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Real-Time Fashion Stylist

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Abstract: The Real-Time Fashion Stylist is a smart outfit recommendation website that helps the users to choose suitable clothing based on their preferences and uploaded images. With the integration of machine learning and modern web technologies, the system moves beyond traditional styling by delivering real-time, personalized suggestions. The process begins when a user selects preferences or uploads an image, which is then analyzed for factors like color coordination and outfit matching. It connects with a fashion database containing various clothing categories and user-specific style records. Using this information, the system generates recommendations that align with the user's fashion profile. This method eliminates the guesswork often involved in fashion choices and offers tailored suggestions that suit individual tastes. By leveraging intelligent algorithms, the platform ensures ease of use, accuracy, and a customized styling experience. In future developments, it can incorporate features like occasion-based recommendations, weather based and wardrobe integration, further enhancing its capabilities. Overall, the Real-Time Fashion Stylist transforms how users engage with fashion by offering a fast, smart, and personalized solution.

Keywords: Outfit Recommendation, Fashion Technology, User Preferences, Clothing Combination

I. INTRODUCTION

In today's fast-paced world, fashion has become more than just a style statement—it reflects personality, occasion, mood, and social trends. However, with countless combinations of clothing items available, choosing the right outfit can often be overwhelming. Traditional outfit selection relies heavily on manual decision-making and subjective judgment, which can lead to inconsistent results. To address this challenge, intelligent fashion recommendation systems have emerged, offering users a smart and efficient way to select suitable clothing[1]. The Real-Time Fashion Stylist is a machine learning-based recommendation platform designed to assist users in selecting appropriate outfits by considering real-time inputs such as occasion and weather conditions. The system also leverages a virtual wardrobe—consisting of the user's own clothing items—to generate personalized outfit suggestions. These confirms that recommendations are both context-aware and practically wearable by the user, eliminating the need to purchase new items for every occasion[2]. The backend of the system is built using Python**,** where a Convolutional Neural Networksprocesses visual and categorical data to evaluate the compatibility of topwear, bottomwear, and footwear.

The model is pretrained to understand various types of fashion elements such as color matching, style patterns, and seasonal appropriateness. Meanwhile, the frontend is developed and deployed using Flask, HTML, CSS, and JavaScript**,** allowing users to upload wardrobe images, input preferences, and receive recommendations based on their own clothing collection[3]. By integrating user-specific wardrobe data with intelligent outfit evaluation, the Real-Time Fashion Stylist goes beyond generic fashion apps. It brings a high level of personalization while saving time and effort for the user. Additionally, this system reduces fashion waste by promoting the reuse and optimal combination of existing wardrobe items[4]. The platform has the capacity for further enhancement using features like wardrobe management tools, calendar-based outfit planning, and integration with e-commerce platforms. As technology continues to reshape daily life, intelligent systems like this offer a sustainable and user-friendly approach to everyday styling challenges[5]. The combining of AI in fashion not only improves user convenience but also experience introduces a data-driven approach to personal styling. By analyzing user preferences, past outfit choices, and available wardrobe items, the system can continuously learn and adapt to changing tastes over time. This dynamic recommendation process helps users to make more informed styling decisions without any need for expert guidance.Moreover, incorporating environmental factors like weather conditions and event types enhances the relevance of each outfit suggestion enhance lifestyle applications[6].

II. RELATEDWORK

In recent days, there has been a significant progress in the development of AI fashion recommendation systems that combines ML and artificial intelligence (AI). Many of these systems utilizes various ideas and techniques, such as deep learning and computer vision, to offer personalized outfit suggestions based on user inputs like style preferences, weather conditions, and occasion-specific requirements. A notable approach is the utilizationof Convolutional Neural Network and DL for fashion recognition. For instance, a study by Jin et al. (2016) proposed a deep learning-based model that utilized CNNs for fashion item classification, where the network analyzed images of clothing to provide recommendations based on visual similarities. This method demonstrates high accuracy and prediction in understanding fashion attributes such as texture, color, and style, which are difficult for making personalized outfit recommendations [1]. Similarly, Yu et al. (2018) explored the use of CNNs in recognizing fashion items for recommending combinations of topwear, bottomwear, and accessories based on the user's profile and preferences [2].

