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Enhancing Fashion Choices: AI-Powered Style Analysis and Recommendations

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ABSTRACT

Fashion has always been an essential feature of our daily routine. It plays an important role in everyone's life. The online fashion market continues to grow, and an algorithm capable of identifying clothing can help companies in the apparel industry understand the profile of potential buyers and focus sales on specific niches. Artificial intelligence capable of understanding, recommending and labeling human clothing is essential, and can be used to improve sales or better understand users. In this paper, we used our own generated dataset, where the total number of data was 1000. The dataset contains total 10 categories such as shirt, punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear. All the data we have collected from online like social media, google, facebook, instagram, linkedin. The topic combines the fields of fashion, style and machine learning to create a system that can analyze fashion images, classifying them into different styles. In this paper I have used the Customize CNN Algorithm, through which we have used the 7 architectures of CNN. The 7 custom CNN methods we used are MobileNetV2, MobileNetV3, EfficientNet B0, EfficientNet B3, Inception V3, DenseNet201 and VGG19. Here we can see that the accuracy of MobileNetV2 is 59%, the accuracy of MobileNetV3 is 75%, the accuracy of EfficientNet B0 is 80%, the accuracy of EfficientNet B3 is 86%, the accuracy of Inception V3 is 60%, the accuracy of DenseNet201 is 65% and the accuracy of VGG19 is 85%.

Keywords: Artificial Intelligence, Fashion Recommendation, Image Processing.

INTRODUCTION

The fashion business is a multifaceted sector that encompasses a wide range of activities, from recycling clothing to producing photographs for online shop catalogs. It is particularly involved in sustainable fashion, which involves generating usable items [2]. The fashion business has to gather and evaluate a lot of digital fashion data in order to identify more valued clients in light of the rapidly expanding fashion companies and the rise of e-commerce behemoths. Artificial intelligence began to blossom with several applications and advances in the fashion industry through different situations including identification, synthesis, analysis, and suggestion [3]. The ability for internet consumers to take images of clothing to search for anything is a big assist with clothing image recognition. Image recognition serves as a search engine by giving results without the need for typing. It is possible to frame the definition of clothing image problem as a classification question [4]. In recent years, research on artificial intelligence (AI) technology has advanced significantly due to the quick growth of computer technology. Among these, the study and use of machine learning-based artificial intelligence systems has advanced quickly [5]. Due to rising economic levels, individuals today seek out new fashions to accessorize themselves and are no more content to wear clothes only to be warm. However, there is no agreed-upon description or categorization scheme for clothing styles, which leads to variations in how various academics classify the same styles [6].

Style and fashion are key aspects of self-expression. This thesis aims to leverage machine learning to analyze fashion trends and provide personalized style advice. Using datasets of fashion images, the study will develop deep learning models like CNNs to identify and categorize fashion features. These models will learn to recognize styles such as streetwear, formal, vintage, and casual. Additionally, recommendation algorithms will offer tailored fashion suggestions based on user preferences. The effectiveness of the models will be evaluated through metrics like precision and recall, and user feedback will measure satisfaction. The goal is to enhance personalized fashion experiences using intelligent analysis and recommendations.

LITERATURE REVIEW

A research effort introduces a deep learning-based multilabel classification algorithm for clothing recommendations, efficiently recognizing and categorizing styles to offer dynamic suggestions tailored to users' preferences [1]. CNNs are used to train images of various fashion styles, achieving high success rates in predicting clothing elements. This research highlights the increasing role of CNN recognition in e-commerce fashion applications [2]. Another paper introduces StyleNet, a deep neural network-based model for style representation learning. Using a multi-task learning framework, StyleNet improves classification accuracy with larger datasets, though its performance is somewhat limited compared to other methods [3]. A study with Adidas AG™ uses deep learning and image processing to classify clothing features like logos, stripes, and colors in final images. The system's high accuracy and reliability make it ideal for Adidas [4]. A paper introduces a knowledge-guided fashion network using Bidirectional Convolutional Recurrent Neural Networks, dependency and symmetry grammars, and attention mechanisms for landmark localization and clothing category classification [5]. The proposal introduces a web application using DC-GANs to create high-end fashion apparel images, featuring techniques like object color translation and color transformation to incorporate the "color palette" [6]. The paper presents a CNN model for camera-based fashion classification, comparing Fashion MNIST with various algorithms. Using a 12,000-image dataset, YOLOv3, TinyYOLO, and Azure Kinect DT, the model identifies three garments with 90% accuracy [7]. The paper presents a CNN model using Fashion MNIST and other algorithms, performing real-time analysis with YOLOv3, TinyYOLO, and Azure Kinect DT on a 12,000-image dataset. The model identifies three garments with 90% accuracy [8]. The paper introduces an image classification method using Inception V3 on fashion datasets, achieving 92.85% accuracy. Data from five fashion brands were scraped, preprocessed, and classified. Future work will expand to more categories and different fashion brands [9]. A study reviews deep learning application in fashion, including object detection, classification, clothes generation, knowledge extraction, and recommendation systems, emphasizing their accuracy and efficiency in integrating AI in fashion data [10].

