D.Y.PATIL AGRICULTURE AND TECHNICAL UNIVERSITY, TALSANDE

SCHOOL OF ENGINEERING AND TECHNOLOGY

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING (DATA SCIENCE)

A MICRO PROJECT-II REPORT

ON

”REGIONAL HEALTHCARE MONITORING USING PYTHON”

B.Tech T.Y (CSE-DS)

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UNDER THE GUIDANCE OF

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(Academic Year: 2025-2026)

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”REGIONAL HEALTHCARE MONITORING USING PYTHON”

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Mini Project-II Guide	**H.O.D**

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REGIONAL HEALTHCARE MONITORING USING PYTHON

”REGIONAL HEALTHCARE MONITORING USING PYTHON”

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B.Tech TY-DS

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Abstract

The proposed project, Regional Healthcare Monitoring using Machine Learning, focuses on analyzing regional health data to identify factors affecting patient recovery, particularly among lung disease patients. The system collects and processes healthcare datasets containing attributes such as age, gender, smoking status, oxygen level, and treatment type. Using algorithms like Random Forest, Decision Tree, and Logistic Regression, it identifies key factors contributing to non-recovery and performs region-wise comparisons of cured and non-cured cases. The system generates interactive dashboards to visualize regional healthcare trends, helping authorities detect high-risk areas. By integrating predictive analytics and data visualization, the project aims to enhance decision-making for healthcare planning and resource allocation. This approach reduces manual monitoring efforts and promotes data-driven public health strategies. Overall, the system supports early detection, improved recovery outcomes, and smarter healthcare management at the regional level.
Keywords— *Regional Healthcare Dataset Prediction, Data Analytics, Machine Learning, Exploratory Data Analysis (EDA).*

Chapter 1

INTRODUCTION

1.1 Overview

In recent years, the healthcare industry has undergone a major digital transformation, with machine learning and data analytics playing a crucial role in improving disease monitoring and patient care. This project, Regional Healthcare Monitoring using Machine Learning, focuses on analyzing patient data to identify regional health trends and the key factors influencing recovery rates, especially among lung disease patients.

The project workflow involves data collection, cleaning, preprocessing, exploratory data analysis (EDA), visualization, and predictive modeling using Python libraries such as Pandas, NumPy, Matplotlib, Seaborn, and Scikit-learn. Interactive dashboards are developed to provide region-wise comparisons of cured and non-cured cases, enabling healthcare professionals and policymakers to make data-driven decisions.

The outcome of this work is a regional-level healthcare monitoring framework that supports early identification of high-risk areas, efficient resource allocation, and improved public health management through continuous, data-driven insights..

The visualization illustrates the proportion of cured and non-cured patients across various regions based on the healthcare dataset. This analysis provides a clear overview of the regional health distribution, helping to identify areas with higher non-recovery rates and regions demonstrating better healthcare outcomes. Such insights assist healthcare authorities and policymakers in recognizing high-risk zones, allocating medical resources effectively, and planning targeted health interventions to improve overall recovery rates.

1.2 Motivation

With the increasing digitization of the healthcare sector, there is a growing need for intelligent systems that can analyze large-scale medical data to improve patient outcomes and regional healthcare planning. Data-driven insights enable healthcare professionals and policymakers to:

- Monitor regional trends in recovery and non-recovery rates
- Identify critical factors influencing patient health, such as smoking habits or oxygen levels
- Detect high-risk regions requiring immediate healthcare interventions
- Support efficient resource allocation and preventive healthcare measures

For students and researchers, this project provides an excellent opportunity to work with healthcare datasets and apply machine learning for real-world analysis. It enhances practical understanding of data preprocessing, visualization, and predictive modeling while building skills essential for healthcare analytics and AI-driven decision-making. Hands-on experience with such systems strengthens technical and analytical abilities for careers in data science and healthcare technology.

Chapter 2

PROBLEM STATEMENT

With the rapid growth of healthcare data and the increasing adoption of digital technologies in the medical field, understanding regional health patterns has become essential for effective public health management. Traditional healthcare systems primarily focus on individual-level diagnosis and treatment, lacking the ability to continuously monitor patient recovery trends across different regions. As a result, healthcare authorities face challenges in identifying non-cured cases, determining causes of treatment failure, and implementing region-specific interventions.

