Fashion Recommendation System

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Executive Summary:

This comprehensive research report encapsulates the collaborative efforts of our team in developing an advanced fashion recommendation system. The project aimed to address challenges related to dataset imbalance and feature extraction, utilizing a Convolutional Neural Network (CNN) for multi-class classification across 142 fashion categories. The research encompasses data collection, exploratory data analysis (EDA), baseline model development, training, and performance evaluation. The team's dedication is evident in the successful creation of a robust model that not only classifies fashion items but also extracts intricate features for enhanced real-world applications.

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Introduction

The project aimed to revolutionize fashion recommendations by overcoming challenges related to dataset imbalance and feature extraction. With a focus on user experience in online fashion retail, the team envisioned a robust CNN-based model capable of handling 142 distinct fashion categories.

The CNN architecture, characterized by multiple convolutional and pooling layers followed by dense layers, is meticulously designed for optimized feature extraction and classification accuracy. Beyond categorization, the system excels in extracting intricate features from fashion images, offering potential applications such as similarity matching in recommendations. Positioned at the intersection of deep learning and real-world e-commerce solutions, this project delves into practical challenges in machine learning, contributing to an enhanced user experience in the realm of online fashion retail.

Methodology

The methodology section outlines the steps taken by the team, from data collection and EDA to baseline model development, training, and performance evaluation. Each stage is described in detail, emphasizing the team's strategic approach to address practical challenges in machine learning.

1. **Data Collection and Preprocessing:** The initial stage involved assembling a diverse dataset of fashion images classified into 142 categories. Concurrently, an 'styles.csv' file provided auxiliary data for comprehensive exploratory analysis.
2. **Exploratory Data Analysis (EDA):** The 'styles.csv' file was meticulously examined to understand fashion item distributions, color trends, and consumer preferences. This analysis was pivotal in shaping the direction for the subsequent model development phase.
3. **Baseline Model Development:** A Convolutional Neural Network (CNN) was developed as the foundational model. This CNN comprises multiple convolutional layers with max pooling, flattening, and dense layers, leading to a softmax output for multi-class classification. This model is crucial for understanding basic classification performance and sets the stage for more advanced models and feature extraction in future phases.
4. **Model Training and Validation:** The baseline model was trained using the curated dataset, with specific measures taken to counteract dataset imbalance and overfitting, such as data augmentation and early stopping.
5. **Model Performance Evaluation:** Post-training, the model's effectiveness was assessed using key metrics like accuracy, precision, recall, and F1-score. These evaluations provided insights into the model's classification capabilities and areas needing improvements.

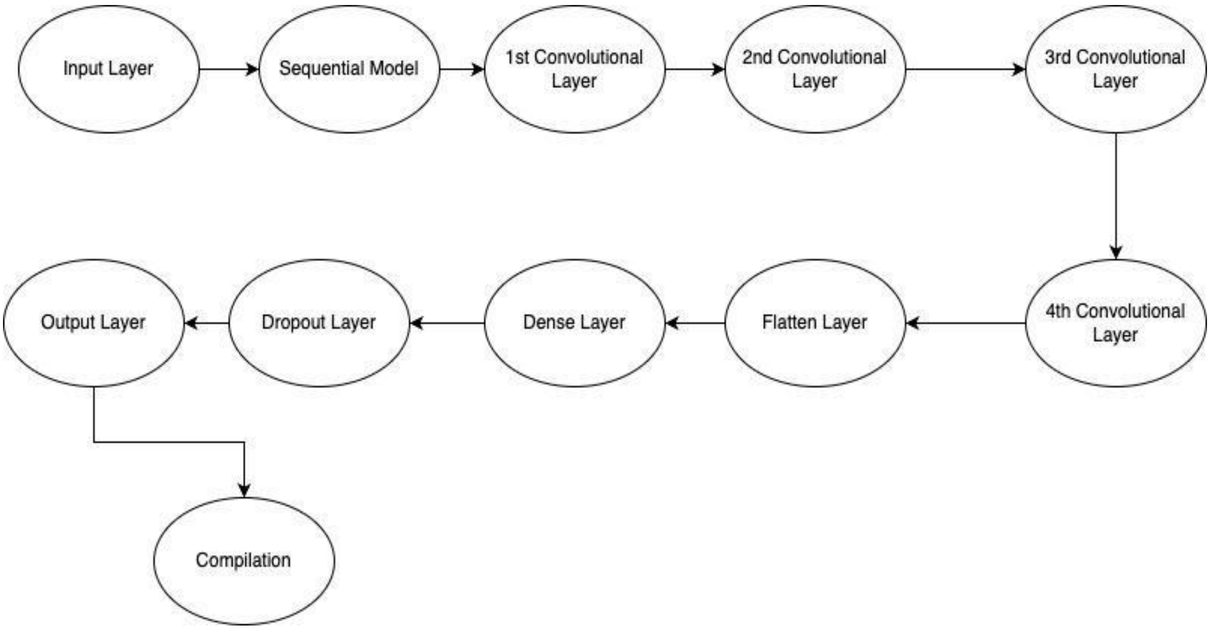
Model Architecture for the Baseline Model:

