Fashion Style Analysis and Recommendation Using Machine Learning & Deep Learning

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled "**Fashion Style Analysis and Recommendation Using Machine Learning & Deep Learning**, submitted by Habiba Khatun, ID No: 201-15-3566 the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 24 January, 2024.

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DECLARATION

I hereby declare that, this project has been done by me under the supervision of **Amatul Bushra, Assistant Professor, Department of CSE** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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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. Today, the impact of deep learning on computer vision applications is increasing every day. Deep learning techniques are applied in many areas like clothing search, automatic product recommendation. 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. As well as tailoring campaigns based on customer tastes and improving user experience. 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, a new deep learning model based on Convolutional Neural Network (CNN) is proposed to solve the classification problem. These networks can extract features from images using convolutional layers, unlike traditional machine learning algorithms. 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 main goal of this project is that research findings can contribute to developing intelligent fashion style analysis and recommendation systems, improving users' fashion preferences and providing a personalized fashion experience. 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%.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1
INTRODUCTION

1.1. 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].

The application of machine learning in production and daily life is growing [5]. Different machine learning techniques may be derived from basic methods for apparel picture recognition [4]. Deep learning techniques are applied to a variety of challenges, including posture estimation, the creation of portrait graphics, the segmentation and recognition of garments in the fashion industry. There is a tendency toward these techniques because, in contrast to conventional machine learning approaches, they are more successful at automated feature extraction and robust discriminating features [2]. However, compared to other common commodities, fashion has far more variance in trends, styles, and designs, making fashion analysis a difficult endeavor. To determine the level of difficulty related to clothes, a great deal of research has been done in the areas of fashion analysis, modeling, recognition, and parsing. All of these studies, which use bounding box prediction to recognize cloth areas, examine significant cues that identify various fabric portions and forecast their characteristics [3].

Style and fashion are significant components of self-expression and identity. The purpose of this thesis is to use machine learning techniques to assess current fashion trends and offer tailored style advice. Various datasets of fashion photos, including apparel items, accessories, and outfit combinations, will be gathered for this project. The main goal of the research is to create deep learning models, such Convolutional Neural Networks (CNN), that can recognize characteristics in photographs and categorize or extract them based on various fashion trends. In order to understand visual representations of many styles, including streetwear, formal, vintage, and casual, models will be trained on labeled data. Furthermore, the thesis will investigate methods to offer customized fashion suggestions based on individuals, such as collaborative filtering or recommendation algorithms. Past encounters and preferences. Metrics like precision, accuracy, and recall will be used to assess the performance of the generated models, and user surveys or studies will be used to gauge user satisfaction. The findings of this study have the potential to enhance users' fashion preferences and offer a customized fashion experience by enabling the development of intelligent fashion style analysis and recommendation systems. In order to develop a system that can evaluate content fashion photos, categorize them into various styles, and provide tailored fashion suggestions, it integrates the domains of fashion, style, and machine learning. You may further hone in on the subject by adding user-generated fashion data or taking into account other factors like seasonality and the compatibility of clothing pieces. As always, work with your thesis adviser to customize the material to your preferences and the resources that are accessible.

1.2. Motivation

This paper mainly uses machine learning and deep learning to make fashion design analysis and recommendations. There are basically 10 categories namely shirt, Punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear. That is, to find out who is wearing what by using computer vision through various algorithms of data science. The main goal of this project is to provide future research with better comparisons between classification methods. Several models have been applied for this, through which we can predict better results.

- Leverage machine learning techniques to analyze fashion trends and provide personalized style recommendations.
- Various datasets of fashion images including clothing items, accessories and clothing combinations will be collected.
- Models will be trained on labeled data to learn visual representations of different styles such as casual, formal, streetwear, vintage, etc.
- The thesis will explore techniques such as collaborative filtering or recommendation systems to provide personalized fashion recommendations based on individual preferences and previous interactions.
- Findings from research can contribute to developing intelligent fashion style analysis and recommendation systems, improving users' fashion preferences and providing a personalized fashion experience.
- The subject combines the fields of fashion, style and machine learning to create a system that can analyze fashion images, classify them into different styles.

1.3. Relational of the Study

Our research paper for Fashion Design Analysis is divided into 10 parts. Our research is divided into 2 categories ie T-shirt/top, Trouser, Pullover, dress, Coat, Sandals, Shirt, Sneaker, Bag and Ankle boots. We found several such works; They also segmented fashion design analysis and made fashion design recommendations using different algorithms like deep learning and machine learning.

1.4. Research Questions

We may have many types of questions in this study. For example-

- What is the aim of this research?
- What drives the undertaking of this research?
- Is there potential for practical gains from this research?
- In what ways can we derive benefits from the findings of this research?
- What are the conclusions drawn from the results of this study?

- What broader implications or outcomes emerge from this study?

1.5. Expected Outcome

- Fashion design analysis is done using artificial intelligence through data science.
- Recommendations are made after fashion design analysis.
- This work aims to leverage machine learning techniques to analyze fashion trends and provide personalized style recommendations.
- The results of this research can contribute to developing intelligent fashion style analysis and recommendation systems, improving users' fashion preferences.
- This topic combines the fields of fashion, style, and machine learning to create a system that can analyze fashion images, classify them into different styles.

1.6. Report Layout

News portals often struggle to harness the full potential of data obtained from online and social media due to ineffective sorting, classification, and analysis processes. The proper utilization of this data becomes crucial for their success. Implementing machine learning (ML), deep learning (DL), and natural language processing (NLP) to automatically classify data presents a promising solution that is not only faster but also more agile, cost-effective, and reliable. The subsequent sections of this paper are organized as follows: Section 2 provides background information, Section 3 outlines the methodology, Section 4 presents experimental results and discussions, and Section 5 explores the societal, environmental, and sustainability impacts. The paper concludes in Section 6.

CHAPTER 2
BACKGROUND

2.1. Terminology

As the global landscape expands, an array of devices dedicated to fashion design analysis and recommendations is proliferating. The ubiquity of these devices is facilitated by the widespread reach of the internet, particularly through online social media platforms. Consequently, the volume of fashion design content is on a steady rise over time. However, a substantial portion of diverse data types remains uncaptured, leading to the loss of valuable online information that could prove beneficial in the future. To address this issue, computer vision is employed to classify all data, documents, and fashion designs. Various machine learning algorithms are applied in this classification process, determining the relevance and utility of the content. This strategic approach ensures that today's data is effectively organized and deemed usable for future applications.

2.2. Related Works/Literature Review

A variety of research studies focus on the application of machine learning and deep learning models in the realm of e-commerce clothing image classification. One study compares traditional machine learning and deep learning approaches, particularly the HOG+SVM algorithm with a Gaussian kernel function and a Convolutional Neural Network (CNN), in identifying pure and dressed clothing images. The HOG+SVM algorithm achieves a notable accuracy of 91.32% for pure clothing images, while the CNN model outperforms it in the case of dressed clothing images [1].

In another study, a novel deep learning model based on Convolutional Neural Networks (CNNs) is proposed for classification problems. This model, optimized using the Keras Tuner tool on the Fashion MNIST dataset, demonstrates improved classification performance by extracting highly discriminative features from images through convolutional layers [2].

A different research effort introduces a multi-stage feature-oriented network for clothing category classification and attribute prediction in visual fashion apparel analysis. Incorporating spatial and channel-based attention and a semi-supervised learning method, this architecture outperforms existing techniques, showcasing robust apparel classification and attribute prediction [3].

With the expanding online fashion market, the utilization of algorithms for garment identification becomes crucial. One paper explores the use of Convolutional Neural Networks and presents four different models using the Fashion-MNIST dataset. The objective is to compare classification methods and identify the most effective labeling method for future research [4].

Yet another study proposes a deep learning-based image classification technique using a CNN model with advanced convolutional and pooling layers. This model incorporates an approximate dynamic learning rate update algorithm for self-adaptation and fast convergence, achieving a classification accuracy of 93% on the FASHION-MNIST dataset [5].

In the context of clothing recommendation, a research effort introduces a multilabel classification algorithm based on deep learning theory. The model efficiently recognizes and classifies clothing styles, providing dynamic recommendations based on users' preferences [6].

CNNs are also employed in training images of different fashion styles to predict clothing elements with high success rates. This research underscores the growing importance of CNN recognition in various fashion-related applications within e-commerce [7].

Another paper proposes a style representation learning model, StyleNet, based on deep neural networks, which enhances classification accuracy through a multi-task learning framework. The model's performance improves with larger datasets, although the classifier's improvement is limited compared to alternative methods [8].

A study in collaboration with Adidas AG ™ leverages deep learning and image processing techniques for the visual classification of clothing features such as logos, stripes, and colors in final rendering images. The system demonstrates high classification accuracy and reliability, making it suitable for use by Adidas [9].

The development of a knowledge-guided fashion network for visual fashion analysis is presented in another paper. This network employs Bidirectional Convolutional Recurrent Neural Networks, dependency and symmetry grammars, and attention mechanisms for landmark localization and clothing category classification [10].

Lastly, a proposal introduces a web application utilizing Generative Adversarial Networks (GAN) technology to generate high-end fashion apparels. Deep Convolutional Generative Adversarial Networks (DC-GANs) are suggested for creating high-quality fashion images, incorporating features like the "color palette" through object color translation and color transformation techniques [11].

The paper presents a CNN model for implementing classifiers on cameras, comparing Fashion MNIST with various algorithms. Real-time analysis was performed on a 12,000-image dataset using YOLOv3 and TinyYOLO, and an Azure Kinect DT. The model identifies at least three garments and achieves 90% accuracy [12].

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The paper proposes an image classification method using Inception V3 for fashion datasets. The method involves scraping data from official websites of five famous fashion brands, preprocessing it, and classifying it using the Inception V3 method. The method achieved an accuracy of 92.86% and 92.85%, distinguishing knitted items from knitwear categories. The model can classify 16 categories of 16 global fashion brands, with an evaluation score of 92.85%. Future work aims to improve the classification of more categories, including teenager and adult categories, children's clothing, and different fashion or cultural brands [14].

A novel semi-supervised multi-task learning approach for clothing category classification and attribute prediction is introduced in this study. Employing a teacher-student (T-S) pair model, the approach focuses on enhancing feature representation by simultaneously learning from labelled and unlabeled samples. Outperforming existing techniques in fashion clothing analysis, the T-S model transfers feature weights and incorporates spatial and channel information for a comprehensive study. Notably, this research marks the first exploration of semi-supervised learning through a multi-task architecture specifically tailored for fashion clothing categories and attributes [15].

In a separate paper, a study on fashion image classification is proposed, utilizing four distinct neural network models. The Multiple Convolutional Neural Network with 15 convolutional layers (MCNN15) model achieves a classification accuracy of 94.04% on the Fashion-MNIST dataset. While the model exhibits promising results for apparel image classification, with 60% and 40% accuracy on the Fashion-Product and household datasets, the improvement in performance is not statistically significant [16].

This paper introduces an innovative extension of the decision tree concept with a vector solution for modeling the fashion preferences of teenagers. The vector decision tree, possessing the functionality of multiple separate decision trees, is designed to make more correlated decisions per leaf, maintaining its generality and simplicity [17].

Conducting a comprehensive review, another study focuses on deep learning (DL) methods within the fashion industry, specifically addressing Object Detection, Fashion Classification, Clothes Generation, Automatic Fashion Knowledge Extraction, and Clothes Recommendation. Deep learning methods are scrutinized for their superior accuracy and time performance. The review offers a detailed overview of datasets and techniques used in deep learning for fashion, particularly within social networks, highlighting their contributions to the integration of AI in fashion data [18].

Additionally, a paper introduces an attention-driven technique for visual fashion clothes analysis, incorporating landmark-driven attention and spatial-channel attention. Enhancing classification efficiency by identifying crucial features and their location in an input image, the proposed architecture outperforms existing techniques in fashion clothes classification and attribute prediction. The model incorporates stacked dilated convolutional blocks and up-sampling techniques for generating high-resolution heatmaps [19].

