Fashion Products Classification

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Abstract

A computer vision system is being developed that can accurately classify clothes in e-commerce images. This will make it easier for customers to find the clothes they want. This means that the computer was taught how to recognize clothes in pictures, using a data-set of fashion images. The task was to classify the images of clothing apparels, cosmetics, foot wears and other miscellaneous fashion products that were collected from online search engines. In the experiments, we evaluate the impact on classification accuracy of a data set of potential improvements. This includes data augmentation by generating diverse backgrounds and increasing the size of the network using ensembles. We are looking at how accurate our predictions are, and how efficient our process is. Finally, we present the achieved accuracy rates in the clothes detection task and outline the most successful network configurations for the classification of the clothes.

Keywords: augmentation, diverse, efficient, classification

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1. Introduction

Today, fashion is an important part of our economy, including the virtual economy on the internet. Nonetheless, today's customers prefer online shopping to regular shopping at malls and stores. Customers expect online stores to provide an easy way to find clothes and accessories that match their tastes Therefore, you need a quality clothing search engine based on customer interests. As an online search engine, there are various problems with analysing clothing images. One, Detection & Rough localization of clothing elements, usually by rectangles. Two, Segmentation Precise pixel-by-pixel localization. Three, Classification of clothes to one of several classes, such as the type of

clothing (dresses, skirts, shoes, etc). Four, Assigning numerous attributes to garments at once, such as pattern, colour, style and size. Five, Description of the garment in natural language. Six, Search for similar (in some respects) clothing items.
Faced with all the above problems, researchers have used a variety of methods to solve them, ranging from handcrafted complex mathematical models to the latest deep learning approaches. Clothes in online search engines are usually well photographed (studio quality, plain white background). A promising technique for this purpose is Deep Learning, especially deep convolutional neural networks, which have proven very successful in classifying images and recognizing clothes. There are many genetic algorithms using deep neural networks that allow us to detect similar elements in images, like the problem described. Thus, using Deep Learning and AI concepts in this project will not only ease the work, but also help make this project more systematic and appropriate.

2. Problem Statement

To develop a computationally cost-effective and accurate classification model for e-commercial diverse fashion products.

2.1. Objective

- To train a model in such a way that it gives an optimal result in terms of accuracy and speed
- The objective is also to minimize the computation
- Enable the sites to also filter out the choices based on the user's preferences

2.2. Importance of Idea

Basically, the motive of this model is to help the online fashion retailers by identifying and classifying the images. By training this model, it will enable the sites to also filter out the choices based on the user's preferences. This way it can also make the site more user friendly and thus benefiting the e-commerce fashion-oriented sites. Filtering out is very essential for these sites in order to provide the user with the product of their wish and needs, hence our model will make sure that the user is able to do so and that too efficiently.

3. Literature survey

S.no	Author	Title	Methology	Drawbacks
1	S. Bhatnagar, D. Ghosal and M. H. Kolekar	Classification of fashion article images using convolutional neural networks(2018)[1]	Three different convolutional neural network architectures along with batch normalization and residual skip connections	Best possible accuracy reached is 92%. High Misclassification rate among similar types of products such as shirts, t-shirts, coats and pullovers
2	DeepAI	Neural Networks for Fashion Image Classification and Visual Search(2020)[2]	Transfer learning with pre-trained models such as VGG19 and Inception V3.	Low accuracy of 87-88% in two of the three categories. High misclassification rate of 55% in shoes category.
3	A. Alamsyah, M. A. Arya Saputra, and R. A. Masrury	Object Detection Using Convolutional Neural Network To Identify Popular Fashion Product(2019)[3]	CNN Model and Inception V2.	Considerable accuracy of 94.74% but needs to improve.
4	DeepAI	A Deep-Learning-Based Fashion Attributes Detection Model(2018)[4]	Modified Version of Faster R-CNN Model.	Imbalanced data with too many negative attributes.

