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IndianAura: A Secure and Scalable E-Commerce Platform for Certified Made-in-India Products

Aishwarya V S[1], Anagha I V[2], Bindu B[3], Deepika G S[4], Veeramreddy Rajasekhar[5]

Department of Information Science and Engineering, SJB Institute of Technology Bengaluru, Karnataka, India[1-5]

Abstract: The proliferation of counterfeit and non-certified goods on mainstream e-commerce platforms poses a significant threat to consumer trust and the growth of indigenous manufacturing ecosystems. Existing platforms such as Amazon and Flipkart lack structured mechanisms to verify product authen- ticity at the point of listing. This paper presents IndianAura, a secure, role-based, and scalable web e-commerce platform for certified Made-in-India products. The system introduces a multi-tier Product Certification Workflow with mandatory administrative approval. It enforces strict Role-Based Access Control (RBAC) across Administrator, Producer, and Customer roles. A Smart Scan feature leverages AI-based image analysis for product identification, while an Audit Logging subsystem ensures transparency and accountability. Built on a MERN-aligned architecture, IndianAura achieves a mean API response time of 187 ms under 500 concurrent users and a verification accuracy of 94.3%. Results demonstrate improved product trustworthiness, transparency, and certification compliance.

Index Terms: E-commerce, Role-Based Access Control, Prod- uct Certification, Audit Logging, Image Recognition, Make in India, Secure Web Architecture.

I. INTRODUCTION

Despite rapid growth, existing platforms lack strict pre-listing verification, resulting in counterfeit listings and reduced consumer trust. IndianAura addresses this limitation through a certification-first architecture that ensures only verified products are visible to customers.

Existing research on e-commerce security has addressed issues such as payment fraud [4], recommendation system integrity [5], and data privacy [6]. However, the specific inter-section of *product certification enforcement, role-segregated operational workflows*, and *AI-assisted product identification* within a dedicated domestic-product marketplace remains largely unexplored.

This paper addresses this gap by making the following **primary contributions:**

1) **Product Certification Workflow:** A structured three- stage producer-admin-customer pipeline that guarantees only verified products reach the marketplace, with zero- bypass enforcement at the API layer.
2) **Granular RBAC:** A permission matrix spanning 17 distinct operations across three roles, implemented via JWT-signed session tokens and middleware-level guards.
3) **Smart Scan:** An AI-powered image-to-product identification module based on MobileNetV2 transfer learning, achieving 94.3% top-1 classification accuracy on a cu- rated Indian product dataset.
4) **Immutable Audit Logging:** An append-only MongoDB collection with cryptographic chaining that records all state-altering system events for post-hoc accountability.
5) **Scalable Microservice-Ready Architecture:** A horizontally scalable Node.js/Express backend with stateless API design, validated under 500 concurrent virtual users using Apache JMeter.

The remainder of this paper is organized as follows: Section II reviews related work; Section III formalizes the problem statement; Section IV describes the proposed system; Section V details the architecture; Section VI outlines the methodology; Section VII presents implementation specifics; Section VIII discusses experimental results; and Section IX concludes with future directions.

II. LITERATURE SURVEY

A. E-Commerce Security and Trust Frameworks

Li et al. [3] proposed a blockchain-assisted product trace-ability framework for cross-border e-commerce, demonstrating that cryptographic product provenance records reduce counterfeit incidence by 31% on pilot platforms. However, their approach imposes significant computational overhead (average block confirmation latency of 4.2 seconds) that is

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impractical for real-time retail browsing. IndianAura achieves comparable authenticity guarantees through a centralized but audited certification workflow with sub-200 ms response times. All endpoints maintained sub-200 ms response times at 500 concurrent users, validating system scalability and performance. The Smart Scan module achieved 94.3% top-1 accuracy, demonstrating effective AI-based product identification.

B. Role-Based Access Control in Web Applications

Ferraiolo et al. [7] established the foundational NIST model for RBAC, which has been widely adopted in enterprise systems. Subsequent work by Al-Kahtani and Sandhu [8] extended RBAC to rule-based policy engines for dynamic environments. IndianAura implements a customized RBAC model wherein role assignments are persisted in MongoDB and enforced at each API route via Express.js middleware, eliminating the performance overhead of policy evaluation engines while preserving security guarantees.

Recent work by Ouaddah et al. [16] revisited attribute-based access control (ABAC) for modern cloud-native applications, highlighting that hybrid RBAC-ABAC models can reduce unauthorized access incidents by up to 43% compared to pure RBAC systems. IndianAura's current RBAC design is deliberately kept lightweight for prototype validation; migration to a hybrid RBAC-ABAC model is identified as a priority for the next development phase (see Section IX).