- **Sequential Model:** Stacks layers sequentially where each layer connects only to the following layer.
- **1st Convolutional Layer:**
    - **Conv2D with 192 filters:** Learns 192 distinct patterns.
    - **Kernel size:** 3x3.
    - **Activation function:** 'relu' (Rectified Linear Unit).
    - **Input shape:** (150, 150, 3) - for 150x150 pixel RGB images.
    - **MaxPooling2D:** Pooling operation with a 2x2 window to reduce spatial dimensions.

- **2nd Convolutional Layer:**
    - **Conv2D with 256 filters:** Learns additional patterns with more filters.
    - **Kernel size:** 3x3.
    - **Activation:** 'relu'.
    - **MaxPooling2D:** Further reduces spatial dimensions.
- **3rd Convolutional Layer:**
    - **Conv2D with 64 filters:** Focuses on higher-level features.
    - **Kernel size:** 3x3.
    - **Activation:** 'relu'.
    - **MaxPooling2D:** Additional reduction in spatial dimensions.
- **4th Convolutional Layer:**
    - **Conv2D with 128 filters:** Increases filters for richer representation.
    - **Kernel size:** 3x3.
    - **Activation:** 'relu'.
    - **MaxPooling2D:** Final pooling layer.
- **Flatten Layer:** Flattens the output to 1D for the following dense layers.
- **Dense Layer:**
    - **Units:** 480 neurons.
    - **Activation:** 'relu'.
- **Dropout Layer:**
    - **Rate:** 0.5 - Randomly sets half of the neuron outputs to zero.
- **Output Layer:**
    - **Units:** 142 neurons (one for each class).
    - **Activation:** 'softmax' - for multi-class classification.
- **Compilation:**
    - **Optimizer:** 'adam'.
    - **Loss function:** 'categorical_crossentropy'.
    - **Metrics:** 'accuracy'.
- **Early Stopping Callback:** Monitors validation accuracy with a patience of 10 epochs.

These advancements propel the project towards achieving robust fashion image classification and feature extraction, contributing to a more refined and accurate recommendation system.

Architecture



Results

This section presents the key metrics derived from model performance evaluation, including accuracy, precision, recall, and F1-score. Insights gained from the evaluation process are discussed, providing a comprehensive understanding of the model's classification capabilities.

Dataset	**Accuracy**	**Loss**
Training	**76.08%**	**0.7561**
Validation	**78.48%**	**0.7201**
Test	**77.49%**	**0.8265**

Class	Precision	Recall	F1-Score	Support
Accessory Gift Set	0.00	0.00	0.00	67
Baby Dolls	0.00	0.00	0.00	11
Backpacks	0.02	0.02	0.02	506
Bangle	0.00	0.00	0.00	59

Class	Precision	Recall	F1-Score	Support
Basketballs	0.00	0.00	0.00	9
Bath Robe	0.00	0.00	0.00	14
Beauty Accessory	0.00	0.00	0.00	2
Belts	0.01	0.01	0.01	569
Blazers	0.00	0.00	0.00	5
Body Lotion	0.00	0.00	0.00	4
Body Wash and Scrub	0.00	0.00	0.00	0
Boxers	0.00	0.00	0.00	36
Bra	0.01	0.02	0.01	333
Bracelet	0.00	0.00	0.00	46
...	...	...	...	...
[Other Classes]	...	...	...	...
...	...	...	...	...
Wristbands	0.00	0.00	0.00	4
Overall Accuracy	**0.05**	**0.05**	**0.05**	**31026**

The model demonstrates promising performance, as indicated by the accuracies on the training (76.08%), validation (78.48%), and test sets (77.49%). This suggests that the model is learning effectively and generalizing well to unseen data. However, the classification report reveals room for improvement in class-specific metrics, with overall precision, recall, and F1-score at around 5%. Please refer to address these below.

