

An Embedded IoT System for Automated Parcel Sorting Based on Distribution Destination Identification and Cloud-Based Data Logging And Real-Time Data Logging

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Abstract

The increasing volume of goods and growing demand for rapid distribution in modern logistics systems require automated sorting technologies that are fast, accurate, consistent, and capable of integrated operational data management. Conventional sorting processes that rely heavily on human operators may introduce destination identification errors, processing delays, and limited operational visibility. This study develops an embedded IoT-based automated parcel sorting system that uses distribution destination as the primary classification variable and links each physical sorting event to a cloud-based operational record. The proposed architecture integrates an Arduino UNO, GM66 barcode scanner, infrared sensor, DC motor conveyor, servo actuator, and ESP8266 communication module connected to Google Sheets. Barcode information is mapped to three distribution regions: East Java (JATIM), Central Java (JATENG), and the Special Region of Yogyakarta (DIY). Experimental testing involved 30 parcel samples. Twenty-eight barcodes were successfully identified, yielding a barcode identification accuracy of 93.33% (95% Wilson confidence interval: 78.68–98.15%). All 28 successfully identified parcels were routed to their corresponding destinations, producing a conditional sorting success rate of 100% (95% Wilson confidence interval: 88.65–100%). The physical sorting response time was approximately 1.5 s, comprising about 1.0 s for barcode scanning and 0.5 s for actuator response. Cloud logging was successful for all successfully processed sorting events (28/28). Failure analysis indicates that barcode acquisition, rather than destination mapping or actuation, was the main source of observed performance loss under the tested conditions. The principal contribution is therefore an integrated, low-cost architecture that couples destination-oriented identification, deterministic physical routing, and digital traceability in one embedded-IoT workflow. Because the original experiment did not include controlled variations of barcode orientation, illumination, conveyor speed, or end-to-end cloud latency, the reported results should be interpreted as prototype-level validation rather than a complete robustness or real-time latency evaluation.

Keywords: *Automated Sorting, Barcode Identification, Internet of Things, Cloud Data Logging, Smart Logistics, Embedded System*

I. INTRODUCTION

The rapid development of digital technologies and the increasing complexity of logistics operations have created a growing demand for faster, more accurate, and digitally integrated distribution processes. In modern logistics, sorting is a critical operational stage because the sorting decision determines the subsequent routing of parcels toward their intended destinations. Recent studies on smart warehouses and intralogistics show that IoT and automation are increasingly used to connect physical handling activities with digital information, monitoring, and decision support [10], [12]. Accordingly, an automated sorting architecture should be evaluated not only by its physical routing performance but also by its ability to generate reliable operational data.

Parcel sorting has traditionally involved substantial manual identification and handling. Such dependence can become a bottleneck when parcel volume increases and when destination information must be captured consistently.

Barcode-based identification offers a direct machine-readable representation of parcel information and has been demonstrated in embedded warehouse applications as a practical mechanism for automated data acquisition and traceability [1], [7]. However, the effectiveness of barcode-based systems remains dependent on the quality and acquisition conditions of the code, making identification reliability an important design and evaluation issue.

Automated sorting studies have employed different sensing and control strategies, including color, dimensions, and other physical characteristics. These approaches demonstrate the feasibility of automated classification, but the classification variable is not necessarily equivalent to the parcel's intended distribution destination. Recent parcel-sorting research has increasingly considered direct destination assignment and automated routing, including camera-based parcel classification and decision models for sorting conveyors [8], [15]. This trend strengthens the case

for evaluating destination-oriented identification separately from the mechanical routing stage.

IoT-based logistics research has also expanded from local automation toward connected warehouse and intralogistics operations. IoT can support identification, tracking, tracing, and operational monitoring, while recent studies emphasize the value of real-time data for warehouse and intralogistics decision-making [5], [6], [10], [12]. Nevertheless, digital connectivity does not automatically establish end-to-end real-time performance; communication delay and successful record persistence should be measured separately.

Barcode-based identification provides an alternative approach because destination information can be encoded into a machine-readable representation and subsequently processed by an embedded control system. Pramana and Mukhaiyar [1] demonstrated the feasibility of barcode-based automated sorting using a microcontroller. More recent work has similarly combined barcode readers, embedded controllers, and real-time data transmission for warehouse management [7]. These studies support barcode identification as a practical interface between physical parcels and digital logistics information, while also indicating the need to evaluate identification performance separately from downstream classification and actuation.

The state of the art therefore shows three complementary research streams: embedded parcel identification and sorting [1], [4]; IoT-enabled warehouse and logistics monitoring [5], [9], [10], [12]; and increasingly automated parcel-routing and warehouse systems [8], [13]. Recent reviews emphasize that IoT in warehousing and intralogistics is particularly valuable when physical operations are connected with traceability and real-time operational information [5], [6], [12]. However, these streams are not always implemented as a compact, low-cost architecture in which the same destination-identification event both triggers physical routing and produces a cloud record.

Despite these developments, a specific research gap remains in the integration of destination-oriented barcode identification, automated physical sorting, and operational data logging within one embedded architecture. Existing work commonly emphasizes either automated classification/routing or warehouse-level digital monitoring, whereas the present study links the two at the event level. The gap is therefore not the invention of a new barcode or IoT technology, but the engineering and experimental validation of a unified destination-oriented workflow in which identification, routing, and traceability are evaluated as distinct but connected performance stages [5], [6], [12].

Barcode acquisition is particularly important because an identification failure propagates to all subsequent stages of the sorting chain. Recent

warehouse research highlights identification, tracking, and traceability as core functions of IoT-enabled operations [10], while barcode-based systems demonstrate the feasibility of direct digital capture [7]. Therefore, the evaluation in this study separates barcode identification accuracy from destination classification, physical sorting success, response time, and cloud logging reliability.

