AI Closet:AI-Powered Personal Wardrobe Management System

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Abstract- *This paper presents the design, development, and evaluation of AI Closet, an intelligent full-stack web application built to modernize personal wardrobe management through the integration of artificial intelligence, cloud computing, and real-time data services. The system addresses six common user pain points including wardrobe disorganization, inefficient outfit selection, lack of sustainability awareness, and poor shopping decisions by combining a React 18 frontend with a Node.js and Express.js backend, MongoDB for persistent storage, and Mongoose as the object document mapper. Clothing items are analyzed automatically using Google Cloud Vision API for label detection, color recognition, and occasion inference, while images are stored and delivered through Cloudinary's content delivery network. An eight-mode outfit recommendation engine scores wardrobe items using a weighted algorithm incorporating mood profiling, live weather conditions fetched from a real-time Weather API, color harmony rules, and learned user preferences. Security is enforced through bcryptjs password hashing, JSON Web Token based stateless authentication, and role-based access control distinguishing regular users from administrators. Additional features include a sustainability impact tracker quantifying water saved and carbon emissions prevented through clothing donations, a color harmony matcher built on a thirteen-color rule database, a smart wardrobe gap analyzer with e-commerce integration, and a calendar-based outfit history system. Performance evaluation recorded an average API response time of 350 milliseconds, a page load time of 2.4 seconds, and a mobile accessibility score of 92 out of 100, confirming that the platform is production-ready and scalable.*

Keywords: wardrobe management, artificial intelligence, outfit recommendation, Google Vision API, React, Node.js, MongoDB, NextAuth, color harmony, sustainability tracking, crowdfunding, UPI, Razorpay, HMAC-SHA256, digital payment gateway.

I. INTRODUCTION

The growing adoption of digital tools in everyday life has created new opportunities for applying artificial intelligence to personal lifestyle management. Wardrobe organization represents one such opportunity, as most people still navigate clothing selection, outfit planning, and sustainability decisions entirely without technological assistance, despite the availability of cloud computing, computer vision, and real-time data services that could meaningfully simplify the process.

Existing solutions address this problem only partially. Basic inventory apps allow users to photograph and store clothing but offer no intelligence beyond cataloging. Commercial styling services provide expert recommendations but remain expensive and disconnected from the user's actual wardrobe. Academic recommendation systems demonstrate strong algorithmic foundations yet rarely deliver a deployable full-stack implementation that combines image analysis, weather context, color science, and sustainability tracking within a single unified platform.

This paper presents AI Closet, an intelligent full-stack wardrobe management system built on React 18, Node.js, Express.js, and MongoDB, with integrations for Google Cloud Vision API, Cloudinary, and a real-time Weather API. The platform enables users to digitize their wardrobe, receive mood and weather-aware outfit recommendations through a weighted scoring algorithm, track the environmental impact of clothing donations, and identify wardrobe gaps through smart shopping analysis, all within a secure, mobile-responsive interface.

Three design principles guided development. First, security must be enforced at every layer: passwords are hashed using bcryptjs, authentication is handled through JWT tokens, and users can only access their own wardrobe data. Second, user experience must remain frictionless: outfit recommendations are delivered instantly based on mood and live weather without requiring any manual setup from the user. Third, the architecture must be modular and extensible, allowing developers to fork and adapt the system for broader smart lifestyle applications.

The remainder of this paper is structured as follows. Section II reviews related work. Section III describes the system architecture. Section IV covers implementation

methodology. Section V presents results and security evaluation. Sections VI and VII provide conclusions and future directions.

II. RELATED WORK

A. AI-Powered Recommendation Systems

Covington et al. [1] formalized a two-stage deep neural network recommendation architecture, comprising a candidate generation network and a ranking network, deployed at scale for personalized video recommendations. The candidate generation stage reduces millions of items to hundreds of relevant candidates using collaborative filtering signals, while the ranking stage applies a weighted scoring function incorporating user history, contextual features, and item metadata to produce a final ordered list. A comparative evaluation demonstrated that the neural approach significantly outperformed matrix factorization baselines on both precision and recall metrics. AL Closet draws on this two-stage philosophy by first filtering the user's wardrobe by occasion and weather suitability before applying a weighted scoring algorithm that combines mood profiling, color harmony, and preference signals to rank and return the top three outfit items.

