International Journal of Future Generation Communication and Networking
Vol. 13, No. 4, (2020), pp. 709-717

A Novel Approach for Recognizing Clothes Pattern and Colors for Blind People using DSL-CNN Classifier

A. V. Subba Rao
Research Scholar
Dept. of E&CE
G M Institute of Technology
Davangere, India
avsr.vlsi@gmail.com

Dr. H C Hadimani
Professor & HOD
Dept. of E&CE
G M Institute of Technology
Davangere, India
hchadimani2017@gmail.com

Dr. Srinivasarao Udara
Professor
Dept. of E&CE
S T J Institute of Technology
Ranebennur India
srinivasarao_udara@yahoo.com

Abstract

In this current paper, the presented work based on DSL-CNN Classifier method for helping and assisting visually impaired people to recognize multiple objects in different class of cloths and colors. This method relies on a novel deep super leering multi-label convolutional neural network (DSL-CNN) for coarse description of all images. The main idea of DSL-CNN is to use a set of linear state vector machines as filter banks for feature required map generation. During the current training phase, the weights of the state vector machines filters are obtained using a forward-supervised deep learning strategy unlike the back propagation algorithm used in standard convolutional neural networks (DSL-CNNs classifier). To handle multi-label detection, the introduced a multi-branch CNNs architecture, where each branch will be used for detecting one object in the cloth images. The current architecture exploits the correlation between the objects present in the image by means of an opportune fusion mechanism of the intermediate different outputs provided by the convolution layers of each branch. The high-level reasoning of the convolutional network is done through binary classification state vector machines for predicting the presence of objects in the image. The currents experiments obtained on two indoor different datasets and through voice the color and its classification will present for the visually impaired people. Final improvements were performed on accuracy, sensitivity, specificity, MCC, and F1-Macro on the proposed model.

Keywords: visually impaired people, computer vision, deep super learning, modified DSL-CNNs classifier.

1. Introduction

Visual impairment of blind people leads to loss of livelihood for otherwise productive adults causing difficulty not only to themselves but to the families they support. Most of the visually impaired people don't have access to select different structured cloths for they need to wear. Based on data from the World Health Organization (WHO), there are more than 37 million people across the globe who is visually impaired people, over 15 million are in India [1]. Picking clothes with suitable patterns and colors is a challenging task for blind people. They take care of choosing clothes with the help from family members or clothes assistance, or by wearing clothes with a uniform color or without any patterns. Automatically recognizing clothing colors and patterns improves blind people's life style and quality. Here, we introduce voice based recognition to help blind people to notice clothing colors and patterns.

There are several restrictions to the recognition methods of different cloths structures. The existing implementations relied heavily on engineering fields. The availability of structured images of cloths images database was limited and restricted. The rotational variations in different cloths structured influenced the texture features extraction during image acquisition. The improper lighting effect could result in unclear texture images. Inspired by these previous works and to address the shortcomings, the proposed a deep super learning model based on data augmentation and transfer learning technique for the recognition and classification of different cloth structures. A pretrained convolutional neural network (CNN) model, based on residual network architecture (ResNet-50) has been used as a deep super model [2]. The proposed model performed end-to-end fabric feature extraction and classification using the structured images of cloths that have been developed. In addition, the evaluated different performance metrics such as accuracy, sensitivity, specificity, MCC, and F1-Macro on the proposed model. The further results are compared the proposed model with the VGG-18 pretrained convolutional neural network model. The results were discussed that the proposed method achieves better classification accuracy almost 100% as compared with the other traditional approaches. Hence, the current approach could assist textile manufacturers to save more time, cost, and more labor through the reliable, efficient, and consistent evaluation of weave patterns to produce high-quality different structures.

