CLOTHING FEATURE EXRACTION AND CLASSIFICATION

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ABSTRACT

This study highlights the importance of an algorithm that can classify clothing types in the fashion industry. This algorithm can help clothing companies understand the profile of potential buyers, focus sales on specific niches, and improve user experience. The study aims to evaluate these classification algorithms using important Convolutional Neural Network (CNN) models such as ResNet152, VGG16, VGG18 and clustering on data sets obtained from sources such as Kaggle and GitHub.

Keywords: Fashion, Classification Algorithms, Convolutional Neural Networks, Data Analysis, Clothing Classification

1. INTRODUCTION

This study highlights the importance of an algorithm that can identify clothing items, which can help companies in the clothing industry understand the profile of potential buyers and focus their sales on specific niches, develop campaigns according to customer taste and improve user experience. In this era of continuous growth of the online fashion market, AI approaches that can understand and label human clothing are necessary and can be used to increase sales or better understand users. This study presents Convolutional Neural Networks (CNN) models that have been shown to be effective in image classification. The specified dataset [1] contains four different CNN models that we will use (resnet152, vgg16, alexnet, densenet201). Our data is a dataset that will help researchers find models that can classify products such as clothing and provides a comparison between major classification methods to find the classification method that labels this data. This project aims to provide future research with comparisons between better classification methods. In this report, code testing was done with resnet152, vgg16, Alexnet, densenet201.

2. RELATED WORK

Rohrmanstorfer, S., Komarov, M., & Mödritscher,[2] Research in the field of Convolutional Neural Networks (CNNs) for fashion image classification is extensive, focusing on optimizing architecture and training strategies. This work follows a trend seen in previous studies, where adaptations of well-known CNN architectures such as AlexNet or VGG-16 are tailored to the characteristics of fashionable datasets.
Transfer learning, an important aspect of the third approach here, has been a focus in the literature. Researchers have sought to leverage pre-trained models from public datasets, particularly MNIST, for specific tasks.
In line with a broader trend, the article addresses the challenges of small dataset size using data augmentation techniques.
In summary, this study contributes to existing research by building on established practices for fashion image classification in CNNs. Exploration of model architectures, transfer learning, data augmentation, and considerations of small data sets are aligned with ongoing efforts to improve the robustness and effectiveness of deep learning models in fashion analysis.

Li, Z., Sun, Y., Wang, F., & Liu, Q.[3] This paper proposes the use of Convolutional Neural Networks (CNNs) for Clothing Classification. He notes that current algorithms have manually designed feature limitations that cause low accuracy issues. The authors create a new database by using clothing images downloaded from the internet and dividing them into 16 categories according to clothing styles.

The CNN architecture is designed to adaptively learn the feature representation of clothes. The experiment compares the proposed CNN model with traditional methods and shows that the CNN model is superior to other algorithms.

Highlighting the traditional feature limitations of previous clothing classification research and the lack of a general clothing database, the article proposes a deep learning-based approach to address these shortcomings and creates a large clothing database.

The clothing database is divided into 16 categories and contains 33,965 examples. CNN architecture consists of four convolutional layers and aims to learn hierarchical features. Experiments show that the CNN model achieves the highest accuracy of 61.22%.

In conclusion, the paper highlights the success of CNNs in recognizing clothing categories, specifically highlighting their ability to learn global knowledge and semantic features. He suggests that in the future, more work should be done to optimize the deep network architecture and expand the database.

Seo, Y., & Shin, K. S.[4], focused on the importance and use of deep learning methods for clothing classification in the fashion industry. In particular, the advantages of Convolutional Neural Networks (CNN) and other deep learning techniques in the recognition, classification and processing of fashion images are discussed. In addition, the difficulties and solutions encountered in clothing classification of these techniques are also examined in detail. The potential of hierarchical classification methods to reduce error rates and increase accuracy in garment classification was emphasized. It is emphasized that the study presented in this article has the potential to obtain more accurate and detailed results in the field of clothing classification in the fashion industry.

3. DATA SET ANALYSIS AND SELECTION

Data Refinement:

At the outline, our dataset comprised a staggering 143 main classes, as depicted in Figure 3.1. Recognizing the challenges associated with training and the potential for reduced accuracy, a strategic decision was made to streamline the data. The solution involved classifying the data into more comprehensive masterCategories, ultimately reducing the number of classes to six. These masterCategories, namely 'Footwear,' 'Accessories,' 'Apparel,' 'Personal Care,' 'Free Items,' and 'Sporting Goods,' formed the basis for our subsequent model development.

