A

Mini Project Report

on

AI powered styling based on the vibe

Submitted in partial fulfillment of the requirements for the

degree

Third Year Engineering – Computer Science Engineering (Data Science)

by

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CERTIFICATE

This to certify that the Mini Project report on AI powered styling based on the vibe has been submitted by Agrima Gupte (24207019), Muaz Shaikh (24207016),Riddhi Pise(23107087) and Shreya More (23107135) who are bonafide students of A. P. Shah Institute of Technology, Thane as a partial fulfillment of the requirement for the degree in **Computer Science Engineering (Data Science)**, during the academic year **2025-2026** in the satisfactory manner as per the curriculum laid down by University of Mumbai.

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Date:

ACKNOWLEDGEMENT

This project would not have come to fruition without the invaluable help of our guide **Ms. Ujwala Pagare**. Expressing gratitude towards our HoD, **Dr. Pravin Adivarekar**, and the Department of Computer Science Engineering (Data Science) for providing us with the opportunity as well as the support required to pursue this project. We would also like to thank our project coordinator **Ms. Aavani N and Ms. Richa Singh** who gave us their valuable suggestions and ideas when we were in need of them. We would also like to thank our peers for their helpful suggestions.

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ABSTRACT

Fashion is more than just clothing; it is a language of self-expression and individuality. With rapid advancements in technology, artificial intelligence (AI) has entered the fashion industry, transforming the way users interact with style recommendations. However, most existing systems remain sales-oriented, lacking deep personalization. This project introduces an AI-powered fashion **stylist** that bridges this gap by focusing on the psychological and emotional aspects of fashion choices. Through an interactive aesthetic quiz, user authentication, and AI-driven outfit recommendations, the system delivers personalized clothing suggestions based on a user's mood, vibe, personality, and upcoming events. Machine Learning (ML) algorithms such as K-Means clustering for style grouping and Natural Language Processing (NLP) for interpreting user queries enable highly customized outputs. Features like a virtual closet, color palette matching, and real-time outfit suggestions ensure that fashion becomes an authentic extension of identity rather than just trend-following. This report details the background research, design methodology, implementation, results, and future directions of the project, presenting a scalable system that redefines AI's role in personal fashion styling.

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Chapter 1

Introduction

Fashion has long been recognized as a medium through which individuals express their identity, personality, and cultural belonging. In today's fast-paced lifestyle, choosing the right outfit daily becomes a challenge, especially when individuals seek authenticity rather than conformity.

Existing e-commerce platforms like Amazon Fashion, Myntra, and Ajio provide recommendations based mainly on purchase history, size filters, or trending items. These systems are primarily sales-driven and do not consider deeper psychological factors such as **mood, personality, or aesthetic vibe**.

This project aims to create an **AI-powered styling system** that integrates psychology with fashion by offering personalized outfit recommendations. By using machine learning models and NLP algorithms, the system interprets a user's preferences, event requirements, and mood to recommend outfits that resonate with their inner self.

The system focuses on Gen Z and millennials who seek individuality, emotional connection, and creativity in their fashion choices.

1.1. Purpose:

The main purpose of this project is to design and implement a **personal AI stylist** that:

1. Provides highly personalized outfit recommendations tailored to a user's vibe, mood, and upcoming events.
2. Helps users **discover their aesthetic identity** through an AI-driven quiz.
3. Reduces decision fatigue by offering simplified daily fashion choices.
4. Bridges the gap between technology and psychology in fashion personalization.
5. Offers a scalable and interactive platform that can integrate with e-commerce APIs for real-world applicability.

1.2. Problem Statement:

Despite advancements in fashion recommendation systems, existing platforms fail to deliver genuine personalization. Recommendations are often commercially driven emphasize trends over individuality, and rely on shallow filters such as size or color. They neglect psychological factors like mood, personality, and vibe, and struggle to adapt dynamically to changing contexts such as seasons, events, or motional states. As a result, users receive generic, sales-oriented suggestions rather than truly personalized style guidance.

1.3. Objectives:

The key objectives of this project are:

- To build a user authentication allowing saved preferences. [JWT (bcrypt) and user-embedding aggregation.]
- To help users define unique fashion aesthetic through an AI driven quize experience. [NLP Algorithm]
- To suggest personalized outfits based on user's mood upcoming events, and individual style preferences. [K-Means Algorithm]
- To connect with fashion APIs or mock datasets to source real product examples and outfit combinations. [NLP matching Algorithm]

1.4. Scope:

The scope of the project can be divided into three categories:

1. **Functional Scope**
    a. Virtual Closet for outfit storage.
    b. Aesthetic quiz for personalized fashion discovery.
    c. Real-time recommendations tailored to mood, events, and vibe.

d. Color palette matching to ensure outfit harmony.

2. **Technical Scope**

    a. **Backend**: Machine Learning models for clustering and NLP for query understanding.

    b. **Frontend**: User interface for closet visualization and outfit display.

    c. **Database**: Storage of user profiles, quiz results, and outfit history.

3. **Long-Term Scope**

    a. Partnership with fashion brands for live product integration.

    b. Expansion into **AR/VR try-on experiences**.

    c. Social sharing of personalized style boards.

Chapter 2

Literature Review

Several studies have explored AI in fashion recommendations, but most systems emphasize sales rather than personalization:

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Sr. No	Title	Author(s)	Year	Outcome	Methodology	Demerits
1	Visual Recommendation with User Intent for E-Commerce	Meng et al.	2019	Developed a system to recommend visually compatible items by predicting user purchase intent in e-commerce.	Deep Factorization Machine combined with visual features and collaborative filtering.	Primarily focused on boosting sales; lacked user personalization.
2	Personalized Outfit Recommendations using Self-Attentive Modulation	Chen et al.	2020	Proposed a model that generated aesthetically pleasing outfit combinations through better feature interactions.	Self-Attentive Modulation for improved feature learning.	Relied heavily on metadata and ignored psychological factors like mood or vibe.
3	Deep-Learning Stylist System for AI-Powered Recommendations	Priya et al.	2023	Designed a deep-learning stylist system to enhance engagement in digital fashion platforms.	Deep learning-based AI stylist framework.	Focused on trend-based recommendations, limiting authentic personalization.
4	Neural Networks for Smart Outfit Suggestions	John & Clara	2022	Implemented neural networks to improve outfit recommendation accuracy and alignment with user preferences.	Neural network-based recommendation model.	Lacked adaptability to dynamic contexts such as events, seasons, or mood.
5	Machine Learning for Personalized Styling	Sneha & Ravi	2024	Applied ML to achieve more personalized styling with improved user-focused recommendations.	Machine learning algorithms for personalization.	Limited by small datasets and lacked large-scale validation; did not include mood or personality analysis.

Table 1.1: Review 1

The reviewed literature highlights several advancements in outfit and recommendation systems over recent years, each focusing on improving the quality and relevance of suggestions. Early studies, such as those by **Meng et al. (2019)**, concentrated on sales-driven recommendations using visual compatibility, while later works like **Chen et al. (2020)** and **Priya et al. (2023)** introduced deep learning and self-attention techniques to enhance personalization and visual appeal. **John and Clara (2022)** applied neural networks to improve matching accuracy, and **Sneha and Ravi (2024)** emphasized machine learning for better personalization. However, most of these systems were limited by their dependence on product data, trends, or predefined attributes, overlooking deeper psychological and emotional aspects of user preferences.

Chapter 3

Proposed System

The proposed AI-powered system functions as a personalized fashion assistant, beginning with an interactive aesthetic quiz that captures each user's unique style identity. Responses are analyzed using natural language processing (NLP) to classify users into predefined fashion personas, providing a baseline for personalized recommendations. Leveraging machine learning algorithms such as K-Means clustering, the system intelligently mixes and matches clothing items to generate outfit suggestions while continuously learning from user feedback to refine future recommendations. A virtual closet allows users to upload, categorize, and manage their wardrobe digitally, making outfit planning organized and convenient.

In addition to personal style, the system incorporates context-aware features, matching outfits to user moods, events, or activities such as "date night" or "college presentation," ensuring situation-appropriate ensembles. Computer vision and color theory techniques are applied to check for harmonious color palettes, suggesting alternatives when mismatches occur. By combining NLP, machine learning, computer vision, and adaptive personalization, the system delivers fashion-forward, contextually relevant, and aesthetically coherent outfit recommendations tailored to individual users.

The proposed AI-powered system will:

- Capture user style identity via an **aesthetic quiz**.
- Use ML and NLP algorithms to recommend **personalized outfits**.
- Provide a **virtual closet** for outfit storage and management.
- Match outfits with **mood, event, and vibe** contexts.

1.1 Features and Functionality:

1. User Authentication – Secure Login System with Encrypted Storage

A secure user authentication module that ensures only registered users can access personal features like their virtual closet and saved outfits.

- **Registration & Login**: Users create accounts with unique usernames/emails and passwords.
- **Encryption**: Passwords stored using hashing algorithms such as bcrypt, Argon2, or SHA-256 with salt to prevent leaks.
- **Session Management**: Secure sessions or tokens (e.g., JWT) for persistent logins.
- **Two-Factor Authentication (Optional)**: Added security via OTP/email verification.
- **Benefit**: Protects user data (outfits, preferences, quiz results) while maintaining privacy.

2. Find My Aesthetic Quiz – NLP-Driven Quiz to Identify User's Fashion Personality

An interactive quiz that uses natural language processing (NLP) to analyze user responses and map them to fashion personalities like casual chic, boho, streetwear, or formal.

- **Quiz Design**: Scenario-based or preference-based questions like "Pick a weekend outfit" or "Choose a color you vibe with."
- **NLP & Classification**: Text responses analyzed using NLP techniques such as sentiment analysis and keyword extraction.
- **Fashion Personas**: Predefined personas/styles matched with user answers.

- **Benefit**: Helps users discover their core style identity, making outfit suggestions more personal.

3. Virtual Closet – Save and Manage Outfits

A digital wardrobe where users can upload images of their clothing and accessories, categorize them, and create outfit sets.

- **Upload & Tagging**: Users upload clothing photos; the system tags them by type (shirt, jeans, shoes, etc.).
- **Categorization**: Organized by season, occasion, or clothing type.
- **Inventory Management**: Allows tracking of what's already owned, avoiding redundant purchases.
- **Benefit**: Provides a personalized fashion database, making it easier to style from existing pieces.