Based on these gaps, this study proposes an embedded IoT-based automated parcel sorting system with distribution-destination identification and cloud-based operational data logging. The system integrates an Arduino UNO, GM66 barcode scanner, infrared sensor, DC motor conveyor, servo actuator, and ESP8266 communication module connected to Google Sheets. The barcode information is processed by the embedded controller to determine the corresponding distribution destination, after which the servo actuator directs the parcel to the designated sorting path. Simultaneously, operational information is transmitted to the cloud platform to create a digital record of the sorting event.

The main scientific contribution of this study is an event-level integration architecture that couples three functional layers: (i) machine-readable destination identification, (ii) deterministic automated physical routing, and (iii) cloud-based operational traceability. Unlike systems that evaluate only physical object classification or only warehouse monitoring, the proposed architecture connects the identification decision directly to both the actuator command and the digital record. The study also contributes an evaluation framework that explicitly separates identification failures from downstream sorting failures, preventing a conditional 100% sorting result from being misinterpreted as 100% end-to-end system accuracy.

The proposed system is implemented for three destination categories: East Java (JATIM), Central Java (JATENG), and the Special Region of Yogyakarta (DIY). System performance is evaluated using barcode identification accuracy, destination classification accuracy, sorting success rate, physical response time, cloud data logging success rate, and a failure-oriented robustness assessment. Because the available experiment did not include controlled repeated trials under varying operating conditions or timestamp-level cloud latency measurements, those aspects are explicitly treated as limitations rather than inferred from the existing data.

II. LITERATURE REVIEW

2.1. Automated Parcel Sorting Systems

Automated parcel sorting is an essential component of logistics automation because it enables goods to be identified, classified, and directed to appropriate distribution routes with reduced dependence on manual operations. Modern

warehouse research treats sorting as part of a broader material-handling and information-flow architecture in which automation, identification, and digital monitoring are increasingly interconnected [5], [11], [13]. An automated sorting system generally integrates sensing devices, a control unit, conveyor mechanisms, and actuators to perform object detection, classification, and physical routing.

Earlier automated sorting studies have demonstrated the feasibility of sensor-based classification, including color-based sorting [2]. More recent parcel-sorting research has moved toward direct destination assignment and automated routing, including camera-based parcel classification and automated conveyor decision models [8], [15]. These developments show that sorting accuracy depends on both the information used for classification and the reliability of the physical routing mechanism.

Warehouse and logistics automation literature also shows a broader shift toward integrated material handling, connected devices, and flexible automation [6], [13]. Rather than evaluating a sorter only by whether an object reaches a bin, recent research increasingly considers information visibility, system integration, adaptability, and operational data as part of the automation architecture.

These studies demonstrate the effectiveness of automated handling for object classification and routing. However, physical characteristics do not necessarily represent the intended distribution destination of a parcel. Destination-oriented sorting therefore requires an identification variable that is directly linked to the logistics decision, such as a barcode or other machine-readable identifier.

2.2. Barcode-Based Parcel Identification

Barcode technology provides a machine-readable method for representing identification information and can be utilized as an input for automated parcel sorting. Recent embedded implementations demonstrate that barcode readers can be coupled with microcontrollers and online platforms to automate data capture and improve traceability in warehouse environments [7]. Unlike classification systems based only on physical characteristics, barcode identification can directly associate parcel information with a predefined distribution decision.

Pramana and Mukhaiyar [1] developed a microcontroller-based goods sorting system using barcode identification. Their study demonstrates the feasibility of integrating barcode reading with an automated sorting mechanism. The use of barcode technology provides an important advantage because the sorting decision can be determined from encoded information rather than relying solely on the physical characteristics of the parcel.

Barcode-based identification is influenced by operational factors such as code orientation, printing quality, scanning distance, and illumination. The present experiment therefore treats barcode reading as a separate performance stage. This separation is important because a barcode acquisition failure prevents the subsequent classification and sorting stages from operating, whereas a correctly acquired barcode can still be misclassified or mechanically misrouted in a different failure mode.

In the context of logistics automation, barcode identification can therefore function as the link between the physical parcel and its intended distribution destination. When integrated with an embedded controller, the information obtained from the barcode can be processed automatically to determine the corresponding sorting route.

2.3. Embedded Systems for Sorting Automation

Embedded systems provide a practical platform for integrating sensing, identification, decision-making, and actuation functions in automated sorting applications. A microcontroller-based architecture enables information obtained from sensors and identification devices to be processed locally before generating control signals for mechanical actuators.

In the proposed system, the embedded architecture consists of an Arduino UNO as the main controller, a GM66 barcode scanner for parcel identification, an infrared sensor for object detection, a DC motor for conveyor movement, and a servo motor for the sorting mechanism. The system operates through a sequential process involving object detection, barcode acquisition, destination classification, actuator activation, and data transmission.

The use of a modular embedded architecture provides flexibility because the classification rules can be modified without fundamentally changing the mechanical structure of the sorting system. In this study, the barcode information is processed to classify parcels into three distribution destinations: East Java (JATIM), Central Java (JATENG), and the Special Region of Yogyakarta (DIY). This destination-oriented classification differs from systems that classify objects primarily according to their physical characteristics.

The embedded controller also functions as the coordination point between the physical sorting process and the digital data communication subsystem. Therefore, the controller does not only determine the sorting route but also provides the operational information required for subsequent cloud-based data logging.

2.4. Internet of Things for Logistics Monitoring and Data Logging

The development of the Internet of Things (IoT) has enabled automated systems to extend

beyond local process control toward connected monitoring and digital data management. Recent studies of smart warehouses and intralogistics emphasize IoT's role in identification, tracking, tracing, operational visibility, and real-time decision support [10], [12]. IoT architectures can connect physical devices with communication networks and cloud platforms, allowing operational information to be transmitted, stored, and accessed remotely.

In logistics applications, cloud-based data logging can provide a digital representation of physical activities by recording parcel identification, destination, sorting status, and processing time. Recent IoT research emphasizes traceability and real-time operational visibility as important capabilities of connected logistics systems [9], [12]. Such data can support monitoring and retrospective analysis even when the physical sorting mechanism itself remains relatively simple.

