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# Artificial intelligence and its implementation in the textile industry

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**Abstract**

Human labor is central to the textile manufacturing sector's many distinguishing features, which also include high levels of fixed-cost investment, a wide variety of product designs and therefore, input materials, unpredictable production volumes, fierce rivalry, and very demanding quality requirements. Automating the hitherto labor-intensive operations with computers, designs, digital components, and artificial intelligence (AI) might make them more fit for these demands. Developing and researching smart computer systems is known as artificial intelligence (AI). Several applications of Intelligence in the textiles sector have been outlined in this idea. It also uses many AI technologies that are often used in the garment and textile industry, such as genetic algorithms, fuzzy logic, expert systems, and neural networks.

**Keywords:** Textile Manufacturing, Fixed Cost Investment, Smart Computer Systems, Artificial Intelligence, Fuzzy Logic.

## 1.Introduction

The textile industry plays a significant role in the economy. It is based on the spinning process, which involves transforming fibres in yarn and subsequently fabric [1]. Fabricated into garments, these undergo dyeing or printing before being transformed into a wide range of practical things, including apparel, home decor, upholstery, and industrial items [2]. The process of making yarn involves using many kinds of fibers [3]. Because of its continued significance, cotton undergoes extensive processing [4]. A vast variety of goods may be made because to the various different processes accessible throughout the spinning phase and fabric-forming phases, as well as the intricate finishing and coloring procedures [5]. In order to improve quality, boost output, decrease operational costs, and exercise in-house control over production, which results in shorter lead times, artificial intelligence is quickly becoming a key tool for processors [6].

The industrialized world's textile sector has begun to reap the benefits of artificial intelligence (AI) methods [7]. They need to put these strategies into action now [8]. The textile sector stands to gain a lot from artificial intelligence systems that can help combine aspects like JIT manufacturing, statistical process control, information, cost, quality, and output [9]. Quality, output, and operational cost reduction are three goals that the textile sector must always pursue. Only productivity mattered a decade ago, but that is no longer the case [10]. Now, just-in-time production, computer-integrated manufacturing, quality, cost, information, and statistical process control are all equally vital [11]. Artificial intelligence methods detect patterns and trends in massive volumes of quantitative data, allowing for their meaningful categorization [12]. The main way to identify trends used to be to use statistical approaches like regression and statistical grouping [13]. In many areas, AI approaches are now more effective than conventional statistical methods. In sectors like fabric inspection and garment production planning, where even little increases in performance result in substantial financial benefits, the textile industry and academic institutes have begun to see the promise of these methodologies [14]. A number of steps in the textile manufacturing process may benefit from artificial intelligence, including fibre grading, yarn property prediction, fabric defect identification, and predictive dye recipes [15]. Similarly, AI has the potential to be used throughout the whole textile manufacturing process, from preproduction to postproduction.

## 2. Revolution of Industry 4.0 in Textiles

Software and computers have become integral components of the production process, bringing in the era known as Industry 4.0 in the industrial sector. Industry 4.0 can only be understood by first tracing its roots to its predecessors. Companies in the production sector are now experiencing the most recent in a line of profound changes in the market. Innovations in production, systems, and technology have accompanied each evolutionary step. Manufacturing history's four eras are:

1. The Industrial Revolution 1.0: The earliest mechanized industrial processes employed water and steam.
2. In Industry 2.0, companies used electric equipment and production lines for more efficient mass manufacturing.
3. In Industry 3.0, computers, micro processing, programming, and telecommunications were introduced.
4. Industry 4.0: The industrial sector now uses the same IT as before, but with a plethora of enhancements. Full software and hardware integration into industrial processes is a primary goal, as is the development of digital networking. Industry 4.0 builds on Industry 3.0 by introducing data-and machine-learning-powered autonomous systems that create smart factories and reduce the need for heavy human intervention.

