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Deep Learning - Driven Fabric Fault Detection Using YOLOv9 in Textile Industrial Sittings

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Abstract:Automated fabric inspection is vital for maintaining quality in modern textile manufacturing, where manual inspection remains slow, inconsistent, and prone to human error. This study presents a deep learning–driven approach for fabric fault detection using YOLOv9, evaluated under real industrial conditions with datasets collected from Chenab Textiles. The dataset encompasses seven defect categories across plain, regularly printed, and randomly printed fabrics. The YOLOv9 framework achieved a mAP@0.5 of 86.3%, a precision of 0.832, and a recall of 0.847, demonstrating robust performance in detecting high-variance defect classes. Comparative experiments with MobileNetV3-SSD highlight YOLOv9's superior accuracy and inference efficiency. The results confirm the model's scalability and practical applicability for deployment in high-speed manufacturing environments, contributing to intelligent textile inspection systems that enhance productivity, reduce economic losses, and support sustainable industrial practices.

Keywords: *Fabric Fault Detection, YOLOv8, MobilenetV2-SSD, Automated Inspection, Texttile Quality Control, Industry 5.0.*

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I. INTRODUCTION

The integration of robotics and artificial intelligence has become fundamental in achieving higher standards of textile quality control, production throughput, and operational stability. The transition toward digitally optimized manufacturing, supported by Industry 4.0 and smart factory principles, enables [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]. Reducing waste and maintaining profitability therefore depend on accurate and timely defect detection.Increasing production costs and material wastage highlight the need for automated inspection solutions that enhance sustainability-driven operations. As industrial facilities move toward automation, human–robot interaction based fault detection has emerged as a practical and dependable alternative to manual inspection. Real-time defect identification supports efficient production workflows and reduces occupational risks. Despite improvements in automated fabric inspection, most existing systems rely on datasets composed of well-aligned and high-quality images acquired under controlled conditions [3]. In contest, real-world industrial environments typically present challenges such as noise, low illumination, motion blur, and non-uniform imaging conditions. Current approaches often specialize in detecting defects in either plain or patterned fabrics, while limited attention has been given to developing a single, unified model capable of addressing plain, regularly printed, and randomly printed textiles [4]. Deep learning has become central to automated defect detection, with convolutional neural network based models such as YOLOv5, Faster R-CNN, and MobileNet demonstrating promising results. However, these methods generally require substantial computational resources and often exhibit limited generalization when applied across diverse fabric types. Many studies have utilized datasets that do not adequately

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reflect real-world production conditions, which restricts their scalability and industrial applicability [5]. To address these constraints, this study introduces a defect detection framework based on YOLOv8, a contemporary object detection algorithm designed to operate effectively on plain, regularly printed, and irregularly printed fabrics encountered in real manufacturing settings. The proposed model is supported by an indigenous dataset collected from Chenab Textiles, incorporating a variety of production scenarios to promote robustness and computational efficiency [6]. The objective of this work is to overcome limitations observed in existing research by developing a lightweight and adaptable defect detection system capable of identifying multiple defect categories within a single model. The approach aims to enhance scalability in industrial environments and facilitate deployment on low-resource devices. Emphasis on computationally efficient architectures such as YOLOv8 ensures accessibility for manufacturers operating with constrained technological infrastructure.

The remainder of this paper is structured as follows. Section 2 provides a review of existing literature on fabric defect detection. Section 3 describes the dataset and methodology, including the application of YOLOv8 and comparative models. Section 4 presents the experimental results and evaluates the perform of the proposed approach, section 5 concludes the study and outlines directions for future research.

II. LITERATURE REVIEW

Proper detection of the fabric defects is critical in ensuring the textile quality and minimizing production losses. This has necessitated the broad specifically statistical, spectral, modelbased, and deep learning studies in automated inspection [7] Statistical and spectral methods, such as co-occurrence matrices and Fourier-based descriptors, play a part in the characterization of texture but often have large memory and computational demands and do not detect fine or irregular defects. Model-based approaches offer systematic analysis of fabric textures, but cannot be applied to large scale faults and are less precise in detecting intricate faults.

Recent progressions on convolutional neural networks have given rise to tremendous advances in detecting flaws on fabrics. CNN-based methods provide better feature extracting functionality, but require high-resolution, well-located images and are mostly trained on plain-coloured or plain-printed fabric. These deficiencies restrict their use in the actual manufacturing conditions where the image quality is compromised by the unsteady lighting condition, movement, and uneven fabric positioning. The reviewed studies in Table I point to the additions made to various model architectures and also demonstrate gaps in terms of robustness, the variety of defect types, and extrapolation to other environment，