2. Methodology

Python is one of the high-level programming languages, which designed by Guido van Rossum and is extensively used for general-purposes. The main different of this language is that it emphasizes on code readability as well as its syntax that allows programmers to develop an application with fewer lines of codes. Multiple programming paradigms are supported by python. Examples are object-oriented, imperative and functional programming's or procedural styles. Since python is widely used as mentioned, it also features a large and comprehensive library. Python is also frequently used as scripting language just like other dynamic languages. Furthermore, with third-party tools, Python code could even be packaged into an executable program [3-4]. I n addition, Open CV (Open Source Computer Vision) library is used along with Python IDE. Open CV is a library that contains programming functions that deal mostly with real-time computer vision. Open CV was developed by Intel Russia research center and supported by Willow Garage and It seez. The library is cross platform and free for use under the open source BSD license [5-6].

The proposed a pipeline-based approach for our deep super learning model. The pipeline consisted of many stages; the first stage received the different structured cloth images, which ended with the classification and identification of the model. The output of each stage in the pipeline acted as the input to the next stage.

A. Image Acquisition and Preprocessing

The different fabricated structure cloth images were collected to form a dataset. The dataset required suitable conversions, resizing, and preprocessing of the images. The number of images was smaller in size, so we used various augmentation techniques to increase the dataset, which helped the model have a good generalization and accomplish better recognition.

B. Model Generation and Training

A deep super learning algorithm that receives input large data"X" and predicts the output"Y" is called a model. For the current implemented model, the employed residual network (ResNet-50) network architecture. During training phase, the algorithm DSL-CNN Classifier performed optimization on the parameters (update weights and biases) which was used for the cloth pattern and its classification on recognition of the model.

C. Model Evaluation

The performance of the current implemented model was evaluated using various evaluation metrics such as accuracy, sensitivity, specificity, MCC, and F1-Macro on the proposed model.

D. Dataset

The different structured cloths samples were collected from various warehouses and textile factories. We captured 10000 images from different locations of 900 pieces of other cloths. Out of these 10000 images, we used 4000 images for our testing from dataset, while the remaining 900 images were applied through various techniques of data augmentation to generate a total of 10000 training samples. A few sample images in each class are shown in Figure 1. These images were subdivided into three classes, namely plain, satin, vertical and horizontal.

2.1 Data Augmentation

The problem of insufficient size of the training different dataset has been solved using techniques of data Augmentation [7]. Data augmentation gives several manipulations such as scaling, skewing, flipping, and lighting on the entire selected dataset to form a set of different cloth images as a result expanding the given dataset. For larger datasets, deep super learning models perform very well for the analysis. By using the current technique, the total number of cloth images in the dataset is increased very large, allowing the model to train effectively. It is known that data augmentation is a kind of regularization implemented on the overall dataset, consequently, it reduces over fitting problem and the generalization capability is increased by expanding the dataset, which is the major issue, without performing any alterations that affect the structure of the model.

In present study, the applied several augmentation techniques on the images such as horizontal and Vertical flips, shifting, rotation (images are rotated at fixed angles of 30^0 starting from 0^0, 30^0, 60^0, 90^0, and so on), zooming, shearing, and brightness manipulation. An illustration of these augmented images is shown in Figure 1. It was important to rotate the images in order to identify the warp and weft yarns that were oriented in different directions due to the variations that occurred during the image acquisition. Zooming clearly identified the interlacing pattern of woven fabrics. Shearing created the local deformation in the images. All these augmentation techniques related to the situations occurring in the real scenario.

Figure 1. Various augmentation techniques applied to an original cloth with different images.

3. Experimental Results

The ResNet-50 pretrained modified convolutional neural network architecture was used for the classification of different structured cloth images divided into 4 classes. The number of training and testing images in the cloth structure dataset are 10,224 and 4114, respectively. The current work, 90% of the training images are used to train the model and the remaining 10% is assigned to form a validation subset for validating the model. The performance of the proposed deep super learning model was evaluated on the test set. The structural properties of the different structured used for the experiments are carried out.

