MJSAT

Malaysian Journal of Science
and
Advanced Technology

journal homepage: https://mjsat.com.my/

Cloth Pattern Recognition Using Machine Learning and Neural Network

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KEYWORDS

Cloth pattern recognition
Radon transform
Gray level co-occurrence matrix
KNN, SVM

ARTICLE HISTORY

Received 14 December 2021
Received in revised form
12 January 2022
Accepted 20 January 2022
Available online 25 January 2022

ABSTRACT

Visually impaired people face a lot of challenges while choosing clothes with complex patterns and colors. Rotation, scaling and variation in the light makes the cloth recognition problem a challenging task. An automatic cloth pattern recognition technique to classify the patterns into four classes namely plaid, striped, irregular and Patternless is developed using image processing, machine learning and deep learning concepts in this work. *MATLAB* is used as the simulation tool of choice. Color classification is done with the help of Hue Saturation Intensity (*HSI*) color model. To recognize clothing patterns, global and local features are extracted. Features extracted include Radon signatures and Grey Level Co-occurrence matrix. Pattern recognition has been done with the help of machine algorithms such as *KNN*, *SVM*, and deep learning networks such as AlexNet, GoogleNet, *VGG-16* and *VGG-19*. To evaluate the effectiveness of the algorithms, *CCNY* Clothing Pattern data-set has been used. The maximum accuracy of 97.9% was obtained using the *VGG-19* deep neural network.

1. INTRODUCTION

The interface between human and machine is developed with the help of Human Computer Interaction (*HCI*). Based on statistics from the World Health Organization (*WHO*), there are more than 285 million visually impaired people around the world, and 39 million of them are blind, out of which over 16 million are residing in India. Visually impaired people face a lot of challenges to choose suitable color and patterns for their clothing and they seek the help of other people or the braille labs and tags. The major challenge for clothing pattern recognition is the intra class variation. The consistent property in clothing pattern is the directionality and this is made use of in cloth pattern recognition and categorizing clothing patterns. This work focusses on pattern recognition in the form of pattern and color of the clothes. The model developed in this work is able to identify the four different patterns and major colors in the clothing.

2. LITERATURE REVIEW

Di Wang [1] in their work have compared the performance of four deep learning models, namely a fully connected model, a custom CNN, MobileNetv1 and MobileNetv2 on the Fashion MNIST dataset. According to their findings, the fully connected and custom CNN models have lower computational complexity but have lower accuracy. On the other hand, MobileNetv1 and MobileNetv2 have higher computational complexity and higher training times but have higher accuracies of 92% and 93% respectively.

Liu et al. [2] have proposed a CNN-based hierarchical classification model. As compared to previous attempts at using a CNN-based approach to classifying clothing images, the proposed method has reduced loss and increased accuracy. The proposed hierarchical CNN is a knowledge-based classifier which conveys hierarchical information and thus is able to achieve a higher accuracy with a lower loss. The authors have tested their approach on the Fashion-MNIST dataset.

Rao et al. [3] have proposed a deep super learning convolutional neural network (*DSL-CNN)* based approach for the classification of clothes based on their colour and pattern. The authors have focussed on learning features specific to the different clothing patterns due to the varied obstacles that are faced during cloth pattern recognition. This is the reason they

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have used a *DSL-CNN* and created their own dataset for the implementation of their algorithmic approach.

Zhang et al. [4] have proposed a texture and shape focused deep learning model for the classification of clothes based on their pattern and texture. They have focussed on extracting clothing attributes such as shape and texture using landmarks. The authors have also found that these features are useful in traditional classification algorithms and that they can efficiently be extracted using the pretrained ImageNet model. Using their model, the authors were able to improve the top 3 classification accuracy by 0.83% and the top 3 attribute recognition recall rate by 1.39% compared to other state of the art methods. Yang et al. [5] have proposed an approach which uses Radon signature and an algorithm which extracts properties from wavelet sub-bands. A combination of these two features have been used to recognize complex clothing patterns. They have used the *CCNY* clothing pattern dataset which consists of four different clothing patterns and 11 colours. Using the approach proposed by the authors, they were able to achieve 92.55% recognition accuracy which was tested by ten visually impaired participants.

