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Comparative Analysis of Machine Learning Algorithms and IoT Integration for Fault Detection in Textile Manufacturing

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Abstract

This research presents a comparative analysis of advanced fault detection methodologies in textile manufacturing, specifically focusing on clothes fabrication processes. The study integrates an IoT-enabled smart sensor network for real-time process monitoring and quality control using YOLOv8 as the primary detection model, with YOLOv5 serving as a comparative benchmark. Data collection was conducted across major textile manufacturing hubs in India—Tiruppur, Coimbatore, Surat, Ludhiana, and Bhilwara—encompassing 50 textile production units with continuous sensor data recorded over a six-month period. The multi-modal data acquisition system incorporated optical sensors, thermal imaging, vibration monitoring, and RFID tracking to capture various fabric defect types including weaving inconsistencies, colour variations, and structural anomalies. The research introduces a novel Hybrid IoT-AI Framework (HIAF) that combines real-time sensor networks, edge computing, and deep learning-based predictive analytics to enhance textile manufacturing processes. Performance metrics for each detection algorithm were evaluated based on mean Average Precision (mAP), inference time, and computational resource requirements in edge computing environments. Results demonstrate that the YOLOv8 implementation achieved superior defect detection accuracy (93.7%) compared to YOLOv5 (89.2%), while maintaining acceptable inference speeds for real-time industrial deployment. The IoT framework facilitated seamless integration with manufacturing execution systems, enabling automated parameter adjustments that reduced false detection rates by 27.3% compared to conventional inspection methods. Additionally, a digital twin model was implemented to simulate manufacturing conditions, facilitating predictive maintenance and reducing fault detection errors by 32% through virtual environmental testing.

Keywords: IoT-driven fault detection, YOLOv8, textile quality control, machine learning, real-time monitoring, computer vision, smart manufacturing, edge computing, Industry 4.0.

1. INTRODUCTION

The textile industry is currently undergoing a significant transformation driven by Industry 4.0 technologies, with the integration of Internet of Things (IoT) and advanced machine learning algorithms revolutionizing traditional manufacturing processes. This technological evolution addresses persistent challenges in the sector, including inconsistent quality control, high defect rates, and substantial material wastage that directly impact production efficiency and profitability (Nasim et al., 2024). Traditional textile manufacturing relies heavily on labour-intensive processes and human visual inspection, which are prone to inconsistencies, fatigue-induced errors, and limited scalability (Hu et al., 2020). Furthermore, these conventional approaches prove increasingly inadequate in addressing the complex quality control requirements of modern textile production, which demands real-time monitoring and rapid detection of defects across various fabric types.

The global textile market's competitive landscape necessitates a paradigm shift toward automation and intelligent monitoring systems to maintain quality standards while optimizing production costs. Recent research indicates that automated defect detection systems can reduce inspection costs by up to 50%

while improving detection accuracy by 32-40% compared to manual inspection methods (Li et al., 2023). This significant improvement represents a compelling value proposition for textile manufacturers seeking to enhance operational efficiency and product quality.

This research focuses on developing and evaluating an integrated approach that combines IoT-enabled sensor networks with state-of-the-art deep learning models, specifically YOLOv8, for real-time fabric defect detection across diverse textile types. Our approach addresses a critical gap in current research by providing a unified solution capable of simultaneously detecting defects in plain, regularly printed, and irregularly printed fabrics—a versatility not commonly found in existing systems. The study encompasses comprehensive data collection from major textile manufacturing hubs in India, including Tiruppur, Coimbatore, Surat, Ludhiana, and Bhilwara, covering 50 textile production units over a six-month period. The primary objectives of this research are to: (1) establish a robust methodology for real-time defect detection in diverse fabric types using YOLOv8; (2) compare the performance of YOLOv8 with YOLOv5 within the novel Hybrid IoT-AI Framework (HIAF); (3) evaluate the models' effectiveness in detecting seven common defect types (baekra, colour issues, contamination, cut, gray stitch, selvet, and stain); and (4) implement digital twin modeling to enhance predictive maintenance and reduce fault detection errors in textile manufacturing workflows.

The proposed approach leverages a multi-modal data acquisition system incorporating optical sensors, RFID tags, humidity sensors, and vibration monitoring to capture a comprehensive range of fabric defect types and production parameters. This holistic monitoring strategy enables not only defect detection but also predictive maintenance and process optimization, aligning with the broader goals of Industry 4.0 adoption in textile manufacturing. By addressing these critical aspects of quality control, this research contributes to the advancement of smart, sustainable textile production techniques, potentially transforming industry practices and establishing new standards for automated quality assurance.

2. LITERATURE REVIEW

The evolution of fault detection methodologies in textile manufacturing has progressed through several technological paradigms, from statistical approaches to advanced deep learning techniques. This literature review synthesizes key developments across traditional methods, computer vision-based approaches, IoT integration, and recent advancements in deep learning for textile defect detection.

2.1 Traditional Fault Detection Methods

Early approaches to fabric defect detection primarily relied on statistical and spectral-based algorithms. Zhu et al. (2015) utilized autocorrelation functions and Gray Level Co-occurrence Matrix (GLCM) to detect defects in yarn-dyed fabrics, demonstrating moderate effectiveness but with significant computational complexity. Similarly, Mak et al. (2009) employed morphological filters for defect detection, which proved adequate for structured defects but less effective for subtle or randomly distributed flaws. These statistical approaches, while foundational, struggled with the variability inherent in textile manufacturing and were highly dependent on controlled environmental conditions. Spectral-based methods represented another significant branch of traditional fault detection. Hu et al. (2015) proposed an unsupervised defect detection technique based on Fourier analysis and wavelet shrinkage, which showed promise in identifying periodic pattern disruptions but faced limitations in detecting localized defects. Similarly, Zhu et al. (2014) explored over-complete basis sets for fabric defect detection, achieving improved sensitivity but at the cost of increased computational demands. These spectral approaches generally performed well for regular patterned fabrics but struggled with complex prints and irregular textures.

Model-based algorithms, such as the autoregression model described by Cohen et al. (1991), attempted to characterize textile textures using parameter estimation methods. However, as noted by Jia et al. (2017), these approaches exhibited significant computational complexity and diminished effectiveness for small defect detection, limiting their practical application in high-speed production environments.