2.3. Comparative Analysis and Summary

Table-1: Summary of Related Works

Paper No	Authors & Year	Dataset	Height Accuracy Model	Height Model (%)
1	J. Xu, Y. Wei (2022)	Fashion-MNIST 70000 Images	HOG+SVM & Small VGG	81.32% & 69.78%
3	M. Shajini and A. Ramanan (2023)	DeepFashion-C	Baseline + SA + CA (multiple-staged, [GAP, GMP])	Category- 86.67% Attribute- 63.18%
4	Rajesh Kumar S (2022)	Fashion-MNIST	CNN Model	-
5	S.-Y. Shin, G. Jo (2023)	Fashion-MNIST 6000 Image	Softmax	83%
6	B. Yang (2022)	Image dataset	Decision Tree	86.25%
8	C. Yan, L. Zhou (2019)	Fashionista, Fashion 144k, SFS	FASTER R-CNN	46.87%
10	W. Wang, Y. Xu (2018)	Large-scale fashion datasets	-	-
11	M. M. Deepthi (2023)	DeepFashion 800K images	DC GAN	-
14	M. Maryamah (2023)	Fashion dataset	Inception V3	87.86%
16	O. Nocentini (2022)	Fashion-MNIST	MCNN15	84.04%
17	P. Kokol (2006)	Fashion Dataset	Decision Trees	-
18	M. Mameli (2022)	This paper is a review paper, which discusses images obtained from social media and various previous datasets.		
19	M. Shajini and A. Ramanan (2020)	DeepFashion-C & FLD	Baseline+ LDA+ SCA (spatial–channel)	Category- 85.60% Attribute- 58.74%

2.4. Scope of the Problem

People are worshipers of beauty. People want that they can always walk in a neat and tidy manner. That's why people want all parts of their body to be neatly arranged. In keeping all these parts tidy, people give the most importance to their clothes, pants and shoes. When going to any kind of important work or event, people get neatly dressed. If not, there is no honor in going to that place. Currently, as a result of the advancement of technology, people are being told what kind of clothes, pants, and shoes will make them look neat. That is, the service is available without any intervention by the machine. This significant change has only come from machine learning and deep learning in data science. By teaching big machines through deep learning in machine learning and data science, they can provide insights into fashion design very quickly and specifically. But even in that case, many times we have to face various problems, such as not being able to match clothes properly, not matching one with another, etc. Different types of machine learning and deep learning. Learning algorithms such as logistic regression, linear regression, random forest classifier, decision tree, naive bias, SVM, CNN, RNN, ANN, LSTM etc. are used in data science. The obtained image data can be used for various fashion designing purposes. Since we will determine the correctness of fashion designing by reviewing information on image-based data, any kind of clothes, clothes, pants, shoes matching can be solved with data science algorithms.

2.5. Challenges

Today's world has come a long way based on data science and artificial intelligence. That is why the challenge is to research so that scientists can revolutionize anything, how to serve people in less time, how to increase the accessibility of the mind in everything and suggest more fashion designing in less time. Currently, many fashion designing establishments are providing services using Data Science. So, the main challenge of this project is how well to train the model with image data through different algorithms and bring out the best performance and give proper advice to people about fashion designing. A little change here will not make people look different or tidy or beautiful. Ignoring these challenges, it is our job to get good results and deliver best performance.

CHAPTER 3
RESEARCH METHODOLOGY

3.1. Design Approach

We proposed a method using Convolutional Neural Network (CNN) to compare images to analyze fashion trends and provide personalized style recommendations. This includes designing a systematic approach to effectively analyze images and provide 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. This research will bridge the gap between technology and state-of-the-art deep learning to analyze fashion trends and provide personalized style recommendations. Which ultimately leads to improved results through more precise identification of fashion trend analysis and recommendations. In other sections, we will detail each step of our proposed approach, from data collection and preprocessing to model training and evaluation, with a focus on ensuring reproducibility, interpretability, and comparative analysis with other relevant methods. The study procedure consists of several steps, as shown in Figure 1.

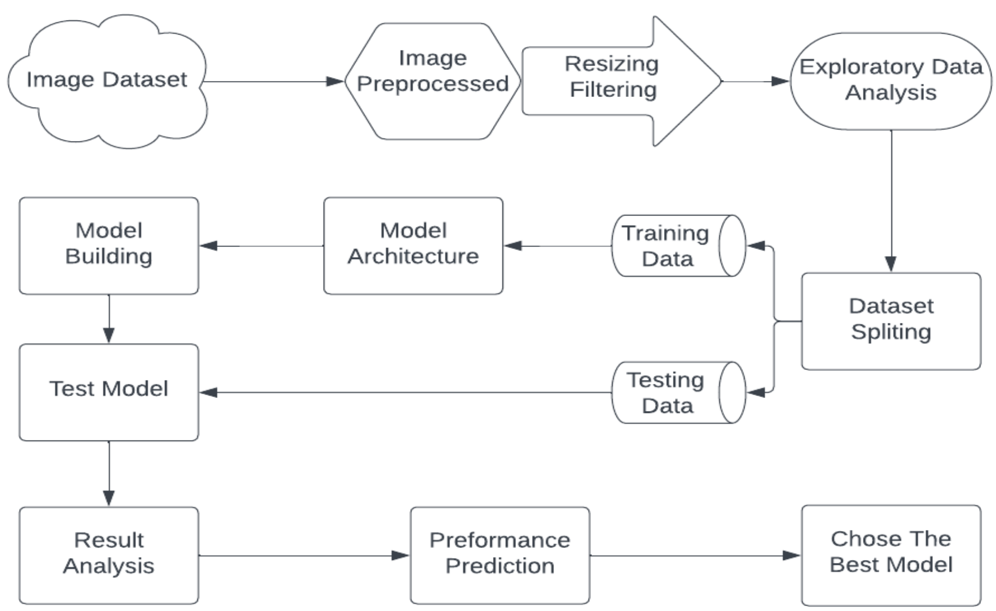

Figure-1: Architecture of Working Process

3.2. Dataset Collection

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.

Table 2. Dataset Example

SL	Class Name	No of Data	Description
01	Shirt	100	The name of this category in the entire dataset is Shirt. The total amount of data in this category is 100. If someone is found wearing a Shirt from the entire dataset, data science algorithms can easily extract it.
02	Punjabi	100	The name of this category in the entire dataset is Punjabi. The total amount of data in this category is 100. If someone is found wearing a Punjabi from the entire dataset, data science algorithms can easily extract it.
03	T-Shirt	100	The name of this category in the entire dataset is T-Shirt. The total amount of data in this category is 100. If someone is found wearing a T-Shirt from the entire dataset, data science algorithms can easily extract it.
04	Blazer	100	The name of this category in the entire dataset is Blazer. The total amount of data in this category is 100. If someone is found wearing a Blazer from the entire dataset, data science algorithms can easily extract it.
05	Sweater	100	The name of this category in the entire dataset is Sweater. The total amount of data in this category is 100. If someone is found wearing a Sweater from the entire dataset, data science algorithms can easily extract it.
06	Saree	100	The name of this category in the entire dataset is Saree. The total amount of data in this category is 100. If someone is found wearing

			a Saree from the entire dataset, data science algorithms can easily extract it.
07	Salwar Kameez	100	The name of this category in the entire dataset is Salwar Kameez. The total amount of data in this category is 100. If someone is found wearing a Salwar Kameez from the entire dataset, data science algorithms can easily extract it.
08	Gaun	100	The name of this category in the entire dataset is Gaun. The total amount of data in this category is 100. If someone is found wearing a Gaun from the entire dataset, data science algorithms can easily extract it.
09	Western Tops	100	The name of this category in the entire dataset is Western Tops. The total amount of data in this category is 100. If someone is found wearing a Western Tops from the entire dataset, data science algorithms can easily extract it.
10	Party Wear	100	The name of this category in the entire dataset is Party Wear. The total amount of data in this category is 100. If someone is found wearing a Party Wear from the entire dataset, data science algorithms can easily extract it.

3.3. Data Preprocessing

Before we can unleash the power of Convolutional Neural Networks (CNNs) to analyze Fashion Design Analyze images, a crucial initial step is to prepare our data. This section will unveil our data preprocessing methods, where we make these images ready for analysis. We'll tackle issues like standardizing image sizes, improving quality, and ensuring that annotations are clear and accurate. By doing so, we're setting the stage for our CNN models to work their magic and uncover essential insights. For preprocessing our goal is make our data as reliable and consistent as possible, so our comparisons are sound. Data preprocessing might not be the glamorous part of our study, but it's the bedrock upon which our entire research stands.

3.3.1. Grayscale

Grayscale preprocessing is a common technique in image processing that involves converting a color image into a grayscale image. Grayscale images represent the intensity of light or brightness of each pixel, typically ranging from black (0) to white (255) in an 8-bit image. The conversion to grayscale simplifies the image data, making it easier to process and analyze. The process of converting a color image to grayscale involves taking into account the intensity of each color channel (red, green, and blue) and combining them to produce a single intensity value for each pixel.

Input Image (Original)	Output Image (Grayscale)
	

3.3.2. Histogram Equalization

Histogram Equalization is a contrast enhancement technique widely used in image processing to improve the visibility of details in an image. It works by redistributing pixel intensities across the entire dynamic range, making the histogram more uniformly distributed. 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. However, it may also amplify noise, and its effectiveness depends on the characteristics of the original image. Despite its simplicity, Histogram Equalization remains a valuable tool in various applications, such as medical imaging, satellite imagery, and computer vision, where enhancing visual features is crucial for analysis and interpretation.

Input Image (Grayscale)	Output Image (Histogram Equalization)

	

3.3.3. Noise Reduction

Noise reduction is a digital signal processing 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. Various algorithms and filters are used to identify and suppress these undesirable elements, aiming to preserve essential details while creating a smoother, cleaner representation. Common approaches include median filtering, Gaussian filtering, and wavelet denoising. In audio, noise reduction methods typically involve spectral analysis and filtering to diminish background noise without compromising the integrity of the desired signal. Effective noise reduction is crucial in applications like photography, audio processing, and telecommunications, where the presence of unwanted noise can degrade the quality and clarity of the original content.

Input Image (Histogram Equalization)	Output Image (Noise Reduction)
	

3.3.4. Final Preprocessed Image

3.4. Data Splitting

The data set we used was about fashion design analysis and recommendation. The data set consisted of several images of fashion design that we could analyze. The total number of pictures there was 1000. A total of 1000 images were divided into 10 categories. The 10 categories are 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.

Figure-2: Class wise Separate Image

For the purposes of this study, the dataset was divided into three distinct subsets to facilitate the training, testing, and validation of the models. This process, commonly known as data splitting, is crucial in machine learning and data analysis to ensure the robust evaluation of model performance. 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. In testing, 20 images in shirt category, 20 images in Punjabi category, 20 images in t-shirt category, 20 images in blazer category, 20 images in sweater category, 20 images in saree category, 20 images in salwar kameez category, 20 images in gown category, 20 images in western tops category and 20 images in party wear category. In training, 70 images in shirt category, 70 images in Punjabi category, 70 images in t-shirt category, 70 images in blazer category, 70 images in sweater category, 70 images in saree category, 70 images in salwar kameez category, 70 images in gown category, 70 images in western tops category and 70 images in party wear category. In validation, 10 images in shirt category, 10 images in Punjabi category, 10 images in t-shirt category, 10 images in blazer category, 10 images in sweater category, 10 images in saree category, 10 images in salwar kameez category, 10 images in gown category, 10 images in western tops category and 10 images in party wear category.

Figure-3: Splitting Image

3.5. Proposed Methodology

3.5.1. MobileNet V2

Google has made their MobileNetV2 computer vision model open source. It is intended to be used for classifier training. The MobileNet series, an effective architecture created especially for mobile and embedded devices, is continued with MobileNetV3. These models are appropriate for real-time applications on devices with limited resources because they balance computational burden with performance. A combination of automated machine learning and manual design is used in the creation of MobileNetV3. Convolutional neural networks, such as MobileNetV3, are optimized for mobile phone CPUs using a mix of hardware-aware network architecture search (NAS), the NetAdapt algorithm, and novel architectural advancements. Furthermore, the manufacturer refined the design under specific latency limitations using a complementary method and a platform-aware neural architecture search (NAS) called NetAdapt. In comparison to previous networks, it employs convolution with depth to drastically cut the number of parameters, creating a lightweight deep neural network. Tensorflow's first mobile computer vision model is called MobileNet [22].

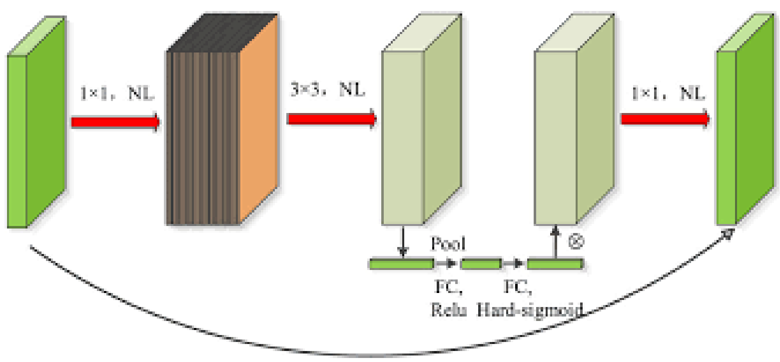

Figure-4: MobileNetV2 Architecture

3.5.2. MobileNetV3

MobileNetV3 is a family of lightweight convolutional neural network (CNN) architectures designed for mobile and edge devices with resource constraints. It is the third iteration in the MobileNet series, following MobileNetV1 and MobileNetV2. MobileNetV3 was introduced by Google in 2019, and it focuses on achieving improved accuracy and efficiency compared to its predecessors.

