Stylesync: Smart Outfit Recommendations

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ABSTRACT
Our "StyleSync: Outfit Recommender" project is an innovative initiative that leverages Machine Learning (ML), Deep Learning (DL), and advanced algorithms to transform the fashion industry. By combining cutting-edge technologies with creative solutions, this project is designed to offer personalized outfit recommendations that align with each user's individual preferences and style.

The system will utilize ML techniques like collaborative filtering, clustering, and decision trees to analyze user data, past fashion trends, and personal style profiles, ensuring accurate and relevant outfit suggestions. Deep Learning methods such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) will be applied to extract complex patterns from images, allowing the system to understand visual appeal and recommend outfits that are aesthetically pleasing.

Additionally, the project will explore the use of reinforcement learning algorithms to improve outfit recommendations over time, based on user feedback and interactions. By continuously adapting to user preferences, the system will enhance its recommendations, providing a more tailored and engaging experience.

General Terms
Outfit Recommender, Deep Learning, Machine Learning, Computer Vision.

Keywords
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1. INTRODUCTION
When it comes to picking the ideal wear for today's busy lifestyle the whole exercise has become pretty complicated and tiresome. The use of technology in fashion has led to the finding of better ways to undertake this and offer users with appropriate outfits recommendations. One of the solutions is the Outfit Recommender system – a highly developed platform that employs Machine Learning (ML), Deep Learning (DL), Computer Vision (CV) and other algorithms to change the outlook on fashion-related decisions.
Outfit Recommender system has to tend to the objective of the user and its functionalities make it more than just a site that offers fashion advice. Given that there are thousands of options for clothes and accessories, the system takes into account the user preferences and the prevailing weather conditions, trends, and style preferences of the targeted clients and comes up with the best recommendations for a perfect combination of outfit.

2. BACKGROUND
2.1 Overview
In recent years, technology and social media have significantly changed the face of the fashion industry over the past years, much more so through a development called outfit recommendation technology. As the name will suggest, this is an emerging trend that essentially revolves around algorithms and data analytics aimed at creating 'ideal' dressing patterns for each person.

These systems can better predict trends that have a connection with the users by using real-time data streams from social media and influencer activity. Most of the platforms also now offer augmented reality features, allowing customers to virtually try on outfits, thereby encouraging engagement and lowering returns.

This has democratized fashion advice and enabled many more people to receive recommendations, while some are also incorporating more sustainable options into the suggestions, thus promoting environmentally friendly choices in the whole process. Indeed, this outfit recommendation technology is changing the face of retail, making for a more personalized and inclusive shopping experience.

3. RELATED WORK
Recent developments in the field of fashion recommendation systems used machine learning to the fullest to improve user experience within e-commerce. Sivaranjani et al. [1] presented a CNN-based system for tailored clothing suggestions. Their system was improved in terms of shopping experience but had a tendency to be interference-prone due to data dependency from users and limited variety within the dataset. Similarly, GUO et al. [2] explored AI in fashion design, where they acknowledged important areas such as detection and synthesis while taking into consideration the need to be better understood for occluded objects and user preferences.

Divitiis et al. [3] have proposed Memory Augmented Neural Networks in order to improve the variability of recommendations by using the external memory even with open debates over its convergence and variability within the datasets. Guillermo et al. [4] presented a content-based system that could scale with unsupervised learning but depends on item attributes, which reduces the possibility to capture complex user preferences. Suvarna et al. [5] achieved high accuracy with deep learning but highlighted significant concerns related to interpretability and resource consumption.

Other innovative approaches include Iso et al.'s [6] GAN-based outfit generation and Koshy et al.'s [8] 'Pocket Fashionista' outfit recommendations. However, even these come with some limitations in clothing representation and contextual factors of clothes. Turkut et al. [9] followed the method of deep learning to carry out a moderate-accuracy framework for textile recommendations. Hsiao et al. [10] tried toward inclusivity for different body types through constraints to specific online catalogs.

Overall, this work has made tremendous progress since Hashmi et al. [11] advanced the virtual try-on technology and Hidayati et al. [12] extracted fashion rules. Still, there are concerns about dataset variability, personalization, and computational efficiency. The future challenges require additional research and innovation to rectify these weaknesses and improve the effectiveness of a fashion recommendation system.

4. LITERATURE SURVEY

4.1 Literature review

In this literature survey section, we will review prior studies and case studies of outfit recommender systems with especial emphasis on the approaches, the assessment criteria, and the considerations on user perspective in the development of these systems. Therefore, in the context of the present state of development of outfit recommendation technology, we shall determine the critical issues and opportunities for the future growth of this type of technology. In the long run, we aim at helping create better outfit recommendation systems which should in turn make the shopping and styling aspects an easier process for everyone.

Sivaranjani et al. [1] specifically tackles a fashion recommendation system for clothes using machine learning techniques, especially CNN. The benefit derived from this system is that it allows for making recommendations based on user preferences to enhance the shopping experience of the users. Media Message: CNN enables high throughput and precise suggestions when handling considerable data. Although, there are certain issues like the fact that the results depend on the data of the users and therefore does not generate a good prediction for the users with less activity on the site. Also, the study has its limitations in the dataset where the range of fashion items and variety of fashion trends could not be sufficiently addressed. Nevertheless, it can be stated that the paper offers an innovative concept of improving the fashion shopping experience with the help of machine learning algorithms.

GUO et al. [2] focuses on the application of the AI concept in fashion design where he identifies fashion detection, fashion synthesis, and fashion recommendation as the areas that require the AI solutions. In the fashion detection field, latest AI techniques like CNN and R-CNN can help to detect fashion items in images & videos assisting designers & retailers in identifying trends & consumer behaviors. There are still some issues with properly identifying hidden or partially occluded objects, as well as with finer details. Fashion synthesis has improved significantly with the help of GANs and diffusion models and can assist designers in developing innovative designs and realistic apparel designs. Disadvantages include the inability to control some aspects of design and retention of meaningful semantic content. Fashion recommendation systems help users to select the right products and coordinate complete ensembles; however, they have limitations in terms of understanding user preferences and offering a wide range of options.

Divitiis et al. [3] looks at the fashion industry and the use of recommender systems in online stores resulting in suggestions that may be limited in variation or simply redundant. The authors do this by introducing a Memory Augmented Neural Network (MANN) architecture to target compatible garment recommendation with garments’ clothing attributes co-occurrence for forming outfits. The model intends to dissociate representations of fashion items and store them in the external memory module; this should enhance the recommendation performance compared to the existing methods. The model proposed only relies on the disentanglement of color/shape features and the usage of External Memory Modules to store matching modalities of top and bottom fashion apparels. The approach extends the well-known controller loss to train memory modules and it has advantages against problems caused by the differences in data distributions to gain compact and complete memories. However, there are issues with the convergence of some of these model variants, and the variation within the dataset raises questions as well. The limitations above call for robustness and ability to generalize for different user preferences and across datasets.

