Fabric Property and Defect Detection using Deep Learning Model

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***Abstract*— Textile manufacturing errors waste a lot of resources and lower the quality of the end products [2]. Visual image analysis using machine learning (ML) techniques may be quite useful in identifying fabric properties and defects. One of the most essential and difficult computer vision jobs in textile smart manufacturing is the automatic fault evaluation of these fabric materials. The objective of the proposed work is to develop effective deep learning models that are trained on fabric photos for quick fabric property and defect identification Convolutional Neural Network (CNN). A modified CNN architecture is used for the fault detection procedure. If the device detects a probable fault in the cloth roll, it stops operating and alerts the adjacent operator who then decides whether to accept or reject the results of the system evaluation, provides the go-ahead for the process to proceed, and switches to the next fabric picture. These findings demonstrate a system that can operate swiftly and effectively while precisely identifying a wide range of faults.**

Keywords— Fabric Materials, Convolutional Neural Network (CNN), Deep Learning.

I. INTRODUCTION

An emerging technology known as machine learning makes it possible for computers to learn autonomously from historical data. Machine learning employs a variety of techniques to create mathematical models and make predictions based on previous knowledge or data.

The spinning, weaving, dying, printing, and finishing procedures, as well as the production of clothing, are all part of the intricate and well-organized process of making fabric in the textile industry. The fabric quality, mechanical considerations, dye type, yarn size, and human factors are only a few of the variables that affect the final product in the textile production line.

In order to examine fabric faults, the textile industry is in great need of an automated and accurate system that can replace labor-intensive, sluggish, inconsistent, and expensive human operators. The most important factor for companies who manufacture textiles is quality control. A traditional technique results in an inspection accuracy of between 60 and 75 percent. It has always been challenging to detect distortion in woven cloth by manual visual inspection.

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II. LITERATURE SURVEY

First, This application was created using/inspiration from the following papers:

In their study "Complex Pattern Jacquard Fabrics Defect Detection Using Convolutional Neural Networks and Multispectral Imaging," M. Sayed et al. In order to detect fabric defects, a new and innovative discipline is presented in this study. Because there aren't any accessible datasets for jacquard textiles, we created and tested on our own unique dataset. For the unsupervised identification of flaws, they utilize and analyses a variety of deep learning models using image pre-processing and convolutional neural networks (CNNs). They recommend two systems: a semi-manual device that uses a simple CNN community for operation on different patterns and an integrated computerized device that uses modern CNN architectures to operate on the whole dataset with the exception of previous sample specification. Contrast-limited adaptive Histogram Equalization (CLAHE), a preprocessing technique, is used to enhance the pictures' characteristics [1]. It is concluded that deep gaining knowledge is environment friendly and can be used for defect detection in complicated patterns. Proposed technique of Efficient Net CNN gave excessive accuracy attaining 99% approximately.[3]

The purpose of Kuan-Hsien Liu et al paper “Unsupervised UNet for Fabric Defect Detection” is to study and explain a neural community primarily based technique for material floor defect detection is proposed. By coaching wonderful smooth samples, it can examine the neural community barring gathering poor faulty samples, which significantly shortens the touchdown time of the total system. The proposed gadget attains 99% detection accuracy.[4]

"Image Blind Denoising with Generative Adversarial Network Based Noise Modeling," by Jingwen Chen et al. considers a usual picture blind denoising problem, which is to do away with unknown noise from noisy images. Discriminative learning-based approaches, such DnCNN, can obtain the most recent denoising findings, but they are no longer applicable to this issue because there aren't any associated coaching data. A method is put out to overcome the obstacle—a brand-new two-step structure. In order to predict the noise distribution across the input noisy images and to produce noise samples, a Generative Adversarial Network (GAN) is first trained. Second, a paired education dataset built from the noise patches acquired in the first stage is used to train a deep convolutional neural network (CNN) for denoising.[5]

"Fabric defect detection with LBP-GLMC," by O. Kaynar et al. discusses that fabric defect detection is quintessential for material quality. In the face of growing material production, the truth that the detection of material faults with the aid of manpower is inadequate in phrases of pace and fantastic has pressured corporations to work with automated structures in this area.

