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# Computer Vision-Based Quality Control on Garment Sewing Lines: Automated Detection of Seam and Surface Defects Using High-Speed Cameras and Deep Learning - A Structured Review and Proposed System Framework

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**ABSTRACT:** Quality control on garment sewing lines still relies largely on manual end-of-line inspection, so defects are found only after value has been added to a faulty piece. This paper examines how high-speed cameras combined with deep learning models such as convolutional neural networks (CNN) and YOLO can detect defects directly on the sewing line, namely thread bunching and loose loops, skipped stitches, uneven seams, fabric misalignment and color mismatch. A structured review with qualitative content analysis was carried out on 18 peer-reviewed studies published between 2009 and 2026, coded by defect type, method, hardware and reported performance, and complemented by an illustrative calculation of image acquisition requirements. Published YOLO-based detectors report a mean average precision at an overlap threshold of 0.5 of about 90% or higher for skipped stitches and related stitch defects, with inference times of 9 to 24 ms, but on small, self-built datasets of 2,700 to 5,000 original images acquired under controlled conditions. Evidence is strong for local stitch defects and moderate for seam geometry, whereas no reviewed study addresses fabric misalignment or color mismatch on the sewing line. The calculation indicates that exposure time, not inference speed, is the binding constraint. A four-layer system framework with three detection branches is therefore proposed. Together with a three-phase roadmap, it gives garment manufacturers, particularly small and medium-sized enterprises, a basis for piloting in-line inspection and identifies the measurements needed to validate it.

**KEYWORDS:** computer vision, sewing defect detection, deep learning, convolutional neural network, YOLO, high-speed camera, garment quality control, in-line inspection

## INTRODUCTION

Sewing is the most labor-intensive stage of garment production and the stage at which most workmanship defects originate. In Vietnam, textiles and garments are a key export sector, with export turnover in 2025 estimated at about USD 46 billion (VCCI, 2025), and buyers' quality requirements leave little tolerance for seam defects in delivered goods. In most factories, however, sewing quality is still checked by eye, by the operator at the machine and by inspectors at the end of the line. Manual inspection is slow, depends on the experience and fatigue of the inspector, and usually detects a defect only after later operations have added value to the faulty piece, so that rework or rejection becomes more costly the later the defect is found.

Deep learning has changed what automated visual inspection can do. Convolutional neural networks (CNNs) learn hierarchical image features directly from data instead of relying on features designed by hand (LeCun et al., 2015), and single-stage detectors of the YOLO family locate and classify objects in one pass over the image, which makes real-time operation possible (Redmon et al., 2016). In manufacturing in general, deep learning has become the mainstream approach to surface defect detection (Yang et al., 2020). In the textile sector, most of this work concerns fabric inspection before cutting: recent reviews cover deep learning-based fabric defect detection (Kahraman & Durmuşoğlu, 2023; Carrilho et al., 2024), algorithms, datasets and inspection systems (Guo et al., 2024), and the YOLO family from version 1 to version 11 (Mao & Hong, 2025).

Defects created during sewing have received far less attention. As early as 2009, Wong et al. noted that much research had addressed fabric defects but little had specifically evaluated the stitching defects of a garment. Deep learning studies of sewing defects have appeared only in the last few years, each dealing with a small number of defect classes, and their results have not been brought together in a form that tells a manufacturer what can be detected reliably on the line, with what equipment, and what remains unproven.

This paper addresses that gap. It considers five defects that are common on sewing lines and visible on the surface of the sewn piece: thread bunching and loose loops, skipped stitches, uneven seams, fabric misalignment and color mismatch between joined pieces. Three questions are asked. First, which of these defects have been detected with deep learning in published studies, and with what reported performance? Second, what image acquisition conditions does a high-speed sewing operation impose on the camera and lighting? Third, how should an in-line inspection system be structured so that it can be adopted step by step, including by small and medium-sized enterprises (SMEs)? The paper is a structured review with a proposed system framework; it does not report new experimental data.

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## LITERATURE REVIEW

### *From handcrafted features to deep learning in textile inspection*

Early automated inspection relied on handcrafted features. For stitching defects, Wong et al. (2009) combined the wavelet transform with a back-propagation neural network, and Yuen et al. (2009) used a segmented window technique with the same type of network for fabric stitching inspection. For color, Zhou et al. (2015) classified the color difference of dyed fabrics with a wavelet-kernel support vector machine fed with CIELAB histograms and local binary pattern texture features, reporting a classification accuracy of 87.5%. These methods work under the conditions for which their features were designed but have to be re-engineered when the fabric, thread or lighting changes.