Yuan et al. [6] have proposed a robust, clothes matching algorithm. The proposed system consists of a camera, speech processor for controlling and configuring the system and a audio feedback element to provide audio output regarding the colour and pattern of the clothes. The authors claim that their approach works in various degrees of illumination, clothing patterns and wrinkling. They have tested their algorithm on two datasets, the colour and matching (*CTM*) dataset and the pattern detection (*TD*) dataset. Miyake et al. [7] have proposed a novel approach of detecting the colour and patterns of clothes. The authors have detected the colour of clothes by converting the RGB values into the LAB colour space and clustering the pixel values using the K-means clustering algorithms. The clothing patterns are detected by smoothing the image using Fast Fourier Transform (*FFT)* and then detecting the horizontal and vertical edges. The authors claim to get an accuracy higher than previous detection methods.

Yang et al. [8] have proposed an approach for classifying clothes into four categories, namely, striped, lattice, special and Patternless. They have extracted structural and statistical features from image wavelet sub-bands and combined these features to create a custom classifier. The authors then tested this algorithm on a database of 627 images of clothes belonging to the four mentioned classes and have claimed to outperform all previous similar methods. Rao et al. [9] have presented a paper that recognizes clothing patterns in plaid, striped, pattern-less, and irregular as in previous work done by Prof. Ying li and identifies clothing colours. To recognize clothing patterns, the authors propose a combination of various techniques such as *SIFT*, Radon Transform, Morphological operators and statistical descriptors. The authors claim that their approach achieves a high accuracy compared to other system.

Gandhi et al. [10] have proposed a novel system for the identification of the pattern and colour of clothes to assist visually impaired people. The proposed system utilizes a *GSM* and an *IOT* module to transmit the cloth pattern information and location to another remote device. It also utilizes a speaker to output the cloth pattern and colour as audio. Stearns et al. [11] have proposed a novel system which is claimed to be able to distinguish between six types of visual patterns viz. solid, striped, checkered, dotted, zigzag and floral. The proposed system utilizes transfer learning on Resnet-101 which was trained using the ImageNet dataset and claims to achieve an accuracy of 96.5% Menakadevi et al. [12] have proposed a system which utilizes Radon transform and scale invariance feature transform to extract features from the clothing dataset. These features are then used to train an *SVM* classifier and then the algorithm was tested on the *CCNY* clothing pattern dataset.

3. METHODOLOGY

The main objective for this work is to design an algorithm for the detection of the colour and pattern of clothing with ease and high accuracy. The figure 1 shown below details the proposed method.

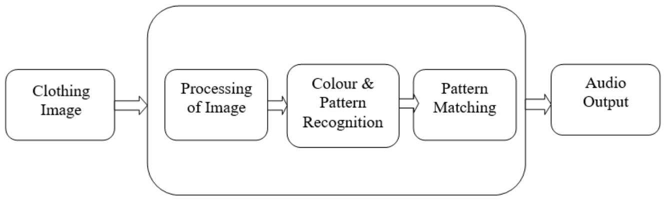


Fig. 1. System block diagram

We have used the *CCNY* clothing pattern dataset which is publicly available for research purposes. Each class in the dataset consists of 158 images, which have been split 70-30 for training and testing, resulting in 110 training images and 48 testing images. Each image has dimensions of 140x140. The input to the system is a clothing image. Pre-processing of image includes functions such as anti-aliasing, smoothening, resizing the image and edge detection. After enhancing the image, next step is the implementation of colour and pattern recognition algorithm. The colour detection has been implemented on *HSI* colour model. The feature extraction includes Radon signature and *GLCM* features. Pattern classification has been performed with the help of *k-NN*, *SVM* and neural networks. Deep learning models have a higher overall accuracy as compared to the *SVM* and *KNN* algorithms. Among the implemented deep learning algorithms, *VGG-19* has the highest accuracy, precision and recall. The output i.e., the pattern and colour are converted into audio form and provided to the user. The *TTS* (Text to Speech) function which is available as an external function is used for delivering the audio output

