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An Optimization Technique For Analyzing Fabric Designs Using CNN Based Fog Computing

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Fabric design analysis is a critical component of the textile industry, affecting various aspects such as production efficiency and consumer satisfaction. Conventional fabric analysis methods typically involve centralized data processing, which can be sluggish and ineffective, particularly when dealing with extensive datasets and intricate designs. Fog computing presents a viable alternative by distributing handling information and positioning computation nearer to the data source. This proposal presents an optimization technique for fabric design analysis that utilizes fog computing. The proposed model includes the following phases: fabric image collection, preprocessing, feature extraction and classification. The fabric images are collected from fog edge devices and various filtering process is applied for image preprocessing. Gray-level co-occurrence matrix is utilized to identify the features and the fabric patterns are classified using ensemble deep learning model. The efficacy of the suggested approach was demonstrated through extensive experiments, which outperformed existing algorithms and achieved higher accuracy. The findings highlight the substantial upside of the proposed approach in automates pattern identification, thus improving productivity and effectiveness in textile production and retail.

Keywords: Fog Computing, Optimization Technique, Fabric design, convolutional neural network, Classification.

1. Introduction

Fabric is a historical innovation of humanity, evolving from handcrafted cloth to contemporary machine-produced digital fabrics. In the production sector of cloth, pattern, the paramount aspect for woven fabrics, significantly influences design, redesign, textural analysis, and the aesthetic appearance of materials [1]. Identification of woven fabric patterns is required prior to further processing by weaving equipment in the production process. Currently, fabric pattern identification primarily relies on traditional processes utilizing eye sight, supplemented by instruments like microscopes or magnifying glasses. This manual examination is generally conducted by a specialist possessing requisite expertise and experience. Nonetheless, it is associated with numerous disadvantages, including excessive labor, inefficiency, and time consumption, as well as psychological aspects such as stress in the body and mind, wooziness, and fatigue that eventually impact the identification outcomes. Consequently, a mechanized examination method is essential to establish the identification of cloth patterns to manufacture superior goods which fulfill client requirements [2]. This paper presents an optimization technique for fabric design analysis that utilizes fog computing.

Fog computing is an emerging new model which delivers processing functions at the edge, facilitating novel applications for the future of the Web. It serves a crucial function in distributed networks by supplying cloud resources, encompassing computational resources at the edge. A conventional fog contains a collection of heterogeneous networked equipment utilized for interaction, and processing in IoT applications [3]. Fog computing offers a practical framework that facilitates local computation and services among data centers and clients of nascent cloud computing. In contrast to cloud, fog aims to delineate a distinct category of delay-sensitive IoT applications, including those in medical care [4], industry [5], and transportation [6].

It is not a standalone model but rather an expansion of cloud to the edge. It consists of three strata: edge, fog, and cloud layer. Figure 1 shows the fog computing three layer structure.

Edge Layer: This layer consists of several end devices that are geographically dispersed. It comprises many IoT smart devices, including mobile phones, autonomous vehicles, humidity sensors, temperature sensors, and surveillance systems, among others [7]. These IoT devices generate substantial volumes of data by sensing physical objects or events. It assumes the duty of retrieving information and transmitting them to a superior layer.

