A project report on

FASHION RECOMMENDER SYSTEMS USING TRANSFER LEARNING MODELS

Submitted in partial fulfillment for the award of the degree of

M Tech (Integrated) Computer Science and Engineering with Specialization in Business Analytics

by

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I hereby declare that the thesis entitled "FASHION RECOMMENDER SYSTEM USING TRANSFER LEARNING MODELS" submitted by me, for the award of the degree of M. Tech (Integrated) Computer Science and Engineering with Specialization in Business Analytics, Vellore Institute of Technology, Chennai, is a record of bonafide work carried out by me under the supervision of Dr. M PRASAD

I further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

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Name:	Name:
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ABSTRACT

This project introduces a personalized Fashion Recommender system, using user-input images for suggestions, diverging from historical purchase reliance. Oftentimes, individuals come across items of interest and seek similar products, making image input a valuable approach to cater to this behavior. Leveraging pre-trained CNN models on the Fashion Product Images Dataset, the system employs a hybrid recommendation approach, merging content-based and collaborative filtering techniques.

The focus is on determining the optimal model among VGG16, DenseNet121, and ResNet-50. Cutting-edge transfer learning facilitates rich visual feature extraction, and cosine similarity identifies the top 5 visually similar fashion products. The project aims to compare the efficiency of VGG16, DenseNet121, and ResNet-50 for feature extraction, providing insights into the most effective CNN model for real-world fashion discovery scenarios.

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LIST OF ACRONYMS

CNN	Convolution Neural Networks
VGG	Visual Geometry Group
ResNet	Residual Network
DenseNet	Densely Connected Convolutional Networks
t-SNE	t-Distributed Stochastic Neighbor Embedding
GANs	Generative Adversarial Networks
LSTM	Long Short-Term Memory
Bi-LSTM	Bidirectional Long Short-Term Memory
RNN	Recurrent Neural Network
k-NN	k-Nearest Neighbors
AUC	Area Under the Curve
ModAI	Fashion Compatibility Dataset
BLEU-4	Bilingual Evaluation Understudy 4
SBPR	Style-aware Bayesian Personalized Ranking
ML	Machine Learning
NLP	Natural Language processing
SBPR	Style-aware Bayesian Personalized Ranking
DNN	Deep Neural Network
BLEU	Bilingual Evaluation Understudy
EDA	Exploratory Data Analysis

Chapter 1

Introduction

1.1 INTRODUCTION

In the contemporary digital era, fashion serves as a powerful means of self-expression and personal identity. However, the ever-expansive and dynamic landscape of the fashion industry can pose a considerable challenge for consumers seeking personalized recommendations that align with their unique style preferences. In response to this challenge, a project has been initiated to develop a state-of-the-art fashion recommender system, leveraging the transformative capabilities of transfer learning models. The vision is to seamlessly merge the visual allure of fashion with advanced machine learning techniques to provide users with tailored recommendations for clothing and accessories.

Recognizing the pivotal role of recommender systems across various domains, the retail industry is increasingly investing in cutting-edge technologies to enhance customer experiences. Fashion, as an enduring and influential aspect of human culture, has witnessed remarkable growth in the textile and apparel industry. As the standard of living rises, individuals naturally gravitate towards fashion as a popular form of aesthetic expression. Humans are inevitably drawn to things that are more visually appealing. This human tendency has resulted in the evolution of the fashion industry over time.

However, the sheer abundance of options in the online fashion marketplace has given rise to a new set of challenges for consumers. Women, in particular, navigate a vast product base, making decision-making a complex task. Moreover, apparel providers need their customers to explore their entire product line so that they can choose what they like the most which is not possible by simply going into a cloth store. Millions of products are now available in online catalogs, saving customers from having to visit many stores, wait in line, or try on clothing in changing rooms. Since the plethora of options available on the e-commerce websites presents new challenges to the customers in identifying their correct outfit, the traditional methods of exploring stores no longer suffice, prompting the need for innovative solutions. In this context, an effective recommendation system is necessary to properly sort, order, and communicate relevant product material or information to users. Recommender systems assist users in navigating large collections of products to find items relevant to their interests. Recommender systems use large amounts of product information and user signals such as product views, followed or ignored items, purchases, or web-page visits to determine how, when, and what to recommend to their customers.

The intricacies of the fashion industry pose unique challenges for building an effective recommendation system. The dynamic nature of fashion, influenced by seasonal trends, festivals, and even global conditions like pandemics, requires adaptive and responsive solutions. To deal with the aforementioned problems, and given the visual and aesthetic nature of fashion products, there is a growing body of computer vision research, leveraging pre-trained CNNs like VGG16, DenseNet121, and ResNet-50, addressing tasks like localizing fashion items, determining their category and attributes or establishing the degree of similarity to other products, to name only a few. While existing computer vision literature may not explicitly consider personalization or recommendation, their predictions and embeddings can be harnessed by recommender systems, mitigating issues of sparsity and the cold start problem.

In summary, this project endeavors to bridge the gap between the ever-evolving world of fashion and the need for personalized recommendations. By fusing visual aesthetics with cutting-edge machine learning, the aim is to provide users with a seamless and enriching experience, navigating the intricate realm of fashion with tailored suggestions that resonate with individual style preferences. The project employs a hybrid recommendation system, merging content-based and collaborative filtering techniques, focusing on determining the optimal model among VGG16, DenseNet121, and ResNet-50. Additionally, the project aims in contributing valuable insights into the most effective CNN model for real-world fashion discovery scenarios. This comprehensive approach seeks to provide personalized and visually-driven fashion recommendations, aligning with the ever-evolving dynamics of the fashion industry.

1.2 OVERVIEW

1.2.1 RECOMMENDER SYSTEMS OVERVIEW

Recommender systems, often referred to as recommendation engines, represent intelligent algorithms designed to enhance user experiences by assisting in the discovery and selection of items from an extensive array of options. These systems leverage user data, preferences, and item characteristics to generate personalized recommendations, thereby fostering greater user engagement. Broadly categorized into collaborative filtering, content-based filtering, hybrid systems, context-aware systems, and knowledge-based systems, these algorithms employ various approaches to provide tailored suggestions based on user behavior and item attributes.

In the context of the project, the recommender system takes center stage as a pivotal solution to the challenges posed by the ever-expansive fashion landscape. This project embraces a hybrid recommendation system, seamlessly merging content-based and collaborative filtering techniques to enhance the precision and relevance of fashion suggestions. Content-based techniques involve the extraction of rich visual features from user-provided images using pre-trained convolutional neural networks, including VGG16, DenseNet121, and ResNet-50. These features encapsulate the essence of users' clothing styles, ensuring a deeper understanding of individual preferences. Content-based recommendation relies on analyzing item characteristics, in this case, visual attributes of fashion items, to provide personalized suggestions. On the collaborative filtering front, similarity-based ranking techniques, such as cosine similarity, come into play. Collaborative filtering is a technique that makes automatic predictions about the preferences of a user by collecting preferences from many users. It identifies the top 5 visually similar fashion products by comparing the extracted features, contributing to diverse and tailored fashion recommendations.

The hybrid nature of the recommender system lies in its adept fusion of these techniques. While content-based methods prioritize visual aesthetics, collaborative filtering techniques refine recommendations based on the similarity of user preferences.

1.2.2 TRANSFER LEARNING OVERVIEW

Transfer learning, a prominent machine learning technique, involves training a model on one task and leveraging the acquired knowledge to enhance performance on a related but distinct task. Within neural networks, transfer learning finds widespread application in image and text-related tasks. Key concepts include pre-trained models, which are initially trained on extensive datasets for tasks like image classification or language modeling, and subsequent fine-tuning, which refines the model on a task-specific dataset. Domain adaptation addresses the challenge of applying a model trained in one domain to a related domain by adjusting it to perform effectively in the target domain.

In the realm of fashion recommender systems, transfer learning is applied through pre-trained convolutional neural networks (CNNs) such as VGG16, DenseNet121, and ResNet-50. These models, initially trained on extensive datasets for tasks like image classification, bring forth a wealth of knowledge about general visual features and patterns. The transfer learning process involves fine-tuning these pre-trained models on a task-specific dataset related to fashion images. This step enables the model to adapt its learned features to the nuances of the new task, enhancing its ability to discern fashion-related attributes and characteristics. Additionally, the project explores the efficiency of VGG16, DenseNet121, and ResNet-50 for feature extraction, aiming to contribute insights into the most effective CNN model for real-world fashion discovery scenarios.

This integration of transfer learning into recommender systems brings forth several benefits. Firstly, it contributes to improved performance, enabling systems to comprehend intricate user preferences and patterns. Secondly, it addresses data limitations, allowing recommender systems to deliver effective results even in scenarios with sparse task-specific data, such as the cold start problem. Moreover, transfer learning facilitates efficient training by initializing models with weights acquired from prior tasks, proving particularly advantageous in resource-intensive tasks like deep learning. Additionally, pre-trained models excel at capturing domain-specific features, whether in images, text, or user interactions, enriching the understanding of items and users within recommender systems.

By incorporating transfer learning models, the project accelerates the training process, mitigates data requirements, and enables the recommender system to capture domain-specific features in images. This not only improves the accuracy and efficiency of fashion recommendations but also ensures the system's adaptability to the dynamic nature of the fashion industry.

1.3 PROBLEM STATEMENT

In the ever-evolving world of fashion, finding the perfect outfit that aligns with individual style preferences can be overwhelming. Traditional recommender systems often fall short in addressing the nuanced complexities of the fashion landscape, grappling with issues such as the cold start problem for new users, the need for efficient feature extraction, and the continual adaptation to evolving fashion trends. This project breaks away from conventional methods and uses user-provided product images to recommend similar fashion items, addressing the challenge of visual inspiration. It aims to assist users in discovering similar fashion items when they are inspired by a specific image they've encountered. By incorporating cosine similarity, we enable the system to suggest the top 5 visually similar fashion products from the database. This approach combines content-based recommendation, driven by image content, with collaborative filtering-like techniques, revolutionizing the fashion discovery experience.

The underlying issue involves the limitations of conventional methods in capturing the nuanced aspects of visual inspiration and translating them into relevant recommendations. The proposed solution involves a hybrid fashion recommender system that leverages pre-trained convolutional neural networks (CNNs) like VGG16, DenseNet121, and ResNet-50. However, the challenge lies in determining the optimal model among these options for efficient feature extraction from the Fashion Product Images Dataset. The project aims to overcome this challenge by comparing the performance of VGG16, DenseNet121, and ResNet-50, contributing valuable insights into the most effective CNN model for real-world fashion discovery scenarios. In essence, the problem statement revolves around enhancing the user experience by seamlessly translating visual inspiration into personalized and visually-driven fashion recommendations through innovative image-based recommendation approaches.

1.4 SCOPE OF THE PROJECT

The scope of this project encompasses the development and optimization of a sophisticated Fashion Recommender system with a focus on elevating the fashion discovery experience. The key components within the project's scope include:

Transfer Learning Models:

The project involves an in-depth exploration and optimization of transfer learning models, specifically VGG16, DenseNet121, and ResNet-50, for effective feature extraction from fashion images. This endeavor seeks to enhance the system's ability to capture rich and meaningful visual features that encapsulate users' unique clothing styles.

Content-Based Recommendations:

The research extends to providing content-based recommendations by leveraging the visual content of user-provided images. Prioritizing visual elements aims to deliver suggestions that align closely with users' aesthetic preferences, contributing to a more visually-driven and satisfying fashion exploration journey.

Hybrid Recommendation Approach

The project explores a hybrid recommendation approach that seamlessly integrates content-based recommendation with collaborative filtering aspects, such as similarity-based ranking. This hybrid model aims to offer diverse and personalized fashion suggestions, combining the strengths of both content-driven and collaborative approaches.

Model Comparison and Evaluation

The efficiency and effectiveness of VGG16, DenseNet121, and ResNet-50 for feature extraction are comprehensively compared using t-SNE, providing valuable insights into how well clusters are formed. This comparative analysis informs the determination of the optimal model for real-world fashion discovery scenarios.

Addressing the Cold Start Problem

The research aims to tackle the "cold start" problem by developing strategies to provide accurate recommendations for new users or fashion items with limited interaction history. Utilizing visual content in these scenarios ensures the system remains adaptive and effective even in the absence of extensive user data.

Overall, the scope of the project is broad, covering various aspects of feature extraction, recommendation approaches, model optimization, and addressing common challenges in the fashion recommendation domain. The ultimate goal is to contribute significantly to the advancement of personalized and visually-driven fashion recommendation systems, enhancing the overall user experience in the realm of fashion discovery.

