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Closet-AI

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Abstract: *ClosetAI is a smart outfit recommendation system that integrates large language models (LLMs) with web scraping and computer vision to provide context-aware fashion suggestions. Utilizing the Gemini API, the system interprets natural language queries from users—such as event types, moods, or occasions—and dynamically scrapes relevant fashion data from the web to enrich its recommendations. The pipeline combines clothing detection and classification with a Gemini-powered backend that understands user intent and preferences, including age, gender, skin tone, and weather conditions.*

ClosetAI processes this multimodal input to generate accurate and personalized outfit recommendations in real time. The backend is served via a lightweight Flask API, ensuring smooth interaction and integration across platforms. By merging LLM-driven comprehension, live data extraction, and vision-based clothing analysis, ClosetAI transforms traditional outfit selection into an intelligent, adaptive experience tailored to individual users.

Keywords: Gemini API, LLM, Web Scraping, Outfit Recommendation, Personalized Fashion AI

I. INTRODUCTION

In today's rapidly evolving digital landscape, artificial intelligence is transforming various aspects of daily life—from communication to healthcare to personal lifestyle. Among these, fashion and clothing selection remain largely manual and subjective, often influenced by mood, occasion, or weather, yet lacking intelligent assistance. This gap creates an opportunity for technology-driven systems to provide personalized, context-aware outfit recommendations that not only enhance individual style but also save time and reduce decision fatigue.

This paper introduces ClosetAI, an intelligent outfit recommendation system that integrates large language models (LLMs), computer vision, and real-time data extraction to deliver highly customized clothing suggestions. The system takes user queries in natural language, processes them through Google's Gemini API to understand intent, and scrapes web data to ensure up-to-date trend awareness. Simultaneously, YOLOv5 is used for clothing detection and classification, enabling a complete understanding of available wardrobe items. Factors such as gender, age, skin tone, and weather conditions are incorporated to tailor recommendations to the user's profile.

Unlike traditional fashion recommendation systems that rely solely on static datasets or limited user input, ClosetAI leverages the combined strength of vision models and language models in a dynamic, cloud-deployed environment. This enables real-time outfit suggestions that adapt to both environmental context and user preferences, making it suitable for real-world deployment across mobile, desktop, or smart mirror interfaces.

By integrating AI-driven insights with real-world relevance, ClosetAI aims to redefine how people interact with fashion, offering a scalable, intelligent, and personalized experience that brings convenience and style to everyday dressing.

II. LITERATURE REVIEW

The fashion industry and e-commerce sector have seen significant growth with the rise of personalized shopping experiences, aided by advances in machine learning (ML) and computer vision. As a result, clothing recommendation systems have become central to online shopping platforms, with a focus on increasing customer satisfaction and sales.

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This section reviews key studies and technological advancements in the domain of fashion recommendation systems, with an emphasis on machine learning, deep learning techniques, and their deployment in real-world applications.

Machine Learning and Computer Vision in Fashion Recommendation:

Machine learning, particularly deep learning, has proven essential in developing systems that offer personalized clothing recommendations based on user preferences and behavior. Early studies in the domain of fashion recommendation, such as those by Zheng et al. (2015), utilized collaborative filtering approaches, which recommend items based on user-item interactions and similarities. However, these systems often struggle with cold start problems, where new users or items lack sufficient interaction data.

Subsequent research integrated deep learning and computer vision to address these limitations. Approaches like convolutional neural networks (CNNs) have been employed to classify and recommend fashion items based on visual features. A significant study by Liu et al. (2019) demonstrated the use of CNNs to extract clothing item features (e.g., color, texture, and shape) from images, improving the quality of recommendations

In addition to visual data, other works focused on incorporating user preferences, such as age, gender, skin tone, and even weather conditions, to enhance recommendation accuracy. For instance, Wang et al. (2018) combined user demographic information with deep learning models to provide personalized outfit suggestions based on user profiles. This method outperformed traditional recommendation systems by delivering more relevant and context-aware suggestions.

III. METHODOLOGY

The methodology adopted for the Closet-AI project follows a comprehensive pipeline from data collection to real-time cloud deployment, ensuring both technical robustness and practical applicability. The process begins with gathering data from reliable sources, focusing on clothing items, user preferences, and weather conditions. These datasets include images, descriptions, and metadata of clothing items sourced from fashion datasets, online retailers, and fashion repositories. Additionally, real-time weather data, such as temperature, humidity, and weather conditions, is collected from platforms. This weather data is crucial for personalizing outfit recommendations based on current environmental conditions.