The integration of IoT into sorting systems can therefore complement automated physical routing. Instead of treating sorting and monitoring as separate processes, an integrated architecture can generate an operational record from the same event that produces the physical sorting decision. In the proposed system, the ESP8266 module acts as the communication interface between the embedded controller and Google Sheets.

Cloud connectivity, however, should not be equated automatically with end-to-end real-time performance. A reliable evaluation should distinguish successful data logging from communication latency, because a system may store every record successfully while still experiencing variable transmission delays. This distinction is consistent with recent IoT research that treats real-time visibility as an operational capability that requires timely data acquisition and communication [10], [12].

2.5. State of the Art and Research Gap

The reviewed studies indicate three main technological directions. First, sensor- and automation-based systems classify and route physical objects [2], [8], [15]. Second, barcode-based systems provide machine-readable identification for warehouse and sorting operations [1], [7]. Third, IoT-enabled warehouse and intralogistics systems extend physical operations with tracking, traceability, and digital information flow [5], [6], [10], [12].

Nevertheless, several research gaps remain. First, classification based on physical characteristics does not directly represent distribution destination information. A parcel's color, height, weight, or dimensions may be useful for object classification, but these parameters do not inherently determine where the parcel should be delivered.

Second, although barcode technology can provide machine-readable parcel information,

barcode identification, automated physical sorting, and cloud-based operational data logging are not consistently evaluated as one event-level workflow. Recent literature confirms the growing importance of integrated IoT and automation in warehousing, but also shows that research often focuses on broader warehouse systems rather than compact destination-oriented sorting prototypes [5], [6], [11].

Third, system performance in automated sorting should not be evaluated solely from the final sorting result. An integrated system involves sequential stages including object detection, identification, classification, actuation, and data transmission. Failure at any stage can affect end-to-end performance. Therefore, this study reports stage-specific metrics and explicitly separates conditional sorting success from overall successful processing.

Based on these gaps, the research opportunity is to develop and experimentally evaluate a compact sorting architecture that uses distribution destination as the primary sorting variable while simultaneously generating a digital operational record. The novelty is positioned as system-level and evaluation-level integration rather than as a claim of a new barcode-recognition or IoT communication algorithm.

2.6. State of the Art and Position of the Proposed System

Previous studies have demonstrated various approaches to automated sorting based on different identification and classification methods. Pramana and Mukhaiyar [1] developed a microcontroller-based sorting system using barcode identification, while Tarigan and Setiono [2] employed a TCS230 color sensor and Schneider PLC for color-based classification. Fauzi et al. [8] developed a PLC-based sorting system using ultrasonic sensing for height classification, whereas Simanjuntak and Risfendra [15] utilized proximity sensors and a load cell integrated with PLC-HMI for classification based on physical characteristics. These studies demonstrate the effectiveness of automated sorting; however, the classification decisions primarily rely on object characteristics or local identification mechanisms and do not directly represent distribution destination information. Furthermore, the reviewed systems have not comprehensively integrated destination-oriented identification, automated physical routing, and cloud-based operational data logging within a unified architecture.

To address these limitations, this study proposes an integrated embedded-IoT sorting system that combines barcode-based destination identification, automated sorting, and real-time cloud data logging. The proposed system employs a GM66 barcode scanner, Arduino UNO, infrared sensor, DC conveyor motor, servo actuator, and ESP8266 communication module to establish an

integrated workflow from object detection and barcode identification to destination classification, physical sorting, and cloud-based data recording. The contribution of this study lies not in introducing a new barcode, microcontroller, or IoT technology, but in integrating these technologies into a destination-oriented sorting and operational traceability framework. System performance is evaluated through barcode identification accuracy, sorting success rate, response time, and data logging reliability, providing a comprehensive assessment of the identification-to-sorting process and its potential for further development in small- and medium-scale logistics automation.

III. RESEARCH METHODOLOGY

This study employed a Research and Development (R&D) method combined with an experimental approach to develop and evaluate an Internet of Things (IoT)-based automated parcel sorting system. The R&D method was used to develop a prototype integrating parcel identification, distribution destination classification, automated sorting control, and real-time operational data logging. The experimental approach was employed to quantitatively evaluate system performance in terms of identification accuracy, classification accuracy, sorting success rate, response time, and cloud-based data communication performance.

The research consisted of six main stages: (1) requirements analysis and literature review, (2) system architecture design, (3) hardware and software design, (4) prototype implementation, (5) experimental testing, and (6) system performance analysis. The research stages were arranged sequentially to ensure that each system component could be evaluated individually and as an integrated system.

3.1. Requirements Analysis and System Specifications

The initial stage involved a literature review of automated sorting systems, barcode identification, embedded systems, Internet of Things, cloud-based monitoring, and real-time data logging for logistics applications. The literature review was used to identify limitations in existing approaches and to define the functional and technical requirements of the proposed system.

The system was designed to perform six main functions: (1) detecting the presence of a parcel on the conveyor, (2) reading the parcel identification barcode, (3) determining the distribution destination based on the barcode information, (4) automatically directing the parcel to the appropriate sorting path, (5) recording the sorting status, and (6) transmitting operational data to a cloud platform.

In this study, distribution destinations were classified into three categories: East Java (JATIM), Central Java (JATENG), and the Special Region of Yogyakarta (DIY). These three categories represent the three sorting paths implemented in the prototype.

The main components consisted of an Arduino UNO as the local controller, a GM66 barcode scanner as the identification device, infrared sensors for parcel detection, a DC motor for conveyor operation, a servo motor as the sorting actuator, and an ESP8266 module for IoT communication. Google Sheets was used as the cloud-based platform for operational data storage and monitoring.

3.2. System Architecture

The system architecture was designed into four main layers: sensing and identification, processing and decision, actuation, and IoT data communication.

The sensing and identification layer consists of an infrared sensor and barcode scanner. The infrared sensor detects the presence of a parcel at the detection point and triggers the barcode scanning process. The GM66 barcode scanner then obtains the parcel identification information.

