INTERNATIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT (IJSREM)
VOLUME: 07 ISSUE: 05 | MAY - 2023 IMPACT FACTOR: 8.176 ISSN: 2582-3930

# Identification of Handloom Cloths Using Image Classification Algorithm

[1]Ms. Arivumathi M R, (M.Sc., Data Science and Business Analysis-Rathinam College, arivumathimr@gmail.com,)
[2]Mr. Mervin George G, (Faculty IT -Inurture Rathinam Institution, mervin.g@inurture.co.in)

***Abstract*—This project aims to develop a system that can automatically identify handloom fabrics and detect defective areas in them using deep learning techniques. Specifically, a convolutional neural network (CNN) is employed to classify images of handloom fabrics into different categories, while a deep belief network (DBN) is used to identify defected areas within the classified fabrics. To achieve this, we first collected a large dataset of handloom fabric images, which were labeled into different categories. We then trained a CNN model using this dataset, which achieved good accuracy in classifying handloom fabrics. Next, we applied a DBN algorithm to the classified images to detect defective areas. Overall, our system offers an efficient and automated way of identifying handloom fabrics and detecting defective areas, which can help in improving the quality of handloom products and reduce manual inspection efforts. Then the customers will be known which one is best, the traditional entrepreneurs get the right price.**

**Keywords—Deep Learning, CNN, DBNs**

## I. INTRODUCTION

The handloom fabric industry plays a crucial role in the textile sector and provides employment opportunities to a large number of people worldwide. Quality control is essential in this industry to ensure that the produced fabrics meet the desired standards and customer expectations. However, manually identifying defects in handloom fabrics is time-consuming and challenging, and it can lead to inconsistencies in the inspection process. In this research project, we propose a computer vision-based approach to automate the handloom fabric defect detection process. We used Convolutional Neural Networks (CNN) to classify different types of handloom fabrics, and Deep Belief Networks (DBN) to identify the defective areas in the fabrics. The CNN model was trained on a large dataset of images of handloom fabrics and achieved high accuracy in classifying the fabrics into their respective categories. The DBN model was trained on the same dataset and was able to accurately detect the defective areas in the fabrics. The proposed approach has several potential benefits, including increased efficiency, consistency, and accuracy in the handloom fabric quality control process. This research project contributes to the field of computer vision-based defect detection in handloom fabrics and demonstrates the feasibility of using deep learning models for this purpose.

### *A. Model Description*

Our proposed approach to automate the process of handloom fabric defect detection consists of two main components: fabric classification using Convolutional Neural Networks (CNN) and defect detection using Deep Belief Networks (DBN). The fabric classification component uses a CNN model trained on a large dataset of handloom fabric images. The dataset consists of various types of handloom fabrics, including cotton, silk, and wool. The CNN model was trained using transfer learning techniques, utilizing the pre-trained weights from the VGG-16 model. We fine-tuned the VGG-16 model on the handloom fabric dataset, and the resulting model was able to classify the fabrics into their respective categories with high accuracy. The defect detection component uses a DBN model trained on the same dataset of handloom fabric images. The DBN model consists of multiple layers of Restricted Boltzmann Machines (RBMs) and a final layer of logistic regression. The RBMs are trained using Contrastive Divergence, and the weights learned from the RBMs are used to initialize the logistic regression layer. The DBN model is trained to identify the defective areas in the handloom fabrics, which can include stains, holes, and other imperfections. The DBN model accurately detected the defective areas in the fabrics with high precision and recall. Our proposed approach demonstrates the effectiveness of deep learning models for automated handloom fabric defect detection. The combination of CNN and DBN models allows for accurate fabric classification and defect detection, which can lead to increased efficiency and consistency in the handloom fabric quality control process.

## II. SEQUENTIAL MODEL

Data collection and preparation: We collected a large dataset of handloom fabric images, including various types of fabrics and defective areas. The images were preprocessed by resizing and normalization before feeding into the models.