3.1 Colour Identification

Normalised Histogram in the HSI colour space is used for colour identification. Depending on the relationship between three components hue, saturation and intensity the colours are quantized to the respective values. The flow chart in Figure 2. explains the logic behind colour identification. Hue is visualized as a wheel of 360 degrees and the colours are quantized in the different ranges and the weights of each colour is the percentage of pixel belonging to this colour.

Saturation value S and Intensity value I determine the amount of white, black and grey colour [6].

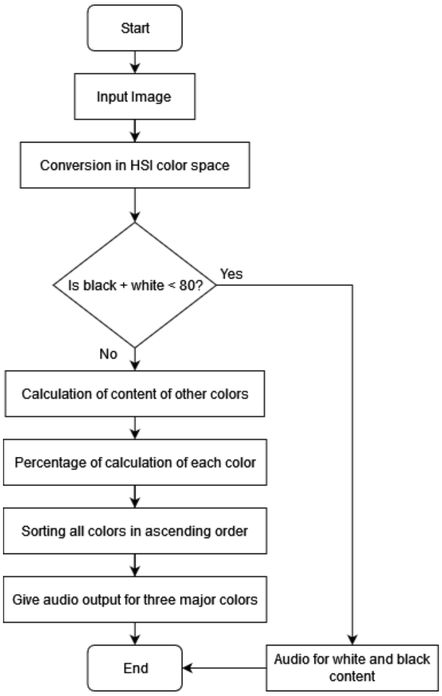


Fig. 2. Colour identification

3.2 Radon Features

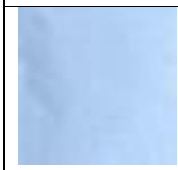
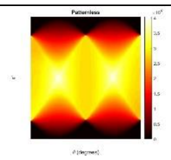
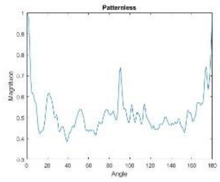
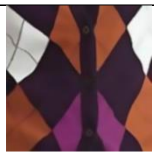
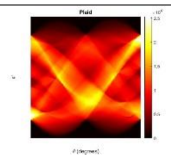
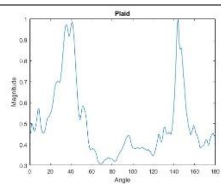
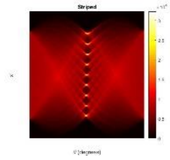
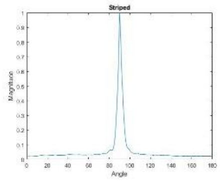
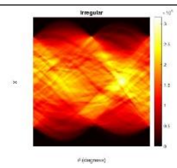
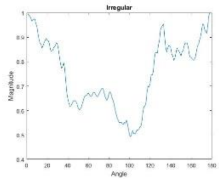
The principal orientation of image is detected with Radon Signature which is based on the Radon transform. Rotation invariance is achieved by rotating the image according to the dominant direction. The Radon transform of a 2-D function i (x, y) is defined as

$$\boldsymbol{R(p,\theta) = \iint_{-\infty}^{\infty} i(x,y)\delta(p - xcos\theta - ysin\theta)\,dx\,dy} \qquad (\mathbf{1})$$

Where p is the perpendicular distance of a projection line to the origin and θ is the angle of the projection line. Radon transform is a vector with dimensions 200x1. Figure 3 gives the input image and the Radon coefficients. Radon transform is applied to different cloth patterns and the Radon features are extracted. Table 1 shows the Radon Transform and the various Radon signatures obtained from the class pattern. Pattern-less and irregular have no dominant direction, plaid has two peaks and striped has one dominant direction.