Several studies have investigated deep learning–based fabric defect detection using various datasets and architectures to improve textile quality inspection. A study using a self-collected dataset with five defect categories employed a VGG with P-CNN model and achieved 93.95% accuracy with 92.53% specificity, effectively filtering nonlinear noise in defect datasets; however, it was incapable of categorizing loud real-world plain faulty samples and banded textiles. An improved Faster-RCNN model trained on a self-collected dataset achieved an mAP of 94.75%, demonstrating accurate detection of small defects, although testing was reserved for future implementation [8]. Another approach integrating cloud-edge computing with MobileNetV2-SSDLite on CF, GF, BPF, and DRF datasets achieved accuracies of 84.42%, 93.06%, 71.19%, and 95.6%, respectively, providing a lightweight solution for resource-constrained environments, though it lacked diverse patterned datasets [9]. Using the AITEX dataset, the Focusing Process and Task Combination Subsystem achieved an F1-score of 0.985, recall of 0.993, and precision of 0.97, significantly enhancing the detection of tiny defects, but the method was implemented only for plain fabrics [10]. A DCGAN-based method on the TILDA textile texture dataset achieved 51.61% accuracy with FNR and FPR values of 12.08% and 49.95%, respectively, highlighting defect regions through fusion maps, although the resulting segmentations were noisy [11]. Furthermore, a YOLO-based approach trained on a three-thousand-sample fabric benchmark dataset achieved 97.3% accuracy while reducing computational cost for embedded systems; however, industrial applications remain unexplored [12]. Cascade-RCNN trained on a self-collected dataset with 19 backgrounds achieved an mAP of 75.4%, successfully detecting defects in printed fabrics, though it was limited to patterns present in the dataset [13]. Similarly, the Siamese Feature Pyramid Network, trained using a fusion of Tile and Tianchi fabric datasets, achieved 47.2% mAP and 83.5% accuracy by extracting multi-scale features through a Siamese network, but required template images for each pattern [14]. The DSLRD model, developed using 98 self-collected images, achieved a TPR of 89.28% and FPR of 0.86%, effectively handling irregular printed fabrics despite deficient resilience [15]. Another study using the TILDA dataset employed Image Pyramid and RGBAAM methods, reducing training time to nearly half of traditional approaches while accurately identifying periodic patterns and defects, although execution time increased for complex patterns [16]. A Deep CNN trained on a newly proposed dataset achieved 72% accuracy with precision and recall values of 0.70 and 0.72, respectively, but was limited to detecting only spot and print mismatch defects [17]. Recent YOLOv8-based approaches have demonstrated significant advancements in textile quality control. Using a custom woven fabric dataset, YOLOv8-m achieved an mAP@0.5 of 87.5% and precision of 0.89, demonstrating scalable deployment capabilities, although it was limited to woven fabric structures [18]. Another study on the AI Textile Faults Dataset compared YOLOv8 variants, where YOLOv8-x achieved an mAP@0.5 of 90.5% and recall of 0.91, mainly focusing on stain-type defects [19]. In addition, the Synthetic-to-Real Textile Defect Benchmark highlighted real-time defect detection under harsh lighting conditions using YOLOv8-l, which achieved an mAP@0.5 of 92.2% with an inference speed of 12 ms/image, although it required GPU-grade edge computing devices [20]. More recently, YOLOv9-based models have been introduced to further improve textile defect detection performance through enhanced feature aggregation and programmable gradient

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information. YOLOv9 demonstrated superior detection accuracy, faster convergence, and improved real-time performance compared with earlier YOLO versions, making it highly suitable for industrial textile inspection systems. Despite these advantages, YOLOv9 models generally require larger computational resources and extensive training datasets to achieve optimal performance in diverse textile environments.

The overall results indicate that there are significant improvements in the use of deep learning in textile inspection, specifically in terms of detection and inference speed. However, the majority of the available methods have low flexibility to different textile arrangements and realistic imaging environments. Models that are optimized on solid fabrics or focus on particular defects in printed materials have created a gap in the literature of a such unified framework in which multi-types of fabrics can be considered in one architecture. An approach to this gap is using models generated using wide and unconstrained industrial data that capture real variability in production. This paper proposes an adaptive method of detection using YOLOv8 that was trained to work efficiently with plain, periodically printed, and irregularly printed fabrics that a person can find in the industrial setting. The model has the advantage of a full set of data obtained in the operating conditions, which provides a better stability and the possibility of a successful deployment in the textile quality control system.

III. PROPOSE METHODOLOGY

The proposed inspection framework incorporates such new technologies as collaborative robotics and artificial intelligence to facilitate accurate and reliable detection of fabric defects in the industrial environment. The system uses anthropomorphic robotic arm with a high resolution camera to record a continuous imaging during fabric transportation. A robot constellation facilitates a secure interaction with the human operators based on the standard safety regulations. A conveyor system is fitted with a photoelectric sensor to coordinate the inspection with the fabric movement and the robotic arm is synchronized with it. The workstation-based detection model is trained to identify several types of defects to offer an automated and precise pipeline of evaluation that can be used in an experimental setuo in real time.

➢ *Dataset*

This paper works with Chenab Textiles Fabrics dataset [10], which is composed of 2,500 images in 7 defect categories that include contamination, selvedge, grey stitch, cut, baekra, colour discrepancies, and stains. The data is plain and regularly and randomly printed fabric samples directly taken out of the manufacturing environment, where there is natural variation in illumination, texture alignment, and defect appearance. The ultimate training and test dataset comprises about 2,800 sample according to the given defect type. Table II sums up the breaking down into training, validation, and testing sets.