MobileNetV3 is specifically designed for resource-constrained devices, such as mobile phones and edge devices, where computational resources, memory, and power consumption are limited. It strikes a balance between model efficiency and accuracy, making it suitable for various real-time applications on devices with constraints. The specific details of MobileNetV3, including the number of layers and parameters, depend on the chosen variant (Large or Small).

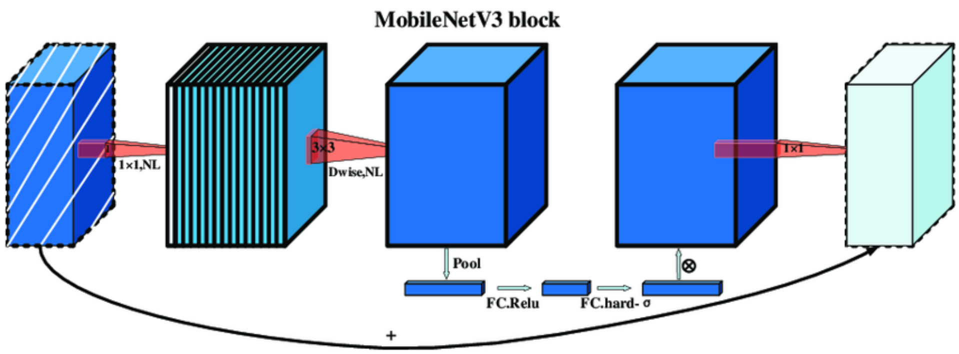

Figure-5: MobileNetV3 Architecture

3.5.3. EfficientNet b0

The convolutional neural network EfficientNet was constructed using the "compound scaling" theory. The long-standing trade-off between model size, accuracy, and computing efficiency is addressed by this idea. Composite scaling refers to the process of scaling a neural network's breadth, depth, and resolution—the three key dimensions.

Width: The number of channels in each neural network layer is referred to as width scaling. The model's accuracy increases when the breadth is increased because it can capture more intricate patterns and characteristics. On the other hand, a model with less width is lighter and more suited for low-resource settings.

Depth: The total number of layers in the network is related to depth scaling. Although deeper models are able to capture more intricate data representations, they also require more processing power. Shallow models, on the other hand, may lose accuracy but are computationally efficient.

Resolution: The size of the supplied picture is altered by resolution scaling. Images with higher resolutions offer more precise information, which might improve performance. They do, however, demand additional processing power and memory. Conversely, lower-resolution photos may result in a loss of fine detail yet consume less resources.

The EfficientNet model was put out in Mingxing Tan and Quoc V. Le's book EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. A set of image classification models called EfficientNets achieves cutting-edge accuracy while being quicker and smaller than earlier models.

Mobile inverted bottleneck (MBConv) layers, a hybrid of inverted residual blocks and depth-based separable convolution, are used by EfficientNet. Squeeze-and-excitation (SE) optimization is another feature of the model design that helps to enhance model performance.

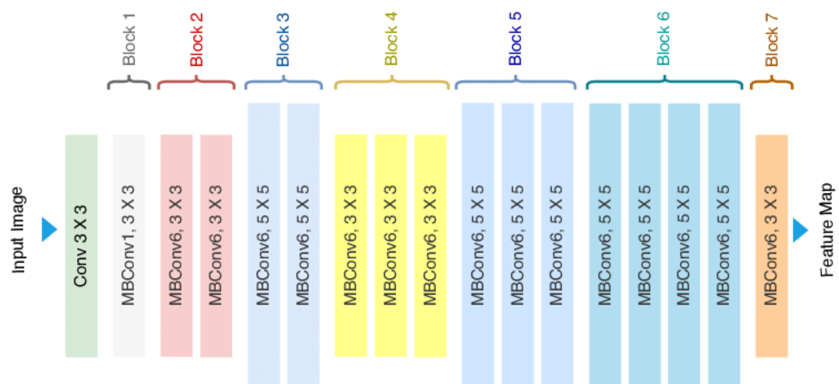

Figure-6: EfficientNet B0 Architecture

By multiplying them with the original feature map, these layers enable the model to learn channel-based feature relationships and provide attention weights that highlight significant information.

There are several versions of EfficientNet with varying scaling coefficients, such EfficientNet-B0, EfficientNet-B1, and so on. Users can choose the best model version for their needs by considering the various trade-offs between model size and accuracy that each variant offers [23].

3.5.4. EfficientNetB3

EfficientNetB3 is part of the EfficientNet family, a series of convolutional neural network architectures designed to achieve optimal performance with highly efficient use of computational resources. Developed by Google researchers, EfficientNetB3 is characterized by a balance between model depth, width, and resolution, providing a scalable and efficient architecture for image classification tasks. EfficientNetB3's architecture introduces compound scaling, where the model's dimensions are uniformly increased to enhance both depth and width. This compound scaling approach ensures that the network becomes more powerful as it grows, making it suitable for diverse computer vision applications. EfficientNetB3 is particularly adept at handling various image resolutions and is known for achieving state-of-the-art performance on image classification benchmarks. Key components of EfficientNetB3 include depth-wise separable convolutions, inverted bottleneck structures, and squeeze-and-excitation blocks. These elements contribute to the model's efficiency and enable it to learn intricate features from images while maintaining computational effectiveness. The EfficientNetB3 architecture is widely used in tasks such as image recognition, object detection, and other computer vision applications, where a balance between model accuracy and computational efficiency is crucial.

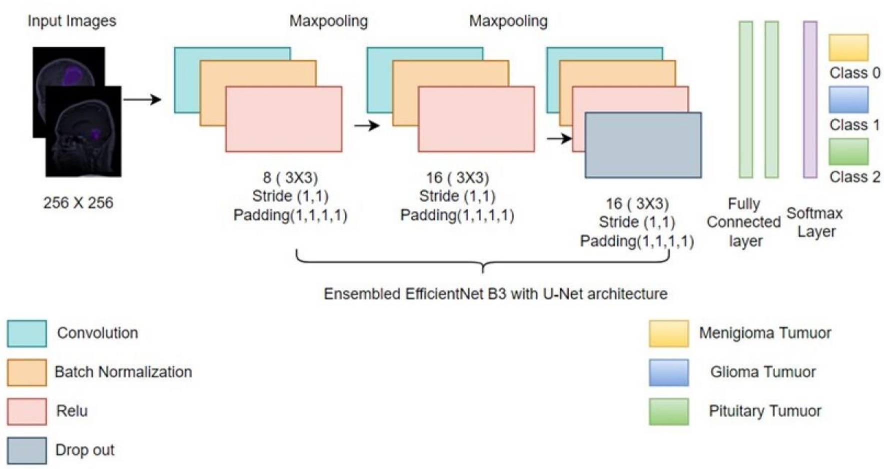

Figure-7: EfficientNetB3 Architecture

3.5.5. Inception V3

Inception v3 is a deep convolutional neural network architecture developed by Google as part of the Inception family. It is renowned for its excellence in image classification tasks and is widely employed in computer vision applications. Released in 2015, Inception v3 builds upon its predecessor, Inception v2, with a focus on improved performance and computational efficiency. The distinguishing feature of Inception v3 is its utilization of inception modules, which are responsible for capturing information at various spatial scales by employing filters of different sizes within the same layer. This allows the network to effectively extract both local and global features from input images, enhancing its capacity for image understanding. Inception v3 incorporates several innovations, including factorized convolutions and batch normalization, contributing to its improved accuracy and faster convergence during training. The architecture also employs auxiliary classifiers at intermediate layers during training, promoting better gradient flow and aiding in mitigating the vanishing gradient problem. Inception v3 has demonstrated state-of-the-art performance on image classification benchmarks and is widely adopted in applications such as object recognition, image segmentation, and transfer learning, where robust feature extraction and representation learning are essential for achieving high-quality results.

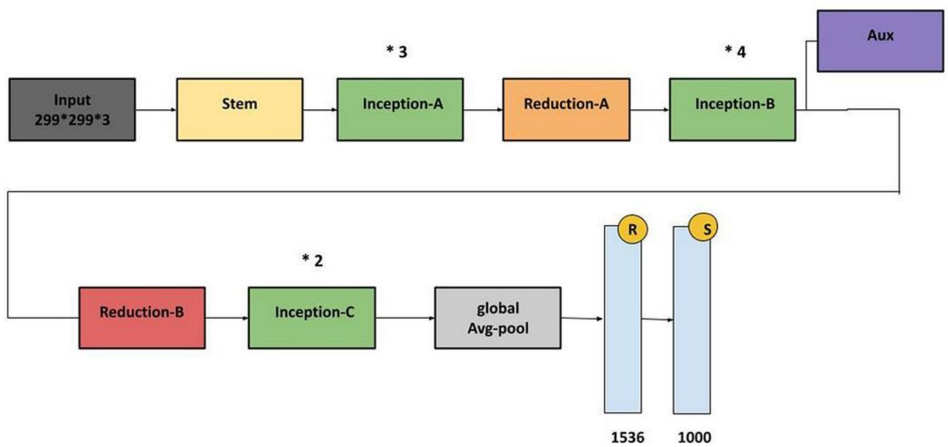

Figure-8: InceptionV3 Architecture

3.5.6. DenseNet201

DenseNet201 is a convolutional neural network (CNN) architecture that belongs to the family of DenseNets (Densely Connected Convolutional Networks). DenseNets differ from traditional CNN architectures by promoting strong feature reuse through densely connected blocks. In a DenseNet, each layer receives inputs not just from the previous layer but also from all preceding layers in the block. This design facilitates feature reuse, which helps in combating the vanishing gradient problem, enhances gradient flow, and encourages feature propagation throughout the network.

The "201" in DenseNet201 refers to the number of layers in the network. It has 201 layers, making it a relatively deep neural network. The architecture includes dense blocks, transition layers, and a global average pooling layer followed by a fully connected layer for classification. DenseNet201 is known for its efficiency in terms of parameter usage and computational resources, and it has been widely used for various computer vision tasks, including image classification and object detection.

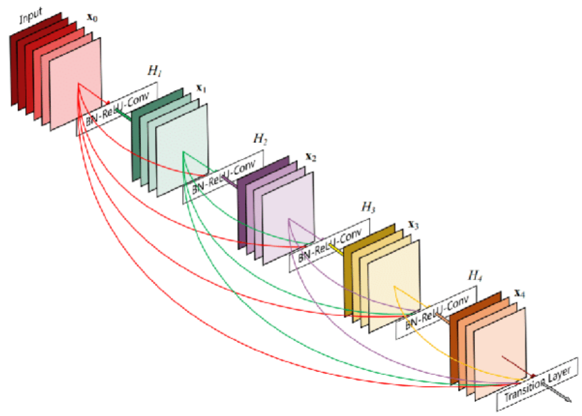

Figure-9: DenseNet201 Architecture

3.5.7. VGG19

VGG19 Architecture The number 19 denotes that VGG is a 19-layer deep neural network (VGGnet). This suggests that VGG19 is a really massive network with a total of about 138 million parameters. Even by today's standards, this network is rather large. Still, the network seems prettier because of the simplicity of the VGGNet19 design. Even just looking at its architecture reveals that they are quite similar. A pooling layer is followed by many convolution layers that reduce the height and width. There are around 64 filters available for use, and we may increase that number to about 128 and finally 256 filters. In the last phases, we may apply the 512 filter. The novel technique to object recognition is based on the VGG architecture. On some tasks and datasets, VGGNet—a deep neural network—performs better than ImageNet. Additionally, it continues to be one of the most popular patterns for image recognition. The VGG19 model, often known as VGGNet-19, supports 19 layers, much as VGG16. In the model, the weight (or convolutional) layers are represented by the numbers "16" and "19" [21].

