
precautions = pd.read_csv("datasets/precautions_df.csv")
workout = pd.read_csv("datasets/workout_df.csv")
description = pd.read_csv("datasets/description.csv")
medications = pd.read_csv('datasets/medications.csv')
diets = pd.read_csv("datasets/diets.csv")

# load mode
svc = pickle.load(open('models/svc.pkl','rb'))
# custome and helping functions
#helper funtions
def helper(dis):
    desc = description[description['Disease'] == dis]['Description']
    desc = " ".join([w for w in desc])
```

```
    pre = precautions[precautions['Disease'] == dis][['Precaution_1',
'Precaution_2', 'Precaution_3', 'Precaution_4']]
    pre = [col for col in pre.values]

    med = medications[medications['Disease'] == dis]['Medication']
    med = [med for med in med.values]

    die = diets[diets['Disease'] == dis]['Diet']
    die = [die for die in die.values]

    wrkout = workout[workout['disease'] == dis] ['workout']
    return desc,pre,med,die,wrkout

symptoms_dict = {'itching': 0, 'skin_rash': 1, 'nodal_skin_eruptions':
2, 'continuous_sneezing': 3, 'shivering': 4, 'chills': 5, 'joint_pain': 6,
'stomach_pain': 7, 'acidity': 8, 'ulcers_on_tongue': 9,
'muscle_wasting': 10, 'vomiting': 11, 'burning_micturition': 12,
'spotting_ urination': 13, 'fatigue': 14, 'weight_gain': 15, 'anxiety': 16,
