E-Commerce Product Classification

1. Introduction

Classification of products is a time-consuming procedure for both service giver and clients, and Ecommerce has expanded fast in recent years, but it is necessary to categorize products. Images provide vital information, as they lead people in proper way. On the other hand, misleading visuals can frustrate users. Analyzing the correctness of an image requires an explanation of it in the same way that a user does. Significant time is being lost in sorting and labeling the items. Deep learning methods(Jha et al., 2021) like CNN can be used for image classification as it gives better accuracy and is the best model to deal with images.

Figure 1 Ecommerce Product Classification

This paper aims to determine how well an Image-based Transfer Learning Framework can categorize E-commerce products. The major contribution of this research is a deep learning framework that combines and categorizes all product classes well with transfer learning models like CNN, VGG19, InceptionV3 and ResNet50, MobileNet within the shortest time and with accurate accuracy.

2. Related Work

We talk about two issues that the e-commerce industry may have to deal with in the future. One has to do with the difficulty sellers have when trying to upload images of their products to a marketplace and the ensuing manual tagging that occurs as a result. As a result of the classification errors, it is no longer listed in search results. Ecommerce platforms require that sellers upload images of their products and tag them with appropriate labels for their products to appear in search results. Because of human involvement, this procedure is prone to error. If the product is misclassified, it may not appear in search results, which could lead to fewer sales or no sales at all.

CNN is an abbreviation for convolutional neural network, which is a deep learning method. CNN is commonly regarded as the best image classification models[1]. However, as excellent as machine learning algorithms are, their classification accuracy is typically restricted in many object types of issues. This article [2] examines the e commerce product image classification approaches used in machine learning to categorize e commerce product pictures. The primary advanced classification methodologies and techniques used to improve classification accuracy are summarised. In 2012, a CNN was employed for the first time to reach a top 5 test error rate of 15.4 percent, while the best research paper the following year had a rate of 26.2 percent. The paper's technique was innovative, and it introduced several deep learning principles into the limelight.[3]Transfer learning approaches are the most effective way to overcome CNN's faults.

3. Materials and Experimental Evaluation

3.1 Dataset

The dataset consists of 796 images with jpeg format. In our initial prospective model, machine learning algorithms were used to classify ecommerce products with four classes, and a comparison of the classifiers for our model was established. Those Television, Sofas, Jeans and T-shirt. Their images are 199,199,199,199 respectively.In our model 80 % dataset is used for training and remaining 20% is used for testing and validation.

Kaggle Dateset Location: *https://www.kaggle.com/datasets/sunnykusawa/ecommerce-products-image-dataset*

3.2 Methodology

The research methodology consists of five steps methodology represented in the figure 2 below.

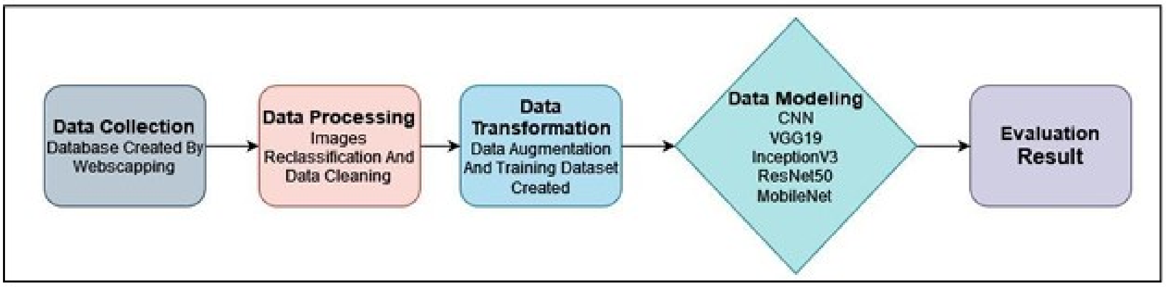

Figure - 2

The first step, **Data collection,.** Where data is gathered to create a dataset for study. it started by getting the data source from Kaggle,

The second step, **Data processing**, involves image reclassification and cleaning. Images are reclassified as there are multiple subcategories. For example, there are 4 subcategories in the ecommerce products.

The third step**, Data Transformation**, consists of the image transformation process, which uses the Image augmentation method. Image augmentation helps to reshape and reconstruct data images. There were 796 images with 4 classes. After this process, there were 796 images in the collection. These augmented datasets are used to create training datasets.

The fourth step, **Data Building,** is the creation of models based on the training dataset. The suggested method focuses on how image data may be used to categorize objects using a transfer learning strategy, making classification simpler and more convenient. Deep learning models are trained to utilize the transfer learning approach. The data modelling stage begins after partitioning data into training and testing sets and developing various models based on the data used. MobileNet is a lightweight network that requires less maintenance and works admirably at high speeds.