In this study, statistics units bought by way of making use of neighborhood binary sample and grey stage co-occurrence matrix characteristic extraction techniques on Tilda cloth records are skilled with synthetic neural networks and two exclusive fashions are created and success charges are compared.[6]

III. METHODOLOGY

Before The Deep Learning convolution neural network algorithm is used to create the suggested system and train and identify the fabric patterns and flaws.

To accurately identify the colors of the cloth, the suggested system also employs the OpenCV framework and RGB color palette dataset. This model enables the system to detect the cloth pattern and the defect with higher accuracy level.

Algorithm :

Step 1: Preprocessing of the data

Step 2: Applying CNN on the training set

Step 3: Predicting the outcome of the test

Step 4: Verify the result's accuracy

Step 5: Visualizing the results of the test set

IV. SYSTEM MODEL

The system uses a dataset of approximately 4500 fabric images that are preprocessed, later to which a deep learning convolutional neural network algorithm to train and classify the fabric patterns and defects is implemented.

The proposed system has the following modules:

- Import the dataset.
- Perform dataset pre-processing.
- Train the dataset and create the model file.
- Classification of converted images through CNN and evaluating results.

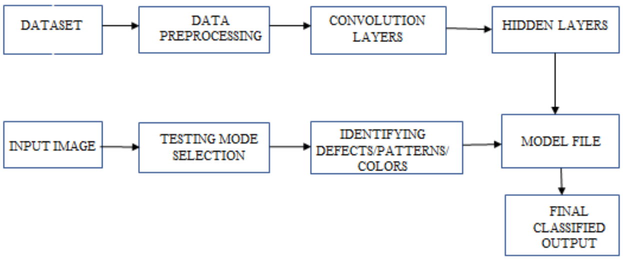

Fig 4.1: Workflow of fabric defect and pattern detection

A. *Deep Learning Algorithm*

Deep learning techniques have recently been widely used by researchers to tackle segmentation and classification challenges as well as defect identification concerns. Right now, there are two types of deep learning-based object detectors: one-stage detectors and two-stage detectors. Classical deep studying algorithms for object detection are listed in Table 1.

One-stage detectors	Two-stage detectors
YOLO	Faster RCNN
SSD	Mask-R CNN
YOLO v2/v3/v4	Cascade RCNN
RefineDet	FPN
Retina Net	R-FCN

Table 4.1: Deep learning object detection techniques.

One-stage detectors often have a rapid detection speed to satisfy the demands of online detection, but the detection accuracy frequently falls short of expectations. The two-stage algorithms, in contrast, offer better detection accuracy but struggle to identify objects quickly enough to match the real-time requirements of the algorithm in production situations. The advantages and disadvantages of one-stage and two-stage detection algorithms in the domain of textile defect identification are very equivalent to those in other fields.

Compared to the one-stage method, the two-stage algorithm is more accurate but moves more slowly. Under the assumption of pleasant detecting accuracy, we hope that the faster the detection speed, the better it will be in the actual usefulness of the material business.

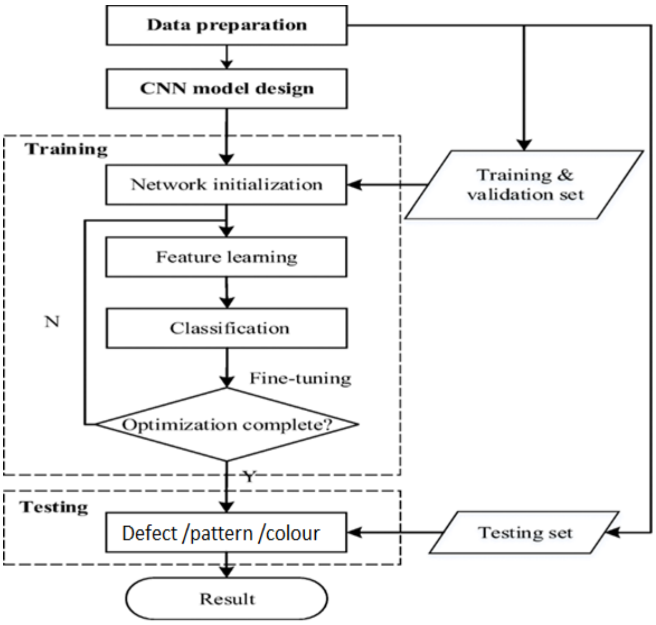

Fig 4.2 : Sequence diagram of color and pattern recognition system

B. *CNN Algorithm*

After the Dataset is preprocessed and trained, they are tested using the CNN algorithm.The setup of the unique CNN architecture utilized in this defect detection system is provided in this figure 3 below.