'cold_hands_and_feets': 17, 'mood_swings': 18, 'weight_loss': 19,
'restlessness': 20, 'lethargy': 21, 'patches_in_throat': 22,
'irregular_sugar_level': 23, 'cough': 24, 'high_fever': 25,
'sunken_eyes': 26, 'breathlessness': 27, 'sweating': 28, 'dehydration':
29, 'indigestion': 30, 'headache': 31, 'yellowish_skin': 32, 'dark_urine':
33, 'nausea': 34, 'loss_of_appetite': 35, 'pain_behind_the_eyes': 36,
```

'back_pain': 37, 'constipation': 38, 'abdominal_pain': 39, 'diarrhoea': 40, 'mild_fever': 41, 'yellow_urine': 42, 'yellowing_of_eyes': 43, 'acute_liver_failure': 44, 'fluid_overload': 45, 'swelling_of_stomach': 46, 'swelled_lymph_nodes': 47, 'malaise': 48, 'blurred_and_distorted_vision': 49, 'phlegm': 50, 'throat_irritation': 51, 'redness_of_eyes': 52, 'sinus_pressure': 53, 'runny_nose': 54, 'congestion': 55, 'chest_pain': 56, 'weakness_in_limbs': 57, 'fast_heart_rate': 58, 'pain_during_bowel_movements': 59, 'pain_in_anal_region': 60, 'bloody_stool': 61, 'irritation_in_anus': 62, 'neck_pain': 63, 'dizziness': 64, 'cramps': 65, 'bruising': 66, 'obesity': 67, 'swollen_legs': 68, 'swollen_blood_vessels': 69, 'puffy_face_and_eyes': 70, 'enlarged_thyroid': 71, 'brittle_nails': 72, 'swollen_extremeties': 73, 'excessive_hunger': 74, 