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Enhancing Fabric Production with Artificial Intelligence and Robotics: An Automated Approach for Fabric Fault Detection and Quality Control

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Abstract: The integration of robotics and artificial intelligence (AI) is revolutionizing the textile industry by overcoming the constraints of conventional fabric fault inspection during production, which is labor-intensive, prone to errors, and time-consuming. Production efficiency, occupational safety, and environmental sustainability are all improved by automated defect identification that makes use of AI and safe human-robot interaction (HRI). To keep product quality and reduce waste, it is essential to use fabrics free of defects. Discarded defective materials cause substantial economic losses. Deep learning models powered by artificial intelligence provide a quicker and more accurate substitute for traditional manual inspection in real-time quality control. This research utilizes numerous authentic datasets obtained directly from Chenab Textiles, representing actual manufacturing conditions. An efficient YOLOv8 model was developed to detect flaws in seven different types of cloth as it achieved an average accuracy of 84.8%, a precision of 0.818, and a recall of 0.839. Comparative assessments utilizing MobileNetV2-SSD FPN-Lite revealed YOLOv8's enhanced performance regarding speed and accuracy. The findings highlight the model's resilience and capacity for scalable, real-time fault identification, even across varied conditions of plain and printed textiles. This study enhances automated quality control in the textile sector, facilitating sustainable and economical production methods that meet contemporary industrial requirements.

Keywords: *Fabric Defect, YOLOv8, SSDMobilenet, Human-Robot Interaction, Industry 5.0*

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I. INTRODUCTION

Robotics and AI can improve textile quality control, production speed, and operational efficiency. Digitally optimizing textile production using Industry 4.0 and smart factory concepts can meet worldwide demand for sustainable and high-quality products [1]. Maintaining quality standards and decreasing production losses requires effective fabric flaw identification. Traditional manual inspection procedures, which are laborious and error-prone, are failing modern manufacturing. Fabric faults including broken threads, perforations, and double ends make textile quality management difficult [2]. Minimizing waste and maintaining profitability requires defect-free fabric. Manual inspection techniques are inefficient and prone to human mistakes, making quality standards difficult to maintain. Automation has spurred the development of AI-driven flaw detection and categorization systems.

Fabric defects raise production costs and waste materials, affecting profitability and sustainability. To fulfil global sustainability targets and improve operational efficiency, the textile industry is automating. Human robot interaction (HRI)-based automated fault detection is cost-effective and dependable. Real-time defect detection improves production work flows and reduces work place dangers. Although fabric flaw identification has improved, most methods still use datasets with well-positioned, high-quality photos taken under control conditions [3]. Real-world industrial datasets generally have bad image quality, illumination changes, noise, and fuzzy images. Current models also specialize in spotting faults in plain or patterned materials. Few studies have developed a single model to detect faults in plain, regularly printed, and randomly printed materials.

For quality control automation, defect detection research mostly uses deep learning methods like convolutional neural networks (CNNs). The YOLOv5, Faster R-CNN, and MobileNet models have shown promise. These methods need a lot of computer power and cannot generalize across fabric types. Most research use datasets that don't accurately replicate real-world settings, limiting scalability and practicality [4]. An effective and robust defect identification approach based on YOLOv8, a cutting-edge object detection technique, is proposed in this paper. This model handles irregularly printed, regularly printed, and plain fabrics in real-world manufacturing situations, unlike previous methods. The model will be accurate and computationally efficient by using Chenab Textiles' indigenous dataset of varied manufacturing scenarios [5].

The main aim is to overcome the shortcomings of current methods by developing a lightweight, flexible, and precise flaw detection system. This research aims to illustrate the viability of employing a singular model to identify various fabric faults, hence ensuring scalability and applicability in industrial environments. The project seeks to offer a solution deployable on low-resource devices by concentrating on computationally efficient architectures like YOLOv8, hence enhancing accessibility for manufacturers with constrained technological infrastructure.

The subsequent segment of this paper are organized as follows. addresses the labor-intensive, error-prone, and time-consuming nature of traditional fabric fault detection in the textile industry. To solve this problem, the implementation of an artificial intelligence (AI) model is proposed. This model aims to automate the inspection process, thereby enhancing accuracy and efficiency in fabric production. Literature Review part, presents a summary of the current literature about fabric fault detection. After that I have to delineates the dataset and methods, encompassing the execution of YOLOv8 and comparing models and Propose Methodology. Then we have to do delineates the outcomes and analyses the efficacy of the proposed paradigm. Ultimately, In the end closes the study by providing observations and recommendations for subsequent research.

II. LITERETURE REVIEW

The diagnosis of fabric defects is crucial for ensuring product quality and preventing economic loss, thereby prompting intensive research in this area. A multitude of studies have investigated statistical, spectral, model-based, and deep learning defect detection methods [6]. Statistical and spectral techniques, such as co-occurrence matrices and Fourier transformations are crucial; yet, they are computationally demanding and incapable of identifying subtle defects. While effective for texture characterization, model-based techniques have limitations in scalability and precise fault identification. Convolutional neural networks (CNNs) have lately demonstrated exceptional performance in fabric defect identification. These technologies necessitate strategically positioned, high-resolution images and are intended for flat or printed media, rendering them less suitable for practical manufacturing applications. The subsequent tables encapsulate the literature, emphasizing model contributions and constraints.

