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AI and IoT for Yarn Defect Detection in the Textile Industry: A Systematic Literature Review

Deni Kurnia[1,2], Agus Sutanto[3]* & Hanif Fakhrurroja[4]

[1]Doctoral Student, Department of Mechanical Engineering, Universitas Andalas, Padang, Indonesia

[2]Department of Mechatronics, Politeknik Enjinering Indorama, Purwakarta, Jawa Barat, Indonesia

[3]Department of Mechanical Engineering, Universitas Andalas, Padang, Indonesia

[4]Research Centre for Smart Mechatronics, Badan Riset dan Inovasi Nasional, Bandung, Indonesia

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The textile industry continues to face yarn defects, which, in turn, reduce product quality and make production inefficient. Conventional manual inspection methods are unreliable and labour-intensive; therefore, combining AI and IoT enables intelligent quality control. This work conducts a Systematic Literature Review (SLR) on the applications of AI and IoT in yarn defect detection, using the PRISMA methodology to select and synthesise articles. A review of publication records across Scopus, ScienceDirect, IEEE Xplore, and Google Scholar, and thus collected 25 peer-reviewed papers from 2014 to 2024. The research trends were classified by production stage, algorithm type, and global distribution. The results show that AI methods, especially image processing, neural networks, and deep learning (including CNN-based models), play a leading role in yarn defect detection, achieving accuracies exceeding 95%. However, the implementation of IoT for real-time monitoring remains underdeveloped, and few studies have examined in-process defect detection. Post-production inspection receives the vast majority of contributions, while pre-production and on-production stages receive less attention. China leads in the number of published papers, followed by Turkey, Egypt, and India. The main challenges lie in combining AI and IoT with legacy systems, ensuring the reliability of data supply, and handling computational and cost constraints. This review concludes that when AI harmonises with IoT, it drives transformative shifts in predictive monitoring and smart manufacturing of textiles. Further studies are expected to focus on real-time IoT-based monitoring, model optimisation, and low-cost implementation towards fully automated, data-driven yarn defect detection systems.

Keywords: Computer vision, Machine learning, Predictive maintenance, PRISMA literature review, Smart manufacturing

Introduction

The textile sector is a significant source of global manufacturing, providing livelihoods to millions across many countries.[1] However, yarn faults—neps, thick/thin places, hairiness, and oil stains[2]—are still a serious problem in the practical use of staple fibers. It not only affects the quality of woven or knitted fabrics but also leads to waste and reduced production efficiency.[3] Fabric imperfections stem from yarn defects, causing a significant amount of economic loss according to studies.[4,5] The current quality control procedures are based to a large extent on visual inspection, which is very laborious, prone to human inconsistency and error, and will have limitations due to fatigue.[6,7]

Artificial Intelligence (AI) and the Internet of Things (IoT) are considered disruptive technologies that have the potential to automate and enhance defect detection and predictive maintenance in the textile industry.[8,9] Several AI methods, such as Machine Learning (ML), Deep Learning (DL), and Computer Vision, have achieved an excellent accuracy rate (usually over 95%) in defect detection and classification of yarn.[10–12] At the same time, IoT enables real-time monitoring of environmental and machine conditions (humidity, tension, vibration), thereby supporting quality control from the outset and process optimization.[13,14]

Several review studies have addressed the use cases of AI and IoT in the textile industry. But most studies focus on fabric quality inspection and defect detection after production. The influence of AI and IoT across all phases of yarn production, particularly in-process monitoring, with real-time defect detection as a key to loss minimization, is scarcely analyzed.[15]

To fill this gap, the present work conducts a Systematic Literature Review (SLR) following

*Author for Correspondence
E-mail: agussutanto@eng.unand.ac.id

PRISMA guidelines[16] to answer the following research questions (RQs): (RQ 1) How has AI and IoT been deployed for yarn defect detection in the textile industry? (RQ 2) Which AI methods or IoT-oriented ones for yarn defect detection are applied more frequently? (RQ 3) What are the main challenges with AI and IoT-based implementation for yarn defect detection?