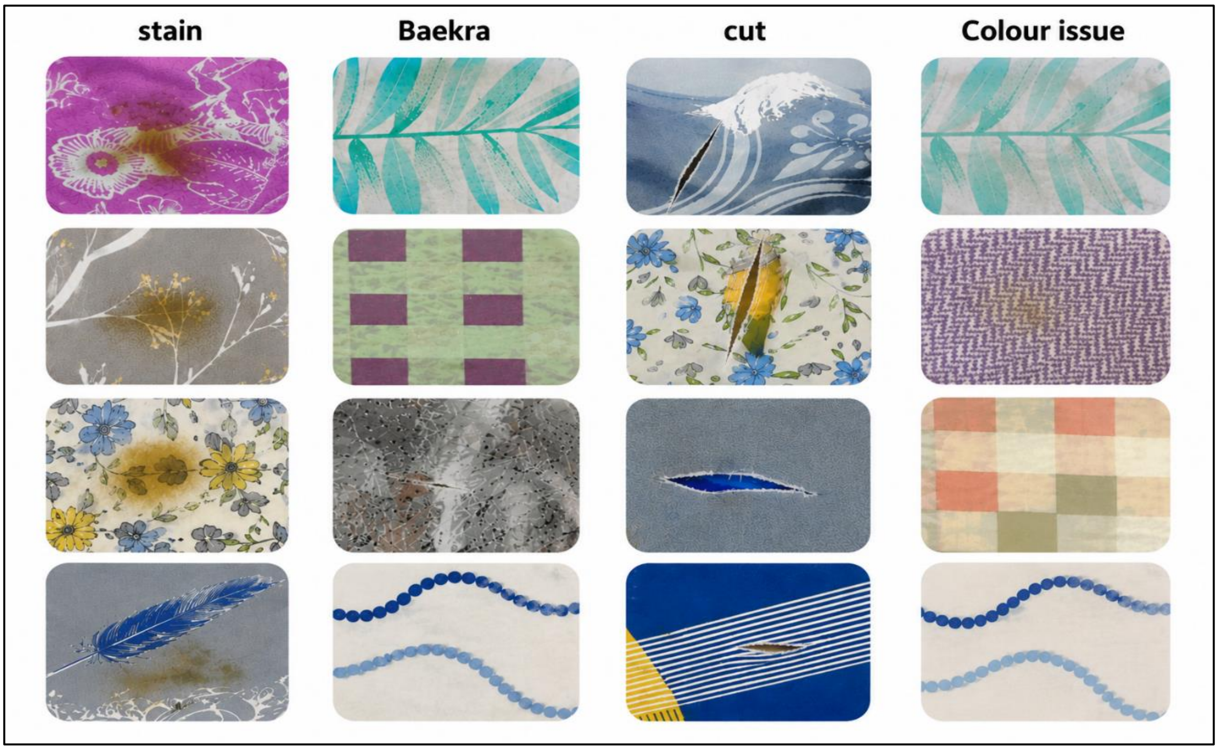

Fig 1 Representative Samples from the Dataset Across Seven Defect Categories.

➢ *Pre-Processing*

Preprocessing was done by rearranging of the raw samples gathered on several days of production and segregating the samples into defect-specific folders. Annotations were performed using Roboflow [25], where all bounding boxes were standardised to square dimensions to align with YOLObased detection requirements. Data augmentation (rotation, horizontal flips, etc.) was used to help with the class imbalance issues, especially for the under-represented defects.

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The dataset is organized across three subsets: training, testing, and validation, with various defect classes recorded for each. In the training set, there are 175 instances of Baekra defects, 272 of Cut, 218 of Selvet, 86 of Color Issues, 148 of Contamination, 228 of Gray Stitch, and 662 of Stain. The testing set contains 17 instances of Baekra, 41 of Cut, 30 of Selvet, 10 of Color Issues, 14 of Contamination, 33 of Gray Stitch, and 112 of Stain. For validation, the dataset includes 48 instances of Baekra, 75 of Cut, 64 of Selvet, 15 of Color Issues, 53 of Contamination, 63 of Gray Stitch, and 208 of Stain. This distribution shows that Stain is the most frequent defect across all subsets, while Color Issues and Gray Stitch are comparatively less common.

Additional samples of publicly available datasets like Defect 1 [20] and FabricDefectDet2 [18] were added to increase the diversity of the dataset. These external samples had a very similar appearance to the collected images in terms of orientation variability and background noise. After augmentation and merging, the dataset was exported in YOLOv9 compatible TensorFLOW, record format and Divided into training, validation and testing data.

- *Innovation and Datasets Characteristics*

Existing textile datasets such as TILDA [19], TIANCHI [20], AITEX [21] are mainly controlled and high-resolution well-aligned defect images with little background variation. While they are adequate for algorithm benchmarking, these types of datasets frequently do not reflect real-life conditions that are encountered in production lines.