The processing and decision layer uses the Arduino UNO to process the barcode information and classify the corresponding distribution destination. The classification result is subsequently used to determine the appropriate sorting path.

In the actuation layer, the classification decision is converted into a control command for the servo motor. The servo moves to a predefined position to direct the parcel to the corresponding JATIM, JATENG, or DIY distribution path. The DC motor drives the conveyor to transport the parcel through the sorting process.

In the IoT data layer, operational information is transmitted through the ESP8266 module to Google Sheets. The recorded data include the barcode identification, distribution destination, sorting status, and process timestamp. This architecture enables physical sorting and digital data logging to operate simultaneously.

The overall system workflow can be represented as:

Object Detection → Barcode Identification → Destination Classification → Sorting Decision → Actuator Activation → Data Transmission → Cloud Logging

3.3. Hardware Design

The hardware was designed by integrating the sensing, identification, processing, actuation, and communication components according to the sequence of the sorting process. The Arduino UNO functions as the main local controller. The GM66 barcode scanner is used to read the parcel identification code, while the infrared sensor

detects the presence of a parcel at the scanning position.

The DC motor drives the conveyor to transport parcels through the sorting path. Once the destination has been determined, the Arduino UNO sends a control command to the servo motor to adjust the sorting mechanism and direct the parcel to the appropriate destination path.

The ESP8266 module serves as the communication interface between the local control system and the cloud platform. The module receives operational information from the Arduino UNO and transmits the data to Google Sheets through a Wi-Fi connection.

The main hardware components are summarized in Table 1.

Table 1. Main System Components

No.	Component	Function
1	Arduino UNO	Main system controller
2	GM66 Barcode Scanner	Parcel identification
3	Infrared Sensor	Parcel detection
4	DC Motor	Conveyor drive
5	Servo Motor	Sorting actuator
6	ESP8266	Wi-Fi-based data communication
7	Conveyor	Parcel transportation
8	Google Sheets	Cloud data storage and monitoring
9	Arduino IDE	Programming envonment (C/C++)

3.4. Software Design

The control software was developed using C/C++ programming through the Arduino IDE. The program implements an event-driven sequence to ensure that each parcel undergoes the identification and sorting processes in a consistent order.

When the infrared sensor detects a parcel, the system activates the barcode scanning process. The barcode data obtained from the scanner are then compared with predefined destination codes stored in the control program. If the barcode is valid, the system determines the corresponding distribution category and the required actuator position.

The destination classification logic is expressed as follows:

```
[
Destination                                     =
\begin{cases}
JATIM, & \text{if barcode code} \in C_{\{JATIM\}} \\
JATENG, & \text{if barcode code} \in C_{\{JATENG\}} \\
DIY, & \text{if barcode code} \in C_{\{DIY\}}
\end{cases}
]
```

where (C_{JATIM}), (C_{JATENG}), and (C_{DIY}) represent the respective sets of barcode codes associated with each distribution destination.

After the destination is determined, the Arduino UNO activates the servo motor according to the corresponding sorting position. The

operational data are subsequently transmitted through the ESP8266 to Google Sheets.

If the barcode cannot be read or the code does not correspond to a predefined destination, the system does not execute a sorting decision based on invalid identification data. Such events are recorded as identification failures for subsequent performance analysis.

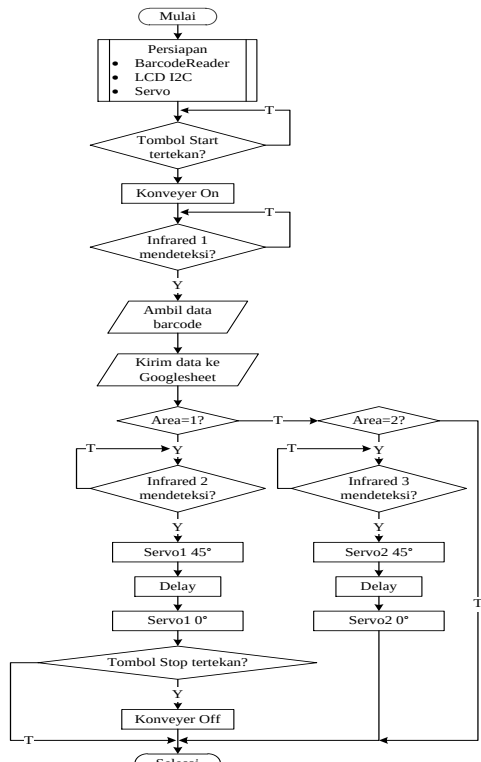


Figure 1. Process Flow Diagram

3.5. System Operating Algorithm

The operating algorithm of the proposed system consists of the following steps:

1. Initialize the sensors, barcode scanner, motor, servo motor, and ESP8266 module.
2. Activate the conveyor to transport the parcel toward the detection point.
3. Detect the parcel using the infrared sensor.
4. Read the parcel barcode using the barcode scanner.
5. Validate the barcode reading.
6. If the barcode is successfully read, classify the distribution destination.
7. Determine the corresponding sorting path.
8. Activate the servo motor according to the classification result.
9. Direct the parcel to the corresponding distribution path.
10. Record the sorting status.
11. Transmit the barcode, destination, status, and process timestamp to Google Sheets through the ESP8266.
12. Return the servo motor to its initial position.
13. Return the system to the standby state for the next parcel.

This algorithm ensures that parcel identification, destination classification, physical sorting, and operational data logging are performed as an integrated process.

3.6. Experimental Procedure

Experimental testing was conducted using 30 parcel samples containing barcodes representing the three distribution destination categories. The samples were used to evaluate system performance from the identification stage through the sorting and data logging stages.

To improve experimental repeatability, all tests were performed using the same hardware configuration, software version, and basic operating procedure. The position of the system components and the operating conditions were maintained during the baseline experiment. Each parcel was processed through object detection, barcode reading, destination classification, sorting, and cloud data logging.