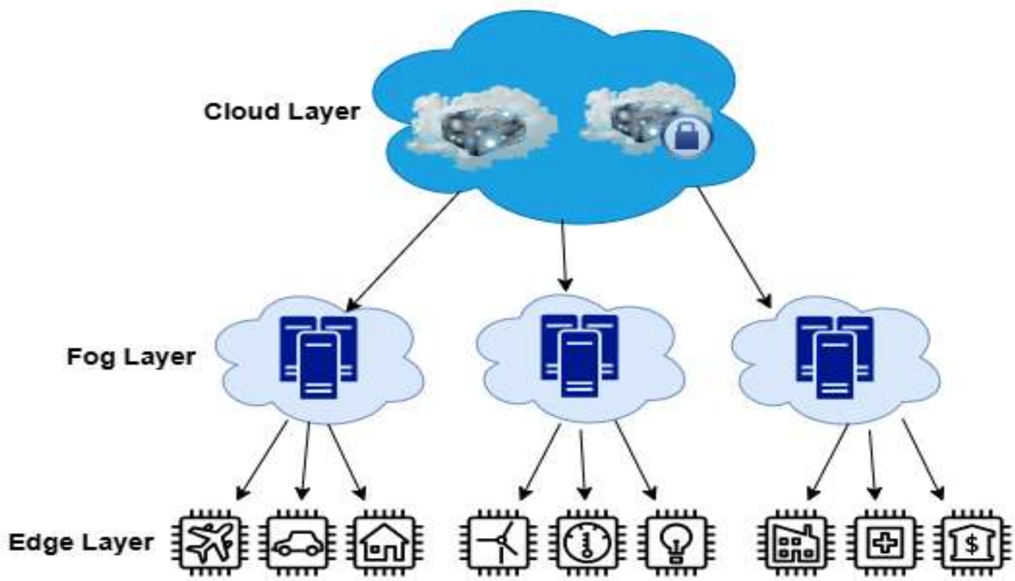


Figure 1 Three Layer structure

Fog Layer: This constitutes the intermediary layer between the cloud and edge devices. The fog layer comprises numerous fog nodes with constrained processing or storage capacities, including routers, switches, gateways, base stations, access points, and cloudlets. This layer's computational capacity enhances the functionality of latency-sensitive applications, facilitating real-time processing. Furthermore, the proximity of the fog to the edge devices facilitated successful interaction. Furthermore, the expansion of cloud to the fog enabled nodes to possess enhanced computing and storage capabilities [8].

Cloud Layer: This layer is situated at the uppermost position. The cloud computing layer consists of several storage devices and high-performance servers, capable of delivering robust storage and computational capabilities to facilitate extended analytical computations and the storing of substantial data volumes. This layer is essential for processing substantial data volumes, data storage, and the management of platform services and monitoring systems.

Fog computing refers to a situation in which several diverse, omnipresent, and distributed gadgets interact and possibly collaborate with one another and the network to execute tasks autonomously, devoid of third-party involvement [9]. In this paper, the fabric images are gathered from edge devices, processed by fog nodes and fabric patterns are stored in cloud for further processing.

Methods for weave pattern detection are often categorized into two primary types: statistical methods and model-based methods. The texture-based statistical technique employs transformed photos. The recognition approach utilizing a database/model employs an approach to classification to recognize and match the weave patterns of fabrics. Xiao et al. [10] employed feature and histogram-based recognition fabric patterns, utilizing fuzzy c-means clustering to distinguish the intersections of threads. Nevertheless, the experiments were constrained by inadequate detection of double-yarn weave patterns and significant rotational changes present in the cloth.

Khan [11] presented a geologically based method for recognizing cloth color, demonstrating robustness despite variations in yarn color and cloth texture. Liu et al. [12] introduced a cloth fault detecting approach employing an improved convolutional neural network for intricate textures. They favored a restricted quantity of photos for experimentation within a highly controlled context. The identification approaches for cloth have numerous limitations. The current investigations predominantly depended on manual feature design. The accessibility of the cloth photos database was restricted. The spinning fluctuations in cloth affected the extraction of texture characteristics during image attainment. Inadequate illumination may lead to indistinct texture images.

This proposal introduces an optimization method for fabric design analysis with fog computing. The proposed model incorporates the following phases: fabric picture collecting, preprocessing, feature extraction and classification. The fabric photos are gathered from fog edge devices, and many filtering processes are employed to preprocess the images. The fabric texture characteristics are discerned utilizing a gray-level co-occurrence matrix, whereas the fabric patterns are categorized employing an ensemble deep learning model.

The remaining part of the paper is structured as follows: Section 2 examines the pertinent literature related to fabric design pattern classification, Section 3 delineates the suggested fabric design analysis, Section 4 outlines the investigational methodology and result analysis, and Section 5 provides the conclusion.

2. Related Work

Iqbal Hussain [13] suggests a deep learning model for the categorization and identification of cloth type. It utilized a residual network to dynamically collect and categorize cloth texture data in a seamless manner. This model is resilient and attains cutting-edge precision despite alterations in the fabric's physical qualities. This model employs less information during training, rendering it operationally economical and hence holds promise for the fabric and apparel industries.

