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Fabric Stain Detection Using YOLOv8

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***Abstract*—Textile industry is only few of the oldest industries in India and also in the world. For many years, fabric checking was mainly done by human workers. The workers inspect the fabric through visual examination to detect any defects or stains. The manual method of inspection exhibits multiple operational difficulties. Workers experience fatigue during extended inspection periods which results in their ability to overlook minor stains. The process requires an extensive amount of time to review the entire fabric inventory. The method of manual inspection produces inconsistent results because various inspectors make different evaluations. The process of fabric inspection becomes challenging because a person needs to examine thousands of meters without making errors. The textile factories encounter difficulties with quality control because of this problem. Our project aims to create an automatic system that detects fabric stains through computer vision (CV) and learning of deep technology.The research employs YOLOv8 which functions as a high-speed object detection system. The system analyzes video content through its frame-by-frame processing capability to identify High Stain and Low Stain patterns on fabric surfaces.**

***Keywords:* Fabric Defect Detection, Yolov8, Deep Learning, Stain Detection, Textile Inspection, Convolutional Neural Network, Automated Grading System**

I. INTRODUCTION

The textile industry serves as a vital component of worldwide manufacturing operations while providing significant employment and economic development to India through its fabric production activities. Textile mills produce millions of meters of fabric every year which requires quality testing for all produced fabric rolls before they can be sold. Workers use manual methods to conduct the inspection process because they need to watch the moving fabric to find any stains or holes or surface defects. The manual inspection process has been in existence for a long time but it requires extensive time and labor because inspectors need to keep their focus on work while needing advanced expertise.

The process of manual fabric inspection faces multiple difficulties because of current requirements in fast-paced manufacturing settings. The continuous fabric inspection work which employees perform during extended periods causes them to become fatigued and less able to focus. Research shows that human inspectors find only part of existing defects because their focus breaks and they rely on personal assessment. Inspection results show different outcomes because each worker produces different results which leads to quality assessment discrepancies. The manual methods which exist today fail to meet production needs and standardized quality control requirements because they are unable to provide accurate predictions while maintaining operational efficiency.

To overcome these limitations, automatic textile defect detection systems based on CV and learning deep have gained significant attention. Recent advancements in object detection models, particularly YOLO (You Only Look Once), enable fast and accurate identification of defects directly from image or video data. In this study, a YOLOv8-based video analysis system is proposed to detect and classify fabric stains into High Stain and Low Stain categories. The system integrates Intersection over Union(IoU)-based tracking to uniquely count defects, generates structured reports, saves annotated outputs, and assigns quality grades automatically. By combining deep learning with practical industrial requirements, the proposed approach aims to improve inspection reliability, reduce human error, and enhance overall quality control efficiency in textile manufacturing.

