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Prediction of Inspection Speed in Fabric Inspection Processes

Yasuhito Nakamura and Yusuke Kajiwara*

Komatsu University, 1-3 Nuno-machi, Kaga City, Ishikawa 923-0861, Japan

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In high-mix low-volume textile production, visual inspection remains essential, and inspection machines continuously acquire process data that can be used as industrial sensing information for production management. We present a sensor-data-driven method to predict inspection speed and completion time in a fabric inspection process. The variability in inspection time complicates the coordination between inspectors and setup workers, leading to process inefficiencies. The aim of this study is to predict the inspection time per meter (*IPM*) to facilitate efficient process management. We analyzed 2098 inspection logs collected from a dyeing and inspection factory. Using random forest regression, we modeled the relationship between *IPM* and factors such as fabric length, defect count, and inspector characteristics. While the global model showed limited accuracy ($R^2 = 0.191$), a stratified analysis based on prediction error revealed that the top 75% of "normal" cases were predicted with high accuracy ($R^2 = 0.807$, mean squared error= 1.062). Conversely, the remaining 25% represented "exception" states ($R^2 = -0.013$) governed by unrecorded delay factors. These results suggest that while *IPM* prediction is highly effective for normal operations, identifying exception states requires additional data on irregular events.

1. Introduction

In the textile manufacturing industry, particularly in high-mix low-volume production, visual inspection remains a vital quality assurance process. Unlike mass production, high-mix environments involve frequent product changes, varying quality standards, and small lot sizes. Although research on automated defect detection using convolutional neural networks (CNNs) has progressed,(1,2) full automation remains difficult because the adjustment of inspection conditions, the maintenance of datasets, and system operation costs are high for diverse products. Consequently, manual visual inspection remains essential in many factories.

From the viewpoint of sensing applications, the inspection line used in this study can be regarded as an industrial sensing system. Each inspection machine continuously acquires winding-length information during fabric transport, and inspectors enter defect findings and job

*Corresponding author: e-mail: yusuke.kajiwara@komatsu-u.ac.jp
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records through a touch-panel interface. These machine-acquired and operator-entered data streams provide online sensing information about process progress, defect occurrence, and operator behavior. Rather than proposing a new hardware sensor, in this study, we focus on converting already available process-sensing data into useful information for production management and work coordination.

In the factory targeted in this study, the inspection process relies on coordination between setup workers and inspectors at each inspection machine. Inspectors perform the visual inspection while the fabric is being wound, whereas setup workers are responsible for preparing the next dyed fabric roll, bringing it to the machine, waiting for an appropriate timing, and collaborating with the inspector when the next fabric is mounted. Thus, the role of the setup worker in this study is limited to machine-side preparation and handoff support for the next inspection cycle.

The management scope addressed in this study is also local and clearly bounded. Specifically, we focus on the operational interval from the start of inspection of the current fabric on a machine to the start of mounting the next fabric on the same machine. During this interval, the setup worker must decide when to prepare and approach the machine so that the next fabric can be supplied without causing inspector waiting time or unnecessary standby time for the setup worker.

The coordination process consists of five steps: (1) the inspector sets the tube core, (2) the inspector visually checks the fabric during winding, (3) the inspector places the finished roll on a cart, (4) the setup worker prepares the next dyed fabric, and (5) both workers collaborate to set the new fabric onto the machine. Because the duration of step (2) varies substantially depending on fabric conditions and inspector characteristics, the transition timing to steps (4) and (5) is difficult to determine in advance. As a result, the inspection process becomes a rate-determining process for machine-level work coordination in high-mix low-volume production.

