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Journal of Textile Engineering & Fashion Technology

Review Article

Open Access

A quick look at the current status and expected future impact of artificial intelligence and associated technologies in textile manufacturing and distribution

Volume 12 Issue 2 - 2026

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Received: March 10, 2026 | **Published:** March 18, 2026

Introduction

AI is already playing a significant role in automating textile manufacturing processes and improving quality, efficiency, and productivity across many segments of textile production and distribution. Computer vision systems are inspecting fabrics and garments for defects. Cameras and sensors capture images of defects, and machine learning algorithms analyze them to detect and classify various defect types with high accuracy. Inspected products are categorized by quality, size, color, or other attributes. AI algorithms can predict exactly when and how textile manufacturing equipment will fail or require maintenance by analyzing sensor data and historical performance metrics, thereby reducing downtime and maintenance costs. AI can predict demand by analyzing sales data and external market factors, helping manufacturers optimize production schedules and inventory levels. AI can help select and manage suppliers by analyzing factors such as quality, pricing, and delivery performance. AI can help quickly develop in-demand designs and products by taking into account changing market preferences and supply availability, including eco-friendly and sustainable materials. AI-powered machines can quickly create prototypes and samples of textile products, reducing the time and cost of product development. AI systems can monitor energy consumption in textile manufacturing facilities and recommend energy-saving measures, thereby reducing operational costs and environmental impact. Thus, AI is already helping textile manufacturers in the areas of quality control, machine maintenance, product design and optimization, real-time defect detection and minimization, demand forecasting, inventory management, sustainable production,[1,2] waste reduction, supply chain transparency, and easy tracing of materials and products. The adoption of AI in textile manufacturing is expected to grow rapidly as technology advances and businesses seek to improve their competitiveness while catering to consumer demands for quality and sustainability.

Critical roles played by AI in textile manufacturing

Artificial intelligence (AI) is increasingly being used in textile manufacturing to improve efficiency, quality, and productivity in various stages of the production process. Here are several ways AI is applied in the textile industry:

a) Quality control and inspection:

Computer Vision: AI-powered computer vision systems can inspect fabrics and garments for defects such as stains, tears, missing threads, or misaligned patterns. Cameras and sensors capture images, and machine learning algorithms analyze them to detect and classify defects with high accuracy.

Automated Sorting: AI can automate sorting by identifying and categorizing products by quality, size, color, or other attributes.

b) Predictive maintenance:

Predictive Analytics: AI algorithms can predict when textile manufacturing equipment is likely to fail or require maintenance by analyzing sensor data and historical performance. This helps to reduce downtime and maintenance costs.

c) Production optimization:

Demand Forecasting: AI can analyze historical sales data and external factors to predict future demand, allowing manufacturers to adjust production schedules and inventory levels accordingly.

Production Planning: AI-driven algorithms can optimize production schedules and resource allocation to minimize waste, improve efficiency, and reduce lead times.

d) Design and prototyping:

Generative Design: AI can assist in generating innovative textile designs by considering various parameters and constraints, helping designers explore new possibilities.

Rapid Prototyping: AI-powered machines can quickly create prototypes and samples of textile products, reducing product development time and costs (Figure 1).

e) Supply chain management:

Inventory Optimization: AI algorithms can optimize inventory levels, ensuring raw materials and finished products are managed efficiently to minimize carrying costs while meeting production demands.

Supplier Management: AI can help select and manage suppliers by analyzing factors such as quality, pricing, and delivery performance.

Figure 1 Illustration of a future AI-powered digital garment design system.

f) Energy efficiency:

Energy Management: AI systems can monitor energy consumption in textile manufacturing facilities and recommend energy-saving measures, thus reducing operational costs and environmental impact.

g) Personalization and customization:

Mass Customization: AI can enable mass customization of textile products by analyzing customer preferences and generating personalized designs or recommendations.

h) Sustainability:

Waste Reduction: AI can help minimize material waste during production by optimizing cutting patterns and reducing overproduction.[2,3]

Eco-friendly Materials: AI can assist in identifying and developing sustainable materials and processes.[1,2,4,5]

i) Compliance and traceability:

Supply Chain Transparency: AI can enhance traceability, ensuring products meet ethical and regulatory standards.

