Analysis and Prediction of Food Delivery Time using Data Mining

A Mini Project Report

Submitted by

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BONAFIDE CERTIFICATE

Certified that this mini project report **"Analysis and Prediction of Food Delivery Time using Data Mining"** submitted as a part of the course of **CB23D31- DATA MINING AND ANALYTICS** is the bonafide work of **RAMYA R – 231401081** who carried out the project under my supervision.

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RAMYA R 231401081

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ABSTRACT

In today’s fast-paced world, online food delivery services have become an integral part of urban life. Customers expect quick and reliable service, making accurate delivery time prediction essential for business success. This project, “Food Delivery Time Prediction using Data Analytics and Visualization,” aims to predict food delivery time based on several key factors such as distance, traffic level, weather conditions, time of day, preparation time, and courier experience.

The dataset was preprocessed and analyzed using R programming, and a Random Forest algorithm was employed to build the prediction model. An interactive Shiny application was developed to allow users to input order details and obtain real-time delivery time predictions. Additionally, a Power BI dashboard was designed to visualize important insights, including average delivery time by distance, traffic level, and weather conditions.

The proposed system provides valuable analytical insights for restaurants and delivery platforms, helping them optimize delivery operations and improve customer satisfaction. This integration of machine learning and visualization tools demonstrates how data-driven decisions can enhance performance in the food delivery industry.

CHAPTER 1

INTRODUCTION

This project focuses on predicting food delivery times using data analytics and machine learning. By analyzing key factors such as distance, weather, traffic, and courier experience, the model provides accurate delivery time predictions. The system integrates R Shiny for prediction and Power BI for visualization. It helps improve efficiency, reduce delays, and enhance customer satisfaction.

1.1 GENERAL:

In the modern era of digital transformation, food delivery applications have become an integral part of everyday life, enabling customers to order food from their favourite restaurants with just a few taps on their mobile devices. The rapid growth of platforms such as Swiggy, Zomato, Uber Eats, and DoorDash demonstrates how technology has revolutionized the food industry. However, one of the key challenges faced by these delivery systems is accurately predicting delivery time for each order.

Delivery time prediction is influenced by multiple dynamic factors such as traffic congestion, weather conditions, delivery distance, courier experience, and preparation time at the restaurant. Any unexpected variation in these factors may cause delays, leading to customer dissatisfaction and loss of business reputation. This project, “Food Delivery Time Prediction using

Data Analytics and Visualization," aims to develop a data-driven solution that can accurately estimate delivery time using real-world data. The project uses R programming for building a machine learning model based on the Random Forest algorithm, and integrates it with an interactive Shiny application for real-time prediction. To enhance visualization and business insights, a Power BI dashboard is designed to represent delivery performance trends across multiple parameters.

By combining predictive analytics and visualization, this system provides valuable insights to restaurants, couriers, and food delivery companies, helping them enhance operational efficiency, plan better delivery routes, and deliver superior customer experiences.

1.2 MOTIVATION:

In the competitive world of online food delivery, customer satisfaction and service reliability are major factors that determine business success. Customers increasingly demand on-time delivery and real-time updates about their orders. A delay of even a few minutes can significantly affect the customer's perception of the service quality.

Food delivery platforms often rely on approximate or static calculations for delivery time, which fail to adapt to real-world variations such as sudden traffic jams or weather changes. This lack of precision results in customer complaints, cancellation of orders, and poor ratings for restaurants and delivery partners.

Hence, the motivation behind this project lies in bridging this gap through data analytics and machine learning techniques. By leveraging predictive modeling, businesses can forecast delivery times more accurately and allocate resources efficiently. For instance, during peak hours or rainy conditions, the system can alert couriers and restaurants in advance about potential delays.

The idea also promotes the data-driven decision-making culture that is essential in the era of digital business. The integration of R Shiny and Power BI demonstrates how analytics and visualization together can transform raw data into meaningful intelligence that supports operational improvements and strategic planning.

1.3 OBJECTIVES

The main objectives of this project are as follows:

- To analyze key factors affecting food delivery time such as distance, weather, traffic, and courier experience.
- To develop a predictive model using the Random Forest algorithm in R to forecast delivery time accurately.
- To design an interactive Shiny web application that enables users to input order details and receive real-time predictions.
- To create a Power BI dashboard for visualizing important insights, including average delivery time by traffic, weather, and distance.
- To improve operational efficiency, reduce customer waiting time, and enhance business decision-making using data analytics.

- To demonstrate how data mining and visualization can be applied together for real-world business optimization.