Deep learning removes much of this manual feature design. A CNN stacks convolution and pooling layers so that early layers respond to edges and textures and later layers to larger structures (LeCun et al., 2015). For inspection, three families of models are relevant: classification networks that label a whole image or patch as defective or not; object detectors that return a bounding box and class for each defect; and segmentation networks that label every pixel. YOLO treats detection as a single regression problem from image pixels to box coordinates and class probabilities (Redmon et al., 2016), and its successive versions have become the leading real-time framework in fabric inspection (Mao & Hong, 2025).

### *Deep learning for fabric defect detection*

Fabric inspection is the most mature textile application. The reviews cited above agree on the main difficulties: defects are small and varied, fabric textures and patterns differ widely, lighting changes, and labeled data are scarce (Kahraman & Durmuşoğlu, 2023; Guo et al., 2024; Mao & Hong, 2025). Two recent studies illustrate what has been achieved in terms of speed. Chen et al. (2025) proposed LWFDD-YOLO, a lightweight model based on YOLOv8n, which reached a precision of 89.4%, a recall of 85.2% and a mean average precision (mAP) of 87.9% on a self-built dataset, with 23.4% fewer parameters than the original model, a file size of 9.2 MB and a detection speed of 163.4 frames per second (FPS) on a graphics processing unit. Machado et al. (2025) deployed YOLOv11n on an embedded NVIDIA Jetson Orin Nano on a live fabric rolling line running at about 15 m/min, with two cameras at 640 x 480 pixels and 30 FPS and diffuse LED lighting; the system reached an mAP at an overlap threshold of 0.5 (mAP@0.5) of 0.821 for holes, creases and color bleeding at about 100 FPS. These results show that real-time inference on low-power edge hardware is achievable in a factory.

### *Deep learning for sewing defect detection*

Sewing defects differ from fabric defects: they are thin, elongated and lie along a seam line, and the thread may be the same color as the fabric. Kim et al. (2022) detected broken stitches using feature maps taken from the early layers of a VGG-16 network pre-trained on general images, without additional training, and reported that the method detected true defects with 92.3% accuracy. Nguyen (2022) segmented defective stitches at pixel level with DeepLabV3+ and EfficientNet. Kim et al. (2023) built an on-machine system from a low-cost single-board computer and camera with a mounting kit for typical industrial sewing machines; using image processing in the HSV color space, it reached a maximum accuracy of 82.5% on a dataset of 880 stitch images and in on-site tests.

YOLO-based studies followed. Xu et al. (2024) improved YOLOv8 for garment sewing defects by adding a small-target detection head, a focal variant of the bounding-box loss and coordinate attention; on 5,000 original images augmented to 30,000, precision rose from 84.6% to 90.2%, recall from 74.9% to 81.2% and mAP@0.5 from 83.5% to 90.2%, while speed fell from 48 to 43 FPS. Latha et al. (2026) trained YOLOv8 on skipped stitches, overlapped stitches, stains and damage, and bobbin thread pull-up, reporting an mAP@0.5 of 90.5% and an average inference time of 24 ms. Ben Abdallah et al. (2026) trained YOLOv11s on 2,700 images of crooked seams, skipped stitches and normal seams, sewn on 11 fabric types and captured with a 1.3-megapixel industrial camera under a ring light; mAP@0.5 was 0.995 for each of the two defect classes at 106 FPS, but the overall figure was 0.774 because the defect-free class was recognized poorly.

Two further studies address practical obstacles. Zheng et al. (2025) combined an image deblurring algorithm with a detection algorithm for the rapid inspection of sewing thread, which is directly relevant to images taken while the fabric is moving. ul-Huda et al. (2024) used a deep convolutional generative adversarial network to synthesize images of unbalanced stitches, open seams, seam puckering and broken stitches from about 4,000 original images, in response to the shortage of training data for stitching defects.

### *Research gap*

Three gaps follow from this body of work. First, each sewing study covers a few defect classes; none of the reviewed studies treats the five defects considered here together. Second, the datasets are small, self-built and mostly acquired on stationary samples, so the reported accuracy says little about performance at sewing speed on a production line. Third, the studies concentrate on the model; the acquisition conditions imposed by a high-speed sewing operation and the way detection results feed back to the operator and to quality management are rarely specified.

## MATERIALS AND METHODS

The study uses a structured review combined with qualitative content analysis of secondary data. It does not follow a full systematic review protocol and uses no primary experimental data.