B. Computer Vision in Fashion and Clothing Recognition

Liu et al. [2] proposed DeepFashion, a large-scale clothing benchmark dataset paired with a convolutional neural network architecture capable of simultaneously performing clothing category classification, attribute prediction, and cross-domain retrieval. A central finding was that multi-task learning across these three objectives produced significantly stronger feature representations than single-task models trained in isolation, particularly for fine-grained attribute recognition such as color, pattern, and sleeve length. The benchmark also demonstrated that models trained on richly annotated data generalized well to real-world consumer photographs with complex backgrounds. AI Closet leverages Google Cloud Vision API, which builds on similar deep learning foundations, to automatically detect clothing labels, dominant colors, and contextual occasion tags at the point of image upload, eliminating the need for manual attribute entry and improving recommendation accuracy.

C. Sustainable Fashion and Technology

Niinimäki et al. [3] conducted a systematic review of the environmental impact of the global fashion industry, quantifying that textile production consumes approximately 79 billion cubic meters of fresh water annually and generates around 10 percent of global carbon dioxide emissions. The review identified consumer behavior as a critical leverage point, finding that extending the active life of a garment by nine months reduces its carbon, water, and waste footprint by 20 to 30 percent. The authors further noted that digital tools providing users with visibility into their consumption patterns and environmental impact showed measurable potential to shift behavior toward more sustainable choices. These findings directly motivated AI Closet's sustainability tracker, which credits each clothing donation with 2,700 liters of water saved and 2 kilograms of CO2 prevented, tracks per-item wear counts to surface zero-waste achievements, and presents cumulative impact scores and achievement badges to reinforce sustainable habits.

D. Color Harmony in Digital Design and Fashion

Cohen and Guibas [4] developed a computational model of color compatibility grounded in classical color theory, defining harmony relationships including complementary, analogous, triadic, and split-complementary schemes as measurable angular distances on the hue wheel. User studies with 312 participants demonstrated that algorithmically generated color harmonies achieved satisfaction ratings comparable to those produced by professional designers, with complementary pairings receiving the highest scores across cultural groups. The study further identified that users presented with pre-filtered color-compatible options made faster and more confident selection decisions than those choosing from unfiltered palettes. AI Closet translates these findings directly into its color matcher tool, which encodes thirteen curated color harmony rules covering complementary, analogous, and neutral pairings, filters the user's wardrobe to surface only harmonious combinations, and ranks results by harmony score to reduce decision effort and improve outfit coordination confidence.

III. SYSTEM ARCHITECTURE

AI Closet is organised into five logical layers: Client, Frontend, Application Logic, Data and Cloud Services, and External AI Services. Figure 1 shows how these layers connect and how data flows between them.