Labeling and Categorization:

Upon closer inspection of the dataset, we observed that the data lacked proper labeling. However, a more detailed examination of the Kaggle dataset revealed that the necessary labeling information was embedded in a JSON file. Leveraging this valuable resource, we successfully categorized the data into classes aligned with our predetermined master categories.

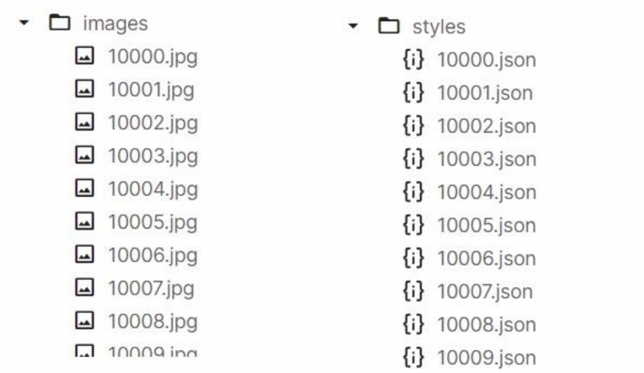

Figure 3.1 Content of Image and Style Files

Refining Class Definitions:

As a result of this categorization process, we initially identified seven classes, including an additional 'Home' category. However, due to the limited representation of examples within the 'Home' class, a decision was made to exclude it from our training data. Ultimately, our models were trained with a focus on the six primary classes: 'Footwear,' 'Accessories,' 'Apparel,' 'Personal Care,' 'Free Items,' and 'Sporting Goods.'

	articleType	count_img
0	Tshirts	7067
1	Shirts	3217
2	Casual Shoes	2845
3	Watches	2542
4	Sports Shoes	2036
...	...	...
138	Ipad	1
139	Cushion Covers	1
140	Body Wash and Scrub	1
141	Shoe Laces	1
142	Suits	1

143 rows × 2 columns

Figure 3.1 articleType classes

Figure 3.2 dataset

4. WORKING PROCESS

The basic stages of the study include the following steps:

4.1 Data Discovery and Preparation:

The journey begins with data exploration via 'fashion-product-images-dataset' from Kaggle. This comprehensive data set includes a CSV file and an array of product images with basic information on category, color, gender, and other attributes.

4.2 Data Analysis and Visualization :

The next phase carefully dives into the data analysis and visualization process. The 'styles.csv' file is examined, and in order to understand the distribution of product types, we visualize it divided into masterCategories as a result of the data processing we did in the 3rd section.

4.3 Data Preprocessing:

Precision in clothes classification requires a targeted approach in the data pre-processing stage. The work focuses on specific types of clothing, focuses on the processing of visual data related to those types, and selects, processes, and saves these images in a new directory. This process aims to create a suitable dataset to train our VGG16 model.

4.4 Model Selection and Design:

After the preprocessing phase, the paper introduces the critical phase of model selection and design. VGG16 stands out for its effectiveness in image classification. Figure 4.1, which presents the architecture of VGG16 in detail, includes the process of selecting the most suitable model to create a powerful clothes classification system.

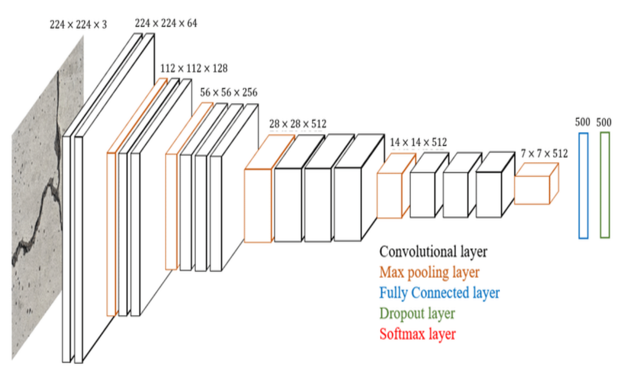

Figure 4.1 Vgg16 Structure

4.5 Training Optimization:

With the prepared data, the training process is optimized with certain carefully selected loss functions and optimization algorithms to tune the VGG16 model to optimal performance.

5. RESULT

From the chart (**Figure 5.1)**, it can be seen that the VGG16 model has the highest accuracy. VGG16 is a 16-layer deep learning model and is known to perform well in learning complex tasks. Resnet152 is a 152-layer deep learning model and is more complex than VGG16. However, as seen in the graph, Resnet152 has lower accuracy than VGG16. This suggests that Resnet152 may be overfitting the training dataset. AlexNet and DenseNet201 are less complex deep learning models. As seen in the graph, these models have lower accuracy than VGG16 and Resnet152.