The actual destination of each sample was defined as the ground truth and compared with the destination determined by the proposed system. The experimental results were recorded in an observation sheet and cross-checked with the data stored in Google Sheets.

Additional experiments may be conducted by varying operating conditions such as barcode-to-scanner distance, barcode orientation, conveyor speed, and illumination conditions. These experiments are intended to evaluate system robustness under different operating conditions.

3.7. Performance Evaluation Parameters

System performance was evaluated using five main parameters:

1. Barcode Reading Accuracy
2. Destination Classification Accuracy
3. Sorting Success Rate
4. System Response Time
5. Cloud Data Logging Performance

3.7.1. Barcode Reading Accuracy

Barcode reading accuracy measures the capability of the scanner to correctly obtain the identification information from the tested parcels.

$$[\text{Accuracy}_{\text{barcode}} = \frac{N_{\text{detected}}}{N_{\text{total}}} \times 100\%]$$

where:

- (N_{detected}) is the number of barcodes successfully and correctly read;
- (N_{total}) is the total number of tested samples.

Of the 30 tested samples, 28 barcodes were successfully read. Therefore:

$$[\text{Accuracy}_{\text{barcode}} =$$

$$\frac{28}{30} \times 100\% = 93.33\%]$$

Barcode reading failures were analyzed separately to identify potential causes of identification failure.

3.7.2. Destination Classification Accuracy

Destination classification accuracy measures the capability of the algorithm to correctly determine the distribution destination based on the successfully read barcode.

$$[\text{Accuracy}_{\text{classification}} = \frac{N_{\text{correct_class}}}{N_{\text{detected}}} \times 100\%]$$

where ($N_{\text{correct_class}}$) represents the number of successfully read barcodes that were correctly mapped to their actual distribution destinations.

This parameter is evaluated separately from barcode reading accuracy because successfully reading a barcode does not necessarily guarantee correct destination classification.

The classification results can also be presented using a confusion matrix for the three destination classes: JATIM, JATENG, and DIY.

3.7.3. Sorting Success Rate

The sorting success rate evaluates the capability of the physical sorting mechanism to direct parcels to the correct distribution path according to the classification result.

$$[\text{SSR} = \frac{N_{\text{correct}}}{N_{\text{identified}}} \times 100\%]$$

where:

- (N_{correct}) is the number of parcels directed to the correct sorting path;
- ($N_{\text{identified}}$) is the number of parcels successfully identified.

In the initial experiment, 28 parcels were successfully identified, and all identified parcels were directed to the correct distribution paths. Therefore:

$$[\text{SSR} = \frac{28}{28} \times 100\% = 100\%]$$

This definition separates the performance of the physical sorting mechanism from barcode identification failures.

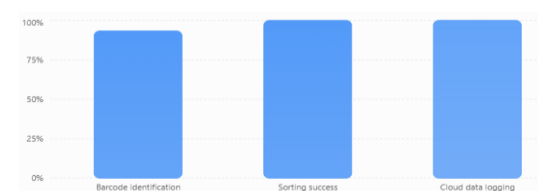


Figure 2. Performance System

3.7.4. System Response Time

System response time measures the time required by the system from barcode identification until activation of the sorting actuator.

The physical sorting response time is calculated as:

$$T_{\text{sorting}} = T_{\text{scan}} + T_{\text{actuation}}$$

where:

- (T_{scan}) is the barcode scanning time;
- ($T_{\text{actuation}}$) is the time between the classification decision and actuator activation.

Based on the initial measurements:

$$T_{\text{scan}} = 1.0, \text{s}$$

and:

$$T_{\text{actuation}} = 0.5, \text{s}$$

Thus:

$$T_{\text{sorting}} = 1.0 + 0.5 = 1.5, \text{s}$$

To evaluate the complete IoT response, the end-to-end response time can additionally be calculated as:

$$T_{\text{E2E}} = T_{\text{sorting}} + T_{\text{logging}}$$

where (T_{logging}) represents the time required for the operational data to become available on the cloud platform.



Figure 3. Response Time System

3.7.5. Cloud Data Logging Success Rate

Cloud data logging performance evaluates the capability of the system to transmit and store operational data completely on the cloud platform.

The data logging success rate is calculated as:

$$DLSR = \frac{N_{\text{logged}}}{N_{\text{sent}}} \times 100\%$$

where:

- (N_{logged}) is the number of data records successfully stored;
- (N_{sent}) is the total number of data records transmitted by the system.

A data record is considered successfully logged when all predefined information, including barcode, destination, sorting status, and process timestamp, is available in Google Sheets.

3.7.6. Cloud Logging Latency

Because the proposed system claims real-time data logging, cloud communication performance is additionally evaluated using logging latency.

$$L_{\text{cloud}} = T_{\text{cloud}} - T_{\text{event}}$$

where:

- (T_{event}) is the timestamp when the operational event is generated by the local system;
- (T_{cloud}) is the timestamp when the corresponding data become available on Google Sheets.

The mean cloud logging latency is calculated as:

$$\overline{L_{\text{cloud}}} = \frac{1}{N} \sum_{i=1}^N L_i$$

This parameter provides a quantitative measure of the real-time characteristics of the proposed IoT data logging system.

3.8. Robustness and Failure-Mode Assessment

A full controlled robustness experiment would vary barcode-to-scanner distance, barcode orientation, conveyor speed, illumination, parcel characteristics, and destination categories. The current experimental dataset, however, contains only the aggregate 30-sample trial and does not retain repeated measurements for each controlled condition. Accordingly, the present revision performs a failure-oriented robustness assessment from the observed barcode failures and reports the missing controlled-condition tests explicitly as limitations rather than inventing results.

1. barcode-to-scanner distance;
2. barcode orientation;
3. conveyor speed;
4. illumination conditions; and
5. variation in distribution destination categories.