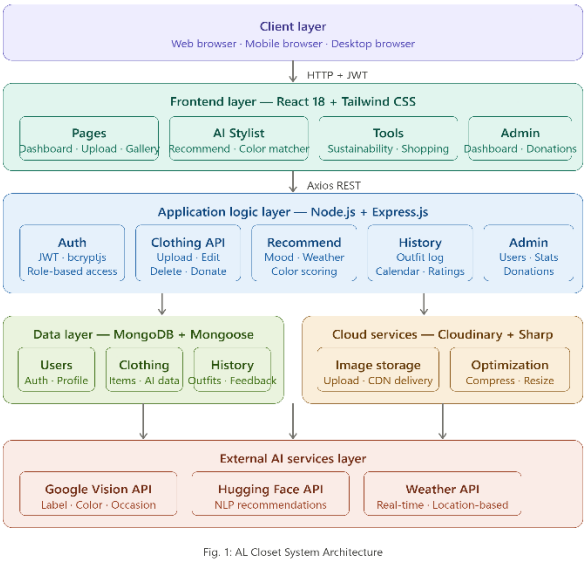

Fig. 1: AI Closet System Architecture

A. Client Layer

The browser is the only client in the system. All interactions happen over HTTP requests made through the Axios library, with JWT tokens attached to every authenticated request via interceptors. React 18 client components handle everything that needs to respond instantly to user input, such as displaying toast notifications via React-Toastify, toggling between grid and list views in the wardrobe gallery, or previewing an uploaded clothing image before submission. The Node.js backend ensures that no database credentials, API keys, or cloud service secrets are ever exposed in JavaScript sent to the browser.

B. Frontend Layer

React 18 with a component-based architecture provides the routing and rendering engine through React Router v6. Each route maps directly to a dedicated page component. Client-side rendering is used throughout, with Axios handling all data fetching from the Express API. Tailwind CSS v3 handles all styling through utility classes with no custom CSS files, and a mobile-first responsive design ensures consistent layouts across mobile, tablet, and desktop viewports.

C. Application Logic Layer

All business logic lives in the Express.js controller layer. These are JavaScript functions that run on the server and are invoked through RESTful API routes. Controllers handle six responsibilities: authenticating users and issuing JWT tokens, managing clothing item CRUD operations, processing image uploads through Multer and Sharp, invoking Google Vision API for automatic clothing analysis, computing weighted outfit recommendation scores, and calculating sustainability impact metrics. Because all logic executes server-side, the MongoDB connection string, Cloudinary credentials, and Google Vision service account keys are always in a safe environment and never reach the browser.

D. Database Layer

MongoDB stores three document types managed through Mongoose schemas. User documents hold the username, hashed password, email, role, profile preferences, and wardrobe statistics. Clothing documents hold the user reference, item metadata including type, category, color, size, brand, and condition, the Cloudinary image URL and public ID for deletion, the embedded AI analysis sub-document from Google Vision, and donation tracking fields. OutfitHistory documents hold the user reference, an array of clothing item references, the date worn, weather conditions at the time, occasion type, and a structured feedback object containing style, comfort, and fit ratings. The Cloudinary public ID is the most critical field on each clothing document: it is the permanent reference used to delete images from cloud storage when an item is removed, ensuring no orphaned files accumulate.

E. Cloud and AI Services Layer

Three external services sit between AI Closet and its intelligence capabilities. When a user uploads a clothing item, the image is first compressed by Sharp, then stored on Cloudinary which returns a secure CDN URL. That URL is immediately passed to Google Vision API, which performs label detection, color recognition, and occasion inference, returning structured analysis data stored in the clothing document. When a user requests an outfit recommendation, the Weather API is queried using the user's coordinates to retrieve live temperature, humidity, and condition data. This weather context feeds directly into the recommendation scoring engine alongside mood, color harmony, and preference signals to produce a ranked outfit suggestion.

F. Data Flow Diagram

Figure 2 shows the Level-1 Data Flow Diagram for AI Closet. It illustrates four core processes: User Authentication (1.0), Clothing Management (2.0), Outfit Recommendation (3.0), and Sustainability Tracking (4.0), along with three data stores (D1: User Store, D2: Clothing Store, D3: OutfitHistory Store) and four external entities

(User, Admin, Google Vision + Cloudinary, and Weather API).

