SAREE TEXTURE ANALYSIS AND CLSSIFICATION USING DEEP LEARNING FRAMEWORK

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Abstract – Indian women have worn sarees for centuries and have a significant market share in their clothing. Despite the ability to identify saree materials with tactile texture and the possibility to purchase online, it may not always be practicable to touch and feel a saree being worn. Moreover, the wide variety of saree materials available in comparison to other types of clothing, as well as the lack of experience in recognizing them, make this challenge even more challenging. The rapid advancement of smartphone technology makes it possible to capture images of cloth to determine the exact material of a saree and make an online purchase. To overcome the aforementioned challenges, a novel deep learning-based saree texture classification framework has been proposed for the rapid classification of saree tactile textures. Deep learning-based segmentation is used to detect visual texture and identify sarees from collected images. For better understanding the introduction of Mask Region-based Convolutional Neural Network (Mask RCNN) was used for generating the saree patches. To categorize saree textures, we propose a deep learning-based VGG-16 network. According to the findings, this pipeline performs better than the current deep learning methods and achieves 97.41% accuracy.

Keywords *– Deep learning, Texture classification, Patch generation, Mask RCNN, VGG-16 network*

1. INTRODUCTION

Recommendation systems are essential in e-commerce, which provide customers with individualized product recommendations based on their browsing habits, buying habits, and product characteristics [1]. These systems can make use of techniques like collaborative filtering, content-based filtering, and deep learning to make suggestions that are pertinent and boost sales. In order to improve product advertising and recommendation systems in e-commerce and give customers individualized and accurate recommendations, distributed expression technology and deep learning are being quickly adopted [2]. Learning clustering representation is being used to improve personalized e-commerce product recommendation systems system has been created that makes use of data from an advertising platform to enhance the performance of recommendations for new internet buyers. Sales grow as a result of the enhanced personalization of recommendations [3]. It is possible to find relevant articles from a big content library by analysing perceptions and preferences of the users. Getting user input on a product's various features might reveal important information about their overall evaluations and preferences. Utilizing this data will enhance personalisation, recommendation systems, and eventually customer happiness. To improve product performance and encourage long-term loyalty, it is crucial to pay attention to user feedback [4, 5].

The CBIR approach involves retrieving images are similar to the query image based on their visual contents rather than their metadata. Traditionally, an image's main elements have been, shape, and color [6]. For the purpose of searching for and locating images, the combination of color, texture, shape and texture. In a pipelined technique for CBIR systems, the properties of texture and color [7]. Comparatively to color and shape features, texture attributes are a more popular CBIR method. Two entirely different images with the same color histogram could exist [8]. For example, the histogram of a black and white image with a checkerboard pattern is identical to that of a half-black, half-white image. The deep layer architecture extracts many styles and properties from an image using CNN, which have been demonstrated to be particularly effective for general image retrieval applications [9,10]. The main contribution of the suggested system is to quickly and simply get the right fit of the query image. The main contributions of the proposed model are as follows:

- The proposed approach creates a specific dataset and the collected images are pre-processed by Gaussian filter to eliminate the noise artifacts from the saree image.

- The pre-processed images are taken as input for generating patches using the Mask RCNN model rather than manual initialization, hence eliminating the need for manual interpretation.
- Deep learning based VGG-19 is introduced for efficient classification of saree texture. The proposed model has been evaluated based on its sensitivity, specificity, accuracy and F1 score.

The rest of the research work was pre-organized as follows. Section-2 encompasses with the literature works, Section-3 designates the comprehensive description of the proposed framework, Section-4 includes results and discussion and Section-5 enfolds with conclusion and future work.

2. RELATED WORKS

Baizal *et al*. (2020) [11] have proposed a computational model that utilizes a generic approach to explore entities and their relationships, which can be applied to various domains. It utilizes domain ontology and dynamically built user profile models as knowledge for generating each interaction between users and the system. The suggested product interaction model is based on functional requirements, over the flat technical computational model that includes algorithms for generating interaction.

In 2020, Sulikowski and Zdziebko [12] proposed a framework to evaluate recommending interfaces based on individual user characteristics and goals. A deep neural network predicts Recommendation efficiency can be measured by position and intensity of selection. Designers and marketers in e-commerce seek to attract and convert users with recommendation interfaces and explored the impact of interface layout, position, and visual intensity on user behavior in a simple online store.