Li et al. [14] introduced a methodology utilizing different approaches to extract information regarding cloth pattern from various orientations. Subsequently, they employed an adaptive mesh model to partition images into sub division for the extraction of gray features. The scheme proved effective for determining overlapping sites in the structure; nevertheless, the study was confined to simple cloth materials only.

Meng et al. [15] propose an automated approach for the simultaneous determination of yarn positioning and pattern recognition. A novel CNN is introduced to forecast the position maps of thread and drifts, enhancing the learning of interrelated features. The pattern and fundamental weave reiterate are discerned by integrating the thread and drift position maps.

Noprisson et al. [16] offer a method for classifying woven cloth patterns with a transfer learning model. It seeks to utilize a transfer learning model and enhances its performance by fine-tuning to illustrate the effectiveness of a transfer learning-based model. The technique of woven cloth pattern classification through fine-tuning can get superior accuracy.

Meng et al. [17] present a comprehensive analysis of the automated identification of characteristics in woven fabrics. The primary structural factors of fabric encompass cloth thickness, weave model, and color that must be specified prior to manufacture and meticulously verified during quality control. This review aids researchers in comprehending and employing automated techniques for identifying fabric structural properties. It may also offer innovative solutions for further recognized challenges in the textile sector, such as fabric identifying defects, fabric aspect analysis, and fabric inverse modeling.

Mamun et al. [18] offer a novel, streamlined technique for recognizing fabric weave patterns using a Bayesian-optimized convolutional neural network. This approach effectively utilizes the spatiotemporal characteristics of the cloth complex exterior structure. Bayesian optimization was employed to identify optimal hyperparameters in CNN-based supervised learning for identification of patterns.

Mao et al. [19] provide a novel methodology utilizing the YOLOv10 model that provides improved recognition accurateness, handling quickness, and identification of the ragged pattern for each cloth type. This model was chosen for its exceptional efficiency, utilizing improvements in deep learning and employing data expansion approaches to enhance flexibility and generalization to diverse fabric designs and materials.

Al Mamun et al. [20] propose a novel strategy for cloth model identification by using multi-linear principal component analysis-based tensor decomposition technique. This approach facilitates cloth model screening in automated scheme by incorporating a camera to record streaming video information of cloth exterior features. The video information is subsequently transformed into consecutive picture frames that represent various cloth patterns. These frames are analyzed to consolidate the cloth exterior pattern.

Zang et al. [21] present a comprehensive framework for the localization of adjacent important spots by automated the traditional identification of minimal recurring patterns in printed cloth pictures. This structure is subsequently developed into an extensive automated retrieval of pictures system, including detailed implementation approaches.

Zhang et al. [22] formulate a clustering technique for autonomously identify design and retrieve colors from multispectral pictures of printed textiles. The pictures obtained from a self-developed scanning scheme are initially transformed into color pictures in the CIELAB color format, followed by the computation of three principle components by principal component analysis to decrease the dimensionality of the multispectral picture. This method identifies color patterns in complex multispectral printed cloth photos with enhanced accurateness and reduced processing time.

3. Proposed Methodology

This section explains the proposed the fabric pattern detection using deep learning model in fog computing. Figure 2 shows the general architecture. The fabric images are gathered from different edge devices, processed by fog nodes, and the fabric patterns are saved in the cloud for subsequent processing.

