Optimizing Delivery Routes for Cost and Reliability

A MINI PROJECT REPORT

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BONAFIDE CERTIFICATE

Certified that this Report titled "**Optimizing Delivery Routes for Cost and Reliability**" is the bonafide work of **DEEPAK S (221801008) and SRIRAAM G V (221801052)** who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

In today’s intricate supply chain landscape, efficient transportation route optimization is crucial for minimizing operational costs and enhancing delivery reliability. Conventional routing approaches, which rely heavily on static heuristics, struggle to respond effectively to real-time variables such as traffic and weather disruptions. This paper introduces an innovative, data-driven route optimization framework tailored for supply chain logistics, integrating the A* algorithm with advanced regression models to boost routing efficiency and delivery accuracy. By harnessing historical shipment data and dynamically incorporating real-time traffic and weather conditions, the system intelligently adapts routes to reduce travel time, optimize resource allocation, and lower fuel consumption. Predictive models further enhance this framework by utilizing historical data to forecast delivery times, detect potential bottlenecks, and enable proactive intervention. Leveraging machine learning techniques and real-time algorithms, the system provides dynamic rerouting capabilities, delivering more accurate delivery estimates while supporting sustainability goals by decreasing emissions and fuel usage. Case studies have validated the framework's efficacy, highlighting significant cost reductions, enhanced on-time delivery rates, and increased customer satisfaction, marking it as a transformative solution in logistics management.

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CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION TO THE PROJECT

In today's fast growing and competitive market, efficient supply chain management is very crucial for business aiming for higher profitability, lower operational cost and superior customer service. The key to an edge over the competition for a supply chain management firm is to maximize logistics and transportation route efficiency. The purpose of this project is to analyse historical shipment and delivery data in order to create a best idea of operation in the firm, in the form of optimizing a logistics strategy so that they can make more data driven decisions about what route to take and what their operational performance needs to be. The project started by collecting and analysing historical shipment data to develop trends, bottle necks, and inefficiencies that inhibit the most efficient transportation routes. This analysis examines specific key performance metrics (i.e. delivery times, route distances, transit delays, and fuel consumption patterns) with the objective of identifying areas where there may be opportunity to improve planning. For example, knowing peak traffic times can help adjust route schedules and delivery times as well as understanding fuel use and route efficiency can enable the firm to reduce costs and minimise environmental impact. the firm will be able to reform its logistics processes strategically with the aim of optimizing routes with the lowest costs, and the most timely service deliveries so that liquidity is improved and spending diminishes the service quality. Ultimately, the optimized routes will make the firm more responsive to customers needs and adaptable to changing demands in the supply chain market. Beyond specific improvements, this project establishes a future-ready framework for efficient, flexible and scalable logistics.

1.2 NEED FOR THE STUDY

With supply chain management there has never been such demand on timely, cost effective and reliable delivery. As customers' expectation of fast and getting predictable deliveries increase along with more competition among logistics providers companies face the pressure to improve their operational efficiency continuously. This study is essential to address the following needs within the supply chain management field:

1. Cost Reduction: The supply chain is full of transportation costs which are often a big dent in operational budgets. Reducing fuel cost, vehicle maintenance and labour costs of longer inefficient routes.
2. Enhanced Delivery Reliability: If delivery times are unpredictable, customers will get dissatisfied and will start to transfer brand reputation and loyalty to competitors. The study analyses historical data in delivery patterns to improve the accuracy of delivery schedules and to alleviate common delay factors.
3. Environmental Impact: By optimizing routes, we can save on fuel meaning we leave a smaller carbon footprint. At the same time, it matches up with growing industry and societal interest in sustainability and minimizes the environmental footprint of transportation.
4. Data-Driven Decision Making: Traditional routing and scheduling methods rely on which can overlook patterns that only data analytics can see. This project will use history study to move away from assumptions and intuition-based decision making to measurable actionable insights.
5. Adaptability to Market Changes: Fuel prices, market demands and delivery expectations all change fast. Therefore, this study is important to build a flexible and responsive logistics framework with capacity to respond to demand fluctuation and price perturbation caused by fuel costs or other market conditions.

6. Competitive Advantage: The whole business operations of a firm in a highly competitive logistics will be highly reliant on routing if it can achieve efficient routing, as it will enjoy cost savings, reliability, and service quality, giving more customers, which will increase firm's profitability.
7. This study provides the supply chain management firm with the capability for identifying and exploiting opportunities to optimize logistics processes; thereby assisting the organization in its continued success in a dynamic and challenging market environment.

1.3 OBJECTIVES OF THE STUDY

The underlying objective of this study is to find the best routes for shipping and deliveries of a logistics and transportation firm based on historical data of shipments and delivery time. Specifically, the study aims to:

Identify Inefficiencies in Current Routes: To identify existing patterns, delays, and bottlenecks in existing logistics route and schedule routes.

1. Reduce Operational Costs: It then develops optimized routing strategies that minimize transportation costs while reducing fuel consumption, vehicle wear and tear, and labour costs due to excessive and inefficient routes.
2. Enhance Delivery Reliability and Timeliness: Reduce the inherent level of predictability in delivery schedules associated with common delay factors and in the solutions to mitigate these factors.
3. Promote Sustainable Practices: To reduce the firm's environmental impact there is the possibility of designing more fuel-efficient routes that lead to a lower carbon footprint.
4. Enable Data-Driven Decision Making: Begin constructing a data analytics framework capable of guiding the firm to provide useful

informed, evidence-based decisions for continuous route optimization and improved allocation of resources.

5. Increase Responsiveness to Market Changes: Support the firm to equip a flexible logistics model, which can adjust to change in demand, traffic conditions, and other external conditions for the improvement of agility and competitiveness.
6. Strengthen Competitive Advantage: Develop a highly efficient, reliable logistics operation which will promote customer satisfaction and place the firm as an industry market leader in the supply chain field.

1.4 OVERVIEW OF THE PROJECT

The main scope of this project is to find ways of optimizing the routing of logistics and transportation routes for a supply chain management firm by converting a historical data on the shipments, times of deliveries and other parts of logistics metrics into data that can be used to compare the subject to others in a like market. By taking a data driven approach, the project seeks to identify inefficiencies in current logistics operations, including extensive delivery times, high fuel consumption, and unnecessary delays, and design more efficient versions of transportation routes that are more economical.

The project’s framework includes several key stages:

1. Data Collection and Preparation: The first step is to collect historical shipment data, delivery times, route distances, fuel consumption, traffic patterns and other important time-to-market figures. We then clean and prepare data for more in depth analysis.
2. Data Analysis and Pattern Recognition: The project uses data analytics tools and techniques to find patterns, peak demand times, recurring bottlenecks and ineffective elements of the current logistics setup. To

serve as benchmarks for improvement, key performance indicators, Average delivery times and route effectiveness are calculated.

3. Route Optimization Modelling: Using insights gained through data analysis, the project designs modified routes and schedules based on optimization algorithms to reduce travel distances and time while maintaining usable delivery. Different optimization methods such as Shortest Path and Predictive Analytics are used to find the best possible routes.
4. Implementation of Optimized Routes: If an optimal routes and schedules are identified, the project proposes a phased implementation to test these improvements. In this phase they adjust logistics planning process, integrate new routing strategies, and train the operations team on new procedure as well.
5. Performance Monitoring and Continuous Improvement: The new routes and schedules are then monitored post-implementation to look for improvements over a baseline metric. The process continues further as is necessary, and further adjustments and fine tuning are done, using real time feedback for continued
6. optimization. Environmental and Cost Impact Analysis: The benefits of optimal logistics are evaluated as a function of cost savings, reduced fuel consumption and environmental impact.

The ultimate goal of this project is to provide the firm with streamlined, adaptive, sustainable logistics operation. The firm will be able to reach greater operational efficiency, lower costs and strengthen its market position in the logistics industry by building a solid foundation for data driven route optimization.

