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Transfer learning-based Fashion Image Classification using Hybrid 2D-CNN and ImageNet Neural Network

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Abstract: ***Many algorithms have been developed as a result of recent advances in machine learning to handle a variety of challenges. In recent years, the most popular transfer learning method has allowed researchers and engineers to run experiments with minimal computing and time resources. To tackle the challenges of classification, product identification, product suggestion, and picture-based search, this research proposed a transfer learning strategy for Fashion image classification based on hybrid 2D-CNN pretrained by VGG-16 and AlexNet. Pre-processing, feature extraction, and classification are the three parts of the proposed system's implementation. We used the Fashion MNIST dataset, which consists of 50,000 fashion photos that have been classified. Training and validation datasets have been separated. In comparison to other conventional methodologies, the suggested transfer learning approach has higher training and validation accuracy and reduced loss.***

Keywords: Machine Learning, Transfer Learning, Convolutional Neural Network, Image Classification, VGG16, AlexNet, 2D CNN.

I. INTRODUCTION

Image classification is a new science and technique that has only recently been established. Its primary research focus is on picture classification and description. The most popular and practical method of conveying or receiving information is through images[1].Image information acquisition, information processing, and processing, feature extraction, judgment, or classification are the primary components of an image classification system[2]. Image categorization has recently grown in popularity among technology developers, owing to the increase in data in various industries such as e-commerce, automotive, healthcare, and gaming. Machine learning (ML) is one of the most commonly used systems for picture classification. However, there are still areas of ML that may be improved. Unsupervised machine learning approaches play a critical role in producing better results than others[3]. When it comes to Image Classification, Machine Vision has its context. This technology can recognize persons, objects, locations, actions, and text in photos. We may easily communicate information with the use of graphics instead of text[4].The use of artificial intelligence software and machines in parallel. Image recognition and classification is a problem with numerous real-world applications that have been around for a long time. To identify suspects in security footage, police might utilize picture recognition and classification. It can be used by banks to assist in the sorting of checks. Google has been employing it in their self-driving car effort more lately. With the increase in picture data, there is a requirement to analyze the data, cluster the data into groups, classify the data, or utilize other methods to manage these datasets[5]. Image classification has traditionally relied on a variety of ML algorithms, including template matching, support vector machines, kNN, and hidden Markov models. Even now, image categorization is one of the most difficult tasks in ML[6]. Classification is a well-known machine learning job that has been gradually improved over the years. However, due to the rapid growth of deep ML in recent years, it has made significant progress. Figure 1 represents the general Image Classification Process.

Figure 1.- Block Diagram of Image Classification Process

CNN's, a family of image-processing techniques, have been used in a variety of applications, including picture classification, object identification, and semantic image segmentation. CNN's can extract adequate features for image classification [4–7] and outperform classic techniques like SIFT, HOG, and SURF due to their excellent capacity to autonomously learn high-level feature representations of pictures. It also has the unusual property of retaining local image relations while dimensionality reduction is performed. This makes it simple for CNNs to capture crucial feature associations in an image while also reducing the number of parameters the algorithm must compute.

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Both 2D and 3 D images can be used as inputs and processed by CNNs[7]; In several problems, the CNN-based technique is utilized to localize and classify pictures. In some cases, hybrid techniques are utilized in conjunction with CNN to increase image classification accuracy. Training a standard CNN-basedmodel on a big image dataset is difficult, and it can take up to six days in some circumstances. A computer vision model's training and validation time can be reduced by using a transfer learning approach. Classification is the methodical grouping of things into groups and categories based on their characteristics. Image categorization was created to bridge the gap between computer and human vision by using data to teach the computer. The image categorization is accomplished by categorizing the image into the appropriate category depending on the vision's content[2]. E-commerce has revolutionized the buying experience by making it easier to shop and get products. It helps customers save time and effort. It employs a variety of tactics, including product recommendations, product classification, and the enhancement of other client services. There are two key concerns: one on the seller's side, product classification through correct labels and product photos, and the other on the customer's side, finding the goods quickly and receiving better recommendations. Human faults make the e-commerce system susceptible. From the standpoint of sellers and customers, any misclassification causes further issues such as products not displaying in search results, showing irrelevant suggestions, low sales or reduced sales, and so on[8]. However, in most applications, the systems rely on extracting a small number of features, i.e., characteristics that can capture specific visual attributes of a picture either globally or locally for its regions. The most difficult is to find significant traits that can effectively differentiate photos and aid in matching the most comparable ones[9].