Guillermo et al. [4] propose a content-based fashion recommender system that employs unsupervised learning techniques and utilizes a dataset known as Fashion MNIST. The system's strengths include its capacity to manage large datasets, scalability for real-world use cases, and the elimination of the need for manual item labeling. However, its reliance on item attributes may restrict its ability to capture personalized and nuanced user style preferences. Moreover, the accuracy of the recommendations is largely dependent on the quality and depth of the item attributes within the dataset, and the system does not take into account contextual factors or current fashion trends. The system's limitations include the absence of collaborative filtering or other personalized methods, which could affect its relevance and accuracy over time, especially if temporal factors are not considered. Additionally, it struggles to handle unconventional fashion items that lack sufficient attributes. In conclusion, while the paper offers an automated and scalable solution for fashion recommendations, further research is needed to address these limitations and enhance its accuracy and relevance.

Suvarna et al. [5] show a clear and extensive development of an approach of how to use deep learning for fashion product recommendation; the proposed model also demonstrates high accuracy and discusses possible improvements and future research directions.s. Due to its flexibility and capacity, it would also perform well in different e-commerce settings of diverse sizes and fashions containing large numbers and ever-changing fashion trends.However, the use of the deep CNN model as used in this study comes with some issues of interpretability because this is more of deep learning and thus may reduce the likelihood of interim decision making. Additionally, training deep versions of CNN is more computationally challenging and requires a lot of data and computational platforms making it difficult in resource constrained environments.The authors then showed that the proposed model outperforms other existing models with a higher accuracy rate that went from 66% to 89%. From the results it is evident that the proposed model has high levels of precision and recall in different classes of fashion products with some classes attaining above 90%.

Iso et al. [6] is designed to observe a replicated personal mood preferred by an individual through the generation of outfit images. The techniques which are so used by the system are GAN architecture, deep learning for segmentation, transfer learning using Inception-v3. The benefits of the system are the capacity to suggest the same outfit as different styles considering the preferences of the user and the ability to create the images of the outfits that correspond to the personal styles of users. Nevertheless, there are some drawbacks that refer to the correspondence between segmentation masks and real clothes, the dearth of compared Japanese style fashion in the offered dataset, and, finally, the inability of the system to create some types of the pants and skirt combinations. This means that the process of collecting data can be bias and also limit the range of styles that may be recommended. In general, it was approved and developed a diverse level of accuracy of the final result within one low and the event that the suggested styles did not reflect the user's personal choice.

Gharaei et al. [7] examines a content based clothing recommender system that implies DNN and CNN approaches. The system has certain benefits including gender as a feature for recommendations, addressing the cold start problem and the low loss evidence. It also incorporates product gender directly, without first going through image retrieving. Furthermore, the system is simple, and, therefore, can generate high speed of recommendations. However, disadvantages of the approach are low precision and using only two attributes for the recommendations. According to findings, the system has an accuracy level of approximately 73.7% and an average of about 0.07% on the time taken to give a recommendation. The dataset on which this study is predicated is a sub-sample of the Fashion Product Images set comprising 14,932 samples out of 44,000.

Koshy et al. [8] present a novel fashion advisor system called 'Pocket Fashionista' which gives outfit and color advice according to the skin color of the user. It has an array like skin color identifier, the color identifier for the outfit, similar outfits, weather predictor, and trial rooms. It is used to increase the user satisfaction towards fashion and to meet the real-time demands of E-commerce platforms.To extract skin tone from a given image three different color spaces (RGB, HSV, YCbR) were used.Algorithms like the Approximate Nearest Neighbors Algorithm for generating the similar clothing recommendation for the users and the K-Means clustering Algorithm for clustering the user skin tone. To determine the sizes of the clothes visually, there is the Circle Hough method applied.Further, there can be added more accessories features to fill up all the outfit. Also taking account of more factors like the body posture and type of event can also be used in giving correct recommendations. In conclusion, the paper tests the idea of more individualized fashion advice and acknowledges the impact of technology in the buying process.

Turkut et al. [9] presents an online recommendation framework for textile products employing deep learning methodology; Specifically, the Convolutional neural network (CNN). It is color compatible and follows patterns as companies for making recommendations. The strengths of the proposed approach embraces successful application of the KNN in different fields, tailored recommendation which is obtained through the online survey and moderate accuracy of 82.08%. Nevertheless, the limitations are as follows: the identification of color compatibility and patterns is limited; other recommendation approaches are not compared; no information about computational resources as well as limitations or issues is provided. In summary, the paper contributes to the extant knowledge regarding innovative use of deep learning for the recommendation of textile products and consequently, the following avenues present the primary lines of action for future studies.

Hsiao et al. [10] Successful clothing recommendation systems have been proposed as a new method of considering five types of women's bodies, while traditional methods were 11%. Its advantage is its inclusiveness and personalisation resulting from the model that can correlate the need for clothes with different body types. Using data from an existing online shopping website also brings realism to the entire series of training. The explanation method improves user endorsement by making the recommendations more transparent. However, some limitations are the following: restricted populations in terms of body shapes because of the online catalog data used, and the possibility of the subjective evaluation of human judgment dimensions. Furthermore, the suggested model may lack the ability to embrace new clothing styles and generalize to different populations, as it pays emphasis to visual features and the learnt attributes only.

Hashmi et al. [11] offers a novel concept for virtual try-on by combining 3D pose mapping and Neural Body Fit to simulate personal outfits. The accuracy levels are high due to the application of GANs and NBF in the model and the possibility of investing in AI to create bespoke clothing outfits. This paper bridges a significant gap in current fashion systems as it enables the user to try on garments of his or her choice on selected human models of his or her choice virtually, making it ideal for virtual try on applications. Nevertheless, due to the high computational cost of the model and insufficiency of the adopted datasets and included clothing types, the approach might be non-scalable and non-universal. Also, the criterion of utilizing existing dataset such as DeepFashion2 and some unfitness of GANs generated outfit when it is validated is another significant factor that must be considered in future study.

Hidayati et al. [12] presents a new approach to extracting learning style rules for various body types with knowledge from fashion topics in SBD. By proposing an image model for clothing styles and body measurements from relational fashion knowledge rules such as celebrity fashionable worn items and fashion suggestions for different body shapes, embedding fashion knowledge styles and shape characteristics yield a joint embedding. This approach utilizes side styles to improve fashion advice, and disseminate patterns from clothing and silhouette clusters for better feature selection. A body style map is developed along with the body shape calculator and the construction of a benchmark dataset for the style recommendation. The study demonstrates how examples of visual style and body shape clusters are propagated and how informative semantic features are selected in these clusters. Three main data sources are employed, 'Style4BodyShape', 'DeepFashion' and 'StyleReference'. The Style4BodyShape dataset is a collection of body measurements of stylish celebrities and their images and DeepFashion offers clothing category and clothing location. The new addition of StyleReference Dataset allows for the determination of the level of stylish refinement and provides an allowance for the compatibility score of the style of clothes and body shapes. The models combined help the fashion industry to comprehend, grasp, and describe the fine structure of fashion concepts and enable creating style recommendation systems based on body shapes and clothing styles. However, the model is trained only on the datasets which contain the images of female clothes that act as a constraint for the model.