CHAPTER 2

REVIEW OF LITERATURE

2.1 INTRODUCTION

Since it has a massive influence on both cost efficiency and customer satisfaction, supply chain management has had a major focus in optimizing logistics and transportation routes. One major component of this logistics cost is transportation costs, which have been found to be significant (at least as much as 60%) contributing to overall logistics expense and which have been studied (see Ballou, 2004) to have the potential to reduce these costs by up to 30%. As Zhan et al. (2019) discuss, advances in data analytics allows for more effective decision making through more exposure to inefficiencies and forecasting delays to create better routing strategies. This project uses historical shipment data to both discover optimization opportunities and shorten transit time. Many routing problems, such as the traveling salesman problem (TSP), and the vehicle routing problem (VRP), are studied. Heuristic and metaheuristic algorithms to minimize travel distance and cost are discussed by Golden et al. (2008) and Laporte (2009), while Derigs et al. (2011) provide techniques such as genetic algorithms for more complex routing requirements. In using the same algorithms, we also designed efficient, cost-effective routes. Also sustainability is essential, McKinnon (2010) argues that optimized routes lower emissions as well as fuel use, in keeping with sustainable practice. According to Chopra and Meindl (2016), logistics should be adaptable enough to respond flexibility to the amount of demand changes. Third, as Lambert and Cooper (2000) argue customer centric approach in logistics firm means that if customers are satisfied, they will become more satisfied if delivery is reliable. These findings from this project are integrated to develop a flexible and sustainable logistics framework that fits with industry best practices.

S.No	Author Name	Paper Title	Description	Journal	Volume/ Year
1.	Zhen Liu Hongwei Wang Huan Chen	Dynamic Routing and Scheduling with Real-Time Data for Enhanced Logistics Operations	This paper examines how real-time data can be used to optimize dynamic routing and scheduling in logistics. It employs MILP and Dynamic Programming to adjust routes based on real-time updates.	Transportation Research Part B: Methodological	2023
2.	Laura Garcia Michael T. Lee Eric Thompson	Data-Driven Optimization of Transportation Routes Using Machine Learning Models	The research focuses on using machine learning models to predict delivery times and optimize routes. It integrates Predictive Analytics and Genetic Algorithms to enhance routing efficiency based on historical data.	European Journal of Operational Research	2022
3.	Daniel Park Emma Johnson Rajiv Patel	Enhanced Route Optimization for Urban Logistics Using Big Data Analytics	The paper investigates the application of Big Data Analytics for urban logistics route optimization, employing Cluster Analysis and Metaheuristic Algorithms, including Simulated Annealing.	Journal of Business Logistics	2024
4.	Ravi Kumar Alice M. Smith Robert J. Brown	Adaptive Route Optimization in Supply Chains Using Reinforcement Learning	The paper applies Reinforcement Learning to optimize transportation routes adaptively. It utilizes Q-Learning to improve routing decisions based on historical data and real-time feedback.	Journal of Machine Learning Research	2022

2.2 FRAMEWORK OF ROUTE OPTIMIZATION

Route optimization in logistics and supply chain management involves determining the most efficient routes to deliver goods, balancing factors like cost, time, reliability, and environmental impact. As companies aim to streamline transportation and meet rising customer expectations, route optimization has emerged as a crucial operational focus. Traditionally, logistics companies relied on manual planning or basic heuristic algorithms, such as the Nearest Neighbor and Savings algorithms, which offered simple routing solutions based on fixed schedules and distance metrics. However, these traditional methods fall short of addressing the complexities of today's supply chain demands, which are influenced by real-time variables like traffic, weather, and delivery urgency. The inability of static routes to adapt to fluctuating conditions often results in increased fuel costs, inefficient driver utilization, and reduced customer satisfaction.

In response to these limitations, advanced algorithms and computational approaches have gained traction. Techniques such as Machine Learning (ML), Genetic Algorithms, and Metaheuristic methods provide predictive capabilities, allowing companies to anticipate delivery times more accurately and optimize routes dynamically. For instance, ML models can be trained on historical data to learn patterns, predict delivery delays, and adjust routes in real time. Moreover, Reinforcement Learning (RL) offers adaptive solutions by continuously learning from routing decisions and updating strategies based on real-time feedback. By integrating these advanced algorithms, companies can address specific challenges such as dynamic route adjustments and congestion, significantly reducing operational costs and improving the reliability of deliveries.

A variety of research also highlights the role of Big Data and Internet of Things (IoT) technologies, which provide real-time data streams, such as GPS, traffic, and weather information. This influx of data supports smarter, data-driven decision-making in route optimization. For instance, by combining route planning with real-time traffic and weather insights, IoT-enabled systems can optimize routes on the fly, reducing delivery delays and ensuring efficient fuel usage. Research also shows that the inclusion of predictive analytics within route optimization strategies can increase customer satisfaction through more accurate delivery windows, enhancing overall supply chain performance.

CHAPTER 3

SYSTEM OVERVIEW

3.1 EXISTING SYSTEM

1. Static Route Planning: Existing systems frequently use static route planning, where routes are calculated based on historical data without incorporating real-time inputs. This method often leads to inefficiencies, as it does not account for unforeseen events such as traffic congestion, accidents, or weather-related disruptions that can affect delivery times.
2. Limited Data Integration: Current systems often struggle with integrating diverse data sources effectively. For instance, while some systems may utilize GPS data for vehicle tracking, they may not effectively incorporate additional real-time information, such as traffic conditions, road closures, or customer preferences. This limitation restricts the ability to make informed routing decisions in real time.
3. Inflexibility to Change: Many existing systems are not designed to adapt quickly to changes in logistics environments. When faced with new constraints or changing conditions, such as last-minute delivery requests or changes in vehicle availability, these systems often require manual intervention, resulting in delays and increased operational costs.
4. Cost and Efficiency Challenges: The traditional route optimization approaches tend to focus primarily on minimizing travel distance or time without adequately considering other factors such as fuel consumption, vehicle capacity, or customer satisfaction. As a result, existing systems may lead to suboptimal resource allocation and higher operational costs.
5. Limited Predictive Capabilities: While some systems attempt to utilize historical data for route planning, they often lack advanced predictive analytics capabilities. Without effective predictive modeling, these systems cannot forecast potential delays accurately, limiting their effectiveness in adapting routes proactively to maintain delivery schedules.

3.2 PROPSED SYSTEM

The proposed system for route optimization in supply chain management aims to address the limitations of existing systems by integrating advanced algorithms and real-time data analytics. This comprehensive solution combines the A* algorithm with regression-based predictive models, enabling dynamic routing that enhances delivery efficiency and reduces transportation costs. The key components and features of the proposed system include the following:

1. Integration of A Algorithm*: The A* algorithm will serve as the foundation for the routing mechanism. It combines the benefits of heuristic and cost-based search methods to identify the most efficient routes based on both distance and estimated travel time. The algorithm's heuristic capabilities allow it to adapt dynamically to changing conditions within the logistics network, taking into account factors such as traffic congestion, road closures, and vehicle constraints.
2. Real-Time Data Acquisition: The system will continuously collect real-time data from various sources, including vehicle GPS locations, traffic conditions, weather updates, and road status. This data will be integrated into the routing decision-making process, enabling the system to make informed adjustments to routes based on current conditions.
3. Predictive Analytics: Regression-based predictive models will be employed to analyze historical shipment data and forecast delivery times accurately. By understanding patterns in past performance, the system can anticipate potential delays and proactively adjust routes to maintain on-time delivery schedules. This predictive capability enhances responsiveness and minimizes disruptions in the logistics chain.
4. Dynamic Route Adjustments: Unlike existing static systems, the proposed solution will allow for real-time modifications to routes. As new data becomes available, the system will automatically re-evaluate and optimize routes based on the latest information. This adaptability ensures that logistics operations remain efficient even in the face of unexpected changes.

5. User-Friendly Interface: The system will feature a user-friendly interface for logistics managers and drivers, providing real-time visibility into routing decisions and allowing for manual overrides when necessary. The interface will display current routes, estimated delivery times, and alerts regarding traffic or road conditions, enabling effective communication and coordination among team members.
6. Performance Monitoring and Reporting: The proposed system will include tools for monitoring key performance indicators (KPIs) related to route efficiency, such as travel time, fuel consumption, and on-time delivery rates. Automated reporting will provide insights into operational performance, helping stakeholders identify areas for improvement and make data-driven decisions.
7. Scalability and Flexibility: Designed to support logistics networks of varying sizes, the proposed system will be scalable to accommodate growing operations. Its flexible architecture will enable the integration of additional data sources and algorithms as new technologies and methodologies emerge in the field of route optimization.