Once the data is collected, it undergoes rigorous preprocessing to ensure consistency and quality for machine learning models. Clothing images are resized, normalized, and augmented using techniques like rotation, flipping, and cropping to ensure model robustness. Textual data, including clothing descriptions, is cleaned through tokenization, lemmatization, and stopword removal. Weather data is processed and integrated with clothing attributes to ensure that outfits suggested by the model are appropriate for the current weather conditions, such as recommending jackets in cold weather or light fabrics during the summer. Key features like clothing type, color, size, fabric, and occasion are then extracted and encoded into numerical or categorical formats for use in the recommendation system.

The next step in the methodology is the development of machine learning models to provide personalized outfit recommendations. A classification model is trained using Convolutional Neural Networks (CNN) to recognize and categorize clothing items based on images. A recommendation system, either collaborative filtering or content-based, is built to suggest outfits based on user preferences, including gender, age, skin tone, and weather conditions. Various machine learning algorithms, such as Random Forest, Support Vector Machines (SVM), and K-Means clustering, are used to identify patterns and suggest suitable clothing. Additionally, advanced deep learning models like Long Short-Term Memory (LSTM) networks and transformer-based architectures.

After training the models, they are rigorously evaluated using performance metrics such as accuracy, precision, recall, F1-score, and user feedback. Accuracy measures how well the model predicts relevant outfits, while precision and recall ensure that the suggestions are both accurate and diverse. The F1-score provides a balanced measure of the model's ability to handle both false positives and false negatives. User feedback is also collected continuously to fine-tune the model and improve the personalization of recommendations. This iterative feedback loop ensures that the system remains effective and evolves according to user preferences over time

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Once the best-performing model is selected, it is serialized using tools like Pickle or Joblib for seamless integration into a cloud-based application. A RESTful API is developed using Flask to facilitate real-time interactions with the model, allowing users to request outfit recommendations on-demand. The entire system is containerized using Docker to ensure consistent runtime behavior across different environments. For deployment, cloud platforms like AWS, GCP, or Microsoft Azure are utilized to ensure scalability, reliability, and real-time accessibility. These platforms also offer auto-scaling capabilities, ensuring that the application can handle high user traffic efficiently.

To make the system user-friendly, a web or mobile-based front-end interface is developed, allowing users to interact with the system easily. The interface enables users to input their preferences such as gender, age, skin tone, and weather conditions. The system then displays personalized outfit recommendations, including images, descriptions, and possible links for purchase. Additionally, a feedback mechanism is built into the interface to allow users to rate the recommendations, which helps further refine the system's suggestions over time. An optional browser extension is also considered, allowing users to get personalized outfit recommendations while browsing online clothing stores.

To ensure long-term effectiveness, the system is equipped with monitoring and logging tools, such as AWS CloudWatch, to track performance and manage user requests. Regular retraining of the models is scheduled to incorporate fresh data, emerging trends, and new user feedback, which helps maintain the relevance of the recommendations. Continuous monitoring allows for the detection of any issues in the system, ensuring that it provides accurate and timely suggestions.

IV. SYSTEM DESIGN AND FEATURES

The Closet-AI system is designed to provide personalized outfit recommendations based on user preferences, weather conditions, and available clothing items. The system is structured to integrate data from diverse sources and utilize advanced machine learning algorithms to deliver a seamless and interactive user experience. Below is an outline of the key components and features that make up the Closet-AI system.

Key Features of Closet-AI:

- Personalized Outfit Recommendations: The system takes into account user preferences such as gender, age, skin tone, and weather conditions (sunny, rainy, winter, etc.) to suggest appropriate outfits. The recommendations are tailored to ensure users are provided with clothing choices suitable for their lifestyle and current environmental conditions.
- Weather-Based Filtering: The system uses real-time weather data to suggest clothing appropriate for the user's current location. For example, it may recommend light fabrics and short sleeves on a hot, sunny day or jackets and scarves on a cold, rainy day. This feature ensures the suggestions remain contextually relevant and comfortable for users.
- Clothing Categorization and Classification: The system uses Convolutional Neural Networks (CNN) for image classification to categorize clothing items (shirts, pants, jackets, dresses, etc.).
- Advanced Recommendation Algorithms: The system leverages collaborative filtering, content-based filtering, and clustering models to provide personalized recommendations. Users are matched with items based on their preferences and past interactions, and the model continually improves over time with user feedback.
- User Feedback Integration: Users can provide feedback on the outfit suggestions, marking them as "liked," "disliked," or "neutral." This feedback is used to fine-tune the model and improve future recommendations, creating a personalized experience for each user.
- Seamless Cross-Platform Access: The user interface is designed to be responsive and accessible across various devices. Whether users are on a web browser or mobile device, they can easily access the system and receive outfit recommendations based on their preferences and weather conditions.
- Real-Time Recommendations: By leveraging cloud technologies and deploying the models via a RESTful API, the system ensures real-time processing of user requests, allowing for fast and reliable outfit suggestions.