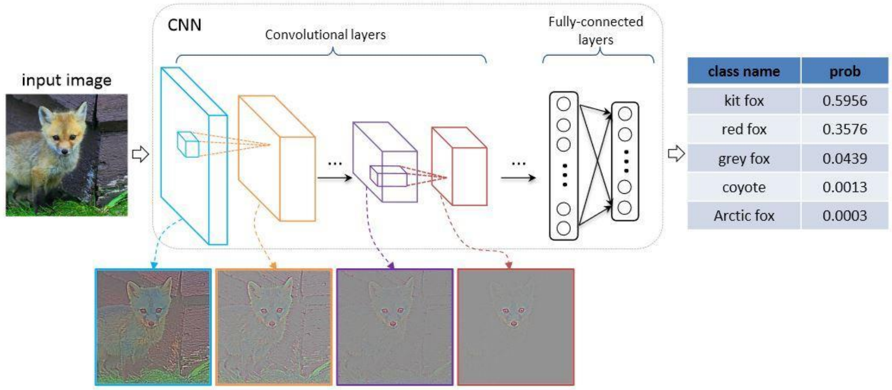

Figure-4: VGG19 Architecture

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1. Discussion

In this paper I have used the Customize CNN algorithm, through which we have used 7 architectures of CNN. The 7 methods of Customize CNN we used are VGG19, MobileNetV2, MobileNetV3, EfficientNet B0, EfficientNet B3, Inception V3 and DenseNet201. From all the methods, it can be seen that the highest accuracy has been found in EfficientNet B0 and EfficientNet B3 methods. Also, the lowest accuracy was obtained using the VGG19 model.

Table-3: Classifiers Description

Model	Description
MobileNetV2	Google has made their MobileNetV2 computer vision model open source. It is intended to be used for classifier training. A combination of automated machine learning and manual design is used in the creation of MobileNetV2. The MobileNet series, an effective architecture created especially for mobile and embedded devices, is continued with MobileNetV2.
MobileNetV3	MobileNetV3 is a family of lightweight convolutional neural network (CNN) architectures designed for mobile and edge devices with resource constraints. It is the third iteration in the MobileNet series, following MobileNetV1 and MobileNetV2. MobileNetV3 is specifically designed for resource-constrained devices, such as mobile phones and edge devices, where computational resources, memory, and power consumption are limited.
EfficientNet B0	The convolutional neural network EfficientNet B0 was constructed using the "compound scaling" theory. The long-standing trade-off between model size, accuracy, and computing efficiency is addressed by this idea. Composite scaling refers to the process of scaling a neural network's breadth, depth, and resolution—the three key dimensions.
EfficientNet B3	EfficientNet B3 is a convolutional neural network architecture that is part of the EfficientNet family, which was introduced by researchers at Google in 2019. The EfficientNet models are designed to achieve state-of-the-art accuracy on image classification tasks while maintaining efficiency in terms of computational resources. EfficientNet models are scaled up or down based on three parameters: depth, width, and resolution.

Inception V3	Inception V3, an improvement over its predecessor Inception V2, incorporates several design changes to increase performance and reduce computational requirements. It is pre-trained on large datasets like ImageNet and is often used in transfer learning situations. Transfer learning involves taking a pre-trained model and fine-tuning it to a specific task or dataset, using knowledge gained from a large dataset to improve performance on the target task.
DenseNet201	DenseNet201 is a convolutional neural network (CNN) architecture. The "201" in DenseNet201 refers to the number of layers in the network. It has 201 layers, making it a relatively deep neural network. DenseNets differ from traditional CNN architectures by promoting strong feature reuse through densely connected blocks. In a DenseNet, each layer receives inputs not just from the previous layer but also from all preceding layers in the block.
VGG19	The multi-layered VGG, or Visual Geometry Group, is a typical deep convolutional neural network (CNN) design. The VGG19 model, often referred to as VGGNet-19, supports 19 layers, much as VGG16. In the model, the weight (or convolutional) layers are represented by the numbers "16" and "19". A convolutional neural network with 19 layers is called VGG-19. Compared to VGG16, VGG19 contains three more convolutional layers.

4.2. Experimental Results and Analysis

4.2.1. MobileNet V2

4.2.1.1. Validation and Training accuracy

Table-4: Validation and Training accuracy table for MobileNetV2

Epoch No	Validation Accuracy	Training Accuracy
Epoch 1	0.71	0.51
Epoch 2	0.90	0.77
Epoch 3	0.96	0.85
Epoch 4	0.84	0.91
Epoch 5	0.96	0.91

The multiclass unbalanced classification issue is the reason why the validation accuracy has not increased by more than 71%, as can be seen from the accuracy plot. Furthermore, the performance of the model may be enhanced by appropriately fine-tuning the vocabulary sizes.

4.2.1.2. Validation and Training loss

Table-5: Validation and Training loss for MobileNetV2

No	Validation Loss	Training Loss
Epoch 1	0.75	1.65
Epoch 2	0.33	0.63
Epoch 3	0.13	0.40
Epoch 4	0.24	0.24
Epoch 5	0.11	0.22

4.2.1.3.Confusion Matrix

In this paper accurate prediction is performed to indicate perfect prediction for shirt, Punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear classes. The confusion matrix revealed the following distribution of predicted and true labels:

We can see from the confusion matrix that the MobileNetV2 report accuracy is 59%.

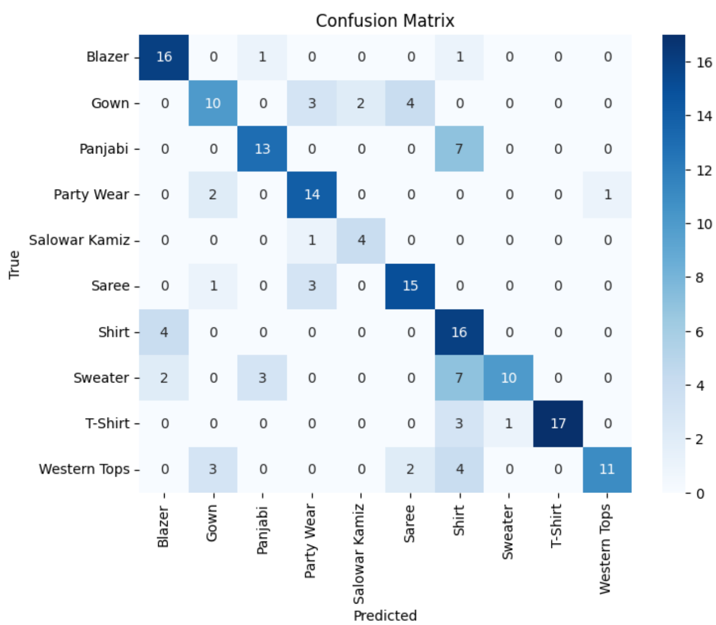

Figure-10: Confusion Matrix for MobileNetV2

4.2.1.4.Classification report

Our dataset consists of 10 classes- shirt, Punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear by analyzing the classes, classification report i.e., precision, recall, f1_score and support showed that MobileNetV2 has 59% assurance report.

Table-6: Classification report of MobileNetV2 Algorithm

Classes	Precision	Recall	F1_Score
Blazer	0.73	0.84	0.78
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

In the classification report we can see that Precision, Recall, F1_Score and Support are extracted for all classes types (shirt, Punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear). Along with finding out Accuracy, Macro Avg, Weighted Avg value has also been found out. Accuracy of MobileNetV2 algorithm is 59%.

4.2.1.5.ROC Curve

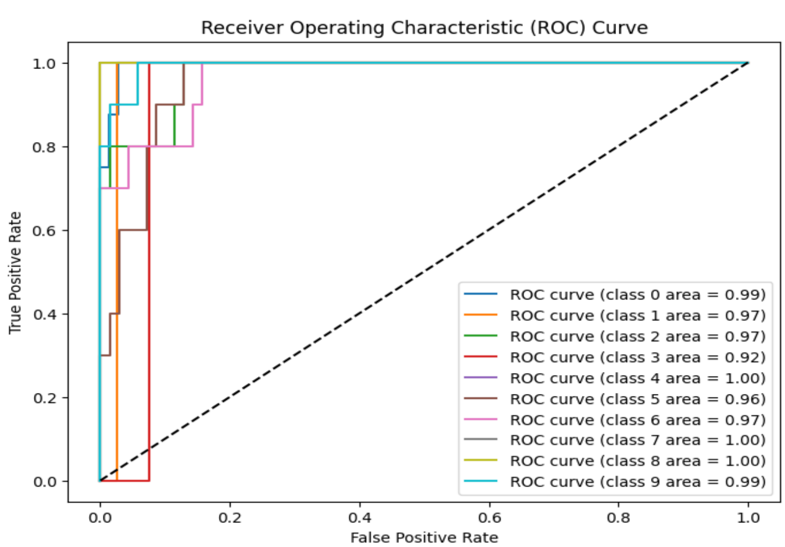

Figure-11: ROC Curve for MobileNetV2

4.2.1.6.Cross Validation & Misclassification Error

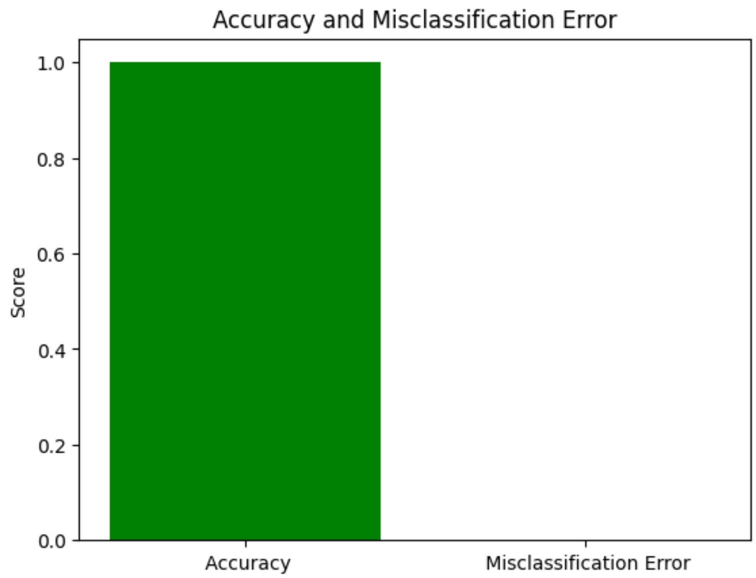

Figure-12: Accuracy and Misclassification Error for MobileNetV2

4.2.2. MobileNet V3

4.2.2.1.Validation and Training accuracy

Table-7: Validation and Training accuracy table for MobileNetV3

Epoch No	Validation Accuracy	Training Accuracy
Epoch 1	0.42	0.31
Epoch 2	0.50	0.70
Epoch 3	0.64	0.82
Epoch 4	0.61	0.88
Epoch 5	0.64	0.92

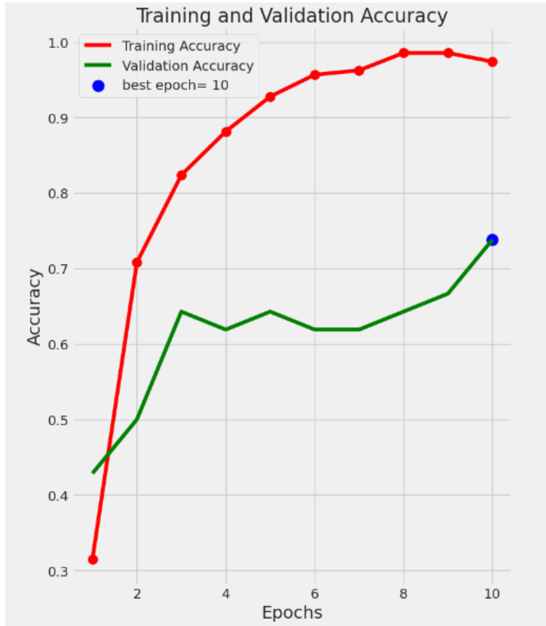

Figure-13: Epochs vs Training & Validation Accuracy Plot for MobileNetV3

The multiclass unbalanced classification issue is the reason why the validation accuracy has not increased by more than 64%, as can be seen from the accuracy plot. Furthermore, the performance of the model may be enhanced by appropriately fine-tuning the vocabulary sizes.

4.2.2.2.Validation and Training loss

Table-8: Validation and Training loss for MobileNetV3

No	Validation Loss	Training Loss
Epoch 1	0.09	0.08
Epoch 2	0.08	0.06
Epoch 3	0.07	0.06
Epoch 4	0.06	0.06
Epoch 5	0.06	0.05

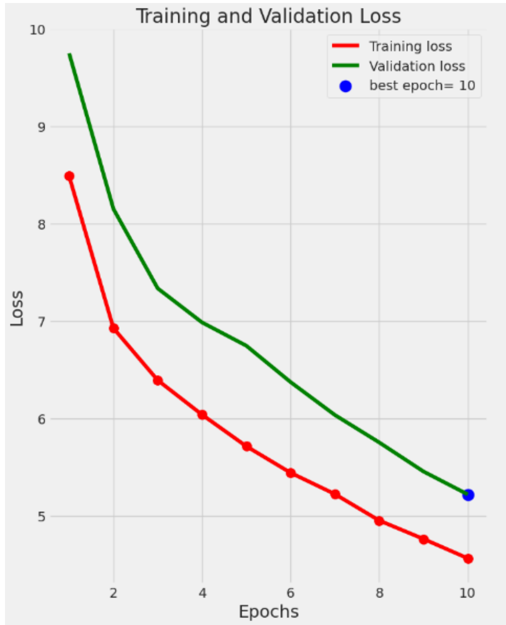

Figure-14: Epochs vs Training & Validation Loss Plot for MobileNetV3

4.2.2.3.Confusion Matrix

In this paper accurate prediction is performed to indicate perfect prediction for shirt, Punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear classes. The confusion matrix revealed the following distribution of predicted and true labels:

We can see from the confusion matrix that the MobileNetV3 report accuracy is 75%.