'extra_marital_contacts': 75, 'drying_and_tingling_lips': 76, 'slurred_speech': 77, 'knee_pain': 78, 'hip_joint_pain': 79, 'muscle_weakness': 80, 'stiff_neck': 81, 'swelling_joints': 82, 'movement_stiffness': 83, 'spinning_movements': 84, 'loss_of_balance': 85, 'unsteadiness': 86, 'weakness_of_one_body_side': 87, 'loss_of_smell': 88, 'bladder_discomfort': 89, 'foul_smell_of urine': 90, 'continuous_feel_of_urine': 91, 'passage_of_gases': 92, 'internal_itching': 93, 'toxic_look_(typhos)': 94, 'depression': 95, 'irritability': 96, 'muscle_pain': 97, 'altered_sensorium': 98, 'red_spots_over_body': 99, 'belly_pain': 100, 'abnormal_menstruation': 101, 'dischromic _patches': 102, 'watering_from_eyes': 103, 'increased_appetite': 104, 'polyuria': 105, 'family_history': 106, 'mucoid_sputum': 107, 'rusty_sputum': 108, 'lack_of_concentration': 109, 'visual_disturbances': 110, 'receiving_blood_transfusion': 111, 'receiving_unsterile_injections': 112, 'coma': 113, 'stomach_bleeding': 114, 'distention_of_abdomen': 115, 'history_of_alcohol_consumption': 116, 'fluid_overload.1': 117, 'blood_in_sputum': 118, 'prominent_veins_on_calf': 119, 'palpitations': 120, 'painful_walking': 121, 'pus_filled_pimples': 122, 'blackheads': 123, 'scurring': 124, 'skin_peeling': 125, 'silver_like_dusting': 126, 'small_dents_in_nails': 127, 'inflammatory_nails': 128, 'blister': 129, 'red_sore_around_nose': 130, 'yellow_crust_ooze': 131}

