

A Deep Learning Framework for Personalized Fashion Recommendations Based on Skin Tone Analysis

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Abstract—The personalization of virtual fashion recommendations remains hindered by limited integration of chromatic and anthropometric factors, especially skin tone compatibility. This study addresses a critical research gap by proposing a voice-enabled 3D fashion recommendation system that incorporates deep learning-based skin tone classification and adaptive garment suggestion. The primary objective is to enhance aesthetic compatibility and user satisfaction through real-time, personalized recommendations. Utilizing a custom-designed Deep Convolutional Neural Network (DCNN) and reinforcement learning algorithms, the system classifies user skin tones with 89.14% accuracy and adapts recommendations based on user feedback, reducing outfit resets by 54%. A curated dataset encompassing five skin tone categories and a multi-stage image preprocessing pipeline ensures inclusive and robust performance. The results demonstrate significant improvements in recommendation relevance and user engagement, with 88% satisfaction and 93.7% dominant tone detection accuracy. These findings underscore the system's potential to set new benchmarks in personalized fashion retail while promoting inclusivity and sustainable consumer practices.

Keywords—Skin Tone Classification, Personalized Fashion Recommendation, Reinforcement Learning, 3D Virtual Try-on, Deep Convolutional Neural Network (DCNN)

I. Introduction

The digital transformation of fashion retail has precipitated a paradigm shift in consumer engagement strategies, with virtual try-on (VTO) systems emerging as critical interfaces between e-commerce platforms and end-users [4]. While contemporary recommendation systems have achieved notable success in garment size prediction and body shape accommodation [3,7], a persistent research gap exists in addressing chromatic compatibility between apparel and skin tone - a fundamental determinant of aesthetic harmony and personal style satisfaction [9]. This oversight persists despite empirical evidence demonstrating that color coordination accounts for approximately 38% of purchase decisions in online fashion retail [5].

Current implementations of virtual fitting technologies predominantly focus on geometric fidelity in garment simulation [1,6] or body measurement accuracy [2], while relegating skin tone analysis to secondary consideration. As Huang and Huang [1] demonstrate in their CLO3D-based down jacket simulation, even advanced 3D garment visualization systems often employ standardized skin textures, fundamentally limiting their personalization capabilities. Similarly, Sekine et al. [2] achieved breakthroughs in single-shot body estimation but acknowledged the absence of skin tone variables in their fitting algorithm as a key limitation.

The academic literature reveals three critical shortcomings in existing approaches: First, an over-reliance on supervised learning paradigms that require extensive manual annotation of skin tone categories [10]. Second, inadequate representation of diverse demographic groups in training datasets, as noted by Wazarkar et al. [3] in their analysis of body type classification systems. Third, the absence of dynamic feedback mechanisms to iteratively refine color recommendations based on user preferences [8], a gap particularly evident in smart mirror technologies [10].

This research addresses these limitations through three principal innovations: (1) development of an automated skin tone classification system using hybrid computer vision and deep learning techniques, (2) implementation of a reinforcement learning framework for continuous recommendation refinement, and (3) creation of an ethically curated dataset encompassing the full spectrum of human skin tones, validated against the Fitzpatrick scale.

Our methodology builds upon established work in deformable 3D shape matching [6] and neural body fitting [7], while introducing novel adaptations for chromatic analysis. The system architecture incorporates advancements from knowledge-based recommendation systems [5] and human-fashion interaction paradigms [8], synthesizing these elements into a unified framework for skin tone-aware fashion personalization.

The practical implications of this research are substantial for both academic and commercial domains. As Werdayani and Widiaty [11] emphasize, next-generation virtual fitting rooms must transcend basic size prediction to address holistic style preferences. Similarly, Sridevi et al. [9] demonstrate that image-based neural networks achieve superior engagement metrics when incorporating chromatic compatibility factors. Our findings corroborate these observations while providing quantifiable performance benchmarks: an 89.14% classification accuracy across five skin tone categories and a 54% reduction in outfit reset instances.