Industry 4.0 represents the present stage of manufacturing's progress, although the field will always undergo new developments. Staying abreast of developments and ensuring your organisation can adjust to new manufacturing methods are of utmost importance. The many advantages that accompany each new development will pass you by if you fight against change. Manufacturing goods that rely heavily on machinery and other forms of automation is known as "industry" in economics. The concept of "Industry 4.0" was born out of a high-tech strategic initiative that advocated for the automation of production processes. Industry 4.0 is a revolutionary approach to managing and organizing value chains. It involves integrating intricate physical gear and gadgets with networked sensors and software. This new level of management allows for improved prediction, control, and planning of corporate and social results. Efficiency and productivity gains via increased automation are key to Industry 4.0's stated goals. In an 'Industry 4.0' setting, industrial systems and components can do more than just monitor and diagnose problems; they can also become self-aware and self-predicting, giving managers a better picture of how things are running. A rapidly growing movement towards more automation and data interchange, "Industry 4.0" represents the technological landscape of the future in production. The combination of state-of-the-art technologies, digital systems, and automated procedures will optimise product quality production. Automation and adaptability; value-added services and enterprises; digitalization, optimisation, and customization of manufacturing; human-machine interaction (HMI); and automated data interchange and communication are the five defining characteristics of Industry 4.0. A more intelligent production process is at the heart of the trends that will shape industry growth in the coming fourth industrial revolution. The market for smart textiles has huge untapped potential. Forecasts indicate that the smart textiles industry will see growth on a worldwide scale. With the help of Industry 4.0 innovations, the hybrid and usually quite disjointed value chains may become more linked, which is necessary for the mass manufacturing of smart textile goods.

## 3. Textile industry AI application

Fiber grading, yarn property prediction, fabric fault identification, and dye recipe forecasting are just a few of the many textile manufacturing processes that may benefit from artificial intelligence. Artificial intelligence (AI) has a wide range of potential applications in the garment industry, spanning from pre- to post-production processes. The value of textiles is diminished when they have flaws in the fabric. Fabric inspection in the textile industry uses Artificial Neural Networks (ANNs) and other forms of Artificial Intelligence to combat this issue. The photos that will be examined are captured by the image acquisition equipment and stored in the appropriate standard format, such as JPEG or PNG. By combining previously extracted features with new, smaller ones, the feature selection approach may lower the dimensionality of the feature set, which is derived from the obtained picture. The ANN is trained and tested using the Multi-Layer Back Propagation technique.

### 3.1. AI on fibre characteristics

High-performance AI system for fibre property and structural investigation. Tools that can easily and quickly measure the fineness of individual fibres; catalogue the various fibres used in a mix and examine their relative proportions in the final product; examine the acquired item and determine the fibre; examine yarn structure for flaws; count Dtex or den circular segment yarns and filaments; Verify and quantify the form and quality of single threads made of synthetic multifilament or Lycra; examine the density of non-woven materials; examine yarn and fibre segments; determine the perimeters and surfaces of sections; examination of mechanical components (such as needle points and spinnerets), processing, storage, and printing of the resulting measurements, as well as distribution graphs, CV%, and minimum, medium, and maximum values.

### 3.2. Yarn spinning AI

"Yarn" is shorthand for both "thread" and the more generic "yarn" in the textile work. A "yarn" is a thin, narrow item with certain durability and linear density made of several short fibers or threads twisted in a nearly parallel fashion down an axis; a "thread" is a string of two or more individual yarns. Various factors influence the quality of yarn. The yarn's evenness is greatly affected by how even the slivers are that are used to make them. Modern cards and draw frames often include auto-levelers attached on them, which manage the sliver uniformity. The Levelling Action Point (LAP) is the distance as measured from the point of draft to the scanning rollers pair. An essential parameter that determines the efficiency of auto-levelers is the quantity of the LAP. The problematic material being monitored by the auto-leveling system should be precisely corrected with an appropriate modification of this point. Numerous material and manufacturing characteristics impact this metric. Due to the complexity involved, it is necessary to take into account all or almost all of the essential influencing aspects in order to determine an appropriate value of LAP. The sliver evenness of the yarn is a crucial quality indicator. Thus, it is crucial to manage the sliver evenness. Achieving this job requires precise adjustment of the auto-levelers installed on contemporary carding and drawing frames. Among the many critical auto-leveling parameters, the Levelling Action Point (LAP) has a significant impact on the uniformity of the shredded paper. Consequently, it is of paramount significance that it be adjusted. Consequently, in order to forecast the optimal value of the Levelling Action Point across various manufacturing and material circumstances, Artificial Neural Networks are used. Frame drawn with an auto-leveler Online sliver weight monitoring is accomplished using a variety of instruments, including tongues and Grove rollers, gas transducers, and others. By detecting changes at the feeding point and synchronizing in rapid management of weight per yard of material, the auto-leveller at the high-speed drawing frame greatly assisted in generating regularities in sliver. The control efficiency changes depending on the auto-leveler type and technology. Based on the notion of an open control loop, the auto-leveller at draw frame operates (Figure 1). A channel and tong roller are used to measure the incoming sliver's thickness according to this approach. While the measuring sliver approaches the sketching point within the main drawing region, the values are saved. The very dynamic servo derivative motor is now adjusting the quantity of draft size. With this, even the most minute discrepancies may be balanced.

