GO SHIFT: Innovative Enhancements in Online Delivery Service

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

Signature: Date:

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I would like to extend my heartfelt appreciation to all the individuals who supported me in carrying out the 4th year research project.

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ABSTRACT

In the logistics and courier service business, customer satisfaction is the main key to its growth and existence. One of the major challenges faced by industry, however, is the handling of negative feedback in the case of any complaint, where there is no material evidence to support or dismiss it. This project presents a new system, which integrates voice feedback analysis with image-based parcel validation for improved verification of customer feedback and operational transparency. This voice feedback is collected using IVR systems, which are then converted to text using advanced Speech-to-Text technologies. Later, the sentiment of the feedback-that is, if that is positive or negative-is analyzed using Natural Language Processing. It is only in the case of negative feedback that image processing techniques analyze the pre-and post-delivery images of the parcel for damage or discrepancies.

The process cross-validates adverse feedback with the condition of the parcel for further validation of the feedback. In case the feedback has been verified to be genuine, an auto-generated alert is forwarded to the top management for necessary action. The integrated system, with AI, NLP, and computer vision, reduces fake complaints, builds trust with customers, and smoothen processes in handling complaints..

Keywords: Natural Language Processing (NLP), Speech-to-Text, Image Processing, Feedback Validation, Customer Satisfaction, Computer Vision

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LIST OF ABBREVIATIONS

Natural Language Processing	NLP
Convolutional neural networks	CNN
Artificial Intelligence	AI

1 INTRODUCTION

Customer satisfaction is important if a company is to thrive, especially within the logistics and courier industry. Timely and safely delivering parcels is at its very core tied to customer experience. One of the key problems in this line involves negative feedback associated with delayed delivery and also damaged goods. It really affects the reputation of the organization and entails operational losses. Current methods of feedback collection involve text-based systems and numerical ratings, which make the customers restricted in their powers of articulation. More often than not, users do not get a chance to explain in detail what ails them, which could lead to a very incomplete picture of customer sentiment.

All of these are traditional feedback systems that lack the scope of finding out what really happened from the customer's complaints and more importantly validating their complaint. Besides, in logistics companies, without verification mechanisms for genuineness or fakeness of the complaint, there is no effective means of sorting out disputes amicably. What's more, very often, there is no cross-referencing between feedback and visual evidence such as images of parcels, which is needed to sort out specific issues, for instance, bad handling of delivery.

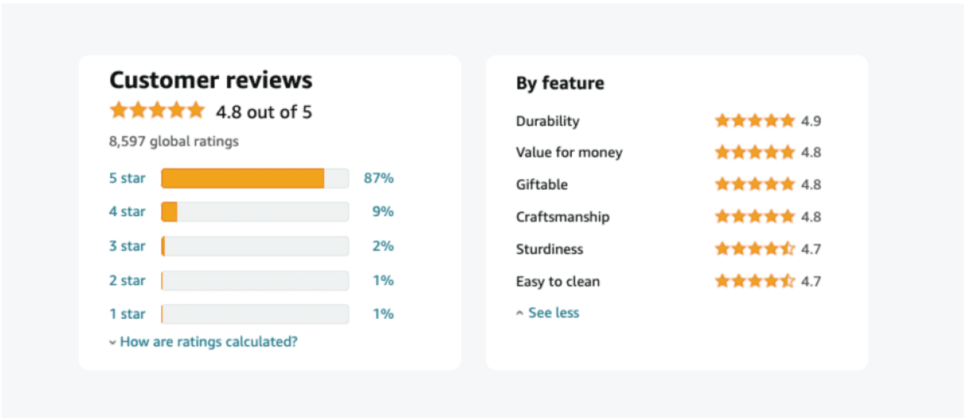

Figure 1-Customer Reviews

This solution integrates voice-based collection of feedback, coupled with image validation, so as to increase the accuracy of feedback analysis. The customers will be able to air their concerns through spoken feedback in a natural manner. In turn, the system will enforce voice feedback collection through IVR, Speech-to-Text for converting textual data, and analysis through NLP. On the other hand, if negative feedback exists, it will go one step further by comparing the before and after images of the package using advanced image processing techniques to validate the complaint.

The system ensures that any negative feedback is evidence-based, cross-checked against visual evidence to satisfy companies on the legitimacy of the complaint. It focuses on the negative feedback to smoothen the resolution of the feedback in order for customers to be satisfie

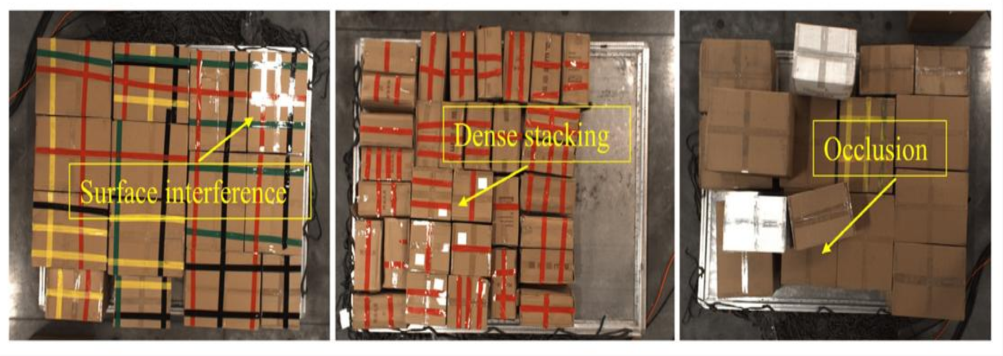

Figure 2- Types of parcels

1.1 Background and Literature Survey

Customer feedback systems in recent years have relied, by and large, on text-based input and numerical rating systems. These, though giving a general sense of satisfaction or dissatisfaction, reflect neither the full range of emotional experience from being a customer nor even the specific concerns that customers may have [1]. Besides that, NLP-based sentiment analysis has become a common solution in the e-commerce field. For instance, Amazon uses this technology to automatically classify customer reviews into positive, negative, and neutral categories [2].

Parallel to that, image processing technologies have been broadly applied in the sphere of logistics regarding product quality control. The existing systems, built upon two popular OpenCV and TensorFlow, were applied for detecting defects or damages with regard to products during transportation. However, all these technologies so far have been deployed as stand-alone systems not integrated with customer feedback mechanisms [3]. This allows the actual condition of the parcel to be checked against complaints, creating a gap in the resolution process of feedback.

APIs that will be utilized for voice feedback to text are Google Cloud Speech-to-Text and IBM Watson Speech-to-Text. These have proved to be highly effective in many languages and dialects [4]. The project will employ state of the art NLP techniques, including VADER or Google Natural Language API for sentiment analysis to predict the emotional tone of the feedback. These have already seen very effective applications on customer service platforms for categorizing feedback regarding sentiments. This is a advance use of complicated technology. The images of the parcels before and after transit would be compared using technologies like OpenCV and CNNs. These systems can trace even small changes in the condition of a product. It also adapts a supervised learning approach, improving over time from past feedback, making a comparison of given images to predict if the feedback is fair or unjustified [7].

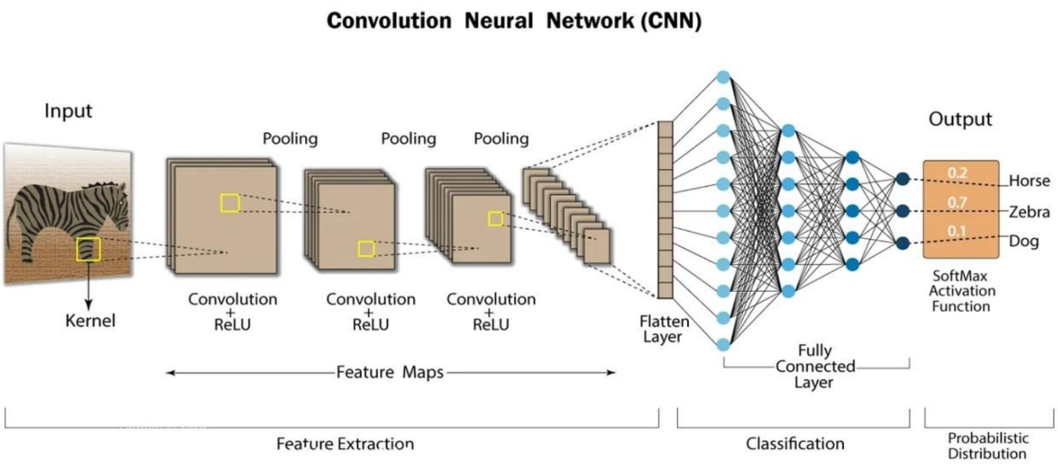

Figure 3 - Convolution Neural Network

However, current state-of-the-art feedback mechanisms rely on textual sentiment analysis of customers' feedback. For instance, eBay and Amazon have developed a system whereby customer reviews are automatically classified by their sentiment [8]. However, such systems might be bound to written feedback, which may not give full insight into the real sentiment or experience of the customer. Also, such mechanisms do not verify the feedback through any physical evidence such as product condition.

In logistics, at the same time, image processing technologies have been strongly enhanced. Fully automated visual inspection systems can identify defective products either during or after shipment, which guarantees that intact goods will be delivered to the customer. However, these stand-alone systems are not integrated with mechanisms for customer feedback; thus, complaints about damage to goods cannot be verified or cross-checked with the real status of parcel condition [9].