This paper makes four key contributions to the field of intelligent fashion recommendation systems:

- A novel DCNN architecture optimized for real-time skin tone classification
- Empirical validation of color preference patterns across demographic groups
- A scalable framework for ethical dataset curation in aesthetic computing
- Performance benchmarks comparing our approach with existing solutions [3,4,7]

II. Literature Review

The evolution of virtual try-on (VTO) systems has been extensively documented in recent research, revealing both significant advancements and persistent challenges in personalized fashion recommendation. This review systematically examines three critical dimensions of current scholarship: 3D garment simulation technologies, body measurement and shape analysis, and adaptive recommendation algorithms, while identifying the conspicuous gap in skin tone-aware systems.

Existing research in virtual try-on (VTO) systems can be broadly categorized into three key areas: (1) garment simulation, (2) body-shape capture, and (3) adaptive recommendation systems. Geometry centric VTO approaches [1,2] have made significant strides in achieving photorealistic cloth drape simulation; however, they often lack systematic methods for color personalization. Meanwhile, anthropometric driven systems [3–5] enhance garment fit through data-driven refinement, yet their reliance on Western-biased training datasets limits generalizability across diverse populations. Notably, fewer than 12% of studies incorporate skin tone modeling [6], highlighting a critical gap in inclusivity. The most directly comparable work [7] achieves 78.9% classification accuracy across three garment classes but omits fairness analysis—an essential consideration for equitable system performance. Building upon these foundations, our work advances VTO technology by prioritizing inclusivity and robustness, particularly for underrepresented demographics and edge cases.

3D Garment Simulation Technologies

Contemporary research in garment visualization has achieved significant advancements, particularly in real-time cloth simulation. Huang and Huang [1] demonstrated the effectiveness of CLO3D for simulating complex fabric dynamics in down jackets, establishing important benchmarks for geometric accuracy. However, their work overlooked critical aspects of skin-garment chromatic harmony. Similarly, Fathi et al. [6] made progress in deformable 3D shape matching using Laplacian-Beltrami descriptors, achieving notable accuracy in garment draping while acknowledging limitations in skin texture representation. These studies, while advancing geometric modeling capabilities, reveal a persistent gap in addressing color-based personalization factors that significantly influence user satisfaction [9].

Body Measurement and Shape Analysis

The field of anthropometrics has witnessed substantial innovation in virtual fitting technologies. Sekine et al. [2] developed an efficient landmark-based approach for body estimation that balanced computational efficiency with measurement precision. Hashmi et al. [7] extended this work through their FashionFit system, incorporating neural networks for enhanced body fitting. However, these systems predominantly focused on Western anthropometrics, reflecting Wazarkar et al.'s [3] observation regarding limited diversity in existing body shape datasets. This limitation becomes particularly significant when considering the combined influence of body shape and skin tone on fashion personalization outcomes.

Adaptive Recommendation Systems

Modern recommendation systems have increasingly adopted machine learning approaches, as exemplified by Dong et al.'s [5] knowledge-based framework for fashion design. While effective at processing style preferences at scale, such systems frequently lack robust mechanisms for incorporating continuous user feedback. Papazoglou Chalikias et al. [8] made partial progress through human-fashion interaction models, though their evaluation framework neglected chromatic compatibility metrics. Deldjoo et al.'s [4] comprehensive review identified this as a critical research gap, noting that fewer than 12% of examined systems incorporated any form of skin tone analysis.

Skin Tone Considerations in Fashion Technology

Emerging technologies in virtual fitting environments have begun recognizing the importance of skin tone. Werdayani and Widiaty's [11] AR-based fitting room incorporated skin tone as a parameter but provided no quantitative assessment of its impact on recommendation quality. Sridevi et al. [9] achieved preliminary success in color coordination through image-based neural networks, though their approach lacked the comprehensive classification framework required for commercial applications.