II. RELATED WORK

Chunjie Zhang et al.[10]suggested a classification method based on image-level hierarchical structure learning. They analyze picture similarity using both visual and semantic data before clustering photos in a hierarchical manner. They calculate visual similarities between one image and each cluster and reweight the similarities using class diversities. The final picture representations for image class predictions are generated by aggregating the re-weighted similarities. The experimental results on the PASCAL VOC 2007 dataset show that the suggested technique is effective, with anmAP of 90.5.SaiyedUmer et al.[11]present a cosmetic product recognition system based on a database of 40 different cosmetic goods. For cosmetic product photos, the support vector machine outperforms logistic regression, k-nearest neighbor, ANN, and decision tree classifiers during classification. Based on a customer's input image, this cosmetic product recognition system is capable of identifying the type of cosmetic product.Huapeng Xu et al.[12]look at a difficult subject known as fine-grained picture classification (FGIC). They describe a novel strategy for facilitating FGIC that makes use of useful prior knowledge from either organized knowledge sources or unstructured text. They present a visualsemantic embedding model that investigates semantic embedding using knowledge bases and text, then trains a new end-to-end CNN framework to map image features linearly to a rich semantic embedding space. The methodology surpasses numerous state-of-the-art algorithms with significant advances, according to test findings on the demanding large-scale UCSD Bird-200-2011 dataset.Fengzi Li et al.[13]outline two potentially difficult issues that the e-commerce business faces. One is the issue that sellers encounter when submitting images of things for sale on a platform and the resulting manual tagging. It causes misclassifications, resulting in its exclusion from search results. Another issue is the potential for a slowdown in order placement when a consumer does not know the correct keywords but has a visual impression of an image. This research investigates ML techniques that can assist us in resolving both of these issues. Visual search, which solves the issue of searching products when the right terms are not known to the user, is a very intriguing use case for ML models. It improves the customer experience by allowing users to look for similar products simply by clicking on a picture of the item in question. For picture categorization, a deep learning CNN based on Keras and Tensorflow is deployed in Python. On the most popular ImageNet dataset, Sushma and Lakshmi[14] investigated the prediction accuracy of three distinct CNN. The major goal of this research is to determine the accuracy of several networks on the same dataset, as well as to assess the consistency of predictions made by each of these CNNs. They conducted a complete prediction study for comparing the performance of the networks for various images. The photos are processed through the Vgg16, Vgg19, and Resnet50 networks, and the results are analyzed. In comparison to Vgg16 and Vgg19, ResNet50 can recognize images with more precision.Image identification or classification using Advanced CNN using TensorFlow framework was discussed by Pradumn Kumar and Upasana[15]. The CIFAR 10 dataset was used to perform classifications on plant leaves in this study. They examine the comparison of multiple models using a given dataset. Advanced CNN achieves all of the objectives with an accuracy of more than 95%,whilst others are unable to deliver results that meet the criteria. For picture classification, advanced CNN is our top priority because adding dense layers and extending epochs yields better results.On picture categorization, TianmeiGuo et al.[16]suggested a basic CNN. The computational cost of this simple network is lower. They also looked at different techniques of learning rate sets and different optimization algorithms for addressing the optimal parameters of the influence on picture classification using CNN. They also confirm that the shallow network has a decent recognition effect.

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III. MODELS& METHODOLOGY

For e-commerce enterprises, where the customer experience is a primary aspect in generating sales income, accurate product labeling is critical.

An issue with product categorization and selling is caused by incorrect labeling. When buyers don't know the name of the thing they want to buy, they can look up photographs to acquire a list of the items they want. To avoid such situations, the company must ensure that products are properly classified across classes such as gender, product category, product kind, and so on. Furthermore, an effective and accurate picture classification algorithm can assist e-commerce in automating online product administration, lowering operational costs and system inconsistencies. To learn from massive sets of photos of products from an e-commerce website, multiple neural network models were trained. To classify images, we use transfer learning using pre-trained models like VGG16 and AlexNet with 2D-CNN.

Image pre-processing is the initial phase, and it aims to improve image data by suppressing undesired distortions, shrinking and/or boosting critical characteristics, making the data better appropriate to the model, and improving performance.