1.4 EXISTING DESIGN

In the existing food delivery ecosystem, most delivery time estimations are based on static calculations or manual judgments. These estimates often rely on average delivery durations derived from historical data without considering current, dynamic variables such as real-time traffic or changing weather patterns. As a result, they tend to be inaccurate and unreliable.

The absence of data-driven intelligence leads to inefficient route assignments and unpredictable delays. Additionally, most systems do not offer visual analytics to identify performance bottlenecks or monitor trends. For example, delivery managers cannot easily observe whether delays are more frequent during certain hours of the day or under specific conditions.

Moreover, customers often receive broad delivery time ranges (for example, “30–45 minutes”), which are not personalized to their specific order scenario. The lack of transparency affects trust and may result in customer dissatisfaction. Hence, there is a pressing need for a predictive and visual analytics solution that can dynamically estimate delivery times based on various contextual factors, helping businesses make smarter and faster decisions.

1.5 PROPOSED DESIGN

The proposed system introduces a data-driven and intelligent approach to estimate delivery time using data mining and machine learning techniques. Unlike existing systems, this approach considers multiple real-time factors that influence delivery duration.

The system architecture includes three major components:

1. Data Processing and Model Building (R):
   The dataset containing order details such as distance, traffic level, vehicle type, and courier experience is preprocessed using R. A Random Forest regression model is trained on this data to predict the delivery time (in minutes).
2. User Interaction Layer (R Shiny):
   The trained model is integrated into a Shiny web application that allows users to input values such as distance, weather, and vehicle type. The app outputs the predicted delivery time instantly and displays a feature importance chart to show which variables most influence the prediction.
3. Visualization and Reporting (Power BI):
   The preprocessed data is imported into Power BI, where multiple charts are created to visualize delivery patterns.
   - Line chart: Average Delivery Time by Distance
   - Bar chart: Delivery Time by Weather
   - Column chart: Delivery Time by Traffic Level
   - Pie chart: Delivery Time by Vehicle Type

This combination of R Shiny for analytics and Power BI for visualization makes the system not only predictive but also interpretable and actionable. Businesses can use these insights to optimize resources, schedule deliveries, and enhance customer experience.

1.6 TOOLS AND TECHNOLOGIES

The project utilizes R Shiny for developing an interactive prediction interface and Power BI for creating dynamic visual dashboards. R programming is used for data preprocessing and model building with machine learning algorithms. Microsoft Excel is employed for dataset preparation and cleaning before analysis.

1.6.1 R Shiny

R Shiny is an open-source web framework that enables the development of interactive web applications directly from R scripts. It allows the integration of predictive models, plots, and user inputs into a single interface. Shiny applications can be deployed online, enabling non-technical users to interact with machine learning models in real time. In this project, R Shiny is used to develop the prediction interface that allows users to enter details and receive instant delivery time predictions. It also displays a visual representation of variable importance for better understanding.

1.6.2 Power BI

Power BI is a business intelligence tool developed by Microsoft for data analysis and visualization. It enables users to connect, transform, and visualize data using interactive dashboards and reports. In this project, Power BI is used to visualize the average delivery time by distance, weather, traffic, and vehicle type. The dashboard provides a clear, interactive view of performance metrics, helping decision-makers monitor and analyze trends in delivery operations.

1.6.3 R Programming

R is a powerful open-source programming language widely used for statistical computing and data analysis. It offers a wide range of libraries that support machine learning, visualization, and data manipulation. In this project, R is used for:

- Loading and preprocessing the dataset.
- Training the Random Forest model.
- Developing the Shiny App interface.
- Major libraries used include randomForest, ggplot2, and readr.

1.6.4 Excel

Microsoft Excel is used as a supporting tool for dataset handling, cleaning, and exporting data. Before importing into R or Power BI, the dataset was first verified, formatted, and organized in Excel to ensure proper structure and compatibility.

Excel plays an essential role in the initial data exploration and validation process before moving into advanced data analysis.

CHAPTER 2

PROJECT DESCRIPTION

People today live in a fast-paced and technology-driven world where convenience plays a vital role in everyday life. Food delivery services have now become an essential part of modern living, providing customers with quick and effortless access to their favorite meals at their doorstep. With the increasing popularity of online food ordering platforms, such as Zomato, Swiggy, and Uber Eats, there has been an enormous rise in customer expectations for faster and more reliable delivery services. In this highly competitive environment, ensuring timely deliveries has become one of the most significant challenges faced by food delivery companies. To achieve customer satisfaction and maintain operational efficiency, companies must be able to predict accurate delivery times based on multiple real-world factors.