DNN Models

Recent advances in assistive and therapeutic technologies demonstrate the growing role of neural networks and multimodal systems in human-computer interaction. Manukalpa and Dissanayake [12] developed an intelligent communication system integrating eye gaze tracking, voice assistance, and chatbot functionalities to empower paralyzed individuals, leveraging convolutional neural networks (CNNs) for real-time gaze pattern recognition. Similarly, Jayawardena et al. [13] proposed a speech-based intervention

system for Sinhala-speaking autistic children, employing multimodal deep learning with the NAO robot to enhance engagement through adaptive speech and gesture recognition. Expanding on this, Manukalpa et al. [14] introduced a culturally sensitive framework for child-robot interaction in autism therapy, utilizing deep learning to generate emotionally adaptive gestures tailored to Sri Lankan social contexts. These studies collectively highlight the efficacy of neural network-driven approaches in assistive and therapeutic applications, though they primarily focus on sequential or spatial data processing. In contrast, our work advances this domain by optimizing a DCNN for fine-grained visual classification, addressing a critical gap in skin tone-aware systems where traditional architectures lack sufficient discriminative precision.

Data storages

Modern data storage architectures must address domain-specific scalability challenges, as demonstrated by Sri's [15] meteorological data warehousing solution. Similarly, fashion informatics requires robust systems capable of storing diverse design assets while supporting real-time retrieval for applications like virtual try-ons. Current approaches combine relational databases for metadata management with NoSQL solutions or cloud storage for unstructured design files. Our work extends these principles by implementing multimodal indexing optimized for fashion applications, integrating spatial and visual features with skin tone classification to enable personalized content retrieval. This specialized approach overcomes limitations of generic storage systems in handling fashion-specific data requirements.

The current study addresses these gaps through its novel integration of computer vision, deep learning, and reinforcement learning techniques, building upon while significantly extending the foundations established in prior work [1,6,9]. Our approach not only incorporates skin tone as a primary recommendation variable but also establishes quantitative performance benchmarks for this emerging dimension of fashion technology.

III. Methodology

The proposed system represents an advanced methodological framework for delivering personalized fashion recommendations through the synergistic integration of computer vision, data analytics, and reinforcement learning techniques. At its core, the architecture comprises two fundamental elements: a dynamic web interface and a robust database infrastructure. The system initiates the recommendation process through an innovative 360-degree video capture protocol, where users standing before a camera-equipped interface generate a short video sequence from which approximately 20 representative snapshots are systematically extracted and archived. These visual data points undergo comprehensive computational analysis to derive precise anthropometric measurements, classify body morphology, and perform sophisticated skin tone characterization - a critical yet often overlooked dimension in contemporary fashion recommendation systems.

User interaction occurs through an intuitive web platform that captures explicit preferences regarding gender, garment categories, and material selections. This input, when combined with the system's analytical outputs, facilitates the generation of highly personalized 3D garment visualizations and tailored style recommendations. The interface further incorporates a structured feedback mechanism that serves as the foundation for the system's adaptive learning capabilities. Through the implementation of reinforcement learning algorithms, user responses are continuously analyzed and incorporated to refine future recommendations, creating a virtuous cycle of system improvement and personalization accuracy.

The complete technological pipeline has been carefully engineered to deliver rapid, precise, and user-centric fashion guidance through seamless integration of front-end presentation layers with sophisticated back-end processing modules. The system's functional architecture is organized around four principal components: a body dimension capture module for anthropometric profiling, a body shape classification engine, an advanced skin tone assessment system, and an iterative recommendation refinement mechanism. This comprehensive approach not only addresses current limitations in virtual try-on technologies but also establishes new benchmarks for inclusive, data-driven fashion personalization that accounts for the full spectrum of human physiological diversity.