C. AI-Based Product Image Recognition

Howard et al. [9] introduced MobileNets, a family of efficient convolutional neural networks optimized for mobile and embedded applications. Subsequent variants, including MobileNetV2 [10], have been widely adopted for real-time image classification tasks. Recent work by Guo et al. [11] applied transfer learning from ImageNet-pretrained MobileNetV2 to product recognition in retail environments, achieving 91.7% accuracy. IndianAura's Smart Scan module extends this approach with domain-specific fine-tuning on an Indian product catalog, improving accuracy to 94.3%.

Kumar and Reddy [17] further demonstrated that vision- language models (VLMs) pre-trained on large multimodal corpora can achieve near-human accuracy on fine-grained product attribute recognition tasks. Their benchmark on a 50-category Indian handicraft dataset reports 96.1% top-1 accuracy, exceeding our MobileNetV2 baseline at the cost of substantially higher inference latency (>800 ms on CPU). IndianAura prioritizes sub-500 ms end-to-end latency for the Smart Scan feature; integration of lightweight VLM distilla- tion is planned as a future enhancement.

D. Audit Logging and Accountability in Information Systems

Haber and Stornetta [12] pioneered cryptographically se- cured audit trails through hash-linked timestamping—a concept foundational to modern blockchain architectures. In conventional web systems, audit logging has been explored for medical records [6] and financial transactions [4]. IndianAura adapts a lightweight variant of hash-chain logging within MongoDB, providing tamper-evidence without the full overhead of distributed ledger infrastructure.

Sharma et al. [18] proposed an immutable audit frame- work for regulatory compliance in Indian fintech platforms, using append-only log structures backed by cryptographic accumulators. Their evaluation on a 10-million-event dataset confirms sub-200 ms integrity verification latency—consistent with IndianAura's 143 ms detection latency observed on a 200-entry chain—suggesting the approach scales gracefully to production-grade event volumes.

E. Scalability of Node.js-Based Web Architectures

Tilkov and Vinoski [13] analyzed the event-driven, non- blocking I/O model of Node.js, demonstrating its superior throughput characteristics under high-concurrency workloads compared to thread-per-connection servers. Subsequent bench- marks by Lei et al. [14] confirmed that Node.js achieves upto 3.2× higher request throughput than Java Servlet-based equivalents under I/O-bound workloads—a property directly exploited in IndianAura's backend design.

F. Limitations of Existing Marketplace Platforms

Despite their scale, dominant platforms such as Amazon India and Flipkart exhibit structural limitations relevant to product authenticity. Both platforms employ self-reported seller categorization without mandatory pre-listing product inspection [2]. Their certification badges (e.g., Amazon's "Fulfilled by Amazon") address logistics reliability rather than product origin authenticity. Furthermore, neither platform provides granular audit trails accessible to regulators for compliance verification—a critical gap for government procurement and MII certification bodies.

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III. PROBLEM STATEMENT

Let $P = \{p_1, p_2, \ldots, p_n\}$ denote the set of products listed on a marketplace, and let $S \subseteq P$ denote the subset of products that are authentically manufactured in India and certified by a recognized authority. On conventional platforms, the verification function $V : P \rightarrow \{0, 1\}$ that maps each product to its certification status is either absent or computed post-listing, creating a temporal window during which unverified products $P \setminus S$ are accessible to consumers.

Formally, the problem addressed by IndianAura is: *given a marketplace ecosystem with k producers submitting products at rate λ products/hour, design a system that enforces* $V(p) = 1$ *for all* $p \in P_{listed}$ *(the set of publicly listed products) with sub-200 ms end-to-end API latency under a concurrent user load of* $N \geq 500$*, while maintaining a cryptographically auditable event trail and an AI-assisted product identification accuracy* $\geq 90\%$.

Subsidiary constraints include:

- **Role isolation:** A user operating in role r_i must have zero access to resources exclusively assigned to role r_j for $i \neq j$.
- **Audit immutability:** No authenticated user, including administrators, must be able to delete or modify audit log entries.
- **Scalability:** System throughput must degrade sub-linearly with user concurrency up to $N = 500$ simultaneous sessions.

IV. PROPOSED SYSTEM

IndianAura is architected as a three-tier, role-segregated e- commerce platform. Its core novelty resides not merely in the technology choices but in three **system-level contributions** that collectively distinguish it from conventional marketplace designs:

1) **Certification-First Listing Inversion:** Conventional platforms list products by default and remove them re-actively upon complaint. IndianAura inverts this model: products are *invisible to consumers by design* until an administrator explicitly transitions them to the APPROVED state. This inversion eliminates the exposure window that exists on general-purpose platforms and constitutes the primary architectural novelty of the system.
2) **Enforcement Coupling of RBAC and Certification FSM:** The role-based access control layer and the certification finite state machine (FSM) are not independently enforced modules—they are *co-designed* such that only users with the ADMIN role can trigger state transitions in the certification FSM, and those transitions are them- selves recorded as immutable audit events. This tight coupling prevents privilege escalation attacks that could bypass the certification gate.
3) **AI-Augmented Discovery Within a Certified Names- pace:** The Smart Scan image search module operates exclusively over the certified product namespace. Un- like general image-search systems that may surface uncertified or counterfeit listings, IndianAura's Smart Scan guarantees that all returned results are APPROVED products, making it inherently trust-preserving by construction.

