Review Article

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# A quick look at the recent advances, current state of utilization and expected future usage of artificial intelligence (AI) in the global textile manufacturing industry


## Abstract

A significant part of the current textile manufacturing industry around the world is managed and governed by individuals who are not sufficiently trained in information technology. While future textile engineers and technologists may come out sufficiently equipped to understand IT and its implications to the textile manufacturing industry, those running the industry today can benefit through simple elaboration of potentially useful IT tools and the many benefits they offer to the textile industry. This is especially true in the case of technologies that surfaced within the last two decades and are already making a sizable impact on products, production processes and the bottom lines of manufacturing industries. Artificial intelligence (AI) and related technologies fall under the category of rapidly emerging technologies that carry the potential to significantly re-shape the global manufacturing and service industries. This paper makes an attempt to describe these technologies and their potential benefits in such a way that textile industry leaders who are not IT experts can understand them to the extent of driving themselves to enthusiastically adopt them.


**Keywords:** global textile, artificial intelligence, data manipulation, software programs

Volume 9 Issue 6 - 2023

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**Received:** December 10, 2023 | **Published:** December 21, 2023

**Abbreviations:** AI, artificial intelligence; NLP, natural language processing; AWS, Amazon web services; DL, deep learning; CNNs, continuous neural networks; IoT, internet of things; ML, machine learning

## Introduction

**Main tools of AI and the role played by them***:* Artificial Intelligence (AI) encompasses a wide range of tools, technologies and software programs that serve various purposes, from data processing and machine learning to natural language processing and computer vision. To understand how AI can be beneficially used in manufacturing, it is necessary to know what these tools are and what kind of roles they play. The technical description in the following paragraphs should be viewed in this context. A minimum level of technical jargon is necessary to make this paper serve its intended purpose.

**Python** is one the most popular programming languages of AI. There are many dedicated libraries connected to Python (e.g., **TensorFlow, PyTorch, Scikit-learn, Keras** and **others)** and the language is believed to be easy-to-use because of its natural language adaptation. **R** is another programming language commonly used for statistical analysis and data visualization. **NLTK** is a Python library for working with human language data. **SpaCy** is a popular Python library for **Natural Language Processing (NLP)** tasks such as text processing, named entity recognition. **OpenCV** is an open-source computer vision library that provides tools for image and video analysis. **YOLO** is a popular real-time object detection framework used in computer vision applications. **OpenAI Gym** is a toolkit for developing and comparing reinforcement learning algorithms. **RLlib** is an open-source library for reinforcement learning. **Pandas is** a Python library for data manipulation and analysis, commonly used in AI for data pre-processing. **NumPy** is a fundamental package for scientific computing in Python, often used for numerical operations.

**Google Cloud** provides AI tools. **Amazon Web Services (AWS)** offers a range of AI services, including Amazon **SageMaker. Microsoft Azure** offers AI services like **Azure Machine Learning and Azure Cognitive Services**. **Matplotlib** is a Python library for creating static, animated, and interactive visualizations**. Seaborn** is a Python data visualization library built on top of **Matplotlib**, with a focus on aesthetics.

**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. Computer vision, combined with **Deep Learning (DL)** and **Continuous Neural Networks (CNNs),** has led to remarkable developments in the area of image and video analysis. 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 to various AI domains, including natural language processing and speech recognition. Cloud computing resources are leveraged to train and deploy large deep learning models because training these models requires substantial computational power. **Internet of Things (IoT)** and **Machine Learning (ML)** are two key technologies that often work together to enhance and expand the capabilities of artificial intelligence. 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 for training models, and IoT provides a continuous stream of data that can be used for AI applications.

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

**How AI is used to inspect, analyze, and classify images and patterns**: Analysis and classification of images (such as fabric defect images) is done through a combination of techniques from computer vision and machine learning.

Here's a high-level overview of how automatic inspection and classification process works:

**Image database:** As a first step, a dataset of labeled images is required to train an AI model for image inspection and analysis. 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.

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

**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.

**Model training:** The AI model is trained using the labeled dataset. In the case of 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.

