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Review

Artificial-Neural-Network-Based Predicted Model for Seam Strength of Five-Pocket Denim Jeans: A Review

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Abstract: This study explores previous research efforts concerning prediction models related to the textile and polymer industry, especially garment seam strength, emphasizing critical parameters such as stitch density, fabric GSM, thread type, thread count, stitch classes, and seam types. These parameters play a pivotal role in determining the durability and overall quality of denim jeans based on cellulosic polymer. A significant focus is dedicated to the mathematical computational models employed for predicting seam strength in five-pocket denim jeans. Herein, the discussion poses the application of AI for manufacturing industries, especially for textile and clothing sectors, and highlights the importance of using a machine learning prediction model for sewing thread consumption, seam strength analysis, and seam performance analysis. Therefore, the authors suggest the significant importance of the machine learning prediction model, as future trends anticipate advancements in AI-driven methodologies, potentially leading to high-profile predictions and superior manufacturing processes. The authors also describe the limitation of AI and address a comprehensive model of risk outlines of AI in the manufacturing-based industries, especially the garments industry. Put simply, this review serves as a bridge between the realms of AI, mathematics, and textile engineering, providing a clear understanding of how artificial-neural-network-based models will be shaping the future of seam strength prediction in the denim manufacturing landscape. This type of evolution, based on ANN, will support and enhance the accuracy and efficiency of seam strength predictions by allowing models to discern intricate patterns and relationships within vast and diverse datasets.

Keywords: artificial neural network (ANN); predicted model; five-pocket denim jeans; AI; industrial revolution 5.0

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1. Introduction

Artificial intelligence is increasingly being integrated into the fields of management science and operational research. Intelligence, often defined as the capacity to acquire and apply knowledge to address intricate challenges, is at the core of AI's development. In the foreseeable future, we can anticipate intelligent machines taking over numerous human functions. Artificial intelligence comprises the study and advancement of intelligent machines and software designed to engage in reasoning, learning, knowledge acquisition, communication, manipulation of data, and perception of their environment. In essence, it revolves around the study of computational methods that enable machines to perceive, think, and act [1]. In other words, artificial intelligence can be described as the process of programming machines to possess a degree of human-like intelligence, enabling them to think and act in a manner akin to humans [2]. Artificial intelligence involves the collection, analysis, and decision-making processes, each reliant on artificial entities, including machines, computer programs, systems, algorithms, and more. Traditionally, AI has been regarded as a subfield within computer science. Nevertheless, its expanding application across various industries and research domains has led to its recognition as a distinct discipline. One notably significant area wherein AI plays a pivotal role is in the pursuit of environmentally friendly and sustainable energy utilization, a matter of paramount importance on a global scale [3].

Intelligence represents the computational part essential for accomplishing objectives [4]. In 1956, John McCarthy coined this term at the inaugural conference dedicated to this field. An early influential paper in the history of artificial intelligence was Alan Turing's work titled 'Computing Machinery and Intelligence' [5]. Turing's argument centered on the idea that if a machine could successfully pass a particular test, it could be considered intelligent. This test, called the Turing test, includes a human "judge" interacting with two entities through a computer terminal: one human and one computer. If the judge consistently struggles to differentiate between the feedback of computer and human, the computer is considered to have passed the test. Figure 1 that depicts the contemporary evolution of artificial intelligence.

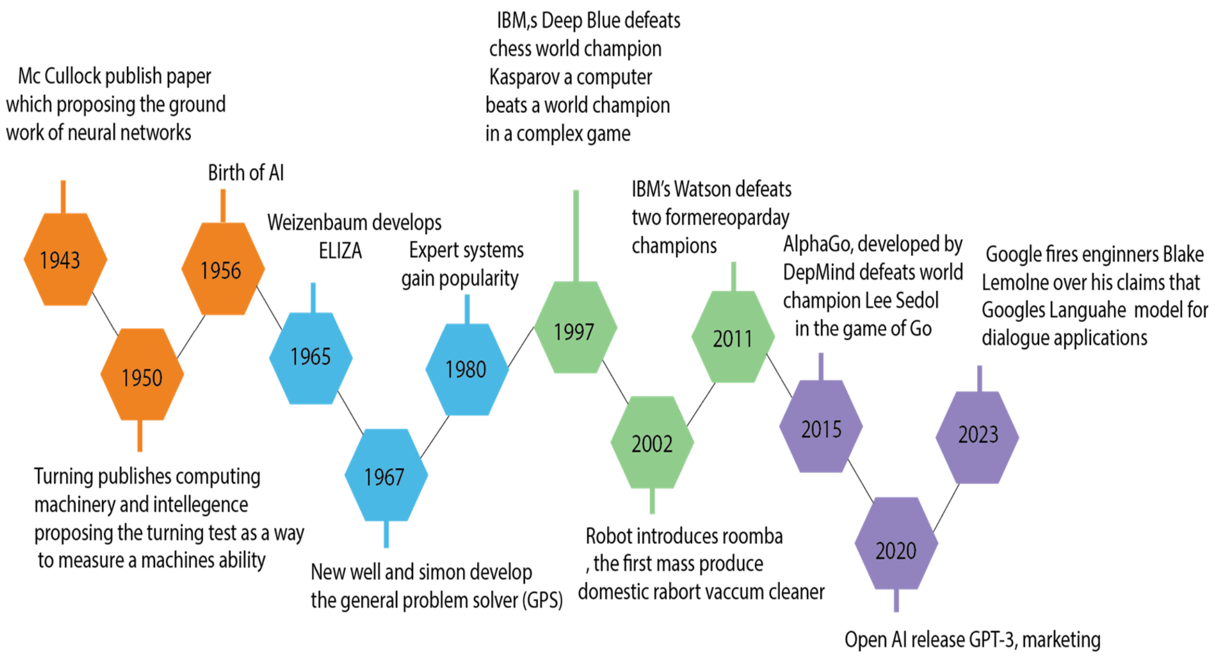

Figure 1. History of artificial intelligence.

Figure 2 depicts the various techniques and their applications in artificial intelligence. It includes artificial neural networks, genetic algorithms, fuzzy logic, and machine learning [1].

When a set of processing units is intricately interconnected, it forms a complex structure that exhibits certain characteristics with biological neural networks. This structure is known as an **artificial neural network**. ANNs are extensive, parallel-distributed processors composed of individual processing units, and they possess a capacity for the storage of experiential knowledge and for facilitating its accessibility for practical use. The process employed for learning within an ANN is referred to as a learning algorithm, with its purpose being the systematic adjustment of the network's synaptic weights in an organized manner to achieve a specific design objective. In practical application, ANNs do not function effectively in isolation; instead, they need to be seamlessly integrated into a cohesive system engineering approach [6].

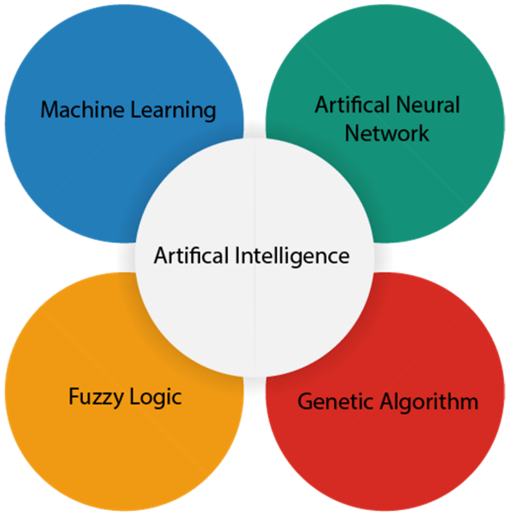

Figure 2. Artificial intelligence techniques and their applications.

