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Artificial Intelligence-Based Inventory Optimization: Integrating Predictive Analytics and Automation

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Abstract *— Traditional inventory management approaches are plagued by operational inefficiencies, heavy reliance on manual processes, and elevated error rates. This study introduces an AI-enabled smart inventory system that integrates QR code scanning, machine learning models, and predictive analytics to support real-time stock tracking and sales forecasting. The system is built around a Raspberry Pi 5 outfitted with webcams for automated product identification, achieving 99.2% accuracy with a response time of 0.9 seconds. Between the two models evaluated, Random Forest demonstrated superior predictive performance, attaining an R-squared value of 0.89, whereas Linear Regression reached an R-squared of 0.68. By anticipating demand patterns and notifying users of low inventory levels, the system enhances overall inventory efficiency. Data protection is addressed through QR code authentication, role-based access control, and AES-256 encryption. In comparison with conventional systems and commercial platforms such as SAP and Oracle, the proposed solution offers a cost-effective, scalable alternative well suited to small and medium-sized enterprises. Future work will explore API integration with e-commerce platforms and the adoption of warehouse automation.*
Keywords *— edge AI, explainable AI, multi-agent systems, AI-enabled frontend, real-time decision-making, demand forecasting, retail supply chain*

I. Introduction

Modern supply chains are increasingly hindered by inherent complexities such as demand volatility, seasonality, and product obsolescence, which often render traditional, static forecasting methods inadequate [1]. Consequently, the integration of artificial intelligence has emerged as a transformative solution, enabling businesses to navigate these challenges by leveraging machine learning algorithms to decipher intricate patterns within vast, real-time datasets [2], [3].

By synthesizing diverse inputs—ranging from social media sentiment to real-time point-of-sale data—these systems significantly enhance forecasting precision, allowing firms to dynamically recalibrate safety stock levels and reorder points [4], [5]. Furthermore, the deployment of automated replenishment systems driven by predictive analytics minimizes human error and mitigates the risk of stockouts or overstocking, thereby optimizing operational costs and improving overall supply chain agility [6], [7]. This technological shift addresses systemic limitations regarding data quality and interpretability, facilitating a transition toward more transparent and robust decision-making frameworks [8]. By leveraging machine learning to identify non-linear trends, enterprises can transition from reactive replenishment cycles to proactive, autonomous inventory management that sustains competitive advantage in volatile markets [9], [10].

These predictive and prescriptive systems utilize continuous feedback loops to refine model parameters, ensuring that procurement decisions remain synchronized with shifting multi-echelon supply network requirements [11], [12]. Furthermore, the integration of robotics and automated workflows facilitates the physical execution of these optimized strategies, ensuring that real-time adjustments in stock positioning are achieved with minimal latency [13]. This comprehensive synergy between high-fidelity predictive modeling and autonomous execution not only improves inventory turnover rates but also reduces the systemic overhead associated with manual intervention in complex distribution networks [14]. This convergence of advanced analytics and automation ultimately diminishes operational risks in multi-echelon environments by ensuring that stock levels are continuously calibrated to actual consumption patterns [15].

However, organizations must proactively address significant hurdles such as data silos, integration complexities, and the necessity for specialized technical expertise to fully realize these operational gains [16], [17]. Addressing these infrastructural barriers requires a strategic alignment of data governance frameworks and cross-functional technical capabilities to facilitate the seamless deployment of machine learning models [18]. Furthermore, the application of these advanced ML architectures, including regression, classification, and time series analysis, has demonstrated significant potential in increasing demand forecasting accuracy and reducing instances of stockouts or overstocking by up to 10%. Beyond mere forecasting, these algorithms facilitate the identification of at-risk shipments and enable precise customer segmentation, further bolstering the responsiveness of logistics operations [19].