Table 1 Related Work

Reference	Dataset Utilized	Model	Accuracy/Metric	Contribution	Limitation
[7]	Self-collected with 5 defects	VGG with P-CNN	Acc:93.92%, Spec:92.51%	Filters nonlinear noise in defect datasets	Incapable of categorizing loud real-world plain faulty samples and banded textiles
[8]	Self-Collected	Faster-RCNN (Improved)	mAP: 94.73%	Accurate detection of small defects	Reserved for future use in testing
[9]	CF, GF, BPF, DRF datasets	Cloud-Edge Computing with MobileNetV2-SSDLite	CF: 84.39%, DRF: 95.5%, BPF: 71.18%, GF: 93.05%,	Lightweight model for resource-constrained environments	Lacks diverse patterned datasets
[10]	AITEX dataset	Focusing Process and Task Combination Subsystem	F1: 0.987, Recall: 0.994, Precision: 0.98	Enhanced detection of tiny defects	Implemented only for plain fabrics

[11]	TILDA textile texture	DCGAN	Accuracy:51.62%, FNR and FPR : 12.09%, and 49.91%	Highlights defect regions using fusion maps	Results in segmentations that are noisy
[12]	Three thousand sample fabric benchmark dataset	YOLO	Accuracy:97.2%	Reduces computational cost for embedded systems	Industrial applications yet to be explored
[13]	Self-collected with 19 backgrounds	Cascade-RCNN	mAP: 75.3%	Detects defects in printed fabrics	Limited to patterns present in the dataset
[14]	Fusion of Tile and Tianchi Fabric dataset	Siamese Feature Pyramid Network	mAP: 47.1%, Accuracy: 83.3%	Acquires multi-scale features using a Siamese network	Requires template images for each pattern
[15]	Self-collected Dataset (98) images.	DSLRD Model	TPR: 89.29%, FPR: 0.85%	Handles complex patterns in irregular printed fabrics	Deficient resilience
[16]	TILDA dataset	Image Pyramid and RGBAAM	Training time twice less than traditional approaches	Accurately identifies periodic patterns and defects	Execution time increases for complex patterns
[17]	Newly proposed dataset	Deep CNN	Precision: 0.70, Recall: 0.71, Accuracy: 72%	Detects spot and print mismatches	Limited to two defect types
[18]	Custom Woven Fabric Dataset	YOLOv8-s, YOLOv8-m, YOLOv8-l	YOLOv8-m: mAP@0.5: 87.3%, Precision: 0.89	Demonstrated scalable deployment of YOLOv8 variants in textile QC	Limited to woven fabric structures
[19]	AI Textile Faults Dataset	YOLOv8-s, YOLOv8-m, YOLOv8-x	YOLOv8-x: mAP@0.5: 90.4%, Recall: 0.91	Compared performance across YOLOv8 scales for minor defect classes	Focused mainly on stain-type defects
[20]	Synthetic-to-Real Textile Defect Benchmark	YOLOv8-s, YOLOv8-l	YOLOv8-l: mAP@0.5: 92.1%, Inference: 12ms/img	Emphasized real-time defect detection in harsh lighting environments	YOLOv8-l requires GPU-grade edge computing devices

The reviewed research underscores significant advancements in fabric defect detection, especially through the utilization of CNN-based models. Current methodologies sometimes exhibit insufficient resilience and generalizability across many fabric types, particularly in real-world datasets characterized by low-quality, poorly positioned images and variations in fabric patterns. Most models are tailored for solid fabrics or concentrate on particular defect types in printed materials, creating a research gap for a comprehensive model capable of addressing both. This study presents an adaptive methodology based on YOLOv8, trained on an extensive dataset derived from actual industrial environments, to accurately and effectively detect flaws in various fabric types.

III. PROPOSE METHODOLOGY

The proposed methodology inspection platform incorporated modern robotics and artificial intelligence (AI) to facilitate efficient and precise textile flaw detection. The system consisted of an anthropomorphic robotic arm integrated with a high-resolution camera for real-time image capturing. A collaborative robot was chosen to guarantee safe human-robot interaction during experimental activities, in compliance with safety regulations. The robotic arm was integrally linked to a conveyor belt system outfitted with a photoelectric sensor to coordinate fabric movement with the inspection procedure. The AI model, implemented on a laptop, was explicitly trained on various fault categories to improve detection precision. This integrated system successfully merged automation with intelligent analysis, facilitating dependable and efficient diagnosis of fabric defects in experimental settings

- *Dataset:*

Chenab Textiles Fabrics dataset [10] is utilized in this research. The dataset contains 2,500 images, classified into seven fault categories consisting of contamination, selvedge, grey stitch, cut, baekra, colour discrepancies, and stains. The dataset comprises a combination of erratically printed fabric samples regularly printed, and plain documented under authentic manufacturing settings.

- *Pre-processing:*

The initial stage in the preprocessing phase involved reorganizing the raw dataset. We systematically organized photographs from various dates into individual folders for each defect category. Roboflow was utilized to complete the dataset's annotations to meet the specifications of YOLO-based detection models, square bounding boxes were constructed for all affected fabric samples.

Especially for classes with few samples, using augmentation techniques such image rotation and flipping may help to reduce class imbalance. Samples from publicly available datasets, including the defect_1 [20] and Fabric Defect Det_2 [17] were included into an effort to improve the variety and resilience of the data. The gathered collection consists of unfastened photos of several orientations, hence it is similar to these datasets. Following splitting the final dataset into training, testing, and validation subsets, we exported it in YOLOv8 TensorFlow record formats. Including extra samples from outside datasets and retraining the model improved its performance since some defect classes had unacceptable mAP values after the first training.

