

# Vastradarpana A Novel Method to Detect Saree Using Image Processing Techniques

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**Abstract**—Identifying authenticated sarees through human vision and feel is a challenging aspect. Secondly Saree industry is multibillion businesses in Indian Industry. Each silk saree cost range from Rs 10000 to Rs 500000. Every consumer tries to identify authenticated saree before purchasing. With today's technology changes we have prepared novel approach to detect the authentication of the saree. This work offers a method for classifying and detecting saree types using computer vision techniques. The visual features of sarees are classified by machine learning and image processing; preprocessing improves the classification model. With the use of region based CNNs (RCNN) extract texture features that are essential for differentiating Kanchivaram Silk Sarees. The model ensures stability across datasets and training conditions, as demonstrated by experimental findings that show its improved accuracy and speed over traditional deep learning techniques. This research increases computer vision in apparel recognition and categorization with applications in e-commerce and fashion recommendation.

**Keywords**—Sarees, Kanchivaram, Rcn, Tensorflow

## 1. INTRODUCTION

Many domains have seen a paradigm shift as a result of the incorporation of deep learning techniques, most notably computer vision and pattern recognition. The textile sector, where traditional clothing like sarees maintains significant cultural and artisanal value globally, is one such benefactor of these improvements. Accurately identifying the many sorts of sarees is important in many situations, which calls for creative solutions. The novel use of convolutional neural networks (CNNs) to differentiate between cotton, chiffon, and Kanjivaram silk sarees is shown in this paper.

Kanjivaram silk sarees offer a special challenge, although cotton and chiffon sarees are clearly distinguished by their different textures and weaving patterns. renowned for their elaborate patterns and sumptuous However, they closely resemble other types

of silk, making human identification methods more difficult and prone to mistakes. Consequently, an automated system that makes use of CNNs becomes essential.

To tackle this problem, we provide a CNN-based method that uses TensorFlow to analyze a variety of datasets that include pictures of cotton, chiffon, and non-silk textiles. A particular focus is on effectively differentiating Kanjivaram silk from other varieties of silk by improving CNN architecture to extract discriminative features from photos of sarees. Our approach's efficacy by extensive experimentation, taking into account multiple performance indicators like accuracy, precision, and recall. The results show that, even in the presence of minute visual variations, our algorithm is remarkably accurate at identifying the type of saree. Moreover, our technique improves interpretability and dependability by offering insightful information about the categorization choices.

## II. LITERATURE REVIEW

An interactive technique for segmenting clothing images using Graph Cuts and super pixels is covered in the [3]. It describes how to segment images using SLIC (Simple Linear Iterative Clustering) to turn pixels into superpixels, define clothing and non-clothing regions interactively, and solve energy function segmentation problems for clothing regions using min-cut/max-flow methods.

The creation of a program that uses deep learning

techniques to automate saree segmentation and enable independent color change of various components is the primary lesson to be learned from this work done in [7]. The technology achieves great accuracy in detecting body areas and saree borders by merging custom-trained Mask R-CNN models for precise segmentation and incorporating MODNet for background removal

Digital image processing for automatically identifying and recognizing various clothing textiles in [4]. In order to identify various fabric kinds based on factors like length, width, height, area, and perimeter ratios, it covers the extraction of fabric characteristics from 2D photos, building a feature extraction system, and evaluating fabric folds. In order to identify different types of fabrics and characterize fabric wrinkles for different materials, the study attempts to extract information about fabric wrinkles from binary and grayscale photographs.

The application of image processing methods from [11] for fabric quality testing in the textile industry is covered in the study paper. In order to increase the effectiveness and precision of fabric inspection, it suggests an automated flaw identification system that makes use of morphological filters and the Gabor wavelet network. A mechanical module with cylindrical rollers, a light source, and a camera to take pictures of the fabric for flaw detection make up the experimental setup. By automating the quality control procedure, the suggested solution seeks to save labour costs and increase defect detection precision.

Research employed in [8] a supervised LVQ neural network to train woven fabrics, and then it can effectively realize the identification and classification of these three fundamental woven fabric structures. The textural qualities of fabric can be adequately reflected by the four distinct elements of the gray-level co-occurrence matrix. When processing fabric images, the two-dimensional wavelet transform not only allows the fabric picture to be smaller

study, but it can also expedite the texture analysis process. With the help of this technique, fabric structure properties may be rapidly extracted, enabling automatic fabric detection and categorization. Furthermore, it frees the artificially employed laborers' textile sector will grow as a result of the increased opportunities for automatic fabric picture identification and categorization brought about by advances in computer technology.