For future controlled robustness experiments, each operating condition should be tested with repeated samples and evaluated using barcode reading accuracy, destination classification accuracy, sorting success rate, response time, and cloud latency. The resulting condition-level measurements should then be compared statistically. The present manuscript does not claim such unperformed experiments.

3.9. Data Analysis

The experimental data are analyzed quantitatively using descriptive statistics. Percentage-based parameters are presented as accuracy or success rates, while time-based parameters are reported using the observed mean or nominal response values available from the prototype measurements. For proportions derived from 30 trials, 95% Wilson confidence intervals are additionally reported to indicate sampling uncertainty. Because the available experiment contains one aggregate operating condition and no repeated independent treatment groups, inferential

comparison tests are not appropriate and are not fabricated.

For classification, a conditional normalized confusion matrix is used to distinguish correct destination mapping from cross-destination errors among successfully read barcodes. For failure analysis, barcode-reading failures are examined separately from classification and actuation failures so that the source of performance degradation can be identified.

The relationship between identification success and sorting success is analyzed separately. Therefore, the conditional sorting success rate is not interpreted as the overall system success rate. This approach prevents a 100% downstream sorting result from masking the two barcode acquisition failures in the 30-sample experiment.

3.10. System Success Criteria

The proposed system is considered functionally successful when it is capable of:

1. reading parcel barcodes and obtaining valid destination information;
2. correctly classifying parcels according to their distribution destinations;
3. directing parcels to the corresponding sorting paths;
4. generating a measurable and consistent sorting response;
5. transmitting operational data to the cloud platform;
6. storing the required operational information without data loss; and
7. providing traceable operational records for subsequent monitoring.

These criteria are used as the basis for evaluating the prototype implementation and determining its potential for further development toward logistics applications involving a larger number of distribution destinations.

IV RESULTS AND DISCUSSION

4.1. System Implementation

The proposed automated parcel sorting system was successfully developed through the integration of a GM66 barcode scanner, infrared sensor, Arduino UNO, DC motor, servo motor, and ESP8266 communication module. The developed system integrates three principal functions, namely parcel identification, destination-based sorting, and real-time operational data logging.

The sorting process begins when the infrared sensor detects the presence of a parcel in the scanning area. The GM66 barcode scanner subsequently acquires the identification code attached to the parcel. The acquired barcode information is processed by the Arduino UNO to determine the corresponding distribution destination. In the implemented prototype, the destination categories consist of East Java

(JATIM), Central Java (JATENG), and the Special Region of Yogyakarta (DIY).

Following the destination classification, the Arduino UNO generates an actuator command corresponding to the identified destination. The servo motor then adjusts its position to direct the parcel toward the designated sorting path. Concurrently, the operational information is transmitted through the ESP8266 module to Google Sheets, where the sorting records are stored for monitoring and traceability purposes.

The implementation demonstrates that the proposed architecture integrates the physical and digital aspects of the sorting process. The physical layer performs parcel identification and routing, whereas the IoT layer provides a digital record of each sorting event. Consequently, the developed system extends the functionality of conventional automated sorting mechanisms by incorporating an operational data management component.

4.2. Barcode Identification Performance

The barcode identification experiment was conducted using 30 parcel samples to evaluate the capability of the GM66 scanner to acquire destination information accurately. The experimental results showed that 28 of the 30 barcode samples were successfully identified, whereas two samples could not be read correctly. Accordingly, the barcode identification accuracy was calculated as 93.33%.

The obtained accuracy indicates that the barcode-based identification mechanism was capable of providing destination information for the majority of the tested parcels. Nevertheless, the occurrence of two unsuccessful readings indicates that the identification subsystem remains a critical factor affecting the overall system performance. Based on observations during the experiment, unsuccessful barcode acquisition may be associated with variations in barcode orientation, printing quality, and illumination conditions in the scanning area.

From a system perspective, the identification stage represents the initial decision point of the proposed architecture. An unsuccessful barcode acquisition prevents the subsequent classification and sorting processes from receiving valid destination information. Therefore, improvements in scanner positioning, barcode quality, illumination control, and scanning distance are expected to contribute directly to improving the overall system reliability.

The obtained result is comparable to the 92% accuracy reported by Tarigan and Setiono [2] for a color-based automated sorting system. The proposed system achieved a 1.33 percentage-point higher identification accuracy. However, this difference should not be interpreted as a direct performance advantage because the two studies employed different sensing mechanisms,

experimental configurations, and classification variables. Instead, the result demonstrates the feasibility of barcode-based identification for destination-oriented parcel sorting.

4.3. Destination Classification and Sorting Performance

The destination classification and sorting experiment was conducted to evaluate the ability of the system to translate barcode information into an appropriate physical sorting action. Of the 30 tested parcels, 28 were successfully identified by the barcode scanner. All successfully identified parcels were subsequently directed to their corresponding distribution paths.

The conditional sorting success rate was therefore calculated as:

$$SSR = 28/28 \times 100\% = 100\%$$

The result demonstrates that no sorting error was observed among the parcels for which valid barcode information was successfully obtained. This finding indicates that the destination mapping algorithm, control logic, and servo-based actuation mechanism operated consistently under the experimental conditions.

It is important to distinguish the conditional sorting success rate from the overall system success rate. The value of 100% represents the performance of the sorting mechanism after successful parcel identification, rather than the performance of the entire sorting process. Considering all 30 tested samples, the proportion of parcels that were successfully identified and subsequently sorted was 28/30, corresponding to an overall successful processing rate of 93.33%.

This distinction provides a more rigorous interpretation of the experimental results because it separates identification errors from sorting errors. The results suggest that the principal limitation of the current prototype is associated with barcode acquisition, whereas the downstream classification and actuation stages demonstrated consistent behavior.

In comparison with previous sorting approaches based on color, dimensions, or weight [2], [4], the proposed system employs distribution destination as the classification variable. This approach is directly related to the operational objective of logistics sorting, in which the primary requirement is to route each parcel to its intended destination rather than merely distinguish its physical characteristics.