Machine learning serves to instruct machines on how to efficiently manage data. When data analysis fails to yield interpretable insights, machine learning steps in. The essence of machine learning lies in its ability to glean insights from data autonomously. Mathematicians and programmers explore diverse methodologies to enable machines to self-learn, especially when confronted with vast datasets. Machine learning relies on a spectrum of algorithms to tackle data-centric challenges. Data scientists emphasize that there is no one-size-fits-all algorithm; the choice depends on factors such as the nature of the problem, the variables involved, and the most suitable model. Some commonly utilized algorithms in machine learning include Supervised Learning, Support Vector Machine, Unsupervised Learning, and Semi-Supervised Learning [7].

Fuzzy logic represents an expansion of Boolean logic, designed to accommodate the notion of partial truth, where truth values can exist between 'entirely true' and 'completely false'. In classical or Boolean logic, there are only two binary values, often expressed as true or false, yes or no, on or off, black or white, start or stop. However, in the real world, many situations are not as straightforward and can fall within a spectrum of possibilities. Fuzzy logic offers an uninterrupted form of reasoning that enables us to describe these shades of gray. For instance, if you were to narrate your day using Boolean logic, it would be categorized as either good or bad. In contrast, fuzzy logic allows for a more nuanced assessment, recognizing the day as being very bad, bad, poor, average, better than average, good, or very good, reflecting the complexity of real-world situations [8].

Genetic algorithm (GA) is a method for optimizing search tools for difficult problems based on genetic selection principles. GA is a population-oriented search and optimization approach that resembles the natural evolution process. The process involves generating a random population initially, and then applying genetic operations such as selection, crossover, and mutation to yield solutions for consecutive generations. GA is applicable in multiple areas, including optimization, machine learning, decision-making, robotics, and research and development. Some of the real-world applications of GA include network routing protocol, image processing, data mining, and scheduling. GA works best in cases of large search space areas possessing multiple parameters [9].

Particle swarm optimization (PSO) draws inspiration from collective behavior observed in animals, such as bird flocking and fish schooling. This inspiration stems from understanding how these animals adjust their paths by interacting with their neighbors and leveraging their personal experiences. In PSO, particles represent potential solutions to the optimization problem and navigate the search space propelled by their own velocities. The modification of a particle's velocity is influenced by both its own past positions and those of its adjacent particles. This collective movement steers the swarm towards optimal solutions, guided by the best solutions found locally and globally. PSO's appeal lies in its simplicity, requiring only a minimal set of parameters for its operation. Its robustness enables it to address a wide array of optimization problems effectively [10].

Ant colony optimization (ACO) is inspired by ants' remarkable ability to discover the shortest route between their nest and a food source. At the heart of ACO lies the concept of pheromone trails. As ants travel, they leave behind pheromones, guiding subsequent ants to follow the same path. The concentration of these pheromones influences the likelihood that ants will choose the shortest path. This path emerges from a combination of pheromone strength and heuristic cues. Additionally, ACO incorporates a mechanism for pheromone evaporation to prevent convergence on suboptimal solutions, ensuring that higher pheromone concentrations highlight and reinforce the most efficient routes [11].

Simulated annealing (SA) is inspired by the annealing process in metallurgy, wherein controlled cooling is used to reduce defects in a material. This process guides the material towards its lowest energy state, analogous to finding optimal solutions in optimization problems. The key control parameter in SA is temperature, which influences the likelihood of accepting suboptimal solutions. At higher temperatures, the algorithm is more likely to accept less optimal solutions, allowing it to explore a broader solution space. Conversely, lower temperatures encourage a more focused exploration around the current solution. The probability of accepting a solution is determined by its quality and the current temperature. The effectiveness of the SA algorithm significantly depends on the cooling schedule, which outlines how temperature decreases over time. This schedule is crucial, as it balances exploration of the solution space with the exploitation of promising areas. With a well-designed cooling schedule, SA can efficiently tackle complex optimization problems and, under suitable conditions, can converge to the global optimum [12].

1.1. Artificial Intelligence in Different Fields of Life

Artificial intelligence has found applications in various fields of life, transforming industries and impacting our daily lives in numerous ways, as mentioned in Figure 3. Figure 3 shows some examples of how AI is being used in different fields.

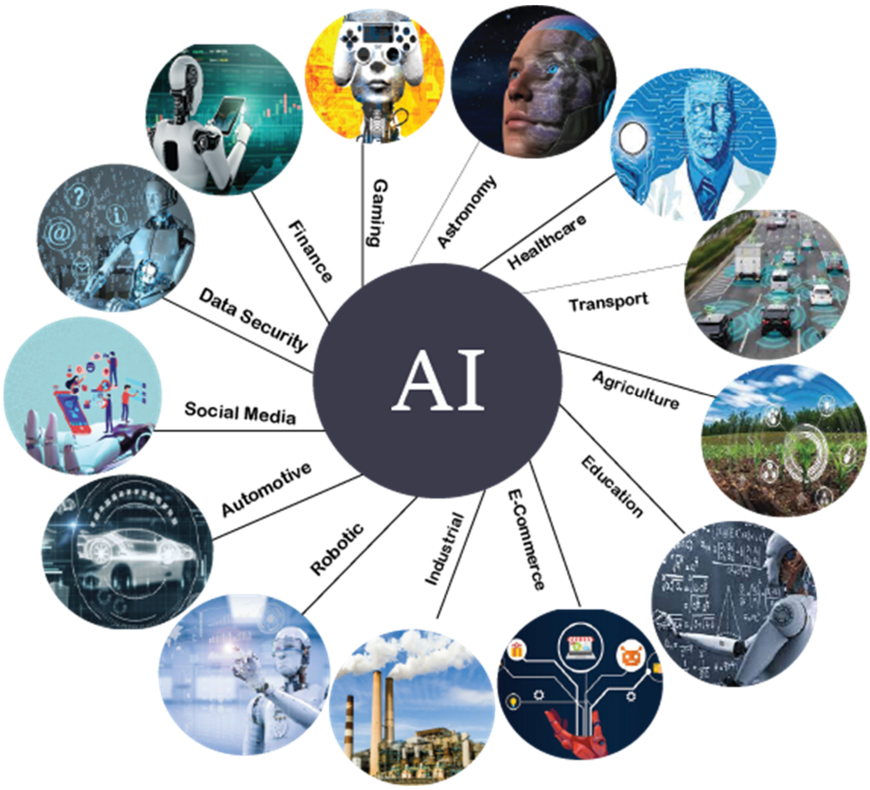

Figure 3. AI in different fields of life.

1.1.1. In the Medical Field

Fuzzy logic is a versatile data management approach that accommodates vagueness and is notably well suited for medical applications, as shown in Figure 4. Its primary application area lies in medical diagnostics, with some relevance in describing biological systems [13]. Various medical applications have explored the utility of fuzzy logic techniques. For instance, detecting lung cancer, acute leukemia, pancreatic cancer, and breast cancer, as well as predicting patient survival in such cases [14]. Additionally, fuzzy logic methods can be applied to characterize medical images, such as MRI images of brain tumors and ultrasound images of the breast [15].

