An RFID-Based Intelligent Package Segregation Framework with Machine Learning, Embedded Controllers, and Reusable Tag Integration

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ABSTRACT

In this era of rapid technological advancement, industrial logistics requires intelligent, dependable, and scalable solutions for automated package segregation. Traditional methods, such as barcode and QR code scanning, are limited by vulnerabilities to physical damage, print degradation, and alignment sensitivity, which result in operational inefficiencies and misclassification. This work introduces a novel RFID-based package segregation framework that leverages machine learning and robotic automation to resolve these issues. Unlike traditional printed codes, RFID supports contactless, robust, and reusable tags that encode hierarchical destination data, including State, District, Mandal, and Village. After delivery, RFID tags are collected, reprogrammed, and reused, which reduces ongoing costs and electronic waste while supporting sustainable operations. System ML models are developed in Python, and the performance of five algorithms—Logistic Regression, K-Nearest Neighbours (KNN), Support Vector Machine (SVM), Decision Tree, and Random Forest—was systematically compared using key metrics: Accuracy, Precision, Recall, F1-Score, Inference Time, and Throughput. Random Forest achieved the highest accuracy at 94%, precision of 92%, recall of 90%, and F1-score of 90%, with efficient throughput and inference time. A servo-driven robotic arm translates the classification output into pick-and-place actions, sorting products into designated boxes to enable reliable, real-time industrial applications.

Keywords: RFID, Machine Learning (ML), Random Forest, Automated Package Segregation, Robotic Arm, Industrial Logistics, Contactless Identification, Reusable Tags, Pick-and-Place Automation, Smart Supply Chain.

INTRODUCTION:

In the modern age, industrial supply chains are attempting to find more dependable, intelligent and adaptable methods of identifying and classifying products. The most popular option still barcodes and QR codes as they are inexpensive and have gained popularity. These optical IDs however, have many faults. They require a sight of line, then the reader must have a good view of the code– and it is difficult on the rush conveyor belt where one has to presently line up to a weather of steps to scan a work [1]. Should the code be scratched, torn or damaged then it can become readable or wrongly read [2], and such bad conditions as dust, moisture, or poor light will only serve to aggravate the issue [3]. In addition, their capacity to hold a large amount of data is not possible and this restricts how well they can be combined in the current data-driven tracking systems [4].

Get RFID which addresses those problems. RFID does not require direct line of sight when reading tags like barcodes, the RFID tag can also read the tags even when they are hidden the inside packaging. That provides you with real time, non-contact, constant recognition of items in motion [5]. The RFID tags are rewritable and reusable and hence more information can be stored in the tags thus suitable in industrial environments [6]. In addition, they are able to read multiple tags simultaneously and this increases throughput compared to the previous barcode method that was sequential [7]. They also resistant to dust, vibration and moisture thus ensuring that it offers good operation even in harsh conditions [8]. Casella and colleagues have identified the RFID changes logistics by increasing traceability and enhancing automation [3].

Although the QR codes can hold much more information than barcodes, they are easily destroyed as scratches, warping of the surface, and a visual repair can destroy the code and this is why the rate of usage of the QR codes is not yet adopted by many companies [10]. Blockchain-based solutions provide more credible data through QR, yet, still require an evident visual reading [11]. Instead, RFID continues to perform in case a tag remains to be partially damaged or covered with an object, which is extremely essential in swift warehouse processes [12]. Today, users are combining RFID with the IoT to monitor items in real-time. Ferdousmou et al. discovered that the IoT-RFID is more scalable [2] however, they also identified the problem of false positives. Ma proposed ML-based repair to cleanse that up [5], and a group by Geigl demonstrated that ML can also be used to pin-point the location of a tag to increase efficiency [7].

RFID is also cool in that the tags may be reused. After delivering a product, the tag can be retrieved, rewritten and tossed onto another batch, which reduces the costs and eliminates electronic waste [6], [24]. This is in line with the circular-economy perspective, maintaining traceability and authenticity and remaining green [3], [20]. It is all that renders RFID a good, economical, and environmental safe option in the logistics of the future.