This project, *Food Delivery Time Prediction using Data Analytics and Visualization*, aims to provide an intelligent and data-driven solution to this problem. By applying data mining and predictive analytics, the project focuses on developing a system that can forecast the expected delivery time based on various parameters that influence delivery duration. The dataset used for this study includes crucial features such as distance (km) between restaurant and customer, weather conditions, traffic level, time of day, vehicle type used for delivery, preparation time (min) required by the restaurant, and courier experience (yrs). Each of these parameters plays a significant role in determining the total time taken for an order to be delivered.

The analysis was carried out by studying how these factors interact and contribute to delays or faster deliveries. For example, during heavy traffic or rainy weather conditions, delivery times tend to increase, whereas shorter distances and experienced couriers contribute to quicker deliveries. The dataset was carefully preprocessed in R to handle missing values, encode categorical variables, and remove unnecessary data to ensure that the model performs efficiently and accurately.

The project implementation involves two major technologies: R Shiny and Power BI. R Shiny is used for the machine learning model development and to create an interactive interface where users can input parameters such as distance, weather, and traffic level to get a real-time prediction of delivery time. The Random Forest algorithm was selected for building the predictive model because of its robustness, high accuracy, and ability to handle both numerical and categorical data efficiently. The model is trained on historical data, learns patterns between the features and the delivery time, and predicts the expected delivery duration for new orders.

In addition to the predictive modeling, Power BI is used for visualization and analysis. The cleaned dataset was imported into Power BI to create an interactive dashboard that provides deeper insights into delivery performance. It visually represents important metrics such as average delivery time by distance, average delivery time by weather and traffic conditions, and delivery performance based on courier experience and vehicle type. These visualizations help in understanding how various parameters affect the overall delivery time and can be used by businesses to make strategic decisions, such as assigning experienced couriers for long-distance deliveries or optimizing delivery routes during high-traffic hours.

The combination of R Shiny and Power BI provides a complete analytical solution—R Shiny focuses on prediction and interaction, while Power BI enhances understanding through data visualization. Together, they enable users to not only predict delivery times but also interpret the results effectively through visual insights. This integration bridges the gap between predictive analytics and real-time decision-making.

Overall, the project demonstrates how data analytics and machine learning can be applied to solve real-world operational challenges in the food delivery industry. By accurately predicting delivery times, restaurants and delivery platforms can improve efficiency, reduce late deliveries, and enhance customer satisfaction. Moreover, the visual insights generated through Power BI help management teams monitor performance, identify delay-causing factors, and implement strategies to optimize service quality. Thus, this project not only supports technical innovation but also contributes to improving the customer experience and business outcomes in the food delivery ecosystem.

2.1 System Architecture:

The system architecture of the *Food Delivery Time Prediction* project shows how data flows through different stages to predict delivery time. It starts with data collection and preprocessing in R, followed by model training using the Random Forest algorithm. The architecture also includes R Shiny for real-time prediction and Power BI for visualizing the final results and insights.

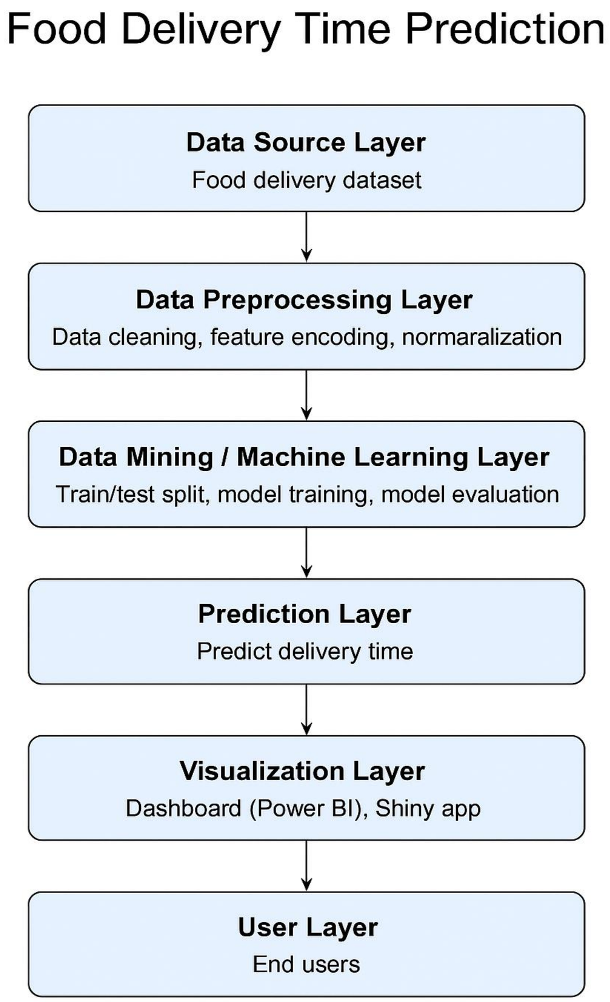

Figure 2.1 – System Architecture of Food Delivery Time Prediction System

In Figure 2.1 , The above diagram shows the overall workflow — from collecting and processing data to predicting and visualizing delivery time.