In comparison, the data set used in this work is taken directly from the assembly line without any manual refining, which retains the illumination differences, the motion blur, the curvature of the fabric and the natural background noise. This provides samples that are better representative of the challenges in actual manufacturing. The dataset contains defects such as cuts, stains, colour inconsistencies and grey stitches, seen in plain, regularly printed and randomly printed materials. This diversity promotes generalization and robustness models.

- *Methodological Framework*

The methodological pipeline, shown in Fig. 2, is centered on computationally efficient architectures, which can be used for high-speed textile inspection. Camera systems installed above the conveyor continuously capture images of fabric for defect analysis. Prior studies show YOLO and MobileNetSSD to be suitable for real-time detection in resource constrained environments [26], [27].

MobileNetSSD FPN-Lite uses the MobileNetV2 backbone [28], where depthwise separable convolutions and inverted residual are used to lower the inference cost. YOLO’s detection problem is viewed as a single-stage regression problem [29], which allows the whole image to be analyzed in a single forward pass.

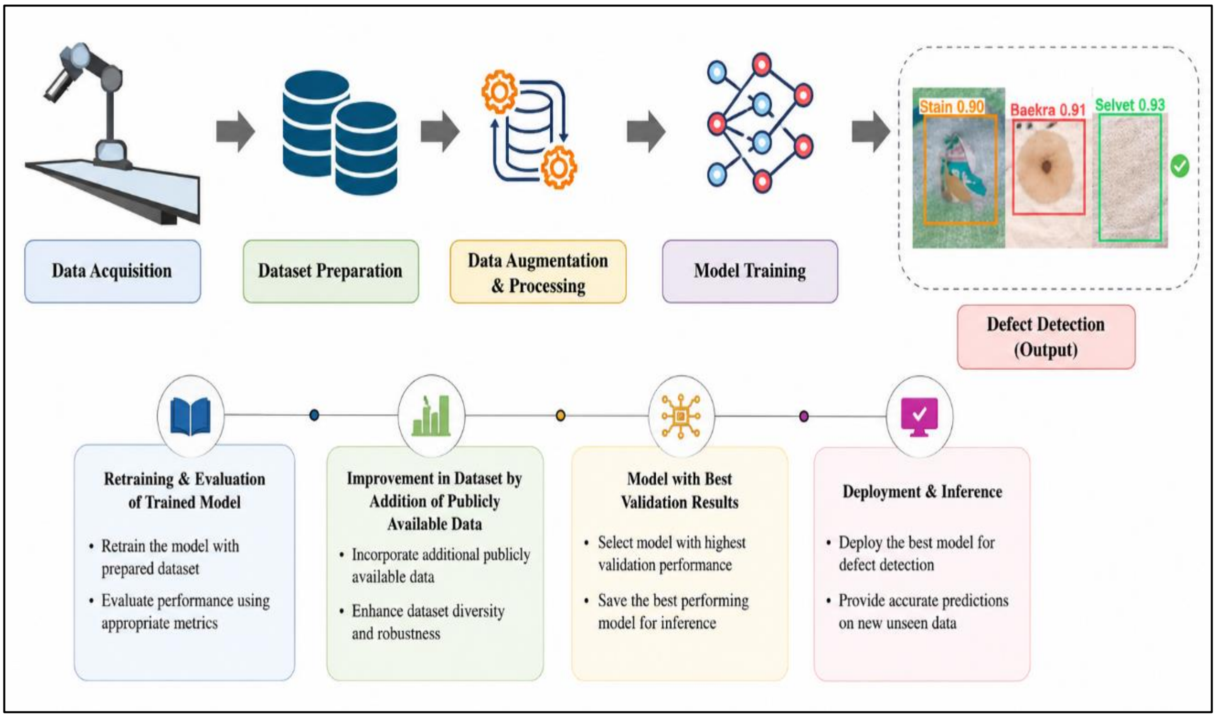

Fig 2 Block Diagram of the Proposed Defect Detection Methodology.

- *YOLOv9 Model Training*

In addition to YOLOv9, training was also carried out using YOLOv9 to assess its performance on the same dataset. The YOLOv9 model demonstrated promising results, achieving a mAP@0.5 of 86.2% and a recall of 0.89 on the test set—slightly outperforming YOLOv8s and YOLOv8m. Notably, YOLOv9 provided superior bounding box stability and better detection under noisy or blurred conditions, attributed to its updated backbone architecture and enhanced spatial pyramid pooling. These results indicate that YOLOv9 may serve as a more robust option for complex or real-time industrial textile inspection scenarios as depicted in Figure 3.