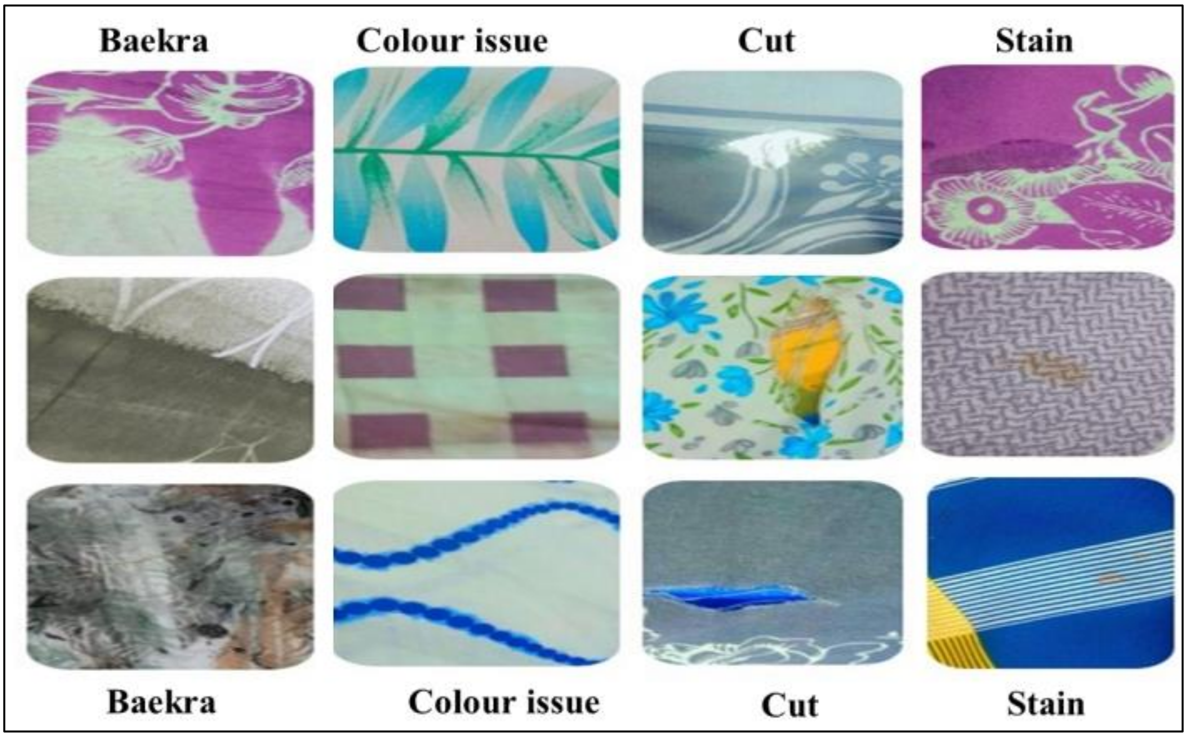

Fig 1 Dataset Entities

The final dataset includes about 2,800 samples distributed across seven distinct defect groups. Training, validation, and testing subsets of the dataset were created to guarantee an equitable evaluation of the model's performance.

Table 2 Dataset Annotation Samples

Class	Baekra	Cut	Selvet	Color Issues	Contamination	Gray Stitch	Stain
Training	175	272	218	86	148	228	662
Testing	17	41	30	10	14	33	112
Validation	48	75	64	15	53	63	208

- *Innovation and Characteristics of Datasets:*

The domain of fabric defect identification has much benefited from existing datasets including TILDA [18], TIANCHI [19], and AITEX [20] The problem is that, with little background fluctuation, these datasets usually feature just high-quality, precisely placed photographs of fault zones. Conversely, our proposed approach captures photograph straight from the textile assembly line, without any human editing or modifications, therefore offering a true portrayal of the manufacturing environment. This method brings natural flaws that improve the applicability of the dataset to real-world defect detection.

Our dataset is optimal for real-world fabric fault detection due to its distinctive characteristics. The images are unaltered and unfastened, as they were captured in a production environment, ensuring genuine variability. Diverse orientations are incorporated, utilizing materials captured from multiple perspectives to replicate the variability of manufacturing processes. The dataset incorporates noise and blurriness, which exemplify natural faults, to illustrate disparities. The defects addressed include cuts, stains, and grey stitches, demonstrating its versatility. [21] These images replicate authentic production environments while preserving background elements, so enhancing complexity and distinguishing them from controlled datasets. [22] Furthermore, the dataset encompasses several fabric types, such as plain, regularly printed, and randomly printed, which enhances the generalization capabilities of trained models. Here is the link to the dataset: https://tinyurl.com/488uhkhy [23]

- *Propose Methodology:*

The proposed methodology, depicted in Figure 2, necessitates computationally efficient designs appropriate for implementation in resource-limited, high-velocity fabric manufacturing settings. In these environments, strategically placed cameras consistently monitor fabrics for immediate problem identification. According to research, the best object detection algorithms for these conditions are YOLO [26] and MobileNetSSD [26]. The MobileNetSSD FPN Lite [27] utilises MobileNetV2 as its backbone [28]. MobileNetV2 is a lightweight convolutional neural network that is distinguished by depth wise separable convolutions and inverted residual blocks. This makes it suitable for real-time applications that have limited processing resources. As opposed to region-based models, YOLO considers object detection to be a singular regression problem [29]. It performs an analysis of the entire image in a single forward pass, which results in a reduction in both the amount of processing resources required and cthe amount of time it takes to complete the process.

