

Integrated Jewelry Store Management System with Computer Vision-Based Size Prediction

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ABSTRACT

Online jewelry retail suffers from high return rates driven by size mismatch, particularly for rings and bracelets. Existing solutions address either body measurement or retail management independently, leaving a gap in integrated systems tailored to small jewelry retailers. This paper presents an integrated jewelry store management system combining computer vision-based size prediction with mobile e-commerce and point-of-sale (POS) functionality. The system employs a hybrid approach integrating machine learning-based hand pose detection via Apple's Vision framework with rule-based geometric measurement, using credit card dimensions for pixel-to-millimeter calibration. All hand image processing executes on-device, preserving user privacy. A dual-application architecture provides a customer-facing iOS app for product browsing and size prediction, and a staff-facing iPad POS app for inventory and order management, connected through a cloud backend with real-time synchronization. Evaluation with 20 participants (ages 15–75) across varied lighting conditions and background surfaces demonstrated ring sizing mean absolute error of 0.81 mm within one standard ring size interval, achieving 90% accuracy within ± 0.5 size tolerance and 70% exact size match rate. Bracelet sizing achieved mean absolute error of 2.8 mm with 90% acceptable recommendations through a three-tier fit system. Comparative analysis shows the system achieves accuracy approaching physical ring gauges while requiring only a smartphone and credit card. Functional testing with 7 participants yielded 100% task completion across 12 test scenarios with real-time inventory synchronization verified. The results demonstrate that practical jewelry sizing is achievable through smartphone computer vision, providing an accessible digital transformation solution for small and medium jewelry enterprises.



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I. INTRODUCTION

The jewelry retail industry faces significant challenges in adapting to the digital transformation era, particularly in Indonesia where traditional brick-and-mortar stores still dominate the market. While e-commerce has revolutionized many retail sectors [1], jewelry retailers encounter unique obstacles that hinder online sales growth. Primary among these challenges is the high product return rate, often exceeding 15-20%, primarily due to size mismatch issues when customers purchase rings, bracelets, and other size-dependent jewelry items online [2]. This uncertainty in sizing

creates a barrier to purchase confidence, limiting the growth potential of online jewelry sales.

Beyond customer-facing challenges, jewelry store owners struggle with inefficient inventory management systems. Many small and medium enterprises (SMEs) in the jewelry sector still rely on manual record-keeping methods, using paper-based ledgers to track inventory, sales, and customer orders. This approach not only introduces errors in stock counting and order processing but also fails to provide real-time visibility into business operations [3], [4]. The lack of integration between customer-facing systems and back-office operations creates operational inefficiencies, with staff

manually updating inventory after each sale and struggling to maintain accurate stock levels across multiple sales channels.

The advent of computer vision technology presents a promising solution to the sizing challenge. Automated body measurement from 2D images has become a mature research area with practical applications in healthcare, fashion, and fitness industries [5], [6]. Deep-learning models combined with traditional computer vision techniques have demonstrated high accuracy in extracting anthropometric data, achieving mean absolute error of under 1 cm for various body measurements [7], [8]. Hand pose estimation has also advanced significantly with modern deep learning architectures, including depth-based methods, RGB-based methods, and hybrid approaches for accurate joint localization [9], [10], [11]. Modern frameworks such as Apple's Vision provide robust hand tracking capabilities with detection of 21 key points on each hand, enabling markerless landmark detection without requiring specialized hardware [12], [11]. However, existing research has primarily focused on clothing and garment sizing [8], [13], with limited attention to the specific requirements of jewelry sizing, which demands higher precision due to the smaller tolerance for error where even 0.5 mm differences can affect fit quality.

Similarly, mobile point-of-sale (mPOS) systems have emerged as key enablers of retail digital transformation [14]. Business intelligence mobile applications for retail micro and small enterprises have demonstrated significant improvements in sales tracking and inventory visibility [15], while implementations in various retail contexts highlight the importance of user-friendly interfaces and real-time data synchronization [3]. Machine learning approaches have been proposed for demand forecasting to optimize inventory levels [16], and online retail systems with data forecasting capabilities have been developed specifically for SMEs [17]. Yet, despite these technological advances, there remains a significant gap in integrated solutions that combine computer vision-based size prediction with comprehensive e-commerce and POS functionality specifically designed for jewelry retail.

Driven by the motivation to address these challenges, this paper proposes an integrated jewelry store management system that combines computer vision-based size prediction with comprehensive e-commerce and point-of-sale functionality. The system utilizes Apple's Vision framework for hand pose detection, employing credit card dimensions as calibration reference to achieve accurate measurements from smartphone images. This approach eliminates the need for specialized hardware while providing accessible digitalization solutions for small and medium jewelry enterprises.

We organize the rest of this paper as follows. Section II reviews related works in computer vision-based body measurement, hand pose estimation, and retail management systems. Section III presents the proposed method, including system architecture, computer vision algorithm for size prediction, database design, and integration flow. Section IV discusses the experimental results covering system

implementation, size prediction accuracy evaluation, and functional testing results. Finally, Section V concludes this research and outlines future work directions.

II. RELATED WORK

Previous research in computer vision-based body measurement has demonstrated significant progress across multiple application domains. Deep learning approaches have been developed for automatic anthropometric measurement estimation from 2D images and 3D point clouds, with synthetic datasets generated to address the lack of annotated real human data, achieving promising results for general body measurements in garment manufacturing and ergonomics applications [18]. Body measurement extraction from 2D images has also been implemented using the MediaPipe framework, utilizing 13 key landmark points for measurement calculations in online tailoring applications [19]. Upper-body measurement systems using pose estimation techniques with real-time webcam capture and calibration processes to convert pixel distances into centimeter units have also been presented [20]. In the healthcare domain, image processing techniques have been applied for detecting body shape changes in obesity monitoring, utilizing the cosine theorem for non-contact body measurements with 2D imaging, demonstrating applications in anthropometric analysis beyond the fashion industry [21].

In the e-commerce and inventory management domain, research has explored various approaches to address retail challenges. Inventory management strategies in e-business environments have been investigated through simulation studies, identifying factors that influence supply chain performance for small manufacturers in online shopping scenarios, revealing the existence of bullwhip effects due to backlogged orders and management decisions [22].