Therefore, we introduce inspection time per meter (*IPM*) as a quantitative indicator of inspection speed and predict inspection completion time from the sensor-derived process information and inspection records. The purpose is to support machine-level operational coordination by helping setup workers determine when to prepare and supply the next fabric roll. In other words, *IPM* estimation is used to improve the timing of the handoff between the ongoing inspection process and the subsequent setup process on the same machine. Using the data from 2098 inspections collected between July and August 2024, we constructed a prediction model using random forest (RF). We integrated log data, management data, and inspector attribute data to analyze the effects of variables such as fabric length, defect count, and inspector characteristics. We demonstrate that while a single model has limitations, stratifying the data into “normal” and “exception” states reveals that the majority of inspections are highly predictable, enabling the identification of the specific conditions where prediction support is effective. The contribution of this paper is a sensing application for smart production support: the sensor-data-driven prediction of manual inspection progress in a real textile factory.

2. Related Work

2.1 Environmental and physical factors

Visual inspection depends heavily on the inspector's visual function and judgment. Megaw[3] and See[4] summarized that environmental factors, such as lighting and pacing, significantly affect performance. Jiang *et al.*[5] and Nakajima *et al.*[6] reported on the effects of LED lighting color and brightness on physiological states and defect detection rates. Furthermore, Drury[7] highlighted the speed–accuracy trade-off (SAT), where prioritizing speed may compromise quality. The results of these studies suggest that inspection time is affected by complex environmental and physical loads.

2.2 Skill and cognitive factors

Inspector proficiency is another major factor. Eye-tracking studies in industrial and medical fields have shown that experts possess more efficient visual search patterns than novices.[8–10] However, simple metrics like "years of experience" may not fully capture these differences. Individual work rhythms and cognitive strategies also play a role in time variability.[11,12]

Manual visual inspection has also been discussed in the international literature from the perspective of human factors and data support. Kujawińska and Vogt[13] reported that the efficiency of visual quality control is affected by ergonomic and organizational human factors in manufacturing environments. More recently, Koch *et al.*[14] presented a mobile web application for the digitization and annotation of manual visual inspection tasks, emphasizing the importance of structured data acquisition even in human-centered inspection work. The findings of these studies support the view that inspection performance should be understood not only as a technical issue, but also as a human-centered process that can be analyzed and supported through digital records.

2.3 Remaining time prediction

In business process monitoring, methods to predict the remaining time of tasks using long short-term memory (LSTM) or Transformers have been proposed.[15–18] However, these studies were often focused on event logs and thus the specific mix of continuous progress (length), product attributes (fabric type), and sporadic events (defects) found in textile inspection were not fully addressed. We address these gaps by using a highly interpretable RF model to quantify delay factors in a real-world setting.

In addition, in broader manufacturing literature, production-time and remaining-time prediction processes have been increasingly discussed. Fang *et al.*[19] proposed a data-driven method for jobs remaining time prediction in discrete manufacturing using the production big data collected from IoT-enabled shop floors. Ruschel *et al.*[20] presented a framework for completion-time prediction and performance analysis in manufacturing systems by considering the behavior of process activities. In these studies, it was demonstrated that time prediction is an important topic in manufacturing decision support. At the same time, it was also suggested that practical prediction accuracy depends on how well process-specific factors are represented, which is particularly challenging in human-centered textile inspection environments.

3. Data, Materials, and Methods

3.1 Experimental setup and data acquisition

The experiment was conducted in a textile factory with dyeing and inspection processes. Inspectors visually checked fabrics for defects while they were wound on up to 21 inspection machines and entered results via a touch panel (Fig. 1). In this study, the inspection machines functioned as process-sensing devices because they continuously provided winding-length measurements at 1 s intervals, while the touch panel served as an event-recording interface for defect-related inspection information.

The appearance of defects varies depending on the fabric type and condition. Typical examples include color bleeding, small colored spots, black spots, color unevenness, and minor scratches. In many cases, it is difficult to define a uniform quantitative threshold for determining whether a visible irregularity should be regarded as a defect. Therefore, defect judgment is made by inspectors on a case-by-case basis, taking into account the product characteristics and visual appearance. Although inspectors follow the factory's common inspection practice, some inter-inspector variation may remain in borderline cases where the visibility or severity of an irregularity is ambiguous. In addition to material type and color, finer visual characteristics of the fabric surface, such as monotone/patterned distinction, pattern density, and texture complexity, may also affect inspection time. However, these finer descriptors were not systematically recorded in the current production data and, therefore, could not be included in the present model.