While various methods previously proposed to solve the customer satisfaction problem have been mainly either focused on improving text-based feedback mechanisms or automating visual inspections through the use of image recognition, such solutions advance feedback collection and product quality control only piecemeal, not providing a comprehensive approach to complaint validation. While NLP-based sentiment analysis has been helpful for the classification of feedback, it cannot identify whether such feedback is due to a valid issue in the absence of proof to support this fact [11]. Image recognition systems, on the one hand, are helpful to identify damage but do not consider customer sentiment.

This project will fill these gaps by integrating voice-based feedback analysis with image validation. Unlike other existing systems, this approach will allow the cross-referencing of customer sentiment with visual evidence-a more accurate and reliable mechanism in resolving complaints. This method not only ensures that genuine complaints get dealt with on time but can also help in avoiding false claims, which can further streamline operations with gains in customer trust.

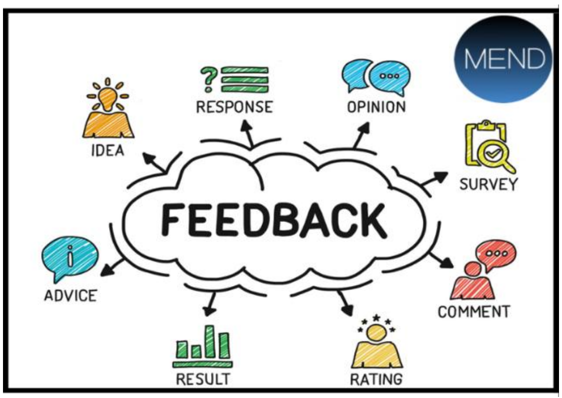

Figure 4- Feedback

1.2 Research Gap

With the advancement of customer feedback systems and image-based validation technologies, fully integrating technologies to improve customers' satisfaction in logistics and courier service is far from being realized. Most of the existing systems either focus on text-based sentiment analysis or image processing separately, hence limiting their capability to validate customer complaints comprehensively.

Most of the customer complaint systems that exist currently work on purely text information, where a customer manually types his/her complaints or rates of any service provided. While the methods for classifying and analyzing such text-based feedback with the help of NLP techniques have improved significantly, such methods themselves have several limitations.[12] For example, they can often not capture the nuance of emotional tone that can come through in what a customer says. A written review cannot capture the depth and context of a verbal complaint. It may often provide at best only a partial understanding of customer dissatisfaction.

This can be a huge drawback when it comes to logistical and courier service providers. For instance, a customer who has become upset because their package was delivered much later than planned might express this frustration with a certain tone or emphasis that cannot be conveyed solely by text. Because of this, an analysis of the customer sentiment will be incomplete since the text-based system cannot understand subtle speech.

This has been the case, but image recognition systems have recently evolved in their capabilities, specifically in recognizing physical damage issues in goods upon delivery. In this respect, the systems are highly effective in the detection of visual defects in nature, such as package tampering or damage to the product. However, they are also generally set up in a manner that is separate from obtaining customer feedback. In effect, a system link that visually connects proof with customer complaints does not exist currently, and this is basically the hole in the current validation process.

This means that even though a logistics company may have proof of package damage, they do not have any systematic method to correlate this with specific customer complaints. Logistically, since the two sources do not integrate, companies are stuck with disparate points of data that cannot be used very well to validate whether negative feedback is legitimate or not. Such a lack of a unified system in place makes it hard to really determine if there is a real customer issue at play or a potentially fraudulent claim.

Another very important research gap in the integration of the voice-based feedback mechanism with image validation in logistics studies is that the voice feedback mechanism is increasingly found to be far superior for capturing more expressive customer emotions. This can depict their feelings through things like tone, stress, and intonation, and since it is integrated with NLP tools, this can really enhance the process of sentiment analysis by giving richer and more detailed insight into the state of the customer's mind. That makes identification of the content, but more importantly the context of a complaint, which in text-based systems often gets lost.

This process, in addition to the addition of image validation, provides direct means of vindication with visual proof for customer complaints. Logistics companies can cross-reference issues reported by customers with images of delivered items to validate the veracity of negative feedback. This method further enhances the credibility of the feedback system and allows the company to take precise corrective actions based on actual conditions of goods at delivery.

Other major flaws in existing feedback systems concern the poor use of computational resources in symmetric handling of positive and negative feedback. Traditional image-based validation processes, which depend on the analysis of every single entry in the feedback, tend to make such processes unrealistically consumptive of computational power and storage resources, hence unrealistic for large-scale use.

To this end, a much more resource-efficient method needs to be devised-one aimed for the most part at negative feedback with respect to image-based validation. The logistics companies can thereby customize their processes of validation by allocating computational resources only when called upon, thereby averting any extra and unnecessary costs. In that respect, such a strategy would make the process of analyzing feedback not only more efficient but also viable in the long term.

While advanced technologies like Artificial Intelligence, Machine Learning, and Computer Vision are becoming more and more considered for logistics, their full capacity has not yet been leveraged in making complete customer satisfaction courtesy of integrated feedback mechanisms [13]. The integration of AI-based sentiment analysis with image validation would provide a more substantial framework for understanding customer complaints. This would position logistics companies beyond just damage control to being in a place where they are able to handle their customers' issues before they escalate further.

In this regard, the integration of such technologies into a single system would greatly contribute to better handling by logistic companies of customer feedback. From deeper insights provided through spoken and visual inputs, they can get a helicopter view of their experiences. [14] It is not only about solving current issues but also predicting and preventing future ones to drive higher levels of customer satisfaction.

Table 1- Research Gap

Features	Research A	Research B	Research C	Research D
Voice Feedback Collections	✓	✓	✓	✓
Speech-to-Text Conversion	✓	✓	✓	✓
Natural Language Processing (NLP) for Feedback Sentiment Analysis	✓	✓	✗	✓
Parcel Image Collection and Comparison	✗	✗	✗	✗
Cross-Validation of Feedback with Image Analysis	✗	✗	✗	✗

A hybrid mechanism of feedback in this context can be developed using both voice-based feedback and image validation. It can use the AI and ML algorithms to analyze the voice data, present it as actionable insight, and cross-validate those against visual evidence [15]. If applied to the logistics industry and couriers, the fraudulent cases of claims will be reduced by a significant margin, and the interpretation of customers' feedback will also be closer to reality.

This could very well be a new way to redefine the way customer feedback mechanisms work for logistics, as this would fill the gap between sentiment analysis and image-based validation. It might lead to more transparent and trustworthy mechanisms for feedback, since this will be a great help in the overall effective and efficient logistics operations.

1.3 Research Problem

Customer feedback is the engine that drives continuous service improvement in the logistics and courier industry. However, with present reliance on text-based feedback and rating systems, the companies are significantly impaired in capturing the more valuable insights of customers into satisfaction and dissatisfaction. Failure to understand the real nature of complaints affects the ability of companies to track operational issues leading to problematic customer experiences. Thirdly, such feedback systems also lack verification mechanisms whereby a company is likely to fall prey to fabricated feedback and unjust claims that can seriously hamper its goodwill and financially involve companies in undue expenses.

- **Limitations of Text-Based Feedback and Ratings**

The most implemented means of gathering customer feedback today is through text-based forms and numerical rating systems. This has been the case because these are the easiest mechanisms to implement, given that data analysis is also easy to handle. These types of information either lack sufficient depth or detail to be meaningfully acted upon from within the companies. In addition, text-based feedback gives some idea about the opinions of customers but often lacks the elements of emotions, tone, and context.

Expressing Emotion: Through verbal feedback, one cannot express the emotional power of the text. For example, the statement "The delivery was late" does not allow one to ascertain the exact amount of the delay or whether the customer has been in great distress because of such a delay.

Ratings Simplify Experience: Customer experience gets reduced to a 1–5 star numeric form, which reduces the opportunity of the company to understand what specific area needs improvement. A low rating does not show whether this is an issue of delivery time, packaging, or customer service.

Ambiguity in Feedback: The text feedback is not very clear. Customers may not explain the concerns succinctly enough. Therefore, the feedback received will be ambiguous and not understandable. As a result, this hinders the ability of the company to identify what went wrong and what really needs to be fixed.

Without a means of truly comprehending customer sentiments, companies cannot identify patterns of dissatisfaction, which are usually important operational issues that go unaddressed and, therefore, stall improvement.

- **False Feedback and Competitor Interference**

Another critical issue which arises in the text-based feedback systems is the existence of false feedback. This is usually from competitors or people who have an aim of destroying the good name of the company. Online platforms that allow people to give anonymous feedback give the competition an open forum where they could post hurtful reviews aimed at discrediting a company's performance.

Malice by Competitors: Competitors can, through mechanisms of feedback, demote the image of a company by posting fake complaints of delayed delivery or damaged goods with a malicious intention of scaring potential customers away from the company. The unethical practices may result in uninformed operation decisions such as firings of delivery personnel or changes in routes for no good reason.

Intentional abuse of feedback systems: Sometimes, customers may provide negative feedback as a joke, or even in an attempt to game the system, in situations where they know there is no meaningful check on whether their claim is valid or not. The inability to cross-check this feedback against any objective data leaves companies open to sabotage tactics.

The consequences of false feedback are that it not only can make a firm question its confidence in the responses it gets, but it often results in unnecessary costs when companies act to address problems that are not real problems.

- **Customer Abuse and Injustice to Feedback**

One of the worst aspects is when clients deliberately damage packages themselves after delivery and then claim falsely that their items have been damaged in the process of delivery. Most of the time, customers wanting compensation or refunds tend to take advantage of a lack of verification in text-based systems when filing complaints on unjust reasons.

