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Artificial Intelligence Intervention in Buttonholing-Machine Faults: A Structured Analysis of the JUKI LBH-1790 Fault Catalogue

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ABSTRACT: Buttonholing is one of the last operations in garment assembly, and a fault there can spoil a nearly finished product. This study identifies which faults of a computer-controlled lockstitch buttonholing machine artificial intelligence (AI) can realistically address, and how. The fault catalogue in the manufacturer's engineer's manual for the JUKI LBH-1790 series was analysed by structured content analysis. Ninety-seven items were extracted: 53 controller error codes, 37 first-level causes of nine sewing troubles and seven causes of five mechanical troubles. Each item was assigned to a root-cause group and to one of four intervention levels: no AI role (L0), assisted diagnosis (L1), detection and prediction (L2) and supervised parameter correction (L3). The ratings are the author's judgement and were not validated on machine data. Six items (6 %) were rated L0, 23 (24 %) L1, 32 (33 %) L2 and 36 (37 %) L3. Sewing troubles offer the most scope: 35 of their 37 causes fall in L2 or L3, and 18 concern thread tension or panel data that the machine already sets digitally. Among error codes, 14 are data-consistency errors suited to parameter recommendation and 11 are motor-load errors suited to condition monitoring, whereas for 23 others, mainly electronic and supply faults, AI can only guide the technician. On this basis, five AI functions are proposed. The analysis gives engineers a prioritised map of AI opportunities for buttonholing machines, in which the largest share lies in settings, not hardware. The proposals are conceptual and require experimental confirmation.

KEYWORDS: buttonholing machine, sewing machine faults, fault diagnosis, artificial intelligence, predictive maintenance, thread breakage, garment manufacturing

INTRODUCTION

A shirt, a pair of trousers or a jacket reaches the buttonholing machine when almost all of its value has already been added. The machine sews a dense zigzag seam around a slit and then cuts the slit with a knife; if the needle thread breaks unnoticed, a stitch is skipped or the knife cuts beside the seam, the garment is usually downgraded or scrapped, because a cut cannot be undone. Buttonholing machines are therefore among the machines in a sewing line whose faults are most costly per occurrence, even though each cycle lasts only a few seconds.

Modern buttonholing machines are mechatronic systems. In the JUKI LBH-1790 series studied here, the needle rocking, cloth feed, presser lifting and both thread trimmers are driven by stepping motors, the needle thread tension is set digitally by an active tension device, the cloth-cutting knife is driven by a double-acting solenoid, and 30 buttonhole shapes and 99 patterns are defined by sewing data entered on an operation panel (JUKI Corporation, 2007). The controller monitors itself and reports faults through error codes, and the manufacturer's engineer's manual lists, for each sewing trouble, the possible causes and the checks to perform. Fault handling nevertheless remains manual: the operator notices a defect or an error code, and a technician works through the checklist.

Artificial intelligence (AI) is often presented as the remedy for such situations, through predictive maintenance, vision-based quality inspection or automatic parameter tuning (Nayak & Padhye, 2018; T. P. Carvalho et al., 2019). For a factory engineer the practical questions are narrower. Which of the faults that actually occur on this machine can AI do anything about? What would it need to measure? And would it act on the machine, or only inform a person? Published work rarely answers these questions for a specific machine type, and for buttonholing machines hardly at all.

This paper addresses them by analysing the complete fault catalogue of one widely used machine. Its objectives are: (i) to extract and count the faults documented by the manufacturer; (ii) to group them by root cause; (iii) to rate each fault on a four-level scale of AI intervention; and (iv) to derive from the result a small set of AI functions, with the signals each requires. The study is analytical: it contains no experiments, and its ratings express reasoned judgement rather than measured performance.

LITERATURE REVIEW

Monitoring of the sewing process

The physical variables that determine stitch quality have been studied for decades. Ferreira et al. (1994) measured needle and bobbin thread tensions simultaneously on a lockstitch machine and described how tensioner setting, speed, fabric and thread affect the tension peaks within a stitch cycle. H. Carvalho et al. (2009) developed a system for measuring needle penetration and withdrawal forces at high sewing speed, with the aim of detecting faulty processing conditions. This line of work shows that thread tension, thread consumption, needle-bar force and presser-foot

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behaviour carry usable information about stitch formation, and that they can be measured on a production machine with strain-gauge, piezoelectric or encoder sensors. In the related field of yarn processing, Ji et al. (2023) combined machine vision with a tension observer to measure yarn tension without contact, an approach that avoids disturbing the thread path.