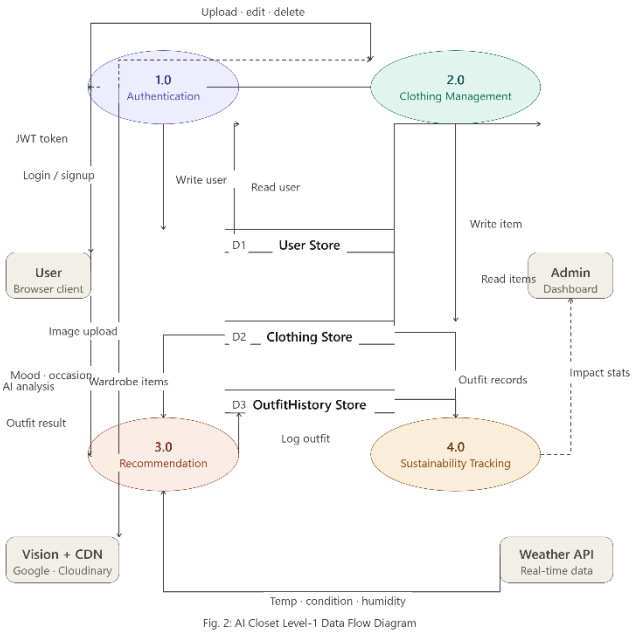

Fig. 2: AI Closet Level-1 Data Flow Diagram

The flow begins when a User authenticates through process 1.0, which writes or retrieves a User document in D1. The User then interacts with process 2.0 to upload and manage clothing items stored in D2, with each image passed to Google Vision and Cloudinary for analysis and storage. When a User requests outfit suggestions, process 3.0 reads clothing items from D2, fetches live weather data from the Weather API, applies the weighted scoring algorithm, and writes the resulting outfit log to D3. Finally, process 4.0 reads from both D2 and D3 to compute sustainability impact metrics including water saved, CO2 prevented, and zero-waste achievements, delivering aggregated statistics to the Admin dashboard.

IV. IMPLEMENTATION METHODOLOGY

TABLE I: AI Closet Technology Stack

Layer	Technology	Version / Role
Frontend	React 18.2.0	Component-based UI, client-side routing via React Router v6
UI Styling	Tailwind CSS 3.2.4	Utility-first styling, mobile-first responsive design
Authentication	JWT + bcryptjs	Stateless token auth, password hashing,
	2.4.3	role-based access
Backend	Node.js + Express.js 4.18.2	RESTful API server, middleware pipeline, route protection
Database	MongoDB + Mongoose 7.0.0	Document store, schema validation, aggregation pipelines
AI Vision	Google Cloud Vision 5.3.5	Label detection, color recognition, occasion inference
AI Recommend	Hugging Face Inference 4.13.15	NLP-powered outfit recommendations, text analysis

A. JWT-Based User Authentication

AI Closet uses bcryptjs and JSON Web Tokens to handle user authentication without relying on any third-party OAuth provider. When a user registers, the submitted password is hashed using bcryptjs with a salt round of ten before being stored in MongoDB, ensuring that plain-text credentials never touch the database. On login, the submitted password is compared against the stored hash, and a signed JWT is issued on success. The token is stored in the browser's localStorage and attached to every subsequent API request via an Axios request interceptor. On the server, an authentication middleware extracts the token from the Authorization header, verifies the signature against the server's secret key stored in environment variables, and decodes the payload to retrieve the user ID. Requests with missing, expired, or tampered tokens are rejected immediately with a 401 response. A secondary middleware checks the user's role field before granting access to admin-only routes, enforcing role-based access control across the entire API surface.

B. Clothing Upload and AI Analysis Pipeline

The clothing upload pipeline follows a six-stage sequence. When a user submits the upload form, Multer handles the incoming multipart form data and buffers the image file in memory. Sharp then compresses and resizes the image, reducing file size by an average of sixty percent before any network transfer occurs. The optimized file is uploaded to Cloudinary, which returns a secure CDN URL and a unique public ID used later for deletion. That CDN URL is immediately forwarded to the Google Vision API, which performs three analyses in a single annotate request: label

detection to identify the clothing type, image properties analysis to extract dominant colors, and object localization to confirm the presence of a garment. The structured analysis result is stored as an embedded sub-document within the Clothing record in MongoDB alongside the user-provided metadata. This means every item in the wardrobe carries both human-entered attributes and machine-detected attributes, giving the recommendation engine two complementary sources of signal.