*Search and selection.* Peer-reviewed journal articles were searched in international academic databases with combinations of the terms sewing defect, stitch defect, seam defect, fabric defect detection, deep learning, convolutional neural network, YOLO, real-time and color difference. A study was included when it (i) concerned the visual detection of defects in sewn seams or on fabric surfaces, (ii) had complete, verifiable bibliographic information, and (iii) described the method and, for experimental studies, reported quantitative performance. Theses, preprints and commercial material were excluded. Eighteen studies published between 2009 and 2026 were retained: ten on sewing or stitching defects, three on fabric inspection or color difference and five reviews. Two foundational works on deep learning and one industry source were used for background only.

*Coding.* Each experimental study was coded against five criteria: defect type, method, dataset, acquisition and computing hardware, and reported performance. The figures in Table 2 are those reported by the original authors; they were obtained on different datasets and are therefore not directly comparable with one another.

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*Synthesis.* The coded evidence was mapped onto the five target defects to judge the strength of evidence for each (Table 1). Image acquisition requirements were then derived by a simple kinematic calculation from assumed sewing parameters (Table 3). Finally, the findings were combined into a system framework (Figure 1) and an implementation roadmap. The calculation and the framework are design proposals that remain to be validated experimentally.

## RESULTS

### *Defect taxonomy and strength of evidence*

The five target defects differ in their visual signature, and this determines which type of model suits them (Table 1). Thread bunching, loose loops and skipped stitches are local anomalies a few millimeters in size and fit object detection. An uneven seam is a property of the seam as a whole, namely variation in stitch length or deviation of the seam line from its intended path, and is better measured geometrically after the stitches have been located. Fabric misalignment concerns the relative position of fabric edges or plies, and color mismatch is a difference in shade between two joined pieces; neither is a local object.

**Table 1. Target defects, visual signature, suitable approach and evidence in the reviewed studies**

| Defect | Visual signature | Suitable approach | Evidence in the reviewed studies |
|---|---|---|---|
| Thread bunching and loose loops | Local accumulation or loops of thread on the fabric surface | Object detection (YOLO family) | Moderate: related classes (bobbin thread pull-up in Latha et al., 2026; thread-related classes in Xu et al., 2024) |
| Skipped stitches | Missing interlacing; one stitch about twice the normal length | Object detection; segmentation | Strong: Latha et al. (2026), Ben Abdallah et al. (2026); broken stitches in Kim et al. (2022, 2023) |
| Uneven seams | Variation in stitch length; seam line deviating from its path | Detection of crooked segments; segmentation followed by geometric measurement | Moderate: crooked seams in Ben Abdallah et al. (2026); uneven stitching in Xu et al. (2024); pixel-level segmentation in Nguyen (2022) |
| Fabric misalignment | Offset between fabric edges, plies or patterns at the seam | Edge and seam segmentation with distance measurement | None found in the reviewed studies |
| Color mismatch | Shade difference between joined pieces | Color calibration and CIELAB color difference; CNN classification | Indirect: color difference of dyed fabric in Zhou et al. (2015); color bleeding in Machado et al. (2025) |

**Source: Compiled by the author.**

### *Reported performance of deep learning models*

Table 2 summarizes the experimental studies. Three observations can be made. First, YOLO-based detectors report an mAP@0.5 of about 90% or higher for skipped stitches and related local stitch defects. Second, inference is fast: 9.4 ms per image for YOLOv11s on a cloud graphics processor (Ben Abdallah et al., 2026), 24 ms for YOLOv8 (Latha et al., 2026) and about 23 ms for the improved YOLOv8 at 43 FPS (Xu et al., 2024); on embedded hardware, Machado et al. (2025) obtained about 10 ms. Third, the datasets are small, between 880 and about 5,000 original images, self-built and acquired under controlled lighting.