Vision-based detection of stitch defects

Deep learning (LeCun et al., 2015) has made camera-based inspection of seams practical. Kim et al. (2022) used the feature maps of a pre-trained convolutional network together with image processing to detect broken stitches and reported an accuracy of 92.3 %. Kim et al. (2023) later implemented an on-machine broken-stitch detector on a low-cost single-board computer and reported a maximum accuracy of 82.5 % in tests on industrial sewing machines. Toan (2022) applied semantic segmentation to defective stitches. A public dataset of 14,565 stitch images covering ten defect types, including skipped and broken stitches, is now available (Jung & Kim, 2025). These studies concern straight lockstitch seams; the dense zigzag structure of a buttonhole has not, to the author's knowledge, been treated separately.

Machine condition monitoring and predictive maintenance

Condition-based maintenance uses measured signals to decide when maintenance is needed (Jardine et al., 2006). Machine-learning methods for this purpose have been reviewed by T. P. Carvalho et al. (2019), Zonta et al. (2020) and Lei et al. (2020); vibration and motor-current signals are the usual inputs, and motor-current signature analysis is attractive because it needs no sensor on the mechanism (Benbouzid, 2000). The cyber-physical architecture of Lee et al. (2015) describes how such functions are layered from data acquisition to self-configuration. Applications to sewing machines are still few compared with those to rotating machinery in heavy industry.

Levels of automation and knowledge-based assistance

Whether an intelligent function should inform, recommend or act is a design decision in its own right. Parasuraman et al. (2000) proposed that automation be described by the type of function (information acquisition, analysis, decision and action) and by its level. For diagnostic knowledge that exists as text, such as service manuals, retrieval-augmented language models can answer questions by grounding the response in retrieved passages (Lewis et al., 2020), which suits step-by-step troubleshooting.

Research gap

The literature thus offers methods, but no machine-specific account of where they apply. Reviews of AI in apparel manufacturing treat sewing in general terms (Nayak & Padhye, 2018); process-monitoring and vision studies address the plain lockstitch machine; and predictive-maintenance reviews do not consider sewing equipment. No study was found that starts from the complete fault list of a buttonholing machine and asks, fault by fault, what AI could contribute. That is the gap this paper addresses.

MATERIALS AND METHODS

Source document and machine

The source is the Engineer's Manual of the JUKI LBH-1790 series computer-controlled, high-speed lockstitch buttonholing machine (No. E352-04; JUKI Corporation, 2007), a 144-page service document. Three parts were analysed: the error code list (Section 11), the troubleshooting tables for sewing, mechanical and electrical troubles (Section 15), and, for context, the specifications, sensor adjustments and data lists. Table 1 summarises the features of the machine that matter for AI intervention, in particular which quantities are already sensed and which are already set electronically.

Table 1. Features of the LBH-1790 series relevant to AI intervention (compiled from JUKI Corporation, 2007).

Feature	Implementation	Relevance
Sewing speed	Standard 3,600 rpm, maximum 4,200 rpm (dry hook: 3,300 rpm)	Speed is a software-limited setting
Needle rocking, cloth feed, presser lift	Stepping motors with origin sensors	Step-out and origin errors are detected; drive currents reflect load
Needle and bobbin thread trimmers	Stepping motors with origin sensors	As above
Main shaft	Motor with encoder, servo control board	Lock, overcurrent and encoder faults are detected
Needle thread tension	Active tension, set digitally for each section of the buttonhole	Tension can be changed by data, without tools
Cloth-cutting knife	Double-acting solenoid with knife sensor	Knife action can be inhibited by the controller
Thread-breakage detection	Detecting plate in contact with the thread take-up spring	Reports a break only after it has occurred
Sewing data and memory switches	30 shapes, 99 stored patterns; soft-start speeds, tie-stitch data, knife settings	Most sewing-trouble remedies are changes to these data
Other inputs	Pedal, stop switch, head-tilt sensor, heat-sink temperature, supply voltage	Available for monitoring

