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An Advanced Machine Vision Technique for Quality Control of Fabric in the Textile Industry

Rifat Arman Chowdhury   Souharda Bhattacharjee   Sajib Sarker   Pulak Deb Roy   Asim Ajwad Gani

Dr. Md. Ashraful Alam
Associate Professor, Department of Computer Science and Engineering, BRAC University

Abstract

The textile industry, using both natural and synthetic materials, often faces defects during production, causing major financial losses. Manual inspection is still common but is slow, inefficient, and error-prone. This paper explores how Machine Vision can automate defect detection more accurately. We analyzed models like YOLOv8n, SSD with VGG16, Faster R-CNN with ResNet-50, and a custom model. We also developed a hybrid two-stage pipeline: YOLOv8l detects defects, and EfficientNet-B0 classifies them. Our pipeline achieved 84.2 precision, 81.9 recall, and 83.0 F1 score. We created a custom dataset of 9,075 images across four defect classes, collected from textile factories to reflect real conditions. Finally, we designed a prototype for industrial automation, demonstrating real-world application with strong accuracy and low computational cost.

Problem Statement

- **Factory Variability:** Different factory setups require the CNN model to be robust and trained to adapt across diverse industrial environments.
- **Image Consistency:** Lighting, shadows, and wrinkles must be controlled during data collection, as they can distort defect detection.
- **Class Imbalance:** Fabric defects occur randomly and at different rates, making it difficult to maintain balanced datasets for effective model training.
- **Preprocessing and Tuning**: Techniques like CLAHE and other image processing methods require careful parameter tuning to avoid introducing artifacts.
- **Real-Time Limitations:** Implementing models in real time is challenged by hardware constraints, high-resolution data, and processing latency, requiring seamless hardware-software integration.

Methodology

Our proposed system utilizes a two-stage pipeline combining YOLOv8l for binary defect detection and EfficientNetB0 for multi-class defect classification. This design ensures efficient computation by applying classification only to regions marked as defective.

Stage 1 – YOLOv8l for binary defect detection

- Detects defect regions using a C2f-based backbone, multi-scale feature fusion, and an anchor-free head.
- Outputs bounding boxes with defect/no-defect labels.

Stage 2 – EfficientNet-B0 for classification

- Cropped defect regions are resized and classified into defect types.
- Uses MBConv blocks with SE modules for high accuracy and efficiency.

This modular pipeline enables scalable and interpretable defect detection with deployment flexibility across resource constrained and industrial environments.