Materials and Methods

Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines are followed in this review. The PRISMA statement, published in 2009, was designed to help systematic reviewers report the rationale for their review, the methods used, and the findings. In light of methodological and terminological developments in systematic review practice over the last decade, the guideline has been revised. The PRISMA 2020 statement supersedes the 2009 version to provide improved reporting guidance based on emerging evidence regarding sources of bias (e.g., knowledge transmission or dissemination), the characteristics of research topics, and the standards expected of survey researchers.[16]

Several Systematic Literature Review (SLR) studies have used the PRISMA framework, such as dynamic capabilities and SME performance[17], identification of critical success factors of Industry 4.0 technologies and development of research agenda[18], studying trends in walkability, etc.[19]

In addition, the PRISMA flowchart summarising the article selection process for this SLR is presented in Fig. 1.

From Fig. 1. Each stage can be explained as follows:

1. Articles Selection Process: Identification, Screening, Eligibility, and Inclusion.
2. Data Abstraction and Analysis.

Articles Selection Process Identification

Identification

A systematic search was conducted across Scopus, ScienceDirect, Google Scholar, and IEEE Xplorer

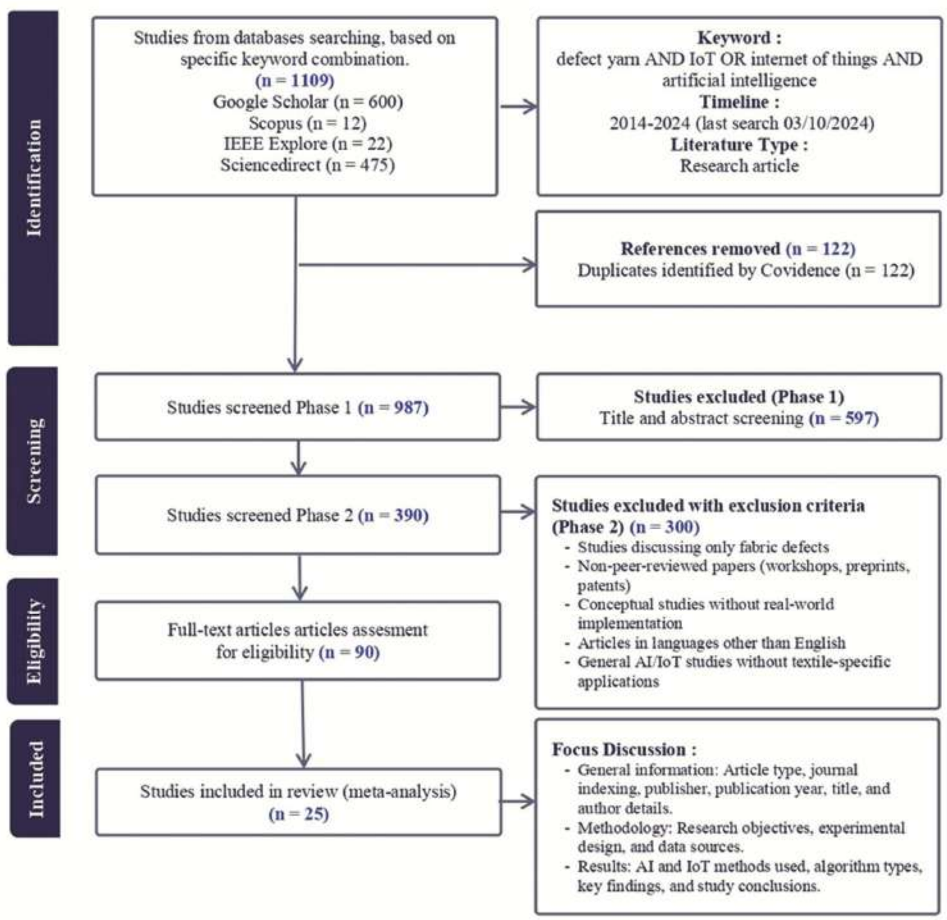

Fig. 1 — The PRISMA flow diagram provides the model for the article selection process

from 2014 to 2024 using the Boolean strings "yarn defect AND (AI OR artificial intelligence)" and "yarn defect AND (Internet of Things OR IoT)". The first search returned 1,109 records, distributed as follows: the most significant number were from Google Scholar (600), followed by ScienceDirect articles (475), Scopus (Elsevier) records (12), and IEEE Xplore (22). The titles and abstracts of studies were screened for duplicates in Covidence.[20] Following the removal of 122 duplicates, 987 articles were screened.