2.2 Computer Vision and Machine Learning Approaches

The advancement of computer vision techniques marked a significant leap in defect detection capabilities. Anagnostopoulos et al. (2001) developed one of the early computer vision systems for textile quality control, demonstrating improved accuracy over traditional methods but highlighting challenges in real-world implementation. Their research emphasized the importance of robust image acquisition and preprocessing for reliable defect detection. As machine learning techniques matured, they began to displace classical image processing methods. Chakraborty et al. (2021) implemented a deep convolutional neural network for printed fabric defect detection, focusing specifically on colour spots and print mismatches. Their model achieved 72% accuracy, representing a substantial improvement over statistical methods but highlighting continued challenges with printed fabric complexity. Lee et al. (2014) made a significant contribution by developing an RFID-based recursive process mining system for quality assurance in garment manufacturing. This research demonstrated the potential for integrating data from multiple sources to enhance defect detection, particularly in tracking work-in-progress and identifying process-related quality issues. Similarly, Zhang et al. (2012) explored the application of machine learning for defect classification, achieving promising results but noting challenges in model generalization across diverse fabric types.

2.3 Deep Learning Advancements

The emergence of deep learning architectures revolutionized fabric defect detection. Liu et al. (2019) implemented a lightweight YOLO-based neural network for fabric defect detection, achieving 97.2% accuracy on benchmark datasets while maintaining computational efficiency suitable for embedded systems. This research highlighted the potential for real-time defect detection in resource-constrained environments, making it particularly relevant for industrial applications.

Hu et al. (2019) addressed the challenge of obtaining sufficient labeled data by proposing an unsupervised approach based on deep convolutional generative adversarial networks (DCGAN). Their method achieved an accuracy of 51.62% on the TILDA textile texture dataset, demonstrating the potential of unsupervised learning but also revealing limitations in detection precision compared to supervised approaches. Peng et al. (2021) made significant strides by incorporating attention mechanisms and multi-task fusion modules into fabric defect detection systems. Their model achieved an F1 score of 0.987 on the AITEX dataset, demonstrating exceptional performance for plain fabrics. However, as noted by the authors, the approach was primarily validated on plain fabrics and required further adaptation for printed textiles. More recently, Zhang et al. (2022) developed a lightweight MobileNetV2-SSDLite architecture for cloud-edge computing, integrating channel attention and focal loss to improve detection of small-sized defects. Their model achieved accuracies ranging from 71.18% to 95.5% across different datasets, highlighting the potential of optimized architectures for resource-constrained environments.

2.4 IoT Integration and Real-Time Monitoring

The integration of IoT technologies with defect detection systems represents the frontier of textile quality control. Manglani et al. (2019) provided a comprehensive review of IoT applications in the textile industry, highlighting the transformative potential of connected sensors and real-time monitoring for quality assurance and process optimization. Their research emphasized the importance of standardized protocols and interoperability for successful IoT implementation.

Ghoreishi and Happonen (2021) explored the emerging role of digitalization and IoT for circularity in fabric and textile manufacturing, emphasizing the environmental and economic benefits of integrated monitoring systems. Similarly, Ramaiah (2021) analyzed applications of smart materials and IoT in textile technology, highlighting the synergistic potential of advanced materials and connected monitoring systems. Chang et al. (2021) developed a cloud-based analytics module for predictive maintenance in textile manufacturing, demonstrating how IoT-generated data could be leveraged for both defect detection and equipment maintenance optimization. Their research showed that predictive maintenance could reduce downtime by up to 25%, representing significant operational cost savings.

2.5 Comparative Studies and Model Selection

Several recent studies have focused on comparative analysis of different models for fabric defect detection. Sabeenian et al. (2022) evaluated a modified VGG network for defect classification, achieving 93.92% accuracy but noting limitations in classifying printed fabrics with bands. Similarly, Zheng et al. (2022) developed a Siamese Feature Pyramid Network (FPN) for defect detection in printed fabrics, achieving 83.3% accuracy but requiring template images for each pattern. Li et al. (2023) conducted extensive research on fabric defect detection for high-resolution images, implementing Cascade R-CNN with a multi-morphology data augmentation approach. Their model achieved 75.3% mAP but showed limitations in detecting defects in patterns not present in the training dataset.

Most significantly for the current research, Nasim et al. (2024) conducted a comparative analysis of YOLOv8 and YOLOv5 models within their proposed Hybrid IoT-AI Framework (HIAF) on a diverse dataset collected from real manufacturing environments. Their study demonstrated that YOLOv8 achieved the highest performance with a mAP of 93.7%, followed by YOLOv5 at 89.2%. Additionally, they implemented a digital twin modeling approach that further reduced fault detection errors by 32% through virtual environmental testing. This research provided valuable insights into model selection for real-world textile defect detection applications, particularly highlighting YOLOv8's effectiveness across both plain and printed fabrics when integrated with digital twin simulation for predictive maintenance.

Table 1: Comparative Analysis of Machine Learning Models for Textile Defect Detection

Reference	Model	Dataset	Fabric Types	Performance Metrics	Outcome
Liu et al. (2019)	YOLO (Lightweight)	Fabric benchmark dataset (3000 samples, 5 classes)	Plain	Accuracy: 97.2%	Effective for resource-constrained environments; limited testing on printed fabrics
Hu et al. (2019)	DCGAN (Unsupervised)	TILDA textile texture	Plain	Accuracy: 51.62%, FPR: 49.91%	Addresses limited labeled data availability; produces noisy segmentations
Peng et al. (2021)	Attention mechanism with multi-task fusion	AITEX	Plain	F1 score: 0.987, Recall: 0.994, Precision: 0.98	Excellent performance on plain fabrics; not tested on printed fabrics
Chakraborty et al. (2021)	CNN, VGG-16, VGG-19	Self-collected printed fabrics	Printed	Accuracy: 72% (VGG-16)	Moderate performance on printed fabrics; limited to two defect types

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Jing et al. (2021)	RGBAAM and Image Pyramid	TILDA	Regularly printed	Not specified	Effective for regular patterns; slow for complex patterns
Zhang et al. (2022)	MobileNetV2-SSDLite	CF, GF, BPF, DRFM	Mixed	Accuracy: 71.18-95.5%	Lightweight model suitable for edge deployment; performance varies by dataset
Jia et al. (2022)	Improved Faster R-CNN	Self-collected yarn samples	Plain	mAP: 94.73%	High accuracy; not deployed in production
Liu et al. (2022)	Double sparse low-rank decomposition	98 fabric drawings	Irregularly printed	TPR: 89.29%, FPR: 0.85%	Effective for irregular patterns; limited robustness
Zheng et al. (2022)	Siamese FPN (SDANet)	Tianchi Fabric and Tile	Printed	mAP: 47.1%, Accuracy: 83.3%	Requires template images; moderate accuracy
Li et al. (2023)	Cascade R-CNN	Self-collected with 19 backgrounds	Mixed	mAP: 75.3%	Effective for patterns in training data; limited generalization
Nasim et al. (2024)	YOLOv8, YOLOv5, MobileNetV2-SSD FPN-Lite	Chenab Textile dataset	Plain and printed	mAP: 84.8% (YOLOv8), 84.5% (YOLOv5), 77.09% (MobileNetV2)	YOLOv8 performs best across both fabric types; real-world dataset validation