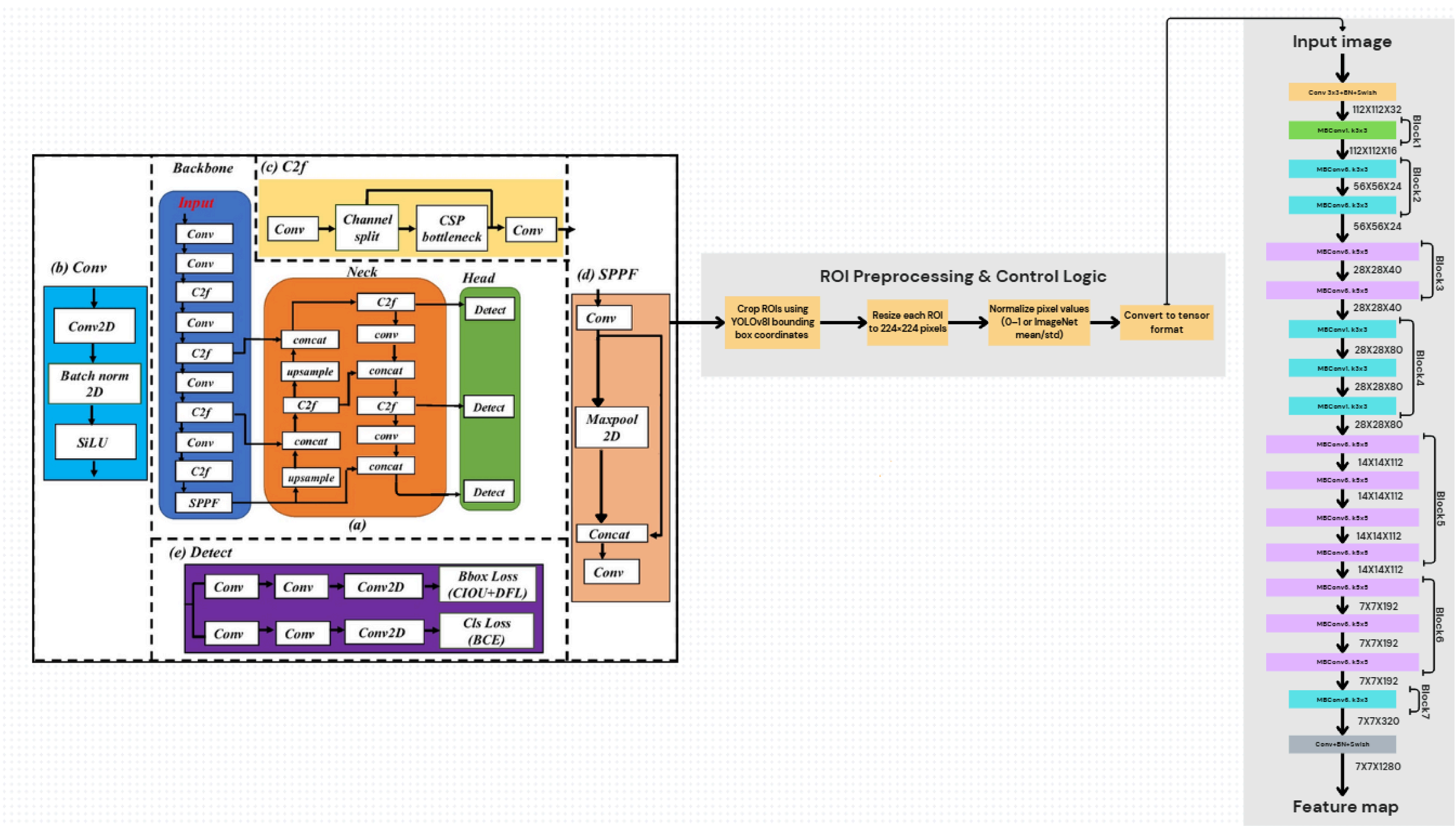
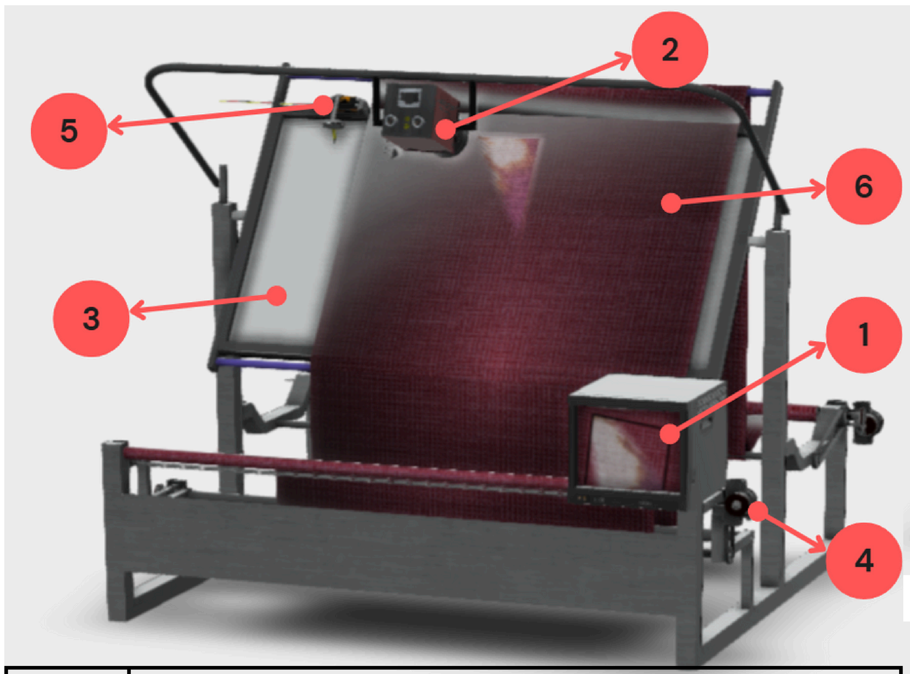


Figure: Proposed pipeline workflow integrating YOLOv8l and EfficientNet B0.