In 2021, Ouyang and Lawlor [13] developed two personalized Character-level deep neural networks that can enhance recommendation accuracy by generating high-quality reviews that meet text-aware recommender systems' input criteria. Additionally, found that generation models were effective in addressing the issue of item sparsity, improving the accuracy of recommendations for users with limited interactions.

In 2021 Ma, L., et al., [14] had suggested using the Flow-based Dual Attention GAN (FDA-GAN) to combine features that are aware of occlusion and deformation for greater generation quality. In particular, deformable local attention and flow similarity attention, which together make up the dual attention approach, may be used to produce the output features for deformable- and occlusion-aware fusion. Create a pose normalization network to learn adaptive normalization from the source person's posture to the target posture in order to keep the source person's pose and overall position consistent.

In 2022 Alirezazadeh, P., et al., [15] had suggested a DML enhance CNN performance in retrieving clothing from consumers to stores. As a result, DML emphasizes negative intraclass compactness while attempting to promote cross-class separability. Top-50 retrieval results for DML's DARN dataset, Consumer-to-Shop Clothes Retrieval Benchmark, and InShop Clothes Retrieval Benchmark, which performed remarkably well at retrieving clothes, were 0.759, 0.921, and 0.87, respectively.

In 2022 Monowar, M.M., et al., [16] introduced AutoRet, a self-supervised image retrieval system based on deep convolutional neural networks (DCNN). A DCNN is used as the standard technique for extracting embeddings from various picture patches. The embeddings are also combined to offer top-notch information for the image retrieval process. Three different datasets are used for the method's benchmarking. Evidently, the suggested strategy performs better when used in a self-supervised way based on the overall benchmark. Additionally, even when just a tiny percentage of labelled data are unavailable, the evaluation shows that the suggested strategy performs with a very convincing level.

From this survey, E-commerce platforms must offer personalized product recommendations to improve customer engagement and sales. The traditional rule-based and collaborative filtering methods, however, have limitations when it comes to handling large datasets. Collaborative filtering is a popular technique for recommendation systems, but it can suffer from the problem of sparsity, where there are too few ratings available for many items, leading to inaccurate recommendations. To overcome this issue, robust feature representation techniques can be used to extract significant characteristics from existing data, such as product attributes, user demographics, and user behaviour.

3. PROPOSED MODELLING

In this section, a novel deep learning model is proposed for effectively detecting, and classifying the saree texture based gathered images. The overall workflow of the proposed model is represented in fig.2.

3.1. Data pre-processing

The image is filtered from becoming submitted to the classification process using a method known as the Gaussian filter. It encompasses a range of operations that are applied to images prior to conducting subsequent analysis or tasks. These methods seek to improve image quality by lowering noise, repairing distortions, and extracting relevant characteristics. Preprocessing approaches minimize image noise, which can impair algorithm performance and accuracy. Noise reduction enhances image quality and aids in the extraction of important information. Preprocessing approaches boost the performance and effectiveness of algorithms by preparing images for upcoming tasks. Better results and interpretations are produced by enhancing image quality and feature representation. The noise-free image with the augmented and annotated dataset of saree is shown in Fig.2. The pre-processed saree images are fed into the Mask RCNN for patch generation.