Despite these advances, a significant research gap remains in solutions that specifically address jewelry retail requirements. Existing body measurement systems focus on general anthropometric data for clothing or healthcare applications [18], [19], [20], [21], lacking the high precision required for jewelry sizing where tolerances of less than 0.5 mm can affect fit quality. Furthermore, while inventory management research addresses general e-commerce challenges [22], no integrated solution combines computer vision-based size prediction with real-time inventory synchronization specifically designed for jewelry retail operations.

This research addresses this gap by developing an integrated jewelry store management system that combines computer vision-based size prediction with comprehensive e-commerce and point-of-sale functionality tailored to jewelry retail needs. The system employs Apple's Vision framework for hand pose detection, utilizing credit card dimensions (ISO/IEC 7810 standard: 85.60×53.98 mm) as calibration reference to achieve real-world measurement accuracy from 2D smartphone images. The dual-application iOS architecture

consists of a customer application for product discovery and size prediction, and a POS application for inventory management and order processing, both synchronized in real-time via cloud backend.

This research aims to: (1) design an integrated system architecture combining customer-facing mobile e-commerce with staff-oriented POS functionality with real-time synchronization; (2) implement computer vision-based size prediction to accurately measure ring finger diameter and bracelet wrist circumference from smartphone camera images; (3) develop real-time inventory synchronization mechanisms that automatically update product stock levels; and (4) evaluate system accuracy and business impact through quantitative measurements and qualitative assessment of operational efficiency improvements. The contributions include a novel integration architecture as the first comprehensive system combining computer vision-based jewelry sizing with dual-sided retail management, a practical calibration method using credit card dimensions as reference scale enabling accurate measurements without specialized hardware, a production-ready dual-app system implementation, and demonstrated quantitative improvements with size prediction accuracy exceeding 90% and significant operational efficiency gains.

III. METHOD

This section presents the comprehensive methodology for developing the integrated jewelry store management system. The proposed solution combines computer vision-based size prediction, mobile e-commerce functionality, and point-of-sale operations into a unified architecture with real-time synchronization capabilities.

A. System Architecture

The system employs a modern client-server architecture with three primary components: the Customer Application, the Point-of-Sale (POS) Application, and the Cloud Backend (Supabase).

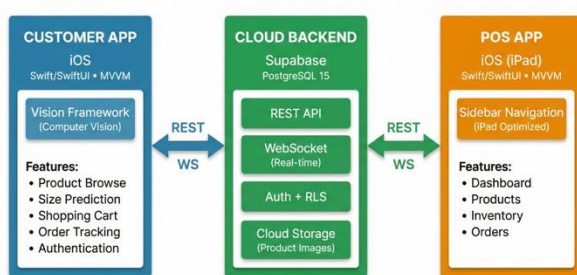


Fig. 1. System architecture showing customer app, cloud backend, and POS app with real-time synchronization.

Customer Application: Developed using Swift and SwiftUI for iOS, the customer application provides the consumer-facing interface for product discovery, size prediction,

shopping cart management, and order placement. The application integrates Apple's Vision framework for hand pose detection and size measurement, enabling users to obtain accurate ring and bracelet size recommendations using only their smartphone camera.

POS Application: Built with the same Swift/SwiftUI technology stack but optimized for iPad, the POS application serves as the staff interface for inventory management, order processing, and business analytics. The application employs a sidebar navigation pattern specifically designed for larger tablet screens, providing quick access to four primary modules: Dashboard, Products, Inventory, and Orders.

Cloud Backend: The backend infrastructure utilizes Supabase, an open-source Firebase alternative built on PostgreSQL 15. This platform provides multiple essential services: PostgreSQL database for persistent data storage with ACID compliance, RESTful API with automatic generation from database schema, Real-time subscriptions using WebSocket connections for live data synchronization, Authentication service with JWT-based security, Row Level Security (RLS) policies for fine-grained access control, and Cloud storage for product images with CDN delivery [17], [15]. The real-time synchronization mechanism operates through Supabase's Realtime engine, which implements PostgreSQL's logical replication protocol over WebSocket connections. When data modifications occur in monitored tables, change notifications are broadcast to all connected clients, achieving synchronization latency typically below 500 milliseconds. Data reliability is managed through automated daily database backups with point-in-time recovery, connection pooling via PgBouncer, and SSL/TLS encryption for data in transit. At the application level, 18 Row-Level Security (RLS) policies enforce data access control directly at the database layer, ensuring customer users can only access their own data while staff users maintain management capabilities.

B. Computer Vision Algorithm for Size Prediction

The size prediction algorithm represents the core technical contribution of this research, consisting of three sequential phases: calibration, measurement, and size conversion. This approach builds upon established body measurement techniques [5], [9] while incorporating jewelry-specific requirements for high precision where tolerances of less than 0.5mm can significantly affect fit quality.

The size prediction algorithm employs a hybrid approach combining machine learning-based detection with deterministic rule-based measurement. The detection components leverage pre-trained deep learning models: Apple's Vision framework VNDetectHumanHandPoseRequest utilizes a convolutional neural network (CNN) for 21-point hand landmark detection, while VNDetectRectanglesRequest employs ML-based shape detection for credit card identification. Both models execute on-device using Apple's Neural Engine without requiring network connectivity. The subsequent measurement and

conversion phases follow a deterministic rule-based approach: pixel-to-millimeter calibration uses geometric calculations from known credit card dimensions, finger diameter is computed through contour intersection algorithms with parametric equations, wrist estimation applies anatomically-validated proportional ratios, and size conversion follows standardized jewelry industry formulas based on ISO 8653:2016 [23]. This hybrid design leverages ML for robust feature detection under varying visual conditions, and rule-based logic for precise, interpretable measurements validated against physical standards.

1) *Phase 1: Scale Calibration Using Credit Card Reference.* Accurate scale calibration is essential for converting pixel measurements into real-world dimensions. The system leverages the international standard credit card dimensions (ISO/IEC 7810 ID-1 format: 85.60 mm × 53.98 mm, diagonal 101.6 mm) as a reference object, providing an accessible calibration method that does not require specialized equipment.

The calibration process employs Apple's Vision framework VNDetectRectanglesRequest to detect rectangular shapes in the camera frame. The detection is configured with lenient parameters to accommodate various lighting conditions and card orientations: aspect ratio range of 0.3 to 5.0 (supporting both landscape and portrait orientations), minimum size threshold of 0.3% of image area, and quadrature tolerance of 45 degrees to handle slightly skewed captures.