Screening

The process of selecting articles included two steps:

1. Title/Abstract Screening from the initial 987 articles, 597 were excluded because they were irrelevant, resulting in a total of 390 articles for full text review.
2. Full Text Screening: The 390 articles were read and assessed again following defined inclusion and exclusion criteria (Table 1), which led to the inclusion of 90 articles.

Eligibility

The screening phase yielded 90 papers selected for full-text examination. Subsequently, 25 articles from this group were selected for data extraction and included in the meta-analysis.

Included

After the aforementioned strict evaluation, 25 articles were selected for a systematic review. An assessment was conducted to determine whether each article met the inclusion criteria before data extraction. The extracted data included:

1. General Information: Distribution of the most contributing journals, annual distribution of published articles, distribution of research by journal sources, and geographical distribution of contributing countries.
2. Methods: AI and IoT methods applied, types of algorithms used, and key findings.

Table 1 — Inclusion and exclusion criteria

Inclusion Criteria	Exclusion Criteria
Studies focused on AI and/or IoT for detecting, predicting, or reducing yarn defects.	Studies discussing only fabric defects
Peer-reviewed journal articles indexed in Scopus/Web of Science	Non-peer-reviewed papers (workshops, preprints, patents)
Experimental studies or model-based approaches (AI, IoT applications)	Conceptual studies without real-world implementation
Published between 2014 and 2024	Articles in languages other than English
Studies explicitly covering yarn defect detection across production stages.	General AI/IoT studies without textile-specific applications

Limitations of Article Selection

Despite the strict eligibility criteria, some limitations should be recognized:

- The review is primarily based on Scopus, Google Scholar, Science Direct, IEEE Xplore, and Web of Science databases, which could omit valuable studies present in regional or industry journals.
- Non-English articles are not included, which might induce language bias (because Chinese or German studies could contain valuable information).
- The exclusion of patents and technical reports that may have insights into AI and IoT applications in an industrial setting, from a focus on peer-reviewed journal articles.

Results

Keyword Mapping

To identify research trends, relevant articles from PRISMA are exported in *.ris* format and imported into Mendeley for keyword adjustment. A **file* is a standard bibliographic format for exchanging publication data. It is primarily used to export records from academic databases to reference managers.[21] The polished papers were subsequently introduced into VOSviewer for keyword co-occurrence analysis. An overlay visualization of the extracted PRISMA-based keywords is presented in Fig. 2, and the classification into four main research clusters is shown in Table 2.

This analysis highlights the main trends in AI and IoT applications for yarn defect detection.

Distribution of the Most Contributing Journals

The quality of publication sources was assessed using the Scientific Journal Rankings (SJR) classification system to evaluate the potential impact of selected articles. The prevalence of high-impact journal articles was identified from the 25 manuscripts:

- 6 articles (24%) were published in Q1 journals,
- 11 articles (44%) in Q2,
- 2 articles (8%) in Q4 and Q3.
- 3 articles(12%) were conference reports.

This result indicates that most published studies on AI and IoT for yarn defect detection have appeared in