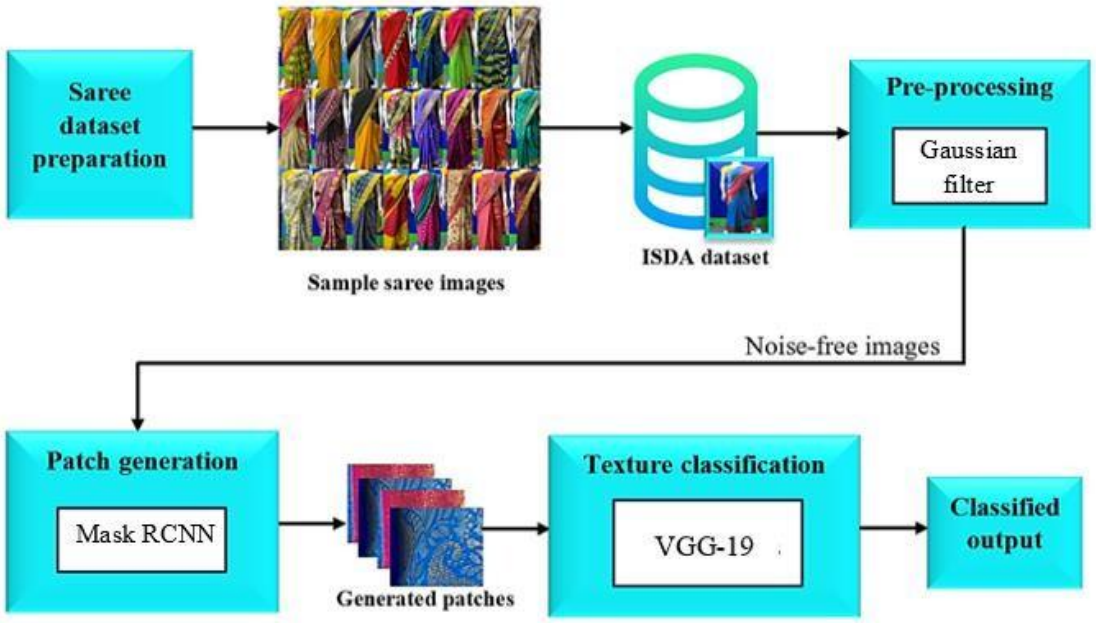
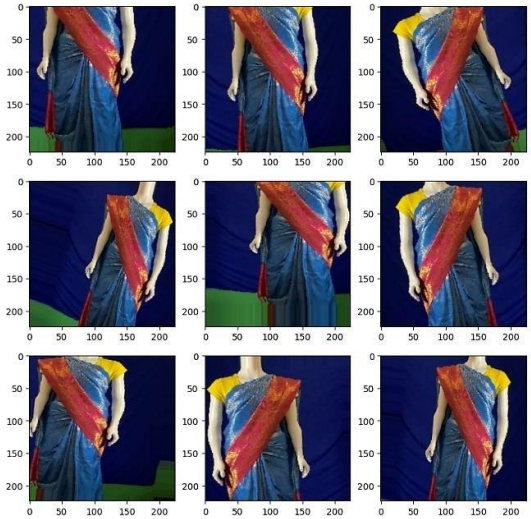


Figure 1. The overall workflow of the proposed model



(a) (b)



(c)

Figure 2. Sample image of (a) input (b) pre-processed image (c) Augmented image

3.2. Patch generation

In this phase, Mask RCNN is used for generating the saree patches to classify the different textures of saree images. Mask RCNN segments the saree images and generates patches based on the trained data. Mask R-CNN adds extra object detection in a wide range of potential regions of interest, allowing precise placement and shape determination of object instances. Mask R-CNN enables the proper labelling of object regions and removals of those object region from the background of each pixel level. Furthermore, Mask R-CNN is utilized to identify the texture of saree by examining the form and edge properties of its mask images. The Mask R-CNN network consists of three layers: the backbone, the RPN, and the RoI as shown is Fig.3.

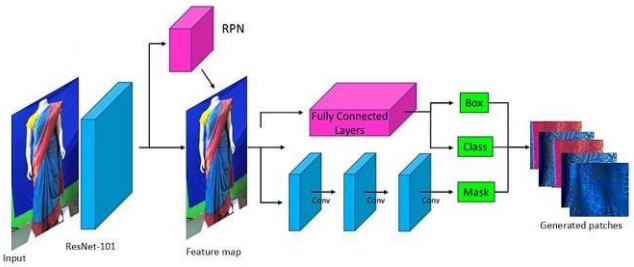


Figure 3. Mask-RCNN architecture for automatic patch generation

The ResNet101 module pre-trained is utilized as the backbone network to extract features of the image. The Mask-RCNN is then trained with gathered database which generates a new weighted model as an enhancement over Mask-RCNN. This includes 4 layers of CNNs and six batch of normalization layers and inclusion of a prediction branch so as to produce a feature maps.

3.3. Texture classification

In this research work, the input images are fed in to the

most relevant aspects of the image. Statistical features like mean, median, variance, standard deviation weighted entropy (WE), standard deviation, and kurtosis are used for feature extraction from structured data. To further enhance the pretrained VGGNet -16 can also be used. The VGG-16 deep learning model is a powerful tool for image classification tasks. It consists of several layers of convolutional and max pooling layers that can extract high-level features from images. This model has been trained on large datasets of images, which has allowed it to learn to recognize patterns and features in images. In a fashion-product image recommendation system, the VGG-16 model can be used for feature extraction. This means that the model is used to identify key visual features of fashion products such as color, texture, and style. These features are then used to give personalized recommendations to consumers based on their aesthetic preferences. The recommendation system can work by taking input from the user, such as a product image or a product description they are looking for. The VGG-16 model can then be used to extract the visual features of the product, and the system can compare these features to a database of fashion products to find similar items. The system can then recommend these similar products to the user. Using the VGG-16 model for feature extraction in a fashion-product image recommendation system can help users discover new products depending on their visual preferences, that they might be interested in, making the shopping experience more personalized and enjoyable.