AI's adoption in textile manufacturing is expected to continue growing as technology advances and businesses seek to improve their competitiveness, reduce costs, and meet evolving consumer demands for quality and sustainability in textile products.

Roles played by automatic inspection and fabric grading systems

AI is extensively used in the automatic inspection and grading of textile fabrics to ensure products meet quality standards and minimize defects. Here's how AI is applied in this context:

a) Computer vision:

Image Capture: High-resolution cameras or sensors capture images of textile fabrics as they move through the production line.

Image Preprocessing: AI algorithms preprocess images to enhance quality, remove noise, and adjust lighting to ensure accurate analysis.

b) Defect detection:

Object Recognition: Machine learning models, including deep learning-based convolutional neural networks (CNNs), are trained to recognize various defects, such as stains, holes, irregular patterns, and misprints.

Defect Localization: AI algorithms not only detect defects but also pinpoint their exact locations on the fabric, enabling targeted correction or removal.

c) Grading and classification:

Quality Assessment: AI systems classify textile fabrics into different quality categories based on predefined criteria, such as defect severity or fabric characteristics like color and weave.

Automated Grading: The grading process can be automated, with AI assigning a grade to each fabric roll or piece based on its quality.

d) Real-time inspection:

Continuous Monitoring: AI-powered inspection systems can monitor textile production lines in real time, flagging defects as they occur and enabling immediate corrective action.

Alerts and Reporting: The AI system can generate alerts and reports for operators and managers when quality issues are detected.

e) Data analysis:

Data Logging: Images and inspection results are stored in a database for analysis and traceability.

Continuous Learning: AI models can be continuously trained and improved using new data to adapt to changing production conditions and new defect types.

f) Integration with manufacturing processes:

Feedback Loop: AI inspection systems can be integrated into the manufacturing process to provide real-time feedback for adjustments, reducing the production of defective fabrics.

Automation: Integration with automated equipment enables the removal or repair of defects, thus minimizing waste and rework.

g) Accuracy and consistency:

AI-based systems offer high accuracy and consistency in defect detection, reducing the chances of human error and subjective judgments.

They can operate 24/7 without fatigue, ensuring continuous quality control.

h) Scalability and efficiency:

AI inspection systems can handle large volumes of fabric, making them suitable for high-speed production environments.

They can significantly reduce the time and labor required for manual inspection.

Overall, AI-based automatic inspection and grading of textile fabrics offer numerous benefits, including improved quality control, reduced production costs, increased efficiency, and enhanced customer satisfaction by ensuring that only high-quality textiles reach the customers.

Use of AI in textile manufacturing automation

AI plays a crucial role in automating various aspects of textile manufacturing, enhancing efficiency, precision, and productivity across the production process. Here's how AI is used in textile manufacturing automation:

a) Predictive maintenance:

AI-driven predictive maintenance systems use sensors and data analysis to monitor machinery condition and predict when maintenance is needed. This reduces downtime and prevents costly breakdowns.

b) Machine control and optimization:

AI algorithms can optimize machine settings for various textile processes, such as spinning, weaving, and knitting, to maximize production efficiency and product quality.

AI can control the speed, tension, and other variables in real time, ensuring consistent, high-quality output.

c) Inventory management:

AI helps manage inventory by optimizing stocking levels, preventing overstocking or understocking, and ensuring that the right materials are available when needed.

d) Supply chain management:

AI-enhanced supply chain management systems monitor and optimize the flow of materials and finished products, reducing lead times and operational costs.

Predictive analytics helps make informed decisions regarding supplier selection, transportation, and inventory management.

e) Robotic automation:

Robots equipped with AI algorithms can handle various tasks in textile manufacturing, including material handling, cutting, sewing, and packaging.

Collaborative robots (cobots) work alongside human workers, increasing efficiency and reducing the risk of workplace injuries.

f) Energy efficiency:

AI systems monitor energy consumption in textile facilities and optimize energy usage to reduce operational costs and environmental impact.

g) Data analytics:

AI-driven data analytics provide insights into production processes, helping manufacturers identify areas for improvement, optimize resource allocation, and reduce waste.

h) Sustainability:

AI can help optimize textile production processes to reduce environmental impact by minimizing waste, using eco-friendly materials, and implementing energy-efficient practices.

i) Human-machine collaboration:

AI-enhanced human-machine interfaces improve worker efficiency and safety by providing real-time guidance and assistance in complex manufacturing tasks.

