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FABRIC IDENTIFICATION AND FABRIC DEFECT DETECTION

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ABSTRACT –

Fabric defect detection and fabric identification are crucial tasks in the textile industry. In this research, we propose an integrated system that combines YOLOv5, a state-of-the-art object detection algorithm, with Generative Adversarial Networks (GANs) and convolutional neural networks (CNNs) for fabric defect detection and identification. Our system achieves high precision and recall rates in detecting various fabric defects, such as stains, holes, and pattern irregularities, using YOLOv5. Additionally, GANs and CNNs automate the fabric identification process by generating realistic fabric images and extracting discriminative features. Experimental results demonstrate the effectiveness and superiority of our integrated approach, providing a comprehensive and automated solution for quality control in the textile industry.

KEYWORDS – YOLO, Convolutional Neural Network, Computer Vision, GAN

I. INTRODUCTION:-

The Clothing Industry includes many different goods, all of which require different kinds of textiles and high-quality fabric. Garment production must be accurate, exact, and of high quality. To ensure that the fabric used in manufacturing is of high quality and that its type can be determined with a quick scan of the fabric. A Garment manufacturer can use their understanding of identifying textile fabrics to determine the kind of fabric and the maintenance required to maintain items made of a given type in good condition. This is an important part of the clothing labeling process that involves identifying the fabric content of the garment. Although a fabric inspection can prevent final product faults, many more aspects make it a crucial step in any production process. Fabric has a variety of flaws, including yarn flaws, weaving flaws, isolated flaws, pattern flaws, wet processing flaws, raising flaws, milling flaws, etc. Consequently, to fix these flaws having a method that can distinguish between cloth with flaws and the unaltered fabric is essential. To fulfill these two needs, we can make sure that the fabric utilized can be detected and is defect-free by using computer vision, neural networks, and YOLO. Therefore, we have developed a model that aids in determining the type of cloth and the flaws it contains, employing the Convolutional Neural Network, Computer Vision, and YOLO after taking pictures and videos of the cloth.

II. PROPOSED SYSTEM:-

Our project is divided into two main components: fabric defect detection and fabric identification. To find and locate flaws in fabric samples, this architecture incorporates picture capture, object identification, defect categorization, and defect visualization methods. The flaw identification technique is learned and fine-tuned using a fabric picture dataset and a pre-trained YOLO V5 model. For quality control and inspection purposes in the fabric sector, the ultimate objective is to offer precise flaw identification, categorization, and visualization. To obtain both fabric defect detection and fabric identification, two models are combined.

Our proposed fabric identification system utilizes Generative Adversarial Networks (GANs) to generate fabric images that closely resemble real fabric samples. GANs consist of two components: a generator and a discriminator. The generator learns to generate synthetic fabric images, while the discriminator learns to distinguish between real and synthetic fabric images. The generator and discriminator are trained iteratively in an adversarial manner until the generator can produce fabric images that are indistinguishable from real fabric samples. The generated fabric images, along with the original fabric dataset, were merged to create a comprehensive training dataset. We utilized a CNN model, a powerful deep learning architecture known for its ability to extract features from images, to train our fabric identification model. By training the CNN on the augmented dataset, the model learned to recognize and classify various fabric types accurately.

The methodology for fabric defect detection using YOLOv5 involves collecting a diverse dataset of fabric images and annotating them with bounding boxes around defect regions. The YOLOv5 architecture is then employed, and the dataset is preprocessed, split into training and validation sets, and fine-tuned using transfer learning techniques. Data augmentation is applied to increase training data diversity. The model is trained using an optimization algorithm, and its performance is evaluated using precision, recall, and F1 score. This methodology ensures a robust fabric defect detection system using YOLOv5, benefiting industries like fashion, textiles, and manufacturing.

a. FABRIC DEFECT DETECTION:-

The methodology for fabric defect detection using YOLOv5 involves several key steps. Firstly, a comprehensive dataset of fabric images is collected, encompassing a wide range of fabric types and defect categories, such as stains, holes, and pattern irregularities. This dataset is then meticulously annotated by marking bounding boxes around the defect regions in the images.