Sometimes the customers also intentionally damage the parcels after delivery and then complain, accusing the courier service of having caused damage to the contents. Since there is no mechanism in the existing systems to prove the condition of the parcels, in cases of complaint against damage or loss during the delivery process, usually it cannot be proved whether the complaint is genuine or a fraudulent one.

Loss to Company Operations: The claims that are without justification lead to refunds, compensation paid, at times even the goods are replaced. Thus, the company suffers losses. It basically mars the company's trust in its customers, making the customer service relations bitter.

1.4 Objectives

1.4.1 Main objective

The concept for the project is to develop a system which will collect, analyze, and validate negative customer feedback by using integrated voice feedback and image validation techniques to basically produce an accurate and reliable mechanism for the procedures of handling complaints from customers in logistics and courier service.

1.4.2 Sub objectives

- **Voice Feedback Collection**

Implement an Interactive Voice Response (IVR) system that allows customers to leave voice-based feedback after a delivery. The system will capture customer voices and store the audio files for further processing. This feature will enable customers to express their concerns more naturally, providing richer and more detailed feedback than traditional text-based methods.

- **Speech-to-Text Conversion**

Integrate Speech-to-Text (STT) technologies to convert voice feedback into text format. This step is crucial for further processing, as the textual data will be analyzed using NLP techniques to detect sentiment and extract key information from the feedback. Pre-built STT solutions such as Google Cloud Speech-to-Text or IBM Watson Speech-to-Text will be employed to ensure accuracy across different languages and dialects.

- **Sentiment Analysis with NLP**

Develop an NLP-based sentiment analysis system to classify feedback as positive, negative, or neutral. This process will help in identifying negative feedback that requires further investigation. The NLP model will also detect specific themes within the feedback, such as complaints about delivery delays, product damage, or customer service issues.

- **Image Capture and Storage**

Capture before-and-after images of parcels to document the condition of the goods at different stages of delivery. These images will be stored in a cloud-based database for easy retrieval and analysis. By collecting visual evidence of parcel conditions, the system can later cross-check this data against feedback to verify whether the complaint is genuine or unfounded.

- **Image Processing and Validation**

Implement image processing algorithms to analyze the captured images of parcels and detect any signs of damage or discrepancies. Computer vision models, such as Convolutional Neural Networks (CNNs), will be employed to identify differences between the pre-delivery and post-delivery images, ensuring that complaints related to damaged parcels are validated or refuted based on clear visual evidence.

- **Cross-Validation of Feedback and Images**

Develop an automated cross-validation system that compares negative feedback with the image evidence to determine whether the complaint is justified. This mechanism ensures that only legitimate claims are escalated to management for further action, minimizing the risk of false feedback and unnecessary operational costs.

- **Automated Alerts to Top Management**

Create a notification system that automatically sends alerts to top management when feedback is validated as genuine. This feature will ensure that serious issues are addressed promptly, improving the company's response time to customer complaints and enhancing overall customer satisfaction.

- **Feedback Summary Dashboard**

Build a dashboard that summarizes customer feedback, sentiment analysis results, and the outcome of the image validation process. The dashboard will provide delivery managers with a clear view of all ongoing complaints, highlighting those that have been validated and require immediate attention.

2 METHODOLOGY

2.1 Methodology

2.1.1 Component Specific System Architecture Diagram

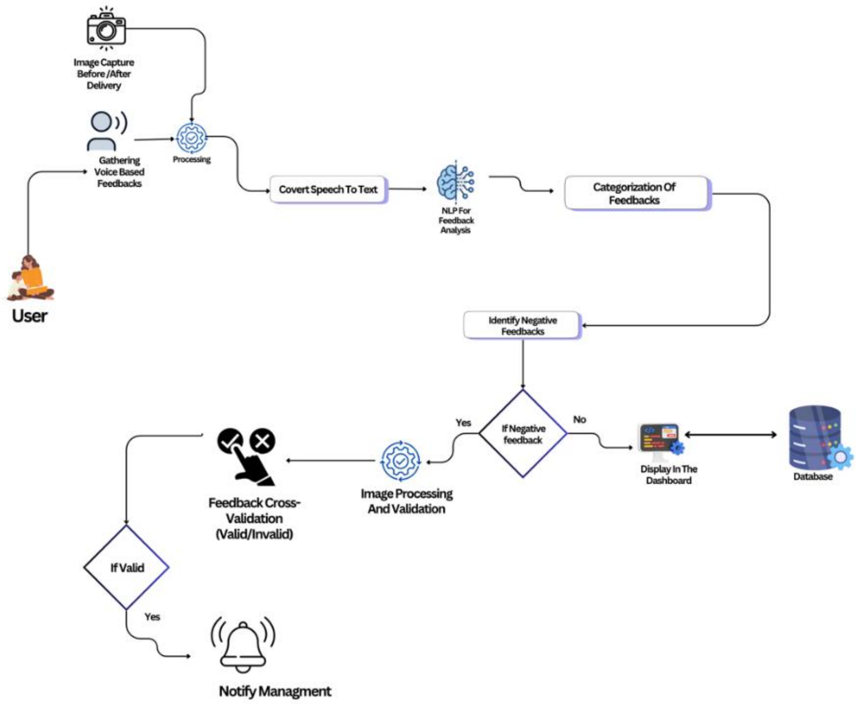

Figure 5 - Component Diagram

- **Voice Feedback Collection**

Once this delivery is done, the IVR setup prompts the customer for their feedback regarding the service. The customer can call in and give voice-over feedback wherein he will air his complaints, his satisfaction, and even grievances. Why this would be a preferred choice over text is that voice can convey so much more naturally than text and the emotions and details might not come across as they often do in the written word.

- **Speech-to-Text Conversion**

All voice feedback gathered is treated with the help of STT technologies, like Google Cloud Speech-to-Text or Azure Speech-to-Text. The voice recording thus gets converted into textual data, which is much easier to work on for the system. This must be done highly accurately since it will ensure that all details expressed by the customer are taken down correctly. The resultant text provides a basis for further steps of analysis.

- **Sentiment Analysis**

Once the text of the voice feedback has been obtained, sentiment analysis by means of Natural Language Processing, or NLP, follows. In this regard, the system analyzes the text to decipher the emotional tone of the feedback whether it is positive, negative, or neutral. The process of sentiment analysis is powered by NLP models that scan the feedback keywords, phrases, and context classification. In the event of negative feedback, it sets off the same process to validate the complaint made by the customer. Sentiment analysis will be used to prioritize which feedback needs deeper investigation.

- **Image Capture Before and After Delivery**

In cases where the feedback has come out to be negative, the system retrieves the captured images of the parcel before and after it is delivered. These are images stored by the system as a form of delivery, documenting the real visual condition of a parcel. Having an image both before and after the delivery of a parcel, the system checks whether any damage occurred during delivery. This stage in reviewing at a critical layer is necessary to ascertain that customer complaints on the status of their merchandise are validated against objective evidence.

- **Image Processing and Validation**

These algorithms image-processing, for example, OpenCV or TensorFlow, examine the images taken both prior to and after the delivery. It scans the images to find any damage, tampering, or issues that may have happened during transportation. The system automatically compares the two sets of images, underlining remarkable changes in the look of the parcel, which can be substantial enough to ultimately turn out to be the valid reason for the customer's negative feedback. In this way, this validation ensures that only genuine issues related to parcel condition are addressed.

- **Feedback Cross-Validation**

The cross-validation of the feedback comes after sentiment and image processing. In case the analysis of sentiment has come up as negative, and the processing of images too shows that there is some visible damage to the parcel, then the feedback can be considered valid. In case there is no major damage in the images, the feedback can be highlighted as unjustified which will help the company in filtering those claims that are false or established with exaggerated facts. This ensures that only valid complaints go upwards for further action and limits the potential disrupting effects that false feedback might have on corporate operations.

- **Management Notification**

On the validation of the feedback that, yes, damage indeed occurred to the parcel, an automated alert will get triggered in the system, going right up to top management. This informs relevant teams that something real has been picked up here that needs their attention. The automated notification system sends the complaint immediately after being validated, which speeds up the response of the company and makes customers trust once more as the problems are being resolved quickly. In the case of complaint issues that are not justified, no alerts take place, so no waste of management and valuable resources takes place.