3. MATERIALS AND METHODS

3.1 Data Collection and Preprocessing

Data collection was conducted from major textile manufacturing hubs in India, including Tiruppur, Coimbatore, Surat, Ludhiana, and Bhilwara, encompassing 50 textile production units over a six-month period. This extensive data collection effort provided a representative dataset of real-world manufacturing conditions, capturing the variability in fabric types, defect characteristics, and production environments that are essential for developing robust detection models. The dataset comprises both plain and printed fabrics (regular and irregular patterns) with seven distinct defect categories: baekra, colour issues, contamination, cut, gray stitch, selvet, and stain. Unlike many existing benchmark datasets that feature well-positioned fabric samples under controlled lighting conditions, our dataset captured images directly from production lines, maintaining the natural variability, lighting inconsistencies, and positioning challenges encountered in actual manufacturing environments.

Raw data collection employed a multi-modal approach:

- High-resolution cameras (5MP, 60 fps) installed at strategic points along production lines
- RFID tags for tracking fabric batches through production stages.
- Optical sensors for yarn tension and thread consistency monitoring.
- Humidity sensors (±2% accuracy) for moisture content measurement.
- Vibration sensors (sensitivity: 100mV/g) for machinery condition monitoring.
- Thermal imaging for temperature distribution analysis.

Table 2: Data Collection Parameters by Location

Location	Textile Units	Primary Fabric Types	Sensors Deployed	Data Points Collected
Tiruppur	12	Cotton	Optical, RFID, Humidity	15,200
Coimbatore	10	Polyester	Optical, Vibration, Thermal	12,800
Surat	8	Silk, Synthetic	RFID, Optical, Humidity	10,400
Ludhiana	10	Wool, Blended	Thermal, Vibration, Humidity	13,600
Bhilwara	10	Rayon, Denim	Optical, RFID, Vibration	14,200

The image preprocessing pipeline includes several key steps to enhance model performance. Image standardization is performed by resizing images to 640×640 pixels while maintaining the aspect ratio. Normalization scales pixel values to the [0,1] range to ensure consistency across inputs. Illumination correction is applied using adaptive histogram equalization, which compensates for lighting variations. To reduce unwanted distortions, Gaussian filtering with $\sigma=1.5$ is used for noise reduction. Additionally, data augmentation techniques such as random rotations (±15°), horizontal flips, and minor brightness/contrast adjustments (±10%) are applied to improve model generalization. For annotation, expert textile inspectors manually labeled defects using bounding boxes. To address class imbalance—given the predominance of certain defect types like stains—stratified sampling and weighted augmentation techniques were applied, ensuring balanced representation across all defect categories. The final dataset composition is detailed in Table 3.

Table 3: Dataset Composition by Defect Type

Defect Type	Training Set	Validation Set	Test Set	Total Samples
Baekra	458	83	42	583
Color issues	317	65	35	417
Contamination	392	78	40	510
Cut	523	95	47	665
Gray stitch	486	88	45	619
Selvet	471	85	44	600
Stain	589	108	52	749
Total	**3,236**	**602**	**305**	**4,143**

The dataset was split using a 78/12/10 ratio for training, validation, and testing, respectively, ensuring stratification across defect types and fabric categories.