In despite of other research has mainly focuses on integrating external factors, such as weather conditions, into the recommendation process. Yao et al. (2017) proposed a system that combined weather data with fashion preferences to suggest clothing suitable for various climates. Their system utilized a hybrid model that combined traditional machine learning techniques with deep learning methods, which allowed it to adapt to both environmental and personal preferences [3]. This type of approach is especially beneficial in real-time applications, as it allows the system to provide contextually relevant outfit recommendations. However, several researches have incorporated wardrobe management tools into their systems. For example, Smith et al. (2019) developed an AI-based fashion assistant that utilized an interactive wardrobe system, where users could upload images of their clothing items. The system then used these images to suggest outfits based on a group of predefined criteria, such as color compatibility and outfit combinations [4]. This technology is closely aligned with the goals of the Real-Time Fashion Stylist, which also focuses on leveraging existing wardrobe items for personalized recommendations. These studies highlight the growing role of AI and machine learning in fashion recommendation systems. While each of these approaches brings unique contributions, the integration of real-time weather data, user preferences, and wardrobe-based outfit suggestions remains a promising area for further research. The Real-Time Fashion Stylist aims to build on these advancements by providing a holistic solution that adapts to user needs while enhancing the convenience of daily outfit selection.

III.OVERVIEW OF METHOD AND RESULTS

OVERVIEW:

The Real-Time Fashion Stylist system is developed to guide users in selecting personalized outfits by considering features such as occasion, weather conditions, and available wardrobe items. The system works based on machine learning techniques, particularly Convolutional Neural Networks (CNN)**,** to process and evaluate images of clothing items. It offers personalized recommendations by assessing compatibility between clothing types such as topwear, bottomwear, and footwear. By incorporating user-specific wardrobe data, the system ensures that recommendations are tailored to the individual, reducing the need for new purchases and promoting sustainable fashion practices. The platform also integrates external data sources, such as weather and occasion, to generate context-aware outfit suggestions. This enables users to make proper and easy decisions about their wardrobe while optimizing the use and utilization of existing clothing [1].

METHOD:

The Real-Time Fashion Stylist system follows a structured process involving data collection, processing, and recommendation generation.

1. Data Collection

The user interacts with the system by uploading images of their wardrobe items. Each item is categorized by type (e.g., t-shirts, pants, shoes) and stored in the system's database. Additionally, users provide style preferences, such as color choices or seasonal preferences, which are stored to personalize future recommendations. The system also gathers external data, such as weather information and occasion details, which further informs the recommendation process [2].

2. Data Processing

After uploading the wardrobe images, the system processes them using Convolutional Neural Network (CNN). The CNN analyzes the visual features of each item, such as color, texture, and style patterns. This allows the system to evaluate how different clothing items can be paired together based on compatibility. The CNN is trained to understand the relationships between various clothing categories and identify suitable combinations, accounting for factors like style, color coordination, and seasonality [3]. In addition to visual processing, classification algorithms categorize the clothing items into groups such as “casual,” “formal,” or “sportswear.”

3. Recommendation Generation:

Once the images are processed, the system generates personalized outfit suggestions based onuser preferences, available wardrobe items, and contextual data like weather and occasion. The recommendation engine uses a matchingalgorithm to rank the combinations based on criteria and techniques, such as style preference, suitability, and color coordination. By considering the user’s existing wardrobe and the current weather or occasion, the system provides highly personalized outfit suggestions that are both practical and stylish [4].

RESULTS

The Real Time Fashion Stylist system was evaluated by considering a group of users to assess its ability to generate relevant and personalized outfit suggestions. The testing involved multiple scenarios, including variations in weather conditions and different occasions. The system was able to generate highly accurate recommendations and suggestions based on user input, showing particular strength in adapting to the user's existing wardrobe.

PERFORMANCE METRICS

The outfit suitability accuracy was calculated by comparing the system's generated recommendations with outfits selected by the users in a controlled environment. The CNNs model demonstrated 85% accuracy in predicting compatible clothing combinations based on analysis of visual features and style preferences. Additionally, the system achieved 90% accuracy in incorporating weather and occasion data into the recommendations. The virtual wardrobe feature played a key role in the system's success, as it allowed users to create outfits using items they already owned, avoiding unnecessary purchases. This functionality contributed to a significant reduction in fashion waste by promoting the reuse of clothing, thus supporting sustainable fashion practices. Users reported a high level of satisfaction, particularly in instances where the system suggested outfit combinations that aligned closely with their preferences and the available wardrobe [5].