1) *Dataset Description:* The Fashion-MNIST dataset, which contains 50,000 training photos of fashion and clothing items collected from classes, is used. Each image has a uniform grayscale 28X28 size. The Fashion-MNIST dataset is intended to be a drop-in substitute for the original MNIST dataset when it comes to evaluating ML techniques.
2) *Performing EDA:* EDA (Exploratory Data Analysis) is a method for summarising the major aspects of a dataset. It is used to comprehend data, gain context for it, comprehend variables and their correlations, and hypotheses that could be beneficial in the development of prediction models. It assists us in analyzing the full dataset and summarising its key aspects, such as class distribution and size distribution. Following the study, we discovered that our dataset could be divided into several groups, so we summed it up and labeled it as an article type.
3) *Data Augmentation:* We can't always increase the amount of training data in machine learning because finding labeled data is expensive. Rotating, cropping, shifting, scaling, and modifying the photographs, can expand the dataset. We can increase the model's accuracy in this way, and it's also a frequent strategy for optimizing the model. When training a model, the Keras DL package allows you to employ data augmentation automatically[17]. With the batch size of 32, rescale= 1/255, rotation= 40, zoom= 20%, horizontal flip= 'True,' validation split= 20% and image size of 32, Image Data Generator (which is a novel approach to create additional data with data) performed for batch image loading and labelling (80, 60, 3). The total images for training and validation after using the augmentation technique are 44018. With 12 training classes, we used (26135 images) from the dataset as a training set, (6533) as a validation set, and (8167 images) as a testing set.
4) *Feature Extraction:* Using the feature extraction technique, we can create new features that are a linear mixture of current features. When compared to the original feature values, the new set of features will have different values. The fundamental goal is to require fewer features to gather the same amount of data. We would believe that selecting fewer features will result in underfitting, but in the case of the Feature Extraction approach, the excess data is usually noise. By changing the location, rotation, and scale of the image shape must not alter the retrieved features[6]. Some of the pictures were also excluded for further processing since they did not fit the training. Following that, we developed a hybrid model based on Transfer Learning with 2D CNN and ImageNet neural networks, which outperforms previous models. For better performance, we built a model with VGG 16 and directly fused it with Alexnet and a two-layer CNN model. After feeding the model with data and allowing it to train, we assess the accuracy of both the training and testing sets.
5) *Transfer Learning:* Transfer learning, as the name implies, involves migrating learned parameters from one model to another to train the new model. Because most data or tasks are linked, previously learned parameters in an existing model (pre-trained model) can be exchanged with the new model in some fashion through transfer learning, allowing the new model to learn more quickly and efficiently than most networks that must start from scratch. Transfer learning is an approach in which we employ a model for our problem that has been trained on enormous amounts of data. As a result, the only way we can train them is to fine-tune the model[18]. The benefit we will receive is that the model will train in a short period. TDS. When a pre-trained model is used as a feature extractor, the final completely connected layer is removed and two new fully connected layers are added to the model. All other patterns and weights are fixed except for these two new levels. Although all weights in the pre-trained model can be initialized, this is not typical, and it is recommended that some of the earlier layers be fixed because they represent general features[19].

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6) *VGG16:* VGG16 is a CNN architecture that was utilized to win the 2014 ILSVR(ImageNet) contest. The most distinctive feature of this VGG16 is that instead of a big number of hyper-parameters, they focused on having convolution layers with a 3x3 filter and a stride 1, and they employed a max pool layer with a 2x2 filter with the same padding all the time. Throughout the entire architecture, it adheres to the max pool and convolution layers technique. Finally, it has two fully connected layers (FC) and a SoftMax for output. The 16 in VGG16 points to the fact that it contains 16 layers with weights[20].The network receives an image with dimensions of (224, 224, 3). The first two layers contain 64 channels each with a 3*3 filter size and the same padding, followed by a stride max pool layer (2, 2). Again, two layers with 128 convolution layers and filter sizes (3, 3), plus a stride max-pooling layer (2, 2). Following that, there are two convolution layers with filter sizes of 3 and 3 and a 256 filter. There are two sets of three convolutional layers, as well as a maximum pool layer. Each has 512 filters of the same size (3, 3) and padding.Following that, there are three fully connected layers, the first of which takes input from the last feature vector and outputs a (1, 4096) vector, the second of which also outputs a (1, 4096) vector, but the third layer outputs 1000 channels for 1000 classes, and the output of the third fully connected layer is then passed to the softmax layer to normalize the classification vector[14].

7) *AlexNet:* AlexNet is a DL model that is a CNN variation. AlexNet is made up of eight layers, starting with five convolutional layers and ending with three fully linked layers. Max-pooling layers are placed after some of the model's convolutional layers. The network employs the ReLU function as an activation function, which outperforms the sigmoid and tanh functions. The network's five convolutional layers are made up of a kernel or filters with sizes of 11 x 11, 5 x 5, 3 x 3, 3 x 3, and 3 x 3. The rest of the network's parameters can be modified based on the training results. On the ImageNet dataset, AlexNet using transfer learning and weights from a pre-trained network performed exceptionally well.