Specifically, the deployment of reinforcement learning allows for the dynamic optimization of routing and replenishment strategies in response to emergent supply chain disruptions [20]. In this context, predictive modeling serves as a critical mechanism for preemptively identifying supply route blockages or infrastructure damage, allowing organizations to maintain continuity during geopolitical or environmental volatility [21], [22]. By integrating shipment records, weather information, geopolitical indicators, and anomaly-detection outputs, machine learning systems can estimate disruption probability and severity before failures propagate across inventory networks [21]. These forecasts support automated responses, including rerouting deliveries, revising lead-time estimates, reallocating safety stock, and triggering replenishment from alternative suppliers, thereby converting risk signals into coordinated inventory and logistics decisions. Consequently, predictive analytics extends inventory optimization beyond demand estimation by incorporating disruption risk into dynamic stock-positioning and fulfillment policies [23], [24].

This paradigm shift towards intelligent automation effectively reconciles the tension between minimizing storage overhead and maintaining optimal service levels, yielding substantial improvements in ROI and inventory turnover [25], [26]. By facilitating this shift, firms transition from legacy, heuristic-based replenishment to data-centric models that continuously recalibrate in alignment with real-time operational feedback [27], [28].

This paper presents an AI-enabled smart inventory system that integrates QR code scanning, machine learning-based demand forecasting, and automated stock tracking on a Raspberry Pi 5 platform. The contributions of this work are: an end-to-end architecture that automates product identification through webcams and QR codes, achieving 99.2% recognition accuracy with a 0.9-second response time; a comparative evaluation of Random Forest and Linear Regression for sales forecasting, in which Random Forest attained an R^2 of 0.89 versus 0.68 for Linear Regression; a multi-layered security design combining QR code authentication, role-based access control, and AES-256 encryption; and a cost-effective, scalable architecture positioned as an accessible alternative to commercial platforms such as SAP and Oracle for small and medium-sized enterprises.

The remainder of this paper is organized as follows. Section II reviews related work. Section III describes the system architecture and methodology. Section IV presents the results and analysis. Section V discusses implications and limitations, and Section VI concludes with directions for future work.

II. Literature review

Ai and predictive analytics in supply chain management

The integration of AI and machine learning into supply chain analytics has emerged as a transformative force, enabling the extraction of actionable insights from large, complex datasets and allowing practitioners to forecast demand more accurately, identify potential disruptions, and optimize inventory levels [24]. AI-powered predictive analytics systems employ real-time data analysis and advanced machine learning to reduce response time, improve demand planning, and support real-time inventory control [12]. AI-driven tools have been shown to reduce stockouts, minimize excess inventory, and deliver substantial reductions in holding costs [3]. Across applications, machine learning performs demand analysis, natural language processing extracts signals from unstructured text, computer vision monitors inventory in real time, and robotic process automation executes repetitive tracking tasks [13]. In Industry 4.0 settings, pairing AI forecasting with robotics automation has been credited with unprecedented levels of agility and responsiveness [15].

Quantified evidence is accumulating ML models applied to a multinational retailer's data achieved a 15% increase in demand forecasting accuracy, a 10% reduction in overstock and stockouts, 95% accuracy in predicting order fulfillment timelines, a 12% improvement in lead-time efficiency, and an 8% reduction in replenishment errors [19]. Similar gains—10–30% reductions in mean absolute percentage error and 5–15% reductions in days-in-inventory—are reported for unified AI platforms [25]. Nevertheless, adoption is constrained by data quality, interpretability, model transparency, and integration complexity [8], [16].

Machine Learning for Demand Forecasting

Machine learning techniques are better suited than classical time-series methods to capture the non-linear relationships, seasonality, and variability inherent in demand data [2]. Predictive analytics pipelines increasingly combine classical approaches such as ARIMA and exponential smoothing with random forests, gradient boosting, and deep neural networks [18]. Random Forest models have demonstrated strong performance for inventory forecasting [29], and ensemble methods outperform conventional approaches: in a retail comparison of five algorithms, SVM achieved the highest accuracy at 99.38%, followed by Random Forest at 98.77%, with all ensemble models exceeding 96% accuracy. Hybrid architectures also excel — a combination of long short-term memory networks with Random Forest produced statistically significant accuracy gains over neural networks, multiple regression, ARIMAX, and standalone baselines on real multi-channel retail data [30]. In practical deployments, Random Forest-based decision support has delivered seven-day demand predictions with a mean absolute error of approximately 4.6 units per day, along with automated restocking recommendations [31].