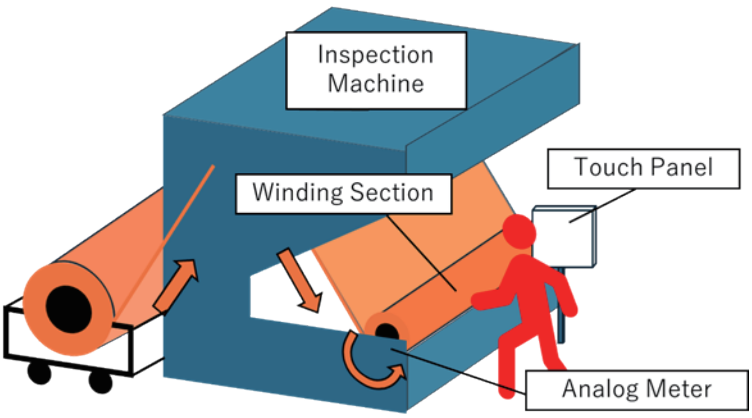

Fig. 1. (Color online) Schematic of the fabric inspection process and experimental setup.

We collected three types of data from 2098 inspections conducted from July 9 to August 30, 2024.

1. Log Data: Winding length recorded every second for each machine (Table 1)
2. Integrated Management Data: Attributes including machine ID, inspector name, date/time, standard length, batch count, fabric type, color, and defect count (Table 2)
3. Inspector Table: Years of experience and "Model Inspector" status for each inspector ID (Table 3)

For the individual-inspector analysis, inspectors with experience of more than 100 inspection cases were selected so that a minimum amount of data was available to characterize inspector-specific tendencies.

Each inspection case analyzed in this study was constructed by linking three data sources. First, the machine log data recorded the cumulative winding length of each inspection machine at 1 s intervals throughout operation. Second, the integrated management data recorded the

Table 1
Structure of log data.

Item	Description
DATE	Date of data acquisition
TIME	Time of data acquisition
Measured length (Unit 1) ... (Unit 21)	Fabric winding length recorded every second for each inspection machine (Units 1 to 21)

Table 2
Integrated management data items.

Item	Description
Machine ID	Identification number of the fabric inspection machine (Units 1–21)
Inspector name	Name of the inspector in charge
Date	Date the inspection was conducted
Start time	Time the inspection started
End time	Time the inspection ended
Standard length	Standard specified length of the fabric
Batch count	Number of times a single inspection order was split
Fabric type	Material of the fabric (e.g., acetate, polyester, nylon)
Color	Color type of the fabric
Defect count*	Number of defects (flaws) found during inspection

*Defect count represents the number of flaws—such as black spots, color variations, and small scratches—identified by inspectors based on their professional experience.

Table 3
Inspector attributes.

Item	Description
Inspector ID	Unique identifier or name for each inspector
Years of experience	Number of years the inspector has been working
Model inspector	Boolean indicating if the inspector is classified as a "Model Inspector"; used in this study as a coarse categorical indicator of practical inspection proficiency

corresponding inspection unit, inspector, date, start time, end time, standard fabric length, batch count, fabric type, color, and defect count for each inspection job. Third, the inspector table provided inspector-level attributes such as years of experience and Model Inspector status. In practical terms, one inspection case corresponds to one fabric-inspection job on one machine, defined by a start time and an end time in the management data. By synchronizing the machine log data with the management record for the same inspection period, we derived the effective inspection time and calculated the target variable *IPM* for each case.