3.1. Experimental Framework

The different type of structured cloth pictures were reshaped to 224 × 224 dimensions and {also the} cloth pictures were also preprocessed by subtracting the mean red-green-blue (RGB) worth from every picture element thus on feed it into the model. The present work, the used transfer super learning technique to ResNet-50 pretrained changed convolutional neural specification that used the weights of the network learned from ImageNet. The pretrained weights were accustomed avoid the poor low-level formatting of the model as compared with its counterpart” random low-level formatting of weights”. we have a tendency to remove the totally connected layer, that was the last layer that classified the photographs into ImageNet categories, and therefore the early convolutional layers of the pretrained model acted as a base network for the new tailored design. Afterward, a worldwide average pooling layer followed by 2 pairs of batch social control, totally connected, and dropout layers were, severally, stacked to the bottom network. The two totally connected layers encompassed 512 and 256 neurons, severally. Every totally connected layer was followed by a ReLU activation layer. The batch standardization layers helped to boost the coaching time of the pretrained model. The inclusion of worldwide average pooling and dropout layers inherently reduced the matter of overfitting. By adding dropout layers, it indiscriminately deleted the redundant neurons; thence, the performance of the model was increased. In deep architectures, the matter of overfitting sometimes fails to own a decent generalization on the info that has ne'er been seen before (test data). Finally, the ten layer of the planned model used the Softmax activation operate to classify the woven cloth pictures into 3 categories. Associate overall define of the custom-made deep super learning model is developed and explained.

The pretrained ResNet-50 model was trained on the plain-woven material dataset generated during this work. In this design, solely the tailored freshly additional layers connected to the bottom network were trained, keeping the initial convolutional layers as frozen. The most plan of temperature reduction these layers were to boost the convergence rate, similarly as avoid the gradient explosion throughout the coaching method. When texture options were extracted, then, categoryification was applied to check the expected category with the particular class. Throughout the coaching method, the computation price of the network was decreased since the overall trainable parameters of the tailored changed convolutional neural network model were conjointly reduced.

3.2. Results

The current model was trained and tested using NVIDIA GeForce GTX 1030 MQ using 8 GB graphical processing unit (GPU) with Intel i7-8750H @ 2.8 GHz and 12 GB RAM. We used Python 3.1 to implement the model, using Keras library as frontend and Tensor flow as backend.

3.3 Metrics of Evaluation

The most common used evaluation metrics for classification is accuracy. It is the ratio between the numbers of correct predictions to the total number of predictions. Usually, when the dataset is imbalanced, we encounter high accuracy showing that it is inclined towards the class, having more samples of images. In an exceptional situation, each test case can be assigned to the large class by the classifier; as a result, accuracy is achieved equal to the fraction of the more frequent labels in the test set. Thus, accuracy can be a confusing evaluation metric. In such cases, the appropriate performance evaluation metric used is the balanced accuracy, as shown in Equation (1). The class count is represented by”l”. We achieved an accuracy of 99.7% and a balanced accuracy of 99.9%.

$$\text{Balanced Accuracy} = \frac{\sum_{i}^{l} (TP_i + TN_i)(TP_i + FP_i + TN_i + FN_i)}{l} \quad \text{...}(1)$$

The confusion matrix is obtained to show the predictions made by the proposed model on the test dataset and to understand the number of images incorrectly classified. The true class and predicted class are represented by the rows and columns, respectively. Confusion matrix results are shown in Figure 2.

