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LocaLens: An AI-Powered Hyperlocal Product Finder for Visual Product Verification and Local Shop Discovery

Neerali Shingavi, Pranali Unde, Soniya Kalbhor
Department of Artificial Intelligence and Data Science
Jaihind College of Engineering, Kuran, India
Corresponding author email: niralishingavi@gmail.com

Abstract: *Finding a specific product in local markets often requires customers to visit multiple shops without knowing its availability, price, quantity, or similarity to the desired product. LocaLens is an AI-powered hyperlocal product finder designed to connect customers with nearby local shops through image-based product discovery. The proposed system allows customers to upload one or more images of a required product together with quantity and location details. Nearby shopkeepers receive relevant requests and provide current product images, availability, quantity, and price. To improve product verification, the system incorporates image-quality assessment and visual similarity analysis using image preprocessing, feature or embedding extraction, and similarity measurement. Multiple visual attributes such as shape, colour, and brand or packaging information can contribute to the final matching score. Customers can also specify ranking preferences such as product similarity, price, distance, availability, and response time. Communication is primarily performed through in-app chat so that direct phone-number or email exchange is not mandatory. The initial scope focuses on jewellery and medicines, with an architecture that can be extended to other product categories. The proposed workflow aims to reduce the time and effort required for local product discovery while helping customers make more informed offline purchasing decisions.*

Keywords: artificial intelligence, hyperlocal product discovery, computer vision, image similarity, product verification, local shopping, location-aware recommendation, personalized ranking.

I. INTRODUCTION

The growth of e-commerce has made product discovery convenient; however, many customers still prefer purchasing selected products from nearby physical stores because of immediate availability, physical inspection, and the convenience of offline purchasing. The difficulty is that local shoppers often have limited information about product availability, price, quantity, and similarity before visiting a store. Traditional local shopping may therefore require customers to visit or contact several shops individually.

A related challenge occurs when a customer has a visual reference rather than an exact product name. This is particularly relevant for visually identifiable products such as jewellery, accessories, and packaged goods. Computer-vision research has established the feasibility of recognizing retail products from images, while location-aware recommender systems have shown that geographical context can improve recommendations [1]–[5]. More recent work has also investigated fine-grained product retrieval using large-scale image and text information [5].

LocaLens addresses this problem through a hyperlocal, image-driven workflow. A customer submits one or more images of the desired product, specifies the required quantity and location, and optionally sets ranking priorities. Relevant nearby shops are identified and requests are routed to suitable shopkeepers. A shopkeeper provides current

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product information and captures product image(s) at response time rather than relying on a previously stored gallery image.

A key research component is visual product verification. Customer and shopkeeper images are subjected to image-quality checks and visual comparison. Feature or embedding representations can be compared using cosine similarity or another experimentally validated metric. Attribute-level scores, such as shape, colour, and brand or package appearance, can be combined into an overall matching score. The system also considers real-time availability and customer-specific ranking preferences.

The research question addressed by this work is: how can visual product verification, geographical shop discovery, real-time local responses, and personalized ranking be integrated into a practical workflow for offline product discovery? The contribution is therefore positioned as an integrated system architecture and methodology rather than as a claim that each individual component is novel.

II. PROBLEM STATEMENT

Customers searching for a specific product in local markets often face limited real-time availability information, the need to visit multiple shops, difficulty identifying a product when only a reference image is available, and difficulty comparing price, quantity, distance, availability, and visual similarity across shops. Delayed shopkeeper responses and privacy concerns may further reduce convenience. Therefore, there is a need for an intelligent hyperlocal system that can verify product images, identify relevant nearby shops, consider current availability, personalize shop ranking, and support privacy-preserving customer–shopkeeper communication.