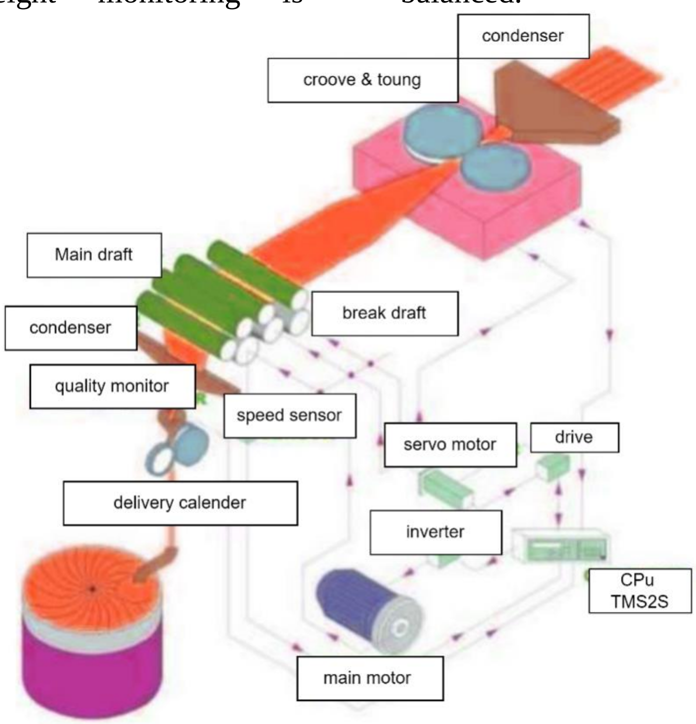


Figure 1: Auto-Leveller at Draw Frame Operates

Improving evenness throughout the short, medium, and long durations is one of the primary goals of the draw frame. Card slivers fed into the draw frame are inherently unequal to an unacceptable degree, and comber slivers include the dreaded piecing, which must be concealed. Short wave sliver uniformity is not the only condition for draw frame performance, as frequently thought. Narrow drafting settings prevent short-length unevenness. However, other yarn quality indicators typically decline. Drafting is essential to yarn quality and formation. Inequalities introduced by each drafting step, from carding to spinning, diminish the quality of the finished cloth.

### 3.3. Yarn quality and fault identification using AI

Yarns made from closely spaced and uniformly sized fibres are the only ones that maintain their quality over time. These fibres can only be obtained by combining fibres from several batches and manufacturing sites. To open, remove, and mix all types of fibres, use a cotton opener, cotton mixer, or cotton cleaning machine. Using centrifugal force and gravity, this procedure removes the majority of pollutants and dust. A more consistent and robust yarn is spun on the automated machine as opposed to the intermittent approach. There is less need for human labor, the factory is cleaner, and the automated unit has a greater continuous production pace. The care used during raw material selection, cotton opening, impurity removal, and cotton blending determine the ultimate yarn quality, regardless of the processing technology utilized (Figure 2).


