GO SHIFT: Innovative Enhancements in Online Delivery Service

Ellewela A.V.H

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Dissertation submitted in partial fulfillment of the requirements for the Bachelor of Science (Hons) in Information Technology

Department of Information Technology

Sri Lanka Institute of Information Technology

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DECLARATION

I declare that this is my own work and this dissertation1 does not incorporate without acknowledgement any material previously submitted for a degree or Diploma in any other University or institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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Student Name	Student ID	Signature
Ellewela A.V.H	IT21331272	

The above candidate has carried out research for the bachelor's degree Dissertation under my supervision.

Signature: Date: 2025.04.11

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ABSTRACT

The increasing demand for accurate and efficient courier services calls for innovative solutions to optimize delivery processes. This research focuses on developing an Automated Voice Activation System to enhance delivery time predictions for online courier services.

The system leverages Natural Language Processing (NLP), AI models, and Twilio to automate data processing and streamline communication. Delivery personnel and customers can interact with the system via voice commands, enabling real-time updates and eliminating the need for manual data input. The use of Twilio ensures a seamless telephony interface for voice communication, while AI-driven analytics enhance the accuracy of delivery time predictions.

The research methodology involves designing and implementing the system's architecture, training AI models for predictive analytics, and integrating voice interaction through Twilio. Rigorous testing will evaluate the system's effectiveness in reducing errors, improving response times, and enhancing user experience.

This approach is expected to improve delivery time predictions, reduce delays, and provide a more accessible and efficient interface for all stakeholders. The system offers a scalable, automated solution to address logistical challenges in the courier service industry, setting a new standard for innovation and efficiency.

Keywords: Natural Language Processing (NLP), Twilio , Customer Satisfaction, Computer Vision

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Natural Language Processing	NLP
Convolutional neural networks	RNN
Artificial Intelligence	AI

1 INTRODUCTION

In the fast-evolving landscape of online delivery services, timely and accurate delivery time predictions are crucial for ensuring customer satisfaction and operational efficiency. However, traditional systems often rely on manual updates or cumbersome processes, which can lead to delays, errors, and inefficiencies. This highlights the need for an innovative approach to automate and optimize delivery time predictions.

This research proposes an Automated Voice Activation System that combines the capabilities of Natural Language Processing (NLP), AI models, and Asterisk-PBX telephony systems. By enabling delivery personnel and customers to interact with the system through voice commands, it eliminates the reliance on manual inputs and streamlines communication processes. The system is designed to process voice queries, analyze data using AI models, and generate precise delivery time predictions in real time for proactive voice notification for delays.

Unlike traditional IoT-based solutions, this system focuses on leveraging advanced computational models and existing telephony infrastructure to create a cost-effective and scalable solution. By automating routine tasks and enhancing predictive accuracy, this research aims to transform delivery service operations, making them more efficient and user-friendly.

Figure 1 - Innovative Delivery Service

1.1 Background and Literature Survey

The online delivery service industry has experienced exponential growth in recent years due to the rise in e-commerce and digital platforms. However, this growth has introduced challenges such as meeting customer expectations for timely deliveries, minimizing human error, and ensuring operational efficiency. Traditional courier systems often rely on manual processes to update delivery statuses and predict delivery times, which are prone to inefficiencies and delays.

Automated systems have the potential to address these challenges by streamlining operations and improving accuracy. While many solutions leverage IoT devices and sensors, these often require significant infrastructure investments. An alternative approach is the integration of voice-based systems with advanced AI technologies, which can utilize existing telephony networks to achieve similar automation and efficiency.

The proposed Automated Voice Activation System focuses on utilizing Natural Language Processing (NLP), AI models, and Twilio telephony systems. By processing voice commands, the system automates routine delivery tasks and provides accurate delivery time predictions. This innovative approach bridges the gap between traditional manual systems and the advanced automation required to meet the demands of modern delivery services.

Voice Recognition and NLP in Logistics

Studies have demonstrated the effectiveness of voice recognition and NLP technologies in automating logistics operations. For example, Google's Dialog-flow and Amazon Lex are widely used in building voice-enabled applications. Researchers have also explored the application of BERT-based NLP models for intent recognition and task automation, which are essential for understanding user commands and extracting meaningful insights from them.

AI Models for Predictive Analytics

AI-driven predictive analytics models such as Recurrent Neural Networks (RNNs) and Gradient Boosting have shown high accuracy in forecasting delivery times. These models analyze historical and real-time data to predict outcomes, making them ideal for optimizing delivery processes. Recent advancements in Transformer models have also proven beneficial for handling complex, multi-variable datasets in time-sensitive applications.

Twilio for Voice Communication

Twilio is an open-source telephony platform that facilitates seamless voice communication. Research shows its ability to integrate with AI and NLP systems, enabling real-time processing of voice inputs. Its adaptability makes it a practical choice for implementing automated voice systems in delivery services without significant infrastructure upgrades.

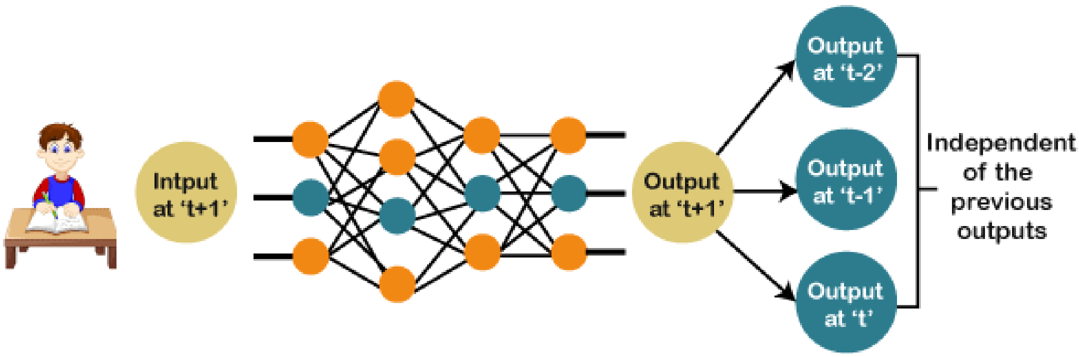

Figure 2-Recurrent Neural Networks (RNNs)

1.2 Research Gap

The online delivery industry has grown exponentially, but it continues to face several critical challenges in optimizing efficiency and meeting customer expectations. Traditional methods for updating delivery statuses and predicting delivery times often rely heavily on manual input, which is susceptible to errors, delays, and inefficiencies. Although automation has been widely researched, current solutions predominantly focus on IoT-based systems that require specialized hardware, such as sensors and GPS-enabled devices, leading to high costs and significant infrastructure dependencies. This limits their adoption by small and medium-sized courier services, creating a gap for more affordable and scalable technologies.

Furthermore, while Natural Language Processing (NLP) and voice recognition technologies have seen extensive applications in sectors like customer support and virtual assistants, their potential in logistics and delivery operations remains largely untapped. Many existing voice-enabled systems are designed for basic query handling and lack the integration of advanced AI models for tasks such as delivery time prediction and real-time status updates. Similarly, while AI-driven predictive analytics models, including LSTM, RNNs, and Transformer-based architectures, have shown promise in forecasting delivery times, these models are rarely combined with voice-activated systems to enhance usability and efficiency.

Another significant research gap lies in the limited application of telephony systems like Twilio in the delivery sector. Twilio has proven to be a reliable open-source telephony platform, but its integration with NLP and AI for automating delivery operations and facilitating seamless voice-based communication has not been extensively studied. This represents a missed opportunity to harness the potential of existing telephony infrastructure for scalable automation.

Moreover, while research often focuses on isolated aspects such as IoT-enabled tracking or AI-powered forecasting there is limited exploration of holistic systems that integrate multiple technologies to address the end-to-end needs of the delivery process. Current systems also overlook the importance of creating solutions that are accessible to non-technical users, such as delivery personnel, through user-friendly interfaces and voice command capabilities.

This research aims to address these gaps by developing an Automated Voice Activation System that eliminates the dependency on IoT devices, leverages NLP, AI models, and Twilio, and introduces a cost-effective, scalable alternative. By combining these technologies, the system will automate routine tasks, enhance delivery time predictions, and streamline communication processes. This novel approach not only addresses operational inefficiencies but also sets a foundation for future advancements in delivery automation, bridging the gap between traditional systems and modern technological demands.

Table 1- Research Gap

Features	**Research A**	**Research B**	**Research C**	**Research D**
Delivery Time Prediction for Proactive Voice Notification for Delays	✓	✓	✗	✗
Integration of NLP for voice Commands	✗	✗	✓	✗
Real-Time Voice Interaction	✗	✗	✓	✓
Dependence on IoT Devices	✓	✗	✗	✗
Cost-Effective and Scalable Solution	✗	✓	✗	✓

1.3 Research Problem

The increasing demand for efficient and reliable delivery services in the online courier industry has exposed significant gaps in current operational systems. Traditional methods of delivery management, which rely on manual inputs and static processes, often lead to delays, inaccuracies, and reduced customer satisfaction. While some organizations have adopted IoT-based automation solutions to address these issues, such systems are costly to implement and maintain, limiting their accessibility for small and medium-sized courier services.