8) *2D CNN:* Convolutional Neural Networks are proven for the images, several studies have shown that they give pleasing results in the audio domain too. In our experiment, we employed a two-dimensional convolutional layer with 16 filters with a kernel size of 2x2 with unitary depth and stride in both dimensions as the first layer. The max-pooling layer comes next, followed by the dropout layer at the CNN block's end[21]. This block's output is provided as input to the following block, and the process is repeated. The network's final MaxPooling layer works over the entire length of the time sequence (i.e., the output of the layer has dimension one for the time axis). After the fourth CNN block, a global average pooling layer is added. Except for the last layer of the network, which is a Dense layer (completely linked) with four nodes and the softmax activation function, the architecture's activation function is ReLu.

IV. ALGORITHMS

A. *Proposed Algorithm*

1) Step 1. Start
2) Step 2. Collect the Fashion MNIST dataset of around 50000 images of different products, reading them in a way that it would not consume all the memory.
3) Step 3. Create ImageDataGenerator to create more data with data.
4) Step 4. Perform Data Augmentation and process flip, zoom, clip, rotation, etc operations.
5) Step 5. Prepare for training and validation. Divide the dataset into training, testing, and validation.
6) Step 6. Create the Transfer Learning model and pre-processed it by applying VGG16 of 5 layers with ImageNet weight and directly fused it with AlexNet.

7) Step7. Apply 2D- CNN on the pre-processed features to achieve higher accuracy.
a) ConvLayer captures the Low-Level features.
b) ReLU Layer converts all negative values to zero.
c) The pooling layer reduces the spatial size of the convolved feature.
d) Flattening converts the data into a one-dimensional array for inputting it to the next layer.
e) A fully connected layer learns non-linear high-level function combinations, as defined by convolution layer performance.

8) Step 8. Measure the model performance.
9) Step 9. End.

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B. J. Proposed Flowchart

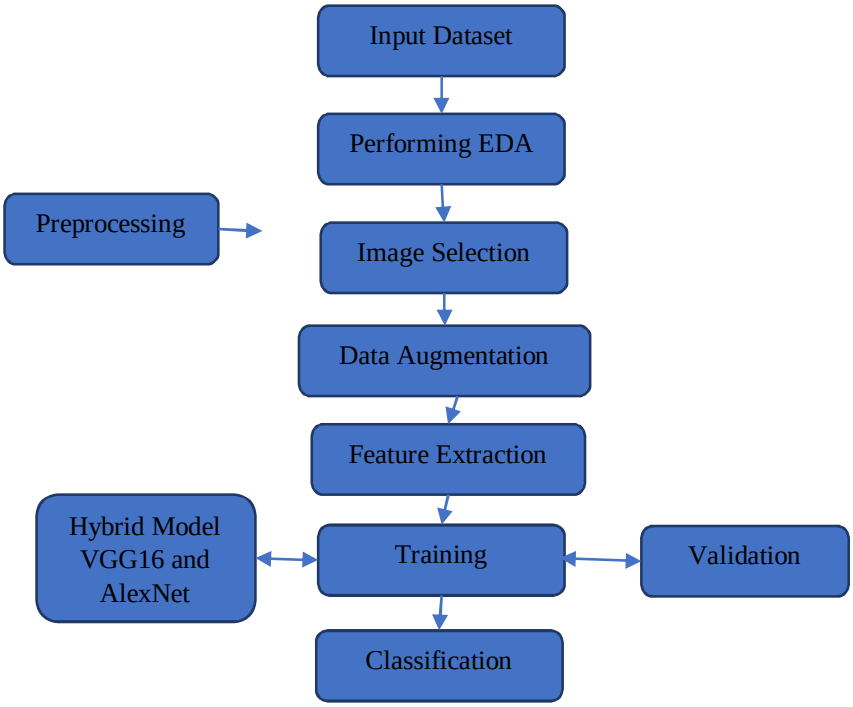

Figure 2.- Flowchart of the Proposed Work

C. Experimental Analysis

Experimental studies were performed to analyze the feature selection accuracy on a given dataset. The simulator was programmed using Python with Keras and TensorFlow libraries. After loading the Fashion MNIST dataset with 50,000 images as Styles.csv with different categories.The different attributes of the dataset are shown below.

id	gender	masterCategory	subCategory	articleType	baseColour	season	year	usage	productDisplayName

Each product image as identified by its numeric id can be mapped to its metadata in styles.csv. Upon the merger of the two, we find instances where image IDs are matched with the IDs in the metadata file. Weconsider these sets of images formodeling.Figure 3 shows the count of products with the master category. After the product counts, we select the subset of data by articleType as represented in Figure 4.