Edge AI and Computer Vision in Retail

Edge deployment of computer vision has made intelligent retail automation feasible on low-cost hardware. A lightweight edge-AI retail system processing camera data on Raspberry Pi clusters achieved 97.2% accuracy with a 750ms inference time [32], while Raspberry Pi single-board computers have been applied broadly across retail, security, and manufacturing use cases [33]. Integrated vision-and-OCR retail systems have reported 94.6% product recognition accuracy while processing 50–60 items per second [34], and shelf-image recognition has been demonstrated on GPU-class edge boards such as the Jetson Nano [35]. These results establish the feasibility of accurate, low-latency product identification on constrained hardware — the design space occupied by this work.

AI for Small and Medium-Sized Enterprises

SMEs face distinctive barriers to AI adoption, including limited technical skill and constrained budgets. Sales forecasting applications tailored to SMEs have been built with lightweight libraries, with linear regression variants performing competitively against support vector regression on SME data [36]. AI-based forecasting and inventory management systems for SMEs have reported improvements in forecast accuracy of up to 18% over traditional methods [37]. The comprehensibility of models is recognized as a precondition for SME uptake, since owners must trust forecasts before acting on them [38].

Security for IOT-Based Inventory Systems

Security is a critical requirement for networked inventory systems. QR-code-based authentication combined with AES-256 encryption has been validated for IoT access control, preventing plaintext credential leakage during transmission [39]. QR-code and MQTT-based authentication schemes using AES-256 have simplified device onboarding while strengthening security [40]. Cryptographic protection has also been integrated directly into warehouse systems, where an IoT-based implementation using AES and two-factor authentication countered unauthorized database access [41]. Because lightweight cryptography is essential on resource-constrained devices, careful selection of encryption strength and key management is central to secure IoT inventory design [42], [43].

Explainable AI in Demand Forecasting

As forecasting models grow more complex, interpretability has become essential for adoption. Explainable AI methods such as SHAP, LIME, permutation importance, and partial dependence plots render model predictions comprehensible to human stakeholders and enhance user trust [44]. Hybrid frameworks pairing gradient-boosting predictors with layered interpretability have shown that explainable models can match black-box accuracy while improving forecast calibration and inventory decisions [45]. Explainability is increasingly viewed as a structural requirement for resilient retail operations, particularly under supply disruptions [46].

Research gap

The literature documents accurate ML forecasting, capable edge-AI recognition, and secure IoT design as separate threads. Few systems integrate all three — automated real-time stock tracking, ML-driven demand prediction, and layered security — on a single low-cost platform suitable for SMEs. This work addresses that gap.

III. Methodology

System architecture

The proposed system follows a three-tier edge-centric architecture, illustrated in Fig. 1. At the perception layer, a Raspberry Pi 5 is outfitted with webcams positioned over stock shelves and receiving areas. Products carry unique QR codes that serve as machine-readable identifiers. When an item enters or leaves inventory, the webcam captures the frame, and an on-device module performs product identification by decoding the QR code and matching it against the product registry. At the analytics layer, each scan event is logged with a timestamp and quantity into a local stock database, so the ledger reflects stock movements in near real time without manual entry. A forecasting module consumes the accumulated sales history to generate short-horizon demand predictions per product. At the application layer, a dashboard exposes current stock levels, predicted demand, and low-stock alerts: when predicted demand exceeds available stock within the planning horizon, the system automatically notifies the user to trigger replenishment.