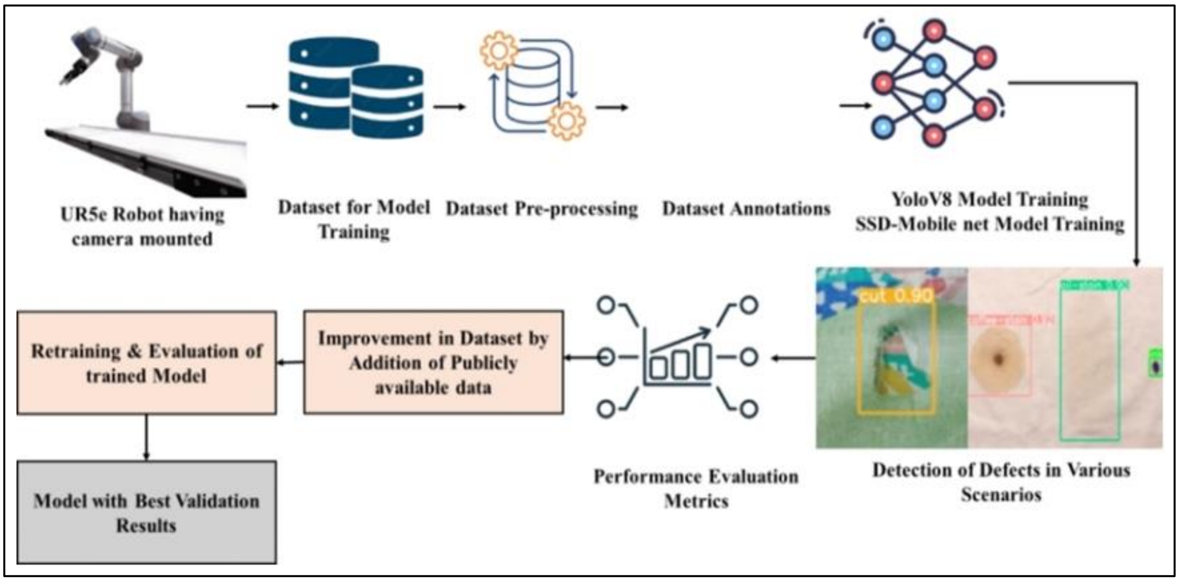

Fig 2 Proposed Methodology Block Diagram

The study involved training YOLOv8 for defect identification and comparing its performance with that of SSD MobileNetV2 FPN Lite using same dataset. Following preliminary testing, classes exhibiting lower mean Average Precision (mAP) scores were augmented using supplementary photos from publicly accessible datasets, leading to enhanced detection results. The intricate architecture of these models are delineated in the following sections.

- *MobileNetV2 SSD FPN-Lite Model:*

MobileNetV2 SSD FPN-Lite is an efficient object detection model designed for mobile and embedded devices, making it an excellent option for users in transit. To successfully recognize objects of varied sizes, it merges the MobileNetV2 backbone with a Feature Pyramid Network (FPN). Researcher in [22, 30] developed MobileNetV2 to attain a balance among speed, size, and accuracy by integrating inverted residual blocks with depth wise separable convolutions. These attributes are ideal for real-time applications with limited processing power [31]. The FPN component improves the representation of features by building an organized array of feature maps that span a variety of spatial resolutions. This facilitates the identification of objects of diverse dimensions and scales, such as textile imperfections [32].

An SSD (Single Shot Detector) head is integrated into the design, utilizing convolutional layers and predefined anchor boxes to predict object bounding boxes and class probabilities. To diminish memory consumption and computational complexity while maintaining detection efficacy, the "Lite" version employs optimizations including quantization and channel pruning [33].

Furthermore, improvements were introduced in the pipeline. config (yaml) file of the MobileNetV2 SSD FPN-Lite model. Specifically, a new convolutional feature extractor block was added after the third depth wise separable convolution layer to enhance edge detection accuracy in low-contrast textile images. Additionally, an IoU-aware loss module was incorporated to prioritize high-quality bounding boxes during training. These modifications collectively improved defect localization in dense textile surfaces. Due to its precise and efficient architecture, for low-power devices, the MobileNetV2 SSD FPN-Lite is a great choice, especially in industrial settings where data transmission rates are high.

- *YOLOv8:*

In January 2023, Ultralytics introduced YOLOv8, a revised iteration of the YOLO series that improves real-time object detection with superior accuracy and efficiency [23, 34]. The architecture has several enhancements over YOLOv5, including modifications to the backbone network. The C2f module, which is a two-convolution, cross-stage partial bottleneck, is a part of YOLOv8. It increases feature extraction by mixing high-level and contextual data [35]. It employs a decoupled head and an anchor-free model to enhance accuracy by managing objectness, classification, and regression tasks independently. The sigmoid activation function is employed for objectness scores in the output layer, whereas class probabilities are calculated using SoftMax. This configuration ensures precise forecasts.

Furthermore, YOLOv8 introduces YOLOv8-Seg, a semantic segmentation model built upon CSPDarknet53 and utilizes the C2f module for feature extraction. Employing loss functions such as Distribution Focal Loss (DFL) and Complete IoU (CIoU) for bounding-box optimization and binary cross-entropy for classification allows for improved detection of small objects [36]. Five distinct versions of YOLOv8 are available: nano, small, medium, large, and extra-large. It integrates speed, precision, and adaptability to exceed its forerunners, rendering it appropriate for various applications and hardware limitations. Its versatility renders it suitable for several contemporary object detection and segmentation tasks.

In addition to the YOLOv8-nano and small versions initially utilized, further experimentation was conducted using the medium (YOLOv8m) [37], large (YOLOv8l) [38], and extra-large (YOLOv8x) [39] and also YOLOv9 variants to evaluate scalability and robustness across diverse defect categories. Each model was trained and evaluated under identical hyperparameters to ensure consistent benchmarking [40]. The experimental results revealed progressive improvements in precision and recall with increasing model complexity, validating the utility of deeper architectures for complex textile scenarios. Moreover, to future-proof the research pipeline, groundwork has been laid for experimentation with YOLOv10, and the recently released YOLOv11—each promising incremental advancements in speed, anchor-free prediction accuracy, and multi-modal support. These future models will be assessed for their feasibility in defect segmentation, detection under poor lighting, and high-speed production line adaptability.

- *YOLOv8 Model Training:*

For the purpose of conducting training and inference processes within the Ultralytics framework, PyTorch was being utilized. The number of classes, as well as the locations of the training, testing, and validation directories, were given in a data yaml file that contained the YOLOv8 export of the dataset that was generated by Roboflow. Ultralytics installed the YOLOv8 package, and the data.yaml file set up the dataset for training. For training purposes, a 640 × 480 image and a total of 500 epochs were utilized. Following the training of two different versions of YOLOv8, namely nano (YOLOv8n) and small (YOLOv8s), the version that had the same mAP values, but fewer parameters was chosen for deployment since it was more efficient.