4. RESULT AND DISCUSSION

This section analyzes and compares the performance of the suggested retrieval framework against various standard benchmarking techniques. This model is implemented in Matlab (2020b). In this result analysis, the images from the gathered dataset for detecting the saree textures have been discussed. The competence of the proposed model and the comparison of machine learning and deep learning algorithms are also provided in this section.

4.1. Performance analysis

The efficiency of the proposed network can be measured using evaluation metrics accuracy, precision, recall, and F1 score. The evaluation metrics of the proposed Model are shown in Table.1. and figure.4.

Table 1. Evaluation metrics of proposed Model

Classes	Accuracy	Precision	Recall	F1 score
1	98.14	98.25	96.01	89.46
2	97.81	97.08	98.28	96.83
3	94.48	95.69	90.73	94.20
4	97.05	96.71	89.04	95.15
5	98.82	93.94	91.38	97.39
6	99.07	99.01	95.72	99.04
7	95.18	89.03	94.03	88.93
8	99.84	90.54	98.48	93.18
9	95.93	93.94	99.10	95.49
10	97.93	96.19	89.49	97.93

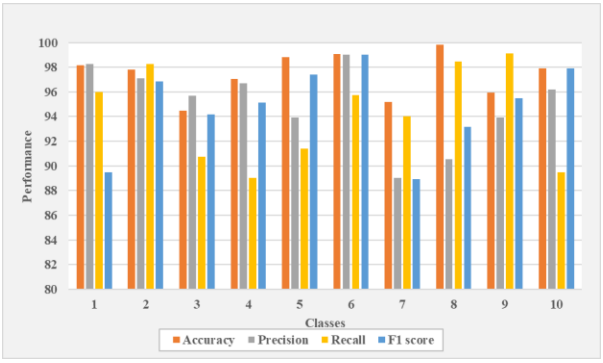
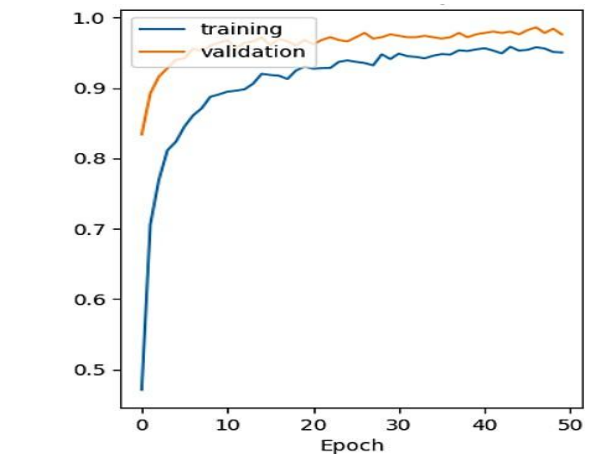
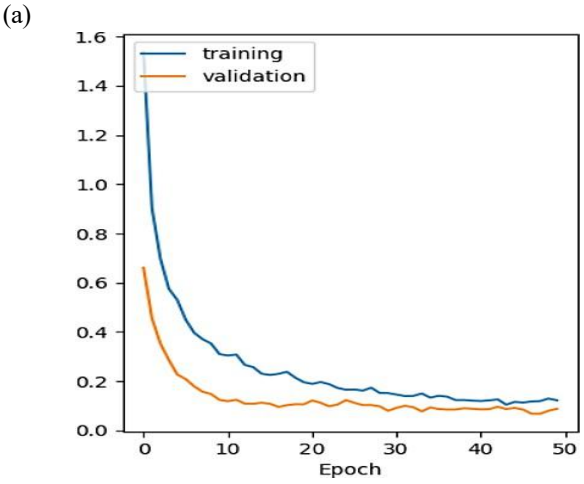


Figure 4. Performance evaluation of the proposed Model

Each class consists of cropped images, and a total of gathered images are used in total as the cropped image data collection. The input data is separated as training and testing set with 80% and 20% data respectively. The model hyperparameters are adjusted while the ideal weights are retained. The overall accuracy attained by the proposed model is 97.42% for 10 different classes of saree texture.



