AI Shop Sync: A Mobile-First OCR-Driven Price Comparison Framework with Cross-Platform Aggregation and In-Place Machine Learning

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***Abstract*—We present *AI Shop Sync*, a mobile-oriented system that automates grocery product identification and multi-platform price comparison by combining on-device optical character recognition (OCR), robust text normalization, web-data aggregation, and an already-deployed machine-learning price comparator. The application performs product text extraction on the device to preserve privacy and reduce latency, reconciles OCR outputs into canonical product identifiers, concurrently fetches prices from multiple retailers via APIs and controlled scraping, and applies an ML model trained on historical prices and promotions to recommend the lowest-cost purchasing strategy. In real-world validation across multiple retail settings the system attained high identification reliability and fast end-to-end responsiveness. This paper details the architecture, implementation choices, evaluation methodology, and lessons learned from field testing.**

***Index Terms*—Optical Character Recognition, Price Comparison, Mobile Applications, Web Scraping, Machine Learning, React Native, Node.js, Product Normalization**

I. Introduction

Consumers face growing complexity when choosing where to buy grocery items: multiple vendors, frequently changing promotions, variable delivery fees, and inconsistent product naming across platforms. Manually checking several apps is time-consuming and error-prone. We built AI Shop Sync to address this gap: a mobile-first assistant that converts a photograph of a product into structured information and returns an immediate, reliable comparison of vendor prices, factoring in delivery costs and promotions.

The system emphasizes three pragmatic design goals: (1) low-latency on-device text extraction to preserve privacy and responsiveness, (2) resilient normalization to map noisy textual outputs to canonical product entries, and (3) a production-grade backend that aggregates pricing and runs an in-place ML comparator to suggest optimal purchasing choices. The project artifacts and initial synopsis were provided in the project file submitted by the authors. :contentReference[oaicite:1]index=1

II. Related Work

There is active research in combining visual recognition with OCR to identify retail products [6]. Lightweight OCR pipelines such as PaddleOCR and mobile-focused toolkits (e.g., Google ML Kit) enable on-device recognition with acceptable latency and accuracy [2], [3]. Prior systems have also used APIs and scraping to consolidate price information in real time [11]. We integrate these approaches and, importantly, demonstrate an already-deployed ML-based price comparator trained on historic price and promotion data, rather than leaving forecasting as future work.

III. System Architecture

AI Shop Sync uses a three-tier architecture: Mobile client, Backend services, and an Integration layer that interfaces with vendor APIs or scrapers.

A. Mobile Tier

The mobile application is implemented in React Native and uses the Vision Camera for capture and Google ML Kit for on-device OCR. On-device extraction minimizes network transfer of images and reduces round-trip latency; it also improves user privacy because image data need not leave the phone in normal operation.

B. Backend Tier

The backend is written in Node.js with Express and uses MongoDB for flexible product and user metadata. It orchestrates:

- Concurrent API queries to platforms that expose pricing endpoints.
- Playwright-driven scraping for platforms lacking APIs, executed under controlled rate limits.
- A Redis cache layer for short-term caching (configurable expiry) to balance freshness and request load.