Figure 2: Ultimate Yarn Quality

The entire spinning process of 40Ne, 50Ne, and 60Ne ring spun yarn followed standard production parameters. The yarn was a blend of cotton and polyester, made from high-quality cotton and polyester fibres. The draw frame stage of spinning continued the sliver blending process. Using the Uster Machine, compare three different types of rings spun yarn—40Ne, 50Ne, and 60Ne—made of a blend of cotton and polyester. They looked at the three yarns' variations in terms of major yarn quality parameters, such as hairiness of spun yarn, coefficients of variation of mass (CVm%), and irregularity or unevenness (U%). The machine's output included both temperature and relative humidity (RH%).

### 3.4 AI-Powered Weaving Method

Woven machine makers have made headway towards Industry 4.0-ready digital machines, but more is needed. Machines that can automatically repair warp breaks, prevent start marks without operator intervention, change styles, form flexible electronic circuits for smart e-textiles, weave dobby and jacquard in multiphase, and weave pattern with variable width and warp density to surpass the speed limit of single-phase machines are all things that weavers are searching.

The development of robotics leading to full automation, the use of the internet of things (IoT) to enable machine makers to obtain and analyse huge data, and the application of artificial intelligence (AI) and analysis to diagnose and forecast disruptive concerns are all necessary steps on the path to Industry 4.0. Since all data is connected from fibre to market, it is important to note that weaving should be connected with upstream yarn production and downstream processes such as fabric finishing, product conversion, and marketing. Threats to manufacturers' data and IP are a big worry since they impede progress towards Industry 4.0. There should be international regulations to safeguard producers' intellectual property and data from cybercriminals since the textile sector is both vast and varied.

The advancement of technology and science has always relied heavily on electronics. The use of computers, microprocessors, and other forms of information technology in the manufacturing of woven textiles has ushered in a new age for the textile industry in the last decade. When it comes to air jet weave and pattern design, the role of microelectronics has been more apparent. The producers of shuttles less looms have fully used the enormous automation possibilities provided by electronics and microprocessors.

AJI's multifunction microprocessor and appropriate software with PC-link allow for the monitoring and control of the aforementioned machine functions, with the latter two even offering optimisation options. The weaving machine and the production management system are able to communicate with each other the microprocessor's bidirectional communication capabilities. Managing the weaving process as a whole has been improved because to the widespread use of electronics, which has reduced the need for a number of human interventions.

### 3.5 AI for Fabric Integrity and Defect Detection

The term "fabric texture" describes how the material feels. There are several adjectives to describe it, including rough, shiny, velvety, smooth, silky, soft, and so on. Fabrics with various weaves have varied textures. Any fabric, including linen, cotton, wool, leather, and silk, may have a texture added to it. In the textile business, several sorts of Fabric goods are made using textile fabric materials. There are two main categories of textiles: natural and synthetic. A relatively recent development, synthetic materials have progressed with the ever-expanding textile industry. Machine mistakes, holes, colour leakage, yarn issues, scratches, and poor finishing are all potential causes of fabric flaws. Automated manufacturing is only one of several fields that may benefit from computer vision and processing of digital images. Since the quality and cost of any textiles product are reliant on the efficacy and efficiency of the automated flaw identification, identifying fabric defects is seen as a difficult problem in the textile industry. The textile industry used to rely on human labor to find fabric flaws during manufacture. The primary problems in manually detecting fabric defects are human tiredness, lack of focus, and the amount of time it takes. These shortcomings and restrictions may be remedied by applications that rely on computer vision and processing of digital images. To overcome these restrictions, several research publications over the last twenty years have suggested computer vision-based applications.