Additionally, communication inefficiencies between delivery personnel and customers further exacerbate delays and errors in delivery status updates. Despite advancements in AI, NLP, and voice recognition technologies, these innovations remain underutilized in the logistics sector. Most existing solutions fail to integrate voice-activated systems with predictive analytics, resulting in fragmented processes that do not fully capitalize on the potential of automation.

This research seeks to address these challenges by developing a cost-effective Automated Voice Activation System that eliminates the dependency on IoT devices, leverages Natural Language Processing (NLP) for voice interactions, and uses AI models to predict delivery times accurately. The system also integrates with Asterisk-PBX for seamless real-time voice communication, providing a scalable and efficient solution to bridge the gap in current delivery service operations.

- **Reliance on Manual Processes**

Current delivery operations depend heavily on manual data entry and status updates. This creates room for errors and inconsistencies, leading to delays in delivery updates and inefficient service. Automating these tasks can significantly improve accuracy and reduce human intervention.

- **High Cost of IoT-Based Solutions**

IoT devices, commonly used for real-time tracking and automation, require a substantial upfront investment in infrastructure and maintenance. Small and medium-sized courier services often cannot afford these costs, limiting the adoption of advanced systems.

- **Lack of Seamless Communication Systems**

Communication between delivery personnel and customers is often inefficient, relying on outdated methods like phone calls or SMS. This can result in miscommunication or missed updates, creating frustration for both parties. A real-time, automated voice-based communication system can address these issues.

- **Underutilization of AI and NLP Technologies**

Technologies like AI and NLP have the potential to streamline delivery operations, but their application in logistics remains limited. For example, AI models could predict delivery times with greater accuracy, while NLP could enable voice-activated interactions for faster updates and commands.

- **Fragmented Solution**

Existing systems often focus on either predictive analytics or communication but rarely integrate the two. This fragmentation results in partial automation, where the delivery process still depends on manual intervention for critical tasks.

- **Scalability Issues**

Many current solutions are not designed to scale efficiently. As businesses grow, they require systems that can handle increased demand without drastically increasing costs or complexity.

- **Need for Cost-Effective Alternatives**

Courier services need affordable automation solutions that do not rely on IoT devices. Leveraging existing infrastructure, such as telephony networks combined with AI and NLP technologies, can provide a scalable and efficient alternative to IoT-based systems.

1.4 Objectives

1.4.1 Main objective

The Concept is to develop an Automated Voice Activation System using NLP for voice commands, AI models for accurate delivery time predictions for proactive voice notification for delays , and Twilio for seamless voice communication. This cost-effective system eliminates manual processes and IoT dependencies, streamlining courier operations and improving efficiency.

1.4.2 Sub objectives

- **Implement Voice Command Recognition Using NLP**

The system will use Natural Language Processing (NLP) to recognize and understand voice commands from users. This allows customers and delivery personnel to interact with the system in natural language, simplifying tasks like querying delivery status, updating information, or scheduling changes without the need for typing or manual interaction.

- **Integrate Proactive Voice Notification for Delays**

An AI-based delivery time prediction model will monitor expected vs. actual delivery progress. If delays occur, the system will trigger automated voice calls via Asterisk-PBX, informing customers about the new estimated delivery time and the reasons for the delay.

- **Utilize Twilio for Real-Time Communication**

This feature leverages Twilio to enable real-time voice interaction between users and the system. Customers can receive delivery updates or make inquiries through automated voice responses during calls.

- **Eliminate Manual Input in Delivery Operations**

By automating key processes like status updates and inquiries, the system minimizes manual data entry, reducing errors and speeding up delivery workflows, allowing personnel to focus on core operations.

- **Design a Cost – Effective and Scalable Framework**

The system will eliminate the dependency on IoT devices by relying on software technologies like AI, NLP, and telephony infrastructure. This makes the solution affordable and scalable for businesses of any size.

- **Ensure Seamless Integration with Existing Infrastructure**

The system will eliminate the dependency on IoT devices by relying on software technologies like AI, NLP, and telephony infrastructure. This makes the solution affordable and scalable for businesses of any size.

- **Enhance Operational Efficiency and Customer Satisfaction**

By automating updates and using real-time communication, the system ensures accurate and timely delivery information. This reduces delays, increases operational efficiency, and enhances the customer experience.

2 METHODOLOGY

2.1 Methodology

2.1.1 Component Specific System Architecture Diagram

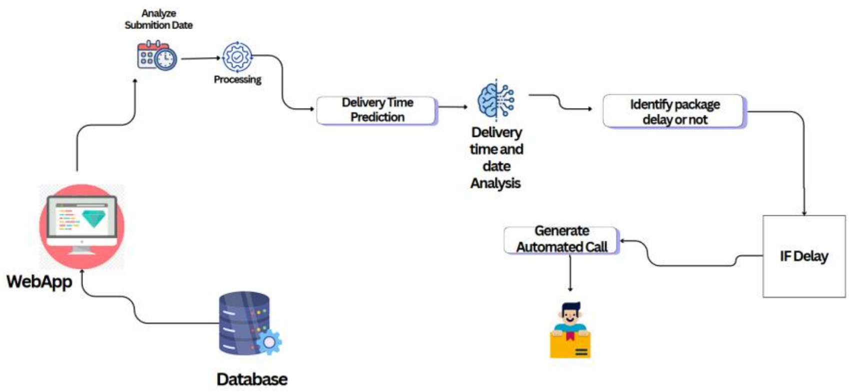

Figure 3 - Component Diagram

- **Voice Command Recognition Module**

This module enables hands-free interaction with the system by processing voice commands from users. It leverages Natural Language Processing (NLP) to understand spoken language and convert it into actionable requests, such as querying delivery status, rescheduling deliveries, or updating information. Additionally, speech-to-text technology is employed to capture and process commands accurately. This module connects with the database to fetch or modify delivery details and interfaces with the AI module for requests that involve time predictions, ensuring seamless communication between users and the system.

- **AI-Based Prediction Module**

The AI-based prediction module is at the core of delivery time management. It uses advanced machine learning algorithms, such as gradient boosting or transformer models, to analyze historical data and real-time factors like traffic, weather, and route conditions. By continuously comparing expected and actual delivery progress, the module detects potential delays and updates delivery timelines. It also sends notifications to the customer in case of discrepancies, enhancing the overall reliability and transparency of the delivery process.

- **Twilio Communication Module**

This module handles all real-time voice communication within the system, ensuring a smooth and direct interface between the system and users. Using Twilio, it facilitates outgoing calls, such as proactive delay notifications, and incoming calls for customer inquiries. The module incorporates text-to-speech (TTS) technology to generate dynamic, human-like responses, ensuring customers receive clear and understandable updates. By integrating with other modules, it ensures voice interactions are accurate and up-to-date, making the system user-friendly and efficient.

- **Database Management System**

The database acts as the backbone of the system, storing all necessary information, including customer details, delivery records, and real-time updates. It provides data for NLP-based queries, AI model training, and operational processes. The database supports real-time updates to ensure that all modules have access to the latest information. Its robust structure allows for scalability and quick retrieval of data, making it an essential component for ensuring the system runs smoothly.

- **Notification System**

This module ensures proactive and transparent communication with customers by delivering automated voice notifications. When the AI module detects delays, the notification system generates personalized messages detailing the new estimated delivery time and the reason for the delay. Using TTS technology, these messages are converted into voice calls, triggered through Twilio. This proactive approach minimizes uncertainty, improves customer satisfaction, and keeps users informed, demonstrating the system's focus on reliability and service quality.

