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Logi-Track: An AI-Enabled Proof-of-Delivery Framework Using OCR, EfficientNet-Lite, and Geo-Validation

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Abstract: The e-commerce platform has grown rapidly since COVID, with contactless delivery becoming prevalent. Every day millions of parcels are shipped across the globe. Today, many Proof-of-Delivery (POD) systems result in damaged items, incorrect deliveries or no proof of where packages were delivered. Static images and OTP confirmation cannot verify parcel damage, location and drop-off positioning at the intended destination. Logi-Track's smart courier verification software solves these problems. The system and method are well described in Logi-Track. However, its influence may increase through quantitative metrics such as latency, predicted accuracy and performance improvements. The device camera does Optical Character Recognition (OCR) to read and interpret the package label while the package label is mapped to the delivery agent's position. Distance verification compares the delivery coordinates with a geo-tag to verify that the photo was taken within a specified radius and declines deliveries outside of it. Failure of any condition results in non-acknowledgement of delivery. The technical stack includes: React Native or Flutter for cross-platform interoperability, EfficientNet-Lite for package damage detection, Google Maps API for location accuracy, and Tesseract for OCR. These elements develop reliable, efficient delivery records. AI-augmented validation takes the place of OTP and photo confirmation, building a scalable, efficient foundation for operational transparency and consumer satisfaction.

Keywords: Proof-of-Delivery; Optical Character Recognition (OCR); Haversine Formula and Efficientnet-Lite; Package Damage Detection; Geospatial Distance Validation; Google Maps.

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1. Introduction

The e-commerce industry has seen rapid expansion over the past decade, with millions of parcels being delivered daily, especially following the rise [12]. This growth has encouraged the implementation of "leave-at-door" delivery policies, improving delivery convenience. Still, it is also exposing vulnerabilities in existing Proof-of-Delivery (POD) mechanisms [13].

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These vulnerabilities increase the risk of misdeliveries, parcel damage, and package theft, highlighting the need for more reliable verification systems in last-mile delivery environments [14]. Two predominant POD systems currently used in logistics are One-Time Password (OTP) verification and static image capture [15]. Are platforms such as Amazon India, Nykaa, and Blinkit limited in addressing modern logistics challenges? OTP-based systems confirm delivery via customer-shared authentication codes. Still, they depend heavily on network availability and cannot verify whether the parcel is in good condition or has been delivered to the correct location [16]. The static photo is used based on the package's delivery confirmation, which provides visual evidence of its placement. Still, it fails to confirm package integrity, label correctness, or the exact positioning at the intended address. These limitations will demonstrate the needs of the multi-layered POD system that is detected and integrated for verification, inspection, and geolocation validation. This model, as shown in the literature review, detects package damage and enables visualization of the damage scores [17]. This system uses a Convolutional Neural Network (CNN) to analyze parcel images captured at the delivery location and detect structural anomalies, such as crushed corners, edge tears, or surface damage, before delivery confirmation.

Prior studies have demonstrated that deep learning-based object detection models, such as YOLOv5, can identify parcel damage in real time, thereby improving accountability in logistics operations [18]. Optical Character Recognition (OCR) is used to extract shipping label information, including customer name, address, and tracking ID, and to match it with the delivery coordinates to ensure it is placed in the correct parcel. Recent research shows that hybrid OCR models that combine deep learning and traditional OCR techniques can achieve high accuracy even in outdoor environments and reduce misdeliveries, thereby improving the reliability of label recognition [19]. The works use AI to detect whether the parcel is damaged, with severe or minor damage, and are also implementing GPS to ensure accurate delivery placement. The system integrates geodesic distance validation using GPS coordinates. The confirmation image of the delivery package can only be submitted if the image is captured within a 2-meter radius of the intended delivery location. Similarly, it uses geodesic distance calculations, and geo-tagged delivery validation has been shown to improve location accuracy and reduce fraudulent delivery confirmations [11]. Our Logi-Track workflow transforms traditional proof-of-delivery mechanisms into a multi-layered, intelligent verification system by combining AI-based damage detection, OCR-based label validation, and geospatial distance verification, thereby integrating transparency, reducing disputes, and strengthening operational accountability in modern e-commerce logistics systems [10].

2. Literature review

Kamathe et al. [1] conducted an extensive survey and data analytics of e-commerce logistics and proof-of-delivery (POD) challenges. The study says that e-commerce companies are losing nearly `50,000 crore every year due to package theft, wrong deliveries, damaged parcels, and fraudulent customer claims. The authors point out that traditional POD mechanisms, which rely mainly on OTP verification and static delivery photos, are insufficient to provide reliable proof of successful delivery. These methods do not allow for validating the package's condition, verifying the delivery address, or preventing fraudulent claims. The study underscores the necessity for sophisticated AI-driven delivery verification systems that combine computer vision, geolocation verification, and intelligent analytics to offer secure, tamper-proof, and reliable proof of delivery, ultimately enhancing customer satisfaction and mitigating financial losses. Öçal et al. [2] examined the efficacy of One-Time Password (OTP)-based authentication systems for last-mile delivery and identified several drawbacks that render them less reliable as standalone proof-of-delivery techniques. OTP verification confirms that a delivery code has been entered, but not that the intended recipient has received the parcel. The study says that nearly 15% of delivery fraud occurs when customers unknowingly share OTPs with delivery agents or over the phone, allowing fake deliveries to be falsely validated. In addition, OTP-based systems do not provide feedback on the package status, the accuracy of the delivery address, or whether the correct parcel was delivered to the recipient. The authors said that combining OTP authentication with AI-based image verification, geolocation validation, and intelligent delivery evidence should build a more secure, reliable, and tamper-proof proof-of-delivery system.