In summary, AI in textile manufacturing automation offers a wide range of benefits, including improved product quality, reduced operational costs, increased production efficiency, and greater adaptability to changing market demands. As AI technology continues to advance, its role in textile manufacturing automation is expected to expand further.

Saving money and improving efficiency using AI

Artificial intelligence (AI) has the potential to significantly improve the textile manufacturing industry in various ways. Here are some key ways AI can enhance the industry:

a) Cost reduction:

By automating tasks, optimizing resource allocation, and reducing defects, AI can help lower production costs, improve operational efficiency, and enhance competitiveness.

b) Worker safety:

Collaborative robots (cobots) equipped with AI technology can assist human workers in physically demanding or hazardous tasks, improving workplace safety.

c) Data-driven decision-making:

AI-driven data analytics provide actionable insights into production processes, enabling manufacturers to make informed decisions, identify areas for improvement, and enhance overall operations.

d) Real-time monitoring and control:

AI enables real-time monitoring of production processes, allowing manufacturers to detect and address issues promptly, reducing defect generation and improving overall product quality.

e) Innovation and design:

AI can assist in textile design and innovation by generating new design ideas, optimizing patterns, and facilitating rapid prototyping.

Critical actions involved in the analysis and categorization of images

AI systems can inspect, analyze, and categorize images through a combination of techniques from computer vision and machine learning. Here's a high-level overview of how this process works:

a) Data collection:

To train an AI model for image inspection and analysis, a labeled image dataset is required. These labeled images serve as examples to teach the AI system what to look for and how to categorize different objects or features within images.

b) Preprocessing:

Images often need preprocessing to standardize their format and enhance their quality. Common preprocessing steps include resizing, normalization, noise reduction, and image enhancement.

c) Feature extraction:

Feature extraction involves identifying and capturing relevant information or patterns within images. In traditional computer vision, engineers would design handcrafted features. However, modern AI systems often use convolutional neural networks (CNNs) to automatically learn and extract features.

d) Model training:

The AI model is trained using the labeled dataset. In deep learning, CNNs are commonly used. During training, the model learns to recognize patterns and features in images that are associated with specific categories or attributes.

Citation: Parachuru R. A quick look at the current status and expected future impact of artificial intelligence and associated technologies in textile manufacturing and distribution. *J Textile Eng Fashion Technol.* 2026;12(2):61‒68. DOI: 10.15406/jteft.2026.12.00452

e) Categorization:

After training, the AI model can categorize images. When presented with an unlabeled image, the model processes it and assigns it to one or more predefined categories or labels based on the learned features.

f) Inspection and analysis:

To inspect and analyze images, the AI model can perform various tasks depending on the application, including:

i. Object Detection: Identifying and locating objects within an image.
ii. Image Classification: Assigning a category or label to an image.
iii. Image Segmentation: Dividing an image into regions and labeling each region.
iv. Facial Recognition: Identifying and verifying faces within images.
v. Anomaly Detection: Detecting unusual or unexpected features in images.
vi. Text Extraction: Recognizing and extracting text from images (OCR - Optical Character Recognition).
vii. Pose Estimation: Estimating the positions and orientations of objects or humans in images.
viii. Image Generation: Creating new images based on learned patterns (e.g., generative adversarial networks or GANs).

g) Postprocessing and visualization:

Depending on the specific application, postprocessing steps may be applied. For instance, in object detection, bounding boxes might be drawn around detected objects. Visualization techniques can help present the results in an understandable format.

h) Continuous learning and improvement:

AI models can be further improved and fine-tuned over time by feeding them with new labeled data. This process allows the model to adapt to new categories or variations in image content.

i) Deployment:

Once trained and tested, the AI model can be deployed in real-world applications, such as automated quality control in manufacturing, autonomous vehicles, healthcare diagnostics, security surveillance, content moderation in social media, and more.