S.no	Author	Title	Methology	Drawbacks
5	A. Hodecker, A. M. R. Fernandes, A. Steffens, P. Crocker and V. R. Q. Leithardt	”Clothing Classification Using Convolutional Neural Networks(2020)[5]	Various CNN Models.	Low accuracy ranging from 90 – 92%.
6	J. Cychnerski, A. Brzeski, A. Boguszewski, M. Marmolowski and M. Trojanowicz	Clothes detection and classification using convolutional neural networks(2018)[6]	SSD300 for clothes detection. SqueezeNet 1.1 and Resnet-50 networks for dress classification.	The dress classification results ranged from 70% accuracy for neckline to 81% for sleeve type attribute and were mostly limited by the ratio of incorrect labels in the datasets.
7	Tuinhof, H., Pirker, C., Haltmeier, M.	Image-Based Fashion Product Recommendation with Deep Learning(2019)[7]	CNN Model (AlexNet and BN-Inception).	Very low accuracy of 80% for texture prediction and 87% for category prediction.
8	Zhou, B., Suleiman, B., Yaqub, W.	Aesthetic-Aware Recommender System for Online Fashion Products(2021)[8]	Brain-inspired Deep Network Model and Bag-of-words Model.	Maximum achievable accuracy of 86.4% for top-5 recommendations.

S.no	Author	Title	Methology	Drawbacks
9	W. Li and B. Xu	Aspect-Based Fashion Recommendation With Attention Mechanism(2020) [9]	Two parallel paths of convolutional neural networks (CNN), long short-term memory networks (LSTM), and attention mechanisms (AFRAM).	CNN do not encode the position and orientation of object. Lots of training data is required.
10	Q. Wu, P. Zhao and Z. Cui	Visual and Textual Jointly Enhanced Interpretable Fashion Recommendation(2020) [10]	Visual and Textual Jointly Enhanced Interpretable Model (VTJEI) using bidirectional two-layer adaptive attention review.	User's historical reviews may contain a lot of noise, which may lead to inaccurate extraction of user preferences. No unified evaluation standard
11	C. -Y. Hsieh and Y. -M. Li	Fashion Recommendation with Social Intelligence on Personality and Trends(2019)[11]	Extracts the fashion trend opinions from social media. Uses a hierarchical structure to classify different types of Trend	Classifications based only on season of wear. Randomly generated recommendations negatively affected the recall score.
12	K. Kawattikul	Product Recommendation using Image and Text Processing(2018) [12]	Feature extraction techniques include HOG, Shape Context and Hu Moments. LSTM Models.	Best achievable accuracy of 85% which is very low.

S.no	Author	Title	Methology	Drawbacks
13	Kotouza, M.T., Tsarouchis, S., Kyprianidis, AC., Chrysopoulos, A.C., Mitkas, P.A.	Towards Fashion Recommendation: An AI System for Clothing Data Retrieval and Analysis(2020) [13]	Clustering Techniques such as : KModes, PAM, HAC, FBHC, and VarSel.	Variance of almost 30% is seen in the results of the algorithms.
14	Kayed, Mohammed & Anter, Ahmed & Mohamed, Hadeer	Classification of Garments from Fashion MNIST Dataset Using CNN LeNet-5 Architecture(2020) [14]	CNN based LeNet-5 Architecture	Limited Product Classification Labels
15	Yang Hu, Xi Yi, Larry S. Davis	Collaborative Fashion Recommendation: A Functional Tensor Factorization Approach(2016) [15]	Gradient boosting-based method is used to learn the nonlinear functions that map the feature vectors from the feature space to a latent space. Proposes a functional tensor factorization method to model the interactions between user and fashion items.	Cold start problem and incorporating social information from social networks

S.no	Author	Title	Methology	Drawbacks
16	Xingchen Li, Xiang Wang, Xiangnan He	Hierarchical Fashion Graph Network for Personalized Outfit Recommendation(2020) [16]	Proposes a Hierarchical Fashion Graph Neural Network (HFGN)	Improvements over other models such as Bi-LSTM, FHN and NGNN yet a low accuracy of about 87.97%.
17	Chen, X., Chen, H., Xu, H., Zhang, Y., Cao, Y., Qin, Z., & Zha, H	Personalized Fashion Recommendation with Visual Explanations based on Multimodal Attention Network(2019) [17]	Fine-grained Visual Preferencing (VECF) Model.	Not all features are appropriate to be explained visually.
18	Z. Yang, Z. Su, Y. Yang and G. Lin	From Recommendation to Generation: A Novel Fashion Clothing Advising Framework(2018) [18]	Novel clothing recommendation model based on the Siamese network and Bayesian personalized ranking, which recommends clothing items that meet user's personalized preference.	Fails to recommend the user based on their price preference to an extent.
19	Lavinia De Divitiis, Federico Becattini, Claudio Baecchi, and Alberto Del Bimbo	Disentangling Features for Fashion Recommendation(2022) [19]	Proposes to use a Memory Augmented Neural Network (MANN) as the central part of their garment recommendation system to pair compatible clothing items.	Common controller loss to train such memory modules as issues arise from uneven data distributions.