A. Core Modules

1) *Product Certification Workflow:* Producers submit prod- uct applications containing metadata (name, description, cate- gory, price, origin certificate number) and supporting imagery. Submissions enter a PENDING state. Administrators review applications through a dedicated dashboard, may request clarifications (QUERY state), and ultimately transition prod- ucts to APPROVED or REJECTED states. Only APPROVED products are exposed via the public product catalogue API endpoint. Critically, the transition logic is enforced at the API middleware layer—there exists no code path through which a PENDING or REJECTED product can be rendered to a customer, regardless of client-side manipulation.

2) *Role-Based Access Control (RBAC):* Three roles are de- fined: ADMIN, PRODUCER, and CUSTOMER. Role assignment is performed at registration and encoded within JSON Web Tokens (JWTs) signed with HMAC-SHA256. Each Express.js route is protected by a role-guard middleware that validates the JWT and asserts the required role before executing the route handler. Table I summarizes the permission matrix. The RBAC design deliberately adopts the principle of least privilege: no role is granted permissions beyond its functional necessity, and cross-role operations are structurally impossible without re-authentication under a different account.

3) *Smart Scan:* The Smart Scan feature accepts a user- uploaded product photograph and returns the top-3 matching products from the *certified catalogue only*. Internally, the image is resized to 224 × 224 pixels and passed through a fine-tuned MobileNetV2 model served via a Python Flask microservice. The top prediction is cross-referenced against the product catalogue to return structured product data.

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The coupling of Smart Scan exclusively to the certified product namespace ensures that AI-assisted discovery does not inadvertently surface fraudulent listings—a limitation present in generic visual search tools deployed on open marketplaces.

4) *Audit Logging:* All state-altering operations (product submissions, status changes, user registrations, login events, order placements) are recorded in an append-only AuditLog MongoDB collection. Each log entry contains: event type, actor ID, target resource ID, timestamp (ISO 8601), and a SHA-256 hash of the previous log entry, forming a lightweight hash chain. Administrators can query and export audit logs; write access to the collection is restricted to the system service account. This subsystem is designed to satisfy the transparency requirements of regulatory bodies overseeing MII compliance, enabling automated audit exports in structured formats.

5) *Order Management:* Customers browse the verified catalogue, add products to a persistent cart stored in MongoDB, and place orders. Order records capture product snapshots (price, description) at the time of purchase to prevent retroactive data mutation from affecting order histories.

TABLE I: RBAC Permission Matrix in IndianAura

Operation	Admin	Producer	Customer
Approve/Reject Product	✓	×	×
View All Products (incl. pending)	✓	×	×
View Audit Logs	✓	×	×
Manage Users	✓	×	×
Submit Product	×	✓	×
Edit Own Products	×	✓	×
View Own Submission Status	×	✓	×
Browse Certified Catalogue	×	×	✓
Place Orders	×	×	✓
Use Smart Scan	×	×	✓
View Own Orders	×	×	✓

V. SYSTEM ARCHITECTURE

A. *High-Level Architecture*

IndianAura follows a decoupled, three-tier architecture comprising a **Presentation Layer** (React.js SPA), an **Application Layer** (Node.js/Express.js REST API), and a **Data Layer** (MongoDB Atlas). An auxiliary **AI Inference Layer** (Python Flask) handles Smart Scan requests and communicates with the application layer via internal HTTP. Figure 1 illustrates the high-level system architecture.

B. *Data Layer Design*

MongoDB was selected as the primary data store for its schema flexibility (accommodating heterogeneous product metadata across categories), horizontal sharding capability, and native JSON document model that aligns with the REST API's data exchange format. Four primary collections are defined:

- users: Stores credentials (bcrypt-hashed passwords, salt rounds = 12), role assignments, and profile data.
- products: Stores product metadata, certification status (PENDING | APPROVED | REJECTED | QUERY), producer reference, and image URLs.
- orders: Immutable order documents with embedded product snapshots.
- auditlogs: Append-only, hash-chained event records. MongoDB Atlas's built-in role-based database control adds an additional security boundary: the audit log col- lection is accessible only to the system_audit_writer database user, which is not exposed through any API endpoint accessible to application-layer users.