To train the fabric defect detection model, the YOLOv5 architecture is employed. The dataset is preprocessed by resizing the images and normalizing the pixel values. Subsequently, the dataset is split into training and validation sets to facilitate model evaluation. The pre-trained YOLOv5 model is fine-tuned specifically for the fabric defect detection task, utilizing transfer learning techniques to adapt the model to the intricacies of fabric defect identification.

To enhance the model's performance and robustness, data augmentation techniques such as random cropping, rotation, and flipping are applied to augment the training data and increase its diversity. The YOLOv5 model is trained using an appropriate optimization algorithm, such as stochastic gradient descent (SGD), with carefully chosen learning rate and batch size parameters. The model's performance is continually monitored on the validation set, and hyper-parameters are adjusted as necessary to improve its accuracy and generalization capabilities.

Once the fabric defect detection model is trained, it is evaluated using various metrics such as precision, recall, and F1 score. The model's ability to accurately identify different types of fabric defects is assessed, considering both individual defect instances and overall performance. The methodology ensures a robust and effective fabric defect detection system using YOLOv5, which can contribute to improved quality control and efficiency in various industries, including fashion, textiles, and manufacturing.

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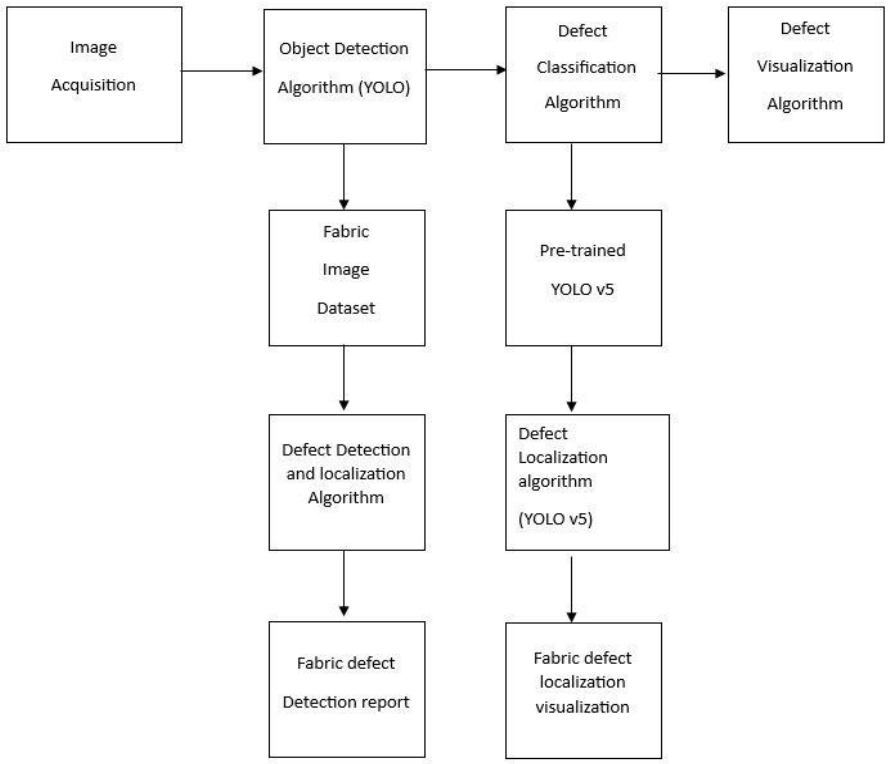

Fig. (a) Fabric Detection Architecture

The fabric images obtained from the acquisition stage are processed using an object detection algorithm, specifically YOLO (You Only Look Once). YOLO is a popular deep learning-based algorithm that can detect and localize objects within an image. The objects detected by the YOLO algorithm are further processed by a defect classification algorithm. This algorithm aims to classify the detected objects into different defect categories, providing information about the specific type of defect present in the fabric. Once the defects are classified, a defect visualization algorithm can be applied to visually represent the detected defects on the fabric images. This can help in understanding the location and extent of the defects. This dataset contains a collection of fabric images that are used to train and evaluate the object detection algorithm (YOLO V5). The dataset provides labeled examples of fabric images with corresponding defect annotations.