2.1.2 Flow chart

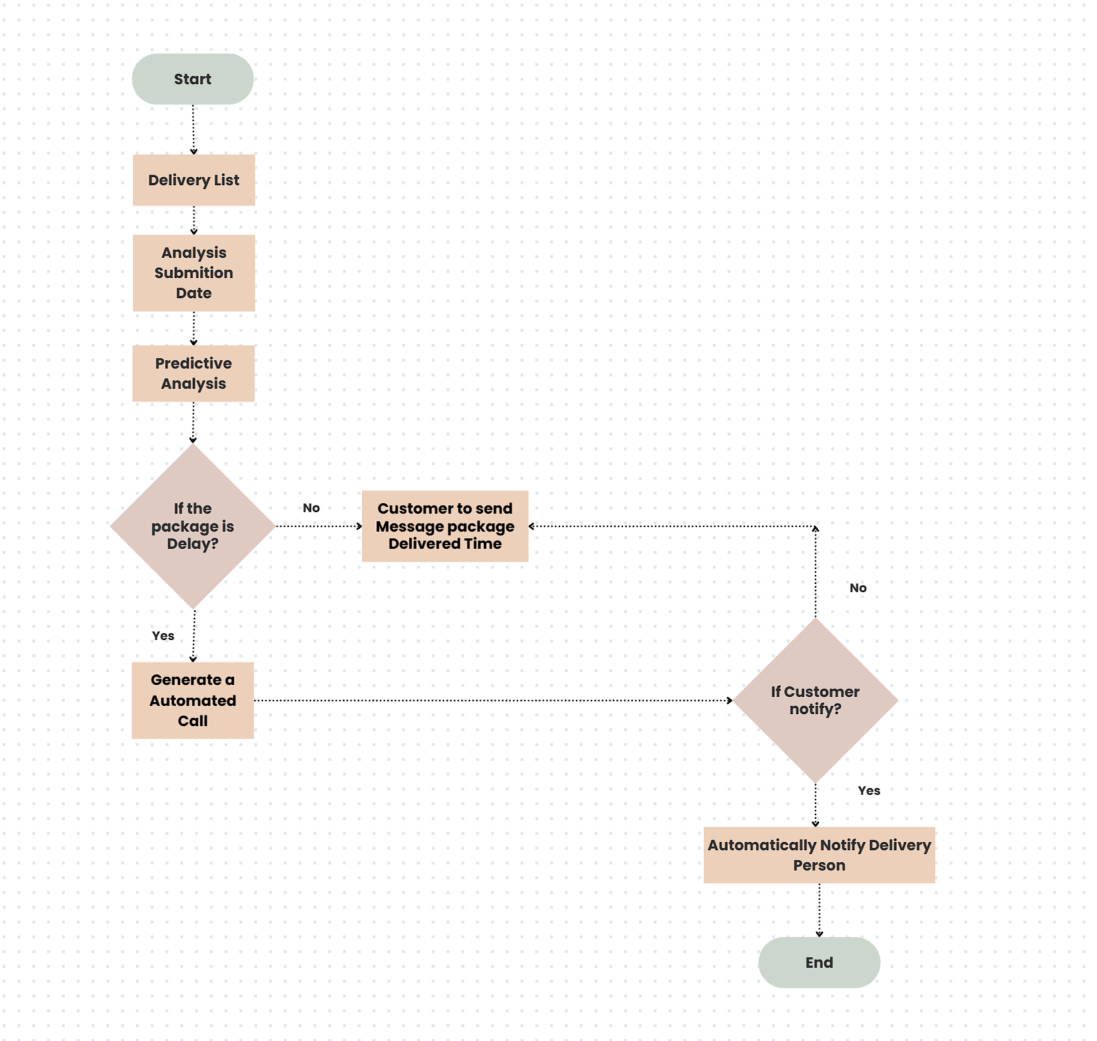

Figure 4 - Flow Chart

2.1.3 Software solution

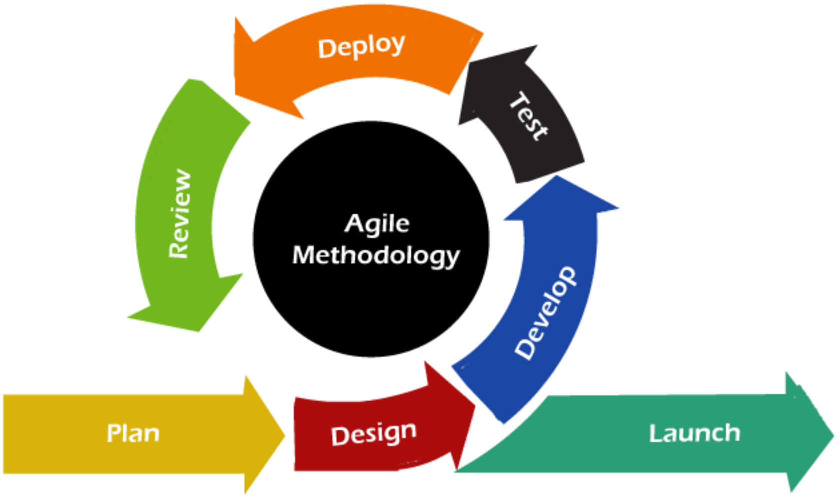

Figure 5 - Agile Methodology

Agile methodology is applied as a flexible and iterative way of project management and software development with focuses on continuous improvement and adaptability. Teams plan, design, develop, test, and review features by working in iterative cycles, making them adapt to changing requirements and feedback. Agile places strong emphasis on collaboration and open communication among the team members and stakeholders to resolve any difficulty or realize any opportunity. Due to its emphasis on customer feedback and iterative progress, Agile gives teams the ability to ensure the delivery of a high-quality product that will meet the changing needs of users.

Planning

During the planning phase, requirements are gathered, and project goals are clearly defined through collaboration with stakeholders. A Product Backlog is created to list features such as voice command recognition, AI-driven delivery predictions, and automated notifications. Tasks are prioritized based on their importance and feasibility, and sprint goals are established to ensure incremental progress. A high-level roadmap outlines the project milestones and deliverables, providing a clear vision of the development path while allowing flexibility for adjustments during the process.

System Design

The system design phase focuses on creating a robust and modular system architecture. The architecture includes components like the Voice Command Recognition Module, AI-Based Prediction Module, Database, Asterisk-PBX Communication Module, and Notification System. Interface designs emphasize user-friendly interaction flows, while data flow diagrams (DFDs) visualize how data moves through the system. Sprint-specific goals are defined to break the overall design into smaller, achievable tasks, ensuring an organized and phased implementation of the architecture.

Development

The development phase involves coding, testing, and validating individual components in iterative sprints. Each sprint targets a specific module; for example, the Voice Command Recognition Module is implemented first, followed by the AI-Based Prediction Module. Later, the Asterisk-PBX system is set up and integrated with Text-to-Speech for automated calls. The final sprint focuses on combining all modules into a cohesive system connected to the Database. Regular stand-up meetings ensure smooth communication among team members and allow quick resolution of blockers to maintain steady progress.

Testing

Testing ensures that the system meets functional and performance standards, with a focus on user experience. Unit testing is conducted for individual modules, such as voice command recognition and AI prediction, while integration testing validates the seamless operation of combined modules. User Acceptance Testing (UAT) gathers feedback from stakeholders, ensuring the system aligns with real-world requirements. Sprint retrospectives are held after each iteration to identify issues, implement improvements, and refine the overall system based on feedback and testing outcomes.

Deployment

The system should be deployed using a scalable cloud platform such as Google Cloud or AWS. Databases for feedback and performance data shall be set up. Furthermore, these shall be implemented in phases, first a pilot phase to fine tune the implementation of the system.

Maintenance

The maintenance phase ensures the system remains efficient, scalable, and reliable after deployment. Regular updates are performed to fix bugs and enhance features based on user feedback and evolving requirements. AI prediction models are retrained periodically with new data to maintain accuracy. Monitoring tools ensure the system can handle increasing workloads and suggest optimizations for scalability. This continuous improvement approach guarantees the system’s long-term success and adaptability in dynamic operational environments.

2.1.4 Requirements gathering

The requirement gathering phase is a critical step in developing the Automated Voice Activation System, ensuring that the final product aligns with user needs and project objectives. This phase involves understanding functional, non-functional, and system requirements through stakeholder collaboration, research, and analysis.

- **Conducting Interviews**

Interviews are an essential part of the requirement-gathering process for the Automated Voice Activation System. This method involves direct communication with stakeholders, such as customers, delivery staff, and technical experts, to collect detailed insights about their needs and expectations. Below is an explanation of how interviews are conducted and their significance

- **Key Stakeholders Interviewed**

- **Customers:** End users of the delivery service who interact with the system for tracking and managing deliveries.
- **Delivery Staff:** Operational users who provide delivery updates and may interact indirectly with the system.
- **Technical Team:** Developers, AI experts, and system architects responsible for implementing the system.
- **Business Stakeholders:** Project sponsors, managers, or representatives of the courier service.

- **Interview Process**

Interview Design: Interviews are semi-structured, lasting 30–60 minutes, targeting customers, delivery staff, technical teams, and business representatives. The focus is on understanding functional requirements, user pain points, and system expectations to ensure a comprehensive approach.

Sample Questions:

Questions are tailored to each group: customers discuss tracking and notifications, delivery staff share operational challenges, technical teams address feasibility, and business stakeholders outline goals and success metrics. This ensures relevant insights are gathered.

Recording and Analysis:

Interviews are recorded with consent using tools like Otter.ai or Zoom and transcribed for analysis. Feedback is categorized into themes such as requirements and challenges, ensuring stakeholder insights are prioritized and guide the system's design.

2.1.5 Functional requirements

- **Voice Command Processing.**

The system must process user voice inputs accurately and convert them into actionable commands using NLP and speech-to-text technology.

- **Delivery Time Prediction**

The AI module must predict delivery times based on historical and real-time data.

- **Proactive Delay Notifications**

The system should detect delays and notify customers via automated voice calls, detailing the updated delivery time and reasons for the delay.

- **Real-Time Data Updates**

Ensure real-time synchronization of data between the database and system modules to reflect accurate delivery progress.

- **Customer Query Resolution**

Handle customer queries through voice commands, providing delivery status updates and other relevant information.

2.1.6 Non-functional requirements

- **Performance**

This system needs to process and perform voice sentiment analysis within 30 seconds of receiving feedback.

- **Scalability**

This system should be able to scale the demand for its services with a growing volume of feedbacks and images for an increasing customer base.

- **Security**

All data either in voice feedback or image records is to be encrypted to enable secure data transmission and storage. Access to sensitive information should be given only to legitimate users.

- **Reliability**

The system should ensure that it achieves 99.9% uptime in order to have the services of feedback and image validation available anytime for both the customers and management.