CHAPTER 3

IMPLEMENTATION AND RESULT

The system was implemented using R Shiny for model development and Power BI for visualization. The Random Forest algorithm accurately predicted delivery times, and the generated dashboard provided valuable insights into the impact of traffic, weather, and distance on delivery performance.

3.1 Dataset Description

The dataset used in this mini project, It contains comprehensive information on food delivery orders and various factors influencing delivery duration.

Column Name	Description
Order_ID	Unique order identification number
Distance_km	Distance between the restaurant and customer
Weather	Weather condition(Sunny,Rainy,Cloudy,etc.)
Traffic_Level	Traffic condition categorized as Low, Medium, High
Time_of_Day	Delivery period categorized (Morning, Afternoon, Evening, Night)
Vehicle_Type	Type of delivery vehicle used (Bike, Scooter,or Car)
Preparation_Time_min	Time taken to prepare the food
Courier_Experience_yrs	Experience of delivery courier
Delivery_Time_min	Actual time taken for delivery

Table 3.1. Dataset Description for Food Delivery Time Prediction

This dataset was used for model training, testing, and visualization using R programming and Power BI. It provided the foundation for understanding patterns in delivery performance and building the predictive system.

3.2 Data Preprocessing

Before developing the machine learning model, several preprocessing operations were carried out to ensure that the data was clean, consistent, and ready for analysis. Data preprocessing is a crucial step that enhances model accuracy and reliability.

The following steps were performed in RStudio:

- Imported the dataset using the readr library.
- Checked for missing or inconsistent data using the command: colSums(is.na(data))
- Encoded categorical variables (such as *Weather*, *Traffic_Level*, and *Time_of_Day*) into factors to make them suitable for training.
- Removed non-essential columns like *Order_ID* to minimize noise in the dataset.
- Verified data distribution using summary statistics and boxplots to detect outliers.
- Ensured that all columns were in appropriate data types for modeling.

After preprocessing, the dataset was clean and structured, enabling smooth model training and accurate prediction.

3.3 Model Building Using R

The Random Forest algorithm was chosen to predict delivery time due to its robustness, accuracy, and ability to handle both categorical and numerical features. It works by combining multiple decision trees to improve prediction performance and minimize overfitting.

Implementation Steps:

1. Loaded the necessary libraries:
   shiny, random Forest, ggplot2, and readr.
2. Imported and cleaned the dataset.
3. Split the dataset into training (80%) and testing (20%) sets.
4. Built the Random Forest model with Delivery_Time_min as the dependent variable.
5. Used 200 trees (ntree = 200) to ensure stability and reduce variance.
6. Predicted delivery times using the trained model and evaluated performance using error metrics.

R Code Snippet:

```
set.seed(123)
model <- randomForest(
  Delivery_Time_min ~ Distance_km + Weather + Traffic_Level +
    Time_of_Day + Vehicle_Type + Preparation_Time_min +
Courier_Experience_yrs,
  data = data, ntree = 200, na.action = na.omit
)
```

The model showed strong predictive accuracy, effectively capturing relationships between independent variables and delivery time.

3.4 Shiny App Development

To make the system more interactive, efficient, and user-friendly, a Shiny App was developed using R. The application combines data analysis, machine learning, and visualization into a single web-based interface. It integrates the trained Random Forest model to generate real-time predictions of delivery time based on user inputs. The app allows users such as restaurant managers, delivery partners, or administrators to enter parameters and instantly obtain accurate time estimates, making it highly practical for day-to-day operations.

Features of the Shiny App:

- **Sidebar Panel:** Allows users to input various delivery parameters such as distance, weather, traffic level, vehicle type, preparation time, and courier experience.
- **Predict Button:** Instantly triggers the Random Forest model to calculate and display the predicted delivery time.
- **Output Panel:** Displays the predicted delivery time in minutes along with clear, readable text.
- **Feature Importance Plot:** Visually represents the factors that most influence delivery duration, helping users understand which conditions affect time the most.
- **Interactive Interface**: Designed with an intuitive layout and responsive design, enabling real-time interaction and quick decision-making.

