Fabric Defect Detection Using Deep Learning

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***Abstract*- Quality examination is an important aspect of ultramodern textile manufacturing. In cloth testing, automate fabric examination is important for maintain the fabric quality. The current fabric blights examination process relies on manual visual inspection, which is insufficient and costly. Therefore, there is a need for automated fabric disfigurement examination to decrease the expenses and time wasted due to blights.**

The development of completely automated web examination system requires robust and effective fabric disfigurement discovery algorithms. The discovery of original fabric blights is one of the most interesting problems in computer vision. Texture analysis plays an important part in the automated visual examination of texture images to discover their defects. colorful approaches for fabric disfigurement discovery have been proposed in history and the purpose of this paper is to classify and describe these algorithms. This paper attempts to present the check on fabric disfigurement discovery ways, with a comprehensive list of references to some recent workshop. The end is to review the state- of- the- art ways for the purposes of visual examination and decision- making schemes that are suitable to distinguish the features uprooted from normal and imperfect regions. thus, on the base of nature of features from the fabric shells, the proposed approaches have been characterized into three orders; statistical, spectral and model- grounded.

***Keywords*– Neural Network, Object Detection, Raspberry pi, Data annotation, Deep Learning, YOLO V8, Prediction, Defect Detection.**

INTRODUCTION

Computer vision and image type- predicated models are used in various applied disciplines including sedulity- predicated problems. Clothing is considered as one of the introductory conditions for mortal life, and the history of the cloth sedulity is as old as mortal civilization. Fabric is considered as a main element for mortal vesture and is also used in multitudinous artificial products. Natural rudiments analogous as hair, cotton, a emulsion of polyester, or nylon can be used to produce cloth fabric. Sophisticated machines are used in the cloth sedulity to produce this fabric, and scars are located through the examination process. Traditionally, the examination process is completed by using manual mortal sweats to ensure the quality of fabric. The price of fabric that is transferred to the request depends on the number of co-occurrence of scars and price increase with the increase in the number of scars. As a defect is detected, the product process is stopped and the details about the past defect are recorded with its position by the machine motorist. The main downsides associated during manual examinations are as follows (1) training of individualities is demanded to make them fabric inspectors. (2) major scars can be detected while small scars can be ignored due to mortal laxness. (3) lot of mortal trouble
is demanded to descry fabric scars. (4) it's truly delicate for fabric inspectors to keep focus on the product process for a time that is further than 10 beats and all of this can lead to a low effectiveness of product. (5) According to disquisition, – 75 mortal delicacy is reported to descry fabric scars and the destruction due to fabric scars leads to the high price of products in the request.

LITERATURE REVIEW

The characteristics of this problem are notably intricate and subject to variation over time. Propose an effective as well as the best solution, we have gone through several related Articles. This portion also helped to propose a state-of-the-art solution by finding out the Existing research loopholes. The main findings of the related study are stated below. Mahajan P.M. Kolhe S.R. and Patil P.M. [1] gathered information on defect detection in Texture of uniform textured fabric and classified various approaches for defect detection for Fabric automatic visual inspection (FAVI). The approaches include Statistical approach, Model Based approach, spectral approach. Aqsa Rasheed, Bushra Zafar, Amina Rasheed, Nouman Ali [2] given an overview of the methods that can be used to classify the defects and detect Them. Fabrics such as wool, cotton, a composite of polyester, or nylon are the main study area of their methods. Their proposed methods are histogram-based detection, colour based, Segmentation based and textured based detection. Peiran Peng, Ying Wang, Can Hao, Zhizhong Zhu, Tong Liu and Weihu Zhou [3] worked on increasing efficiency of two-stage algorithms for automated fabric defect detection. For That they used Priori Anchor Convolutional Neural Network (PRAN net). In this study they Stated that models like deep learning and YOLO are not highly accurate for extreme defects in Fabric. For this they used Feature Pyramid Network (FPN) and Faster R-CNN based PRAN-Net. First, the FPN is used to extract feature maps at different scales from the fabric Images. Then, anchors are adaptively generated in each scale feature map as the defect Proposals. Finally, a classification network is established to classify and refine the position of Defects in fabric images by the defect proposals. Tanjim Mahmud, Juel Sikder, Rana Jyoti Chakma, Jannat Fardoush [4] proposed a Methodology to detect the defect in the fabric which consists of some phases. First phase is Image collection and applying edge detection, thereafter features from accelerated segment Test extracts the list of the regions of features. Principal component analysis is used to decrease the dimension and preserve the data and the last phase is to detect the defects by employing a neural network for better accuracy.