**Classification:** After training, the AI model can be used to classify images under different categories. 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.

**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.

**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.

**Deployment:** Once trained and tested, the AI model can be deployed in real-world applications, such as automated inspection of fabric defects.

To summarize, 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 are capable of performing a wide range of tasks and are used in various industries to automate image-related processes and tasks.

**How AI is currently helping progressive textile manufacturers:** AI is already playing a significant role in automating textile manufacturing processes and in improving the quality, efficiency, and productivity in many segments of the industry. Computer vision systems inspect fabrics and garments for the whole range of defects. Cameras and sensors capture images of defects, and machine learning algorithms analyze them to detect and classify different types of defects with high level of accuracy. Inspected products are categorized based on their quality, size, color, and other attributes. AI algorithms can predict when and how exactly textile manufacturing equipment would fail or require maintenance by analyzing data from sensors and historical performance measures, thus reducing downtime and maintenance costs. AI can predict demand for products by analyzing sales data and related market parameters, thus helping manufacturers to optimize production schedules and inventories. AI can help in selecting and managing suppliers by analyzing performance parameters such as quality, pricing, and delivery schedules. AI can assist to quickly develop in-demand designs by taking into account changing market preferences and availability of supplies, including eco-friendly and sustainable materials. AI-powered machines can create prototypes and samples of textile products quickly, reducing the time and cost of product development. AI systems can monitor energy consumption in textile manufacturing facilities and recommend energy-saving measures, thus helping to reduce operational costs and environmental impact. Therefore, it is easy to see that AI is already helping textile manufacturers in the areas of quality control, machine maintenance, product design and optimization, real time detection and minimization of defects, demand forecasting, inventory management, sustainable production, waste reduction, supply chain transparency and to easily trace materials and products through the long pipe line. The adoption of AI in textile manufacturing is expected to grow rapidly as technology advances and businesses seek to improve their competitiveness in the midst of emerging consumer demand for quality and sustainability.

## Recent AI based advances in the area of automated fabric inspection, defect detection and classification

Visual human inspection of fabric defects is time-consuming and is known to give a low degree of accuracy. More accurate and consistent evaluation is possible through the use of automatic inspection systems based on computer vision. Automated inspection offers a number of advantages, including enhanced product quality, reduced labor costs, improved worker safety and reduced of human errors. Within the last 2-3 decades, several techniques of automatic fabric inspection have been developed such as model-based and spectral systems. However, most of these automated systems are off-line systems and they are associated with significant lag time between the actual production and fabric inspection.

**Automated real-time inspection systems**: In recent years, more efficient real-time systems have emerged such as Barco Vision's **Cyclops** system, Elbit Vision System's **I-Tex4,** and Zellweger Uster's **Fabriscan** system.[1] These online systems can be implemented on the loom with a very high degree of accuracy and they represent the future of fabric inspection in the textile industry. Most of the ongoing R and D efforts also focus on real-time inspection and timely correction of problems. Mahmood et al.[2] observe that automatic systems greatly improve the accuracy, reliability, and speed compared to the human inspection system. In addition, they say that automatic inspection provides a high fault detection rate, helps reduce labor costs, improves product quality, and increases the efficiency of the manufacturing process. Their work demonstrated how discrete wavelets and digital fabric imaging can be used to inspect the quality and structural uniformity of the fabric. It revealed that normal quality fabric (fabric with no defects) shows a steady interval structure, while most faults in the fabric disrupt the steady formation. Checking the disruption patterns in the fabric gave useful information on defects. The

**Citation:** Parachuru R. A quick look at the recent advances, current state of utilization and expected future usage of artificial intelligence (AI) in the global textile manufacturing industry. *J Textile Eng Fashion Technol.* 2023;9(6):190–194. DOI: 10.15406/jteft.2023.09.00355

system proposed by the researchers was able to detect and precisely indicate the location of the defect in the fabric. The book entitled, 'Computer Vision and its Application in Detecting Fabric Defects' written by Eldessouki[3] talks about different types of fabric defects and techniques for analyzing their images. In the image analysis section, a combination of statistical (spatial) and Fourier transform (spectral) techniques are discussed for extraction of useful information from images. Principal component analysis (**PCA**) is recommended to reduce the dimensionality of the input feature dataset. To classify defects, artificial neural networks is recommended as a decision assisting soft tool. Practical application of these principles is discussed in the last section and an over view of future opportunities are discussed in the closing chapter. Timothy et al.[4] present a taxonomy of inspection systems based on their sensory input. The benefits and feasibility of automated inspection are also discussed along with common approaches to visual inspection. System specifications and their influence on the dimensional tolerances are reviewed.