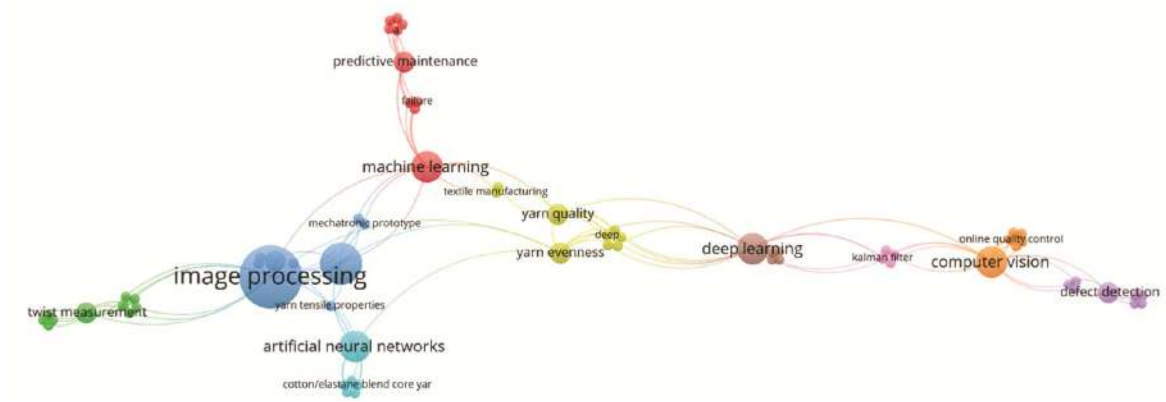

Fig. 2 — Overlay visualisation of the keywords

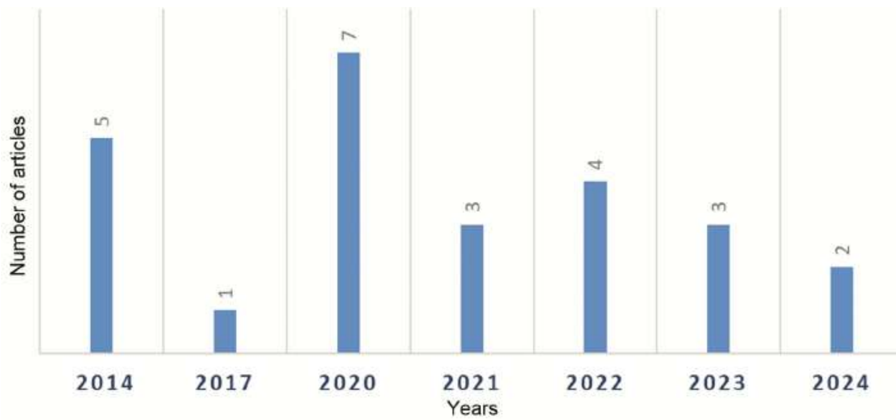

Fig. 3 — Year-wise distribution of reviewed articles (2014–2024)

Table 2 — Clustered keywords from VOS viewer

Clusters	Keywords
1	Computer vision, deep learning, defect detection, yarn evenness, yarn quality
2	Image processing, twist measurement, yarn
3	Artificial intelligence, artificial neural networks
4	Machine learning, predictive maintenance

reputable journals, demonstrating strong academic interest and rigorous peer review in this area.

In addition, an analysis of publication types indicated that 84% of the included studies were journal articles and 16% were conference papers. This suggests that journals are the primary publication outlets for sharing AI and IoT applications for yarn defect detection research, given the detailed methodologies and experimental validation required.

Annual Distribution of Published Articles

A graph showing the annual distribution of these recruited articles over the past decade (2014–2024) is shown in Fig. 3. The year with the most publications was 2020 (7 articles, 28%), followed by 2014 (5,20%), 2022 (4,16%), and both 2021 & 2023 (3–12%).

According to the temporal distribution of the literature, 2015, 2016, 2018, and 2019 show no publications, indicating that these years had no related academic contributions. Interestingly, this might suggest that:

- Research has been scarce (pre-2017), as the textile industry has not had AI and IoT implementation.
- An increase in interest can be observed around 2020, which could be associated with the advances in (a) Deep Learning, (b) Computer Vision, and (c) IoT-based monitoring systems.

Distribution of Research by Journal Sources

The 25 papers were published in top journals, demonstrating interdisciplinary research domain. The distribution across various disciplines is given in Table 2:

- Fibres and Polymers Journal published three papers (12%), the most in this study.
- There were two papers (8%) from each of the Alexandria Engineering Journal, IEEE Access, and Journal of Engineered Fibers and Fabrics.

- The rest of the articles were distributed over 18 different journals (4% each), which indicates that AI and IoT research aimed at yarn defect detection is diffused rather than concentrated into a small number of outlets.

The variety of journal sources indicates a wide range of research across engineering, textile technology, artificial intelligence, and industrial automation.

Table 2 — Number of reviewed articles per journal.

Publisher	Number of articles
Alexandria Engineering Journal	2
Computers in Industry	1
Digital Signal Processing	1
Electronics (Switzerland)	1
Fibres and Polymers	3
IEEE Access	2
ICRAIE 2014	1
International Journal of Engineering and Technology Innovation	1
Journal of Engineered Fibres and Fabrics	2
Journal of Hunan University (Natural Sciences)	1
Journal of Industrial Textiles	1
Journal of Shanghai Jiao Tong University (Science)	1
Journal of the International Measurement Confederation	1
Optik	1
Research Journal of Textile and Apparel	1
Sensors	1
Journal of Physics: Conference Series	1
Textile Bioengineering and Informatics Symposium Proceedings 2020	1
Textile Research Journal	1
Journal of Theoretical and Applied Information Technology	1

Geographical Distribution of Contributing Countries

The contribution of geographical research on AI and IoT applications in textile defect detection was examined to identify the countries that conducted the most studies. As shown in Fig. 4, the top five countries of origin in terms of contributors are:

- China: seven papers (28%), taking the dominance of AI-driven defect detection and smart manufacturing.
- Egypt & Turkey: four papers (16%) each, in the domain of IoT-based monitoring of textile quality.
- India: three papers (12%), all about predictive maintenance with AI.
- Other participating countries are Iran (8%), Portugal (4%), France (4%), Italy (4%), and Taiwan (4%).