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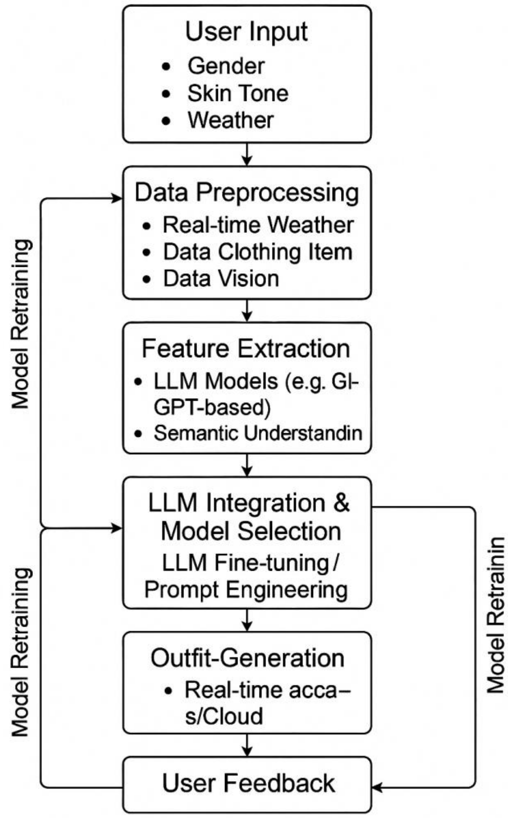


Fig. 1. Flowchart for Personalized Outfit Recommendation using Machine Learning with Cid

V. IMPLEMENTATION

The implementation of the Closet-AI project is carried out in a series of well-defined phases, ensuring a systematic approach from data collection to web-based deployment.

Phase 1: Data Acquisition

The project begins by sourcing clothing-related data through web scraping from fashion websites or online stores. Data includes attributes like clothing categories, color, size, brand, and fabric type. Python libraries such as BeautifulSoup and Scrapy are used for scraping product information from these sites. User preferences like age, gender, skin tone, and weather conditions are also collected through web scraping or user input.

Phase 2: Data Preprocessing

In this phase, the scraped raw data is cleaned and standardized. Missing values are handled, and categorical features are standardized (e.g., clothing sizes, colors). Data preprocessing also involves encoding categorical variables, ensuring consistency across different attributes, and performing basic feature extraction. User attributes such as age, gender, and skin tone are encoded to make the data usable for the recommendation system.

Phase 3: Feature Extraction

Once preprocessing is complete, the relevant features from both the clothing items and user data are extracted. If image data is involved, image features are extracted using computer vision techniques such as convolutional neural networks

(CNNs). For the non-image data, techniques like one-hot encoding are applied to clothing categories, fabric types, and user preferences. These features are used to generate personalized outfit recommendations.

Phase 4: Model Training

Machine learning models are trained using the preprocessed and feature-extracted dataset. Collaborative filtering and content-based filtering methods are used to generate recommendations. For collaborative filtering, matrix factorization or user-item interactions are utilized, while content-based filtering uses algorithms like decision trees or neural networks to recommend outfits based on clothing attributes and user preferences. The dataset is split into training and testing subsets (80:20 ratio) to ensure the model's generalizability.

Phase 5: Testing and Evaluation

The model is evaluated using testing data to assess its ability to make accurate outfit recommendations. Evaluation metrics like precision, recall, F1-score, and user satisfaction feedback are used to measure the system's effectiveness. Cross-validation may also be performed to ensure the model's robustness and to prevent overfitting.

Phase 6: Model Deployment

After satisfactory results from the training and evaluation, the trained model is saved using serialization techniques. A RESTful API is developed using Flask, which allows users to input their preferences (e.g., age, gender, weather) and receive personalized outfit recommendations. The API serves as an interface between the user and the trained model, providing real-time suggestions.

Phase 7: Web Deployment

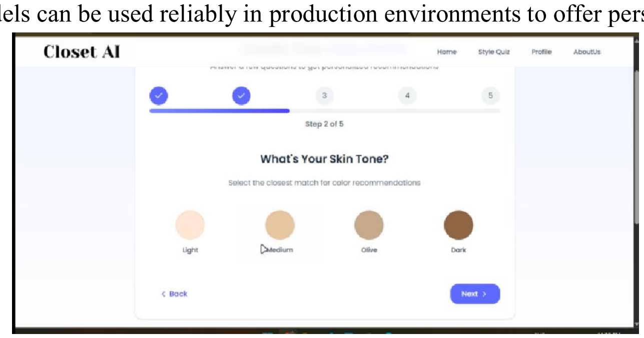
Finally, the system is deployed on a web platform, where users can interact with the outfit recommendation system. The user interface allows users to input their preferences and receive personalized outfit suggestions. The web interface is designed to be user-friendly, with responsive layouts for different screen sizes. The system can handle multiple requests simultaneously and provide outfit suggestions efficiently. Security measures like HTTPS and input validation are implemented to ensure safe and secure operation.