The goal in writing this review paper is to provide a comprehensive analysis of the several computer vision-based methods now used to identify fabric flaws in the textile industry. Operations in the frequency domain, texture-based detection of defects, sparse feature-based operations, image morphology operations, color-based techniques, image segmentation-based approaches, and new advancements in deep learning are all thoroughly covered in the proposed research. It also presents and discusses the performance assessment criteria for automated fabric flaw identification. There includes an extensive discussion of the limits and shortcomings of the previously published studies, as well as potential avenues for future study. An extensive overview of computer vision and image processing applications for detecting various fabric faults is presented in this research paper. There are many moving parts to the automated visual inspection process, and they all need to work together in intricate ways. Given the potential savings in staff costs and other advantages, it is economically viable to invest in an automated fabric inspection system. Figure 3 depicts the general layout of an automated textile web testing system. An inspection machine's electrical and mechanical connections, a lighting system, a computer console housing processor, a bank of cameras set in parallel along the web to be examined, and so on make up the system. An algorithm at the front end of the inspection system uses tremendous parallelism to limit data flow to only the area of interest during picture collection. In this section, they will quickly go over the main features of this system:

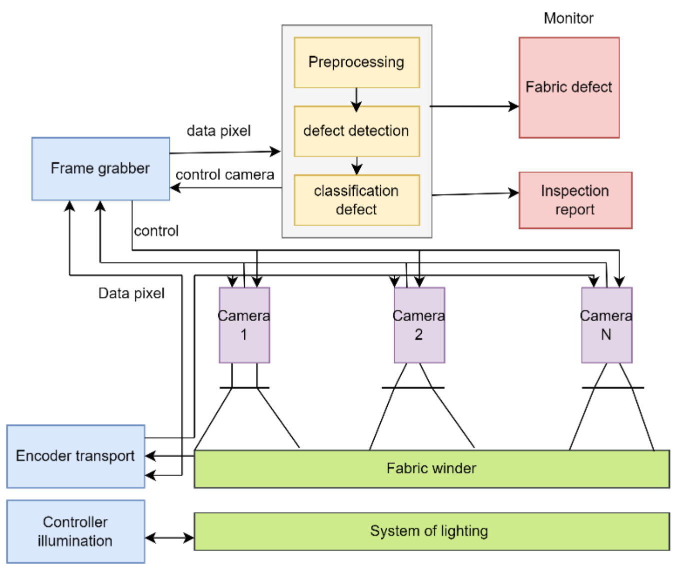


Figure 3: Layout of an Automated Textile Web Testing System

**Power supply:** Simplifying an inspection challenge relies heavily on the quality of the gathered photographs. The quality of the picture is greatly impacted by the kind and intensity of the lighting. A thorough analysis of several lighting schemes for automatic visual assessment has been carried out by Bachelor. Visual inspection lighting often falls into one of four categories: front, rear, fiber-optic, or structured. For the purpose of inspecting fabrics, lighting removes a shadow and glare effects. Fibre optic lighting is another option for fabric examination; it eliminates shadows and glare while evenly lighting items. However, for textile webs that are 6-8 feet wide, fiber-optic lighting is not cost-effective due to its high implementation cost. In some cases, the lighting controller will use a fuzzy logic control strategy that makes use of a feedback photo-resistor in order to keep the light intensity constant.

**Camera:** Machine vision makes use of a wide range of cameras that vary greatly in terms of sensor type, resolution, readout speed, accuracy, and other variables. The photosensor's pixels and object Field of View (FOV) restrict a camera's resolution. FOV depends on background and flaws.

Fabric inspection cameras typically use either line scanning or area scanning as their scanning method of choice (Figure 4). Line scanning methods make use of a network of linear array photosensors; the vertical resolution is proportional to the product of the object's (web's) moving velocity and the camera's scan rate (line rate). Line scan cameras need additional circuitry to combine several line scans into a whole picture, which is a drawback as they cannot provide a full image all at once. Area scan cameras do not need transport encoders and provide bidirectional inspection resolutions that are not affected by the speed of objects on the web. Due of the exorbitant price of line scan cameras right now, web inspection solutions that don't break the bank often include arrays of area scan cameras. Cameras using CCD or CMOS photosensors are considered state-of-the-art for both area scan and line scan applications. Compared to CCD photosensors, CMOS ones have a lower price point, use less power, and have a better degree of on-chip functionality. CMOS sensors are less sensitive than CCD sensors owing to increased uniformity and lower fill factor. Researchers have used CMOS area scan and TDI line scan cameras to check fabric flaws.