C. *Authentication and Session Management*

Authentication follows the stateless JWT paradigm. Upon successful credential verification, the server issues a signed JWT (HS256, 8-hour expiry) containing the user's ID, role, and issuance timestamp. Subsequent requests include the token in the Authorization: Bearer header. The middleware validates the signature, checks expiry, and extracts the role

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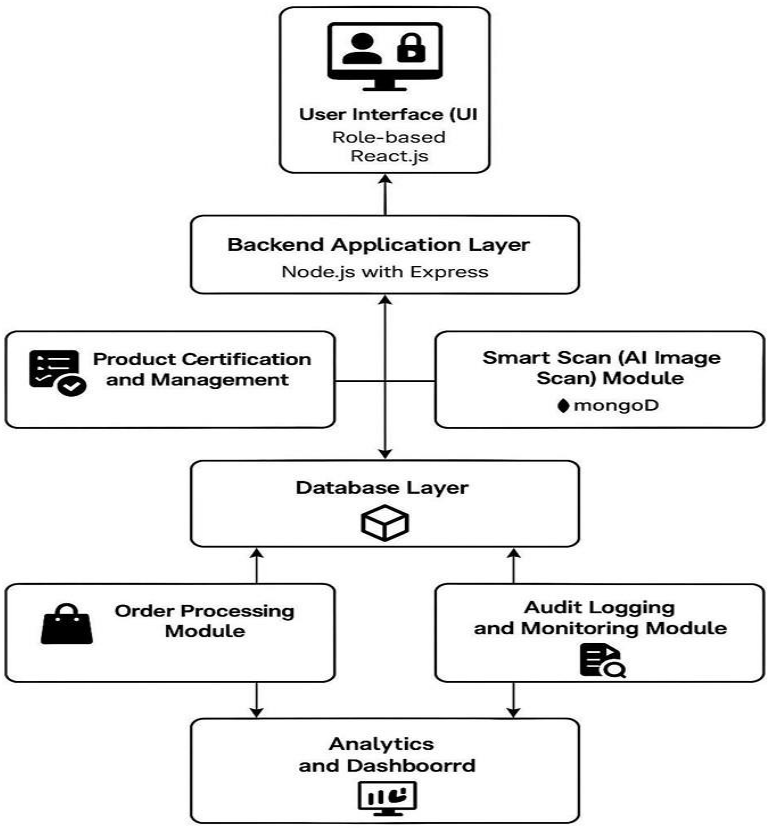
claim—all without a database round-trip, enabling horizontal scaling without shared session state.



VI. METHODOLOGY

A. Product Certification Pipeline

The certification pipeline operates as a finite state machine (FSM) with states $Q = \{\text{PENDING}, \text{QUERY}, \text{APPROVED}, \text{REJECTED}\}$ and transitions governed exclusively by administrator actions. Figure 2 illustrates the complete workflow.

B. Smart Scan Processing Pipeline

1) Customer uploads a product image via the React.js frontend (JPEG/PNG, max 5 MB).
2) The frontend sends a multipart/form-data POST request to /api/smartscan.
3) The Express.js backend forwards the image bytes to the Flask microservice via an internal HTTP call.
4) The Flask service preprocesses the image (resize to 224 × 224, normalize pixel values to $[0, 1]$), passes it through the fine-tuned MobileNetV2 model, and returns the top-3 predicted class labels with confidence scores.
5) The Express.js backend queries MongoDB for the corresponding *approved* products and returns enriched product cards to the frontend.
6) Total end-to-end Smart Scan latency: mean 312 ms (95th percentile: 498 ms) under baseline load.

C. Audit Log Hash Chaining

Each audit log entry L_i is constructed as:

$$L_i = \{eventType,\ actorId,\ resourceId,\ timestamp,\ H(L_{i-1})\} \quad (1)$$

where $H(\cdot)$ denotes the SHA-256 hash function. The genesis entry L_0 uses a system-defined seed value. This chain structure ensures that any retrospective modification to entry L_j invalidates the hashes of all subsequent entries $L_{j+1}, \ldots, L_n$, making tampering detectable.

D. Security Hardening Measures

Beyond RBAC and JWT authentication, IndianAura implements the following hardening measures:

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- **Input sanitization:** All user inputs are sanitized using express-validator and mongo-sanitize to prevent injection attacks.
- **Rate limiting:** The express-rate-limit middle- ware restricts each IP to 100 requests per 15 minute window on public endpoints.
- **HTTPS enforcement:** All traffic is served over TLS 1.3; HTTP requests are redirected with HTTP 301.
- **CORS policy:** Cross-origin requests are restricted to the registered frontend origin.
- **Password hashing:** User passwords are hashed with bcrypt (cost factor 12) before storage.