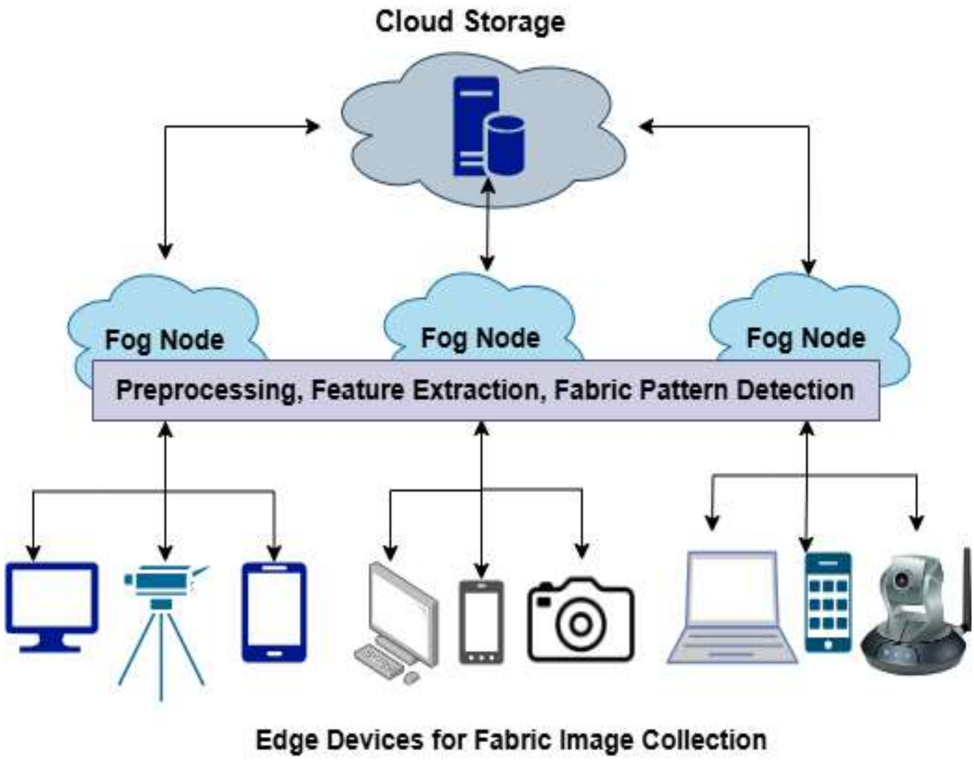


Figure 2 General Architecture

The proposed model comprises the following phases: fabric image acquisition, preprocessing, feature extraction, and classification. The fabric photos are gathered from fog edge devices, and several filtering processes are employed to preprocess the images. The fabric texture characteristics are recognized using a gray-level co-occurrence matrix, while the fabric patterns are classified using an ensemble deep learning model.

3.1 Fabric Image Collection

The images of fabrics have been gathered to create a dataset. The samples were collected from different edge devices. The dataset contains five different types of fabric pattern: checked, dotted, floral, solid and stripped. Figure 3 shows the sample fabric image.

(a) Checked (b) Dotted (c) Floral (d) Solid (e) Stripped

Figure 3 Sample Collected Fabric Image

3.2 Preprocessing

Preprocessing constitutes the preliminary phase of image processing techniques. This procedure enhances picture quality and increases the classification performance. Preprocessing involves low-contrast illumination adjustment, noise elimination, blurriness correction, and image improvement. The preprocessing steps of this paper encompass size normalization, color conversion, filtering, and CLAHE.

In the preliminary phase of preprocessing, each image are reduced to 512 × 512 pixels. The fabric images are frequently available as RGB color image. Let I be the original RGB image. The RGB image is transformed into its grayscale equivalent using,

$$\mathrm{I_{gray}} = (0.3 * \mathrm{I_{red}}) + \left(0.59 * \mathrm{I_{green}}\right) + (0.11 * \mathrm{I_{blue}}) \quad (1)$$

Where I_{red}, I_{green}, and I_{blue} denote the Red, Green, and Blue color pixels of the original picture.

Image filtering is employed for denoising purposes, specifically to eliminate noise from fabric images. The Laplacian filter serves as a method for image denoising. The Laplacian of a picture detects areas with quick intensity variation and exemplifies a second-order enhancement derivative. It is particularly effective in revealing fine details within an image. A Laplacian operator can enhance any function characterized by sharp discontinuities. The Laplacian L(m,n) of an picture with pixel intensity values I(m,n) is defined as follows:

$$\mathrm{L(m,n)} = \frac{\partial^2 \mathrm{I}}{\partial \mathrm{m}^2} + \frac{\partial^2 \mathrm{I}}{\partial \mathrm{n}^2} \quad (2)$$

Contrast-limited adaptive histogram equalization (CLAHE) was utilized to improve the picture contrast and features. The visual efficacy of CLAHE is more practical and aids in reducing noise distortion. CLAHE was utilized on the grayscale image to enhance its contrast at the tile level. CLAHE histogram equalization consistently adjusts the photos, so improving their overall contrast. Figure 4 shows the pre-processed images.