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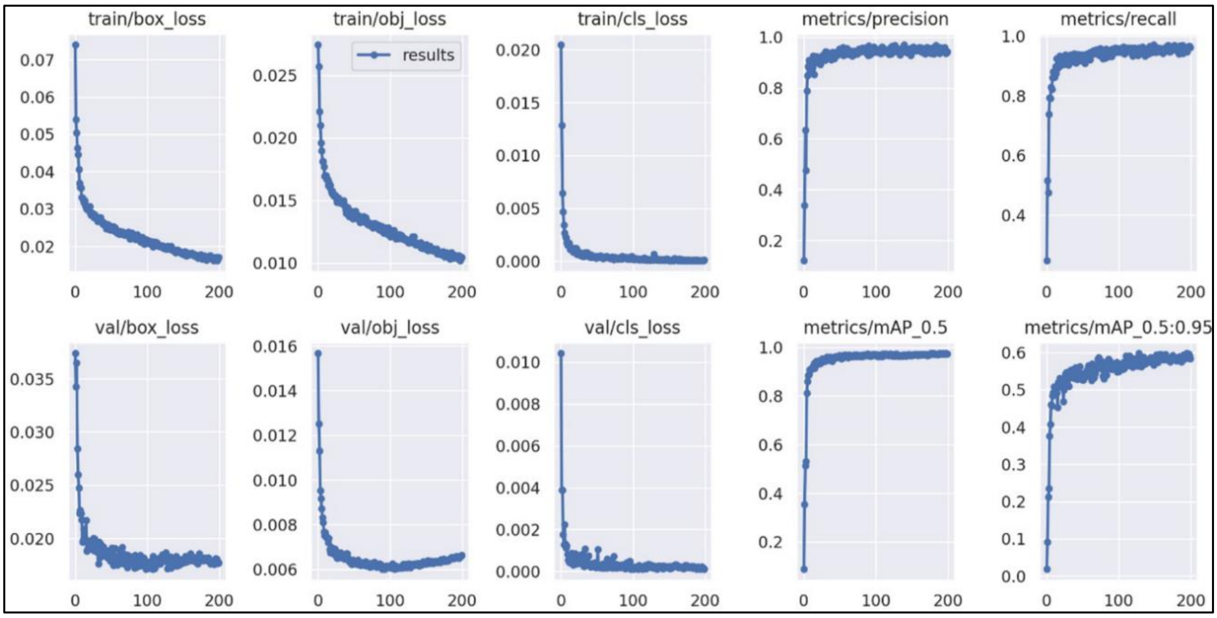

Fig 3 Training Curves of YOLOv9 During Model Optimization.

➢ *SSD-MobileNetV2-FPN Model Training*

SSD-MobileNetV2-FPNLite experiments were conducted using TensorFlow with TFRecord-formatted datasets. Two training regimes were tested. The first involved 6,000 steps with a batch size of 16, a 0.01 base learning rate, and 1,000 warm-up steps. This configuration achieved a mAP@0.5 of 62.71% and mAP@0 .5:0 .95 of 27 .5%. The second experiment extended training to 20,000 steps with a base learning rate of 0.08 and a warm-up learning rate of 0.0266 . Performance improved to a mAP@0.5 of 77.09% and and mAP@0 .5:0 .95 of 39 .61%. Loss convergence trends are shown in Fig. 4.