**Deep learning for defect detection and classification**: The use of deep learning approach in the textile industry for the purpose of defect detection became increasingly popular in recent years. The work of Yavuz Kahraman et al.[5] investigated the implementation of deep learning approaches for the detection of fabric defects. The authors analyzed several recent publications on defect detection using deep learning technique. The methods, databases, performance rates, and architecture types of these systems are compared with each other. The advantages and disadvantages of these approaches have also been examined. Srikant Brua et al.[6] focused on applying deep learning for smart detection of defects in colored fabrics. The working and reliability of the fabric defect detection system was evaluated through vigorous experiments on colored fabric samples with different defects. Dongmei Mo and his co-author[7] proposed a novel model which can learn high-level representation from the automatic observations of the input images. It is claimed that the method recognizes defects of various shapes, patterns and textures, instead of only locating defects of specific patterns. Experimental results showed that the method is superior to the state-of-the-art deep hash methods in terms of fabric defect classification. Tomas Almeida and his associsates[8] proposed a fabric defect detection system based on deep learning and false negative reduction concepts. A custom convolutional neural network (CNN) was used for defect detection. Additionally, false negative reduction methods were used in the system to minimize the high cost of false negatives. With the inclusion of false negative reduction capability, an average of 95% accuracy in defect detection was achieved. The results also demonstrated the ability of the system to detect many different types of defects with good accuracy while being faster and computationally simple. The work of Nuria Velasco-Pérez and his associates[9] talked about defect detection in woven fabrics by means of convolutional neural networks. The study proposed and validated deep learning models applied to automatically control the quality of fabrics produced on sophisticated high-speed looms operating under a wide range of conditions. More precisely, convolutional neural networks were validated on real-life images gathered from the production line.

**Improved defect detection in pure color fabrics with no periodic patterns and in patterned fabrics with texture variation:** In their recent work, Huosheng Xie, Yafeng Zhang and Zesen Wu[10] observe that image blocking method is widely used in most image-based fabric defect detection systems. These methods, according to them, directly segment the images, which causes the feature information contained in the image to be less useful. They also observe that setting the image block size to be the same as the periodic-pattern can alleviate the problem to some extent, but the period calculation still remains complicated, and the positioning accuracy needs improvement. Because pure-color fabrics (fully dyed single color fabrics) have no periodic patterns, they feel that the existing defect detection methods for periodic texture fabrics are ineffective in the defect detection of pure-color fabrics. In their opinion, it is challenging to develop algorithms that can be used to detect defects in pure-color fabrics as well as in periodic pattern fabrics which carry a variety of textures and defect types. In view of this, the authors proposed a new fabric defect detection system that uses an image pyramid and a direction template. The image pyramid is applied for defect detection in periodic pattern fabrics without the need to calculate the size of periodic-pattern. The direction template is introduced to further reduce false detection rate. The algorithm first constructed an Image Pyramid for fabric images that do not contain any defects. This action resulted in a set of images with gradually reduced resolution of the fabric image. Then, a random sliding of the window in each layer of the image in the image pyramid is practiced to get image blocks and the image blocks are used as inputs for the image reconstruction model. A 'Stacked De-noising Convolutional Auto-Encoder (SDCAE)' is used for image reconstruction. Subsequently the model is trained, output images obtained, input and output images are divided into blocks, a similarity measure matrix of the blocks calculated and finally defective image blocks are roughly located. In the last step, the direction template set of the input images is constructed, the difference between the "rough-positioning" blocks and their corresponding direction template calculated and used to precisely locate the defective blocks. The experimental results showed that the proposed algorithm can achieve better defect localization accuracy, and receive better results in detection of pure-color fabrics, compared with traditional methods. A graphical abstract of the model building process as shown by the authors[10] is shown in Figure 1.