4.2 Summary of Literature Survey

A literature review is an impartial and analytical overview of existing research literature related to a specific topic being considered for study. This overview is presented here.

Table 1. Summary of Literature Survey

Paper Name	Observation
Fashion Recommendation System Using Machine Learning. Published By: 2023 4th International Conference on Smart Electronics and Communication (ICOSEC) [1]	Advantage: By utilizing CNN, KNN, and RESNET50, the system can generate five recommendations based on the user's input image. Disadvantage: The paper notes that a larger and more varied dataset is typically better for training models that are more accurate and adaptable to new data. The dataset used in this study might not adequately represent the full range of fashion items and styles.
AI Assisted Fashion Design: A Review. Published By: IEEE Access [2]	Advantage: Enhanced detection models improve productivity for designers by minimizing the need for manual identification. Fashion parsing offers personalized styling, trend analysis, and fashion suggestions. Item retrieval systems integrate personalized recommendations to facilitate efficient searches. Image-guided and sketch-guided synthesis models provide valuable inspiration and direction to fashion designers, enabling the creation of realistic and diverse fashion items that expand design possibilities. GANs and diffusion models transform image style transfer. Task-based and input-based recommender systems help users find appropriate fashion items, assist in creating complementary outfits, and offer personalized suggestions for various scenarios. Disadvantage: Fashion parsing may encounter difficulties in unconstrained environments with limited tags and annotations. Item retrieval methods require extensive training and fine-tuning. Image-guided synthesis models may produce less satisfactory outcomes if the texture of the input image is not distinct. Randomness in diffusion models can lead to suboptimal results. Some models may struggle with pattern design. Fashion recommendation systems heavily depend on image recognition and metadata, which can be limited or inaccurate. Data bias can affect the diversity and accuracy of recommendations, and concerns over user privacy and data security persist.
Disentangling Features for Fashion Recommendation. Published By: ACM Transactions on Multimedia Computing, Communications, and Applications [3]	Advantage: The model can be easily adapted for both garment recommendation and outfit compatibility estimation tasks, making it highly versatile in the fashion industry. By using separate color and shape data augmentations during training, the model learns to extract disentangled features, enhancing the interpretability of its recommendations. The introduction of an improved memory module with an adaptive controller and separate memory banks boosts the model's ability to identify suitable pairings for different attributes, such as shape and color. Disadvantage: The shape-based variant of the model showed inconsistent performance across different datasets, suggesting challenges in handling dataset variability, especially with complex datasets. Additionally, the 'Ours NoPenalty' variant experienced convergence issues, pointing to limitations in the model's flexibility during certain training processes and the need for a more advanced loss function formulation.

Content-based Fashion Recommender System Using Unsupervised Learning. Published By: TENCON 2021 - 2021 IEEE Region 10 Conference (TENCON) [4]	Advantage: The model emphasizes reconstructing the input image, which is then used as the output for recommendations across 11 different product categories. Disadvantage: It has not been implemented on a real e-commerce website and only considers product similarity for the purpose of reconstruction and recommendation.
An Efficient Fashion Recommendation System using a Deep CNN Model. Published By: 2022 the International Conference on Automation, Computing and Renewable Systems (ICACRS) [5]	Advantage: The proposed deep CNN model demonstrates high accuracy, utilizing strong feature extraction to deliver accurate fashion product recommendations. Its scalability and flexibility ensure optimal performance in dynamic e-commerce settings, effectively handling large datasets and adapting to changing fashion trends. Disadvantage: The deep CNN model's lack of interpretability makes it difficult to understand its decision-making process. Additionally, its heavy resource demands during training and reliance on large datasets could limit accessibility and introduce potential biases. Addressing these challenges will require efforts to improve interpretability, optimize resource use, and mitigate data biases.
Fashion Recommendation System Reflecting Individual’s Preferred Style. Published By: 2021 IEEE 10th Global Conference on Consumer Electronics (GCCE) [6]	Advantage: The fashion recommendation system can customize the same outfit for different users by considering their unique style preferences, offering personalized suggestions. By modifying the input outfit, the system can adjust factors like color, texture, and more to align with users' style choices, improving the level of customization. Disadvantage: The system's dependence on biased data, such as popular outfits and stereotype-driven influences, could limit the variety and inclusivity of recommended styles, potentially reinforcing existing fashion biases. Additionally, the accuracy of segmentation masks may be compromised if the background is not properly removed.
Content-based Clothing Recommender System using Deep Neural Network. Published By: 2021 26th International Computer Conference, Computer Society of Iran (CSICC) [7]	Advantage: This paper introduces a content-based clothing recommender system that incorporates gender as a feature, effectively tackling the cold start problem and achieving low loss. Additionally, the system offers fast recommendations due to its simplicity, as it uses product gender directly instead of extracting gender from an image. Disadvantage: However, the system shows lower accuracy, which could limit its ability to offer highly precise recommendations. Moreover, it relies on just two features for generating recommendations, restricting the scope and depth of its suggestions.
A Complexion based Outfit color recommender using Neural Networks. Published By: 2021 International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT) [8]	Advantage: This system offers multiple benefits for both users and e-commerce platforms. Users can virtually try on recommended outfits, enhancing their shopping experience by seeing how the clothes fit their body. It provides weather-based, seasonal outfit suggestions to meet real-time customer demand. The system also accurately recommends outfit colors based on the user's skin tone, utilizing advanced techniques such as skin segmentation and classification. Additionally, it uses the Cosine Similarity method to suggest similar outfits, making it a valuable tool for both users and e-commerce sites. The Image Warping technique is applied to fit the outfits onto 2D or 3D images, and the HoughCircles method is used to estimate the size of clothing. Disadvantage: The system categorizes outfits into 46 different types, which means it may not perfectly capture every category. It also overlooks other factors such as posture, hairstyle, and facial features. The model used, ResNet-18, is relatively simple, and more complex models could be employed by adding additional layers. Furthermore, the system currently does not include accessory recommendations.