Cui et al. [3] examined the effectiveness of image-capture verification systems used by courier and logistics services to provide proof of delivery. The research revealed that large courier firms such as DTDC and India Post predominantly rely on static delivery photographs as proof of a successful delivery. But the authors found that almost 40% of delivery dispute cases can’t be definitively resolved by photos alone. Factors that greatly reduce the reliability of static photo-based verification include poor image quality, poor lighting, blurred or incomplete parcel images, GPS spoofing, or failure to detect parcel damage. The study shows that combining image capture with AI-based damage detection, optical character recognition (OCR), and GPS-based location validation can provide tamper-resistant, comprehensive proof of delivery, enhancing delivery accuracy, reducing fraudulent claims, and improving customer confidence in logistics services. Rodoplu and Yıldız [4] designed a deep learning-based parcel damage detection system that employs YOLOv5, Convolutional Neural Networks (CNNs), and StyleGAN3 to improve the dependability of package inspection in the last-mile delivery process. The YOLOv5 model detects objects in real time and accurately identifies structural defects, such as dents, tears, crushed corners, and damaged edges, on parcel boxes. StyleGAN3 is used to generate synthetic training images to improve the model's robustness and detection performance under different environmental conditions. The proposed system also automates parcel inspection within a 2-meter radius of the delivery point to ensure damage assessment is completed before the parcel is handed over to the customer. The findings show that AI-powered damage detection significantly reduces damaged deliveries, enhances accountability for deliveries, reduces customer disputes, and improves the overall efficiency and reliability of proof-of-delivery systems.

Mathpal [5] proposed a Convolutional Neural Network (CNN) based image classification method for automated package damage detection in logistics and delivery systems. The model presented here is intended to detect visible damage, such as damage at the corners, edges, and surfaces of the parcel boxes, which are usually caused during transportation and handling, with images of the parcel boxes. CNN extracts discriminative visual features from labeled training images and effectively distinguishes between damaged and undamaged packages across varying lighting and environmental conditions. The system captures images and records the parcel's status before delivery, providing reliable visual evidence and increasing accountability among courier services and customers. The study shows that integrating CNN-based damage detection into proof-of-delivery workflows improves customer confidence through objective, automated verification of parcel condition, reduces disputes, enhances package-handling standards, and strengthens quality assurance.

Sayeesh et al. [6] proposed a hybrid framework for Optical Character Recognition (OCR) that integrates Tesseract OCR with CNN-based deep learning models to improve the accuracy of parcel label recognition in logistics applications. Experimental results show that the hybrid approach achieves more than 90% recognition accuracy even when parcel labels are tilted, partially occluded, blurred, or captured under poor lighting conditions. This robustness is especially crucial in real-world delivery environments where courier personnel often work outdoors under varied weather and illumination conditions. The system accurately extracts recipient details, addresses, tracking numbers, and other essential information from parcel labels, significantly reducing wrong-address deliveries and manual verification errors. The research finds that integrating OCR with deep learning improves delivery efficiency, supports automated proof-of-delivery systems, and enhances the overall reliability and accuracy of last-mile logistics operations.

Faizy and Sutopo [7] investigated the use of Tesseract OCR and deep learning-based OCR methods for the automated recognition of parcel labels in logistics and courier services. The proposed system accurately extracts critical information such as recipient names, delivery addresses, tracking numbers, and barcode information from parcel labels without manual data entry. The system combines traditional OCR with deep learning algorithms to enhance text recognition accuracy, even when labels are damaged, rotated, blurred, or captured under difficult lighting conditions. The information extracted is then compared with the relevant delivery records to verify that the correct parcel is delivered to the intended destination. The research finds that intelligent OCR significantly reduces misdelivery and human error, improves operational efficiency, and enhances the accuracy of proof-of-delivery systems through automated, accurate parcel identification.

Tigani [8] performed a survey and data analytics study to investigate the key challenges in last-mile package delivery and customer satisfaction. The research found that a staggering number of customers had been victims of package theft or wrong, late, or doorstep deliveries. The results suggest that a significant portion of these incidents stemmed from incorrect address labels, human errors during delivery, and the lack of robust location verification methods. The study says traditional proof-of-delivery systems are inadequate to prevent such problems and recommends that delivery systems should have GPS-based location validation. GPS technology can reduce misdeliveries and improve delivery accuracy, minimize fraudulent claims, and build customer trust in e-commerce and logistics services by verifying that the delivery person is physically at the right location before confirming the delivery. Chmielewski and Sibilski [9] introduced a GPS-based location-validation framework to precisely verify the location of delivery personnel during the proof-of-delivery process using the Haversine formula. The system computes the distance between the courier's real-time GPS coordinates and the customer's registered delivery location. It only allows delivery confirmation when the courier is within a predefined 2-meter radius of the destination. This also effectively prevents fraudulent delivery confirmations from remote locations or incorrect locations. It also reduces the risk of errors caused by manual location reporting. The proposed framework improves delivery authenticity, minimizes package misdeliveries and false claims, and offers strong location-based evidence by incorporating accurate geospatial validation into last-mile delivery operations. The study finds that integrating GPS proof verification and smart proof-of-delivery technologies can greatly enhance logistics security, operational transparency, and customer assurance in the present e-commerce delivery systems.