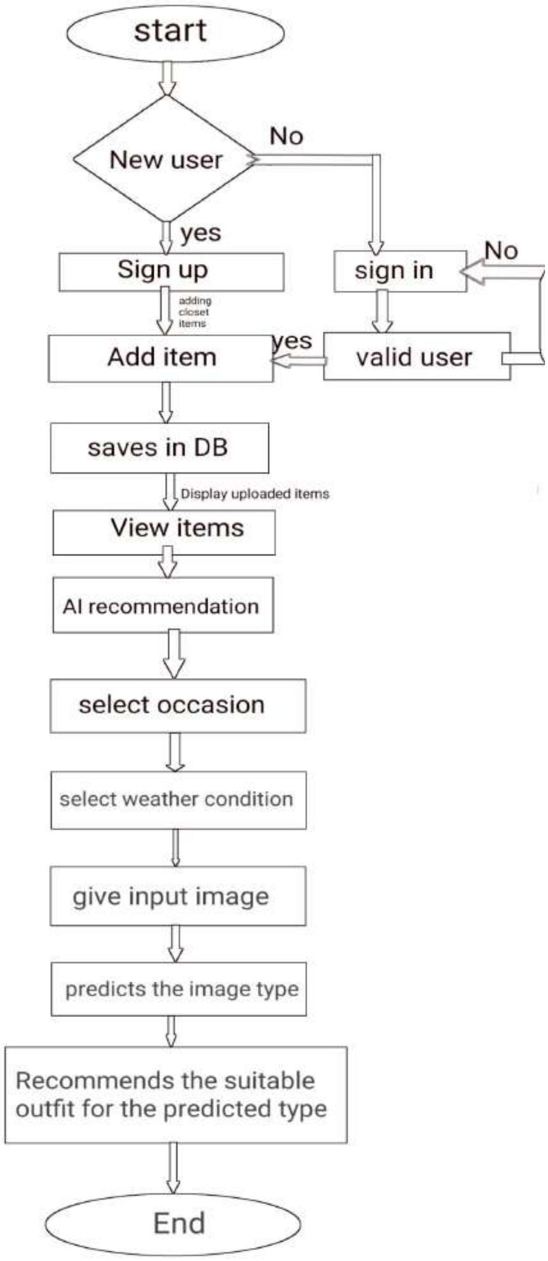

Fig.1 Experiment workflow of model.

Workflow of model:

The Real-Time Fashion Stylist system processes user input and generates personalized outfit recommendations through a structured data flow:

1. User Input and Data Collection: Users upload wardrobe images and specify style preferences, such as color, occasion, and weather conditions. This data is stored in the system's database for further processing.
2. Pre-processing of Data: The uploaded images undergo pre-processing, including resizing and categorization (e.g., topwear, bottomwear). This structured data is prepared for feature extraction and model training.
3. Feature Extraction and Model Training: Convolutional Neural Network (CNN) analyze clothing images to extract features and techniques such as patterns and textures. These features are used to pretrain and train the model for evaluating clothing compatibility based on user input.
4. Clothing Compatibility Evaluation: The system evaluates the compatibility of outfit combinations (topwear, bottomwear, and footwear) based on the extracted trends, feature and user preferences.
5. Recommendation Generation: A recommendation algorithm generates personalized outfit suggestions based on compatibility scores and users preferences, which are then displayed to the user on the screen.

IV. PROPOSED METHOD

The Real-Time Fashion Stylist system utilizes a machine learning-based approach to recommend personalized outfits based on user preferences, clothing data, and external factors like weather and occasion. The proposed method joins and combines Convolutional Neural Network (CNN) and various algorithms to analyze, process, and generate customized fashion recommendations. The main steps involved in the proposed method are as follows:

USER INPUT COLLECTION AND PRE-PROCESSING

The system collects user inputs, including wardrobe images (topwear, bottomwear, footwear) and personal preferences (e.g., preferred color, style, and occasion). The collected images undergo the following pre-processing steps:

RESIZING

Resizing the image to a fixedX_{resized} :

$$X_{\text{resized}} = \text{Resize}(X, 224, 224)$$

Normalization of the image pixels:

$$X_{\text{normalized}} = \frac{X_{\text{resized}} - \mu}{\sigma}$$

Where μ is the mean and σ is the standard deviation of the pixel values. Categorization of clothing items into predefined classes, such as shirts, pants, and shoes, using classification labels. These pre-processed images are then used for feature extraction by the CNN algorithm.