Chapter 2

Back Ground

2.1 LITERATURE REVIEW ON RECOMMENDER SYSTEMS

In the dynamic and ever-evolving realm of fashion recommender systems, a thorough literature survey illuminates valuable insights from key research papers, each contributing distinctive approaches to tackle the multifaceted challenges in this domain. In recent years, the fusion of generative models and collaborative filtering has emerged as a promising avenue for enhancing personalized recommendation systems "Visually-Aware Fashion Recommendation and Design with Generative Image Models (2017)" stands out as a pioneering work, leveraging Generative Adversarial Networks (GANs) to create a personalized recommendation system that incorporates collaborative filtering techniques. This innovative approach involves the generation of entirely new fashion items that align seamlessly with individual user preferences [1].

Complementing this, "An LSTM-Based Dynamic Customer Model for Fashion Recommendation (2017)" dives into the intricacies of sequential user behavior modeling using Long Short-Term Memory (LSTM). While recognizing the computational intensity associated with LSTMs, the paper underscores their efficacy in capturing evolving user preferences over time [2]. Expanding the spectrum, "Generating Top-N Items Recommendation Set Using Collaborative, Content-Based Filtering, and Rating Variance (2018)" introduces a hybrid system that strategically combines content-based and collaborative filtering techniques. This unique fusion prioritizes precision in recommendations, achieving higher precision even with shorter recommendation lists, addressing the common issue of overwhelming recommendation lists in e-commerce [3].

Meanwhile, "Learning Fashion Compatibility with Bidirectional LSTMs (2017)" explores the nuanced facets of fashion recommendation, emphasizing the joint learning of visual-semantic embeddings and compatibility relationships through Bidirectional LSTMs. While effective, the paper notes the computational intensity of these models, especially when dealing with extensive datasets [4].

A notable addition to this landscape is "Image-Based Fashion Product Recommendation with Deep Learning (2019)," which introduces a two-stage deep learning framework. This framework utilizes a trained CNN classifier for feature extraction from input images and a modified k-nearest neighbors (k-NN) algorithm for ranking in the feature space. This approach not only enriches the robustness of the recommendation system but also aligns well with individual customer styles [5]. The study "Personal Recommendation using Deep Recurrent Neural Networks in NetEase (2016)" contributes a real-time recommendation approach for e-commerce. By treating user sessions as sequences of web pages and deploying deep recurrent neural networks, this paper demonstrates a continuous monitoring and enhancement of user interactions, providing valuable insights for dynamic and evolving user preferences [6]. On a parallel trajectory, "Learning to Style-Aware Bayesian Personalized Ranking for Visual Recommendation (2019)" elevates the visual recommender systems by incorporating style features. The paper introduces Style-aware Bayesian Personalized Ranking (SBPR), emphasizing the integration of style features into recommendation models, particularly for implicit feedback scenarios [7].

"Different from these studies is the work titled "Deep Learning-based Large-Scale Visual Recommendation and Search for E-Commerce (2017)," which addresses the need for a unified Visual Search and Recommendation system. This paper proposes VisNet1, a Deep Convolutional Neural Network capable of capturing visual similarity across various semantic levels. The model's successful deployment at Flipkart, India's largest e-commerce platform, highlights its practical applicability in handling a massive catalog of 50 million products [8]."

"Advancing Performance of Retail Recommendation Systems (2020)" introduces two recommendation models for J. Hilburn, a custom-fit men's clothing company, aiming to enhance customer insights and boost sales. The first model is a content-based collaborative filtering approach, while the second model represents a novel ensemble approach. This ensemble method combines clustering, K-nearest neighbors (KNN), and time series models, with results feeding into a neural network for generating clothing recommendations. The ensemble model achieves higher accuracy, as measured by AUC, compared to the baseline model [9].

"Adaptable Recommendation System for Outfit Selection with Deep Learning Approach (2021)" addresses the limitations of traditional systems by proposing a recommendation system that relies on user preferences. This system operates in two phases: short-term memory, constantly updated with user interactions, and long-term memory based on a deep neural network (DNN). It encompasses three key stages: Database Generator for encoding garment visual characteristics, Model Ranking for scoring recommendations, and implicit profiling for updates based on user preferences [10]. "Diagnosing fashion outfit compatibility with deep learning techniques (2023)" introduced a method for diagnosing outfit compatibility using clothing images, creating a novel dataset called ModAI. Image captioning techniques were employed to generate compatibility suggestion texts, demonstrating a BLEU-4 score of 0.62 [11].

"Multi Clustering Recommendation System for Fashion Retail (2023)" proposed a recommendation system using a multi-clustering approach for items and user profiles. Leveraging data mining techniques, the system addressed the "cold start" problem, resulting in a 3.48% increase in buyer attention and purchases [12]. "Multi-Task Learning and Gender-Aware Fashion Recommendation System Using Deep Learning (2023)" focused on improving efficiency and result quality by incorporating gender detection, object detection, similarity generation, and recommendation components. The system outperformed existing methods in both accuracy and performance [13].

"Fashion recommendation based on style and social events (2023)" introduced an additional semantic layer based on dressing style, capturing mood and emotion through color combinations and assessing appropriateness for social events. The integration of style and event classifiers into a garment recommendation framework enabled recommendations conditioned on both style and occasion [14]. The intersection of computer vision and natural language processing within the fashion domain was explored in "Clothes image caption generation with attribute detection and visual attention model (2021)." This paper significantly improved the performance of clothes image captioning while minimizing misleading attention [15].

This comprehensive survey showcases the diverse approaches in the literature, addressing key challenges and pushing the boundaries of fashion recommender systems. These collective contributions propel the evolution of fashion recommender systems, offering diverse perspectives and innovative solutions to enhance personalization, handle sequential data, and integrate deep learning techniques for more accurate and efficient recommendations.

2.2 THEMES DISCOVERED IN REVIEW

Personalization and User-Centric Approach

Personalization is a central theme in fashion recommender systems, acknowledging the diverse and subjective nature of individual preferences. Many papers emphasize the importance of personalization in fashion recommendation systems. They aim to tailor recommendations to individual users' preferences, styles, and needs, recognizing that one size does not fit all in fashion. Papers such as [1,3,7] leverage advanced techniques, including Generative Adversarial Networks (GANs) and Style-aware Bayesian Personalized Ranking (SBPR), to create systems that tailor recommendations to users' unique styles and needs. These approaches emphasize the importance of understanding users on a granular level, considering not only their explicit interactions but also latent style features.

Image Analysis and Deep Learning

Computer vision and deep learning play a pivotal role in understanding fashion images. Papers like [1,5] utilize Convolutional Neural Networks (CNNs) for image analysis, enabling systems to understand clothing attributes and styles from images. Paper [1,2] introduces a Deep Convolutional Neural Network (VisNet 1) for unified visual search and recommendation, demonstrating its effectiveness on a massive e-commerce platform. These papers highlight the transformative impact of deep learning techniques in decoding intricate patterns and styles from visual data, enhancing the capability of recommender systems.

Sequential Data Modelling

The modeling of sequential data is a crucial aspect of recommender systems, particularly when dealing with evolving user behavior over time. Recurrent neural networks (RNNs) and LSTM models are frequently employed to capture evolving user preferences. Papers like [2, 4] employs Long Short-Term Memory (LSTM) models to capture evolving user preferences over time. Paper [6] introduced a deep recurrent neural network to monitor and enhance user interactions in real-time. These models go beyond static recommendations, recognizing the temporal aspect of fashion choices and the evolution of user preferences.

Multi-Modal Approaches

Some papers explore multi-modal recommendation, combining image analysis with textual data (such as product descriptions) to provide more comprehensive and informative recommendations. Paper [3] proposes a system that combines content-based and collaborative filtering techniques. Paper [5] introduces a two-stage deep learning framework integrating CNN classifiers and k-nearest neighbors (k-NN) algorithms for ranking in feature space. These papers showcase the importance of leveraging multiple data modalities to offer richer and more informative recommendations.

Addressing Cold Start Problem

Paper [9] introduces recommendation models for a custom-fit men's clothing company, aiming to address the cold start problem through clustering and ensemble approaches. These papers highlight efforts to improve recommendations for users with sparse interaction histories, a common challenge in recommender systems.

Integration of Semantic Layers

Some papers introduce additional semantic layers, considering aspects like mood, emotion, appropriateness for social events, and even outfit compatibility. This reflects a broader understanding of fashion beyond visual appeal, incorporating contextual and emotional elements.

Efforts Towards Real-world Deployments

Several papers highlight efforts to deploy and validate their models in real-world scenarios. This includes the development of large-scale visual recommendation systems and unified search and recommendation systems for e-commerce platforms.

Scalability and Real-time Recommendation

Scalability and real-time recommendation are identified as crucial considerations in fashion recommender systems. Paper [8] introduces a large-scale visual recommendation and search system successfully deployed on a major e-commerce platform. These papers recognize the challenges of handling large catalogs and dynamic inventory, emphasizing the importance of real-time responsiveness in fashion recommendations.

2.3 IDENTIFICATION OF GAPS BASED ON CURRENT SCENARIO

Short-Term and Long-Term Trends

While many systems focus on capturing users' long-term style preferences, there is a growing need to address short-term trends and immediate fashion interests, which are prevalent in the industry. Users today seek a balance between timeless styles and on-the-moment trends. To bridge this gap, future research should explore adaptive algorithms that dynamically adjust recommendations to align with both the user's long-term preferences and current fashion trends.

Cold Start Problem

Despite progress, handling the cold start problem, especially for new users with limited data, remains a challenge. Innovations in addressing this issue are required. Future research should focus on developing robust solutions that leverage alternative data sources, user profiling techniques, or hybrid models to enhance recommendations for new users, thus improving the overall user experience.

Style and Aesthetic Recognition

Recognizing and recommending fashion items aligned with users' unique style and aesthetic preferences remains intricate due to the subjective nature of individual styles. This requires more nuanced understanding of fashion. Future research should explore advanced computer vision and deep learning techniques to enhance style recognition, considering factors like color combinations, garment types, and overall fashion aesthetics.

Real-Time Interaction

Real-time user interactions, such as clicks and views, are crucial for providing up-to-the-minute recommendations. The gap in real-time interaction integration highlights the need for algorithms capable of processing user actions promptly. Research should focus on developing event-driven architectures and real-time recommendation strategies. Emphasizing user engagement patterns and understanding evolving preferences in the moment can lead to more contextually aware and responsive recommender systems. More research is needed to integrate real-time feedback into recommendation systems.

Scalability and Efficiency

With the increasing scale of fashion retail platforms, scalability and efficiency in handling large catalogs and dynamic inventory are critical considerations for recommender systems. There is a need for research that addresses the scalability challenges of recommender systems in the context of large-scale fashion platforms. Innovations in algorithmic efficiency and distributed computing can contribute to systems that handle extensive product catalogs with ease. Future research should explore scalable architectures, parallel processing, and optimization techniques to accommodate the expanding datasets and evolving inventories of large-scale fashion platforms.

In conclusion, the in-depth examination of the identified gaps underscores the importance of adopting a comprehensive strategy. Future investigations in fashion recommender systems ought to strive for an incorporation of short-term and long-term trends, inventive resolutions for the cold start problem, a sophisticated grasp of user styles, prompt responsiveness to real-time interactions, and the development of scalable, efficient architectures. This multifaceted approach is essential to meet the dynamic and evolving demands of the fashion industry.

Chapter 3

Research

3.1 RESEARCH CHALLENGES

In the pursuit of developing a Fashion Recommender system, several research challenges must be addressed to ensure its effectiveness and adaptability in the dynamic landscape of user-generated content and evolving fashion trends.

Data Quality and Variation: One of the primary challenges is the inherent variability in user-generated images, encompassing differences in quality, resolution, and background clutter. The task of achieving consistent and high-quality feature extraction from such diverse inputs poses a significant hurdle that demands meticulous attention.

Model Bias: Another critical research challenge pertains to mitigating model bias when optimizing transfer learning models for extracting meaningful visual features from fashion images. Transfer learning models inherit biases from the source data they were trained on, necessitating strategies to minimize biases and ensure fair and unbiased recommendations.

Multi-Modal Integration: Integrating multi-modal information, such as combining image analysis with textual data, adds complexity to the recommendation system. Effectively fusing different types of data to provide comprehensive and informative recommendations requires sophisticated modeling techniques.

Scalability: Scalability and efficiency constitute additional challenges, particularly in the context of handling large fashion databases and accommodating varying user loads. Building a system that can seamlessly scale to meet the demands of an expanding user base while maintaining efficiency is paramount for delivering a responsive and user-friendly experience.