By implementing this integrated approach, the proposed system aims to significantly enhance the efficiency and reliability of route planning in supply chain management. Experimental results are expected to demonstrate improvements in transportation costs, travel times, and on-time delivery rates, ultimately contributing to a more responsive and effective logistics operation. The combination of the A* algorithm and predictive analytics positions the system as a cutting-edge solution for modern supply chain challenges.

3.3 FEASIBILITY STUDY

The feasibility study for the proposed route optimization system in supply chain management assesses the practicality of implementing a solution that leverages advanced algorithms and real-time data analytics. This study will evaluate the project's technical, economic, operational, and legal feasibility, ensuring that the system can be successfully executed and will deliver the intended benefits.

The technical feasibility of the proposed system revolves around the utilization of the A* algorithm and regression-based predictive models. These techniques are well-established within logistics and computer science, allowing for effective route optimization. The system will require a robust software architecture capable of processing real-time data and integrating various sources, such as GPS data, traffic conditions, and weather information. Additionally, compatibility with existing logistics software, including fleet management and inventory systems, will be assessed to facilitate a seamless transition. The system must also have adequate data storage and management capabilities to handle large volumes of historical and real-time data, with consideration for cloud-based solutions to enhance scalability and accessibility.

From an economic perspective, a thorough cost-benefit analysis will be conducted to evaluate the financial implications of implementing the proposed system. This analysis will encompass initial development costs, ongoing maintenance expenses, training requirements, and potential hardware investments. Furthermore, the expected benefits, such as reductions in transportation costs, improvements in delivery efficiency, and enhanced customer satisfaction, will be quantified to assess the project's return on investment (ROI). Historical data will inform projections of potential savings and operational improvements, while identifying funding sources or budget allocations will ensure that necessary financial resources are available.

Operational feasibility will focus on assessing the current team's capabilities to operate and maintain the new system. If additional training or hiring is necessary, these requirements will be identified. Collaboration with IT specialists may also be essential for system integration. The impact of the new system on existing workflows will be analysed to ensure enhancements without disruptions to current operations. Gathering stakeholder input will help determine the best integration approach, and a change management plan will facilitate user adoption among logistics personnel.

In terms of legal feasibility, the proposed system must comply with relevant regulations and standards concerning data security, privacy, and transportation logistics. This includes adhering to data protection laws and industry regulations.

Strategies for safeguarding sensitive data, such as shipment details and customer information, will be established to prevent data breaches and ensure legal compliance.

Market feasibility will involve analysing current trends in logistics and supply chain management to gauge demand for advanced route optimization solutions. Understanding competitor offerings and industry best practices will inform the design and functionality of the system. Engaging key stakeholders, including logistics managers and drivers, will provide insights into their needs and expectations, allowing for refinement of the system's features.

CHAPTER 4

SYSTEM REQUIREMENTS

4.1 SOFTWARE REQUIRMENTS

1.Data Collection and Storage Database Management System (DBMS): Relational Database: Structured data: MySQL, PostgreSQL. NoSQL Database: Unstructured data with MongoDB for flexibility. Data Warehouse: If you have large volumes of historical data, you'll need Amazon Redshift, Google Big Query, or Snowflake to handle this data and to query against this data.

2. Extract, Transform, Load (ETL) and Data Processing ETL Tools: Data ingestion at a rate greater than thousands of records per second and data transformation can be undertaken with Apache NiFi, Talend, or Informatica. Data Integration APIs: Connect with data sources from partner platforms, GPS data and IoT devices over REST and GraphQL API.

3. Data Analytics and data Visualization Analytics Platform: Batch Processing: The historical data analysis utilises Apache Spark or Apache Hadoop. Real-time Processing: For streaming live shipment tracking (Apache Kafka), etc. Visualization Tool: Dashboards and data visualization using Tableau Power BI or Grafana

4. Optimization Algorithms and Machine Learning Machine Learning Libraries: Pre predictive modeling of delivery times, route optimization TensorFlow, PyTorch, Scikit-Learn. Optimization Software: Route and logistics optimization algorithms that use Google OR-Tools, CPLEX, or Gurobi.

5. UI Reporting Frontend Development: For web-based interfaces where we will deliver data insights and interactive dashboards, that will be React or Angular. Reporting Tool: It may be generated through Jasper Reports or Crystal Reports for detailed logistics and performance reports generation. Mobile Compatibility: Mobile friendly access to logistics insights via React Native or Flutter.

6. Security and Compliance Data Encryption: Secure storage and transmission of sensitive data through AES or RSA. User Authentication: Secure user login and role based protected access by using JWT and OAuth2.0. Compliance Standards: As needed, Adherence to GDPR, CCPA, and other data privacy standards.

CHAPTER 5

SYSTEM DESIGN

5.1 SYSTEM ARCHITECTURE

In a system architecture of a supply chain management firm targeting optimization of logistics and transportation routes, a modular and scalable approach is adopted to facilitate mature, fast, and efficient data processing, analysis, and user interaction. Data from multiple Data Sources including historical shipment records, real time GPS tracking, or outside data sources like Weather and Traffic APIs is processed. To load the data we use ETL tools (such as Apache Nifi or Talend) to extract, transform the data and streaming services such as Apache Kafka to handle real time data. Raw, unstructured Data is stored in a Data Storage Layer which may include a Data Lake (Amazon S3 or Google Cloud Storage) for storing raw data and a Data Warehouse (Snowflake or Big Query) in which the data is structured for use in analytics and