S.no	Author	Title	Methology	Drawbacks
20	Bellini, P., Palesi, L.A.I., Nesi, P. et al	Multi Clustering Recommendation System for Fashion Retail(2022) [20]	KMeans Model	Small changes involve recalculating all distances between items or customers.
21	O. Sonie, M. Chelliah, and S. Sural	Personalised Fashion Recommendation using Deep Learning(2019) [21]	Multi-layer Perceptron (MLP) Model.	MLP include too many parameters because it is fully connected.
22	Sha, Dandan & Wang, Daling & Zhou, Xiangmin & Feng, Shi & Zhang, Yifei & Yu, Ge	An Approach for Clothing Recommendation Based on Multiple Image Attributes(2016) [22]	Based on Color Matrix.PHOG, Fourier, and GIST Feature Extraction for Collar and Sleeves.	Just a supplementary to present-day classification and recommendation systems.
23	Jo, Jaechoon & Lee, Seolhwa & Lee, Chanhee & Lee, Dongyub & Lim, Heuiseok.	Development of Fashion Product Retrieval and Recommendations Model Based on Deep Learning(2020) [23]	Image-Based Similar Product Retrieval Model using CNN Classifier.Sketch-Based Similar Product Retrieval Model using GAN.	Maximum precision achieved is 0.809 and 0.493 respectively.

4. Software Requirements

We intend on using Python as the implementation language. The main advantage of using Python in ML/DL tasks is its various libraries which facilitate image manipulation, model training, plotting various plots and graphs

of metrics.
The libraries and software in use are:

- Tensorflow: The core open-source library to help you develop and train ML models. It is developed and maintained by Google. It is easy to use and allows a number of operations which help generate powerful deep learning models
- Keras: It is an API built on top of Tensorflow to ease its use and perform various operations with fewer lines of code.
- Numpy: It is a library for matrix operations and scientific computations. NumPy brings the computational power of languages like C and Fortran to Python, a language much easier to learn and use. With this power comes simplicity: a solution in NumPy is often clear and elegant.
- Pandas: It is a fast, powerful, flexible and easy to use open source data analysis and manipulation tool, built on top of the Python programming language. We are going to use it for dataset manipulation.
- OpenCV: It is an open-source computer vision and image processing library with a vast potential. It was originally written in C++ but a Python version is also available.
- Matplotlib: It is a comprehensive library for creating static, animated, and interactive visualizations in Python. It is easy to use and can be used to plot various graphs, diagrams and visualize data.
- Google Colab: Colaboratory, or "Colab" for short, is a product from Google Research. Colab allows anybody to write and execute arbitrary python code through the browser, and is especially well suited to machine learning, data analysis and education. More technically, Colab is a hosted Jupyter notebook service that requires no setup to use, while providing free access to computing resources including GPUs. It is free to use for everyone.

5. Proposed Model

5.1. Dataset Description

The dataset consists of images of fashion products like clothes, accessories, etc and a .csv file with the labels related to each image. There are more than

44.4k images with each having dimensions of (256, 256, 3). This dataset is available on Kaggle with variable dimensions. The original dataset is much larger due to large dimensions of images.

	id	gender	master	sub	article	color	season	year	usage	name
0	/content/fashion_small/resized_images/15970.jpg	Men	Apparel	Topwear	Shirts	Navy Blue	Fall	2011.0	Casual	Turtle Check Men Navy Blue Shirt
1	/content/fashion_small/resized_images/39386.jpg	Men	Apparel	Bottomwear	Jeans	Blue	Summer	2012.0	Casual	Peter England Men Party Blue Jeans
2	/content/fashion_small/resized_images/59263.jpg	Women	Accessories	Watches	Watches	Silver	Winter	2016.0	Casual	Titan Women Silver Watch
3	/content/fashion_small/resized_images/21379.jpg	Men	Apparel	Bottomwear	Track Pants	Black	Fall	2011.0	Casual	Manchester United Men Solid Black Track Pants
4	/content/fashion_small/resized_images/53759.jpg	Men	Apparel	Topwear	Tshirts	Grey	Summer	2012.0	Casual	Puma Men Grey T-shirt