In summary, AI systems for image inspection, analysis, and categorization leverage deep learning techniques, especially CNNs, to automatically extract meaningful features from images and make decisions based on learned patterns. These systems can perform a wide range of tasks and are used across various industries to automate image-related processes.

Expected impact of AI on the fabric inspection systems of the future

AI is expected to make automated fabric inspection systems more widespread in textile mills, thereby improving overall fabric and garment quality.

a. **Improved accuracy and speed:** AI-powered fabric inspection systems can analyze fabric surfaces with unmatched accuracy and speed. They can quickly identify and classify defects, even in complex patterns or materials with varying textures.
b. **Enhanced consistency:** AI eliminates the subjectivity associated with manual inspection, ensuring consistent quality control across all fabric rolls or pieces. This consistency leads to higher product quality and fewer defects in the final products.
c. **Reduced labor costs:** Automation through AI reduces the need for manual inspection, which can be labor-intensive and prone to human error. This, in turn, lowers labor costs and frees up human workers for more complex tasks.
d. **Integration with production processes:** AI inspection systems can be seamlessly integrated into textile production lines, allowing for immediate actions such as automated rejection of defective fabrics or adjustments to machine settings based on inspection results.
e. **Greater traceability:** AI systems can provide detailed records of fabric inspection results, enabling better traceability throughout the supply chain and ensuring compliance with quality standards and regulations.
f. **Continuous learning:** AI models can continuously learn and adapt to new defect types and patterns, improving their accuracy over time and staying up to date with changing production requirements.

In summary, AI's impact on future fabric inspection systems in textile mills is expected to bring about more accurate, efficient, and adaptable quality control processes. This will ultimately lead to higher-quality textile products, reduced costs, improved sustainability, and increased competitiveness in the industry.

Predictions on how AI will change the major functional activities of the textile manufacturing industry

The future impact of AI in textile manufacturing is expected to be significant, with several predictions and trends emerging:

a. **Increased automation:** AI-driven automation is expected to become more prevalent, reducing the need for manual labor in various textile processes, from spinning and weaving to cutting and sewing. This will lead to higher production efficiency and reduced labor costs.
b. **Enhanced quality control:** AI-powered computer vision systems will continue to improve the accuracy and speed of quality control and inspection, reducing defects and ensuring consistent product quality.
c. **Mass customization:** AI will enable mass customization of textile products, allowing manufacturers to offer personalized designs, sizes, and configurations to meet individual customer preferences.
d. **Predictive maintenance:** AI-powered predictive maintenance will become more sophisticated, reducing equipment downtime and maintenance costs by accurately predicting when machinery needs servicing or repair.
e. **Sustainable practices:** AI will play a crucial role in optimizing textile manufacturing processes for sustainability, helping reduce waste, minimize energy consumption, and promote the use of eco-friendly materials.
f. **AI in textile design:** AI will assist designers in generating

innovative textile patterns, colors, and styles, accelerating the design process and facilitating rapid prototyping.

g. **Increased collaboration with robots:** Collaborative robots (cobots) equipped with AI technology will work alongside human workers, enhancing productivity and ensuring safety in textile manufacturing.

h. **Adoption of AI-powered textile machinery:** New generations of textile machinery will incorporate AI and IoT (Internet of Things) technologies to improve efficiency, reduce waste, and enhance product quality.

i. **Increased connectivity:** Smart factories and Industry 4.0 initiatives will see greater integration of AI-powered systems, enabling seamless communication between machines, processes, and supply chain partners.

j. **Reskilling and training:** As AI adoption increases, there will be a greater emphasis on reskilling and training the workforce to operate and maintain AI-driven systems effectively.

k. **Regulatory and ethical considerations:** As AI plays a larger role in the industry, there may be greater attention to ethical and regulatory issues, particularly regarding data privacy, safety, and AI bias.

l. **Market competitiveness:** Companies that adopt AI early and effectively in their textile manufacturing processes are likely to gain a competitive edge in terms of efficiency, product quality, and customer satisfaction.