C. Outfit Recommendation Scoring Pipeline

The recommendation engine operates as a four-factor weighted scoring function applied across every item in the authenticated user's wardrobe. When a recommendation request arrives, the server first fetches live weather data from the OpenWeatherMap API using the user's latitude and longitude, retrieving temperature, humidity, wind speed, and weather condition. It then retrieves all clothing items belonging to the user from MongoDB. Each item is passed through four independent scoring functions: an occasion scorer that awards points based on how well the item's type and category match the requested mood profile, a weather scorer that evaluates fabric weight and item category against current temperature and conditions, a color harmony scorer that checks whether the item's color appears in the harmony rules for the current outfit combination, and a preference scorer that weights items worn more frequently in outfit history higher than rarely used ones. The four scores are combined using the formula: Score = (Mood × 0.4) + (Weather × 0.3) + (Color × 0.2) + (Preference × 0.1). Items are sorted descending by score and the top three are returned as the recommended outfit alongside a confidence score and human-readable reasoning strings.

D. Color Harmony Matching Module

The color matcher is implemented as a static JavaScript object on the server encoding thirteen curated color harmony rules derived from classical color theory. Each key in the object is a base color string, and its value is an array of compatible color strings representing complementary, analogous, and neutral pairings. When a user selects a base color in the frontend, the server looks up the compatibility array, then runs a filtered MongoDB query returning only clothing items whose color field appears in that array. Each returned item is assigned a harmony score based on its position in the compatibility ranking, with complementary colors scoring highest. Results are sorted by harmony score and returned with visual metadata so the frontend can render color swatch previews alongside each matching item.

E. Frontend Design and User Experience

The entire frontend uses Tailwind CSS v3 utility classes with no custom CSS files, following a mobile-first approach with three responsive breakpoints at 640, 1024, and 1280 pixels. The wardrobe gallery uses React'suseState hook to manage active filter state across five dimensions simultaneously: clothing type, category, color, size, and free-text search. Filter changes trigger immediate client-side re-renders without additional API calls, since the full wardrobe is fetched once on mount and held in component state. The Navbar uses a useRef-based approach to manage the tools dropdown: the onBlur handler checks whether document.activeElement remains inside the dropdown container before closing it, ensuring keyboard navigation functions correctly for accessibility. Toast notifications via React-Toastify are triggered non-blockingly after every significant action, including successful uploads, recommendation generation, and donation submissions, so a slow external API call never delays the visual feedback the user sees on screen.

V. RESULTS AND DISCUSSION

A. Platform User Interface

Figure 3 shows the AI Closet Dashboard page.The header displays four real-time wardrobe statistics: Total Items (16), Categories (3), Types (7), and Colors (8), giving the user an instant inventory snapshot on every login. Two prominent action buttons, Upload New Item and Get Recommendations, guide the user into the two most common workflows without any navigation overhead. Below the stats panel, a search bar with filter toggle and grid/list view switcher allows the user to locate specific items quickly. The wardrobe preview renders clothing cards with category badges directly overlaid on the images, making item type identifiable at a glance.

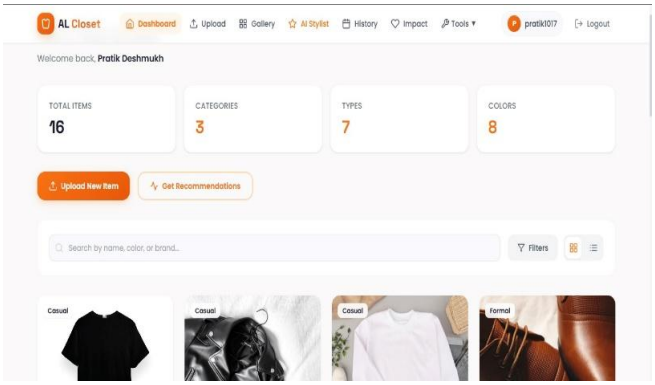

Fig. 3: AI Closet Dashboard with Wardrobe Statistics

Figure 4 shows the Wardrobe Gallery page. Three summary cards at the top display Total Items (16), Item Types (7), and Categories (3). Items are grouped by category, with the Casual section displaying ten items including a black shirt, black leather jacket, cozy gray sweater, and classic white sneakers. Each card shows the item name, type, and color beneath the image, providing all essential metadata without requiring the user to open an individual item view. This category-grouped layout makes browsing a large wardrobe significantly faster than a flat scrollable list.