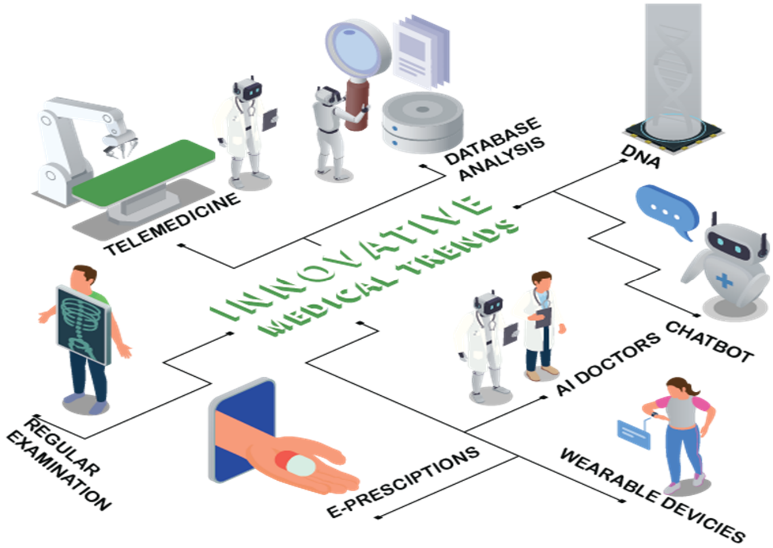

Figure 4. AI in the medical field.

1.1.2. In the Energy Sector

AI has numerous utilizations in the energy sector, as shown in Figure 5. It can be employed to enhance the efficiency of energy storage systems, such as batteries and pumped hydro storage [16]. It can be used to optimize the energy consumption of buildings, factories, and other facilities, reducing energy waste and lowering costs [17]; to enhance the efficiency of renewable energy systems, such as wind turbines and solar panels, by predicting weather patterns and adjusting output accordingly [18]; to predict energy demand and supply, helping utilities to plan and manage their operations more effectively. AI possesses the capability of revolutionizing the energy sector by improving efficiency, reducing costs, and increasing the use of renewable energy sources [19].

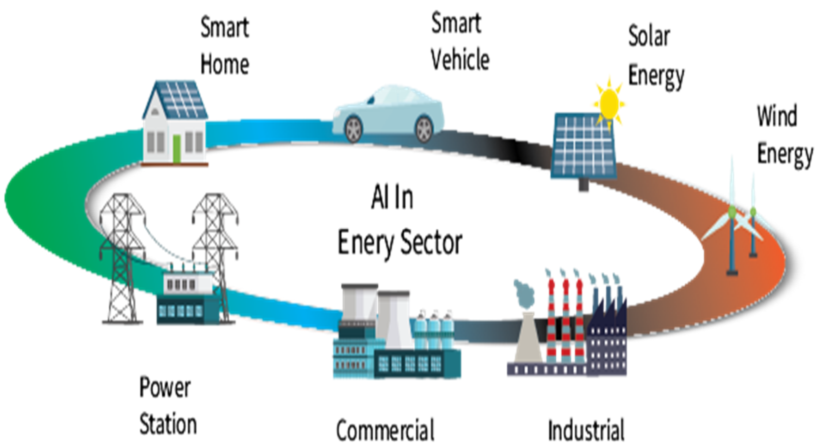

Figure 5. AI in the energy sector.

1.1.3. AI in the Industrial Sector

In industrial sectors such as power generation, mining, and machinery, AI is revolutionizing operations with its predictive capabilities and efficiency enhancements. In the power industry, AI-driven predictive maintenance optimizes equipment performance, reduces downtime, and enhances grid reliability through accurate demand forecasting and smart grid management. Mining operations benefit from AI-enabled autonomous vehicles, predictive maintenance to prevent breakdowns, and advanced resource exploration techniques, improving safety and efficiency. In machinery, AI ensures optimal production processes with predictive maintenance, quality control through machine vision, and streamlined supply chain management, leading to higher productivity and cost savings [20].

1.1.4. In Power System Stabilizers

The application of AI in power system stabilizers has been an area of active research in recent years. One of the most promising AI techniques for PSS is the use of artificial neural networks. ANN is a category of machine learning algorithm capable of acquiring knowledge from data and generating predictions derived from that learning [21].

1.1.5. AI in Robotics

Artificial intelligence finds extensive applications in the realm of robotics, as illustrated in Figure 6. In the context of robotics, AI entails the utilization of artificial intelligence techniques for the programming and control of robots. Robotics, a subset of artificial intelligence, involves the use of mechanical devices, typically computer-controlled, to execute tasks demanding precision, or tasks that are tedious or hazardous for humans. Among the diverse applications of AI, robotics stands out as an area that captivates public interest and holds significant potential for benefiting humanity [22].

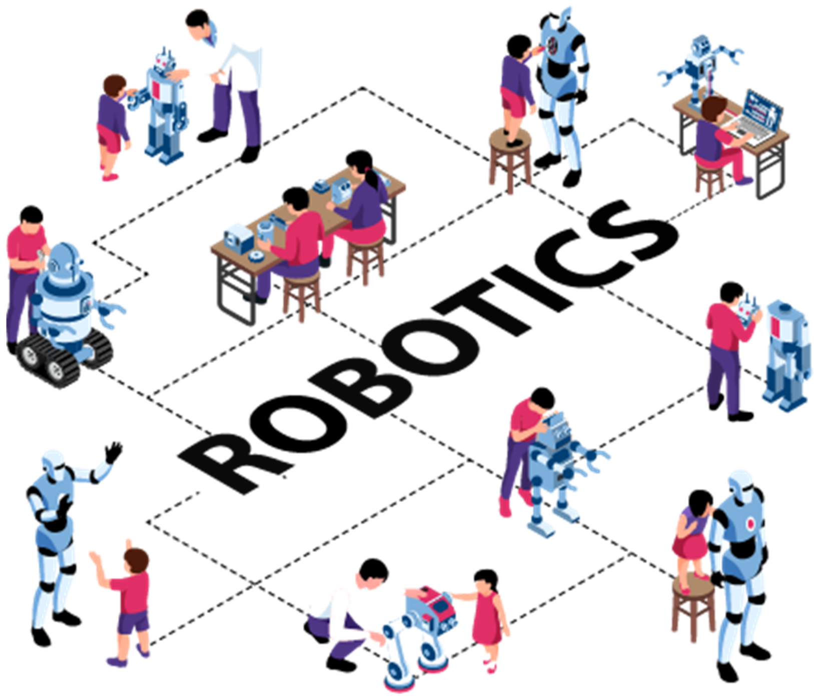

Figure 6. AI in robotics.

1.1.6. In the Education Field

AI has a meaningful effect on the field of education, as shown in Figure 7. AI-powered systems can help with tasks such as grading, personalized learning, and even tutoring. In addition, AI can be used to provide expertise and answer student questions. AI might transform the responsibilities of teachers and they will play an important role as facilitators.

AI may also change where and how students learn, with the potential for programs to be accessed from anywhere in the world at any time [2].

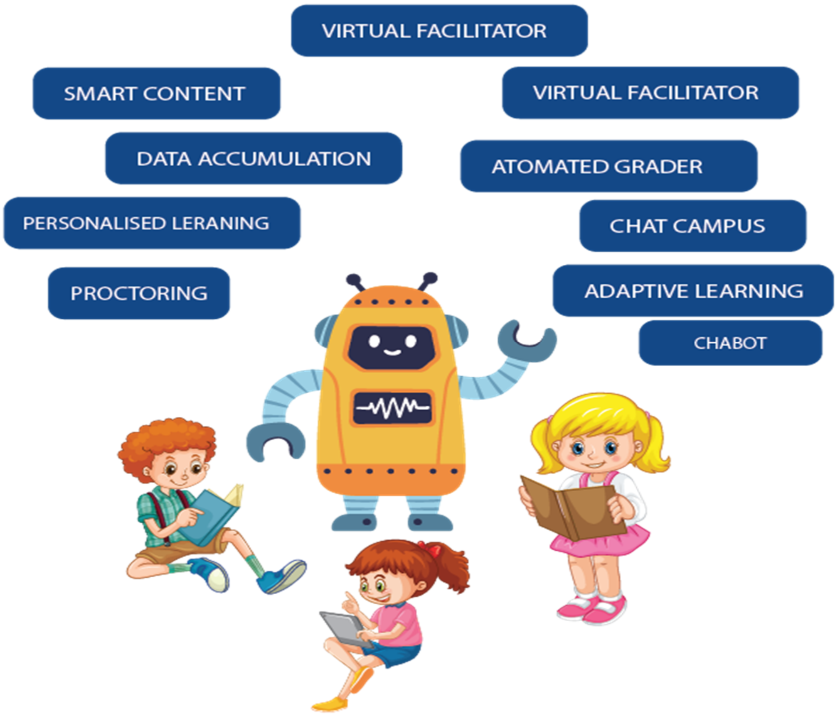

Figure 7. AI in the education field.