3.2 Preprocessing

To ensure data quality, we applied the following preprocessing steps:

1. Noise Removal:
   Periods where winding stopped for more than 5 min were considered breaks or external tasks and deducted from the inspection time. Inspections shorter than 5 min or with missing data were excluded.
   The effective inspection time T_{eff} (s) was calculated from the elapsed time between the recorded start time t_{start} and end time t_{end} of each inspection. From the second-by-second machine log data, we identified interruption intervals as continuous periods during which the measured winding length did not increase for more than 300 s. Let Δt_j denote the duration of the j-th interruption interval. Then, T_{eff} is defined as

$$T_{eff} = (t_{end} - t_{start}) - \sum_j \Delta_j, \tag{1}$$

   where the summation is carried out at all interruption intervals satisfying $\Delta t_j > 300$ s within the inspection period. In this way, T_{eff} reflects only the active inspection time and excludes long stops attributable to breaks, waiting, or auxiliary tasks.
2. Conflict Resolution: Overlapping records on the same machine or chronologically contradictory entries (e.g., start time after end time) were removed.
3. Category Aggregation: Fabric types were grouped into acetate, polyester, and nylon. Rare types were excluded. Colors were mapped to RGB values and classified into five clusters (black, dark, gray, light, and white) based on the Euclidean distance to representative points.
4. Synchronization: Log and management data were synchronized on the basis of date and time stamps.

3.3 Analysis model

We used RF regression to predict *IPM* and analyze feature importance. The target variable *IPM* (s/m) is calculated as

$$IPM = \frac{T_{eff}}{L}, \tag{2}$$

where T_{eff} is the effective inspection time (s) after deducting interruptions and L is the fabric length (m). The elapsed inspection time per case, measured from the recorded start time to end time, varied substantially across inspections. In the present dataset, the raw inspection duration ranged from approximately 10 to 479 min before interruption subtraction. Because this duration strongly depends on fabric length and temporary interruptions, in this study, we used *IPM* as a normalized target variable.

The explanatory variables were total length (m) (standard length batch count), fabric type, color brightness, defect count, years of experience, and Model Inspector status. Here, “years of experience” was used as a quantitative indicator of accumulated work history, whereas “Model Inspector status” was included as a binary categorical indicator to test whether a practical factory-side proficiency label provides additional predictive information beyond experience alone.

Hyperparameters were optimized using Optuna[18] to minimize mean squared error (*MSE*). The selected parameters are listed in Table 4.

4. Results

4.1 Global model evaluation

Table 5 shows the evaluation results of the global model trained on all inspectors. The coefficient of determination, R^2, was 0.191 and *MSE* was 22.306, indicating that a single model struggles to explain the variance across all inspections.

Table 6 shows the feature importance. “total length” was the most dominant factor (0.602), followed by “defect count” (0.137) and “inspector” (0.135). Interestingly, “years of experience” (0.056) had low importance.

The average experience of inspectors was years. This suggests that inspection speed depends more on individual “working styles”—defined here as the specific rhythm and decision-making speed of an inspector—rather than cumulative years of experience. For example, some inspectors maintain a constant speed regardless of fabric length, while others slow down significantly when encountering specific defect types.

Table 4
Hyper parameters of RF.

Parameter	Value
Number of estimators (n_estimators)	196
Max depth (max_depth)	30
Min samples split (min_samples_split)	13
Min samples leaf (min_samples_leaf)	10

Table 5
Evaluation results of the prediction model (all inspectors).

Model	Sample size (Train + Test)	R^2	*MAE*
Global model	1545	0.191	2.164

Table 6
Feature importance of the prediction model (all inspectors).

Variable	Feature importance
Total length	0.602
Defect count	0.137
Inspector	0.135
Years of experience	0.056
Color brightness	0.045
Model inspector	0.012
Fabric type	0.011

4.2 Stratified analysis by prediction error

To understand the low accuracy, we stratified the data on the basis of prediction error (absolute difference between actual and predicted values). Table 7 presents the results.