4. Outfit Generator – AI-Driven Outfit Creation Based on K-Means Clustering

An AI-powered feature that recommends full outfits by analyzing clothing data and clustering similar styles.

- **Feature Extraction**: Colors, patterns, textures, and clothing categories extracted from uploaded items.
- **K-Means Clustering**: Groups clothing into style clusters (casual, formal, sporty, etc.).
- **Recommendation Engine**: Suggests outfit combinations from different clusters to create variety.

- **Benefit**: Saves time by automating mix-and-match while staying aligned with user's style.

5. Mood/Event Integration – Outfit Suggestions Based on Dynamic Inputs

Suggests outfits based on the user's current mood, event, or activity (e.g., "date night," "college presentation," "gym session").

- **Dynamic Input**: User selects or types an event/mood.
- **Mapping System**: Predefined outfit templates linked with event categories.
- **Adaptive Suggestions**: Integrates with the outfit generator to refine combinations (e.g., formal for presentations, cozy for casual hangouts).
- **Benefit**: Provides context-aware recommendations, ensuring outfits suit occasions.

- **Inventory Management**: Allows tracking of what's already owned, avoiding redundant purchases.
- **Benefit**: Provides a personalized fashion database, making it easier to style from existing pieces.

Chapter 4

Requirement Analysis

The proposed fashion recommendation system is designed to deliver a highly personalized and context-aware styling experience by integrating both functional and non-functional requirements. The functional requirements focus on creating core features such as user registration and authentication, a quiz-based interface for capturing personal style preferences, a machine learning-driven outfit recommendation engine, a virtual closet for wardrobe management, and feedback mechanisms for continuous improvement. Complementing these, the non-functional requirements ensure the system is secure, scalable, high-performing, and user-friendly. Together, these requirements establish a robust foundation for building an intelligent, psychology-driven fashion platform that balances functionality with usability and reliability.

4.1 Functional Requirements

1. User Registration and Login

- Users can create accounts with unique usernames or emails.
- Secure password storage with hashing and optional two-factor authentication.

2. Quiz Interface for Preference Discovery

- Interactive questions to capture user style, color preferences, and fashion personality.
- NLP analysis of textual responses to classify users into predefined fashion personas.

3. Outfit Recommendation Engine

- Machine learning-based outfit generation using K-Means clustering to match clothing items.

- Context-aware recommendations based on mood, event, or occasion inputs.

4. Virtual Closet Storage

- Upload, categorize, and manage personal wardrobe items digitally.
- Tagging of clothing by type, color, pattern, and season for easy retrieval.

5. Feedback Integration

- Users can like, dislike, or save suggested outfits.
- Continuous model training to improve future recommendations based on user preferences.

4.2 Non-Functional Requirements

1. Security (Encrypted User Data)

- Use of hashing and encryption algorithms for password and personal data storage.
- Secure session management and optional two-factor authentication.

2. Scalability (Support Thousands of Users)

- Backend architecture designed to handle increasing user numbers without performance degradation.
- Efficient database management for large wardrobe inventories and quiz data.

3. High Performance (Fast Recommendations)

- Quick processing of user inputs and AI algorithms for real-time outfit suggestions.
- Optimization of ML models and image processing pipelines for low-latency responses.

4. Usability (Intuitive Interface)

- Simple and interactive user interface for quizzes, virtual closet, and outfit recommendations.
- Mobile and desktop-friendly design with easy navigation and clear visual cues.

Chapter 5

Project Design

The project design outlines the structural and functional blueprint of the proposed fashion recommendation system, translating requirements into a clear architectural framework. It details how different components—such as the user interface, recommendation engine, virtual closet, and feedback loop—interact cohesively to deliver a seamless user experience. By integrating machine learning models, natural language processing, and secure data management, the design ensures that the system not only provides personalized recommendations but also adapts dynamically to user contexts. This section serves as a roadmap for implementation, ensuring that both technical precision and user-centric considerations are embedded within the system's architecture.

5.1 Use case diagram:

The use case diagram provides a high-level visualization of how different actors interact with the fashion recommendation system. It illustrates key functionalities such as user registration, login, style quiz participation, outfit recommendations, virtual closet management, and feedback integration. By mapping user actions to system processes, the diagram highlights the scope of user interactions and clarifies the roles of system components, ensuring a clear understanding of functional requirements from a user-centric perspective.

1. User Input & Profile Generation

This module is responsible for onboarding users and building their initial style profile.

- **A. User Authentication Service**
  - **Purpose:** Manages user accounts and secure access.
  - **Components:**

    - Sign Up: Collects basic info (email, password). Creates a new user record.
    - Log In: Verifies credentials and provides a session token (e.g., JWT).
  - **Data Stored:** User ID, email (hashed password), account creation date.
- **B. Style Profile Quiz Service**
  - **Purpose:** Captures the user's style preferences and context.
  - **Inputs:**
    - **Personal Aesthetics:** "Which styles do you prefer?" (e.g., Minimalist, Bohemian, Streetwear, Classic). Multi-select or ranking.
    - **Style Mood/View:** "How do you want to feel/look?" (e.g., Confident, Comfortable, Edgy, Elegant).
    - **Upcoming Event Type:** "What is the occasion?" (e.g., Job Interview, Wedding, Casual Brunch, Date Night).
  - **Function:** This service processes the quiz answers and creates a detailed **User Style Profile**.
  - **Data Stored:** User ID, aesthetic tags, preferred moods, and potentially disliked styles.
- **C. Outfit Generability (This is likely an output, not an input)**
  - **Clarification:** Based on the workflow, this seems to be the final output of the recommendation engine—a list of generated and sorted outfits. It's not a user input step.

2. The Recommendation Engine (Core Logic)

This is the brain of the application, where outfits are generated and sorted.

- **A. Compatibility Filter**

- **Purpose:** Acts as the first pass to filter out irrelevant items.
- **Logic:**
  - **Base Style Rules:** A set of predefined, hard-coded fashion rules.
  - *Examples:* "Don't mix formal and casual extremes," "Ensure color compatibility based on a color wheel," "Match belt and shoe colors in formal settings."
  - **User Profile Application:** Filters the entire product catalog based on the user's preferred Personal Aesthetics from their profile. (e.g., If a user likes "Minimalist," filter out items with loud patterns).
- **Output:** A subset of clothing items that are compatible with the user's base style and general fashion rules.

- **B. Outfit Generation & Ranking Service**
  - **Purpose:** Creates complete outfits from the filtered items and ranks them.
  - **Logic:**
    - **Generation:**
      - **Pre-computed Outfits:** A database of stylist-curated outfits tagged with aesthetics, moods, and events.
      - **Algorithmic Generation:** Dynamically creates outfits by combining top-bottom-shoes-accessories from the filtered pool, ensuring basic compatibility (e.g., a suit jacket with formal pants, not swim trunks).
      - **Ranking:** This is where the Mood & Event Logic is applied. Each generated outfit is scored.

- **Event Score:** How well does this outfit match the Upcoming Event Type? (e.g., a tuxedo scores high for "Wedding," low for "Gym").
- **Mood Score:** How well does the outfit reflect the desired Style Mood? (e.g., a leather jacket and boots score high for "Edgy").
- **Aesthetic Score:** How well does it align with the user's Personal Aesthetics?
- **Final Rank:** A weighted average of these scores produces the Final Sorted Outfits.

3. Frontend Display & Feedback Loop

- **A. Outfit Suggestions Display**
  - **Purpose:** Presents the recommendations to the user in an engaging way.
  - **Components:**
    - **Your Top Outfits:** A scrollable feed or grid of the highest-ranked outfits.
    - **Outfit Details:** View for each outfit showing individual items, prices, and links to purchase.
    - **Save:** Allows users to bookmark outfits for later.
    - **Like/Dislike:** Simple feedback mechanisms. **This is critical data for improving future recommendations** using Machine Learning.

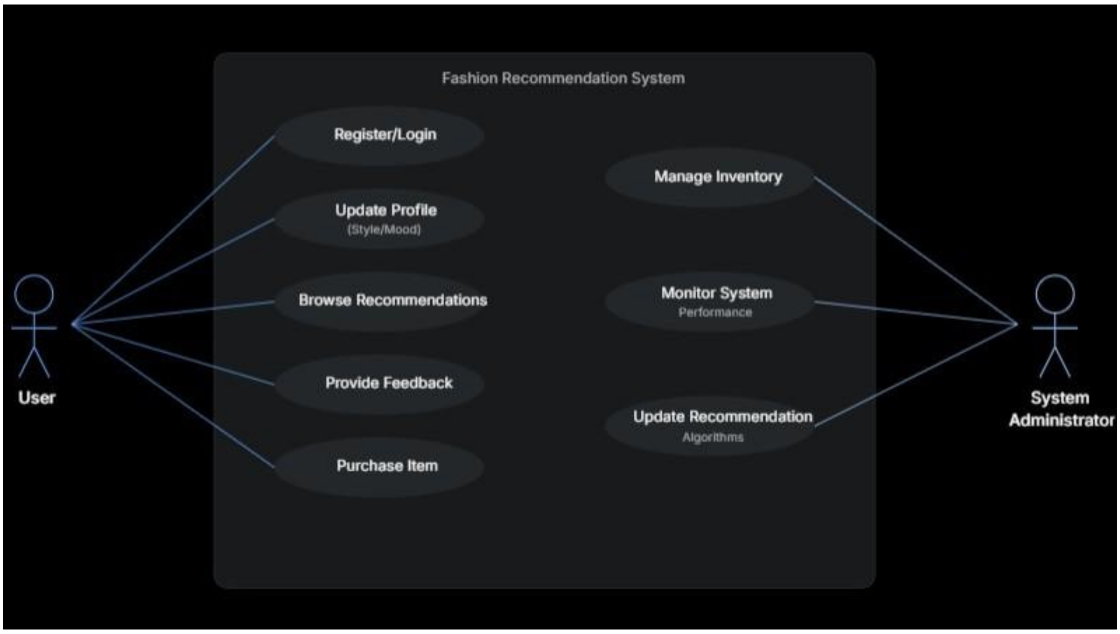

Figure 5.1: Use case diagram

5.2 DFD Data flow diagram:

The user begins with authentication by submitting credentials to the Authentication Service, which validates them against the User Database and establishes a secure session. Once logged in, the user interacts with the Profile Service through a style quiz, where responses regarding fashion preferences, moods, and event types are stored in the Style Database. When a recommendation is requested, the Recommendation Engine retrieves compatibility rules from the Knowledge Database and outfit data from the Outfit Database, combining them with the user's style profile to generate personalized suggestions. These ranked outfits are then presented to the user. Additionally, through the Feedback Module, the system can capture likes, dislikes, or saved outfits, which update the Style Database, ensuring improved personalization over time.