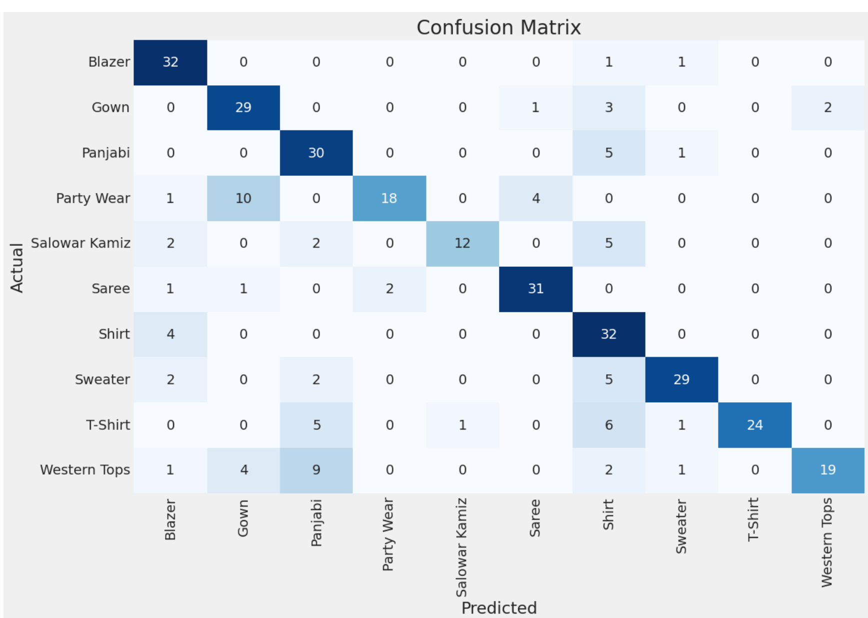

Figure-15: Confusion Matrix for MobileNetV3

4.2.2.4.Classification report

Our dataset consists of 10 classes- shirt, Punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear by analyzing the classes, classification report i.e., precision, recall, f1_score and support showed that MobileNetV3 has 75% assurance report.

Table-9: Classification report of MobileNetV3 Algorithm

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
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

In the classification report we can see that Precision, Recall, F1_Score and Support are extracted for all classes types (shirt, Punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear). Along with finding out Accuracy, Macro Avg, Weighted Avg value has also been found out. Accuracy of MobileNetV3 algorithm is 75%.

4.2.3. EfficientNet B0

4.2.3.1.Validation and Training accuracy

Table-10: Validation and Training accuracy table for EfficientNetB0

Epoch No	Validation Accuracy	Training Accuracy
Epoch 1	0.57	0.40
Epoch 2	0.71	0.76

Epoch 3	0.88	0.88
Epoch 4	0.97	0.92
Epoch 5	0.97	0.95

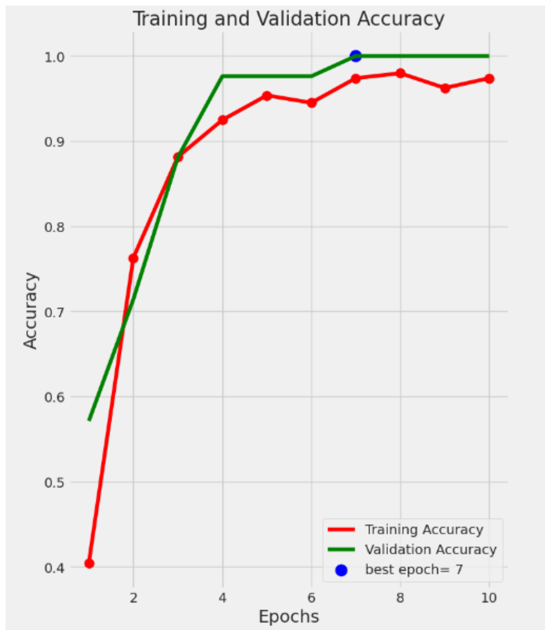

Figure-16: Epochs vs Training & Validation Accuracy Plot for EfficientNetB0

The multiclass unbalanced classification issue is the reason why the validation accuracy has not increased by more than 97%, as can be seen from the accuracy plot. Furthermore, the performance of the model may be enhanced by appropriately fine-tuning the vocabulary sizes.

4.2.3.2.Validation and Training loss

Table-11: Validation and Training loss for EfficientNetB0

No	Validation Loss	Training Loss
Epoch 1	0.10	0.09
Epoch 2	0.08	0.08
Epoch 3	0.07	0.07
Epoch 4	0.07	0.06
Epoch 5	0.06	0.06

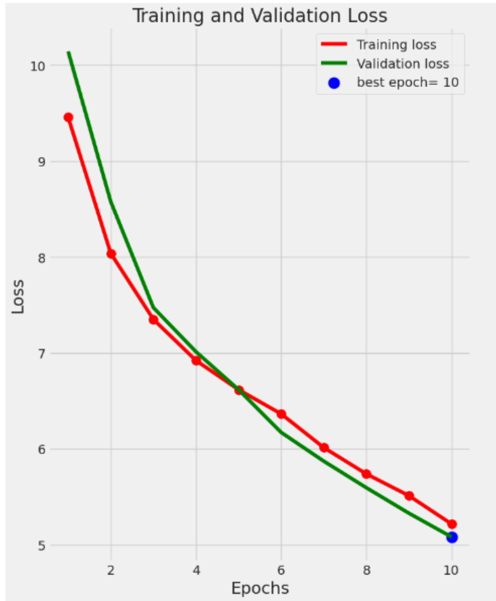

Figure-17: Epochs vs Training & Validation Loss Plot for EfficientNetB0

4.2.3.3.Test set Accuracy and Error

Accuracy on the test set is 80.75 %.

Table-12: Test set Accuracy and Error

Model	Loss	Accuracy
EfficientNetB0	1.5447	0.8075

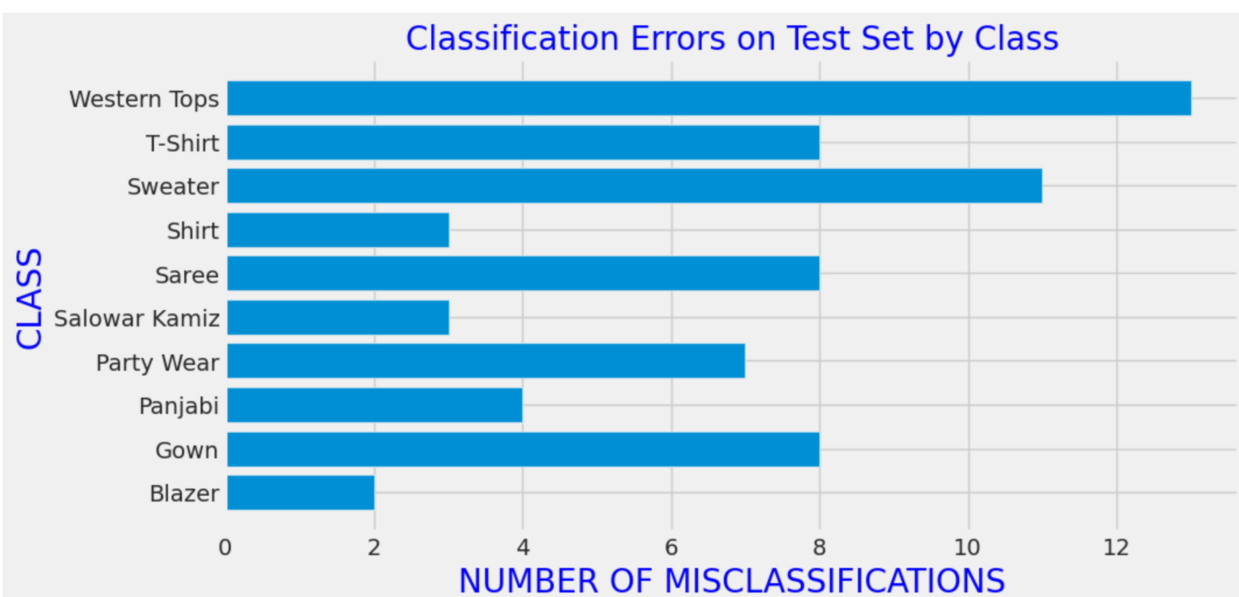

Figure-18: Test Set Error by Class wise

4.2.3.4.Confusion Matrix

In this paper accurate prediction is performed to indicate perfect prediction for shirt, Punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear classes. The confusion matrix revealed the following distribution of predicted and true labels:

We can see from the confusion matrix that the EfficientNetB0 report accuracy is 80%.

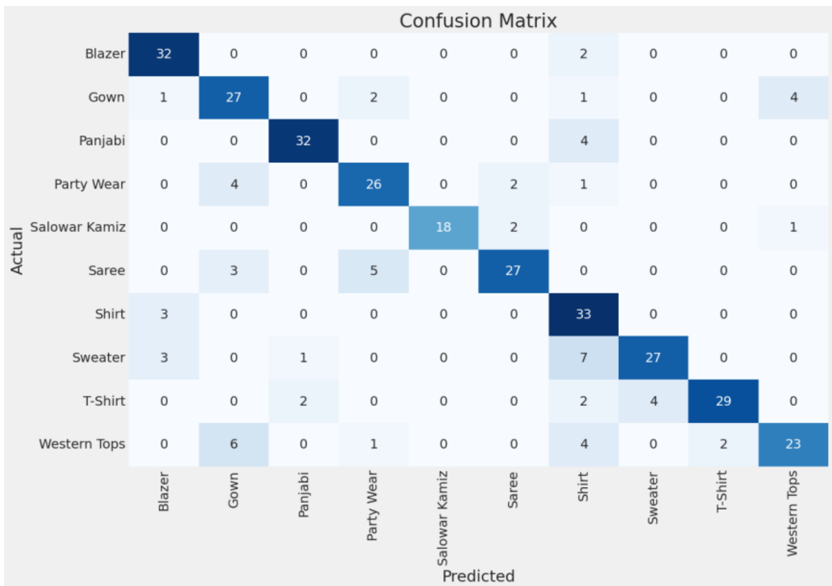

Figure-19: Classification Report for EfficientNetB0

4.2.3.5.Classification report

Our dataset consists of 10 classes- shirt, Punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear by analyzing the classes, classification report i.e., precision, recall, f1_score and support showed that EfficientNetB0 has 81% assurance report.

Table-13: Classification report of EfficientNetB0 Algorithm

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

In the classification report we can see that Precision, Recall, F1_Score and Support are extracted for all classes types (shirt, Punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear). Along with finding out Accuracy, Macro Avg, Weighted Avg value has also been found out. Accuracy of EfficientNetB0 algorithm is 80%.

4.2.4. EfficientNet B3

4.2.4.1. Validation and Training accuracy

Table-14: Validation and Training accuracy table for EfficientNetB3

Epoch No	Validation Accuracy	Training Accuracy
Epoch 1	0.57	0.44
Epoch 2	0.78	0.78
Epoch 3	0.97	0.90
Epoch 4	100.0	0.93
Epoch 5	100.0	0.95

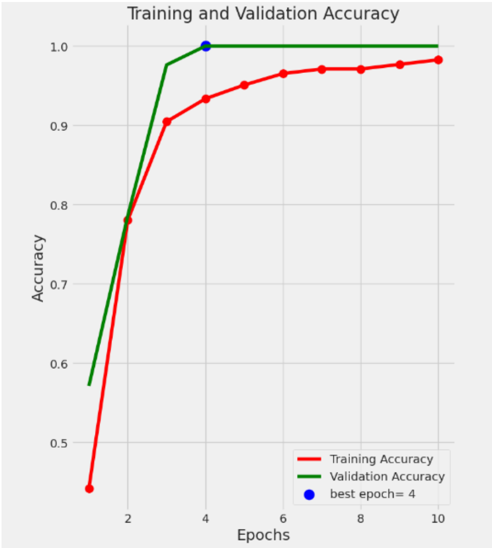

Figure-20: Epochs vs Training & Validation Accuracy Plot for EfficientNetB3

The multiclass unbalanced classification issue is the reason why the validation accuracy has not increased by more than 100%, as can be seen from the accuracy plot. Furthermore, the performance of the model may be enhanced by appropriately fine-tuning the vocabulary sizes.