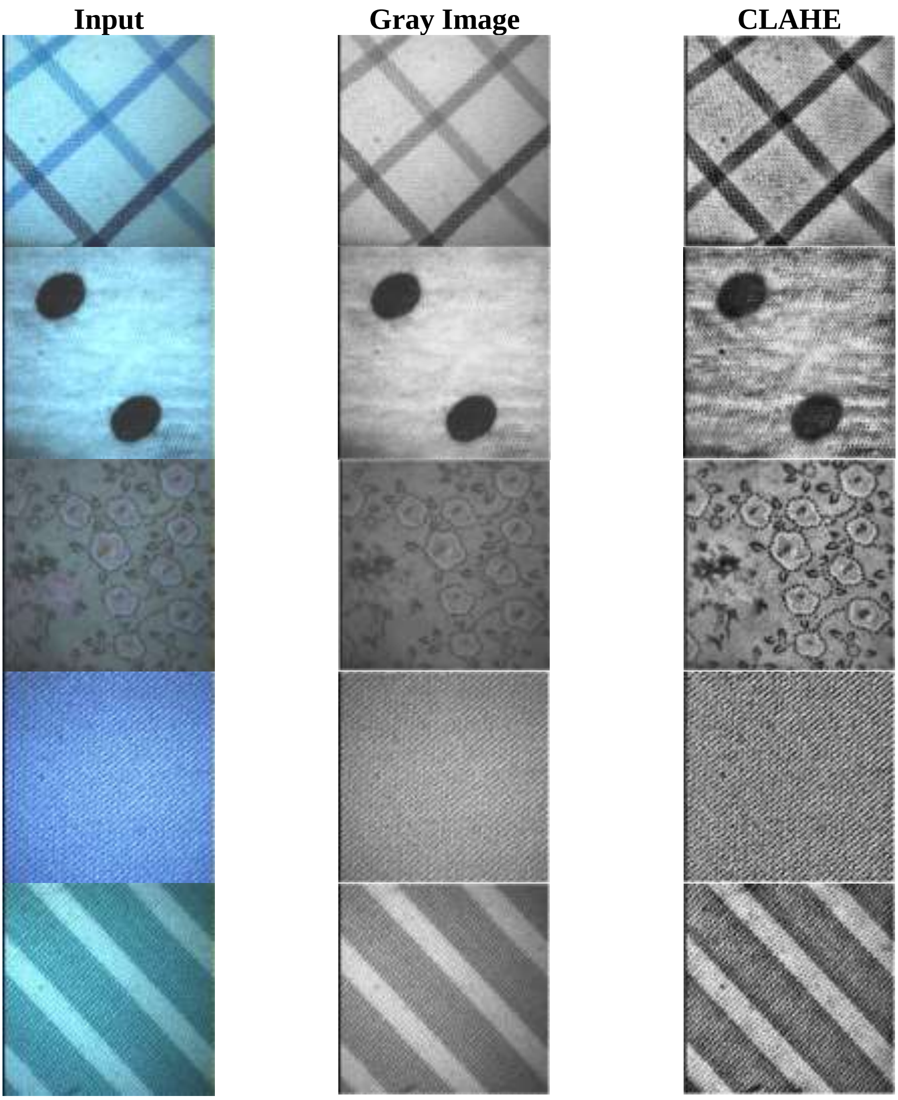


Figure 4 Pre-processed Image

3.3 Feature Extraction

The features of fabric images are extracted using gray-level co-occurrence matrix (GLCM). GLCM is a technique that delineates the textural characteristics of images by illustrating the relationships among neighboring pixels. The primary computation processes are (i) extraction of the gray image, (ii) computation of gray levels, (iii) determination of feature values between neighboring pixels, and (iv) generation of the feature matrix [23]. The matrix consisted of the recurrent appearance of sequential pairs of pixel values in a specified way. It enables GLCM to provide a distinct array of texture information dependent on gray scale, kernel size, and orientation [24]. In this work, the following GLCM features are extracted.