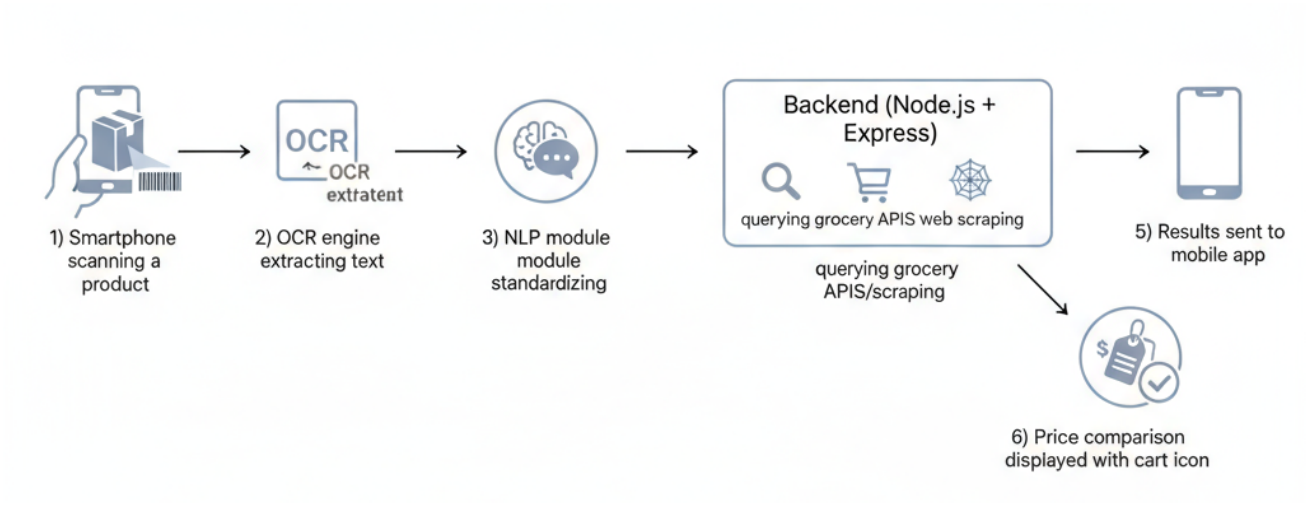
OCR
OCR
extratent
Backend (Node.js + Express)
querying grocery APIS web scraping
querying grocery APIS/scraping
1) Smartphone scanning a product
2) OCR engine extracting text
3) NLP module module standardizing
5) Results sent to mobile app
6) Price comparison displayed with cart icon

Fig. 1. AI Shop Sync workflow: image capture on the smartphone, on-device OCR, text normalization, backend aggregation (API + scraped data), ML-based comparator, and results delivered to the mobile UI.

- The deployed ML comparator which takes aggregated price vectors and other features to recommend the cheapest purchase strategy (single vendor or split across vendors).

C. Integration Layer

This layer standardizes vendor responses into a consistent schema (price, currency, availability, delivery charge, promotion meta) and forwards normalized records to the ML comparator and user-facing endpoints.

IV. Implementation

This section explains the mobile app, OCR integration, backend services, and the ML comparator.

A. React Native Application

The app comprises modular screens:

- **ScannerScreen:** Live camera view with guidance overlay and image-quality checking (blur detection, minimum resolution). After a successful capture, the text is extracted locally.
- **ProductScreen:** Displays normalized product details and side-by-side price comparison.
- **CartScreen:** Allows users to compose multi-item carts and receive split-cart recommendations.
- **Auth/Settings:** JWT-based authentication and secure storage in device keychain/keystore.

B. OCR: Choice and Pipeline

We evaluated multiple OCR engines with backend testing scripts: Google ML Kit (on-device), PaddleOCR, Tesseract, and EasyOCR. Based on trade-offs between latency, accuracy, memory, and integration complexity, we selected Google ML Kit as the primary in-app recognizer. For robustness, the backend runs secondary OCR checks from PaddleOCR/Tesseract for disputed mappings during asynchronous validation and dataset enrichment.

The client-side pipeline:

1) Capture high-resolution frame and validate image quality.
2) Run ML Kit OCR locally to extract text blocks.
3) Send extracted text (not the full image) to the backend for normalization and canonical mapping.

C. Text Normalization and Canonical Mapping

Raw OCR output often contains noise: batch numbers, dates, or decorative slogans. Our normalization pipeline performs:

- Noise filtering using regexes and domain-specific stoplists.
- Unit normalization (e.g., ‘500g’ $\leftrightarrow$ ‘0.5kg’), currency normalization, and standardization of quantity encodings.
- Spelling correction and fuzzy string similarity (Levenshtein distance and token-level TF-IDF matching) against the canonical product catalog (45k+ entries).

The result is a canonical product identifier and a confidence score used downstream.