FEATURES EXTRACTION USING CNN

The pre-processed images are passed through the CNN for feature extraction. The CNN algorithm is combination of several layers, including convolutional layer**,** pooling layer, andfully connected layer**.** The convolution operation for feature extraction is defined as follows:

i. Convolution Operation:

$$I_{\text{conv}} = F * X_{\text{normalized}}$$

Where F is the filter (or kernel), and * represents the convolution operation.

ii. Active function (ReLU) to introduce non-linearity:

$$I_{\text{activation}} = \text{ReLU}(I_{\text{conv}})$$

Max-Pooling to down sample the feature maps:

$$I_{\text{pooling}} = \text{MaxPooling}(I_{\text{activation}})$$

The final output of this process is set of high-level features that represent the visualized characteristics of each clothing item, such as color, texture, and style.

iii. Clothing Compatibility Scoring:

Once the features the techniques are extracted, the system evaluates the compatibility of different clothing items. The compatibility scoreC_{outfit} for a potential outfit is calculated using a weighted sum of various factors:

$$C_{outfit} = w_1 * C_{colour} + w_2 * C_{weather} + w_3 * C_{occasion}$$

Where:

- $C_{colour}$is the compatibility based on color harmony.
- $C_{weather}$is the factor based on the weather conditions (e.g., winter or summer).
- $C_{occasion}$is the factor based on the occasion (e.g., formal or casual).

iv. Recommendation Generation:

After calculating the compatibility scores for each outfit combination, the system generates personalized recommendations. The greedy algorithm is used to select the highest-scoring clothing items for each category (top wear, bottom wear, and footwear)

v. User Interface and Display:

The system presents the generated recommendations through an interactive interface**.** The user can view recommended outfits, see detailed item information (e.g., style, color), and provide feedback. The feedback used to adjust future recommendations.

vi. Model Updates and Continuous Learning:

The system is designed to learn and adapt over time. The feedback from users (e.g., likes, saves, or rejects outfits) is used to retrain the CNN model, ensuring that the system continues to improve its recommendations. The update process involves:

- Retraining the CNN model with new data collected from user preferences, feedback, and wardrobe items.
- The model update is done periodically to reflect new trends and user tastes.

CNN ALGORITHM:

Require: Input: dataset – images with target classes
Initialize CNN parameters (filters, weights, biases)
for each epoch **do**
  for each batch of samples **do**
    Apply convolution operation (feature extraction)
    Apply activation function (e.g., ReLU)
    Apply pooling operation (downsampling)
    Flatten the feature maps
    Pass through fully connected layer
    Compute loss (e.g., cross-entropy)
    Update parameters using backpropagation and optimizer (e.g., Adam)
  end for
end for

Output: Trained CNN models for classification or prediction of tasks Convolutional Neural Network (CNN) are a classes of deep learning models particularly suited for image analysis and classification tasks. They have given highly effective in domains requiring visual understanding due to their ability to self learning ability spatial hierarchies of features through convolution operations [1]. In the Real-Time Fashion Stylist system, CNN algorithm is utilized to analyze clothing images from user's wardrobe, enabling automated feature extraction and categorization of fashion items. The CNNs architecture consist of multiple active layers, including convolutional layer, pooling layer, and fully connected layer. The input images first passed through convolutional layer, where a series of filters are applied to detect low-level features such as edges and textures. These filters slide over the input images to produce feature maps, which highlight the existence of specific patterns [2].