ML takes RFID even further. ML was applied by Vales-Alonso and Lopez-Matencio to crunch RFID signals and approximate package size [8]. Random Forests Ensemble tricks, particularly Random Forests, slice through the noisy data with a sound accuracy [15]. Random Forests were originally discussed by Liaw and Wiener, and it is now considered an option of choice when classifying RFID data [15]. Briefly, RFID + ML will provide you with the intelligent sorting of products.

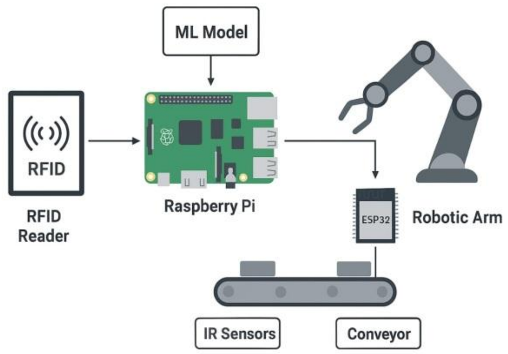

Figure1: Architectural framework of the proposed RFID–ML–robotics system for intelligent and automated product segregation.

The current study fills these gaps by developing a holistic RFID-ML-robotics system for automated segregation of industrial products (Figure 1). The system uses RFID and Random Forest-based classification at the edge. This approach guarantees real-time, accurate, and robust identification. The ESP32-based actuation layer controls the robotic arm's movement. It offers flexible segregation into containers for different delivery addresses. The conveyor system is equipped with IR sensors that dynamically regulate product positions and decrease scanning misalignment errors. Cost-effectiveness and environmental responsibility are ensured through the retrieval and reprogramming of RFID tags after delivery. Figure 1's architecture provides an end-to-end solution. It integrates strong sensing, machine intelligence, secure networking, and robotic actuation for next-generation industrial logistics.

Hardware Implementation:

The hardware implementation of the system is structured into four functional modules—power management, sensing, processing, and actuation—to enable automated product segregation. All components are shown in Fig. 2 and marked (A–L). The process begins with the switched-mode power supply (SMPS) (A), which provides a regulated 12 V DC output. A buck converter (B) steps this down to 5 V to power low-voltage modules such as the

Raspberry Pi, PCA9685, and servo motors. A DC geared motor drives the conveyor belt (C), transporting products for scanning and sorting. Conveyor control is managed by the Raspberry Pi Pico (E), which receives inputs from two IR sensors (D). The first sensor detects incoming products and activates the conveyor, while the second sensor halts the belt at the scanning point.