Figure 1: Data set of Model

5.2. Dataset Graphs

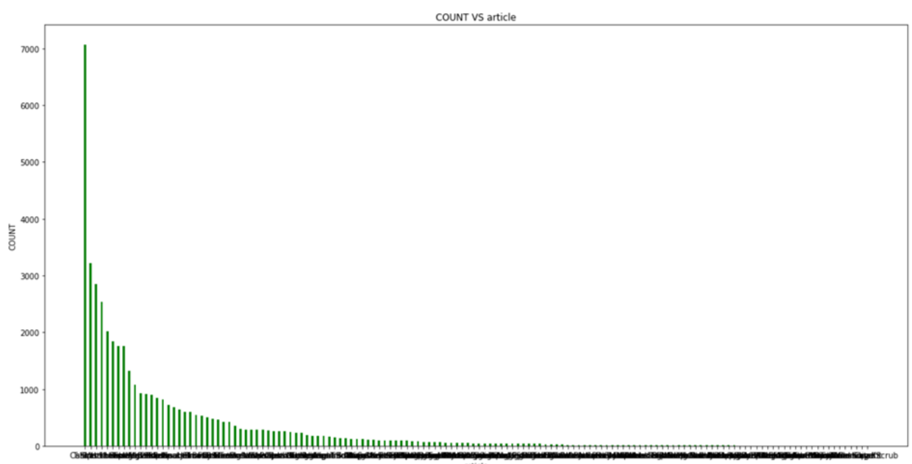

Figure 2: Article Counts

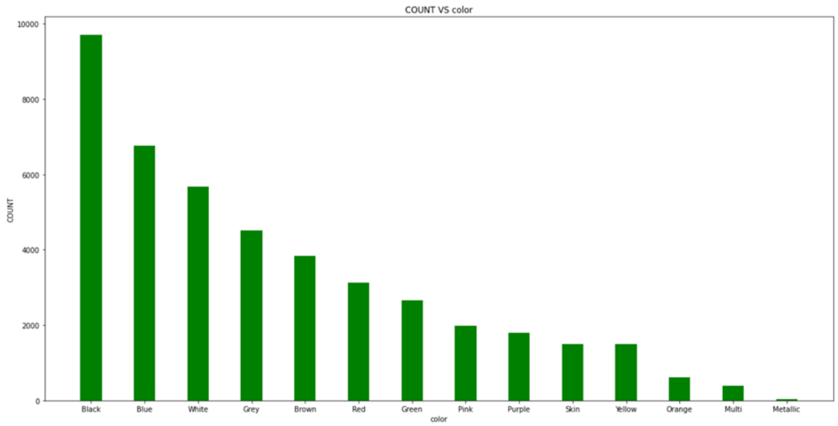

Figure 3: Color Counts

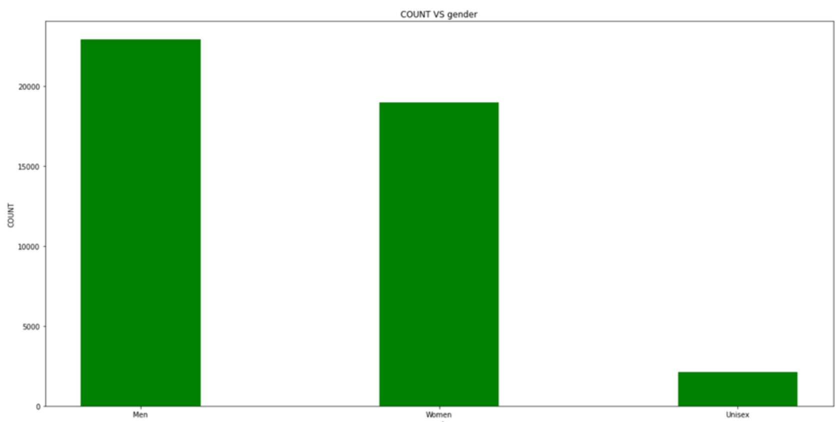

Figure 4: Gender Counts

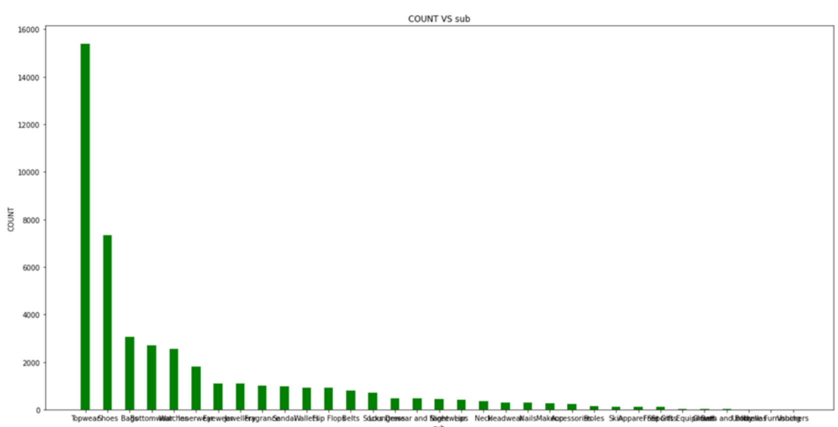

Figure 7: Sub Counts

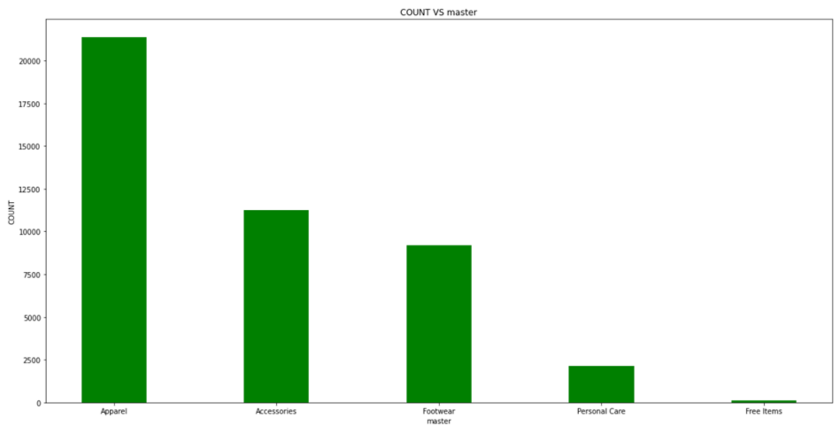

Figure 5: Master Counts

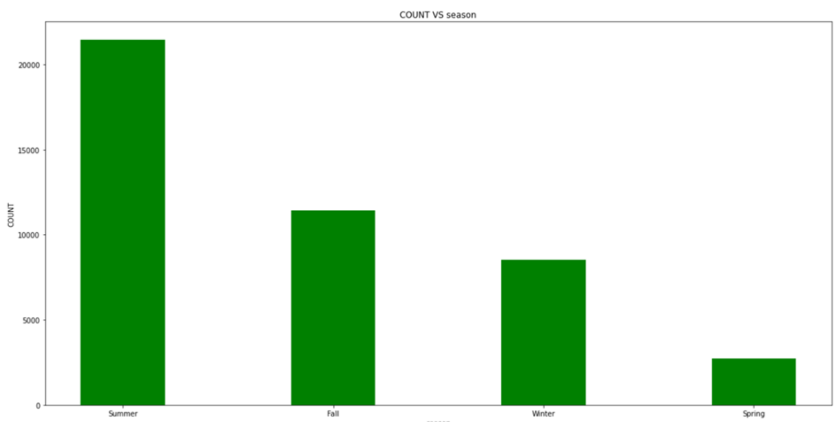

Figure 6: Season Counts

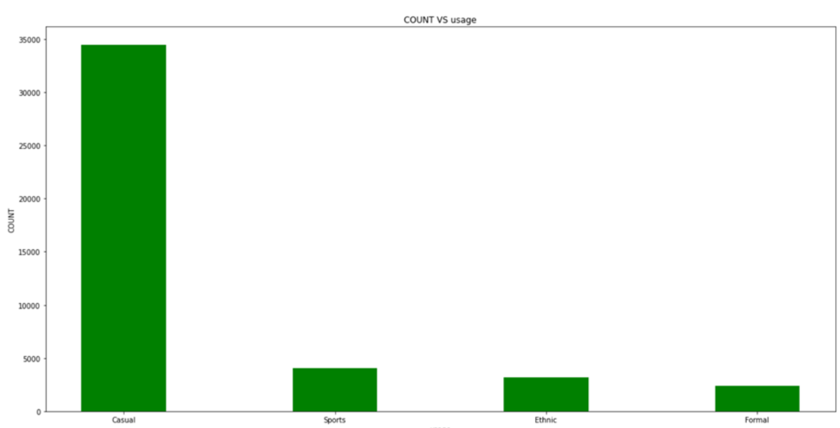

Figure 8: Uasage Counts

5.3. Methodology

Our framework is general in terms of the choice of image features. We have used ResNET-152 (Residual Neural Network) for the extraction of features of the image. Results indicate that features extracted by RNN with many layers perform