Fig. 3. Input image and Radon coefficients

Table 1. Radon transform and signature of cloth patterns

Image	Radon transform	Radon Signature
 Patternless		
 Plaid		
 Striped		
 Irregular		

3.3 GCLM Features

A GLCM is a matrix where the number of rows and columns is equal to the number of Gray levels (G) in the image. Gray Level Co-Occurrence Matrix (GLCM) has proved to be a popular statistical method of extracting textural feature from images. According to co-occurrence matrix, Haralick defines fourteen textural features measured from the probability matrix to extract the characteristics of texture statistics of remote sensing images. GLCM is an 8x8 matrix. We have used four important features, contrast, homogeneity, energy and correlation. These features are calculated by following formulas

$$\text{Energy}= \sum_{i,j=0}^{N-1}\left(P_{ij}\right)^2$$

$$\text{Homogeneity}=\sum_{i,j=0}^{N-1}\frac{(P_{ij})}{1+(i-j)^2}$$

$$\text{Contrast} = \sum_{i,j=0}^{N-1} P_{ij}(i-j)^2$$

$$\text{Correlation} = \sum_{i,j=0}^{N-1}\frac{P_{ij}(i-\mu)(j-\mu)}{\sigma^2}$$

P_{ij}: Element i, j of the normalized symmetrical GLCM

N: Number of Gray levels in the image as specified by Number of levels in under Quantization.

μ: the GLCM mean (being an estimate of the intensity of all pixels in the relationships that contributed to the GLCM). Different GLCM features for clothing images with different patterns are extracted. Table 2 shows the GLCM features obtained with different cloth patterns.

Table 2. GLCM features along with cloth patterns

Image	**Contrast**	**Homogeneity**	**Energy**	**Correlation**
 Patternless	1.108	0.621	0.2615	0.8768
 Plaid	0.053	0.992	0.6627	0.9740
 Striped	0.533	0.885	0.2361	0.8111
 Irregular	0.163	0.202	0.6602	0.9188

Radon signatures and GLCM features are applied as features to the Machine learning algorithms and back propagation network.

3.4 *Classifiers*

Classification is the process of assigning the inputs to different output classes. The classification may be done with supervised or unsupervised algorithms. The classifiers used in this work are k-NN classifier and SVM classifier. Neural networks are also used for classification.

In pattern recognition, the k-nearest neighbour algorithm (k-NN) is a non-parametric method used for classification and regression. In machine learning, support vector machines (SVMs, also support vector networks) are supervised learning models with associated learning algorithms that analyse data used for classification and regression analysis. Neural networks are a collection of neurons connected by interconnection called weights and they perform similar to that of brains. There are three layers called the input layer, middle layer called the hidden layer and the output layer. Figure 4 shows the structure of the neural network.