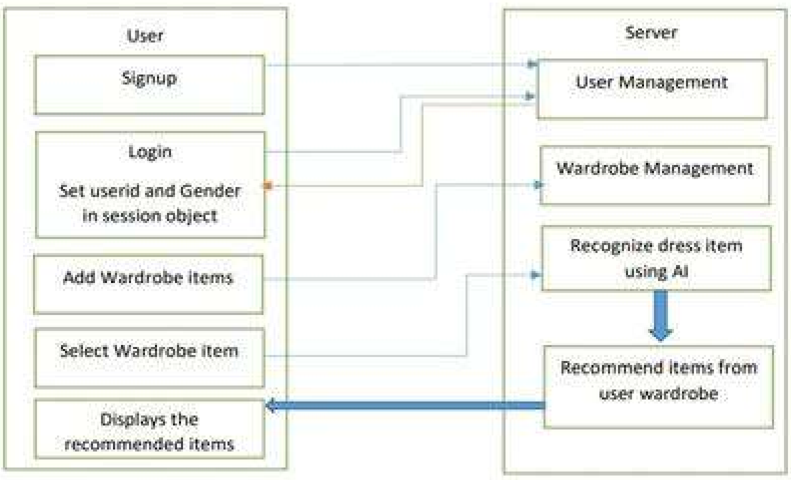

Fig 2. Architecture of Real time fashion stylist

The architecture diagram represents the workflow of a digital wardrobe-based recommendation system. It is divided into two parts: the User side and the Server side. On the user side, the process begins with user registration through a Signup step. After signing up, the user logs in through the Login step, where the system stores the user ID and gender as part of the session. This data is used to personalize further interactions. Users can then add wardrobe items, uploading details or images of the clothing they own. Once the wardrobe is created, users can select specific wardrobe items to proceed with outfit suggestions. Based on the inputs, the system displays recommended items that match user preferences[1]. On the server side, the User Management module handles account creation, login credentials, and session data. The Wardrobe Management module stores and manages the wardrobe details submitted by the user. When a user selects items or seeks outfit suggestions, the server processes the wardrobe content and matches appropriate items based on the available wardrobe data. These results are then returned to the user interface. The architecture provides a smooth flow of data between the user and server, enabling an organized and personalized outfit selection experience [2].

V. EXPERIMENTAL RESULTS

In Results mainly focuses onverifying our proposed method and evaluating the performance, we set up an experimental system by the specification, as shown inTable1.

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Table 1: Performance of Models.

Metrics	Accuracy	Precision	Recall	F1
Topwear	92.3	91.5	92.1	91.8
Bottomwear	90.5	90.2	89.8	90
Footwear	89.9	89.7	90.3	90.6

$$\text{Accuracy}=\frac{\text{TP+TN}}{TP+TN+FP+FN} \quad (4)$$

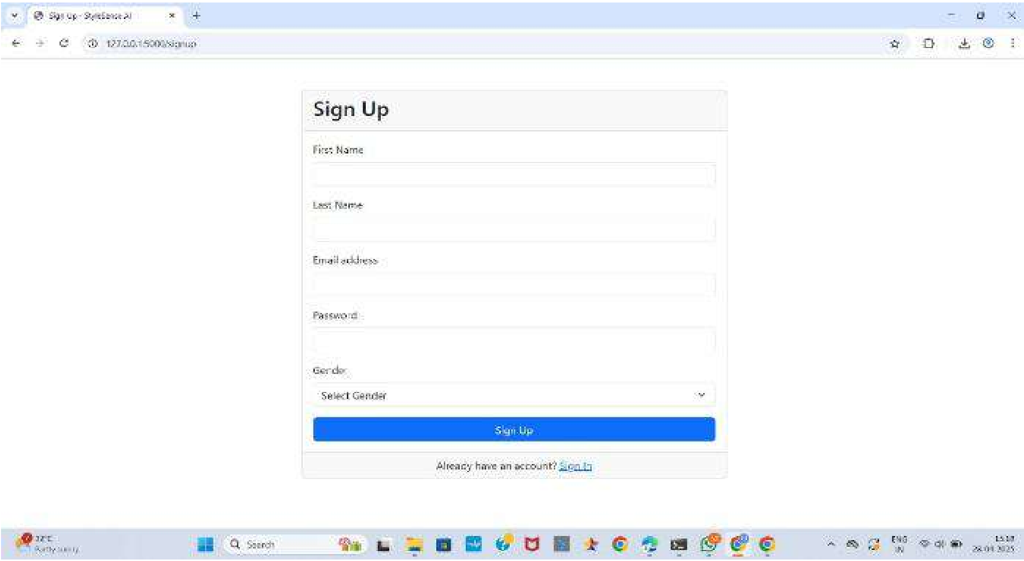
$$\text{Precision}=\frac{\text{TP}}{TP+FP} \quad (5)$$