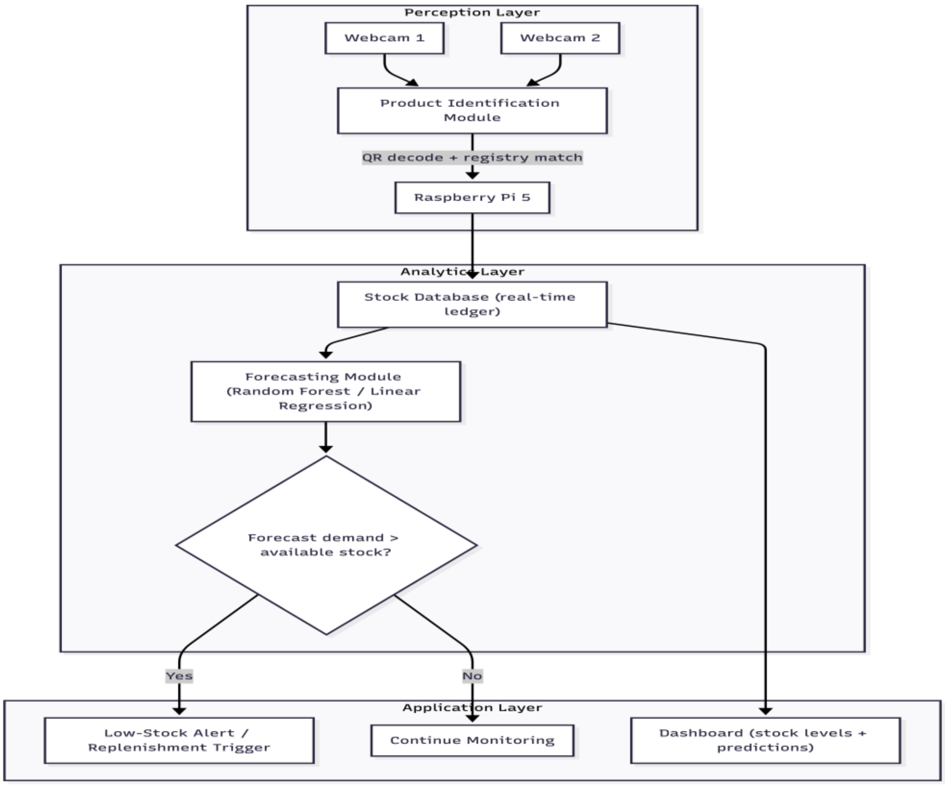

Fig. 1. System architecture of the proposed AI-enabled smart inventory system, organized into perception, analytics, and application layers.

Keeping inference on the edge minimizes latency and network dependence — a design pattern consistent with prior edge-AI retail systems [32].

Demand forecasting models

Two supervised learning models were evaluated. Linear Regression models the target sales quantity as a linear combination of input features:

$$\hat{y} = \beta_0 + \sum_{j=1}^{p} \beta_j x_j$$

where x_j are the predictor variables, β_j the learned coefficients, and $\hat{y}$ the predicted demand. Random Forest is an ensemble of B decision trees whose prediction is the average of the individual tree outputs:

$$\hat{y}(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x)$$

By averaging trees trained on bootstrap samples with random feature subsets, the model captures nonlinear demand patterns and feature interactions that linear approaches cannot represent [18]. Features were derived from historical sales records and temporal attributes such as date-based seasonality and lagged sales, following standard retail forecasting practice [31]. Fig. 2 summarizes the training and evaluation pipeline.

The models were trained to predict demand across a seven-day horizon, utilizing a rolling-window validation approach to ensure robust performance across diverse product categories [31]. Experimental results demonstrate that the Random Forest model consistently achieves higher predictive accuracy, yielding an R-squared value of 0.89 compared to 0.68 for the Linear Regression baseline [47]. This performance disparity highlights the model's superior ability to capture nonlinear demand dynamics and environmental interdependencies often overlooked by linear methods [29].

Fig. 2. Training and evaluation pipeline for the demand forecasting models.