RESEARCH METHODOLOGY

A. Design Approach

We proposed using Convolutional Neural Networks (CNNs) to analyze images and offer personalized style recommendations, leveraging a dataset of 1000 real images across 10 categories such as shirts, t-shirts, sarees, and blazers. This research aims to integrate advanced deep learning techniques with fashion analysis, enhancing accuracy in trend identification and style suggestions. The approach covers data collection, preprocessing, model training, and evaluation, emphasizing reproducibility and comparative analysis with other methods. This systematic method bridges technology with fashion insights, promising improved results in personalized style recommendations and trend analysis.

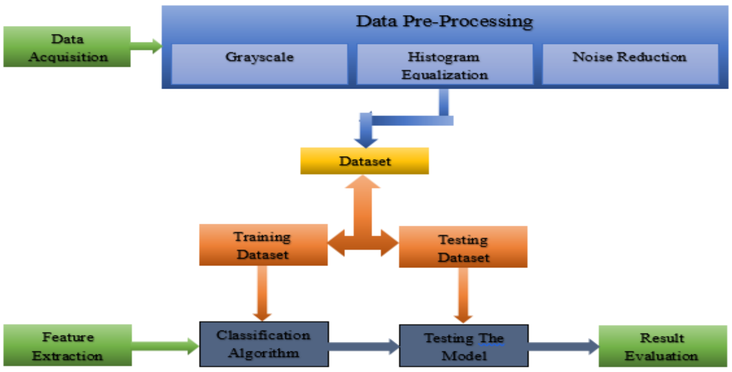

Fig. 1. Architecture of Working Process

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B. Dataset Description

This study identified images in ten categories to analyze fashion trends and provide personalized style recommendations. To analyze fashion trends and provide personalized style recommendations, we used our own generated dataset, with a total of 1000 datasets. The dataset contains a total of 1000 real images which are divided into 10 categories such as shirt, Punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear. 100 images in shirt category, 100 images in Punjabi category, 100 images in t-shirt category, 100 images in blazer category, 100 images in sweater category, 100 images in saree category, 100 images in salwar kameez category, 100 images in gown category, 100 images in western tops category There are images and there are 100 images in party wear category. In this research, a systematic approach was adopted to ensure the integrity of the results obtained from the models. To assess the performance of the models, a train-test split was employed. Specifically, an 70-20-10 split was utilized, allocating 70% of the data samples for model training, 20% for model testing the remaining 10% for validation.

Fig. 2. Splitting Image

Fig. 3. Class wise Separate Image

C. Data Preprocessing

In the data preprocessing stage, we address tasks such as standardizing image dimensions, enhancing quality, and verifying the accuracy of annotations. Our objective is to ensure the reliability and consistency of our data.

1. Grayscale: Grayscale preprocessing shown in Figure 2 involves converting a color image into a grayscale image. The process involves considering the intensity of each color channel (red, green, and blue) and combining them to produce a single intensity value for each pixel.

Figure 4: Grayscale preprocessing

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2. Histogram Equalization: Histogram Equalization illustrates in Fog. 3 is a contrast enhancement technique widely used in image processing to improve the visibility of details in an image. The process involves transforming the pixel values in an image so that the cumulative distribution function of the histogram becomes nearly linear. This equalization enhances the overall contrast, bringing out details in both dark and bright regions of an image.