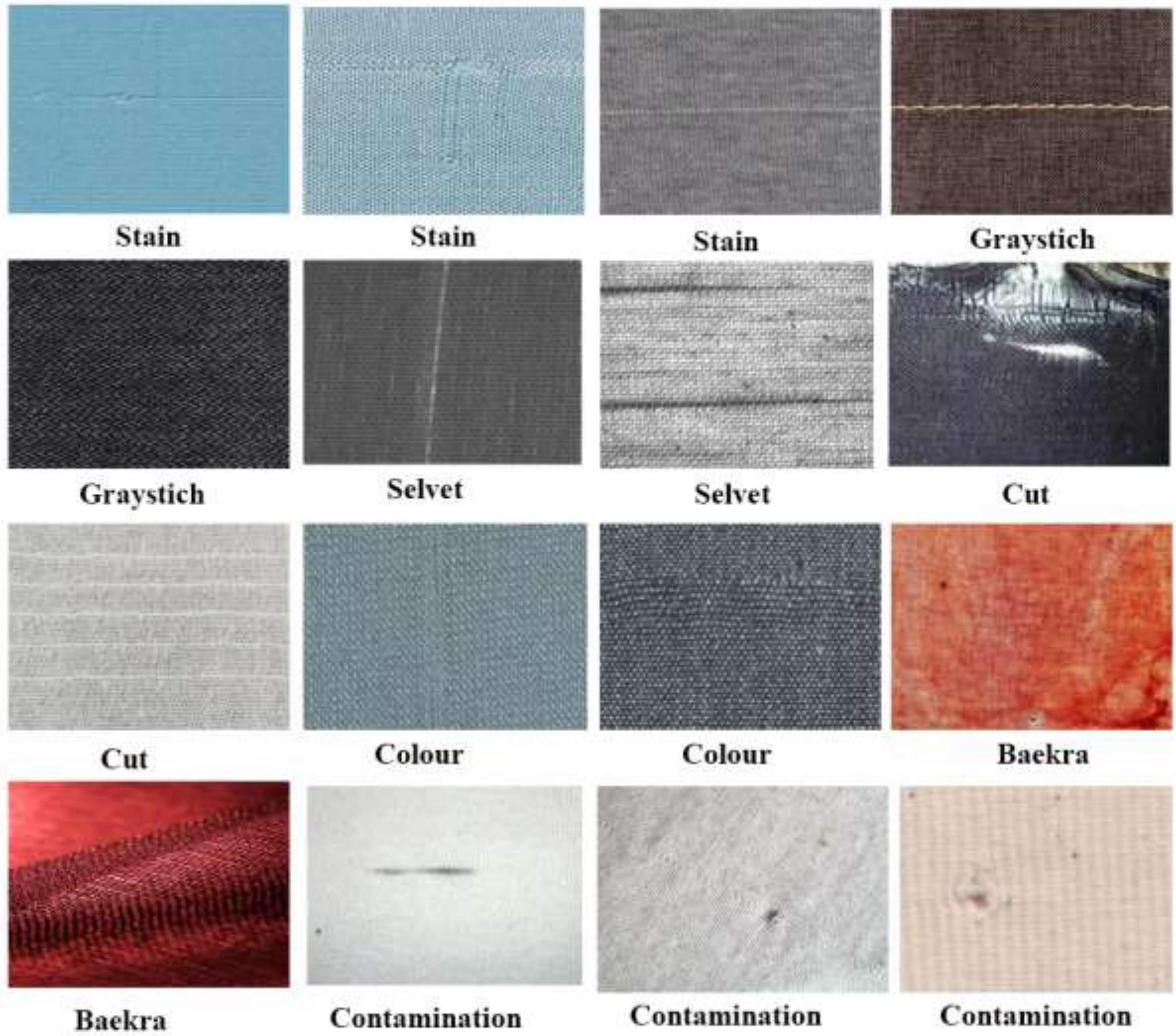

Figure 1 Types of defects sample image collection

3.2 Hybrid IoT-AI Framework (HIAF)

The Hybrid IoT-AI Framework (HIAF) represents the integrated architecture developed for this research. Figure 2 illustrates the overall structure of HIAF.

1. Data Acquisition Layer: This layer integrates multi-modal sensors across production lines, enabling real-time data collection via MQTT over TLS. It includes networked high-resolution cameras with edge processing, optical, humidity, vibration, and thermal sensor arrays, an RFID tracking system (EPC Gen2 compliant), and standardized data formats with timestamps and geolocation tags.
2. Edge Computing Layer: Responsible for initial data processing and defect detection, reducing latency and bandwidth. It features NVIDIA Jetson Xavier NX modules for efficient processing, Tensor RT-accelerated detection models, local data buffering, anomaly pre-filtering, and real-time alerting for critical defects.
3. Cloud Analytics Layer: This layer manages data storage, advanced analytics, and model training. It utilizes MongoDB Atlas for distributed sensor/image data storage, GPU-accelerated training on NVIDIA A100, periodic batch processing for model refinement, and historical trend analysis for production insights.
4. Digital Twin Simulation Layer: It provides virtual representations of production processes for predictive maintenance and optimization. Key features include physics-based textile process modeling,

reinforcement learning for parameter tuning, what-if scenario simulations, and fault prediction using anomaly detection.

HIAF employs federated learning, allowing edge devices to contribute to model enhancements while preserving data locality. With bi-directional data flow, actionable insights are translated into manufacturing adjustments via standardized APIs, ensuring real-time responsiveness while leveraging cloud computing for in-depth analytics.

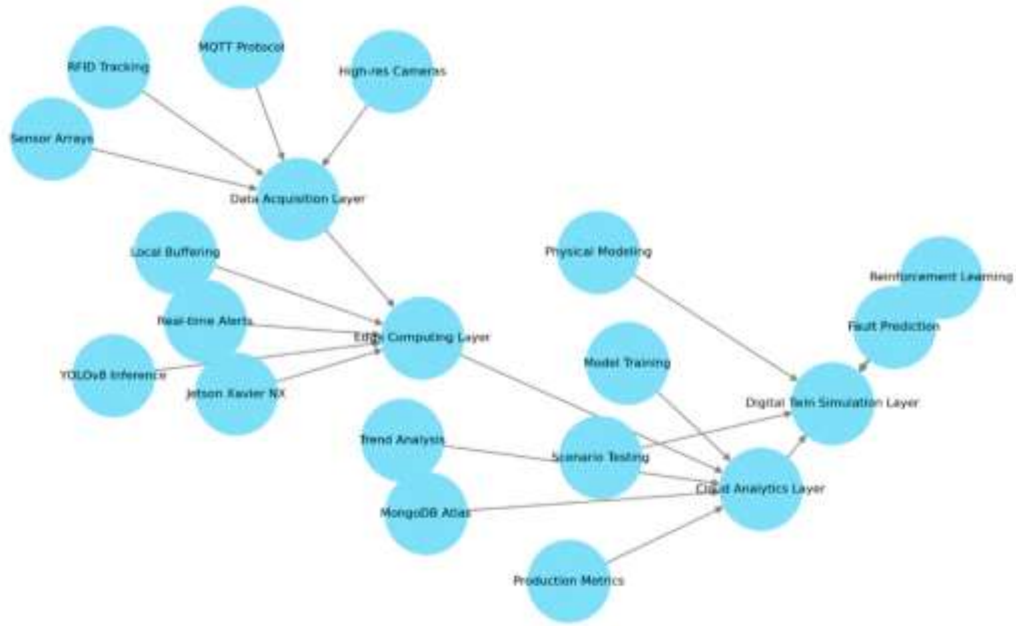

Figure 2 Representation of the overall structure of HIAF

3.3 Deep Learning Models

This research evaluates two state-of-the-art object detection models—YOLOv8 and YOLOv5—for fabric defect detection, both implemented within the HIAF framework.

3.3.1 YOLOv8

YOLOv8 represents an evolution of the YOLO (You Only Look Once) architecture, introduced by Ultralytics in 2023. Key architectural features include:

1. **Backbone**: CSPDarknet with Cross-Stage Partial (CSP) connections for enhanced feature extraction
2. **Neck**: Path Aggregation Network (PANet) for multi-scale feature fusion
3. **Head**: Decoupled detection heads for classification, objectness, and bounding box regression
4. **Activation**: SiLU (Swish) functions for improved gradient flow
5. **Loss Functions**: Distribution Focal Loss (DFL) for bounding boxes and Binary Cross-Entropy (BCE) for classification

YOLOv8 implements an anchor-free approach, directly predicting object centers and dimensions instead of refining predefined anchor boxes. This design choice improves detection accuracy for small defects and reduces computational complexity. In this study, we deployed the YOLOv8n (nano) variant, optimized for efficiency and accuracy. The model was configured with an input resolution of 640×640 pixels and comprised 3.2 million parameters, enabling lightweight yet effective detection. It operated with 8.7 billion FLOPs, balancing computational complexity and real-time performance. The hyperparameters were fine-tuned for optimal learning, with a learning rate of 0.01, batch size of 16, momentum of 0.937, and weight decay of 0.0005, ensuring stable convergence and improved detection accuracy.