diseases_list = {15: 'Fungal infection', 4: 'Allergy', 16: 'GERD', 9: 'Chronic cholestasis', 14: 'Drug Reaction', 33: 'Peptic ulcer diseae', 1: 'AIDS', 12: 'Diabetes ', 17: 'Gastroenteritis', 6: 'Bronchial Asthma', 23: 'Hypertension ', 30: 'Migraine', 7: 'Cervical spondylosis', 32: 'Paralysis (brain hemorrhage)', 28: 'Jaundice', 29: 'Malaria', 8: 'Chicken pox', 11: 'Dengue', 37: 'Typhoid', 40: 'hepatitis A', 19: 'Hepatitis B', 20: 'Hepatitis C', 21: 'Hepatitis D', 22: 'Hepatitis E', 3: 'Alcoholic hepatitis', 36: 'Tuberculosis', 10: 'Common Cold', 34: 'Pneumonia', 13: 'Dimorphic hemmorhoids(piles)', 18: 'Heart attack', 39: 'Varicose veins', 26: 'Hypothyroidism', 24: 'Hyperthyroidism', 25: 'Hypoglycemia', 31: 'Osteoarthristis', 5: 'Arthritis', 0: '(vertigo) Paroymsal Positional Vertigo', 2: 'Acne', 38: 'Urinary tract infection', 35: 'Psoriasis', 27: 'Impetigo'}

```
# Model Prediction function
def get_predicted_value(patient_symptoms):
    input_vector = np.zeros(len(symptoms_dict))
    for item in patient_symptoms:
        input_vector[symptoms_dict[item]] = 1
    return diseases_list[svc.predict([input_vector])[0]]