1.1.7. In the Fashion Industry

Artificial-intelligence-based tools have been utilized to address many dimensions of the fashion industry, including apparel design, production, retail, and supply chain management [23]. These AI-based tools encompass predictive forecasting models for anticipating fashion trends and consumer demands. The incorporation of AI into the fashion industry results in reduced production costs, minimized wastage, increased customer satisfaction, and a decreased environmental footprint [24]. The different tools of AI in the fashion industry are shown in Figure 8.

Figure 8. AI in the fashion industry.

2. Artificial Intelligence in the Textile Industry

The textile and polymer industry involves economic activities aimed at producing polymer-based fibers, threads, fabrics, clothing, and textile items used for various purposes, such as home decoration and industrial use. In the realm of manufacturing, textiles stand as one of the most ancient and intricate sectors, encompassing a wide range of sub-categories that manage the entire production process, from raw materials and progression stages to the finished product [25].

The textile manufacturing industry relies heavily on labor, involves significant fixed capital investments, and encompasses various product designs and materials. It faces fluctuating production levels, intense competition, and frequently requires high product quality. To fulfill these criteria, manual labor-intensive techniques must undergo a conversion into automated processes, utilizing computers, models, digital components, and artificial intelligence [26]. Different implementations of AI in the textile sector are illustrated in Figure 9 below.

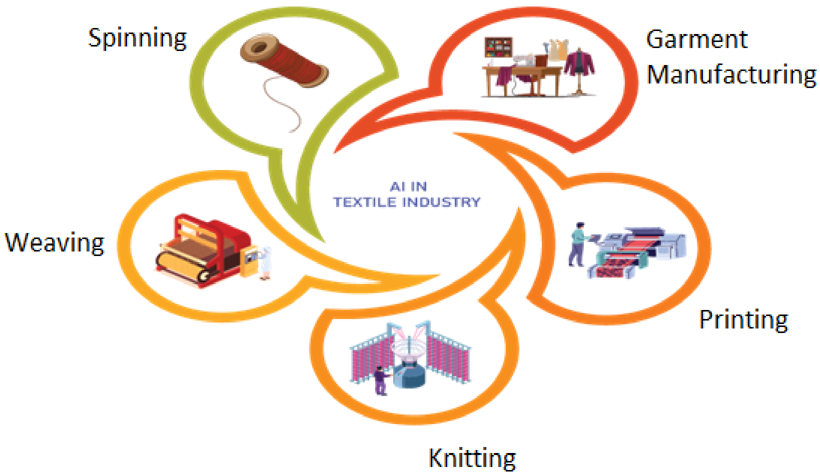

Figure 9. AI in the textile industry.

2.1. *AI in Analyzing Fiber Characteristics*

Advanced AI-integrated computer systems have been designed for analyzing fiber properties and structure, as illustrated in Figure 10. They can quickly and easily assess the fineness of individual fibers, distinguish between different fibers in blends, and calculate their composition percentages. Additionally, they can identify the type of fiber in purchased materials, analyze the yarn structure for defects, measure circular section yarns and filaments in Dtex or den, evaluate the quality and shape of Lycra or synthetic multifilament threads, assess non-woven fabric density, analyze yarn and fiber sections, measure section surfaces and perimeters, and inspect mechanical components. The system can also process, store, and print measurements, including minimum, average, and maximum values, CV%, and distribution graphs [27].

Figure 10. AI in analyzing fiber characteristics.

2.2. AI in Spinning

Automation in spinning, which used to involve manual processes like picking and ginning, has evolved significantly. The High-Volume Instrument system has made cotton fiber testing much faster and more accurate, enhancing measurements of various cotton properties [28]. Various spinning techniques and improvements in ring spinning machines, as well as automated yarn fault detection and splicing methods, have enhanced production quality and efficiency. Robots handle heavy tasks and package collection, reducing the need for skilled labor [29].

ANN is a specific type of AI, and there are other types of AI that have been used in spinning as well. ANNs are being used in spinning to predict yarn properties, as shown in Figure 11. For example, fuzzy logic has been used to optimize the spinning process by controlling the twist level and yarn diameter. In another study, a hybrid intelligent system combining genetic algorithms and neural networks was used to optimize the spinning process parameters for producing high-quality yarns. Additionally, machine learning algorithms have been used to forecast yarn characteristics based on process parameters [6].

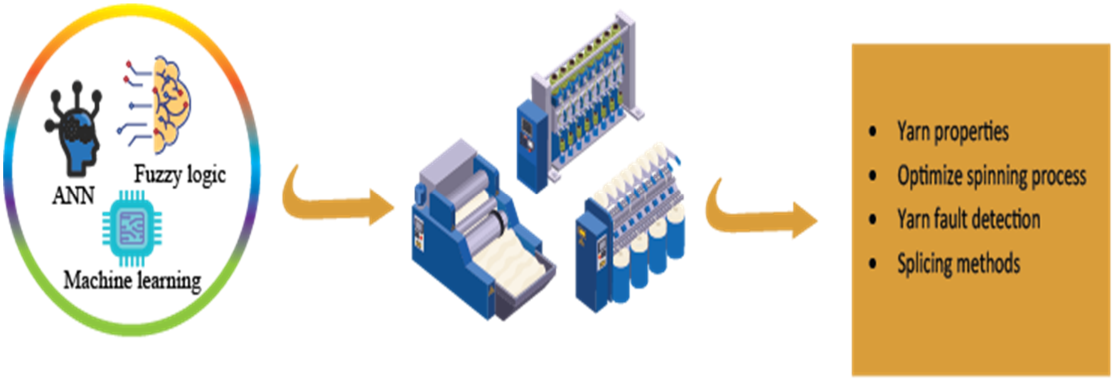

Figure 11. AI in spinning.

2.3. AI in Fabric Manufacturing

Multiple AI techniques have found applications in fabric manufacturing, encompassing fuzzy logic, neuro-fuzzy systems, adaptive neuro-fuzzy inference systems, and ANN. These methods have been employed across different stages of fabric production, like sizing, weaving, and knitting, to create models and optimize various production parameters, as shown in Figure 12. For instance, ANFIS is utilized to forecast parameters like residual bagging bend height, bursting strength in knitting, and spirality, while ANN is employed to predict variables like exit moisture, number of end breaks, size add-on, and warp breakage rate during the sizing process. Fuzzy logic is used to create models for weft yarn insertion velocity, air permeability, and compressed air consumption in weaving [30].