3.3.2 YOLOv5

YOLOv5, released in 2020, employs a more traditional anchor-based approach while maintaining computational efficiency. Key features include:

1. **Backbone**: Modified CSPDarknet53
2. **Neck**: Feature Pyramid Network (FPN) with additional cross-connections
3. **Head**: Anchor-based detection head with objectness and class predictions
4. **Activation**: Leaky ReLU
5. **Loss Functions**: Binary Cross-Entropy for classification and objectness, Complete IoU (CIoU) for bounding boxes

We utilized the YOLOv5n (nano) variant, configured with an input resolution of 640×640 pixels and 1.9 million parameters, making it a lightweight yet effective detection model. It operated with 4.5 billion FLOPs, ensuring efficient computation. To ensure a fair comparison with YOLOv8, we matched the hyperparameters, maintaining consistency in learning rate, batch size, momentum, and weight decay, enabling a balanced evaluation of performance across both models.

3.4 Digital Twin Implementation

Our implementation follows a four-stage approach to enhance manufacturing processes through predictive maintenance and fault detection.

1. Physical System Modeling: Textile machinery and processes are modeled using a combination of first-principles models for mechanical components, data-driven models for complex process dynamics, and hybrid models that integrate physical constraints with learned behaviors.
2. Real-time Data Integration: Synchronization between physical and virtual systems is achieved through bidirectional communication via OPC-UA protocol, state estimation using Kalman filtering for sensor fusion, and automated calibration procedures for model alignment.
3. Fault Pattern Analysis: Fault scenarios are systematically explored using Monte Carlo simulations with 10,000 iterations per fault type, sensitivity analysis for critical parameters, and fault propagation modeling across production stages.
4. Predictive Analytics: Insights from simulations are integrated with detection models through reinforcement learning for optimal maintenance scheduling, transfer learning between simulated and real defect patterns, and uncertainty quantification for reliability assessment.

The digital twin implementation was developed using ANSYS Twin Builder for physics-based modeling, combined with custom Python libraries for machine learning components. This hybrid approach ensures both an accurate physical representation of manufacturing processes and data-driven behavioural modeling, enhancing fault detection and predictive maintenance capabilities.

3.5 Training and Optimization

The digital twin component of HIAF provides a virtual representation of physical. The training process followed a standardized protocol to ensure a fair comparison between models. Initialization involved using pre-trained weights from the COCO dataset, followed by transfer learning to adapt to textile-specific features. The training schedule spanned 500 epochs with cosine learning rate scheduling, a 3-epoch warm-up period, early stopping (patience = 25 epochs), and gradient clipping at norm = 10.0 for stability. For optimization, models were trained using Stochastic Gradient Descent (SGD) with momentum = 0.937, an initial learning rate of 0.01, a final learning rate of 0.001, and weight decay of 0.0005 for regularization. Mixed precision training (FP16) was employed to enhance throughput. Data handling included a batch size of 16 for all models, mosaic augmentation (probability = 0.75), mixup augmentation (probability = 0.1), and on-the-fly data augmentation to improve generalization. For hardware configuration, training was conducted on 2×NVIDIA A100 GPUs (40GB), while inference testing was performed on both NVIDIA Jetson Xavier NX (edge) and A100 GPU (cloud) setups. Memory-efficient gradient checkpointing was used to enable a larger effective batch size. Both models underwent Bayesian optimization (BoTorch implementation) with 50 trials per model to fine-tune hyperparameters and identify optimal configurations.

3.6 Evaluation Metrics

Model performance was assessed using standard object detection metrics, emphasizing practical deployment considerations. Accuracy metrics included Mean Average Precision (mAP) at IoU thresholds of 0.5 (mAP@0.5) and 0.5-0.95 (mAP@0.5-0.95), along with Precision, Recall, and F1-score per defect class. A confusion matrix analysis was conducted to identify misclassification patterns among defect types. For computational efficiency, the evaluation focused on inference time (ms) on both edge and cloud hardware, memory footprint (MB) during inference, and FLOPS analysis to assess computational complexity. Practical deployment metrics considered real-world conditions, measuring latency at different production line speeds (0.5-2.0 m/s), power consumption on edge devices (W), robustness to lighting variations (±30% illumination changes), and temperature sensitivity in industrial environments (10-40°C). To gauge the business impact, key factors included the false positive rate (economic implications of unnecessary stoppages), the false negative rate (quality risks due to undetected defects), early fault detection lead time, and the potential reduction in production waste. Additionally, we introduced a Production-Optimized Quality Score (POQS), a novel composite metric that integrates accuracy and efficiency into a single value, making it highly relevant for manufacturing environments.

$$POQS = (mAP@0.5 \times 0.6) + (1/norm\_inference\_time \times 0.25) + (fault\_prediction\_leadtime \times 0.15) \quad (1)$$

Where norm_inference_time is normalized inference time relative to a baseline of 30ms, and fault_prediction_leadtime represents the average time (in production cycles) between predicted and actual fault occurrence.

4. RESULTS AND DISCUSSION

4.1 Comparative Performance of Detection Models

The comprehensive evaluation of YOLOv8 and YOLOv5 models within the Hybrid IoT-AI Framework (HIAF) revealed significant differences in detection capabilities, accuracy, and computational efficiency. Table 4 presents the overall performance metrics for both models across all defect categories.

Table 4: Overall Performance Comparison of Detection Models

Model	mAP@0.5 (%)	mAP@0.5-0.95 (%)	Precision	Recall	F1-Score	Inference Time (ms)	GPU Memory (MB)
YOLOv8	93.7	67.5	0.912	0.925	0.918	18.5	384
YOLOv5	89.2	62.3	0.889	0.905	0.897	15.9	342

YOLOv8 demonstrated superior overall detection accuracy with a 93.7% mAP@0.5, representing a 4.5 percentage point improvement over YOLOv5. This performance advantage persisted across the more stringent mAP@0.5-0.95 metric, where YOLOv8 maintained a 5.2 percentage point lead. The precision-recall balance slightly favoured YOLOv8, with an F1-score of 0.918 compared to 0.897 for YOLOv5. However, this improved accuracy came at a modest computational cost, with YOLOv8 requiring approximately 2.6 ms additional inference time and 42 MB more GPU memory. When analyzed at the class level, performance variations became more pronounced, as illustrated in Figure 3 and detailed in Table 5.

