International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

Novel MobileNet based Multipath Convolutional Neural Network for defect detection in fabrics

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Abstract—Automatic fabric defect detection and classification is the most important process in the textile industry to ensure the fabric quality. In the existing systems, a learning based method is used for detecting defects in plain weave fabrics. In this paper, a novel MobileNet based Multipath Convolutional Neural Network (MMPCNN) architecture is proposed for detection and classification of simple and complex patterned fabric defects. In the proposed MMPCNN architecture, MobileNet model is used in the first path. In this, Gabor filter bank is used instead of conventional filters in the first convolution layer. A simple convolutional neural network architecture with Gray Level Co-occurrence Matrix (GLCM) features as an input is used in the second path of the MMPCNN architecture. Gabor filters are more useful for analyzing the texture with different orientations and scales. Each Gabor filter parameter has its own impact on analyzing the texture and extracting the information from the texture. Therefore, in this paper, the use of Gabor filter parameters in MMPCNN architecture is analyzed. The proposed model is experimented on the TILDA textile image database and it is able to achieve 100% accuracy with reduced trainable parameters for fabric defect detection and classification.

Keywords- Gabor Filter, Gray Level Co-occurrence Matrix, Convolutional Neural Networks, Multipath Convolutional Neural Networks, MobileNet based Multipath Convolutional Neural Networks

I. INTRODUCTION

Deep Convolutional Neural Network architectures (Kevin Jarrett&KorayKavukcuoglu 2009; Lecun&Kavukcuoglu2010; Lee2009) have substantial advantages over other popular models for image classification. In particular, series models have improved dramatically in Large-Scale Visual Recognition Challenges (Russakovsky et al. 2015). A network was suggested (Calderón et al. 2003) to investigate Dennis Gabor's filter using CNNs. Calderon recommended adding a Gabor filter instead of a traditional filter bank within their CNN architecture at an early stage. A boosting approach is added to this Gabor based CNN (GCNN) architecture, producing better outcomes. The boosting strategy provided is similar to dropout and proved effective for better generalising test data. Gabor filters can be seen to have an impact on the development of CNNs. Calderon built this GCNN to take advantage of feature extraction using Gabor filters and empower these feature detectors by feeding them into a CNN. Hence Gabor filters combined with CNN enhance the performance of the network.

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A lightweight MobileNet model is developed (Howard et al. 2017a) for mobile applications such as object detection, image classification etc. This lightweight model is developed using depthwise separable convolution that minimizes the amount of trainable parameters. The CNN model (Sarwar et al. 2017) is built with the Gabor filter bank in the early convolution layers, advancing the research of other comparable Gabor CNNs (GCNN). In the GCNN model, the Gabor filter bank is used instead of conventional filter bank in the early convolution layers of the network. The main idea of this architecture is to reduce the network's complexity.

Backpropagation, gradient descent, and weight changes inside layers are all known to be computationally expensive. But, in CNN it is not necessary to apply these computing methods in its layers because the trained layers in the network are replaced with fixed Gabor kernels. A new GCNN model (Luan et al. 2018) is developed by applying the Gabor filter bank to all the convolution layers in the network. The main idea of using the Gabor filter in CNN is to reduce the number of trainable parameters. During the convolution process, the Gabor filter bank is used instead of the traditional filter bank. This will create a Gabor of Filters (GoF) that extracts the texture information from the inputs. Also, it improves the performance of the network without employing many additional parameters. A novel application of the Gabor filter (Özbulak&Ekenel 2018b) is investigated to check whether the Gabor filter initialization takes the role of transfer learning. The method is implemented as an alternative for employing a pre-trained model and transferring it into an unknown environment. The Gabor filter naturally resembles the low-level features that are learnt from the first layer of CNN. Ozbulak built a CNN model with Gabor filters as the first layer with uniform distribution based on this idea.