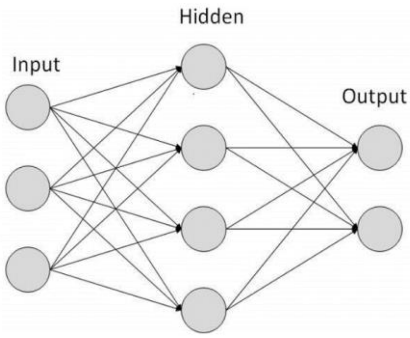


Fig. 4. Neural Network

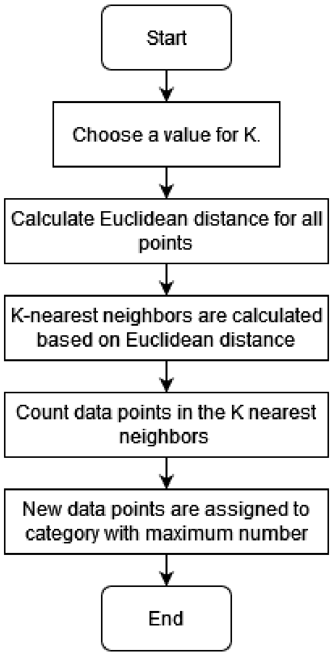


Fig. 5. KNN Algorithm

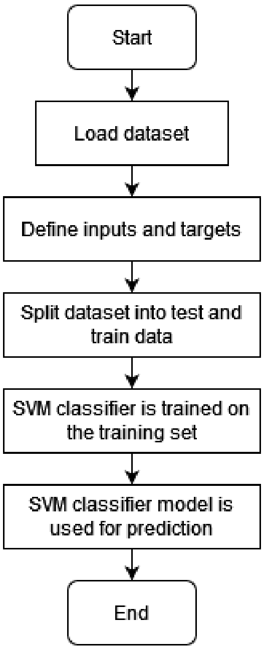


Fig. 6. SVM Algorithm

In deep learning networks such as AlexNet, GoogleNet, *VGG-16* and *VGG-19*, the extracted features are used to train the model to classify the clothing patterns based on these features.

(a) AlexNet –
AlexNet is one of the earliest architectures in Deep Neural Networks, consisting of 14 layers and requiring an input of size 227x227x3. It uses a combination of convolution, max pooling, dropout and fully connected layers to extract the relevant features from the images to train the model and then classify the input images given to it.

(b) GoogleNet –
GoogleNet is a variant of the inception network, another popular Deep Neural Network consisting of 27 layers and requiring an input of size 224x224x3. It uses a combination of inception modules alternated with two max pooling layers to efficiently down sample the image to effectively extract its features.

(c) VGG-16 and VGG-19 -
As the name suggests, *VGG-16* and *VGG-19* are Deep Neural Network architectures consisting of 16 and 19 layers respectively. They have used fixed size (3x3) convolutions to increase the depth of the network and max pooling layers to reduce the feature volume.

4. RESULTS

The results obtained with all the three networks are discussed below. The performance matrix used are

1. Confusion matrix gives the performance of the designed model on the test data whose output class is known. It gives the predicted label with reference to the actual label.

2. A receiver operating characteristic curve, or ROC curve, is a graphical plot that illustrates the performance of a binary classifier system as its discrimination threshold is varied. The curve is created by plotting the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings

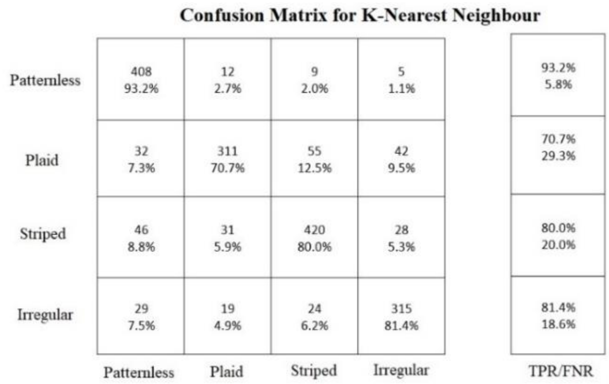


Fig. 7a. Confusion matrix k-NN classifier

Figure 7a. shows the confusion matrix of the KNN classifier. The results of the True class vs predicted class for the three patterns striped, plaid, irregular and pattern-less are shown. Pattern-less is predicted with the highest accuracy of 93.2%. The overall accuracy of the KNN algorithm is obtained to be 81.33% with 94% precision and 79.22% recall.