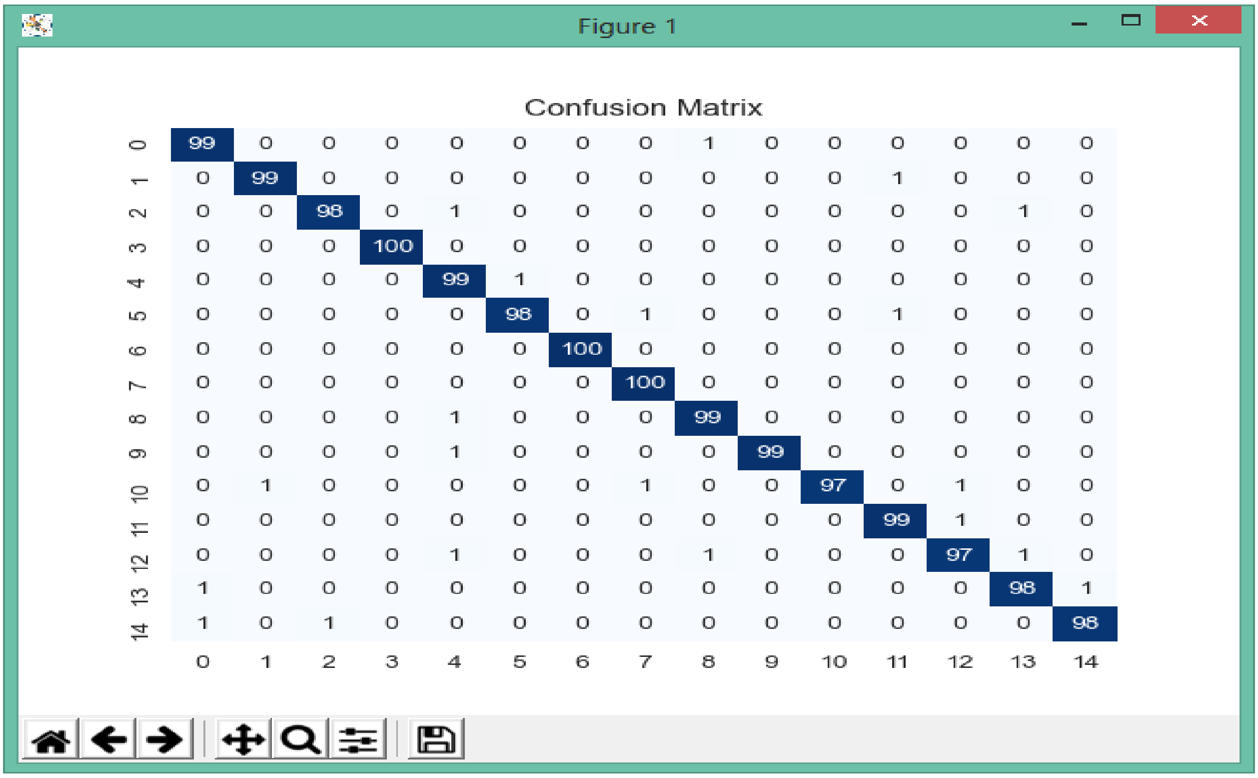

Figure 2. Confusion matrix for plain, other structures of cloths patterns,

Result Analysis:

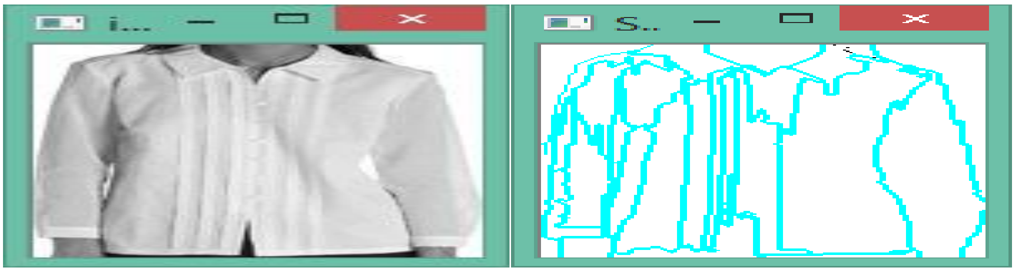

Figure 3. Input image Segmented Layer

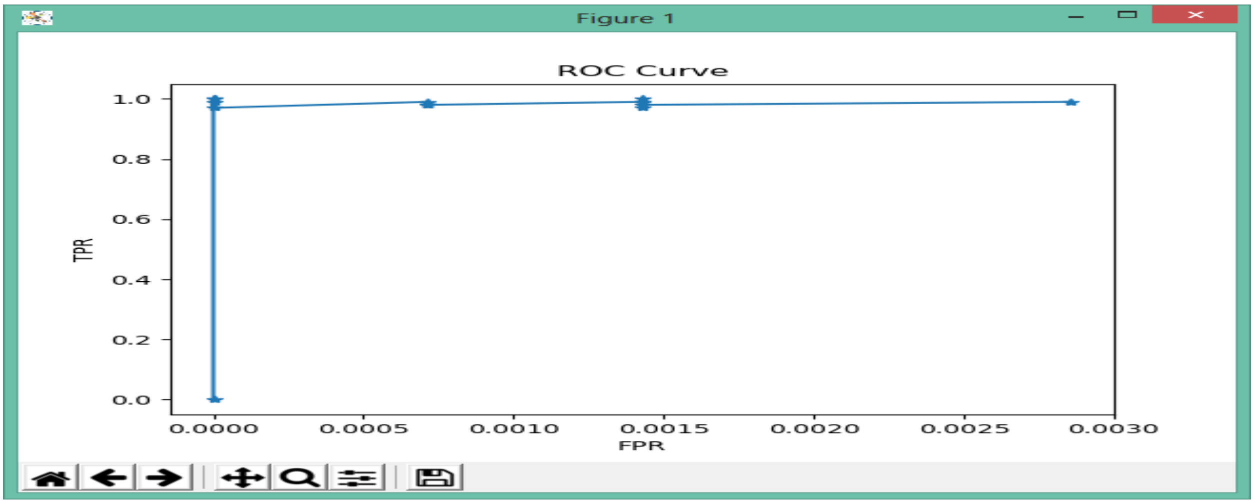

Figure 4. ROC Curve

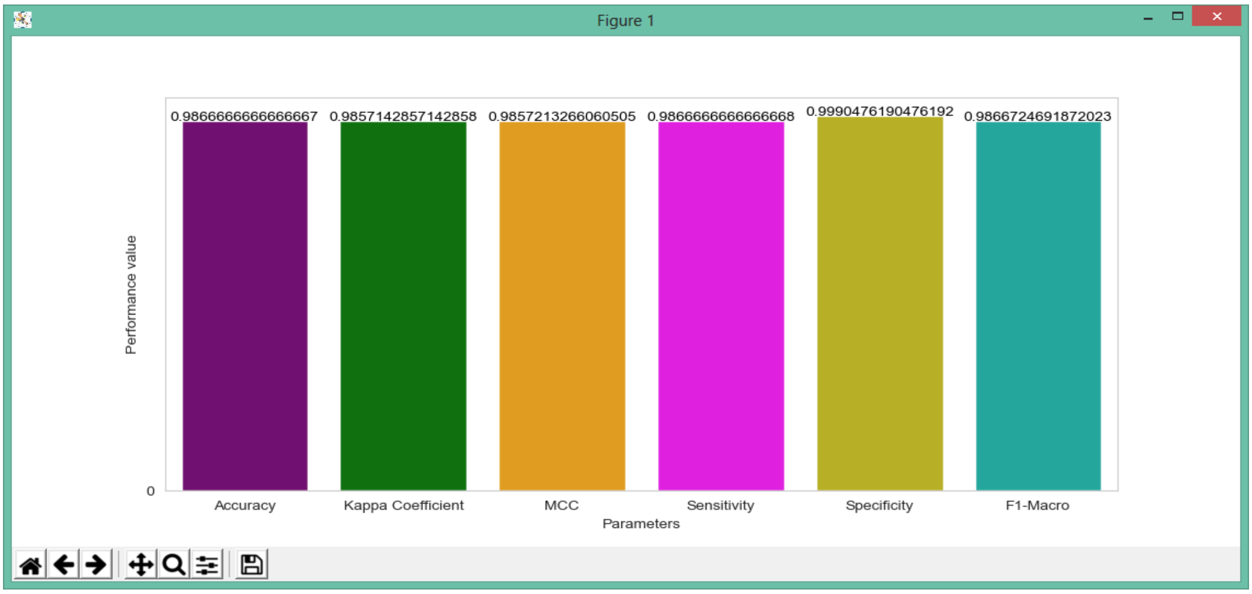

Figure 5.Performance Chart

The averaged precision, Accuracy, and F1-Macro values were calculated for the proposed current model on the test with large amount of dataset. The detailed performance analysis of these values based on each class are given in Table 1.The average accuracy, sensitivity, specificity, MCC, and F1-Macro values were 99.9%.