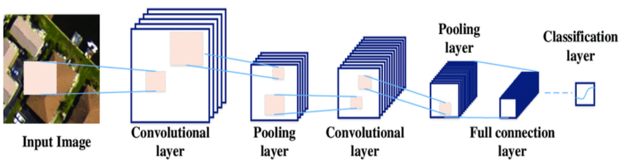

Fig 4.3 : CNN architecture 1

Instead of using other, more complex state-of-the-art deep learning models, a simpler architecture was adopted because this system needs to be able to swiftly analyze the images from multiple cameras to allow the roll to be evaluated as quickly as possible [7]. Only fault detection is carried out at this step-in order to further speed up the system, leaving defect classification for later.

C. Dataset Pre-Processing

In data pre-processing the enhancing and resizing of images is done because the dataset images are individually varied from their size so to train the data image resizing is mandatory.

Enhancing techniques: Gray scale conversion and histogram equalization.

In addition to image resizing, histogram equalization and grayscale transformation were also carried out to improve the contrasts between the items seen in the photographs. This can highlight the differences between the faulty location and the homogeneous fabric structure as shown in Figure 3 and figure 4.

Fig 4.4 : Normal image

Fig 4.5: Preprocessed image after enhancing techniques

D. Training and Testing:

The CNN training model is built once the data has been pre-processed. The training and testing process of CNN has several steps:

Step 1: Upload Dataset-Open the image file. The format of the file can be JPEG, PNG, BMP, etc. Resize the image to match the input size for the Input layer of the Deep Learning model. Convert the image pixels to float datatype.

Step 2: The Input layer is the input of the whole CNN. In the neural network of image processing, it generally represents the pixel matrix of the image.

The third step is to extract picture features using the convolutional layer. Shallow features are extracted via a low-level convolutional layer (such as edges, lines, and corners). Low-level features are sent into a high-level convolutional layer to learn more abstract features [8].

Step 4: As shown in the CNN's above structure, a Pooling layer is inserted after any Convolutional layers. It calculates the maximum or average of the input and samples the output of the Convolutional layers by sliding a filter of some size with some stride size.

Step 5: The dense layer, or strongly linked neural network layer, is the standard. The most often and widely utilized layer is this one. Dense layer performs the operation below on the input and then returns the result.

The model file is prepared after training the dataset, and during the classification test, the picture is imported and pre-processed, and CNN prediction is performed using the model file, and the result is classed.

E. Training the CNN

The CNN training model is developed using the VGG-16 Architecture following data pre-processing.The model's accuracy is enhanced by hyperparameter modification. The complexity layers, which are the fundamental building elements of a CNN and have a hierarchical structure, are used to visualize the CNN's structure in this investigation. Prior to the forecasting step, deep CNNs employ unique network circumstances and quick-fire combinations of characteristics. The first complexity layer's focus is on the input space, and the layer's output is a point chart. The following convolutional layer's input and output are point charts that represent the input space. The programmer decides how many convolutional layers to use.

All of the fabric photos in the test set are diagnosed using the CNN after it has been trained using the training set. The parameters used to gauge the effectiveness of the CNN algorithm are displayed in the table below.

	Layer Type	Output Shape	Param
Input Layer	Input	64 x 64 x 3	0
Hidden Layer 1	Conv1	64 x 64 x 32	896
	ReLU	64 x 64 x 32	0
	Pool1	32 x 32 x 32	0
Hidden Layer 2	Conv2	32 x 32 x 64	18496
	ReLU	32 x 32 x 64	0
	Pool2	16 x 16 x 64	0
Hidden Layer 3	Conv3	16 x 16 x 128	73856
	ReLU	16 x 16 x 128	0
	Pool3	8 x 8 x 128	0
Classification layer	Flatten	8192	0
	Dense1	16	131088
	ReLU	16	0
	Dense2	64	1088
	ReLU	64	0
	Dense3	128	8320
	ReLU	128	0
	Dense4	2	258

Fig 4.6: The parameters of each level for CNN.