A CNN model with an optimization algorithm (Dixit et al. 2019) is developed for filter parameters optimization in the convolution layer, weight and bias optimization in the dense layers for the image recognition problems. With the help of this optimization algorithm, the number of trainable parameters is reduced. A Histogram back projection-based CNN model is designed by the researchers (Sun et al. 2019) for fabric defect detection. In this approach, histogram back projection is utilised for the segmentation of defected regions in the fabric. This approach is analyzed with the help of the simple patterned fabrics of the TILDA textile image database. A fabric defect detection system with three-dimensional band reject filter (Tola et al. 2021) is developed for removing noise from the input fabric images. In this approach, a specific energy threshold function is used to categorize the fabrics as defective or defect free. This approach is validated using simple patterned fabrics taken from the TILDA textile image database. A model is developed (Li et al. 2017) for detecting a defect in the fabrics using a Fisher criterion-based stacked autoencoder. The performance of this model is evaluated using simple and complex patterned fabrics with better results.

A model for fabric defect detection using a histogram of oriented gradient (HOG) features with SVM (Cuifang et al. 2020) is designed to enhance the performance. But this method fails to detect defects in the complex patterned fabrics taken from TILDA textile image database resulting in average performance. A CNN model is developed for fabric defect detection with a traditional SVM classifier (Qiu et al. 2021). In this approach, a traditional SVM classifier is used instead of a softmax layer in the state of the art architectures for detecting defects in fabrics. The author's proved that the proposed architecture performance is better than the state of the art CNN architectures for fabric defect detection systems. The researchers developed a CNN model for defect detection in fabrics(Li et al. 2021). In this model, the fabric defect detection process is done in two phases; the Segmentation phase and defect detection phase. In the segmentation phase, defect regions are segmented, and it is given as input to the defect detection module of CNN. The author's used four different datasets for analyzing the network's performance. But all the dataset contains only simple patterned fabrics.

Although much progress has been made, there is still a challenge for improvement in terms of internal processes and how image data affects the speed of the network. In this paper, CNN models which provide better results for texture classification are addressed. To improve the CNN performance for detecting defects in fabrics, a novel Multipath CNN is designed to overcome the weakness of the single path model. These paths learn different features of images and retain more valid features than the single path model.

II. PROPOSED MULTIPATH CONVOLUTIONAL NEURAL NETWORK (MPCNN) ARCHITECTURE

Proposed multipath CNN is intended to categorize various fabric defects, as well as the defect-free fabrics that serve as the benchmark for predicting the other defect. This multipath CNN extracts the features in two paths. In the first path, it extracts the features using the Gabor filter, whereas, in the second path, GLCM is used to extract the co-occurrence feature information. These features are more useful for detecting fine details of the images throughout the feature extraction processes. These features are processed further in their respective paths, and then the concatenated output is given to its output layer. The advantage of Multipath CNN is that any number of pathways may be included in the CNN model for the better performance of the network. Also, it takes advantage of including more features for detection and classification of fabric defects. Multipath CNN is more reliable than traditional CNNs. Multipath CNNs, on the other hand, are more complex than traditional CNNs. As a result, there is a trade-off between the performance and the complexity of CNNs.

A. VGG-16 based MPCNN (VMPCNN) Architecture

Multipath Convolutional Neural Network (MPCNN) is a type of CNN architecture that processes the data in more than one path. Multipath CNN takes the input and processes it in different paths, and extracts the different features. Then the extracted features are combined and processed again to produce the most precise output. Moreover, there is no restriction on the number of paths in multipath CNN, so that the richness of features that are extracted from the multipath CNN model is improved. Multipath CNNs are more reliable but they are more complex than single path CNNs. Hence, there is a trade-off between the accuracy and the complexity involved in predicting fabric defects.

The proposed VGG-16 based Multipath CNN has two paths wherein VGG-16 with Gabor filter in the first path, and in the second path, SCNN takes the input from GLCM. The concatenation layer is used to concatenate the features and then the resultant features are given to the dense layers. Finally, the softmax layer is used as a classifier for classifying the different classes of fabric defects. A VGG-16 based Multipath CNN architecture is shown in Figure 1. In Multipath CNN architecture, VGG-16 architecture is used in one path. In this, the first convolution layer has 64 filters of size 3×3. Then the output features are activated through Rectified Linear Unit (ReLU). Gabor filter is used in the first convolution layer instead of the standard filter bank. The idea of using the Gabor filter bank is to explore the texture information about the image in different orientations. This is shown in Figure 1.