III. OBJECTIVES

- Develop an AI-assisted hyperlocal product discovery system for nearby local shops.
- Enable product requests using one or more images, required quantity, and location.
- Perform image-quality verification and request re-upload when an image is unsuitable.
- Compare customer reference images with current shopkeeper-captured product images.
- Provide attribute-wise similarity measures for characteristics such as shape, colour, and brand or packaging.
- Shortlist nearby shops using location and distance-based filtering.
- Consider current availability, quantity, price, and shopkeeper response time.
- Provide personalized shop ranking according to customer-selected priorities.
- Provide privacy-preserving in-app communication without mandatory exchange of phone numbers or email addresses.
- Improve the visibility of local businesses by connecting relevant customer requests with nearby shops.

IV. LITERATURE REVIEW

Research relevant to LocaLens can be grouped into four areas: retail product recognition, fine-grained visual retrieval, location-aware recommendation, and context-aware or offline retail recommendation.

A. Retail Product Recognition

Santra and Mukherjee surveyed computer-vision approaches for automatic identification of products in retail stores and organized methods around feature-based, geometric, saliency-based, and detector-based approaches [1]. Wei et al. reviewed deep-learning methods for retail product recognition and discussed challenges involving image classification, object detection, datasets, and real-world retail conditions [2]. Merler et al. demonstrated the difficulty of recognizing grocery products when reference images and real-store images differ in imaging conditions, providing the GroZi-120 dataset and evaluating classical visual matching approaches [3]. Melek, Battini Sönmez, and Varlı provided a later exhaustive review of datasets and computer-vision or machine-learning approaches for grocery shelf product recognition, emphasizing challenges related to dataset creation, updating, and the scale of product categories [4].

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B. Fine-Grained Product Retrieval

Zhang et al. introduced FGPR, a large-scale benchmark for fine-grained product retrieval containing nearly 360,000 images and more than 85,000 categories. The study also investigated multimodal retrieval using visual and optical-character-recognition information [5]. This direction is relevant to LocaLens because local-shop responses may contain products that are visually similar but differ in fine-grained details. LocaLens therefore treats visual similarity as a measurable score rather than assuming that a visual match automatically proves exact product identity.

C. Location-Aware Retail Recommendation

Yang, Cheng, and Dia proposed a location-aware recommender system for mobile shopping environments that combines customer shopping needs with location-dependent vendor offers [6]. Dehaqani et al. developed a store location-based recommender system that combines product interests with user and store locations to produce ranked store recommendations [7]. Zeng et al. investigated location-aware real-time recommendation for brick-and-mortar retailers, demonstrating the relevance of real-time and spatial context in physical retail [8]. Yu et al. studied shop-type recommendation using social-media and location-based-service information, showing that location and commercial context can be jointly used for shop-related recommendations [9]. Zhao et al. further investigated personalized location recommendation by combining geographical distance with additional contextual attributes [10].

D. Context-Aware and Offline Retail Recommendation

Liu et al. surveyed context-aware mobile recommendation and highlighted the role of contextual information, including location, together with privacy and interface considerations [11]. Lee and Kim studied personalized recommendation in small-format offline retail and demonstrated that recommender systems can be adapted to physical stores [12]. Together, these studies support the use of customer context and offline retail information in LocaLens.

V. RESEARCH GAP

The reviewed literature demonstrates substantial progress in visual product recognition [1]–[5], location-aware recommendation [6]–[10], and context-aware or offline retail recommendation [11], [12]. However, these research areas are generally addressed as separate problems. Existing visual recognition systems primarily identify products from images, while location-aware systems primarily recommend stores, vendors, or points of interest according to location and contextual preferences. LocaLens frames the gap around the integration of these capabilities into a physical local-shopping workflow. In particular, the proposed system combines customer-provided visual references, image-quality verification, multi-image comparison, nearby-shop shortlisting, current shopkeeper-captured images, multi-attribute similarity assessment, real-time availability, customer-preference-based ranking, and privacy-preserving in-app communication. The research contribution is therefore the system-level integration and experimental evaluation of these components, not a claim that each individual technique is new.

VI. PROPOSED METHODOLOGY

A. Customer Request Generation

The customer initiates a request by providing one or more images of the desired product, required quantity, and location. Multiple images can represent different views of the same product and provide richer evidence for visual verification. The customer may also specify ranking priorities such as lower price, shorter distance, higher similarity, faster response, or greater availability.