An Online Recommendation System Using Deep Learning for Textile Products. Published By: 2020 International Congress on Human-Computer Interaction, Optimization, and Robotic Applications (HORA) [9]	Advantage: The system emphasizes color compatibility for textile products, which is a useful feature for customers looking to match items with their existing products. The proposed method achieves an overall accuracy of 82.08%, indicating its ability to deliver reliable recommendations. Disadvantage: The system primarily relies on patterns as the basis for recommendations, without taking into account other important factors like price, brand, or customer reviews, which may limit the relevance of its suggestions. Additionally, the paper does not compare the proposed CNN-based approach with other recommendation methods, such as collaborative filtering or content-based approaches, to highlight its advantages.
ViBE: Dressing for Diverse Body Shapes. Published By: 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) [10]	Advantage: The system takes diverse body shapes into account, offering a more inclusive and personalized clothing recommendation experience. By providing tailored suggestions based on individual body types, it enhances user satisfaction and overall experience. Disadvantage: One major limitation is the exclusion of male body types, which restricts the system's applicability to female users and limits its broader reach. Additionally, the focus on full-body clothing recommendations rather than items specific to individual body parts may not fully address the varied preferences and needs of users with different body shapes. The reliance on online catalog data may introduce biases toward body types commonly represented in the fashion industry, reinforcing existing stereotypes and norms. The subjectivity and variability of human judgment in evaluations also raise concerns about the consistency and reliability of the system's recommendations. Furthermore, the model's reliance on learned features and attributes may hinder its ability to adapt to new or unseen clothing styles, limiting its effectiveness in keeping up with the evolving fashion trends. These challenges underscore the need for further research to develop more inclusive and adaptable body shape recommendation systems.
FashionFit: Analysis of Mapping 3D Pose and Neural Body Fit for Custom Virtual Try-On. Published By: IEEE Access [11]	Advantage: This paper introduces an innovative approach to virtual try-on systems, providing a novel and clear model for visual compatibility through fashion image inpainting and virtual try-on. By utilizing advanced technologies like Generative Adversarial Networks (GANs) and Neural Body Fit, the model achieves high accuracy, representing a significant breakthrough in the field. It allows users to virtually try on custom-selected garments tailored to specific individuals, addressing a crucial gap in current fashion platforms and offering a more personalized and inclusive shopping experience. Moreover, the system's ability to generate custom clothing outfits using AI sets a new benchmark for the industry, demonstrating the potential to revolutionize virtual fashion try-on experiences. Disadvantage: One challenge is that the model used in this study is computationally intensive, which could lead to slower processing times and require significant computational resources. Additionally, the model is limited to the clothing categories available in the DeepFashion2 dataset, restricting the range of garments that can be virtually tried on. The absence of certain garments in the dataset may result in incomplete coverage of clothing items, reducing the model's applicability in real-world scenarios. Furthermore, the model's accuracy may be lower when tested with outfits generated by GANs, suggesting difficulties in generalizing to new and unseen data.
Dress With Style: Learning Style From Joint Deep Embedding of Clothing Styles and Body Shapes. Published By: IEEE TRANSACTIONS ON MULTIMEDIA [12]	Advantage: The model provides personalized style recommendations based on individual body shapes and clothing preferences, addressing a wide range of fashion needs. By utilizing deep multimodal representation learning, it enhances the user experience with customized fashion suggestions. The joint deep embedding of clothing styles and body shapes represents an innovative approach in fashion technology, which could lead to more advanced and effective recommendation systems in the future. Disadvantage: The model's training on datasets that mostly feature female clothing images may limit its relevance for male or gender-neutral fashion contexts. This could introduce biases or limitations in the model's recommendations, potentially affecting user satisfaction and perception, especially for individuals outside the scope of the model's training data.

Table 2. Types of approaches

Type of Approach	Techniques	Accuracy
Deep Learning, Machine Learning and Image Recognition [1]	CNN, ResNet-50, KNN (Euclidean distance and Cosine Similarity)	N/D
Artificial Intelligence And Deep Learning [2]	Fashion detection: CNN, fashion grammar based, retrieval based, joint image segmentation and labeling, Mask R-CNN, M-CNN, Cross-scenario retrieval, hierarchical superpixel merging, DARN, FashionSearchNet, PAFs, global-local embedding, Co-CNN, image co-segmentation, region co-labeling, domain-adaptive dictionary learning, attribute activation maps. Fashion Synthesis: GANs, Conditional Adversarial Networks, Virtual Garment Display Network, Neural Style Transfer, Spatial Segmentation Mask, Texture and Shape Disentanglement, Heatmap-Guided Semantic Disentanglement, Conditional Feature Interaction, FiLMedGAN, M6-UFC. Fashion Recommendation: Scenario-Oriented recommendation system, DFR, SFR, CRAFT, MANNs, SAFRS, LPAE, ARTEMIS.	N/D
Machine Learning and Memory Augmented Neural Networks (MANNs) [3]	Multi-Layer Perceptron, Memory Controller Training	AUC of 88.08 for combined approach, 80.77 for shape approach, 81.61 for color approach on IQON3000 dataset. AUC of 88.13 for combined approach, 81.37 for shape approach, 79.48 for color approach on FashionVC dataset.
Image Processing, Unsupervised Neural Network, Data Mining, Latent-Space Representation, Digital Signal Processing [4]	CNN	Loss in dataset: 0.001
Deep Convolutional Neural Network [5]	CNN, Stochastic gradient descent (SGD), Adam optimization, Cosine similarity	CNN: 89.02%
Deep Learning [6]	GANS	N/D
Deep Learning [7]	Deep Neural Network, CNN	CNN: Precision: 73.7%. Average Time: 0.07%.
Deep Learning [8]	CNN, ResNet-18, Approximate Nearest Neighbors, K-Means Clustering	92.61%

Deep Learning [9]	CNN	Accuracy: 82.08% Precision: 82.00% Recall: 83.50% F1-score: 82.30%
Deep Learning [10]	CNN, ResNet-50, Collaborative Filtering	Mean AUC of 0.611
Computer Vision, Deep Learning [11]	Variational Autoencoders (VAEs), Generative Adversarial Networks (GANs), Neural Body Fit (NBF)	80%
Deep Learning [12]	GoogleNet Inception-v3, Bi-DNN, CNN	0.73 (73%)

4.3 Inference

While the existing research in the field of fashion recommendation systems has made significant advancements in personalized recommendations, outfit generation, and color compatibility, there is a noticeable gap in the representation and recommendation of diverse fashion styles, especially those pertaining to specific cultural or regional fashion preferences. The majority of the reviewed papers focus on general fashion trends and preferences, often overlooking the nuances of specific styles such as Japanese fashion, traditional clothing, or cultural attire.

Additionally, there is limited exploration of the impact of user demographics, such as age, gender, and body shape, on fashion recommendations. There doesn't exist any existing system that can provide recommendations based on body shape, color complexion, hair style and similar characteristics of the user in a single platform. Understanding how these factors influence user preferences and style choices could lead to more accurate and relevant recommendations tailored to individual needs.