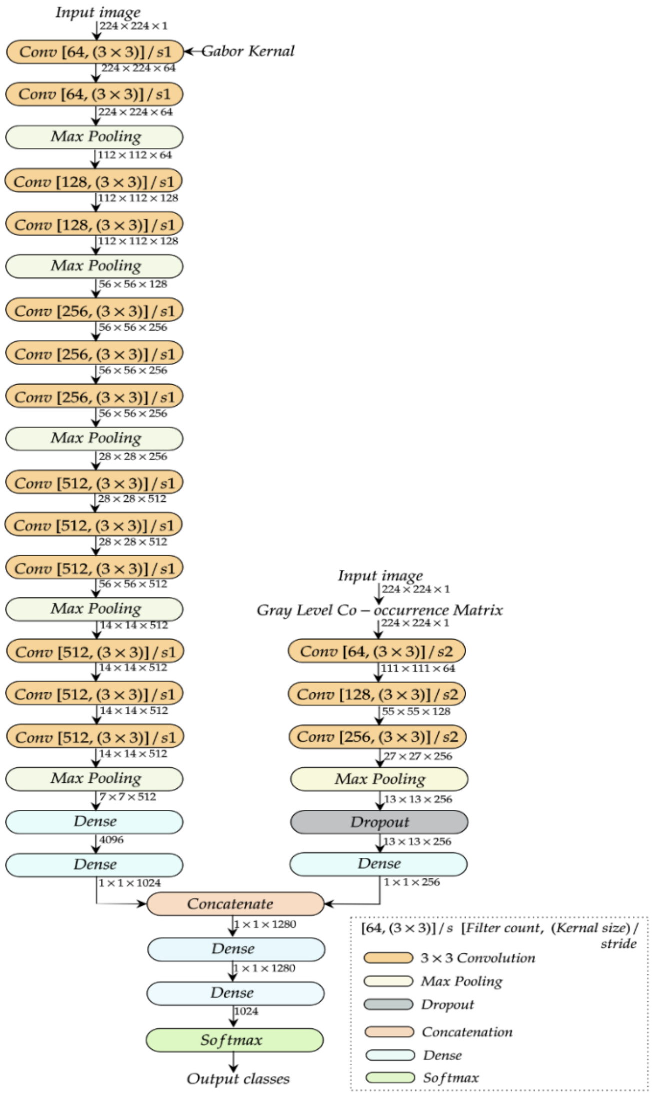

Figure 1. VGG-16 based Multipath CNN

B. MobileNet based MPCNN (MMPCNN) Architecture

In computer vision, CNN architectures have grown increasingly popular. Modern CNNs, on the other hand, are becoming deeper and more complicated for achieving better results. To cater to this problem, MobileNet CNN (MCNN) architecture is designed with a reduced number of parameters. MobileNet is a lightweight model that often uses Depthwise Separable Convolutions instead of conventional convolutions.

MobileNet includes two new global hyperparameters, namely width multiplier and resolution multiplier that creates the model trade-off between accuracy and latency. These hyper-parameters help the researchers to select the appropriate model size based on their problem constraints. MobileNet based Multipath CNN (MMPCNN) architecture is depicted in Figure 2. In this architecture, the MobileNet structure is used in the first path and the Simple CNN is in another path. In the first path, Gabor filters are used in the first convolution layer instead of the standard filter bank in CNN. This is shown in Figure 2. In this architecture, depthwise separable convolution is used to reduce the number of trainable parameters. In the second path, GLCM is used as an input to the network. Then the concatenation layer is used to concatenate the information's obtained from both the paths. The concatenated output is then given to the dense layer. Finally, the softmax layer is used to predict the output class of data. This is shown in Figure 2.