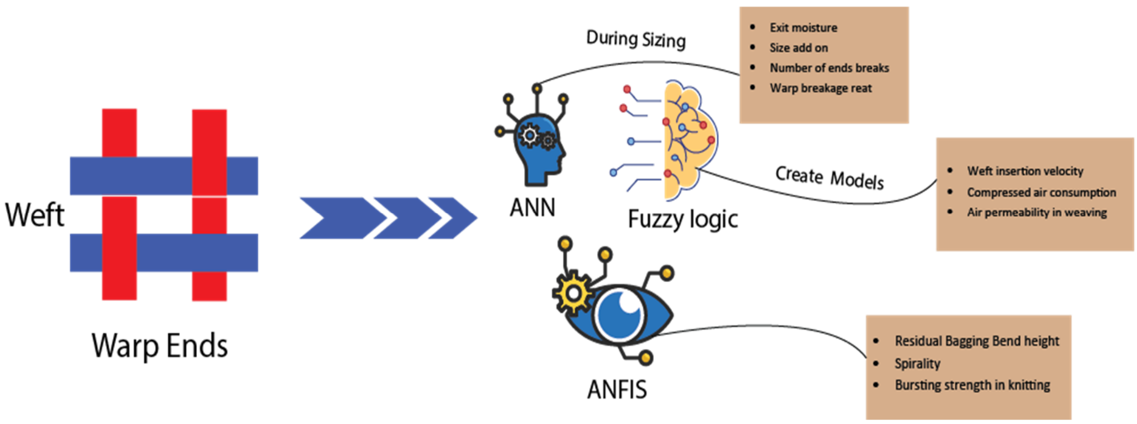

Figure 12. AI in fabric manufacturing.

2.4. AI in Dyeing, Finishing, and Printing

Following fabric or garment production, the dyeing, printing, and finishing stages are crucial. Several innovative systems, such as Wooly, BAFAREX, and SMARTMATCH, have been created to simplify and enhance these processes. Wooly, for instance, empowers dyers with chemical and physical data, streamlining wool finishing. BAFAREX is tailored for dyeing cotton and polyester–cotton items, utilizing vat dyes and disperse dyes. SMARTMATCH, on the other hand, focuses on color matching. Various other expert systems assist in dyeing and finishing tasks, enhancing efficiency and accuracy in textile production. One notable development is Fuzzy CLIPS, a fuzzy version of CLIPS, which created a diagnostic expert system called DEXPERT. This system is primarily designed to troubleshoot issues in dyeing cotton materials, and is capable of diagnosing a range of faults and offering corrective suggestions [31].

3. Artificial Intelligence in Textile Testing

The integration of artificial intelligence into the textile industry has become more prevalent, significantly impacting the testing of textile garments and enhancing efficiency, accuracy, and speed across various processes. Various tests are routinely performed on textile garments to ensure their quality and adherence to industry standards. The incorporation of AI into these fabric testing procedures offers manufacturers the opportunity to achieve heightened accuracy, increased efficiency, and an overall improvement in product quality. The utilization of AI enables more sophisticated and data-driven decision-making throughout the entire textile manufacturing and testing lifecycle. The following are some common tests wherein AI plays a crucial role:

3.1. Tensile Strength Tests

Tensile strength testing is a mechanical test that assesses the endurance of a fabric subjected to a force hauling it apart. It evaluates the maximum force a fabric can survive before breaking. Tensile strength is a critical property for fabrics, as it signifies the material's ability to endure stretching and pulling forces during use. This test helps manufacturers ensure that fabrics meet strength requirements for specific applications, such as in garments, wherein resistance to tearing or stretching is essential. AI assists in computerizing the testing process and analyzing the data obtained during tensile strength tests. Moreover, AI-based tools such as ANN and linear regression are being used to predict fabric tensile strength based on input parameters such as ends per inch, picks per inch, warp yarn strength and its elongation, and weft count [32].

3.2. Tear Strength Tests

In order to investigate the force needed to propagate a tear in a fabric, tear strength tests are undertaken. This involves exposing a fabric sample to controlled tearing forces. Tear strength is crucial for assessing a fabric's resistance to tearing or ripping. This test helps to determine the fabric's durability and performance, especially in applications wherein resistance to tearing is essential, such as in workwear or outdoor fabrics. AI assists in automating tear strength testing by analyzing images or videos of the tearing process. Computer vision algorithms are being used that accurately measure tear propagation and provide insights into tear resistance. Moreover, using AI techniques such as linear regression, linear regression models have been developed that accurately predict fabric tear strength based on some input parameters such as yarn count, yarn strength, and fabric linear density [33].

3.3. Stiffness Tests

Stiffness testing measures a fabric's rigidity or flexibility. A bending tester is commonly used to assess how much a fabric bends under a specific load. Stiffness is an important factor in applications like apparel, in which the drape and feel of the fabric impact comfort and aesthetics. This test ensures that fabrics meet the desired stiffness or flexibility for their intended use. AI assists in the analysis of bending behavior by processing data from tests. Machine learning algorithms learn patterns related to stiffness and flexibility and help manufacturers to assess and control these properties more efficiently. Moreover, using AI techniques such as artificial neural networks, models have been developed that accurately predict fabric stiffness based on various fabric parameters such as weft yarn number and its density, weaving pattern, finishing treatments, and concentrations. ANN-based models accurately predict fabric stiffness before production using these parameters [34].

3.4. Abrasion Resistance Tests

Abrasion testing involves subjecting a fabric to rubbing or abrasion to evaluate its ability to withstand wear over time. Fabrics in daily use, such as clothing or upholstery, experience friction and wear. Abrasion resistance testing helps manufacturers assess how well a fabric will hold up under repeated use, providing insights into its long-term durability. AI has optimized the testing process with its ability to predict the abrasion resistance of a fabric based on its composition, weave, and other factors. Using ANN, models have been made that accurately predict fabric stiffness based on various fabric parameters such as yarn count, twist level, pile yarn material type, and pile length [35].

3.5. Pilling Resistance Tests

Pilling resistance testing assesses a fabric's tendency to form pills, which are small, raised clusters of fibers on the fabric surface caused by friction during wear. Pilling affects the appearance and feel of textiles, particularly in garments. This test helps manufacturers to evaluate the fabric's resistance to pilling and to ensure that it maintains a smooth and attractive appearance over time. AI, particularly computer vision, assists in automating pilling resistance testing by analyzing images of fabric surfaces. Algorithms identify and quantify the extent of pilling and provide a more objective and efficient assessment. Using AI techniques such as ANN, models have been made that accurately predict the pilling propensity of fabrics based on various parameters actors such as fiber tenacity, diameter, length, and curvature, as well as yarn type, twist, hairiness, and fabric construction. This helps in quickly identifying fabrics with better pilling resistance for use in garments [36].

3.6. Shrinkage Tests

Shrinkage testing evaluates the extent to which a fabric shrinks when exposed to moisture, heat, or other factors. Shrinkage can impact the fit and size of garments after washing or exposure to different conditions. Shrinkage testing helps manufacturers predict and control the amount of shrinkage a fabric may undergo, ensuring that garments maintain their intended size and shape throughout their lifespan. AI assists in automating shrinkage testing by analyzing data from testing machines. Moreover, using machine learning algorithms and factorial design analysis, prediction models have been made that predict the potential shrinkage of a fabric based on its composition and historical shrinkage data. This predictive capability helps manufacturers to estimate and control fabric shrinkage more efficiently [37].

3.7. Crease Recovery Tests

Crease recovery testing measures a fabric's ability to recover its original shape and smoothness after being subjected to creasing or folding. Fabrics in garments often experience creasing during use, transportation, or storage. Crease recovery testing ensures that the fabric can regain its original appearance after being folded, providing insights into the garment's overall wrinkle resistance and appearance retention. AI assists in automating crease recovery testing by analyzing images or data from testing machines. Machine learning algorithms are being used that can learn patterns associated with good crease recovery and provide a quicker and more objective assessment. Moreover, some models have been developed that predict crease recovery properties of fabric using two parameters: bending rigidity and bending hysteresis. This helps manufacturers to understand how well a fabric can recover from creases, influencing decisions on garment design and materials [38].