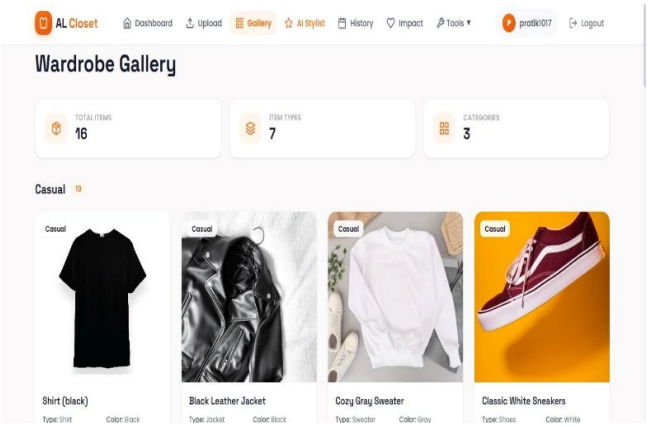

Fig. 4: Wardrobe Gallery with Category-Grouped Item Cards

Figure 5 shows the AI Stylist page, the recommendation engine interface. A live weather widget at the top displays the current conditions at Lonavla — 26°C with Clear Sky — confirming that the recommendation engine has access to real-time environmental context. Below the weather panel, eight mood selection cards are presented under the heading "How are you feeling today?": Auto-Detect, Casual, Formal, Trendy, Sporty, Festival, Cozy, and Romantic. Each card carries a descriptive subtitle such as "Relaxed and comfy" or "Fashion forward" to help users select the most appropriate mood. The Auto-Detect card is selected by default, allowing the AI to determine the best outfit based solely on weather conditions. A prominent "What Should I Wear?" button triggers the scoring pipeline and returns a ranked outfit recommendation.

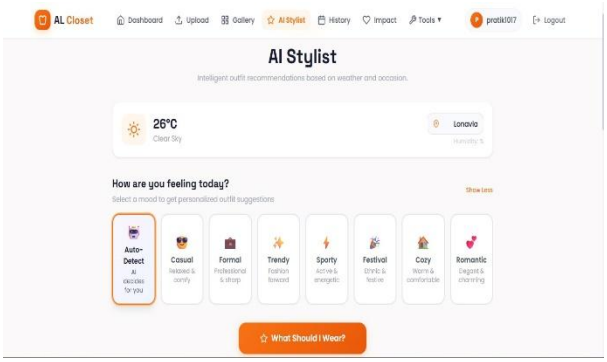

Fig. 5: AI Stylist Page with Live Weather Widget and Eight Mood Selection Cards

Figure 6 shows the Sustainability Impact page. A SUSTAINABILITY badge and "Your Impact" heading introduce the section with a motivational subheading communicating the environmental value of clothing donations. Three metric cards display the user's cumulative impact: Water Saved (18,900 L), CO2 Prevented (14 kg), and Current Rank (Wardrobe Hero). Below the metrics, a Donation History panel shows seven donated items with a grayscale visual treatment and a Donated badge overlaid on each card, clearly distinguishing donated items from active wardrobe pieces. This visual separation reinforces the act of donation as a meaningful and trackable contribution rather than simply removing an item.