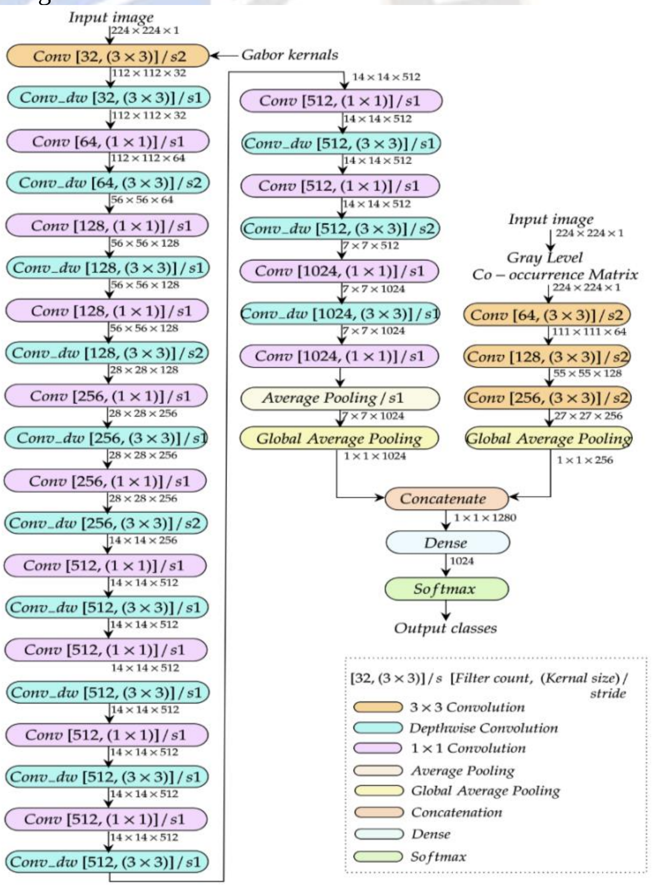

Figure 2. MobileNet based Multipath CNN Architecture

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III. RESULTS AND DISCUSSION

A. Performance analysis of VGG-16 and VMPCNN with and without Gabor filter

The original and Gabor based CNN models are trained on the TILDA textile image dataset with 10 classes (9 defective fabric classes and 1 defect-free fabric class). Their performance metrics are analyzed to understand the impact of the Gabor filter. The performance of VGG-16 architecture is analyzed on the TILDA textile image. The use of the Gabor filter bank overcomes the drawbacks present in the standard filter bank of the convolution layer. This Gabor filters in the early convolution layers helps in extracting the texture information with different orientations. To examine its performance, various CNN models are investigated by replacing their own filter bank with the Gabor filters. The specification of the hyperparameters used for the analysis of VGG-16 and VMPCNN is shown in Table I.

TABLE I. HYPERPARAMETERS OF THE NETWORK ARCHITECTURE

Sl. No.	Hyperparameter	Value
1	Decay Learning Rate (L.R)	0.0001
2	Decay	0.0001/50
3	Batch size	24
4	Optimizer	Adam
5	Weight Initialization technique	Glorot uniform
6	Epochs	50
7	Loss function	Sparse categorical cross entropy
8	Classifier	Softmax
9	Total number of input images	8000

TABLE II. PERFORMANCE METRICS OF GABOR FILTER IN VGG-16 AND VMPCNN

Filtering Approach	Average of 10 classes				Trainable parameters
	Training		*Validation*		
	Accuracy %	*Loss*	*Accuracy %*	*Loss*	
VGG-16	100	6.4251e-07	99.37	0.0220	134,300,362
VGG-16 with Gabor filter	100	8.1582e-08	99.50	0.0423	134,300,362
VMPCNN	99.50	0.0599	97.50	0.0658	539,322,850
VMPCNN with Gabor filter and GLCM	100	1.1319e-06	99.72	0.0400	539,322,850

The performance metrics of VGG-16 and VMPCNN (with and without Gabor filter & GLCM) architecture for detection and classification of fabric defects is shown in Table II. By analyzing the results of VGG-16 and VMPCNN models, Gabor filter-based models achieve better results than the traditional filter-based models. By comparing the results of VGG-16 with Gabor filters and VMPCNN with Gabor filter and GLCM, VMPCNN with Gabor filter and GLCM achieve a 0.22% improvement in validation accuracy, 5.4% reduction in validation loss. The various performance metrics of VGG-16 and VMPCNN with and without the Gabor filter are analyzed in Table III.

TABLE III. PERFORMANCE METRICS OF VGG-16 AND VMPCNN WITH AND WITHOUT GABOR FILTER

Filtering Approach	Average of 10 classes			
	Precision (%)	*Recall (%)*	*F_1 score (%)*	*Cohen's kappa*
VGG-16(Own filter)	99.93	99.38	99.65	0.966
VGG-16(Gabor filter)	99.93	99.51	99.72	0.973
VMPCNN(Own filter)	99.03	98.21	98.61	0.858
VMPCNN(Gabor filter and GLCM)	99.93	99.79	99.86	0.986