By integrating AI into fabric testing processes, manufacturers can achieve higher accuracy, increase efficiency, and improve overall product quality. This allows for more sophisticated and data-driven decision-making throughout the textile manufacturing and testing lifecycle. Some other studies related to the integration of AI into textile testing have been mentioned below in Table 1.

Table 1. AI in textile testing.

Sr.	AI Type	Method	Application	Ref.
1.	Structural Equation Modeling	Mathematical analysis, finite element analysis, and ANN software, Python 3.12.0.	The mechanical properties of thread and fabric that influence seam strength in apparel manufacturing were identified with this technique.	[39]
2.	Artificial Neural Network	Digital fabric images, fully connected multi-layered ANN	Most common textile defects were identified using this technique.	[40]
3.	Image Processing	Image quantitative analysis, analysis algorithms	This technique was used to develop a more universal and accurate method for measuring yarn hairiness.	[41]
4.	Artificial Neural Network	Counter-propagation neural networks	This was used to identify the combinations of dyes and to determine the appropriate dyes for achieving a required color in textile printing.	[42]
5.	Artificial Neural Network	Multi-layered perception neural network model, scanner-based NN technique	This technique was used for the prediction of color on cotton fabric using different dyes.	[43]
6.	Artificial Neural Networks and Genetic Algorithms	Image processing algorithms	This was used for characterizing yarn properties accurately and to predict the visual appearance of fabrics.	[44]
7.	Image Processing	Algorithms and computational methods to analyze and manipulate images	Using this technique, the coefficient of yarn hairiness was determined automatically.	[45]
8.	Artificial Neural Network	Fourier transform analysis and back propagation neural network	This was used to detect and classify different textile defects.	[46]
9.	Opto-electronic Processing Technique	Computational modeling, MATLAB software	This technique was used to detect faults in fabric during the process of weaving.	[47]
10.	Image Processing	Image acquisition and mathematical analysis	This was used to identify and classify different types of yarn defects, such as neps, snarls, thick and thin places, and slubs.	[48]
11.	Artificial Neural Network	Back propagation algorithm and multi-layer perception neural network	Evaluation of warp breakage rates was undertaken using this technique in textile weaving.	[49]
12.	Artificial Neural Network	Recurrent neural network, long short-term memory	This technique was used to improve the accuracy of dyeing recipe prediction and to avoid the metamerism phenomenon.	[50]

Table 1. *Cont.*

Sr.	AI Type	Method	Application	Ref.
13.	Artificial Neural Network	Feed forward back propagation network	This was used to estimate the necessary dyeing time for achieving the desired color intensity for reactive HE dyes on cotton fabric.	[51]
14.	Image Analysis	Image processing algorithm and mathematical analysis	This technique was used to estimate the fundamental structural characteristics of yarn thickness, hairiness, and twist.	[52]
15.	Artificial Neural Network	Neuro-fuzzy inference system and computational modeling	This technique was used to predict the yarn strength, concerning fiber strength, elongation, uniformity index, short fiber content, fineness, and upper half mean length.	[53]
16.	Artificial Neural Network	Radial basis neural network modeling	This was used to predict the K/S value of reactive dyes used in fabric dyeing.	[54]
17.	Artificial Neural Network and Genetic Algorithms	Radial basis neural network modeling	Using this technique, an optimal formula for color coordination was developed by using the nonlinear correlation between dye concentration and textile reflectivity.	[55]
18.	Digital Image Processing	Two-dimensional Fourier transformation patterns	This was used to determine weave types and to detect the characteristic patterns of woven fabrics.	[56]
19.	Image Analysis	Image processing algorithm	This technique was used to measure the yarn twist.	[57]
20.	Image Analysis	Image acquisition and image processing	This was used to monitor the textile raising process, i.e., assessment of the elevation and density of fibers protruding from an elevated fabric surface (pile).	[58]
21.	Artificial Neural Network	Perceptron artificial neural network and image processing	This was used to detect and classify the yarn faults and to grade them based on appearance.	[59]

4. Artificial Intelligence in Garment Manufacturing

Garment manufacturing has evolved through technological advancements, embracing high-speed sewing machines, computer-aided designing, computer-aided manufacturing, innovative cutting and pressing techniques, and the integration of robotics as depicted in Figure 13. The infusion of these technologies results in significantly enhanced productivity and work quality, transitioning the clothing industry from traditional labor-intensive methods to a fully self-operating and computer-aided sector. Automation spans various aspects of garment production, comprising computer-aided designing, computer-aided manufacturing, fabric inspection, fabric spreading, fabric cutting, sewing, pressing, material handling, and the role of radio frequency identification in automation [60].

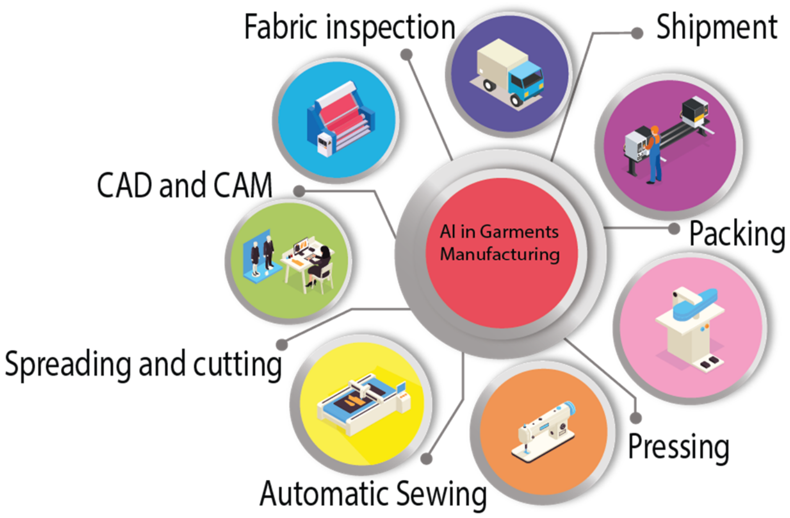

Figure 13. AI in garment manufacturing.

4.1. In Fabric Inspection

Automated fabric defect detection is vital for overcoming the limitations of manual inspection, ensuring enhanced accuracy and efficiency. Advanced garment inspection systems are under development to minimize or eliminate manual intervention, leading to improved fabric quality. Various sensing technologies, such as light and laser beam reflection and video image processing, are employed in automatic detection systems like Barco Vision's Cyclops, Zellweger User's Fabric-Scan, and Elbit Vision System's I-Tex [61]. Advanced fabric inspection systems based on artificial intelligence can automatically detect faults during the fabric inspection process, as shown in Figure 14. Various approaches, including statistical, spectral, and model-based methods, are employed. In these methods, the fabric image is processed using specialized software or AI tools to extract relevant information pertaining to faults. Through this automated process, faults are identified and the system marks these areas on the fabric, streamlining the inspection and quality control processes in textile manufacturing.