The rise of data-driven technologies and machine learning has opened new opportunities to analyze large-scale healthcare datasets efficiently. However, manual analysis of patient records is time-consuming, error-prone, and often fails to reveal complex relationships between health factors such as age, smoking habits, oxygen level, treatment type, and chronic infections. Therefore, an automated system that leverages machine learning to uncover regional health disparities and factors influencing non-recovery is essential.

This project aims to develop a Regional Healthcare Monitoring System that utilizes machine learning algorithms—including Random Forest, Decision Tree, and Logistic Regression—to analyze patient health data and identify the major contributors to non-recovery. The system also performs region-wise comparisons of cured and non-cured patients, providing valuable insights for healthcare authorities, researchers, and policymakers.

The ultimate goal is to transform raw healthcare data into actionable insights that support proactive healthcare decision-making. By visualizing regional recovery trends and highlighting influential factors, this project contributes to improving patient outcomes, optimizing medical resource allocation, and promoting data-driven public health strategies.

Chapter 3

SOFTWARE REQUIREMENT SPECIFICATION

3.1 Functional Requirements

The key functionalities implemented in this project include:

- Import and load dataset into Python environment
- Clean dataset by handling missing values and duplicates
- The model should analyse regional-wise data and calculate the percentage of cured and non cured patients.
- Apply ML models such as Logistic Regression, Random Forest,Descision Tree.
- Generate accuracy score, confusion matrix, and classification report

3.2 Non-Functional Requirements

Performance:

- Models should train efficiently within practical time
- Visualizations should load without delay

Usability:

- Code should be well-commented and easy to understand
- Result charts must be clear and labeled

Security:

- Patient data must be handled securely without exposure of personal information.

3.3 Software Requirements

Software Requirements:

- Operating System: Windows / Linux / macOS
- Python 3.9+
- Development Tools: Jupyter Notebook / Google Colab
- Libraries:
  - Pandas, NumPy
  - Matplotlib, Seaborn
  - Scikit-learn

3.4 Hardware Requirements

Hardware Requirements:

- Minimum 4GB RAM (8GB recommended)
- Dual-core processor or above
- Stable internet connection (for Google Colab)

3.5 ER Diagram

The ER diagram shows relationships between restaurant data attributes.

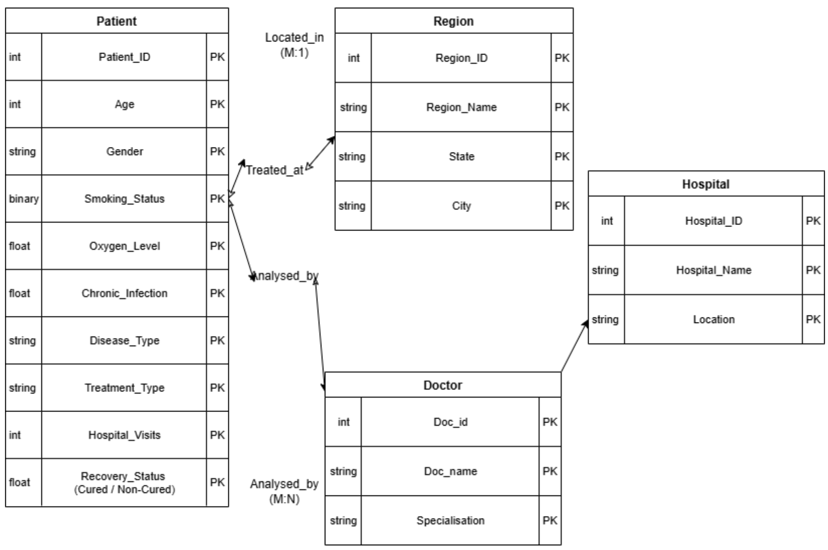

Figure 3.1: ER Diagram of Regional Healthcare Dataset

Chapter 4

METHODOLOGY

The methodology adopted in this project follows a complete Data Science and Machine Learning workflow designed to analyze regional healthcare data effectively. The primary objective is to extract meaningful insights from patient datasets and develop predictive models to identify key factors influencing recovery and non-recovery among lung disease patients. The process involves several systematic steps, including data collection, cleaning, preprocessing, exploratory data analysis (EDA), feature selection, model training, evaluation, and result interpretation. Machine learning algorithms such as Random Forest, Decision Tree, and Logistic Regression are applied to ensure accurate and interpretable outcomes. Each stage of the methodology is carefully executed to maintain data quality, enhance model reliability, and provide actionable insights for regional healthcare monitoring and decision-making.