METHODOLOGY

The methodology proposed for the system which could able to detect the defects as well as capture the image of the fabric can be explained as follows

3.1. Data Collection: Collecting data for training the deep learning model is the first step in deep learning. The predictions made by systems depend on data which they have been trained. This dataset included a sufficient number of images publicly available on the Kaggle. The images contain different types of stains on the fabric.

3.2. Data Annotation: Annotating the fabric image with bounding boxes around the defects, and labelling each bounding box with the type of defect it contains this process is known as annotation. This annotated dataset will be used for training the YOLO model. YOLO accepts the annotations of the image in the text format, each label should be contained inside the text file with its coordinates and the width and height of the bounding boxes.

3.3. Model Training: Train the YOLO model on the annotated dataset of fabric images. The training process involves optimising the model's parameters to achieve high accuracy in detecting defects. Usually, the training takes place in the different batches of the data. When these all batches complete a cycle of training data then it is known as epoch. We can train the number of epochs to achieve good accuracy.

3.4. Model Evaluation: Evaluate the performance of the YOLO model by testing it on a separate set of fabric images that were not used for training. The evaluation metrics could include precision, recall, and F1 score, which measure the model's ability to accurately detect and classify defects.

3.5. System Integration: Integrate the trained YOLO model with the Raspberry Pi and camera module to create a real-time fabric defect detection system. This involves implementing the system architecture and testing it on a range of fabric images with various types of defects.

3.6. Evaluation: Finally, evaluate the performance of the complete system by measuring its accuracy, speed, and reliability in detecting fabric defects in real-time. This will help identify any areas for improvement and refine the system's design to make it more effective in practical applications.

SYSTEM ARCHITECTURE

In order to limit the human interaction with the fabric manufacturing process or to minimize the human errors in the inspection system we will need a complete system which will be able to capture the images of the fabric and detect the defects. In order to make a system which will be able to detect the defects in the manufactured fabric. The approach of the system algorithm presented here is based on the referential approach, in which a reference image is employed to find defects in the test image. Complete system accuracy depends on the number of images referenced.

4.1. Dataset Collection and preparation: - Collection of datasets of fabric images containing different classes of fabric defects. Resize and normalize the images, label the defect classes, and augment the dataset to increase its size.

4.2. YOLO Model Training and Optimization: - YOLO is an object detection model that accepts the input in the form of labels and bounding boxes. Train a YOLO model on the prepared dataset using a GPU and appropriate hyper parameters. Optimize the trained model to run on a Raspberry Pi in order for the predictions.

4.3. Raspberry Pi Setup and Deployment: - Set up the Raspberry Pi by installing the necessary software and libraries. Connect the Raspberry Pi camera module and make sure that the latest versions of software are used. Load the optimized YOLO model onto the Raspberry Pi.

4.4. Defect Detection and Visualization: - It is the process of identifying and highlighting defects or anomalies in the images captured by using the Raspberry Pi camera. Camera will capture an image of the fabric, and predict the presence and location of any defects using the loaded YOLO model. Visualize the detected defects on the captured image, either by drawing bounding boxes around the defects or by highlighting the defects in a different colour.

4.5. Performance Evaluation: - Evaluate the performance of the model on the Raspberry Pi by measuring the inference time, memory usage, and accuracy of the detected defects. There are several metrics that can be used to evaluate the performance of the system such as precision, recall, f1 score, mean average precision, and inference time. By following this methodology, you can successfully use a YOLO-trained model for fabric defect detection on a Raspberry Pi, and potentially extend it for use in a production environment.