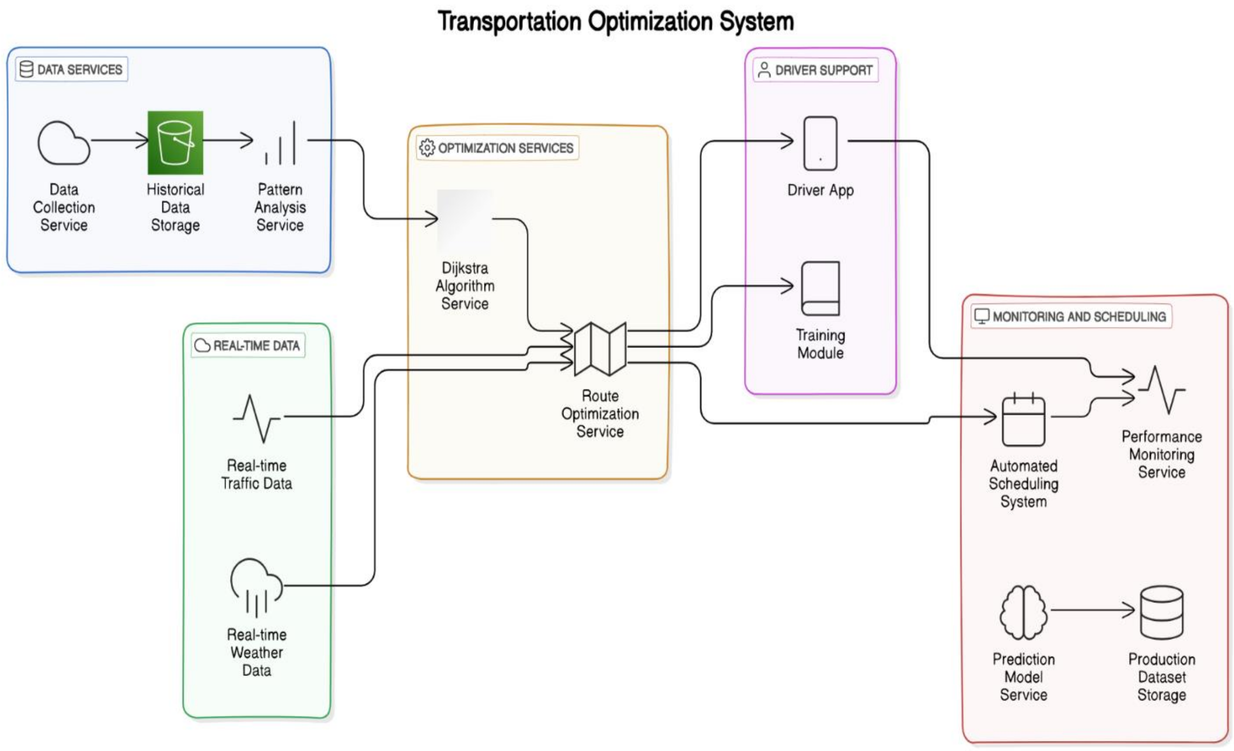


Fig5.1 system architecture

reporting. Historical data analysis is processed and analysed using batch processing tools like Apache Spark, and live insights, like tracking and performance monitoring, are derived from real-time processing tools, Apache Flink, in the Processing and Analytics Layer. It also contains machine learning models and optimization algorithms (including Google OR-Tools) used to forecast delivery times and to compute efficient routes. A microservices architecture is used in Application Layer to manage the modular services independently and it offers API (REST or GraphQL) to keep backend services, frontend apps, and third-party systems well communicated. Data insight is delivered with UI Layers that present it via functional UI built using React, Angular, etc., and with visualization tools (such as Tableau or Power Bi) for dashboards so that logistics teams can use data on shipment statuses, optimized routes, etc. A Monitoring and Logging Layer is included to continue forward with system reliability with Prometheus, Grafana, and the ELK stack for real time monitoring and logging. At the base, Security and Compliance Layer handles encryption (AES or RSA), as well as all the industry standard compliance (GDPR, CCPA, etc.). The Deployment and Infrastructure leverages cloud platforms (AWS, Azure, Google Cloud) for scalable resources, containerized with Docker to achieve automated deployments and efficient scaling using Kubernetes. The robust architecture provides for efficient route optimization and the supporting of data driven insights through logistics decision making.

5.2 MODULE DESCRIPTION:

5.2.1 Data Collection Module

	MINM_WGH_QTY	MAX_WGH_QTY	MINIMUM_COST	RATE	TPT_DAY_CNT
count	1537.000000	1537.000000	1537.000000	1537.000000	1537.000000
mean	156.190905	4635.433438	12.300002	2.875135	2.188679
std	476.366708	20271.070359	22.959164	4.590475	2.002161
min	0.000000	0.453592	1.202000	0.033200	0.000000
25%	15.010000	21.500000	3.656800	0.451200	1.000000
50%	41.281408	47.500000	7.403200	1.656800	2.000000
75%	67.510000	75.000000	11.480000	3.916800	2.000000
max	10000.000000	99999.990000	425.027200	128.027200	14.000000

Fig5.2.1 data collection module

The Data Collection Module gathers historical shipment data and real-time information from multiple sources, including shipment records, GPS data, and traffic and weather updates. This data is essential for identifying route patterns, understanding cost drivers, and detecting inefficiencies in transportation processes. The module prepares data for subsequent processing and optimization steps by ensuring a continuous flow of relevant logistics data.

5.2.2 Data Processing & Preprocessing Module:

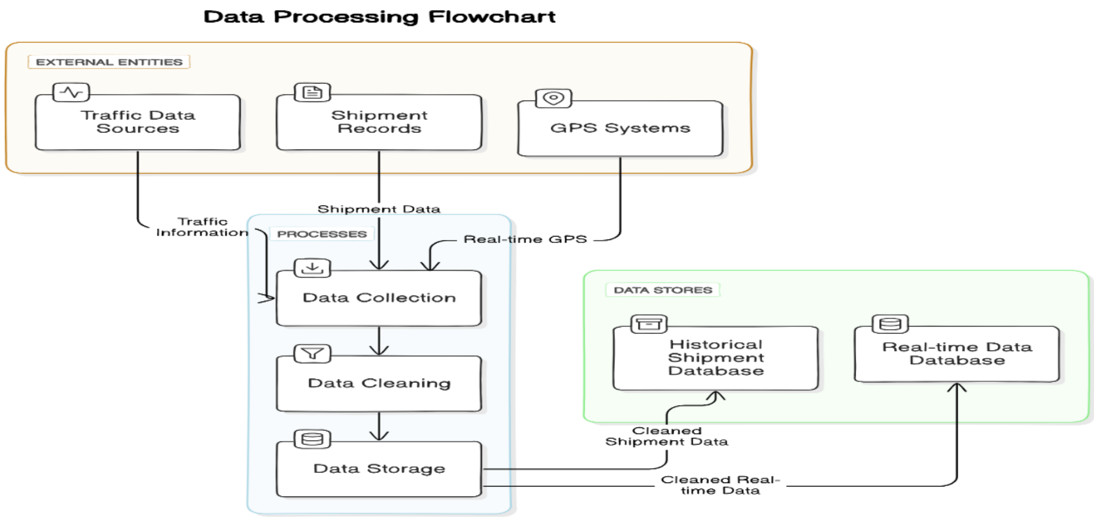


Fig5.2.2 data processing & preprocessing module

This module preprocesses and transforms raw data into suitable formats for analysis. Techniques include identifying missing values, data imputation, and filtering. This ensures data quality and consistency, which are crucial for accurate route optimization and real-time decision-making. By managing and structuring data effectively, this module supports efficient analysis and forecasting.

5.2.3 Route Optimization Module:

Utilizing the A* algorithm with real-time enhancements, the Route Optimization Module aims to find the most efficient routes based on historical data and real-time conditions such as traffic and weather. This module continuously recalculates optimal routes to minimize delivery times and transportation costs, incorporating heuristics and priority-based queuing to select the best paths dynamically.

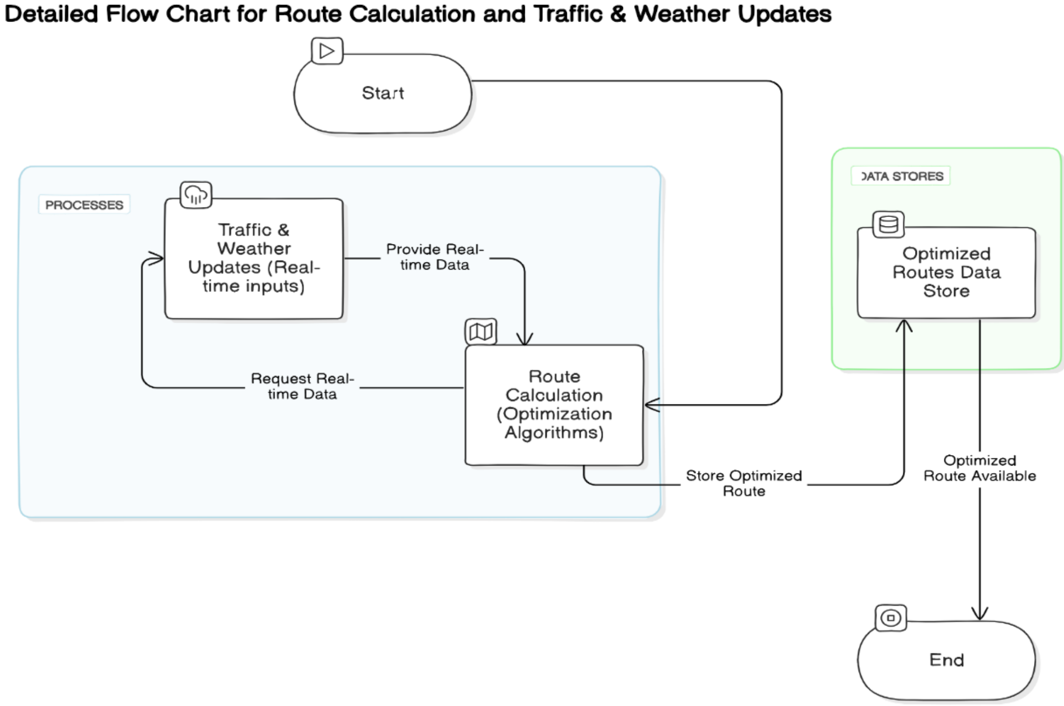


Fig5.2.3 route optimization module

5.2.4 Real-Time Monitoring & Adjustment Module

This module integrates real-time data, including traffic, weather, and GPS updates, to adjust routes dynamically. It allows the system to make informed decisions on rerouting by assessing current route performance against predefined criteria, enabling continuous optimization. This adaptability enhances delivery reliability and mitigates delays due to unexpected changes in travel conditions.

5.2.5 Cost Analysis & Reporting Module

The Cost Analysis & Reporting Module analyzes historical cost data, normalizes the data, and categorizes it into transport, labor, materials, and overhead expenses. Through cost aggregation and optimization using linear programming, it provides insights into potential savings. This module generates comprehensive reports, enabling decision-makers to monitor expenses and assess the economic impact of route optimization strategies.