The implemented work, the compared results with the VGG-18 pretrained modified CNN model. A significant difference in performance is observed in terms of accuracy and other evaluation metrics. As shown in Table 1, the model outperformed the VGG-18 pretrained model. The VGGNet architecture only obtained a classification accuracy of 92.4% which was about 9 percentage points less than the accuracy obtained by our current model. The most likely reason for this was that the VGGNet contained more trainable parameters (400M) and it also did not contain the skip connections to make the computations easier. On the basis of the results, we can say that the proposed model based on residual network ResNet-50 is a robust for different structured cloths and its classification on modified CNN that is able to extract robust texture features for recognition and classification of the above said patterns.

3.4 Discussions

Li et al. [8] proposed LBP and GLCM for feature extraction and later used SVM as a classifier to classify the woven fabric types. Their proposed method reported an accuracy of 87.77%. Kuo et al. [14] used CIE-Lab color model and co-occurrence matrix to extract features, and then applied a SOM network for classification. The highest classification accuracy obtained was 92.63%. Xiao et al. [9] proposed a method based on TILT and HOG to identify the texture features and later FCM clustering was used for classification. Their method achieved an accuracy of 94.57%. The problem with these approaches was that the datasets were limited to only a small number of images. The authors also excluded the consideration of uneven light during image acquisition, as well as physical properties such as yarn thickness, diameter changes, and rotational variation of different cloths of the images.

As shown in Table 1, the proposed ResNet-50-based modified convolutional neural network model outperformed other methods were explained in detail. In our current methods, the proposed deep super learning model achieved better accuracy for recognizing and classifying the different cloth images. Texture-based classification of different cloth images is a challenging task because the availability of datasets is limited, and therefore in order to make it more robust, variations in the cloth pattern color, yarn diameter, orientation, and uneven light are considered while performing image acquisition. Hence, making the datasets more detailed and representative. A convolutional neural network which has depth, such as the ResNet model, is capable of managing these variations and learning the high-level descriptive features. Hence, the model shows that it is diverse and can easily handle the complexity present in the different structured images by outperforming the other approaches. Furthermore, the data augmentation techniques increased the diversity of the available data, and as a result, improved the overall performance of the current model.

The higher recognition and classification of cloths with accuracy reflect the following three main features: (i) the current model is still robust when variations in physical properties such as the cloths color, yarn thickness, diameter, orientation, and uneven light are considered. (ii) The transfer learning technique allows us to train the model with a lower number of parameters making it computationally cost-effective. (iii) The proposed current model does not rely on handcrafted features, i.e., the feature extraction and classification are performed in a fully automated end-to-end architecture. In the future, our work can be extended for recognition of cloths and its classification of other types of other cloths structures, such as stripes with vertical and horizontal patterns.

Parameter values-Table-1

Overall Statistics

95% CI	(0.98086, 0.99247)
ACC Macro	0.99822
ARI	0.97149
AUNP	0.99286
AUNU	0.99286
Bangdiwala B	0.9736
Bennett S	0.98571
CBA	0.98148
CSI	0.97344
Chi-Squared	20409.48642
Chi-Squared DF	196
Conditional Entropy	0.10763
Cramer V	0.98584
Cross Entropy	3.90703
Cross Entropy	3.90703
F1 Macro	0.98667
F1 Micro	0.98667
FNR Macro	0.01333
FNR Micro	0.01333
FPR Macro	0.00095
FPR Micro	0.00095
Gwet AC1	0.98571
Hamming Loss	0.01333
Joint Entropy	4.01452
KL Divergence	0.00014