**Table 2. Summary of the experimental studies reviewed**

| Study | Defects | Method | Data and hardware | Reported result |
|---|---|---|---|---|
| Wong et al. (2009); Yuen et al. (2009) | Stitching defects | Wavelet transform or segmented window with a back-propagation neural network | Not coded | Classification of stitching defects (handcrafted features) |
| Kim et al. (2022) | Broken stitch | Feature maps of pre-trained VGG-16 with image processing | Images of the sewing operation | 92.3% accuracy on true defects |
| Nguyen (2022) | Defective stitches | DeepLabV3+ with EfficientNet (segmentation) | Not coded | Pixel-level segmentation of defective stitches |
| Kim et al. (2023) | Broken stitch | HSV color space and edge detection | 880 images; Raspberry Pi 4 B and camera mounted on the machine | Maximum accuracy 82.5%, including on-site tests |
| Xu et al. (2024) | Four sewing defect classes, including broken threads and uneven stitching | YOLOv8 with small-target head, focal loss and coordinate attention | 5,000 images augmented to 30,000 | mAP@0.5 90.2% (baseline 83.5%); 43 FPS |

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| Study | Defects | Method | Data and hardware | Reported result |
|---|---|---|---|---|
| ul-Huda et al. (2024) | Unbalanced stitch, open seam, seam puckering, broken stitch | DCGAN image synthesis | About 4,000 original images | Synthetic defect images for data augmentation |
| Zheng et al. (2025) | Sewing thread defects | Deblurring combined with a detection algorithm | Not coded | Rapid detection on blurred images |
| Latha et al. (2026) | Skipped and overlapped stitches, stains and damage, bobbin thread pull-up | YOLOv8 | Annotated sewing defect images | mAP@0.5 90.5%; 24 ms per image |
| Ben Abdallah et al. (2026) | Crooked seam, skipped stitch | YOLOv11s | 2,700 images, 11 fabric types; 1.3-megapixel camera, ring light | mAP@0.5 0.995 per defect class, 0.774 overall; 106 FPS |
| Chen et al. (2025) | Fabric defects | LWFDD-YOLO (improved YOLOv8n) | Self-built fabric dataset | mAP 87.9%; 163.4 FPS; 9.2 MB |
| Machado et al. (2025) | Holes, creases, color bleeding (fabric) | YOLOv11n on Jetson Orin Nano | 5,104 images; two cameras; line at about 15 m/min | mAP@0.5 0.821; about 100 FPS |
| Zhou et al. (2015) | Color difference of dyed fabric | Wavelet-kernel support vector machine on CIELAB and texture features | Dyed fabric images | 87.5% classification accuracy |

**Source: Compiled by the author from the cited studies. Figures are as reported by the original authors on different datasets. "Not coded" indicates that the detail was not extracted in this review.**

***Image acquisition requirements at sewing speed***

The reviewed studies mostly photograph stationary samples. On the line, the seam moves under the camera, and motion blur becomes the first problem, as the work of Zheng et al. (2025) on deblurring indicates. Table 3 gives an illustrative calculation for a lockstitch operation, assuming a sewing speed of 4,000 stitches per minute and a stitch length of 2.5 mm. The average fabric feed is then about 167 mm/s. Because the feed is intermittent, the peak speed during the feed stroke is higher than the average; a factor of two is assumed here.

**Table 3. Illustrative calculation of image acquisition requirements (assumed parameters)**

| Quantity | Assumption or formula | Value |
|---|---|---|
| Sewing speed | Assumed | 4,000 stitches/min |
| Stitch length | Assumed | 2.5 mm |
| Average fabric feed speed | 4,000 x 2.5 mm / 60 s | About 167 mm/s |
| Peak feed speed | Assumed 2 x average (intermittent feed) | About 333 mm/s |
| Permissible motion blur | Assumed about half a thread width | 0.1 mm |
| Maximum exposure time | 0.1 mm / 333 mm/s | About 0.3 ms |
| Field of view along the seam | Assumed | 40 mm (16 stitches) |
| Minimum frame rate for 50% overlap | 167 mm/s / 20 mm | About 8.3 frames/s |
| Time available per frame | 1 / 8.3 | About 120 ms |
| Image scale at 1,280 pixels across 40 mm | 40 mm / 1,280 | About 0.03 mm/pixel |

**Source: Author's calculation. The assumed values are for illustration and must be replaced by measured values for each operation.**

Two conclusions follow. First, the binding constraint is exposure time, not frame rate or inference speed. An exposure of about 0.3 ms requires a global-shutter sensor and strong, preferably strobed, lighting, or image capture synchronized with the dwell phase of the feed, when the fabric is momentarily at rest. In this sense the "high-speed" requirement concerns the shutter more than the number of frames per second. Second, the time available per frame, about 120 ms, is at least five times longer than the inference times of 9 to 24 ms reported in Table 2, so that a lightweight detector on embedded hardware leaves a margin for pre-processing and for additional branches. A 1.3-megapixel camera of the kind used by Ben Abdallah et al. (2026) gives an image scale of about 0.03 mm per pixel over a 40 mm field of view, enough to resolve a sewing thread across several pixels.