The model file is prepared after the training dataset, and the test picture is imported and preprocessed during classification. CNN prediction is then performed using the model file, and the result is categorized.

F. Testing the Deep CNN

Following the preparation of the training dataset, the test image is imported and preprocessed in order to perform classification on it. Then, using the model file, CNN prediction is carried out, and the outcome is categorized.

Once the Convolutional neural network has been trained, all the images in the test set are diagnosed using the training set. The percentage of each diagnosis may be found for each unique case. The performance of the Convolutional neural network's suggested parameters is depicted in Figure 7 below.

$$\textbf{Precision} = \frac{\text{True Positive}}{\text{Actual Results}} \quad \text{or} \quad \frac{\text{True Positive}}{\text{True Positive + False Positive}}$$

$$\textbf{Recall} = \frac{\text{True Positive}}{\text{Predicted Results}} \quad \text{or} \quad \frac{\text{True Positive}}{\text{True Positive + False Negative}}$$

$$\textbf{Accuracy} = \frac{\text{True Positive + True Negative}}{\text{Total}}$$

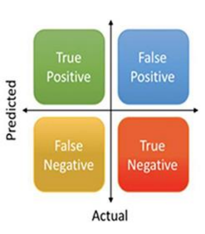

Fig 4.7: Parameters

The shortcomings of recently published research are circumvented by our study design. Loads of dataset are fed for machine learning or AI-based training in order to create effective categorization models. For the first time, augmented pictures based on effective classification models for fabric images and its flaw detection have therefore been successfully developed in the current work. The time and effort needed to construct highly accurate defect detection models were greatly reduced thanks to this method.

These observations show that the system can accurately and quickly identify a diverse array of defects while operating quickly and efficiently.

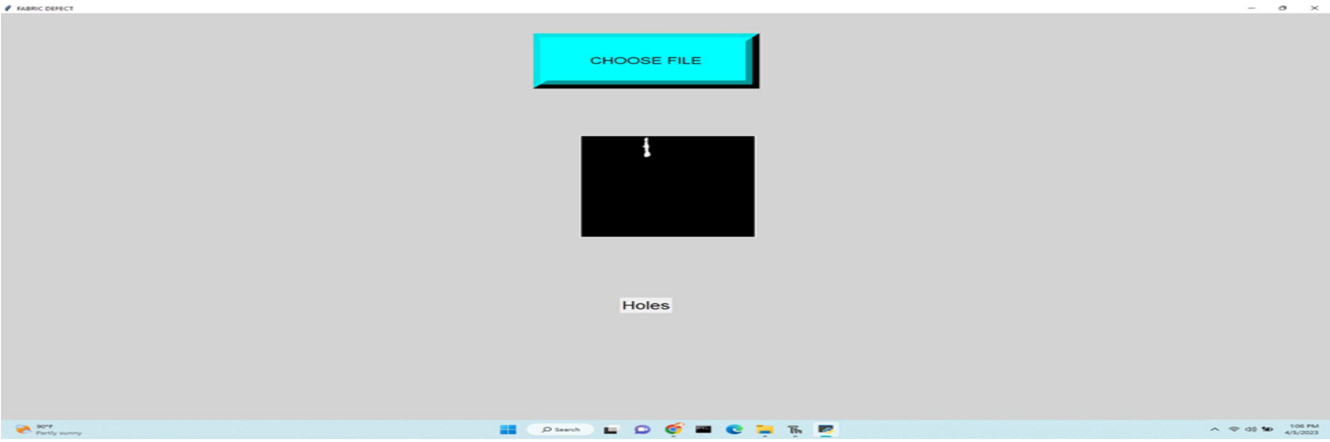

Fig 4.8: Defect from the chosen image (holes).