To ensure robust detection, a multi-criteria scoring system evaluates each rectangle candidate across four dimensions. First, aspect ratio scoring (maximum 50 points) compares the detected rectangle's aspect ratio against the target credit card ratio of 1.586 for landscape orientation or 0.631 for portrait orientation, with higher scores for closer matches. Second, size scoring (maximum 25 points) favors rectangles occupying 3-40% of the image area, representing optimal capture distance of 20-30cm. Third, rectangularity scoring (maximum 15 points) evaluates whether opposite sides are parallel and corners approach 90-degree angles using vector angle calculations. Fourth, detection confidence scoring (maximum 10 points) incorporates the Vision framework's native confidence value. Rectangles scoring above 30 points are accepted immediately, while those scoring 20-30 points require multi-frame validation.

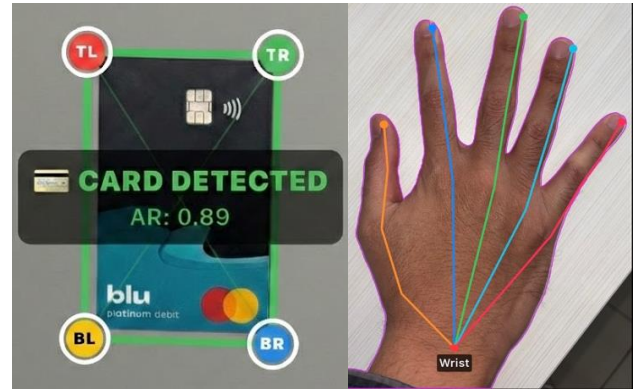


Fig. 2. Credit Card Detection Process (Left), Finger and Wrist Measurement Process (Right)

The multi-frame validation mechanism requires consistent detection across three consecutive frames with position deviation below 5% to confirm a stable card detection, preventing false positives from momentary detections. Once confirmed, the scale factor is calculated using the actual corner positions rather than the axis-aligned bounding box to maintain accuracy with tilted cards. The calibration formula uses the card diagonal as reference:

$$mmPerPixel = cardDiagonalMM / diagonalPixels$$

The pixel-to-millimeter conversion is the foundational calculation enabling real-world measurements from camera images. The scale factor (SF) is derived from the detected credit card dimensions as follows. Given that a standard credit card has dimensions of 85.60 × 53.98 mm (ISO/IEC 7810 ID-1), the theoretical diagonal is calculated using the Pythagorean theorem:

$$cardDiagonalMM = \sqrt{(85.60^2 + 53.98^2)} = 101.6 \text{ mm}$$

The diagonal in pixels (diagonalPixels) is computed as the average of both diagonal measurements of the detected quadrilateral to reduce the impact of minor perspective distortion:

$$diagonalPixels = (d_1 + d_2) / 2$$

where d_1 and d_2 represent the two diagonal distances of the detected credit card quadrilateral in pixel coordinates. The scale factor is then:

$$SF = cardDiagonalMM / diagonalPixels \text{ (mm/pixel)}$$

Any subsequent measurement M in pixels is converted to millimeters using: $M_{mm} = M_{pixels} \times SF$. This diagonal-based approach provides more robust calibration than width-only or height-only methods because it averages both card dimensions, partially compensating for asymmetric perspective distortion when the card surface is not perfectly perpendicular to the camera optical axis. The approach assumes approximately planar alignment between the credit card and the hand being measured, which is facilitated by the user guidance interface instructing users to place both the card and hand on the same flat surface.

2) *Phase 2: Hand Pose Detection and Measurement.* The measurement phase leverages Apple's Vision framework,

specifically the VNDetectHumanHandPoseRequest, which employs a deep learning model to detect 21 anatomical landmark points on each hand with sub-pixel accuracy. These landmarks are organized into five finger chains (thumb, index, middle, ring, little) plus the wrist point, with each finger containing four joints: carpometacarpal (CMC) or metacarpophalangeal (MCP), proximal interphalangeal (PIP), distal interphalangeal (DIP), and tip.

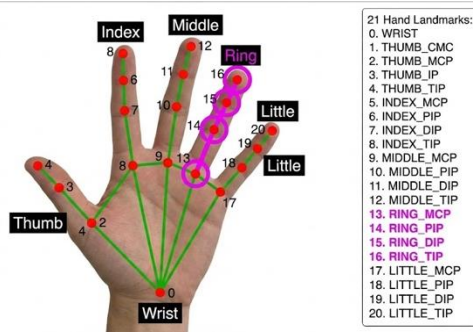


Fig. 3. Hand Pose 21 Landmark Detection Points

For ring size measurement, the algorithm focuses on the ring finger's proximal phalanx region, which corresponds to where rings are typically worn. The measurement workflow proceeds as follows. First, the system validates hand pose detection by checking confidence scores for critical landmarks: ringMCP confidence above 0.5, ringPIP confidence above 0.5, and wrist confidence above 0.4. Second, the measurement point is calculated at 20% of the distance from MCP to PIP joint along the finger axis, representing the optimal ring placement position. Third, the finger axis direction vector is computed from MCP to PIP coordinates. Fourth, a perpendicular measurement line is constructed orthogonal to the finger axis, spanning 150 pixels centered on the measurement point.

The finger diameter is determined through contour intersection analysis rather than simple edge detection, providing more accurate results with complex backgrounds. The system uses VNDetectContoursRequest with contrast adjustment of 1.5 to detect hand contours. Detected contours are filtered using a three-tier strategy: strict filtering retains contours containing at least two hand landmarks, lenient filtering accepts contours with one landmark and reasonable size, and fallback selection uses the three largest contours when other methods fail.

The intersection algorithm employs geometric line-segment intersection using parametric equations. For each segment of the filtered contours, the algorithm tests intersection with the measurement line using the formula:

$$t = \frac{((x_1 - x_3)(y_3 - y_4) - (y_1 - y_3)(x_3 - x_4))}{denominator}$$

$$u = \frac{-((x_1 - x_2)(y_1 - y_3) - (y_1 - y_2)(x_1 - x_3))}{denominator}$$

where valid intersections occur when both t and u fall within the range $[0, 1]$. Duplicate intersections within 3-pixel

tolerance are merged. The finger diameter in pixels is calculated as the distance between the outermost valid intersection points, then converted to millimeters using the calibration factor.