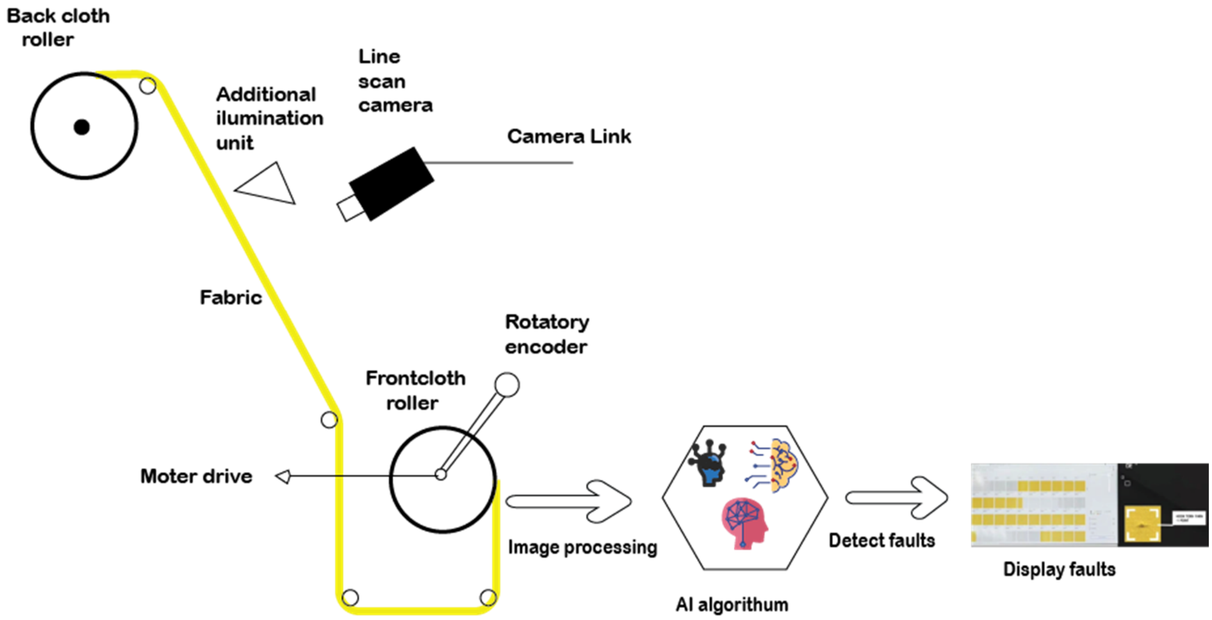

Figure 14. AI in fabric inspection.

AI plays a key role in fault inspection, utilizing pretrained neural networks for detecting and marking faults during fabric manufacturing, and assisting in fabric selection based on the clothing's intended application. AI applications in fabric fault inspection include back-propagation-algorithm-based ANN for defect recognition; image analysis and ANN for knitted fabric fault detection; back-propagation-learning-algorithm-based ANN for woven and knitted fabric classification; automated visual inspection using the wavelet transform for patterned fabric defects; and identification of defects in woven fabrics through ANN-versed structuring components [62].

4.2. In Computer-Aided Design and Manufacturing Systems

In garment manufacturing, designers create paper patterns, later digitized for computer use, forming the basis for two-dimensional patterns that constitute a garment's 3D structure. CAD software (0.21.2) is widely applied for patternmaking, digitizing, grading, and marker planning. AI research aims to automate clothing pattern development, with systems like Inui's AI-integrated CAD enabling user-preferred design searches. Kim and Cho's genetic algorithm-based system predicts optimal women's dress designs based on human preferences. Additionally, Fang and Ding's expert knowledge-based system automates basic pattern preparation, Lin's intelligent design system meets customer demands, and Fan et al. developed an intelligent system which predicts drape images for women's clothing styles [62].

In the realm of garment manufacturing automation, the emergence of 3D whole body scanners is notable. These 3D body scanning devices can capture the three coordinates X, Y, and Z for the whole human body, as shown in Figure 15. Then, appropriate software can convert these data into accurate body dimensions. The scanned data can be used to create patterns for different types of garments. For creating patterns, different software programs like Gerber AccuMark (V14) are used to create patterns. These 3D body scanners create digital copies of the human body and combine them with clothing patterns to produce tailored garments. Adapted digitized clothing patterns can undergo further processing, such as automated grading and cutting, enhancing efficiency and customization [63].

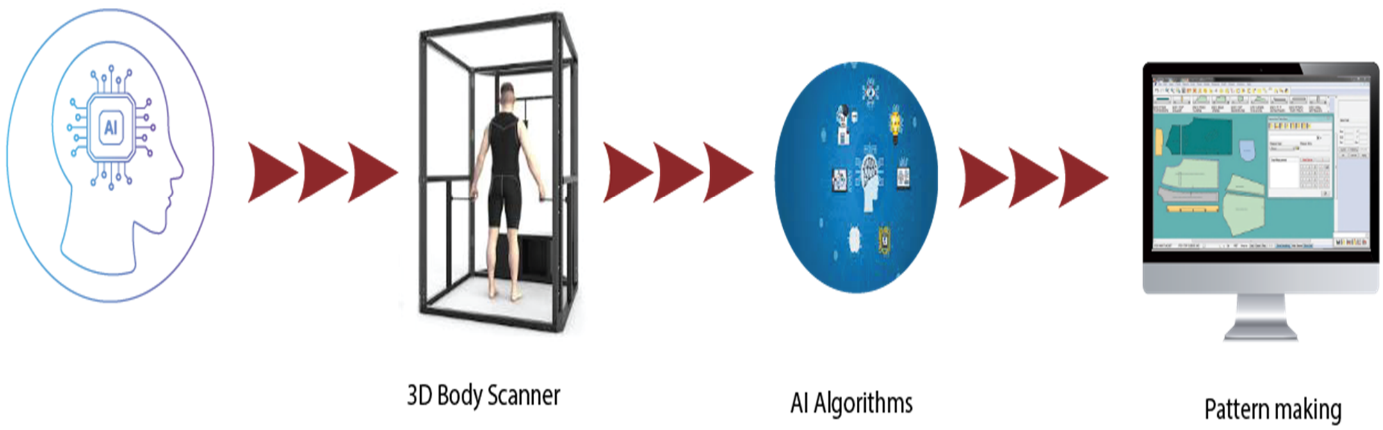

Figure 15. In CAD and CAM Systems.

4.3. In the Spreading and Cutting of Fabrics

Advanced AI-based automatic fabric spreading machines operate on a spreading table to facilitate efficient fabric spreading. These machines are equipped with various AI algorithms, including fuzzy logic, machine learning, and expert systems, as shown in Figure 16. Fabric parameters such as length, width, and ply counts can be input through the liquid crystal display touch screen on the machine. The machine then automatically spreads the fabric for the specified number of plies and halts once the desired ply count is achieved. Additionally, the machine is designed to slow down as it approaches both ends, ensuring careful alignment of the fabric grain line. This alignment is monitored with the assistance of sensors, contributing to the precision and reliability of the fabric spreading process in textile manufacturing. Automatic spreading machines facilitate tension-free spreading of multi-ply fabrics, with operations conducted in either semiautomated or fully automated modes. In semiautomated spreading, operators move along the table, smoothing the lay surface, identifying faults, and deciding whether to retain or cut them. Fully automated spreading, suited for easily spread high-quality materials, involves presetting parameters, allowing the machine to autonomously lay, cut, count, and stop after the required plies [64].

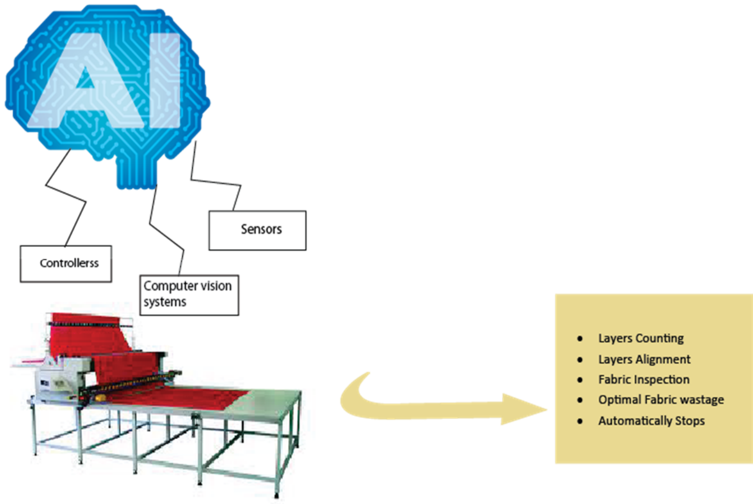

Figure 16. AI in the spreading and cutting of fabrics.