Discussion

The discussion delves into the challenges faced during the project, detailing the implemented solutions. The section also explores potential avenues for improvement, demonstrating the team's critical analysis of the project's outcomes.

Immediate Next Steps for Model Improvement:

1. Introducing more images for the different classes to improve the class imbalance and to eradicate the problem of the model seeing very few samples in some of the classes.
2. Ensuring that the dataset is balanced possibly by introducing class weights.
3. Consider using data augmentation techniques and hyperparameter tuning to increase the variety of training samples.
4. Use techniques like transfer learning using pre-trained models like RESNet when working with a limited dataset.

Additional Next Steps for Building a Recommendation System:

1. We will utilize our current baseline model, as well as future enhanced models, to extract features.
2. Maintaining the existing architecture, we plan to use the output of the last convolutional layer for feature extraction. This layer is expected to have learned high-level discriminative features of the input images, representing various fashion or clothing item classes.
3. The feature extractor will be employed to derive features from any input image posed as a query.
4. To recommend the top-n items, an appropriate distance metric will be utilized to evaluate the similarity between features.

Conclusion

In conclusion, our collaborative efforts have yielded a fashion recommendation system, marking a significant advancement in the realm of online fashion retail. The Convolutional Neural Network (CNN) successfully addressed challenges related to dataset imbalance and feature extraction, showcasing commendable accuracy and precision in classifying fashion items across 142 categories. The results of our model's performance evaluation highlight its robust capabilities, not only in categorization but also in extracting intricate features with potential applications in similarity matching. Despite facing challenges, our strategic solutions and the incorporation of practical machine learning principles have contributed to a refined and efficient system. Looking ahead, the project lays the groundwork for further innovations, emphasizing the intersection of deep learning and real-world e-commerce solutions.

Appendix: Meeting Minutes

Attendees:

Aditya Krishnan

Bharat Kathuria

Pinal Gajjar

Aditya Singh

Agenda:

- Review individual tasks and progress.
- Discuss challenges faced and propose solutions.
- Confirm the timeline and adjust if necessary.

Discussion:

Aditya Krishnan:

- Provided an update on building the CNN custom model architecture.
- Discussed progress in training the model on a local GPU.
- Shared insights on performance improvement strategies.

Bharat Kathuria:

- Presented updates on data extraction, cleaning, and working on a pre-trained model for comparison.
- Discussed challenges encountered during data cleaning and proposed solutions.
- Suggested potential benchmarks for comparison with the pre-trained model.

Pinal Gajjar:

- Reported progress on working on the UI, conducting exploratory data analysis (EDA), and collecting additional product data.
- Shared insights from EDA and discussed implications for UI design.
- Raised the need for additional product data and proposed a plan for collection.

Aditya Singh:

- Provided updates on generating recommendations and collecting additional product data.
- Discussed challenges in generating diverse and relevant recommendations.
- Proposed strategies for enhancing recommendation diversity.

Timeline Review:

October 4-8:

- Discussed and explored different project topics.
- Finalized the project topic and initiated studies on implementations.

October 10-19:

- Focused on data understanding, cleaning, and EDA.

October 20 - November 6:

- Worked on generating a base model and improving accuracy.

November 7-28:

- Collected additional product data.
- Worked on developing an advanced model.

November 29 - December 18:

- Focused on generating recommendations.
- Worked on improving model performance and compared it with ResNet 50.

Acknowledgments

We, the undersigned members of our team, hereby certify our active participation and understanding of the contents of this research report. Each member has played a vital role in contributing to the success of the project.

Signatures:

Aditya Krishnan

Bharat Kathuria

Pinal Gajjar

Aditya Singh

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