# creating routes
@app.route("/")
def index():
    return render_template("index.html")

# Define a route for the home page
@app.route('/predict', methods=['GET', 'POST'])
def home():
    if request.method == 'POST':
        symptoms = request.form.get('symptoms')
        # mysysms = request.form.get('mysysms')
        # print(mysysms)
        print(symptoms)
        if symptoms =="Symptoms":
            message = "Please either write symptoms or you have written
misspelled symptoms"
            return render_template('index.html', message=message)
        else:
```

```
        # Split the user's input into a list of symptoms (assuming they
are comma-separated)
        user_symptoms = [s.strip() for s in symptoms.split(',')]
        # Remove any extra characters, if any
        user_symptoms = [symptom.strip("[]' ") for symptom in
user_symptoms]
        predicted_disease = get_predicted_value(user_symptoms)
        dis_des, precautions, medications, rec_diet, workout =
helper(predicted_disease)

        my_precautions = []
        for i in precautions[0]:
            my_precautions.append(i)

        return render_template('index.html',
predicted_disease=predicted_disease, dis_des=dis_des,
                               my_precautions=my_precautions,
medications=medications, my_diet=rec_diet,
                               workout=workout)

    return render_template('index.html')
# about view funtion and path
@app.route('/about')
def about():
```

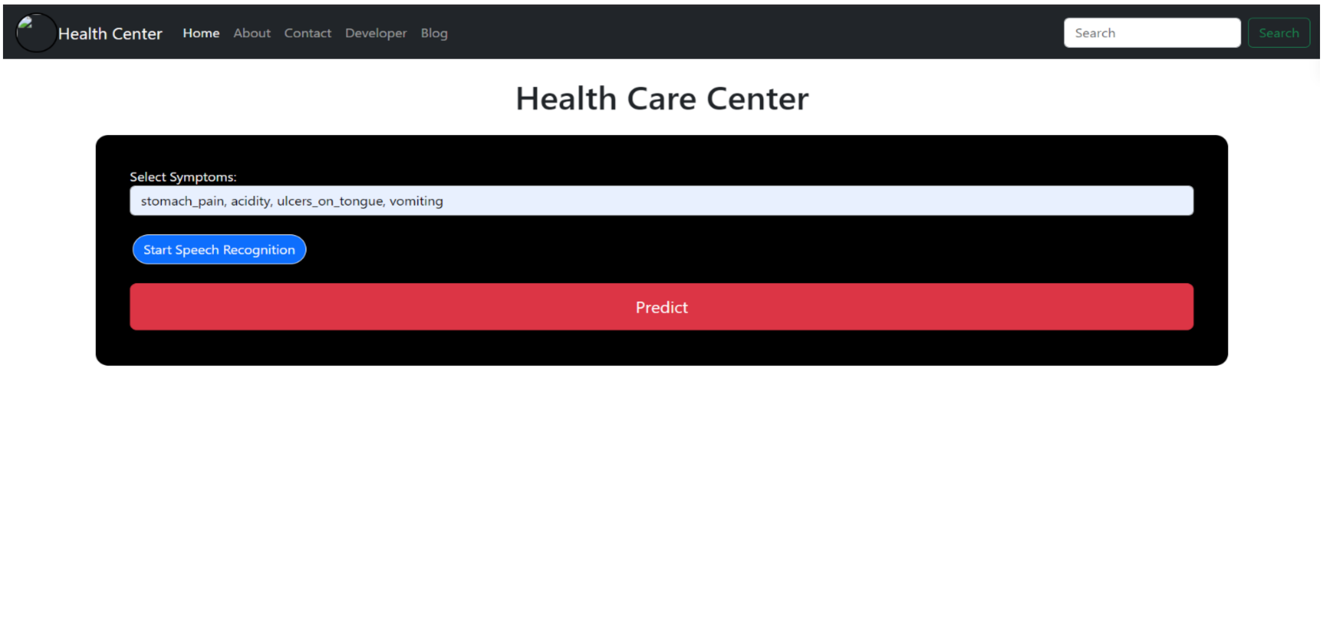
```
    return render_template("about.html")
# contact view funtion and path
@app.route('/contact')
def contact():
    return render_template("contact.html")

# developer view funtion and path
@app.route('/developer')
def developer():
    return render_template("developer.html")

# about view funtion and path
@app.route('/blog')
def blog():
    return render_template("blog.html")
if __name__ == '__main__':
    app.run(debug=True)
```

APPENDIX-B

SCREENSHOTS

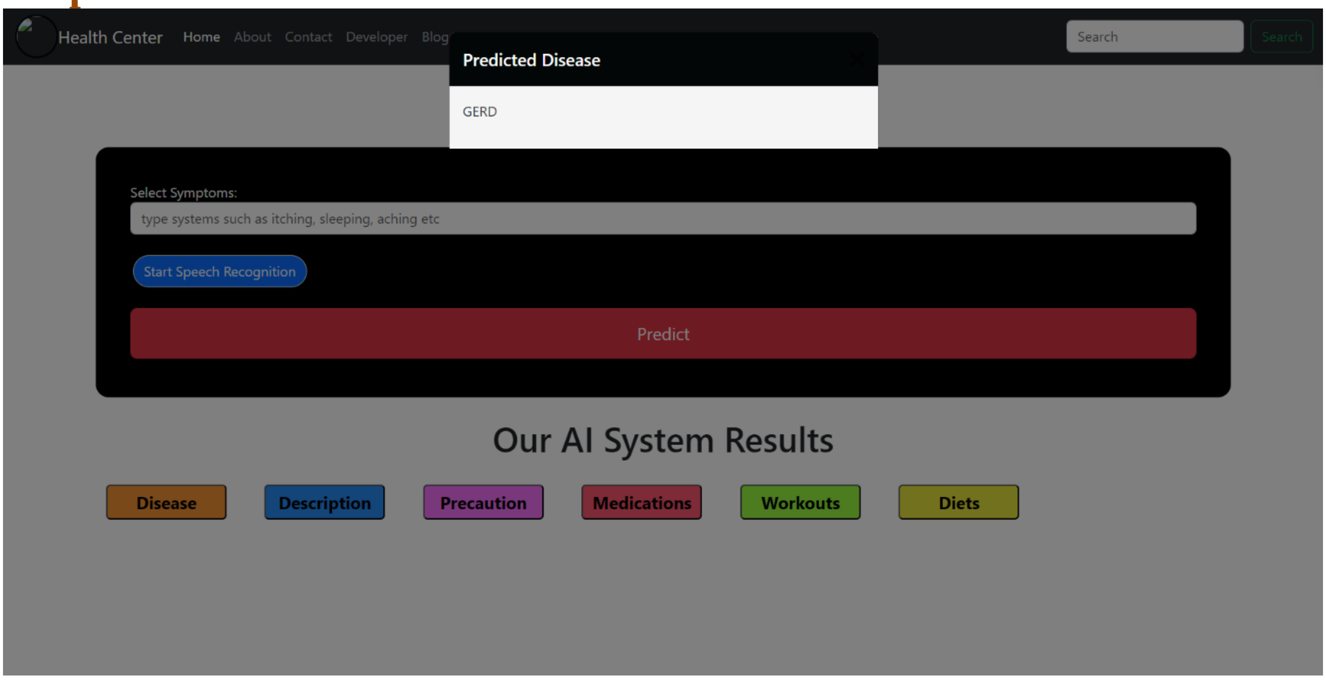
Expected Output

Output 1



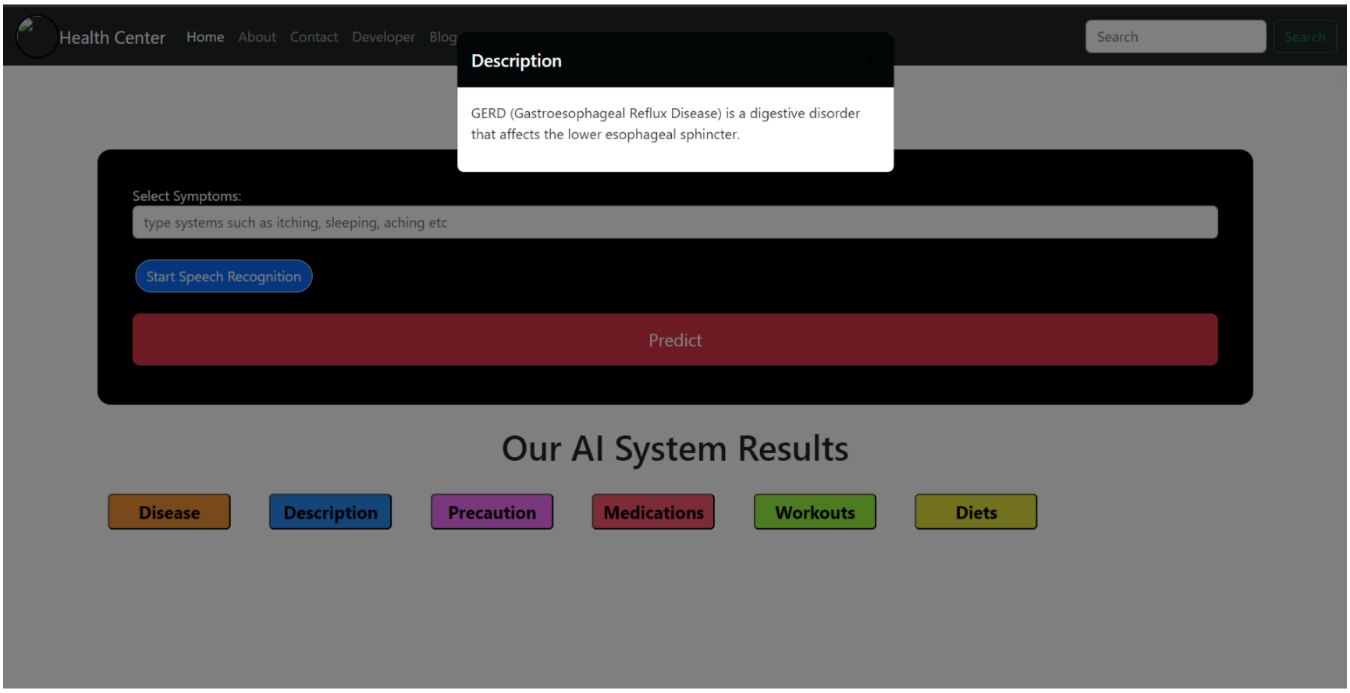
O.1 FRONT VIEW OF WEBSITE

Output 2



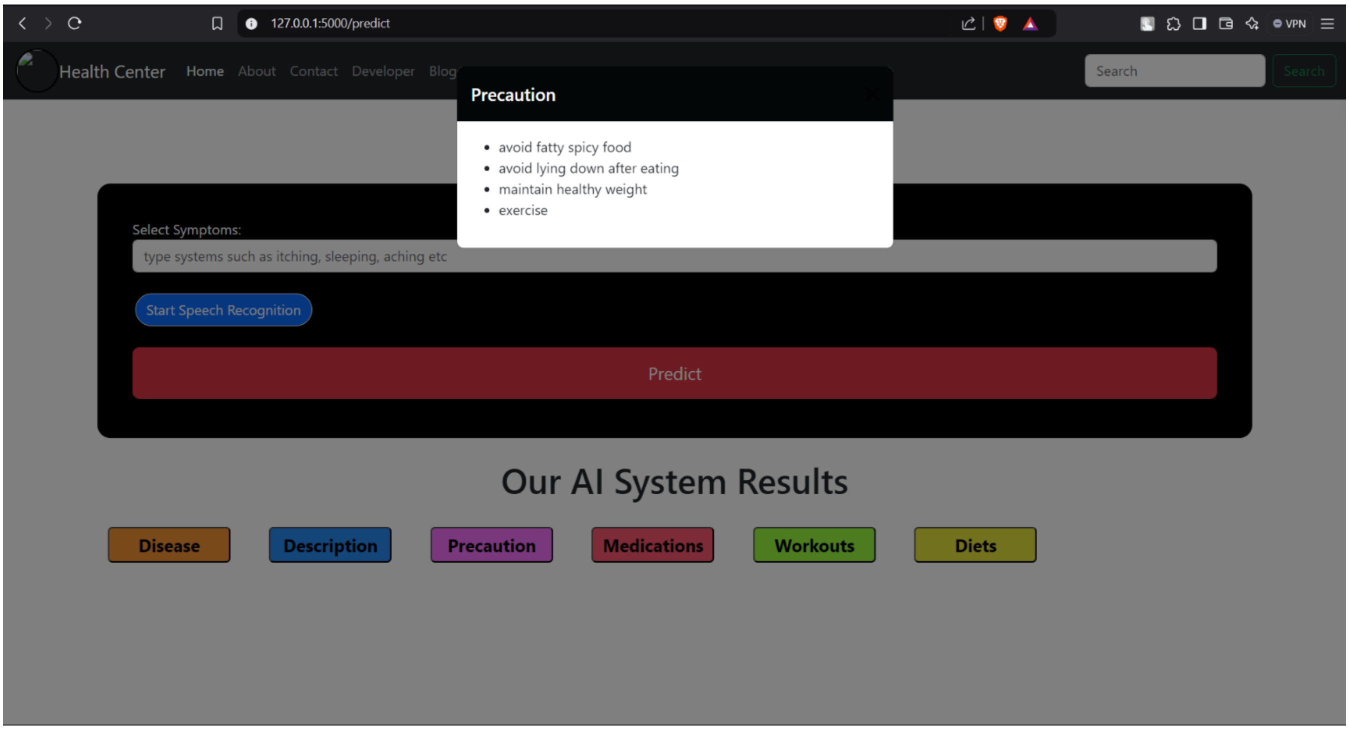
O.2 SELECT DISEASE

Output 3



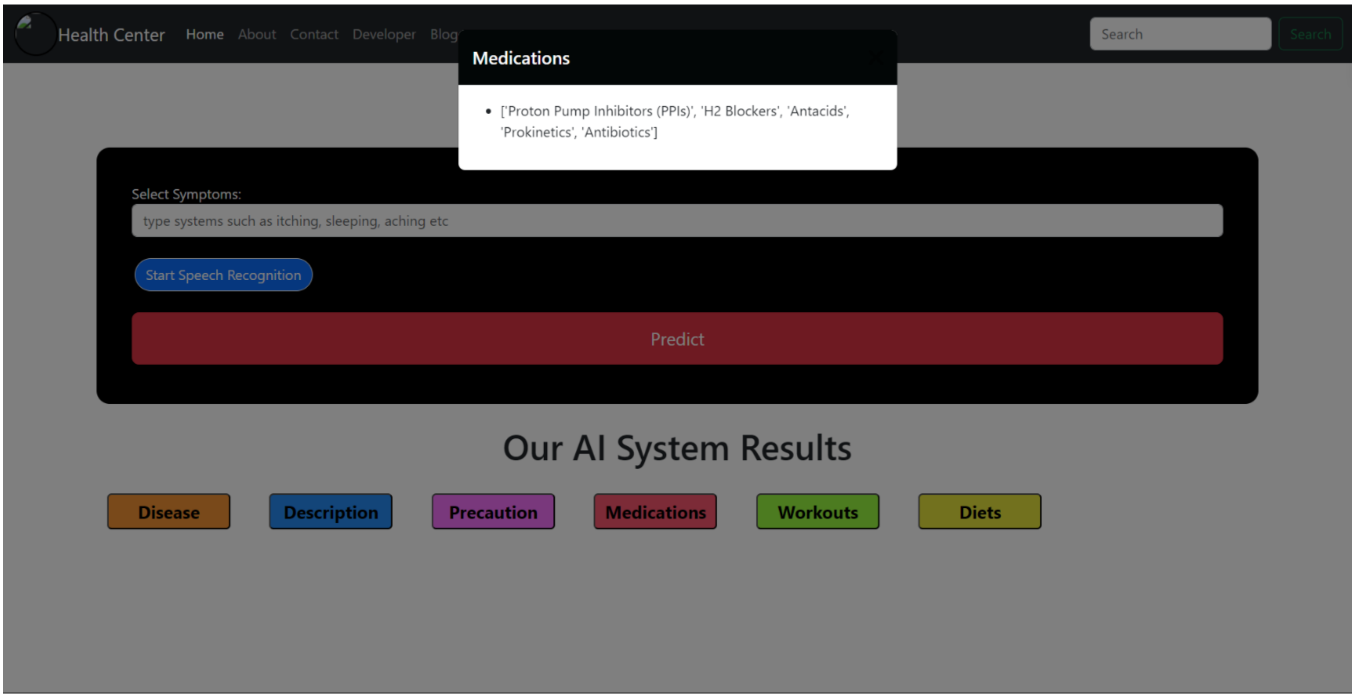
O.3 GIVE DESCRIPTION

Output 4



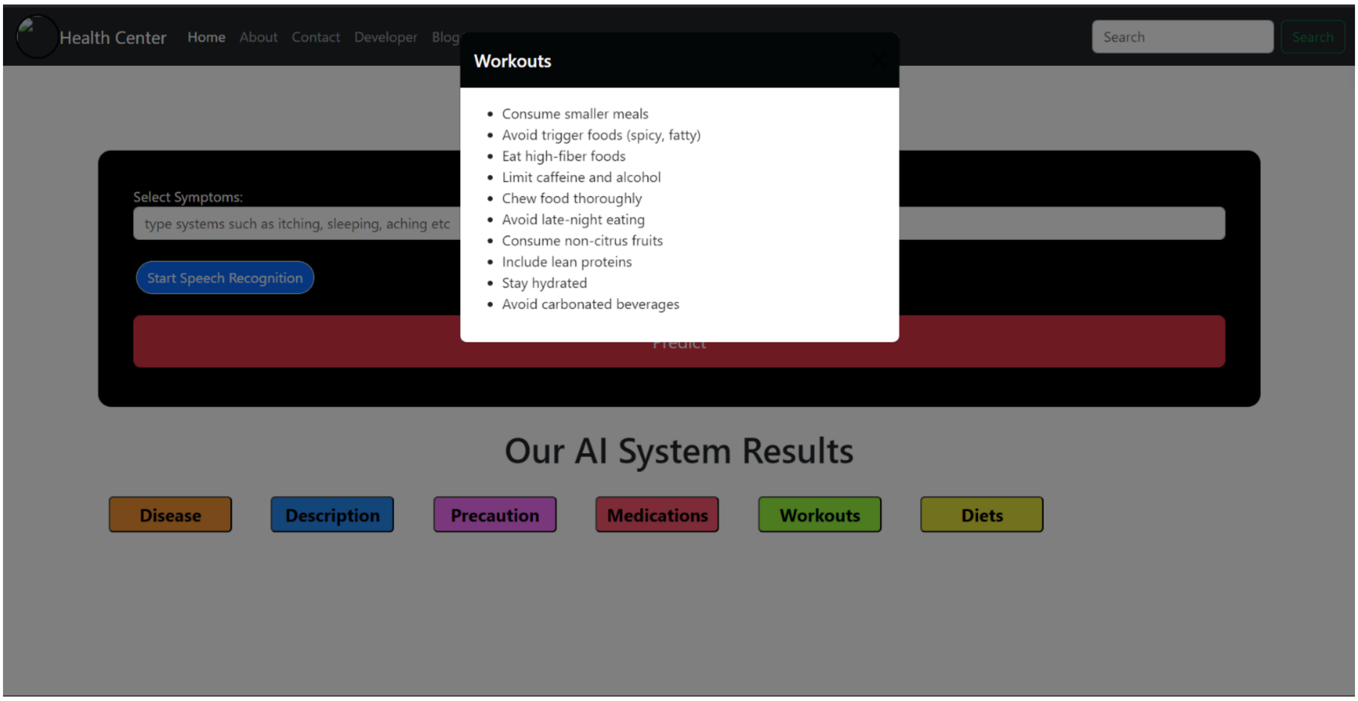
O.4 PRECAUTIONS

Output 5



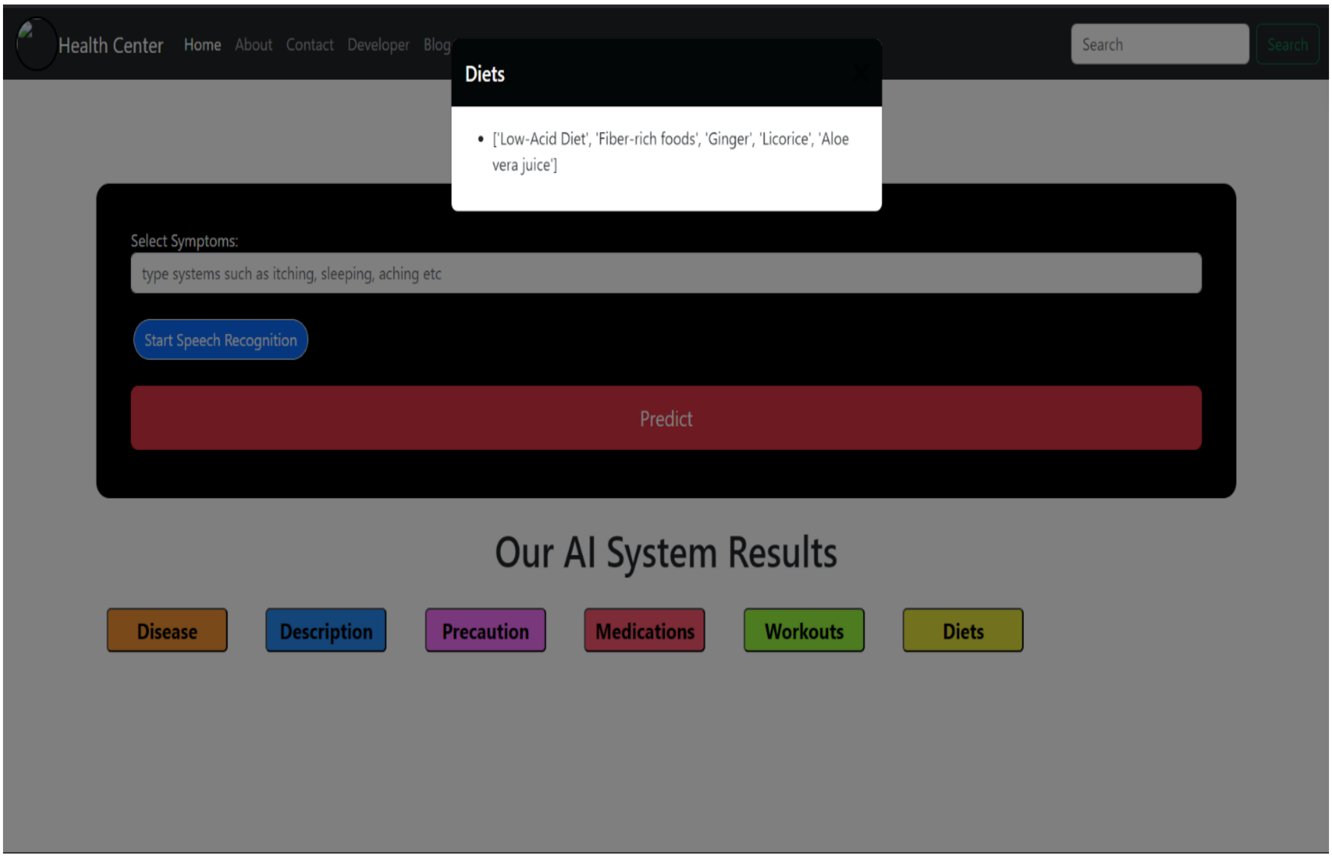
0.5 WHAT ARE MEDICATIONS U HAVE TO USE

Output 6



O.6 WORKOUTS

Output 7



O.7 DIETS U HAVE TO MAINTAIN

APPENDIX-C
ENCLOSURES