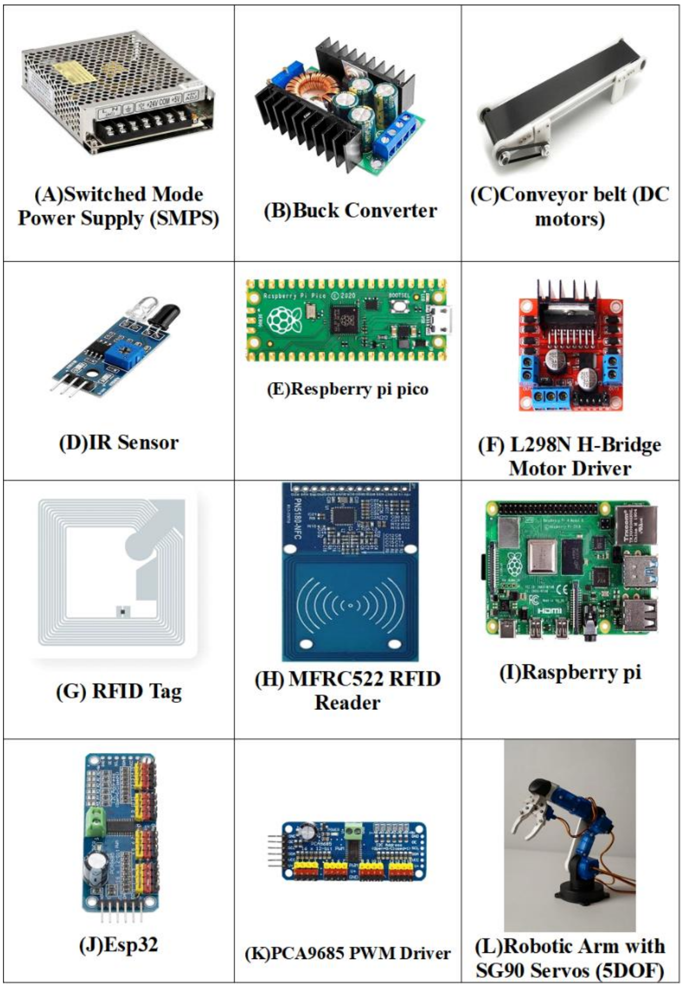

Figure 2: Constituent hardware assemblies of the RFID–ML–robotic integration.

Each product carries an RFID tag (G) with a unique ID. When the conveyor stops, the MFRC522 RFID reader (H) scans the tag and transmits the data to the Raspberry Pi (I), the system's central processing unit. The Raspberry Pi extracts features and executes the Random Forest machine learning algorithm to classify the product. The classification output is then sent to the ESP32 microcontroller (J), which initiates robotic actuation. For precise multi-channel servo control, the ESP32 interfaces with the PCA9685 PWM driver (K), generating the required pulse signals. The robotic arm (L), built using SG90 micro servo motors, provides five degrees of freedom to execute accurate pick-and-place operations into designated bins.

A key feature of the proposed framework is the reusability of RFID tags, which enhances both economic and environmental sustainability. After delivery, RFID tags are collected, reprogrammed, and reused in subsequent shipping cycles. This significantly lowers recurring costs by avoiding disposable identifiers and reduces electronic waste in large-scale logistics. In high-volume e-commerce operations, tag reuse supports a circular logistics model, improving operational efficiency and contributing to long-term sustainability across the supply chain.

Software Implementation:

The process starts with raw input, which includes RFID tag identifiers and IR sensor signals collected at the conveyor entry point. The data is labelled by the data labeller, then filtered into feature datasets by the featuriser. This step also removes noise and makes the data consistent. The orchestrator acts as the main entrance and channels the normalized features to the model builder. In this stage, labelled datasets are trained with the Random Forest classifier. The trained model is deployed to a server running on the Raspberry Pi, which performs real-time inference via a front-end interface provided over PuTTY. The evaluator compares predictions with test data to determine performance measures. The monitor displays ongoing feedback at any time and helps ensure system stability for industrial use. Lastly, classification results go to the ESP32 controller. This controller drives the PCA9685 PWM driver, which operates pick-and-place robotic arm actions. This end-to-end solution integrates raw inputs, feature processing, model training, real-time inference, and robotic actuation. It achieves efficient, scalable, and sustainable package segregation in industrial logistics.

To ensure robust classification performance, five supervised machine learning algorithms—Logistic Regression, k-Nearest Neighbours (KNN), Support Vector Machine (SVM), Decision Tree, and Random Forest—were trained on labelled datasets and evaluated using Accuracy, Precision, Recall, F1-score, and computational efficiency. Comparative analysis revealed that the Random Forest classifier outperformed all other models, achieving the highest accuracy, superior generalization ability, and low inference time. This makes Random Forest the most reliable and effective algorithm for real-time classification within the proposed RFID-based goods segregation system.

Random Forest Classifier:

The algorithm in Fig.3 is known as the Random Forest. This ensemble-based supervised learning method builds many decision trees by bootstrapping the training data. Each tree is trained on a random subset of data. At each node, a random subset of features is chosen to split, providing diversity and addressing overfitting typical in single decision trees. After the trees are constructed, each tree makes a prediction. The ultimate prediction is made by majority voting, as shown in the bootstrap aggregation phase. This mechanism supports strong classification, even when the data is noisy or high-dimensional. In RFID-based product segregation, such an architecture enables proper mapping of tag identifiers to categories, balancing predictive accuracy and generalization. The ensemble prediction can be mathematically described as follows.

$$\hat{y} = \text{mode}\{h_1(x), h_2(x), \ldots, h_T(x)\}$$

where $h\ (x, t)$ is the prediction of the $t\hat{}th$ tree and T is the overall number of trees.