Table 2. Conditional Normalized Confusion Matrix for Destination Classification

Actual \ Predicted	JATIM	JATENG	DIY
JATIM	100%	0%	0%
JATENG	0%	100%	0%
DIY	0%	0%	100%

The matrix is conditional on successful barcode acquisition. Because all 28 successfully

read parcels were routed to their correct destinations and no cross-destination error was recorded, the observed conditional matrix contains only diagonal outcomes. The original dataset does not retain per-destination sample counts, so raw class frequencies are intentionally not invented.

4.4. System Response Time

System response time was evaluated to determine the temporal performance of the physical identification-and-sorting chain. The available measurement indicates approximately 1.0 s for barcode scanning and 0.5 s for actuator response, yielding an observed physical sorting response time of approximately 1.5 s.

The physical sorting response time was therefore obtained as:

$$T_{\text{sorting}} = T_{\text{scan}} + T_{\text{actuation}} \quad T_{\text{sorting}} = 1.0 + 0.5 = 1.5 \text{ s}$$

The observed physical response time of approximately 1.5 s indicates that the embedded control chain can generate the actuator command within a short interval under the tested prototype conditions. Because repeated timestamp-level measurements are not available, this value is reported as an observed prototype response rather than as a population estimate.

The use of deterministic barcode-to-destination mapping contributes to the relatively low computational requirement of the system. Unlike computationally intensive image-based classification approaches, the proposed system determines the destination by matching the acquired barcode information with predefined destination codes. This approach is appropriate for a prototype intended to demonstrate destination-based sorting using low-cost embedded hardware.

The observed 1.5 s physical response time is discussed only as a prototype-level measurement. Direct numerical comparison with studies using different hardware, sensing mechanisms, conveyor speeds, and timing definitions would not provide a controlled benchmark.

It should also be emphasized that the reported 1.5 s represents physical sorting response time and does not include cloud communication latency. The present dataset does not contain event-to-cloud timestamps, so an end-to-end latency value cannot be calculated without introducing unsupported data. The revised manuscript therefore avoids describing 1.5 s as complete IoT end-to-end latency.

4.5. Cloud-Based Data Logging Performance

The cloud-based data logging experiment was conducted to evaluate the capability of the proposed system to transmit and store operational information generated during the sorting process. The recorded information consisted of the barcode identification, distribution destination, sorting status, and process timestamp.

The experimental results showed that all operational records generated from successfully identified parcels were transmitted through the

ESP8266 module and stored on Google Sheets. Thus, the cloud data logging success rate was 100% for successfully processed events (28/28). This result should not be interpreted as 100% end-to-end system reliability because two of the 30 parcels failed at the barcode identification stage.

The successful implementation of cloud-based data logging provides an additional functionality beyond the physical sorting mechanism. Each sorting event generates a corresponding digital record, thereby establishing a basic traceability mechanism for the sorting process. Such traceability can support operational monitoring and facilitate the retrieval of historical sorting information.

The use of Google Sheets as the cloud data repository also provides a relatively simple implementation approach because it does not require the deployment of a dedicated database server. This characteristic makes the proposed architecture potentially applicable to small- and medium-scale logistics environments where low-cost digital monitoring is required.

The 100% logging success rate indicates successful transmission and storage for the 28 valid sorting events, but it does not quantify communication delay. Because event-generation and cloud-availability timestamps were not retained in the experimental dataset, end-to-end cloud latency cannot be calculated retrospectively. This limitation is explicitly reported to avoid overstating the real-time capability of the prototype.

4.6. Robustness and Error Analysis

The available data support a failure-oriented robustness analysis rather than a full multi-condition robustness experiment. Among 30 tested parcels, 2 barcode acquisitions failed and 28 succeeded, corresponding to an observed failure rate of 6.67%. The failures were observed during barcode acquisition, while no downstream destination-classification or physical-sorting error was recorded among the 28 successfully identified parcels. This stage-wise pattern indicates that the identification interface is the dominant observed vulnerability of the prototype.

The two failed readings were observed under the prototype's normal operating conditions. Based on the experimental observations already documented, plausible contributing factors include barcode orientation, printing quality, and illumination. However, the existing dataset does not record controlled repetitions for each factor, so no causal percentage can be assigned to any individual factor. A controlled robustness test varying these factors is therefore required before claiming performance stability across operating conditions.

The main practical implication is that improvement should initially target barcode acquisition: fixed scanner positioning, controlled scanning distance, consistent illumination, and

higher-quality barcode printing. The downstream classification and actuation stages did not contribute observed errors in the present sample, but their robustness at higher conveyor speeds and larger destination sets remains unvalidated.

Table 3. Summary of Experimental Performance

Parameter	Result	Interpretation
Barcode identification	28/30 = 93.33%	2 acquisition failures; 95% Wilson CI: 78.68–98.15%
Destination classification	28/28 = 100%	No observed misclassification among successfully read barcodes
Physical sorting	28/28 = 100%	No observed routing error after valid identification
Physical response time	≈1.5 s	≈1.0 s scanning + ≈0.5 s actuator response
Cloud data logging	28/28 = 100%	Successful for successfully processed events; latency not measured
Observed barcode failure rate	2/30 = 6.67%	Failure-oriented robustness indicator; causes not isolated experimentally

4.7. Integrated System Performance

The experimental results demonstrate that the proposed architecture successfully integrates parcel identification, destination classification, automated physical sorting, and cloud-based operational data logging within a single embedded IoT system. The system achieved a barcode identification accuracy of 93.33% (28/30), a conditional sorting success rate of 100% (28/28), an observed physical sorting response time of approximately 1.5 s, and a cloud data logging success rate of 100% for successfully processed events (28/28). The barcode accuracy has a 95% Wilson confidence interval of 78.68–98.15%, while the conditional sorting success rate has a 95% Wilson confidence interval of 88.65–100%.

The system achieved a barcode identification accuracy of 93.33%, a conditional sorting success rate of 100%, a physical sorting response time of 1.5 s, and a cloud data logging success rate of 100% under the tested conditions.