II. LITERATURE SURVEY

Nasim et al. proposed a deep learning–based fabric defect detection system in [1]. Their method focused on real-world manufacturing conditions and showed strong robustness to noise and illumination changes, though performance depended heavily on dataset quality and careful model training. Jin's team introduced an improved YOLOv8 model for in real defect fabric detection in [2]. The method achieved higher accuracy and faster inference through architectural refinements, but required GPU support to consistently meet real-time industrial constraints. Ma et al. developed a lightweight YOLOv8n-based defect detection approach in [3]. The model reduced parameters and computation while maintaining well accurate, it suits for embedded devices, though complex defect patterns were still challenging. Mei's research presented an enhanced YOLOv8n algo for defect fabric detection in [4]. By optimizing extraction of feature & detection heads, accuracy improved notably, but small defect localization remained sensitive to resolution changes. Kim and Lee explored artificial intelligence–based fabric defect detection in [5]. Their work compared multiple AI-driven approaches for identifying defects in textile manufacturing, demonstrating competitive detection accuracy, although the system required substantial training data to generalize across diverse fabric types. Machado et al. presented a preliminary deep learning framework combining artificial intelligence and computer vision for textile defect detection in [6]. The system use CNNs to automate inspection and reduce manual effort, though further optimization was needed before full industrial deployment. Mao and Hong conducted a comprehensive review of YOLO object -based detection models from YOLOv1 - YOLOv11 for in real defect fabric inspection in [7]. The survey highlighted architectural evolution, strengths in speed and accuracy, and remaining challenges such as dataset diversity and domain generalization. Li et al. Improved & proposed an YOLOv4-based algorithm for defect fabric surface detection in [8]. The method introduced anchor optimization and dual-channel feature enhancement, achieving high mAP, though computational cost made real-time edge deployment more demanding. Lin et al. designed an efficient fabric defect detection system based on improved YOLOv5 in [9]. The work integrated Swin Transformer modules to handle small defects, achieving fast detection speeds, though accuracy on highly irregular defect shapes still needed improvement. Zhou et al. proposed DCFE-YOLO, a novel YOLOv8-based fabric defect detection method in [10].The model incorporated Dynamic Snake Convolution and Channel Priority Convolutional Attention, achieving significant gains in precision and mAP, though added modules slightly increased computational overhead. Song et al. improved & proposed an YOLOv8-based textile defect detection algorithm in [11]. The method introduced dual-axis attention and optimized feature pyramid network for multi-scale defect recognition, achieving high accuracy and fast inference, though performance varied slightly across different fabric textures. Sun et al. developed an improved YOLOv8n model for seamless fabric defect detection in [12]. The work introduced SPPF-LSKA and CARAFE up mpling to improve feature extraction and reduce information loss, achieving better precision and recall, though generalization to non-seamless fabric types required further validation. Islam et al. introduced Fabric SpotDefect, the first annotated dataset for fabric spot and stain detection in [13]. The dataset covered diverse fabric types and stain categories annotated in YOLOv8 and COCO formats, providing a useful training benchmark, though limited lighting conditions may affect industrial generalization. Keerthan et al. analyzed multiple YOLO variants for automatic textile stain detection in [14].Their quantitative comparison showed YOLOv8 outperforming earlier versions, but detection accuracy decreased for low-contrast stains on patterned fabrics. Mai et al. designed a YOLOv11-based defect fabric surface detection system for real production conditions in [15]. The system showed reliable factory-level performance, though dataset size and diversity remained limiting factors for broader deployment. Gu et al. introduced DF-YOLO for enhanced generalization in fabric defect detection in [16]. The model combined frequency domain and spatial features with BiFPN-based neck and CBAM attention, achieving strong cross-texture generalization, though model complexity increased compared to standard YOLO. Lu et al. presented YOLO-BGS, an enhanced YOLOv8n model for textile production processes in [17]. The system achieved 96.6% mAP by integrating Bi-directional FPN, Shuffle Attention, and Global Attention mechanisms, though multi-module design added computational overhead for edge deployment. Chen et al. proposed LWFDD-YOLO, a lightweight YOLOv8-based fabric defect detection model in [18]. The method replaced the standard C2f module with Generalized Efficient Layer Attention and Cascaded Group Attention for improved feature diversity and real-time performance, though accuracy on very small and low-contrast defects needed further improvement. Qi et al. investigated YOLO for detecting and classifying defective products in industrial images in

[19].The study demonstrated high detection accuracy with real-time capability, though limitations remained in handling overlapping defect regions and class imbalance. Carrilho et al. presented a broad survey of recent based CV defect fabric detection approaches in [20]. The review highlighted the superiority of learning of deep methods over techniques of traditional while emphasizing the need for standardized datasets and robust real-world evaluation benchmarks.

III. PROPOSED METHODOLOGY

3.1 Overview of Detection Approach

The proposed fabric stain detection-based system is on a deep learning–driven object detection framework utilizing the YOLOv8 architecture. YOLOv8 (You Only Look Once, version 8) performs object detection in a single forward pass, enabling real-time processing with high accuracy. Unlike traditional multi-stage detectors, YOLOv8 integrates extraction of feature , bounding box regression, & classification into a unified network architecture.

3.2 Data Processing Pipeline.

The overall working pipeline of the proposed system begins by loading the input fabric inspection video using OpenCV. The video is processed frame by frame, where each frame is resized to 640 × 640px to match the input requirements of the YOLOv8 model. The resized frames are then passed to the YOLOv8 model, which performs detection objects & generates outputs such as bounding box coordinates, confidence scores, and class labels.

To ensure reliability, only identification with a confidence score greater than 0.40 are considered valid, and the system retains only the relevant classes, namely High Stain and Low Stain. The detected stain regions are highlighted by drawing bounding boxes on the frames. These processed video frames are then saved and combined to generate an output video showing the detected stains.