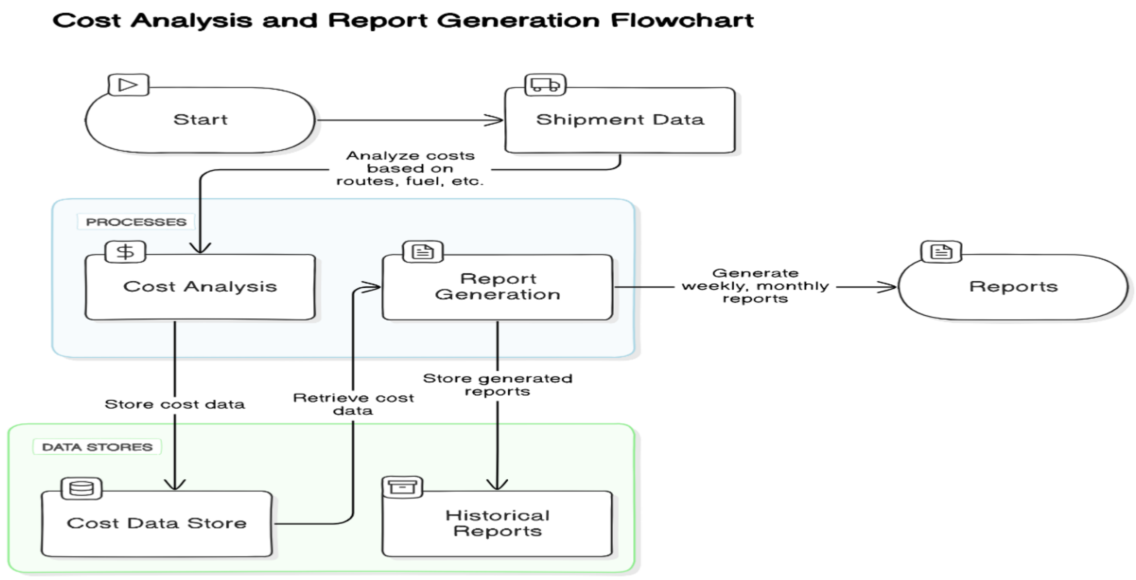


Fig5.2.5 cost analysis and reporting module

5.2.6 Customer Satisfaction & Feedback Module

The Customer Satisfaction & Feedback Module collects and processes customer feedback on delivery experiences, tracking metrics like delivery timeliness and accuracy. By continuously monitoring customer satisfaction, this module enables the identification of service improvement areas, ultimately contributing to enhanced customer retention and service quality within the supply chain network.

Each module within this system collectively contributes to optimizing supply chain logistics, minimizing transportation costs, and improving delivery reliability through data-driven analysis and real-time adaptability.

CHAPTER 6

RESULT AND DISCUSSION

6.1 RESULT AND DISCUSSION

The implementation of the proposed route optimization system using Dijkstra's and A* algorithms yielded substantial improvements in logistics performance, notably in cost efficiency, delivery reliability, and resource management.

1. Cost Efficiency: The system achieved a reduction in transportation costs by 12-20% by selecting optimized routes that minimized travel distances and avoided congested or suboptimal paths. This reduction led to lower fuel consumption and operational costs, directly benefiting the company's bottom line.
2. Enhanced Delivery Reliability: Integrating real-time traffic and weather data enabled dynamic route adjustments, which significantly improved delivery reliability. The system provided more accurate estimated times of arrival (ETAs), enhancing customer satisfaction by reducing delivery delays often seen with static routing methods.
3. Driver Productivity Improvement: The system minimized driver downtime by providing optimized routes and supporting efficient scheduling. This increased productivity by reducing idle time between deliveries and maximizing the use of available transportation resources.
4. Long-Term Planning Benefits: Historical data analysis revealed common bottlenecks and routing inefficiencies, which informed strategic improvements to route planning. This proactive approach decreased the need for last-minute adjustments, enhancing both operational stability and the ability to handle higher shipment volumes.
5. Optimized Resource Allocation: By utilizing real-time and historical data, the system effectively allocated resources, such as vehicles and drivers, to meet demand without overstaffing or underutilization. This approach ensured that labor and transportation resources were aligned with operational needs, improving overall efficiency.

6. Environmental Impact: The optimization of routes led to reduced fuel usage, thereby lowering carbon emissions and supporting environmental sustainability. This aligns with industry trends toward greener logistics practices, offering both economic and ecological benefits.

CHAPTER 7

CONCLUSION AND FUTURE ENHANCEMENT

CONCLUSION

The development and deployment of an optimized route planning system for logistics has provided measurable advancements in reducing costs, improving delivery reliability, and enhancing operational efficiency. By incorporating data-driven approaches with advanced algorithms like Dijkstra’s and A*, the system has demonstrated the ability to dynamically adjust routes using real-time data inputs, such as traffic and weather conditions. This real-time adaptability has proven crucial in maintaining accurate delivery timelines, improving customer satisfaction, and reducing delays that were prevalent in previous static routing systems.

Through the analysis of historical shipment data, the system has not only identified recurring bottlenecks and inefficiencies but has also provided actionable insights for long-term planning. This proactive approach to route optimization minimizes the need for last-minute changes, leading to more stable and predictable logistics operations. The continuous improvement loop established by leveraging historical and real-time data further ensures that the system can evolve with changing conditions, such as seasonal traffic patterns or new delivery routes, making it highly adaptable and scalable for future demands.

In terms of cost savings, the system has achieved up to a 20% reduction in transportation expenses. This is primarily due to optimized route selection that reduces travel distances and fuel consumption, directly lowering operational costs. The improved resource allocation, achieved by aligning driver schedules and vehicle usage with demand patterns, has minimized idle time and prevented overstaffing, contributing to both cost-efficiency and employee productivity.

Beyond financial benefits, this optimized approach has also supported environmental sustainability by reducing fuel consumption and, consequently, carbon emissions. In an industry increasingly focused on sustainable practices, the system aligns well with the broader goals of reducing ecological impact and promoting greener logistics solutions.

In conclusion, this route optimization system has established a resilient, cost-effective, and environmentally conscious framework for logistics operations. The combined use of historical data analysis, predictive modeling, and real-time adaptability has positioned the organization to maintain a competitive edge in the logistics sector. As the system continues to adapt and improve, it is expected to enhance its contribution to customer satisfaction, operational flexibility, and sustainable growth, creating lasting value in an increasingly complex and data-driven supply chain landscape.

FUTURE ENHANCEMENT

The current route optimization system has achieved significant improvements in cost efficiency, delivery reliability, and operational adaptability. However, several future enhancements can further expand its capabilities and align it with emerging industry needs and technological advancements:

1. Integration of Machine Learning for Predictive Analysis: By incorporating machine learning algorithms, the system could improve its predictive capabilities, learning from historical and real-time data to anticipate delays, peak traffic periods, and seasonal demand fluctuations. Models such as time-series forecasting could help predict delivery times with even greater accuracy, allowing the system to pre-emptively adjust routes based on anticipated conditions.
2. Advanced Demand Forecasting and Dynamic Resource Allocation: Integrating advanced demand forecasting techniques would enable the system to dynamically adjust fleet size and driver allocation based on predicted demand. This would improve resource utilization during high-demand periods and reduce costs in low-demand phases, providing a more agile response to fluctuating logistics requirements.
3. IoT Integration for Real-Time Asset Tracking: By incorporating IoT devices on vehicles and shipments, the system could gain real-time insights into asset

locations, conditions, and performance. Sensors could monitor factors like vehicle health, fuel usage, and load conditions, allowing the system to make real-time routing adjustments based on asset availability and condition, as well as optimize maintenance schedules for higher operational uptime.