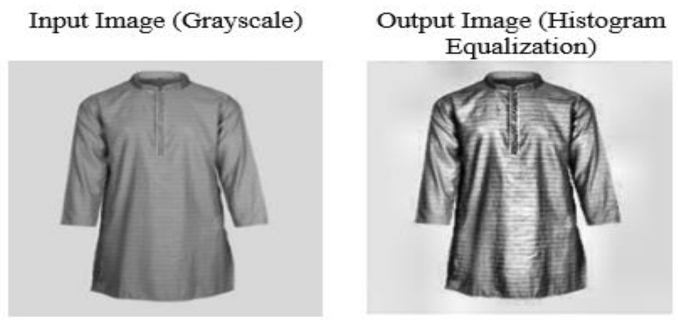

Figure 5: Histogram Equalization

3. Noise Reduction: Noise reduction shown in Figure 4 is a technique employed to minimize unwanted artifacts or random variations in data, often present in images, audio recordings, or other signals. In the context of images, noise can manifest as graininess, speckles, or other irregularities.

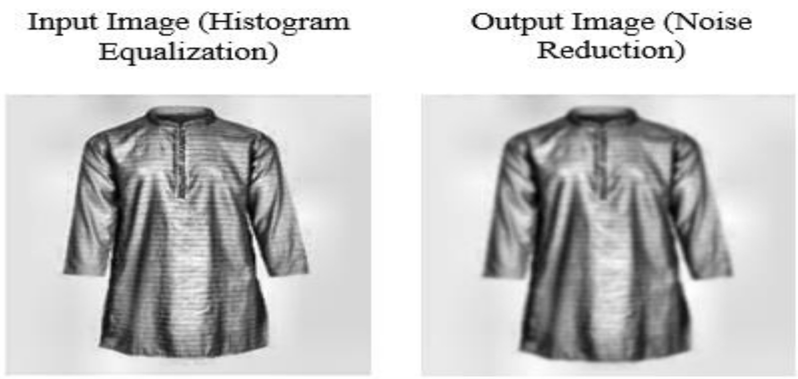

Figure 6: Noise reduction

Fig. 7. Final Preprocessed Image

EXPERIMENTAL RESULTD AND DISCUSSION

A. MobileNet V2

Table 1: Classification Report of MobileNet V2

Classes	Precision	Recall	F1_Score
Blazer	0.73	0.84	0.78

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Gown	0.56	0.50	0.53
Panjabi	0.71	0.67	0.69
Party Wear	0.62	0.81	0.70
Saree	0.67	0.22	0.33
Shirt	0.43	0.53	0.47
Sweater	0.32	0.67	0.43
T-Shirt	0.73	0.40	0.52
Western Tops	0.76	0.68	0.72
Salower Kamiz	0.83	0.56	0.67
Accuracy			0.59
Macro Avg	0.64	0.59	0.58
Weighted Avg	0.64	0.59	0.58

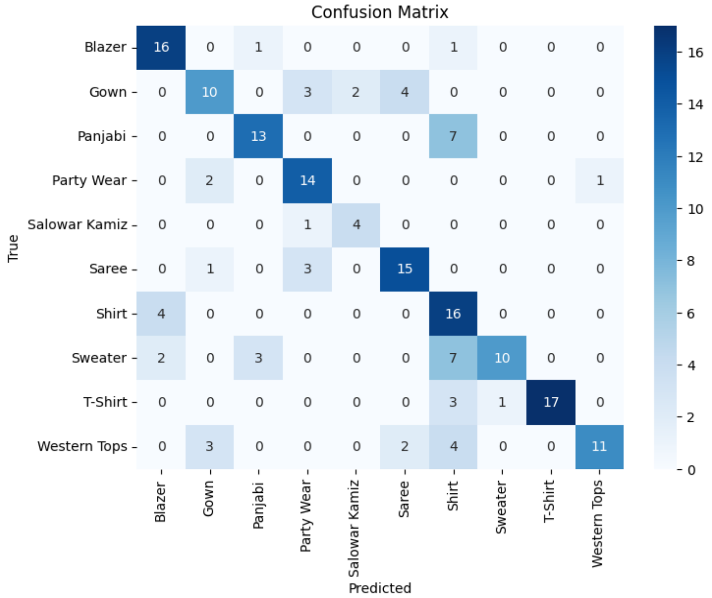

Fig. 8. Confusion Matrix for MobileNet V2

B. MobileNet V3

Table 2: Classification Report of Mobile net V3

Classes	Precision	Recall	F1_Score
Blazer	0.74	0.94	0.83
Gown	0.66	0.83	0.73
Panjabi	0.63	0.83	0.71
Party Wear	0.90	0.55	0.68