The data were divided into "Normal state" (top 75% with smallest errors) and "Exception state" (bottom 25% with largest errors).

- Normal state (Top 75%): The model achieved high accuracy with $R^2 = 0.807$, $MSE = 1.062$, and $MAE = 0.727$.
- Exception state (Bottom 25%): The model failed completely with $R^2 = -0.013$ and $MSE = 136.235$.

This indicates that for 75% of routine operations, the inspection time is highly predictable using the current variables. The remaining 25% are likely governed by unrecorded sporadic delay factors (e.g., sudden machine trouble and complex judgment requirements) not captured in the current dataset.

4.3 Individual inspector analysis

We analyzed individual models for the nine inspectors who had experience with more than 100 inspection cases. Rather than focusing on specific inspector IDs, we examined how the dominant explanatory factors differed across inspectors. As a result, the inspectors could be broadly categorized into two tendencies.

The first tendency was a length-dependent pattern, in which *IPM* changed mainly in accordance with fabric length and remained relatively stable with respect to defect count. This pattern suggests that some inspectors worked at a relatively constant pace and that the total inspection workload was governed primarily by the amount of fabric to be processed.

The second tendency was a defect-dependent pattern, in which *IPM* was more strongly affected by the number of detected defects than by fabric length. This pattern suggests that, for some inspectors, additional judgment and confirmation associated with defect handling had a stronger effect on inspection speed.

In addition to these two tendencies, some inspectors showed low or negative R^2 values even in the individual models. This indicates that their inspection-speed variability was affected by factors not sufficiently captured in the current dataset, such as subtle fabric-specific difficulty, temporary interruptions, or other unrecorded operational conditions. This suggests that

Table 7
Results of stratified evaluation based on prediction error.

Group	Sample size	R^2	*MAE*
Normal state (top 25%)	387	0.407	0.718
Exception state (bottom 75%)	1158	0.205	2.843
Normal state (top 50%)	773	0.632	0.884
Exception state (bottom 50%)	772	0.121	3.832
Normal state (top 75%)	1159	0.807	0.727
Exception state (bottom 25%)	386	−0.013	6.95

inspection speed depends more on individual inspector characteristics than on cumulative years of experience alone. In this paper, "working style" refers to an inspector-specific tendency in speed control during inspection, including pacing behavior, sensitivity to defect occurrence, and decision-making during visual judgment. For example, some inspectors maintain nearly constant *IPM* across fabric lengths, whereas others slow down when the need for defect-related confirmation increases.

5. Conclusions

We addressed the instability in coordination between setup workers and inspectors in high-mix low-volume textile production by proposing a sensor-data-driven method for predicting inspection finish time on the basis of *IPM*. In the investigated factory, inspection machines continuously measured winding length, and inspection results were recorded via the touch-panel system; together, these data functioned as an industrial sensing system for monitoring manual inspection progress.

Using RF on 2098 real-world inspection cases, we found that (1) a global model had limited accuracy ($R^2 = 0.191$), whereas routine "normal state" inspections corresponding to 75% of the data were predicted with high accuracy ($R^2 = 0.807$); (2) the remaining "exception state" cases (25%) were not predictable with the current variables ($R^2 = -0.013$); and (3) inspector identity and fabric length had higher effects than years of experience. These results indicated that existing process-sensing signals can be effectively transformed into actionable production-management information for synchronizing inspectors and setup workers. The practical significance of the proposed method is not factory-wide scheduling but machine-level coordination between inspectors and setup workers. Within the management scope considered in this study—from the start of the current inspection to the mounting of the next fabric on the same machine—*IPM* estimation provides a basis for deciding when setup workers should prepare and approach the machine. Therefore, the proposed method can reduce idle time for setup workers and waiting time for inspectors in routine operations.