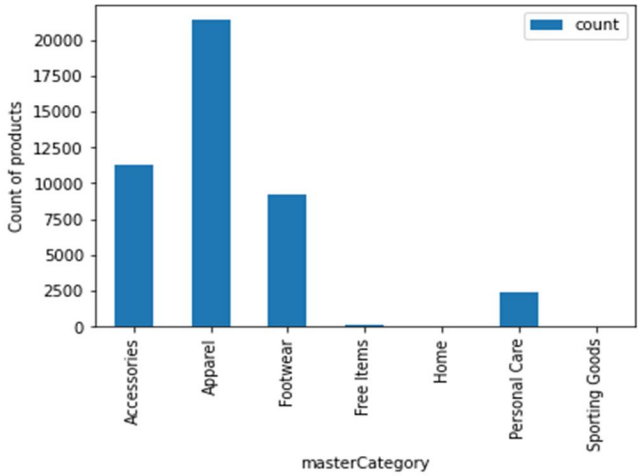

Figure 3.- Figure shows the count of products with the master category.

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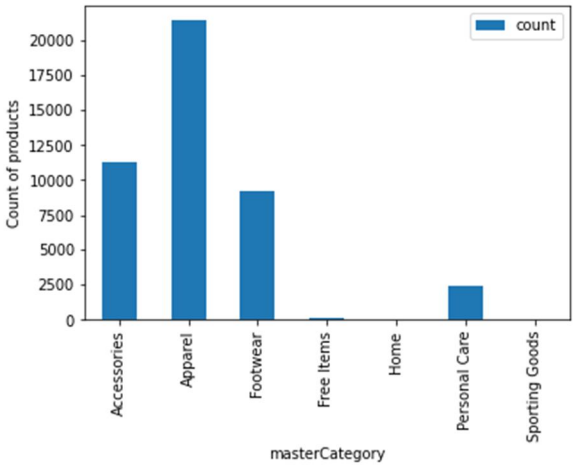
Out[36]:

	id	gender	masterCategory	subCategory	articleType	baseColour	season	year	usage	productDisplayName	image_name	articleType_count
0	15970	Men	Apparel	Topwear	Shirts	Navy Blue	Fall	2011.0	Casual	Turtle Check Men Navy Blue Shirt	15970.jpg	3215
1	39386	Men	Apparel	Bottomwear	Jeans	Blue	Summer	2012.0	Casual	Peter England Men Party Blue Jeans	39386.jpg	608
2	59263	Women	Accessories	Watches	Watches	Silver	Winter	2016.0	Casual	Titan Women Silver Watch	59263.jpg	2542
3	21379	Men	Apparel	Bottomwear	Track Pants	Black	Fall	2011.0	Casual	Manchester United Men Solid Black Track Pants	21379.jpg	304
4	53759	Men	Apparel	Topwear	Tshirts	Grey	Summer	2012.0	Casual	Puma Men Grey T-shirt	53759.jpg	7065

Figure 4.- Figure shows the selection subset data by articleType.

With processing the dataset, we check the count of products with their masterCategory after and before the selection count. Figure 5 and 6 shows the count of products after and before selection. Further, we check the count of products with subCategory for multiclass before clipping and after clipping. Figure 7 and 8 show the subCategory before selection and after selection.



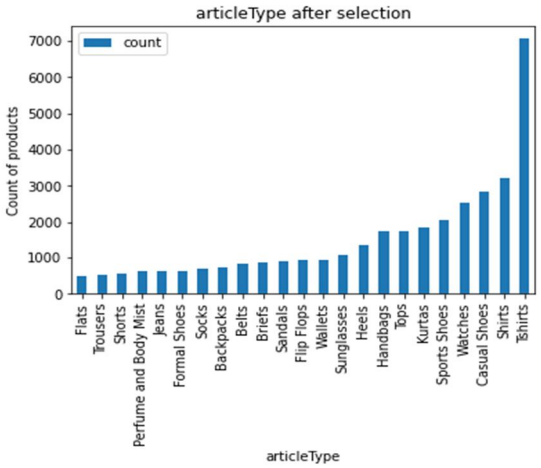
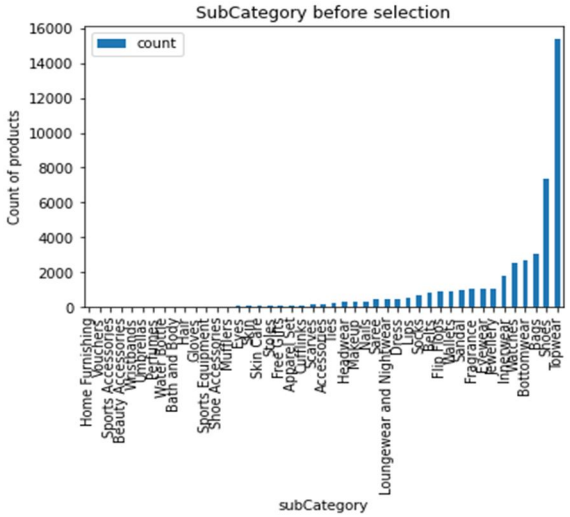