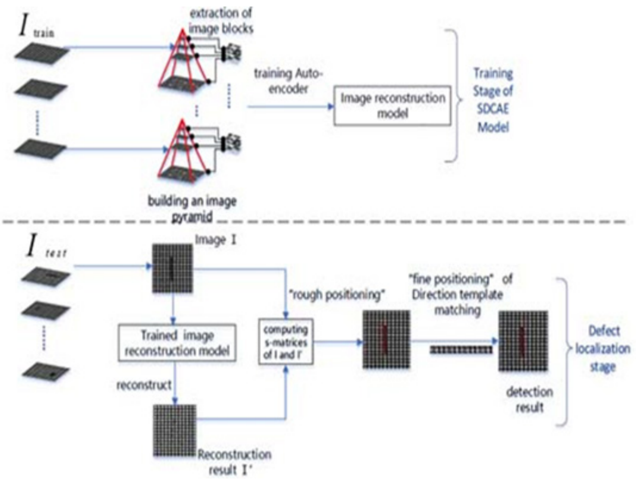


**Figure 1** Graphical abstract of the model building process.[10]

Hongge Yao and his co-workers[11] proposed incorporating an attention mechanism to build an improved deep learning defect detection network. According to the authors, problems in automatic inspection arise due to density unevenness, confusion, and the presence of small target defects, which are difficult to detect. The data augmentation strategy proposed by them enriched the number of samples of each defect type, and the enriched samples were extracted by the feature extraction network integrated with the attention mechanism. This improved the feature extraction ability of confusable defect types and small defects. According to Yongkai Zou and his co-workers,[12] detection of many small and weak target defects remains challenging in modern high speed production environments. They proposed a lightweight segmentation system that meets real-time industrial production requirements, where the defect sample image is repaired based on the image repair mechanism of a generative adversarial network model. After the repair, the difference between the defect sample and the repaired sample was obtained and subsequent processing, such as denoising and enhancement was done. Finally, the defect areas are segmented. The model was specifically designed for the segmentation of weak and small defects. It is claimed that the system offers good image restoration quality with low mean absolute error and high structural similarity index. Additionally, the model was found to be lightweight with good real-time performance.

## Other recently developed and emerging applications of AI in textile manufacturing

**AI systems for the advancement of fashion industry:** The research article by Sabrina Sareen[13] explores the potential of AI in redefining various aspects of fashion industry, from design and manufacturing to customer experience and sustainability. According to the author, by leveraging AI algorithms, machine learning, and data analytics, apparel companies can tap into a wealth of opportunities for innovation, efficiency, and creativity. The article highlights how AI is already empowering fashion designers, manufacturers, and retailers to create cutting-edge designs, optimize production processes, and deliver personalized experiences to customers. It argues that AI is playing a crucial role in driving sustainability and material innovation, helping industry to address environmental concerns and promote responsible practices. Overall, this review article underscores the transformative power of AI in redefining fashion and emphasizes the need for responsible and sustainable implementation of AI to unlock its full potential. According to Barbara Sylvestor[14] AI has all the potentialities to take over each step of the fashion value chain and its capabilities can be disruptive in nature. In her work, she covered augmented reality (AR), virtual reality (VR) and AI technologies with practical examples. The analysis described what has happened and is happening in the industry based on the many challenges imposed by Covid-19. In conclusion, observes that AR, VR and AI carry the potential to reinforce the digitization process of the industry and these are likely to play a critical role in the evolution of the fashion media and technology ecosystem. George Stylios[15] argues that to develop the textile and apparel industries further, the nature of interaction between machinery, fabric and operatives has to be taken into account. He also says that this poses some real problems in developing realistic solutions for future industrial development. He feels that it is important to give enough consideration to fabric-machine-human interactions in order to propose the next generation of manufacturing systems.