Furthermore, the lack of exploration into sustainable fashion practices and ethical considerations in the recommendation process. Incorporating elements of sustainability, such as eco-friendly materials or circular fashion concepts, could provide users with recommendations aligned with their values and preferences.

5. PROPOSED SYSTEM

Outfit Recommender System is meant to present appropriate outfits to the user according to his or her preference, the type, and fashion. This system is an outfit selection system designed to help users decide on the appropriate attire by operating a mechanism that can learn from user input to provide optimal dressing solutions. As the users interact with the system, the system will be able to change the precision and reliability of the recommendation for the particular user.

5.1 Existing System Architecture

The current system [10] utilizes ResNet-50 for feature extraction from clothing images and 3D body estimation for body shape analysis. Based on the extracted features, the system classifies clothes into five categories according to the body type of fashion models using CNN. The fashion model set only includes adult female models, with no representation of male models or individuals from other demographics. The clothes are further categorized into two types: full-body clothes and specific body items. When a user provides an image, the system recommends clothes that match their body type. However, the recommendation accuracy for specific body items is low, so these are not used by the system. The system effectively recommends full-body clothes with a mean AUC of 0.611. Additionally, users have the option to virtually try on the recommended clothes in a virtual environment.

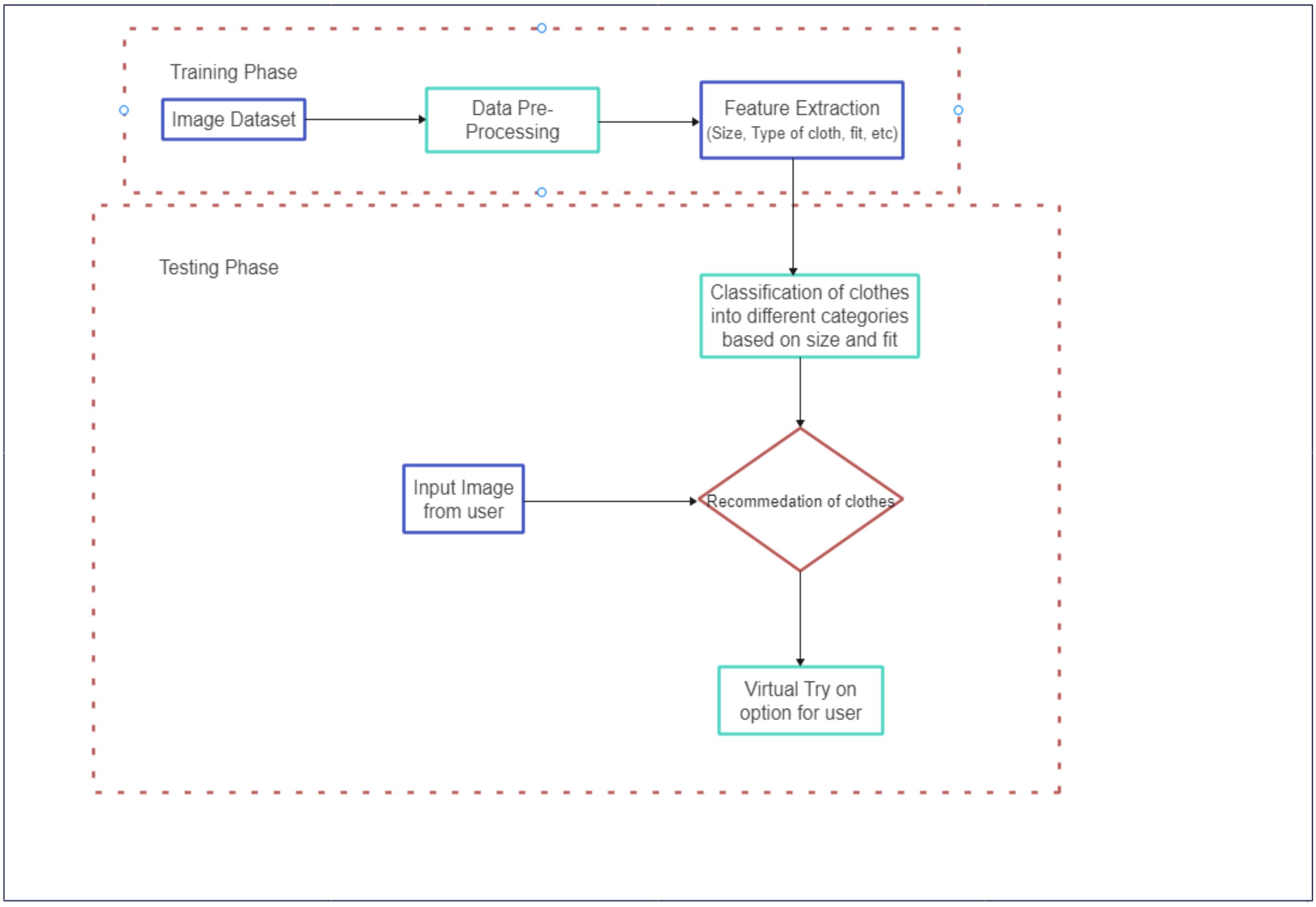

Figure 1: Existing system architecture [10]

Table 3. Existing Dataset

Dataset Name	Count	Subsets
Fashion-MNIST; DeepFashion2; FashionAI; Polyvore [2]	70,000; 491,647; 80,000; 1 million	grayscale images; annotations; landmark; outfit compositions
IQON3000; FashionVC [3]	672,335; 20,726	fashion items; outfits
Birdsnest [10]	999	fashion models
StyleReference [12]	2,160	body shapes

5.2 Input and Output Specifications of Existing System

5.2.1 Input Specification

The input of the user is taken as an image file, which is used to recommend clothes to the user on the basis of their body shape. Since the system is designed for the recommendation of clothes for adult females, the input image should be of an adult female, or the user can only be an adult female. [10]

5.2.2 Output Specification

An output image that is nothing but the recommended clothes for the user. The user has the option to try on these recommendations for themselves, i.e., these output images will be mapped to the input image of the user for virtual trial purposes. [10]

5.3 Proposed System Architecture

The proposed system includes the following components:

5.3.1 Dataset

The proposed system incorporates several datasets, including ones for skin complexion, body type, clothing, and more. It utilizes the Fashion Product Images (Small) dataset.

5.3.2 Feature Extraction

The features are extracted from the datasets as well as the input image and text from the user.

5.3.3 Classification of Clothes

The clothes are classified according to body type, fit, occasion and similar characteristics.

5.3.4 Feature Database

The feature database contains the features that were extracted from the dataset. The database contains a list of features extracted from images and texts.

5.3.5 Query Features

The query features are derived from the features input query and preserved. Color, shape, texture, and keywords are the extracted features.