China's superiority may be due to substantial capital investment in AI research and smart manufacturing, particularly in the textile industry, as part of major market subdivisions.[22] Turkey,[23] India,[24] and Egypt,[25] are examples of this growing interest in AI textile quality control in emerging markets.

It is also compatible with https://statista.com.[26] The global textile industry remains strong in 2024, and a few leading players control yarn production for each type (cotton/wool/synthetic fibers). The top countries in global textile trade are shown in Fig. 5.

Among these, China has emerged as a dominant player in the field. China – textile yarn. China continued to dominate the world in 2022, with textile yarn exports valued at US$16.3 billion, equivalent to tens of billions of yuan, thereby extending its lead as the world's largest exporter. China is the world's

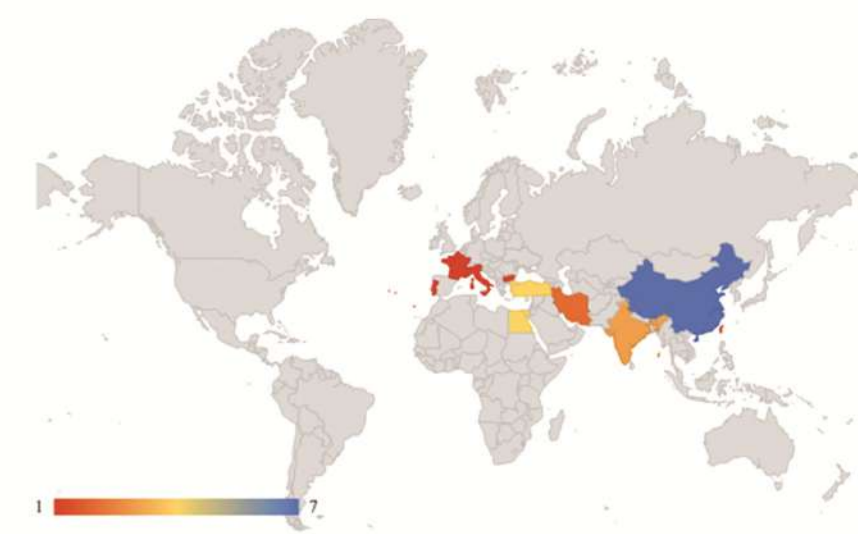

Fig. 4 — Geographic distribution of contributing countries

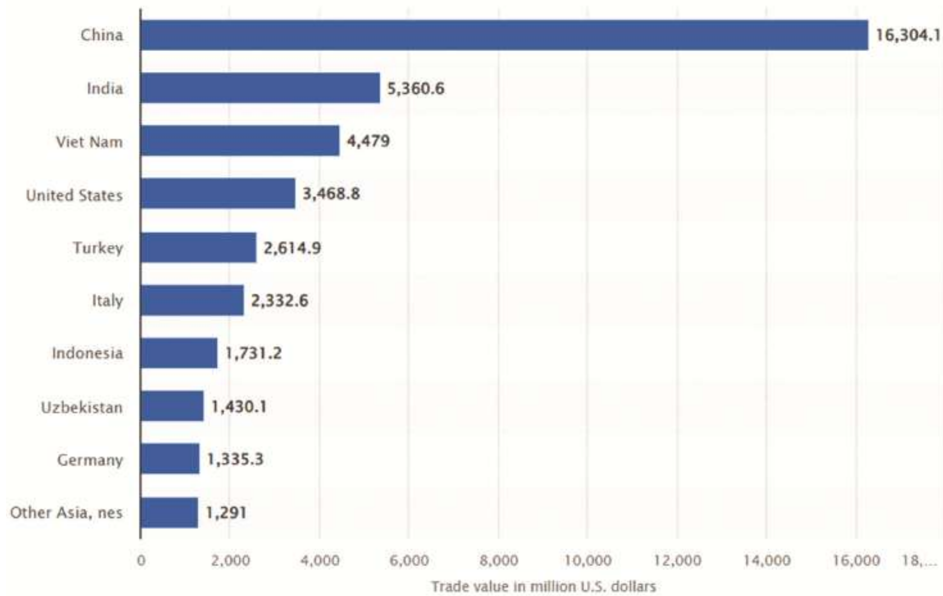

Fig. 5 — Trade value in million U.S. dollars

largest wool producer, with 356,193 tons produced this year. The country is a major producer of cotton (it produced 27.5 million 480-pound bales in 2023, accounting for a large share of global cotton output). Such successes are undeniable evidence of China's great power and its contributions to the worldwide textile industry.

Yet the lack of contributions from the central garment-producing countries, including Bangladesh, Vietnam, and Indonesia, suggests that research uptake in these regions remains low, providing fertile ground for future studies.

Discussion

Data Abstraction and Analysis

RQ1: How have AI and IoT been utilised for yarn defect detection in the textile industry?

China has made significant contributions to research on yarn defect detection over the last five years. In 2020S, attention was paid to the detection of traditional bobbin yarn surface defects and inconsistent quality using a visual saliency analysis method, which achieved higher accuracy and more complete defect segmentation than conventional methods. The Diameter Image Processing Unit (DIPU) method, described in detail in Guang *et al.*[27], was also introduced this year to provide a robust foundation by exploring machine vision and image processing technologies to mitigate the influence of random effects from fibre shape variation on measurement accuracy.[28] Further advancements in research on yarn-quality prediction using machine learning and the BMNN algorithm[29], as well as studies on the identification and prediction of yarn-machine damage.[30] These results emphasize the changing role of AI in post-production defect inspection as well as predictive maintenance, where manufacturers can predict defects before they even happen. A summary of the significant findings from each study is presented in Table 3.

Table 3 — Summarises the utilisation of AI and IoT in the yarn production phase