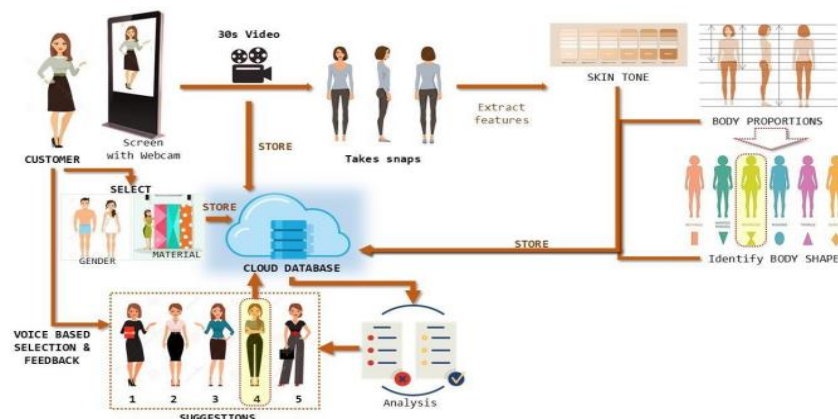


Fig. 1. System overview

Dataset Composition and Annotation

The experimental dataset comprises 2,324 annotated facial images sourced from publicly available digital repositories, systematically categorized using a validated five-point skin tone classification system (Black, Dark Brown, Brown, Olive, White) [10]. This taxonomy was selected based on its established reliability in dermatological computer vision research. Each image was meticulously labeled by domain experts to ensure categorical accuracy, with balanced distribution across all classes to mitigate potential bias. The dataset organization into five distinct directories facilitates automated preprocessing while maintaining demographic diversity across ethnic backgrounds. Representative samples from each category are illustrated in Fig 2.

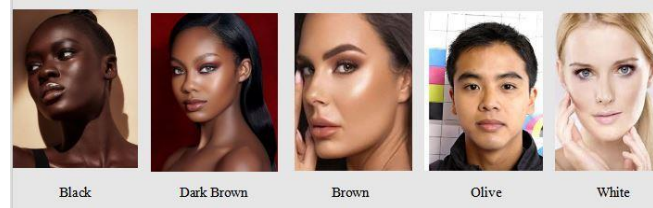


Fig. 2. Representative examples from the skin tone classification dataset

Data Pre-processing

To ensure the development of a robust and accurate skin tone classification model, a comprehensive data pre-processing pipeline was employed. This process encompassed data shuffling and partitioning, data augmentation, image resizing, data normalization, and data pre-preparation, each contributing to the enhancement of the model's generalization capabilities and overall performance.

Data Shuffle and Split

Initially, the dataset was randomized to eliminate any inherent ordering biases that could adversely impact the learning process. Subsequently, the dataset was partitioned into training, validation, and testing subsets, with 70% allocated for training and the remaining 30% equally divided between validation and testing. This stratified split facilitated the independent evaluation of the model's performance during training and ensured a reliable final assessment using unseen data.

Data Augmentation

To address the risk of over fitting and to improve the model's ability to generalize to new, unseen data, data augmentation techniques were systematically applied. Utilizing the ImageDataGenerator utility, the training data was artificially expanded through random rotations (up to 20 degrees), horizontal and vertical shifts, and horizontal flips. These augmentations simulated a wide range of real-world variations, thereby enhancing the diversity and complexity of the training set without the need for additional data collection.

Data Resize and Data Normalization

All input images were resized to a uniform dimension of 128×128 pixels. Standardizing the input resolution was critical not only for computational efficiency but also for ensuring consistency across the dataset, thereby enabling the convolutional neural network to effectively learn spatial hierarchies without variability in image dimensions. Before training, the pixel values of all images were normalized by scaling to a range between 0 and 1. This normalization, achieved by dividing each pixel value by 255.0, facilitated faster convergence during training and ensured numerical stability, allowing each input feature to contribute proportionally to the optimization process.