Style and Aesthetic Recognition: Recognizing and understanding users' unique style and aesthetic preferences present a nuanced challenge. Developing models that can comprehend the intricacies of fashion styles and recommend items that align with individual tastes demand advanced feature extraction and representation techniques.

Cold Start Problem: This problem adds another layer of complexity, requiring solutions to provide accurate recommendations for new users or items with limited interaction history. Addressing this challenge involves developing methods that can effectively leverage available information to make relevant and personalized suggestions, even in the absence of extensive user data.

Concept drift: It poses an ongoing challenge as user preferences and fashion trends evolve over time. Transfer learning models may struggle to adapt quickly to these shifts, potentially resulting in outdated recommendations. Tackling concept drift requires continuous monitoring and adaptation mechanisms to ensure that the Fashion Recommender system remains attuned to the dynamic nature of user preferences and fashion dynamics.

3.2 RESEARCH OBJECTIVE

The research objective is to develop an engaging fashion discovery system that optimizes transfer learning models to extract meaningful visual features from fashion images. It aims to provide content-based recommendations, enhancing the user's fashion discovery experience by analyzing the visual content of user-provided images. The hybrid recommendation approach combines content-based and collaborative filtering methods to offer diverse and personalized fashion suggestions.

A primary focus of the research is on optimizing the use of transfer learning models for effective feature extraction from fashion images. This involves harnessing the capabilities of models like VGG16, DenseNet121, and ResNet-50 to extract rich and meaningful visual features that encapsulate the essence of users' clothing styles. The goal is to enhance the system's ability to comprehend and learn from user-provided images, ultimately improving the precision and relevance of fashion recommendations.

The research objective also extends to providing content-based recommendations, leveraging the visual content of user-provided images to enhance the fashion discovery experience. By prioritizing visual elements, the system aims to deliver recommendations that align more closely with users' aesthetic preferences, contributing to a more visually-driven and satisfying user experience.

A key aspect of the research is the exploration of a hybrid recommendation approach. This approach integrates content-based recommendation, utilizing image features, with collaborative filtering aspects such as similarity-based ranking. The objective is to create a hybrid model that offers diverse and personalized fashion suggestions, combining the strengths of both content-driven and collaborative approaches. Model comparison using t-SNE is incorporated to assess how effectively clusters are formed, providing valuable insights into the system's recommendation capabilities.

Furthermore, the project addresses the "cold start" problem inherent in scenarios involving new users or fashion items with limited interaction history. By focusing on utilizing visual content in these challenging scenarios, the Fashion Recommender system endeavors to remain adaptive and effective, even when confronted with a scarcity of user data. Collectively, these research objectives position the project at the forefront of advancing personalized and visually-driven fashion recommendation systems, contributing to a more immersive and tailored fashion exploration experience for users.

Chapter 4

Data

4.1 DATASET DESCRIPTION

The dataset utilized in this research originates from the burgeoning e-commerce industry, offering a rich and diverse collection of information for comprehensive analysis. Comprising a vast array of professionally shot high-resolution product images, the dataset provides a visually compelling exploration of various fashion items. These images serve as a crucial component for the implementation of cutting-edge technologies in the realm of computer vision and image processing.

In addition to the visual data, the dataset encompasses multiple label attributes meticulously entered during the cataloging process. These attributes serve as key metadata, offering insights into the diverse characteristics and features of each product. Furthermore, the dataset includes descriptive text accompanying each product. These textual comments provide additional context and information about the product characteristics, offering a textual dimension to complement the visual and metadata components. The combination of high-quality images, detailed label attributes, and descriptive text forms a multi-modal dataset that is well-suited for research and development in the fields of computer vision, machine learning, and natural language processing. The richness and diversity of the data present exciting opportunities for creating innovative solutions in the ever-evolving landscape of e-commerce and fashion technology.

4.2 CONTENT

The dataset comprises two essential components:

- image.csv: This file includes references to professionally shot high-resolution product images.
- styles.csv: This file contains metadata associated with each product, offering valuable attributes for analysis.

Each product in the dataset is uniquely identified by an ID, such as 10010, which corresponds to a specific product in the catalog. A comprehensive mapping to all the products is available in the styles.csv file. This file serves as a key to access the corresponding product image located at images/10010.jpg and the complete metadata from styles/10010.json. The image.csv and styles.csv will be combined before further processing and research.

Metadata Attributes: The styles.csv file incorporates key attributes that shed light on various aspects of the fashion products. These attributes include:

S.NO	ATTRIBUTE	DESCRIPTION
1	id	The unique product ID assigned in the catalog.
2	gender	The target gender for the clothing.
3	masterCategory	The primary category of the product.
4	subcategory	The secondary category providing additional classification.
5	articleType	The specific type of clothing item.
6	baseColor:	Descriptive color name.
7	season	The fashion season the product is intended for.
8	year	The fashion year of the product.
9	usage	The intended use or purpose of the clothing item.
10	productDisplayName	The title or name of the product.

Table 4.2 Attribute description of styles.csv

Recognizing the potential size constraints of the complete dataset, a more manageable version has been employed, known as the small version, with a size of 280MB. This version ensures ease of accessibility and quicker initiation for research purposes.

Figure 1.1 Fashion Image Data

id	gender	masterCategory	subCategory	articleType	baseColour	season	year	usage	productDisplayName	image
15970	Men	Apparel	Topwear	Shirts	Navy Blue	Fall	2011	Casual	Turtle Check Men Navy Blue Shirt	15970.jpg
39386	Men	Apparel	Bottomwear	Jeans	Blue	Summer	2012	Casual	Peter England Men Party Blue Jeans	39386.jpg
59263	Women	Accessories	Watches	Watches	Silver	Winter	2016	Casual	Titan Women Silver Watch	59263.jpg
21379	Men	Apparel	Bottomwear	Track Pants	Black	Fall	2011	Casual	Manchester United Men Solid Black Track Pants	21379.jpg
53759	Men	Apparel	Topwear	Tshirts	Grey	Summer	2012	Casual	Puma Men Grey T-shirt	53759.jpg
1855	Men	Apparel	Topwear	Tshirts	Grey	Summer	2011	Casual	Inkfruit Mens Chain Reaction T-shirt	1855.jpg
30805	Men	Apparel	Topwear	Shirts	Green	Summer	2012	Ethnic	Fabindia Men Striped Green Shirt	30805.jpg
26960	Women	Apparel	Topwear	Shirts	Purple	Summer	2012	Casual	Jealous 21 Women Purple Shirt	26960.jpg
29114	Men	Accessories	Socks	Socks	Navy Blue	Summer	2012	Casual	Puma Men Pack of 3 Socks	29114.jpg
30039	Men	Accessories	Watches	Watches	Black	Winter	2016	Casual	Skagen Men Black Watch	30039.jpg

Figure 1.2 Overview of Meta Data (styles.csv)

4.3 DATA ANALYSIS

Resolution and Quality of Images: Assessment of image resolution and quality for consistency. The provided resolution (60, 80) indicates that the image has a width of 60 pixels and a height of 80 pixels. The mode "RGB" signifies that the image is in the red, green, blue color mode.

A) DISTRIBUTION OF PRODUCTS ACROSS CATEGORIES

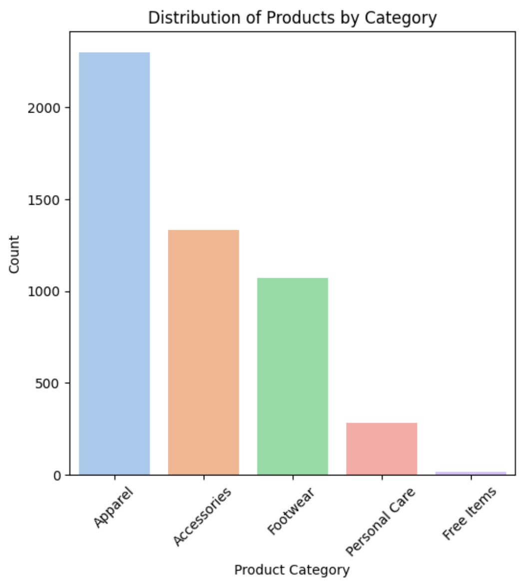

Figure 1.3

The bar chart highlights that "Apparel" is the most popular category, indicating a significant interest in clothing items. Following closely are "Footwear" and "Accessories," emphasizing their substantial presence in the dataset. Interestingly, "Personal Care" and "Free Items," though less dominant, still contribute significantly to the product catalog.

B) GENDER DISTRIBUTION

Examination of the distribution of products across gender categories.

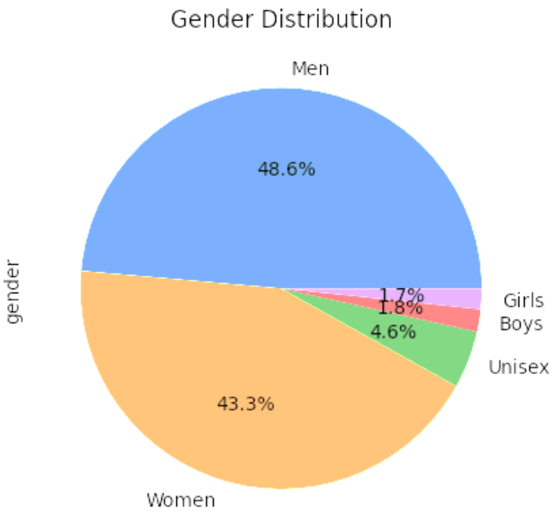

Figure 1.4

C) COUNT OF WEARABLE/CLOTHING PRODUCTS BY CATEGORY

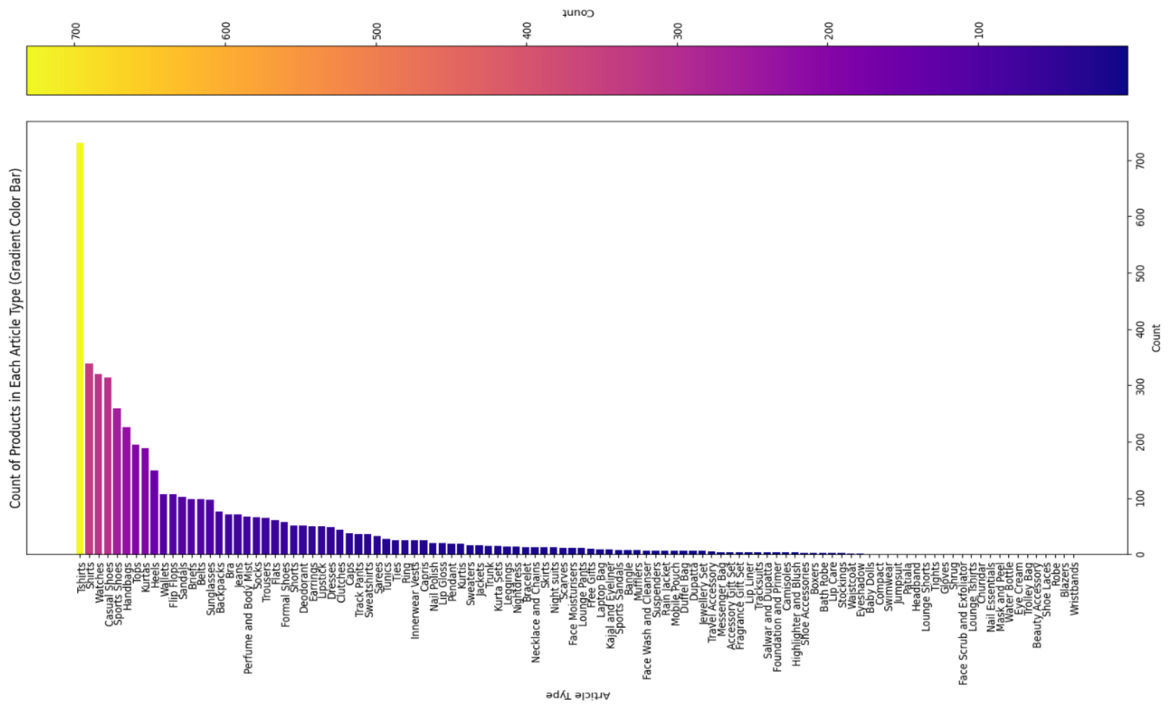

Figure 1.5

The bar chart provides a detailed breakdown of wearable and clothing products, revealing the most popular categories among shoppers. The highest counts are observed for "T-shirts," "Shirts," "Dresses," "Footwear," "Handbags," "Watches," and "Accessories."