5.3.6 Similarity Measurement

Query image features are compared with dataset features. A set of relevant images is retrieved then arranged in descending order of similarity.

5.3.7 Virtual Try-On

The virtual environment for users to try different recommended clothes on themselves.

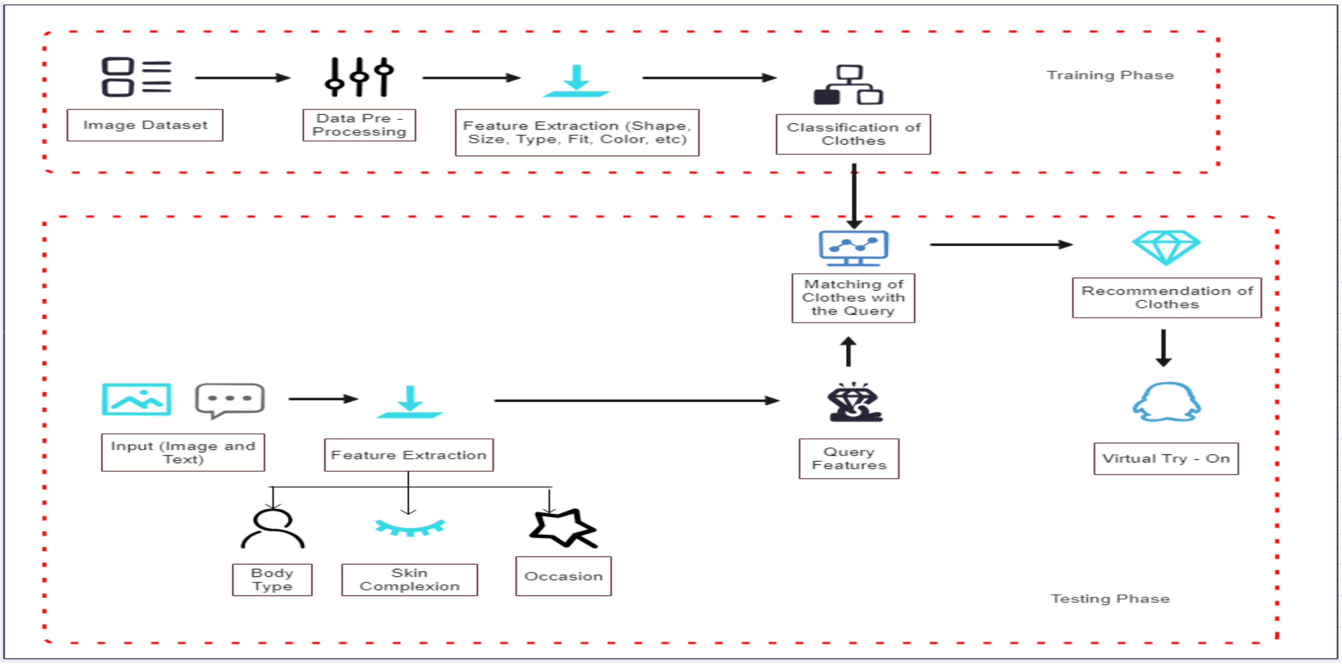

Figure 2: Proposed system architecture

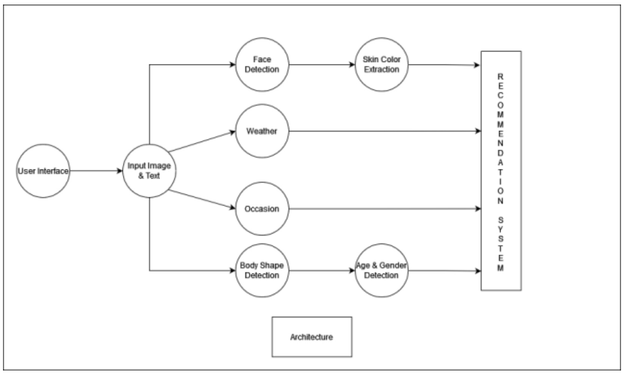

Figure 3:Block diagram for Feature Extraction

5.4 Datasets Used

Table 4. Dataset Details

Dataset Used	No. of Images	Types of Images	No. of Categories
Fashion Product Images (Small)	44,000	Dresses, shirts, pants, shoes, etc.	50

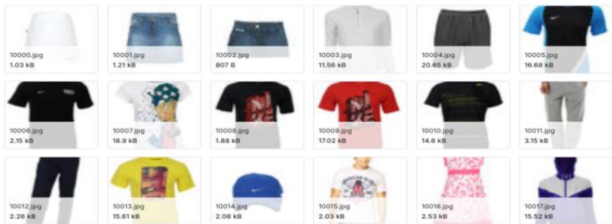

Figure 4: Sample of Dataset

5.5 Input and Output Specifications of Proposed System

5.5.1 Input Specification

The input of the user is taken as an image to determine the body shape and skin complexion of the user and a textual description of the occasion or event for which the user wants to get recommendations. Since the system is not specifically designed for adult females, the input image can be of any gender or age demographic, and the user can be of any gender or belong to any age demographic.

5.5.2 Output Specification

An output image that is nothing but the recommended clothes for the user. The user has the option to try on these recommendations for themselves, i.e., these output images will be mapped to the input image of the user for virtual trial purposes.

5.6 Use Case

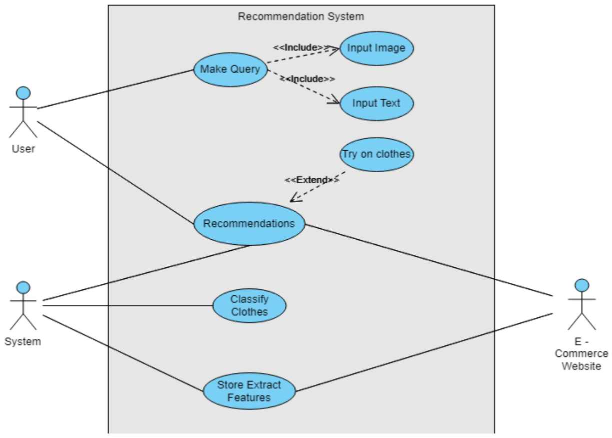

Figure 5: Use Case Diagram

6. METHODOLOGY

In this section, the proposed methodology for the outfit recommendation system is presented. The system is based on the ResNet-50 deep learning model for feature extraction from clothing images, and cosine similarity is utilized for recommending similar outfits based on the user's preferences and wardrobe.

6.1 Data Collection

The first step in developing the outfit recommendation system involves collecting a large dataset of clothing images. The dataset contains various categories of clothing, including tops, bottoms, shoes, and accessories. Each clothing item is labeled with metadata indicating the type, color, and style of the item. This labeled dataset serves as the foundation for training the recommendation system.