Yarn production phase	Number of articles
pre-production	9
on-production	2
post-production	14
TOTAL	25

According to Table 3, AI and IoT technologies used for yarn defect solutions have been analyzed across three significant production-line stages: pre-production, on-production, and post-production. The stages include pre-production – the stage before yarn production on the machine, on-production – when the yarn is being formed, and post-production – when the yarn has been finished and made into fabric.

At the pre-production stage. Four papers were published in 2020, which was the most productive year. The authors of these studies also developed models to predict yarn quality properties.[33] ANN models were also employed in order to predict the tensile properties of cotton and blended yarns with success.[34] More recently in 2024, they have worked on enhancing the learning ability of machine learning models using hyperparameter optimization and cross-validation techniques and achieved an accuracy of 92% on their test set.[35]

In the research on post-production, there are 14 papers addressing this phase. Research has fluctuated over the last decade, and 2014 was as busy a year for contributing articles as any in this period, with 5. Later works also employed image processing and machine learning techniques for defect detection. For instance, image processing was used by researchers to identify quality defects (neps, snarls, thick-and-thin places, oil-stained yarns) earlier in 2014.[(31)] Machine learning-based PRPS could also support defect detection, enabling enhancements. Some of these works demonstrated the strong performance of PNN classifiers, achieving accuracies of 96%-99%.[(32)] More recently, in 2024, new AI for quality control innovations have been applied to textile IQC with ML techniques such as decision trees and random forests.[10]

Finally, studies on real-time defect detection during production are rare, with only two papers published in 2021–2022. The first proposed method implemented a web-based system to detect nep online by measuring contamination evenness using image processing and computer vision.[12] Another study on humidity and temperature monitoring, yarn breakage control, and quality improvement used the IoT.[36] These findings emphasize the need for more data on online monitoring methods during scale-up.

RQ2: What are the most commonly used AI techniques or IoT-based approaches for yarn defect detection?

Responses to the most used AI methods and IoT-based approach: Table 4 summarizes the Findings from each reviewed study.

Based on the findings in Table 4 regarding the categorization of AI and IoT techniques, Fig. 6 is provided to classify AI types into two subsystems: Learning and Perception. Learning encompasses machine learning methods such as classification (SVMs, decision trees) and regression (logistic regression, random forests). Perception addresses tasks such as object detection and image segmentation.