4.2.4.2.Validation and Training loss

Table-15: Validation and Training loss for EfficientNetB3

No	Validation Loss	Training Loss
Epoch 1	0.09	0.09
Epoch 2	0.08	0.08
Epoch 3	0.07	0.07
Epoch 4	0.06	0.07
Epoch 5	0.06	0.06

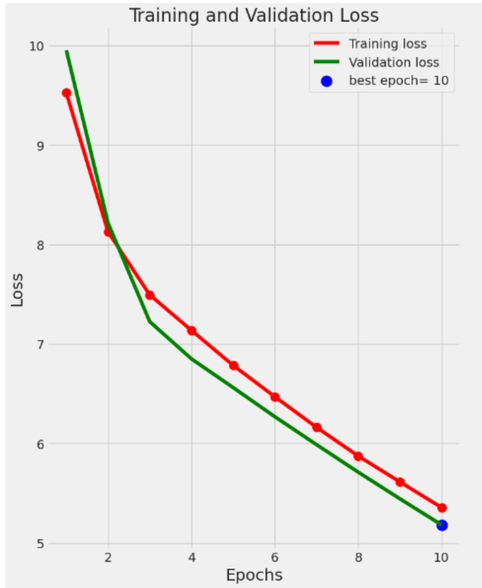

Figure-21: Epochs vs Training & Validation Loss Plot for EfficientNetB3

4.2.4.3.Confusion Matrix

In this paper accurate prediction is performed to indicate perfect prediction for shirt, Punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear classes. The confusion matrix revealed the following distribution of predicted and true labels:

We can see from the confusion matrix that the EfficientNetB3 report accuracy is 86%.

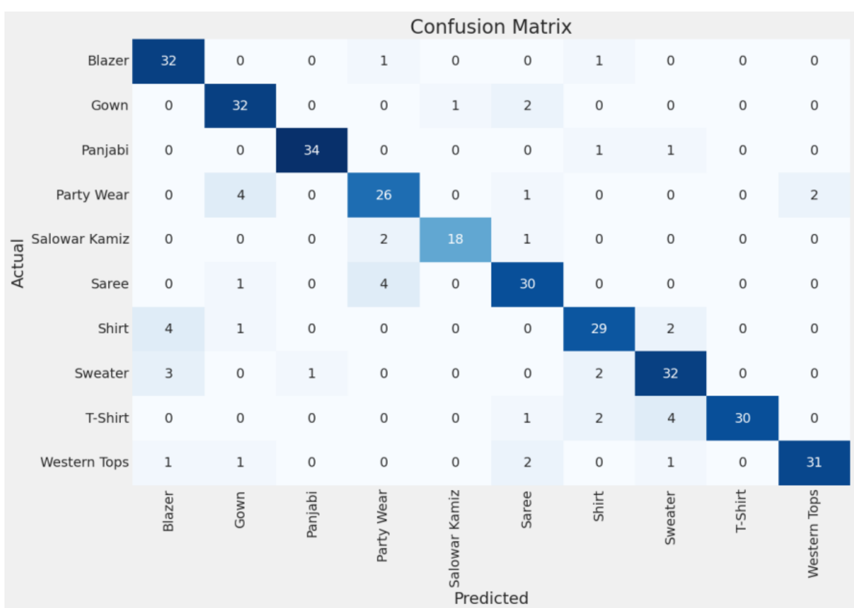

Figure-22: Classification Report for EfficientNetB3

4.2.4.4.Classification report

Our dataset consists of 10 classes- shirt, Punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear by analyzing the classes, classification report i.e., precision, recall, f1_score and support showed that EfficientNetB3 has 86% assurance report.

Table-16: Classification report of EfficientNetB3 Algorithm

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

In the classification report we can see that Precision, Recall, F1_Score and Support are extracted for all classes types (shirt, Punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear). Along with finding out Accuracy, Macro Avg, Weighted Avg value has also been found out. Accuracy of EfficientNetB3 algorithm is 86%.

4.2.4.5.Test set Accuracy and Error

Accuracy on the test set is 86.47 %.

Table-17: Test set Accuracy and Error

Model	Loss	Accuracy
EfficientNetB3	0.47	0.8647

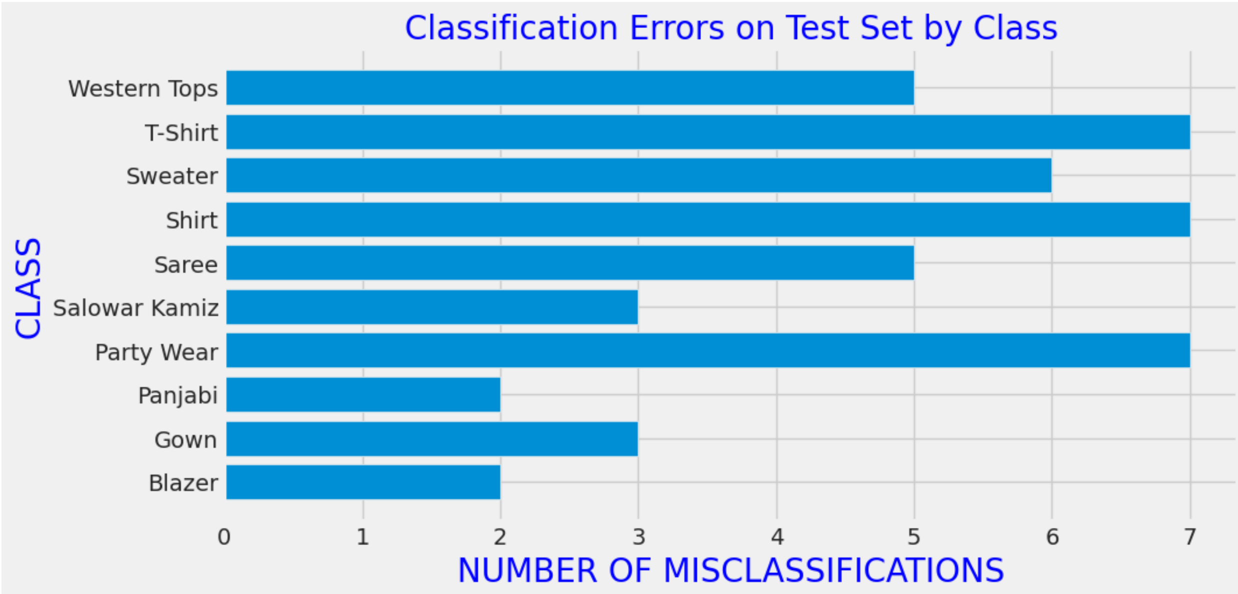

Figure-23: Test Set Error by Class wise

4.2.5. Inception V3

4.2.5.1. Validation and Training accuracy

Table-18: Validation and Training accuracy table for Inception V3

Epoch No	Validation Accuracy	Training Accuracy
Epoch 1	0.43	0.31
Epoch 2	0.65	0.59
Epoch 3	0.90	0.76
Epoch 4	0.68	0.81
Epoch 5	0.87	0.80

The multiclass unbalanced classification issue is the reason why the validation accuracy has not increased by more than 87%, as can be seen from the accuracy plot. Furthermore, the performance of the model may be enhanced by appropriately fine-tuning the vocabulary sizes.

4.2.5.2. Validation and Training loss

Table-19: Validation and Training loss for Inception V3

No	Validation Loss	Training Loss
Epoch 1	1.57	3.26

Epoch 2	1.09	1.32
Epoch 3	0.38	0.76
Epoch 4	0.66	0.58
Epoch 5	0.38	0.55

4.2.5.3.Confusion Matrix

In this paper accurate prediction is performed to indicate perfect prediction for shirt, Punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear classes. The confusion matrix revealed the following distribution of predicted and true labels:

We can see from the confusion matrix that the Inception V3 report accuracy is 60%.

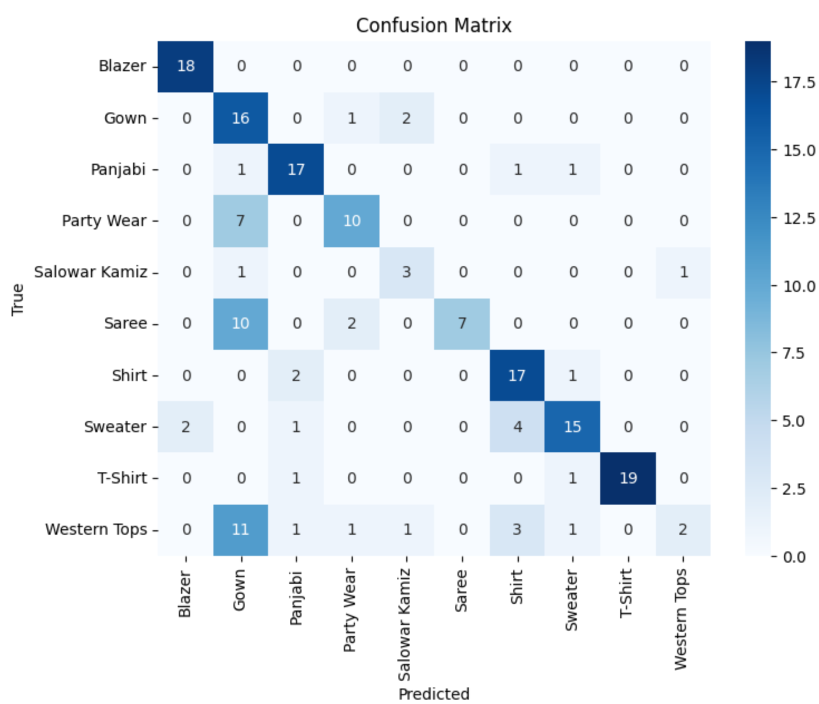

Figure-24: Confusion Matrix for InceptionV3

4.2.5.4.Classification report

Our dataset consists of 10 classes- shirt, Punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear by analyzing the classes, classification report i.e., precision, recall, f1_score and support showed that Inception V3 has 60% assurance report.

Table-20: Classification report of Inception V3 Algorithm

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

In the classification report we can see that Precision, Recall, F1_Score and Support are extracted for all classes types (shirt, Punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear). Along with finding out Accuracy, Macro Avg, Weighted Avg value has also been found out. Accuracy of Inception V3 algorithm is 60%.

4.2.5.5.ROC Curve

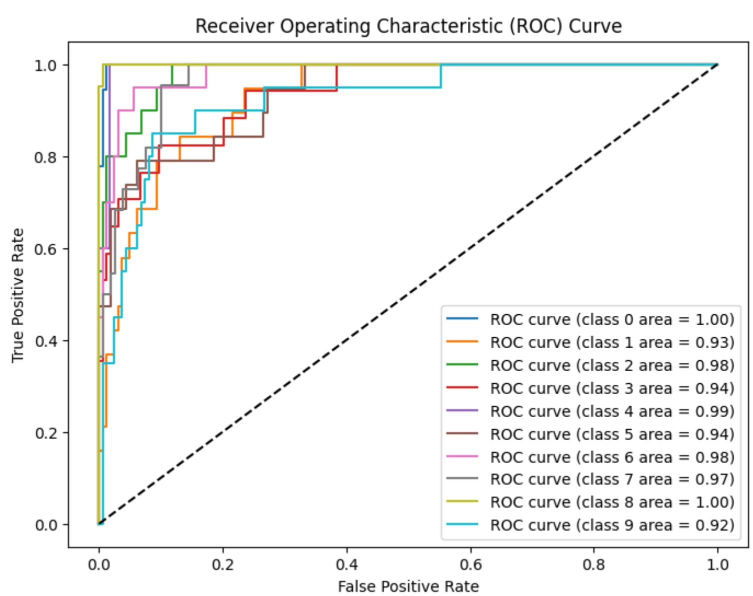

Figure-25: ROC Curve for InceptionV3

4.2.5.6.Cross Validation & Misclassification Error

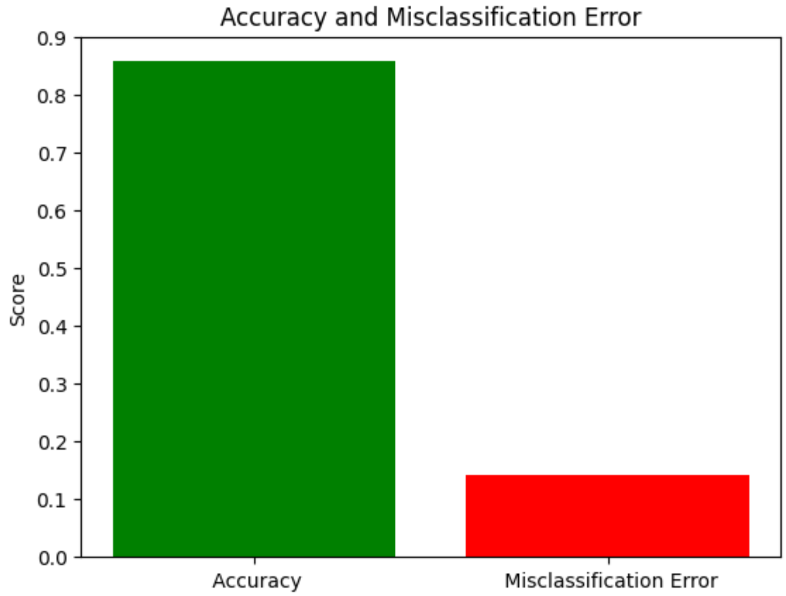

Figure-26: ROC Curve for InceptionV3

4.2.6. DenseNet201

4.2.6.1.Validation and Training accuracy

Table-21: Validation and Training accuracy table for DenseNet201

Epoch No	Validation Accuracy	Training Accuracy
Epoch 1	0.53	0.42
Epoch 2	0.75	0.77
Epoch 3	0.87	0.89
Epoch 4	0.90	0.91
Epoch 5	0.93	0.92

The multiclass unbalanced classification issue is the reason why the validation accuracy has not increased by more than 93%, as can be seen from the accuracy plot. Furthermore, the performance of the model may be enhanced by appropriately fine-tuning the vocabulary sizes.