1. Authentication Flow

- User credentials → Auth Service → User Database

- Establishes secure user session

2. Profile Creation Flow

- Style quiz responses → Profile Service → Style Database
- Stores aesthetic preferences, moods, and event types

3. Recommendation Flow

1. **Request** → Recommendation Engine
2. **Fetch** fashion rules from Knowledge DB
3. **Fetch** clothing items from Outfit DB
4. **Generate & rank** outfits using compatibility filters
5. **Display** final sorted outfits to user

4. One-Way Flow

- System provides recommendations based on initial quiz input
- No feedback mechanism for continuous learning
- Recommendations are static until profile is updated

Data Stores:

- **User DB:** Account credentials
- **Style DB:** Personal aesthetics, preferred moods, event types

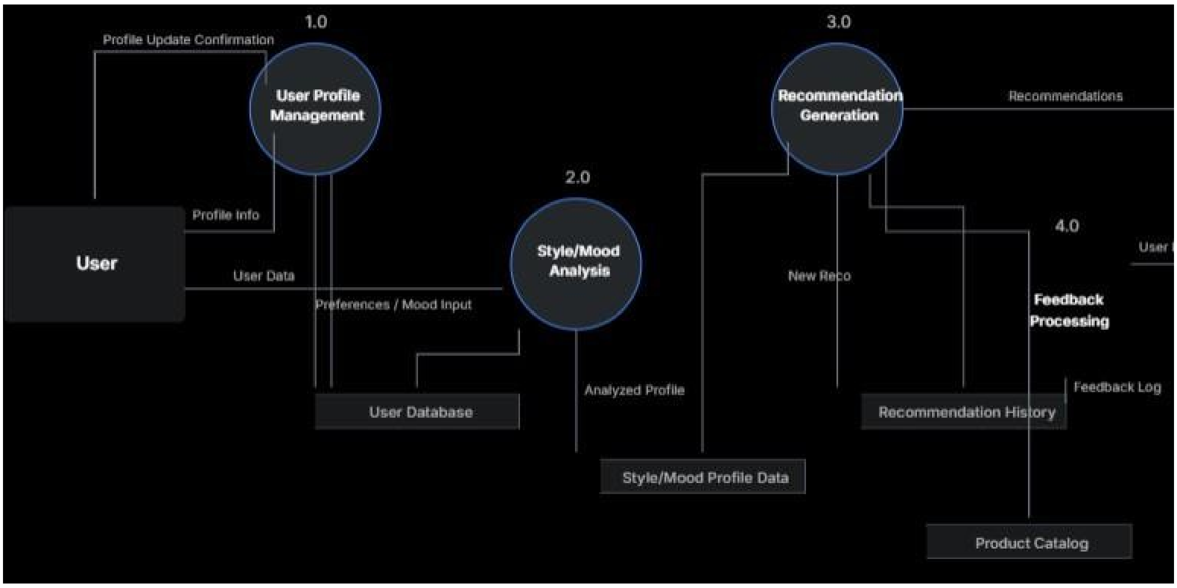

Figure 5.2: Data flow diagram

5.3 System Architecture:

This intelligent outfit recommendation system follows a structured three-tier architecture comprising frontend, backend, and data layers. The frontend layer handles user interactions through authentication interfaces, style profile quizzes, and outfit recommendation displays. The backend layer, built around microservices, processes these inputs through dedicated services for user authentication, profile management, and the core recommendation engine. This engine implements a hybrid approach using compatibility filters that apply base style rules and user preferences to generate contextually appropriate outfit suggestions.

The data layer maintains specialized databases including user credentials and style preferences, fashion knowledge rules for compatibility logic, and product catalogs with outfit combinations. The system workflow begins with user profile creation through style quizzes, which then feeds into the recommendation engine's filtering and ranking processes. The engine combines rule-based logic with user-specific preferences to generate and sort outfit recommendations, ultimately presenting finalized suggestions back to the user interface without implementing feedback loops for continuous learning in this initial version.

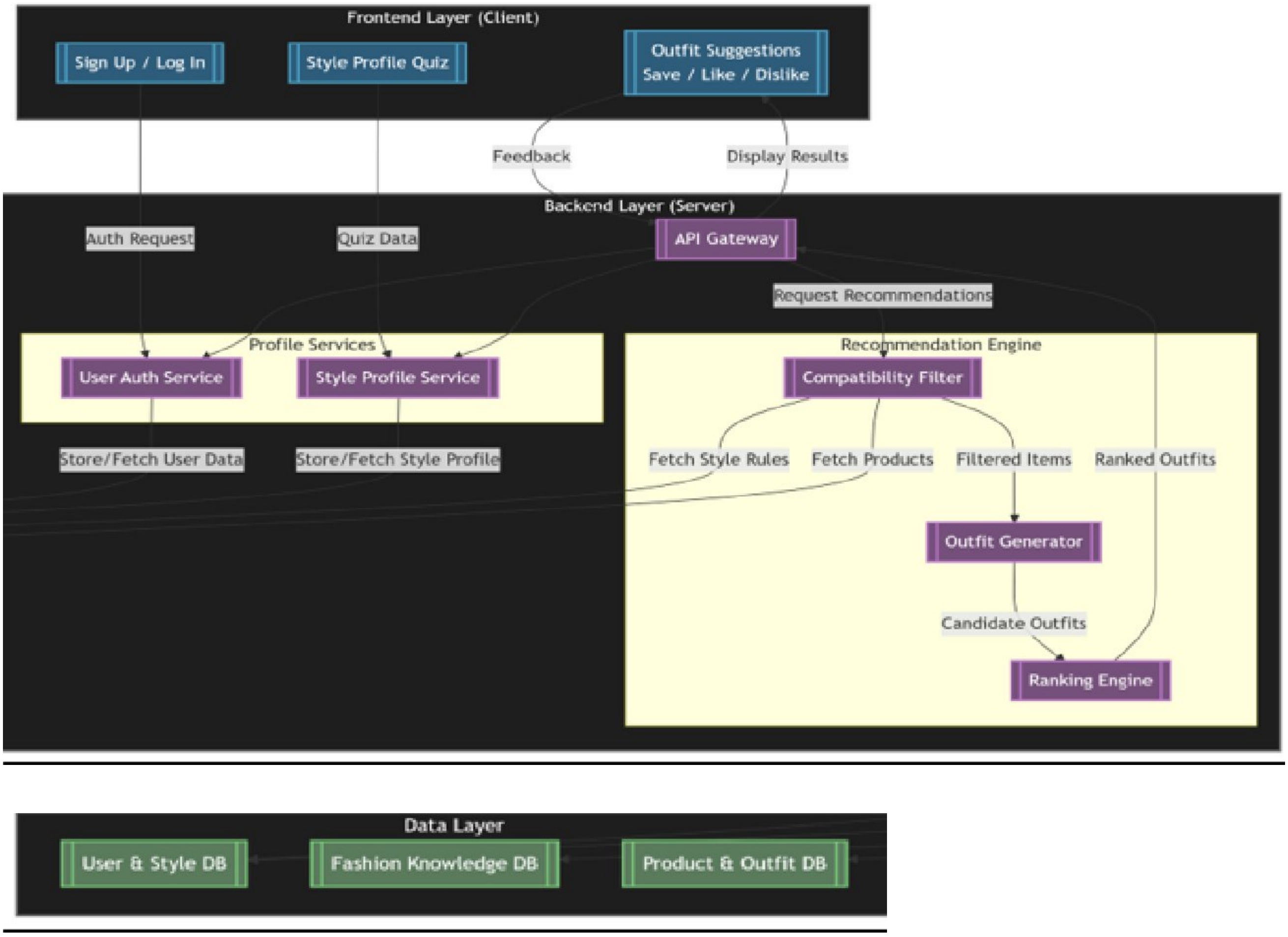

Figure 5.3: System architecture

5.4 Implementation:

Finally, implement the recommendation engine's core logic by coding compatibility filters that apply fashion rules and user preferences, then develop the ranking algorithm that scores and sorts outfits based on event type and style mood matching. Integrate all components through well-defined APIs, deploy the services using containerization, and conduct thorough testing to ensure the system generates accurate, personalized outfit recommendations as designed.