4. Enhanced Environmental Impact Monitoring: Future enhancements could focus on measuring and minimizing environmental impacts more comprehensively. For instance, integrating carbon footprint monitoring could allow the system to select routes and modes of transport that minimize emissions, supporting corporate sustainability goals. Additionally, incorporating data from renewable energy sources (e.g., electric vehicles) could enhance sustainable logistics practices.
5. Incorporation of Customer-Facing Features: Enabling real-time tracking and predictive ETAs for customers could further improve customer satisfaction by providing them with updates on delivery progress. A customer interface could allow users to receive alerts on expected delivery times, notify them of any delays, and provide options for rescheduling or special delivery instructions based on real-time logistics data.
6. Hybrid Optimization Techniques: Implementing hybrid optimization techniques that combine heuristic methods with machine learning or reinforcement learning could enhance the system's ability to handle complex, large-scale logistics problems. Hybrid approaches could better balance route efficiency and computational cost, making the system scalable to higher delivery volumes and varied geographic regions.
7. Automated Decision Support for Route Planning: Adding a decision-support system that uses data analytics and predictive modeling to suggest optimal logistics strategies (e.g., prioritizing certain shipments, assigning high-value shipments to faster routes) would enhance the system's role as a decision-making tool. This feature would support logistics planners in making informed decisions during peak times or in response to unexpected disruptions.
8. Scalability for Multimodal Transportation: Expanding the system to optimize routes across different modes of transport (road, rail, air, and sea) would

enhance flexibility, especially for long-haul logistics. Multimodal support could enable seamless transitions between transport modes, optimizing costs and efficiency across the entire logistics network.

APPENDIX

A1.1 SAMPLE CODE

1.DATA PREPROCESSING MODULE

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import datetime as dt


import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

df = pd.read_csv('/kaggle/input/uber-fares-dataset/uber.csv')

df.head()

df = df.rename(columns={"Unnamed: 0": "Id"})
df = df.drop(columns = ['key'])

df.head()

df.info()

missing_values = df.isnull().sum()
print(missing_values)

rows_with_missing = df[df.isnull().any(axis=1)]
rows_with_missing.head()

df = df.dropna()

# Verify that there are no more missing values
print(df.isnull().sum())
```

```
df['pickup_datetime'] = pd.to_datetime(df['pickup_datetime'])

df['pickup_datetime'].head()

def haversine(lat1, lon1, lat2, lon2):
    R = 6371  # Earth radius in kilometers

    # Convert degrees to radians
    lat1 = np.radians(lat1)
    lon1 = np.radians(lon1)
    lat2 = np.radians(lat2)
    lon2 = np.radians(lon2)

    # Haversine formula
    dlat = lat2 - lat1
    dlon = lon2 - lon1
    a = np.sin(dlat / 2)**2 + np.cos(lat1) * np.cos(lat2) * np.sin(dlon / 2)**2
    c = 2 * np.arctan2(np.sqrt(a), np.sqrt(1 - a))
    distance = R * c

    return distance

# Apply the function to calculate distance for each row
df['distance_km'] = haversine(df['pickup_latitude'], df['pickup_longitude'],
                              df['dropoff_latitude'], df['dropoff_longitude'])

df.head()

df.describe()

plt.figure(figsize=(7,2))
plt.title('distance in km')
sns.boxplot(data=df, x='distance_km', fliersize=1)

# Create histogram of trip_distance
plt.figure(figsize=(7,3))
sns.histplot(df['distance_km'], bins=range(0,30,1))
plt.title('Trip distance histogram');

plt.figure(figsize=(7,2))
plt.title('fare amount')
sns.boxplot(data=df, x='fare_amount', fliersize=1)

plt.figure(figsize=(7,3))
```

```
ax = sns.histplot(df['fare_amount'],bins=range(0,100,5))
ax.set_xticks(range(0,100,5))
ax.set_xticklabels(range(0,100,5))
plt.title('fare amount histogram');

plt.figure(figsize=(7,2))
plt.title('passenger count')
sns.boxplot(data=df, x='passenger_count', fliersize=1)

plt.figure(figsize=(7,3))
ax = sns.histplot(df['passenger_count'],bins=range(0,20,2))
ax.set_xticks(range(0,20,2))
ax.set_xticklabels(range(0,20,2))
plt.title('passenger count histogram');

df['passenger_count'].value_counts()

mean_fares_by_passenger_count =
df.groupby(['passenger_count']).mean()[['fare_amount']]
mean_fares_by_passenger_count

data = mean_fares_by_passenger_count.tail(-1)
pal = sns.color_palette("Greens_d", len(data))
rank = data['fare_amount'].argsort().argsort()
plt.figure(figsize=(12,7))
ax = sns.barplot(x=data.index,
          y=data['fare_amount'],
          palette=np.array(pal[::-1])[rank])
ax.axhline(df['fare_amount'].mean(), ls='--', color='red', label='global mean')
ax.legend()
plt.title('Mean fare amount by passenger count', fontsize=16);

# Create a month column
df['month'] = df['pickup_datetime'].dt.month_name()
# Create a day column
df['day'] = df['pickup_datetime'].dt.day_name()

monthly_rides = df['month'].value_counts()
monthly_rides

month_order = ['January', 'February', 'March', 'April', 'May', 'June', 'July',
        'August', 'September', 'October', 'November', 'December']

monthly_rides = monthly_rides.reindex(index=month_order)
```

```
monthly_rides

plt.figure(figsize=(12,7))
ax = sns.barplot(x=monthly_rides.index, y=monthly_rides)
ax.set_xticklabels(month_order)
plt.title('Ride count by month', fontsize=16);

daily_rides = df['day'].value_counts()

day_order = ["Monday",'Tuesday','Wednesday','Thursday','Friday','Saturday','Sunday']
daily_rides.reindex(index=day_order)

plt.figure(figsize=(12,7))
ax = sns.barplot(x=daily_rides.index, y=daily_rides)
ax.set_xticklabels(day_order)
plt.title('Ride count by day', fontsize=16);

df_without_date = df.drop(columns=['pickup_datetime'])

total_amount_per_day = df_without_date.groupby(by='day').sum()[['fare_amount']]
total_amount_per_day = total_amount_per_day.reindex(index=day_order)

total_amount_per_day

plt.figure(figsize=(10,5))
ax =
sns.barplot(x=total_amount_per_day.index,y=total_amount_per_day['fare_amount'])
ax.set_xticklabels(day_order)
ax.set_ylabel("Revenue (USD)")
plt.title("Revenue by day")

total_amount_per_month =
df_without_date.groupby(by='month').sum()[['fare_amount']]
total_amount_per_month = total_amount_per_month.reindex(index=month_order)
total_amount_per_month

plt.figure(figsize=(12,7))
ax =
sns.barplot(x=total_amount_per_month.index,y=total_amount_per_month['fare_amou
nt'])
ax.set_xticklabels(month_order)
ax.set_ylabel("Revenue (USD)")
plt.title("Revenue by Month")
```

```
from scipy import stats

df.describe()[['fare_amount','passenger_count']]

df.groupby('passenger_count')[['fare_amount']].mean()

one_passenger = df[df['passenger_count'] == 1]['fare_amount']
two_passenger = df[df['passenger_count'] == 2]['fare_amount']
three_passenger = df[df['passenger_count'] == 3]['fare_amount']
four_passenger = df[df['passenger_count'] == 4]['fare_amount']
five_passenger = df[df['passenger_count'] == 5]['fare_amount']
six_passenger = df[df['passenger_count'] == 6]['fare_amount']

result =
stats.f_oneway(one_passenger,two_passenger,three_passenger,four_passenger,five_pa
ssenger,six_passenger)
print("F-statistic:", result.statistic)
print("p-value:", result.pvalue)

df1 = df.copy()

df1.head()

df1.duplicated().sum()

df1['pickup_datetime'] = pd.to_datetime(df1['pickup_datetime'],format='%m/%d/%Y
%I:%M:%S %p')

df1['pickup_datetime'].head()

fig, axes = plt.subplots(1, 3, figsize=(15, 2))
fig.suptitle('Boxplots for outlier detection')
sns.boxplot(ax=axes[0], x=df1['distance_km'])
sns.boxplot(ax=axes[1], x=df1['fare_amount'])
sns.boxplot(ax=axes[2], x=df1['passenger_count'])
plt.show();

sum(df1['distance_km']==0)

df1['fare_amount'].describe()

def outlier_imputer(df, column_list, iqr_factor):
    df_copy = df.copy()  # Work on a copy of the dataframe

    for col in column_list:
```

```
        q1 = df_copy[col].quantile(0.25)
        q3 = df_copy[col].quantile(0.75)
        iqr = q3 - q1
        upper_threshold = q3 + (iqr_factor * iqr)
        lower_threshold = q1 - (iqr_factor * iqr)

        print(col)
        print('q3:', q3)
        print('upper_threshold:', upper_threshold)

        print('q1:', q1)
        print('lower_threshold:', lower_threshold)