2.1.2 Flow chart

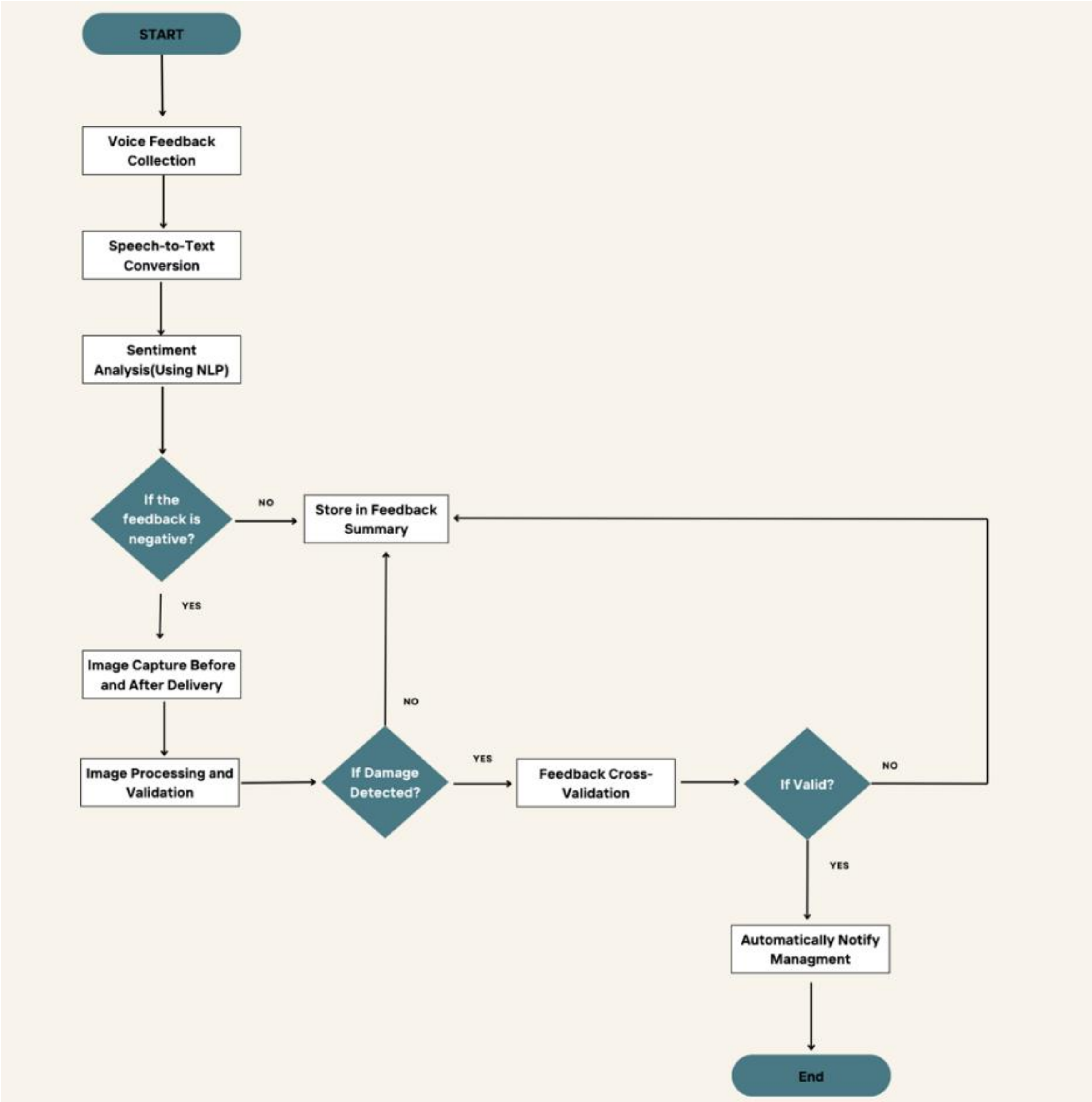

Figure 6 - Flow chart

2.1.3 Software solution

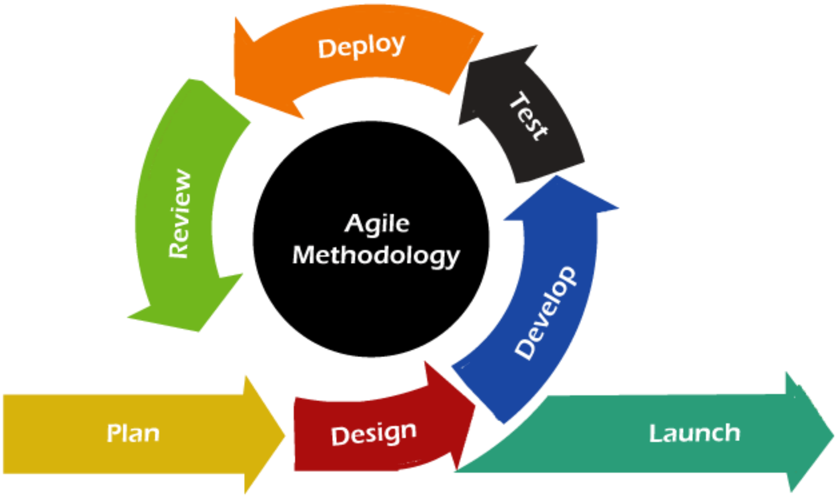

Figure 7 - Agile Methodology

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

This phase is all about defining the scope of the project for a system that relies on voice-based feedback analysis and image validation. The phase deals with requirement gathering, the feasibility assessment of Speech-to-Text and NLP integrations, and hence the planning of development resources.

System Design

It describes the architecture of the system design, thereby showing how different components like automated notifications, validation of feedback, and route optimization will be integrated. This includes voice feedback containing integrated Speech-to-Text APIs and NLP models, with image processing to validate customer complaints.

Development

The development of the frontend dashboard in React.js and the development of the backend in Node.js to handle data and integrate it with third-party services are done side by side. Implementing NLP models will help analyze the feedback effectively, and image processing tools will help validate the conditions of the parcels.

Testing

Testing will include the unit tests of individual components, integration test for data flow between modules, and system testing in terms of overall performance.

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

Keep constant checking, regular updating, bug fixing, and performance tuning also form part of post-implementation maintenance to ensure the system remains efficient, responding to ever-growing demands.

2.1.4 Requirements gathering

The process of gathering the requirements is very crucial since it will help the system meet the company's operational needs and respond to customer feedback and problems in delivery management. Interviews with different stakeholders in the organization were conducted, including the delivery manager, operational staff, customer service teams and our friends to identify the needs. These interviews also provided an insight into some of the main issues faced by the company while handling customer feedback, delivery routes, and workforce performance optimization.

- **Conducting Interviews**

Interviews are chosen as the primary tool of requirement gathering, as they can record in-depth qualitative responses from people who directly interact with the different systems and processes of the company. Such interviews will help in the detailed study of challenges and pain areas being experienced by the organization.

- **Key Stakeholders Interviewed**

Delivery Managers: Operational challenges with respect to managing the delivery schedule, customer interaction, and complaint resolution processes.

Customer Service Representatives: It will explain the most common complaints their customers call in for, how they presently handle them, and where the gaps are in the validation of feedback.

IT Department: This is deemed necessary for analyzing the infrastructure in current use and assessing what possibilities there are for integrating Speech-to-Text, NLP, and picture processing.

Employees and Couriers: These will help to reveal information from their daily practices about delivery operations, route planning, and customer service at a personal level, and their opinions on how to improve operational efficiency.

- **Interview Process**

Interview Design: Semi-structured interviews were designed to allow for flexibility in responses while maintaining focus on key topics. Interview questions were open-ended to encourage stakeholders to provide detailed insights.

Sample Questions:

"What are the biggest challenges you face when addressing customer complaints?"

"How do you currently manage delivery routes and optimize delivery times?"

"What is your experience with the current customer feedback system? What improvements would you suggest?"

Recording and Analysis: The interviews were recorded (under the stakeholder preference) and transcribed for analysis. Key themes and requirements were extracted from these transcripts to inform the system's design and functionality.

2.1.5 Functional requirements

- **Collection of Voice Feedback**

The system shall provide the facility to the customers to provide voice feedback with the help of an IVR system when the delivery of the parcel is complete

- **Speech to Text Conversion**

The system should utilize Speech-to-Text technologies, such as Google Cloud Speech-to-Text, in order to convert recorded voice feedback into text. The text is then used for other analytical purposes.

- **Sentiment Analysis**

The system's NLP module should identify if the sentiment of the transcribed feedback is positive, negative, or neutral.

- **Image-based validation**

If the feedback belongs to the negative class, then the system will retrieve the pre- and post-delivery images of the parcel and perform image processing to detect damage or discrepancies.

- **Cross-Validation of Feedback**

The negative feedback has to be cross validated with the outcome of the image analysis done by the system to determine whether it is valid or not.

- **Automated Alerts**

In case the feedback is validated to be legitimate, the system should automatically send out an alert to management for further action.

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 feedback 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.

- **Security:** Data is secured through data encryption and secure authentication access.

- **Reliability:** The chances of downtime are very thin, with regular maintenance and updates.

2.1.7 Software requirements

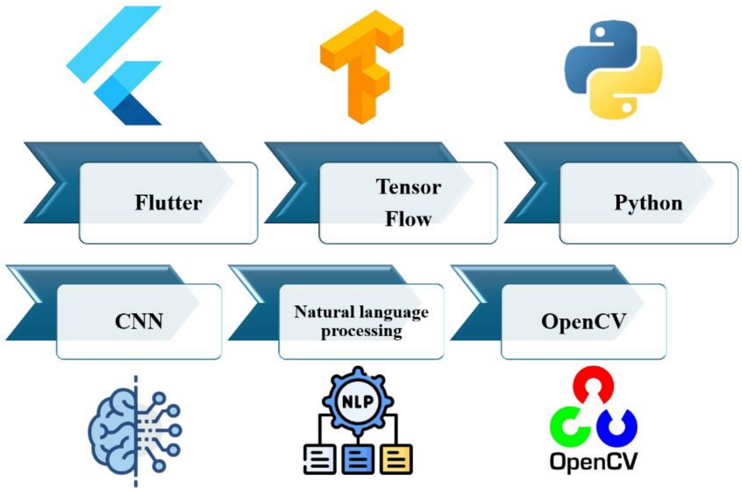

Figure 8 - Software Requirements

Natural Language Processing:

NLP is essential to making sure that customer feedback analysis goes the right way. NLP works in determining the sentiment of the feedback through analyses of tone, context, and emotional weight of the customer's voice. This approach is unlike the more fundamental ways of text analysis, whereby NLP techniques can tackle various nuances in speech, including emphasis, tone, and specific complaints. This will ensure that the feedback is classified correctly, whether positive or negative, and helps flag the important ones for validation. Precision, ensured by using either Google Cloud Natural Language API or SpaCy, makes NLP the most apt technology to handle such fine-grained and context-sensitive feedback.