Extraction of fault items

Three sets of items were extracted. (1) Every distinct error code in the error code list was counted once, giving 53 codes. (2) For each of the nine sewing troubles in Section 15(1), the first-level causes (numbered 1-1, 1-2 and so on in the manual) were counted, giving 37 causes; second-level causes were read to understand each first-level cause but were not counted separately. (3) The first-level causes of the five mechanical troubles in Section 15(2) were counted in the same way, giving seven. The 49 error-code procedures in Section 15(3) were used to understand the codes; four codes (E023, E024, E801 and E902) appear in the list without a procedure. The three operation-panel troubles in Section 15(3) (no display, no back-light, key not working) were left out because they are not sewing or machine faults in the sense of this study. The unit of analysis is therefore the documented fault item, 97 in total.

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Classification scheme

Each item was classified twice. First, it was assigned to a root-cause group derived inductively from the manual: six groups for error codes and eight for sewing-trouble causes. Second, it was rated on the four-level scale in Table 2, adapted from the levels-of-automation concept of Parasuraman et al. (2000). The rating answers the question: what is the highest level at which an AI function could plausibly contribute, given the signals that exist or could be added at moderate cost and the settings that the controller already exposes? Three rules were applied. A fault whose remedy is a change of sewing data, memory-switch data or digitally set tension was rated L3. A fault whose remedy is a mechanical adjustment or part replacement, but whose onset should be visible in a measurable signal, was rated L2. A fault whose diagnosis is a deterministic sequence of wiring, fuse or component checks was rated L1, and a fault that arises outside the machine or is a deliberate operator action was rated L0.

Table 2. Scale of AI intervention used for rating the fault items.

Level	Name	Definition	Example
L0	No AI role	The cause lies outside the machine or is a deliberate action; a fixed rule is sufficient.	Supply over-voltage; stop switch pressed
L1	Assisted diagnosis	The controller already identifies the fault; AI retrieves and explains the checking procedure.	Wrong EEP-ROM type; communication fault
L2	Detection and prediction	A learned model detects or anticipates the fault from signals; a person carries out the remedy.	Rising motor load before step-out; worn knife
L3	Supervised parameter correction	The remedy is a change of digital settings; AI proposes the change and the operator confirms it.	Start-of-sewing tension; tie-stitch data

The classification follows the logic of content analysis, in which text units are assigned to explicitly defined categories (Krippendorff, 2018), and resembles the cause-oriented tabulation used in failure mode and effects analysis (Stamatis, 2003). It was carried out by the author alone. No inter-rater check was made, and no occurrence frequencies were available, so each documented item carries equal weight regardless of how often it occurs in production.

RESULTS

Error codes

Table 3 lists the 53 error codes by group and Figure 1 shows their intervention levels. The largest group, with 14 codes, consists of sewing-data consistency errors: combinations of knife length, eyelet dimensions, bar-tack length, tie-stitch settings and presser size that cannot be sewn. Eleven codes concern motor load or mechanism motion: main-shaft lock, step-out of the presser-lifting and trimmer motors, needle-bar upper-position failure, failure of five stepping-motor axes to find their origin, and failure of the knife to return. Ten codes concern the power supply or temperature, eight concern memory, software version or configuration, seven concern sensors, encoders or communication, and three are process or operator events (stop switch, thread breakage and head tilt). By level, six codes were rated L0, 17 L1, 16 L2 and 14 L3.

Table 3. Error codes of the LBH-1790 series by root-cause group and intervention level.

Group	Error codes	Number	Level
A. Sewing-data consistency	E024, E099, E486, E487, E488, E489, E492, E493, E494, E495, E496, E497, E498, E499	14	L3: 14
B. Memory, software, configuration	E001, E018, E061, E062, E703, E704, E943, E946	8	L1: 8
C. Motor load and mechanism motion	E007, E023, E025, E026, E030, E907, E908, E909, E910, E911, E999	11	L2: 11
D. Sensor, encoder, communication	E303, E304, E730, E731, E733, E915, E916	7	L1: 7
E. Power supply and thermal	E801, E802, E811, E813, E901, E902, E903, E904, E905, E918	10	L0: 4, L1: 2, L2: 4
F. Process and operator events	E050, E052, E302	3	L0: 2, L2: 1
Total		**53**	L0: 6, L1: 17, L2: 16, L3: 14