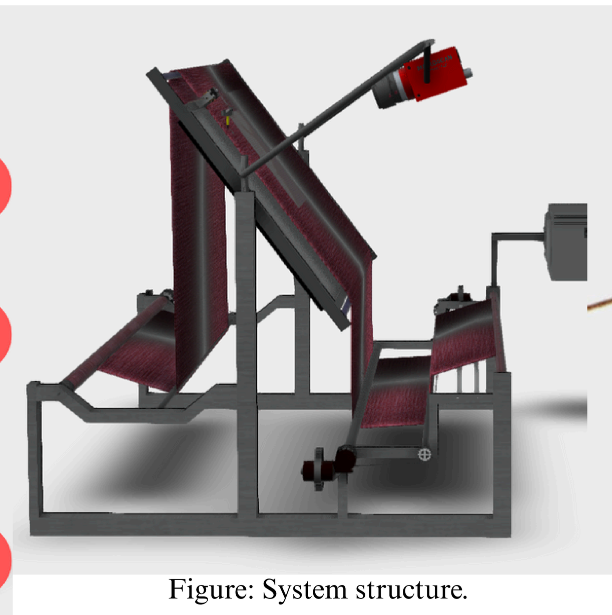


Figure: System structure.

Figure: Marker mechanism overview..

Num	Label
1	Host PC
2	Camera
3	Lightbox enclosure
4	Brushed DC windshield wiper motor
5	Servo motor for marker
6	Fabric roll

Figure: System overview with component labels.

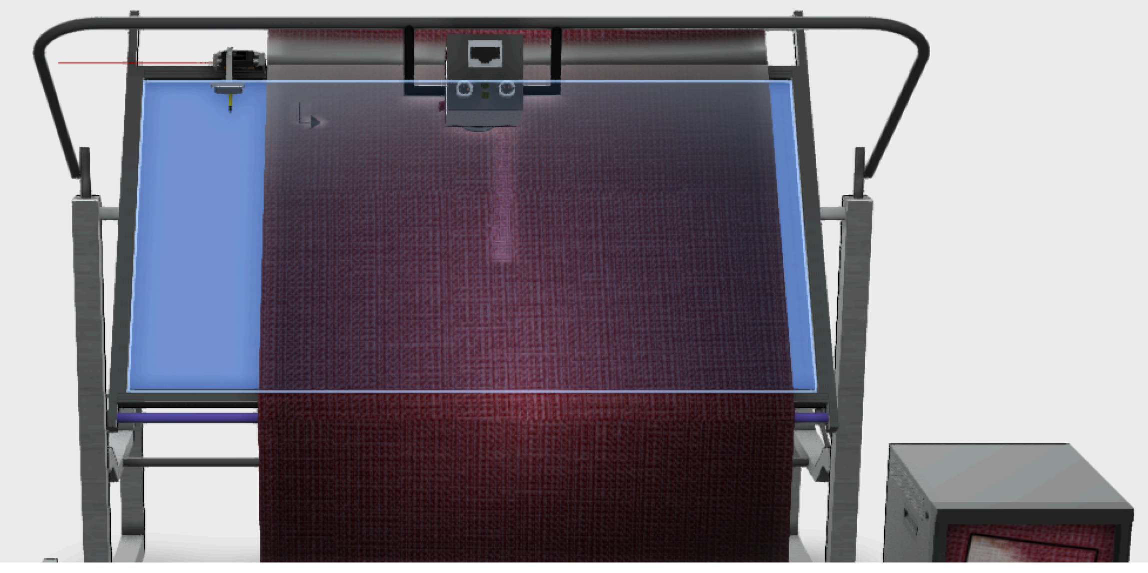


Figure: Camera position with illuminated lightbox.

For the system to work following equations are used

Capture Time:

$$\Delta t = \frac{RPM \times 2\pi}{60} \quad ....1$$

Linear Velocity of Roller:

$$v_m = \frac{RPM \times 2\pi}{60} \quad ....2$$

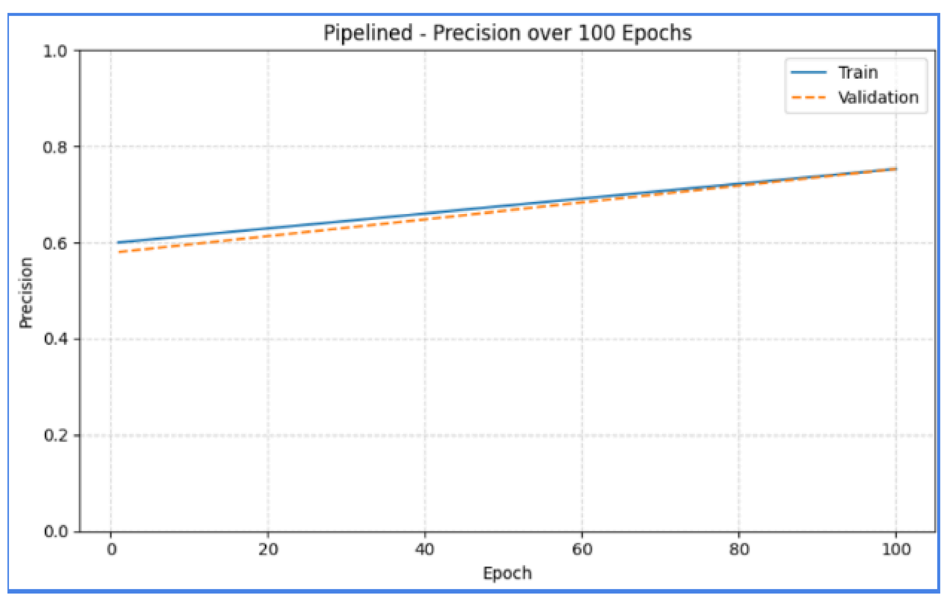
Response Time:

$$T_m = \frac{D}{v_m} \quad \text{Where: } D = \frac{\text{Lightbox Width}}{2} \quad ....3$$

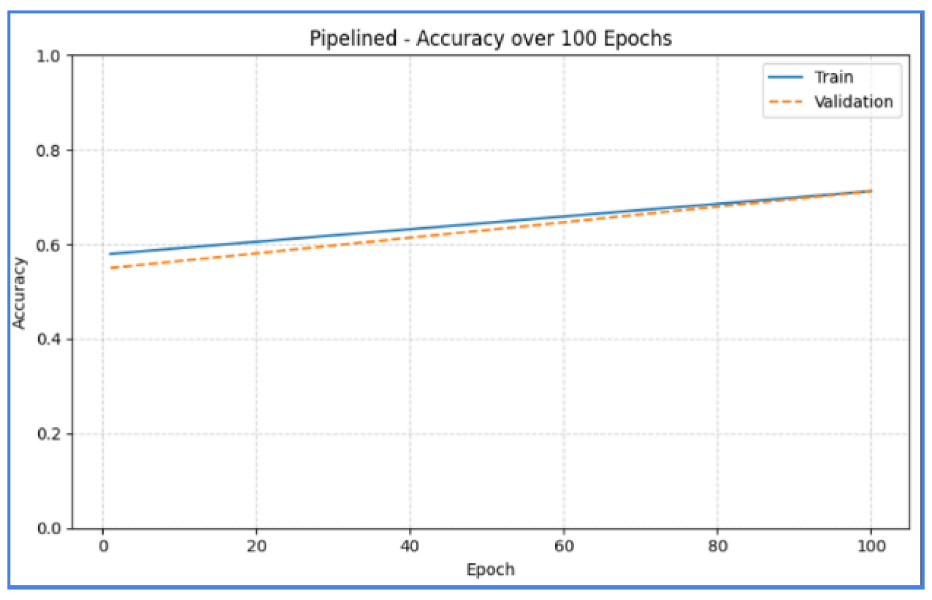
Total Marking Time:

$$\text{Total Marking Time, } M_T = \text{Capture Time} + \text{Detection Time} + \text{Response Time} \quad ....4$$