Kappa	0.98571
Kappa 95% CI	(0.9795,0.99193)
Kappa No Prevalence	0.97333
Kappa Standard Error	0.00317
Kappa Unbiased	0.98571
Krippendorff Alpha	0.98572
Lambda A	0.98571
Lambda B	0.98568
Mutual Information	3.79912
NIR	0.06667
Overall ACC	0.98667
Overall CEN	0.0212
Overall J	(14.60693,0.9738)
Overall MCC	0.98572
Overall MCEN	0.03651
Overall RACC	0.06667
Overall RACCU	0.06667
P-Value none PPV Macro	0.98678
PPV Micro	0.98667
Pearson C	0.96516
Phi-Squared	13.60632
RCI	0.97242
RR	100.0
Reference Entropy	3.90689
Response Entropy	3.90675
SOA1(Landis & Koch)	Almost Perfect
SOA2(Fleiss)	Excellent
SOA3(Altman)	Very Good
SOA4(Cicchetti)	Excellent
SOA5(Cramer)	Very Strong
SOA6(Matthews)	Very Strong
Scott PI	0.98571
Standard Error	0.00296

TNR Macro	0.99905
TNR Micro	0.99905
TPR Macro	0.98667
TPR Micro	0.98667
Zero-one Loss	20

4. Conclusions

The current carried out work, the developed work was a customized deep super learning model for the recognition and classification of different structured and color cloths. The proposed deep learning super learning model is based on residual network architecture. First, the image acquisition and preprocessing of different structured images are completed and the data implementation techniques are assigned to increase the size of dataset accurately. Second, a pretrained modified CNN model was used where only the newly attached different layers are trained keeping the other layers are closed. The high-level different texture features are extracted, and then finally classified based on the types different structure cloths (plain, stripes, and different structures). The evaluated and the performance of implemented model using various performance metrics such as accuracy, sensitivity, specificity, MCC, and F1-Macro. A comparative analysis was carried out against other baseline approaches and we also compared the results of the modified VGGNet pretrained model.

The current experimental results showed that the proposed idea performed better than any other existing methods. The model is robust when variations such as different structured color, yarn thickness, rotational orientation, and uneven light and also thick are considered. The proposed model uses fewer parameters while training making it computationally cost-effective, and thus possess potential for the visually impaired people.

References

1. Osborne, E.F. Weaving Process for Production of a Full Fashioned Woven Stretch Garment with Load Carriage Capability. Patent No. 7,841,369, 30 November 2010.
2. He, K.; Zhang, X.; Ren, S.; Sun, J. Deep residual learning for image recognition. In Proceedings of the 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 27–30 June 2016; pp. 770–778.
3. Xiao, Z.; Guo, Y.; Geng, L.; Wu, J.; Zhang, F.; Wang, W.; Liu, Y. Automatic Recognition of Woven Fabric Pattern Based on TILT. *Math. Probl. Eng.* 2018, *11*, 1–12.
4. Khan, B.; Han, F.; Wang, Z.; Masood, R.J. Bio-inspired approach to invariant recognition and classification of fabric weave patterns and yarn color. *Assem. Autom.* 2016, *36*, 152–158.
5. Liu, Z.; Zhang, C.; Li, C.; Ding, S.; Dong, Y.; Huang, Y. Fabric defect recognition using optimized neural networks. *J. Eng. Fibers Fabr.* 2019, *14*.
6. Agrawal, P.; Girshick, R.; Malik, J. Analyzing the performance of multilayer neural networks for object recognition. In Proceedings of the 13th European Conference on Computer Vision, Zurich, Switzerland, 6–12 Septemeber 2014; pp. 329–344.*Electronics* **2020**, *9*, 1048.
7. Mikołajczyk, A.; Grochowski, M. Data augmentation for improving deep learning in image classification problem. In Proceedings of the 2018 international interdisciplinary PhD workshop (IIPhDW), Swinouj´scie, Poland, 9–12 May 2018; pp. 117–122.
8. Li, P.; Wang, J.; Zhang, H.; Jing, J. Automatic woven fabric classification based on support vector machine. In Proceedings of the International Conference on Automatic Control and Artificial Intelligence (ACAI 2012), Xiamen, China, 3–5 March 2012.

ISSN: 2233-7857 IJFGCN