### III. PROPOSED WORK

Our suggested approach uses Region-Based Convolutional Neural Networks (RCNN) in combination with Python libraries like OpenCV, TensorFlow, and Flask to create a reliable system for recognizing various sorts of sarees. Initially, we will gather a wide range of saree photos from web sources or by hand-picking them, covering all kinds, materials, hues, and designs. Next, in order to improve model resilience, we will preprocess the dataset by standardizing image resolutions and enhancing the data through transformations including flipping, rotating, and brightness modifications.

The Faster RCNN architecture will be employed in the RCNN implementation to effectively identify and pinpoint areas of interest (ROIs) in the saree photos. Furthermore, a CNN model that has already been trained, such as ResNet or VGG, will be adjusted to extract features from these ROIs, obtaining the fine information required to identify the type of saree. After that, a TensorFlow/Keras classification model will be created to group the retrieved features into various saree categories.

The process of transforming an image from full color to various degrees of grey is called grayscaling, or

grayscale conversion. A single intensity number, usually ranging from black (0 intensity) to white (maximum intensity, frequently 255 in digital photos), represents the color of each pixel in a grayscale image. When an image is converted to grayscale, its color information is eliminated while its brightness is preserved. This makes processing and analysis easier, particularly when dealing with activities where color information is not required or significant.

The technique of splitting an image into discrete areas or segments according to pixel intensity values is known as segmentation, more precisely binarization. When an image is binarized, it is transformed into a binary format in which each pixel is assigned a threshold value and is therefore classed as either black (0) or white (1).

Setting a threshold divides pixels into two groups during the binarization process: those with intensity values above the threshold turn white, and those with values below it turn black. In image processing, this method is frequently applied to problems including object detection, character recognition, and image analysis.

There are several ways to do binarization, including adaptive thresholding, which uses different thresholds for different regions of the image, and global thresholding, which applies the same threshold to the whole image.

Convolutional Neural Networks (CNN) are vital in image data analysis, extracting features that aid in object recognition and

scoring. They consist of convolution layers, activation functions like ReLu, and pooling layers (like Max Pooling) for downsampling. CNNs evolve from basic edge detection to complex feature extraction, with models like AlexNet, ZFNet, VGG, GoogLeNet, and ResNet marking significant advancements. ResNet's introduction of residual connections revolutionized deeper network training, leading to improved accuracy and efficient architectures like SENet, MobileNets, NASNet, and EfficientNet. Visualizing CNNs helps understand their learned features, aiding in model verification and interpretation of activation maps and feature descriptors.

A subset of the dataset will be used for training the model, while the remaining piece will be kept aside for testing and validation in order to guarantee generalization and performance assessment. The model's performance will be evaluated using measures like accuracy, precision, recall, and F1-score. The hyperparameters will then be adjusted for optimization. User-friendly online application development would be made possible by integration with the Flask web framework, allowing users to upload saree photos for identification.

The system will go through extensive testing after it is deployed to ensure that it functions and is accurate. Our methodology aims to give a dependable and effective solution for saree type recognition by fusing Python frameworks with sophisticated deep learning algorithms. This approach may be applied to a wide range of applications, including those in the fashion sector.

prior to classification.

Because of its accurate region proposal process, which can better handle the variety in saree kinds, RCNN may have an advantage in saree type detection. In comparison to YOLO, it may be more accurate in capturing subtleties and minute characteristics, especially when working with finely detailed classifications like saree kinds. But it's crucial to take into account elements like training data, model tuning, and computational resources for practical deployment.

#### Comparison between Yolo and Rcn

Given that RCNN can effectively capture fine-grained information, it may be superior for saree type detection. In order to ensure that possible regions holding saree details are not overlooked during detection, RCNN's Selective Search produces region proposals with good recall. Furthermore, RCNN is able to properly pinpoint saree kinds, which is essential for reliable identification thanks to its comprehensive search over region proposals. While Faster R-CNN is faster than RCNN for both training and inference, its reliance on the Region Proposal Network (RPN) for proposal generation may make it less capable of capturing fine-grained features than RCNN's Selective Search. This might lead to a marginal decrease in accuracy or the intricacies of saree type recognition being overlooked. Therefore, RCNN's comprehensive technique may be chosen for tasks requiring high precision and accurate localization despite its higher computational cost.