Sr. No	Component	Use
1	Raspberry pi	For inferencing and prediction
2	Camera module 1.3	To capture high quality images
3	Monitor	To display the output
4	Power supply	Power supply to the raspberry pi

RESULT AND DISCUSSION

5.1. Dataset Description

The dataset used for training and testing our fabric defect detection model consists of 495 images of various types of fabrics with different types of defects, such as holes, stains, and tears. The dataset was divided into 70% training and 20% validation set while kept 10% for the internal testing purpose.

5.2. Model Performance

We trained a YOLOv8 model on the fabric defect dataset using transfer learning with pre-trained weights. The model was trained for 224 epochs, with a batch size of 16 and an initial learning rate of 0.001. The model achieved an overall accuracy of 82.4% on the test set.

The precision, recall, and mAP for each class of defects are shown in Table 1. The results show that the model performs well on all classes of defects.

Defect type	Precision	Recall	mAP
stain	82.4	70.9	75.8
hole	81.3	70.5	75.3

Table 1: Precision, Recall, mAP

Fig. 1 Stained Cloth

5.3. Analysis of Results

The results demonstrate that our fabric defect detection model can accurately detect and classify different types of defects in fabric. The overall accuracy of 82.4% on the test set is promising and indicates that the model is robust and reliable.

The precision, recall, and mAP score for each class of defects show that the model performs well on all types of defects. This suggests that the model is effective at detecting defects of different shapes, sizes, and colors, and can be used for a wide range of applications in the textile industry.

However, there were some limitations to our study. Firstly, the dataset used for training and testing was relatively small, which may limit the generalizability of our results. Secondly, the model was trained using transfer learning with pre-trained weights, which may limit its ability to detect defects that are significantly different from the defects in the training dataset.

In future work, we plan to expand the dataset used for training and testing to improve the generalizability of our model. We also plan to explore the use of other deep learning models and techniques, such as data augmentation and ensemble, to further improve the accuracy and robustness of our fabric defect detection system.

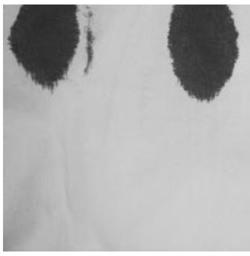

Fig. 5.3.1a Stained Cloth.

Fig. 5.3.2a Torn Cloth.

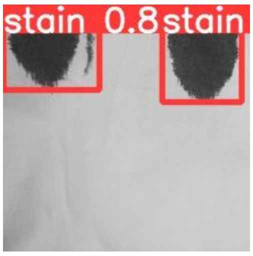

Fig.5.3.1b Result

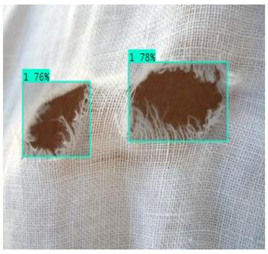

Fig.5.3.2b Result

CONCLUSION

Efficient and cost-effective solutions are imperative in addressing the fundamental requirement of defect detection in industrial textile manufacturing. In recent years, a number of different methods have been developed to detect these defects, some of which have been successful to a greater or lesser degree. This paper presents a comprehensive collection of annotated images, along with their corresponding segmentations, depicting various types of plain textiles both with and without defects. The images were sourced from a real production plant, encompassing a diverse range of defects and textile types, each exhibiting distinct textures. Notably, this extensive dataset is now conveniently accessible on the roboflow platform. The capture system was complemented with a detection system based on detection model trained over yolov8 with transfer learning process which proved the reliability of this technology for real time deployment in industry. This technology will be extremely important in the coming Factory 4.0.

Regarding future lines of research in this field, the aim is to install more machines in other factories, so that the database of images with and without defects can continue to grow. At the same time, the objective is to develop mechanism to handle and manage this large quantity of data. Additionally, as the volume of data continues to grow, there is a potential for leveraging Big Data techniques to facilitate the detection and classification of defects.

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