D) WORD CLOUD ANALYSIS OF PRODUCT TITLES

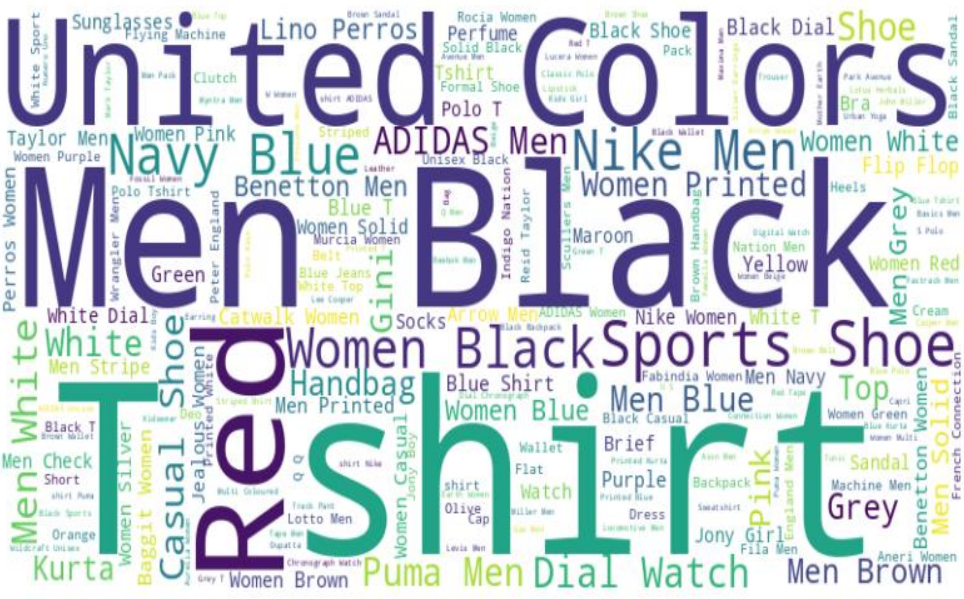

Figure 1.6

The word cloud visually represents the most common product titles in the dataset. Larger words indicate more frequent occurrences. This analysis provides a quick glimpse into the prevalent product titles, offering a qualitative understanding of the dataset's content.

E) PRODUCT TRENDS OVER THE YEARS

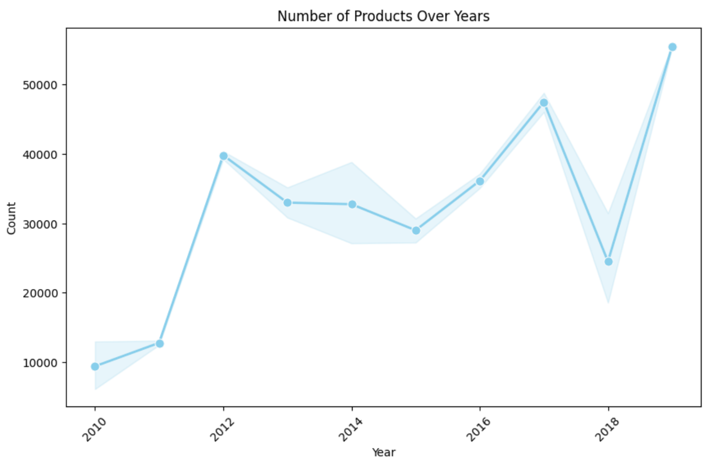

Figure 1.7

The line graph charts the number of products over the years, uncovering interesting trends. From 2010 to 2014, there is a steady increase in the number of products, peaking in 2016. Subsequently, there is a slight decline in 2018. This temporal analysis aids in recognizing shifts in product introductions and market dynamics, potentially influencing strategic decisions.

F) POPULAR PRODUCT USAGE CATEGORIES

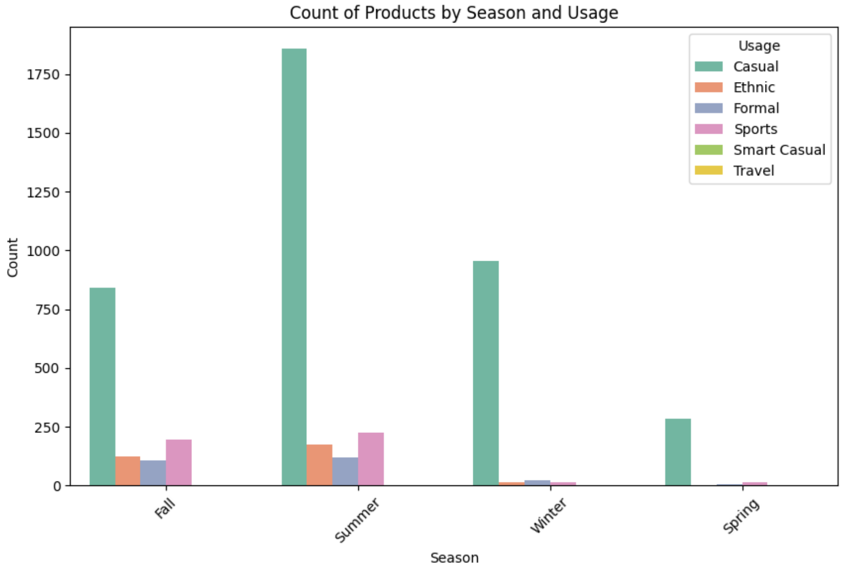

Figure 1.8

The chart depicting product usage categories highlights that "Casual" is the most popular, followed by "Sports." This observation implies that consumers predominantly seek products that offer comfort and versatility. Understanding usage preferences is crucial for tailoring marketing strategies and ensuring that products align with consumer lifestyles.

Chapter 5

Methodology

5.1 METHODOLOGY

Problem Definition

The challenge addressed is the overwhelming nature of finding the perfect outfit in the dynamic world of fashion. The goal is to create a fashion recommender system that assists users in discovering similar fashion items based on a specific image, breaking away from conventional methods.

Data Collection

The dataset used for this project is obtained from the Kaggle, presenting a vast array of professionally shot high-resolution product images. The data includes multiple label attributes describing the products, such as gender, master category, subcategory, article type, color, season, year, usage, and product display name. The dataset is a combination of images, styles, and metadata that provides a rich source for training and evaluation.

Exploratory Data Analysis (EDA)

EDA is conducted to gain insights into the dataset. This involves visualizing the distribution of products across different categories, analyzing the gender distribution, examining primary and secondary categories, understanding color representation, exploring trends across fashion seasons and years, and investigating usage patterns. EDA guides the understanding of the dataset's characteristics and informs subsequent steps.

Data Preprocessing

Data preprocessing is a crucial step to ensure the quality and compatibility of the dataset for training and evaluation. This involves combining the 'image.csv' and 'styles.csv' datasets, which include essential attributes such as product ID, gender, category information, color, season, year, and usage. Additionally, handling missing data, normalizing images, and encoding categorical variables are performed during this stage.

Model Planning

In the initial phase of model planning, the choice of transfer learning models is formalized. Three prominent transfer learning models, namely Densenet121, Resnet150, and VGG16, are selected for their established capabilities in image feature extraction. These models are chosen for their diversity and depth, recognizing that different architectures might capture varying levels of complexity in fashion images. The selected models are pre-trained on ImageNet and serve as feature extractors. To use them as feature extractors, the final output layer is removed, as the objective is not classification but rather feature extraction. The resulting convolutional layer output is processed through global average pooling and flattening layers, generating a linear feature vector for each image. This step ensures that the models' learned features, particularly those indicative of fashion-specific patterns, are preserved for subsequent recommendation tasks.

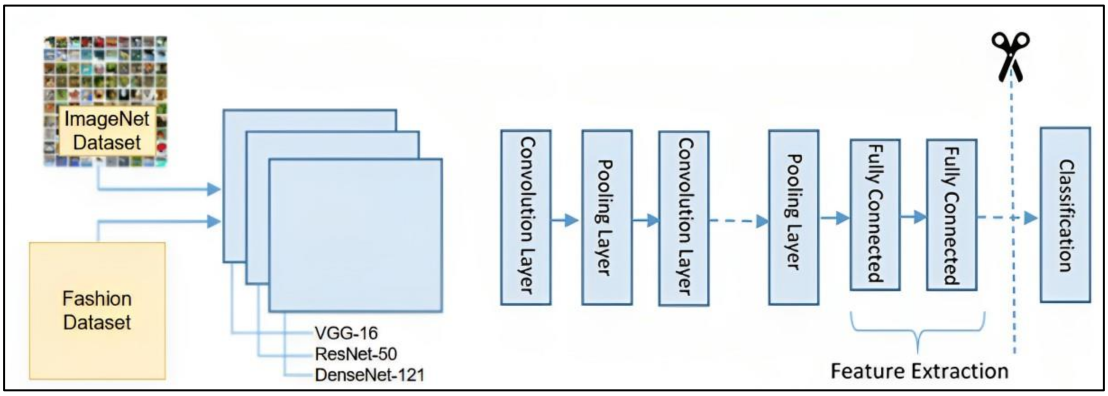

Figure 1.9

Model Building

The core of the methodology involves building and training the neural networks using the pre-processed dataset. The chosen transfer learning models act as feature extractors, and the extracted features are then utilized for recommendation purposes. The models are trained using appropriate hyperparameters, and the training process includes optimizing for the cosine similarity metric. Transfer Learning Models (Densenet121, Resnet150, VGG16) are applied on the Fashion Dataset and the input/test image. After extracting features from the input/test image and the images in the dataset, we apply cosine similarity and recommend the similar products.

Cosine Similarity for Recommendations

Cosine similarity is employed as the metric to measure the similarity between feature vectors extracted from the pre-trained models. The computed cosine similarity scores are utilized to identify the top visually similar fashion products for a given input image. The recommendations are based on the highest cosine similarity scores, indicating products with similar visual features.

Cosine similarity measures the similarity between two vectors of an inner product space. It is measured by the cosine of the angle between two vectors and determines whether two vectors are pointing in roughly the same direction. Given two n-dimensional vectors of attributes, A and B, the cosine similarity, cos(θ), is represented using a dot product and magnitude as

$$\text{cosine similarity} = S_C(A, B) := \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \cdot \sqrt{\sum_{i=1}^{n} B_i^2}},$$

Figure 1.10

where Ai and Bi are the ith components of vectors A and B, respectively.

This mathematical technique determines the cosine of the angle between two vectors and provides a value ranging from -1 (completely dissimilar) to 1 (identical). In the context of fashion recommendation, cosine similarity served as an effective measure to identify how closely the visual features of two fashion items aligned.

Recommender Engine

The recommender engine is the final stage where the top recommendations are generated based on the cosine similarity scores. For each test image, the feature vectors of all training images were computed, and cosine similarity scores were calculated. The engine identifies the products with the highest scores, reflecting the most visually similar items to the input image. The top K recommendations are then presented to the user, providing a curated list of fashion products that align with their preferences. The value of K could be adjusted to fine-tune the system's sensitivity to similarity.

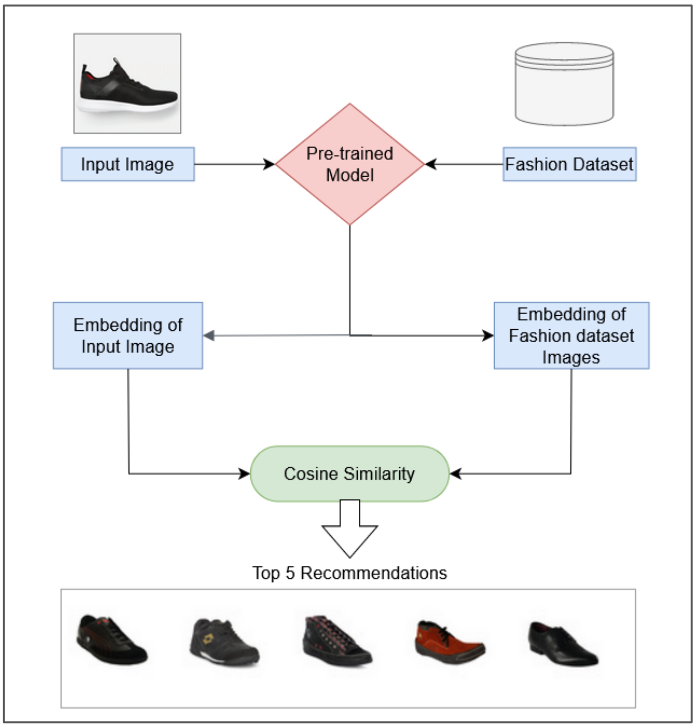

Figure 1.11 Flow Chart

Visual Analysis and Evaluation

Visual analysis of results, particularly using t-SNE, is conducted to understand the spread and clustering of the dataset in the learned feature space. Evaluation metrics are employed to assess the effectiveness of the recommender system in providing visually similar fashion product recommendations.