In addition, detection details such as the number of stains and their categories are recorded in a CSV file for further analysis. Finally, based on the results detection, the system computes the overall fabric quality grade, enabling automated inspection and reporting.

3.3 Mathematical Formulation Used

(i). Intersection over Union (IoU)

IoU is used to evaluate the overlap b/w 2 bounding detected boxes and to track stains across consecutive frames are discussed in [2] and [7].

$$IoU = \frac{\text{Area of Intersection}}{\text{Area of Union}} \qquad \text{Eq. (1)}$$

Where,

• The area of intersection represents the shared overlapping area between two bounding boxes.

• Area of Union is the total combined area of both bounding boxes.

If the Intersection over Union value is greater than or equal to 0.45, the detected objects are treated to represent the same stain instance.

(ii). Confidence Score Filtering

Each detection is validated using the confidence threshold mentioned in [2] and [3].

$$Detection = \begin{cases} Valid, & \text{if } confidence \geq 0.40 \\ Invalid, & \text{if } confidence < 0.40 \end{cases}$$

Eq. (2)

Where,

• Valid represents detections accepted by the system for further processing

• Invalid represents detections rejected due to low confidence scores.

• Confidence indicates the prediction probability generated by the YOLOv8 model.

• 0.40 is the minimum confidence threshold used in the proposed system.

(iii). Fabric Grading Criteria

The final fabric grade is computed using the total number of detected stains and high-stain count:

$$Grade = \begin{cases} C, & \text{if } High\_count \geq 5 \text{ OR } Total\_detections \geq 15 \\ B, & \text{if } Total\_detections \geq 6 \text{ OR } 1 \leq High\_count \leq 4 \\ A, & \text{otherwise} \end{cases}$$

Eq. (3)

Where,

• Grade A indicates good fabric quality with very few or no detected stains.

• Grade B indicates moderate fabric defects requiring attention.
• Grade C indicates poor fabric quality with a more number of detected stains.

3.4 IoU-Based Tracking Algorithm.

To prevent duplicate reporting of stains across consecutive frames, a tracking mechanism is implemented. where each entry contains a unique stain ID, bounding box coordinates, and the last seen frame index.

For each new detection, the Intersection over Union is computed with all existing tracked stains. When the IoU value is greater than or equal to 0.45, the detection is matched with stain and its bounding box is updated. If no matching stain is found, a new stain ID is assigned. Also, tracking list. This way, unique instances of a stain are properly counted and not detected in multiple frames.

(I). Flowchart

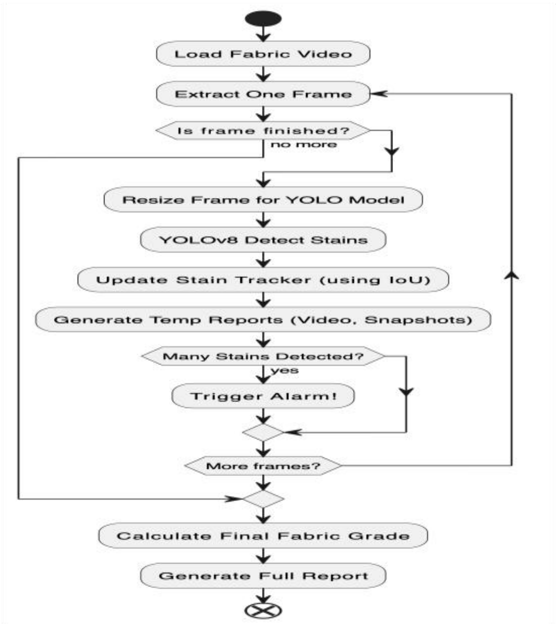


Fig 1: Flowchart

This flowchart in Fig 1 is showing how the fabric stain detection system works step by step. First the video file is uploaded and frames are taken out one by one. Each frame goes to YOLOv8 model which finds stains on fabric. If confidence is good enough then system checks if this stain was seen before using IoU calculation. After processing all frames the system gives grade to fabric and makes reports. If too many defects are there then alert sound plays to warn the operator about poor quality fabric.

IV. PROPOSED MODEL

4.1 Model Architecture Overview

The proposed system uses the YOLOv8 architecture, which have a backbone architecture for feature extraction and a detection head for predicting bounding boxes. The developed model is stored as best.pt, which contains optimized weights. The model takes trained on fabric stain images to detect three classes: High Stain, Low Stain, and No Stain.