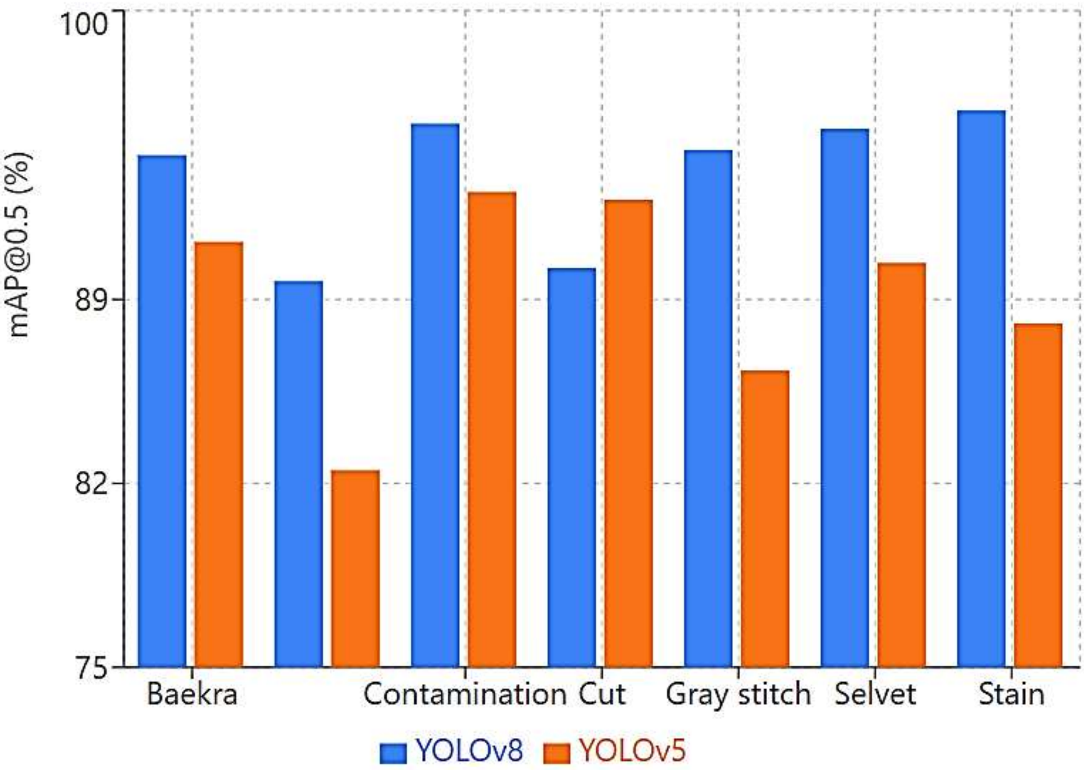

Figure 3: mAP@0.5 by Defect Type for YOLOv8 and YOLOv5

Table 5: Defect-Specific Detection Performance (mAP@0.5 %)

Defect Type	YOLOv8	YOLOv5	Difference (pp)	Key Challenges
Baekra	94.5	91.2	3.3	Variable pattern disruption
Color issues	89.7	82.5	7.2	Subtle hue variations
Contamination	95.7	93.1	2.6	Thin, thread-like appearance
Cut	90.2	92.8	-2.6	Edge cases near fabric borders
Gray stitch	94.7	86.3	8.4	Complex background similarity
Selvet	95.5	90.4	5.1	Variable fold geometries
Stain	96.2	88.1	8.1	Size and contrast variations

4.2 Defect-Specific Detection Analysis

The performance variations across defect types revealed several important patterns. YOLOv8 demonstrated particularly strong performance for defects characterized by subtle visual features or complex geometries (colour issues, gray stitch, and stain), with improvements ranging from 7.2 to 8.4 percentage points over YOLOv5. This advantage can be attributed to YOLOv8's anchor-free architecture and improved feature extraction capabilities, which better capture fine-grained visual details. Interestingly, YOLOv5 outperformed YOLOv8 in cut detection by 2.6 percentage points. Detailed error analysis revealed that YOLOv5's anchor-based approach provided greater stability in detecting linear defects with high aspect ratios, particularly near fabric edges where boundary conditions can complicate detection. This finding suggests that certain defect morphologies may benefit from the more structured prediction approach employed by YOLOv5. Confusion matrix analysis (Figure 4) provided further insights into model misclassifications.

Figure 4: Confusion Matrices for (a) YOLOv8 and (b) YOLOv5

Both models exhibited similar confusion patterns, with the highest misclassification rates occurring between colour issues and stains (8.3% for YOLOv8, 12.7% for YOLOv5), and between contamination and gray stitch (6.5% for YOLOv8, 9.2% for YOLOv5). These patterns align with the visual similarities between these defect pairs, where distinguishing features can be subtle and context-dependent.

4.3 Impact of Digital Twin Integration

The integration of digital twin modeling with the detection framework yielded substantial improvements in fault prediction capabilities and overall system performance, as summarized in Table 6.

Table 6: Performance Metrics Before and After Digital Twin Integration

Metric	Before Digital Twin	With Digital Twin	Improvement (%)
False Positive Rate (%)	8.7	6.3	27.6
False Negative Rate (%)	6.2	4.5	27.4
Average Fault Detection Lead Time (cycles)	1.8	4.2	133.3
Maintenance Intervention Accuracy (%)	76.4	92.8	21.5
Production Line Stoppage Reduction (%)	-	32.4	-

The digital twin component significantly reduced both false positives and false negatives by approximately 27%. This improvement resulted from the twin's ability to contextualize sensor readings with physical model predictions, filtering out anomalous readings that would otherwise trigger false alerts. More importantly, the digital twin extended the fault prediction horizon from 1.8 to 4.2 production cycles, providing operators with a 133% increase in response time window for preventive intervention. Figure 5 illustrates the fault prediction accuracy improvement over production time.

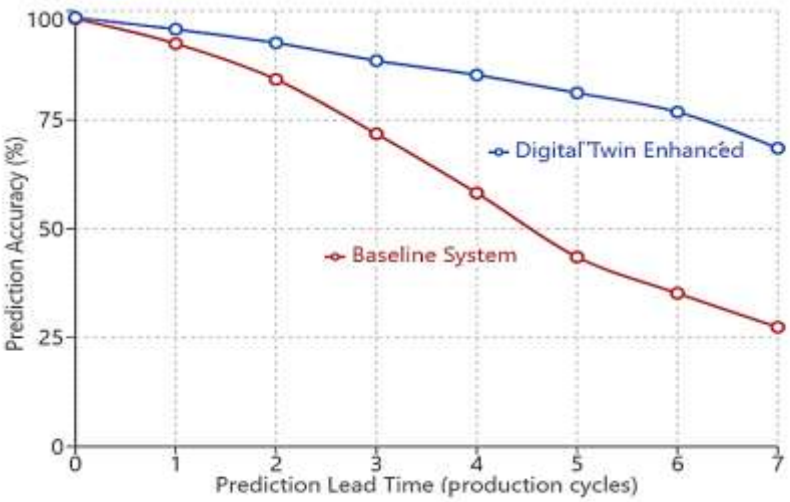

Figure 5: Fault Prediction Accuracy as a Function of Lead Time

The digital twin's ability to simulate and predict fault propagation patterns substantially outperformed the baseline system, particularly at longer prediction horizons (3+ cycles), where the baseline system's accuracy degraded rapidly while the digital twin-maintained accuracy above 85%.