Overall, the chart (Figure 5.1) shows that VGG16 is the best machine learning model for prediction. Resnet152, while more complex, has lower accuracy than VGG16 due to overfitting. AlexNet and DenseNet201, while less complex, have lower accuracy.

The graph (Figure 5.1) also shows the impact of model complexity on accuracy. More complex models have the potential for higher accuracy. However, more complex models are more likely to be overfitting the training dataset. Therefore, when determining the complexity of the model, it is important to consider the balance between accuracy and the possibility of overfitting.

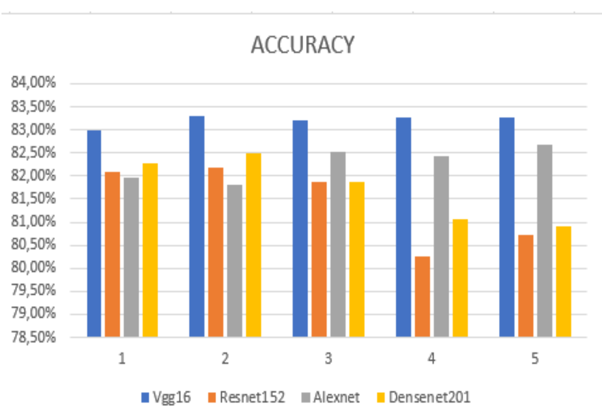

Figure 5.1 Accuracy values of all models

5.1 Performance Evaluation:

The effectiveness of the trained VGG16 model is rigorously evaluated using key performance metrics, especially accuracy.

epoch	train_loss	valid_loss	accuracy	time
0	0.771221	0.680073	0.809068	18:04

epoch	train_loss	valid_loss	accuracy	time
0	0.678618	0.625778	0.821782	19:34
1	0.615829	0.612756	0.825158	19:01
2	0.584341	0.598192	0.826395	19:30
3	0.523921	0.601779	0.828420	19:12
4	0.471528	0.600780	0.826170	19:06

Figure 5.2 Vgg16 Result

5.2 Overfitting Analysis:

In the table above (Figure 5.2), training loss (train_loss) decreases over time, while accuracy (accuracy) increases. This shows that the model is starting to perform well on the training dataset. However, as the validity loss (valid_loss) becomes larger than the training loss, it becomes clear that the model does not perform well on the test dataset. In this example, it can be seen that the overfitting of the model occurs in the 4th epoch. This indicates that the model has learned too much detail in the training dataset and therefore becomes less generalizing to the data.

To prevent overfitting, the following precautions can be taken:

- ✓ The complexity of the model can be reduced. A less complex model is less likely to learn noise and random variations in the training data set.
- ✓ Regularization is available. Regularization is a technique that helps reduce the complexity of the model.
- ✓ By taking these precautions, you can reduce the likelihood of overfitting and make your model perform better in the real world.

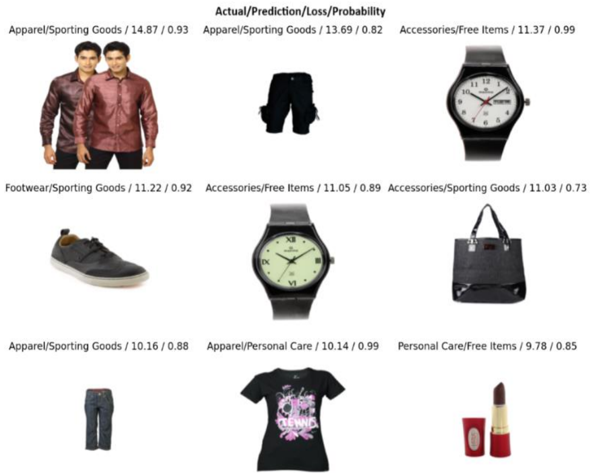

Figure 5.3 Misclassifications after Training

When we wanted to look at the incorrect classifications after training, we obtained the results in Figure 5.3. For example, in the first example, although the real class of the data is "apparel", the model classified it as "sporting goods". That's why we see that the loss value is large. Because in case of misclassification, the loss value becomes large.