By following this structured methodology, the fashion recommender system is designed to leverage the strengths of transfer learning models, incorporate cosine similarity for accurate recommendations, and deliver a seamless user experience in the dynamic world of fashion.

5.2 PROJECT ARCHITECTURE

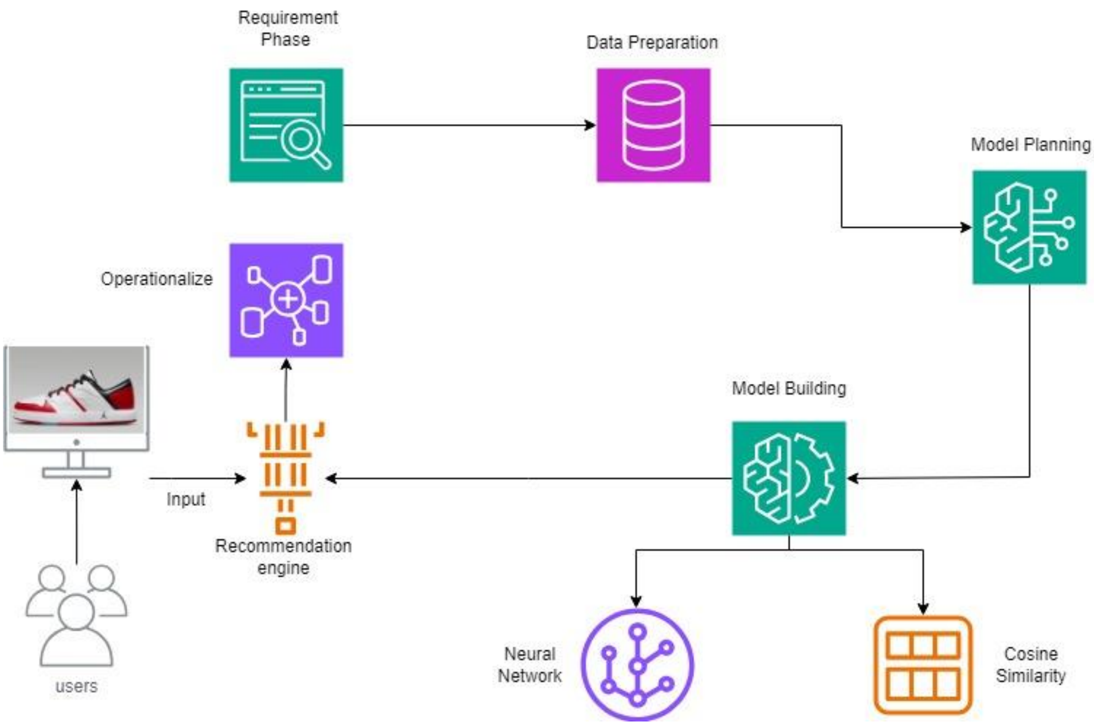

Figure 1.12 Recommender system using pre-trained models

5.3 TOOLS USED:

The entire methodology was implemented using Google Collaboratory, a cloud-based platform known for its seamless integration with Jupyter Notebooks. Collaboratory provided a robust environment for exploratory data analysis, preprocessing, cleaning, model planning, building, evaluation, and visualization. Its cloud-based nature ensured scalability and efficient sharing of the project.

Chapter 6

Models

In the dynamic landscape of fashion recommendation systems, the exploration of transfer learning models has been instrumental in revolutionizing the user experience. This project delves into a detailed analysis of three prominent transfer learning models—VGG16, ResNet50, and DenseNet121—each bringing unique characteristics to the forefront.

6.1 VGG – 16

VGG16 stands for "Visual Geometry Group 16." It is a deep convolutional neural network architecture designed for image recognition and classification tasks. VGG16 was developed by the Visual Geometry Group at the University of Oxford and is characterized by its simplicity and effectiveness. The "16" in its name refers to the fact that it has 16 weight layers, including 13 convolutional layers and 3 fully connected layers. VGG16 has been widely used as a pre-trained model for various computer vision applications due to its strong performance on image recognition tasks.

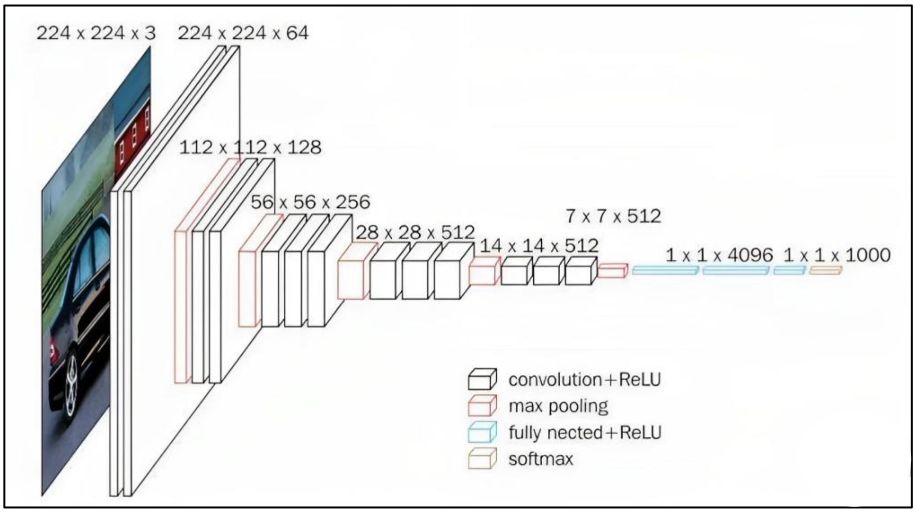

Figure 1.13 Architecture of VGG-16

The VGG16 model, renowned for its simplicity and proficiency in capturing intricate image patterns, was the initial focus of this endeavour. Trained on the extensive ImageNet dataset, VGG16 demonstrated moderate performance in recommending visually similar fashion products. Visual analysis using t-SNE revealed notable clustering patterns within the learned feature space.

However, it became evident that its broad image feature representation might not capture the subtle complexities inherent in fashion items, raising the need for more sophisticated models. While VGG16 provided a foundational understanding, the pursuit of enhanced recommendation systems necessitated a shift towards exploring alternative pre-trained models like ResNet50 and DenseNet121.

To enhance the system's efficacy, the upcoming efforts involved experimenting with models such as ResNet50, and DenseNet121. By doing so, we aim to identify a model that comprehensively captures the unique visual attributes and textures inherent in fashion items. Additionally, fine-tuning these models on the specific dataset will be paramount, ensuring a more tailored and precise recommendation mechanism.

6.2 RESNET – 50

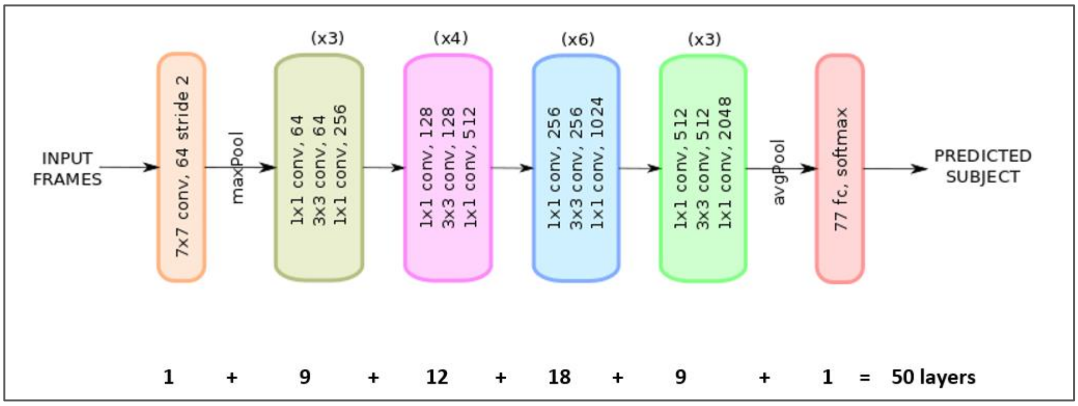

Figure 1.14 Architecture of ResNet50

Subsequently, the exploration extended to the ResNet50 model, a pivotal component of the ResNet architecture celebrated for introducing residual connections, ResNet50 comprises 50 layers. Residual connections enable the training of exceptionally deep networks by facilitating the flow of information.

These connections address the vanishing gradient problem, making ResNet50 highly suitable for image classification tasks. In the context of fashion recommendation, ResNet50 excelled in capturing detailed features, showcasing its efficacy in discerning nuanced characteristics of clothing items. However, the computational complexity associated with deeper networks became a notable consideration.

While the model performed well, visual analysis using t-SNE suggested more overlap between clusters compared to DenseNet121. The ResNet50 graph exhibited a pronounced separation between Apparel and Accessories clusters, indicating differences in feature learning.

6.3 DENSENET – 121

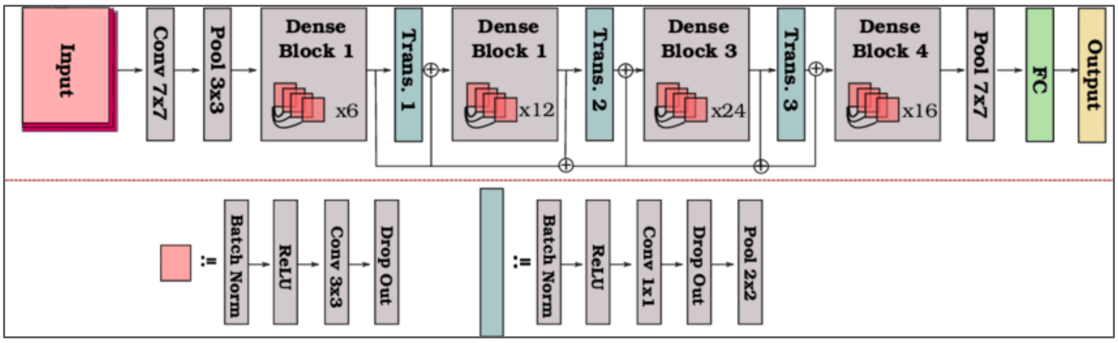

Figure 1.15 Architecture of DenseNet121

The analysis further embraced DenseNet121, a member of the DenseNet architecture known for its densely connected blocks. DenseNet is a convolutional neural network where each layer connects to all subsequent layers, promoting enhanced connectivity and enabling robust feature extraction. This characteristic makes DenseNet121 particularly adept at tasks requiring intricate feature extraction, such as image classification and object detection.

The unique approach of forming direct connections between all layers promotes feature reuse and optimizes information flow, resulting in efficient parameter usage and improved model performance. Despite potential computational overhead, its parameter efficiency and robust feature extraction capabilities positioned DenseNet121 as a compelling choice for capturing the diverse visual attributes of fashion products. The model demonstrated superior performance, providing more relevant and accurate recommendations compared to VGG16. Visual analysis using t-SNE showed distinct and well-separated clusters, indicating better discriminative features.

Comparison

Each transfer learning model brings its set of advantages and disadvantages to the table. VGG16, with its simplicity, may be computationally more efficient but might lack the capacity to capture fine-grained details. ResNet50, on the other hand, overcomes the vanishing gradient problem but introduces greater computational demands due to its depth. DenseNet121 strikes a balance with its densely connected architecture, optimizing information flow and parameter usage, although at the expense of potential computational overhead.

The selection among these models is contingent on various factors, including computational resources, interpretability, and the specific requirements of the fashion dataset. The project underscores the significance of fine-tuning these pre-trained models on the specific dataset, a crucial step in tailoring the models to fashion-related tasks and ensuring optimal performance. The journey through these transfer learning models contributes not only to the understanding of their individual strengths and weaknesses but also guides the exploration of more sophisticated and tailored approaches for fashion recommendation systems in the future.

Chapter 7

Experimentation and Results

7.1 VISUAL ANALYSIS USING T-SNE

The t-SNE algorithm was applied for visual analysis of learned feature spaces. t-SNE (t-distributed stochastic neighbor embedding) was employed to visualize high-dimensional data embeddings from each transfer learning model. This technique helps reveal patterns and clusters in the data. In the exploration of the latent space, which serves as a lower-dimensional manifold for high-dimensional images, the objective is to observe instances of the dataset in close proximity. Given that the latent space is not inherently two-dimensional, the t-SNE dimensionality reduction technique is employed to facilitate visualizations and analyze the dataset's spread.

By visualizing the neighborhoods of different classes in the resulting 2D plane, distinct clusters generated by embeddings become apparent, reinforcing the meaningfulness of the extracted features. Subsequent plots depicting embeddings from various transfer learning models reveal a compelling separation not only by broad categories but also, in finer detail, by subcategories. This separation emphasizes the effectiveness of transfer learning models in capturing intricate features unique to each fashion class, offering valuable insights into the interpretability and discriminative power of the learned representations.