4.2 System Components

The system is composed of the following major components:
(i). Detection Module: This module loads the YOLOv8 model and performs inference on each video frame. The input frame is resized to 640×640 pixels, and the model generates bounding box coordinates along with class labels and confidence scores.

(ii). Tracking Module: This module implements an IoU-based tracking mechanism to maintain a list of active stains. Each stain is assigned a unique ID together with its bounding box and last seen frame. Stains not detected for 30 consecutive frames are removed.

(iii). Reporting Module: This module generates multiple output formats to present the detection outcomes clearly. It produces an annotated video with bounding boxes and labels drawn on detected stains for visualization. It also captures snapshot images at regular intervals when detections are present. In addition, a CSV file is generated to store frame-wise detection statistics, and a summary report provides overall results such as total detections, stain distribution, and final fabric grade.

4.3 Label Normalization Process

To ensure consistency, detected labels are normalized. Labels containing “high” are mapped to “High Stain,” labels containing “low” are mapped to “Low Stain,” and labels containing “no” or “clean” are mapped to “No Stain.”

4.4 Grading System Logic

The fabric quality is graded based on detection counts:
Grade A: Very few or no defects
Grade B: Moderate number of defects
Grade C: High number of defects

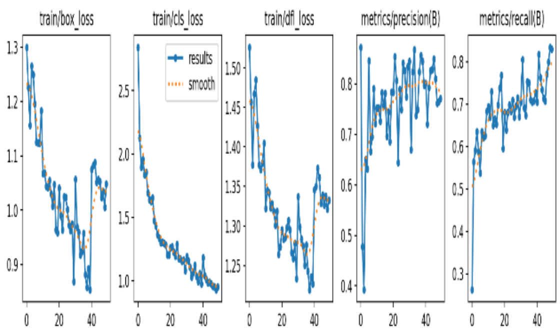
4.5 Alert Mechanism

When the total number of detections exceeds a predefined threshold (e.g., 1000), the system triggers an alert. This includes a warning message and an audible beep, indicating that the fabric quality is unacceptable. This feature supports real-time monitoring in industrial environments.

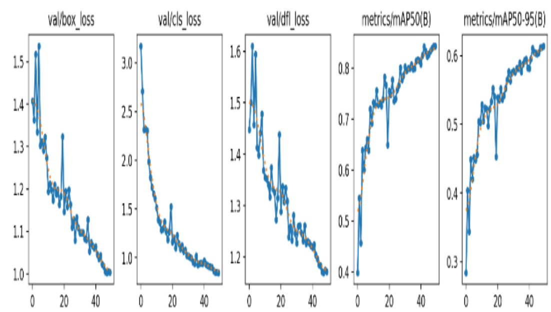
V. RESULTS AND DISCUSSION

5.1 Training Results

The YOLOv8 model was trained for multiple epochs using the fabric stain dataset. During training, the loss values decreased steadily, indicating that the model learned effectively. The reduction in box loss and classification loss shows improvement in localization object & classification accuracy. At the time same , the mean Average Precision (mAP@0.5) increased consistently across epochs, demonstrating better detection performance



2(a) 2(b) 2(c) 2(d) 2(e)



2(f) 2(g) 2(h) 2(i) 2(j)

Fig 2 : Training Performance Graph (Loss vs Epoch and mAP curves)

Fig 2 shows that the training & validation losses decrease over epochs, while precision & recall, and mAP increase. This indicates that the models is learning effectively and achieving good detection performance. Where each graph are described below, Fig. 2(a) illustrates the training box loss decreasing over epoches, indicated improved boxes of bounding localization accuracy during training. Fig. 2(b) demonstrates that the classification loss decreases gradually, which indicates that the model is learning to classify stain categories more accurately. Fig. 2(c) presents the reduction in Distribution Focal Loss (DFL) during training, indicating improved object boundary prediction and localization precision. Fig. 2(d) highlights the increase in precision over epochs, demonstrating that the model produces less false positive detections. Fig. 2(e) depicts a steady improvement in recall, indicating that the system is able to detect more actual stain instances correctly. Fig. 2(f) represents the continuous decrease in validation box loss, indicating good localization performance on unseen validation data. Fig. 2(g) explains the gradual reduction in validation classification loss, demonstrating improved classification capability during validation. Fig. 2(h) displays the reduction in validation DFL loss over epochs, indicating better object boundary estimation on validation images. Fig. 2(i) reflects the steady increase in mAP@0.5, demonstrating improved overall detection accuracy of the YOLOv8 model. Finally, Fig. 2(j) outlines the mAP@0.5:0.95 performance across multiple IoU thresholds, indicating stable and reliable model accuracy