Figure 4: Fabric inspection

**Encoder for transport:** Transport encoders give camera master timing pulses. Transport encoder wheel touches fabric winder. Line scan cameras' pixel resolution depends on transport encoder resolution. A perfect picture may be captured by the line scan sensors at any speed since they slavishly follow the pace of the conveyance. Any unwanted change in the speed of the shaft rollers may be controlled using the velocity data collected by the transport encoder.

**Grabbers for frames:** The frame grabber takes the pixel data from each camera and turns it into a digital picture. The many camera inputs are a challenge for all web inspections systems, including the fabric inspection system. For certain setups, this is accomplished by connecting the camera and frame grabber via a video multiplexer device. Using a separate frame grabber device for each camera is a costly solution for handling several cameras. This allows concurrent image pixel data processing on multiprocessor systems. The host computer receives frame grabber output in ISA, VESA, PCI, or industrial bus formats.

**Computer serving as the host:** There are primarily three types of host computer functions.

i. Detection and categorization of defects: The host computer receives the picture data received from the frame grabbers. This picture data has to be processed by the host computer in order to identify defects utilising complex algorithms. Depending on their magnitude or place of origin, the identified flaws in the recorded picture data are grouped into several categories.

ii. Lighting and control of the camera: The host processor is in charge of loading the camera's control setup settings externally. These settings are often initialized when the device turns on or controlled manually via the GUI. The host computer is also in charge of the illumination controller's settings, which regulate the web's lighting intensity.

iii. The host computer is responsible for a number of input/output system control tasks as well. Some examples of the functions that fall under this category include the Graphical User Interface (GUI), the Interrupt Service Routine (ISR), and the ability to print or save a compressed defect map.

In order to examine the textile web, which is moving at a pace of 15-20 meters per minute, a single multipurpose host computer cannot analyse the large number of visual data collected. Consequently, the majority of systems rely on a single processor to identify any and all picture flaws captured by a particular camera. Implementing complex defect detection algorithms in real time often necessitates the use of extra DSP processors for each of these processors. There are a number of desirable categories into which all found flaws are placed. Vagueness, incompleteness, and ambiguity are the three forms of uncertainty that fabric flaws exhibit. Major challenges in classifying fabric flaws include the enormous amount of defect classes, the similarity between classes, and the variation within classes.

### 3.6. AI colour matching

Customers care a lot about the colour of a product (Figure 5). People often associate a product's visual appeal with its perceived quality. This is crucial in the textile business as it is in many others. A product's colour may be “acceptable” or “unsatisfactory” or “too light”, “too orange” or “too red”. The disparity between the sample and the ideal product standard might be seen visually or quantitatively to inform such evaluations. Tolerances may be set after this disparity is measured.

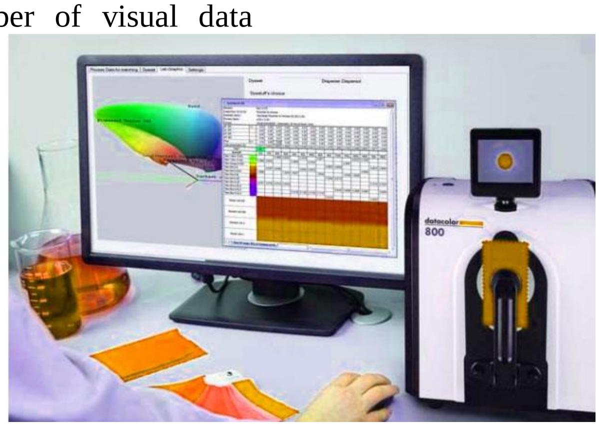

Figure 5: AI colour of a product

The approval process would get bogged down due to the need for meticulous human intervention, as the old method of colour tolerancing, which relied on numerical descriptions of colour through "instrumental tolerancing systems," often produced many false positives when contrasted with visual inspections. One solution to this issue might be the creation of an AI-powered platform with a Pass/Fail (P/F) capability, akin to Defect Identification, which could enhance the precision and effectiveness of instrumental tolerance. As it generates the tolerances, this platform may factor in past data of human operators' visual inspection outcomes. Testing the system with fresh batches allows for the automated setting of AI tolerances, effectively teaching it to identify successful and unsuccessful samples.