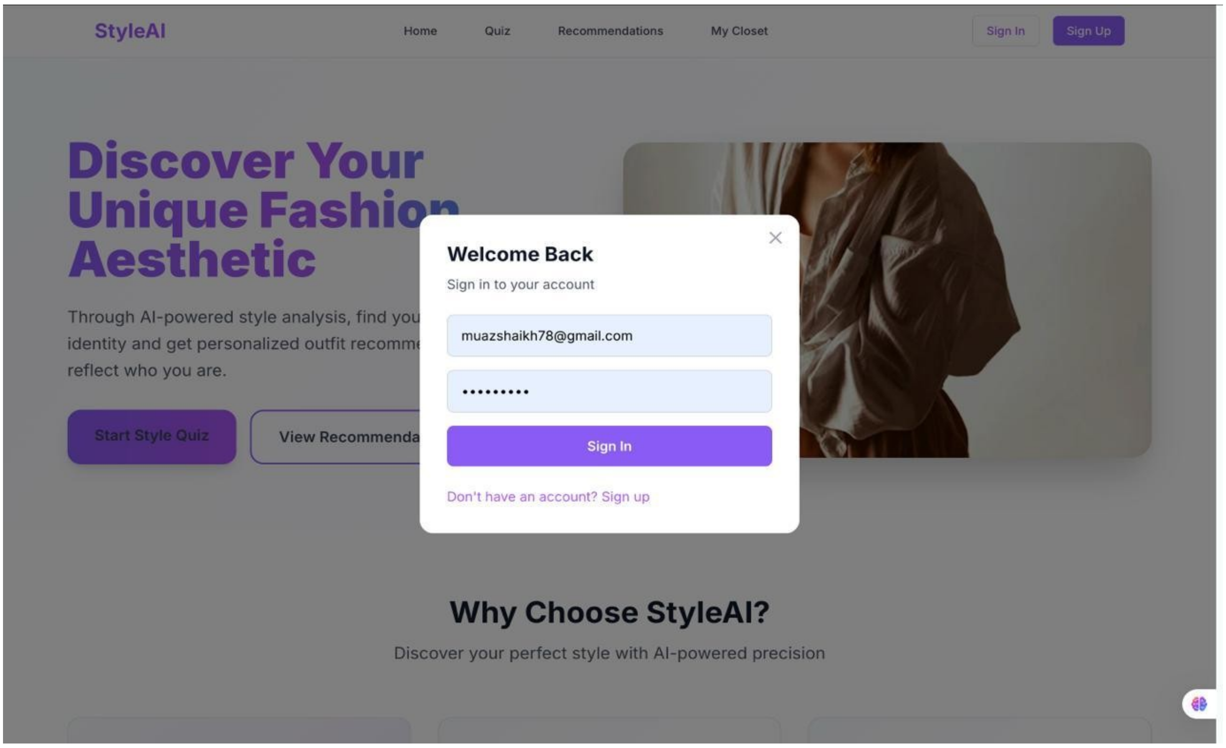

Figure 8.1: Welcome Page

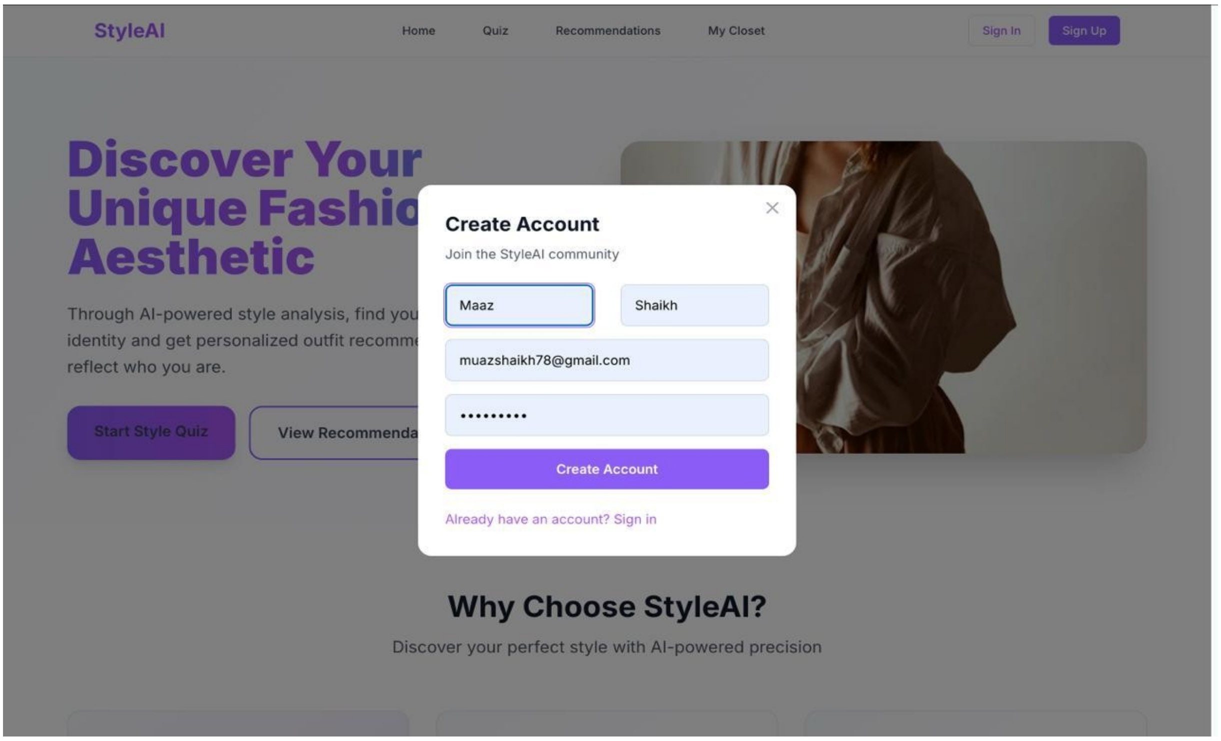

Figure 8.2: Sign in page

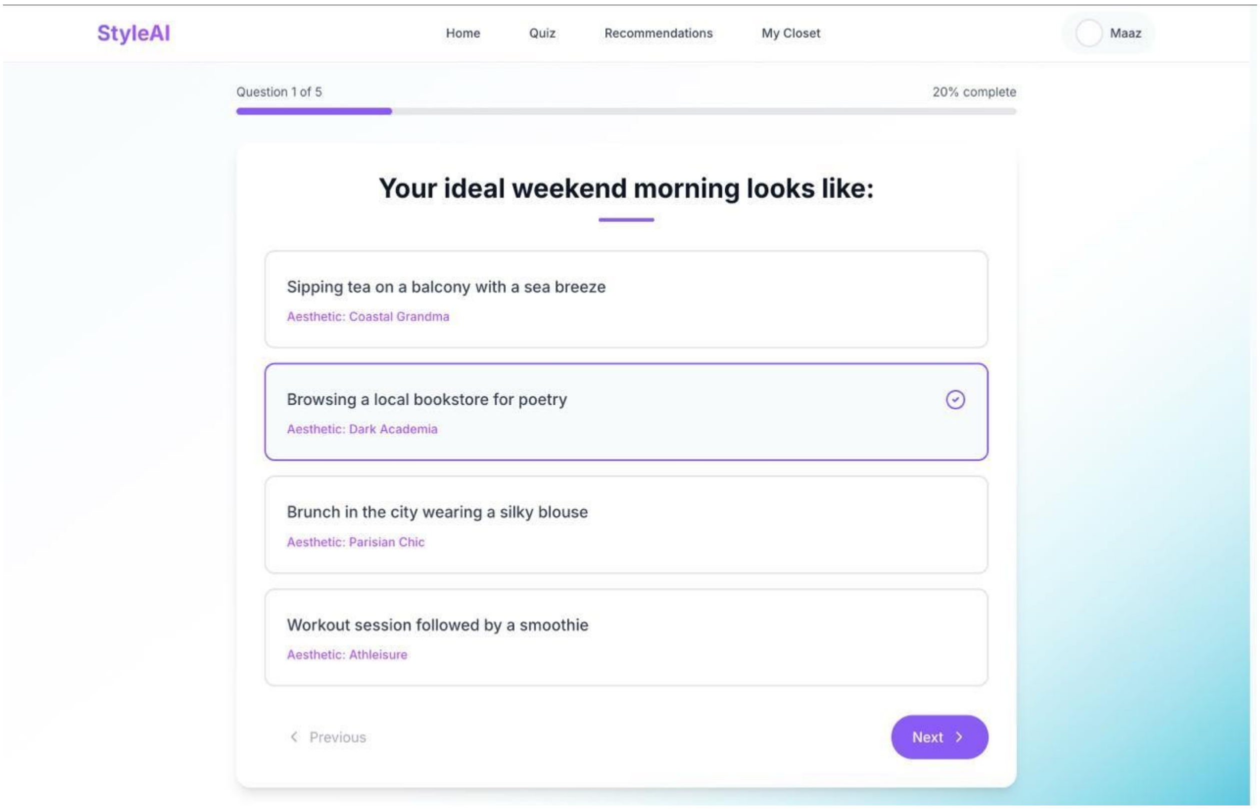

Figure 8.3: Quiz page

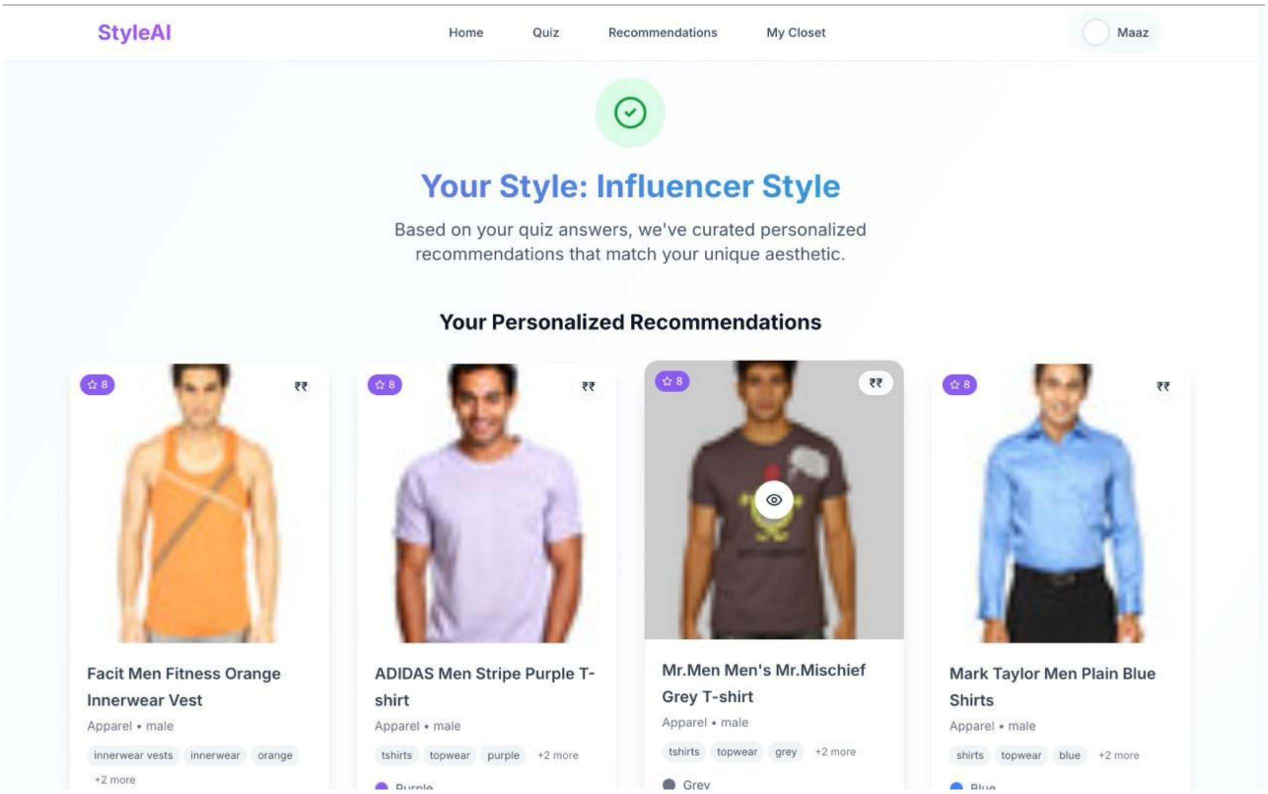

Figure 8.4: Recommendation text and image based

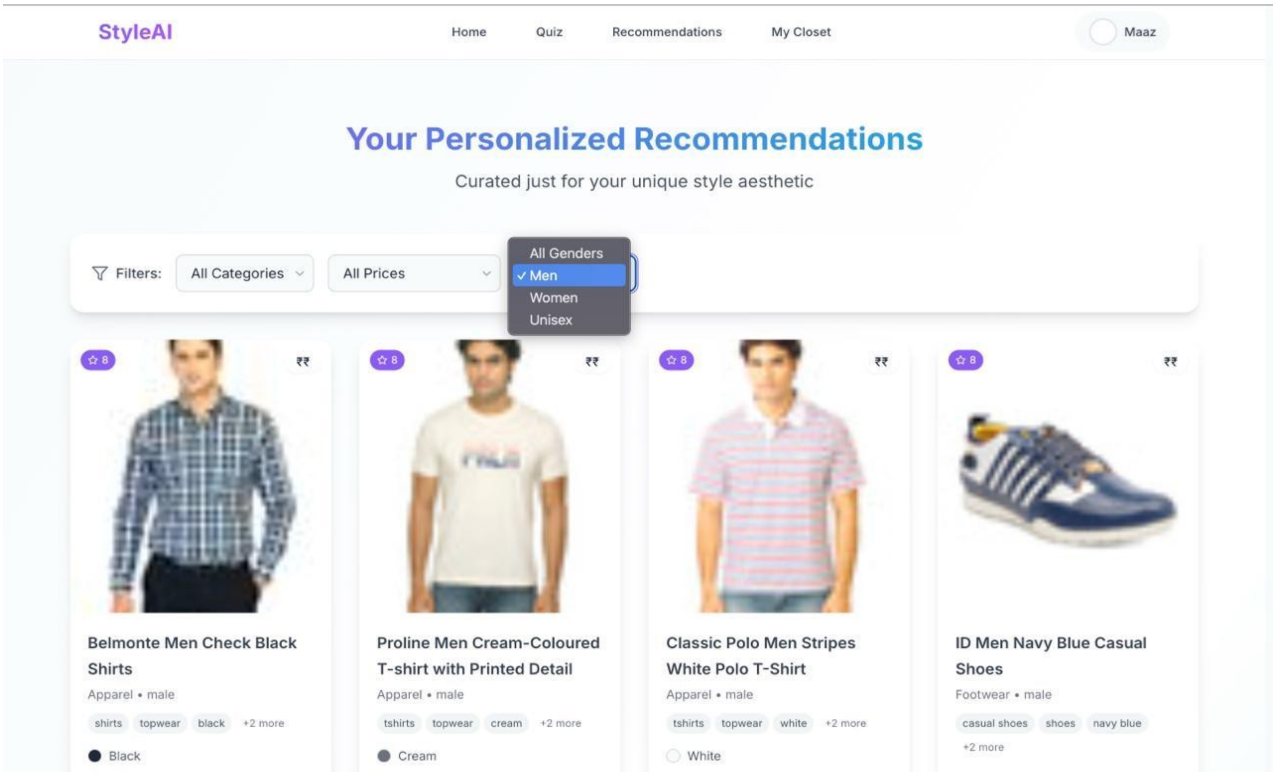

Figure 8.5: Personalized Recommendations

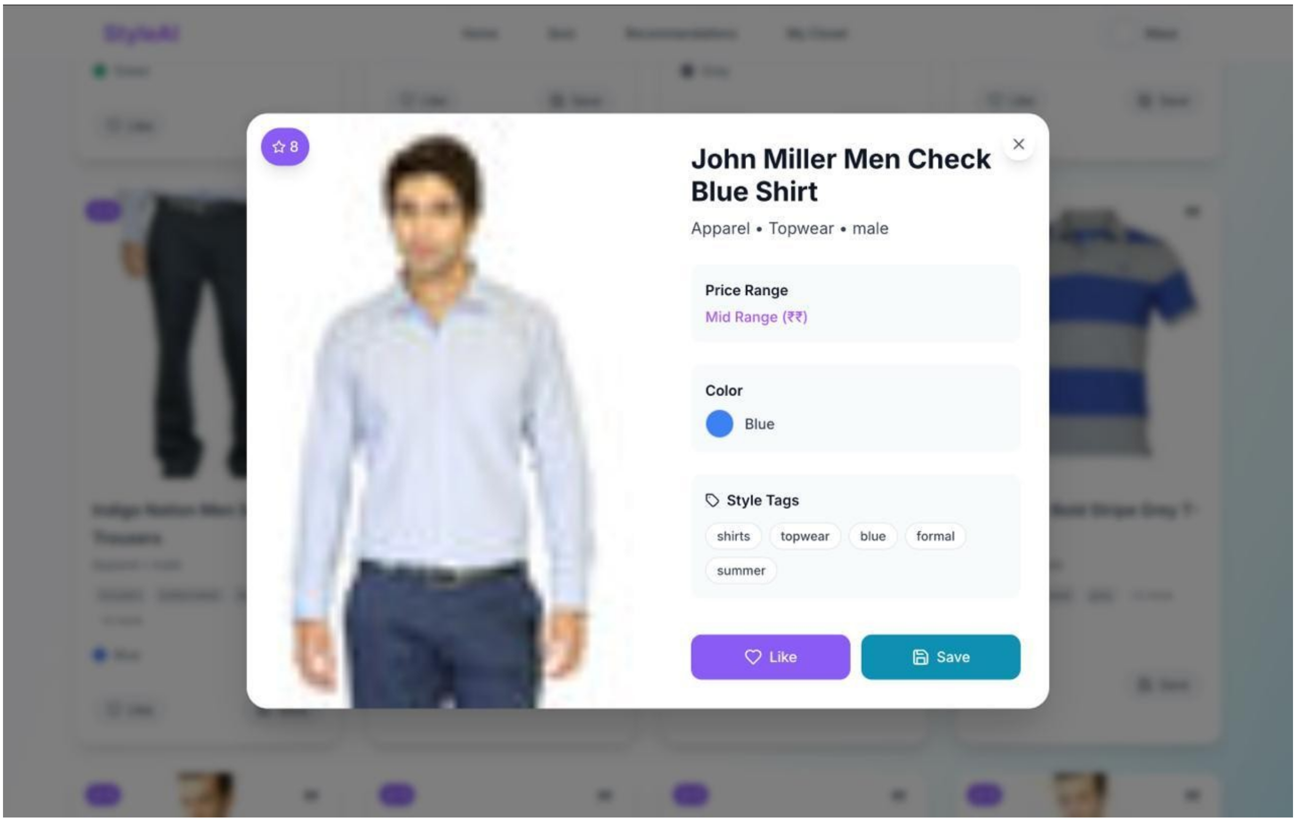