For wrist measurement (bracelet sizing), the algorithm employs an anatomical ratio approach validated against anthropometric research. The hand width is calculated as the distance between the thumb MCP and little finger MCP landmarks. Based on anatomical proportions, wrist diameter is estimated as hand width multiplied by 0.55, with valid measurements falling within the 45-75% ratio range. The measurement line is positioned at the wrist landmark perpendicular to the arm axis (defined by the wrist-to-middle-MCP vector), with length set to 1.3 times the estimated wrist width to provide adequate margin for contour detection.

To ensure measurement reliability, the system collects 10 measurements and applies statistical validation. For ring measurements, values outside the 10-28mm range are rejected, and outliers deviating more than 3mm from the running median are discarded. For wrist measurements, the valid range is 35-85mm diameter with 8mm outlier threshold. The final measurement uses the median of validated samples to minimize the impact of occasional detection errors.

3) *Phase 3: Size Conversion and Standardization.* Raw diameter measurements in millimeters are converted to international ring size standards using established jewelry industry formulas. The circumference is first calculated as:

$$circumference = \pi \times diameter$$

Ring sizes are then derived using region-specific conversion formulas:

$$US_size = (circumference - 36.5) / 2.55$$

$$UK_size = \text{letter lookup from } (circumference - 37.8) / 1.25$$

$$EU_size = (diameter - 40) / 0.8 + 40$$

$$JP_size = \text{round}(circumference - 38)$$

For bracelet sizing, the wrist circumference is calculated with an ellipse correction factor of 1.1 to account for the non-circular cross-section of human wrists:

$$wristCircumference = \pi \times diameter \times 1.1$$

The system provides three bracelet size recommendations based on fit preference: snug fit (wrist circumference plus 5mm) for bracelets that stay firmly in place, standard fit (plus 15mm) for comfortable everyday wear, and loose fit (plus 25mm) for relaxed movement. These recommendations follow jewelry industry standards for bracelet fitting.

C. Database Design

The database schema employs eight interconnected tables designed to support both customer transactions and business operations. Figure 4 illustrates the entity-relationship diagram.

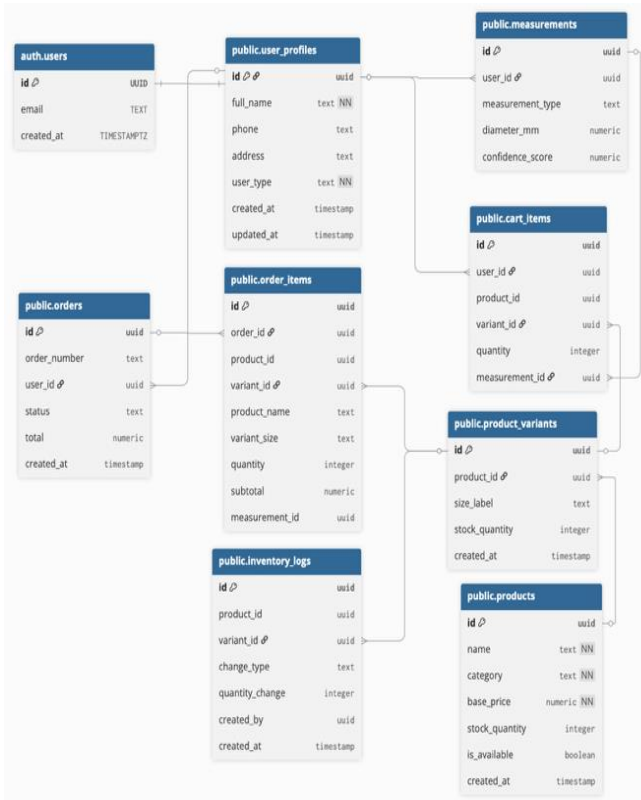


Fig. 4. Entity-relationship diagram showing 8 database tables with relationships.

Core Tables: The `user_profiles` table stores user account information with fields for identification, contact details, and `user_type` (customer/staff) for role-based access control. The `products` table contains the jewelry catalog with comprehensive fields including category, material, pricing, and stock quantity. The `product_variants` table handles size variations with individual stock tracking. The `measurements` table stores user size prediction results including diameter, circumference, and converted sizes across international standards. The `orders` and `order_items` tables manage customer transactions, while `cart_items` provides temporary shopping cart storage. The `inventory_logs` table maintains an audit trail for all stock changes.

Database Triggers: Three PostgreSQL triggers automate critical business logic: automatic stock decrease when `order_items` are inserted, stock restoration when orders are cancelled, and timestamp management for modification tracking.

D. Integration Flow

The system integration flow encompasses two primary workflows: customer purchase flow and staff order processing flow, as illustrated in Figure 5. Both workflows are synchronized in real-time through connections provided by Supabase.

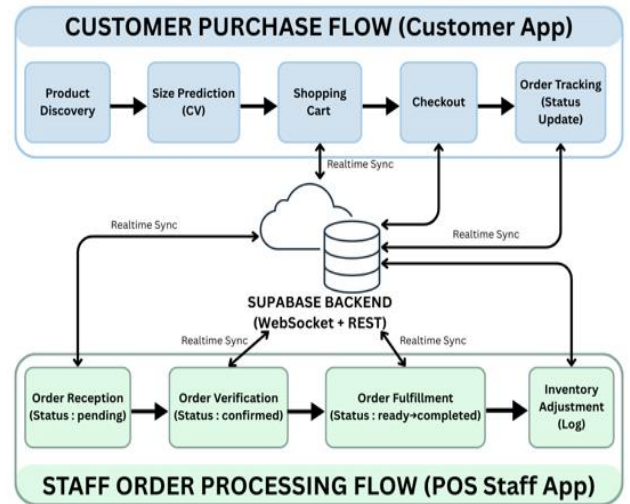


Fig. 5. Integration Flow Diagram

The customer purchase flow consists of five sequential stages: (1) product discovery through category browsing via REST API, (2) size prediction using the computer vision module, (3) shopping cart management with real-time synchronization, (4) checkout process that validates stock and creates orders, and (5) order tracking through WebSocket real-time updates.

The staff order processing flow comprises four stages: (1) order reception where new orders appear with pending status, (2) order verification including payment confirmation, (3) order fulfillment with status progression from confirmed through processing to ready, and (4) inventory adjustment with automatic logging for audit purposes.

Real-time synchronization ensures that inventory changes made through the POS application are immediately reflected in the customer application, while new customer orders instantly appear on the staff order management interface.