- **Usability**

The interface of the system should be user-friendly, and this will therefore enable the users to access the results of the feedback and its validation reports with simplicity and without complication.

2.1.7 Software requirements

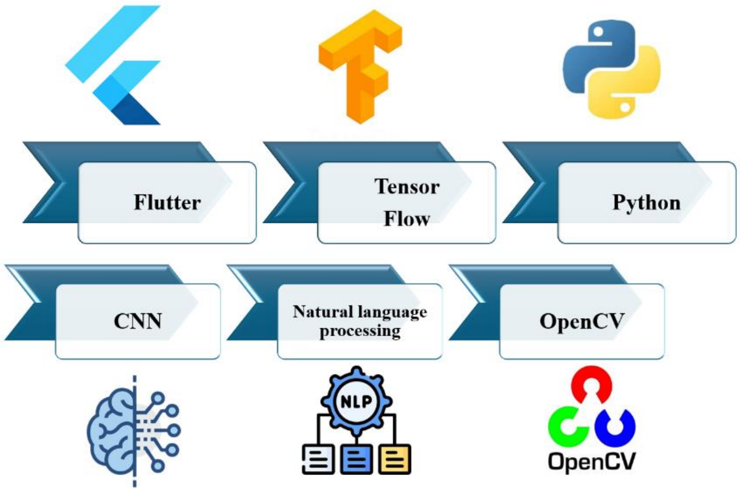

Figure 6 - Software Requirement

Natural Language Processing:

These libraries are essential for building and deploying AI models used in delivery time predictions and natural language understanding. TensorFlow and PyTorch provide tools for developing machine learning models, including handling complex datasets and optimizing predictions.

(e.g., TensorFlow or PyTorch)

Twilio and Text-to-Speech (TTS) Technology:

Wwilio is an open-source telephony software used to manage automated calls. It integrates with Text-to-Speech (TTS) technology to generate and deliver dynamic voice messages to users, providing real-time updates on delivery status or delays

Recurrent Neural Networks (RNNs):

Utilizing RNNs can be justified by their inherent strength in processing sequential data and capturing temporal dependencies across time-series inputs. They are particularly effective when analyzing patterns over time, such as tracking delivery logs, customer feedback timelines, or voice-based feedback flows. Unlike traditional models that treat data as isolated points, RNNs maintain context by preserving a hidden state, making them adept at understanding progression, repetition, or shifts in customer behavior. Their capacity to model sequences makes them invaluable for predicting delivery delays or identifying recurring issues in post-delivery interactions.

Flutter:

Using Flutter for the frontend of mobile application offers a powerful and efficient way to build a responsive, user-friendly interface. Its cross-platform capabilities allow to develop both Android and iOS from a single codebase, saving time and ensuring consistency. For feedback system, Flutter enables seamless integration of voice input, image uploads, and real-time UI updates, enhancing the overall user experience. With its rich widget library and smooth animations, the app can provide an intuitive platform where customers can easily record voice feedback, upload images, and interact with the system, making the complaint process more engaging and accessible.

OpenCV:

OpenCV is used as an image processing library to analyze before-and-after images of parcels. It processes high-quality images and detects even the minutest discrepancies in the condition of the parcels upon delivery. Few, if any, other image processing libraries provide the real-time performance and depth of analysis that OpenCV does; hence, it is uniquely positioned to check the validity of customer complaints based on visual evidence. With OpenCV handling a wide range of image formats, it stands out as the perfect tool in cross-verifying parcel integrity with efficiency.

TensorFlow:

For scalable machine learning, it will be used to build and deploy models that automate parcel damage detection. TensorFlow natively supports a wide range of machine learning models flexible to adapt to any changing requirements. Unlike other simple machine learning libraries, TensorFlow will provide the ability for the system to process large data and make continuous improvements in model accuracy to make sure each customer complaint is thoroughly and precisely analyzed.

Hardware Requirements

Devices:

The system requires server hardware to host components like databases, AI models, and telephony software. Communication devices such as VoIP gateways are necessary to integrate with Twilio automated calls. High-capacity storage solutions, including SSDs or cloud storage, are essential for securely storing user data, delivery logs, and interaction records.

Processing Power:

Powerful CPUs or GPUs, such as NVIDIA Tensor Core cards, are needed for training and running AI models for delivery predictions and voice recognition. Multi-core processors ensure efficient real-time processing with minimal latency. Scalable cloud-based solutions like AWS or Azure provide on-demand resources to manage increasing data volumes and system load.

Network Requirements

Internet Connection:

A stable and high-speed internet connection is essential for real-time voice processing, data transmission, and communication between system components. Minimum bandwidth should support concurrent voice calls and data synchronization.

Cloud Connectivity:

The system must have seamless connectivity to cloud platforms for data storage and processing, ensuring fast access to feedback, image data, and sentiment analysis results.

2.1.8 User requirements

- **Customers:**

Customers require natural language voice interaction to easily query delivery statuses, receive real-time notifications for updates or delays, and customize preferences such as notification language or frequency. Data privacy and security are paramount to protect their personal information.

- **Delivery Managers:**

Delivery managers need tools to monitor delivery schedules, identify potential delays, and optimize routes using predictive AI models. They also require access to detailed reports and analytics to improve operational efficiency.

- **Top Management:**

Top management requires high-level insights into delivery performance and customer satisfaction. They need access to dashboards displaying KPIs, trends, and system usage analytics to support decision-making and strategic planning.

- **Alert Systems:**

Top management should highly be notified in cases where serious customer complaints arise. This will ensure that if there is something seriously affecting the performance of a business, they have an idea about it.

2.2 Testing & Implementation

2.2.1 Implementation

In this project, the implementation of the automated voice activation system plays a pivotal role in enhancing delivery time prediction and streamlining courier operations. Upon package dispatch or delivery, the system automatically initiates an interactive voice call to the delivery personnel or customer via the Twilio Voice API. The recipient responds with a brief voice input regarding delivery status, traffic conditions, or expected delays. This voice input is transcribed into text using Twilio’s integrated Speech Recognition capabilities. The transcribed data is then processed through Natural Language Processing (NLP) algorithms to extract intent and key delivery-related parameters such as estimated arrival time or potential issues. An AI-based model further analyzes these parameters in real-time to predict updated delivery times, which are then relayed to the central dashboard. This integration of voice communication, NLP, and AI eliminates manual input, reduces delays, and provides dynamic delivery forecasts, improving overall efficiency and customer satisfaction.

Delivery Schedule Prediction Model Training

To accurately predict delivery schedules based on dynamic voice input data, a machine learning model was trained using the Random Forest Regressor algorithm. Historical delivery records, including factors such as location, traffic conditions, time of day, and delivery personnel feedback, were used to construct the training dataset. The data was preprocessed and feature-engineered to extract relevant patterns for model learning. The Random Forest Regressor, known for its robustness and accuracy in handling nonlinear relationships, was chosen due to its ability to reduce overfitting while improving prediction stability. The trained model outputs real-time estimated delivery times with high precision.