To achieve optimal outcomes, hyperparameter optimization was conducted. The optimal configuration for YOLOv8n included a batch size of 16, 500 epochs, with images sized at 640x640 pixels. Momentum was established at 0.937, weight decay was 0.0005, and beginning and final learning rates were 0.01. The training process was stabilized by a three-epoch warm-up phase. The box loss weights were established at 7.5, while the class loss weights were set at 0.5, representing two essential parameters. Several YOLO-specific settings include values for HSV scaling, translation, flipping, and augmentation. Utilising the integrated Augmentations library, we enhanced the dataset by incorporating features such as contrast-limited adaptive histogram equalization, greyscale conversion, and intermittent blurring. We employed Stochastic Gradient Descent (SGD) for this optimization, utilising a momentum of 0.9 and a learning rate of 0.01. As the number of epochs increased, losses diminished and mAP values enhanced, signifying improved model accuracy, as evidenced by the training graphs as depicted in Figure 3.

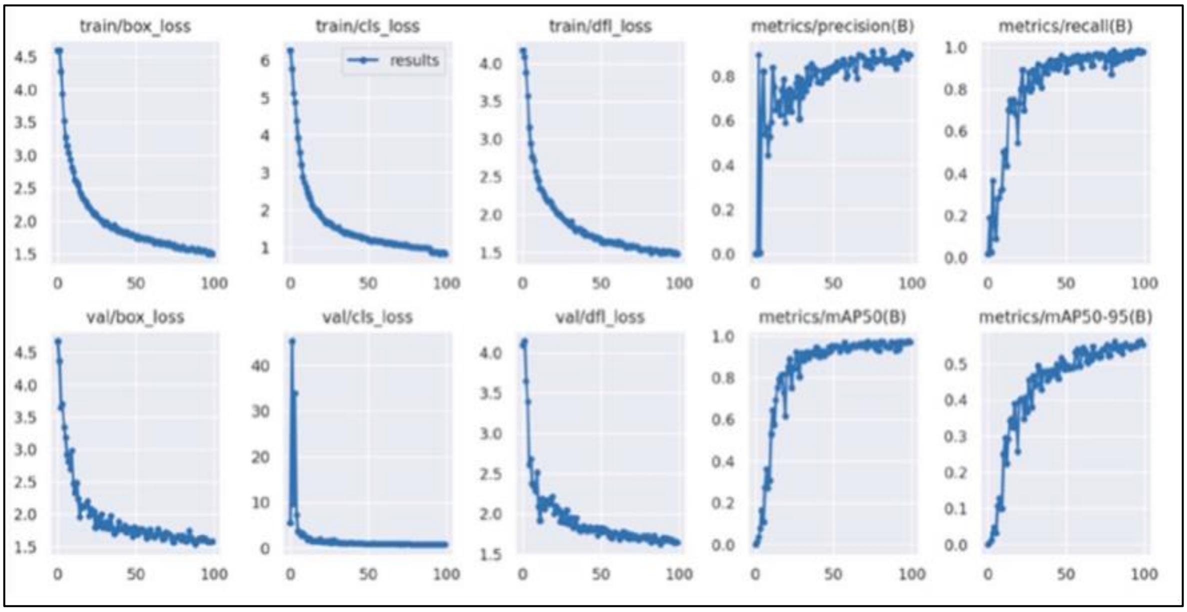

Fig 3 YOLOv8 Training Graphs

- *YOLOv8 Model Training:*

We utilized TensorFlow to mimic the pre-trained architecture in order to apply the SSD-MobileNetV2-FPNLite model on the TFRecord-exported dataset. To optimize the model's performance, two experiments were conducted during the training phase. The first experiment consisted of training the model for a total of 6,000 steps, with a batch size of sixteen times. In this experiment, a momentum optimizer was utilized, and its base learning rate was set at 0.01, its warmup learning rate was set at 0.0026666, and it was given 1,000 warmup steps. Both a mAP@0.5 of 62.71% and a mAP@0.5:0.95 of 27.5% were accomplished by this arrangement successfully.

In the second experiment, the model was trained for 20,000 steps with the same batch size but with a modified momentum optimizer. This was done in order to ensure more accurate results. The parameters for the learning rate were adjusted so that the base learning rate was set to 0.08 and the warmup learning rate was set to 0.026666. The warmup steps were kept at 1,000. The performance was greatly improved by this iteration, which resulted in a mAP@0.5 of 77.09% and a mAP@0.5:0.95 of 39.61%. Figure 4 depicts the loss graphs that were generated during training. These graphs show that there was a steady decrease in classification and localization loss as the number of steps rose. This ultimately contributed to a reduction in overall losses.