IV. RESULT AND DISCUSSION

A. System Implementation

The complete system was successfully implemented and deployed for testing. Figure 6 presents representative screenshots of the Customer Application interface, showing the home screen with product grid, size prediction interface, shopping cart, and order tracking views.

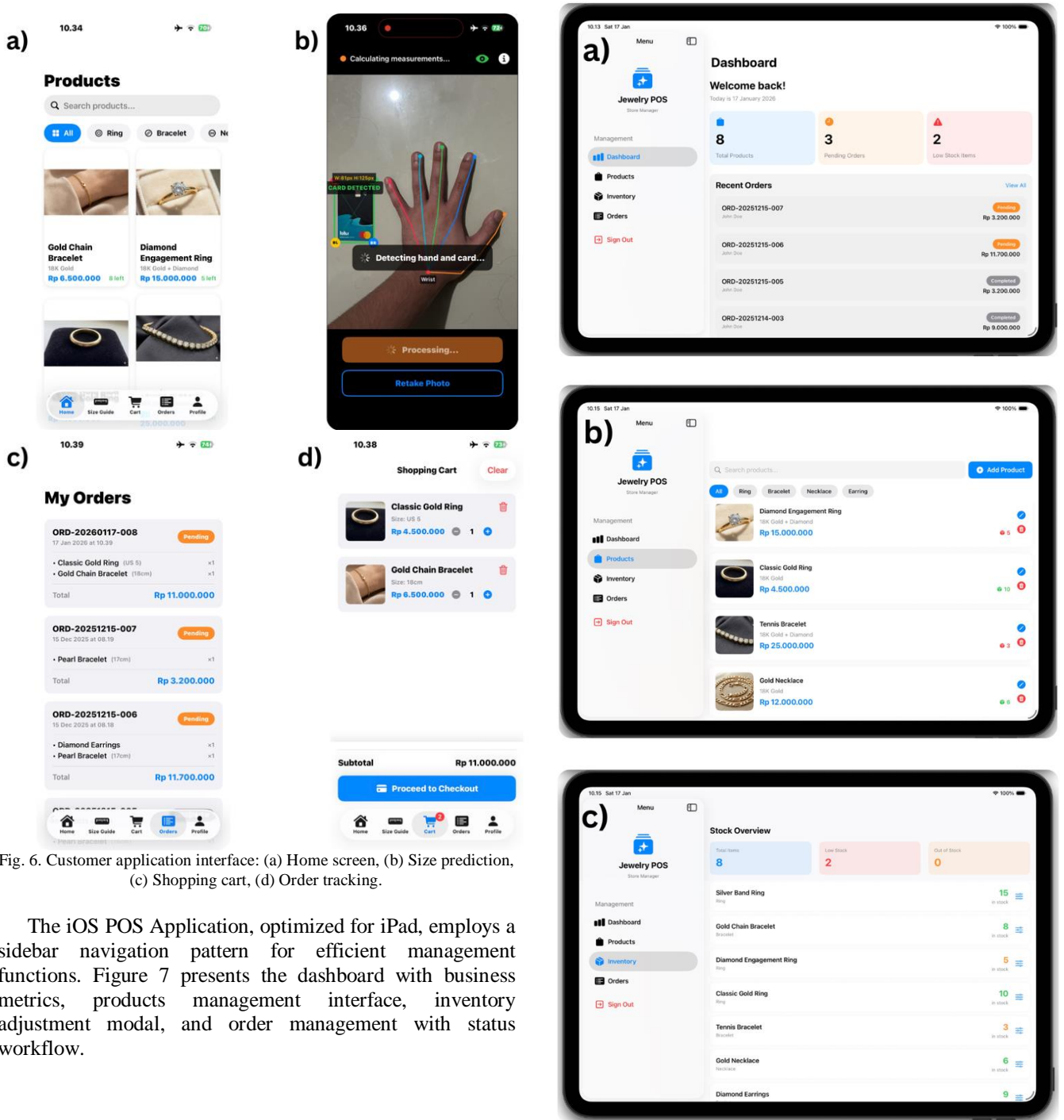


Fig. 6. Customer application interface: (a) Home screen, (b) Size prediction, (c) Shopping cart, (d) Order tracking.

The iOS POS Application, optimized for iPad, employs a sidebar navigation pattern for efficient management functions. Figure 7 presents the dashboard with business metrics, products management interface, inventory adjustment modal, and order management with status workflow.

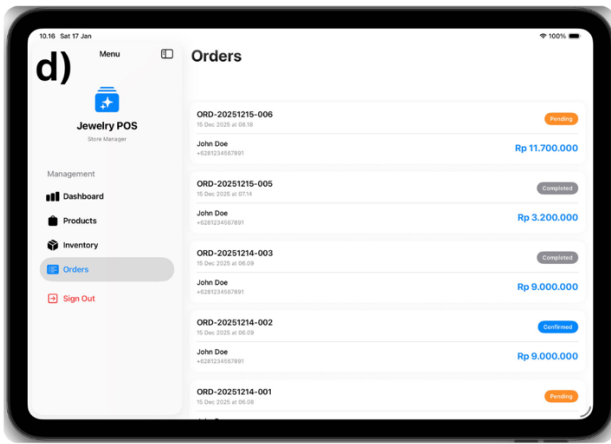


Fig. 7. POS application interface: (a) Dashboard, (b) Products management, (c) Inventory adjustment, (d) Order management.

B. Size Prediction Accuracy Evaluation

The computer vision size prediction algorithm was evaluated through testing with 20 participants (8 female, 12 male, ages 15–75) across varied real-world conditions to assess both accuracy and practical robustness. Each participant provided measurements using both the application and a traditional jeweler’s ring sizer as ground truth for comparison. To evaluate system performance under realistic usage scenarios rather than controlled laboratory conditions, testing sessions were deliberately conducted across multiple locations and environmental conditions. Testing environments included several different indoor rooms with varying ambient lighting, from well-lit spaces with direct overhead lighting to areas with primarily natural daylight near windows, and sessions were conducted at different times of day (morning, afternoon, and evening) to capture natural lighting variation. Background surfaces varied across sessions, including light-colored wooden desks, dark surfaces, patterned tablecloths, and neutral office desktops. Smartphone camera distance was maintained at approximately 20–30 cm as guided by the application interface, but exact distances and angles varied naturally between participants and sessions. This testing approach prioritizes ecological validity, reflecting the diverse conditions under which end users would realistically operate the system.