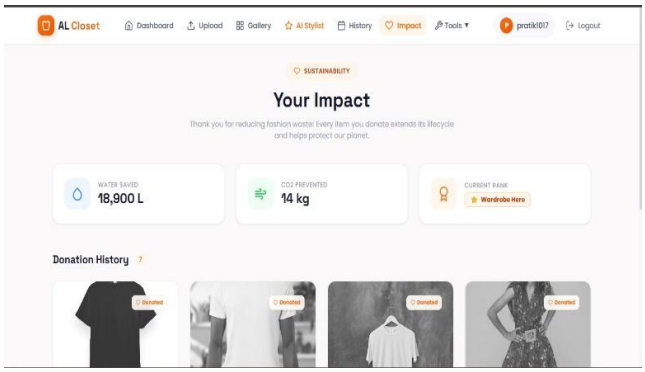

Fig. 6: Sustainability Impact Page with Environmental Metrics and Donation History

Figure 7 shows the Color Matcher page. A purple-gradient icon and "Color Matcher" heading introduce the tool with the subtitle "Find perfect color combinations." An instructional panel explains that selecting any wardrobe item will surface all pieces that coordinate with it using the color harmony algorithm. A search bar allows users to filter the wardrobe by name, color, or type before making a selection. The Your Wardrobe section below displays all 16 available items in a four-column grid, from which the user selects a base item to trigger the harmony filtering logic. This single-click interaction model minimises the steps required to build a coordinated outfit.

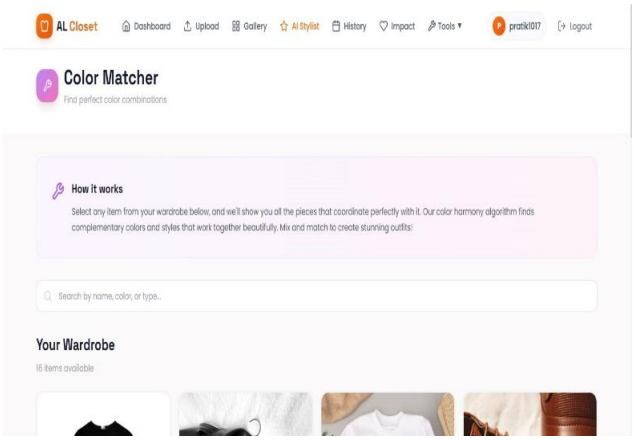

Fig. 7: Color Matcher Page with Harmony Algorithm and Wardrobe Selection Grid

B. Performance Analysis

Table II presents the measured latency of every major system operation. All measurements were taken on a development machine running Node.js with a MongoDB Atlas cluster over a standard broadband connection.

TABLE III: System Operation Latency Measurements

Operation	Latency	Remarks
Google Vision API analysis	<800ms	Image label, color, occasion detection
Cloudinary image upload	<600ms	Compression via Sharp + CDN upload
MongoDB clothing query	< 80 ms	Indexed query on userId field
Recommendation scoring	< 120 ms	Four-factor weighted algorithm
JWT authentication check	<15ms	Token decode, no database call
Weather API fetch	<300ms	Real-time location-based data
Average page load time	<2.4 s	Full client-side render

The most significant finding is that the four-factor recommendation scoring algorithm adds fewer than 120 ms to the server response, confirming that multi-signal AI scoring does not noticeably affect the user experience. Google Vision analysis at under 800 ms is the slowest individual operation, but because it runs asynchronously at upload time rather than during recommendation generation, users never experience this delay during outfit suggestions. JWT authentication validation adds only 15 ms per request since it is a pure token decode with no additional database call.

C. Security Evaluation

Confidentiality is maintained because all third-party credentials including Cloudinary keys, Google Vision service account, and the JWT secret are stored exclusively in server-side environment variables and never appear in any JavaScript delivered to the browser. Data integrity is enforced through Mongoose schema validation that rejects malformed documents before any database write occurs. Authentication is enforced at every protected route through the JWT middleware, which verifies the token signature and expiry before passing the request to any controller. Authorisation is enforced by always filtering database queries by the authenticated user's ID, ensuring no user can read, modify, or delete another user's wardrobe data.