3. Methodology

The Parcel Damage Dataset, Shipping Box Defect Dataset, Logistic Parcel Damage Dataset (LPDD), and augmented synthetic images are collectively used to train the model to recognize real-world parcel damage conditions, such as scratches, crushed corners, folded edges, and torn surfaces, that may be fully damaged or slightly damaged at the edges or the overall parcel. By combining these datasets to improve the model's ability to detect both minor and major structural defects under different lighting conditions, angles, and transportation scenarios, the work can ensure accurate damage assessment before delivery. So our Logi-Track operational pipeline is engineered to ensure real-time parcel validation and hazard detection, with no reliance on the system's cloud latency:

Real-time Frame Acquisition: The system initiates continuous capture of visual data and information via the mobile device's camera sensor, implemented with Flutter for the mobile application. To balance this, frames are downsampled to 320 × 320 pixels. The image capture frequency is maintained between 10 and 20 frames per second (fps), providing sufficient temporal resolution to track movement and package condition without saturating the processor.

Localized Edge Inference: The raw pixel data of the captured image is fed directly into the device's Edge TPU (Tensor Processing Unit) or specialized AI accelerator. By performing inference entirely in local memory, the system bypasses the traditional CPU-based bottlenecks. This stage involves executing the EfficientNet-Lite architecture, which analyses the spatial features of the frame to identify parcel labels and assess structural integrity.

Probabilistic Thresholding and Class Filtering: To ensure this, filters are applied to low-probability detections and environmental noise in the captured image, effectively eliminating false positives. The system is programmed to prioritize the high-impact classes, such as shipping the labels, specific damage types, and logistical obstacles, ensuring that only mission-critical data proceeds to the next stage.

Volatile Memory Management: A core feature of our Logi-Track methodology is to ensure privacy and high-speed data handling of the captured image. The entire pipeline captures the distance estimation of the parcel and operates strictly within Volatile Random Access Memory (RAM). The system permanently stores the device and network modules during the inference phase, enabling low-latency processing and ensuring that the system's sensitive visual data is never written to disk, thereby maintaining the user's strict data security protocols.

OCR Shipping Label: The shipping label dataset, containing extracted fields such as customer name, address, phone number, and tracking ID, is used to train and validate the OCR module to accurately extract and verify the customer's address from parcel labels. The label ensures that the system can correctly read, identify, and match the intended recipient of the parcel with the delivery location provided by the customer during the verification process.

GPS Location: GPS coordinates are collected during field testing, along with Google Maps geolocation data and the Geo Life GPS trajectory dataset, which are used to test and validate the distance verification module. These datasets help to ensure the accurate calculation of the delivery man's proximity to the destination and enable enforcement of the 2-meter geodesic distance constraint for reliable proof-of-delivery validation.

4. Results and Discussions

This system uses a Convolutional Neural Network (CNN) to analyze parcel images captured at the delivery location and detect structural anomalies, such as crushed corners, edge tears, or surface damage, before delivery confirmation (Figure 1).

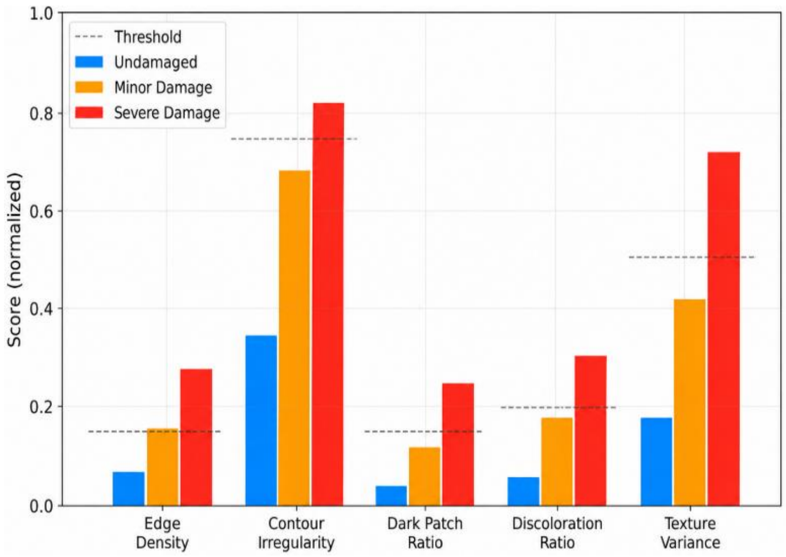

Figure 1: Package damage detection scores across severity levels

Table 1 shows that CNN-based methods achieve the highest accuracy (98.4%), whereas YOLO- and OCR-based systems are prone to issues such as low-light conditions, distorted labels, and computational complexity.