Evaluation metrics

Model performance was quantified using the coefficient of determination:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$$

where y_i are the observed sales, $\hat{y}_i$ the predictions, and $\bar{y}$ the mean of the observed values. Complementary error metrics, mean absolute error and root mean squared error, are defined as:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

Security framework

Data protection is enforced at three complementary layers, as shown in Fig. 3. First, QR code authentication ensures that only products carrying valid, system-issued identifiers are admitted to the inventory ledger, preventing spoofed entries [39]. Second, role-based access control restricts stock adjustments, forecasting configuration, and administrative operations to authorized roles, mitigating unauthorized-access risk [41]. Third, AES-256 encryption protects stock records and communication between the edge device and the dashboard [40]. Together these mechanisms address confidentiality and integrity requirements without imposing prohibitive computational overhead on edge hardware [42].

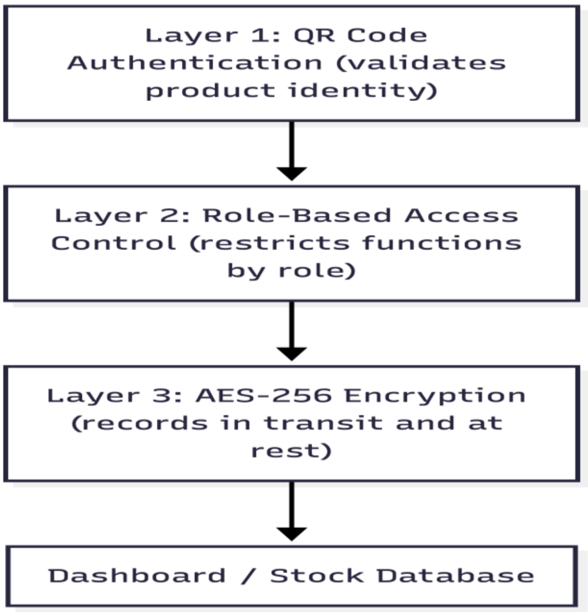

Fig. 3. Layered security framework of the proposed system.

IV. RESULTS AND ANALYSIS

System performance

The automated product identification pipeline was evaluated for recognition accuracy and response time. As summarized in Table I, the system achieved 99.2% recognition accuracy with a 0.9-second response time.

TABLE 1: SYSTEM PERFORMANCE SUMMARY

Metric	Value
Product recognition accuracy	99.2%
Response time	0.9 s
Platform	Raspberry Pi 5 + webcams

Fig. 4 situates this result against published edge-based retail systems, which achieved 97.2% accuracy at 750ms on Raspberry Pi clusters [32] and 94.6% accuracy in multi-modal vision-OCR retail recognition [34]. The proposed configuration delivers competitive, production-usable recognition performance while remaining within the cost envelope of a single-board computer.