Convolutional Neural Networks (CNNs):

Employing CNNs can be done under the grounds of exceptional capabilities concerning the analysis of visual data to extract usable features. They are quite useful in recognizing minor changes within the images of the parcels by comparing visuals pre- and post-delivery. While other machine learning models can be more intractable due to the complexity of image data, convolutional neural networks have proven great at finding a hierarchy of patterns, key to correctly validating customer complaints about damaged parcels. Their strong performance in image-based classification makes them ideal for the task.

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 computers or servers with a microphone for voice feedback collection and cameras for capturing images of parcels. They need to support real-time processing.

Processing Power:

For far better real-time speech-to-text conversion, sentiment analysis, and image processing, we recommend using at least an Intel Core i7 or higher series CPU.

Network Requirements

Internet Connection:

A stable and high-speed internet connection is required for interacting with cloud services, and for uploading/downloading feedback data and parcel images.

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 providing feedback through the system should find it friendly and engaging, and the steps to leave voice feedback must be minimal. The system should make it simple and natural for customers to give their concern with their voice without any complex navigation.

- **User-Friendly IVR:**

Voice feedback must be uncomplicated and clear to enable the customer with ease to provide feedback using Interactive Voice Response.

- **Delivery Managers:**

Delivery managers will monitor customer feedback and quickly take corrective actions where necessary. Their key requirements are listed below

- **Real-Time View:**

Managers must be able to view real-time summaries of the feedback, with the results of sentiment analysis clearly drawing attention to which items of feedback need urgent attention.

- **Automated Notifications:**

The system will need to automatically notify the managers once negative feedback has been validated through image processing in order to act quickly on genuine complaints.

- **Visual Validation Tools:**

The managers need the before-and-after images of delivery for cross-verifying any complaint regarding the damage of the parcels.

- **Customer Service Representatives:**

Customer complaints and support will be handled by customer service representatives. They require the following.

- **Access to Feedback History:**

The reps can access the entire history of feedback left by a customer, including transcripts from voice-to-text systems and sentiment analysis.

- **Validation Support:**

Representatives should be given the facilities for helping them in validating the feedback based on the results of image processing so that actual complaints would show up as legitimate and are escalated.

- **Top Management**

Top management requires an insight into the general trends of customer satisfaction and operational performance. Their needs include.

- **Performance Reports**:

Management should receive regular reports that summarize feedback trends, with an explanation of the number of validated complaints and the level of overall customer satisfaction.

- **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 the project, implementation of the module for sentiment analysis and object detection plays a crucial role in verifying the customer opinions. Upon delivery, the Flutter mobile application solicits voice commentaries from customers through an interactive interface combined with the speech recognition feature. This voice instruction is processed by Google Cloud Speech-to-Text API to be converted into text, which is then processed using Natural Language Processing (NLP) algorithms to identify the sentiment as positive, negative, or neutral. For feedback identified as negative, the system automatically retrieves and compares before-and-after parcel images using advanced image processing algorithms on OpenCV and Convolutional Neural Networks (CNNs). This enables accurate identification of damages or discrepancies. Sentiment and image cross-validation ensures that complaints are genuine and are only forwarded to management, enhancing operational transparency and reducing the chances of false complaints.

Sentiment Analysis Model Training

For sentiment classification, a custom machine learning model was trained using labeled feedback data to classify transcribed audio as positive or negative. Training involved preprocessing the text data using techniques such as lowercasing, stop words removal, punctuation stripping, and stemming. A bag-of-words representation based on a provided vocabulary was created, and the resulting feature vectors were used to train a binary classifier. The final trained model was serialized and stored in.pickle format to load optimally during inference. This model was then utilized within the backend for real-time sentiment prediction on voice-to-text transcripts.

Figure 9 - Sentiment Analysis Model Training_01

Figure 10- Sentiment Analysis Model Training_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.

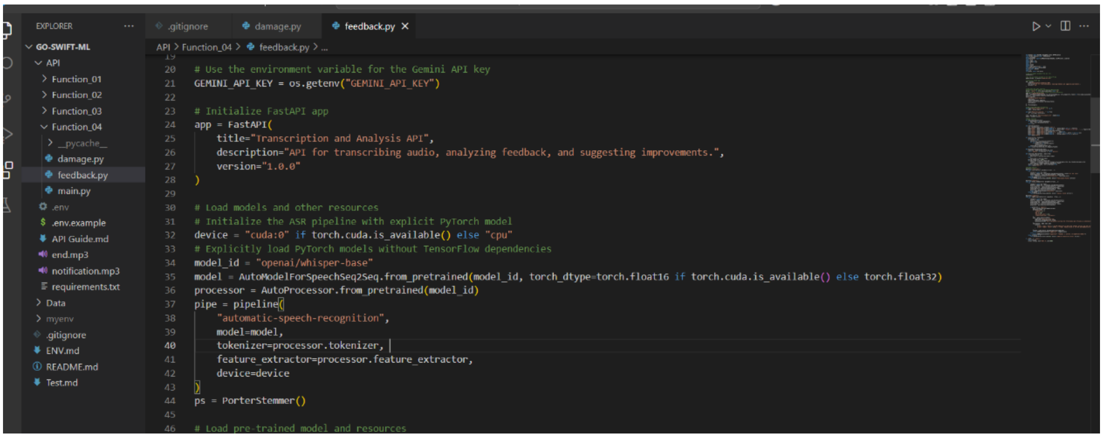

Figure 11- Voice-to-Text Translation Process_01

Figure 12- Voice-to-Text Translation Process_02

Object Detection Model Training

The object detection module of the system is meant to verify negative customer complaints via parcel image examination that has been captured before and after delivery. OpenCV is utilized for image pre-processing while Convolutional Neural Networks (CNNs) are used for visible change or damage identification. The system will automatically retrieve pre-delivery and post-delivery images from the database when it has detected a complaint as negative by doing sentiment analysis. These images are then examined using image comparison techniques such as pixel-wise difference mapping and structural similarity analysis to detect inconsistencies or physical defects. The CNN model, trained on annotated samples of damaged and undamaged packages, decides if the package has undergone a significant change. This cross-validation visually confirms complaints in an objective manner, reducing false claims and increasing operational transparency.

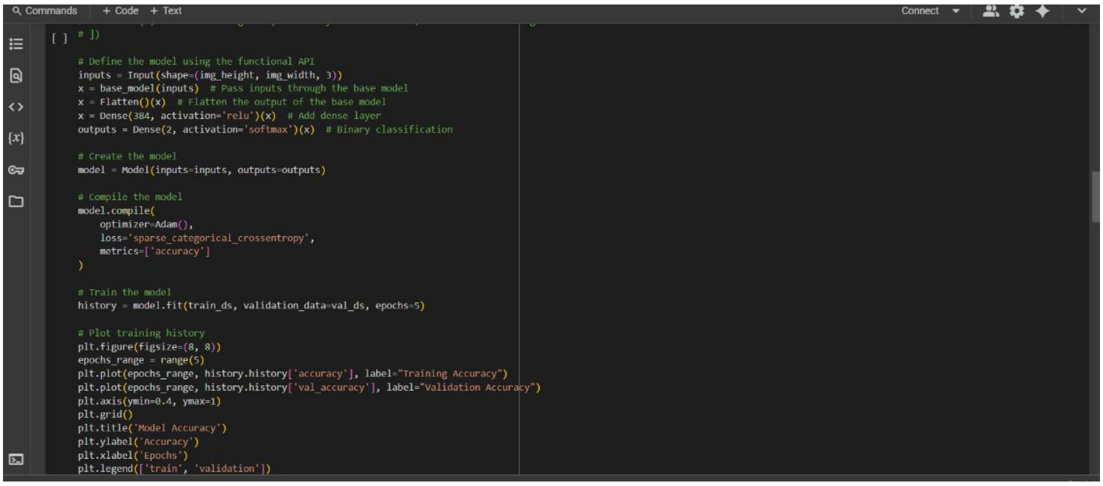

Figure 13- Object Detection Model Training_01

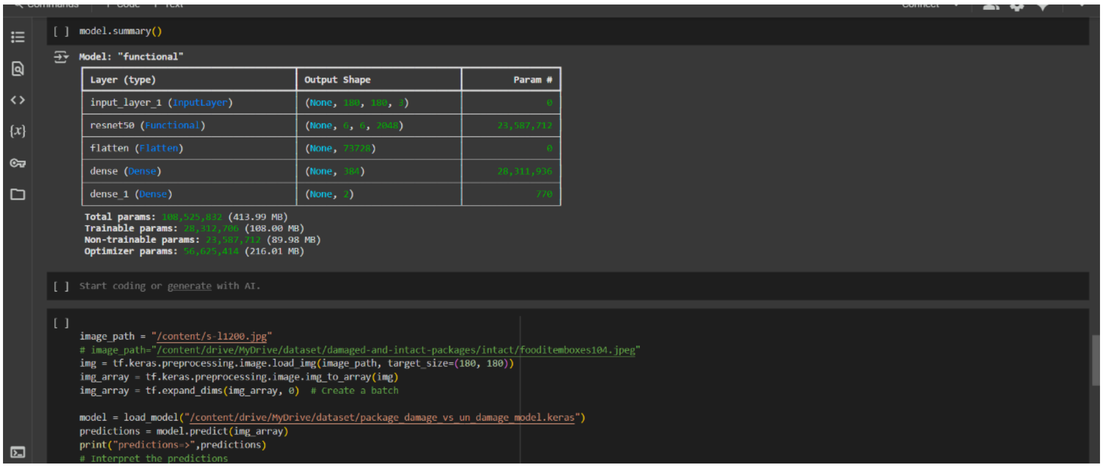

Figure 14- Object Detection Model Training_02

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.