By analyzing the result in Table 3, VMPCNN with Gabor filter and GLCM gives maximum precision, recall, F1 score, and Cohen's kappa compared to VGG-16 (with and without Gabor filter) and VMPCNN with its own filter. The VMPCNN with Gabor filter and GLCM achieve 0.28% improvement in recall, 0.14% improvement in F1 score, 1.31% improvement in Cohen's kappa compared to VGG-16 with Gabor filter. This result implies that the proposed VMPCNN with Gabor filter and GLCM model predicts more than 99% of the defective as well as defect-free fabric classes correctly. Therefore, VMPCNN with Gabor filter and GLCM model gives better results in terms of accuracy. However, this better performance is achieved with a maximum number of trainable parameters and 50 epochs. Due to the maximum trainable parameters, the computational complexity of the VMPCNN model also increases and results in maximum computational time. To cater to this problem, the lightweight MobileNet model, namely MMPCNN is used instead of the VGG-16 model in the first path of Multipath CNN architecture.

B. Performance Analysis of MMPCNN with and without Gabor Filter

The specification of the hyperparameters used for the analysis of MMPCNN architecture is shown in Table IV.

TABLE IV. HYPERPARAMETERS OF THE NETWORK ARCHITECTURE

Sl. No.	Hyperparameter	Value
1	Decay Learning Rate (L.R)	0.0001
2	Decay	0.0001/30
3	Batch size	24
4	Optimizer	Adam
5	Weight Initialization technique	Glorot uniform
6	Epochs	30
7	Loss function	Sparse categorical cross entropy
8	Classifier	Softmax
9	Total number of input images	8000

TABLE V. PERFORMANCE METRICS OF MMPCNN

Filtering Approach	Average of 10 classes				Trainable parameters
	Training		*Validation*		
	Accuracy (%)	*Loss*	*Accuracy (%)*	*Loss*	
MMPCNN (Own	99.59	0.0093	96.69	0.1441	6,057,802

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

filter)					

From Table 5, it is observed that MMPCNN with its own filter bank predicts the training dataset correctly with reduced trainable parameters, but it fails to predict the test dataset correctly. Though the number of trainable parameters of MMPCNN model is reduced, its validation accuracy is reduced by 3% when compared to VMPCNN with Gabor filter and GLCM.

The performance graph of Training and Validation Accuracy and loss of MMPCNN is shown in Figure 3. From the graph, it is clear that there is instability in the result of both accuracy and the loss function. To cater to this problem, the Gabor filter bank is used instead of a conventional filters in the first convolution layer of MobileNet in the first path. In addition to that, GLCM is used as an input to the second path of the MMPCNN for extracting detailed texture information.

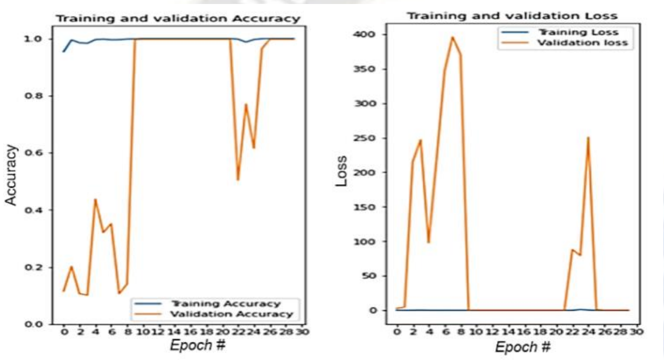

Figure 3. Performance graph of MMPCNN

In this section, the impact of each Gabor filter parameter in MMPCNN with Gabor and GLCM architecture is analyzed. The Gabor filter bank remains constant during all tests in which every parameter is verified and it is modified once per test. For each test, the Gabor filter bank remains static, but the learning ability of the created Gabor filter is improved through training. The chosen values are similar to the values in the literature (Pham2019; Özbulak&Ekenel2018a) so that they can be compared in the next tests. The Gabor filter parameter values are chosen based on the entries in Table 6.

Table VI shows a list of Gabor filter parameters and their ranges within the Gabor Filter. In this, the Gabor parameter θ and ψ values at 0° and 360° give the same result. For the implementation of MMPCNN, 32 Gabor filters are used. Each parameter modification is subjected to a single test. For example, in the first test, the σ value is 2 while the other Gabor filter variables remain constant. In the second test, the σ value is incremented based on Table VI, while the other Gabor filter variables remain constant. The same procedure is repeated for the entire parameters. For further tuning of Gabor filter parameters, the previous best Gabor parameters such as σ_b, λ_b, θ_b, γ_b are considered.