***Proposed system framework***

On this basis, a four-layer framework is proposed (Figure 1). Layer 1 is image acquisition at the sewing head: a global-shutter camera with a fixed field of view immediately behind the presser foot, diffuse or ring LED lighting of stable color temperature, a trigger derived from the machine, and a mounting kit that retrofits to existing machines, following the on-machine approach of Kim et al. (2023). Layer 2 is edge inference. After pre-processing, three branches run on the same image. Branch A is a YOLO-family detector for local defects: skipped stitches, thread bunching

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and loose loops, and broken stitches. Branch B locates the seam and the fabric edges by segmentation and measures stitch-length uniformity, seam straightness and the offset between edges or plies. Branch C compares the color of the joined pieces with a reference in the CIELAB color space after color calibration. The three branches correspond to the three kinds of visual signature in Table 1.

Layer 3 turns detections into a response on the line: decision logic based on confidence, severity and persistence over several frames, feedback to the operator by alarm and display, and optionally a stop signal or marking of the piece. Layer 4 stores each defect with its type, position, time, machine, operator and order, supports analysis of defect rates by machine and operation, and maintains the model: new and misjudged images are collected, labeled again and used for periodic re-training, which is shown as the feedback loop to Layer 2.

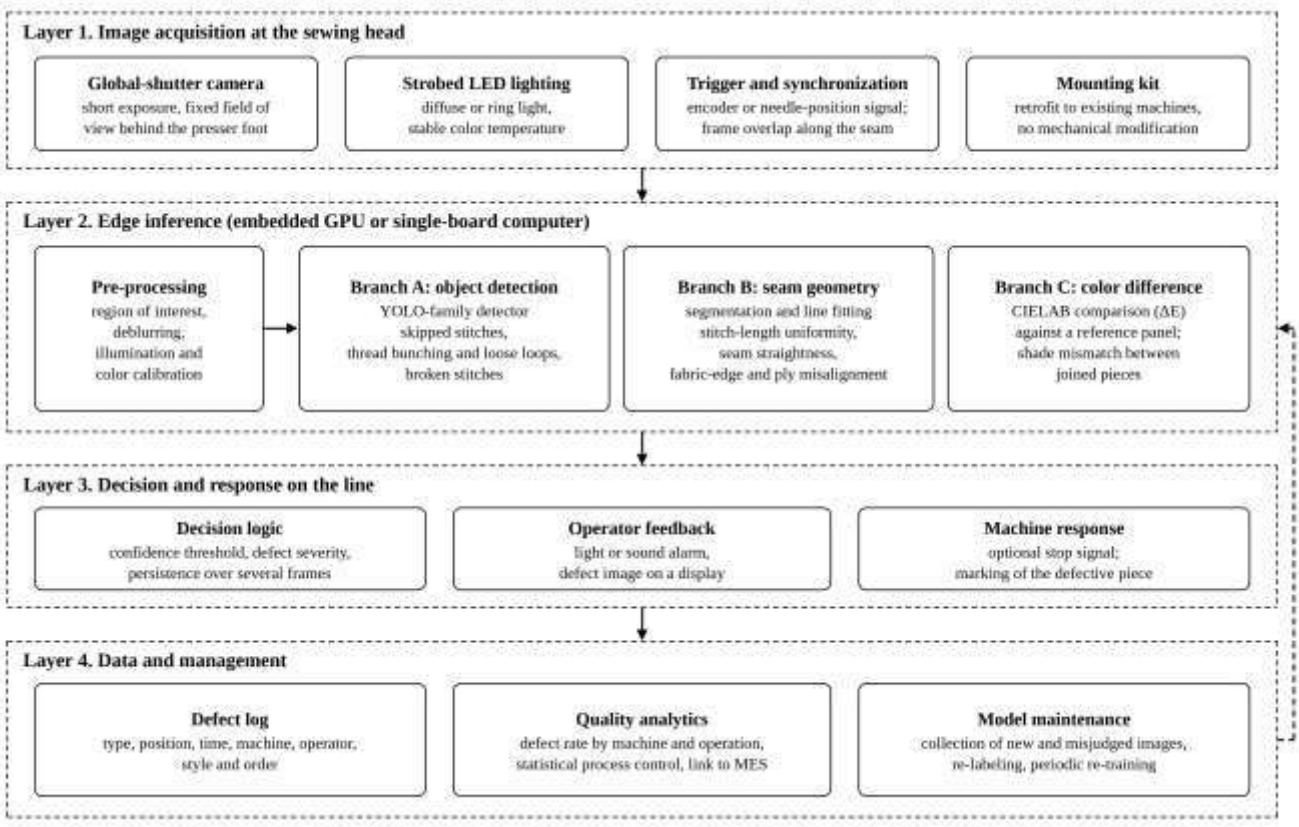


**Figure 1. Proposed four-layer framework for in-line computer vision quality control on a sewing line**
**Source: Proposed by the author on the basis of the literature synthesis.**