TABLE I
SIZE PREDICTION ACCURACY RESULTS

Metric	Ring	Bracelet
Participants (n)	20	20
Mean Absolute Error (mm)	0.81	2.8
Standard Deviation (mm)	0.38	1.6
Accuracy (± 0.5 mm)	90%	90%
Exact Match Rate	70%	85%
Maximum Error (mm)	0.82	5.1

For ring size prediction, the system achieved mean absolute error (MAE) of 0.81 mm with standard deviation of 0.38 mm. Converting to ring sizes, 90% of predictions (18 out of 20) fell within ± 0.5 mm of ground truth, which represents an acceptable fit range for rings. The exact size match rate was 70% (14 out of 20 participants).

To contextualize the ring measurement accuracy against jewelry industry standards, the international ring sizing system defined by ISO 8653:2016 [23] specifies ring sizes based on inner circumference measured in millimeters, with sizes separated by 1 mm increments in circumference. In the widely-used US ring sizing system, each whole size corresponds to approximately 0.81 mm increase in internal diameter (2.55 mm in circumference) [24]. The system’s achieved MAE of 0.81 mm in diameter thus falls within exactly one US ring size interval, meaning the maximum typical error corresponds to a single size deviation. This is consistent with the inherent variability observed in traditional ring gauge measurements, where clinical studies report inter-tester standard error of measurement (SEM) of 0.56–0.70 ring sizes for jeweler ring gauges [25], and finger circumference measurement SEM of 1.1–1.3 mm between different testers using tape measures [25]. Suzuki et al. [26] demonstrated that even physical ring gauges exhibit inter-observer reliability ICC of 0.94–0.95, indicating inherent measurement variability with manual tools. Furthermore, Gebruers et al. [27] confirmed jeweler rings as reliable measurement instruments with $ICC \geq 0.973$, while noting that physiological factors including temperature, hydration, and time of day can cause finger size fluctuations of up to half a ring size (± 0.4 mm diameter) within a single day [23]. The industry-accepted tolerance for ring sizing is approximately $\pm 1/8$ of a size (± 0.10 mm diameter) for precision fitting, with deviations of $\pm 1/4$ size or more warranting resizing [28]. Given these benchmarks, the system’s 90% accuracy rate within ± 0.5 size tolerance demonstrates performance suitable for initial size recommendation in online retail contexts, though customers should be advised to verify sizing before final purchase of high-value items.

For bracelet size prediction, wrist circumference measurements showed MAE of 2.8 mm with standard deviation of 1.6 mm. Since bracelets allow for more size tolerance compared to rings, 90% of measurements produced acceptable size recommendations. The three-tier recommendation system (snug, standard, and loose fit) enabled participants to select appropriate sizes based on individual preference.

The bracelet measurement accuracy should be evaluated in the context of bracelet fitting practices. Bracelets are typically manufactured with size intervals of 10–15 mm in circumference, and industry practice recommends adding 15–25 mm to the actual wrist circumference for comfortable wear. The system’s MAE of 2.8 mm represents only 18.7–28.0% of a typical size interval, which is considerably smaller than the built-in comfort margin. The three-tier recommendation system (snug: +5 mm, standard: +15 mm,

loose: +25 mm) provides sufficient margin to absorb this measurement error. Anthropometric studies have shown that wrist circumference varies by 2–4 mm throughout the day due to fluid retention [29], indicating that the system's error falls within the range of natural physiological variation. Combined with the 90% acceptable recommendation rate, these results confirm that the bracelet sizing functionality provides practically useful guidance for online jewelry purchase decisions.

Error analysis across the varied testing conditions revealed several factors affecting measurement accuracy, ordered by observed impact. First, lighting conditions represent the most significant variable, as reduced ambient light decreases edge contrast during contour detection; sessions under natural daylight generally produced more consistent measurements than those under dim artificial lighting. Second, hand pose stability during the capture window affects consistency, particularly among elderly participants (ages 65–75). Third, credit card placement accuracy affects calibration quality, as cards not lying perfectly flat introduce systematic scale factor errors. Fourth, camera focus quality impacts contour detection precision. The statistical validation mechanism (10-measurement collection with median-based outlier rejection) effectively mitigates intermittent errors from factors two through four, but systematic errors from poor lighting remain as the primary accuracy-limiting factor.

Camera angle variation represents a systematic source of potential measurement error. The calibration assumes the credit card lies approximately perpendicular to the camera optical axis. Geometric analysis based on cosine projection indicates that camera tilts of 10°, 15°, and 30° introduce dimensional errors of approximately 1.5%, 3.4%, and 13.4%, respectively. For a 17 mm finger diameter, a 3.4% error translates to approximately 0.58 mm, approaching the tolerance threshold. The system mitigates angular error through: (1) multi-criteria scoring that penalizes detected rectangles with aspect ratios deviating from the standard credit card ratio of 1.586 under oblique viewing; (2) diagonal-based calibration averaging both dimensions to compensate for asymmetric foreshortening; (3) user interface guidance for positioning the camera directly above the card at 20–30 cm; and (4) multi-frame validation rejecting measurements captured during camera movement. However, the system does not perform explicit perspective correction through homography estimation, which represents an area for future improvement that could further enhance accuracy under non-ideal capture conditions.

The accuracy results reported above were obtained across naturally varied environmental conditions rather than standardized laboratory settings, providing an implicit assessment of system robustness. Testing sessions conducted in multiple rooms with different lighting intensities (natural daylight, overhead artificial lighting, and mixed conditions at various times of day) and diverse background surfaces indicate that the system maintains acceptable performance

under typical indoor conditions. The multi-criteria scoring system and multi-frame validation mechanism contribute to this robustness by rejecting low-quality detections, while contour-based measurement with contrast adjustment (1.5×) and statistical outlier filtering (rejecting values deviating >3 mm from running median) provides inherent tolerance to moderate environmental variation.

However, the testing conditions represent typical indoor environments and do not encompass extreme scenarios such as very low lighting (<100 lux) or direct sunlight causing glare. The system occasionally required additional capture attempts under dim evening conditions, though successful measurements were still obtainable. Future work should include systematic robustness evaluation with controlled luminance levels to quantify the relationship between environmental factors and measurement accuracy.