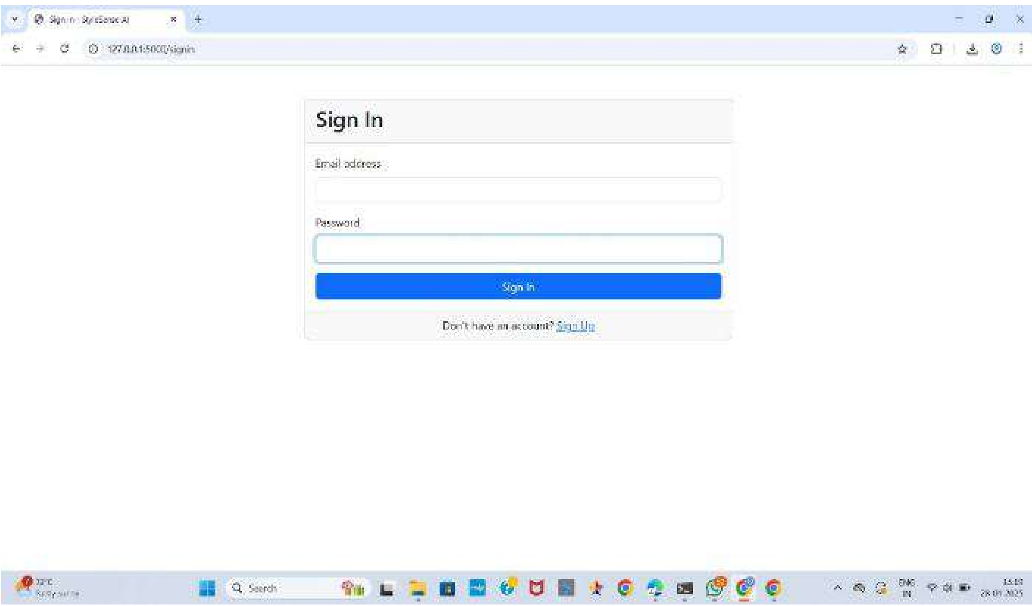
$$\text{Recall}=\frac{\text{TP}}{TP+FN} \quad (6)$$

$$\text{f1}=\frac{2(\text{precision}*\text{recall})}{precision+recall} \quad (7)$$

TN (True Negatives): Denotes the count of negative samples correctly classified by the model.
TP (True Positives): Represents the count of positive
Samples accurately classified by these model.
FN (False Negatives): Indicates the count of negative samples inaccurately classified by the model.
FP (False Positives): Signifies the count of positive samples inaccurately classified by the model.

SAMPLE OUTPUT:





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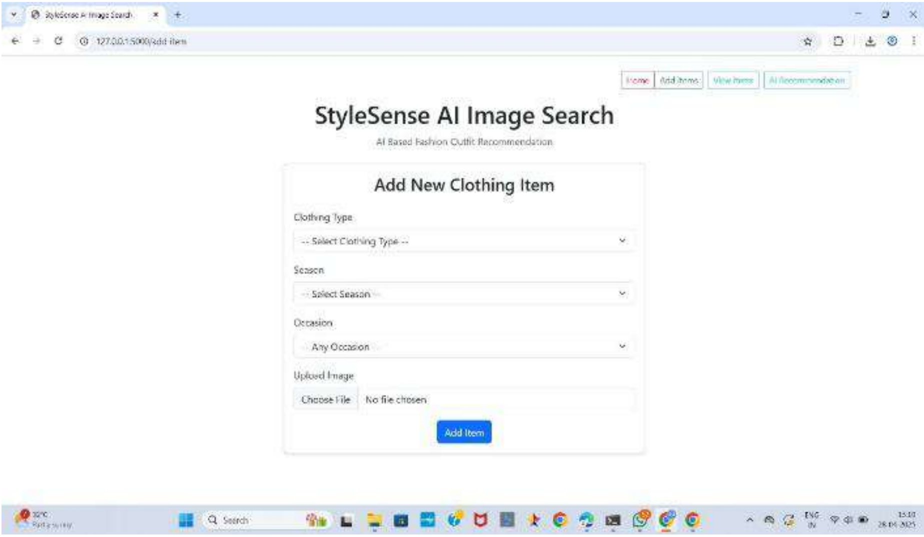