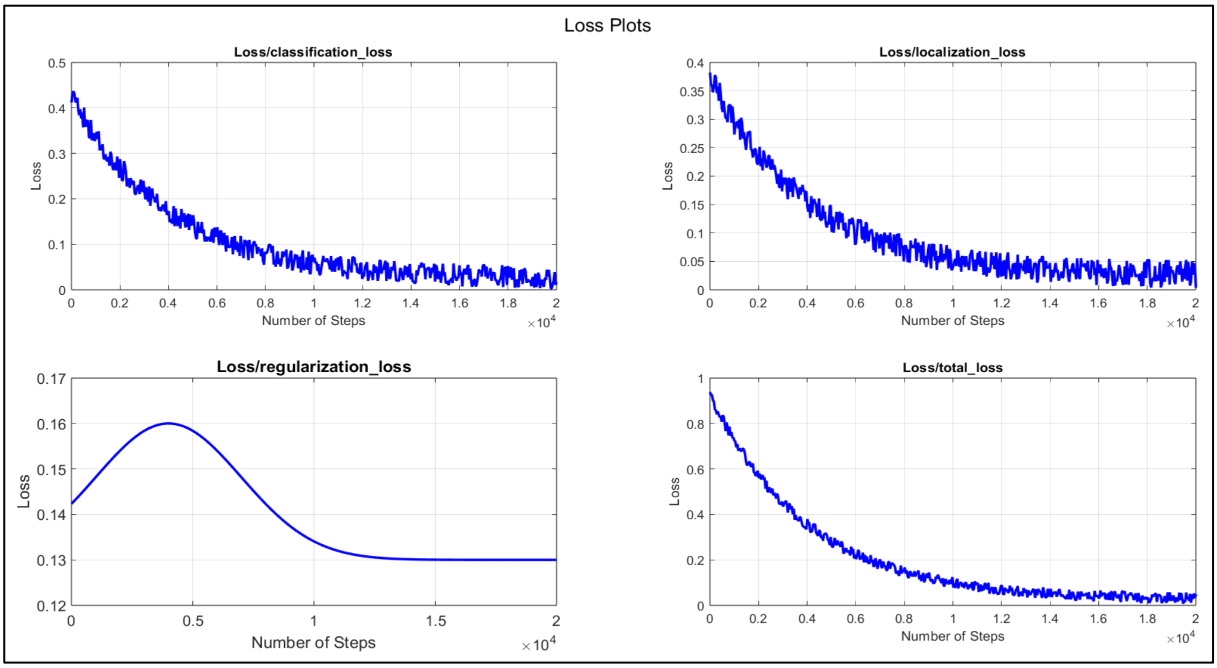

Fig 4 Traning Loss Curves for SSD-MobileNetV2-FPNLite Model

IV. EXPERIMENTAL RESULTS AND ANALYSIS

Model performance was evaluated using mean Average Precision (mAP), precision, and recall across all defect categories. These metrics were used to assess the detection accuracy at both the individual class level and the overall system level. The SSD-MobileNetV2-FPNLite model achieved a test mAP@0.5 of 77.09%, with detailed results summarized in Table III. Among all defect categories, the contamination class achieved the highest mAP, followed by the baekra and stain classes, indicating strong detection capability for representative textile defects. Precision and recall values further demonstrated the reliability of the model, particularly for the contamination class, which achieved a recall value of 1.0. These findings indicate that SSD-

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MobileNetV2-FPNLite can consistently detect multiple fabric defect categories, although some performance variation exists among classes.

The YOLOv9 model demonstrated improved performance on both training and testing datasets, as shown in Table IV. YOLOv8 achieved a training mAP@0.5 of 83.8% and further improved test performance to 84.8%. The contamination class obtained the highest mAP of 95.7%, while baekra and stain achieved 94.5% and 92.2%, respectively. Precision and recall values across all categories confirmed the robustness and reliability of YOLOv8 for detecting diverse fabric defects with high accuracy.

In terms of computational efficiency, YOLOv9 achieved an average processing speed of 11.5 ms per image for 280 test samples with an input size of 32×3×640×640. The preprocessing stage required 1.4 ms, inference consumed 8.4 ms, and post-processing took 1.7 ms. These results demonstrate that YOLOv9 is highly suitable for real-time industrial fabric defect detection applications.

Table 1 Performance of YOLOv9 Across Training Training – YOLOv9

Metrics/Classes	All	Color Issues	Baekra	Cut	Contamination	Selvet	Gray Stitch	Stain
mAP@0.5	70.10%	70.10%	86.30%	85.40%	83.90%	83.20%	73.40%	92.10%
mAP@0.5–0.95	41.10%	41.10%	59.00%	58.90%	53.20%	52.90%	54.60%	64.20%
Recall	0.673	0.673	0.827	0.822	0.802	0.792	0.629	0.895
Precision	0.729	0.729	0.911	0.898	0.792	0.781	0.732	0.914

Table 2 Performance of YOLOv9 Across Testing Testing – YOLOv9

Metrics/Classes	All	Color Issues	Baekra	Cut	Contamination	Selvet	Gray Stitch	Stain
mAP@0.5	77.60%	77.60%	71.80%	71.10%	91.80%	91.30%	76.10%	93.00%
mAP@0.5–0.95	41.50%	41.50%	50.20%	49.80%	66.90%	66.20%	57.60%	60.40%
Recall	0.827	0.827	0.713	0.709	0.843	0.839	0.699	0.938
Precision	0.751	0.751	0.686	0.684	0.884	0.881	0.798	0.891

In a test set consisting of 280 data samples with input dimensions of (32, 3, 640, 640), the YOLOv9 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.

V. DISCUSSION

A comparative view of the mAP values of all deployed models can be found in figure 6 . YOLOv9 obtained the best overall mAP of 84.8% and was consistently better than SSDMobileNetV2-FPNLite in most classes of defects. Notable improvements were seen in the contamination category, cut category and selvedge category and stain category as well, which suggests that YOLOv9 detects structural and textural variations more effectively.