TABLE VI. GABOR FILTER PARAMETER

Parameter	Range	Chosen values
Standard Deviation(Sigma, σ)	[2, 22]	[2, 6, 10, 14, 18, 22]
Wavelength (Lamda,λ)	[0, 100]	[0, 20, 40, 60, 80, 100]
Orientation (Theta,θ)	[0, 300]	[0, 60, 120, 180, 240, 300]
Spatial Aspect Ratio (Gamma,γ)	[0, 300]	[0, 60, 120, 180, 240, 300]
Phase Offset (Psi,ψ)	[0, 300]	[0, 60, 120, 180, 240, 300]

TABLE VII. GABOR FILTER INITIALIZATION

Test Case	Sigma	Lambda	Theta	Gamma	Psi
Sigma	[2, 22]	50	0	150	0
Lambda	σ_b	[0, 100]	0	150	0
Theta	σ_b	λ_b	[0, 300]	150	0
Gamma	σ_b	λ_b	θ_b	[0, 300]	0
Psi	σ_b	λ_b	θ_b	γ_b	[0,300]

The Gabor filter parameters used in each test are listed in Table VII. In this, one parameter will change with evenly divided intervals while the other parameters will remain static. For the analysis of the entire test, GLCM is calculated with the displacement distance of 1 and with the angle of 0°.

TABLE VIII. PERFORMANCE METRICS OF MMPCNN WITH DIFFERENT SIGMA VALUES

Gabor Parameters	Sigma	Average of 10 classes			
		Training		*Validation*	
		Accuracy %	*Loss*	*Accuracy %*	*Loss*
	2	100	3.8117e-09	99.50	0.5001
ksize = 3×3	6	100	0.0000e+00	99.75	0.1709
Lambda = 50	10	100	7.4413e-11	99.50	0.5825
Theta =0	14	100	0.0000e+00	99.87	0.3501
Gamma = 150	18	100	1.0132e-5	100	0.0215
Psi = 0	22	99.94	0.0363	99.87	0.0320

Table VIII shows the performance metrics of MMPCNN with different Sigma values when other Gabor filter parameters are kept constant. By comparing the results, the accuracy percentage increases when increasing the σ value from 2 to 18, and it achieves maximum validation accuracy at σ=18. For further σ values, the accuracy decreases like a Gaussian curve. By comparing this result with the MMPCNN with its own filter bank, MMPCNN with Gabor filter parameter (σ=18) achieves a 3.31% of improvement in validation accuracy and an 85.07% reduction in the validation loss.

Figure 4 shows the performance graph of Training and Validation Accuracy and loss of MMPCNN with Gabor filter in the first layer of MobileNet for σ=18. From the graph, it is clear that the performance of the MMPCNN is improved, but

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

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still, there is instability in the result of both accuracy as well as loss function.

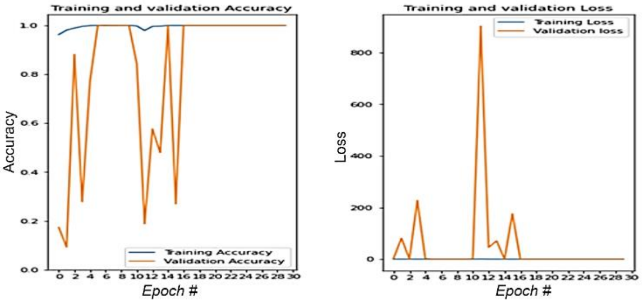

Figure 4. MMPCNN with Gabor filter performance graph for σ= 18

TABLE IX. PERFORMANCE ANALYSIS OF MMPCNN WITH DIFFERENT PSI VALUES

Gabor Parameters	Psi	Average of 10 classes			
		Training		*Validation*	
		Accuracy %	*Loss*	*Accuracy %*	*Loss*
ksize =3×3 Sigma = 18 Lamda =60 Theta =180 Gamma =180	0	100	7.1076e-07	99.77	0.0485
	60	100	9.4518e-07	100	1.6086e-05
	120	100	5.5498e-08	99.87	0.0247
	180	100	1.2194e-06	99.62	0.1085
	240	100	1.1830e-06	99.87	0.0570
	300	100	1.0674e-06	100	1.1558e-04

Table IX shows the performance analysis of MMPCNN with different ψ values when the other Gabor filter parameters are kept constant. By comparing the results, it is observed that the training accuracy of all the ψ values is the same. But the highest validation accuracy with minimum loss is achieved for the ψ value of 60, and beyond this ψ value, validation accuracy is decreased.