Contrast: Contrast quantifies the spatial occurrence of an picture and represents a distinct aspect of the GLCM. It is defined as the dissimilarity among the maximum and minimum values of neighboring pixel sets. It assesses local difference within the picture. A picture characterized by low dissimilarity exhibits a attention of GLCM values near the principal diagonal and displays low spatial occurrences.

$$\text{Contrast} = \sum_{x=1}^{N}\sum_{y=1}^{N}(x-y)^2 \qquad (3)$$

Homogeneity: It evaluates the uniformity within the image, yielding higher values for lesser dissimilarity in gray color among paired elements. I It is especially responsive to the existence of near-diagonal features in the GLCM. The value attains its highest point when the elements inside the image are congruent. GLCM contrast and homogeneity exhibit a strong inverse correlation, indicating that as contrast increases, homogeneity diminishes, provided energy remains constant.

$$\text{Homogeneity} = \sum_{x=1}^{N}\sum_{y=1}^{N}\frac{P(x,y)}{1+(x-y)^2} \qquad (4)$$

Dissimilarity: Dissimilarity quantifies local variations within an image linearly.

$$\text{Dissimilarity} = \sum_{x=1}^{N}\sum_{y=1}^{N}P(x,y)\times|x-y| \qquad (5)$$

Angular Second Moment (ASM): This metric assesses textural homogeneity by evaluating repeats in pixel pairs, thereby identifying texture disorders within pictures. The greatest value for the angular second moment is one, with upper values indicating a consistent periodic gray level distribution.

$$\text{ASM} = \sum_{x=1}^{N}\sum_{y=1}^{N}P(x,y)^2 \qquad (6)$$

Energy: It is derived as the square root of the ASM, exhibiting higher values when the window displays orderliness.

$$\text{Energy} = \sqrt{\sum_{x=1}^{N}\sum_{y=1}^{N}P(x,y)^2} \qquad (7)$$

Entropy: It quantifies the chaos of an image and has a negative correlation with Energy. Entropy is elevated when the image exhibits significant textural complexity or contains substantial noise.

$$\text{Entropy} = \sum_{x=1}^{N}\sum_{y=1}^{N} P(x,y) \times \log\left(P(x,y)\right) \qquad (8)$$

Correlation: This metric measure the linear relationship among the gray tones of the picture.

$$\text{Correlation} = \sum_{x=1}^{N}\sum_{y=1}^{N} \frac{(x-\mu_x)(y-\mu_y)}{\sqrt{(\sigma_x)(\sigma_y)}} \qquad (9)$$

N indicates the quantity of gray levels, whereas P(x, y) signifies the standardize value of the grayscale at coordinates x and y. μ and σ represents the mean and variance.

3.4 Fabric Pattern Classification

This section delineates the suggested ensemble model for fabric pattern classification. An ensemble approach is a meta-algorithm that amalgamates various machine learning algorithms into a unified forecast. Ensemble networks amalgamate several autonomous models to produce a more effective output. Deep ensemble learning models integrate the benefits of deep and ensemble learning to enhance the overall generalization performance of the final model. This paper integrates Inception V3, ResNet50, and VGG16 models for the detection of fabric patterns.

Inception V3: A versatile and dependable CNN architecture can be employed for diverse image classification and recognition tasks. The Inception V3 architecture comprises numerous modules, each consisting of a sequence of convolutional layers with filters of varying dimensions. Image classification significantly depends on the model's capacity to acquire information at various sizes, rendering it a crucial element of the procedure.

VGG16: The VGG16 architecture comprises two fully linked layers following a series of 16 convolutional layers. The convolutional layers enable the network to produce intricate and detailed feature representations of the input image utilizing tiny filters (3x3) and a stride of 1. The architecture is defined by its simplicity, which significantly facilitates comprehension and execution. It operates efficiently for tasks pertaining to picture classification. Numerous prevalent deep-learning frameworks, in which it has already undergone training, enhance its simplicity. VGG16 presents certain constraints: The model is both resource-intensive and substantial in size. The selection of hyperparameters can influence outcomes. It does not possess the equivalent resistance to occlusions and noise as certain contemporary CNN models.

ResNet50: It is frequently utilized for image classification. The principal novelty of ResNet50 is the implementation of residual blocks. A residual block is a crucial element that allows the network to capture more complex features while reducing the likelihood of overfitting. The ResNet50 architecture consists of a series of residual blocks. A shortcut connection is located after the first two convolutional layers of each residual block. The residual block can obtain the input's residual through the shortcut link, rather than depending exclusively on the input itself. As a result, the network exhibits reduced susceptibility to overfitting and enhanced efficiency.

The proposed model employed a stochastic optimization method, specifically the Adam optimizer, for parameter optimization. The learning rate is established at 0.0001. The dropout rates were set at 0.50. The batch size was configured at 32.