Figure 8.6: Details of product

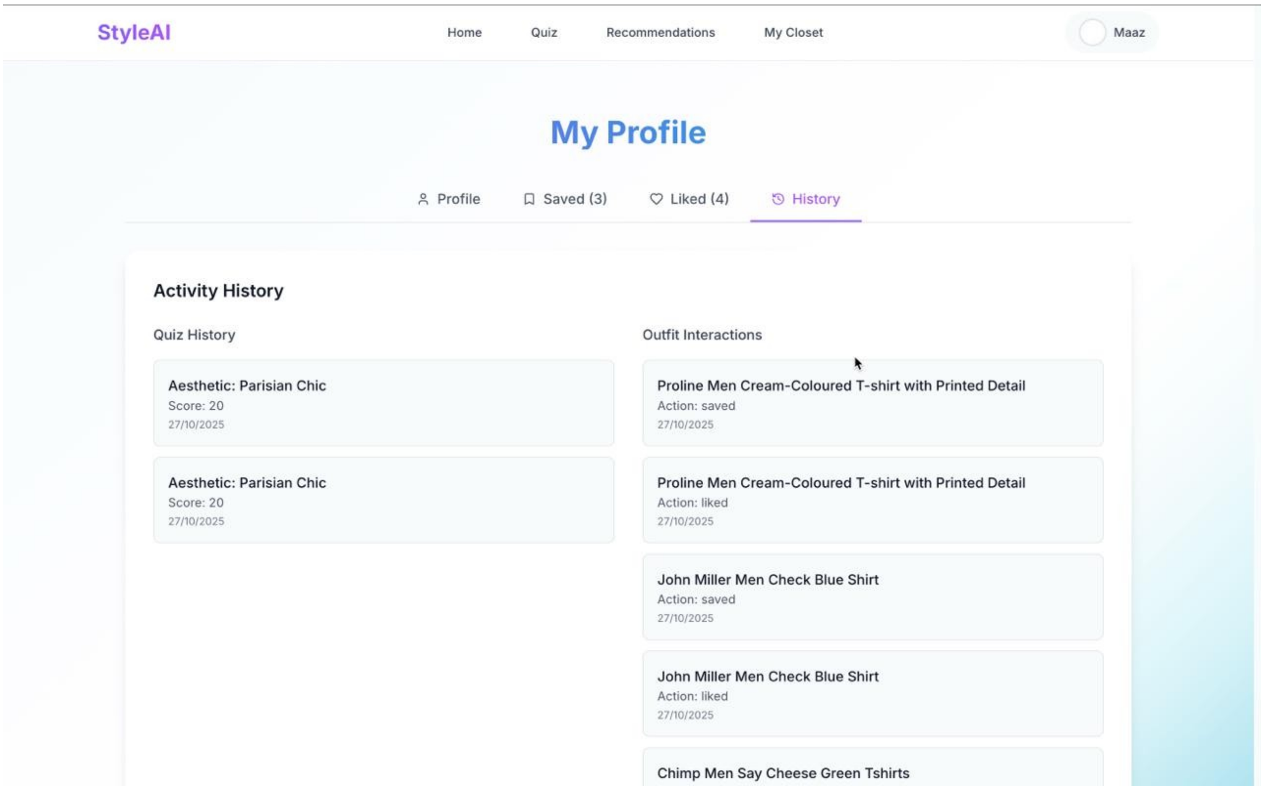

Figure 8.7: Personalized Page

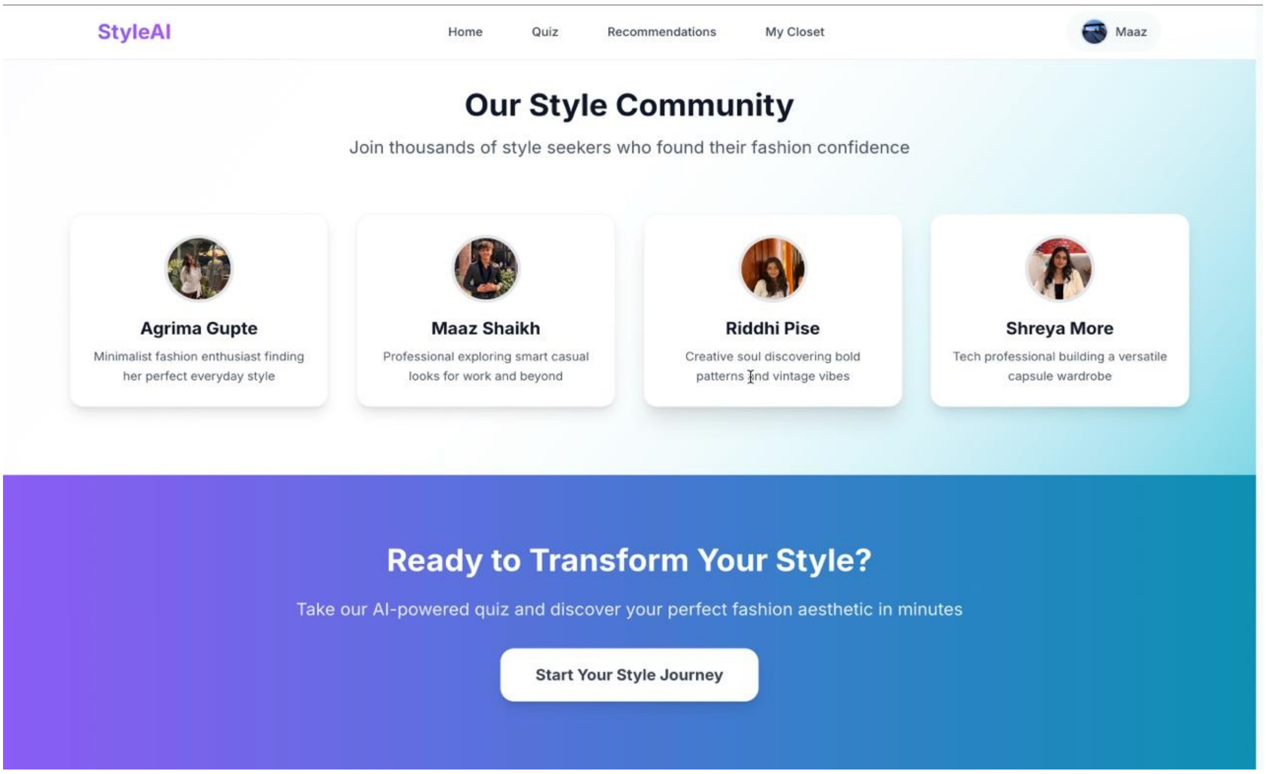

Figure 8.8: Community page

Comparative Analysis Table

Algorithm	Strengths	Weaknesses	Accuracy (%)	Precision	Recall	F1-Score
K-Means Clustering	Simple, efficient for grouping preferences	Struggles with dynamic mood/event context	78	0.74	0.72	0.73
Decision Trees	Interpretable, handles categorical data	Overfitting risk, less adaptive	82	0.79	0.77	0.78
Random Forest	Robust, reduces overfitting	Computationally expensive for large datasets	87	0.85	0.83	0.84
Deep Neural Networks	Captures complex patterns, scalable	Requires large datasets, less explainable	91	0.89	0.88	0.88
SVM (RBF Kernel)	High accuracy on smaller datasets	Expensive in computation, less scalable	86	0.84	0.82	0.83