4.1 Workflow

The overall workflow for this project is structured as follows:

1. **Dataset Collection:** Dataset sourced from Kaggle, containing Hospitals details,. Imported into Python using Pandas.
2. **Data Cleaning:** Involves removal of duplicates, null values, and irrelevant characters. Missing, and text fields are standardized.
3. **Feature Encoding & Engineering:** Categorical features such as gender, smoking status, chronic infection, and treatment type are encoded using Label Encoding and One-Hot Encoding techniques to make them suitable for machine learning models. Continuous attributes like age, oxygen level, and lung capacity are standardized to maintain uniform data scales. A new target feature — recovery status (classified as cured or non-cured) — is created to support patient outcome classification and predictive analysis. These preprocessing steps ensure that the dataset is clean, consistent, and ready for effective model training and evaluation.
4. **Exploratory Data Analysis (EDA):** Visualizations using Matplotlib and Seaborn are performed to uncover key healthcare insights, such as:
   - Regional distribution of cured and non-cured patients

- Impact of factors like age, smoking status, and oxygen level on recovery
- Correlations between treatment type, hospital visits, and recovery outcomes
- Identification of high-risk regions with higher non-recovery rates

5. **Model Training & Evaluation:** Supervised algorithms (Logistic Regression, Decision Tree, Random Forest) are trained on 80% of the data and tested on 20%. Models are evaluated using Accuracy, Precision, Recall, F1-score, and Confusion Matrix.

6. **Results Interpretation:** The best-performing machine learning model is identified through comparative analysis of algorithms such as Random Forest, Decision Tree, and Logistic Regression. Visual and statistical summaries are utilized to interpret healthcare patterns, recovery trends, and the key factors influencing non-recovery among patients. The generated insights help highlight region-wise disparities and assist healthcare authorities in making informed, data-driven decisions to improve patient outcomes and optimize medical resource distribution.

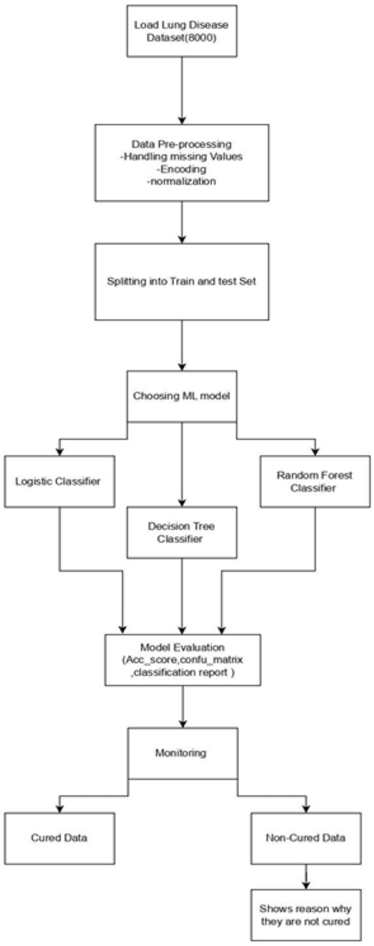

Figure 4.1: Proposed Flowchart of Regional Healthcare Monitoring Using Python

4.2 Machine Learning Models Used

- **Logistic Regression:** Used as a baseline classifier to predict whether a patient is cured or non-cured, providing interpretable coefficients for each health attribute.
- **Decision Tree:** Captures complex and nonlinear relationships among features such as smoking status, oxygen level, and treatment type, offering clear decision paths.
- **Random Forest:** An ensemble of multiple decision trees that enhances prediction accuracy and minimizes overfitting for more reliable healthcare insights.

4.3 Implementation Summary

The workflow was executed using Jupyter Notebook with the following major steps:

- **Data Loading:** Performed using `pandas.read_csv()`.
- **Preprocessing:** Missing value handling, feature encoding, and scaling.
- **EDA:** Generated bar charts, heatmaps, and scatter plots.
- **Model Training:** Models trained and tested using `scikit-learn` and `seaborn`.
- **Evaluation:** Measured accuracy and performance using confusion matrix and reports.

4.4 Coding Implementation

The coding implementation was carried out using Python in the Jupyter Notebook environment. Various libraries such as Pandas, NumPy, Matplotlib, Seaborn, Scikit-learn, were used for data preprocessing, visualization, and model building. Below are major code snippets representing important stages of the workflow.