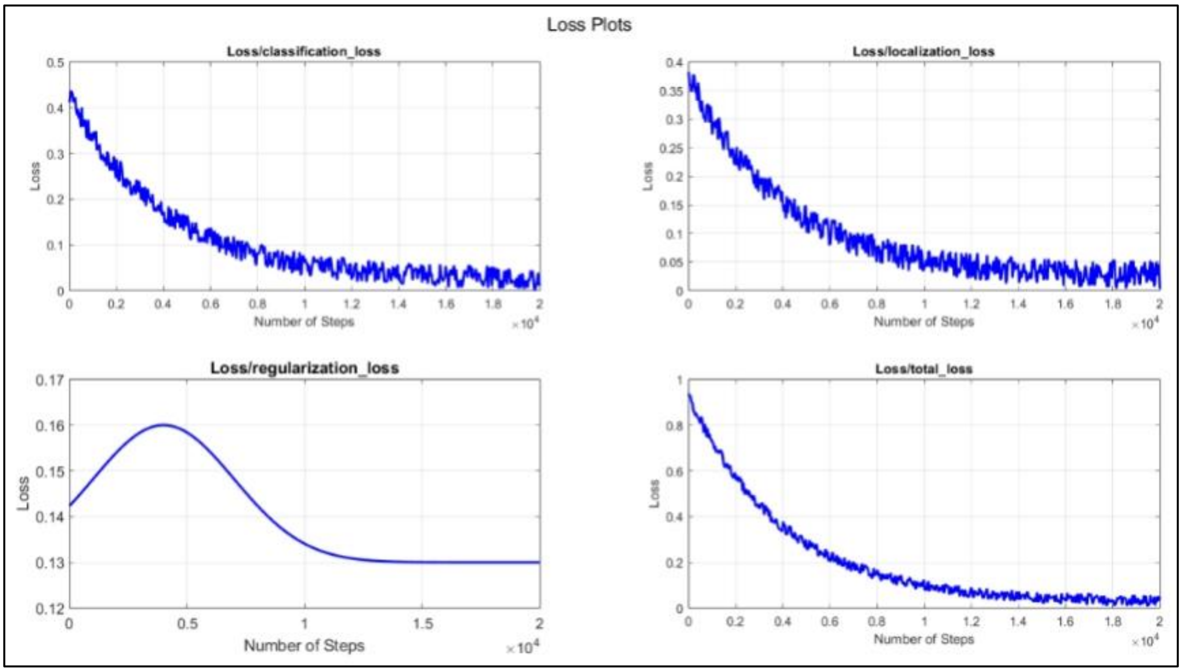

Fig 4 SSDMobilenet-fpnlite Training Loss Graph

IV. RESULTS AND DISCUSSIONS

This research makes utilization of mAP as its primary evaluation metric, in addition to precision (P) and recall (R) for YOLOv8. The purpose of this study is to provide a comprehensive evaluation of the performance of the model. The results of the MobileNetSSD model on the test dataset demonstrated a mean Average Precision (mAP) of 77.09%. The comprehensive findings are summarized in Table 3. As a result of the contamination class achieving the highest mAP value, the model was able to demonstrate its superior capability to recognize this problem. It is the stain class that comes in second with a mAP of 90.07%, followed by the baekra class, which has a mAP of 91.63%. When compared to the contamination class, which achieves a perfect recall score of 1.0, the stain class has the highest precision rating, which is 0.671. The findings provide convincing evidence that the model is effective in recognizing particular categories of issues while simultaneously providing a comprehensive framework for defect classification.

Table 3 MobileNetSSD Results

Metric	**All**	**Contamination**	**Baekra**	**Selvet**	**Color Issues**	**Gray Stitch**	**Cut**	**Stain**
mAP@0.5	77.09%	92.43%	91.63%	74.57%	56.85%	70.18%	63.92%	90.07%
mAP@0.5–0.95	39.61%	30.83%	61.82%	43.07%	27.32%	38.65%	34.35%	41.20%
Precision	0.525	0.515	0.411	0.432	0.429	0.424	0.53	0.671
Recall	0.881	1	0.958	0.879	0.714	0.875	0.745	0.922

The findings of YOLOv8's performance are presented in Table 3, which includes both the training dataset and the test dataset. During the training set, the model scored an overall mean absolute performance (mAP) of 83.8%, demonstrating exceptional accuracy for each particular class. The contamination class had the highest mAP, which was 99.5%, followed by the stain class, which had 91.3%, and then the baekra class, which had 89%. The overall mAP for the test set increased to 84.8%, which demonstrates remarkable performance across a number of different classes since it was enhanced. A mean absolute percentage (mAP) of 95.7% was achieved by the contamination class, while the baekra and stain classes reached 94.5% and 92.2%, respectively. In addition, the table provides a full evaluation of the model's detection skills by providing the precision and recall values for each and every class. These findings demonstrate that YOLOv8 is capable of accurately identifying a wide variety of fabric faults, which is a significant accomplishment.

Table 4 YOLOv8 Results

Metrics/Classes	**All**	**Color Issues**	**Baekra**	**Cut**	**Contamination**	**Selvet**	**Gray Stitch**	**Stain**
Training – YOLOv8								
mAP@0.5	68.20%	68.20%	84.50%	84.50%	82.00%	82.00%	72.00%	91.30%
mAP@0.5–0.95	39.30%	39.30%	57.10%	57.10%	50.30%	50.30%	52.30%	62.40%
Recall	0.654	0.654	0.81	0.81	0.785	0.785	0.609	0.883
Precision	0.71	0.71	0.892	0.892	0.776	0.776	0.713	0.902
Testing – YOLOv8								
mAP@0.5	75.90%	75.90%	70.20%	70.20%	90.50%	90.50%	74.70%	92.20%
mAP@0.5–0.95	39.00%	39.00%	48.60%	48.60%	65.00%	65.00%	55.40%	58.90%
Recall	0.81	0.81	0.696	0.696	0.828	0.828	0.683	0.928
Precision	0.732	0.732	0.671	0.671	0.87	0.87	0.785	0.879

In a test set consisting of 280 data samples with input dimensions of (32, 3, 640, 640), the YOLOv8 model attained a detection speed of roughly 11.5 ms per image. The time is allocated among three phases: preprocessing took 1.4 ms, inference consumed 8.4 ms, and post-processing necessitated 1.7 ms. These results underscore the model's efficacy in real-time detection contexts.