YOLO V5 refers to the pre-trained version of the YOLO algorithm. It is trained on a large-scale dataset and can be used as a starting point for fabric defect detection and localization. The pre-trained model can be fine-tuned or used as is depending on the specific requirements. The Defect Detection and Localization algorithm combines the pre-trained YOLO V5 model with additional layers or modifications to specifically address the task of fabric defect detection and localization. It takes fabric images as input and produces bounding boxes or masks around the detected defects, along with their class labels. The output of the defect detection and localization algorithm is a report that summarizes the detected defects in the fabric images. It may include information such as the location, type, and severity of the defects. The Fabric Defect Localization Visualization component takes the output of the defect detection and localization algorithm and generates visualizations that highlight the detected defects on the fabric images. These visualizations can be used for further analysis and decision-making.

b. FABRIC IDENTIFICATION:-

A dataset of fabric images is collected. The dataset includes images of various fabric types, such as acrylic, artificial fur, artificial leather, blended fabrics, chenille, corduroy, and cotton. Each fabric type is represented by a separate class. The fabric images are preprocessed by resizing them to a standard size and normalizing the pixel values. Additionally, textual descriptions or metadata associated with the fabric samples can also be incorporated into the training process for improved fabric identification accuracy. During the GAN training process, the generator learns to generate fabric images from random noise inputs. The discriminator is trained to distinguish between real fabric images and synthetic fabric images produced by the generator. The training involves optimizing the generator and discriminator models using appropriate loss functions, such as the Wasserstein loss or hinge loss, and optimizers, such as RMSprop or Adam. The training process continues until the generator can generate fabric images that are visually similar to real fabric samples.

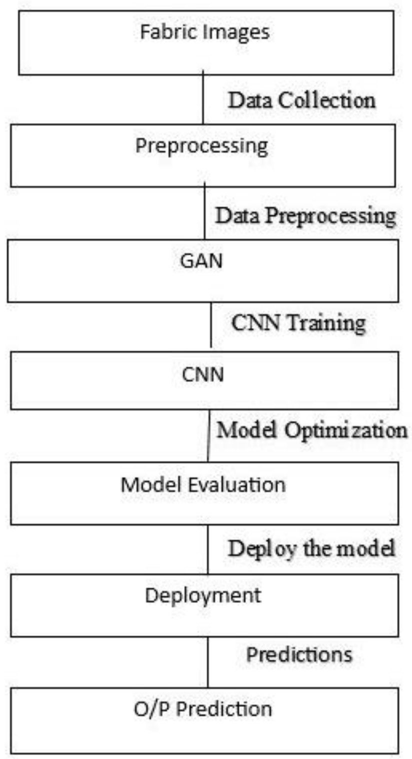

Fig. (b) Fabric Identification Architecture

To train the model, we collected a dataset comprising fabric images representing various fabric types, such as acrylic, artificial fur, artificial leather, blended fabrics, chenille, corduroy, and cotton. Each fabric type is assigned a separate class. However, we faced the challenge of having a limited dataset available for training. To overcome this obstacle, we turned to Generative Adversarial Networks (GANs) as a potential solution. GANs offer the capability to generate synthetic fabric images that closely resemble real fabric samples. By leveraging GANs, we can expand our

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dataset and increase its size and diversity, compensating for the scarcity of real fabric images. We conducted experiments using different GAN architectures such as Wasserstein GAN (WGAN) and Deep Convolutional GAN (DCGAN) to generate realistic fabric images. These generated images capture the visual characteristics and patterns present in real fabric samples. Next, we combined these synthesized fabric images with our existing training dataset, creating a larger and more comprehensive dataset that encompasses both real and synthetic fabric images.