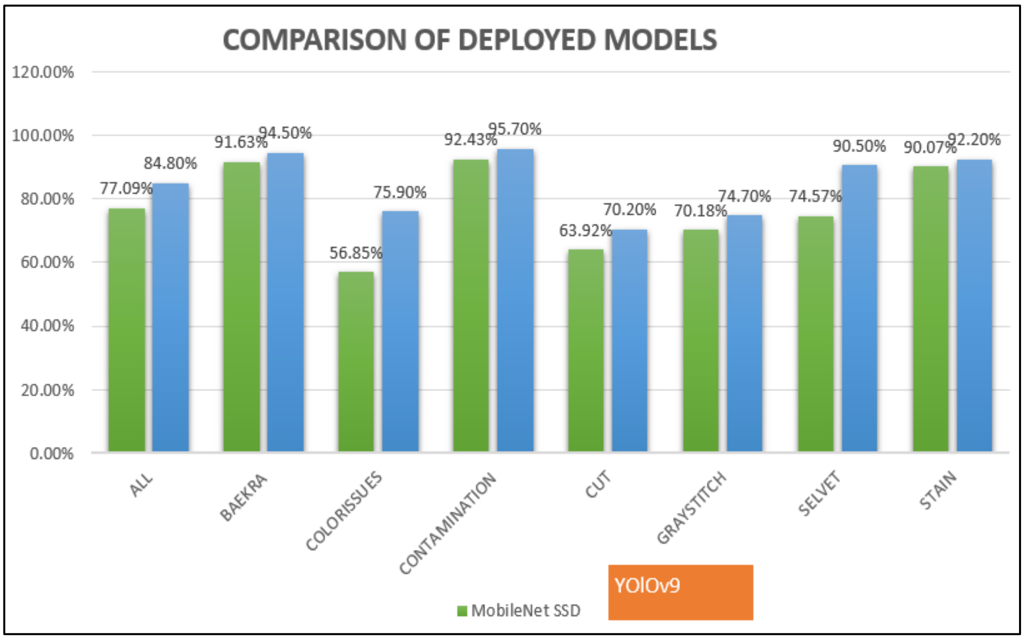

Fig 6 Comparison of Deployed Models Based on mAP Performance

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A class-wise ensemble approach was also tried to improve defect specific accuracy. Although some classes, such as baekra and contamination, showed better performance, the overall performance of accuracy was reduced to 82% as a result of decreased mAP of other classes. These observations point to the inherent trade-offs inherent in ensemble-based optimization, especially with classes that have heterogeneous distributions of features.

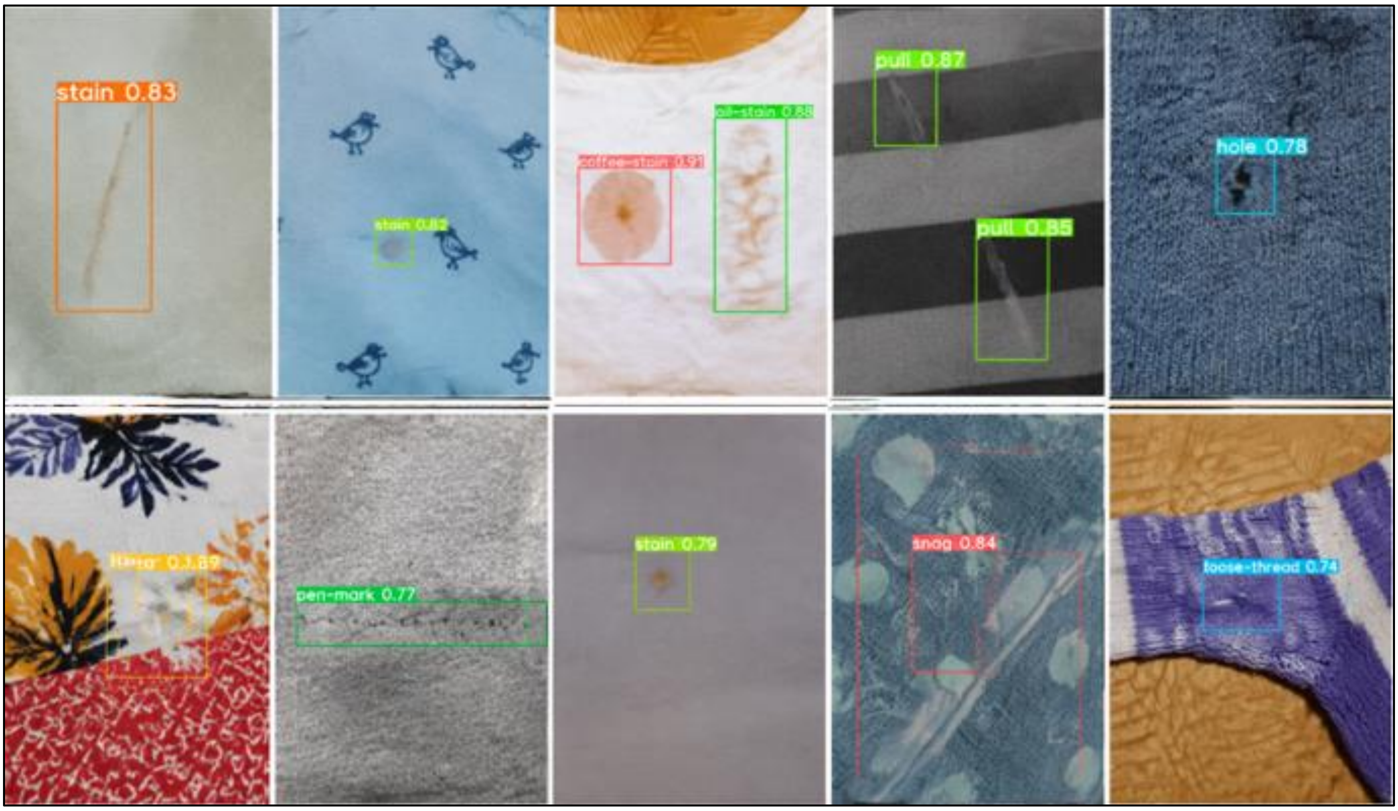

Fig 7 YOLOv9 Detection Outcomes on Representative Test Images

YOLOv10 had lower mAP@0.5 and mAP@0.5-0.95 results(82.6% and 56.7%), which is possibly a result of the suboptimal hyperparameter configurations. Future investigations can be dedicated to fine-tuning these parameters to make models more stable. YOLOv8, on the other hand, succeeded in keeping strong confidence scores across defect categories, i.e.0.86-0.80 for cuts, 0.90 for stains, 0.86-0.85 for grey stitch,0.81 for contamination. The colour issues category had a lower confidence score of 0.49, and representative additional samples are needed.