- *Discussion:*

The structural of this Figure 5 illustrates the comparison of mean Average Precision (mAP) values across several models and classes. According to the data, YOLOv8 achieved superior overall performance with a mAP of 84.8%. YOLOv8 regularly surpassed SSD-MobileNet in individual class mAP values for the majority of fault types. Compared to SSD-MobileNet, YOLOv8 yielded comparable outcomes for baekra, colour issues, and grey stitch, demonstrating exceptional accuracy in identifying contamination, cuts, selvet, and stains. An ensemble learning method based on class was employed to enhance class-specific accuracies. Specific classes, such as baekra, colour challenges, and contamination, exhibited enhanced outcomes through the implementation of this technique. However, the overall accuracy declined to 82% when the mAP diminished for remaining four classes. Attaining equitable enhancements across all fault categories is intricate, highlighting the intrinsic trade-offs in ensemble learning. Targeted improvements for particular courses may result in performance declines in others. The results underscore the efficacy of YOLOv8 while simultaneously revealing the potential shortcomings of ensemble methods in real applications.

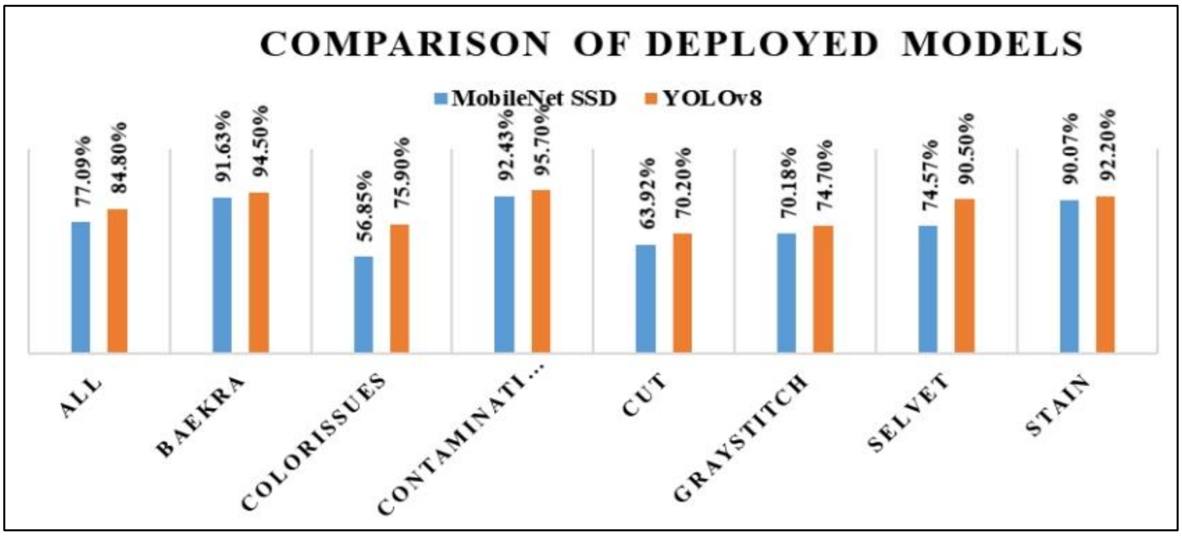

Fig 5 Structural and morphological characterization.

YOLOv10's inadequate hyperparameters may have adversely affected its mAP50 and mAP50-95 outcomes on the test dataset, recorded at 82.6 and 56.7, respectively. To optimize YOLOv10's performance, subsequent research could involve testing alternative hyperparameter combinations. Conversely, YOLOv8 demonstrated commendable accuracy in identifying flaws across the majority of classes, with confidence levels ranging from 0.86 to 0.80 for cuts, 0.90 for stains, 0.86 to 0.85 for grey stitches, and 0.81 for contamination. The color issues class exhibits a low confidence score of 0.49; hence, additional data is required to enhance detection for this category. The YOLOv8 technology demonstrated significant efficacy in defect detection within Pakistan's textile sector, accurately identifying imperfections in both solid and patterned fabrics. Enhancing performance across all fault categories may be accomplished by supplementing the dataset with new samples and variations