From the perspective of sensing applications, the results of the present study demonstrate that sensor data analysis is useful not only for automatic defect detection but also for monitoring and supporting human-centered inspection operations in textile manufacturing. Future work will expand the sensing framework by incorporating machine-status signals, interruption events, and more detailed defect information so that exception states can be detected and handled more reliably in practical factory environments.

References

1 Y. Kahraman and M. B. Durmusoglu: Text. Res. J. **93** (2023) 1485.
2 L. Carrilho, K.-H. Choi, J. C. Nunes, and J. M. R. S. Tavares: Electronics **13** (2024) 466.
3 E. D. Megaw: Appl. Ergon. **10** (1979) 27.
4 J. E. See: Sandia National Laboratories Report, SAND2012-8590 (2012).
5 X. Jiang, D. Li, B. Kao, T. Koga, K. Hirate, J. Munakata, and N. Yoshizawa: J. Environ. Eng. (AIJ) **75** (2010) 683 (in Japanese).
6 R. Nakajima, Y. Uchino, T. Hida, and T. Matsumoto: Jpn. J. Ergon. **54** (2018) 153 (in Japanese).
7 C. G. Drury: Ergonomics **37** (1994) 747.
8 Y. Yashiro, G. Wang, F. Hatori, and N. Yabuki: J. JSCE **77** (2021) I_1 (in Japanese).
9 H. L. Kundel and P. S. La Follette: Radiology **103** (1972) 523.
10 R.-J. Dzeng, C.-T. Lin, and Y.-C. Fang: Saf. Sci. **82** (2016) 56.
11 Y. Tontani, Y. Kajiwara, F. Harada, and H. Shimakawa: Recent Research in Telecommunications, Informatics, Electronics and Signal Processing (2013) p. 127.
12 Y. Tontani, K. Nishide, T. Hayakawa, F. Harada, and H. Shimakawa: Proc. 12th Forum on Information Technology (2013) p. 623 (in Japanese).
13 A. Kujawińska and K. Vogt: Manage. Prod. Eng. Rev. **6** (2015) 25. https://doi.org/10.1515/mper-2015-0013
14 J. Koch, D. Jevremovic, and T. Schüppstuhl: Procedia CIRP (2024) "Mobile Web App for the Digitization and Annotation of Manual Visual Inspection Tasks." https://doi.org/10.1016/j.procir.2024.08.373
15 A. E. Márquez-Chamorro, M. Resinas, and A. Ruiz-Cortés: IEEE Trans. Serv. Comput. **11** (2018) 962.
16 N. Tax, I. Verenich, M. La Rosa, and M. Dumas: CAiSE 2017 (Springer, 2017) p. 1.
17 I. Verenich, M. Dumas, M. La Rosa, F. M. Maggi, and I. Teinemaa: ACM Trans. Intell. Syst. Technol. **10** (2019) 1.
18 F. A. Bukhsh, A. Saeed, and R. Dijkman: arXiv preprint arXiv:2104.04966 (2021).
19 W. Fang, Y. Guo, W. Liao, H. Yu, S. Chen, and K. Li: Int. J. Prod. Res. **58** (2020) 2751. https://doi.org/10.1080/00207543.2019.1602744
20 E. Ruschel, E. F. R. Loures, and E. A. P. Santos: Comput. Ind. Eng. **151** (2021) 106972. https://doi.org/10.1016/j.cie.2020.106972

About the Authors

Yasuhito Nakamura received his Bachelor's degree from Komatsu University in 2025. He is currently a Master's student at Komatsu University. His research interests include visual inspection processes in the textile industry and time prediction using machine learning techniques, such as random forest. His work is focused on optimizing process management in high-mix low-volume production environments.

Yusuke Kajiwara is a professor in the Department of Production Systems Science at Komatsu University, where he has been serving since April 2024. He is engaged in research that leverages machine-learning-based image processing and biosignal analysis. In parallel, he also conducts research on applying AI technologies to the field of education, focusing on learning support and the development of human resources.