Most of the studies considered in this review are based on two main AI approaches (Fig. 7):

1. **Computer Vision** – Interprets and processes visual data to detect defects, which uses techniques including:

Table 4 — Summarises the algorithm of AI and IoT from each reviewed study

Authors, Year	AI/IoT Algorithmic Approach
Nateri *et al*., 2014[(31)]	Image Processing
Semnani, 2014[(37)]	Image Processing & Back Propagation Neural Network (BNN)
Ghosh *et al*., 2014[(32)]	Probabilistic Neural Network (PNN)
Süle, 2014[(38)]	Multi-Step Gradient Based Thresholding (MSGBT)& Hough Transform (HT)
Fayala *et al*., 2014[(39)]	Multilayer Feed-Forward Neural Networks (ANN)
Yıldırım *et al*., 2017[(40)]	The Broyden-Fletcher-Goldfarb-Shanno (BFGS) &ANN
Doran & Sahin, 2020[(33)]	ANN & Support Vector Machine (SVM)
Farooq *et al*., 2020[(41)]	Deep Neural Network
El-Geiheini *et al*., 2020[(34)]	ANN trained with the Levenberg-Marquardt Backpropagation
Süle, 2020[(38)]	Image Processing & Diffraction Limited Incoherent Imaging (DLIM)
El-Geiheini *et al*., 2020[(42)]	Image processing & ANN
Jing *et al*., 2020[(27)]	DoG Wavelet Threshold Denoising &Frequency Tuned Visual Saliency
Li *et al*., 2020[(28)]	Machine vision & Image Processing
Haleem *et al*., 2021[(12)]	Image Acquisition & The Viola-Jones Object Detection Algorithm
Shi *et al*., 2021[(43)]	Deep Learning (CNN) & Computer Vision
Jiang *et al*., 2021[(29)]	Broad Multilayer Neural Network (BMNN)
Kalavathi Devi *et al*., 2022[(36)]	—
Zhang *et al*., 2022[(44)]	Image Acquisition
Zhu *et al*., 2022[(30)]	Ensemble Empirical Mode Decomposition (EEMD), SVM&BAS
Sudha *et al*., 2022[(45)]	Deep Belief Neural Network
Lu *et al*., 2023[(46)]	Long Short-Term Memory (LSTM) Neural Network
Pereira *et al*., 2023[(47)]	Image Acquisition & Neural Network
Bao *et al*., 2023[(48)]	Machine Vision & Deep Learning Methods
Trankov *et al*., 2024[(10)]	Machine learning
Elkateb *et al*., 2024[(35)]	AdaBoost algorithm

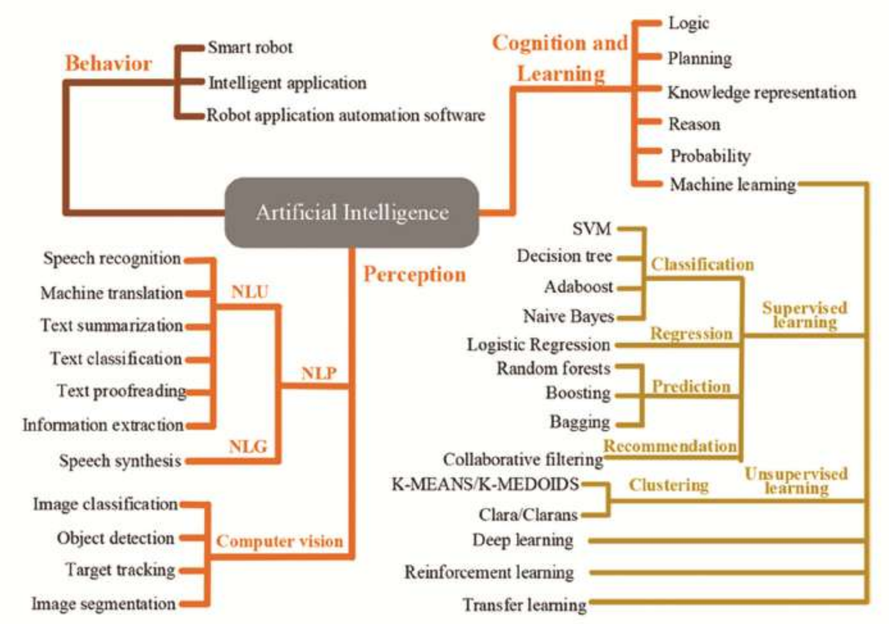

Fig. 6 — The brief AI hierarchy[49]

- Image processing techniques for detecting defects.
- Multi-step gradient-based thresholding (MSGBT) for segmentation.
- Hough transform (HT) for feature extraction.