## COMPARITIVE CASE STUDIES

### Comparison between Yolo and Rcn

Popular object identification algorithms YOLO (You Only Look Once) and RCNN (Region-based Convolutional Neural Network) take various approaches. YOLO divides the image into grids and predicts bounding boxes and class probabilities directly, with an emphasis on speed and real-time processing. Conversely, region proposals are used by RCNN-based techniques, such as Faster R-CNN, to localize objects

## IV. SYSTEM ARCHITECTURE

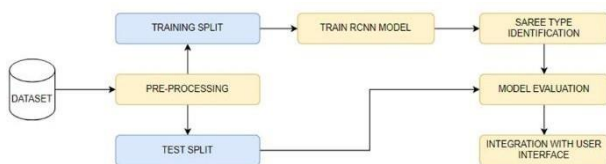
In order to get accurate classification findings and meet the needs of practical applications in the textile sector, a methodical workflow is demonstrated by the proposed architecture for saree type identification. Pre-processing is the first step, during which photos go through necessary changes such scaling, normalization, and data augmentation. These procedures are essential for getting the dataset ready

and improving the model's capacity to pick up distinguishing characteristics linked to various saree kinds. The dataset is split into separate training and testing sets after pre-processing.

This section helps the Convolutional Neural Network (CNN) model understand and generalize patterns from the data by streamlining its training and assessment. The network is subjected to the training split during CNN model training, when it gains the ability to correctly distinguish saree kinds using the extracted features. After training, the CNN model evaluates input photos and makes very accurate predictions about the matching saree type. This process is known as saree type identification. For real-time applications, where quick and precise saree identification is crucial, this functionality is vital.

In order to evaluate how well the trained CNN model is performing, model evaluation is essential. Using the testing split, performance metrics like accuracy, precision, and recall are calculated, offering valuable information on the generalization and efficacy of the model.

Ultimately, a user-friendly interface incorporates the trained CNN model to guarantee smooth communication with end users. Through this integration, stakeholders can use the model for activities like inventory management and quality control in the textile industry, which improves accessibility and usability. This design shows promise as a practical and accurate solution with a wide range of real-world applications.



**Dataset:** This is the set of saree photos that the saree type recognition model was trained and tested on. It acts as the system's main source of foundational data.

**Pre-processing:** To improve the caliber and diversity of the photos, pre-processing techniques including downsizing, normalization, and data augmentation are used prior to feeding the dataset into the model. This

**Training Split:** The training split and the test split are the two subsets that make up the dataset. A subset of the dataset used to train the Region-based Convolutional Neural Network (RCNN) model is contained in the training split.

**Train RCNN Model:** This component uses the training split data to depict the RCNN model's training phase. In this stage, the model gains the ability to identify saree types and extract features from the given photos.

**Test Split:** The performance of the trained RCNN model is assessed using the remaining fraction of the dataset, referred to as the test split. To test the model's capacity to generalize to new examples, this subset is kept apart from the training set.

**Saree Type Identification:** After training, the RCNN model can determine the kind of saree that is depicted in an input image. This part symbolizes the inference process, which is how the model forecasts things based on the features it has learned.

**Model Evaluation:** Various metrics, including accuracy, precision, and recall, are used to assess the model's performance once it has made predictions on the test split. This stage helps pinpoint areas in need of improvement and offers insights about the model's efficacy.

**Integration with User Interface:** The last phase is integrating the user-friendly interface that has been trained with the learned model to facilitate user interaction with the system. Users may submit saree photos through this interface, and the system provides correct identifications; this makes it practical and accessible for real-world use cases.