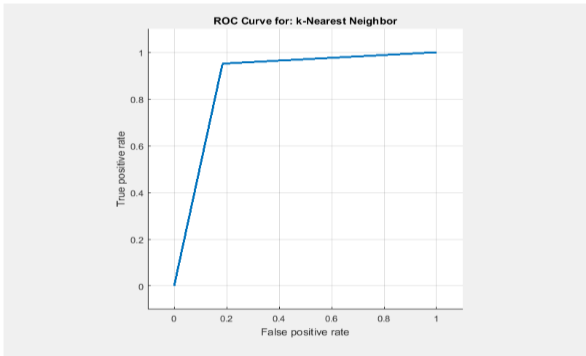


Fig. 7b. ROC curve k-NN classifier

Figure 7b shows ROC in which X axis represents False positive and Y axis represents True positive rate. After false rate reaches 0.198, true rate tends to unity.

Confusion Matrix for Support Vector Machine

	Patternless	Plaid	Striped	Irregular	TPR/FNR
Patternless	293 63.0%	50 10.8%	86 18.5%	36 7.7%	63.0% 37.0%
Plaid	35 7.8%	293 66.7%	70 15.9%	41 9.6%	66.7% 33.3%
Striped	33 6.0%	71 12.9%	393 71.6%	52 2.5%	71.6% 28.4%
Irregular	21 4.9%	43 10.1%	19 4.5%	342 80.5%	80.5% 19.5%

Fig. 8a. Confusion matrix SVM classifier

Figure 8a. shows the confusion matrix of SVM classifier. The irregular class has the highest accuracy of 80.5% while the overall accuracy of the SVM algorithm is obtained to be 70.45%.

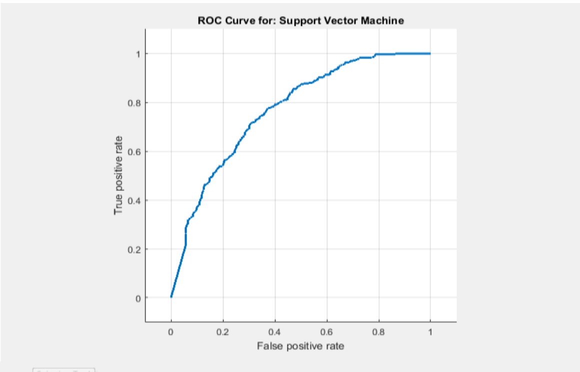


Fig. 8b. ROC curve SVM classifier

Figure 8b shows the ROC curve of SVM classifier. ROC of the KNN classifier is better than the SVM classifier. False positivity is high in the case of SVM classifier.

Confusion Matrix for AlexNet

	Irregular	Patternless	Plaid	Striped	TPR/FNR
Irregular	46 88.5%	2 3.8%	4 7.7%	0 0.0%	88.5% 11.5%
Patternless	0 0.0%	43 100.0%	0 0.0%	0 0.0%	100.0% 0.0%
Plaid	0 0.0%	2 4.3%	43 93.5%	1 2.2%	93.5% 6.5%
Striped	1 2.1%	0 0.0%	0 0.0%	46 97.9%	97.9% 2.1%

Fig. 9a. Confusion matrix for AlexNet.

The CNN based approach yields better results when compared to the earlier machine learning based KNN and SVM approaches. AlexNet produces the highest accuracy for the detection of the Patternless class of 100%, while having an overall accuracy of 94.7%.

Confusion Matrix for GoogleNet

	Irregular	Patternless	Plaid	Striped	TPR/FNR
Irregular	44 86.3%	4 7.8%	1 2.0%	2 3.9%	86.3% 13.7%
Patternless	1 2.2%	43 95.6%	0 0.0%	1 2.2%	95.6% 4.4%
Plaid	2 4.1%	0 0.0%	44 91.7%	2 4.2%	91.7% 8.3%
Striped	0 0.0%	0 0.0%	2 4.5%	42 95.5%	95.5% 4.5%

Fig. 9b. Confusion Matrix for GoogleNet.

GoogleNet has overall lower accuracy as compared to AlexNet. The Patternless class has the highest accuracy of 95.6% while the overall network has an accuracy of 92.0%.