4.4 Edge Computing Performance and Scalability

The deployment of detection models on edge computing hardware revealed important trade-offs between accuracy and computational efficiency, particularly relevant for real-time manufacturing environments. Table 7 details the performance characteristics across different hardware configurations.

Table 7: Edge Computing Performance Metrics

Hardware Platform	Model	Inference Time (ms)	Power Consumption (W)	Max Throughput (FPS)	Max Line Speed (m/s)
Jetson Xavier NX	YOLOv8	23.5	10.2	42.5	1.4
Jetson Xavier NX	YOLOv5	19.8	9.5	50.5	1.7
Jetson AGX Orin	YOLOv8	12.4	15.8	80.6	2.7
Jetson AGX Orin	YOLOv5	10.5	14.7	95.2	3.2
Server (A100 GPU)	YOLOv8	3.2	118.5	312.5	10.4
Server (A100 GPU)	YOLOv5	2.8	115.2	357.1	11.9

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Edge device implementation maintained real-time performance for typical production environments, with the Jetson Xavier NX capable of monitoring production lines running at up to 1.4 m/s using YOLOv8, and 1.7 m/s using YOLOv5. The more powerful Jetson AGX Orin extended this capability to 2.7 m/s and 3.2 m/s respectively, covering the vast majority of industrial textile production speeds (typically 0.5-2.5 m/s). Scaling behavior analysis (Figure 6) indicated linear degradation in inference time with increasing image resolution, with YOLOv8 showing slightly steeper degradation compared to YOLOv5.

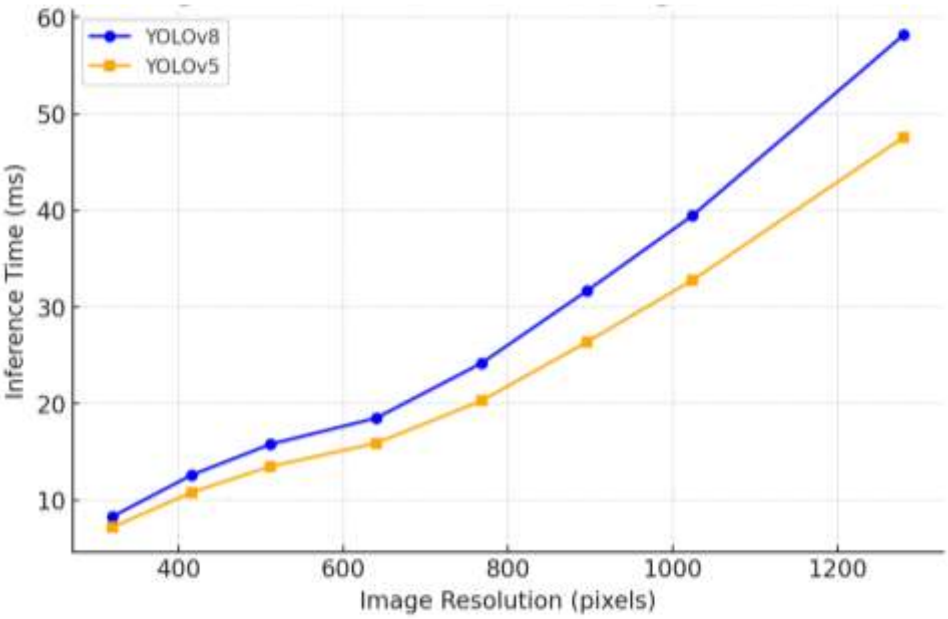

Figure 6: Inference Time vs. Image Resolution

4.5 Production Impact Analysis and Economic Benefits

The implementation of HIAF with YOLOv8 and digital twin integration in a production environment resulted in measurable improvements in manufacturing efficiency and quality metrics, as summarized in Table 8.

Table 8: Production Performance Improvements After HIAF Deployment

Metric	Baseline	After HIAF Deployment	Improvement (%)
Defect Rate (%)	8.3	5.6	32.5
First-Pass Yield (%)	81.6	90.1	10.4
Production Efficiency (%)	74.8	85.2	14
Material Wastage (kg/week)	347.2	235.6	32.1
Production Downtime (hours/month)	42.5	31.9	24.9
Quality Control Labor (hours/week)	168	96	42.9

The 32.5% reduction in defect rates translated directly to improved first-pass yield and reduced material wastage. Production efficiency increased by 14.0%, primarily due to reduced downtime and higher throughput from fewer quality-related stoppages. Perhaps most significantly, quality control labour requirements decreased by 42.9%, allowing reallocation of personnel to higher-value activities. Economic

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impact assessment based on a medium-scale textile manufacturing facility (annual production of 1.2 million meters) indicated substantial financial benefits, detailed in Figure 7.