6.2 Data Preprocessing

Before feeding the dataset into the ResNet-50 model, preprocessing is performed to standardize the images. The images are resized to a fixed dimension of 224x224 pixels, ensuring uniformity across the dataset. Pixel values are normalized to a range of 0 to 1. Additionally, all images are converted to the RGB color format to maintain consistency. These preprocessing steps ensure the input data is in a suitable format for the model and can be effectively processed during training.

6.3 Feature Extraction with ResNet-50

For the feature extraction phase, the ResNet-50 architecture is employed. ResNet-50 is a convolutional neural network with residual learning capabilities, making it well-suited for extracting deep features from the clothing images. The model consists of 16 residual blocks, grouped into five stages. These residual blocks enable the network to learn hierarchical features and mitigate issues related to vanishing gradients.

The pre-trained ResNet-50 model, initially trained on a large-scale image dataset (e.g., ImageNet), is fine-tuned on the clothing dataset. The feature vectors extracted from the final convolutional layer of the network are used for subsequent similarity analysis. Specifically, the output from the final residual block is passed through a global average pooling layer, which reduces the spatial dimensions of the feature maps while retaining the depth of the features. These feature vectors are then used to compare clothing items and recommend similar outfits.

6.4 Cosine Similarity for Outfit Recommendation

Once the feature vectors for each clothing item have been extracted, cosine similarity is used to measure the similarity between items in the wardrobe and items in the dataset. Cosine similarity is calculated as:

$$\text{Cosine Similarity} = \frac{A \cdot B}{||A||\ ||B||}$$

where A and B represent the feature vectors of two clothing items, and $||A||$ and $||B||$ are their magnitudes. A higher cosine similarity score indicates that the two items are visually similar in terms of extracted features. By computing cosine similarity between the user's owned items and all items in the dataset, the system identifies the most similar clothing items.

Outfit recommendations are generated by selecting the top-N most similar items based on the cosine similarity scores. These recommendations are tailored to the user's wardrobe and preferences, ensuring personalized and relevant outfit suggestions.

6.5 Model Training and Fine-Tuning

The ResNet-50 model undergoes fine-tuning to adapt to the specific characteristics of clothing images. Initially, the model is pre-trained on a large image dataset such as ImageNet. Fine-tuning is then carried out by training the model on the clothing dataset, updating the model’s weights using backpropagation. During this phase, the model learns to refine its feature extraction capabilities to capture visual features specific to clothing items, improving its ability to recommend outfits based on user preferences.

The training process involves using a standard cross-entropy loss function to evaluate the model's performance and update the weights through backpropagation. The training process is repeated for several epochs until the model achieves satisfactory performance in terms of accuracy and convergence.

6.6 Evaluation and Performance Metrics

To assess the performance of the outfit recommendation system, various evaluation metrics are employed, including accuracy, precision, and recall. These metrics measure how effectively the system is able to recommend relevant items based on the cosine similarity scores. Additionally, user feedback and interaction with the system are used to fine-tune the recommendation thresholds and improve the relevance of suggestions.

6.6.1 Precision

Precision is the number relevant to the query building retrieved images with respect to the total number of retrieved images.

$$\text{Precision} = \frac{\text{No. of retrieved relevant images}}{\text{No. of relevant images}}$$

6.6.2 Recall

Recall is the number of relevant to the query building retrieved images with respect to the number of identical query building retrieved images.

$$Recall = \frac{No.\,of\ retrieved\ relevant\ images}{No.\,of\ retrieved\ images}$$

6.6.3 Accuracy

Accuracy is defined as how the values that are measured are close to the intended target (value) or simply, an assessment of correctness. Thus, if the measurements are accurate, then the values are close to the target. For the calculation of accuracy with respect to each class, The following formula has been used.

$$Accuracy = \frac{Total\ true\ positive\ samples}{Total\ number\ of\ samples}$$

6.7 Inference and User Interaction

For inference, the trained ResNet-50 model is used to extract features from the clothing images and generate recommendations for the user. When a user inputs their preferences, such as specific clothing items or styles they own, the system calculates the cosine similarity between the user’s selected items and those in the database. The system then recommends the top-N most similar items as potential outfit combinations. This interaction ensures that the recommendations are personalized, helping users make informed decisions about their wardrobe choices.

7. HARDWARE AND SOFTWARE SPECIFICATIONS

The experiment setup is carried out on a computer system which has the different hardware and software specifications as given in Table V and Table VI respectively.

Table 5. Hardware Details

Processor	2.40GHz Intel
RAM	8 GB
HDD	512 GB
Graphics	2 GB

Table 6. Software Details

Operating System	Windows 10
Programming Languages	Python, HTML, CSS, JavaScript
IDE	VS Code
Database	MongoDB
Packages	PIL, NumPy, Keras, TensorFlow

8. RESULTS

In this outfit recommendation system, the user begins by uploading a full-body image and entering text details about the weather and occasion. The image undergoes preprocessing to enhance visibility of key features like body shape, while the text input is parsed to extract specific information about the weather (e.g., hot, cold, rainy) and occasion (e.g., casual, formal). The processed image is passed through a convolutional neural network (CNN) trained on a dataset of 44,000 images, which extracts essential visual features such as body landmarks, clothing types, and style details like color, texture, and pattern.

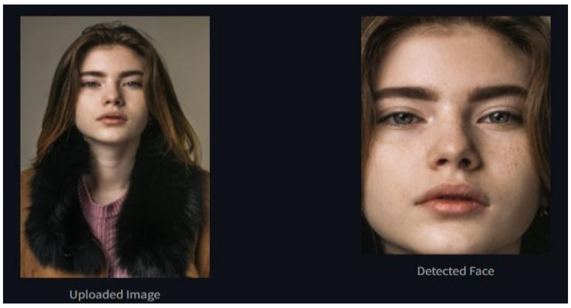

Figure 6: Face detection

Figure 7: Face detection & Skin Color Extraction

Figure 8: Age & Gender Detection

Figure 9: Body Shape Detection

These extracted image features, along with contextual data from the user's input, enable the system to match and prioritize outfits that are both suitable for the environment and align with social expectations. The model generates a selection of personalized outfit recommendations that align with the user's style and occasion needs, ensuring options that are comfortable, stylish, and seasonally appropriate. Each recommended outfit is displayed with additional details, allowing the user to view various combinations and refine selections for the best fit. This workflow combines image-based analysis with contextual factors to provide a curated set of outfits tailored to the user's body type, weather, and occasion.