Table 1: Comparison analysis of existing studies in the smart delivery verification system

Authors	Method	Accuracy	Limitation
Rodoplu and Yıldız [4]	YOLOv12	93.3%	Low-light issue
Cui et al. [3]	OCR+YOLO	89.5%	Distorted labels
Öçal et al. [2]	CNN	98.4%	High computation

The Logi-Track system is a conceptualized delivery-tracking system for the deliveryman to verify that the parcel has been delivered correctly to the customer. The literature review covers the work completed by OCR, Geospatial validation, etc.; it primarily describes rather than analyses in depth. and a lack of critical comparison between existing systems. A comparative analysis highlights the limitations of YOLO-based detection and traditional OCR methods, which improve clarity (Figure 2).

Figure 2: Traditional vs proposed delivery system

The bar graph shows the level of damage to the parcel when comparing the traditional and proposed delivery systems, with the parcel potentially showing minor damage. The works can compare and visualize both the traditional POD and the proposed AI system of damage check, location accuracy, and fraud prevention (Figure 3).

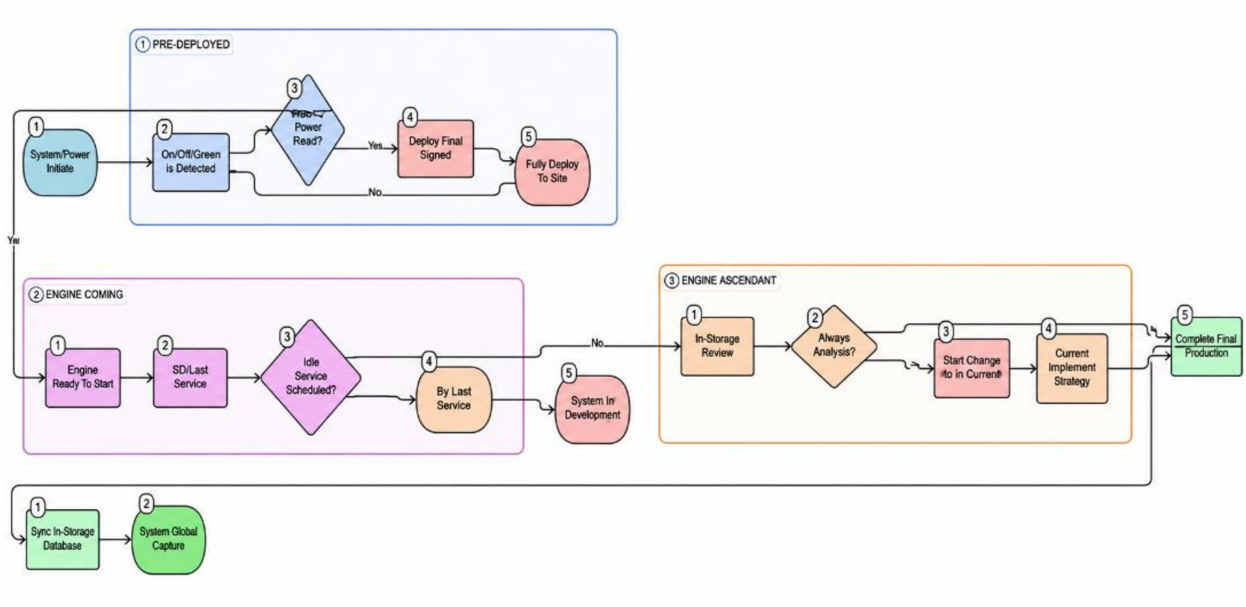

Figure 3: Workflow diagram

The architecture of our logi-track system comprises three modules: Data Capture of Intelligence, Multi-Factor Verification, and Real-time Synchronization. By implementing all these components, the system creates a unit where delivery evidence is not only recorded, but also. Our Logi-Track employs a robust client-server architecture, where the mobile application performs high-edge processing on a high-edge processing unit to reduce parcel damage at edges or corners and minimize latency. To ensure this, the operational reliability in areas will fluctuate the network connectivity, and the system uses Tesseract for localized computer vision tasks. This edge computing approach enables immediate parcel analysis, inspection, and verification without continuous cloud communication. Meanwhile, the backend of our paper is implemented using Firebase, which handles the heavy lifting of real-time data persistence, user authentication, and secure cloud storage. It ensures a seamless connection between courier agencies and the central database, helping reduce parcel damage. In this method, Logi-Track implements two pipelines that have distinct computer vision. The parcel integrity pipeline is the first to utilize Optical Character Recognition (OCR), processed by Tesseract, which extracts the Tracking ID and generates this data. This data is cross-verified in real-time against the digital manifest to eliminate wrong-house errors during delivery. Simultaneously, the second pipeline plays a major role as a Convolutional Neural Network (CNN) for comprehensive damage assessment. This model detects structural anomalies, such as crushed corners on packages or liquid leakage, providing a verifiable record of the package's condition at the exact moment of drop-off. To address the industry's side challenge of "false deliveries" (Figure 4).