4.2.6.2.Validation and Training loss

Table-22: Validation and Training loss for DenseNet201

No	Validation Loss	Training Loss
Epoch 1	1.13	1.93
Epoch 2	0.66	0.69
Epoch 3	0.34	0.40
Epoch 4	0.23	0.28
Epoch 5	0.17	0.22

4.2.6.3.Confusion Matrix

In this paper accurate prediction is performed to indicate perfect prediction for shirt, Punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear classes. The confusion matrix revealed the following distribution of predicted and true labels:

We can see from the confusion matrix that the DenseNet201 report accuracy is 65%.

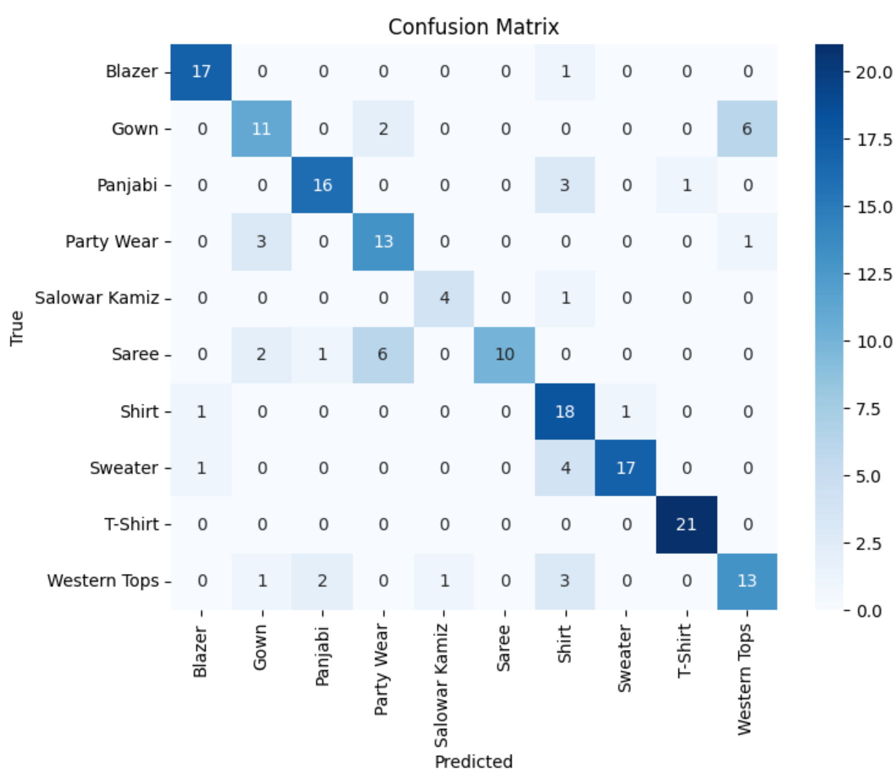

Figure-27: Confusion Matrix for DenseNet201

4.2.6.4.Classification report

Our dataset consists of 10 classes- shirt, Punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear by analyzing the classes, classification report i.e., precision, recall, f1_score and support showed that DenseNet201 has 65% assurance report.

Table-23: Classification report of DenseNet201 Algorithm

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

In the classification report we can see that Precision, Recall, F1_Score and Support are extracted for all classes types (shirt, Punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear). Along with finding out Accuracy, Macro Avg, Weighted Avg value has also been found out. Accuracy of DenseNet201 algorithm is 65%.

4.2.6.5.ROC Curve

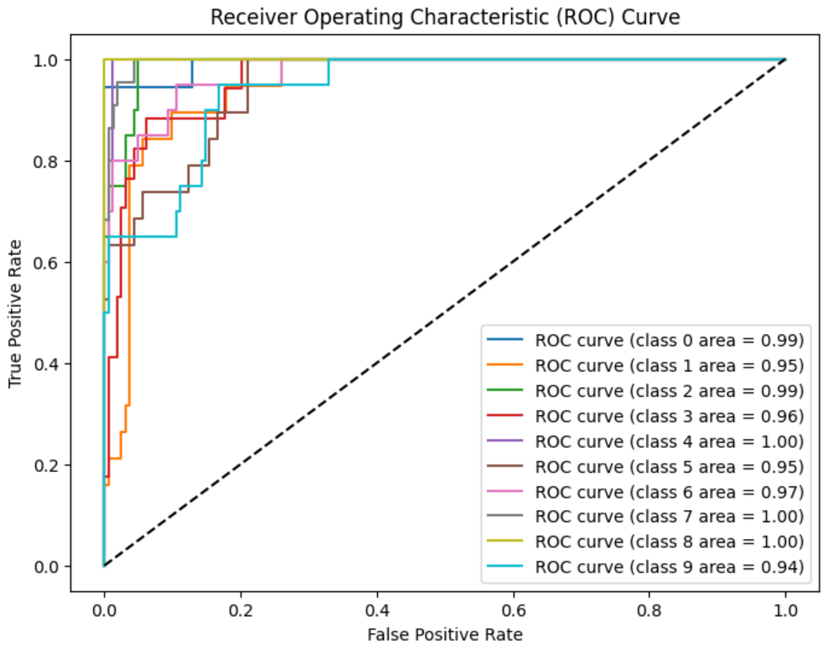

Figure-28: ROC Curve for DenseNet201

4.2.6.6.Cross Validation & Misclassification Error

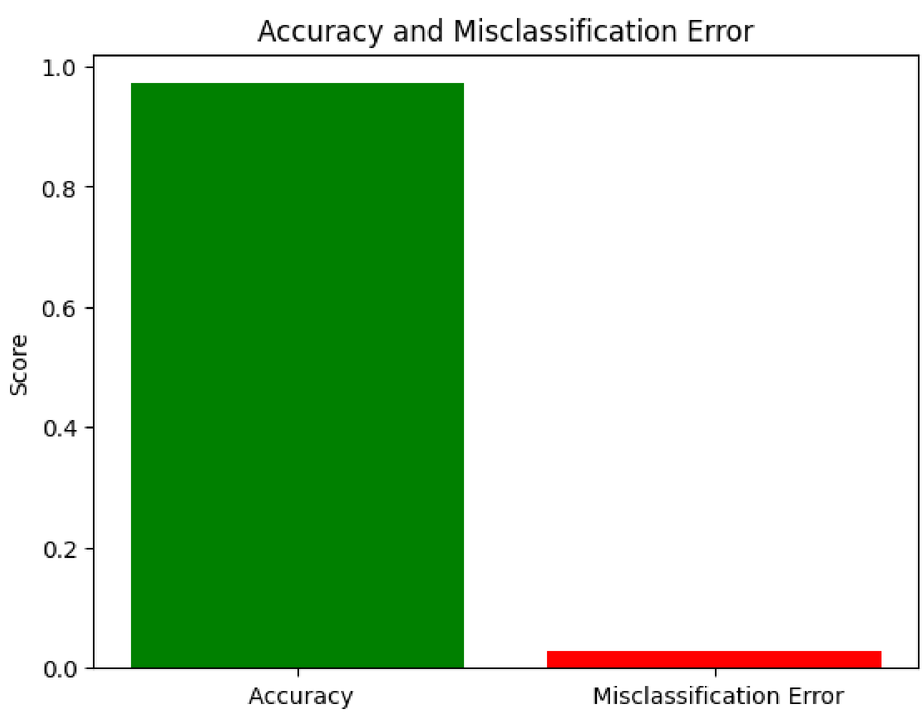

Figure-29: Accuracy and Misclassification Error for DenseNet201

4.2.7. VGG19

4.2.7.1. Validation and Training accuracy

Table-14: Validation and Training accuracy table for VGG19

Epoch No	Validation Accuracy	Training Accuracy
Epoch 1	0.65	0.63
Epoch 2	0.80	0.89
Epoch 3	0.81	0.94
Epoch 4	0.81	0.97
Epoch 5	0.81	0.97

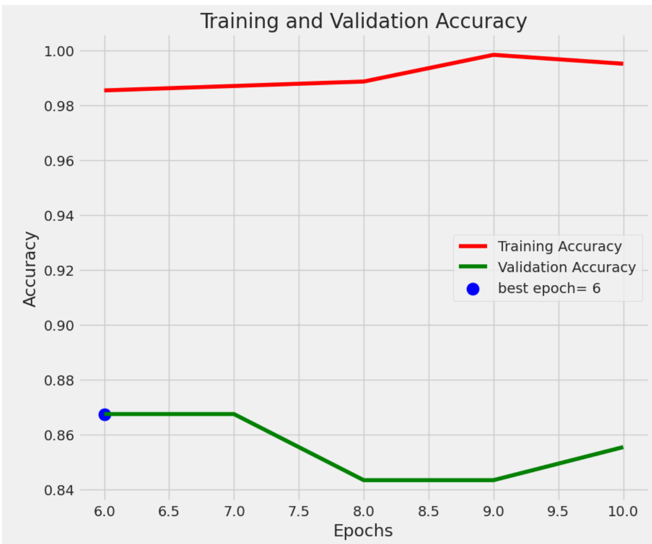

Figure-20: Epochs vs Training & Validation Accuracy Plot for VGG19

The multiclass unbalanced classification issue is the reason why the validation accuracy has not increased by more than 81%, as can be seen from the accuracy plot. Furthermore, the performance of the model may be enhanced by appropriately fine-tuning the vocabulary sizes.

4.2.7.2. Validation and Training loss

Table-15: Validation and Training loss for VGG19

No	Validation Loss	Training Loss
Epoch 1	14.84	15.33

Epoch 2	13.17	13.332
Epoch 3	11.86	12.04
Epoch 4	10.84	10.97
Epoch 5	9.95	10.04

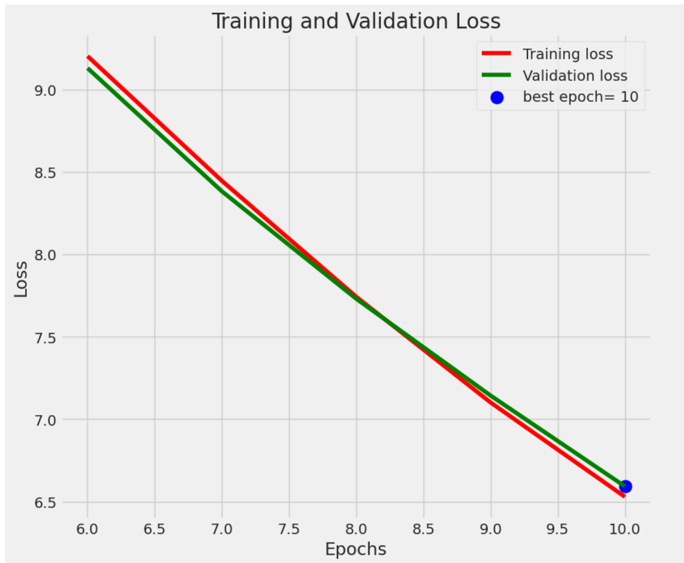

Figure-21: Epochs vs Training & Validation Loss Plot for VGG19

4.2.7.3.Confusion Matrix

In this paper accurate prediction is performed to indicate perfect prediction for shirt, Punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear classes. The confusion matrix revealed the following distribution of predicted and true labels:

We can see from the confusion matrix that the VGG19 report accuracy is 85%.