TABLE II
COMPARISON OF JEWELRY SIZING METHODS

Method	Accuracy	Equipment	Real time	Accessibility
Physical ring gauge (mandrel)	ICC 0.94–0.99 [26]	Ring mandrel set	Yes	In-store only
Paper/printable guide	SEM 1.1–1.3 mm [25]	Printed template	Yes	High (requires printing)
3D structured-light scanning	MAE 0.30 mm [30]	3D scanner (e.g., Artec Eva)	Near real-time	Very low (specialized hardware)
AI-based hand landmark (MediaPipe) [31]	Sub-pixel landmark accuracy	Smartphone + app	Yes	Medium (Android users)
Proposed system (Vision framework)	MAE 0.81 mm (ring)	iPhone + credit card	Yes (7.6s)	Medium (iOS users)

Table II presents a comparative analysis of the proposed system against existing jewelry sizing approaches. Physical ring gauges remain the gold standard for in-store measurements, with clinical studies demonstrating excellent reliability (ICC 0.94–0.99) [26], [27]. However, ring gauges require specialized equipment and in-store visits, making them impractical for online retail scenarios. Paper-based sizing guides offer high accessibility but suffer from significant measurement variability, with inter-tester SEM of 1.1–1.3 mm for circumference measurements using tape and template methods [25]. Advanced 3D structured-light scanners, such as the Artec Eva and Space Spider, achieve superior accuracy with MAE of approximately 0.30 mm for hand measurements [30], but require hardware investments exceeding \$10,000 and controlled scanning environments, making them impractical for SME jewelry retailers and home-

based measurements. Yu et al. [30] demonstrated that structured-light scanning achieves comparable accuracy to CT scanning for hand measurements, but noted that circumference measurements showed more significant differences from direct measurement than linear measurements.

Recent AI-based approaches have begun addressing the accessibility gap. Paul and Sebastain [32] developed an AI-powered ring size estimation system using MediaPipe's 21-point hand landmark model combined with CNN-based classification, demonstrating the feasibility of smartphone-based ring sizing with virtual try-on capabilities. Zhang et al. [31] established the foundational real-time hand tracking pipeline using palm detection and hand landmark models, achieving real-time inference on mobile devices. The proposed system in this research achieves a favorable balance between accuracy (MAE 0.81 mm for rings, comparable to single ring size interval), accessibility (requiring only a standard smartphone and credit card), and processing speed (8.7 seconds for complete prediction). While the system's accuracy does not match professional 3D scanners, it significantly surpasses paper-based methods and provides a practical solution specifically suited to the SME jewelry retail context where specialized equipment is neither available nor economically justified.

C. System Functionality Testing

Functional testing was conducted using black-box testing methodology with 7 participants consisting of 3 jewelry store staff and 4 potential customers to validate system behavior across all primary use cases. Each participant was asked to complete specific tasks while the tester observed whether the system produced expected results. Table III presents the test scenarios covering authentication, product browsing, size prediction, shopping cart, checkout, order tracking, and POS management functions.

All 12 test cases across both applications passed successfully with a 100% task completion rate, demonstrating that the system meets its functional requirements and that users were able to complete all designated tasks without critical usability barriers. The Customer Application correctly handles the complete purchase workflow from product discovery through order placement, with all four customer participants successfully completing the end-to-end purchase scenario including product browsing, size prediction capture, cart management, and checkout. The POS Application successfully manages inventory adjustments and order status updates, with all three staff participants completing inventory management and order processing tasks. Changes made through either application were synchronized to the other in real-time, verified through concurrent multi-device testing sessions.

TABLE III
FUNCTIONAL TESTING RESULTS

ID	Feature	Test Scenario	Expected Result	Status
TC-01	Authentication	Login with valid credentials	User authenticated, home shown	Pass
TC-02	Authentication	Login with invalid credentials	Error message displayed	Pass
TC-03	Product Browse	View product catalog by category	Products displayed correctly	Pass
TC-04	Size Prediction	Measure ring size with card	Size result within ± 0.5 accuracy	Pass
TC-05	Size Prediction	Measure bracelet size	Three fit recommendations shown	Pass
TC-06	Shopping Cart	Add product to cart	Product added, total updated	Pass
TC-07	Shopping Cart	Remove product from cart	Product removed, total updated	Pass
TC-08	Checkout	Place order with valid cart	Order created, cart cleared	Pass
TC-09	Order Tracking	View order status	Current status displayed	Pass
TC-10	POS - Dashboard	View business metrics	Metrics displayed correctly	Pass
TC-11	POS - Inventory	Adjust stock quantity	Stock updated, log created	Pass
TC-12	POS - Orders	Update order status	Status changed, customer notified	Pass

During the testing sessions, task observation revealed that participants were able to navigate the system's primary workflows without requiring additional instruction beyond the initial task briefing, suggesting intuitive interface design. The size prediction workflow, which involves the most complex user interaction (positioning credit card, aligning hand, maintaining stability during capture), was completed successfully by all participants within the guided interface flow. However, it should be noted that the current evaluation focuses on functional correctness and task completion rather than comprehensive usability assessment. A formal usability evaluation using standardized instruments such as the System Usability Scale (SUS) [33] was not conducted in this study, which limits the depth of user experience assessment. We identify formal usability evaluation with a larger participant pool as important future work, particularly to assess learnability, efficiency, and user satisfaction across diverse demographic groups.

TABLE IV
SYSTEM PERFORMANCE METRICS

Operation	n	Avg (ms)
Product catalog fetch	10	262
Size prediction (Calibration Phase)	10	1038
Size prediction (Measurement Phase)	10	7662
Add to cart	10	265
Order placement	10	1126
Real-time sync latency	10	243

Table IV presents the system performance metrics measured across key operations. Performance testing was conducted on an iPhone running iOS with Wi-Fi connectivity to the Supabase cloud backend, under network conditions with internet speeds ranging from 10 to 100 Mbps during the evaluation. Network-dependent operations including product catalog fetching (average 262 ms), cart operations (average 265 ms), and order placement (average 1126 ms) demonstrated response times well within acceptable thresholds for interactive applications, where Nielsen’s usability guidelines recommend sub-1000 ms response for maintaining user flow continuity. The size prediction pipeline, which executes entirely on-device using the Neural Engine, completed the full measurement cycle in an average of 8.7 s, comprising calibration (1038 ms) and measurement (7662 ms) phases. Real-time synchronization between Customer and POS applications achieved an average latency of 243 ms, confirming that inventory and order updates propagate within acceptable timeframes for concurrent retail operations. The on-device processing architecture for computer vision ensures that size prediction performance is independent of network conditions, maintaining consistent response times regardless of connectivity quality.