The fifth step, **Evaluation and Results**, involves assessing built models' performance using criteria like execution time. Accuracy, precision, recall, and the F1-score are some of the evaluation variables utilized to measure the models' effectiveness in this research project. For the outcomes stage, which focused on analyzing the obtained information and findings, plots of Epoch vs Accuracy and Epoch versus Loss are shown.

The results of multiline plot is shown in figure 3

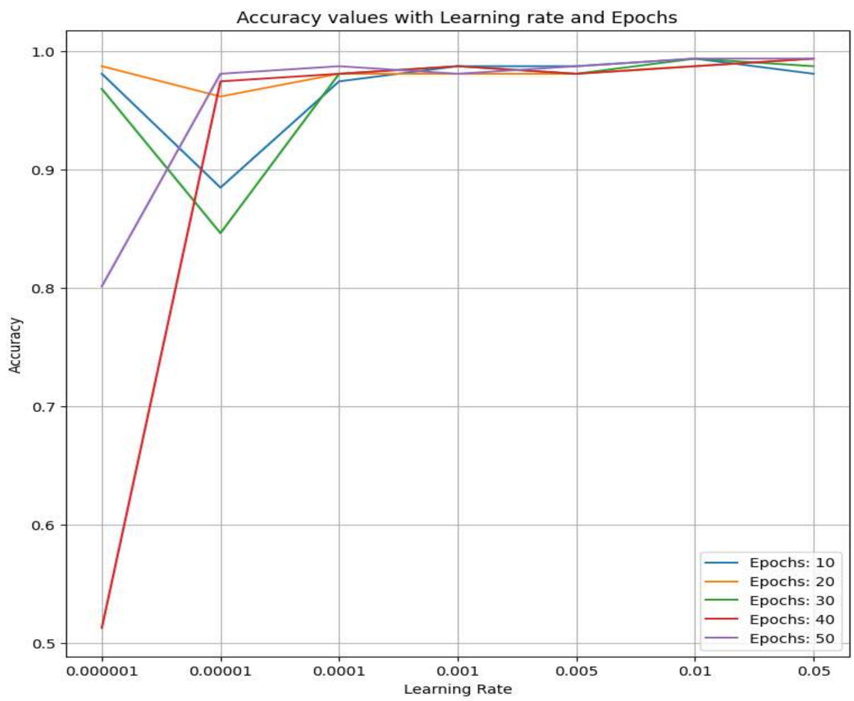

Figure – 3

Epochs/learning rate	0.000001	0.00001	0.0001	0.001	0.005	0.01	0.05
10	0.9807	0.8846	0.9743	0.9871	0.987	0.994	0.981
20	0.9871	0.9615	0.9807	0.9807	0.981	0.987	0.994
30	0.9679	0.8461	0.9807	0.9871	0.981	0.994	0.987
40	0.5128	0.9743	0.9807	0.9871	0.981	0.987	0.994
50	0.8012	0.9807	0.9871	0.9807	0.987	0.994	0.994

3.3 Results

The confusion matrix of AI model as shown in figure 4

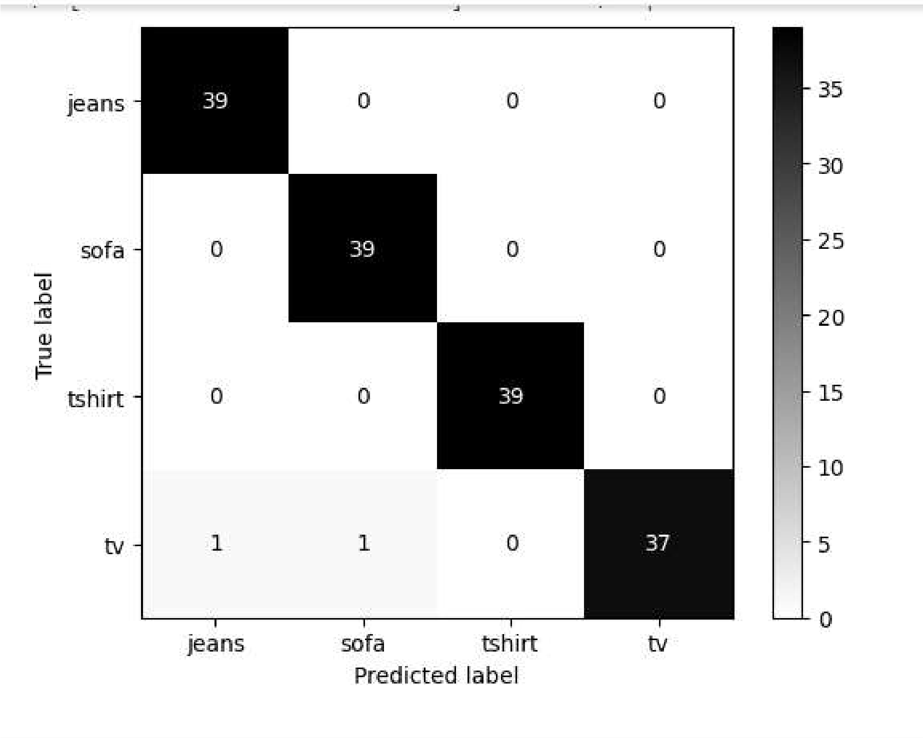

Figure - 4

The proposal model classifies ecommerce products with accuracy rate 99%.The classification report is shown in figure 5