Figure 5.-Before Selection with masterCategoryFigure 6.- After Selection of articleType



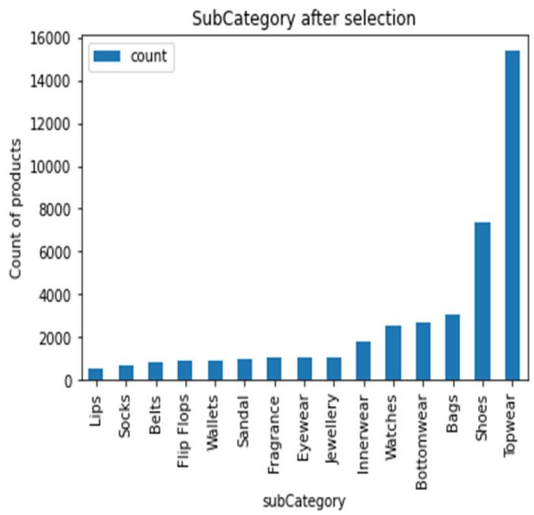


Figure 7.- Before Section of subcategory Figure 8.- After Selection of subCategory

Figure- Figure and shows the subCategory before selection and after selection.

Pre-processing Image Data Generator performed for batch image loading and labelling (80, 60, 3) with the batch size of 32, rescale= 1/255, rotation= 40, zoom= 20%, horizontal flip= 'True', validation split= 20% and image size of 32. The total images for training and validation after using the augmentation technique are 44018. With 12 training classes, we used (26135 images) from the dataset as a training set, (6533) as a validation set, and (8167 images) as a testing set.

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With Transfer Learning apply VGG16 with 5 layers of ImageNet weight. We use 4 Convolutional layers with neuron size as (96, 256, 384, and 384) and passing this to 4 Dense layers of neuron size as (4096, 4096, 1000, 512). After applying batch normalization with the Relu activation function. The different parameters of the models are as-

Table 1:Different parameters of the proposed model.

Activation Function	Relu
Max pooling	2D (2,2)
Dropout Layer with	40%
Output	SoftMax function
Optimizer	ADAM
Learning rate	(0.00001)
Epoch	50

After the training and testing of models, the training and validation accuracy peaked at 0.90 as represented in the below graphs in figure 9.To understand the model performance further in detail, we use a confusion matrix for checking True Label and Predicted Label. The confusion matrix is shown in figure 10.

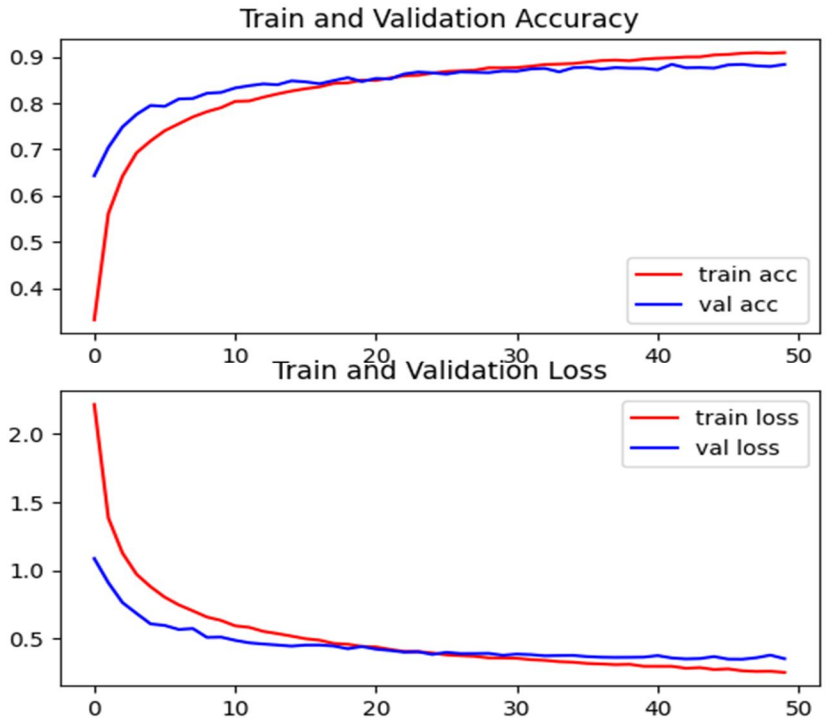

Figure 9.- Graphs representing Training and Validation Accuracy and Loss for the proposed model.