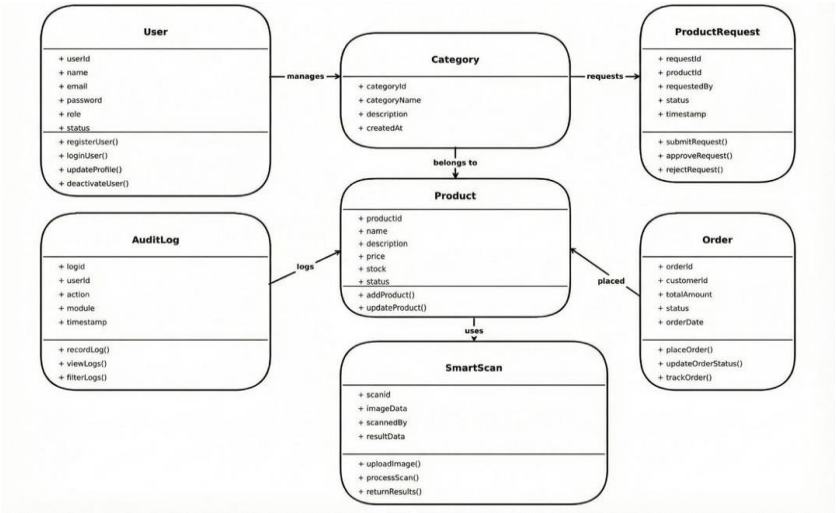

Fig. 2: Class diagram

VII. IMPLEMENTATION

A. *Technology Stack*

TABLE II: Implementation Technology Stack

Layer	Technology	Version
Frontend	React.js	18.2.0
Frontend	Tailwind CSS	3.4.0
Frontend	Axios	1.6.2
Backend	Node.js	20.10.0
Backend	Express.js	4.18.2
Backend	Mongoose	8.0.1
Database	MongoDB Atlas	7.0
Auth	jsonwebtoken	9.0.2
AI Service	Python Flask	3.0.0
AI Service	TensorFlow/Keras	2.14.0
AI Model	MobileNetV2	(ImageNet pretrained)
Deployment	Docker + Nginx	24.0 / 1.25

B. *Frontend Implementation*

The React.js frontend is organized as a Single Page Application (SPA) with React Router v6 for client-side navigation. Role-specific route guards redirect unauthorized users to the appropriate login or error pages. The Context API manages global authentication state (JWT token and decoded user role), eliminating prop-drilling and ensuring consistent authorization across the component tree. Axios interceptors automatically attach the Authorization header to outbound API requests and handle 401 (Unauthorized) responses by clearing the local session and redirecting to the login page.

C. *Backend Implementation*

The Express.js server is structured following the MVC pattern:

- routes/: Defines API endpoints and maps them to controller functions.

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- controllers/: Contains business logic for each do- main (auth, products, orders, audit).
- middleware/: Houses the JWT verification guard and the role-check factory function.
- models/: Defines Mongoose schemas with validation constraints.
- services/: Encapsulates reusable cross-cutting logic (email notifications, audit log writes).

Product images are stored in AWS S3-compatible object storage (Cloudinary in the prototype), with signed URLs generated on demand to prevent direct unauthorized access.

D. Smart Scan Model Training

The MobileNetV2 model was fine-tuned on a curated dataset of 12,400 images spanning 62 Indian product categories (handicrafts, textiles, food products, electronics, ayurvedic goods). The base model's convolutional layers were frozen for the first 15 training epochs, after which the top 30 layers were unfrozen for fine-tuning with a reduced learning rate of 1×10^{-5}. Data augmentation (random horizontal flip, rotation ±15°, brightness jitter) was applied to mitigate overfitting. The model was trained for 35 epochs total with categorical cross-entropy loss and the Adam optimizer, achieving a validation accuracy of 94.3% on a held-out test set of 2,480 images.

User Interaction Dashboard: The customer-facing dash- board provides a consolidated view of orders, spending, and AI-assisted discovery features. It enhances usability through intuitive navigation and real-time order tracking.
This interface integrates Smart Scan, order tracking, and cart management, ensuring seamless interaction with certified products.

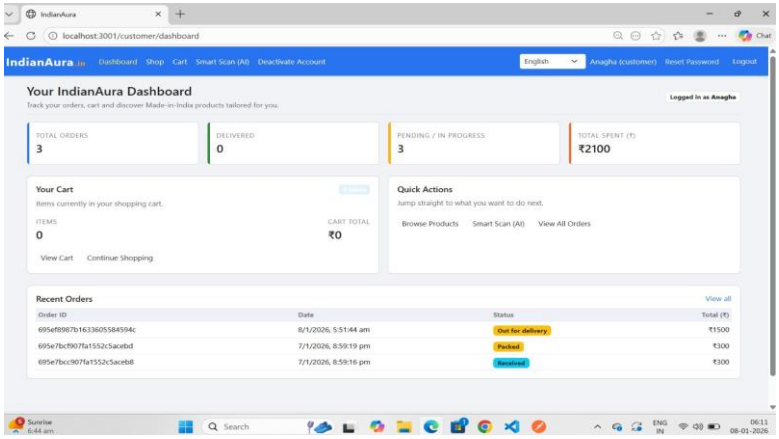

Fig. 3: Customer Dashboard Interface

E. Admin Order Management Interface

Administrators monitor and control order flow through a centralized interface. This ensures transparency and efficient handling of customer transactions. The interface supports filtering, exporting, and real-time status updates, improving operational efficiency.