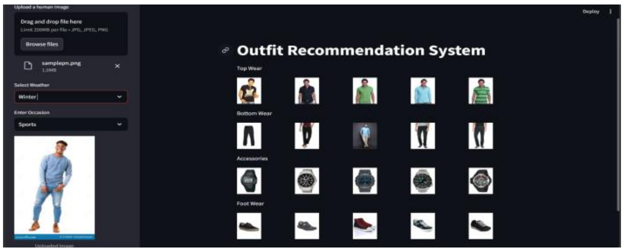

Figure 10: Outfit Recommendation for Male

Figure 11: Outfit Recommendation for Female

Figure 12: Similar Outfit Recommendation for Male

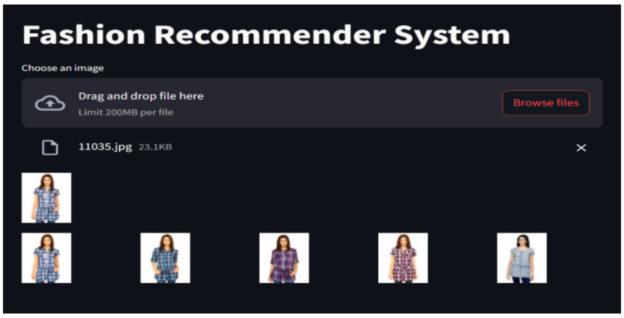

Figure 13: Similar Outfit Recommendation for Female

9. PERFORMANCE EVALUATION

An evaluation metric quantifies the performance of a predictive model. This typically involves training a model on a dataset, using the model to make predictions on a holdout dataset not used during training, then comparing the predictions to the expected values in the holdout dataset. Precision and Recall are based on understanding and measure of relevance.

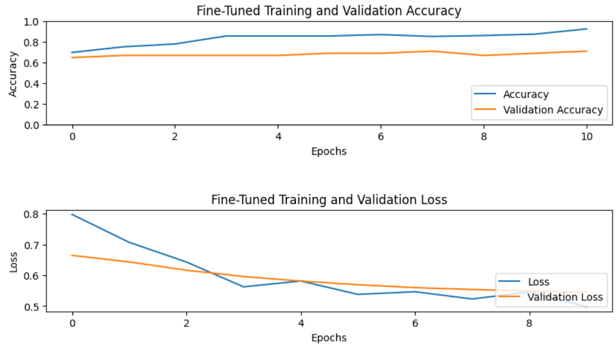

Figure 14: Training Accuracy and Loss for Gender Detection

The figure demonstrates the performance of a model for gender detection in terms of accuracy and loss over several epochs. The accuracy graph shows that both training and validation accuracy improve steadily, with validation accuracy slightly lower than training accuracy, which may suggest mild overfitting as the model trains. The loss graph shows a consistent decrease in both training and validation loss over the epochs, indicating the model's optimization during training. The parallel trends between training and validation loss also suggest that the model generalizes relatively well.

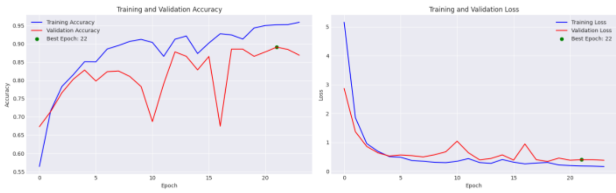

Figure 15: Training Accuracy and Loss for Age Detection

This figure represents the model's performance for age detection. The accuracy graph shows a sharp increase during the initial epochs, followed by fluctuations in validation accuracy, which suggests that the model struggles to generalize on the validation data. The training accuracy steadily improves throughout. The loss graph exhibits a sharp decrease in both training and validation loss in the initial epochs. However, the validation loss displays fluctuations, indicating possible overfitting or variability in the performance across different age groups.

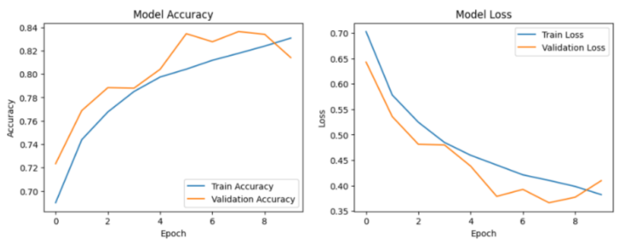

Figure 16: Training Accuracy and Loss for Skin Tone Detection

The figure shows the accuracy and loss trends for the skin tone detection model. Both training and validation accuracy increase steadily across epochs, with a slight drop toward the later epochs, indicating a potential issue with overfitting as the training progresses. The loss graph shows that both training and validation loss decrease significantly, although the validation loss starts to fluctuate slightly in the later epochs, suggesting that the model may not be fully stable on unseen data despite its good overall performance.

Epoch	Training Loss	Validation Loss	Model Preparation Time	Accuracy
1	No log	0.255447	0.005600	0.904821
2	0.112800	0.253229	0.005600	0.905129
3	0.112800	0.247708	0.005600	0.909371
4	0.109200	0.250833	0.005600	0.907597
5	0.101300	0.249500	0.005600	0.906980
6	0.101300	0.255748	0.005600	0.905283
7	0.097000	0.252122	0.005600	0.908523
8	0.097000	0.261417	0.005600	0.903587
9	0.098100	0.254243	0.005600	0.906672
10	0.092800	0.249651	0.005600	0.908754
11	0.092800	0.248088	0.005600	0.909834
12	0.088000	0.251238	0.005600	0.909063
13	0.088000	0.249874	0.005600	0.909063
14	0.085500	0.248059	0.005600	0.909911

Figure 17: Performance Evaluation for Recommendation System

This table outlines the performance of the recommendation system across multiple epochs. It shows the training loss, validation loss, model preparation time, and accuracy for each epoch. The model achieves low training and validation losses, with consistent preparation times. The accuracy values are high across all epochs, consistently above 90%, indicating a strong overall performance of the recommendation system. The fluctuations in validation loss are minimal, suggesting that the model generalizes well to new data while maintaining efficient processing time.

10. CONCLUSION

The outfit recommender project aims to utilize machine learning, deep learning and artificial intelligence algorithms to provide personalized outfit recommendations to users based on their preferences, body type, style, skin tone and the occasion. By analyzing user input such as clothing choices, favorite colors, style preferences, and the photo of the user, the system generates tailored outfit suggestions from a database of clothing items and accessories. The project focuses on improving user experience, enhancing fashion choices, and promoting self-expression through technology. Key features include a user-friendly interface, real-time outfit suggestions, and the ability to save and share favorite looks. The project aims to revolutionize the way people approach fashion and empower users to make confident and stylish outfit choices effortlessly.

11. FUTURE SCOPE

11.1 Integration with E-commerce Platforms

The outfit recommender can be integrated with e-commerce platforms to allow users to directly purchase the recommended clothing items, creating a seamless shopping experience and driving sales for retailers.

11.2 Personal shopping assistant

The outfit recommender can be integrated into a personal shopping app to help users find the perfect outfit for any occasion. By analyzing user preferences and style trends, the app can suggest outfits that match the user's taste and fit requirements.

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