Overall, the Shiny App acts as the front-end of the project, connecting users with the machine learning model. It allows restaurants, couriers, and managers to predict delivery times quickly for different scenarios. This improves accuracy, decision-making, and overall operational efficiency.

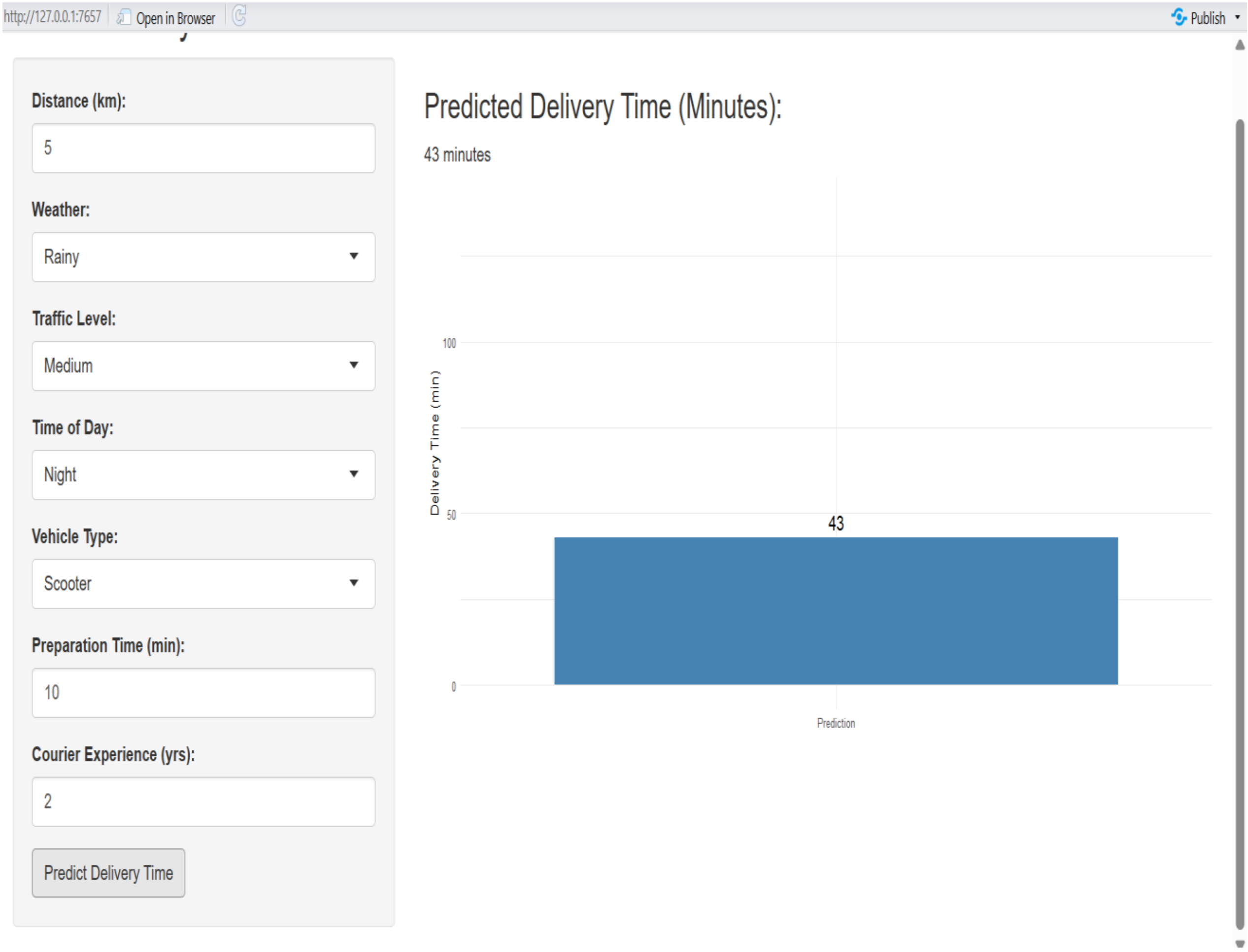

Figure 3.1 – Shiny App Output for Delivery Time Prediction

In figure 3.1 , The Shiny App provides an intuitive web-based interface. Users can input details such as distance, traffic level, vehicle type, and weather, and the system will immediately display the predicted delivery time. It also visualizes feature importance, highlighting key contributors like distance, traffic, and weather conditions that influence delivery time the most.

3.5 Power BI Dashboard

After generating predictions from the R model, the cleaned dataset was imported into Microsoft Power BI to design an interactive and visually appealing dashboard. Power BI was used to analyze the relationships between various factors such as distance, weather, traffic, and courier experience, and how they impact overall delivery time. The dashboard provides clear visual insights into delivery performance, allowing users to quickly identify trends and problem areas.