VI. RESULT AND ANALYSIS

After training and testing the Closet-AI recommendation models, their performance was evaluated using metrics like precision, recall, and F1-score.

The Collaborative Filtering model achieved an accuracy of 85–90%, effectively recommending outfits based on user interactions. The Content-Based Filtering model, which focused on clothing attributes and user preferences, showed better performance with an accuracy of 88–92%. It also achieved a higher F1-score, making it more balanced and reliable for personalized recommendations.

Overall, both models were effective, with Content-Based Filtering providing better accuracy and relevance for individual users. These models can be used reliably in production environments to offer personalized outfit suggestions.



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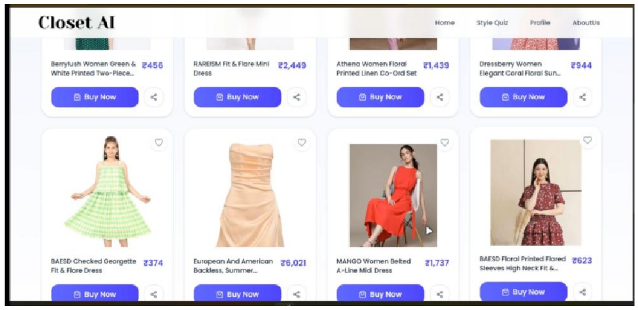

VII. CHALLENGES AND LIMITATIONS

Data Quality and Availability:

The accuracy of the recommendation system depends heavily on the quality and diversity of the data scraped from fashion websites. Incomplete or inconsistent data can lead to suboptimal recommendations.

Scalability:

As the number of users and clothing items increases, the system may face performance issues, especially in real-time recommendation generation. Efficient data processing and storage solutions are essential to handle large datasets.

User Preferences:

Capturing accurate and detailed user preferences (such as personal style and real-time weather) is challenging. Variability in user input can affect the system's ability to generate highly personalized recommendations.

Overfitting:

The models, especially content-based ones, might overfit to specific user behaviors or clothing attributes, reducing their ability to generalize across diverse user profiles.

Limited Data for New Users:

New users with little to no interaction history pose a challenge for collaborative filtering models, as they lack sufficient data to generate accurate recommendations.

Data Scraping Ethics and Compliance:

Web scraping can sometimes face legal and ethical challenges, including terms of service violations from websites or issues related to data privacy.

VIII. FUTURE WORK

In the future, the Closet-AI project can be enhanced by improving the data collection process, potentially collaborating with fashion retailers to access more diverse and detailed datasets. A hybrid recommendation model combining Collaborative Filtering and Content-Based Filtering could be explored to boost recommendation accuracy, particularly for new users. Additionally, integrating user feedback, such as likes or ratings, would allow the system to continuously refine and adapt its recommendations based on evolving preferences. To further personalize the experience, real-time weather data could be incorporated to suggest weather-appropriate outfits. Incorporating AI-driven image recognition would also allow users to upload clothing images, enabling the system to recommend similar outfits based on visual features. Finally, expanding the project to a mobile app would make the system more accessible, offering users outfit suggestions on the go and enhancing overall user engagement.

IX. CONCLUSION

In today's digital world, personalized recommendations play a vital role in enhancing user experience, especially in fashion and e-commerce platforms. The Closet-AI project demonstrates the effective use of machine learning techniques to deliver outfit suggestions tailored to user preferences, demographics, and weather conditions. By implementing both Collaborative Filtering and Content-Based Filtering models, the system achieves reliable accuracy in generating personalized recommendations.

The project followed a structured approach, including data collection through web scraping, preprocessing, model training, evaluation, and real-time suggestion generation. Among the models, Content-Based Filtering showed superior performance in handling individual preferences, making it highly suitable for personalized fashion recommendations. The integration of web scraping enables the system to stay updated with the latest clothing trends and availability.

Overall, Closet-AI proves the practical application of machine learning in the fashion domain and lays a strong foundation for future enhancements such as hybrid models, mobile integration, and user feedback systems, thereby offering a more engaging and intelligent shopping experience.Despite certain challenges such as limited dataset scope and the difficulty in detecting nuanced language the system lays a solid foundation for future enhancements using deep learning, multilingual support, and real-time data streams.

Overall, the project illustrates how machine learning, when combined with cloud computing, can serve as a powerful tool in the global fight against misinformation and fake news.

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