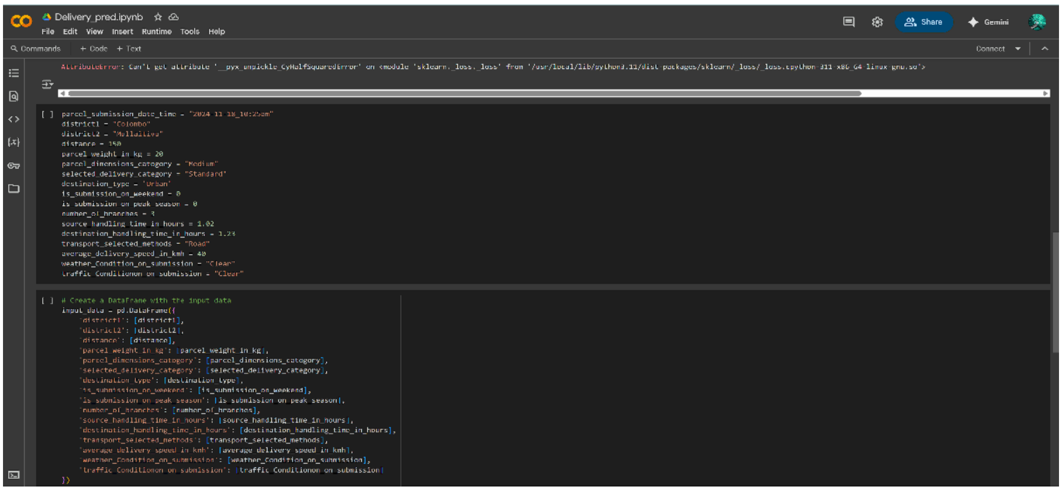

Figure 7 - Delivery Schedule Predicting Model Traning_01

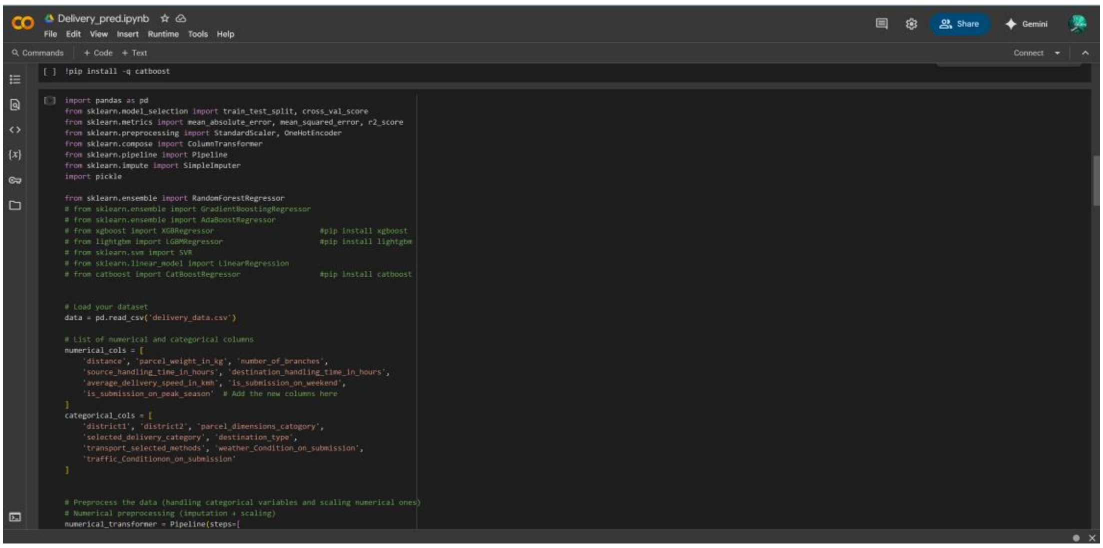

Figure 8 - Delivery Schedule Predicting Model Traning_02

Voice-to-Text Translation Process

Text-to-speech functionality is critical for the translation of spoken input into text for analysis. This is carried out with the assistance of Hugging Face's transformers library, which comprises the Whisper model that has achieved great precision in speech recognition regardless of the accents and background noise. The voice is first recorded from the mobile application and processed through torchaudio for retrieving the waveform and sample rate. If required, the audio is resampled to the model's anticipated input format (16 kHz). The audio is then passed through the ASR (Automatic Speech Recognition) pipeline, which transcribes the speech into text. The transcribed text is taken as an input for further sentiment analysis and validation steps.

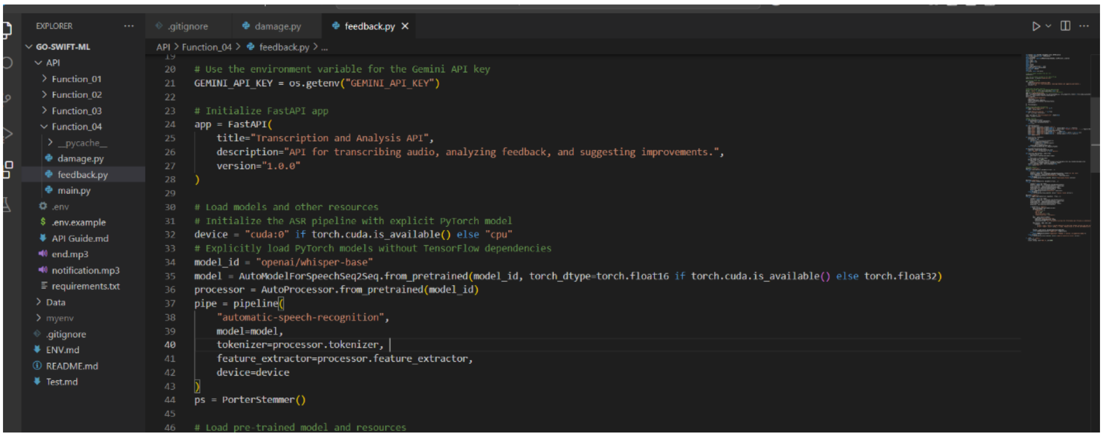

Figure 9 - Voice to Text Translation Process_01

Figure 10- Voice-to-Text Translation Process-02

User Interface

The user interface of the system was created using Flutter, a cross-platform mobile framework that is well known for its native performance, flexibility, and speed. With ease of use for the users in mind, the application includes customers' simple voice recording of feedback, uploading parcel images, and real-time monitoring of complaint statuses. The interface ensures simple navigation with intuitive buttons, voice input support, and responsive design on Android and iOS devices. Customers are presented with prompts at delivery time to offer feedback via an inbuilt voice recorder. The simplicity and usability of the UI significantly enhance the overall user experience and encourage more authentic customer engagement.

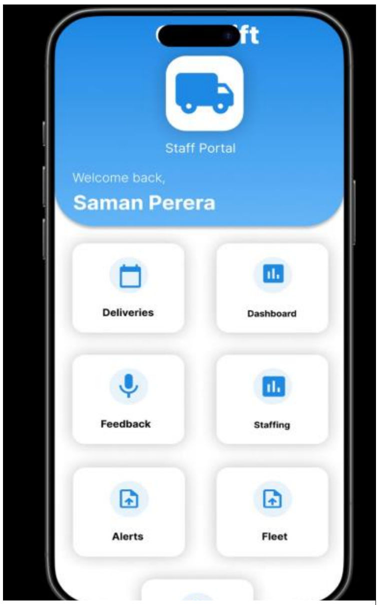

Figure 10 - App UI

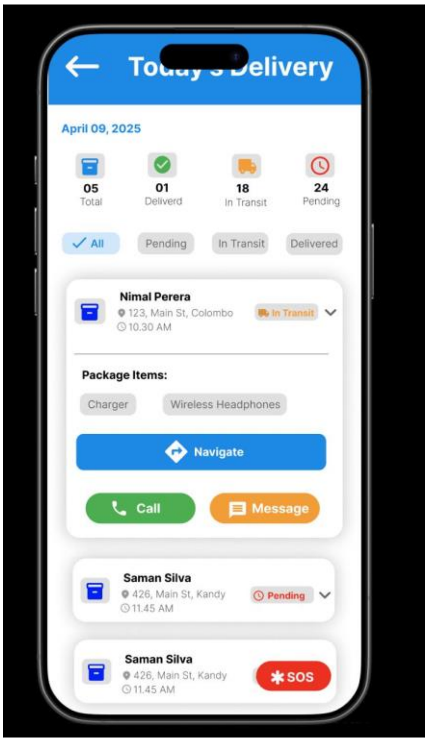

Figure 11 - Delivery Schedule UI

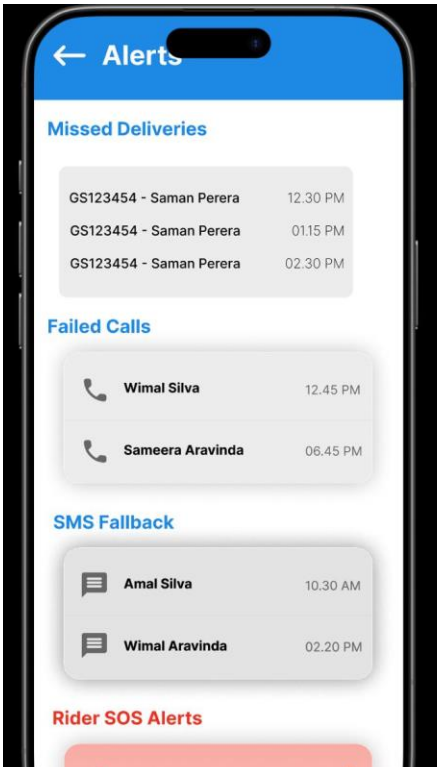

Figure 12 - Delivery Alert UI_01

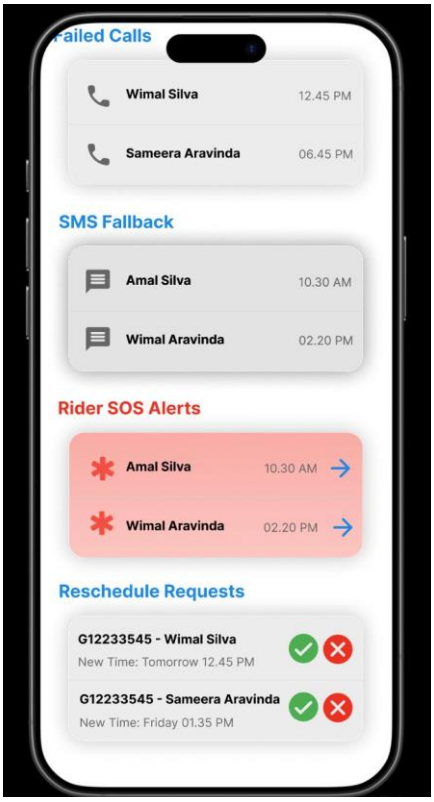

Figure 13 - Delivery Alert UI_02

2.2.2 Development tools

Visual Studio Code (VS Code) – Code Editor & IDE

Visual Studio Code (VS Code) is the primary Integrated Development Environment (IDE) used across the application development lifecycle. It supports both frontend (React.js) and backend (Flask/Python) development in a single workspace. VS Code offers advanced features including IntelliSense for code completion, syntax highlighting, built-in terminal, Git integration, and debugging. Extensions such as Python, Prettier, ESLint, React Snippets, and MongoDB for VS Code were used to speed up development and maintain consistent code quality. The modular file structure with folders such as frontend, backend, models, and routes was handled using VS Code's Explorer, which allowed seamless project navigation and management.