2. **Machine Learning** – Used for predictive modelling and classification, such as:

- Backpropagation neural networks (BNN).
- Artificial neural networks (ANN).
- Convolutional neural networks (CNN).
- Deep learning algorithms.

As shown in Fig. 7, AI is not limited to a single algorithm. Several works are hybrid between these networks, performing image processing followed by pure BNNs[37] or mixing machine vision with deep learning.[48] Combined with other unambiguous defect-detection methods, this interdisciplinary methodology yields higher precision and efficiency in defect recognition than traditional procedures.[50]

Notably, it is observed that while the AI space is increasingly exploited, IoT remains underexplored in the literature reviewed. A few studies are addressing the role of IoT in yarn quality assurance; for instance, one focuses on humidity and temperature control for defect prevention[36], and another addresses the real-time classification of stop reasons in knitting machines. Given the availability of comprehensive low-level machine data, significant operational benefits are demonstrated to be realisable through the systematic application of wrapping and vision systems.[35] These studies imply that although IoT

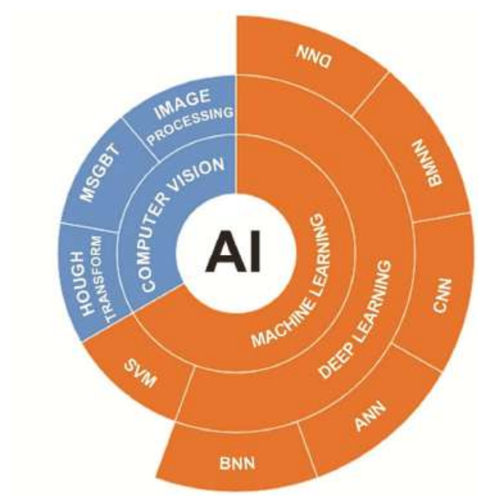

Fig. 7 — The role of AI in the Classification of the review articles

brings the promise of predictive maintenance, research needs to be conducted for a combination of IoT and an AI-based fault detection framework.

RQ3: What are the key challenges in implementing AI and IoT for yarn defect detection?

This work examines the main challenges in implementing AI and IoT for yarn defect detection in the textile industry. The fundamental challenges to address include data accuracy and consistency, as well as the ways AI and IoT technologies can interface with traditional manufacturing systems. The additional requirements of real-time processing significantly increase the implementation challenge, as they require substantial computational hardware resources and highly optimised algorithms.[14] Moreover, the considerable capital required to install and operate such technologies limits their adoption. Solving these problems in depth is crucial for realising the full potential and efficiency of AI and IoT in yarn defect elimination and overall production control.[35] Apart from defect detection, AI can also perform predictive maintenance in supply chains to assist manufacturers in more efficient resource utilisation and demand prediction.[10,34] Moreover, AI has a significant role in accelerating sustainable textiles by promoting circular fashion, reducing waste, and optimising resource use.[5,35,51] While AI has the potential to be transformative, bringing it into practice presents significant hurdles, including data quality, the ethical use of the technology, and the integration of new processes with traditional ones. Overcoming these challenges is a prerequisite for realising the potential of AI and IoT to enable innovation and sustainability in the textile sector.

Conclusions

The study emphasizes the growing importance of AI in yarn defect detection and the relatively limited attention paid to its integration into real-time, IoT-enabled textile manufacturing applications. This gap presents future opportunities for those interested in AI-IoT frameworks to enable intelligent operations across industries through continuous monitoring and predictive maintenance, while also improving quality-control applications. Despite the success of AI methods (including image processing, neural networks, and deep learning) for detecting conditions from data, among other tasks, there remain obstacles to integrating these techniques into real-time IoT-driven monitoring systems. In future work, hybrid solutions that combine computer vision, deep learning, and IoT sensing warrant further exploration to enhance detection accuracy and timeliness. Furthermore, developments in research on production performance and cross-domain applications may also contribute to scalability and real-world use. Although this study recognizes that there are currently no holistic AI-IoT integration studies, it is noteworthy that the literature has made little progress in suggesting future research on this kind of fusion. Development of this line of study may lead to the design of innovative, automated, and sustainable quality control systems for textiles with multiple industrial applications.

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