Using this augmented dataset, we employed a Convolutional Neural Network (CNN) for training our fabric identification model. The CNN model learns from the merged dataset, allowing it to recognize and classify various fabric types accurately. By training the model on a diverse dataset that includes both real and generated fabric images, we enhance its ability to generalize and make accurate predictions on fabric types, even in cases where we have limited real fabric samples. Through this approach, we effectively address the challenge of limited data availability for fabric identification. By leveraging GANs to generate realistic fabric images and combining them with the training dataset used for the CNN model, we create a robust fabric identification system that can accurately determine the fabric type based on visual characteristics, contributing to improved fabric analysis and decision-making processes

III. RESULTS:-

We created the model with the use of CNN, computer vision, and YOLOv5. Giving both fabric identification and defect detection is advantageous. The overall accuracy of the model is 75%. It accurately detects faults with a defect detection accuracy of 75% and a fabric identification accuracy of 79%, identifying stains, filth, line defects of threads, and other defects. Additionally, it provides information about the flaws, such as the size of the stain and the area covered.

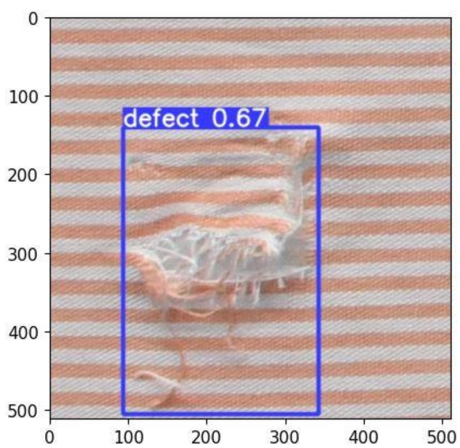

Fig. (c) Fabric tear Defect identified

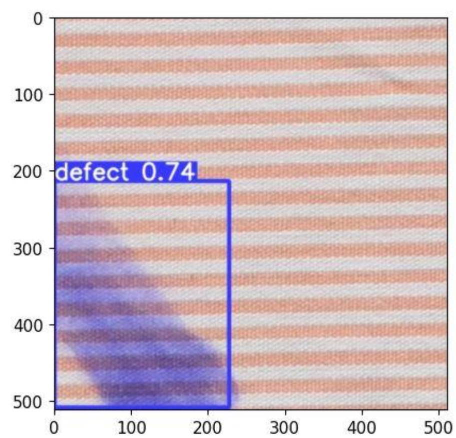

Fig. (d) Fabric Spot Defects Identified

Fig. (c) Shows the tear of fabric defect identified by the model correctly and Fig. (d) Different color spot was identified correctly.

For fabric defect detection, we employed the YOLOv5 model, a popular and efficient object detection algorithm. Our experiments yielded the following results:

Precision: 0.741

Recall: 0.5

mAP50-95: 0.341

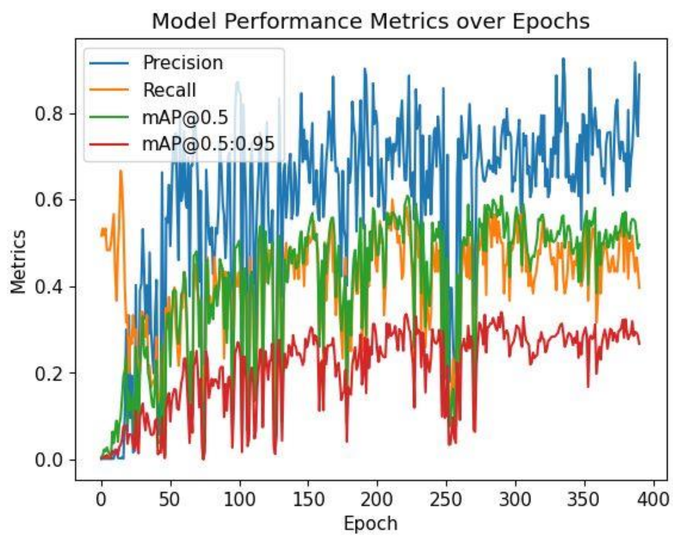

Fig. (e) Model Performance Metrics over Epochs

These results indicate that our model is capable of detecting fabric defects with a reasonable level of accuracy. The precision of 0.741 demonstrates that our model can correctly identify true positive cases, while the recall of 0.5 shows that it can find half of the actual defects in the dataset. The mAP50-95 score of 0.341, which is the mean average precision calculated at IoU thresholds ranging from 0.5 to 0.95, further supports the effectiveness of our defect detection model.

We have shown the use of a CNN-based fabric identification system and a YOLOv5-based fabric flaw detection system. The two technologies are designed to raise the standard of textile goods and give clients precise information about the textiles that were used to make their clothing. The technique for identifying fabric problems, including holes, stains, and rips, has a high level of accuracy. The faults were successfully identified and a bounding box was created around them using the YOLOv5 method.

IV. CONCLUSION:-

In conclusion, our research project demonstrates the potential of deep learning techniques in the field of fabric identification and defect detection. By leveraging the power of YOLOv5 for defect detection and GANs for dataset augmentation, we aim to develop a robust and accurate system that can significantly contribute to the textile industry. To enhance quality control and lower the production of faulty goods, the system may be included in the textile manufacturing process. The fabric identification method identified the kind of fabric used in a garment with great accuracy. The color, texture, and pattern aspects that the CNN algorithm successfully extracted from the fabric photos and applied to categorize the fabric type. To accurately tell clients about the textiles used in their clothing, the technique may be employed in the retail sector. The use of fabric fault detection and identification technologies has shown encouraging results.

The proposed fabric identification system based on Generative Adversarial Networks and Convolutional Neural Netwroks offers a promising solution for automating and improving the fabric identification process. By generating realistic fabric images, the system enables objective and efficient fabric identification, reducing reliance on manual inspection and limited feature extraction techniques. It holds great potential for applications in fashion design, textile manufacturing, and quality control. By effectively addressing the limited data availability challenge, this system contributes to improved fabric analysis and decision-making processes. Future work can focus on enhancing the system's performance by incorporating advanced GAN architectures, exploring additional fabric characteristics, and expanding the dataset to include a wider range of fabric types and variations.

V. REFERENCES:-

1) R. S. Sabeenian and M. E. Paramasivam, "Defect detection and identification in textile fabrics using Multi-Resolution Combined Statistical and Spatial Frequency Method," 2010 IEEE 2nd International Advance Computing Conference (IACC), 2010, pp. 162-166, doi: 10.1109/IADCC.2010.5423017.

2) T. Almeida, F. Moutinho and J. P. Matos-Carvalho, "Fabric Defect Detection With Deep Learning and False Negative Reduction," in IEEE Access, vol. 9,pp.81936-81945,2021,doi: 10.1109/ACCESS.2021.3086028.

3) Khan, Ayub & Abir, Nafis & Rakib, Mohammad Abu Nasir & Bhuiyan, E. & Howlader, Md.Ramij. (2017). A Review Paper on Textile Fiber Identification. IOSR Journal of Polymer and Textile Engineering. 04. 14-20. 10.9790/019X-04021420.

4) A. 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), 2020,pp.1-8,doi:10.1109/IJCNN48605.2020.9206901

5) Rui Jin 1,2 and Qiang Niu School of Computer Science and Technology, China University of Mining and Technology, Xuzhou, China Changzhou Vocational Institute of Textile and Garment, Changzhou, China; "Automatic Fabric Defect Detection Based on an Improved YOLOv5"https://doi.org/10.1155/2021/7321394