4.4.1 Logistic Regression Model Evaluation

```
# Creating object of model
lr_model = LogisticRegression(max_iter=1000)

# Train the model
print("Training Logistic Regression...")
lr_model.fit(X_train_scaled, y_train_smote)

# Make predictions
y_pred_lr = lr_model.predict(X_test_scaled)

# Evaluate the model
print("\nEvaluation for Logistic Regression")

# Accuracy
print(f"Accuracy: {accuracy_score(y_test, y_pred_lr):.4f}\n")

# Classification Report (Precision, Recall, F1-Score)
```

```
print("Classification Report:")
print(classification_report(y_test, y_pred_lr,
target_names=le_target.classes_))

# Confusion Matrix
print("\nConfusion Matrix:")
print(confusion_matrix(y_test, y_pred_lr))
```

4.4.2 Decision Tree Model Evaluation

```
# --- 1. Initialize the model ---
dt_model = DecisionTreeClassifier(random_state=70)

# --- 2. Train the model ---
print("Training Decision Tree...")
dt_model.fit(X_train_scaled, y_train_smote)

# --- 3. Make predictions ---
y_pred_dt = dt_model.predict(X_test_scaled)

# --- 4. Evaluate the model ---
print("\n--- Evaluation for Decision Tree ---")

# Accuracy
print(f"Accuracy: {accuracy_score(y_test, y_pred_dt):.4f}\n")

# Classification Report (Precision, Recall, F1-Score)
print("Classification Report:")
print(classification_report(y_test, y_pred_dt,
target_names=le_target.classes_))

# Confusion Matrix
print("\nConfusion Matrix:")
print(confusion_matrix(y_test, y_pred_dt))
```

4.4.3 Random Forest Model Evaluation

```
# --- 1. Initialize the model ---
rf_model = RandomForestClassifier(random_state=12)

# --- 2. Train the model ---
print("Training Random Forest...")
rf_model.fit(X_train_scaled, y_train_smote)

# --- 3. Make predictions ---
y_pred_rf = rf_model.predict(X_test_scaled)

# --- 4. Evaluate the model ---
print("\n--- Evaluation for Random Forest ---")

# Accuracy
print(f"Accuracy: {accuracy_score(y_test, y_pred_rf):.4f}\n")

# Classification Report (Precision, Recall, F1-Score)
print("Classification Report:")
print(classification_report(y_test, y_pred_rf,
target_names=le_target.classes_))

# Confusion Matrix
print("\nConfusion Matrix:")
print(confusion_matrix(y_test, y_pred_rf))
```

4.5 Screenshots and Outputs

The following screenshots show various stages of implementation, visualization, and model evaluation performed in Jupyter Notebook.