4. Experimental Results

This segment delineates a set of experimentation designed to assess the efficacy of the suggested approach. There are 2500 fabric images are collected and each category (checked, dotted, floral, solid and stripped) contains 500 images. In this study, 70% of the training photos (1750 images) are allocated for model training, the left over 30% is designated for testing (750 images). The proposed ensemble model compared with VGG16, ResNet-50 and Inception V3.

The suggested methodology is assessed utilizing accuracy, precision, recall and F1-score.

Accuracy is the predominant statistic employed for evaluating categorization performance. It is the proportion of accurate forecasts to the entirety forecast made.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \qquad (10)$$

Where TP and TN indicate true positive and negative, FP and FN indicates false positive and negative.

Precision denotes the ratio of accurately classified positive class occurrences to the total instances classified as belonging to that class.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \qquad (11)$$

Recall indicates the total number of instances of a positive class that are accurately classified.

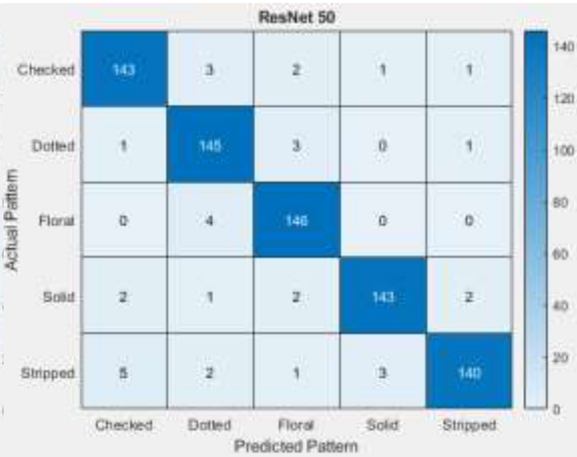
$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \qquad (12)$$

The F1-Score is computed to provide a equilibrium among precision and recall, as evaluating precision and recall separately fails to encompass all dimensions of accuracy. The F1-score varies between 0 and 1, with elevated values signifying enhanced model efficacy. .

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \qquad (13)$$

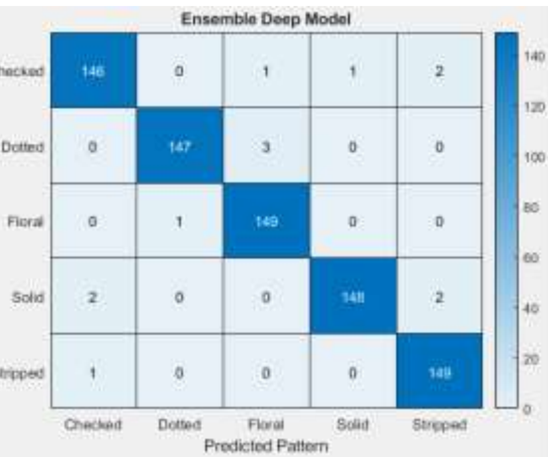
The confusion matrix is generated to illustrate the forecast of the suggested approach on the test data and to measure the number of misclassified photos. The actual pattern is signifying by the rows, while the forecasted pattern is signifying by the columns. Figure 5 shows the confusion matrix for different learning model.

(a) Inception V3 Model



(b) ResNet-50 Model

(b) VGG16 Model



(c) Ensemble Deep Model

Figure 5 Confusion Matrix for different model

The average accuracy, precision, recall, and F1-score metrics were computed for the suggested approach. The comprehensive evaluation of these values for each class is presented in Table 1. The mean values for accuracy precision, recall, and F1-score were more than 98%.

Table 1 Ensemble Model Classification Metrics

Pattern / Metrics	Accuracy	Sensitivity	Specificity	Precision	F-Measure
Checked	99.07	97.99	97.33	97.66	99.07
Dotted	99.47	99.32	98.0	98.66	99.47
Floral	99.34	97.39	99.33	98.35	99.34
Solid	99.34	99.33	97.37	98.34	99.34
Stripped	99.34	97.39	99.33	98.35	99.34

Table 2 shows performance metrics comparisons for different model. The ensemble model presented in Table 2 surpassed alternative methods. The suggested ensemble deep learning model attained superior accuracy in detecting and categorizing woven fabric images. The classification of fabrics based on texture presents significant challenges due to the restricted availability of datasets. To enhance robustness, fluctuations in cloth color, thread length, direction, and uneven lighting are taken into account during image collecting. Consequently, enhancing the datasets to be more comprehensive and representative. A deep neural network, like the ensemble model, can effectively handle these variances and learn descriptive attributes. Consequently, the model demonstrates diversity and adeptly manages the difficulty inherent in fabric picture, surpassing alternative methods.