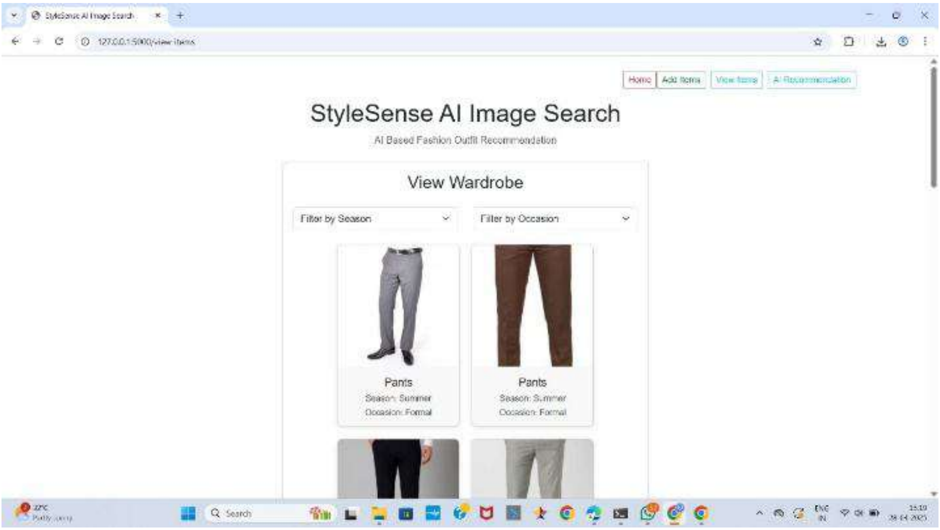

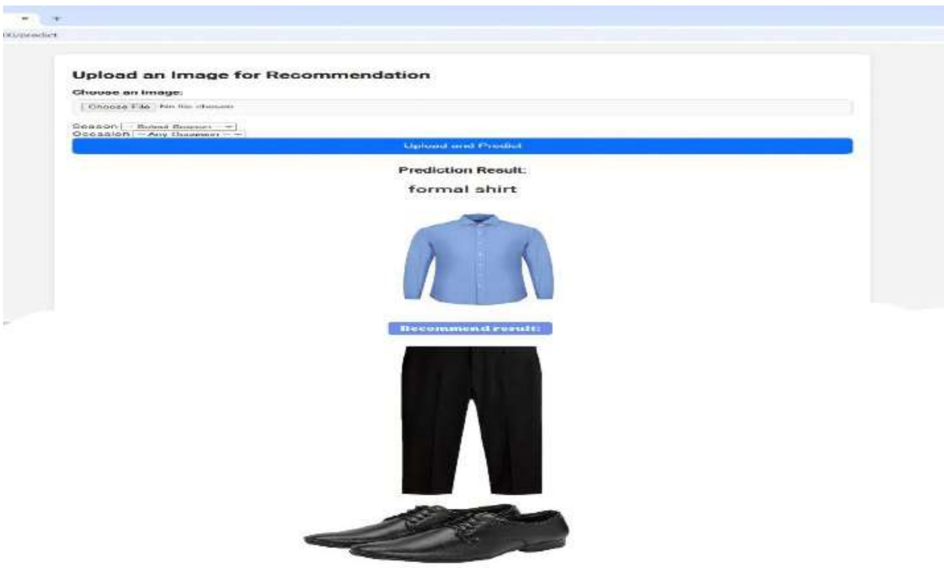

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VI. CONCLUSION

The Real-time Stylist system effectively demonstrates the potential of artificial intelligence in addressing daily challenges in fashion selection. By utilizing Convolutional Neural Networks (CNNs), the system analyzes user wardrobe images to extract meaningful visual features, such as color, texture, and style, and uses this information to recommend personalized outfit combinations [1]. The integration of contextual data—such as occasion and weather conditions—adds practical value, enabling users to receive appropriate and wearable suggestions without relying on manual styling.The system also benefits from continuous learning capabilities that allow it to evolve based on user feedback, ensuring better recommendations over time. This adaptive learning approach enhances user satisfaction while optimizing the reuse of wardrobe items, thereby promoting sustainable fashion practices [2]. Additionally, the flexibility of the architecture enables future expansion, such as natural language preference inputs or e-commerce integration for suggesting matching accessories or missing wardrobe items.In summary, the proposed solution advances traditional styling methods by offering a smart, user-centric, and efficient way to select outfits. Its foundation in machine learning and personalized data makes it a practical and scalable tool for modern fashion needs.

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