## v. RESULTS

The above image compares the accuracy of saree recognition for three different types: cotton, chiffon, and non-silk (Kanjivaram Zari). The accuracy level attained by the detecting method for

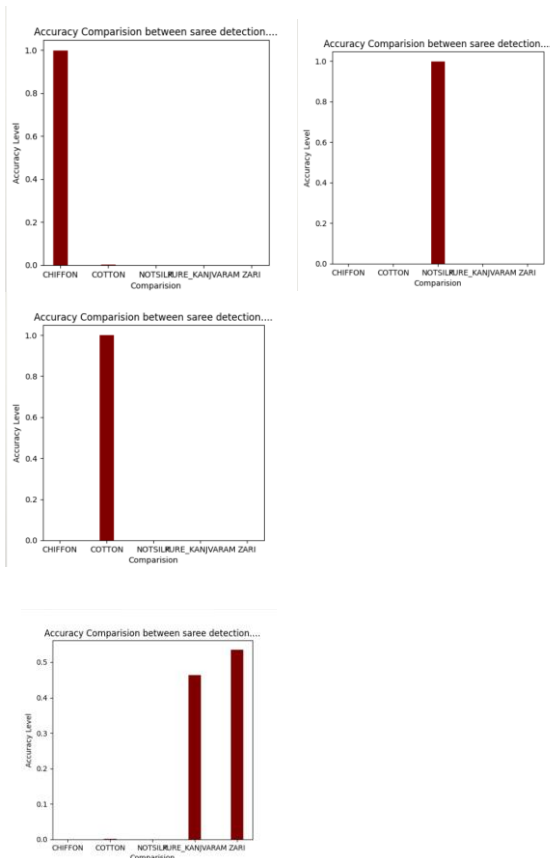


every type of saree is shown on the graph.

The accuracy level is represented by the vertical axis, which has a range of 0 to 1, with 1 denoting the maximum precision. Every horizontal bar represents a distinct type of saree, and the length of the bar signifies the accuracy level attained for that specific variety.

It is clear from the comparison that the detection method performs noticeably better at distinguishing non-Silk (Kanjivaram Zari) sarees than Chiffon and Cotton sarees. A noticeably longer bar, corresponding to Non-Silk (Kanjivaram Zari) identification, indicates a significantly greater accuracy level.

This comparison offers insightful information about how well the saree detecting technology performs with various saree kinds. Stakeholders can evaluate the efficacy of the system in precisely distinguishing sarees made of different materials by examining the accuracy levels.



In addition, the detection system's output—which includes segmented photos, original photographs, greyscale images, and an accuracy comparison graph—allows users to decide how best to classify sarees. With the help of the visual representation of accuracy levels, users may confidently identify the type of saree based on the findings that are presented.


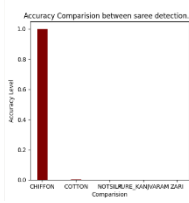
All things considered, the detection system shows promise, especially when it comes to correctly recognizing Non-Silk (Kanjivaram Zari) sarees, which helps to increase work efficiency for saree type identification.

## VI. TESTING

Testing is the process of evaluating a system or its component(s) with the intent to find whether it satisfies the specified requirement or not. Testing is executing a system in order to identify any gaps, errors, or missing requirements in contrary to the actual requirements. Testing is one of the most challenging steps of the software development process. It requires close attention to detail and cannot be completed if you don't apply a methodical approach

### Testcase 1

Provide a saree image with a known type, such as a cotton or silk. system correctly identifies and extracts the feature with high accuracy.

Input image	Output image	Result
		Pass

## VII. CONCLUSION

The suggested saree type detection project provides a thorough solution by utilizing Python frameworks and cutting-edge deep learning algorithms. The research attempts to reliably classify saree kinds based on many parameters like fabrics, colours, and designs through careful data pretreatment and model training. The system detects regions of interest for categorization and efficiently extracts information from saree images by utilizing pre-trained CNN models and Region-Based Convolutional Neural Networks (RCNN). Accurate classification of sarees is ensured through integration with TensorFlow/Keras, which improves the classification process even more.


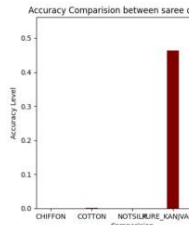
Metrics for performance evaluation verify the model's efficacy and capacity for generalization, and end users can easily use it thanks to its intuitive connection with the Flask web framework. The project has the ability to transform saree classification procedures and boost productivity in the textile sector, as demonstrated by its methodical workflow and comprehensive post- deployment testing. All things considered, the suggested method for saree type recognition seems promising, and it has potential uses in the fashion industry as well as other fields.