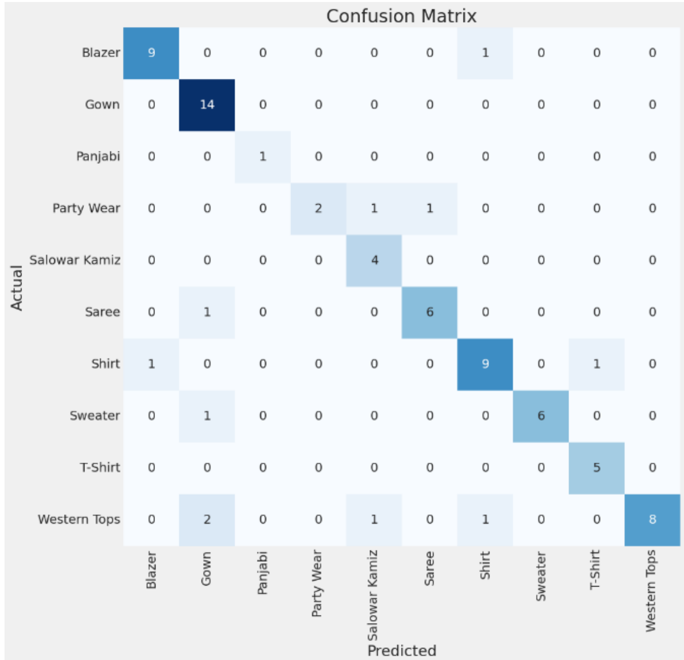

Figure-22: Classification Report for VGG19

4.2.7.4.Classification report

Our dataset consists of 10 classes- shirt, Punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear by analyzing the classes, classification report i.e., precision, recall, f1_score and support showed that VGG19 has 85% assurance report.

Table-16: Classification report of VGG19 Algorithm

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

In the classification report we can see that Precision, Recall, F1_Score and Support are extracted for all classes types (shirt, Punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear). Along with finding out Accuracy, Macro Avg, Weighted Avg value has also been found out. Accuracy of VGG19 algorithm is 85%.

4.2.7.5.Test set Accuracy and Error

Accuracy on the test set is 85 %.

Table-17: Test set Accuracy and Error

Model	Loss	Accuracy
VGG19	6.73	0.8533

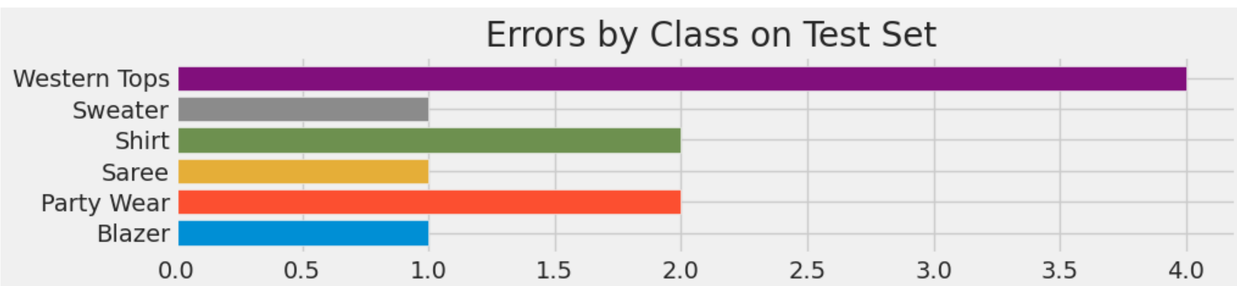

Figure-23: Test Set Error by Class wise

4.2.8. Overall Classification Report:

Fashion design recommendation systems leverage machine learning and deep learning to provide personalized and on-trend suggestions to users. These systems analyze user preferences, historical fashion choices, and current trends to generate tailored recommendations. Machine learning algorithms process vast amounts of data, considering factors such as clothing styles, colors, and patterns, to understand individual tastes. Deep learning, particularly Convolutional Neural Networks (CNNs), can extract intricate features from fashion images, enhancing the accuracy of recommendations. These models learn complex patterns and styles, enabling them to discern subtle nuances in clothing designs. The recommendation process involves training the models on diverse datasets, incorporating information on clothing attributes, user behaviors, and the ever-evolving fashion landscape. As users interact with the system, it continuously refines its predictions, adapting to changing preferences and emerging trends. Fashion design recommendation systems not only enhance user experience by offering tailored suggestions but also benefit retailers by improving customer engagement and conversion rates. By combining the power of machine learning and deep learning, these systems contribute to a more personalized and dynamic fashion landscape, revolutionizing how individuals discover and embrace new styles.

In this paper I have used the Customize CNN Algorithm, through which we have used the 6 architectures of CNN. The 7 custom CNN methods we used are MobileNetV2, MobileNetV3, EfficientNet B0, EfficientNet B3, Inception V3 and DenseNet201. 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%.

Table-24: 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
EfficientNet B0	0.80	0.83	0.81	0.81
EfficientNet 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

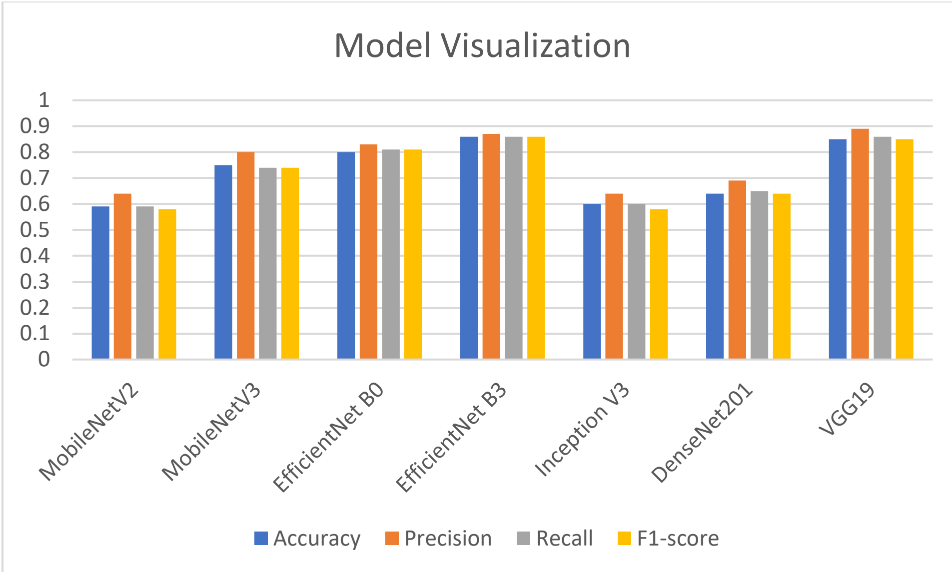

Figure-30: Overall Model Visualization

CHAPTER 5

IMPECT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1. Impact on Society

People are worshipers of beauty. People want that they can always walk in a neat and tidy manner. That's why people want all parts of their body to be well-groomed. In keeping all these parts tidy, people give the most importance to their clothes, pants and shoes.

- All these actions have a good effect on the society, because if everyone analyzes the fashion trends, wears neat clothes according to the recommendations, then a sense of innovation will prevail in the society.
- The said society or country or nation will be considered different or premium from other other countries or nations or communities.
- If someone comes from outside society or country or nation, then we will develop good, beautiful and positive attitude about our own society or country.
- Analyzing fashion trends, if everyone chooses color combinations and wears clothes according to recommendations, many new things need to be bought. Then society or country's economy will advance.
- If there is a lack or shortage of clothes in this sector, the country or society will create an attitude to produce clothes itself.
- Various small and large industries or companies will be created and move forward based on this sector.
- If the small and big industries or companies are established, the people of all professions of the country will get work opportunities here, that is, unemployment will decrease.
- The company will meet the needs of the country and earn foreign currency by exporting abroad.
- Besides earning foreign exchange, it will help to increase the foreign reserve of the country.

5.2. Impact on Environment

By analyzing fashion trends and making recommendations, the sector will have a good impact socially as well as environmentally. Environmentally there are two types of feedback, good and bad. As people tend to be neater for fashion trend analysis and recommendations, people will continue to buy different types of clothes. The income of the traders will increase through the purchase of clothes, as a result of which the traders will feel happy by selling them. Again the customers will be happy to buy their essentials, new things everyday. When both parties are happy, people in other professions will also be happy to sell more things around them. And this joy will spread into the environment and take the environment to another dimension.

Along with the positives on the environment, there are also some negatives. Various clothing industries will be created based on fashion trends and recommendations. As a result, different types of thunderous substances will be released from the industrial factories regularly. If the raw materials are thrown in different directions, the environment will be polluted.

5.3. Ethical Aspects

Fashion trend analysis and recommendations have a specific strategy. The fashion trend analysis and recommendation companies can take an autonomous approach. Generally, fashion trend analysis and recommendations sometimes put people in an unpleasant situation with wrong information. For example: recommending one garment with another, suggesting color combinations in reverse, suggesting one thing with another, and giving wrong information about anything related to different subjects. These problems are sometimes due to system bugs, but also due to fraudulent activities. However, fashion trend analysis and recommendations sometimes spread negative news against people by misinforming or deceiving people. However, today online fashion trend analysis and recommendations are less fake than ever. This means that we should all care about ethics and use social media or online ethically.

5.4. Sustainability

To keep our data or images in different categories we need to divide our data or images into different classifications. Thus, fashion trends can be recognized in various categories for analysis and recommendation. From now on the information and images can be used and with the aim that the information and images can be used for any valuable reason. This is why there should be a long system, in which any kind of information and images can be pre-processed and divided into different categories by applying different algorithms. That's why having a plane is important for long-range thinking.

CHAPTER 6
SUMMARY, CONCLUSION, RECOMENDATION AND IMPLEMENTATION FOR FUTURE RESEARCH

6.1. Summary of the Study

In contemporary times, the influence of deep learning on computer vision applications is rapidly expanding. Its applications span various domains, including clothing search and automatic product recommendations. The integration of deep learning techniques in artificial intelligence has become instrumental in comprehending, suggesting, and categorizing human clothing, offering valuable insights for enhancing sales strategies and understanding user preferences. Presently, artificial intelligence is tailored to aid researchers in discovering models for effectively classifying fashion-related datasets. The paper under consideration not only introduces a novel deep learning model based on Convolutional Neural Network (CNN) to address classification challenges but also presents a comparative analysis of primary classification methods. Unlike conventional machine learning algorithms, CNNs excel in feature extraction from images through their convolutional layers, showcasing the paradigm shift brought about by deep learning in handling complex tasks in the realm of fashion-related data. 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. The main goal of this project is that research findings can contribute to the development of intelligent fashion style analysis and recommendation systems, to improve users' fashion choices. 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 VGG19, MobileNetV2, MobileNetV3, EfficientNet B0, EfficientNet B3, Inception V3 and DenseNet201. 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%.

6.2. Conclusions

In contemporary times, the influence of deep learning on computer vision applications is continually growing. This transformative technology finds application in various domains, including clothing search and automatic product recommendation. The integration of deep learning techniques into artificial intelligence has become indispensable for comprehending, suggesting, and categorizing human clothing, offering valuable insights to enhance sales strategies and gain a deeper understanding of user preferences. The development of artificial intelligence capable of understanding, recommending, and labeling human clothing has far-reaching implications, contributing not only to improved sales performance but also to a more nuanced understanding of user behaviors. This signifies a pivotal shift in leveraging advanced technologies to cater to the evolving needs of industries, marking a significant advancement in the realm of computer vision and artificial intelligence applications. The main goal of this project is that research findings can contribute to the development of intelligent fashion style analysis and recommendation systems, to improve users' fashion choices. 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. 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. In this paper, a new deep learning model based on Convolutional Neural Network (CNN) is proposed to solve the classification problem. These networks can extract features from images using convolutional layers, unlike traditional machine learning algorithms. 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 VGG19, MobileNetV2, MobileNetV3, EfficientNet B0, EfficientNet B3, Inception V3 and DenseNet201. 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%.

6.3. Implication for Further Study

In this study, we show how to analyze fashion trends and suggest different categories of clothing. In future we will work with more and more categories. A process of analyzing and recommending fashion trends can be implemented using various data science techniques including machine learning and deep learning algorithms to classify different types of algorithms. More sophisticated algorithms will be used in the future by analyzing fashion trends and implementing a recommendation process. This study only demonstrated the use of 3 models of the CNN algorithm; However, other algorithms will be incorporated in the future to further classify such data as it analyzes fashion trends and makes recommendations. In addition, this paper is divided into 10 categories: shirt, Punjabi, t-shirt, blazer, sweater, saree, salwar kameez, gown, western tops and party wear. Additional sections will be added in the future. In the future, the algorithms used in this article will be able to predict fashion trends with more precision and make recommendations.

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