Multiple visualizations such as bar charts, line charts, pie charts, and KPI cards were created to display average delivery time by different parameters. A slicer was also added to filter and analyze data interactively. Through these visuals, users can easily observe that delivery time tends to increase with longer distances, poor weather, and higher traffic levels.

Overall, the Power BI dashboard acts as the analytical component of the project, transforming raw data and model outputs into meaningful business insights. It helps restaurants and delivery managers monitor key performance metrics, identify bottlenecks, and make data-driven decisions to improve delivery efficiency and customer satisfaction.

Power BI Visuals Implemented:

- **KPI Cards:** Displayed *Average Distance*, *Average Delivery Time*, and *Total Orders*
- **Pie Chart:** Orders and Distance by *Vehicle Type*
- **Bar Chart:** *Delivery Time by Weather Condition*
- **Line Chart:** *Delivery Time by Traffic Level*

- **Combo Chart:** *Delivery Time and Distance by Time of Day*
- **Slicer:** Enabled filtering by *Order ID, Traffic Level,* and *Weather*

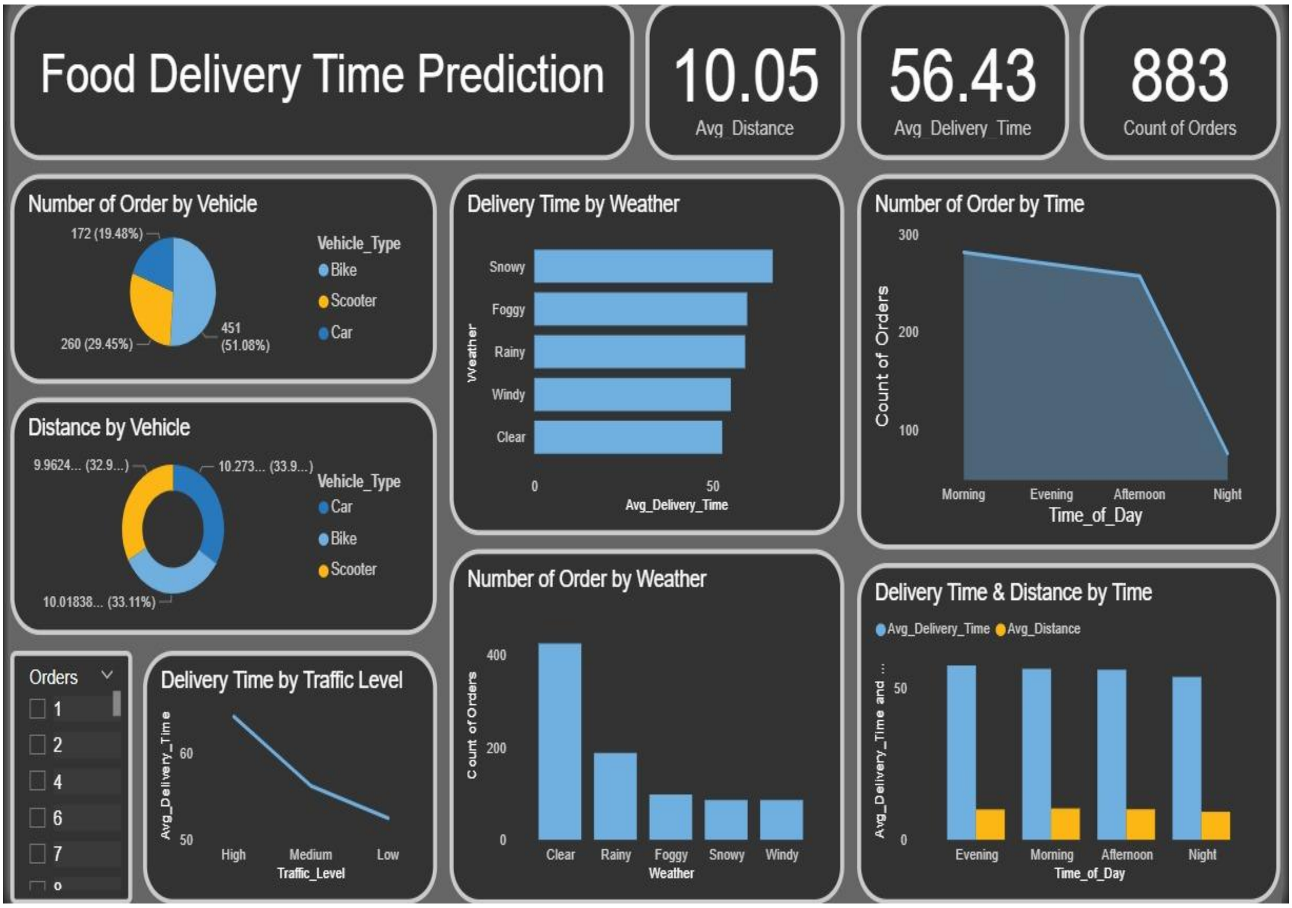

Figure 3.2 – Power BI Dashboard for Food Delivery Time Analysis

In Figure 3.2 , The Power BI dashboard delivers clear, visual insights into delivery operations. It reveals that deliveries tend to take longer in rainy or foggy weather and when traffic levels are high. It also shows how experienced couriers and lighter traffic result in faster deliveries. Users can filter and compare multiple parameters interactively, aiding in data-driven decision-making.

3.6 Results and Observations

The implementation of the *Food Delivery Time Prediction* project produced several significant results and insights that highlight the effectiveness of using data analytics and visualization techniques in real-world scenarios. The Random Forest model developed in R demonstrated strong predictive performance, efficiently estimating food delivery times across various conditions and datasets. It accurately analyzed multiple influencing parameters such as distance, traffic level, weather conditions, and courier experience, thereby producing reliable predictions for delivery duration.

One of the major findings was that weather and traffic conditions were the most dominant factors affecting delivery performance. During adverse weather conditions like rain or fog, and under high traffic congestion, the model predicted longer delivery durations. On the other hand, deliveries made during clear weather or using efficient vehicle types showed reduced time intervals. These observations were consistent with real-world expectations, validating the model's predictive capability.

The Power BI dashboard provided powerful visual insights into the data and confirmed the analytical results. It was observed through charts and graphs that delivery time tends to increase with longer distances, poor weather, and heavy traffic. The dashboard also revealed that couriers with higher experience levels completed deliveries faster and more efficiently than less experienced ones. The visual representation made it easier to identify patterns and correlations that may not be immediately evident from raw data, supporting data-driven decision-making for logistics and operations teams.