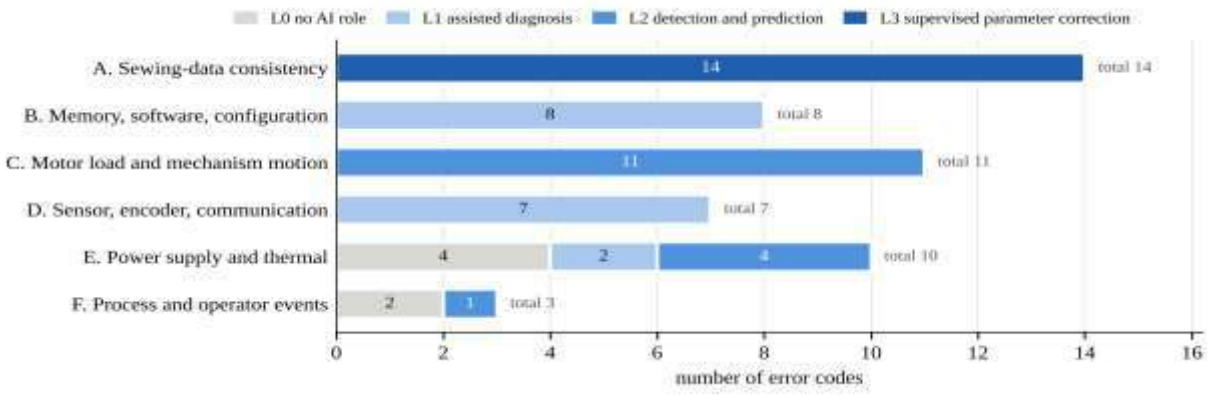

Figure 1. Intervention levels of the 53 error codes by root-cause group.

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Sewing troubles

Table 4 lists the nine sewing troubles with the number of documented causes. Needle thread breakage has 12 first-level causes and stitch skipping seven; together they account for 19 of the 37 causes. Figure 2 groups the causes by root. Nine concern thread tension (the tension set on the panel for the parallel and bar-tack sections, the thread take-up spring, or the bobbin thread), and nine concern other panel data or memory-switch settings such as the number, pitch and width of tie stitches, the tension at the start and end of sewing, and the soft-start speed. Six concern mechanical timing or position (needle-bar height, needle-to-hook timing, trimmer position and timing, thread guide position), five concern wear or surface damage on the thread path, hook, needle bar or thread presser spring, and two each concern needle selection and installation, sewing speed, fabric and presser condition, and threading or hook contamination. By level, two causes were rated L1, 14 L2 and 21 L3.

Table 4. Sewing troubles documented in the manual, number of first-level causes and their root-cause groups.

Sewing trouble	Causes	Root-cause groups (number of causes)
1. Needle thread breakage	12	thread tension (2); panel sewing data and memory switches (2); mechanical timing and positions (2); wear and surface damage (1); needle selection and installation (1); sewing speed and needle heat (1); fabric and presser condition (1); threading and hook contamination (2)
2. Stitch skipping	7	thread tension (1); mechanical timing and positions (1); wear and surface damage (2); needle selection and installation (1); sewing speed and needle heat (1); fabric and presser condition (1)
3. Needle thread slip-off	6	panel sewing data and memory switches (3); mechanical timing and positions (1); wear and surface damage (2)
4. Needle thread remains	3	panel sewing data and memory switches (2); mechanical timing and positions (1)
5. Crest of seam wobbles	2	thread tension (2)
6. Thread frays	3	thread tension (2); panel sewing data and memory switches (1)
7. Needle breaks	2	thread tension (1); mechanical timing and positions (1)
8. Sewing occasionally disordered	1	thread tension (1)
9. Tie stitches protrude at 2nd bar-tack	1	panel sewing data and memory switches (1)
Total	**37**	