B. Image Quality Verification

Before visual matching, images are checked for suitability. Blurred, excessively dark, poorly framed, or otherwise unsuitable images should be rejected and followed by a re-upload request. Customers may select multiple images from their gallery. Shopkeepers are expected to capture product images at the time of responding, supporting more current visual evidence of availability.

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C. Nearby Shop Shortlisting

The customer's location is used to identify relevant shops within a configurable search radius. Shops can first be filtered by product category and then shortlisted using geographical distance and availability-related criteria. The Haversine formula can be used to estimate the great-circle distance between customer and shop coordinates.

D. Visual Product Verification

Customer and shopkeeper images are preprocessed and converted into visual representations using a suitable computer-vision or vision-language model. Similarity between representations can be calculated using cosine similarity or another validated metric. The resulting value is interpreted as a visual similarity score and not as a probability of exact product identity.

E. Multi-Attribute Similarity Analysis

Product verification can be represented through multiple attributes rather than one undifferentiated value. Depending on the selected model and product category, shape, colour, brand or company text, packaging appearance, and other visible characteristics may be evaluated separately. Attribute weights and decision thresholds must be experimentally validated.

F. Personalized Shop Ranking

After eligible responses are collected, the system calculates a ranking score according to customer-selected priorities. A normalized weighted model can be represented as:

$$R = w\square M + w\square P + w_dD + w_aA + w_qQ + w_tT$$

where M is the product-match score, P is the price preference score, D is the distance score, A is the availability score, Q is the quantity score, T is the response-time score, and w represents the corresponding customer-defined weight. The weights can be normalized so that rankings remain comparable across requests.

G. Real-Time Availability

Shopkeeper responses contain the current product image, available quantity, price, and confirmation status. Availability is treated as dynamic information. A response may become ineligible if the requested quantity is unavailable or if the shopkeeper withdraws the response.

H. Privacy-Preserving Communication

Customer–shopkeeper communication is primarily handled through in-app chat. Phone numbers and email addresses are not required to be exchanged. If in-app communication becomes impractical in an exceptional situation, the customer may voluntarily request phone-based communication with appropriate consent.

VII. SYSTEM ARCHITECTURE

The proposed architecture uses the backend API as the central coordinator between customer and shopkeeper interfaces, AI services, location services, notifications, cloud image storage, communication services, and the structured database. The customer application creates a product request, while the shopkeeper application returns current product information. The backend validates and routes requests, coordinates image processing and matching, stores structured records, and prepares ranked results.

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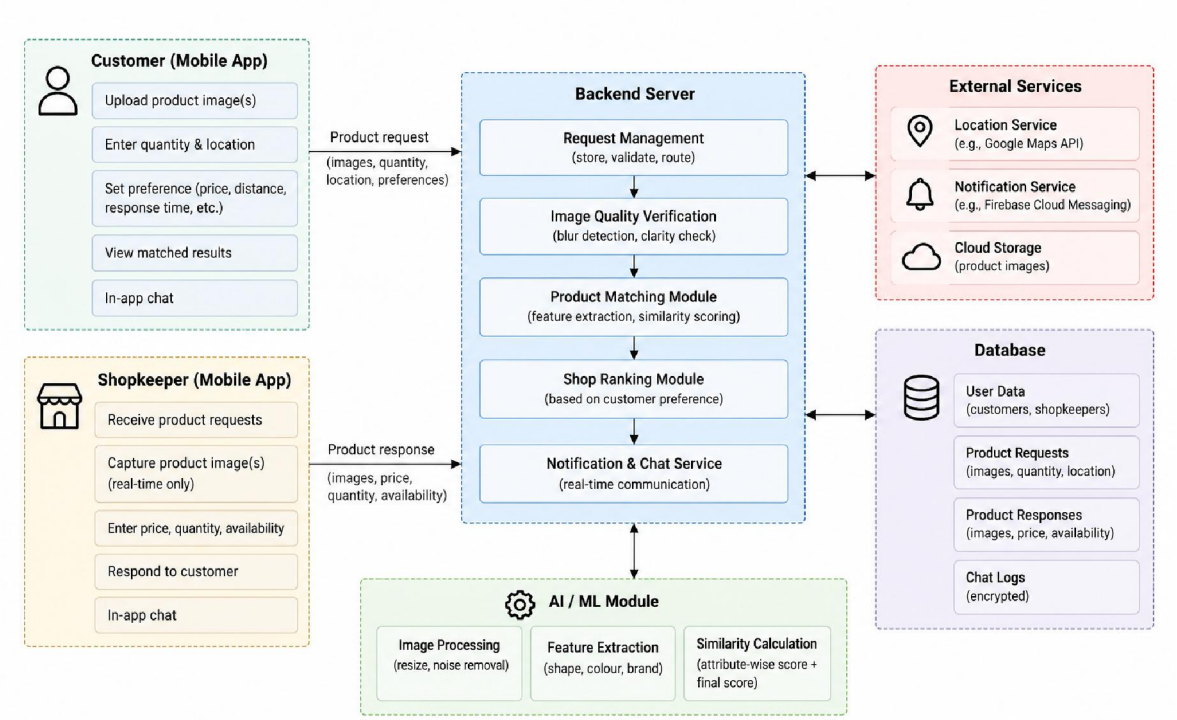