Classification Report :

	precision	recall	f1-score	support
0	0.97	1.00	0.99	39
1	0.97	1.00	0.99	39
2	1.00	1.00	1.00	39
3	1.00	0.95	0.97	39
accuracy			0.99	156
macro avg	0.99	0.99	0.99	156
weighted avg	0.99	0.99	0.99	156

Figure - 5

3.4 Discussion

In this paper, drawing a comparison between traditional CNN and transfer learning.

A basic CNN model with 5 blocks of convolutional, activation, and pooling layers was used followed by fully connected layers.

The figure 6 that shows the graphs for accuracy and loss with increasing epochs for a basic CNN, it can be seen that the model tends to overfit on the training data which leads to almost 90% train accuracy while the test accuracy gets sinking low as the epochs proceed.

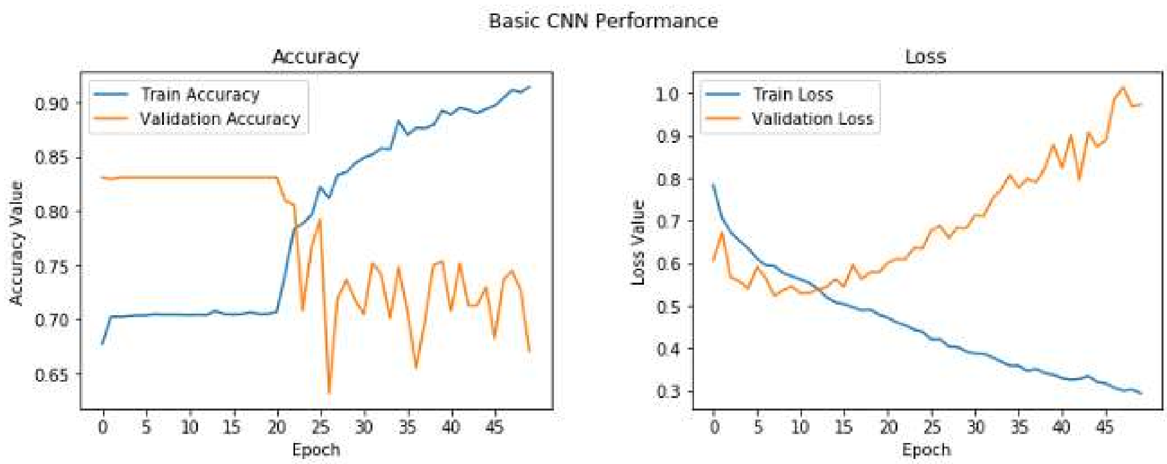

Figure – 6 Accuracy for Basic CNN performance

The proposed model project involved applying transfer learning to various product images from the ecommerce website and testing the model.

The proposal model classifies ecommerce products with accuracy rate 99%.The classification report is shown in figure 7

Classification Report :

	precision	recall	f1-score	support
0	0.97	1.00	0.99	39
1	0.97	1.00	0.99	39
2	1.00	1.00	1.00	39
3	1.00	0.95	0.97	39
accuracy			0.99	156
macro avg	0.99	0.99	0.99	156
weighted avg	0.99	0.99	0.99	156

Figure – 7

4. Future Work

What are the major shortcomings of your current method? For each shortcoming, propose additions or enhancements that would help overcome it.

5. Conclusion

In the future, this algorithm can be applied to deeper levels of categories to get even better product taxonomy. For example, currently the category electronics was taken as a whole. To improve this, sub categories from within electronics such as laptops, TVs, tablets, etc. can be considered as separate entities and individual models can be built for each one of them to classify products into more granular chunks. Also, this approach can be combined with near matching to act like a recommender. So, once a product has been classified into its respective category, an extension of the current algorithm can be introduced that finds from within the database similar products since it already has product and category information. This, if implemented in real time can be very useful to display similar products to the users once they land at the product of their choice to provide them with more relevant options for the kind of item they are looking for.

6.Reference

1. Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., Huang, Z., Karpathy, A., Khosla, A., Bernstein, M., Berg, A.C., Fei-Fei, L., 2015. ImageNet Large Scale Visual Recognition Challenge. Int. J. Comput. Vis. 115, 211–252. https://doi.org/10.1007/s11263-0150816-y
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