The R Shiny application served as an interactive platform where users could input new parameters such as distance, time of day, traffic level, and courier experience to instantly obtain a predicted delivery time. This real-time prediction capability makes the system highly practical for restaurants, food delivery platforms, and logistics companies seeking to optimize operations and enhance customer satisfaction.

Furthermore, the integrated use of machine learning (R Shiny) and business intelligence (Power BI) provided a holistic approach to analysis and visualization. While R Shiny focused on building and deploying the predictive model, Power BI complemented it by presenting clear, data-driven visual insights. This combination not only improved the accuracy of predictions but also provided an intuitive interface for understanding performance trends and making informed business decisions.

Overall, the results confirm that the developed system successfully meets its objectives. It provides accurate predictions, identifies key influencing factors, and enables effective visualization for decision support. The project thus offers a scalable and efficient framework that can be extended further for real-time integration in commercial food delivery systems.

CHAPTER 4

CONCLUSION AND FUTURE ENHANCEMENTS

4.1 Conclusion

The project *"Food Delivery Time Prediction using Data Analytics and Visualization"* successfully demonstrates how predictive modeling and data analytics can be leveraged to enhance the efficiency of modern food delivery systems. By analyzing various real-world factors such as distance, traffic level, weather, time of day, vehicle type, preparation time, and courier experience, the developed system accurately predicts the expected delivery time for any order.

The Random Forest algorithm, implemented in R, proved to be an effective and reliable method for handling both categorical and numerical data, producing high accuracy in predicting delivery durations. The use of R Shiny provided an interactive interface that enables users to input parameters and instantly receive a prediction, making the model practical and user-centric. On the other hand, Power BI facilitated the creation of dynamic dashboards that offer deep insights into data trends, such as how weather, traffic, and courier experience influence delivery times.

This integration of predictive analytics and visualization tools creates a complete analytical ecosystem that supports decision-making for businesses in the food delivery domain. The project not only meets its primary objectives but also demonstrates the potential of machine learning in improving real-world logistics, reducing delays, and increasing customer satisfaction. Overall, this system provides a scalable, efficient, and interactive solution that can significantly benefit food delivery platforms by offering accurate delivery forecasts and operational insights.

4.2 Future Enhancements

While the current system performs effectively, there are several opportunities to enhance its functionality and real-world applicability in future versions:

- **Integration of Real-Time Data:**
  Incorporating live data sources such as real-time traffic APIs and weather updates would allow the system to make dynamic, real-time predictions rather than relying solely on historical data.