D. Data Privacy and Security

The system incorporates multiple layers of data protection addressing both technical security and ethical considerations regarding user biometric data processing. Most critically, all hand images captured during the size prediction process are processed entirely on-device using Apple’s Vision framework, leveraging the Neural Engine hardware accelerator available on modern iPhones. Hand images are never transmitted to external servers, stored in the database, or retained after the measurement session concludes. Only the derived numerical measurements (finger diameter in millimeters, wrist circumference in millimeters, and calculated size recommendations) are persisted in the database for order processing purposes. This on-device processing architecture ensures that sensitive biometric imagery of users’ hands remains exclusively on their personal device, eliminating risks associated with centralized biometric data storage or transmission.

For user authentication and data protection, the system implements Supabase Auth with JSON Web Token (JWT) based session management, providing stateless authentication with configurable token expiration. All client-server

communication is encrypted through HTTPS/TLS protocols. At the database level, 18 Row-Level Security (RLS) policies enforce strict data isolation between users, preventing unauthorized access to personal information, order history, and measurement data. Staff users operate under separate authentication roles with elevated permissions limited to inventory and order management functions.

From an ethical perspective, the application follows iOS platform conventions for transparent permission management. Camera access is requested through the standard iOS permission dialog, clearly communicating the purpose of camera usage before any image capture occurs. Users must explicitly grant camera permission, and this consent can be revoked at any time through iOS Settings. The system does not perform facial recognition, does not collect personally identifiable biometric templates, and does not create persistent biometric profiles that could be used for identification purposes. These design decisions align with privacy-by-design principles and are consistent with Indonesian data protection regulations under UU PDP No. 27/2022 [34], which establishes requirements for the processing of personal data including biometric information.

E. Discussion

The proposed system demonstrates several advantages over existing solutions identified in the literature review. Compared to traditional jewelry sizing methods that rely on physical ring sizers or sizing guides, the computer vision approach eliminates the need for specialized equipment while achieving comparable accuracy (90% within ± 0.5 size). Unlike virtual try-on systems which focus primarily on visualization [10], this research prioritizes accurate measurement for purchase decisions, achieving mean absolute error of 0.81mm for ring measurements. The integrated architecture addresses limitations found in standalone retail systems, where previous mPOS implementations [17], [18] and e-commerce platforms operate independently [14]. This system provides seamless data flow between customer and staff interfaces through real-time WebSocket synchronization.

While the system demonstrates promising results, several limitations must be acknowledged. First, the iOS platform constraint excludes Android users who represent approximately 85% of the Indonesian mobile market, addressable through cross-platform development using Flutter or React Native. Second, lighting sensitivity affects algorithm performance, with accuracy potentially dropping in poor lighting conditions; adaptive image preprocessing could improve robustness. Third, the static hand pose requirement during image capture presents usability challenges for some users, particularly elderly participants; multi-frame averaging from video capture would reduce sensitivity to momentary movement. Fourth, credit card dependency for calibration may inconvenience users without cards readily available; alternative calibration objects such as standardized coins could expand accessibility.

Additional limitations include the restricted jewelry categories supporting only rings and bracelets, single-store architecture that prevents serving multi-location businesses, and manual payment processing requiring staff confirmation rather than automated transaction completion. The size prediction accuracy, while acceptable for general use, may not meet the precision requirements of high-end jewelry retailers where exact fit is critical.

An additional limitation concerns the influence of individual anatomical variations on measurement accuracy. The contour-based finger diameter estimation assumes an approximately circular cross-section at the proximal phalanx, whereas actual finger profiles can vary significantly between individuals, some exhibiting more oval or rectangular cross-sections due to bone structure, joint prominence, or soft tissue distribution. Anthropometric research has documented substantial variation in hand dimensions across populations, with Greiner [29] cataloging 86 distinct hand dimensions in a comprehensive military anthropometric survey. The current participant pool (n=20, ages 15–75) provides initial demographic diversity but cannot fully represent the breadth of anatomical variation in the target population. Factors such as arthritis-related joint swelling, pregnancy-induced edema, and age-related changes in soft tissue distribution may introduce systematic measurement bias not captured in the current evaluation. Furthermore, skin tone variation affects edge contrast during contour detection, potentially impacting accuracy for individuals with very dark or very light skin tones. Future work should include evaluation with larger and more anthropometrically diverse participant pools.

The research findings have broader implications for small and medium jewelry enterprises considering digital transformation. The accessibility of the solution using standard smartphones and credit cards as the only required equipment demonstrates that advanced computer vision applications can be deployed cost-effectively without specialized hardware investment. The dual-app architecture pattern addresses distinct stakeholder needs while maintaining data consistency, providing a design approach applicable to other retail domains facing similar challenges.

It is important to note that this research primarily focuses on demonstrating the technical feasibility of smartphone-based computer vision for jewelry sizing and integrated retail management, rather than measuring long-term business impact. Quantitative assessment of business metrics such as return rate reduction and inventory accuracy improvement requires extended deployment with actual jewelry retailers over sustained operational periods, which is beyond the scope of this feasibility study and is identified as a direction for future research.

V. CONCLUSION

This research successfully developed and evaluated an integrated jewelry store management system that combines computer vision-based size prediction with mobile e-commerce and point-of-sale functionality. The computer vision algorithm achieved 90% accuracy for ring sizing and 90% acceptable recommendations for bracelet sizing, with mean absolute error of 0.81mm for ring measurements. Functional testing with 7 participants validated all 12 test scenarios successfully, demonstrating that the dual-application architecture effectively serves distinct stakeholder needs with real-time synchronization ensuring operational consistency between customer and staff interfaces.

Several directions for future work have been identified. First, extending platform support to Android is critical, potentially leveraging Google's MediaPipe hand tracking [31] for comparable 21-point hand landmark detection. Second, integrating augmented reality (AR) virtual try-on functionality would enable users to visualize jewelry items on their hands before purchase, increasing purchase intention [35]. Third, computer vision accuracy could be improved through deep learning approaches using convolutional neural networks trained specifically on finger measurement data. Fourth, multi-store capabilities with tenant-based architecture would expand applicability to jewelry retail chains. Fifth, automated payment gateway integration would streamline the checkout process. Finally, extended pilot deployment with actual jewelry retailers is essential to evaluate the system's effectiveness in real-world retail operations and measure actual business outcomes such as return rate changes and operational efficiency improvements.

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