Table 2 Performance metrics comparison

Model	Accuracy	Precision	Recall	F-Measure
Inception V3	94.67	94.67	94.71	94.69
VGG16	92.82	92.82	92.86	92.84
ResNet50	95.47	95.48	95.51	95.49
Ensemble	98.27	98.27	98.28	98.28

Figure 6 shows the performance metrics comparison.

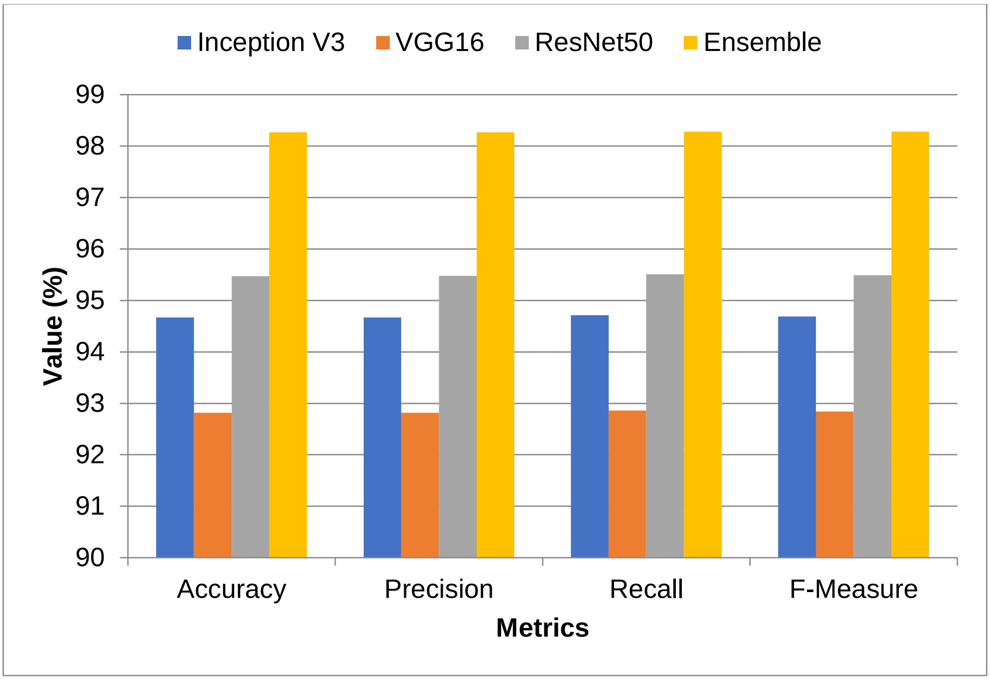


Figure 6 Metrics Comparison

The elevated recognition and classification accuracy indicate three primary characteristics: The model remains resilient when accounting for variations in physical attributes, including cloth color, thread width, length, direction, and uneven lighting. The ensemble learning technique enables model training with fewer parameters, rendering it computationally economical. (iii) The proposed model operates without reliance on manually generated features; characteristic extraction and categorization occur within a completely automatic end-to-end framework.

5. Conclusion

This work presents a fabric pattern detection using an ensemble deep learning model in fog computing. The proposed deep learning model incorporates Inception V3, ResNet50, and VGG16 architectures. Initially, photos are gathered from the fog edge devices, followed by the preprocessing of fabric images. The fabric pattern features are collected and subsequently detected according to checked, dotted, floral, solid, and striped. The effectiveness of the suggested model is assessed by multiple performance criteria. A comparison was conducted beside alternative baseline methodologies. The experimental findings indicated that the proposed strategy outperformed other current investigations. Future study will address issues in image processing for woven fabric motifs, including fabric flaws and lighting conditions that hinder fabric identification.

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