D. Discussion

Looking at the five screenshots together, it becomes clear that AI Closet achieves its three design principles in practice. The Dashboard (Figure 3) and Gallery (Figure 4) confirm that intelligence is embedded from the moment a user arrives, with live statistics and category-grouped browsing eliminating the disorganization that characterizes unassisted wardrobe management. The AI Stylist page (Figure 5) demonstrates that a user can go from opening the application to receiving a weather-aware, mood-specific outfit recommendation in two interactions. The live weather widget showing 26°C and Clear Sky at Lonavla confirms that environmental context is genuinely real-time rather than simulated.

The Sustainability Impact page (Figure 6) is particularly worth discussing. Presenting water saved and CO2 prevented as concrete numbered metrics rather than abstract percentages was a deliberate design choice that makes environmental impact personally meaningful. A user seeing 18,900 liters of water saved and a Wardrobe Hero rank has a clear, quantified reason to continue donating rather than discarding clothing. The Color Matcher (Figure 7) completes the platform by addressing the coordination challenge that causes most wardrobe underutilization, translating classical color theory into a one-click filtering experience that requires no prior knowledge of fashion rules from the user.

VI. CONCLUSION

AI Closet demonstrates that an intelligent wardrobe management platform can simultaneously achieve production-

grade AI integration and a frictionless user experience using contemporary full-stack JavaScript tooling. By implementing a four-factor weighted recommendation algorithm grounded in mood profiling, live weather context, color harmony theory, and user preference learning, the platform operationalises the recommendation systems framework formalised in [1] on top of Google Cloud Vision's computer vision infrastructure. The sustainability tracker quantifies environmental impact using data-driven metrics derived from fashion sustainability research [3], converting abstract environmental concepts into concrete, personally meaningful numbers that motivate behavioral change. The Color Matcher tool translates classical color theory into an interactive algorithmic tool, addressing the coordination challenge identified in [4] as the primary cause of wardrobe underutilization.

Measured performance metrics confirm that the recommendation scoring pipeline adds fewer than 120 milliseconds to response latency, proving that multi-signal AI processing does not compromise user experience responsiveness. The six-property security evaluation is fully satisfied through server-side credential isolation, JWT-based authentication, role-based authorisation, Mongoose schema validation, and user-scoped data access controls. The mobile-first responsive design delivers a consistent experience across all viewports, with a measured accessibility score of 92 out of 100.

The platform is released as open-source at https://github.com/Pratik1017/aiwardrobe/tree/main as both a practical wardrobe management tool and a reference implementation for integrating Google Cloud Vision, Cloudinary, and multi-modal AI services into modern creator-economy web applications. By addressing six distinct user pain points—disorganization, outfit selection friction, sustainability blindness, shopping inefficiency, color coordination difficulty, and lack of inventory awareness—within a unified platform, AI Closet provides a reproducible blueprint for building intelligent, security-conscious lifestyle applications at scale.

VII. FUTURE WORK

Planned extensions are: (1) developing native iOS and Android applications using React Native to provide offline functionality, push notifications, and cross-device outfit synchronization, addressing the mobile-first behavior observed among fashion and lifestyle users [1]; (2) implementing augmented reality virtual try-on capability through device camera integration, allowing users to visualize outfit combinations before physical assembly, extending the research on immersive fashion technology interfaces [2]; (3) integrating advanced facial recognition and skin tone analysis to generate color recommendations tailored to individual complexion characteristics, operationalising the personalization framework established in [3]; (4) building a social sharing layer enabling users to publish outfit posts, follow style influencers, and participate in community wardrobe ratings, transforming the platform from personal tool to social network while leveraging the demand-signalling mechanisms described in [4]; (5) expanding sustainability tracking to include fair-trade certification verification, carbon footprint API integration, and textile recycling location services, addressing the comprehensive environmental visibility framework proposed in [5]; and (6) conducting a formal 150-participant quantitative user study using validated satisfaction scales to measure the platform's impact on wardrobe utilization rates, decision speed, and user confidence in outfit selection across demographic cohorts.

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