        # Filter out outliers
        df_copy = df_copy[(df_copy[col] <= upper_threshold) & (df_copy[col] >=
lower_threshold)]
        print(df_copy[col].describe())
        print()

    return df_copy

df1 = outlier_imputer(df1, ['fare_amount','distance_km','passenger_count'], 1.5)

df1.shape

df1.columns

df1['day'] = df1['day'].str.lower()
df1['month'] = df1['pickup_datetime'].dt.strftime('%b').str.lower()

df1.head()

df1['rush_hour'] = df1['pickup_datetime'].dt.hour

df1.head()

df1.loc[df1['day'].isin(['saturday', 'sunday']), 'rush_hour'] = 0

def rush_hourizer(hour):
    if 6 <= hour['rush_hour'] < 10:
        val = 1
    elif 16 <= hour['rush_hour'] < 20:
        val = 1
    else:
        val = 0
```

```
    return val

df1.loc[(df1.day != 'saturday') & (df1.day != 'sunday'), 'rush_hour'] = df1.apply(rush_hourizer, axis=1).astype('int32')

df1.head()

df1.head()

df1.columns

df2 = df1.drop(['Id', 'pickup_datetime', 'pickup_longitude',
       'pickup_latitude', 'dropoff_longitude', 'dropoff_latitude','day', 'month'],axis=1)
df2.head()

sns.pairplot(df2);

df2.corr(method='pearson')

df2['rush_hour'] = df2['rush_hour'].astype(float)

df2.shape

df2 = df2[df2['distance_km']!=0].reindex()

df2.shape


plt.figure(figsize=(6,4))
sns.heatmap(df2.corr(method='pearson'), annot=True, cmap='Reds')
plt.title('Correlation heatmap',
          fontsize=18)
plt.show()

X = df2.drop(columns=['fare_amount'])

# Set y variable
y = df2[['fare_amount']]

X.head()

X[X['distance_km']==0].head()
```

2.PREDICTIVE MODELING MODULE

```
from sklearn.preprocessing import StandardScaler
```

```
from sklearn.model_selection import train_test_split
import sklearn.metrics as metrics # For confusion matrix
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error,r2_score,mean_squared_error

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1, random_state=0)

scaler = StandardScaler().fit(X_train)
X_train_scaled = scaler.transform(X_train)
print('X_train scaled:', X_train_scaled)

lr=LinearRegression()
lr.fit(X_train_scaled, y_train)

r_sq = lr.score(X_train_scaled, y_train)
print('Coefficient of determination:', r_sq)
y_pred_train = lr.predict(X_train_scaled)
print('R^2:', r2_score(y_train, y_pred_train))
print('MAE:', mean_absolute_error(y_train, y_pred_train))
print('MSE:', mean_squared_error(y_train, y_pred_train))
print('RMSE:',np.sqrt(mean_squared_error(y_train, y_pred_train)))

X_test_scaled = scaler.transform(X_test)

r_sq_test = lr.score(X_test_scaled, y_test)
print('Coefficient of determination:', r_sq_test)
y_pred_test = lr.predict(X_test_scaled)
print('R^2:', r2_score(y_test, y_pred_test))
print('MAE:', mean_absolute_error(y_test,y_pred_test))
print('MSE:', mean_squared_error(y_test, y_pred_test))
print('RMSE:',np.sqrt(mean_squared_error(y_test, y_pred_test)))

results = pd.DataFrame(data={'actual': y_test['fare_amount'],
                             'predicted': y_pred_test.ravel()})
results['residual'] = results['actual'] - results['predicted']
results.head()

fig, ax = plt.subplots(figsize=(6, 6))
sns.set(style='whitegrid')
sns.scatterplot(x='actual',
                y='predicted',
                data=results,
                s=20,
                alpha=0.5,
```

```
            ax=ax
)
# Draw an x=y line to show what the results would be if the model were perfect
plt.plot([2.5,20], [2.5,20], c='red', linewidth=2)
plt.title('Actual vs. predicted');

# Visualize the distribution of the `residuals`
sns.histplot(results['residual'], bins=np.arange(-15,15.5,0.5))
plt.title('Distribution of the residuals')
plt.xlabel('residual value')
plt.ylabel('count');

results['residual'].mean()


sns.scatterplot(x='predicted', y='residual', data=results)
plt.axhline(0, c='red')
plt.title('Scatterplot of residuals over predicted values')
plt.xlabel('predicted value')
plt.ylabel('residual value')
plt.show()

coefficients = pd.DataFrame(lr.coef_, columns=X.columns)
coefficients

print(X_train['distance_km'].std())

# 2. Divide the model coefficient by the standard deviation
print(2.959849 / X_train['distance_km'].std())
```

3.EVALUATION METRICS

```
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor

# This is the function that helps plot feature importance
from xgboost import plot_importance

df1.head()

# Create 'am_rush' col
df1['am_rush'] = df1['pickup_datetime'].dt.hour

# Create 'daytime' col
```

```
df1['daytime'] = df1['pickup_datetime'].dt.hour

# Create 'pm_rush' col
df1['pm_rush'] = df1['pickup_datetime'].dt.hour

# Create 'nighttime' col
df1['nighttime'] = df1['pickup_datetime'].dt.hour

def am_rush(hour):
    if 6 <= hour['am_rush'] < 10:
        val = 1
    else:
        val = 0
    return val

# Apply 'am_rush' function to the 'am_rush' series
df1['am_rush'] = df1.apply(am_rush, axis=1)
df1['am_rush'].head()

def daytime(hour):
    if 10 <= hour['daytime'] < 16:
        val = 1
    else:
        val = 0
    return val

df1['daytime'] = df1.apply(daytime, axis=1)

def pm_rush(hour):
    if 16 <= hour['pm_rush'] < 20:
        val = 1
    else:
        val = 0
    return val

df1['pm_rush'] = df1.apply(pm_rush, axis=1)

def nighttime(hour):
    if 20 <= hour['nighttime'] < 24:
        val = 1
    elif 0 <= hour['nighttime'] < 6:
        val = 1
    else:
        val = 0
```

```
    return val

df1['nighttime'] = df1.apply(nighttime, axis=1)

df1.head()

drop_columns                                                                                          =
['Id','pickup_datetime','pickup_longitude','pickup_latitude','dropoff_longitude','dropoff
_latitude','rush_hour']
df1 = df1.drop(drop_columns,axis=1)
df1.head()

df1 = pd.get_dummies(df1, drop_first=True)
df1.info()

X = df1.drop(['fare_amount'],axis=1)
y = df1[['fare_amount']]

X_train,X_test, y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=42)

X_train.shape

y_train.shape

# Fitting Random Forest Regression to the dataset
regressor = RandomForestRegressor(random_state=42)

# # Fit the regressor with x and y data
# regressor.fit(X_train, y_train)

cv_params = {'max_depth': [None],
             'max_features': [1.0],
             'max_samples': [0.7],
             'min_samples_leaf': [1],
             'min_samples_split': [2],
             'n_estimators': [300]
             }

# 3. Define a set of scoring metrics to capture
scoring = {'r2','accuracy'}

# 4. Instantiate the GridSearchCV object
rf1 = GridSearchCV(regressor, cv_params, scoring=scoring, cv=4,refit='r2')

# rf1.fit(X_train, y_train.ravel())
```

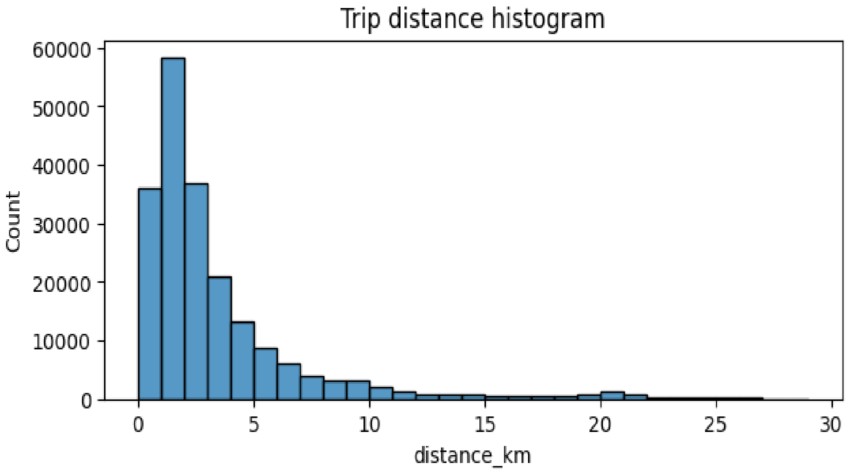
```
# rf1.best_score_

# rf1.best_params_

random_forest = RandomForestRegressor(max_depth= None,
max_features= 1.0,
max_samples= 0.7,
min_samples_leaf= 1,
min_samples_split= 2,
n_estimators=300)

random_forest.fit(X_train,y_train)