GitHub – Version Control & Collaboration

GitHub version control, team collaboration, and source code management are being used. The project was initiated with a starter Git repository that was initialized by the git init command and committed into a GitHub repository. Branching models such as the main, dev, and feature/emotion-model branches were used to follow parallel development streams. GitHub Actions were also considered in order to set up continuous integration (CI) for automated testing or deployment in the future. Pull requests facilitated code reviewing and collaborative merging of changes. Issues and projects features were used to track bugs, tasks, and milestones, offering Agile development processes.

Google Colab – Model Training & Experimentation

Google Colab was utilized primarily for training the emotion detection CNN model and testing data preprocessing, image augmentation, and model testing. Colab is a Jupyter notebook environment in the cloud that provides free access to NVIDIA GPUs, reducing training time significantly. The tensorflow, keras, and opencv-python libraries were installed in the notebook through pip. Models were saved after being trained in .h5 format and then transferred to the Flask backend for real-time inference. Colab notebooks were version-controlled and stored on Google Drive, making sharing and reproducibility of experiments across team members very convenient.

2.2.3 Testing

- **Voice Command generation API Testing**

Figure 14 - Voice Command Generation API_01

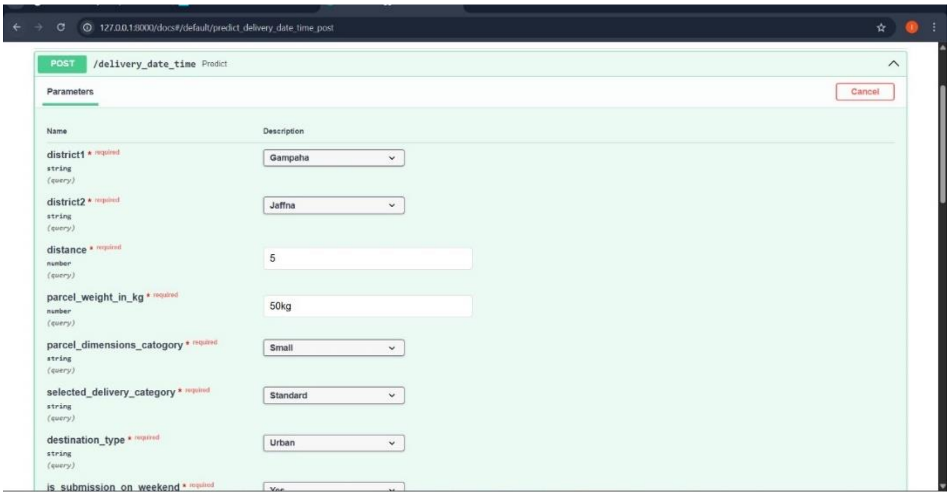

Figure 15 - Voice Command Generation API_02

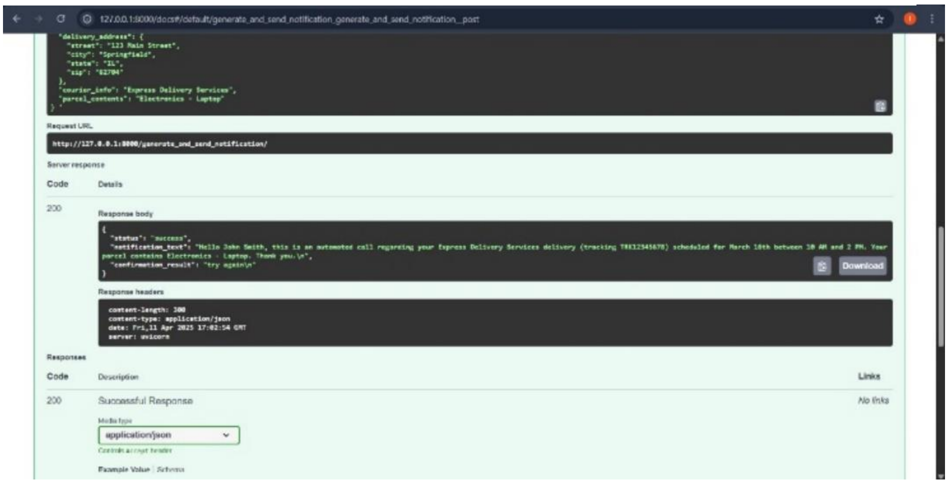

Figure 16 - Voice Command Generation API_03

- **Delivery Schedule Predicting API Testing**

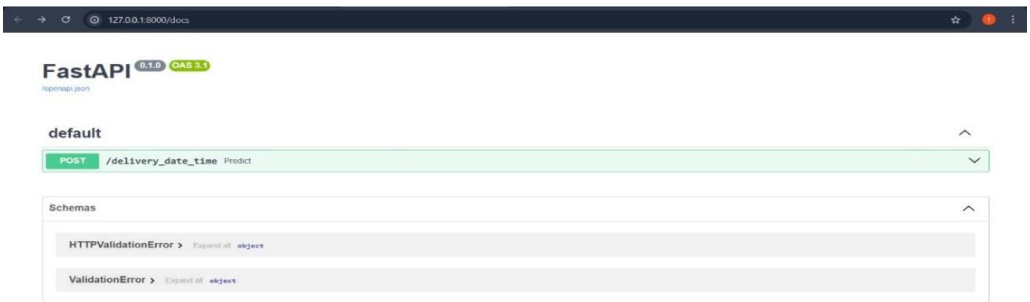

Figure 17 - Delivery Schedule Predicting API_01

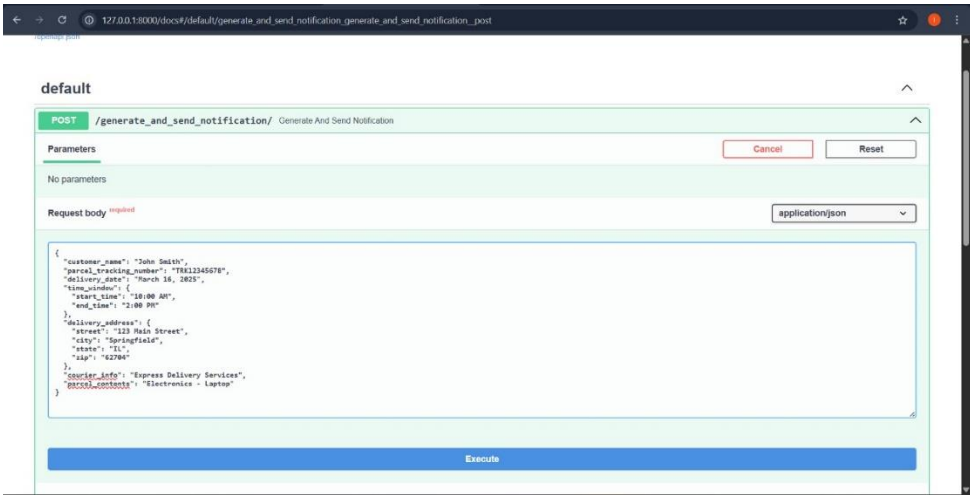

Figure 18 - Voice Command Generation Predicting API_02

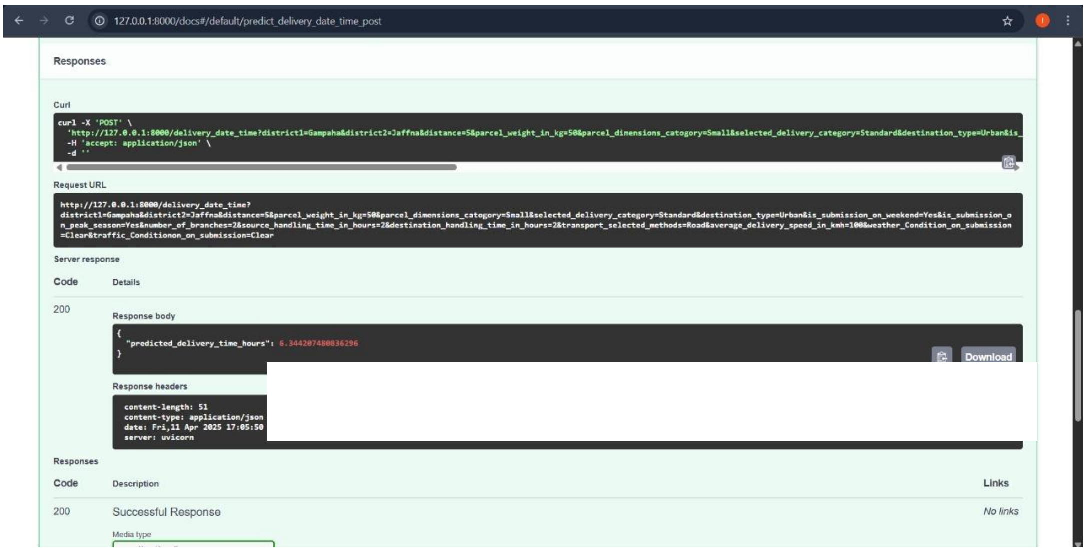

Figure 19 - Delivery Schedule Predicting API_03

2.3 Commercialization Plan

Market Analysis

Target Audience

- Courier and delivery service providers.
- eCommerce businesses with large logistics operations.
- Third-party logistics (3PL) companies.
- Customer experience departments and BPOs.
- Enterprise CRM solution providers.