- **Route Optimization using GPS:**
  Implementing GPS-based route optimization can help couriers find the fastest possible routes, further reducing delivery time and improving efficiency.

- **Mobile Application Development:**
  A dedicated mobile application can be developed that connects directly with the Shiny backend, allowing restaurant managers and couriers to access predictions and analytics on the go.

- **Expansion of Dataset:**
  Extending the dataset to include data from multiple cities and geographical regions will improve the generalization and robustness of the model across different conditions.

- **Integration with Cloud Platforms:**
  Deploying the system on cloud services like AWS or Azure can enable large-scale, real-time data processing and facilitate integration with commercial food delivery networks.

In conclusion, this project establishes a strong foundation for predictive analytics in the food delivery domain. With the suggested enhancements, it has the potential to evolve into a comprehensive intelligent system that combines machine learning, real-time analytics, and smart routing, ultimately revolutionizing the way delivery times are managed and optimized in the food industry.

CHAPTER 5

LEARNING OUTCOMES

Through the completion of this project, we gained valuable knowledge and hands-on experience in multiple aspects of data analytics and predictive modeling:

- **Data Preprocessing and Analysis in R:** We learned how to clean, preprocess, and explore datasets effectively using R, handling missing values, outliers, and categorical variables to ensure accurate analysis.
- **Application of Machine Learning Algorithms:** We applied machine learning techniques, specifically predictive models, to forecast delivery times. This included understanding model selection, training, testing, and evaluating model performance for real-world data.
- **Development of Interactive Dashboards in R Shiny:** We gained practical experience in building user-friendly, interactive dashboards in R Shiny, allowing stakeholders to visualize predictions and explore data dynamically.
- **Designing Analytical Reports in Power BI:** We learned how to integrate insights into comprehensive reports using Power BI, creating visualizations and dashboards that facilitate data-driven decision-making.

CHAPTER 6

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APPENDIX (FULL R SHINY CODE)

```r
# Install required packages
install.packages("shiny")
install.packages("randomForest")
install.packages("ggplot2")
install.packages("readr")

# Load required libraries
library(shiny)
library(randomForest)
library(ggplot2)
library(readr)

# Load dataset (update path as needed)
data <- read_csv("C:/Users/ramya/Downloads/Food_Delivery_Times.csv")

# Remove missing values
data <- na.omit(data)

# Train Random Forest Model
set.seed(123)
model <- randomForest(
  Delivery_Time_min ~ Distance_km + Weather + Traffic_Level +
    Time_of_Day + Vehicle_Type + Preparation_Time_min +
Courier_Experience_yrs,
```

```
  data = data, ntree = 200
)

# Shiny App
ui <- fluidPage(
  titlePanel("Food Delivery Time Prediction Dashboard"),

  sidebarLayout(
    sidebarPanel(
      numericInput("distance", "Distance (km):", value = 5, min = 1, max =
30),
      selectInput("weather", "Weather:", choices = unique(data$Weather)),
      selectInput("traffic", "Traffic Level:", choices =
unique(data$Traffic_Level)),
      selectInput("timeofday", "Time of Day:", choices =
unique(data$Time_of_Day)),
      selectInput("vehicle", "Vehicle Type:", choices =
unique(data$Vehicle_Type)),
      numericInput("prep", "Preparation Time (min):", value = 15, min = 5,
max = 60),
      numericInput("experience", "Courier Experience (yrs):", value = 2,
min = 0, max = 20),
      actionButton("predict", "Predict Delivery Time")
    ),

    mainPanel(
```

```
      h3("Predicted Delivery Time (Minutes):"),
      textOutput("prediction"),
      plotOutput("plot")
    )
  )
)

server <- function(input, output) {

  observeEvent(input$predict, {
    newdata <- data.frame(
      Distance_km = input$distance,
      Weather = input$weather,
      Traffic_Level = input$traffic,
      Time_of_Day = input$timeofday,
      Vehicle_Type = input$vehicle,
      Preparation_Time_min = input$prep,
      Courier_Experience_yrs = input$experience
    )

    pred <- predict(model, newdata)

    output$prediction <- renderText({
      paste(round(pred), "minutes")
    })
```

```
    output$plot <- renderPlot({
      ggplot(data.frame(Prediction = pred), aes(x = "Prediction", y =
Prediction)) +
        geom_col(fill = "steelblue") +
        labs(x = "", y = "Delivery Time (min)") +
        ylim(0, max(data$Delivery_Time_min)) +
        geom_text(aes(label = round(Prediction)), vjust = -0.5, size = 5) +
        theme_minimal()
    })
  })
}

shinyApp(ui = ui, server = server)
```