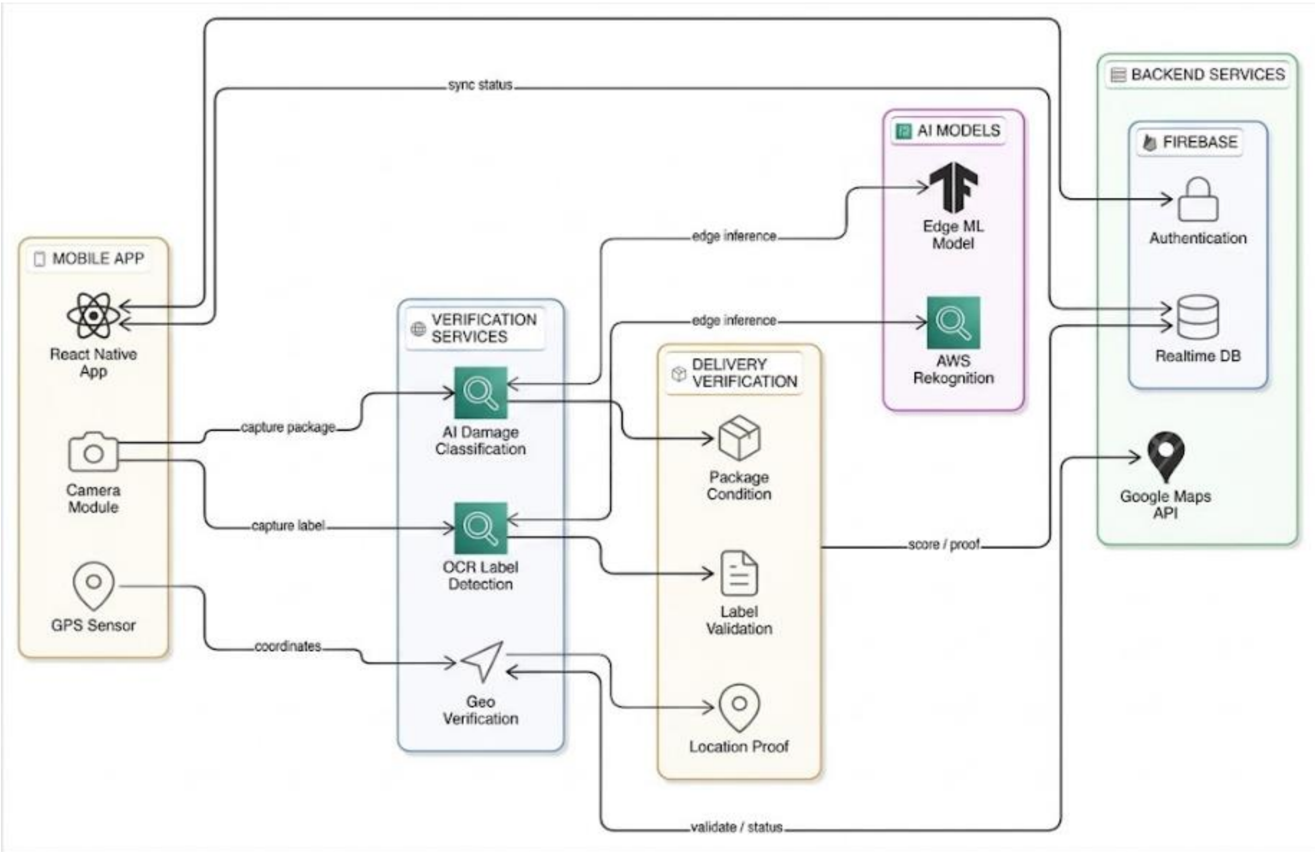

Figure 4: Architecture diagram

Logi-Track introduces a strict geospatial fencing mechanism. By integrating the Google Maps API for GPS, the system retrieves the precise coordinates of the intended destination and compares them with the courier's live GPS data. The system enforces a mandatory 2-meter proximity rule, which is calculated using the Haversine formula to determine the shortest distance over the earth's surface by:

$$d = 2R \,.\, \mathrm{atan2}(\sqrt{a}, \sqrt{(1-a)})$$

Where:

$$a = \sin^2(\Delta\varphi/2) + \cos(\varphi_1)\cos(\varphi_2)\sin^2(\Delta\lambda/2)$$

R=6,371,000m

φ_1, φ_2=latitudes

$\Delta\varphi = \varphi_2 - \varphi_1$

$\Delta\lambda = \lambda_2 - \lambda_1$

The Haversine formula is used to calculate the shortest distance between two points using their latitudes and longitudes. The works were analyzed and used for navigation. The final phase of the framework involves the compilation and secure transmission of the Proof of Delivery (POD) Process. The technological stack is chosen to ensure both performance and security (Table 2).