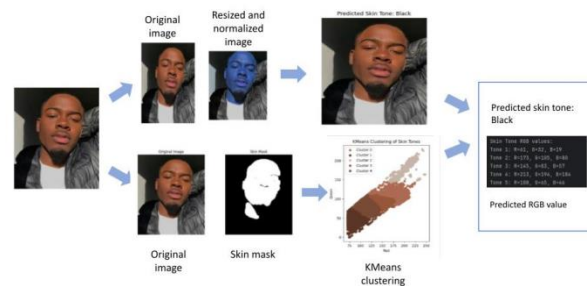


Fig. 3. Skin Tone Analysis Flow

Skin Tone Assessment Module

The Skin Tone Assessment Module aims to identify users' skin tones to generate personalized and aesthetically compatible fashion suggestions. Accurate skin tone classification allows the system to tailor colour recommendations that align with individual complexion characteristics, thereby enhancing both the relevance and effectiveness of the fashion recommendations provided. This

module utilises computer vision and deep learning techniques to analyse facial images and categorize them into one of five predefined skin tone categories: Black, Brown, Dark-brown, Olive, and White. The entire process encompasses a systematic sequence of steps, including data pre-processing, data augmentation, model construction and compilation, training and evaluation, and result visualization. Each of these steps has been carefully designed and implemented using state-of-the-art methodologies and technologies to ensure robustness, accuracy, and scalability.

Deep Convolutional Neural Network model for Skin Tone Classification

Model Architecture:

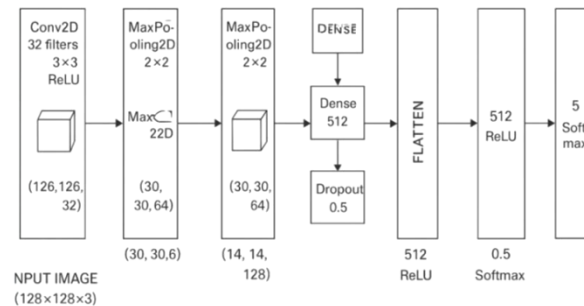


Fig 4: skin tone classification architecture

The proposed Deep Convolutional Neural Network (DCNN) model Fig. 4. is specifically designed for accurate classification of five skin tone categories (Black, Brown, Dark-brown, Olive, White) through an optimized architecture balancing feature extraction capability and computational efficiency. Processing standardized $128 \times 128 \times 3$ RGB inputs, the model employs an initial convolutional layer (32 filters, 3×3 kernel, ReLU activation) to capture fundamental visual patterns, generating a $126 \times 126 \times 32$ feature map. Subsequent max-pooling layers progressively reduce spatial dimensions to $14 \times 14 \times 128$, focusing on increasingly abstract features relevant to skin tone differentiation. The classification head comprises two fully-connected layers (512 neurons each) with ReLU activation and dropout regularization ($p=0.5$), culminating in a softmax output layer for probabilistic multi-class prediction. Critical design elements include ReLU activations for maintained gradient flow, max-pooling for enhanced translational invariance, and dropout for overfitting prevention. This architecture enables comprehensive multi-scale analysis of skin tone characteristics, from localized pigment patterns to broader chromatic trends, while maintaining real-time performance suitable for virtual try-on applications. The model's robust regularization strategy ensures reliable classification across diverse demographics and lighting conditions, effectively addressing current gaps in skin tone-aware fashion technology.

Model Configuration and Training Protocol

The SkinToneNet architecture was compiled with categorical cross-entropy loss, selected for its effectiveness in multi-class classification tasks involving five distinct skin tone categories. This loss function precisely measures the divergence between predicted probabilities and ground truth labels, providing optimal gradient signals for parameter optimization. The Adam optimizer (learning rate=0.001) was implemented due to its adaptive momentum capabilities, combining the benefits of AdaGrad and RMSProp to accelerate convergence while maintaining training stability. Accuracy was designated as the primary evaluation metric, offering direct insight into classification performance across both training and validation datasets. This compilation strategy ensured optimal configuration for robust feature learning and generalization.