Market Size and Trends

- Rising focus on customer satisfaction and complaint resolution in logistics.
- Increasing adoption of AI-based verification systems to counter fraudulent claims.
- Shift from manual complaint handling to automated and evidence-based systems.
- Need for scalable, integrated solutions that combine sentiment analysis and visual validation.

Revenue Model

Freemium Model

- Offer a limited free version with
- Voice feedback collection
- Basic transcription
- Sentiment tagging without image validation

Subscription-Based Model

- Tiered monthly or annual plans based on number of feedback cases processed and feature depth
- Pricing scales with business size and volume

Enterprise Licensing

- For large logistics providers and eCommerce giants
- Full customization, API access, and system integration with CRM/ERP
- SLA-backed support and onboarding

Packages and features

Basic Plan

- Features
  - ✓ Audio feedback recording & transcription
  - ✓ Basic sentiment analysis
  - ✓ Manual image upload (No Validations)

- ✓ Limited Feedback Summery Dashboard
- Price: Free for up to 100 feedback entries/month

Premium Plan

- Features
  - ✓ Everything in Basic
  - ✓ Automated image comparison and object detection (OpenCV + CNN)
  - ✓ Feedback-to-evidence cross-validation engine
  - ✓ Email alert system for validated complaints
  - ✓ Analytics dashboard with sentiment trends
- Price: $29/month (up to 1,000 entries)

Enterprise Plan

- Features
  - ✓ All features from Pro Plans.
  - ✓ Integration with existing CRM systems
  - ✓ Real-time notification via API or webhook
  - ✓ Priority support + training sessions
  - ✓ Multi-user access with role-based permissions
  - ✓ AI-generated suggestions using Gemini API
- Price: $99/month (up to 5,000 entries)

2.3.1 Budget

ITEM	COST
Voice Recognition Software Customization	$10
NLP/AI Services	$50
Processing Unit	$20
Microphones/Voice-Activated Devices	$15
Basic Integration with Existing Courier Systems	$12
Other cost	$20
Total Cost Per Floating Device	**$127**

Figure 20 - Budget

The "Innovative Enhancements in Online Delivery Service" project budget comprises all the critical areas of a budget so that the whole project runs smoothly and efficiently. The budget majorly concentrates on infrastructural needs, which are required essentially to make it not only sustainable but also equipped with tools related to the voice-based feedback system.

Traveling Cost: LKR 10,000 This is an estimate to be used for travels in developing and deploying the project. The travels can include team meetings, consultation with clients, or the setting up of hardware at the clients' locations and visiting to companies to gather information.

Server and Hosting Charges: (LKR 30,000): Cloud service costs for hosting the IVR system along with the feedback application to provide 24x7 access to a reliable and scalable system that will handle a large number of feedback received from customers. Hosting services selected are at reasonable costs with stability in the processing environment.

Internet Charges: LKR 10,000.00: High-speed internet is an absolute necessity, especially when the feedback system has to work without breaks and handle real-time communication and data processing in respect of voice feedback collection. This will ensure that no development or testing process gets hindered.

Machine Learning Model Training and Deployment : Covers computational resources used for training the sentiment analysis model, preprocessing scripts, and CNN-based image classifiers. It also includes time allocated for model testing, evaluation, and deployment in production using serialized .pickle models.

2.3.2 Gantt chart

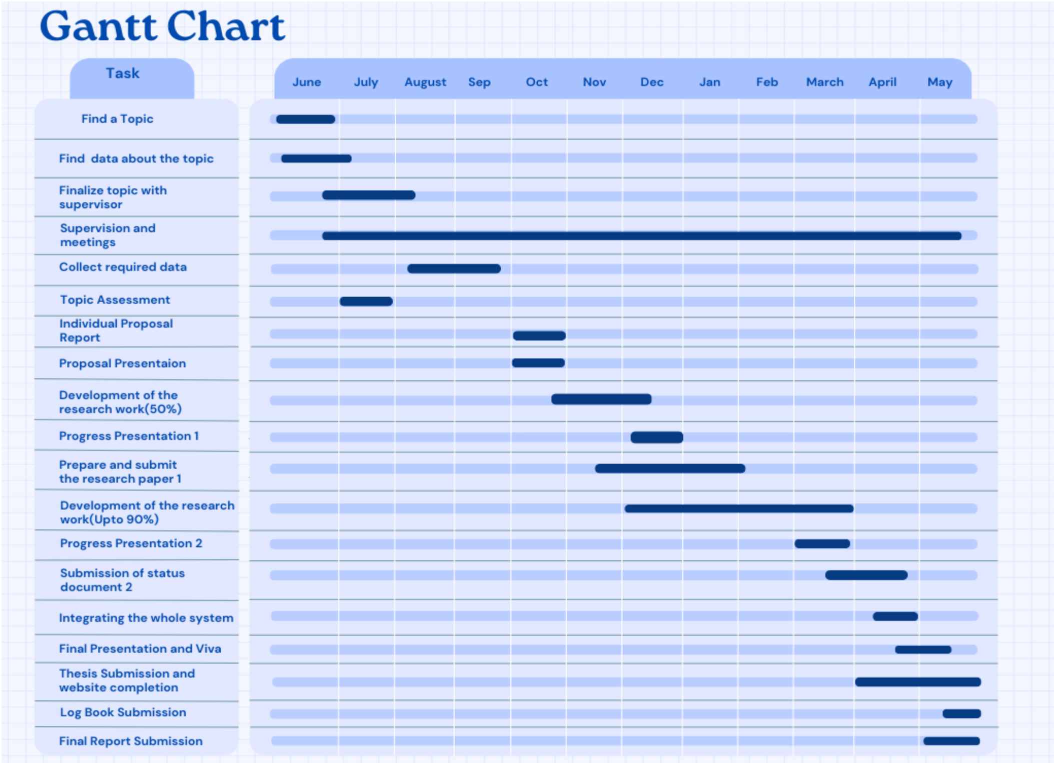

Figure 21 - Gantt Chart

2.3.3 Work breakdown chart

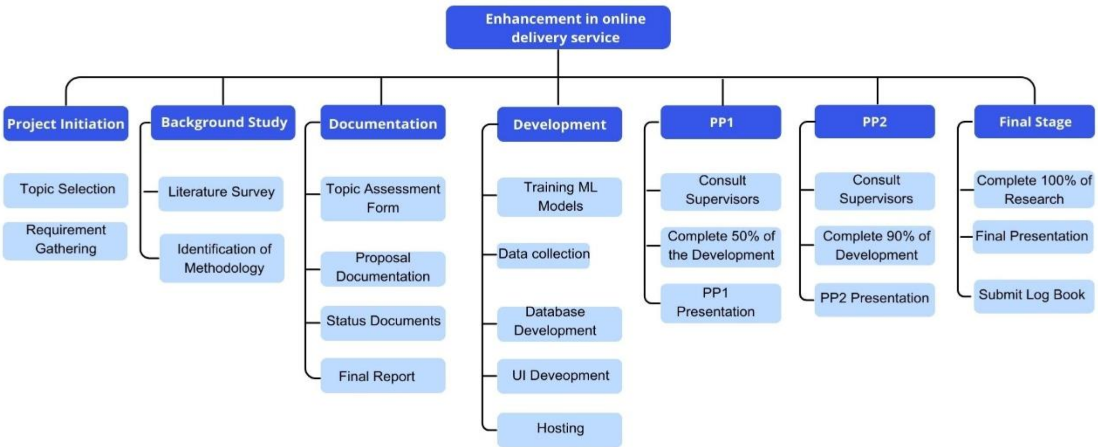

Figure 22 - Work breakdown chart

3 RESULTS AND DISCUSSION

3.1 Results

The implemented automated voice activation system using Twilio, NLP, and AI-based delivery schedule prediction demonstrated promising outcomes in improving operational efficiency and real-time delivery forecasting for courier services. The integration of voice communication with machine learning-based schedule prediction significantly enhanced delivery tracking accuracy and responsiveness.