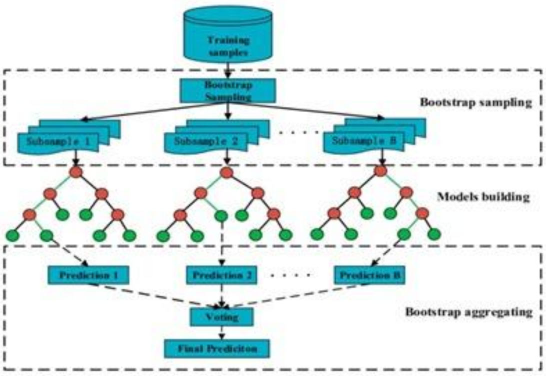

Figure 3: Structural representation of the Random Forest classifier employed for RFID-based segregation.[41]

Result:

The proposed RFID-based automated goods segregation system was successfully implemented and tested in both hardware and software modules. When an item is placed on the conveyor, the entry IR sensor signals the conveyor motor. As the package reaches the second IR sensor, the conveyor stops to enable accurate scanning of the RFID tag, as shown in Figure 4. After classification, the robotic arm performs the pick-and-place task and segregates the package to the proper bin, as illustrated in Figure 5. Segregation bins were arranged hierarchically into state, district, and mandal, mimicking real-life e-commerce logistics. Additionally, RFID tags were reused after final delivery to promote sustainability. The tags were returned to the warehouse following order completion and reprogrammed for reuse in future shipments, thus reducing operational costs and electronic waste. Within e-commerce logistics, this practice ensures cost efficiency and enhances tracking by allowing products to be monitored across delivery cycles without reprinting or relabeling. The reusability of RFID tags supports circular logistics models by conserving materials and promoting environmentally responsible operations, while maintaining product authenticity and reliable destination mapping.

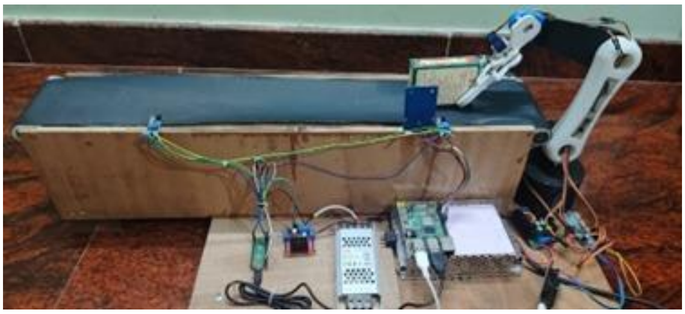

Fig.4 RFID scanning process after the package reaches the second IR sensor.

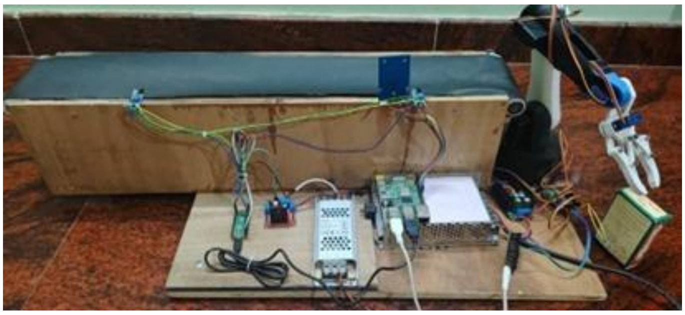

Fig.5 Robotic arm performing pick-and-place operation into designated bins.

Table I: Comparison of ML Algorithms Performance on RFID-based Classification

Algorithm	Accuracy(%)	Precision(%)	Recall(%)	F1(%)
Logistic Regression	85	83	81	82
Decision Tree	88	85	84	84
Support Vector Machine	90	89	86	87
K-Nearest Neighbors	87	85	83	84
Random Forest Classifier	94	92	90	90

In parallel with hardware validation, the machine learning (ML) module was implemented on the Raspberry Pi using the Putty interface for remote execution. The classification performance was evaluated using Accuracy, Precision, Recall, and F1-score.