## REFERENCES

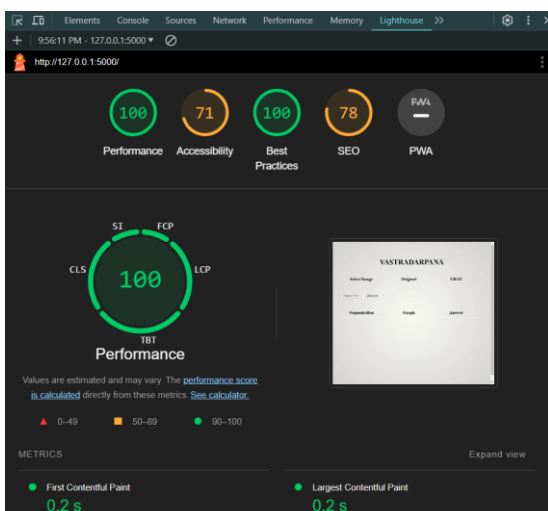
- [1] W. Jianxia, Z. Guang, M. Hongxia and Q. Min, "Feature Extraction of the Fabric Image," 2007 8th International Conference on Electronic Measurement and Instruments, Xi'an, China, 2007, pp. 2-714-2-717, doi: 10.1109/ICEMI.2007.4350781.
- [2] Y. Worku, B. H. Belay and B. Tadege, "A Multitask Learning Approach for Habesha Fashion Cloth Recognition and Classification," 2023 International Conference on Information and Communication Technology for Development for Africa (ICT4DA), Bahir Dar, Ethiopia, 2023, pp. 85-89, doi: 10.1109/ICT4DA59526.2023.10302242.

### Testcase 2

Provide a saree image with a known type but having subcategory in it  
system correctly identifies and provide result as average of both with maximum accuracy

Input image	Output image	Result
		Pass

### Website performance testing results



- [3] L. Weilong, "Interactive Clothing Image Segmentation Based on Superpixels and Graph Cuts," 2013 International Conference on Computer Sciences and Applications, Wuhan, China, 2013, pp. 659-662, doi: 10.1109/CSA.2013.160...
- [4] Z. Zhao and Y. Zhou, "Clothing Fabric Automatic Recognition," 2018 10th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC), Hangzhou, China, 2018, pp. 24-27, doi: 10.1109/IHMSC.2018.00014.
- [5] N. Sajitha and S. P. Priya, "Artificial Intelligence based Optimization with Extreme Gradient Boosting for Fabric Defect Detection and Classification Model," 2023 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS), Erode, India, 2023, pp. 509-515, doi: 10.1109/ICSCDS56580.2023.10104910.
- [6] Seo, Y., & Shin, K. S. (2019). Hierarchical convolutional neural networks for fashion image classification. *Expert Systems with Applications*, 116, 328-339. <https://doi.org/10.1016/j.eswa.2018.09.022>
- [7] N. Karanth et al., "Automatic Classification and Color Changing of Saree Components Using Deep Learning Techniques," in *IEEE Access*, vol. 12, pp. 9586-9593, 2024, doi: 10.1109/ACCESS.2024.3352649...
- [8] Z. Zhao and Y. Zhou, "Clothing Fabric Automatic Recognition," 2018 10th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC), Hangzhou, China, 2018, pp. 24-27, doi: 10.1109/IHMSC.2018.00014....
- [9] Mehta and R. Jain, "An Analysis of Fabric Detection Techniques for Textile Industry Quality Control," 2023 World Conference on Communication & Computing (WCONF), RAIPUR, India, 2023, pp. 1- 5, doi: 10.1109/WCONF58270.2023.10235154.
- [10] C. da Silva BarrosM, E. Firmeza Ohata, S. P. P. da Silva, J. Silva Almeida and P. P. Rebouças Filho, "An Innovative Approach of Textile Fabrics Identification from Mobile Images using Computer Vision based on Deep Transfer Learning," 2020 International Joint Conference on Neural Networks (IJCNN), Glasgow, UK, 2020, pp. 1-8, doi: 10.1109/IJCNN48605.2020.920690
- V. Agilandeswari, J. Anuja, E. D. George and R. Prasath, "Fabric quality testing using image processing," International Conference on Information Communication and Embedded Systems (ICICES2014), Chennai, India, 2014, pp. 1-4, doi: 10.1109/ICICES.2014.7033989.