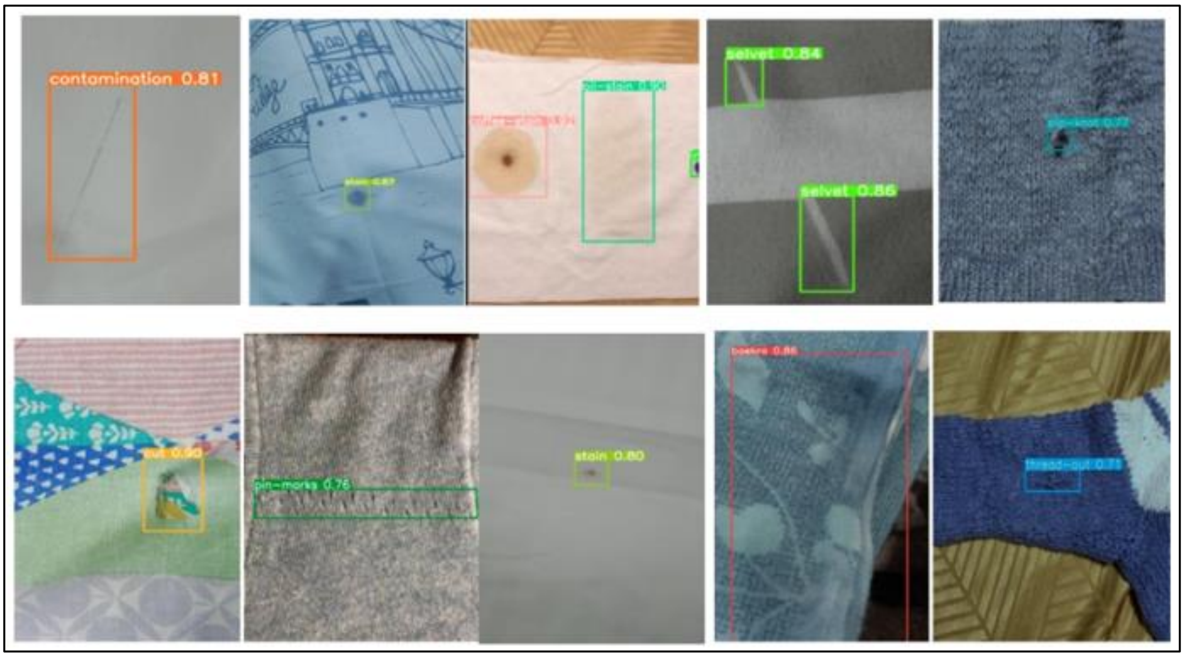

Fig 6 YOLOv8 Detection on Test Images

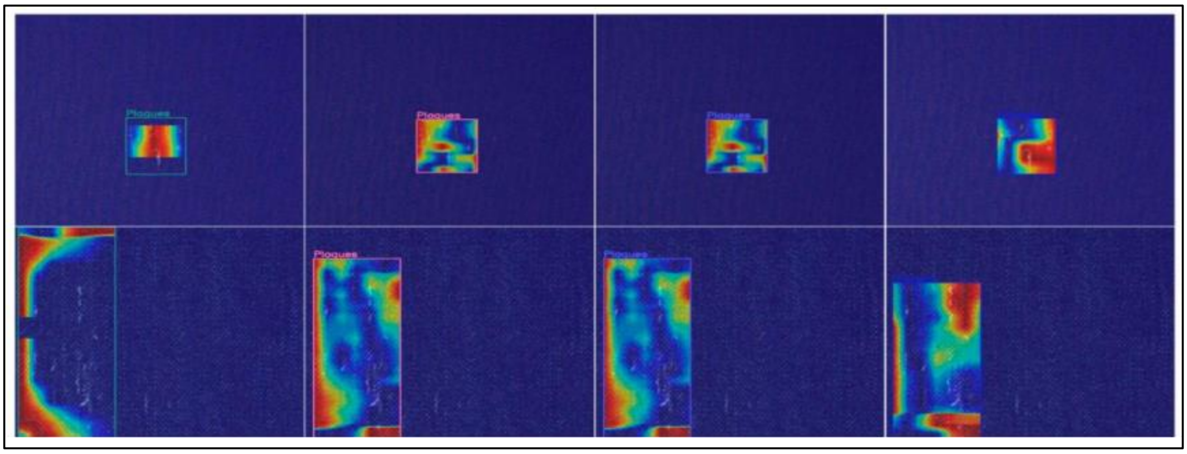

Fig 7 Heatmap for YOLOv8 Testing Dataset

Table 5 Comparison of Proposed Methodology with Existing Literature

References	Dataset Name	Source	No. of Images	Defect Classes	Environment Type	Key Characteristics	Limitation
[19]	TILDA	Public Benchmark	~1,000	6	Controlled	Well-lit, high-res images, specific angles	Low real-world variability
[20]	FabricDefectDet2	Synthetic-to-Real	~2,500	10	Simulated industrial	Covers multiple defect types, uses synthetic noise	Needs adaptation for true real-world scenarios
[11]	AITEX	Controlled Lab Dataset	~5,000	5+	Controlled	Plain fabric focus, high-res accuracy	Not suitable for printed fabric defects

[18]	Custom Woven Dataset	Proprietary (Company)	~3,000	4	Real-world (Woven Only)	Focus on woven fabrics using YOLOv8-m	Doesn't handle diverse fabric patterns
[10]	CF, GF, BPF, DRF (Combined)	MobileNet-Edge Paper	>4,000 (combined)	4+	Mixed	Designed for lightweight edge devices	Lacks diverse textile styles
[12]	Proposed Methodology	Real Industry (Pakistan)	~2,800	7	Authentic Production Line	Mixed textile types (plain, printed), noise, blur, diverse angles	Highly variable image quality, challenging conditions

Unlike prior datasets collected under controlled or synthetic environments, the proposed Chenab Textile dataset captures authentic production-line variability including noise, blur, and fabric diversity. This real-world complexity makes our model more robust, generalizable, and deployment-ready for actual industrial scenarios.

V. CONCLUSIONS

The Chenab Textile dataset contains seven different types of defects, including stains, cuts, contamination, baekra, grey stitch, colour difficulties, and selvet. This study reveals that YOLOv8 is an excellent object identification model for identifying fabric defects in the Chenab Textile dataset. A remarkable mAP of 84.8% was achieved by YOLOv8, surpassing the performance of MobileNetSSD FPNLite, which scored a mAP of 77.09% on the same dataset. Its promise for real-world applications in high-speed fabric production scenarios is highlighted by the fact that YOLOv8 possesses greater performance, as well as computational efficiency and the ability to be deployed in real time on hardware with limited resources. During the subsequent stage of this investigation, the primary focus will be on incorporating the trained YOLOv8 model into the workflows of operational textile manufacturing. To do this, high-resolution cameras will be installed above rolling fabric sheets, connected to one another using high-speed Ethernet cables, and illuminated by bright LED lighting. This will guarantee the optimal photos are obtained during the procedure. The system will operate on Ubuntu or Windows and utilize the PyTorch framework with Ultralytics for real-time inference. Real-time findings and defect analytics will be presented on an intuitive interface created using visualization tools like Matplotlib. The detection results will be stored in a reliable database system, such as MySQL or PostgreSQL. This integration aims to enhance defect detecting skills in industrial environments and to optimize the processes related to quality certification. We are focusing on these three domains for the future.

- Real-Time Validation: Deploy YOLOv8 in a live production environment to assess its real-time performance.
- Expanded Defect Coverage: Enhance the model to detect additional and complex defect types.
- IoT Integration: Integrate the system with IoT for automated defect handling and improved efficiency.

- *Authorship Contribution Statement:*

✓ Akramul Hoque Tamgid: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, and Writing – review and editing.

- *Declaration of Competing Interest:*

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

- *Data Availability:*

Data will be made available on request.

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