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Saree	0.92	0.57	0.71
Shirt	0.86	0.89	0.87
Sweater	0.54	0.89	0.67
T-Shirt	0.87	0.76	0.81
Western Tops	1.00	0.65	0.78
Salower Kamiz	0.90	0.53	0.67
Accuracy			0.75
Macro Avg	0.80	0.74	0.74
Weighted Avg	0.80	0.75	0.75

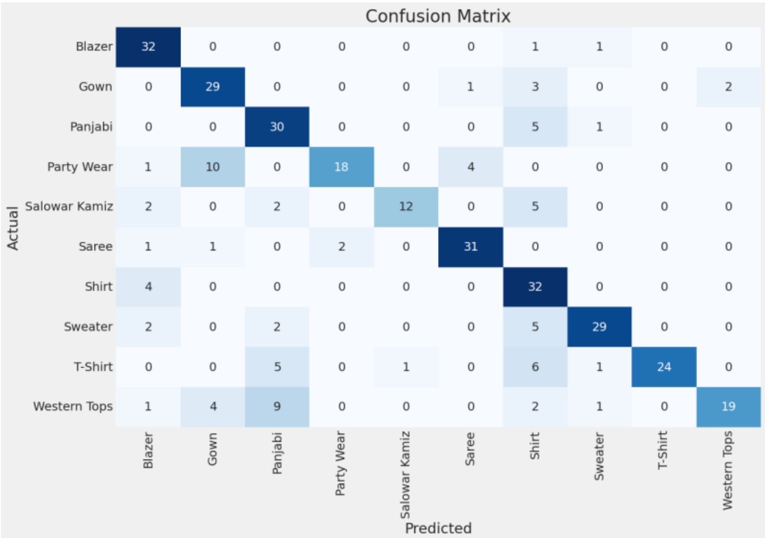

Fig. 9. Confusion Matrix for MobileNet V3

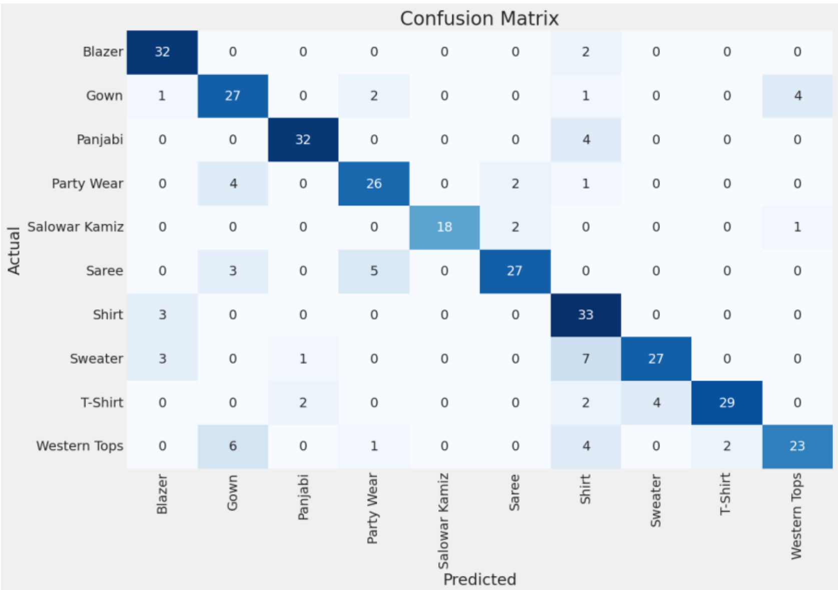

Fig. 10. Confusion Matrix for EfficientNet B0

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C. EfficientNet B0

Table 3: Classification Report of Efficientnet B0

Classes	Precision	Recall	F1_Score
Blazer	0.82	0.94	0.88
Gown	0.67	0.77	0.72
Panjabi	0.91	0.89	0.90
Party Wear	0.76	0.79	0.77
Saree	1.00	0.86	0.92
Shirt	0.87	0.77	0.81
Sweater	0.61	0.92	0.73
T-Shirt	0.87	0.71	0.78
Western Tops	0.94	0.78	0.85
Salower Kamiz	0.82	0.64	0.71
Accuracy			0.80
Macro Avg	0.83	0.81	0.81
Weighted Avg	0.82	0.80	0.80