Table 2: Comparison between traditional POD and the proposed logi-track

Feature	Traditional System	Logi-Track
OTP Verification	Yes	Yes
GPS Validation	No	Yes
OCR Address Check	No	Yes
Damage Detection	No	Yes
Fraud Prevention	Low	High

The frontend is built with Flutter, a mobile framework, to provide a cross-platform interface for couriers. Once the AI validates the parcel condition and the GPS confirms the location, the resulting metadata, including geo-tags and timestamps, is stored in Firebase Firestore. At the same time, high-resolution encrypted images of the delivery are hosted in Firebase Cloud Storage. This dual storage approach ensures that the evidence is tamper-proof: it cannot be manipulated, modified, or altered without detection. If someone tries to change the address, the system will either prevent it or show that it was changed. It is easily accessible for future audits or customer inquiries.

The delivery success rate pie graph is designed to analyze, but it is still strict and reliable. Upon authentication, the courier selects an assigned delivery, which activates the background geospatial monitoring. As the courier approaches the destination, the system continuously verifies the GPS radius only when the 2-meter threshold is met, and the camera interface becomes accessible. The courier then scans the parcel, allowing the OCR engine to verify the label identity and the CNN model to analyze the frame for any physical damage. After that, it is automatically validated to confirm the package's identity and condition, and a notification is sent to the customer to complete the delivery cycle. The paper is implemented in Python, the main programming language. It is well-structured and integrates multiple components, including EfficientNet-Lite, OCR label recognition, Geolocation Validation, and the Haversine formula. So, this can be emphasized by comparing how it is integrated into the framework to improve it (Figure 5).

Figure 5: A sample parcel not accepted

OpenCV is used for image processing, Tesseract OCR is for extracting shipping label text, and Streamlit is for developing the web interface. Google Maps API is integrated for GPS-based location verification. All tools were obtained from official open-source repositories and developer platforms (Figure 6).

Figure 6: A sample parcel accepted

The Logi-Track evaluation has been carried out using the proposed system, which has been successfully implemented and evaluated using parcel images, shipping labels, and real-time GPS coordinates. The system integrates the geo-tagged distance validation, OCR-based label recognition, and EfficientNet-Lite damage detection to ensure it is POD. The GPS module validation uses the Haversine formula to determine whether the delivery agent is at the correct location within an acceptable radius, based on GPS coordinates (Figure 7).

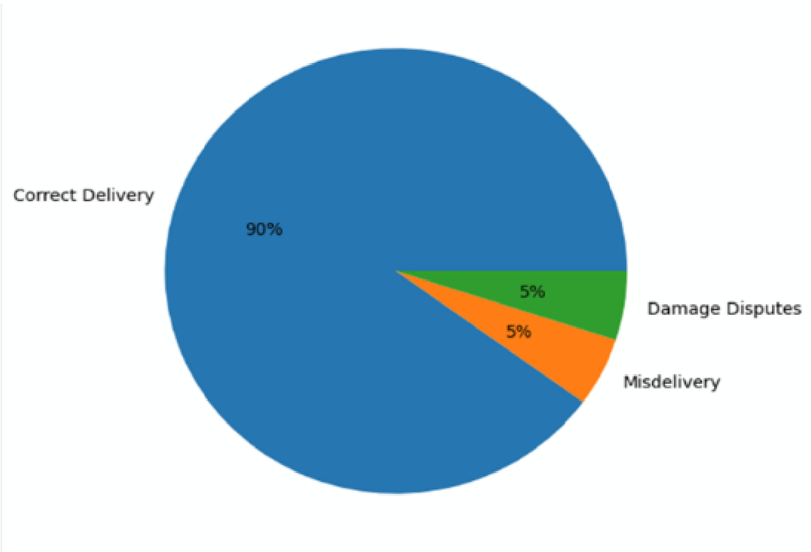

Figure 7: Delivery success rate with the proposed system

The OCR module enriches the high recognition accuracy in extracting the customer details, such as name, address, and tracking ID, under normal conditions. Even with slightly tilted or partially visible labels, the system maintains stable performance through image preprocessing. The damage detection module uses EfficientNet-Lite to classify parcels into undamaged, slightly damaged, and severely damaged categories. It identifies crushed corners, torn surfaces, and folded edges, reducing the risk of undetected damage during delivery (Table 3).

Table 3: Performance evaluation of the proposed logi-track modules

Module	Accuracy	Precision	Recall
OCR	91.2%	90.5%	89.8%
Damage Detection	93.8%	92.6%	91.9%
GPS Validation	95.4%	94.8%	94.1%

4.1. Prototype Implementation and System Output

This image shows end-to-end delivery verification using AI to check whether the package is being delivered. It is also used to check whether the delivery agent is at the correct location or at the wrong one (Figure 8).