***Implementation roadmap***

A three-phase roadmap is suggested for factories, and for SMEs in particular. Phase 1 (pilot on one operation): fit one camera unit to a long straight seam operation, collect and label images of local defects from the factory's own fabrics and threads, and train Branch A; track precision, recall, the false alarm rate per shift and the share of defects caught at the machine. Phase 2 (extension): add seam-geometry measurement (Branch B), extend to more machines and connect the alarm to the operator's display. Phase 3 (integration): add color comparison (Branch C), link the defect log to production management and establish routine re-training. Each phase should proceed only when the indicators of the previous one show a benefit.

**DISCUSSION**

The review shows that the claim often made for computer vision in sewing, that deep learning can detect seam defects in real time, is supported for one group of defects and not yet for the others. For skipped stitches and similar local defects, several independent studies report an mAP@0.5 of around 90% or more with inference times well below what a sewing line requires (Xu et al., 2024; Latha et al., 2026; Ben Abdallah et al., 2026). This is consistent with the fabric inspection literature, where lightweight YOLO variants already run in real time on edge devices (Chen et al., 2025; Machado et al., 2025).

The figures need to be read with caution. The datasets are small and self-built, with defects often produced deliberately on a limited set of fabrics, and results obtained on different datasets cannot be ranked against one another. The result of Ben Abdallah et al. (2026) is instructive: the two defect classes were detected almost perfectly, yet the defect-free class was recognized poorly, and on a production line, where nearly all seams are good, this is the behavior that determines the false alarm rate. A system that stops the operator for false alarms will be switched off, so the false alarm rate per shift is as important as mAP. Data scarcity can be eased by synthetic images (ul-Huda et al., 2024), but synthetic data do not replace images from the factory's own materials.

For fabric misalignment and color mismatch at the sewing stage, no direct evidence was found in the reviewed studies. The approaches proposed in Branches B and C are reasoned from related work, namely pixel-level segmentation of stitches (Nguyen, 2022) and color difference classification

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of dyed fabric (Zhou et al., 2015), and should be regarded as hypotheses. Color in particular is sensitive to lighting, so that a detector trained for stitch defects cannot simply be extended to shade; a calibrated measurement is required.

The acquisition calculation shifts the emphasis of the engineering problem. Published work concentrates on model architecture, whereas at sewing speed the exposure time and lighting decide whether the model receives a usable image at all. Low-cost hardware of the kind demonstrated by Kim et al. (2023) and Machado et al. (2025) suggests that the investment per machine can be modest, which matters for SMEs, although neither the cost nor the return has been quantified here.

The study has limitations. It is based on secondary data and a structured, not a systematic, search, so relevant studies may have been missed. For some studies only the published abstract-level information was coded. The framework and the calculation have not been tested on a sewing line, and the assumed sewing parameters are illustrative.

## CONCLUSION

Automated detection of sewing defects with cameras and deep learning is technically within reach for local stitch defects such as skipped stitches and thread bunching: published YOLO-based models report an mAP@0.5 of about 90% or higher with inference times of 9 to 24 ms. Evidence is weaker for uneven seams and absent, in the studies reviewed, for fabric misalignment and color mismatch on the sewing line. At sewing speed the critical requirement is a short exposure, of the order of 0.3 ms under the assumptions used here, with matching lighting; inference speed is not the bottleneck.

The paper proposes a four-layer framework with three detection branches matched to the visual signature of each defect, and a three-phase roadmap that starts with a single operation and local defects. For manufacturers, the practical implications are to begin where the evidence is strongest, to build a dataset from their own fabrics and threads, and to judge the system by the false alarm rate and the share of defects caught at the machine as well as by model accuracy.

Further research should validate the framework on a production line: measure detection performance and false alarms at sewing speed for all five defects, build and publish a multi-class sewing defect dataset acquired in motion, test the segmentation and color branches, and quantify the cost and the reduction in rework.

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