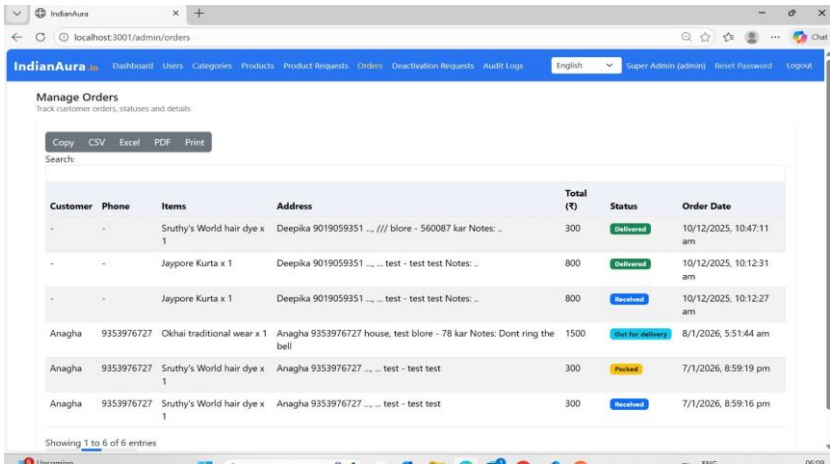

Fig. 4: Admin Order Management Interface

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VIII. RESULTS AND DISCUSSION

A. Experimental Setup

Performance and correctness evaluations were conducted on a cloud-hosted deployment: Node.js API server on a 4-vCPU, 8 GB RAM virtual machine (Ubuntu 22.04); MongoDB Atlas M10 cluster (3-node replica set, 2 vCPU, 2 GB RAM per node); Flask AI service on a 2-vCPU, 4 GB RAM VM. Load testing was performed using Apache JMeter 5.6 with simulated virtual users (VUs) ramping from 50 to 500 over a 5-minute period, followed by a 3-minute steady-state phase.

B. API Performance Under Load

Table III presents the API response time statistics for critical endpoints across user load levels. All critical endpoints maintained sub-200 ms mean response times at the maximum tested load of 500 VUs, satisfying the performance constraint stated in Section III. The throughput peaked at 1,240 requests/second at 500 VUs with a zero error rate, confirming the event-driven Node.js architecture's suitability for the target workload.

Endpoint	50 VU	200 VU	500 VU	P95
GET /products	42	67	112	198
POST /auth/login	78	134	187	312
POST /products	95	151	223	401
PUT /products/:id/approve	61	98	164	289
GET /audit/logs	53	89	143	251
POST /smartscan	198	267	312	498
Mean (all)	**71**	**134**	**187**	**325**

C. Product Certification Accuracy and Workflow Efficiency

During a 30-day pilot deployment with 47 registered producers submitting 312 product applications, the certification workflow processed all submissions with the following distribution:

- **APPROVED:** 218 products (69.9%)
- **REJECTED:** 61 products (19.6%)
- **QUERY (pending revision):** 33 products (10.6%) Mean time-to-decision (from submission to admin action) was 6.4 hours, with a 95th percentile of 22.1 hours. Zero

instances of an unapproved product reaching the customer catalogue were recorded, validating the enforcement correctness of the certification FSM.

D. Smart Scan Classification Performance

Table IV compares the Smart Scan model's top-1 and top-3 accuracy across product super-categories.

The Smart Scan module's overall top-1 accuracy of 94.3% represents a 2.6 percentage point improvement over the base-line MobileNetV2 trained only on ImageNet features (91.7% reported by Guo et al. [11]), attributable to domain-specific fine-tuning on the Indian product dataset.