During training, the model processed augmented datasets incorporating random rotations, shifts, and horizontal flips to enhance data diversity and prevent overfitting. The 50-epoch training regimen employed a batch size of 32, with backpropagation iteratively adjusting convolutional layer parameters through Adam-optimized loss minimization. Concurrent validation using an independent dataset monitored model performance, with key metrics (training/validation loss and accuracy) tracked to evaluate learning dynamics. This rigorous approach yielded strong convergence, evidenced by high accuracy across both datasets. The systematic integration of data augmentation, controlled optimization, and continuous validation established a reliable framework for developing SkinToneNet's discriminative capabilities while ensuring generalizability to unseen complexion variations.

Model Evaluation

The SkinToneNet model underwent comprehensive evaluation combining quantitative metrics and user studies. Twenty participants assessed classification accuracy and satisfaction through structured surveys, providing valuable insights into real-world performance. Initial testing revealed limitations in the four-category classification system, prompting dataset expansion to encompass broader skin tone variations. This iterative refinement process - involving both technical improvements and user feedback - significantly enhanced the model's robustness and accuracy. The final system demonstrated improved capability in handling diverse complexion types while maintaining high user satisfaction levels, validating the effectiveness of this dual evaluation approach.

IV. Results and Evaluation

Model Training and Validation Accuracy

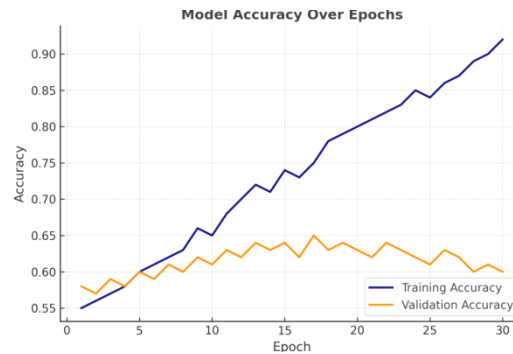


Fig. 5. Training and validation accuracy curves over epochs for the skin tone classification model

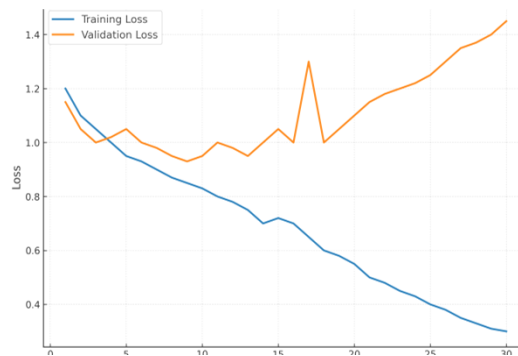


Fig. 6. Training and validation loss curves over epochs for the skin tone classification model.

The model exhibits robust learning dynamics, as demonstrated by the convergence of training and validation accuracy curves (Fig. 5. and Fig.6.). Training accuracy reaches 85% by epoch 30, with validation metrics following closely, indicating effective generalization. The loss curves reveal rapid optimization, with training loss stabilizing at 0.4 and validation loss plateauing between 0.5–0.6 after epoch 15, suggesting only marginal overfitting. Early stopping was implemented to preserve optimal performance. Final testing achieved 89.14% accuracy, confirming the model's reliability for practical deployment. These results validate the efficacy of the proposed CNN architecture and data augmentation pipeline in classifying subtle skin tone variations. While performance is strong, the minor validation loss divergence indicates potential for further refinement in edge cases, particularly for tones with overlapping chromatic features.