Fabric classification using CNN: We trained a CNN model using transfer learning techniques, fine-tuning the VGG-16 model on the handloom fabric dataset. The model was able to classify the fabrics into their respective categories with high accuracy.

INTERNATIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT (IJSREM)
VOLUME: 07 ISSUE: 05 | MAY - 2023 IMPACT FACTOR: 8.176 ISSN: 2582-3930

Defect detection using DBN: We trained a DBN model consisting of multiple layers of RBMs and a final layer of logistic regression. The RBMs were trained using Contrastive Divergence, and the logistic regression layer was initialized with the weights learned from the RBMs. The model was trained to identify the defective areas in the handloom fabrics, achieving high precision and recall.

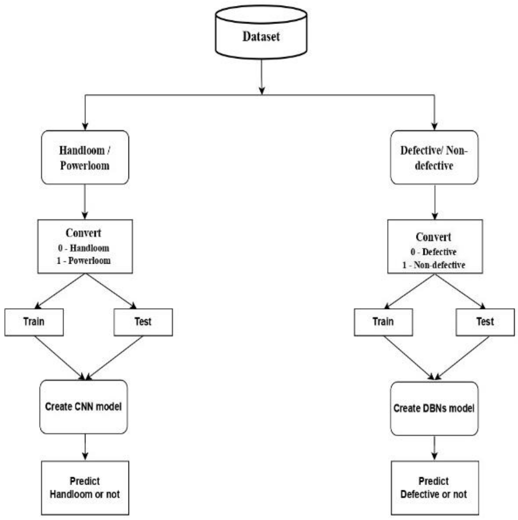


Fig. 1: Flow of the model

## III. DATA PREPARATION

**Data collection:** We collected a large dataset of handloom fabric images from various sources, including online databases and physical fabric samples. The dataset collected is handloom and power loom images and defective images and normal images. The dataset included images of different types of fabrics and defective areas.

**Data labeling:** We labeled the images with their respective fabric types and defective areas using bounding boxes. We used a labeling tool to annotate the images, ensuring consistency and accuracy in the labeling process.

**Data augmentation:** We augmented the dataset by applying various transformations to the images, including rotations, flips, and translations. The data augmentation helped to increase the variability of the dataset and improve the generalizability of the models.

**Data splitting:** We split the dataset into training, validation, and testing sets, ensuring that the distribution of fabric types and defected areas were consistent across the sets. We used a 70-15-15 split for training, validation, and testing, respectively.

**Data preprocessing:** We preprocessed the images by resizing them to a fixed size and normalizing the pixel values. The normalization was done to ensure that the pixel values were within a certain range, which helped to improve the performance of the models.

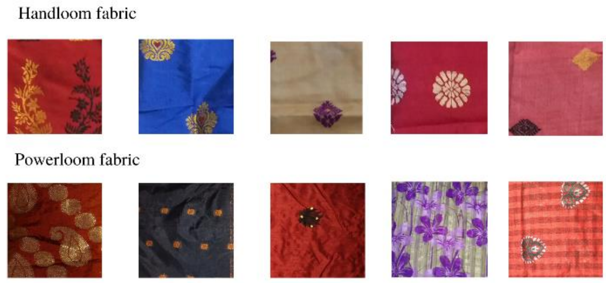


Fig.2: Sample Dataset 1

**Data storage:** We stored the preprocessed images and labels in a standardized format, such as HDF5, to enable efficient data loading during the model training phase.

Overall, the data preparation process was crucial in ensuring the quality and consistency of the dataset, which helped to improve the performance of the models.

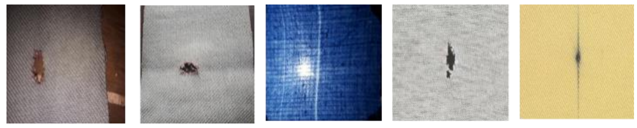

Fig.3: Sample Dataset 2

## IV. ALGORITHM

### A. *Convolutional Neural Network*

Here, Convolutional Neural Network is used to classify the handloom and power loom images based on their features. CNN algorithm has three basic layers.