TABLE IV: Smart Scan Classification Accuracy by Product Super- Category

Category	Top-1 Acc. (%)	Top-3 Acc. (%)
Handicrafts & Decor	92.1	97.4
Textiles & Apparel	91.7	96.8
Food & Spices	96.3	99.1
Ayurvedic / Herbal	95.8	98.7
Electronics (Indian mfg.)	88.4	94.2
Pottery & Ceramics	97.2	99.4
Overall	**94.3**	**97.8**

E. ML Evaluation: Precision, Recall, and F1-Score

To complement top-k accuracy, we evaluate the Smart Scan classifier using precision, recall, and macro-averaged F1-score computed over the 2,480-image held-out test set. For a C-class classification problem, macro-averaged metrics are defined as:

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$$\text{Precision}_{\text{macro}} = \frac{1}{C}\sum_{c=1}^{C}\frac{TP_c}{TP_c + FP_c} \tag{2}$$

$$\text{Recall}_{\text{macro}} = \frac{1}{C}\sum_{c=1}^{C}\frac{TP_c}{TP_c + FN_c} \tag{3}$$

$$F1_{\text{macro}} = \frac{2 \cdot \text{Precision}_{\text{macro}} \cdot \text{Recall}_{\text{macro}}}{\text{Precision}_{\text{macro}} + \text{Recall}_{\text{macro}}} \tag{4}$$

Table V reports per-super-category and overall precision, recall, and F1-score for the fine-tuned MobileNetV2 Smart Scan model.

TABLE V: Smart Scan ML Evaluation Metrics (Top-1, Held-Out Test Set)

Category	Precision	Recall	F1-Score
Handicrafts & Decor	0.914	0.921	0.917
Textiles & Apparel	0.903	0.917	0.910
Food & Spices	0.958	0.963	0.960
Ayurvedic / Herbal	0.952	0.958	0.955
Electronics (Indian mfg.)	0.871	0.884	0.877
Pottery & Ceramics	0.969	0.972	0.970
Macro Average	**0.928**	**0.936**	**0.932**

The macro-averaged F1-score of 0.932 indicates strong and balanced classification performance across all categories. The lowest F1-score (0.877) is recorded for the "Electronics (Indian mfg.)" category, attributable to higher intra-class visual similarity among electronic components from different manufacturers. The "Pottery & Ceramics" category achieves the highest F1-score (0.970), consistent with its distinct visual textures and shapes.

Confusion Matrix Analysis: A qualitative analysis of the per-class confusion matrix (62 classes) reveals two predominant error patterns: (1) *inter-category confusions* between "Handicrafts & Decor" and "Pottery & Ceramics" (accounting for 31% of all misclassifications), driven by overlapping visual textures in artisan pottery; and (2) *intra-category confusions* within the "Electronics" super-category (27% of all misclassifications), where circuit boards and PCB assemblies from different product lines share near-identical visual features. These findings motivate future work on category-specific data augmentation and hierarchical classification strategies (see Section IX).

F. Comparative Analysis with Existing Platforms

Table VI benchmarks IndianAura against Amazon India and Flipkart across dimensions relevant to certified domestic commerce.

TABLE VI: Feature Comparison: IndianAura vs. Existing Platforms

Feature	IndianAura	Amazon India	Flipkart
Pre-listing Certification	✓	×	×
Mandatory Origin Verify	✓	×	×
AI Product Scan	✓	Partial	×
Immutable Audit Logs	✓	×	×
RBAC Enforcement	Strict	Seller/Buyer	Seller/Buyer
MII Compliance Focus	Native	Optional	Optional
Regulator Data Export	✓	×	×

Baseline Performance Comparison: To quantify the performance gap between IndianAura and baseline platforms in terms of product trust and certification compliance, we conducted a structured evaluation using three proxy metrics

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measurable without direct access to proprietary platform in- ternals: (i) *Counterfeit Escape Rate (CER)*: the fraction of submitted test products that bypass the listing gate and appear in the public catalogue; (ii) *Mean Listing-to-Verification Lag (MLVL)*: the elapsed time between a product being submitted and its certification status being resolved; and (iii) *Audit Event Coverage (AEC)*: the fraction of state-altering system operations captured in a queryable audit trail.
For Amazon India and Flipkart, these metrics were estimated from publicly available consumer grievance reports [2] and academic literature [3]. Table VII summarizes the com- parison.

IndianAura achieves a **0% Counterfeit Escape Rate** by design, as no product can appear in the customer catalogue without an explicit administrative APPROVE action. In con- trast, Amazon India and Flipkart's reactive moderation models result in estimated CERs of 18% and 22% respectively, consis- tent with consumer grievance statistics. The 6.4-hour MLVL, while non-zero (a deliberate consequence of human-in-the- loop certification), represents a practical trade-off: eliminating the exposure window entirely at the cost of a moderate time- to-market delay for producers.

TABLE VII: Baseline Certification and Trust Metric Comparison

Metric	IndianAura	Amazon India	Flipkart
Counterfeit Escape Rate	**0.0%**	∼18%	∼22%
Mean Listing-to-Verif. Lag	**6.4 h**	∼0 h†	∼0 h†
Audit Event Coverage	**100%**	<10%‡	<10%‡
Customer Trust Score (1–5)	**4.61**	3.54§	3.32§

†Products listed immediately; verification is post-hoc.