significantly better than the traditional hand-crafted features. Features extracted by RNN which are pre-trained on a large image dataset are also effective on other vision tasks.

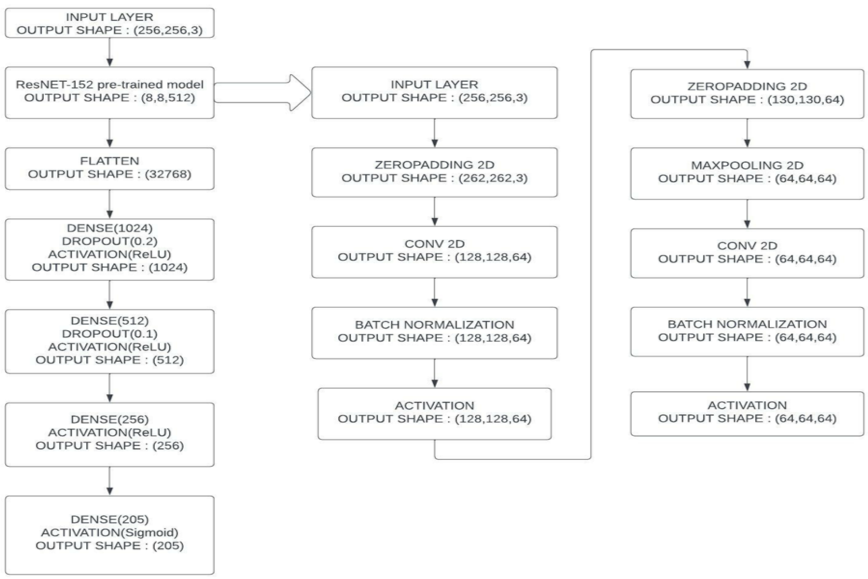

Figure 9: Process Model Diagram

An original image is being passed through a Convolutional 2D Batch Norm layer and the features of the same have been extracted. Next step we do is to perform Pooling so that the image gets down-sampled and then repeat the same process as mentioned above. Finally, we Flatten the features and pass it through a Fully Connected Neural Network and get the end classification of the image. The end classification of the image which we got has to be checked with our predictions we made earlier, whether it was correctly predicted or not.

5.4. Pseudocode

Psedocode as follows:
Connect Gdrive.

Connect to Kaggle.
Import files from Kaggle.
Remove unnecessary files and folders.
Import libraries.
Read .csv file.
Convert ID column to full path.
Remove irrelevant columns.
Check for missing values.
Create a separate test dataset which consists of missing data.
Display images with corresponding labels from train dataset.
Replace duplicate labels and plot count of each unique label in a column.
Encode target columns.
Create Data Pipeline.
Create Model Architecture.
Create custom loss and metrics.
Compile model.
Train model by passing training data through data pipeline & into the model.
Save trained model.
Plot losses and metrics.
Test model on testing data and visualize the results.