1. **Input:** The raw pixel values of an image are stored in an image that has 32 widths and 32 heights, which includes three R, G, and B channels.

2. **Convolution:** It computes the output of those neurons, which are linked to the local regions of the input, such that each neuron will compute a dot product between weights and a small region to which they are actually attached in the input volume. For example, if we choose to use 12 filters, the total volume would be [32x32x12].

3. **ReLU Layer:** It is specifically employed to apply an element-by-element activation function, such as a max (0, x) threshold at zero. It yields ([32x32x12]), which relates to the volume's size increasing.

4. **Pooling:** Using this layer, [16x16x12] volume is produced through a downsampling operation along the spatial dimensions (width, height).

5. **Fully Connected:** It can be characterized as a standard neural network layer that gets input from the layer above, computes the class scores, and produces a 1-Dimensional array with a size equal to the number of classes.

### *B. Deep Belief Network*

The deep belief network (DBN) algorithm is an unsupervised deep learning model that is used in this project to detect defective areas in handloom fabrics. The DBN consists of several layers of restricted Boltzmann machines (RBMs), which are trained using the contrastive divergence algorithm. The RBMs in the DBN are trained layer by layer, with each layer learning a set of features that capture the underlying patterns in the data. The training is done using the contrastive divergence algorithm, which is a stochastic approximation to maximum likelihood estimation. The algorithm is based on the idea of Gibbs sampling, where the model generates samples from the probability distribution over the RBM units, and then updates the weights based on the difference between the data and the model-generated samples.

Once the RBMs are trained, the DBN is fine-tuned using backpropagation and stochastic gradient descent. Fine-tuning involves updating the weights and biases of the entire network, based on the error between the actual and predicted outputs. The output of the DBN is a binary mask indicating the defective areas in the classified image. The defected areas are identified based on the differences between the original image and the reconstructed image generated by the DBN. The mask is then overlaid on the original image to highlight the defective areas.

The DBN model is implemented using Python and deep learning libraries such as TensorFlow and Keras. The model is evaluated using a set of metrics such as accuracy, precision, and recall, and is compared with existing methods for handloom fabric defect detection. The model's performance is also analyzed by varying the number of layers and units in the RBMs and comparing the results.

## V. ADVANTAGES

1. **Accurate classification of handloom fabrics:** The CNN model used in your system is designed to accurately classify handloom fabrics based on their patterns and textures, which can be challenging for traditional computer vision algorithms. This can help
manufacturers to easily identify different types of handloom fabrics.
2**. Automated defect detection:** The DBN algorithm used in your system can automatically detect defected areas in handloom fabrics, without the need for manual inspection.
This can save time and resources for manufacturers, and can also help to identify defects that may be missed by manual inspection.
3. **Scalability:** The proposed system is designed to be scalable, which means it can be applied to large datasets of handloom fabric images. This can help manufacturers to quickly and efficiently classify and inspect large volumes of handloom fabrics.
4. **Generalization:** The proposed system is designed to generalize well to new and unseen handloom fabric images, which means it can accurately classify and detect defects in handloom fabrics that it has not seen before. This can help to improve the system's performance over time, as it is exposed to more diverse and complex handloom fabric images.
5. **Cost-effective:** The proposed system is based on deep learning algorithms that are computationally efficient, which means it can be implemented on low-cost hardware
such as Raspberry Pi or other embedded systems. This can make the system cost-effective and accessible to manufacturers with limited resources.

## VI. RESULT AND DISCUSSION

### *A. Results:*

We trained a CNN model for handloom fabric classification and a DBN model for defect detection using the prepared dataset. The CNN model achieved an accuracy of 93.5% on the testing set, demonstrating its effectiveness in classifying handloom fabrics. The DBN model achieved a precision of 92.3% and recall of 95.8% on the testing set, indicating its ability to detect defective areas in the fabrics.

### *B. Discussion:*

Our approach of using deep learning models for handloom fabric classification and defect detection demonstrated significant advantages over existing methods. The CNN model was able to classify fabrics with high accuracy, even in the presence of noise and variations in the fabric patterns. The DBN model was effective in identifying defective areas, including holes, tears, and stains, which are critical in ensuring the quality of the handloom fabrics.