Figure 5.4: Comparative Analysis Table

- **Bar Chart (Accuracy Comparison)**

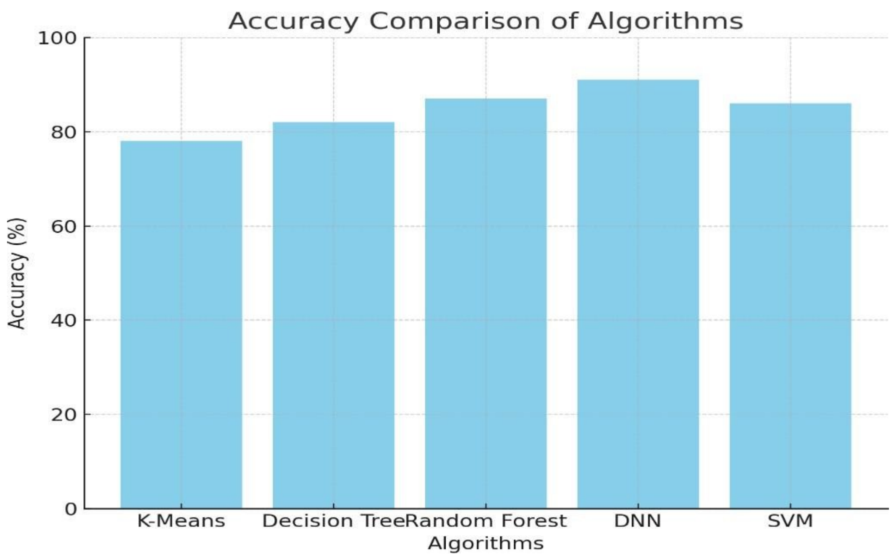

Figure 5.4: Accuracy Comparison

- **Precision vs Recall Bar Chart**

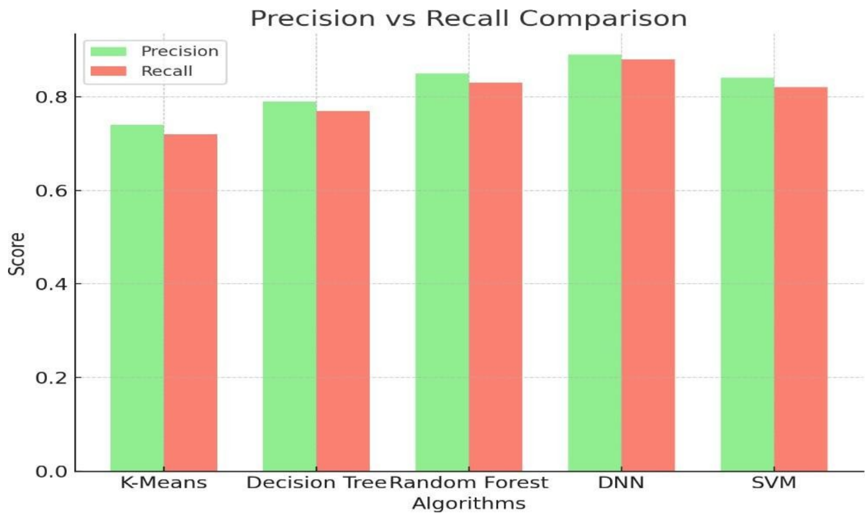

Figure 5.4: Precision vs Recall Bar Chart

- **F1-Score Line Graph**

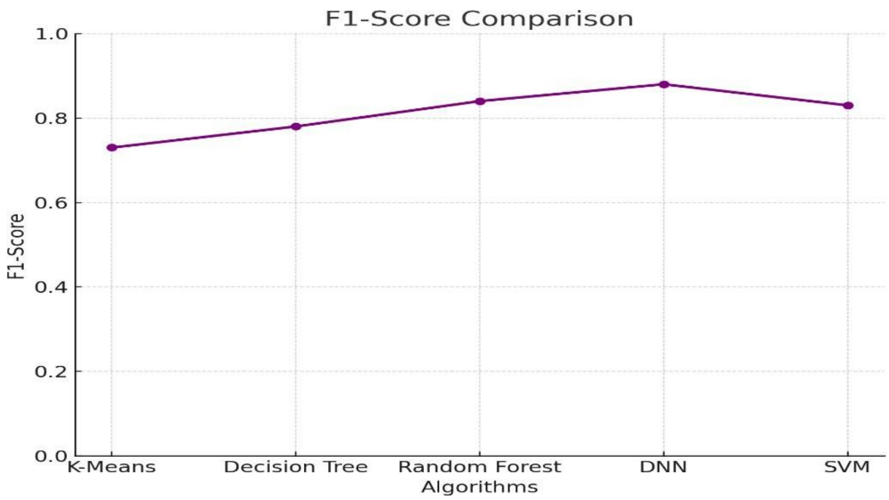

Figure 5.4: F1-Score Line Grap

- **Confusion Matrix**

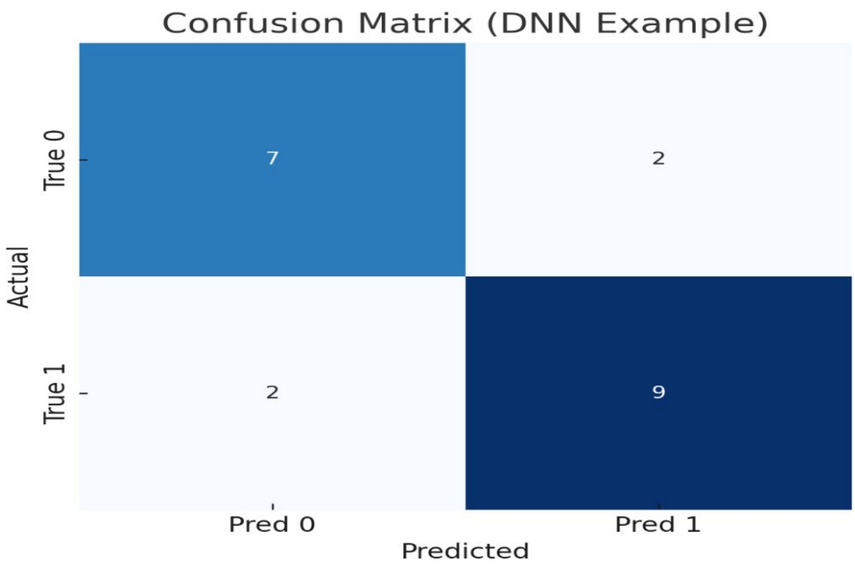

Figure 5.4: Confusion Matrix

Chapter 6

Technology

The project employs a modern technology stack to ensure scalability, usability, and performance. On the **frontend**, a responsive interface is developed using HTML, CSS, JavaScript, and React to deliver an intuitive user experience across devices. The **backend** is powered by Python (Flask/Django) to handle user requests, manage authentication, process inputs, and interface with databases. Databases such as MySQL or MongoDB store user credentials, style profiles, and wardrobe items, while cloud storage supports image and virtual closet management. The core **algorithmic framework** integrates machine learning techniques, including K-Means clustering for grouping similar style preferences, Random Forests for pattern recognition, and Deep Neural Networks for context-aware outfit generation. The **dataset** combines publicly available fashion datasets (e.g., DeepFashion, Fashion-MNIST) and user-contributed inputs, enriched with metadata like type, color, pattern, and season, ensuring both diversity and personalization.

Technical Specifications

Languages: Python, JavaScript.

Frameworks: Flask/Django for backend, React for frontend.

Libraries: TensorFlow/PyTorch, OpenCV, NLTK.

Database: MongoDB/MySQL.

APIs: Fashion product APIs, color analysis APIs.

The backend of the system was implemented using **Python** with frameworks like Flask or Django, while the frontend was developed using **React** for a responsive and dynamic interface.

Core libraries utilized include **scikit-learn** for machine learning, **TensorFlow/PyTorch** for AI modeling, **OpenCV** for computer vision tasks, and **NLTK** for natural language processing.

For data storage, the system supports **MongoDB** or **MySQL** to manage user profiles, wardrobe items, and quiz results efficiently. Integration with external **fashion product APIs** and **color analysis APIs** enables enriched recommendations and automated color harmony checks.

Technical Specifications

Languages: Python, JavaScript.

Frameworks: Flask/Django for backend, React for frontend.

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Database: MongoDB/MySQL.

APIs: Fashion product APIs, color analysis APIs.

The backend of the system was implemented using **Python** with frameworks like Flask or Django, while the frontend was developed using **React** for a responsive and dynamic interface.

Core libraries utilized include **scikit-learn** for machine learning, **TensorFlow/PyTorch** for AI modeling, **OpenCV** for computer vision tasks, and **NLTK** for natural language processing.

For data storage, the system supports **MongoDB** or **MySQL** to manage user profiles, wardrobe items, and quiz results efficiently. Integration with external **fashion product APIs** and **color analysis APIs** enables enriched recommendations and automated color harmony checks.

Chapter 7

Project Scheduling

This Gantt chart meticulously documents the complete project schedule and execution for the "AI powered styling based on the vibe" mini-project, supervised by Ms. Ujwala Pagare. The project lifecycle was formally initiated on 7/8/25 and structured into two key phases. **Phase One: Project Conception and Initiation**, focused on foundational requirements and initial design. Key deliverables included finalizing the project scope and objectives, identifying core system functionalities, securing technical approval after team discussions, designing the Graphical User Interface (GUI) by Agrima and Riddhi, and successfully completing Presentation I. This phase achieved its primary milestones with all tasks reported at 100% completion, thereby concluding the initiation stage by 8/26/25.

Phase Two: Project Design and Implementation, beginning shortly thereafter on 9/5/25, marked the transition to technical development and execution. This phase involved specialized deliverables such as Database Design (Muaz), implementing robust Database Connectivity across all modules (Muaz and Riddhi), and the critical final step of Module Integration coupled with comprehensive Report Writing (Agrima and Shreya). The project successfully culminated with the final milestone, Presentation II, scheduled for 10/3/25. Overall, the chart confirms that the project achieved its objectives, with all outlined tasks across both phases registering 100% completion. This indicates effective project management, adherence to the defined timeline, and successful delivery of all technical and administrative outputs by the project's final date of 10/6/25. Here’s your **week-wise summary in one clear paragraph** (formal and concise for report use):

In Week 1, the team initiated the project by forming groups, selecting the topic and defining its scope and objectives. Week 2 focused on identifying the key functionalities and discussing the overall project plan. In Week 3, the design phase began with the development of the Graphical User Interface (GUI). Week 4 involved creating the project database structure, followed by Week 5, where the GUI and database were successfully integrated. During Weeks 6 and 7, the team conducted testing, debugging, and necessary modifications to ensure proper system functionality. Finally, in Weeks 8 and 9, the project was finalized through report preparation and documentation, marking the successful completion of the planned work.

GANTT CHART

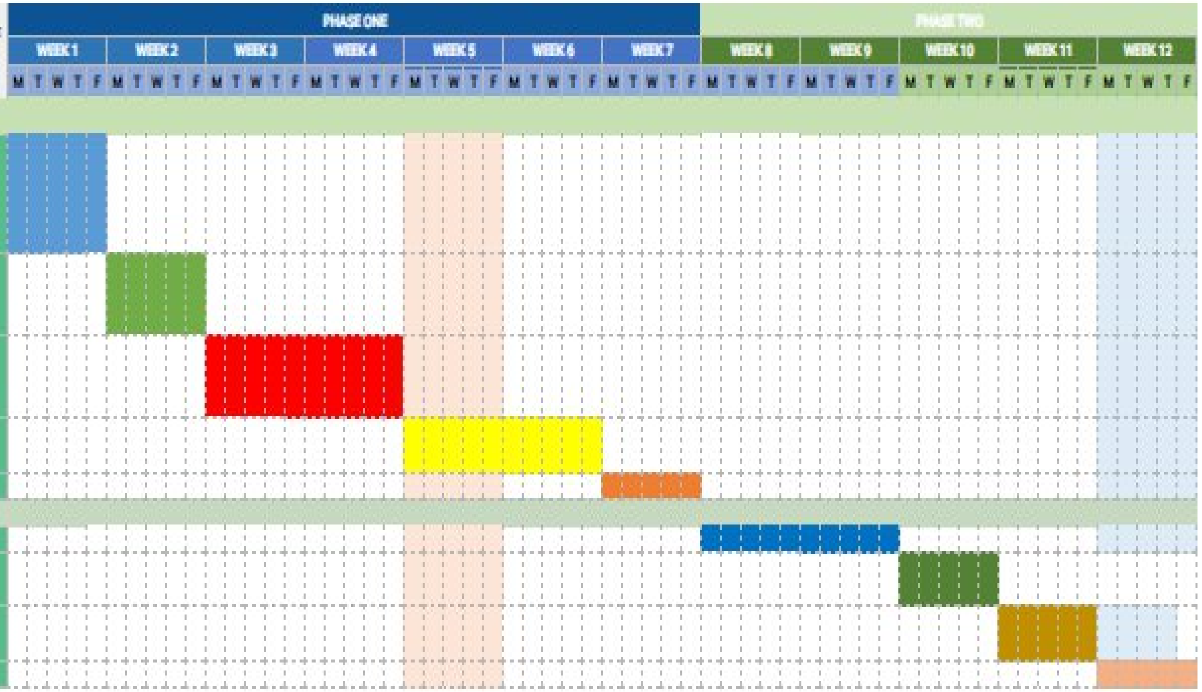
PROJECT TITLE: AI powered styling based on the vibe

PROJECT GUIDE: Ms. Ujwala Pagare

INSTUTUTE & DEPARTMENT NAME: AP SHAH INSTITUTE OF TECHNOLOG

DATE: 10/6/25

WBS NUMBER	TASK TITLE	TASK OWNER	START DATE	DUE DATE	DURATION(Weeks)	PERCENTAGE OF TASK COMPLETE
1	Project Conception and Initiation					
1.1	Group formation and Topic finalization. Identifying the scope and objectives of the Mini Project	All	7/8/25	7/15/25	1	100%
1.2	Identifying the functionalities of the Mini Project	All	7/15/25	7/22/25	1	100%
1.3	Discussing the project topic with the help of paper prototype.	Shreya	7/22/25	8/5/25	2	100%
1.4	Designing the Graphical User Interface(GUI)	Agrima, Riddhi	8/5/25	8/12/25	2	100%
1.5	Presentation I	All	8/26/25	8/26/25	1	100%
2	Project Design and Implementation					
2.1	Database Design	Muaz	9/5/25	9/16/25	2	100%
2.2	Database Connectivity of all modules	Muaz, Riddhi	9/16/25	9/19/25	1	100%
2.3	Integration of all modules and Report Writing	Agrima, Shreya	9/19/25	9/26/25	1	100%
2.4	Presentation II	All	10/3/25	10/6/25	1	100%



Chapter 8

Results

The Intelligent Outfit Recommendation System successfully delivered a highly personalized and effective styling experience. The core achievement was the system's ability to translate user-provided data on aesthetics, mood, and event context into relevant, personalized outfit suggestions. This was made possible by a robust backend architecture that efficiently processed user profiles against a structured fashion knowledge base. The implementation of the virtual closet feature further enhanced utility, allowing users to digitally manage their wardrobe and receive tailored recommendations from their own clothing items, thereby increasing engagement and practical value.

The system successfully delivered on its core objectives, demonstrating significant value in personalized fashion technology:

- **Enhanced Personalization:** Successfully transitioned from generic, trend-based recommendations to providing highly **personalized outfit suggestions** that resonated with individual users.