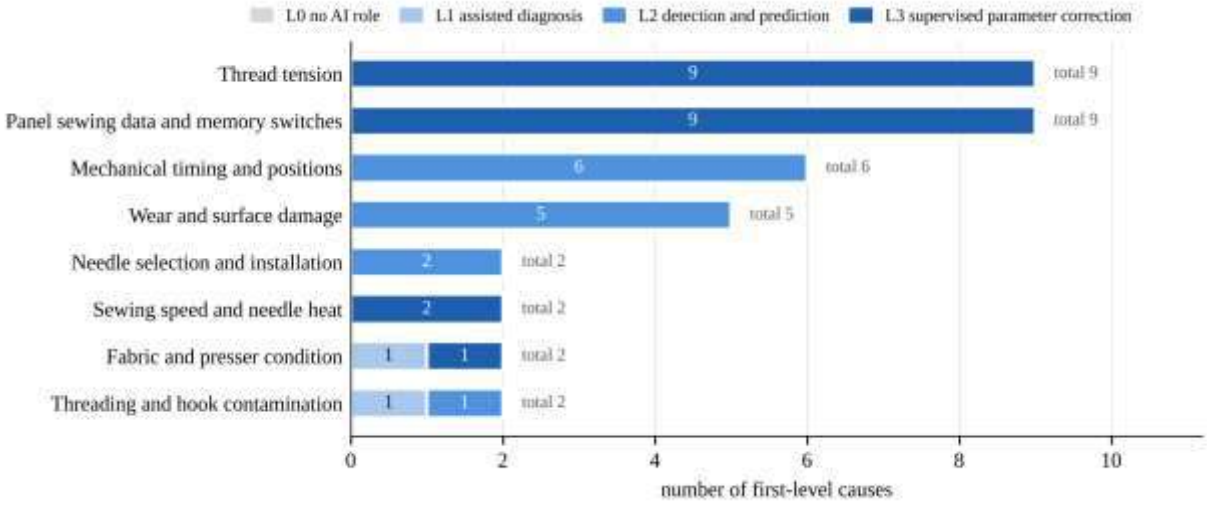

Figure 2. Intervention levels of the 37 first-level causes of sewing troubles by root-cause group.

Mechanical troubles

The five mechanical troubles are an improper needle height at stop, a knife that fails to drop, a knife that fails to cut, a knife that fails to return and a presser that fails to work. Of their seven first-level causes, four are installation or connection faults (rated L1), two are a dull knife and binding of the knife drive by play or cutting waste (L2), and one, the knife biting into soft material, is remedied in part by the knife-groove setting and the knife-return power setting (L3).

Overall distribution

Table 5 combines the three sets. Of the 97 items, six (6.2 %) were rated L0, 23 (23.7 %) L1, 32 (33.0 %) L2 and 36 (37.1 %) L3. The share rated L2 or L3 is 30 of 53 for error codes, 35 of 37 for sewing-trouble causes and three of seven for mechanical causes.

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Table 5. Distribution of the 97 fault items over the intervention levels.

Item set	L0	L1	L2	L3	Total	L2 + L3 (%)
Error codes	6	17	16	14	53	57
Causes of sewing troubles	0	2	14	21	37	95
Causes of mechanical troubles	0	4	2	1	7	43
All items	**6**	**23**	**32**	**36**	**97**	**70**
Share of all items (%)	6.2	23.7	33.0	37.1	100	

DISCUSSION

Where AI can intervene

The first observation is that settings, not hardware, account for the largest share of addressable faults. Eighteen of the 37 sewing-trouble causes are remedied by changing a tension value or a panel datum, and the machine already sets these electronically. The manual's remedies read like control rules: increase the tension at the start of sewing, reduce the soft-start speed, widen the tie stitch, reduce the speed to 3,300 rpm or less for polyester thread or knit fabric. A learning system that relates fabric, thread and buttonhole shape to settings that worked before, and proposes them at style change, would act on exactly these causes. The 14 data-consistency error codes belong to the same family: the controller already rejects impossible combinations, and an assistant could go one step further and propose the nearest valid combination instead of an error number.