Table I summarizes the comparative performance of five algorithms: Logistics Regression, the decision tree, the support vector machine (SVM), K-Nearest Neighbours (KNN), and the random forest. Random Forest was the best classifier, achieving the highest accuracy of 94, precision of 92, recall of 90, F1-score of 90, inference time of 18 ms/sample, and throughput of 56 items per second. Logistic Regression and decision tree performed moderately. KNN exhibited increased calculation overhead. SVM was also competitive in terms of accuracy (90%), but had a much longer inference time. This made SVM less suitable for real-time environments compared to Random Forest.

To comprehensively benchmark the machine learning algorithms, bar graph visualisations were employed. This offered a clear, intuitive comparison across models. Figure 6 illustrates the accuracy outcomes. Here, Random Forest emerged as the dominant classifier, achieving 94% accuracy. This result surpassed all other algorithms by a significant margin. Logistic Regression reached 82% and Decision Tree 85%, while SVM and KNN had 90% and 87%, respectively. Figure 7 shows the precision analysis. Random Forest set the benchmark with 92%, demonstrating its ability to minimise false positives. The remaining algorithms clustered within the lower range of 82-86%.

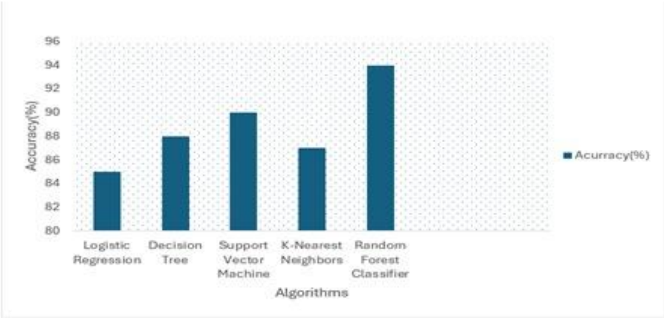

Figure 6. Accuracy comparison of different machine learning algorithms for RFID-based product segregation.

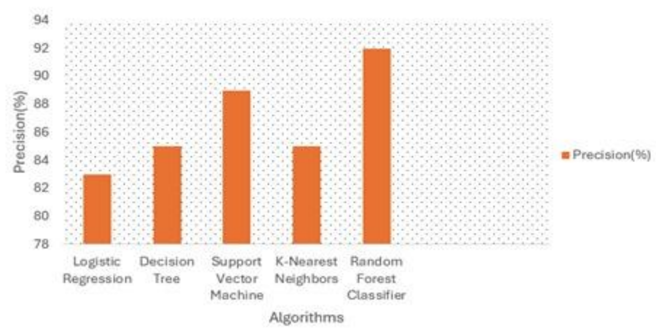

Figure 7. Precision comparison of different machine learning algorithms for RFID-based product segregation.

Conclusion:

This paper has presented an RFID-ML-robotics architecture for automatic goods segregation. It involves a combination of RFID sensing, Raspberry-PI machine learning, and robotic actuation. The hardware prototype included RFID product identification and IR sensors to control the conveyor. A Raspberry Pi handled product classification. An ESP32-controlled robotic arm was powered via a PCA9685 controller. The system effectively divided products into hierarchical bins: state, district, and mandal, based on real-world e-commerce distribution needs. RFID tags were reused after the end of the delivery period. This made the system both cost-effective and eco-friendly. At the software level, five supervised learning algorithms were applied and tested on Accuracy, Precision, Recall, and F1-score. The findings revealed that the Random Forest classifier provided the best accuracy (94%), F1-score

(90%), and low inference time (18 ms/sample). This is suitable for real-time deployment. Support Vector Machine was more competitive in accuracy but had a longer inference time. Logistic Regression, Decision Tree, and KNN had moderate throughput. The hardware-software platform achieved a cumulative positioning of 98 percent over 100 trials. The average end-to-end execution was 2.3 seconds per product. The results confirm that the proposed system is a sustainable and scalable solution for automated logistics. Future work will extend the framework with deep learning models for greater flexibility. IoT-based cloud monitoring will aid large-scale integration. Advanced robotic actuation will also be explored. Greater emphasis will be placed on systematic retrieval and optimized reuse of RFID tags to enhance both economic feasibility and environmental responsibility in e-commerce logistics.

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