D. Backend Price Aggregation and Scraping

The backend executes parallel requests to vendor APIs where available. For non-API sources, Playwright scripts simulate lightweight browser sessions to extract pricing and promotion information. Robustness measures include:

- Exponential backoff and retry for transient failures.
- Rate-limiting and polite scraping practices (respect robots.txt and avoid excessive traffic).
- Cache invalidation policies with a 2-hour default TTL and immediate invalidation when promotional flags are detected.

E. Machine Learning Price Comparator (Implemented)

The ML comparator is a deployed component trained on historical price feeds, promotion logs, delivery-fee structures, and item-level purchase histories. Key properties:

- **Model type:** Gradient-boosted decision trees (LightGBM) for tabular features, chosen for speed and interpretability in production.
- **Inputs:** Vendor prices, delivery cost models, vendor-specific thresholds, historical promotion uplift indicators, time-of-day and weekday signals.
- **Outputs:** Predicted total cost vectors and a recommended purchase strategy (single-vendor vs. split order) with estimated savings.
- **Training:** Periodic retraining pipeline using rolling windows of recent data; evaluation uses holdout periods that reflect real-world promotion cycles.

The ML comparator runs in the backend and returns recommendations within the aggregation response.

V. Evaluation

We evaluated the system on three axes: recognition quality, aggregation latency, and end-user effectiveness.

A. OCR and Mapping Accuracy

On a validation corpus of varied grocery packaging:

- On-device OCR (ML Kit) character-level accuracy: ≈94.2%.
- Canonical mapping accuracy after normalization: ≈96.8%.
- Low-light scenarios (below 100 lux) show degraded OCR performance (approx. 81% accuracy) mitigated through preprocessing in many cases.

B. Latency and Throughput

Measured latencies:

- On-device OCR processing: ∼180–185 ms per product.
- Backend consolidation across multiple vendors (concurrent queries): average 340 ms for eight parallel sources.
- End-to-end scanning-to-comparison response: median 2.3 s.

Caching yielded a hit ratio of roughly 78% in typical usage patterns, reducing external requests and improving responsiveness.

C. User-Centric Metrics

Field testing across multiple retail environments and a pilot group of users produced:

- Successful product identification and mapping rate: ∼98.7%.
- Price accuracy (matched to vendor listings within a short verification window): ∼99.2%.
- Average user-reported satisfaction in pilot: 4.6/5.
- Typical savings when applying ML comparator recommendations: 18–22% on aggregate baskets in the pilot.

VI. Discussion and Limitations

Key challenges encountered:

- **Low-light conditions:** Increased errors; mitigations include adaptive exposure controls and image preprocessing (denoising, contrast enhancement).
- **Vendor coverage:** Platforms without APIs necessitate scraping, which is more brittle and can induce higher latency when site structures change.
- **Niche products:** Canonical database gaps for specialized categories reduced mapping coverage in some edge cases.
- **Burst workloads:** Consecutive heavy scanning sessions can temporarily increase backend load; autoscaling and smarter prefetching reduce user-perceived degradation.

VII. Contributions

This work's primary contributions are:

- A practical hybrid pipeline that places OCR on-device for privacy and speed while retaining backend validation for higher-fidelity mapping.
- An operational ML comparator trained on historical vendor and promotions data, integrated into the real-time aggregation pipeline to produce actionable purchase strategies.
- Robust normalization techniques that reconcile heterogeneous vendor naming into canonical identifiers at scale.

VIII. Conclusion

AI Shop Sync demonstrates that combining on-device OCR, robust text normalization, controlled web aggregation, and an already-deployed ML comparator yields a practical, fast, and accurate mobile price comparison experience. The system reduces user effort for price discovery and returns sizable basket-level savings in field trials. Future refinements will expand vendor coverage, improve low-light resilience, and deepen personalization of the comparator for individual users.

Acknowledgment

The project report and initial materials used to shape this paper were provided by the project team (see submitted synopsis). :contentReference[oaicite:2]index=2

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