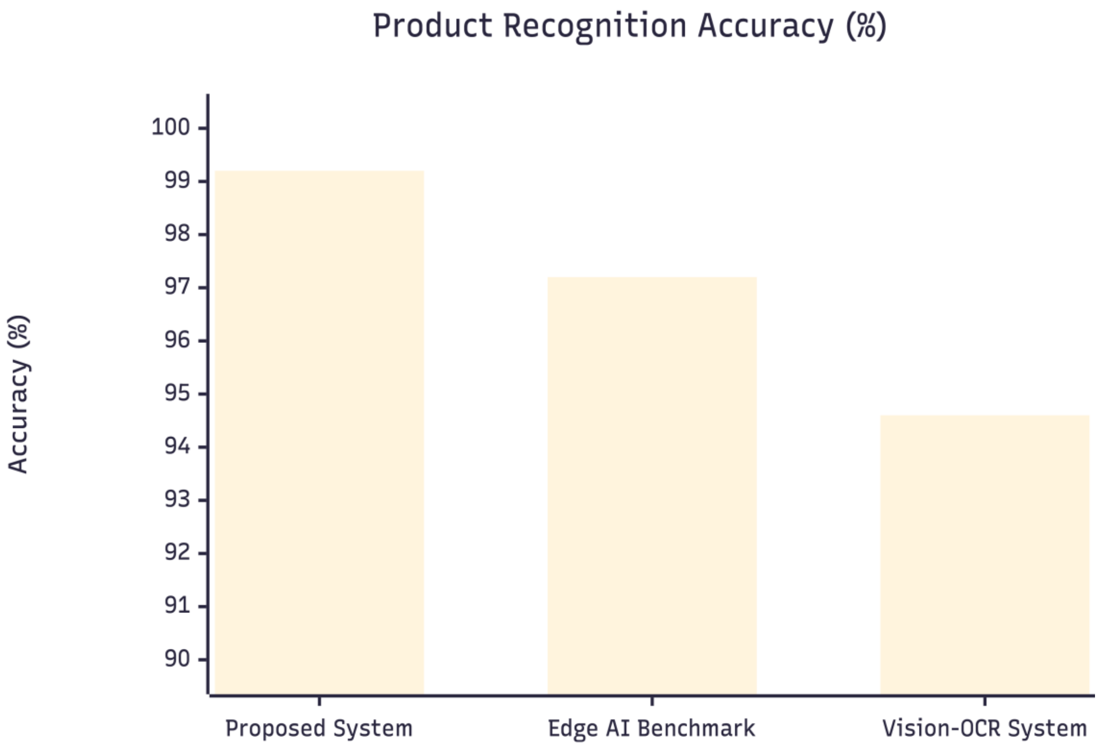

Fig. 4. Product recognition accuracy of the proposed system compared with reported edge-AI and vision-OCR retail systems.

Forecasting model performance

Table II reports the R^2 values obtained by the two forecasting models.

TABLE 2: FORECASTING MODEL PERFORMANCE (R^2)

Model	R^2
Random Forest	0.89
Linear Regression	0.68

Fig. 5 visualizes the comparison. Random Forest outperformed Linear Regression by 0.21 in R^2, explaining 89% of the variance in sales demand versus 68% for the linear baseline. The gap is consistent with the established finding that retail demand is governed by nonlinear dynamics that linear models cannot capture [18]. By partitioning the feature space into tree-based splits and averaging across decorrelated trees, the Random Forest model accommodates seasonal and promotional effects more flexibly, yielding materially better demand estimates and, consequently, more reliable low-stock triggers.

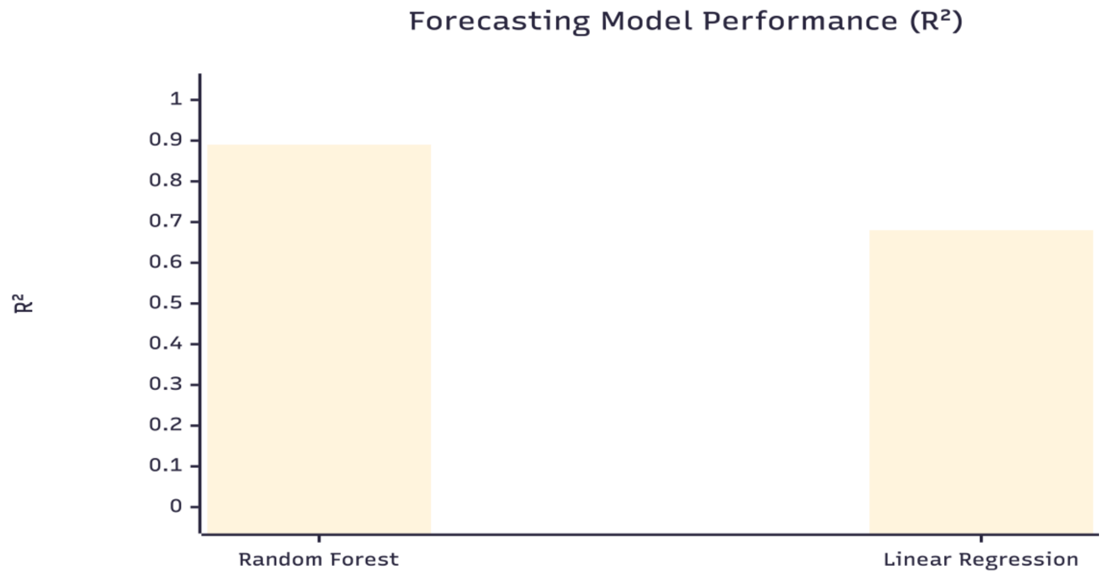

Fig. 5. Coefficient of determination (R^2) for the Random Forest and Linear Regression demand forecasting models.