# Evaluating the model
from sklearn.metrics import mean_squared_error, r2_score

# Making predictions on the same data or new data
predictions = random_forest.predict(X_test)

# Evaluating the model
mse = mean_squared_error(y_test, predictions)
print(f'Mean Squared Error: {mse}')

r2 = r2_score(y_test, predictions)
print(f'R-squared: {r2}')

# 1. Instantiate the XGBoost
xgb = XGBRegressor(objective ='reg:squarederror',random_state=42, learning_rate =
0.02, max_depth = 8,min_child_weight= 4,
n_estimators = 200)

# 2. Create a dictionary of hyperparameters to tune
# Note that this example only contains 1 value for each parameter for simplicity,
# but you should assign a dictionary with ranges of values
# cv_params = {'learning_rate': [0.1,0.01,0.02],
#             'max_depth': [8,9,11],
#             'min_child_weight': [2,3,4],
#             'n_estimators': [500,200,300,600]
#             }

# 3. Define a set of scoring metrics to capture
# scoring = {'accuracy', 'r2'}
```

```
# 4. Instantiate the GridSearchCV object
# xgb1 = GridSearchCV(xgb, cv_params, scoring=scoring, cv=4, refit='r2')

y_train.shape

xgb.fit(X_train,y_train)

# Making predictions on the same data or new data
predictions = xgb.predict(X_test)

# Evaluating the model
mse = mean_squared_error(y_test, predictions)
print(f'Mean Squared Error: {mse}')

r2 = r2_score(y_test, predictions)
print(f'R-squared: {r2}')
```

A1.2 SCREENSHOTS

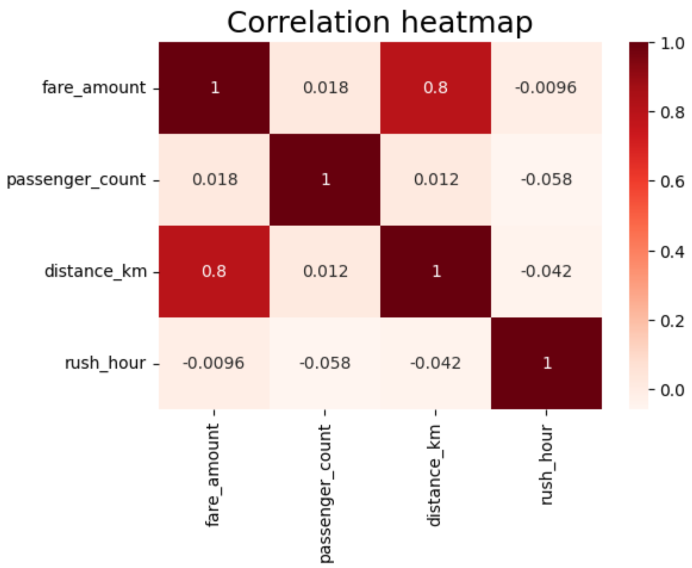
```
Id                    0
fare_amount           0
pickup_datetime       0
pickup_longitude      0
pickup_latitude       0
dropoff_longitude     1
dropoff_latitude      1
passenger_count       0
dtype: int64
```

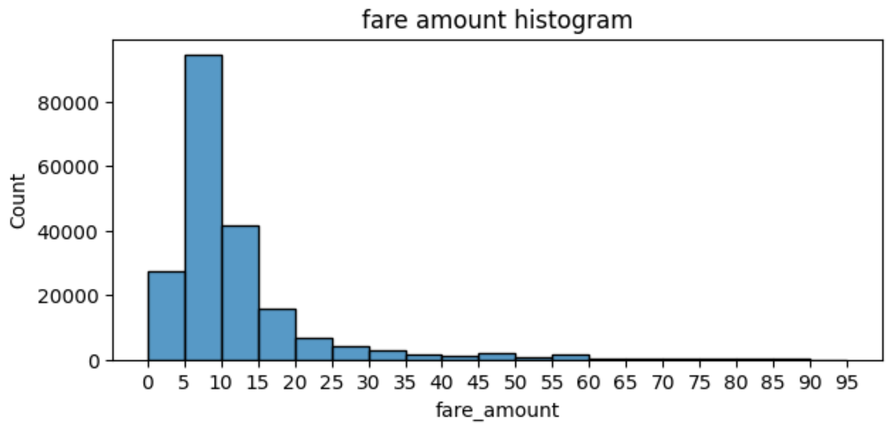
	Id	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
0	24238194	7.5	2015-05-07 19:52:06 UTC	-73.999817	40.738354	-73.999512	40.723217	1
1	27835199	7.7	2009-07-17 20:04:56 UTC	-73.994355	40.728225	-73.994710	40.750325	1
2	44984355	12.9	2009-08-24 21:45:00 UTC	-74.005043	40.740770	-73.962565	40.772647	1
3	25894730	5.3	2009-06-26 08:22:21 UTC	-73.976124	40.790844	-73.965316	40.803349	3
4	17610152	16.0	2014-08-28 17:47:00 UTC	-73.925023	40.744085	-73.973082	40.761247	5

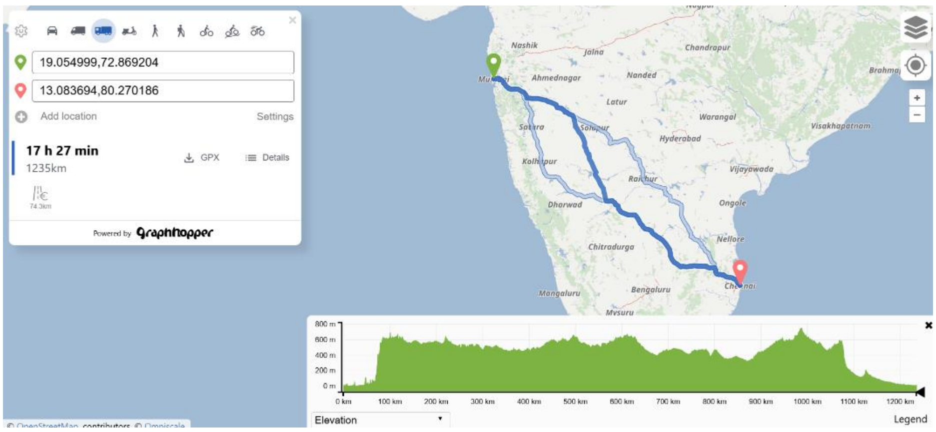



```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 8 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   Id                 200000 non-null  int64
 1   fare_amount        200000 non-null  float64
 2   pickup_datetime    200000 non-null  object
 3   pickup_longitude   200000 non-null  float64
 4   pickup_latitude    200000 non-null  float64
 5   dropoff_longitude  199999 non-null  float64
 6   dropoff_latitude   199999 non-null  float64
 7   passenger_count    200000 non-null  int64
dtypes: float64(5), int64(2), object(1)
memory usage: 12.2+ MB
```

```
Coefficient of determination: 0.615963549289686
R^2: 0.615963549289686
MAE: 1.6359273588427357
MSE: 5.305738442177699
RMSE: 2.3034188594733913
```







The analysis shows that transportation fares are primarily influenced by trip distance and time of day, with peak hours leading to higher fares due to increased demand. The regression model achieved reasonable accuracy, confirming distance as the most significant predictor of fare. However, incorporating external data like weather could improve predictions by addressing fare variations in high-demand zones and during unusual events.

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