DENSE NET 121

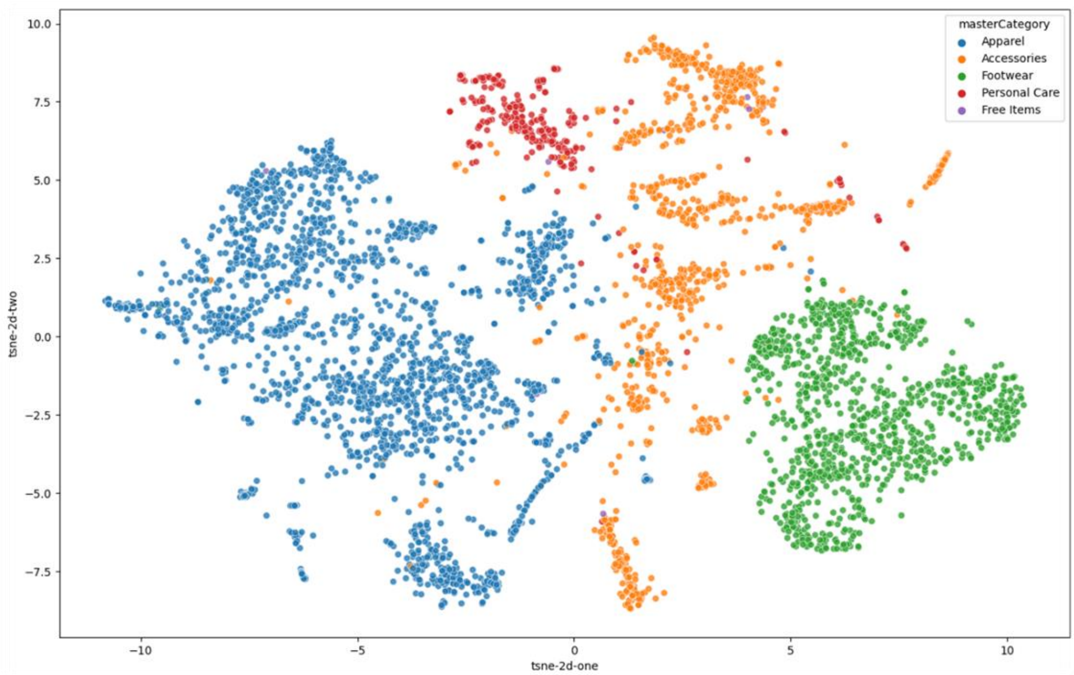

Figure 1.16 DenseNet-121 masterCategory

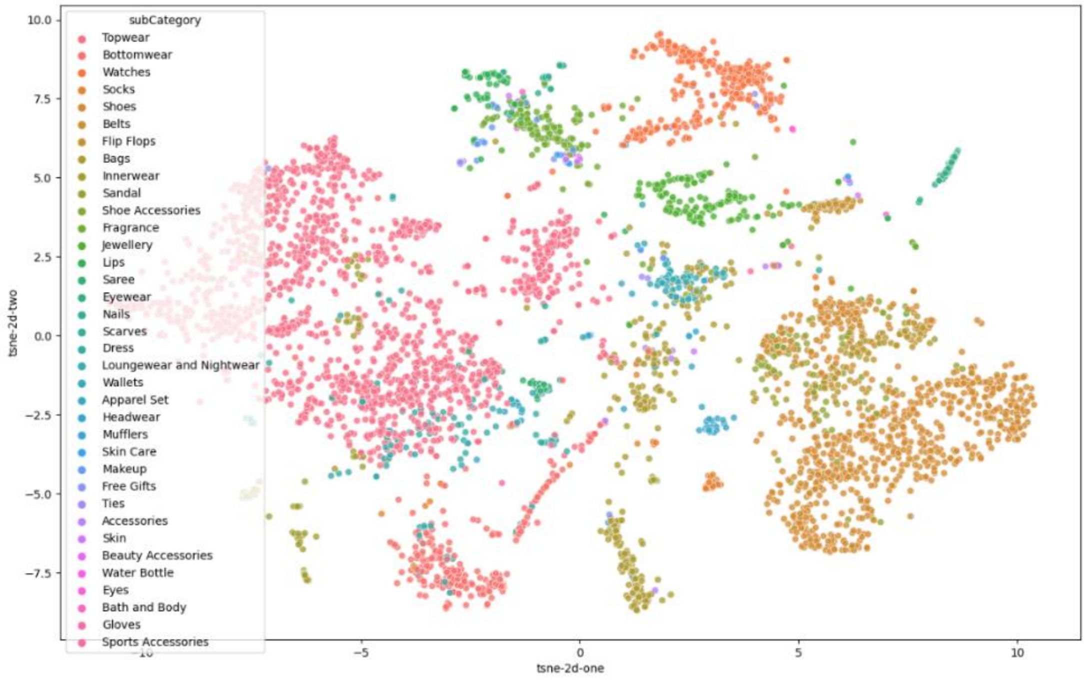

Figure 1.17 DenseNet-121 subCategory

The graph produced by the DenseNet model embeddings shows the clustering of the data based on the learned features. The data points are coloured according to the masterCategory column, which shows that the clusters are generally well-aligned with the different categories.

- Some of the categories are more tightly clustered than others, which suggests that the DenseNet model is able to learn more discriminative features for these categories.
- The Footwear category is the most tightly clustered, which suggests that the DenseNet model is able to learn very discriminative features for this category.
- The Personal Care and Free Items categories are the most spread out, which suggests that the DenseNet model is having more difficulty learning discriminative features for these categories.
- There is some overlap between the clusters, which is likely due to the fact that some of the categories are similar to each other. For example, the Accessories and Apparel clusters overlap to a certain extent, which makes sense since these two categories are closely related.

RESNET-50

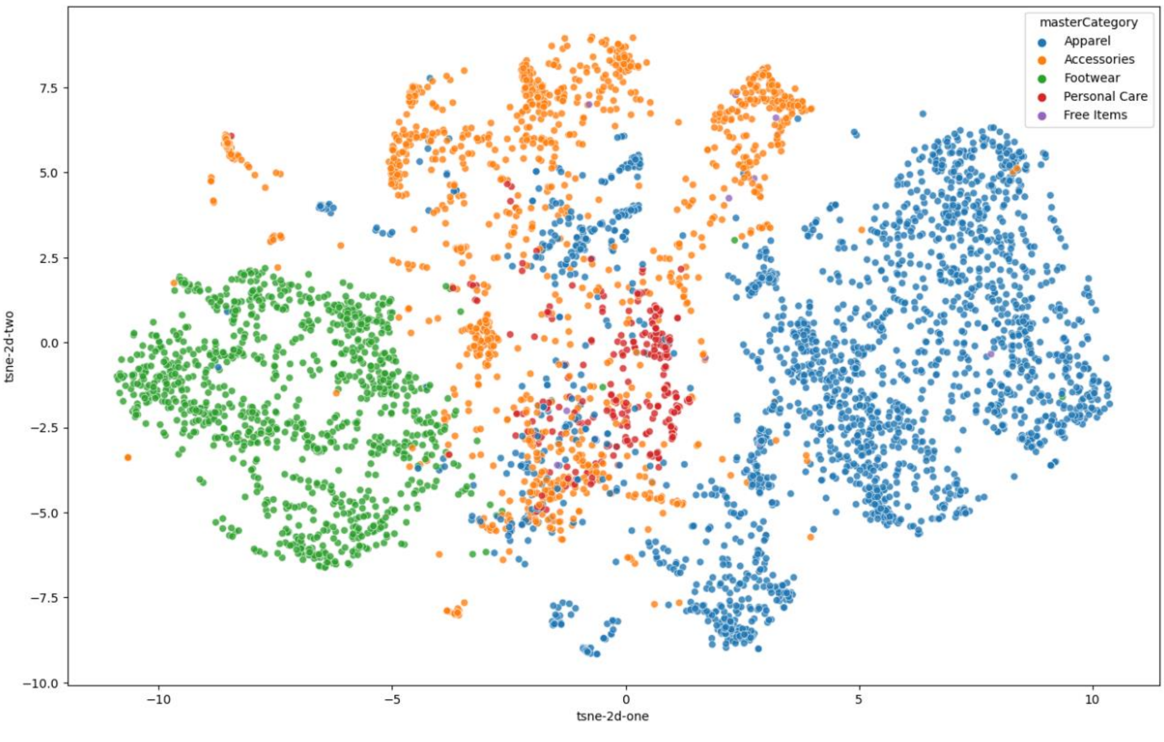

Figure 1.18 ResNet50 masterCategory

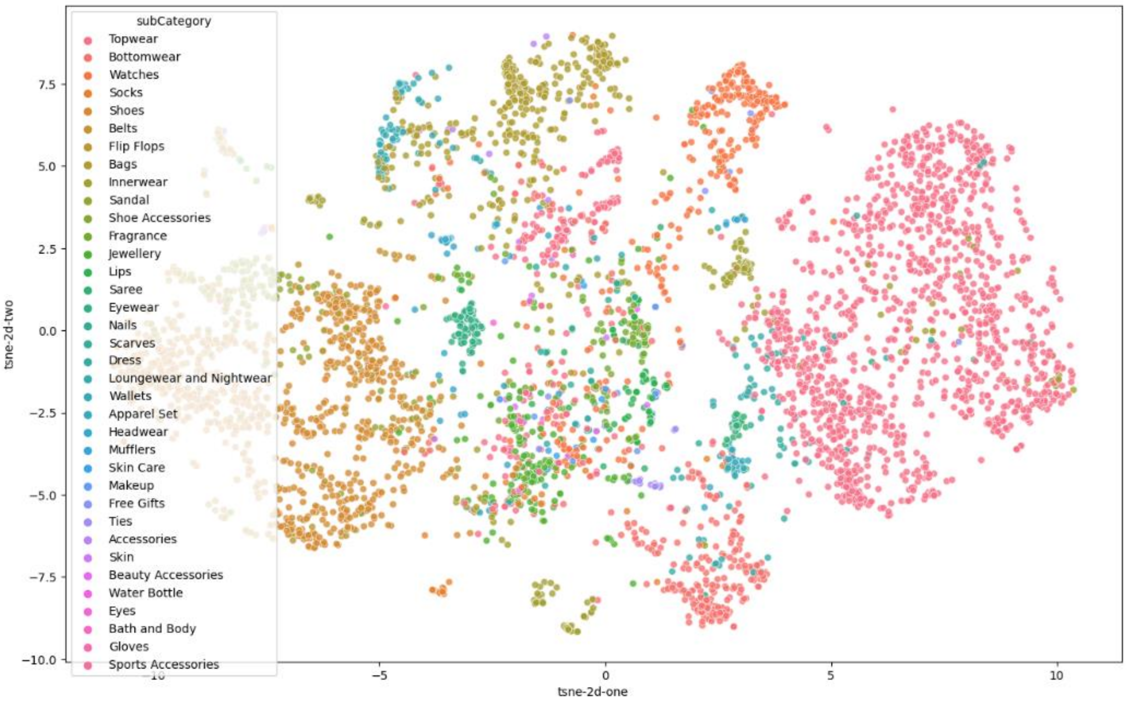

Figure 1.19 ResNet50 subCategory

The graph produced by the ResNet50 model embeddings shows the clustering of the data based on the learned features. The ResNet50 graph shows more overlap between the clusters than the DenseNet121 graph. This suggests that the DenseNet121 model is able to learn more discriminative features than the ResNet50 model.

- Additionally, the ResNet50 graph shows a more pronounced separation between the Apparel and Accessories clusters than the DenseNet121 graph.
- The Footwear category is still the most tightly clustered, which suggests that both models are able to learn very discriminative features for this category.
- The Personal Care and Free Items categories are still the most spread out, which suggests that both models are having more difficulty learning discriminative features for these categories.