Confusion Matrix for VGG-16

	Irregular	Patternless	Plaid	Striped	TPR/FNR
Irregular	45 95.7%	1 2.2%	1 2.1%	0 0.0%	95.7% 4.3%
Patternless	0 0.0%	44 93.6%	1 2.1%	2 4.3%	93.6% 6.4%
Plaid	1 2.0%	2 4.0%	43 87.8%	3 6.2%	87.8% 12.2%
Striped	1 2.2%	0 0.0%	2 4.5%	42 93.3%	93.3% 6.7%

Fig. 9c. Confusion Matrix for VGG-16.

VGG-16 performs similar to GoogleNet, with accuracy still lower than AlexNet. The Irregular class has the highest accuracy of 95.7% while the network as a whole has an accuracy of 92.6%.

Confusion Matrix for VGG-19

	Irregular	Patternless	Plaid	Striped	TPR/FNR
Irregular	45 97.8%	0 0.0%	0 0.0%	1 2.2%	97.8% 2.2%
Patternless	0 0.0%	47 97.9%	0 0.0%	1 2.1%	97.9% 2.1%
Plaid	2 4.1%	0 0.0%	47 95.9%	0 0.0%	95.9% 4.1%
Striped	0 0.0%	0 0.0%	0 0.0%	45 100.0%	100.0% 0.0%

Fig. 9d. Confusion Matrix for VGG-19.

VGG-19 has the highest accuracy among all the networks under consideration. The striped class achieves the highest accuracy of 100% while the overall network accuracy is obtained to be 97.9%.

The above results show that the Deep Neural Network based classifiers have a higher accuracy as compared to the previous KNN and SVM based machine learning approaches.

VGG-19 has the highest reported overall accuracy. This is due to the deeper layer structure of VGG-19 which is more effective in extracting the features of the patterns in clothing. As can be observed, the irregular pattern has a lower accuracy for AlexNet and GoogleNet due to its lower number of layers. This supports the hypothesis that a deeper network is better able to classify more complex patterns and thus have higher overall accuracy.

Table 3 shows the classification accuracy obtained with different machine learning and neural network-based classifiers. As can be observed, the accuracies for the Patternless class are the highest when using a neural network-based classifier while SVM classifier classifies the irregular class with the highest accuracy. The KNN algorithm follows suit of the neural networks, having highest accuracy for the Patternless class.

Table 3. Comparison of classification accuracy

	Irregular	Patternless	Plaid	Striped
KNN	81.4%	93.2%	70.7%	80%
SVM	80.5%	63%	66.7%	71.6%
AlexNet	88.5%	100%	93.5%	97.9%
GoogleNet	86.3%	95.6%	91.7%	95.5%
VGG-16	95.7%	93.6%	87.8%	93.3%
VGG-19	97.8%	97.9%	95.9%	100%

Tables 4 and Table 5 show the comparison of precision and recall of all the implemented algorithms on a per class basis. The precision and recall values are highest for VGG-19 among the other algorithms being tested. These results further confirm that VGG-19 is the best algorithm for the classification of clothes based on their pattern and colour.

Table 4. Comparison of Precision

	Patternless	Plaid	Striped	Irregular
KNN	0.94	0.707	0.8	0.81
SVM	0.63	0.667	0.716	0.805
AlexNet	0.885	1	0.935	0.979
GoogleNet	0.863	0.956	0.917	0.955
VGG-16	0.957	0.936	0.878	0.933
VGG-19	0.978	0.979	0.959	1

Table 5. Comparison of Recall

	Patternless	Plaid	Striped	Irregular
KNN	0.7922	0.8338	0.8268	0.8051
SVM	0.767	0.6411	0.6919	0.7261
AlexNet	0.9149	0.9149	0.9787	0.9787
GoogleNet	0.9149	0.9361	0.8936	0.9361
VGG-16	0.9361	0.9149	0.8936	0.9574
VGG-19	1	1	0.9574	0.9574

Table 6 shows the output of the colour detection algorithm on the cloth. The various colour components and their percentages are displayed. The main components present are blue, black and white.