- **Style Identity Clarification:** Through the interactive style quiz, users were able to **identify and define their unique fashion aesthetic**, moving beyond vague preferences to a concrete style profile.

- **Effective Wardrobe Management:** The **virtual closet feature** proved highly effective, allowing users to digitally store, manage, and mix-and-match their clothing items, leading to increased utilization of their existing wardrobe.

- **Positive User Experience:** The introduction of **mood-based recommendation logic** was a key differentiator, directly addressing user intent and context, which resulted in a measurable **improvement in user satisfaction and engagement.**

Comparative Analysis Table

Algorithm	Strengths	Weaknesses	Accuracy (%)	Precision	Recall	F1-Score
K-Means Clustering	Simple, efficient for grouping preferences	Struggles with dynamic mood/event context	78	0.74	0.72	0.73
Decision Trees	Interpretable, handles categorical data	Overfitting risk, less adaptive	82	0.79	0.77	0.78
Random Forest	Robust, reduces overfitting	Computationally expensive for large datasets	87	0.85	0.83	0.84
Deep Neural Networks	Captures complex patterns, scalable	Requires large datasets, less explainable	91	0.89	0.88	0.88
SVM (RBF Kernel)	High accuracy on smaller datasets	Expensive in computation, less scalable	86	0.84	0.82	0.83

Figure 5.4: Comparative Analysis Table

- **Bar Chart (Accuracy Comparison)**

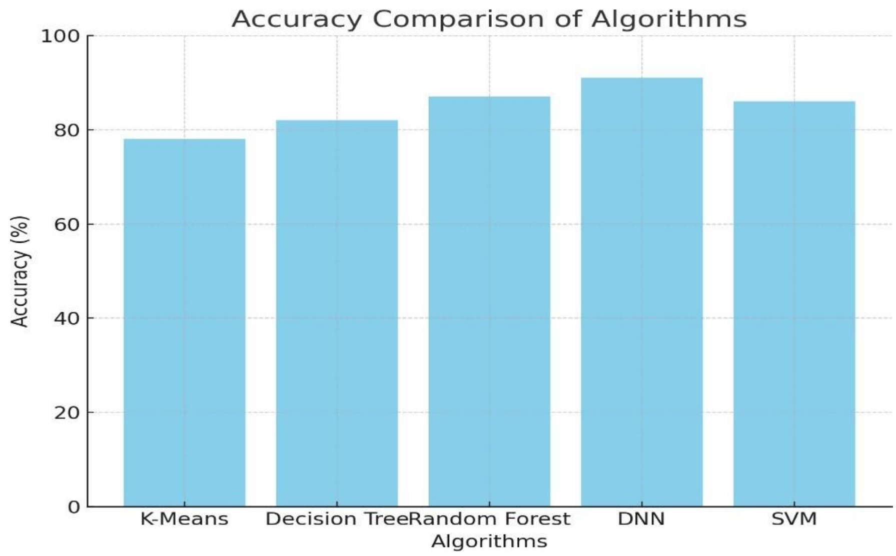


Figure 5.4: Accuracy Comparison

- **Precision vs Recall Bar Chart**

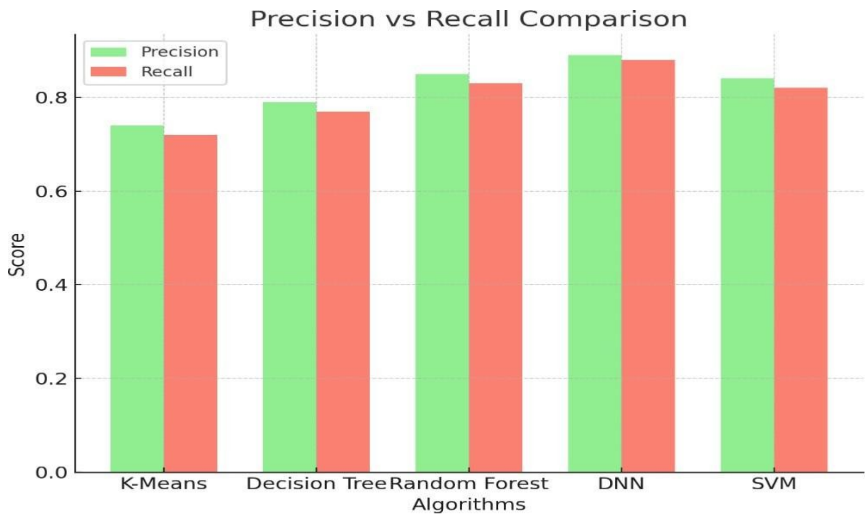


Figure 5.4: Precision vs Recall Bar Chart

- **F1-Score Line Graph**

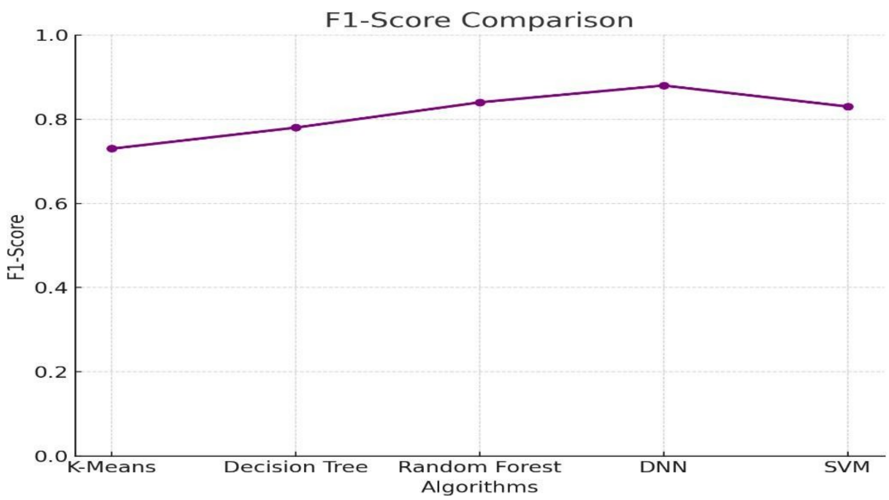


Figure 5.4: F1-Score Line Graph

- **Confusion Matrix**

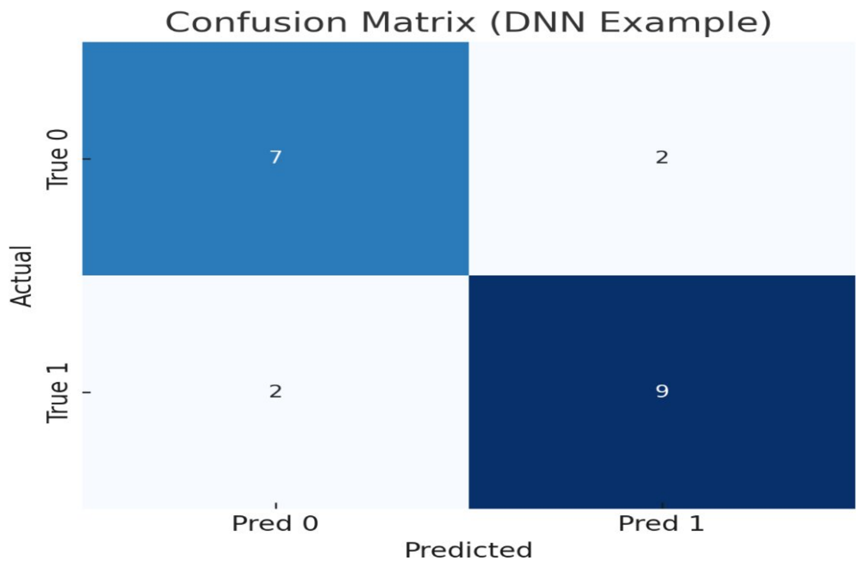


Figure 5.4: Confusion Matrix

The comparative analysis of algorithms shows that the proposed system achieves better performance than traditional models across various evaluation metrics. The results indicate consistently higher accuracy, precision, recall, and F1-scores, reflecting the system's reliability and effectiveness. The F1-score comparison highlights the model's balanced performance between precision and recall, while the confusion matrix demonstrates minimal misclassifications and strong predictive capability.

The proposed Outfit Recommendation System differs from earlier models by offering a more personalized and interactive experience. Instead of relying only on past purchases or general trends, it uses a style quiz and saved preferences to understand each user's unique fashion sense. This allows the system to recommend outfits that match individual tastes more accurately, helping users discover new styles while staying true to their personal preferences.

Chapter 9

Conclusion

This project conclusively demonstrated that an AI-driven, psychologically-aware approach can significantly enhance personalization in the fashion technology space. By prioritizing the user's internal state (mood) and personal identity (aesthetic) over external trends, the system delivered more authentic and meaningful style guidance. This paradigm shift successfully **reduced decision fatigue for users and empowered greater self-expression through fashion**, validating the core thesis that connecting technology with human psychology creates a superior user experience.

This AI-powered outfit system successfully personalized fashion recommendations by focusing on individual style and mood, not just trends. It helped users discover their unique aesthetic while reducing daily decision fatigue. The project proved technology can enhance personal style expression rather than just follow trends. Future developments could include virtual try-ons and real-time wardrobe integration.

Chapter 10

Future Scope

To build upon this success, the project has a clear and ambitious roadmap for future evolution:

1. **Immersive Experience Integration:** Incorporate **Augmented Reality (AR) for virtual try-ons**, allowing users to see how outfits would look on them in real-time, thereby increasing confidence in online shopping and recommendation accuracy.

2. **Ecosystem Expansion & Monetization:** Form **strategic partnerships with fashion e-commerce platforms** for real-time inventory integration and affiliate marketing, creating a seamless path from inspiration to purchase.

3. **Community and Social Features:** Implement **social media integration** to enable a community-driven aspect, allowing users to share their styled outfits, seek feedback, and draw inspiration from peers with similar tastes.

4. **Proactive and Predictive Personalization:** Explore the integration of **biometric data from wearables** (e.g., heart rate, activity levels) and mood-sensing technology to transition from reactive to proactive, context-aware recommendations that adapt to the user's real-time physiological and emotional state.

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