VGG-16

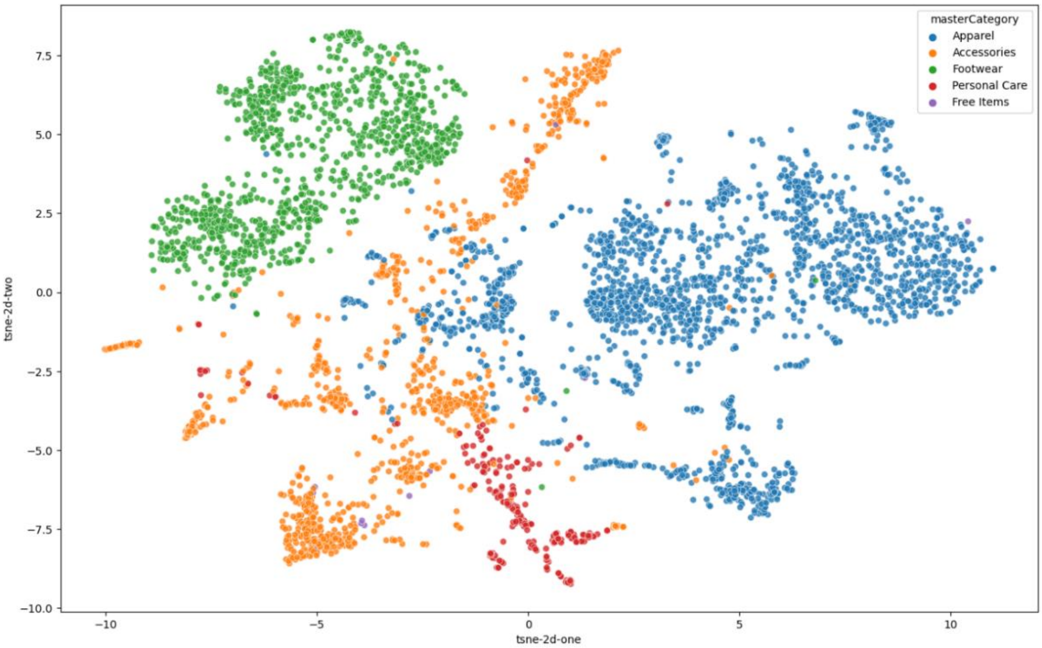

Figure 1.20 VGG16 masterCategory

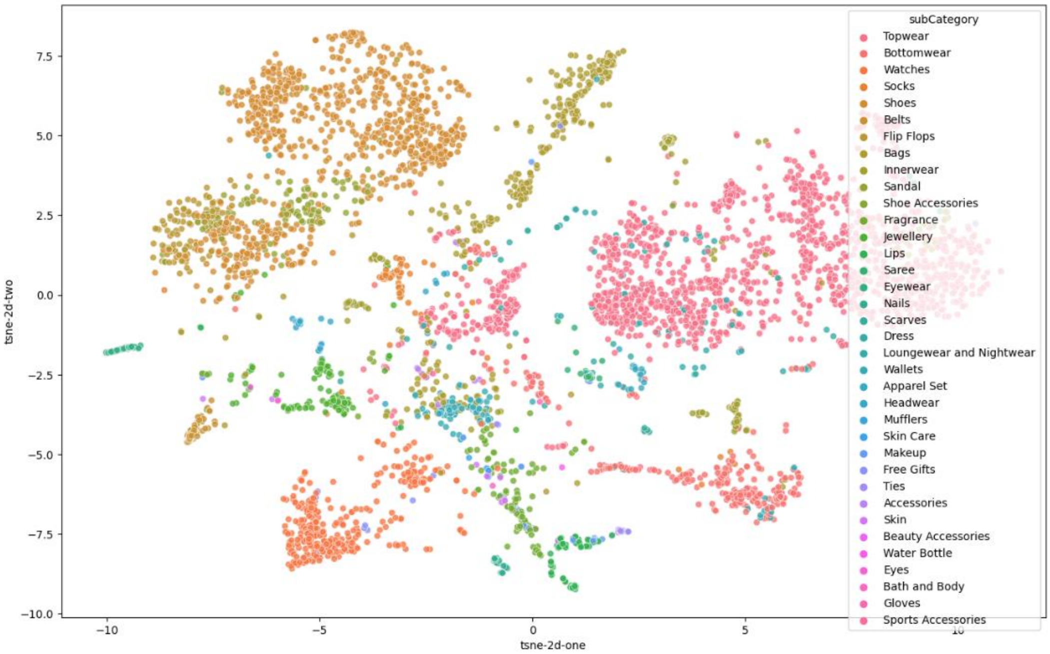

Figure 1.21 VGG16 subCategory

The VGG16 graph shows the least pronounced cluster separation and the most overlap between clusters. This suggests that the VGG16 model is learning the least discriminative features of the three models. One possible explanation for this is that the VGG16 model is shallower than the DenseNet and ResNet models. This means that it has fewer layers, which can limit its ability to learn complex features.

Additionally, the VGG16 model does not use any skip connections. Skip connections are a technique that allows the model to learn features from multiple layers, which can improve the discriminative power of the model.

Characteristic	**VGG16**	**DenseNet121**	**ResNet50**
Cluster separation	Least pronounced	Most pronounced	Somewhere in between
Overlap between clusters	Most	Least	Somewhere in between
Separation between Apparel and Accessories clusters	Less pronounced	Less pronounced	More pronounced

Table 7.1.1 Key differences

DenseNet121 exhibited well-separated clusters, indicating its ability to discern subtle differences between fashion categories. ResNet50, while effective, showed more overlap between clusters.

The main difference between the three models is the way that they learn features. VGG16 is a sequential model, which means that the features are learned in a linear order. DenseNet is a densely connected model, which means that each layer is connected to all of the previous layers, facilitating efficient reuse of previously learned features. ResNet is a residual model, which means that each layer learns a residual function that is added to the input of the layer.

The conclusion effectively highlights that DenseNet stands out as the most effective model for learning discriminative features due to its architecture, fostering feature reuse. ResNet is considered a good choice as well, while VGG16 is noted as the least effective among the three models for learning discriminative features.

7.2 COMPARISON OF MODEL PERFORMANCES

The evaluation of model performance based on the visual similarity of recommended products to the input image is a crucial metric. The ability of a recommendation model to provide visually coherent suggestions indicates its effectiveness in understanding and capturing the essential features of the input image. In essence, a well-performing model should excel in recommending items that align with the visual characteristics, such as style, color, and other relevant attributes, exhibited in the input image. Conversely, a poorly performing model may fail to grasp these visual cues, resulting in recommendations that are visually dissimilar or, worse, entirely irrelevant to the user's query. The performance of the recommendation models can be assessed by the following criteria:

- Visual similarity: The recommended products should be visually similar to the input image.
- Cosine similarity: The cosine similarity scores between the input image and the recommended products should be high.
- Diversity: The recommended products should be diverse, representing a variety of styles and brands.

It is important to note that the model performance may also depend on the quality and diversity of the training data. If the training data is biased towards a particular shoe type or colour, the model may be more likely to recommend products that match that bias. Additionally, the model performance may also be affected by the specific hyperparameters used to train the model.

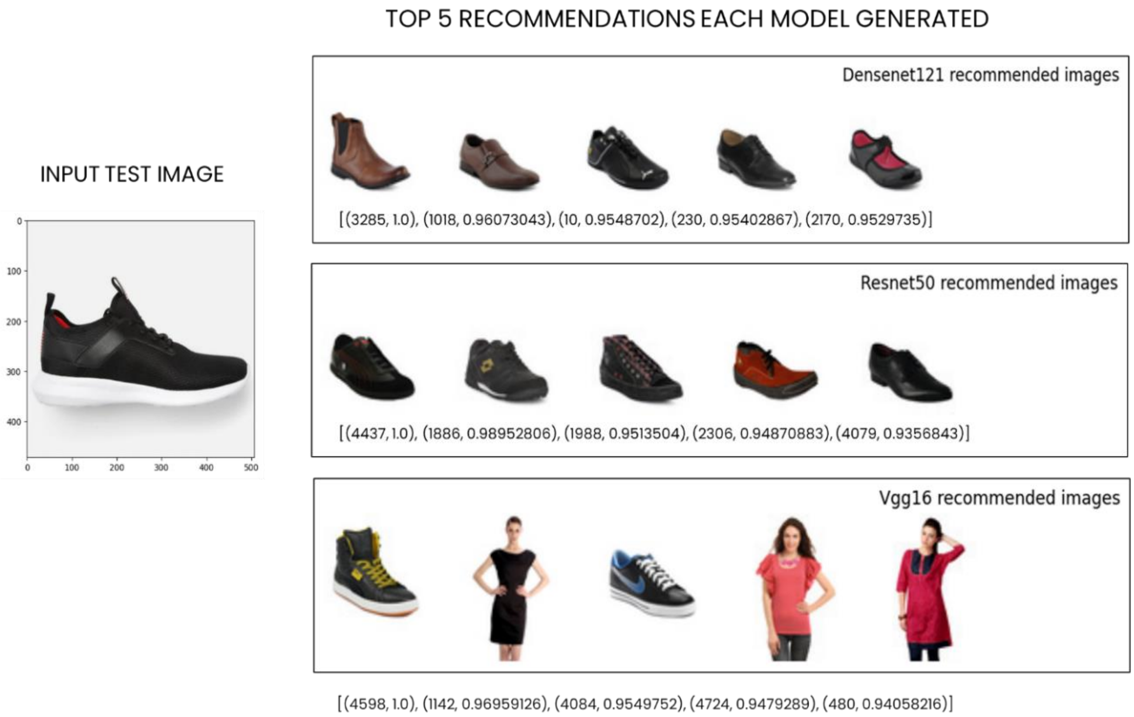

Figure 1.22 Recommendations

Based on the top 5 recommendations provided by each model, it is evident that ResNet-50 and DenseNet121 outperforms VGG16 in terms of recommendation accuracy. The recommendations generated by ResNet-50 are more visually similar to the input image, demonstrating its superior feature extraction capabilities. The model has successfully identified the key visual features of the input image, such as the shoe type, color, and has used this information to recommend similar products. Similar to Resnet50, Densenet121 also recommends products that are visually similar to the input image.

For example, the top 3 recommendations generated by ResNet-50 are all sneakers with a similar design to the input image, while the top 3 recommendations generated by DenseNet121 include a variety of footwear styles, including boots, formal wear , and dress shoes. VGG16 performs poorly in identifying footwear, with three out of five recommendations suggesting apparels. This suggests that ResNet-50 and DenseNet121 are able to capture the specific visual features of the input image and identify similar products.

Recommendations of products from different categories by ResNet50 and Desnet121

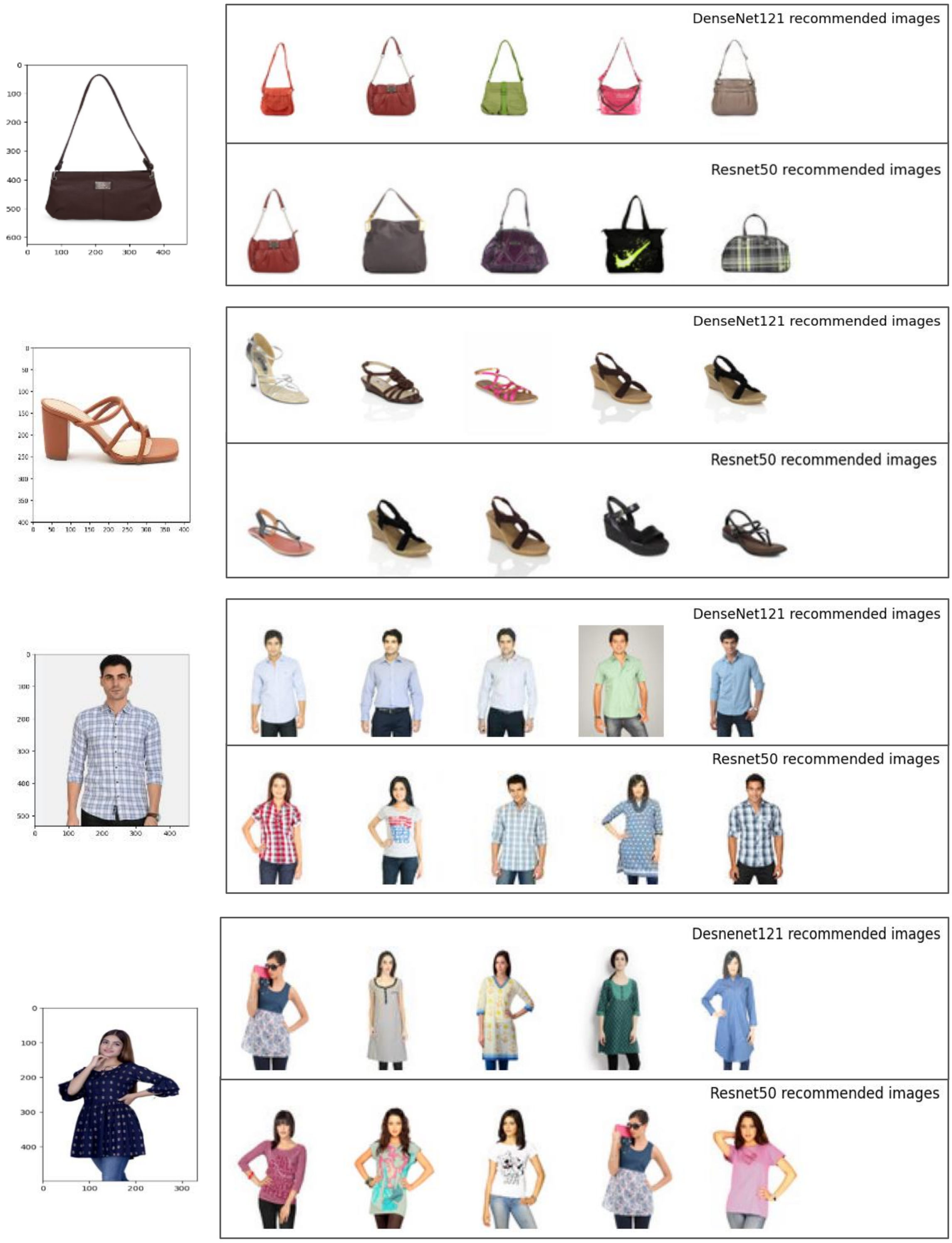

Fig 1.23

When provided with an image from accessories category, both the models recommended visually similar looking products. Under apparel category, the resnet50 model was able to recommend products with similar patterns. While desnet121 recommended products based on color and type.