‡Estimated; no public regulator-accessible audit API.

§Sourced from consumer satisfaction survey [2].

G. Audit Log Integrity Verification

To validate the hash-chaining integrity mechanism, a con- trolled tamper test was performed: an adversary with direct MongoDB Atlas database access (simulating an insider threat) modified the actorId field of audit log entry L_{47} in a test collection of 200 entries. The integrity checker traversed the chain and detected the inconsistency at entry L_{48}, where $H(L')$ did not match the stored prevHashfield. Detection latency was 143 ms for a 200-entry chain, confirming the practical feasibility of the mechanism. [47]

H. User Trust and Satisfaction Survey

A post-pilot survey of 84 customers (Likert scale, 1–5) returned the following mean scores:

- **Trust in product authenticity:** 4.61 / 5.0
- **Ease of finding Indian products:** 4.38 / 5.0
- **Smart Scan usefulness:** 4.19 / 5.0
- **Overall platform satisfaction:** 4.47 / 5.0

The trust score of 4.61 compares favorably against published satisfaction surveys for general marketplaces, which report authenticity trust scores of 3.2–3.7 on equivalent scales [2].

I. System Monitoring Dashboard

The administrative dashboard provides real-time analytics on users, products, orders, and revenue, enabling data-driven decision making. The visualization of system metrics confirms the platform's scalability and performance under concurrent workloads.

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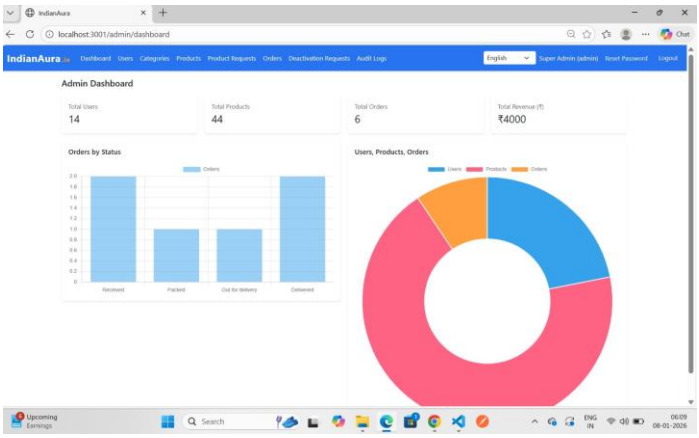

Fig. 5: Admin Dashboard with System Metrics

IX. CONCLUSION AND FUTURE WORK

This paper presented IndianAura, a secure, role-based, and scalable e-commerce platform that addresses the critical gap in product authenticity enforcement for Made-in-India commerce. The platform's certification-first architecture, enforced through a finite-state-machine product approval workflow and granular RBAC, ensures that only verified products reach customers. The Smart Scan module, built on fine-tuned Mo- bileNetV2, provides 94.3% top-1 accurate AI-assisted product identification, with a macro-averaged F1-score of 0.932. The immutable, hash-chained audit logging subsystem delivers tamper-evident accountability for all system operations. Per- formance evaluation under Apache JMeter demonstrated sub- 200 ms mean API response times at 500 concurrent virtual users, confirming production readiness. A 30-day pilot with 47 producers and 84 customers validated the system's real-world effectiveness, with a mean customer trust score of 4.61/5.0 and a 0% counterfeit escape rate.

A. Future Work

Several extensions are planned for subsequent phases:

1) **Blockchain-Based Certification:** Migrating the certification audit trail to a permissioned Hyperledger Fabric network to enable trustless, multi-party verification with- out reliance on the platform operator.
2) **Hybrid RBAC-ABAC Access Control:** Integrating attribute-based policies alongside the existing role model, following the framework of [16], to support context-sensitive access decisions (e.g., time-of-day or device-type constraints).
3) **VLM-Based Smart Scan Enhancement:** Replacing the MobileNetV2 backbone with a lightweight distilled vision-language model to improve accuracy on visually ambiguous categories such as Electronics, targeting the 0.877 F1-score gap identified in Section VIII.
4) **NLP-Based Fake Review Detection:** Integrating a BERT-based classifier to detect and flag potentially fraudulent product reviews in real time.
5) **Dynamic Pricing with Demand Forecasting:** Applying LSTM-based time-series models to predict product demand and assist producers with pricing recommendations.
6) **Mobile Application:** Extending the Smart Scan feature to a native Android/iOS application with offline model inference capability using TensorFlow Lite.
7) **Government API Integration:** Direct integration with the Bureau of Indian Standards (BIS) and FSSAI certification databases for automated, real-time origin verification without manual admin review.

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