The second observation is that thread breakage deserves priority. It has the most documented causes (12), it spans nearly all root-cause groups, and its consequence on this machine is severe: the manual warns that if the thread-breakage detecting plate is misadjusted, breakage is not detected and the knife still cuts the cloth (JUKI Corporation, 2007). The built-in detector is a contact on the take-up spring that reports a break after it has happened. The thread-tension studies of Ferreira et al. (1994) and the needle-force measurements of H. Carvalho et al. (2009) suggest that tension peaks and penetration forces change before a break when a needle is damaged, the thread path is scratched or the timing has drifted. A model trained on such signals could warn before the break and, at the least, inhibit the knife, which is an L2 intervention with a direct effect on scrap.

The third observation concerns the electromechanical drives. Eleven error codes report that a motor has stalled, lost steps or failed to find its origin, and the first check the manual prescribes for most of them is to look for a place of heavy load in the mechanism. These codes appear when the fault is already complete. Because the axes are driven by stepping motors and a servo main motor, load is reflected in the drive currents, and motor-current analysis (Benbouzid, 2000) or anomaly detection on the cycle signature (Lei et al., 2020) could reveal rising friction from lack of grease, lint or a dulling knife before step-out occurs. The same reasoning applies to the four thermal and overcurrent codes.

The fourth observation is a limit. For the 23 codes rated L0 or L1, which mainly concern memory, software version, connectors, encoders, fuses and supply voltage, AI has little to add to detection: the controller identifies the fault and the manual gives a deterministic sequence of checks. Here the useful contribution is to make that sequence quickly accessible, for example through a retrieval-based assistant that returns the relevant procedure, connector number and page for an error code in the technician's language (Lewis et al., 2020). This is L1 by design, and claims of predictive maintenance for such faults should be treated with caution.

Proposed AI functions

Figure 3 and Table 6 translate these observations into five functions. They are ordered by the amount of additional hardware they need. Parameter recommendation and the diagnostic assistant require only access to the sewing data and to documents, and could be implemented outside the machine. Drive-condition monitoring needs access to motor-current signals inside the control box. Thread-break prediction needs a thread-tension or needle-force sensor, and vision inspection needs a camera at the work clamp, where the buttonhole is presented flat and in a fixed position, a more favourable geometry than a running seam. The vision function would also catch defects that have no error code and no entry in the cause tables other than their symptom, such as seam wobble or protruding tie stitches, and its output could serve as the quality label that the other functions need for training.

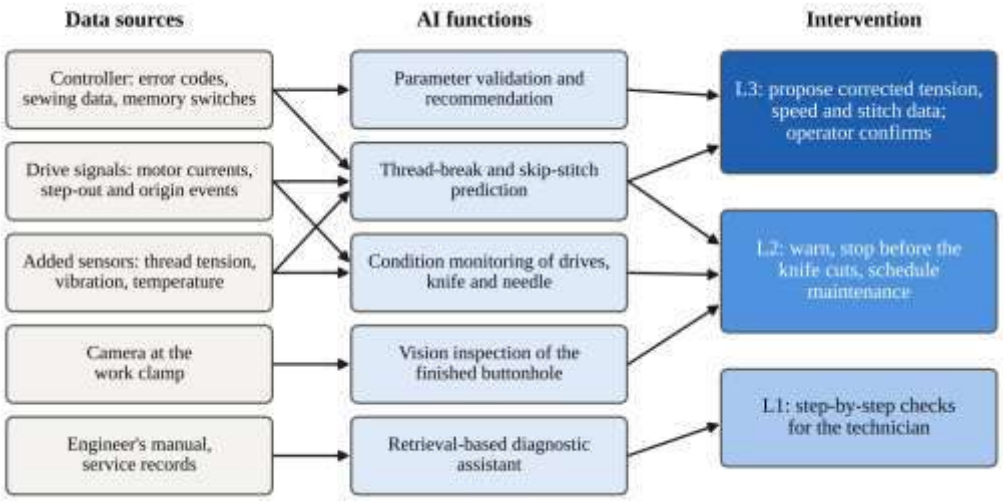

Figure 3. Proposed AI functions for the buttonholing machine, their data sources and their intervention levels.

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Table 6. Proposed AI functions, target faults and requirements.