5.2 Detection Results

The trained model was tested on fabric inspection videos. The system successfully detected stains and classified them into High Stain and Low Stain categories. The system achieved an overall detection accuracy of approximately 85–90%. It was able to detect multiple stains within a single frame and provided bounding boxes with confidence scores. The detection results also include additional information such as frame number, dominant stain type, and total detections.

Fig 3: Annotated Fabric Stain Detection Output

Fig 3 shows the annotated detection output where stains are identified and classified as High and Low Stain with bounding boxes. Each detection is labeled with a confidence score, which represents the model's prediction accuracy. The output also displays additional information such as frame number, dominant stain type, and total detections.

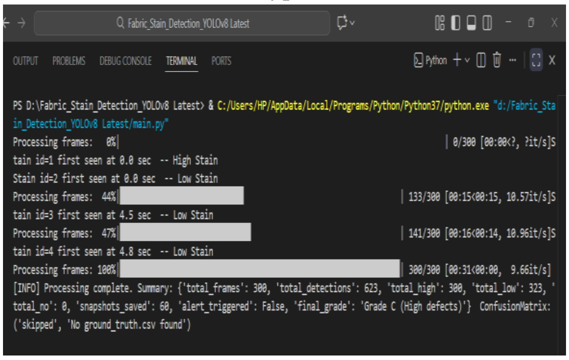


Fig 4: Timestamp-Based Detection Log Output

Fig 4 shows the console-based detection log with timestamp information for each detected stain. The system records the exact time (in seconds) when a stain first appears in the video, along with its classification (High or Low Stain). It also displays processing progress and final summary details such as total detections and fabric grade. This demonstrated the effectived of the timestamp feature in tracking stain occurrence over time.

Fig 5: Alert Warning Output

Fig 5 shows the alert warning generated when the number of detected stains exceeds the predefined threshold. The system displays a clear warning message that shows "Too much stain detected" to indicate that it has detected an unusual condition. The system provides real-time monitoring capabilities which allow users to take immediate action needed for quality control purposes

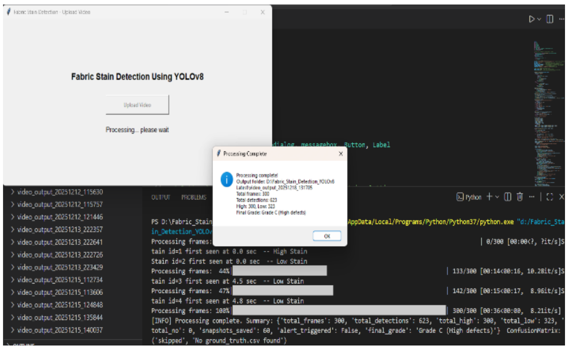


Fig 6: Output Interface and Final Result Summary

Fig 6 shows the system interface during and after processing the input fabric video. The interface shows the upload option, processing status and a pop up window that showcases the complete summary details including total frames, total detections, and final fabric grade. It also demonstrates the abilites of the system to produce output such as annotated video, detection log and statistical results. The final grading (Grade C in this case) is the quality of the fabric based on the defects detected.

VI. CONCLUSION

This project has successfully developed an automated fabric stain detection system using the YOLOv8 deep learning model. The system is capable of processing fabric videos and detecting High Stain and Low Stain defects in real time with good accuracy. The IoU-based tracking algorithm ensures that each unique stain is counted only once, even when it appears across multiple consecutive frames. The proposed system can help textile industries improve their quality control process by reducing dependence on manual inspection, which is often prone to errors and inconsistency. Future work can include adding more defect types such as holes, tears, and color variations. The system can also be integrated with production line cameras for continuous real-time monitoring. Overall, this research demonstrates that CV & learning of deep technologies can be effectively applied to solve real-world industrial problems in the textile sector, making quality inspection faster, more accurate, and more reliable than traditional manual methods.

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