To further evaluate the model performance, it would be helpful to conduct a more rigorous user study with a larger and more diverse group of users. The user study could assess the following factors:

- How visually similar are the recommended products to the input image?
- How relevant are the recommended products to the user's interests?
- How satisfied are users with the recommended products?

By collecting this feedback, it would be possible to identify the model that performs best on average, as well as the specific areas where each model can be improved

Comparative analysis of VGG16, DenseNet121, and ResNet50 revealed that DenseNet121 consistently outperformed others in terms of recommendation accuracy and discriminative feature learning. The results emphasized the importance of choosing the right transfer learning model for fashion recommendation tasks.

Chapter 8

Conclusion

In conclusion, our project endeavoured to create a robust fashion product recommender system, emphasizing a data-driven and visually related approach for generating effective recommendations. Leveraging the power of convolutional neural networks (CNN) and transfer learning, our system allows users to upload random fashion images, generating similar product recommendations based on image features and textures. The utilization of cosine similarity as the measurement metric, coupled with the extraction of features using pre-trained models like DenseNet121, ResNet50, and VGG16, aimed to address the challenges posed by the relatively small fashion dataset. The project effectively addressed the challenges of a limited fashion dataset through successful implementation of transfer learning. Through meticulous experimentation and comparative analysis, it became evident that DenseNet121 emerged as the standout performer among the pre-trained models. The t-SNE algorithm further affirmed the efficacy of the DenseNet121 model by revealing distinct and well-separated clusters in the learned feature space, indicative of its ability to discern subtle differences between fashion categories. The architecture of DenseNet, with its densely connected blocks fostering feature reuse, contributed to its superior performance in learning discriminative features.

While ResNet50 also exhibited commendable results, VGG16 was identified as the least effective model in learning discriminative features for fashion product recommendations. The project highlighted the importance of model architecture in capturing the complexities of fashion items, and DenseNet121 stood out as a promising choice for achieving this goal. In essence, the findings underscore the efficacy of transfer learning, especially with the DenseNet121 model, in developing a fashion recommender system that not only provides accurate and visually similar product recommendations but also demonstrates a nuanced understanding of the diverse landscape of fashion categories. As the fashion industry continues to evolve, the adaptability and discriminative capabilities of such recommender systems become increasingly crucial for delivering personalized and relevant suggestions to users.

Chapter 9

Future Work

Several avenues for future work present themselves to further enhance and expand upon the capabilities of the fashion recommender system developed in this project:

Fine-Tuning and Customization: Fine-tuning the pre-trained models on the specific fashion dataset could lead to improved performance. Customizing the models to better understand the nuances of fashion features and styles specific to the dataset would contribute to more accurate recommendations.

Exploration of Additional Models: Beyond the explored models like DenseNet121, ResNet50, and VGG16, there exists a vast landscape of pre-trained models. Experimenting with and incorporating other architectures, such as EfficientNet or MobileNet, may reveal models better suited to the intricacies of fashion product recommendation. Exploring Generative Adversarial Neural Networks (GANs) for more accurate recommendations.

Ensemble Learning: Implementing ensemble learning techniques by combining predictions from multiple models could potentially enhance the robustness and diversity of recommendations. This approach involves leveraging the strengths of different models to achieve a more comprehensive understanding of user preferences.

User Feedback Integration: Incorporating a feedback loop from users would enable continuous improvement. Collecting and analysing user feedback on recommended products can help refine the models over time, ensuring that the system adapts to evolving fashion trends and individual user preferences.

Dynamic User Profiles: Developing a system that dynamically updates user profiles based on real-time interactions and changing preferences would contribute to a more adaptive and personalized recommendation experience. This involves continuously learning from user behaviour to provide up-to-date and relevant suggestions.

Integration with E-commerce Platforms: Collaborating with e-commerce platforms to integrate the recommender system directly into their interfaces could enhance the user experience. Seamless integration would allow users to receive personalized fashion recommendations during their shopping journeys.

Incorporation of Textual Data: Expanding the recommendation system to consider textual data, such as product descriptions and user reviews, could provide a more comprehensive understanding of fashion items. Natural Language Processing (NLP) techniques could be employed for this purpose.

Scalability Considerations: As the dataset grows and user traffic increases, ensuring the scalability of the recommender system becomes crucial. Implementing strategies to handle larger datasets and a growing user base will be essential for sustained performance.

By exploring these avenues, the fashion recommender system can evolve into a more sophisticated, user-centric, and adaptable tool, providing valuable insights and recommendations in the dynamic realm of fashion.

Appendices

GANs (Generative Adversarial Networks):

Generative Adversarial Networks are a class of artificial intelligence algorithms used in unsupervised machine learning. In the context of fashion recommendation systems, GANs are leveraged to generate new fashion items based on learned distributions of existing fashion images. GANs consist of two neural networks, a generator, and a discriminator, trained simultaneously through adversarial training.

Fine-Tuning:

Fine-tuning refers to the process of adjusting the parameters of a pre-trained neural network on a specific dataset. In the context of fashion recommendation, fine-tuning is essential when using pre-trained models like VGG16, ResNet, or DenseNet. This process ensures that the model adapts to the unique features and textures present in the fashion product images, enhancing the system's overall performance.

CNN (Convolutional Neural Network)

Convolutional Neural Networks are deep learning models particularly effective for image recognition and processing. In the context of fashion recommendation, CNNs are often used as pre-trained models to extract visual features from fashion images. These features can then be utilized for similarity comparison and recommendation generation. At the core of CNN architecture is the convolutional layer, which employs convolutional operations to extract hierarchical features from input images. These layers are adept at capturing spatial hierarchies and local patterns, enabling the network to discern intricate details and robustly represent visual information. Pooling layers, often interleaved with convolutional layers, contribute to spatial down sampling, reducing computational complexity while retaining essential features. This down sampling enhances the network's ability to generalize and recognize patterns across varying scales.

Furthermore, CNNs commonly incorporate activation functions like ReLU (Rectified Linear Unit) to introduce non-linearities, enabling the network to learn complex relationships and better model real-world visual data. The utilization of fully connected layers at the network's end facilitates high-level feature aggregation and abstraction, ultimately leading to accurate predictions or classifications. Noteworthy CNN architectures include LeNet, AlexNet, VGGNet, and more recently, deeper and more complex models like ResNet and DenseNet, which leverage skip connections for improved gradient flow and feature reuse.

Collaborative Filtering

This technique relies on user-item interaction data to identify patterns and preferences. User behaviors, such as item ratings or purchase history, are leveraged to infer preferences and generate recommendations. Collaborative Filtering can be further classified into user-based and item-based methods. User-based approaches recommend items based on the preferences of users with similar tastes, while item-based methods identify items similar to those the user has shown interest in. Matrix factorization, an extension of collaborative filtering, enhances recommendation accuracy by decomposing the user-item interaction matrix into latent factors.

Content-Based Filtering:

In contrast, Content-Based Filtering recommends items by analyzing their intrinsic features. This method profiles both users and items based on attributes such as genre, keywords, or textual descriptions. The system matches user preferences with item characteristics, offering recommendations tailored to individual tastes. Content-Based Filtering is particularly effective in addressing the cold-start problem, where there is limited historical user interaction data.

Hybrid recommender systems often combine collaborative filtering and content-based approaches to capitalize on their respective strengths, providing more accurate and diverse recommendations. This symbiotic relationship aligns with the evolving landscape of recommendation algorithms, striving to deliver personalized and engaging content experiences for users.

t-SNE (t-Distributed Stochastic Neighbor Embedding)

t-SNE is a dimensionality reduction technique used to visualize high-dimensional data in a lower-dimensional space. The fundamental idea behind t-SNE is to model pairwise similarities between data points in the original high-dimensional space and the lower-dimensional space. It uses a probability distribution to measure similarities in both spaces, aiming to minimize the divergence between them. Notably, t-SNE is particularly effective in revealing clusters and patterns in the data, making it invaluable for exploratory data analysis.

In the context of fashion recommendation systems, t-SNE can be applied to reduce the dimensionality of the latent space, enabling the analysis of the spread of the dataset and the identification of clusters, especially when using transfer learning models. The resulting visualization facilitates the interpretation of intricate relationships between data points, offering insights into the underlying structure of the dataset.

Cosine Similarity

Cosine Similarity is a metric used to measure the cosine of the angle between two non-zero vectors. In fashion recommendation systems, cosine similarity is often employed to assess the similarity between feature vectors extracted from fashion images. This metric aids in identifying visually related fashion items and is crucial for generating effective product recommendations.

System Architecture

An overview of the system architecture is included in this section, elucidating the integration of content-based and collaborative filtering techniques within the hybrid fashion recommender system. The architectural details highlight the flow of processes, from image input to recommendation output, showcasing the seamless synergy of these techniques for an enhanced fashion discovery experience.

CSV (Comma-Separated Values:

CSV is a plain-text format used to represent tabular data, where each line in the file corresponds to a row of the table, and values within each row are separated by commas (or other delimiters like semicolons or tabs). CSV is a simple, widely supported, and human-readable format commonly employed for data exchange between spreadsheet applications and databases.

Natural Language Processing (NLP)

Natural Language Processing (NLP) stands as a pivotal field in artificial intelligence, focusing on the interaction between computers and human language. Within this multidisciplinary domain, various techniques and methodologies enable machines to comprehend, analyze, and generate human language.

NLP encompasses fundamental components such as tokenization, breaking down text into meaningful units, and part-of-speech tagging, assigning grammatical categories to words. Named Entity Recognition (NER) identifies and classifies entities in text, while sentiment analysis gauges the emotional tone. Machine translation facilitates cross-language communication, and topic modeling unveils latent themes within a corpus. Word embeddings, representing words as vectors, capture semantic relationships crucial for NLP tasks.

Applications of NLP are pervasive across industries. Chatbots and virtual assistants leverage NLP for natural language understanding, while text summarization automates the extraction of key information. Information extraction transforms unstructured data into structured formats, and speech recognition enables machines to transcribe spoken words. Question answering systems utilize NLP to comprehend and respond to user queries.

Sequential Data Modeling

Sequential Data Modeling is a branch of machine learning dedicated to handling data that unfolds over time, such as time-series, speech, or natural language. This approach recognizes and exploits the temporal dependencies inherent in sequential information, offering powerful tools for prediction, classification, and generation tasks.

Key Aspects of Sequential Data Modeling:

Recurrent Neural Networks (RNNs): Specialized architectures designed to capture sequential dependencies by maintaining hidden states that evolve with each input.

Long Short-Term Memory (LSTM): An extension of RNNs, equipped with memory cells that allow the network to retain and selectively update information over long sequences, mitigating the vanishing gradient problem.

Gated Recurrent Unit (GRU): A simplified version of LSTM, offering similar capabilities with fewer parameters.

Sequence-to-Sequence Models: Applied in tasks like machine translation, summarization, and speech recognition, these models process input sequences and generate corresponding output sequences.

Temporal Convolutional Networks (TCN): Employing convolutional layers for capturing temporal patterns, particularly effective for long-range dependencies.

Sequential Data Modeling finds applications in diverse domains, including predicting stock prices, understanding speech patterns, and generating coherent text. Its significance lies in its ability to harness the contextual information embedded in sequential data, providing valuable insights and enabling sophisticated predictions. As technology evolves, the continual refinement of sequential data models remains crucial for addressing real-world challenges in dynamic and evolving datasets.

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