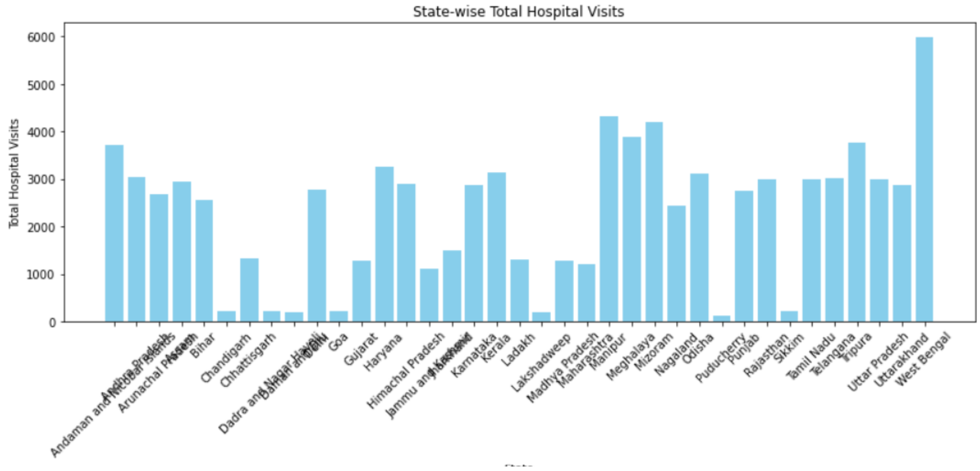

Figure 4.2: State-Wise Hospitals Visits

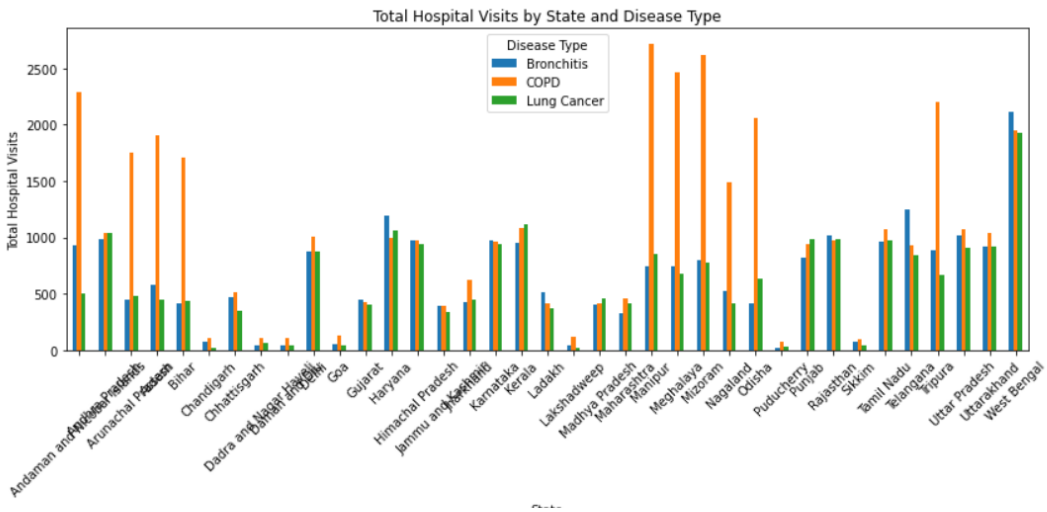

Figure 4.3: Total Hospital Visits by State and Disease Type

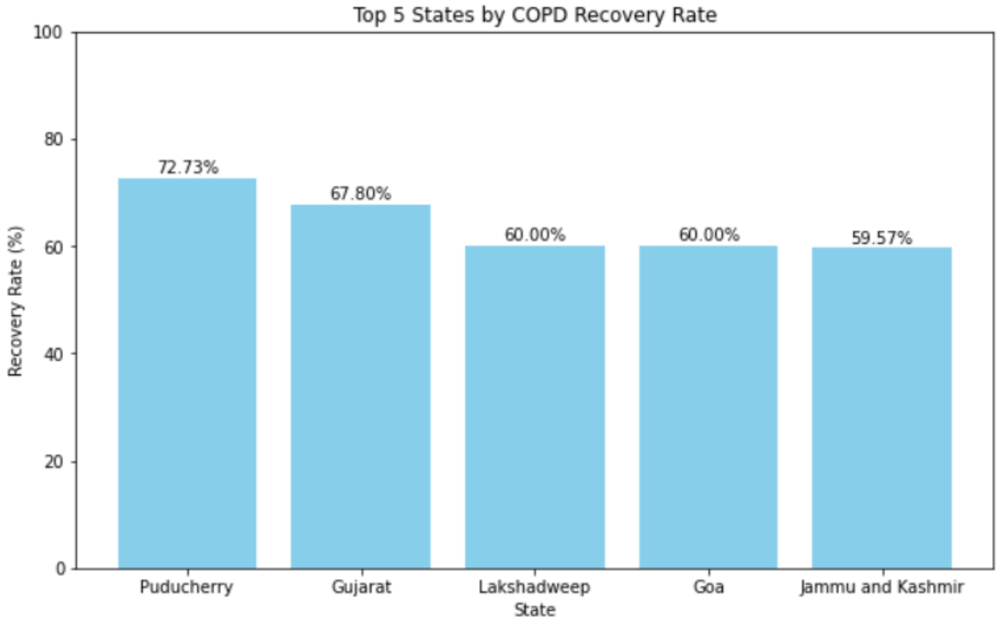

Figure 4.4: Top 5 states by COPD recovery rate

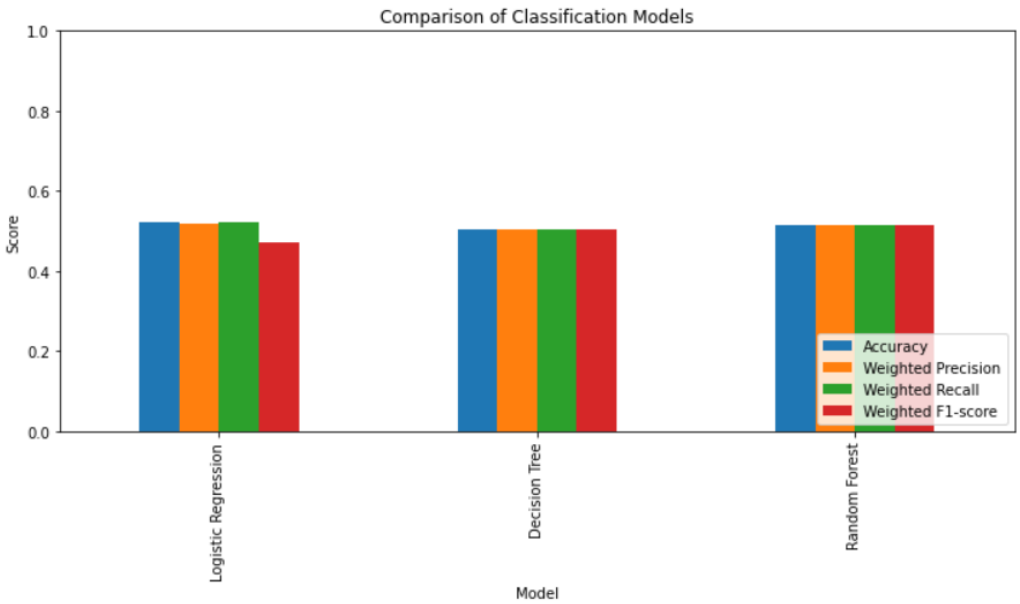