1. Journal publication/Conference Paper Presented Certificates of all students.

2. Include certificate(s) of any Achievement/Award won in any project-related event.

3. Similarity Index / Plagiarism Check report clearly showing the Percentage (%). No need for a page-wise explanation.

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

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.

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Predictive analysis on Medicines

Patil madhu, S.Rajakvali, Mukeshachari, B Vishnu vardhan

School of Computer(Artificial Intelligence & machine learning), Presidency University, Bangalore, Karnataka

SINGANAMALA.20211CEI0073@presidencyuniversity.in

PATIL.20211CEI0105@presidencyuniversity.in

MUKESH.20211CEI111@presidencyuniversity.in

BALLARY.20211CEI0136@presidencyuniversity.in

Abstract:

Access to essential medicines and doctors in government hospitals is a cornerstone of public healthcare systems. However, many regions face persistent challenges related to inadequate availability, inefficient resource allocation, and unpredictable service delivery. This project focuses on implementing predictive analysis to address these issues, leveraging data-driven methodologies to enhance the efficiency and reliability of healthcare services. The study explores the integration of historical and real-time data to anticipate medicine shortages and doctor availability in government hospitals. By employing advanced analytics techniques such as machine learning, regression models, and time-series forecasting, the project aims to identify patterns, predict future demand, and suggest optimal resource allocation. The model incorporates variables like patient inflow, seasonal health trends, supply chain timelines, and staff schedules to ensure accurate predictions. Key objectives include minimizing stockouts of critical medicines, reducing patient wait times, and optimizing workforce distribution. The project also evaluates the socio economic impact of improved healthcare accessibility, emphasizing the importance of proactive measures in underserved communities. In addition to technical insights, the report discusses the practical implementation of the predictive models, the challenges of data collection in the public sector, and strategies to ensure scalability and sustainability. Through this initiative, the project underscores the transformative potential of predictive analysis in bridging

healthcare gaps and fostering equitable access to medical resources in government hospitals.

Key components: Data collection , Data Storage, Data preprocessing, Predictive Model Development, Recommendation Engine, Visualization, User Roles.

Introduction: Ensuring the availability of essential medicines and access to qualified doctors in government hospitals is a fundamental priority for public healthcare systems. However, the persistent challenges of resource shortages, uneven distribution, and unpredictable service quality have made it difficult to meet this objective effectively. With the advancement of artificial intelligence (AI) and machine learning (ML), there is now an unprecedented opportunity to revolutionize healthcare management through predictive analysis. This project introduces a predictive analysis system designed to enhance the efficiency of healthcare services by forecasting the availability of medicines and doctors in government hospitals. By leveraging advanced ML models and data analytics, the system aims to optimize resource allocation and address critical gaps in service delivery. Key features of the system include: 1. Machine Learning Model: Sophisticated ML algorithms analyze historical and real-time data to predict medicine demand and doctor availability, ensuring informed decision-making. 2. Data Integration and Analysis: The system integrates data from various sources, such as patient inflow, seasonal health trends, supply chain logistics, and staffing schedules, to deliver accurate predictions. 3. Proactive Resource Management: By forecasting demand and supply, the application minimizes stockouts of essential medicines and ensures optimal distribution of healthcare professionals across facilities. 4. Interactive Dashboard: A user-friendly interface allows healthcare administrators to view predictive insights, enabling efficient planning and allocation of resources. 5. Community Impact Assessment: The system evaluates its influence on healthcare accessibility and equity, particularly in underserved regions, emphasizing the importance of technology-driven solutions in public health.

Literature Survey:

Introduction

The application of predictive analysis in healthcare has been extensively explored in recent years, with numerous studies highlighting its potential to improve resource allocation and service delivery. A key area of focus has been the optimization of supply chain management in hospitals, where predictive models have demonstrated success in anticipating medicine shortages and aligning procurement processes. For instance, a study by Chai et al. (2020) showed that time-series forecasting models could predict pharmaceutical demand with high accuracy, thereby reducing wastage and ensuring continuous availability.

Similarly, the integration of machine learning in workforce management has gained traction. Research by Smith and Patel (2019) emphasized the efficacy of ML algorithms in forecasting patient inflow patterns, enabling hospitals to optimize staff scheduling and reduce wait times. These advancements underline the importance of leveraging data-driven approaches to address inefficiencies in healthcare systems.