D. Efficient Net B3

Table 4: Classification Report of Efficient net B3

Classes	Precision	Recall	F1_Score
Blazer	0.80	0.94	0.86
Gown	0.82	0.91	0.86
Panjabi	0.97	0.94	0.96
Party Wear	0.79	0.79	0.79
Saree	0.94	0.86	0.90
Shirt	0.81	0.86	0.83
Sweater	0.82	0.81	0.82
T-Shirt	0.83	0.84	0.82
Western Tops	0.80	0.81	0.89

Salower Kamiz	0.94	0.86	0.89
Accuracy			0.86
Macro Avg	0.87	0.86	0.86
Weighted Avg	0.87	0.86	0.86

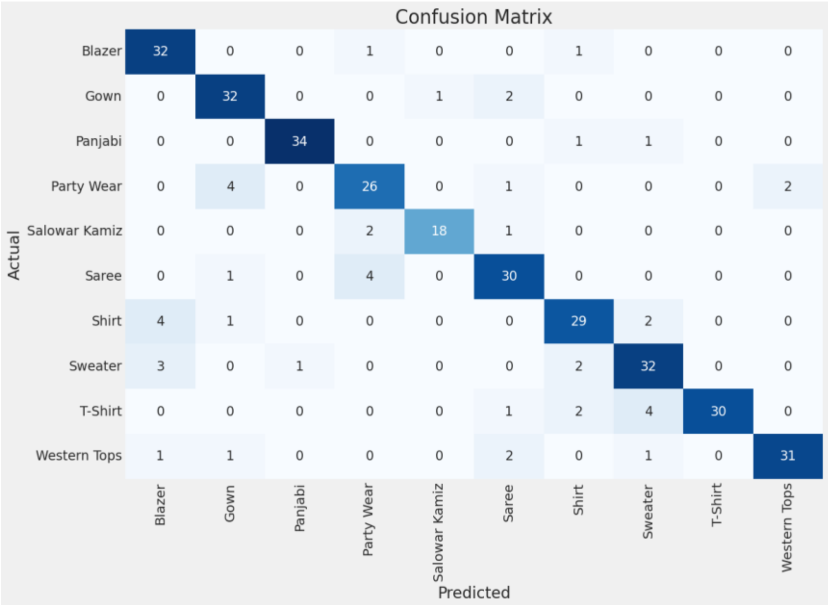

Fig. 11. Confusion Matrix for EfficientNet B3

E. Inception V3

Table 5: Classification Report of Inception V3

Classes	Precision	Recall	F1_Score
Blazer	0.90	0.95	0.92
Gown	0.33	0.83	0.47
Panjabi	0.68	0.83	0.75
Party Wear	0.71	0.62	0.67
Saree	0.50	0.17	0.25
Shirt	1.00	0.41	0.58
Sweater	0.48	0.67	0.56
T-Shirt	0.68	0.65	0.67
Western Tops	0.79	0.79	0.79
Salower Kamiz	0.33	0.06	0.10
Accuracy			0.60
Macro Avg	0.64	0.60	0.58
Weighted Avg	0.64	0.60	0.58