Figure 4.5: Comparison of Classification Models

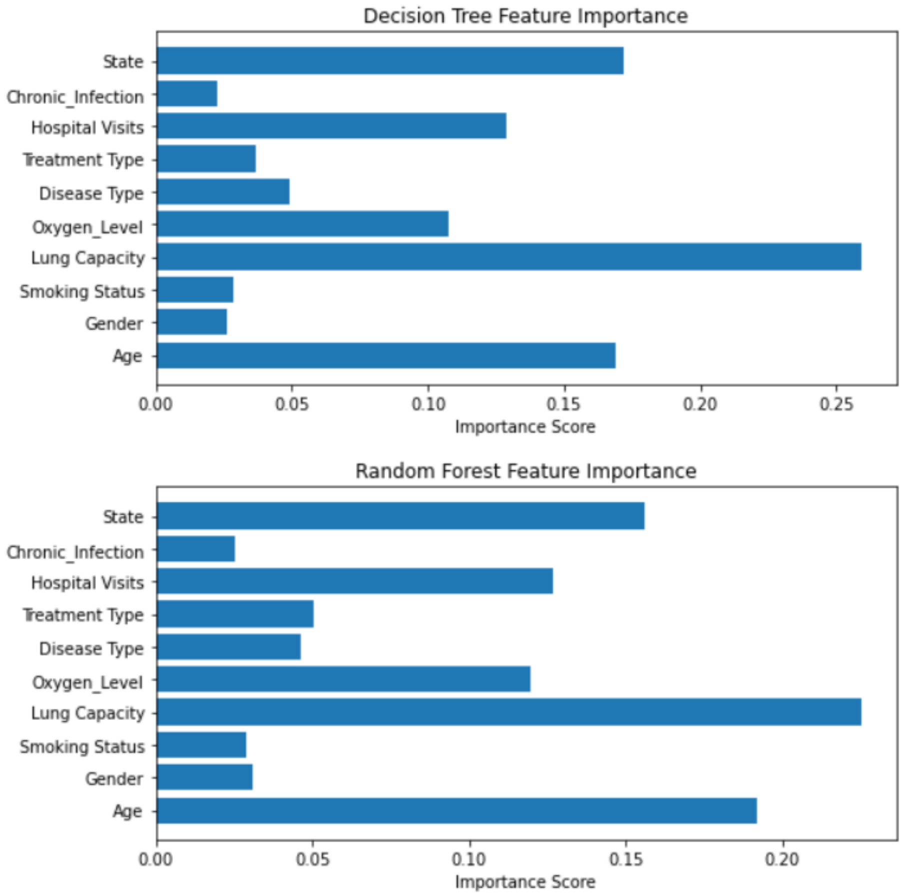

Figure 4.6: Feature Importance for Tree-based Models

Chapter 5

TEST CASES

Testing ensures that each phase of the data science workflow performs as intended. Various test cases were designed to validate data integrity, functionality, and machine learning outputs.