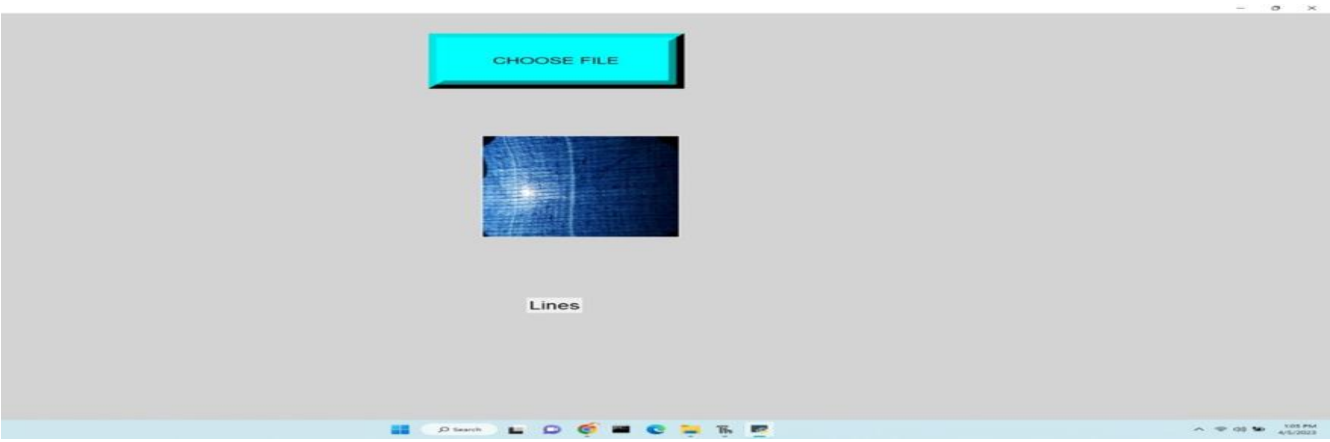

Fig 4.9: Defect from the chosen image (lines).

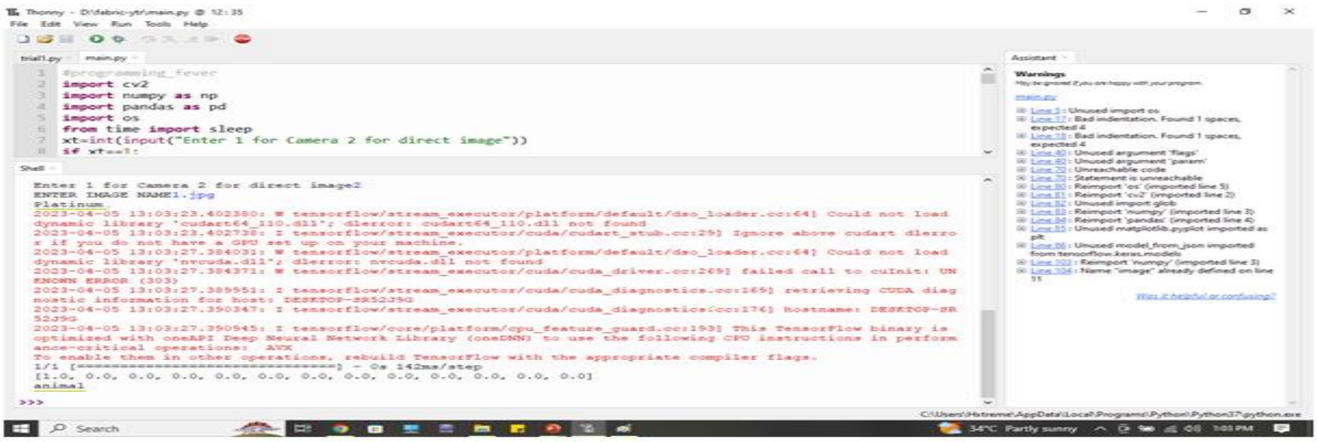

Fig 4.9: Pattern detection.

VI. Conclusion

In conclusion, this system enables the model to detect the cloth pattern and the defect with higher accuracy level. There are several processes in the proposed model. The fabric image captured by the image acquisition system is pre-processed to enhance the defective area using histogram equalization and grey scale conversion. Then, the fabric problem is found using image analysis. To build a reliable and computationally efficient system, a modified CNN architecture is employed for the defect detection process. The system's operation is halted and the nearby operator is informed if it discovers a potential flaw in the fabric roll. The operator then accepts or rejects the system evaluation and gives the go-ahead for the procedure to continue and move on to the subsequent fabric image. These observations show that the system can accurately and quickly identify a diverse array of defects while operating quickly and efficiently.

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