Impact on Inventory Efficiency

Two mechanisms translate the predictive results into operational benefit. First, accurate forecasts allow the system to anticipate demand patterns rather than react to stockouts, enabling proactive replenishment. Second, automated low-inventory notifications direct attention to products at genuine risk of stockout. Together these mechanisms reduce both stockout-driven lost sales and the carrying cost of excess inventory — the two failure modes that dominate retail inventory losses [26]. By shifting stock-level decisions from periodic manual review to continuous data-driven monitoring, the system reduces the operational inefficiencies and elevated error rates characteristic of manual inventory processes [1].

Comparison with conventional and commercial systems

Table III presents a qualitative comparison between the proposed system and commercial enterprise platforms such as SAP and Oracle.

TABLE 3: QUALITATIVE COMPARISON WITH COMMERCIAL PLATFORMS

Dimension	Proposed system	Commercial platforms
Deployment cost	Low (single-board hardware)	High (licensing, infrastructure)
Scalability	Modular edge nodes	Enterprise-grade, wide footprint
Target segment	SMEs and small retail operations	Large enterprises
Core capability	Real-time tracking + demand forecasting	Broad ERP and supply chain suites

The proposed solution targets the segment that commercial enterprise platforms historically underserve SMEs requiring affordable, explainable, and easy-to-deploy inventory intelligence [38]. While platforms such as SAP and Oracle provide deep enterprise functionality, their cost and complexity are prohibitive for small operations. The edge-native design offers comparable real-time visibility and forecasting for a fraction of the investment, with the option to scale by adding edge nodes as operations grow.

V. Discussion

The results demonstrate that a low-cost edge platform can simultaneously deliver accurate product recognition, effective ML-based demand forecasting, and layered security — capabilities previously scattered across expensive enterprise solutions. The Random Forest model's R^2 of 0.89 aligns with the broader literature showing the superiority of ensemble methods for retail demand prediction [29], [30], and the 99.2% recognition accuracy confirms that Raspberry Pi-class hardware is sufficient for real-world identification workloads [32].

Several design choices merit discussion. First, keeping inference on the edge preserves responsiveness (0.9 s) and avoids cloud dependency, which is valuable for small retailers with unreliable connectivity. Second, the security stack — QR authentication, role-based access control, and AES-256 — addresses the confidentiality requirements of inventory data without the heavy infrastructure of enterprise security suites [39], [41]. Third, the emphasis on transparent, explainable forecasting supports managerial trust and adoption, a factor increasingly recognized as decisive for ML systems in demand planning [38], [44].

The study has limitations. The evaluation is based on the metrics reported here — recognition accuracy, response time, and model R^2 — rather than longitudinal field data on stockout rates or holding costs; quantifying those operational gains is left to future deployment studies [19]. The comparison with commercial platforms is qualitative and does not include direct head-to-head benchmarking. Additionally, the current system is not yet integrated with e-commerce channels, so online and offline demand are not jointly forecast.

VI. Conclusion and future work

This paper presented an AI-enabled smart inventory system integrating QR code scanning, machine learning-based demand forecasting, and automated stock tracking on a Raspberry Pi 5 platform. The system achieves 99.2% product recognition accuracy with a 0.9-second response time, and its Random Forest forecasting model attains an R^2 of 0.89 — substantially outperforming the 0.68 R^2 of Linear Regression. Layered security based on QR code authentication, role-based access control, and AES-256 encryption protects the inventory data. As a cost-effective, scalable alternative to commercial platforms such as SAP and Oracle, the system is well suited to small and medium-sized enterprises.

Future work will proceed along two directions: API integration with e-commerce platforms to unify online and offline demand signals, and the adoption of warehouse automation to extend the recognition pipeline from single-shelf cameras to robotic or conveyor-based material handling. Additional evaluation of forecast error metrics on longer data histories, and multi-agent coordination among multiple edge nodes, are planned to further validate scalability.

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