5.3 Confusion Matrix

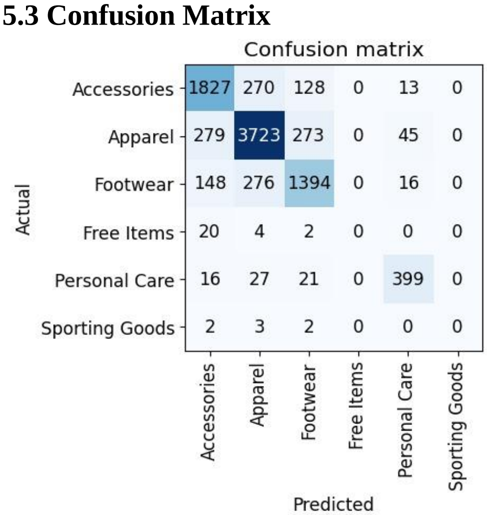

Figure 5.4 Confusion Matrix

Figure 5.4 is a confusion matrix. It is a table used to measure the performance of a machine learning model. The matrix has two columns and six rows showing actual and predicted classes.

The number in each column and row indicates the number of items predicted correctly or incorrectly in that class. For example, 1827 items were correctly predicted for the predicted class "Accessory" versus the actual class "Accessory".

According to this matrix, the model performs well overall. The highest accuracy rates are achieved for apparel (86%), personal care products (86%) and accessories (81%). The lowest accuracy rates are obtained for free items (0%) and sporting goods (0%).

Overall, this matrix shows that the model performs well. However, further improvements can be made in some areas. For example, the model can learn to more accurately identify freebies and sporting goods.

6. TIMELINE

Week 1: A Comprehensive Overview of the Fashion Industry
• We focused on data analysis models used in the fashion industry.
• We evaluated popular models and analyzed their advantages and disadvantages.
• We explored how AI models used in the fashion industry may evolve in the future.

Week 2: Data Analysis for Clothing Classification
• We focused on data processing steps and analysis.
• We examined data set selection processes and image processing techniques.
• We offered insights into the importance of correct categorization in the fashion industry.

Week 3: AI Model Selection and Application
• We examined pre-trained AI models for fashion product classification.
• We found models such as CNNs, Transfer Learning (VGG16, ResNet, YOLO, Inception) suitable.
• We introduced the main purpose of using the CIFAR-10 dataset.

Week 4: Lightning.ai Application and CIFAR-10 Dataset
• We performed artificial intelligence coding using the Lightning.ai library.
• We explored the CIFAR-10 dataset, highlighting its uses and applications in machine learning research.

• We discussed the advantages of Lightning.ai and various use cases of CIFAR-10.

Week 5: Training and Model Evaluation with fast.ai
• We focused on the fast.ai library used in the fashion industry.
• We gave information about Fast.ai's democratic artificial intelligence training.
• We evaluated the training results and created a confusion matrix showing the model's correct and incorrect predictions.

Week 6: We trained AlexNet, Vgg16, ResNet152, DenseNet 201 models.
• The most suitable model was selected based on their model accuracy and confusion matrices.

7. CONCLUSION AND FUTURE STUDIES

In this study, clothing classification algorithms that play an important role in the clothing industry are discussed. These algorithms can help clothing companies understand the profile of potential buyers, focus sales on specific niches, and improve user experience. In this study, we aimed to evaluate these classification algorithms using important Convolutional Neural Network (CNN) models such as ResNet152, VGG16, AlexNet and DenseNet201. Our data is created using datasets from sources such as Kaggle and GitHub.

Our VGG16 model reached the highest accuracy rate with an accuracy rate of 83%. Our AlexNet model achieved the second highest accuracy rate with 82% accuracy. Our DenseNet201 model achieved the third highest accuracy rate with an accuracy rate of 80%. Our ResNet152 model reached the lowest accuracy rate with an accuracy rate of 80%.

Our results show that CNN models are effective for the clothing classification task. However, there are some improvements that can be made to achieve better results. For example, we can try more advanced model architectures. We can also leverage pre-trained models using transfer learning techniques.

Future studies may further advance research in this area. For example, models can be trained better by creating new data sets. Additionally, better results can be achieved by designing new model architectures and using new transfer learning techniques.

In addition, if we design a less complex model ourselves, overfit can be prevented, training time can be reduced, and the accuracy rate can thus be higher than the values we get with transfer learning, as the model complexity will decrease. Finally, research in this area can help achieve better customer experience and higher sales in the apparel industry.

8. REFERENCES

[1]https://www.kaggle.com/datasets/paramaggarwal/fashion-product-images-dataset

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