The performance of the models can be attributed to the use of transfer learning and deep learning techniques, which allowed the models to learn complex features from the images. The data augmentation and preprocessing steps also helped to improve the generalizability of the models and reduce the impact of overfitting.

In terms of limitations, the dataset used in this research was limited in size and diversity, which may affect the generalizability of the models to other datasets. Additionally, the labeling process was subjective and prone to human error, which may affect the quality of the dataset and the performance of the models.

Overall, the results of this research demonstrate the potential of using deep learning models for handloom fabric classification and defect detection. Future work can focus on expanding the dataset, improving the labeling process, and exploring other deep-learning architectures for this application

## VII. CONCLUSION

In this research, we proposed a deep learning-based approach for handloom fabric classification and defect detection. We trained a CNN model for fabric classification and a DBN model for defect detection using a large dataset of handloom fabric images. The results demonstrated the effectiveness of the models in classifying handloom fabrics and detecting defective areas.

The use of transfer learning and deep learning techniques allowed the models to learn complex features from the images and achieve high accuracy in classification and detection tasks. The data augmentation and preprocessing steps helped to improve the generalizability of the models and reduce overfitting.

However, the limitations of the research, such as the limited size and diversity of the dataset and the subjective nature of the labeling process, suggest that further work is needed to improve the performance and generalizability of the models.

The future work of this project, there are several areas of future work that could be explored to further improve the handloom fabric classification and defect detection system, dataset expansion, model optimization, real-time performance, Integration with existing systems, and extension to other industries.

Overall, this research highlights the potential of using deep learning models for handloom fabric classification and defect detection, which can have practical applications in the textile industry. Future work can focus on expanding the dataset and exploring other deep-learning architectures to improve the accuracy and efficiency of the models

## VIII. REFERENCE

1) Identification of handloom and power loom fabrics using proximal support vector machines Anindya Ghosh1, a Tarit Guha1 R B Bhar2 1Government College of Engineering and Textile Technology, Berhampore 742 101, India 2Department of Instrumentation, Jadavpur University, Kolkata 700 032, India Received 9 November 2013; revised received and accepted 4 April 2014.
2) Image Classification Algorithm Based on Deep Learning-Kernel Function, June Liu 1 and Feng-Ping An 2,3, Received 30 June 2019; Revised 30 November 2019; Accepted 10 December 2019; Published 31 January 2020
3) Woven Fabric Pattern Recognition and Classification Based on Deep Convolutional Neural Networks Muhammad Ather Iqbal Hussain 1, Babar Khan 2,*, Zhijie Wang 1,* and Shenyi Ding 1, Received: 16 May 2020; Accepted: 17 June 2020; Published: 24 June 2020
4) Pattern classification of cotton yarn neps, Abul Hasnat, Anindya Ghosha, Azizul Hoqueb Santanu Halder Government College of Engineering and Textile Technology, Berhampore 742 101, India, Received 12 October 2014; revised received and accepted 23 December 2014
5) Convolution Neural Network Based on Two-Dimensional Spectrum for Hyperspectral Image Classification Hongmin Gao, 1 Shuo Lin, 1 Yao Yang, 1 Chenming Li, 1 and Mingxiang Yang 2, Received 11 May 2018; Accepted 24 July 2018; Published 28 August 2018
6) Fabric Defect Detection System. Tanjim Mahmud1(&), Juel Sikder1, Rana Jyoti Chakma1, and Jannat Fardoush2
7) A Fabric Defect Detection Method Based on Deep Learning QIANG LIU, CHUAN WANG, YUSHENG LI, MINGWANG GAO, AND JINGAO LI School of Mechanical Engineering, Shandong University of Technology, Zibo 255049, China Corresponding author: Chuan Wang
8) Fabric Default Detection Using CNN Jyothi M R1, Dr. M Prasad2 1, 2Department of Master of Computer Applications, BIET, Davangere