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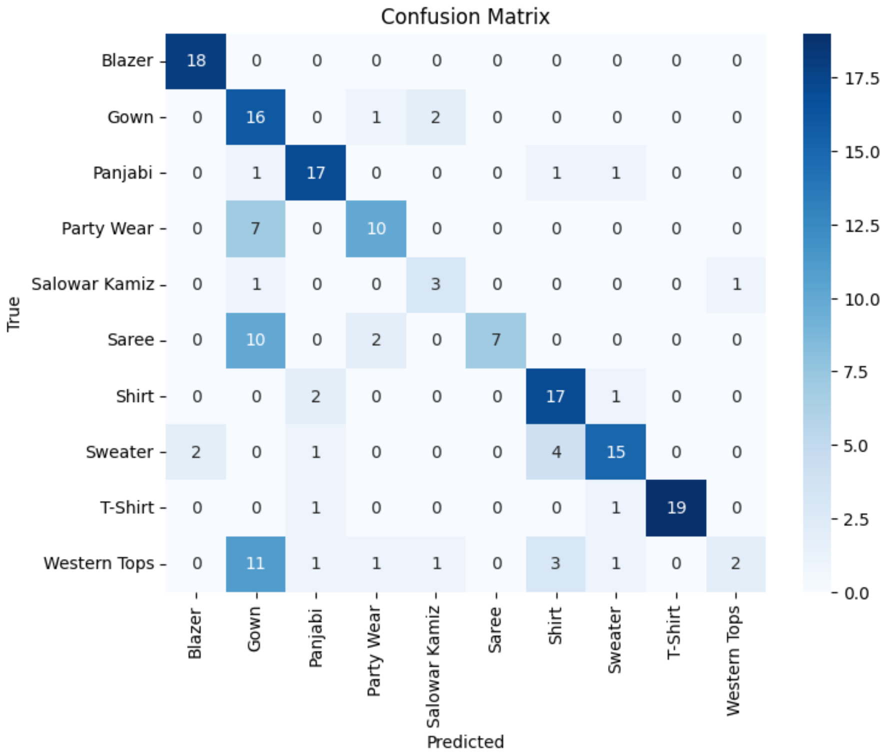

Fig. 12. Confusion Matrix for Inception V3

F. DenseNet 201

Table 6: Classification Report of Dense Net 201

Classes	Precision	Recall	F1_Score
Blazer	0.89	0.89	0.89
Gown	0.59	0.56	0.57
Panjabi	0.74	0.78	0.76
Party Wear	0.62	0.81	0.70
Saree	0.80	0.22	0.35
Shirt	0.90	0.53	0.67
Sweater	0.37	0.61	0.46
T-Shirt	0.67	0.60	0.63
Western Tops	0.77	0.89	0.83
Salower Kamiz	0.55	0.61	0.58
Accuracy			0.65
Macro Avg	0.69	0.65	0.64
Weighted Avg	0.69	0.65	0.65