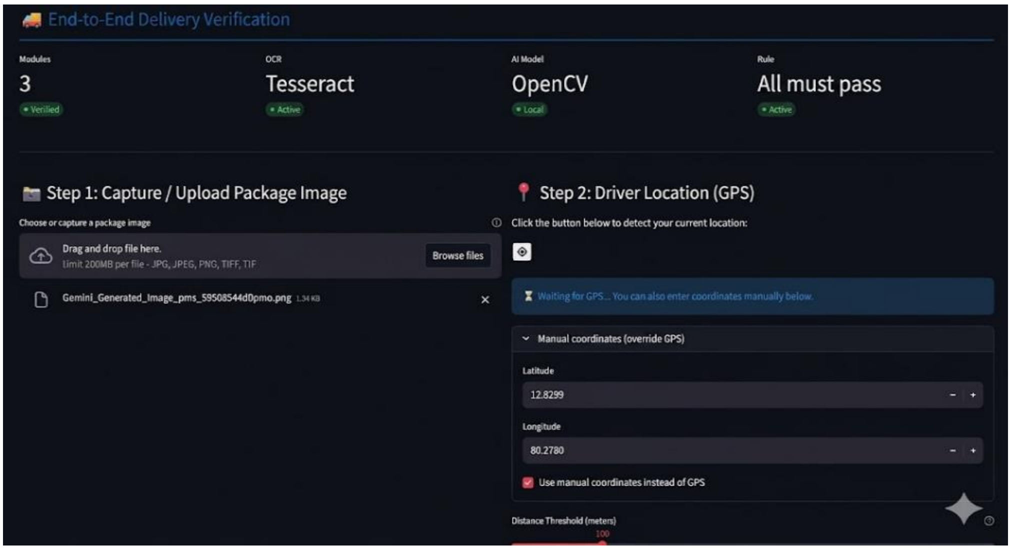

Figure 8: Delivery package verification by GPS through coordinates

It is checked by verifying the GPS coordinates. The first step is to capture the parcel in the camera and upload it to the application. The second step is to check whether the delivery agent is in the precise location. It detects the deliveryman's longitude and latitude range using GPS. Logi-Track also has a manual entry for the coordinates. And the distance threshold can be customized to the delivery agent's needs (Figure 9).

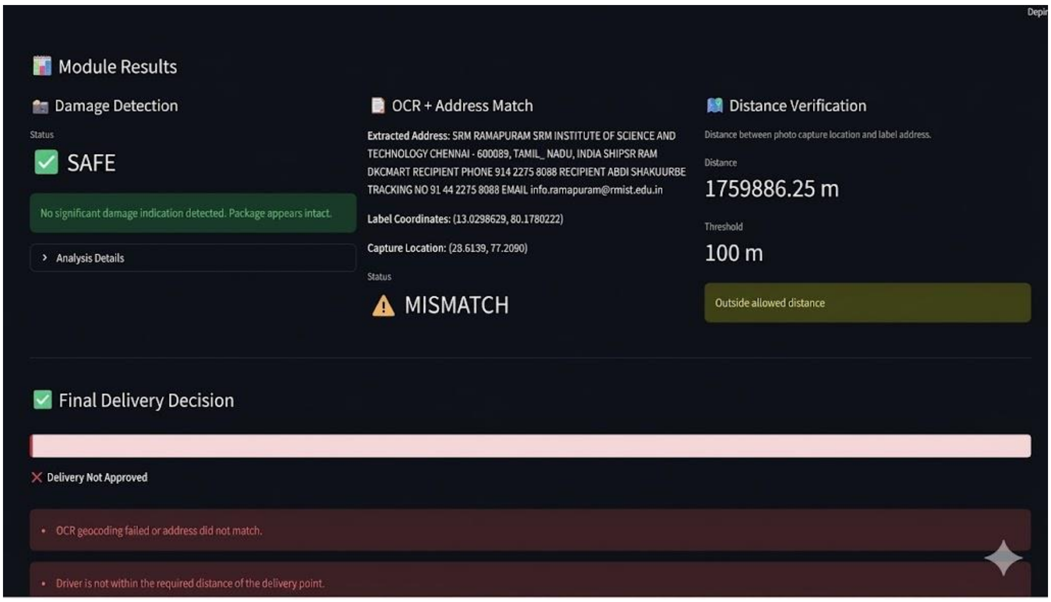

Figure 9: Module results of the delivery package

This image shows the module results of the parcel after completing the verification process. EfficientNet-Lite will detect the parcel, including edges, corners, and other features. The OCR recognizes the image and displays a message if the parcel matches; then it indicates that the package is safe. If it shows a flag, it indicates that the package is a mismatch. After the parcel status is confirmed, distance verification is performed for the next step, making it easier for the deliveryman to reach the correct location (Figure 10).