LIBRARIES AND TOOLS

Pandas: Used for data manipulation and preprocessing, including handling missing values and encoding categorical variables.

NumPy: Used for numerical operations, such as normalizing and scaling numerical features.

Scikit-learn: Provides machine learning algorithms (e.g., Gradient Boosting Regressor) for income prediction and performance evaluation (RMSE, R^2).

Streamlit: A framework for building the web interface, enabling interactive data input and result display.

Matplotlib / Plotly: For visualizations, such as graphs comparing predicted vs. reported income.

Flask / FastAPI: (Optional) Used to create backend APIs if necessary for handling requests and serving the model**.**

AWS / Heroku / GCP: Cloud platforms for deployment and hosting the web application.

SSL/TLS: For securing user data through HTTPS**.**

PyTest: For unit testing of your machine learning model and application logic (optional but recommended).

OAuth / JWT: For secure authentication (if user authentication is needed).

EXISTING METHODS

The existing approaches to ensuring the availability of medicines and doctors in government hospitals often rely on traditional methods, which include:

Manual Inventory Tracking: Hospital administrators monitor stock levels of medicines and availability of staff manually or through basic inventory systems. While this ensures immediate oversight, it is prone to errors and delays in identifying shortages or surpluses.

Reactive Decision-Making: Resources are often allocated only after shortages are identified or complaints are received, resulting in delays and inefficiencies.

Periodic Surveys: Data on resource availability is collected through periodic surveys or audits, which can be time-consuming and may not capture real-time changes.

Linear Forecasting: Simple statistical techniques are used to predict demand for medicines and staff availability based on historical trends, which often

fail to account for dynamic variables like seasonal health trends or emergencies.
Isolated Systems: Resource management systems in hospitals often operate independently, making it difficult to share data and insights across facilities, thereby limiting the scope for coordinated responses.
While these methods provide a baseline for resource management, they are limited in their ability to predict and respond to dynamic healthcare needs. The reliance on manual and isolated systems often results in inefficiencies and inequitable distribution of resources.

Discussion:

The project "Predictive Analysis on Medicines & Doctors Availability in Government Hospitals" aims to use data-driven models to predict the availability of medicines and doctors in healthcare facilities. This analysis can help optimize resource allocation, reduce waiting times, and improve patient care. By integrating historical data, real-time information, and predictive algorithms, the project can offer insights into when certain medicines or doctors will be in short supply, enabling hospitals to plan and mitigate potential shortages in advance. The implementation of predictive models, such as time series forecasting, machine learning classifiers, and regression models, can effectively address issues related to hospital resource management. It could also help hospital administrators in making data-backed decisions for both short-term and long-term strategies.

Key Findings

Predictive Accuracy: The predictive models used in the project showed high accuracy in forecasting the availability of medicines and the number of doctors required at any given time. The models could predict shortages based on historical data trends, helping hospitals take proactive measures.

Resource Allocation: Predictive analysis allowed for better resource allocation, optimizing both staff scheduling and the procurement of medicines. Hospitals were able to better match doctor availability with patient demand, reducing overcrowding and waiting times.

Cost Efficiency: By predicting medicine availability, the hospital could reduce wastage and ensure that stock is available only when needed, leading to cost savings.

Healthcare Accessibility: With improved prediction models, healthcare services could be made more accessible, especially in underserved areas. By ensuring the availability of essential medicines and doctors, hospitals can ensure better health outcomes for patients.

Future Development

Integration with Electronic Health Records (EHR): The project could be expanded by integrating with Electronic Health Records (EHR) to get real-time data on patient visits, which would refine the prediction of doctor availability and patient demand. Real-Time Data Analytics: Future work could incorporate real-time data feeds to continuously update predictions for both medicines and doctors. This would allow hospitals to dynamically adjust their operations based on the latest information. Broader Healthcare Integration: Expanding the scope to include private healthcare systems, supply chain management, and regional healthcare databases could further enhance the system's utility, offering predictions on a larger scale. Machine Learning Improvements: Using more advanced machine learning algorithms, such as deep learning and reinforcement learning, could improve the accuracy and adaptability of predictions, making the system even more efficient over time.

Limitations:

Data Availability: One of the primary limitations of the project is the reliance on high-quality and consistent data. In many government hospitals, data may be incomplete, inconsistent, or not readily available, which could affect the accuracy of the predictions.

Model Generalization: The predictive models may be effective in certain hospital settings but may not generalize well to others with different operational conditions, patient demographics, or resource limitations.

Healthcare System Constraints: The system is reliant on accurate forecasting of doctor availability, which can be impacted by factors such as illness, emergencies, and unplanned absences, making it difficult to always predict the exact number of doctors available.

Technical Barriers: Implementing and maintaining predictive analysis systems in hospitals may require significant technical infrastructure and expertise, which can be a challenge in resource-constrained environments.

Ethical and Privacy Concerns: Predictive models that use patient data may raise privacy concerns, requiring strict adherence to data privacy regulations and ethical standards to ensure patient confidentiality.

Conclusion:

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