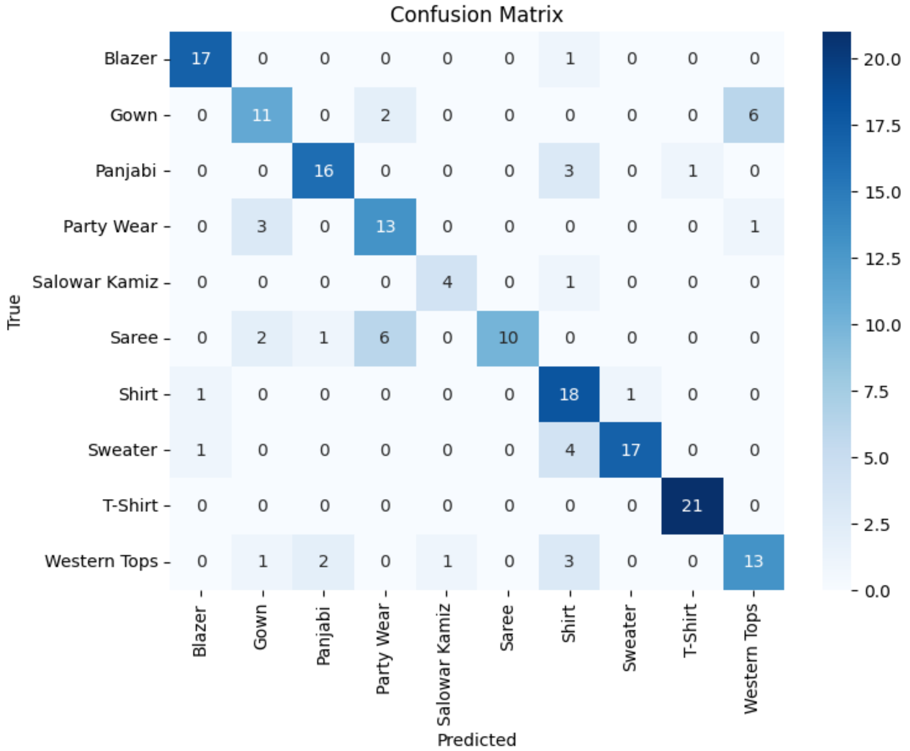

Fig. 13. Confusion Matrix for DenseNet 201

G. VGG19

Table 7: Classification Report of VGG19

Classes	Precision	Recall	F1_Score
Blazer	0.90	0.90	0.90
Gown	0.78	1.00	0.88
Panjabi	1.00	1.00	1.00
Party Wear	1.00	0.50	0.67
Saree	0.67	1.00	0.80
Shirt	0.86	0.86	0.86
Sweater	0.82	0.82	0.82
T-Shirt	1.00	0.86	0.92
Western Tops	0.83	1.00	0.91
Salower Kamiz	1.00	0.67	0.80
Accuracy			0.85
Macro Avg	0.89	0.86	0.85
Weighted Avg	0.88	0.85	0.85

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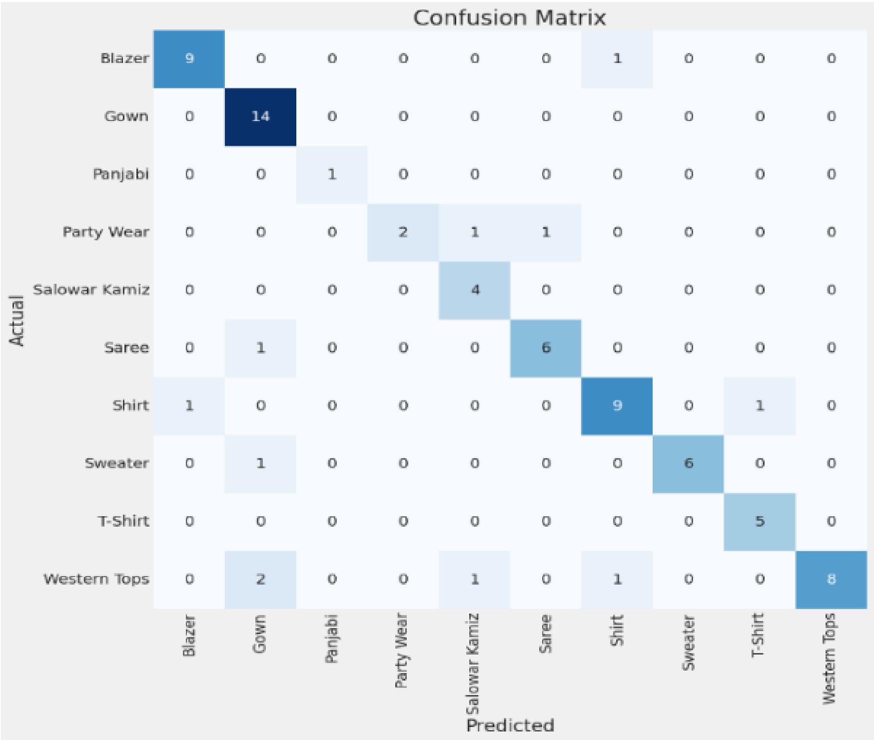

Fig. 14. Confusion Matrix for VGG19

H. Overall Classification Report

Fashion design recommendation systems employ machine learning and deep learning to deliver personalized and current style suggestions based on user preferences and fashion trends. Machine learning algorithms analyze vast datasets, considering clothing styles, colors, and patterns to understand individual tastes. Deep learning models, like Convolutional Neural Networks (CNNs) such as MobileNetV2, MobileNetV3, EfficientNet B0, EfficientNet B3, Inception V3, DenseNet201, and VGG19, extract intricate features from fashion images to enhance recommendation accuracy. Each architecture's performance varies: EfficientNet B3 achieves the highest accuracy at 86%, followed by EfficientNet B0 (80%), VGG19 (85%), MobileNetV3 (75%), DenseNet201 (65%), MobileNetV2 (59%), and Inception V3 (60%). These systems continuously learn from user interactions, refining suggestions based on evolving preferences and trends, benefiting both users and retailers by enhancing engagement and conversion rates in the dynamic fashion landscape.