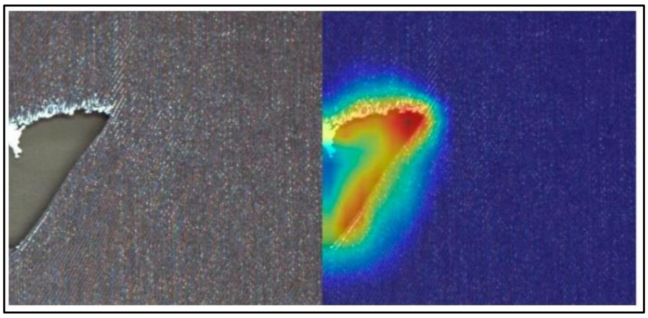

Fig 8 Heatmap Visualization for YOLOv9 Predictions on Test Data

Examples of YOLOv9 detections and corresponding heatmaps are presented in Figures 6 ,7 and 8. A comparative summary of datasets used in previous studies and the proposed methodology is given in Table

Table 3 Comparison of Proposed Dataset with Taxitile Datasets

Dataset Name	Source	No. of Images	Defect Classes	Environment Type	Key Characteristics	Limitation	References
TILDA	Public Benchmark	~1,000	6	Controlled	Well-lit, high-res images, specific angles	Low real-world variability	[19]
FabricDefectDet2	Synthetic-to-Real	~2,500	10	Simulated industrial	Covers multiple defect types, uses synthetic noise	Needs adaptation for true real-	[20]

						world scenarios	
AITEX	Controlled Lab Dataset	~5,000	5+	Controlled	Plain fabric focus, high-res accuracy	Not suitable for printed fabric defects	[11]
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	[18]
CF, GF, BPF, DRF (Combined)	MobileNet-Edge Paper	>4,000 (combined)	4+	Mixed	Designed for lightweight edge devices	Lacks diverse textile styles	[10]
Proposed Methodologyssss	Real Industry (Bangladesh)	~2,800	7	Authentic Production Line	Mixed textile types (plain, printed), noise, blur, diverse angles	Highly variable image quality, challenging conditions	[12]

The Chenab Textiles dataset exhibits much stronger real-world alignment because of its addition of blur, noise, fabric orientation and combination of varying categories of textiles, to improve model. generalizability.

VI. CONCLUSION

The preparation tested automated fabric defect detection using Chenab Textiles dataset which consists of 7 defect classes such as stains, cuts, contamination, baekra, grey stitch, colour-related problems and selvedge imperfections. YOLOv9 performed well in all classes and the model achieved amAP@0.5 of 84.8% and outperformed SSD-MobileNetV2 -FPNLite, which got a mAP@0.5 of 77.09%. The results establish YOLOv9 as an effective and computationally efficient detection framework that can be deployed for real-time detection in high-speed textile manufacturing environments.

The results show that YOLOv9 can provide a feasible solution for industrial defect inspection because of its capability of fast inference speed, strong detection performance in different fabric types, and compatibility with hardware with resource constraints. These attributes make YOLOv9 a good candidate for use in quality inspection systems for production lines.

Further research will be done on how to implement the trained model in real-world manufacturing processes. This integration will include high resolution overhead camera systems, controlled illumination, and high speed communications interfaces to assure consistent imaging conditions. Real-time inference will be supported on the Ubuntu or Windows platform based on the PyTorch - Ultralytics ecosystem with results visualized using an interactive monitoring interface. Detection logs and analytics will be stored in structured database such as MySQL or PostgreSQL to support traceability and quality reporting.

➢ *Further Research Will Advance the System Along Three Primary Directions:*

- Real-time validation: Validation of model performance in real time within industrial settings during continuous operation.
- Expanded defect coverage: Expansion of the detection framework to other and more complex types of defects.
- IoT-enabled integration: Development of an interconnected inspection pipeline for automatic defect handling and improved production efficiency.

The overall results show that combining vision-based deep learning models and textile manufacturing processes can be a huge improvement in identifying defects and making the manufacturing process more reliable, with the potential for developing a scalable and Industry-ready quality control system.

➢ *Authorship Contribution Statement*

Conceptualization, A.H.T. and A.M; methodology, Y.Z., R.S., and L.N.; software, A.H,T, A.M; validation, A.H.T. and R.S., formal analysis, A.H.T., A.H, and M.A.H.T; investigation, Y.Z.; resources, A.H.T., A.M., data curation, L.N., and R.S.; writing original draft preparation, R.S.; writing review and editing, M.M., and A.H.T.; visualization, A.H.T, R.S.; supervision, Y.Z.; project administration, Y.Z.; funding acquisition, Y.Z. All authors have read and agreed to the published version of the manuscript.

➢ *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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