**Miscellaneous developments applicable for textile manufacturing industry:** Nuno Gonçalves and co-workers[16] talked about development of a new technological solution for the automatic characterization of yarn mass parameters (linear mass, diameter, and hairiness) based on image processing and computer vision techniques. A custom-made application developed in LabVIEW from National Instruments with the IMAQ Vision Toolkit was used to acquire, analyze and process the yarn images. Some experimental results using cotton and polyester yarns were collected and compared with a commercial solution for validation. According to the authors, this approach allows to gather and present a more comprehensive quality picture of the yarn. The book of F. Pereira and Associates[17] talks about a prototype yarn quality system called 'Yarn System Quality (YSQ)' to measure different yarn parameters. According to the authors, the YSQ prototype for quality measurement of the yarn under laboratory conditions, can perform yarn periodic error analysis, quantify statistical yarn parameters, and establish a reliable method of yarn characterization using new signal-processing approaches. The system, according to them can measure and give mean yarn diameter in millimeters, while also reflecting on hairiness. Further, they observe that the system is immune to variations of ambient temperature, humidity, and illumination level.

The work of Oliver J. Fisher and his associates[18] demonstrated that active learning is a promising approach for developing accurate and efficient machine learning models for grading cotton crops. Random forest classification models were developed using supervised learning, semi-supervised learning, and active learning to determine the grade of Egyptian cottons. It was observed that active learning models achieved higher predictive accuracy with 46% less input of labelled data. The work of C.D. O'Donoghue and J.G. Prendergas[19] talked about the use of computerized maintenance management systems (CMMSs). It described how such a system implemented in a medium sized Irish textile manufacturing company improved machine efficiency and reduced machine down time. Kuo and other collaborating authors[20] worked on a computer-based imaging system for the identification and classification of woven fabric weave patterns. This work analyzed the fabric images to obtain the warp and weft floats by the pixel gray-level cumulative values. It then cut out the image of the warp and weft floats to obtain the texture feature values, and used the Fuzzy C-Means (FCM) algorithm to identify the warp and weft floats. Thread float identification results defined the digital matrix of the fabric weave patterns. Finally, weave classification was done using a trained two-stage back-propagation neural network system. This study confirmed that fabric patterns can be identified and classified accurately using the method developed.

## Summary

Similar to the artificial intelligence used in other manufacturing industries, the AI used in the textile manufacturing industry utilizes a number of different technological tools to continuously monitor production processes, in process materials and end products with a view to extract information on all possible deviations that may be associated with negative implications. The technologies used in AI collaborate with each other to interpret the signals picked up in in real-time monitoring so that problems can be solved either before they occur or soon after they surface. The currently realized and expected future benefits of AI to the textile manufacturing industry are summarized below:

### Current benefits to textile manufacturers

**Quality control**: AI improves fabric inspection, thus reducing defects enhancing product quality.

**Predictive maintenance**: AI predicts machine maintenance needs, reducing downtime and costs.

**Production efficiency**: AI optimizes processes, boosting productivity and resource utilization.

**Demand forecasting**: AI enables accurate demand predictions and efficient inventory management.

**Sustainability**: AI minimizes energy wastage and consumption, promoting eco-friendly practices.

**Customization:** AI facilitates mass customization, meeting individual customer preferences.

**Supply chain optimization**: AI enhances supply chain management, reducing lead times and costs.

**Worker safety**: Collaborative robots with AI improve workplace safety.

**Data analytics**: AI-driven analytics provide insights for process optimization and decision-making.

**Innovation**: AI assists in textile design and innovation, accelerating product development.

### Expected future benefits

**Increased automation**: AI will further automate textile processes, reducing manual labor.

**Real-time monitoring**: AI will enable continuous process monitoring and control.

**Enhanced quality control**: AI-driven quality control will become even more accurate and efficient.

**Predictive maintenance**: AI's predictive maintenance systems will become more advanced.

**Sustainability focus**: AI will play a larger role in sustainable textile manufacturing.

**Market competitiveness**: AI adoption will enhance industry competitiveness.

## Acknowledgments

None.

## Funding

None.

## Conflicts of interest

Authors declare that there is no conflict of interest.

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