Fig. 1. System architecture of LocaLens.

VIII. ALGORITHMS AND INTELLIGENT STRATEGIES

A. Image Quality Assessment
B. Product Category Identification
C. Haversine Distance Calculation
D. Visual Similarity Matching
E. Multi-Attribute Matching
F. Weighted Shop Ranking
G. Request Routing

Image Quality Assessment detects blur and other image-quality problems before matching; unsuitable images trigger re-upload. Product Category Identification can use image classification or a suitable vision model, while OCR may support extraction of product or brand text from packaged medicine images. Haversine Distance Calculation supports radius-based shop shortlisting. Visual Similarity Matching compares image representations using cosine similarity or another validated metric. Multi-Attribute Matching evaluates selected visible attributes and combines them using experimentally validated weights. Weighted Shop Ranking combines product similarity, distance, price, availability, quantity, response time, operating status, and other factors according to customer priorities. Request Routing sends requests to shops satisfying category and geographical constraints and triggers relevant notifications.

IX. TECHNOLOGY STACK AND IMPLEMENTATION

The proposed mobile interface is planned using Flutter and Dart. Python with FastAPI can provide backend services and REST APIs. PostgreSQL can store structured records such as users, shops, product requests, responses, and ranking-related data. OpenCV and a suitable pretrained computer-vision or vision-language model can support image processing and matching. Cloud storage can hold customer and shopkeeper product images. Firebase Authentication

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and Firebase Cloud Messaging can support authentication and push notifications. Google Maps or an equivalent mapping service can support location visualization and geographical operations. Visual Studio Code, Git, GitHub, and Postman can support development and testing. Model choice, similarity thresholds, attribute weights, and ranking coefficients should be finalized after evaluation rather than fixed solely from design assumptions.

X. EXPERIMENTAL EVALUATION FRAMEWORK

Because numerical performance depends on the final model, dataset, and implementation, no fabricated performance values are reported. Evaluation should use representative customer reference images and shopkeeper-captured product images covering different lighting conditions, viewpoints, image qualities, and product categories.

A. Image Quality Evaluation
B. Visual Matching Evaluation
C. Attribute-Level Evaluation
D. Shop Ranking Evaluation
E. System Performance

Image Quality Evaluation should measure correct rejection of unsuitable images and acceptance of suitable images using precision, recall, and F1-score where labelled data are available. Visual Matching Evaluation should use labelled same-product, similar-but-not-identical, and different-product pairs and report precision, recall, F1-score, and confusion matrices for selected thresholds. Attribute-Level Evaluation should examine shape, colour, and brand or package-text components where reliable labels exist. Shop Ranking Evaluation can compare personalized weighted ranking with baseline strategies such as nearest-shop-only and lowest-price-only using metrics such as Precision@K, Recall@K, and NDCG@K. System Performance should measure request-to-response latency, image-processing time, notification delay, and response success rate.