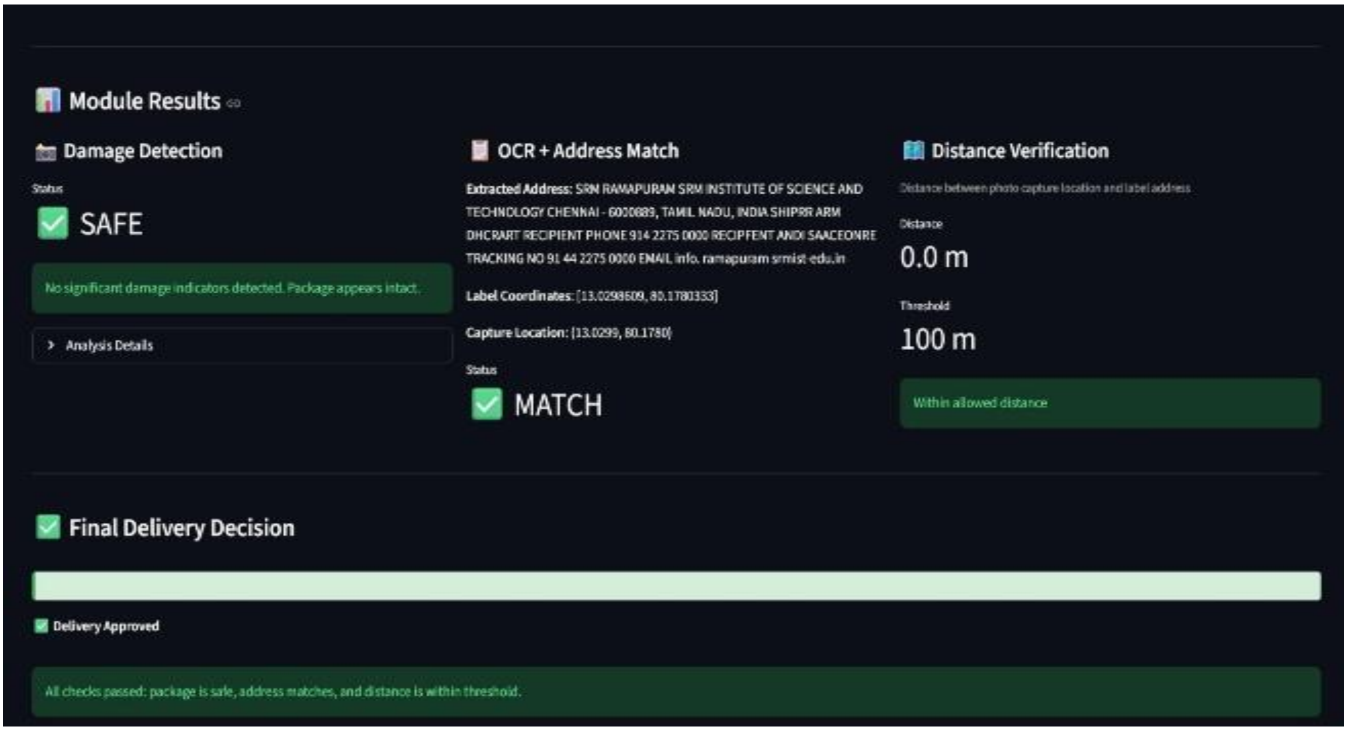

Figure 10: The delivery package is verified

5. Conclusion

This paper presents the 'Logi-Track: An AI-Enabled Proof-Of-Delivery Framework Using OCR Based Label Recognition, EfficientNet-Lite Package Damage Detection, and Geo-Tagged Distance Validation', a significant shift from traditional delivery checking to multi-layered checking using artificial intelligence and the global positioning system, verified for the e-commerce logistics sector. In traditional Proof-of-Delivery systems, the fraud rate associated with OTPs is 15%, and there are no parcel integrity checks. That's how the researchers analyzed the traditional method and implemented a multi-layered validation framework. The implementation of OpenCV and Tesseract OCR ensures that parcels are delivered by cross-verifying the physical labels, whether it could be barcode reads or QR codes, and checked by digital manifests. The AI detects damage to the package modules, eliminating the grey area in delivery disputes by providing time-stamped evidence of the package's condition, even detecting minute scratches or folded edges before the customer accepts it. After that, the application of the Haversine formula via the Google Maps API enforces a 2-meter proximity rule, effectively neutralizing proximal fraud that falsely claims a market distance. After integrating a high-performance Python and Edge-AI stack, Logi-Track demonstrates how it reduces damage disputes and misdeliveries. Logi-Track aims to ensure the correct delivery of the customer's parcel, reduce the damage rate, and deliver packages in perfect condition by mitigating poor handling, inadequate packaging, weak tracing, and sorting errors. In future iterations of this work, it could be incorporated into blockchain-based systems to decentralize further and secure the evidence chain, ultimately establishing an accountable relationship among e-commerce platforms, couriers, and the end consumer. The Logi-Track results validate the system's functional capabilities, demonstrating its successful implementation. Moreover, the evaluation lacks quantitative measures such as latency, accuracy, precision, recall, and processing time. Additionally, the project system summarises the system's contribution, but some may contain redundancies. So, this can be enriched by emphasizing the real-world impact.

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Data Availability Statement: The study uses data from Logi-Track, an AI-enabled proof-of-delivery framework that integrates OCR-based label recognition, EfficientNet-Lite-based package damage detection, and geo-tagged distance validation. Supporting datasets and related materials are available from the corresponding author upon reasonable request, subject to applicable institutional policies and ethical considerations.

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Conflicts of Interest Statement: All authors declare that they have no competing financial, professional, academic, or personal interests that could have influenced the design, execution, analysis, or publication of this research. All datasets, software tools, and referenced sources have been appropriately acknowledged and cited.

Ethics and Consent Statement: The authors affirm that the research was conducted in accordance with recognised ethical standards and institutional requirements. Necessary permissions and approvals were obtained where applicable; informed consent was secured from all participants; and appropriate safeguards were implemented to ensure confidentiality, privacy, and the responsible management of research data.

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