Table 2:Comparison of Specificity results

Accuracy	Training	Testing
Base	0.84	0.87
Proposed	0.90	0.89

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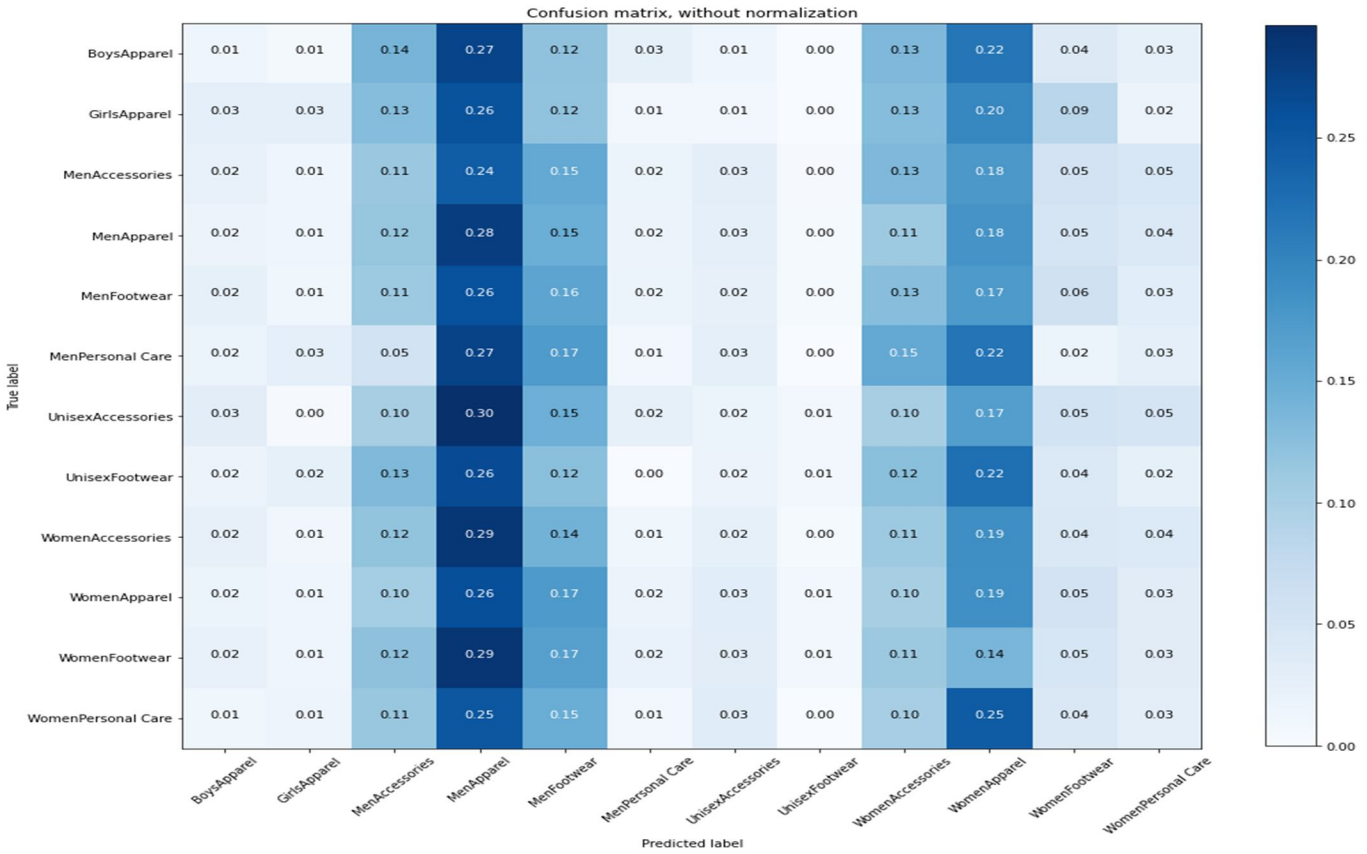

Figure 10.- Confusion Matrix from classification by True label and Predicted label.

Table 2shows that our proposed Hybrid 2D CNN model with VGG16 and AlexNet pretrained models by Transfer Learning shows superior results than the other conventional models.