### 3.7. AI in garment production

Production of garments encompasses a wide range of activities, such as cutting, sewing, processing, repairing, assembling, finishing, and any other form of preparation for wearing. This includes a wide variety of items, such as hats, gloves, handbags, hosiery, ties, and clothing. An article of clothes is called a garment. Both art and technology come together in the garment industry. Design creation, CAD, and automation have all seen significant developments in the garment manufacturing industry. Unfortunately, cutting and sewing together at least a pair of cloth remains the central subject in modern garment production, as it was in earlier iterations. Sewing machines are used to make most garments. Some machines still utilize the main format. Product creation, planning for production, and material selection are major garment manufacturing subjects today. PCD, spreading, cutting, and stitching; joining methods; and seamless garment manufacturing help fulfil customer requirements. The needs at the point of sale are being met by advancements in garment finishing, control of quality, and care labels. In order to improve quality, boost output, decrease operational costs, and exercise in-house control over production, which results in shorter lead times, artificial intelligence is quickly becoming a key tool for processors. The industrialized world's textile sector has begun to reap the benefits of artificial intelligence (AI) methods. They need to put these strategies into action now. The textile sector stands to gain a lot from artificial intelligence systems that can help combine aspects like JIT manufacturing, statistical process control, information, cost, quality, and output. Quality, output, and operational cost reduction are three goals that the textile sector must always pursue. While production was once the sole concern, that is no longer the case. Now, just-in-time production, computer-integrated manufacturing, quality, cost, information, and statistical process control are all equally vital.

AI finds trends and patterns to classify massive volumes of quantitative data. Until recently, statistical grouping and regression were the main ways to identify patterns. Traditional statistical methods are often outperformed by AI. These strategies have begun to appeal to the textile research and industry institutes, particularly in garment production sectors like fabric inspection and planning, where even little performance improvements may provide huge financial advantages.

Fashion technology benefits from additive manufacturing because it makes it easier to design and construct clothes, embellishments, and meshes. This technique gives designers great geometrical flexibility. 3D printing and scanning are enabling innovations that will transform fashion and textile manufacturing and commerce (Figure 6). Individualized footwear and apparel will soon be available from 3D printers, functional fabrics will have new avenues to explore, and the advent of 4D printing will usher in an era of unparalleled 3D capability with exciting new uses. In addition to 3D technology, 3D printing is altering the garment industry's value chain from design and development to delivery. Before mass manufacturing, the designer built one or more expensive prototype and sample collections for a two-dimensional product. A 3D simulation may replace these cost drivers. The programme can now test cuts, colors, and patterns on virtual avatars. Avatar folds and movement are lifelike.

Figure 6: 3D printing and scanning

The collection is created quicker, more accurately, and cheaper using 3D simulation. Shortening prototype manufacturing eliminates idle time and waiting, allowing variations at any moment. This allows the organisation to adapt quickly to new trends. The 3D scan data underpins all 3D applications. After data is recorded digitally and three-dimensionally, 3D printing is a natural next step. Individual apparel purchases might follow in the near future:

- Self-body 3D scan
- Avatar creation
- Online tests
- Online clothes and type guidance recommendation
- 3D model online purchasing
- Model 3D printing

## 4.Conclusion

Developed nations are not the only ones where artificial intelligence is not yet widely used in textile technology. The textile industry in poor nations continues to have issues with production and quality control, but there is enormous potential for artificial intelligence technology to help alleviate these concerns. The need of efficiently and effectively tackling complicated issues is driving the use of artificial intelligence (AI) technology in the textile industry. The textile industry relies on manual work for manufacturing and quality control. In AI innovation, technologies are developed to increase operational efficiency and effectiveness. Machine vision, prediction, inspection, grading, detection, identification, and other fundamental operations form the basis of artificial intelligence technology. Humans are responsible for carrying out all these tasks, which are often seen as boring and sometimes have unclear results. Through the use of technology, AI may improve the efficiency and precision of these fundamental behaviour, hence eliminating issues and labor-intensive tasks.

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