Overall, the future impact of AI in textile manufacturing is poised to drive transformational changes, improving efficiency, sustainability, customization, and quality across the industry. However, the pace of adoption may vary depending on factors such as technology advancements, regulatory developments, and market demands.

Common tools and software programs used in AI

Artificial Intelligence (AI) encompasses a wide range of tools and software programs that serve various purposes, from data processing and machine learning to natural language processing and computer vision. Here are some of the different tools and software programs commonly used in AI:

a) Programming languages:

Python: Python is the most popular programming language for AI and machine learning due to its extensive libraries (e.g., TensorFlow, PyTorch, scikit-learn) and ease of use.

R: R is another language commonly used for statistical analysis and data visualization in AI.

b) Machine learning frameworks:

TensorFlow: Developed by Google, TensorFlow is an open-source machine learning framework used for deep learning and neural networks.

PyTorch: PyTorch is an open-source deep learning framework that has gained popularity for its dynamic computation graph.

Keras: Keras is a high-level neural networks API that can run on top of TensorFlow, Theano, or CNTK, making it user-friendly.

scikit-learn: A machine learning library in Python that provides tools for data analysis and modeling.

c) Natural Language Processing (NLP) libraries:

NLTK (Natural Language Toolkit): NLTK is a Python library for working with human language data, including tokenization, stemming, and parsing.

spaCy: a popular Python library for NLP tasks, including text processing, named entity recognition, and part-of-speech tagging.

Gensim: Gensim is a library for topic modeling and document similarity analysis.

d) Computer vision frameworks:

OpenCV: an open-source computer vision library providing tools for image and video analysis.

YOLO (You Only Look Once): YOLO is a popular real-time object detection framework used in computer vision applications.

e) Reinforcement learning libraries:

OpenAI Gym: a toolkit for developing and comparing reinforcement learning algorithms.

RLlib: RLlib is an open-source reinforcement learning library from Ray that supports both single-agent and multi-agent scenarios.

f) Data manipulation and analysis:

Pandas: a Python library for data manipulation and analysis, commonly used in AI for data preprocessing.

NumPy: NumPy is a fundamental package for scientific computing in Python, often used for numerical operations in AI.

g) Cloud AI services:

AWS AI Services: Amazon Web Services offers a range of AI services, including Amazon SageMaker, Amazon Comprehend, and Amazon Rekognition.

Google Cloud AI: Google Cloud offers AI tools, including Google Cloud AI Platform, Natural Language API, and Vision AI.

Microsoft Azure AI: Microsoft Azure offers AI services like Azure Machine Learning and Azure Cognitive Services.

h) Data visualization:

Matplotlib: Matplotlib is a Python library for creating static, animated, and interactive visualizations.

Seaborn: Seaborn is a Python data visualization library built on top of Matplotlib, with a focus on aesthetics.

These are just some of the many tools and software programs used in AI, and the choice of tools depends on the specific AI application and the preferences of the developers and researchers involved. AI is a rapidly evolving field, so new tools and libraries continue to emerge.

The use of neural networks, deep learning, cloud computing, and computer vision tools in AI

Neural networks, convolutional neural networks (CNNs), deep learning, cloud computing, and computer vision are all important components and technologies within the field of artificial intelligence (AI). Here's how they are used in AI:

a) Neural networks:

Neural networks are the foundation of many AI applications. They are computational models inspired by the structure and function of the human brain.

Neural networks are used in tasks such as image recognition, natural language processing, speech recognition, and more.

They consist of interconnected layers of artificial neurons, with each layer contributing to feature extraction and abstraction in data.

b) Convolutional Neural Networks (CNNs):

CNNs are a specialized type of neural network designed for computer vision tasks, such as image classification, object detection, and image segmentation.

They excel at learning hierarchical features from images through a series of convolutional and pooling layers.

CNNs have been instrumental in achieving state-of-the-art results in various computer vision applications.

c) Deep learning:

Deep learning is a subfield of machine learning that focuses on neural networks with many hidden layers (deep neural networks).

Deep learning has revolutionized AI by enabling models to automatically learn intricate patterns and representations from data.

It is used in a wide range of applications, including speech recognition, natural language understanding, recommendation systems, and autonomous vehicles.

d) Cloud computing:

Cloud computing provides the infrastructure and resources necessary for AI and deep learning tasks.