(a)



(b)

Figure 5. (a) Accuracy curve and (b) Loss curve of the proposed model

In Figure.5 (a), the accuracy curve was outlined with epochs on the horizontal axis and the accuracy on the vertical axis. As the number of epochs increases, the accuracy of the VGG-16 progresses. Figure.5(b) shows the epochs and loss range that reveals when the epochs are increased than the loss

of the VGG-16 decreases. The proposed VGG-16 achieves high accuracy range for classifying the various textures.

4.2 Comparative analysis

The efficiency of traditional networks was measured for validating that the results of the proposed Model attain high accuracy. This assessment was conducted in contrast with the proposed Mask RCNN and conventional networks Fast RCNN, and Faster RCNN.

Table 2. Comparison of patch generation networks

Networks	Accuracy	F1 score	Precision	Recall
Fast R-CNN	92.8	89.14	93.51	92.58
Fast R-CNN	93.40	91.02	88.98	93.87
Mask R-CNN	97.42	96.98	98.84	95.94

The proposed Mask R-CNN model is contrasted with three current strategies in a comparative analysis. The effectiveness of DL models as a whole is contrasted with the proposed approach in Table.2. The Mask R-CNN is contrasted with DL techniques such as Fast RCNN and Faster RCNN. Performance evaluation was based on various metrics like precision, recall, and accuracy of the DL technique. However, conventional networks have performed less well than the proposed networks. Mask R-CNN progresses the detection accuracy by 3.82%, and 4.36%, better than Fast R-CNN, and Faster R-CNN respectively.

Table 3. Comparison of texture classification networks

Networks	Accuracy	F1 score	Precision	Recall
AlexNet	95.81	94.08	91.28	90.83
LeNet	94.48	93.69	92.73	92.20
VGG-16	97.42	95.03	93.68	94.76

The proposed VGG-16 is contrasted with three current strategies in a comparative analysis. The effectiveness of DL models as a whole is contrasted with the proposed approach in Table3. The VGG-16 is contrasted with DL techniques such as AlexNet and LeNet. Performance evaluation was based on various metrics like precision, recall, and accuracy of the DL technique. However, conventional networks have performed less well than the proposed networks. The proposed VGG-16 progresses the detection accuracy by 1.65%, and 3.10%, better than AlexNet and LeNet respectively.

Table 4. Comparison of state-of-the-art techniques and proposed model

Authors	Method	Accuracy
Xiang, J., et al., (2019) [17]	Deep CNN	82.9%
Shin., et al., (2023) [18]	Improved CNN	92.87%
Alotaibi, (2020) [19]	Deep Auto DNN	93.4%
Proposed model	MaskRCNN	97.41%

From table.4, the performance criterion was used to compare various state-of-the-art techniques based on their accuracy for texture classification. To evaluate the efficacy of numerous approaches, the experimental period of testing images from the attained gathered dataset in the testing stage was calculated as shown in Table 5. However, the traditional networks not performed well than Model. The proposed Model increases the overall accuracy range by 14.8%, 4.54%, and 4.01% better than Deep CNN [17], Improved CNN [18], and DeepAuto DNN [19] respectively. However, the prior networks were not processed better contrasted to the proposed Model. From Table 3 it is clear that our novel network is higher than the prior methods. So, the determined fallouts of the proposed technique are highly reliable for identifying the texture of sarees.

5. CONCLUSION

This work presents a deep learning-based saree texture classification framework for the rapid classification of saree textures. Deep learning-based segmentation is used to detect visual texture and identify sarees from collected images. For better understanding the introduction of Mask RCNN was used for generating the saree patches. To categorize saree textures, we propose a deep learning-based VGG-16 network. According to the findings, this pipeline performs better than the current deep learning methods and achieves 97.41% accuracy for identifying the texture of sarees. From the analysis, the proposed Mask R-CNN progresses the detection accuracy by 3.82%, and 4.36%, better than Fast R-CNN, and Faster R-CNN respectively. The proposed Model increases the overall accuracy range by 14.8%, 4.54%, and 4.01% better than Deep CNN, Improved CNN, and DeepAuto DNN respectively.

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