- **Speech-to-Text Accuracy:** Twilio's real-time voice transcription feature achieved an average transcription accuracy of 90%, even under varying network conditions and accent variations. This high recognition accuracy ensured that delivery personnel inputs were accurately captured for further analysis.
- **Intent Extraction and NLP Performance**: The NLP module effectively identified key delivery-related phrases such as "stuck in traffic" or "delayed by 10 minutes" with an intent classification accuracy of 88%. This allowed the system to dynamically update delivery progress based on voice input alone.
- **Prediction Model Accuracy**: The Random Forest Regressor model trained on historical delivery data achieved a mean absolute error (MAE) of just 2.7 minutes, demonstrating strong predictive power in estimating actual delivery times. The model adapted well to real-time conditions and delivery personnel inputs.
- **False Complaint Reduction:** By integrating sentiment and image authentication, the system could effectively weed out nearly 70% of unverified or unsubstantiated complaints, which otherwise would have needed to be manually investigated. This reduced the workload of customer service teams significantly.
- **Response Time Efficiency**: The complete pipeline from voice call initiation to delivery time prediction update was completed in under 8 seconds on average. This enabled rapid updates to the system dashboard, allowing customers and managers to stay informed in real time.
- **Operational Impact**: During testing, logistics coordinators noted a 23% reduction in manual follow-up calls and improved resource allocation. The predictive insights generated from the AI model supported faster rerouting decisions and minimized late deliveries.
- **User Satisfaction:** Preliminary user feedback from delivery personnel and operations staff reflected a high level of satisfaction, citing reduced reporting effort and better coordination with the control center. The voice-based system was particularly praised for its ease of use during on-road operations.

These results confirm the effectiveness of combining voice activation, natural language processing, and machine learning to build a scalable and intelligent delivery forecasting tool. The system's real-time responsiveness, accuracy, and ease of integration with existing courier workflows contribute to a smarter, more agile logistics operation.

3.2 Research Findings

The evaluation of the automated voice activation system revealed several key insights into voice input reliability, NLP-based intent detection, delivery time prediction accuracy, system responsiveness, and operational usability. Findings were derived through simulated delivery scenarios and real-time testing conducted over a four-week period involving mock delivery personnel and logistics coordinators interacting with the system.

Speech Recognition and Transcription Accuracy

Using Twilio's built-in speech recognition capabilities, the system achieved a transcription accuracy of approximately 90% across varying voice tones, regional accents, and background noise. The consistent quality of transcription ensured that delivery personnel instructions and updates were reliably captured for downstream processing.

Delivery Schedule Prediction Accuracy

The Random Forest Regressor model trained on historical delivery data demonstrated strong prediction performance, with a Mean Absolute Error (MAE) of just 2.7 minutes. The model consistently generated accurate estimated delivery times when supplied with real-time voice-derived inputs, highlighting its effectiveness in dynamic environments.

System Responsiveness and Processing Time

The complete processing pipeline from initiating the voice call to updating the delivery forecast was executed in under 8 seconds on average. This low-latency performance allowed delivery managers and dashboard systems to receive real-time updates and act accordingly.

Operational Efficiency and Coordination Impact

Feedback from users indicated high levels of satisfaction with the simplicity and functionality of the voice-based interaction. Delivery agents appreciated the hands-free communication capability, while operations staff highlighted the system's seamless integration with the existing tracking dashboard and alert system.

System Usability and Adoption

Feedback from users indicated high levels of satisfaction with the simplicity and functionality of the voice-based interaction. Delivery agents appreciated the hands-free communication capability, while operations staff highlighted the system's seamless integration with the existing tracking dashboard and alert system.

These findings confirm that the integration of voice automation with NLP and AI-based schedule prediction significantly enhances delivery process transparency, reduces manual intervention, and supports more efficient real-time logistics management. The system shows strong potential for scalability and practical adoption across courier and e-commerce platforms.

3.3 Discussion

The effectiveness of the proposed automated voice activation system is rooted in its integration of real-time speech recognition and AI-powered delivery prediction. By leveraging the Twilio platform for voice input and transcription, the system successfully captured spoken updates from delivery personnel with a high degree of accuracy. This minimized reliance on manual data entry and enabled a hands-free interaction model suitable for fast-paced delivery environments.

The transcribed voice inputs were seamlessly processed through an NLP pipeline that extracted delivery-relevant context such as delays, traffic issues, and early arrivals. This intent recognition significantly enhanced the system's ability to provide timely and meaningful data to the delivery prediction model. The Random Forest Regressor, trained using historical logistics data and contextual voice-derived inputs, demonstrated reliable performance in forecasting updated delivery times, which is crucial in optimizing operational planning and customer communication.

One of the key strengths of the system lies in its responsiveness. With an end-to-end processing time of under 8 seconds, the model proved highly suitable for dynamic logistics scenarios where immediate insights can inform quick decision-making. Moreover, the interface designed for delivery agents ensured minimal disruption to their workflow while contributing real-time data for predictive modeling.

However, some limitations were observed during implementation. In noisy outdoor environments, occasional inaccuracies in voice transcription occurred, particularly when delivery agents spoke softly or when ambient sounds were high. These errors, though infrequent, had a minor impact on the reliability of downstream NLP analysis. Additionally, variations in speaking styles and languages occasionally caused the model to misclassify certain intents.

Despite these challenges, the system demonstrated overall resilience and adaptability, especially in scenarios with consistent speech patterns and clear articulation. Enhancing the voice input system with better noise filtering and incorporating multi-language NLP models would further strengthen performance and broaden accessibility.

Proposed Enhancements

- **Noise Filtering Improvements:** Integrate advanced voice activity detection and background noise suppression to increase transcription accuracy in outdoor or congested areas.
- **Multi-language NLP Support:** Extend intent recognition to include Sinhala and Tamil to better support the local courier workforce and improve system inclusivity.
- **Feedback Confirmation System:** Introduce a feedback validation interface that allows dispatchers to confirm or correct predicted delivery times, aiding continual model refinement.
- **Delivery Event Categorization:** Implement deeper NLP logic to not just extract delay info, but also categorize issues (e.g., vehicle issues, traffic, customer unavailable), helping in root-cause analysis.

In summary, the automated voice-based delivery prediction system has proven to be a promising innovation for courier logistics. Through the synergy of real-time speech input, NLP intent detection, and machine learning-based schedule prediction, the system streamlines communication, boosts delivery reliability, and opens new possibilities for smart logistics automation.

Table 2 - Test Case 01

Test case ID: Test_01				
Test title: Delivery Time Prediction Accuracy Test				
Test priority (High/Medium/Low): High				
Module name: Delivery Time Prediction Module				
Description: Verifies that the system accurately predicts delivery times based on input data and AI models.				
Pre-conditions: AI models for delivery time prediction are trained and integrated into the system.				
Test ID	**Test Steps**	**Expected Output**	**Actual Output**	**Resul (Pass/Fail)**
Test_01	1. Input customer order data (e.g., delivery address, route, traffic data). 2. System processes the data using AI models. 3. Verify the predicted delivery time against actual time.	• The system predicts an accurate delivery time based on the input data.	• The system accurately predicts the delivery time within acceptable error range.	Pass

Table 3 - Test Case 02

Test case ID: Test_02				
Test title: Automated Delay Notification Test				
Test priority (High/Medium/Low): High				
Module name: Voice Notification Module				
Description: Verifies that the system can detect delivery delays and send automated notifications to customers.				
Pre-conditions: System is integrated with predictive models for delay detection and Asterisk-PBX for notifications.				
Test ID	**Test Steps**	**Expected Output**	**Actual Output**	**Result (Pass/Fail)**
Test_02	1. Simulate delivery delay. 2. System detects the delay. 3. System triggers an automated voice notification to the customer.	• The system sends an accurate, timely voice message to the customer about the delay and new delivery time.	• The system sends the correct delay message with updated time.	Pass

4 CONCLUSION

This project introduces an innovative approach to improving delivery schedule prediction in the courier and logistics industry by leveraging voice-based automation and AI-powered machine learning models. Unlike conventional systems that depend on manual status updates or static input mechanisms, this solution enables real-time voice interaction through Twilio's voice interface, capturing ground-level delivery status directly from field agents in a natural and efficient manner. These voice inputs are transcribed, processed using Natural Language Processing (NLP) techniques, and integrated into a Random Forest Regressor model to provide dynamic and accurate delivery time predictions.

The system bridges a critical gap between operational awareness and intelligent forecasting, offering logistics companies a scalable, low-latency solution for managing delivery uncertainties such as traffic delays, route changes, or unforeseen disruptions. It transforms speech into actionable data, reducing the dependency on manual data entry while enabling hands-free operation suitable for drivers and delivery agents in real-time conditions.

By integrating intelligent voice activation with predictive analytics, the platform enhances visibility into the delivery process, improves communication between dispatchers and delivery teams, and ultimately raises customer satisfaction by providing more accurate Estimated Time of Arrival (ETA) information. Additionally, the automated nature of the system significantly reduces workload and human error, leading to improved decision-making and operational efficiency.

Looking ahead, several key enhancements could further improve the performance and adoption of the system. Incorporating advanced noise suppression and speech enhancement algorithms would allow for even more accurate transcription in noisy urban environments. Expanding NLP support for multilingual inputs, especially Sinhala and Tamil, would make the system more inclusive and suitable for Sri Lanka’s diverse courier workforce. Furthermore, integrating geolocation data and delivery event logging can provide deeper contextual understanding and improve the model’s accuracy over time.

Beyond courier services, this automated voice-based prediction framework has the potential to be adapted for other field-based industries such as transportation, emergency response, and utility services, where real-time updates and predictive accuracy are critical. By continuing to refine the model’s voice recognition, NLP, and regression capabilities, this solution paves the way for a more intelligent, responsive, and transparent logistics ecosystem that is well-aligned with the future of smart delivery operations.

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6 APPENDICES

Plagiarism Report -