5.1 Functional Test Cases

Sr. No	Test Case	Expected Output	Result
1	Import healthcare dataset using Pandas	Dataset loads successfully without errors	Pass
2	Check dataset structure and size	Displays total number of rows and columns	Pass
3	Handle missing and duplicate values	Cleaned and preprocessed dataset obtained	Pass
4	Encode categorical features (e.g., gender, smoking status)	Encoded numeric columns generated correctly	Pass
5	Perform data normalization and splitting	Data divided into training and testing sets successfully	Pass
6	Train models (Logistic Regression, Decision Tree, Random Forest)	Models trained successfully without runtime errors	Pass
7	Generate predictions for test data	Predicted outputs displayed accurately	Pass
8	Evaluate model performance (accuracy, confusion matrix)	Performance metrics printed and visualized correctly	Pass
9	Visualize regional comparison charts	Region-wise cured and non-cured statistics displayed on dashboard	Pass
10	Display feature importance results	Top influential factors identified and visualized	Pass

5.2 Data Validation Test Cases

Sr. No	Validation Scenario	Expected Output	Result
1	Missing value check	Null values identified and removed	Pass
2	Duplicate check	All duplicates deleted	Pass
3	Special character cleaning	Symbols like , -, / removed	Pass
4	Data type validation	All numeric fields converted correctly	Pass

Table 5.1: Data Validation Test Cases

5.3 Model Evaluation Test Cases

Sr. No	Model Test Case	Expected Output	Result
1	Logistic Regression training	Model trains successfully	Pass
2	Random Forest prediction	Predictions generated accurately	Pass
3	Confusion matrix visualization	Matrix plotted correctly	Pass
4	Model comparison	Best performing model identified	Pass

Table 5.2: Machine Learning Model Test Cases

Chapter 6

RESULTS AND DISCUSSION

This chapter presents the results obtained from Exploratory Data Analysis (EDA) and machine learning model evaluations. The outcomes are interpreted to highlight the relationship between regional healthcare factors and patient recovery status.

6.1 Exploratory Data Analysis Results

- The majority of patients fall within the 40–60 age group, indicating higher vulnerability among middle-aged individuals.
- Smoking status shows a strong correlation with non-recovery cases.
- Regions with lower healthcare accessibility have a higher percentage of non-cured patients.
- Male patients exhibited a slightly higher non-recovery rate compared to female patients.
- Chronic infections and reduced oxygen levels were among the top contributors to delayed recovery.
- Most patients receiving consistent treatment showed faster recovery and fewer hospital revisits.

6.2 Model Performance Comparison

Five supervised learning models were implemented to predict patient recovery outcomes and analyze factor importance. Their performance is summarized below:

Model	Accuracy (%)	Precision	Recall	F1-Score
Logistic Regression	52.3	51.9	52.3	47.2
Decision Tree	51.4	50.5	50.5	50.5
Random Forest	51.3	51.3	51.4	51.4