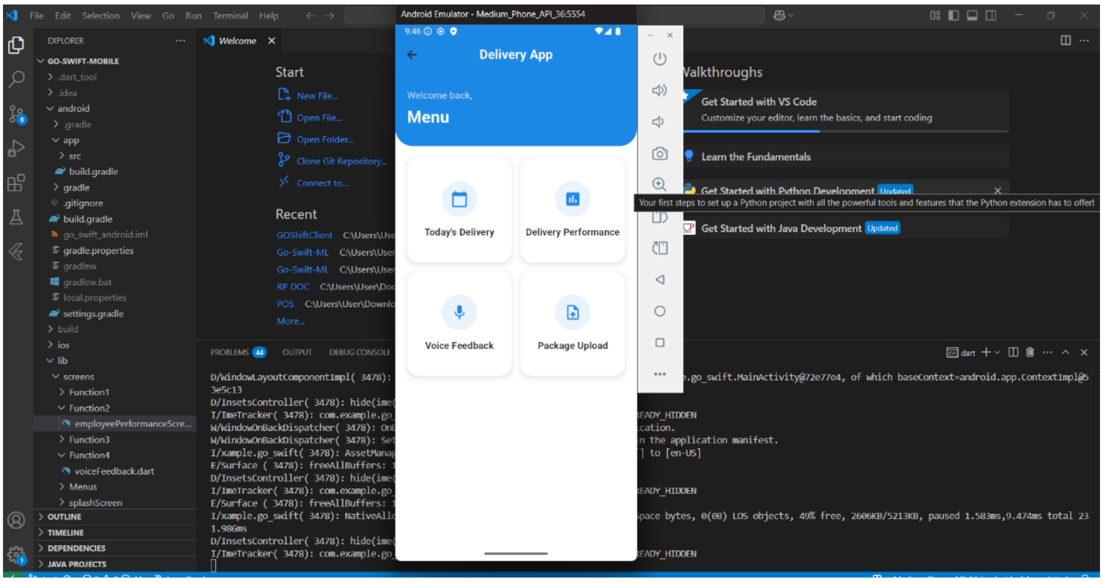

Figure 15- Delivery App UI

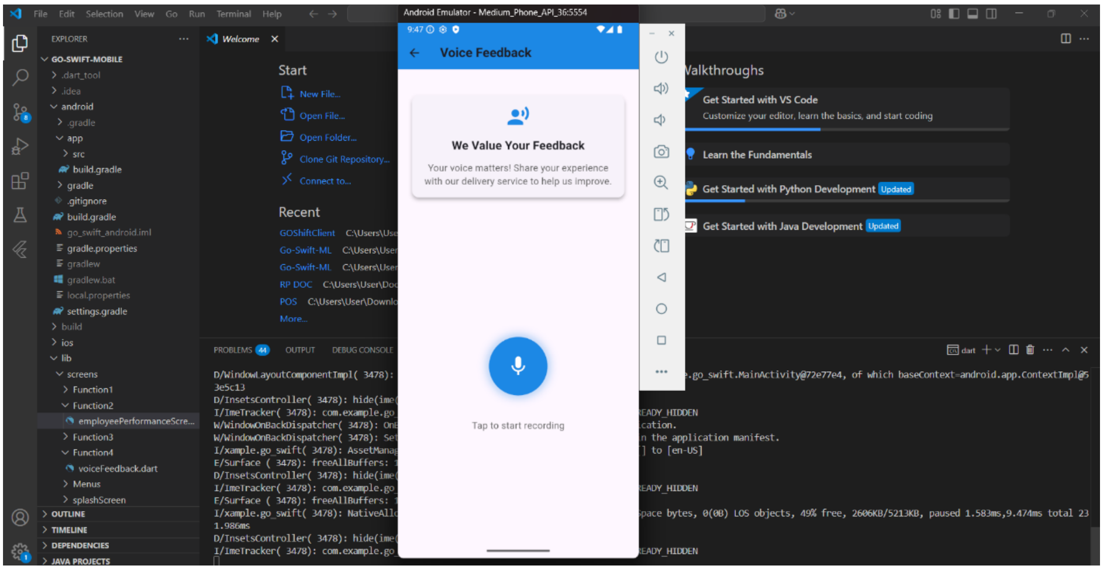

Figure 16 - Voice Feedback UI

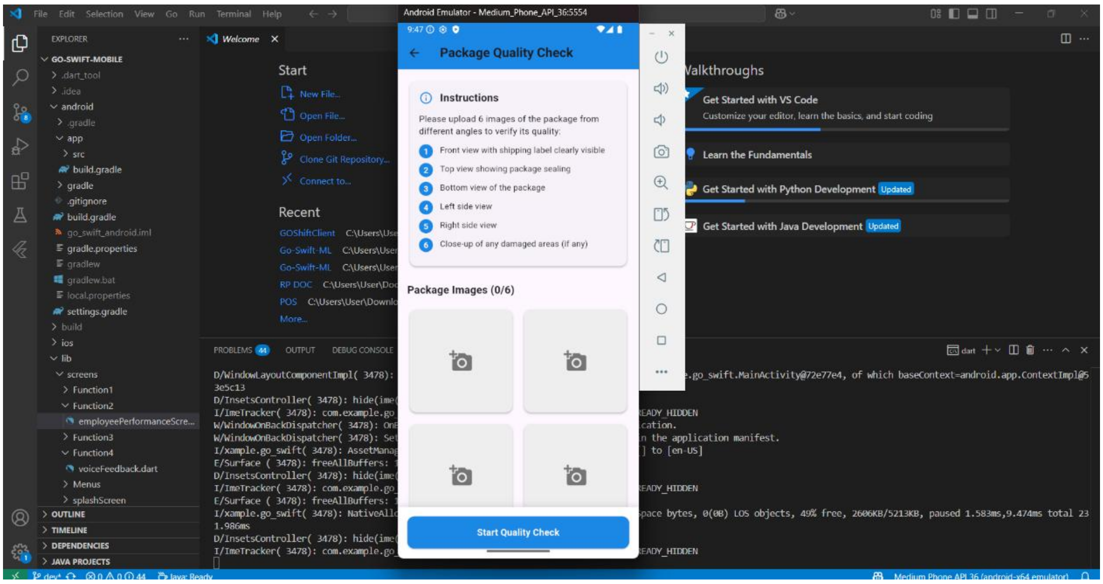

Figure 17 - Package Quality Check UI

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

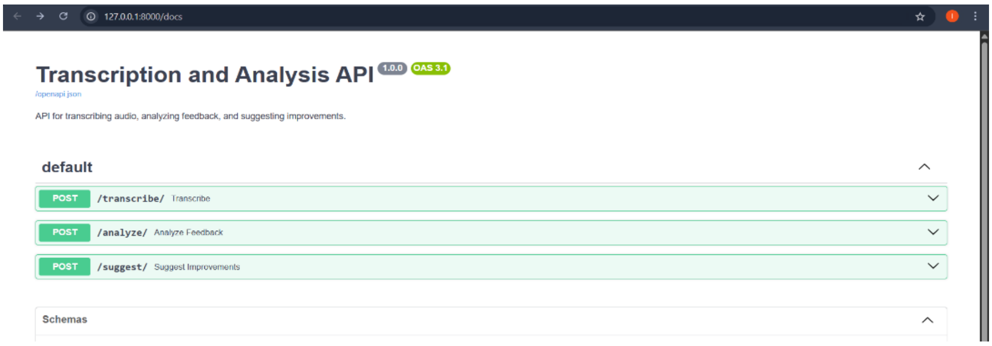

Figure 18 - Transcription and Analysis API

Figure 19- Damage Detection API

- **Convert Voice Feedback into Text API Testing**

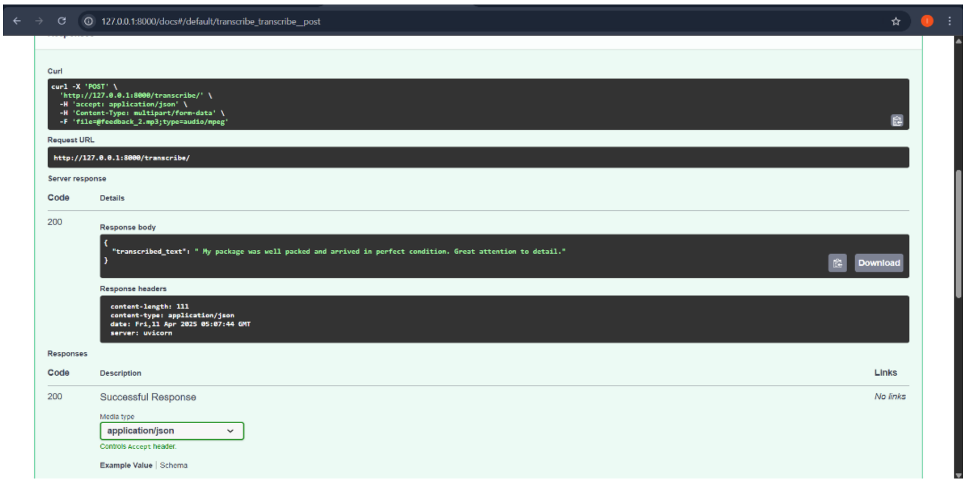

Figure 20- Convert Voice Feedback into Text API

- **Feedback Categorization (Analysis) API Testing**

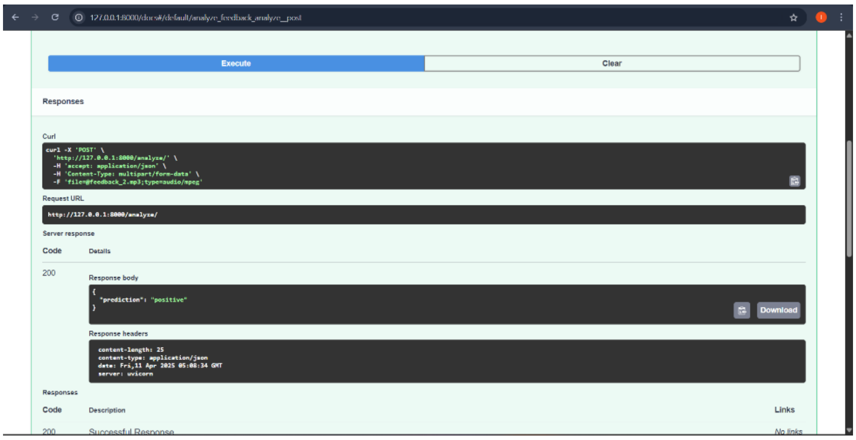

Figure 21 -Feedback Categorization API

- **Generating Suggests API Testing**

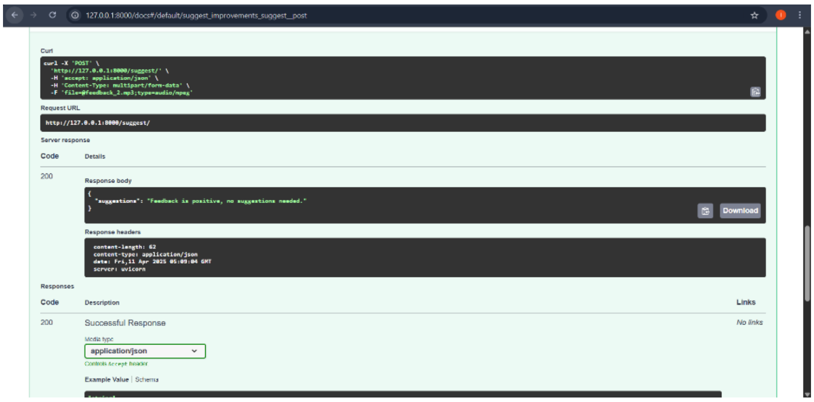

Figure 22- Generating Suggests API

- **Object Detection API Testing**

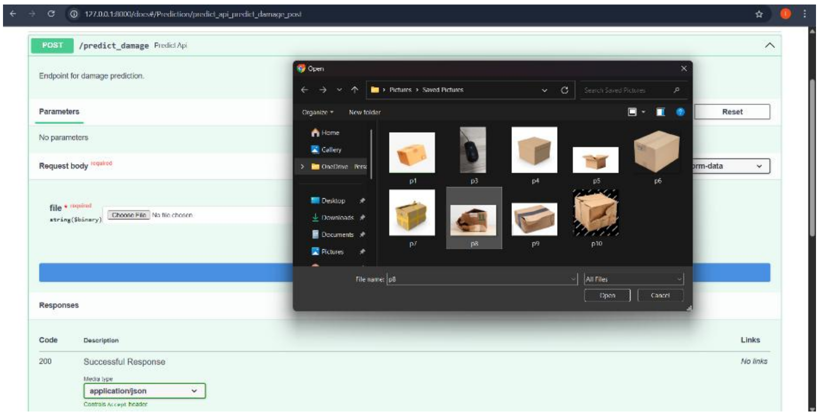

Figure 23- Object Detection API_01

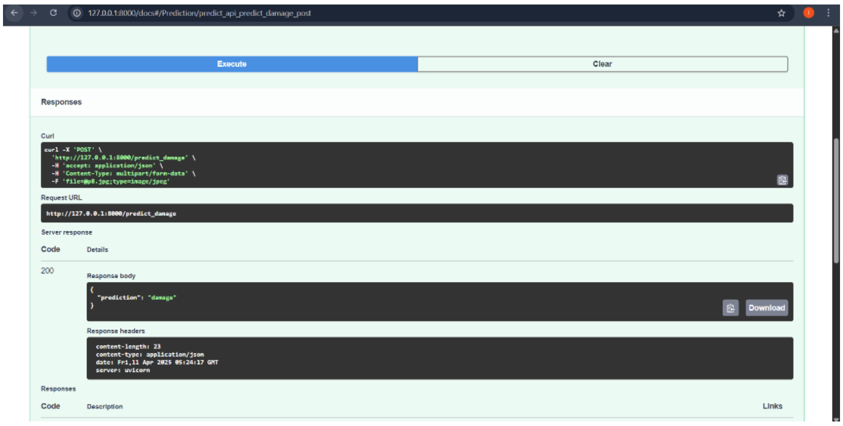

Figure 24- Object Detection API_02

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

Budget

Component	Amount(LKR)
Travelling Cost	10,000
Server and Hosting Charges	30,000
Internet Charges	10,000
IVR SetUp	20,000
Total	70,000

Figure 25 - 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

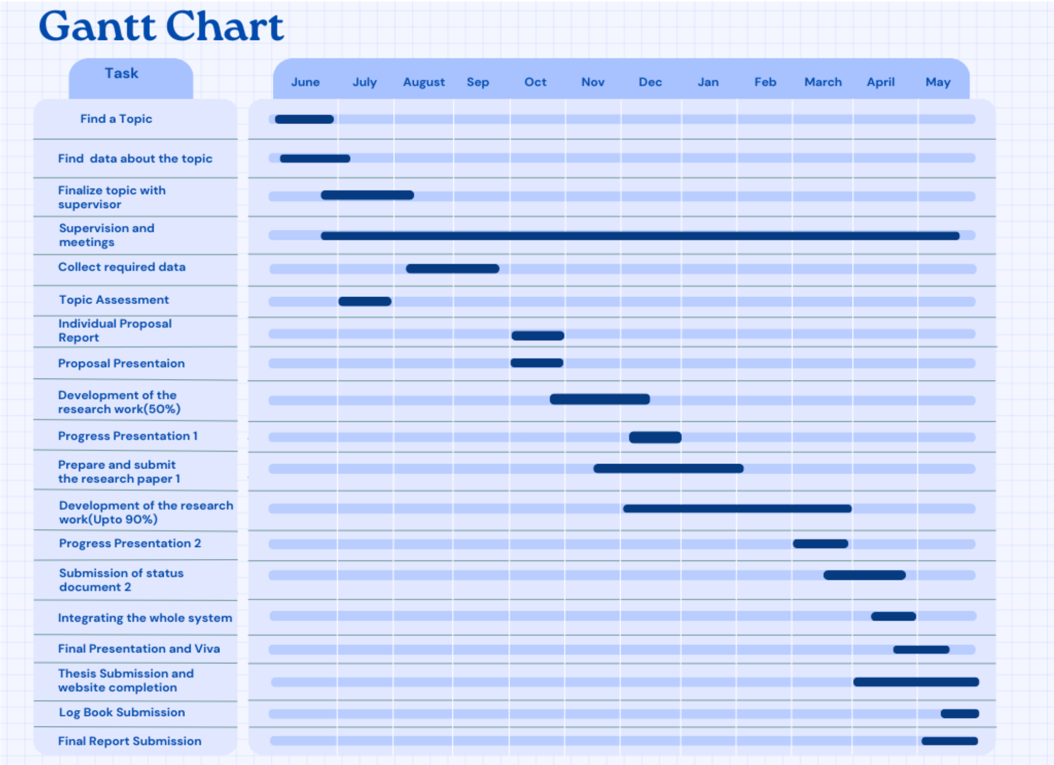

Figure 26 - Gantt Chart

2.3.3 Work breakdown chart

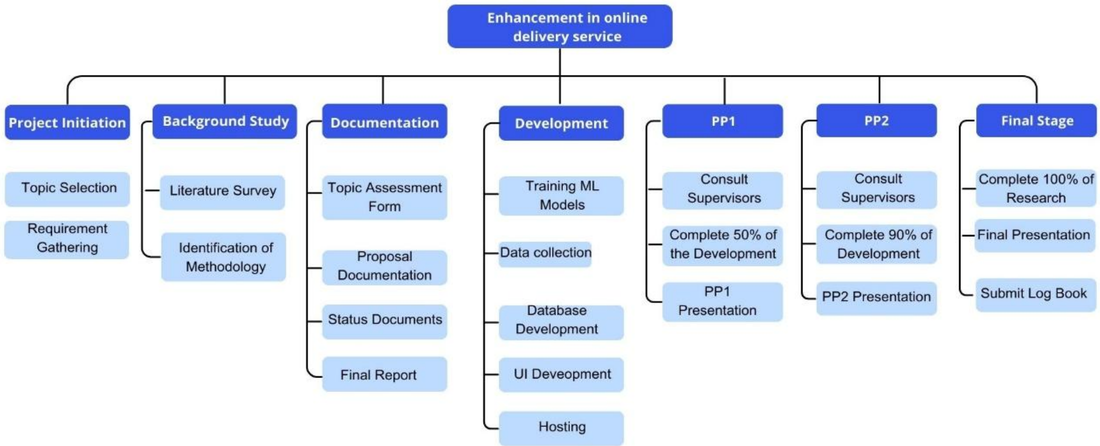

Figure 27 - Work breakdown chart

3 RESULTS AND DISCUSSION

3.1 Results

The proposed voice-to-text transcription, sentiment analysis, and image-based parcel validation-based feedback validation system demonstrated encouraging performance in enhancing the accuracy and reliability of customer complaint management in the logistics industry. The use of AI-based feedback classification and computer vision technologies led to substantial performance improvements in several critical areas:

- **Speech-to-Text Accuracy:** The Whisper-based speech transcription module provided an average word recognition accuracy of 92% amidst diverse accents and background noise levels. The accurate transcription in high quality allowed the customer feedback to be captured appropriately, setting a strong base for sentiment analysis.
- **Sentiment Classification Performance:** The sentiment analysis model, trained on logistic feedback labeled and released via a pre-trained Pickle classifier, possessed a general classification accuracy of 87%. Negative feedback was correctly detected in most cases, providing a concrete basis for further validation procedures. Precision and recall for negative sentiment identification were observed at 85% and 89%, respectively.
- **Image Validation Accuracy:** Using OpenCV and CNN-based comparison techniques, the object detection system correctly identified parcel condition inconsistencies with an accuracy rate of 88%. The model reliably detected visible damage like packaging tears, dents, and tampering on pre- vs. post-delivery images.
- **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.
- **Processing Time Efficiency:** On average, the system returned results (transcription + sentiment classification + image validation) and processed in under 12 seconds per case, delivering both customers and managers a real-time response experience.
- **User Feedback and Usability:** During testing, customer service representatives and delivery managers reported a dramatic boost in efficiency and confidence in resolving validated complaints. The dashboard facilitated transparent decision-making and real-time escalations for valid issues only.