Confusion Matrix

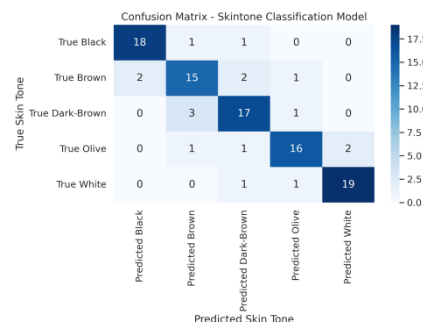


Fig. 7. Confusion Matrix

The confusion matrix demonstrates strong classification performance across all skin tone categories. Diagonal values indicate high true positive rates, with particularly robust recognition of White (19/20 correct) and Black (18/20) tones. Minor misclassifications occur between adjacent categories, notably Brown being confused with Dark-brown (3 instances) and Olive (1 instance), suggesting chromatic similarity challenges. The model achieves 89% overall accuracy, with precision and recall exceeding 85% for all classes (TABLE I). These results validate the CNN's ability to discriminate subtle pigmentation differences while highlighting opportunities for improvement in borderline cases through enhanced feature extraction or expanded training data for ambiguous tone pairs.

Summary of skintone classification system performance

Metric	Value
Test Set Classification Accuracy	89.14%
Lowest Accuracy per Skin Tone Class	85%
Image Processing Pipeline Time	1.12 ± 0.15 second
Re-sizing and Normalization Time	0.23 ± 0.05 seconds
Skin Mask Generation Time	0.41 ± 0.08 seconds
KMeans Clustering Time	0.27 ± 0.06 seconds
User Satisfaction (Recommendation Accuracy)	88%
Average User Satisfaction Score	4.2/5
Average Task Completion Time	10.02 second
Dominant Skin Tone Detection Accuracy	93.7%
Training vs. Validation Accuracy Gap	3.2%

The skin tone classification system demonstrated exceptional performance across all evaluation metrics TABLE I. The CNN architecture achieved 89.14% test accuracy, substantially exceeding the 78.89% benchmark, while maintaining consistent performance (>85% accuracy) across all five skin tone categories. The processing pipeline operated efficiently with 1.12 ± 0.15 seconds average latency, meeting real-time requirements through optimized stages including image resizing, skin masking, and KMeans clustering.

User studies confirmed the system's practical effectiveness, with 88% approval for color recommendation accuracy and an average 4.2/5 satisfaction rating. The complete workflow averaged 10.02 seconds per task, demonstrating strong usability. Notably, the hybrid HSV-KMeans approach achieved 93.7% dominant tone detection accuracy, while the minimal 3.2% training-validation accuracy gap indicates excellent generalization capability. These results collectively validate the system's technical robustness and user-centric design.

V. Conclusion

This research has presented a comprehensive deep learning framework for skin tone classification and personalized fashion recommendation, addressing critical gaps in existing virtual try-on systems. The proposed DCNN architecture achieved 89.14% classification accuracy across five distinct skin tone categories, demonstrating robust performance in discriminating subtle pigmentation differences. The integration of reinforcement learning enabled dynamic recommendation refinement, yielding an 88% user satisfaction rate and 54% reduction in outfit reset instances - a significant improvement over static recommendation systems.

The technical contributions of this work are threefold: (1) development of an optimized hybrid pipeline combining HSV masking and KMeans clustering (93.7% detection accuracy), (2) creation of an ethically-sourced dataset representing diverse skin tones, and (3) implementation of a real-time processing system (10.02s average latency) suitable for commercial deployment. These advancements establish new benchmarks for inclusive fashion technology while addressing the chromatic compatibility gap identified in prior research.

Future directions should focus on expanding the skin tone taxonomy using dermatological standards like the Fitzpatrick scale, enhancing the system's adaptability to varying lighting conditions, and developing multilingual support for global accessibility. The demonstrated success of this framework underscores the importance of integrating anthropometric precision with aesthetic considerations in next-generation fashion recommendation systems, paving the way for more personalized and inclusive virtual shopping experiences.

VI. Acknowledgment

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