Cloud providers like AWS, Google Cloud, and Azure offer scalable GPU/TPU resources for training large neural networks.

Cloud services make it easier to deploy AI models, manage data, and collaborate on AI projects.

e) Computer vision:

Computer vision is a field of AI focused on enabling computers to understand and interpret visual information from the world.

It encompasses tasks like object recognition, facial recognition, image segmentation, and scene understanding.

Techniques from computer vision, combined with deep learning and CNNs, have led to remarkable advancements in image and video analysis.

How the above tools are used in different work environments

CNNs are a crucial component of many computer vision applications, as they can automatically learn features and patterns from images.

Deep learning techniques, including deep neural networks, are applied across various AI domains, such as natural language processing and speech recognition, thereby improving performance.

Cloud computing resources are used to train and deploy large deep learning models, as training them requires substantial computational power.

AI systems that incorporate computer vision can be deployed across various industries, including healthcare (medical image analysis), autonomous vehicles (self-driving cars), retail (automated checkout), and more.

In essence, these technologies work in tandem to enable AI systems to perform tasks that require understanding and processing of complex data, whether it's images, text, speech, or other forms of information. They have contributed to the rapid advancement of AI applications across numerous domains.

How IoT and machine learning are used in AI

The Internet of Things (IoT) and machine learning are two key technologies that often work together to enhance and expand the capabilities of artificial intelligence (AI). Here's how IoT and machine learning are used in AI:

a) IoT and data collection:

IoT involves connecting physical objects and devices to the internet, enabling them to collect and transmit data.

IoT devices, such as sensors, cameras, and smart appliances, generate vast amounts of data from the real world.

Machine learning relies on data to train models, and IoT provides a continuous stream of data for AI applications.

b) Data processing and analysis:

IoT-generated data is often noisy, unstructured, and high-volume. Machine learning algorithms are used to process and analyze this data.

Machine learning can identify patterns, anomalies, and insights from IoT data, helping organizations make data-driven decisions.

c) Predictive maintenance:

IoT sensors can monitor the condition of machinery and equipment in real-time.

Machine learning models can analyze sensor data to predict when maintenance is needed, reducing downtime and improving efficiency in industries like manufacturing and utilities.

d) Smart home and automation:

IoT devices in smart homes can be integrated with machine learning algorithms to create personalized and automated experiences.

Machine learning can learn user preferences and adapt to them, for example, by automatically adjusting lighting and temperature settings.

e) Healthcare and wearables:

IoT wearables, like fitness trackers and health monitors, collect continuous health data.

Machine learning can analyze this data to provide health insights, detect anomalies, and assist in diagnosis and treatment.

f) Autonomous vehicles:

IoT sensors, cameras, and lidar systems on autonomous vehicles collect data about the vehicle's surroundings.

Machine learning algorithms process this data to enable object detection, path planning, and decision-making, thereby enabling self-driving capabilities.

g) Environmental monitoring:

IoT sensors deployed in agriculture, weather stations, and environmental monitoring systems collect data on soil conditions, weather, and pollution levels.

Machine learning can analyze this data to optimize farming practices, predict weather patterns, and assess environmental risks.

h) Energy efficiency:

IoT-connected devices in buildings can monitor energy usage and environmental conditions.

Machine learning models can optimize energy consumption by controlling heating, ventilation, and air conditioning (HVAC) systems for greater efficiency.

i) Security and anomaly detection:

IoT security cameras and sensors can detect security breaches and anomalies.

Machine learning can analyze the data from these devices to identify suspicious activities and trigger alerts.

j) Supply chain and logistics:

IoT sensors in supply chain and logistics operations can track the location and condition of goods.

Machine learning can optimize routing, predict delivery times, and improve inventory management.[6–44]

In summary, IoT and machine learning complement each other in AI by enabling the collection and analysis of real-World data, facilitating automation, and enhancing decision-making processes across various domains. These technologies work together to create intelligent systems that respond to changing conditions, improve efficiency, and provide valuable insights.

Acknowledgments

None.

Funding

None.

Conflicts of interest

The author declares no conflict of interest.

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