AI function	Target faults	Signals and data	Added hardware	Method family	Level
Parameter validation and recommendation	Group A error codes; tension, tie-stitch, start/end and speed causes of sewing troubles	Sewing data, memory switches, style record (fabric, thread, shape)	None	Rule checking with learned recommendation (e.g. nearest-neighbour or tree models)	L3
Thread-break and skip-stitch prediction	Needle thread breakage, stitch skipping, E052	Thread tension or needle-bar force per stitch; speed; stitch position in the pattern	Tension or force sensor	Time-series classification or anomaly detection	L2 (L3 if speed or tension is adapted)
Condition monitoring of drives, knife and needle	Group C error codes; E901, E902, E905, E918; dull knife; knife-drive binding	Motor currents, step-out and origin events, heat-sink temperature, cycle counts	Current sensing; optionally vibration	Anomaly detection on cycle signatures; trend models	L2
Vision inspection of the finished buttonhole	Skipped stitches, seam wobble, fraying, protruding tie stitches, knife position	Image of each buttonhole in the work clamp	Camera and lighting	Convolutional network for classification or segmentation	L2
Retrieval-based diagnostic assistant	Groups B and D error codes; E903, E904; installation and connection faults	Error code, engineer's manual, service records	None	Retrieval-augmented language model	L1

Comparison with the literature

The functions proposed here are assembled from techniques that have been demonstrated separately: broken-stitch detection by convolutional networks (Kim et al., 2022; Toan, 2022), on-machine inspection with low-cost hardware (Kim et al., 2023), sensor-based monitoring of stitch formation (H. Carvalho et al., 2009) and data-driven condition monitoring (T. P. Carvalho et al., 2019; Zonta et al., 2020). What the present analysis adds is the mapping to a concrete fault catalogue. That mapping changes the emphasis. Much published work on AI for sewing concerns the detection of defects after they occur; in this catalogue, the largest group of causes is one where the appropriate response is a changed setting, which calls for recommendation and supervised correction rather than detection alone. In the terms of Parasuraman et al. (2000), the opportunity lies as much in decision support as in information acquisition.

Limitations

The results must be read with their basis in mind. (1) The ratings are the judgement of a single analyst and were not checked by a second rater or by experiment; another analyst could reasonably rate some items one level higher or lower. (2) Items were counted, not weighted. The manual gives no occurrence frequencies, so a rare memory fault and a daily thread break each count once; a factory's own stoppage records would be needed to weight them. (3) The analysis covers one machine series and one manual edition; machines with different drives or without digital tension would give a different distribution. (4) L3 interventions assume that an external system can read and write sewing data and memory-switch data. The manual documents these data but not an open interface for changing them during production, so implementation may depend on the manufacturer. (5) No claim is made about the accuracy any of the proposed functions would achieve on buttonholes; the accuracies cited from the literature were obtained on other seams and machines. (6) Any function that changes settings or inhibits the knife affects product quality and safety and would need validation and an operator override.

CONCLUSION

A structured analysis of the manufacturer's fault catalogue for a computer-controlled lockstitch buttonholing machine yielded 97 fault items: 53 error codes, 37 causes of sewing troubles and seven causes of mechanical troubles. Rated on a four-level scale, 37 % of the items are open to supervised parameter correction, 33 % to detection or prediction, 24 % to assisted diagnosis only, and 6 % offer no role for AI. Sewing troubles, and thread breakage in particular, offer the most scope, because about half of their causes are settings the machine already controls electronically. Electronic and supply faults offer the least.

Five AI functions follow from the analysis: parameter validation and recommendation, thread-break and skip-stitch prediction, condition monitoring of drives, knife and needle, vision inspection of the finished buttonhole, and a retrieval-based diagnostic assistant. The first and last need no additional sensors and are the natural starting point. Future work should weight the catalogue with stoppage data from a garment factory, have the ratings reviewed by maintenance technicians, record thread-tension, current and image data on a buttonholing machine to test whether breakage and drive faults can in fact be anticipated, and examine with the manufacturer how settings could be changed safely by an external system.

ETHICAL AND COMPLIANCE STATEMENTS

Originality. This manuscript is original work that has not been published or submitted elsewhere.

Conflict of interest. The author should confirm: The author declares no conflict of interest and has no commercial relationship with the machine manufacturer.

Funding. The author should state the funding source, or: This research received no external funding.

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Research ethics. The study analyses a published technical document and involved no human participants or animals; ethical approval was not required.

Data availability. The item-by-item classification underlying Tables 3 to 5 is available from the author on request.

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