Table.6. Color detection output

Colour Output	
White	22.0501
Black	4.4370
Blue	71.8138
Yellow	0.1013
Cyan	1.1440
Red	0.0788

5. CONCLUSION

In conclusion, a simple technique is proposed and realized that takes a big step towards enabling the visually impaired people to become more independent. This enables them to pick out their clothes based on the colour and pattern of the clothing item by reporting to them in the audio format using the standard available text to speech library.

The implementations that have been demonstrated are based on machine learning and deep learning approaches. In machine learning, the popular SVM and KNN classifiers were used. In the deep learning approach, basic architectures like AlexNet, GoogleNet, VGG-16 and VGG-19 were used. The deep learning approaches provide a higher overall accuracy due to their ability to automatically extract the relevant features. This is not present in the machine learning approach as the feature extraction step has to be performed prior to applying the machine learning based classification algorithms. The overall accuracy for VGG-19 was obtained to be the highest at 97.9%.

REFERENCES

[1] Di, Wang. "A comparative research on clothing images classification based on neural network models." In 2020 IEEE 2nd International Conference on Civil Aviation Safety and Information Technology (ICCASIT, pp. 495-499. IEEE, 2020.

[2] Liu, Yuanjun, Gaofeng Luo, and Feng Dong. "Convolutional Network Model using Hierarchical Prediction and its Application in Clothing Image Classification." In 2019 3rd International Conference on Data Science and Business Analytics (ICDSBA), pp. 157-160. IEEE, 2019.

[3] Rao, AV Subba, H. C. Hadimani, and Srinivasarao Udara. "An Identification of Automatic Clothing Pattern and Color Recognition through Voice Recognition for Visually impaired people." Journal of Critical Reviews 7, no. 16 (2020): 2488-2495.

[4] Zhang, Yuwei, Peng Zhang, Chun Yuan, and Zhi Wang. "Texture and Shape Biased Two-Stream Networks for Clothing Classification and Attribute Recognition." In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 13538-13547. 2020.

[5] Xiaodong Yang,Shuai Yuan and YingLiTian, “Assistive Clothing Pattern Recognition for Visually Impaired People” ,in IEEE transactions on Human-Machine Systems, Vol. 44, no. 2, April 2014

[6] S. Yuan, Y. Tian, and A. Arditi, “Clothes matching for visually impaired persons,” J.Technol. Disability, vol. 23, no. 2, pp. 75–85, 2011.

[7] Masao Miyake, YoshitsuguManabe, Yuki Uranishi, MasatakaImura and Osamu Oshiro, “Voice Response System of Color and Pattern on Clothes for Visually Handicapped Person”, in35th Annual International Conference of the IEEE EMBS Osaka, Japan, 3 - 7 July, 2013

[8] Xiaodong Yang, Shuai Yuan and YingLiTian, “Recognizing clothes patterns for blind people by confidence margin-based feature combination,” in Proc. Int. ACM Conf. Multimedia, 2011, pp. 1097–1100

[9] N DurgaRao,, Dr. G Sudhavani, P Balakrishna,, Dr. K Gouthami,” Cloth Pattern Recognition With Four Features(RSSM)”,in 2015 International Symposium on Advanced Computing and Communication (ISACC)

[10] Gandhi, Omkar, and Sanskar Dendage. "Cloth And Pattern Recognition for Visually Impaired People." (2019).

[11] Stearns, Lee, Leah Findlater, and Jon E. Froehlich. "Applying transfer learning to recognize clothing patterns using a finger-mounted camera." In Proceedings of the 20th International ACM SIGACCESS Conference on Computers and Accessibility, pp. 349-351. 2018.

[12] Menakadevi, N., T. Nagarjuna, and K. Nehru. "Pattern Recognition for Visually Impaired People Using Radon Signature." (2020).