Table 8: Classifiers Description

Model	Accuracy	Precision	Recall	F1-score
MobileNetV2	0.59	0.64	0.59	0.58
MobileNetV3	0.75	0.80	0.74	0.74
Efficient Net B0	0.80	0.83	0.81	0.81
Efficient Net B3	0.86	0.87	0.86	0.86
Inception V3	0.60	0.64	0.60	0.58
DenseNet201	0.64	0.69	0.65	0.64
VGG19	0.85	0.89	0.86	0.85

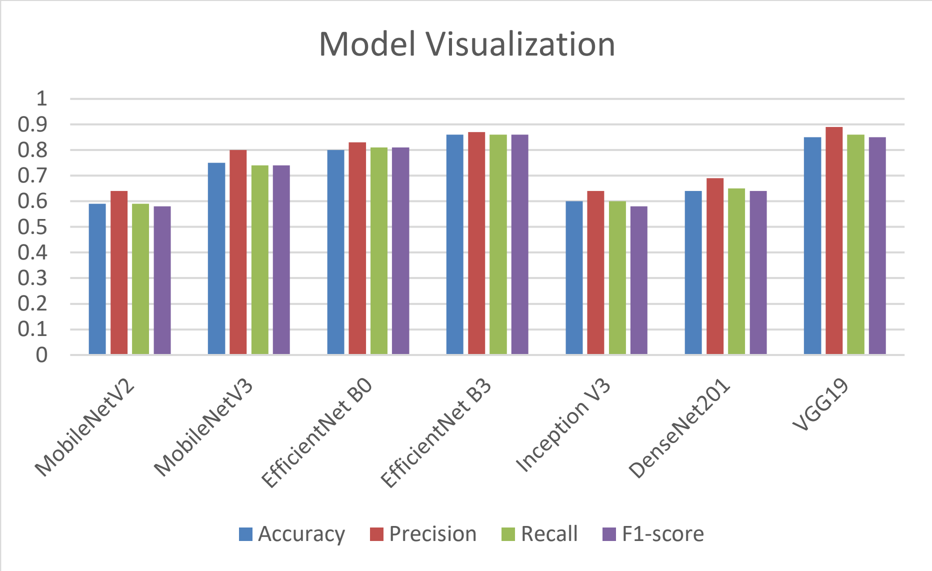

Fig. 15. Overall Model Visualization

DISCUSSION

The integration of deep learning, particularly Convolutional Neural Networks (CNNs), in fashion-related computer vision applications is transformative. CNNs excel in extracting intricate features from fashion images, aiding in tasks like clothing classification and trend analysis. This approach leverages a custom dataset of 1000 real images across 10 categories, enhancing accuracy in style identification. The study employs seven CNN architectures—VGG19, MobileNetV2, MobileNetV3, EfficientNet B0, EfficientNet B3, Inception V3, and DenseNet201—yielding varied accuracy rates. EfficientNet B3 notably achieves the highest accuracy at 86%, underscoring the efficacy of deep learning in refining fashion analysis and recommendation systems, crucial for enhancing user fashion choices and retail strategies.

CONCLUSION

In conclusion, the integration of deep learning in computer vision, particularly in fashion-related applications like clothing search and recommendation systems, signifies a significant advancement. These technologies enhance the understanding and categorization of human clothing, providing valuable insights for improving sales strategies and understanding user preferences. The development of intelligent fashion style analysis and recommendation systems, utilizing Convolutional Neural Networks (CNNs) such as VGG19, MobileNet, EfficientNet, Inception, and DenseNet, demonstrates their effectiveness in extracting image features and classifying fashion items into diverse styles. This research contributes to evolving AI capabilities that cater to dynamic fashion landscapes, aiming to enhance user fashion choices and industry competitiveness.

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