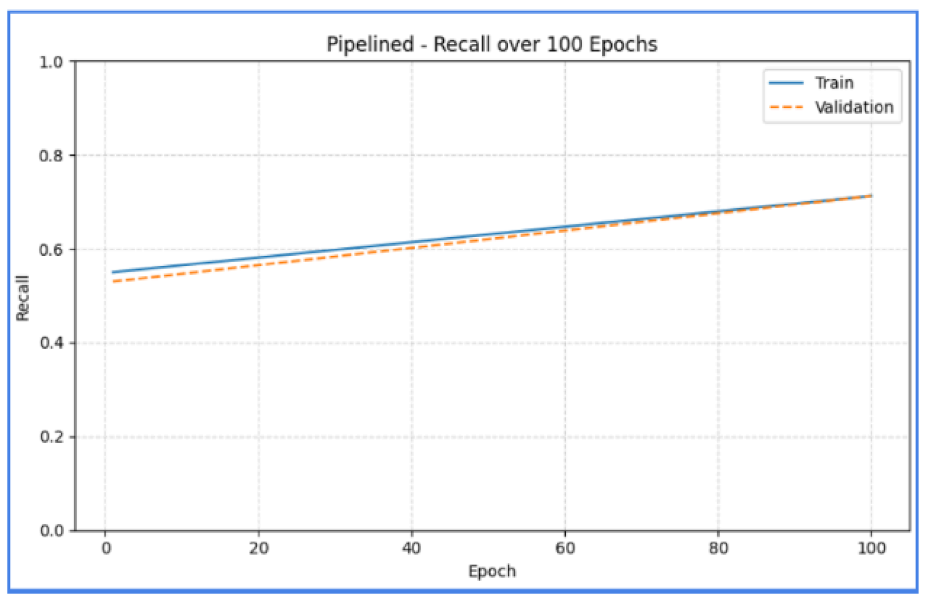
Results & Analysis



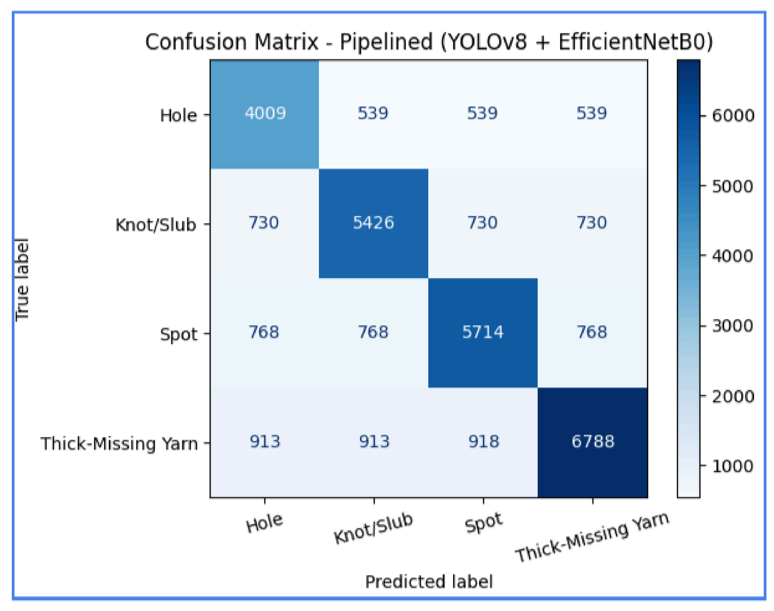
The model shows a relatively high precision, indicating that when it predicts a defect, it is correct about 75% of the time, reducing the chances of falsely labeling good fabrics as defective.



A recall of about 71% shows the model can identify the majority of actual defects, although a few subtle ones might still be missed, suggesting room for improvement in capturing harder-to-detect flaws.



The pipeline achieves 73% accuracy, reflecting that overall, most predictions in both defect and non-defect are correctly classified, showing a balanced and reliable performance across the dataset.



The confusion matrix highlights that it is particularly strong in recognizing defect types like knot/slub and thick/missing yarn, though there remains some confusion between similar defect classes, which could be refined with further class balancing or advanced augmentation.

Relevance to BEAR Themes and National Challenges

The textile industry, using both natural and synthetic materials, often faces defects during production, causing major financial losses. Manual inspection is still common but is slow, inefficient, and error-prone. This paper explores how Machine Vision can automate defect detection more accurately. We analyzed models like YOLOv8n, SSD with VGG16, Faster R-CNN with ResNet-50, and a custom model. We also developed a hybrid two-stage pipeline: YOLOv8l detects defects, and EfficientNet-B0 classifies them. Our pipeline achieved 84.2 precision, 81.9 recall, and 83.0 F1 score. We created a custom dataset of 9,075 images across four defect classes, collected from textile factories to reflect real conditions. Finally, we designed a prototype for industrial automation, demonstrating real-world application with strong accuracy and low computational cost.

Reference

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