By comparing this result with the MMPCNN with its own filter bank, MMPCNN with Gabor filter parameter (ψ=60) achieves 3.31% of improvement in validation accuracy and 92.47% of reduction in the validation loss.

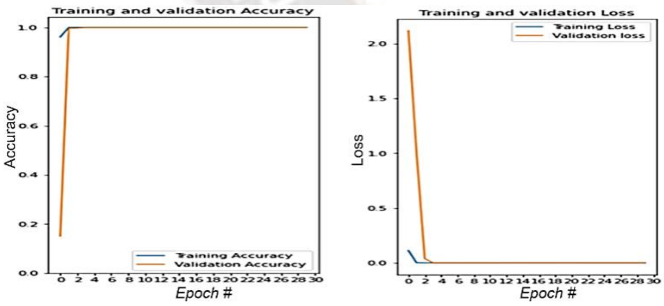

Figure 5. MMPCNN performance graph for ψ= 60

Figure 5 shows the performance graph of Training and Validation Accuracy and loss of MMPCNN with Gabor filters in the first layer of MobileNet for the ψ value of 60. From the graph, it is observed that the maximum accuracy and minimum loss is achieved within the minimum number of epochs. By comparing the results of MMPCNN with different Gabor filter parameters, the maximum validation accuracy of 100% and the minimum loss of 1.6086e-05 are achieved with the Gabor filter parameter values of ksize=3×3, Sigma=18, Lamda=60, Theta=180,Gamma=180 and Psi=60.

Table X shows the performance metric of MMPCNN for defect detection and classification with the Gabor filter parameter values of ksize=3×3, Sigma=18, Lamda=60, Theta=180,Gamma=180 and Psi=60.

By analyzing the results in Table 5.13, it is observed that MMPCNN architecture gives 100% precision and recall values. This result indicates that MMPCNN detects all the defective and defect-free fabric classes correctly without any deviations. The MMPCNN architecture achieves 100% of F1 score, which indicates that there is a perfect balance between precision and recall. The maximum Cohen's kappa value of 1 is achieved by MMPCNN, resulting in good agreement between all the classes of data.

TABLE X. PERFORMANCE METRICS OF MMPCNN FOR DEFECT DETECTION AND CLASSIFICATION

Sl. No.	Defect type	Precision %	Recall %	F_1 score %	Cohen's kappa	Training parameters
1.	Holes	100	100	100	1	6,057,802
2.	Ladder	100	100	100	1	
3.	Snag	100	100	100	1	
4.	Stain	100	100	100	1	
5.	Thread defect	100	100	100	1	
6.	Single fold	100	100	100	1	
7.	Thick bar	100	100	100	1	
8.	Thin bar	100	100	100	1	
9.	Slub	100	100	100	1	
10.	Defect Free	100	100	100	1	

IV. CONCLUSION

Convolutional Neural Network is widely used nowadays in many texture classification problems. However, the conventional filter bank used in CNN's may fail to extract fine details of the texture image. Gabor filters can be used as an alternate for the conventional filters of CNN with the same hyperparameters. This Gabor filter bank will extract the texture information that is more useful for detecting defects in the fabric. With the help of this information, the CNN performance is improved. This improved performance is achieved with less number of filters and reduced computational complexity for simple patterned fabrics. To improve the performance of the architecture for complex patterned fabric, novel multipath CNN architectures are designed. In MMPCNN with Gabor and GLCM, each of the Gabor filter parameters has a different effect on training the dataset. Some Gabor parameters influence the performance of the network much, and some may not. The effectiveness of the proposed novel MMPCNN architecture with the Gabor and GLCM is validated using the TILDA textile image database. A novel MMPCNN architecture with Gabor and GLCM for fabric defect detection achieves better result in terms of accuracy and loss. By comparing the results, Gabor filter parameter values of ksize=3x3, Sigma=18, Lamda=60, Theta=180, Gamma=180 and Psi=60 offers the maximum accuracy of 100%.

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