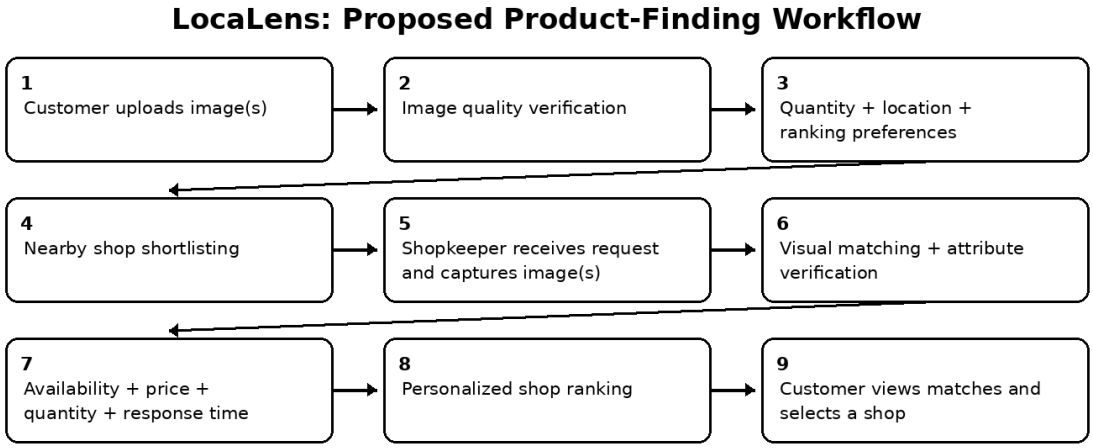


Fig. 2. Workflow of the proposed LocaLens system.

XI. EXPECTED OUTCOMES AND DISCUSSION

The expected outcome is a functional workflow that reduces unnecessary physical visits by helping customers identify nearby shops likely to have the requested product. The visual verification stage provides evidence beyond text-only product names, while attribute-level scores can make matching decisions more interpretable. Personalized ranking allows different customers to prioritize different factors rather than enforcing one fixed ranking policy. Evaluation should determine whether image-quality filtering improves matching reliability, whether multi-image input improves robustness, how well visual similarity separates exact or acceptable matches from visually similar alternatives, and

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which ranking weights provide useful results. Numerical performance values should be added only after controlled experiments are completed.

XII. LIMITATIONS

- Visual similarity does not necessarily prove exact product identity, particularly for products with similar appearance.
- Matching quality depends on image quality, viewpoint, lighting, occlusion, and visible product details.
- Real-time availability depends on timely and truthful shopkeeper responses.
- The initial system focuses on selected categories and may require category-specific validation.
- Location services, image uploads, notifications, and chat depend on network and device availability.
- Medicine-related functionality requires additional safety, prescription, regulatory, and verification safeguards; the system should not be treated as a medical-advice system.

XIII. FUTURE SCOPE

Future work can extend LocaLens to electronics, clothing, groceries, hardware, and daily-use products. Advanced visual models can improve fine-grained product matching and multi-image verification. A future AI chatbot can help customers identify an appropriate product category when the same type of product may be available through different store categories. Additional extensions may include multilingual interaction, voice-based search, wider geographical coverage, product reservation, online payment, and analytics for local shopkeepers.

XIV. CONCLUSION

LocaLens proposes an AI-assisted approach to hyperlocal product discovery that connects customers with nearby local shops using visual product references, location information, current shopkeeper responses, and intelligent ranking. The methodology combines image-quality verification, visual similarity analysis, multi-attribute product verification, personalized shop ranking, real-time availability, and privacy-preserving in-app communication. Rather than replacing offline shopping, the system is designed to make local shopping more efficient by helping customers identify suitable shops before visiting them. The proposed evaluation framework provides a basis for validating image matching, ranking strategies, and real-time response performance after implementation.

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