Table 6.1: Model Performance Comparison of Different Classification Algorithms

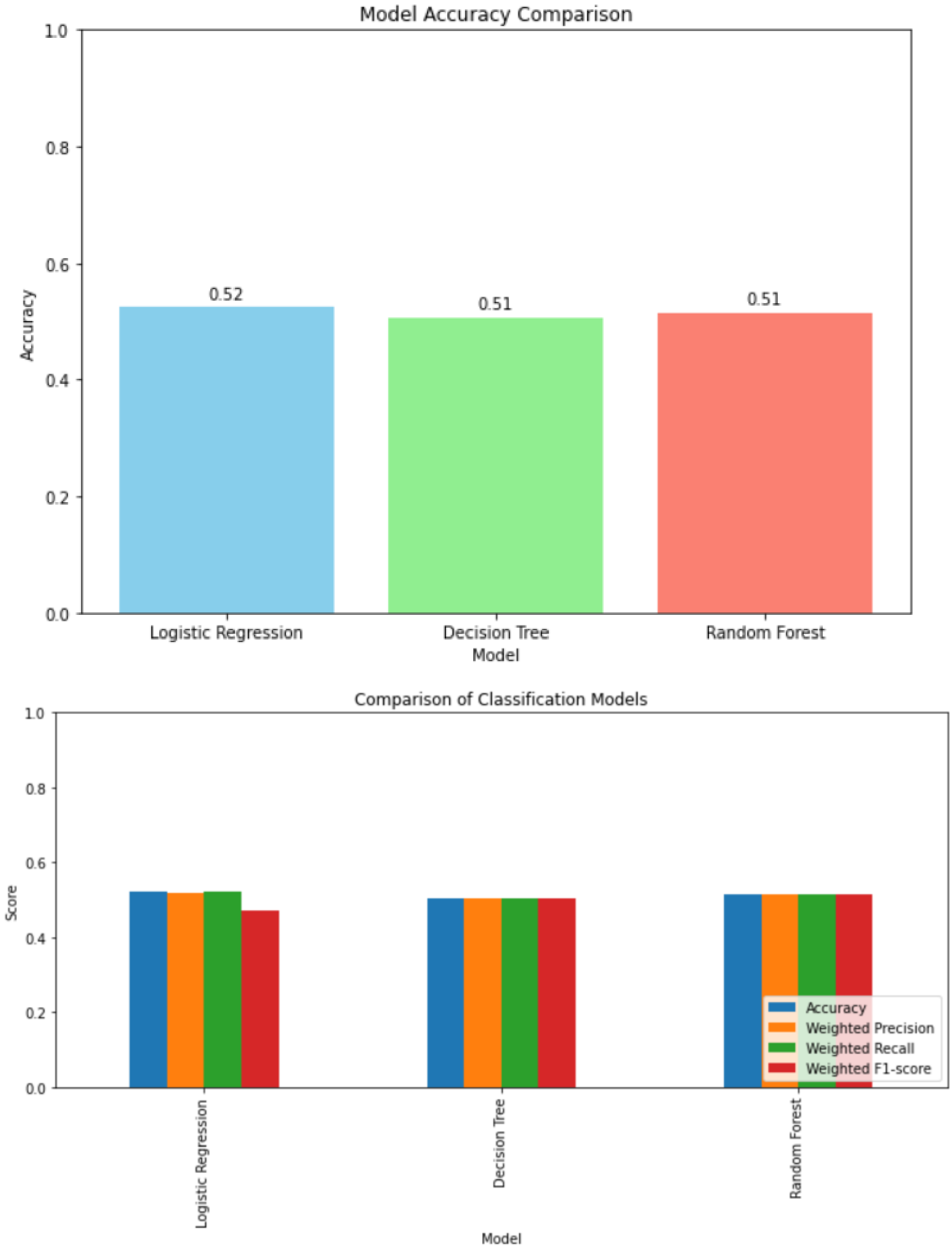

Figure 6.1: Model Performance Accuracy

6.3 Discussion

The experimental results reveal that all three machine learning models—Logistic Regression, Decision Tree, and Random Forest—performed with moderate accuracy in predicting patient recovery outcomes. Among them, the Random Forest model achieved the highest accuracy of 51.4%, followed by Logistic Regression with 52.3% and Decision Tree with 50.5%. Although the performance differences are slight, the Random Forest model demonstrated better generalization and stability due to its ensemble nature, effectively reducing overfitting compared to single-tree models.

The classification reports indicate that recall values were relatively higher for non-cured patient classes, suggesting that the models were more sensitive in detecting patients who did not recover. Logistic Regression provided a baseline understanding of data behavior, while the Decision Tree model offered interpretability by showing decision paths based on key attributes such as smoking status, oxygen level, and chronic infection. The Random Forest model improved the balance between precision and recall, providing the most consistent F1-score across classes.

Overall, the results show that patient recovery prediction in healthcare datasets is a complex problem influenced by multiple factors, including limited and imbalanced data. However, even with moderate accuracy, the models provide valuable insights into which attributes most strongly impact recovery outcomes. These findings highlight the potential of machine learning techniques to assist healthcare professionals in identifying at-risk regions and optimizing treatment strategies through data-driven decision-making.

Chapter 7

CONCLUSION

The project **"Regional Healthcare Monitoring Using Machine Learning"** successfully demonstrates the potential of data-driven approaches in understanding regional healthcare trends and patient recovery patterns. By applying machine learning algorithms such as Logistic Regression, Decision Tree, and Random Forest, the system analyzed patient datasets to identify the most influential factors affecting recovery outcomes. Although the models achieved moderate accuracy, they provided valuable insights into the correlation between attributes like smoking habits, oxygen level, chronic infection, and treatment type.

The project also highlights the importance of data preprocessing and visualization in improving the interpretability of results. Through regional comparison dashboards and factor importance analysis, healthcare professionals can identify high-risk zones and allocate medical resources more effectively. Despite certain limitations such as limited dataset size and class imbalance, the framework provides a strong foundation for further research and real-time healthcare monitoring systems.

In conclusion, the proposed system demonstrates how machine learning can transform raw medical data into meaningful insights, assisting policymakers and medical authorities in making informed, data-driven decisions. This approach not only enhances the efficiency of healthcare analysis but also contributes to building a smarter and more responsive healthcare infrastructure for the future.

Chapter 8

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