The stage-wise results indicate that the principal observed performance loss occurred during barcode acquisition. Once a valid barcode was obtained, the destination mapping and servo-based sorting sequence produced no recorded classification or actuation error in the 28 successful cases. This distinction is important because the conditional 100% sorting result describes

downstream performance only and should not be interpreted as an overall system accuracy of 100%.

The finding suggests that the first priority for improvement is the identification subsystem rather than the actuator mechanism. Practical improvements include controlling scanner distance and orientation, improving barcode printing quality, stabilizing illumination, and adding acquisition-quality checks before the parcel enters the routing stage.

From an architectural perspective, the proposed system establishes a sequential relationship between:

Barcode Identification → Destination Classification → Physical Sorting → Cloud Data Logging

The integration of these functions provides a continuous flow of information from the physical parcel to the digital monitoring platform. Therefore, the proposed system does not merely automate the physical movement of parcels but also establishes a digital representation of the sorting process.

The comparison indicates that most previous approaches have emphasized classification based on physical characteristics such as color, height, weight, or dimensions. These approaches are useful for material classification; however, they do not directly encode the destination information required for distribution-oriented logistics.

The proposed approach introduces destination-based classification using barcode information, allowing the classification result to be directly associated with the intended distribution path. This design is therefore more closely aligned with parcel distribution operations.

The integration of cloud-based data logging represents an additional contribution. Conventional sorting systems generally focus on the physical classification and routing of objects, whereas the proposed architecture combines physical automation with digital operational traceability. As a result, the system is capable of producing both a physical output, in the form of parcel routing, and a digital output, in the form of a cloud-based sorting record.

Thus, the contribution of the proposed research lies not in the individual use of barcode scanning, embedded control, or IoT communication, but in the integration of these technologies into a unified destination-oriented sorting architecture with operational data traceability.

4.8. Limitations and Implications

Despite the promising experimental results, several limitations should be considered when interpreting the findings.

First, the evaluation involved only 30 parcel samples and three destination categories. Consequently, the results represent prototype-level validation and the confidence intervals remain

relatively wide, particularly for barcode identification accuracy.

Second, barcode identification accuracy was 93.33%, with two observed acquisition failures. The available observations suggest sensitivity to barcode orientation, printing quality, and illumination, but the experiment did not isolate these factors through controlled repeated trials.

Third, the physical sorting response time of approximately 1.5 s does not include communication latency between the ESP8266 and the cloud platform. Because cloud event timestamps were not retained, end-to-end latency cannot be reconstructed from the current dataset.

Fourth, the present implementation employs only three distribution destinations. Although additional destinations can theoretically be incorporated through modification of the destination mapping and actuator configuration, the scalability of the system has not yet been experimentally validated.

These limitations define the next experimental stage: a larger balanced sample, repeated trials under controlled barcode orientation, scanning distance, illumination, conveyor-speed, and destination conditions, together with event-level cloud timestamps. Such experiments are required to establish robustness, end-to-end latency, and scalability quantitatively.

4.9. Research Contribution

Based on the experimental findings, the proposed system provides three principal contributions. First, it uses machine-readable barcode information to associate each parcel with its intended distribution destination. Second, the identification result is directly transformed into a physical sorting action through a deterministic embedded control architecture. Third, the same sorting event is recorded through an IoT-based cloud logging mechanism.

The scientific contribution is therefore an event-level integration and evaluation framework rather than a new barcode-recognition algorithm. The framework explicitly separates identification, classification, actuation, and data-logging outcomes, making it possible to identify where performance is lost. This distinction is useful for low-cost logistics prototypes because a downstream 100% sorting result can otherwise conceal upstream identification failures.

V. CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

An embedded IoT-based automated parcel sorting system integrating barcode destination identification, physical routing, and cloud-based operational logging has been successfully developed and evaluated at prototype level. The architecture combines a GM66 barcode scanner,

infrared sensor, Arduino UNO, DC conveyor motor, servo actuator, and ESP8266 communication module to connect the physical sorting workflow with a digital operational record.

In the 30-sample experiment, 28 barcodes were successfully identified, yielding 93.33% identification accuracy (95% Wilson confidence interval: 78.68–98.15%). All 28 successfully identified parcels were correctly routed, producing a conditional sorting success rate of 100% (95% Wilson confidence interval: 88.65–100%). The observed physical sorting response was approximately 1.5 s, while cloud logging succeeded for all 28 successfully processed events.

The principal contribution is the event-level integration of destination-oriented identification, deterministic physical routing, and digital traceability in a compact embedded-IoT architecture. The stage-wise evaluation also shows that barcode acquisition was the dominant observed source of performance loss, while no downstream classification or sorting error was recorded after successful identification.

The findings should nevertheless be interpreted as prototype-level evidence. The experiment used only 30 samples, three destinations, and one controlled operating condition, and it did not provide the repeated condition-level data or event timestamps needed to quantify full robustness and end-to-end cloud latency.

5.2 Recommendations

Future research should increase the sample size and test balanced destination classes under controlled variations in barcode orientation, scanning distance, printing quality, illumination, parcel dimensions, and conveyor speed. Repeated trials should be used to estimate condition-specific confidence intervals and, where appropriate, conduct inferential comparisons between operating conditions.

Further investigation should record local event timestamps and cloud-availability timestamps to quantify end-to-end latency, alongside long-duration communication reliability and data-loss rates. For larger-scale applications, the architecture can be connected to a dedicated database or warehouse-management platform and extended with dashboards, anomaly detection, and predictive analytics after the basic identification and routing robustness has been established.

For further development toward larger-scale logistics applications, the proposed architecture could be integrated with a dedicated database, web-based dashboard, centralized warehouse management system, or advanced analytics. Machine learning or predictive analytics could subsequently be incorporated to support adaptive routing, anomaly detection, and predictive maintenance. These developments are expected to

improve the scalability, reliability, and intelligence of the proposed IoT-based sorting system.

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