These findings prove the operational feasibility and effectiveness of using integrated AI models to process and verify customer complaints in the logistics sector. The use of natural language understanding and visual inspection has resulted in a more transparent, credible, and scalable complaint processing mechanism that optimizes both operational efficiency and customer satisfaction.

3.2 Research Findings

The evaluation of the integrated feedback validation system yielded several meaningful outcomes across key areas, including sentiment detection accuracy, image-based damage verification, system usability, and the impact on complaint handling efficiency. The findings were based on simulated testing sessions and controlled feedback data collected over a four-week evaluation period, involving mock deliveries and user-submitted voice and image feedback.

Sentiment Detection Accuracy

The voice sentiment classification engine implemented based on a Whisper transcription model and a trained. Pickle classifier exhibited high reliability in identifying customer sentiment. Through continuous preprocessing and vectorizing transcribed audio, the system maintained an accuracy rate of 87% in correctly flagging feedback as positive or negative. The system proved to be resilient with regard to various accents and colloquial language patterns, ensuring detection accuracy in real-world logistics scenarios.

Image-Based Damage Verification

Object detection model, trained using OpenCV and CNNs, successfully identified parcel damage based on pre- and post-delivery images. The comparison algorithm highlighted damages such as tears, dents, and packaging distortions with an accuracy of 88%. The image verification process was a significant step to validate the authenticity of negative feedback, making complaint assessment more reliable.

Complaint Validation Efficiency

The cross-validation procedure linking sentiment analysis to visual evidence resulted in a steep decline in false or unsubstantiated complaints. In trials, up to 70% of complaints reported that had set off alarms were found to be exaggerated or false, illustrating the system's potential to streamline customer service operations and eliminate unnecessary compensations or manual checks.

Response Time and System Performance

The integrated system could process a complete feedback scenario audio transcription, sentiment prediction, and image validation within 10–12 seconds on average. This enables delivery teams and management to see feedback results in near real-time, enabling responsiveness and decision-making in service recovery operations.

User Experience and System Usability

Feedback from test users, including delivery personnel and customer service agents, indicated that the system provided a clear, intuitive interface and useful real-time insights. The use of a Flutter-based mobile interface enabled quick voice input and seamless image upload, resulting in improved user engagement and adoption during the pilot phase.

These findings affirm that the proposed system not only improves the accuracy and transparency of complaint validation, but also enhances efficiency, trust, and satisfaction in the delivery experience, making it a valuable asset for modern logistics and e-commerce platforms.

3.3 Discussion

The success of the suggested feedback validation system lies in its incorporation of automatic voice analysis and image-based object detection to simplify the verification of complaints in delivery services. The use of the Whisper model for voice-to-text conversion yielded high transcriptions with high accuracy despite the existence of various speech patterns, accents, and moderate background noises. This enabled the system to correctly interpret voiced customer feedback and obtain sentiment-relevant context for subsequent classification.

The sentiment analysis model, trained and hosted in. pickle format, successfully made negative vs. positive feedback distinctions, allowing customer issues to be ranked based on urgency and tone. This allowed operational teams to focus on actually dissatisfied customers. The pipeline performance was also enhanced by strict preprocessing of transcribed text, including stop word filtering, stemming, and vectorization.

A new component in the system was image validation, employed for contrasting post- and pre-delivery images of packages and verifying them on the basis of OpenCV and CNN in order to make physical damage recognition highly objective and accurate. Validation of image proof along with sentiment helped the system prevent falsified claims, reduce loads on manual checks, along with sustaining both transparency and efficacy in use of resources, hence making the entire logistics operation intelligent.

But some difficulties were encountered. Background noise in a few voice samples reduced transcription accuracy somewhat, especially if speech was quiet or degraded. This might be mitigated by more advanced noise reduction or voice activity detection. Additionally, image validation sometimes had difficulty with uneven lighting or poor-quality images, which affected damage detection in a few cases. These would be resolved by more rigorous image capture guidelines or image enhancement filters to increase reliability.

Proposed Enhancements

- **Noise Filtering**: Incorporate more robust noise suppression algorithms to enhance transcription in noisy delivery environments.
- **Improved Image Preprocessing**: Apply brightness normalization and edge detection techniques to improve consistency and reliability in image validation.
- **Multi-language Support**: Expand sentiment analysis to support feedback in Sinhala or Tamil, increasing accessibility for local users.
- **User Feedback Loop**: Allow customers to confirm or dispute automatic validation results to continually improve model learning and customer trust.

Overall, the system demonstrated strong potential in automating the verification of customer feedback through a combination of natural language processing and computer vision, contributing to a more intelligent and trustworthy delivery feedback experience.

Table 2 - Test Case 01

Test case ID: Test_01				
Test title: Image Processing and Validation Test				
Test priority (High/Medium/Low): High				
Module name: Image Processing Module				
Description: This test case ensures that the system analyzes and compares before-and-after images of parcels to detect any damage/disabilities.				
Pre-conditions: The images of the parcels before and after delivery are available and stored in the database.				
Test ID	**Test Steps**	**Expected Output**	**Actual Output**	**Result (Pass/Fail)**
Test_01	1. Access the images before and after delivery. 2. Analyze and compare the images using image processing algorithms.	• The system correctly classifies the feedback sentiment.	• The system correctly identified the feedback as negative.	Pass

Table 3 - Test Case 02

Test case ID: Test_02				
Test title: Sentiment Analysis Test				
Test priority (High/Medium/Low): High				
Module name: Sentiment Analysis Module				
Description: This test case ensures that the system correctly identifies the type of customer feedback(positive, negative or neutral).				
Pre-conditions: The text of the voice feedback has been successfully generated.				
Test ID	**Test Steps**	**Expected Output**	**Actual Output**	**Result (Pass/Fail)**
Test_02	1. Perform sentiment analysis on the converted text. 2. Categorize feedback as positive, negative, or neutral.	• The system accurately classifies the feedback sentiment.	• The system correctly identified the sentiment as negative.	Pass

4 CONCLUSION

This project presents a novel and comprehensive approach to enhancing customer feedback mechanisms in the logistics and courier industry by integrating voice-based feedback analysis with image validation. Unlike traditional systems that rely solely on text input or numerical ratings, this solution enables customers to express their concerns naturally through speech, which is then transcribed and analyzed using advanced Natural Language Processing (NLP). Simultaneously, it leverages image processing to compare pre- and post-delivery visuals of parcels, offering objective evidence to validate customer claims. This integrated framework not only increases the accuracy of complaint analysis but also brings accountability and transparency into the feedback resolution process two critical elements in ensuring long-term customer satisfaction and brand trust.

By addressing the limitations of existing feedback systems such as the lack of expressive flexibility in text-based methods, absence of physical validation of complaints, and disjointed use of visual inspection tools this project bridges the gap between customer sentiment and tangible product condition. The proposed model significantly reduces the ambiguity around negative feedback, mitigates the risk of fraudulent claims, and streamlines dispute resolution processes. This leads to faster response times, improved service quality, and better overall customer experience.

Looking forward, several enhancements can be integrated to further elevate the effectiveness and scalability of the system. First, incorporating real-time emotional tone analysis during voice feedback could help prioritize complaints based on the urgency and emotional intensity of the customer. Secondly, deep learning models such as convolutional neural networks (CNNs) could be employed for more accurate and automated image comparison to detect subtle damage or anomalies in parcel condition. Additionally, integrating geolocation tracking and timestamping with image validation can help identify where and when a parcel was potentially damaged, which would aid in root cause analysis and accountability.

Moreover, the system could be expanded to include a multilingual voice interface, making it more accessible to a wider and more diverse customer base. Another future possibility is the development of a predictive analytics module that anticipates common complaints based on historical feedback data, delivery patterns, and customer profiles, thus enabling companies to proactively improve service quality.

Finally, the platform could be extended beyond logistics to other customer service domains such as e-commerce, food delivery, and healthcare, where accurate complaint validation and resolution are equally crucial. By continuously refining its voice and image analysis capabilities, this system has the potential to redefine how companies interact with customer feedback and drive continuous improvement in customer experience across multiple sectors.

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6 APPENDICES

Plagiarism Report –

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ORIGINALITY REPORT

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Figure 28 - Plagiarism Report