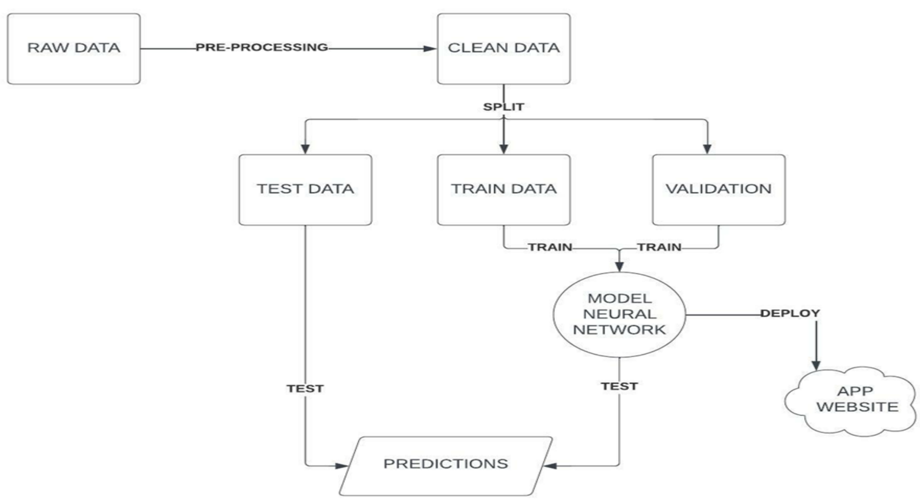

Figure 10: Work Flow Diagram

6. Result Analysis

Accuracy results for each category of classification provides us with an understanding of how efficient our model is as compared to the established traditional models.

```
Epoch 1/5
1377/1377 [==============================] - 1371s 978ms/step - loss: 4.5410 - gender_accuracy: 0.8815 - master_accuracy: 0.9762 - sub_accuracy: 0.8868 - article_accuracy: 0.7099 -
color_accuracy: 0.4768 - season_accuracy: 0.6184 - usage_accuracy: 0.8549 - lr: 1.0000e-04
Epoch 2/5
1377/1377 [==============================] - 1350s 980ms/step - loss: 2.2818 - gender_accuracy: 0.9362 - master_accuracy: 0.9948 - sub_accuracy: 0.9729 - article_accuracy: 0.8904 -
color_accuracy: 0.7365 - season_accuracy: 0.7419 - usage_accuracy: 0.9185 - lr: 1.0000e-04
Epoch 3/5
1377/1377 [==============================] - 1355s 984ms/step - loss: 1.5456 - gender_accuracy: 0.9577 - master_accuracy: 0.9965 - sub_accuracy: 0.9855 - article_accuracy: 0.9328 -
color_accuracy: 0.8076 - season_accuracy: 0.8058 - usage_accuracy: 0.9446 - lr: 1.0000e-04
Epoch 4/5
1377/1377 [==============================] - 1353s 982ms/step - loss: 1.0561 - gender_accuracy: 0.9694 - master_accuracy: 0.9970 - sub_accuracy: 0.9907 - article_accuracy: 0.9592 -
color_accuracy: 0.8669 - season_accuracy: 0.8631 - usage_accuracy: 0.9635 - lr: 1.0000e-04
Epoch 5/5
1377/1377 [==============================] - 1352s 982ms/step - loss: 0.7262 - gender_accuracy: 0.9809 - master_accuracy: 0.9981 - sub_accuracy: 0.9944 - article_accuracy: 0.9722 -
color_accuracy: 0.9056 - season_accuracy: 0.9126 - usage_accuracy: 0.9738 - lr: 1.0000e-04
```

Figure 11: Propose Model Accuracy Table

Our proposed model gives a loss of 0.7262 and gender accuracy of 98.09%, master accuracy of 99.81%, sub accuracy of 99.44%, article accuracy of 97.22%, color accuracy of 90.56%, season accuracy of 91.26%, usage accuracy of 97.38% after being trained for 5 epochs. These results are obtained by having the initial learning rate of 0.001.

7. Conclusion

Using ResNET-152 Architecture, we were able to achieve an accuracy of above 90% in all of the classification categories and an outstanding accuracy of 99.81% in MASTER class. We can clearly see how Batch Normalization and Pooling help improve the overall accuracy and significantly reduce the training time. These are an improvement on the various other deep learning models proposed by reputed research papers for the fashion products classification purpose.

8. Future Work

Identifying an article type in the fashion industry is a crucial task. This model can serve as a building block for a service which shows related fashion articles based on a given image. This work can also be extended to image and video indexing. It can also be very useful in improving seller experience in listing their merchandise on the platform. sellers can add pictures in their products and automated image-to-text machine learning algorithms can generate suitable tags to label them. This can lessen the inaccuracies in labelling products which sometimes have an effect on the call for adversely as the goods aren't rendered correctly inside the search results.

Furthermore, we can step up the proposed project, for instance, adding more attributes depending on which our model can predict the dressing code (like is it formal or informal in terms of percentage) of the person whose picture is being taken as an input by the program. Hence, the output will be that how formally dressed the person is in terms of percentage, the higher the percentage, the more formally dressed the person is. This can help regulate the decency in the dressing style of the students in schools and colleges, and also of the employees in offices.

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