V. CONCLUSIONS

For both service providers and clients, organizing and looking for products is a time-consuming procedure. The time spent sorting and labeling the merchandise wastes a lot of time. Training a large dataset takes a lot of effort and computer resources. Without engaging any human assistance at any stage, picture recognition is an essential side of image processing for machine learning. We look into how picture categorization is done with an imagery backend in this research.For our learning model, we took a few thousand Fashion photographs and divided them into two categories: test dataset and training dataset. The results of the studies reveal that the photographs are accurately identified even when the identical images are scaled in different sizes, clipped, or rotated to create an altogether new image for the input, demonstrating the algorithm's effectiveness. In terms of training and testing of classification models, the transfer learning approach has demonstrated substantial advances. We employed a hybrid transfer learning strategy based on VGG-16 and 2D CNN.

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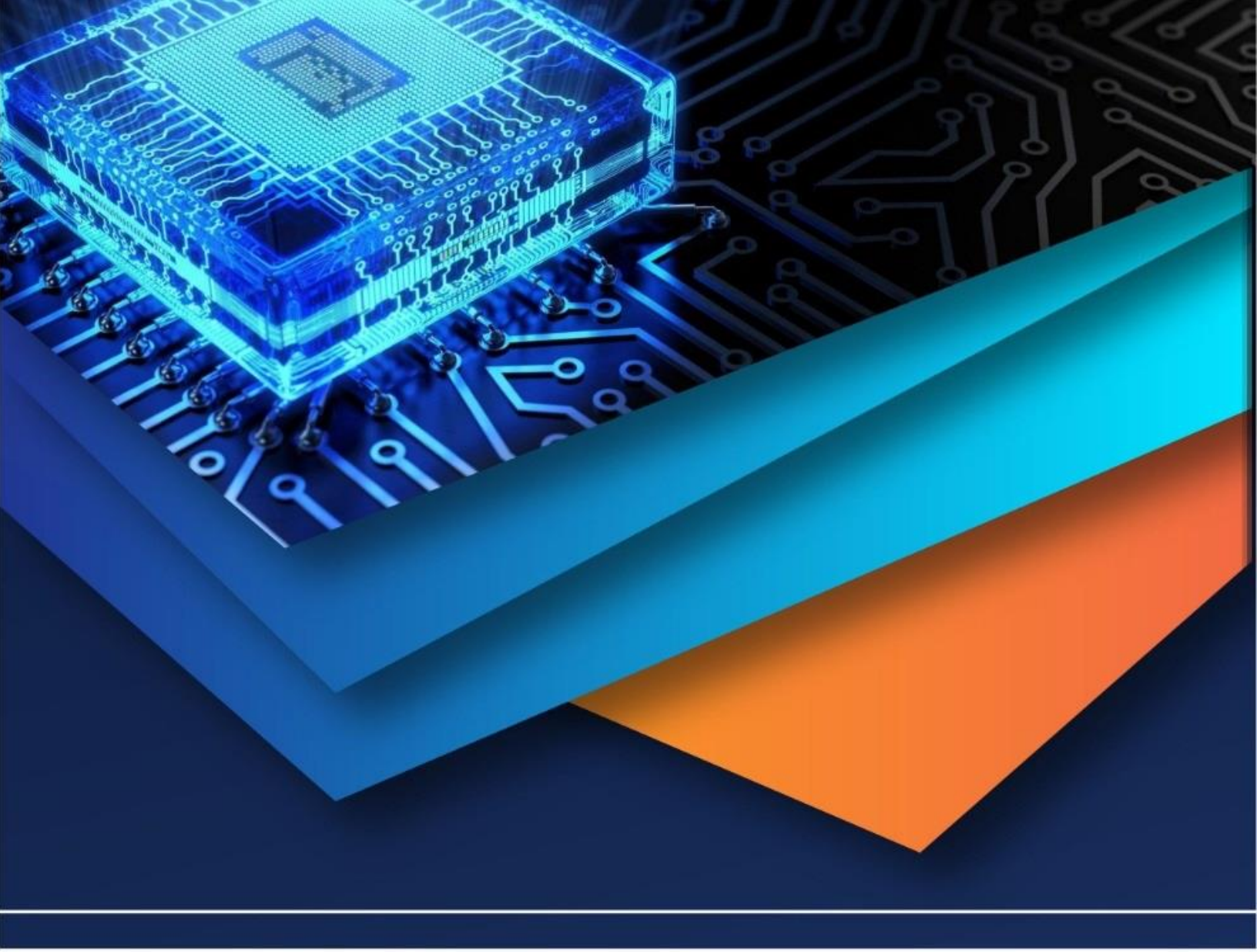

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