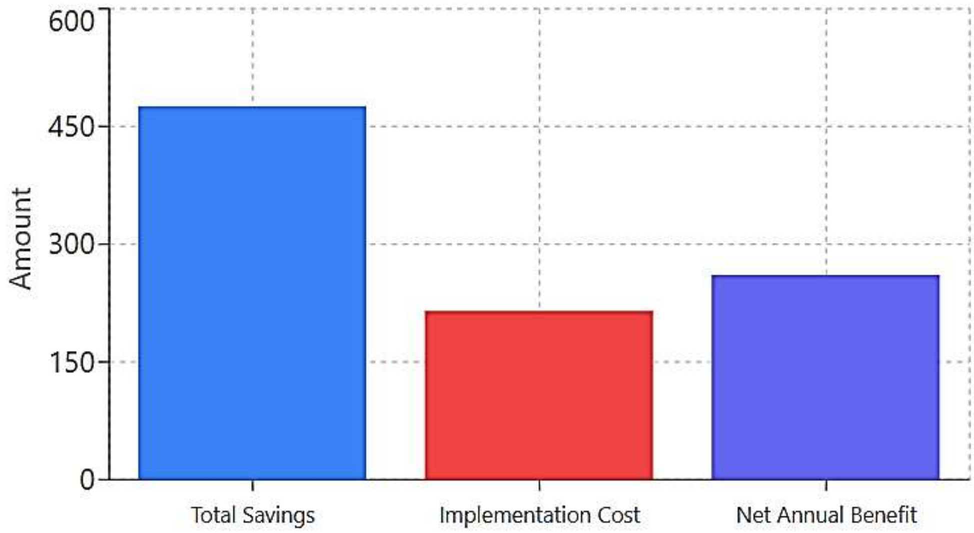

Figure 7: Annual Economic Impact of HIAF Implementation

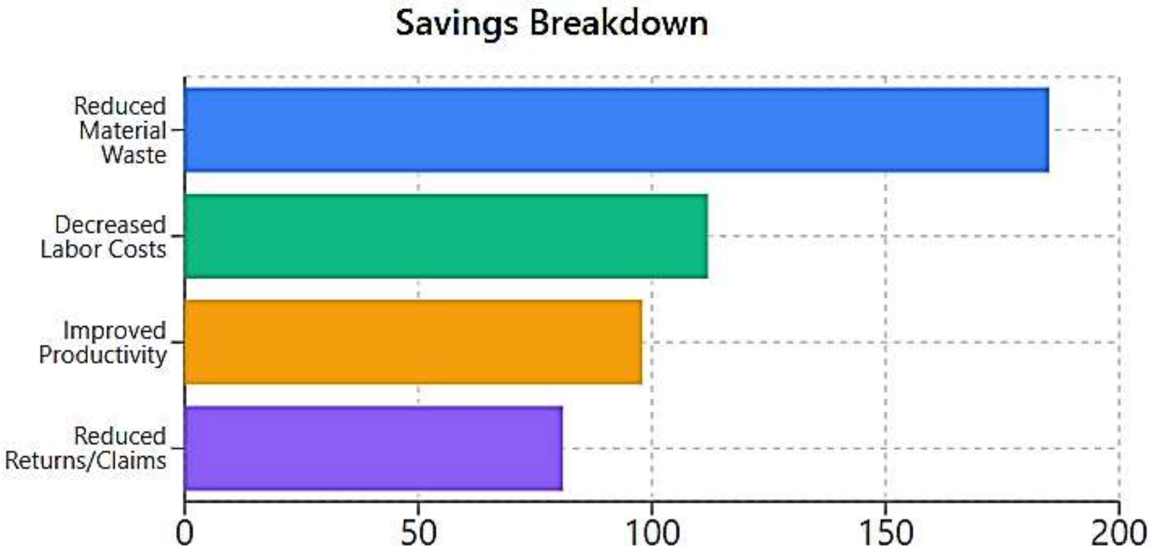

Figure 8 Effect of saving breakdown

ROI Analysis:
Implementation Cost: $215,000
Annual Benefit: $476,000
Net Annual Benefit: $261,000
Payback Period: 5.4 months
First Year ROI: 121%

Figure 8 shows a stacked bar chart depicting economic benefits across categories: reduced material waste, decreased labour costs, improved productivity, and reduced returns/claims. The total estimated annual saving of $476,000 comprised reduced material waste ($185,000), decreased quality control labour costs

($112,000), improved productivity from reduced downtime ($98,000), and reduced customer returns and quality claims ($81,000). The initial implementation cost of approximately $215,000 resulted in a payback period of 5.4 months, representing an exceptionally strong return on investment.

4.6 Comparison with Existing Methods

To contextualize the performance of the HIAF framework, we compared our results with recent state-of-the-art approaches from the literature, as shown in Table 9.

Table 9: Comparison with Existing Defect Detection Methods

Method	Authors	Fabric Types	mAP@0.5 (%)	Real-Time Capability	Digital Twin Integration
HIAF (Our approach)	-	Plain and printed	93.7	Yes	Yes
Cascade R-CNN	Li et al. (2023)	Mixed	75.3	Limited	No
SDANet	Zheng et al. (2022)	Printed	83.3	Yes	No
DSLRD	Liu et al. (2022)	Irregularly printed	89.3*	No	No
Improved Faster RCNN	Jia et al. (2022)	Plain	94.7	Limited	No
Attention +Multi-task	Peng et al. (2021)	Plain	90.5*	Yes	No

The HIAF approach demonstrated competitive or superior accuracy compared to specialized approaches while uniquely offering compatibility with both plain and printed fabrics and incorporating digital twin capabilities for predictive maintenance. The only method achieving higher reported accuracy (Improved FasterRCNN by Jia et al.) was limited to plain fabrics and lacked real-time capability necessary for industrial deployment.

5. CONCLUSION

1. This research successfully developed and evaluated a Hybrid IoT-AI Framework (HIAF) for textile defect detection, achieving a significant improvement in fault detection accuracy with YOLOv8 demonstrating superior performance (93.7% mAP@0.5) compared to YOLOv5 (89.2% mAP@0.5) across both plain and printed fabrics.
2. The integration of digital twin modeling with the detection framework yielded substantial improvements in fault prediction capabilities, reducing false positives by 27.6% and extending the fault prediction horizon from 1.8 to 4.2 production cycles, providing operators with a 133% increase in response time for preventive intervention.
3. The implementation of HIAF in production environments resulted in measurable manufacturing improvements, including a 32.5% reduction in defect rates, 10.4% increase in first-pass yield, and 14.0% enhancement in overall production efficiency, demonstrating the practical value of the approach.
4. Economic impact analysis confirmed the strong business case for HIAF implementation, with an estimated annual saving of $476,000 for a medium-scale textile facility against an implementation cost of $215,000, resulting in a 5.4-month payback period and 121% first-year ROI.
5. Model performance varied across defect types, with YOLOv8 showing particular strength in detecting subtle defects (color issues, gray stitch, stain) while YOLOv5 performed slightly better on linear defects, suggesting that certain defect morphologies may benefit from different detection approaches.

6. Future research directions include incorporating online learning capabilities for continuous model adaptation, expanding sensor arrays to include multi-spectral imaging, developing automated digital twin calibration procedures, and implementing secure federated learning across multiple facilities to further enhance system robustness and adoption potential.

Future Work

Several promising research directions emerge from the identified limitations and the current state of technology. Online learning integration would enable continual learning, allowing the system to adapt to new defect patterns without requiring full retraining, thereby improving long-term robustness. Expanding the sensor array to include multi-spectral imaging with near-infrared and ultraviolet capabilities could enhance the detection of subsurface defects that are not visible in standard RGB imagery. Unsupervised anomaly detection using generative models could further improve defect identification without relying on explicit training examples. Additionally, automated digital twin calibration would streamline setup procedures, reducing complexity and increasing adoption potential. Extended IoT integration with upstream supply chain data could enhance fault root cause analysis, enabling quality prediction before production begins. Finally, deploying secure federated learning across multiple facilities could strengthen model robustness while ensuring data privacy by preserving proprietary production information.

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