Similarly, automatic cutting machines cater to various fabric types, using markers fed to a computer via USB. The cutting head autonomously shifts to cut pattern pieces in accordance with the marker, employing methods such as laser, knife, or waterjet cutting. Laser cutters offer advantages in terms of accuracy, preventing fabric fraying, ensuring precise edges, and eliminating the need for blade changes. The benefits of fully automatic cutting over manual methods include enhanced ease, accuracy, and efficiency in cutting both single and multiple plies, and achieving perfect cuts on the first attempt [60].

4.4. In Marker Making

Various traditional and automated methods for marker making are employed in the garment industry, utilizing different software programs. However, there is ongoing research aimed at enhancing production by decreasing time, minimizing fabric wastage, and optimizing marker efficiency. Researchers have explored artificial-intelligence-based systems for marker making to achieve these objectives. Approaches like the two-step method proposed by Han and Na focus on initial layout and final marker development. Yeung and Tang introduced a sophisticated strategy, combining marker-making problems with genetic algorithm techniques for optimal efficiency. ANN models, as suggested by Ozel and Kayar, calculate marker making time based on various factors. Genetic algorithms are also utilized to address pattern processing and layout optimization issues and minimize fabric wastage in apparel manufacturing, as shown in Figure 17. Furthermore, computer-aided design software aids in marker tracing [65].

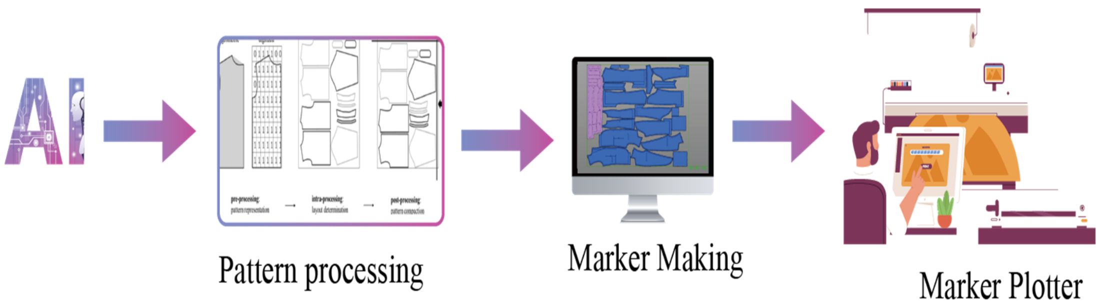

Figure 17. AI in marker making.

4.5. In Sewing Automation Equipment

Expertise in and command over sewing machines are crucial for apparel manufacturers to ensure the production of excellent quality garments and enhance production effectiveness. Currently, the sewing process involves manual adjustments through a "trial and error" approach at the start of operations. Automation is considered essential to improve apparel quality and optimize machine functions. Various research efforts focus on eliminating machine adjustments, reducing setup times, and enhancing sewing machine production.

Researchers have explored innovative approaches, such as a wavelet ANN-based online classifier for fabric type and plies, a combined PID/fuzzy logic controller for adaptation to different sewing conditions, and a fuzzy logic regulator for the vertical motion of the presser foot, which can automatically adjust its pressing equipment settings as shown in Figure 18. Additionally, hierarchical robot control systems with fuzzy decision mechanisms and neuro-controllers have been proposed to regulate tensional forces during robotized sewing processes. These systems demonstrate efficiency, robustness, and flexibility in handling various fabrics. Other studies involve a nonlinear ANN model for a sewing machine fitted with a BLDC motor, a six-axis robotic hanger system for inspecting knitted garments, and a fuzzy-tuned PID control algorithm for efficient performance in noisy environments. These approaches aim to automate and optimize sewing machine operations, reducing reliance on manual adjustments and improving the quality and efficiency of garment production [66].

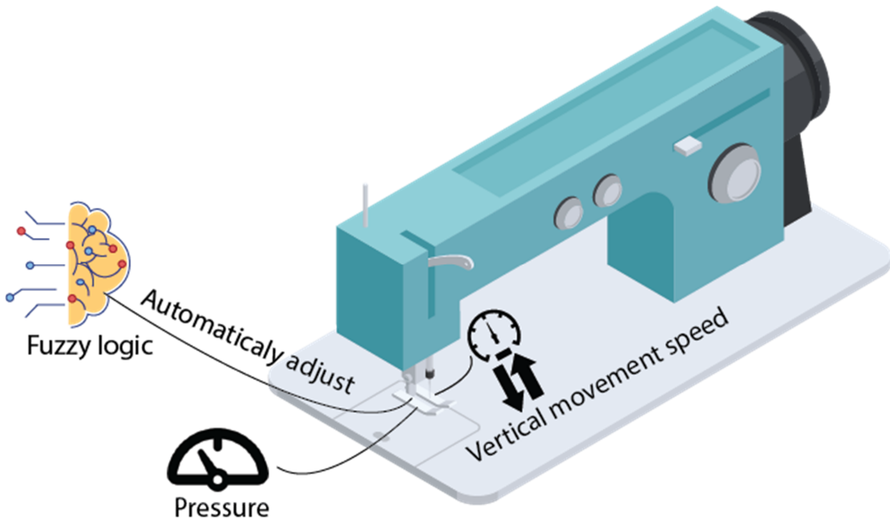

Figure 18. AI in sewing automation equipment.

4.6. In Pressing

To enhance the visual appeal of products before reaching customers, significant strides have been made in automating the pressing operation. Despite various technical innovations in pressing technology, the availability of automation tools remains confined.

Commercially, there are technologies like pressing robots, shirt finishers, and shirt pressers, in which AI algorithms are used. These can analyze fabric types and recommend or automatically adjust pressing equipment settings, ensuring the optimal combination of temperature and pressure for each material as shown in Figure 19. This prevents damage and improves efficiency.

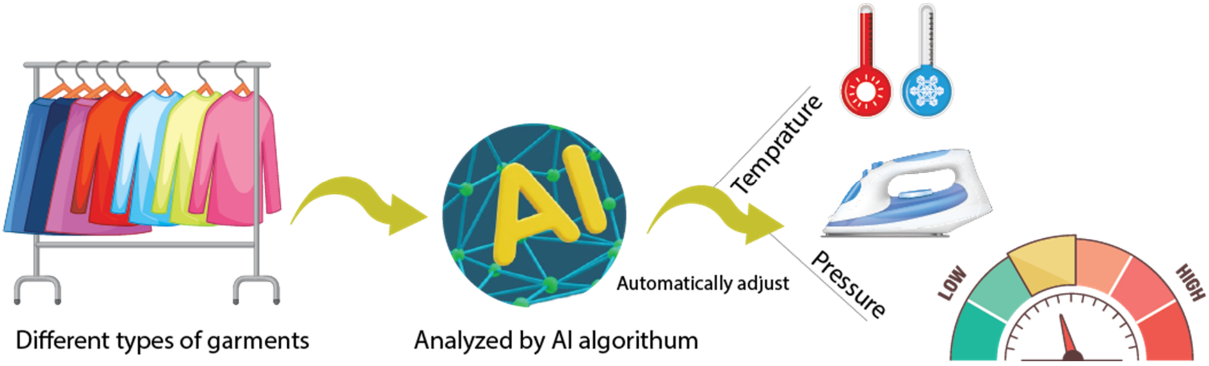

Figure 19. AI in pressing.

However, manual labor is still commonly required for tasks such as loading or removing garments into the buck, smoothing, and shaping. Achieving comprehensive automation in the entire garment production process necessitates substantial advancements, particularly in pressing, complementing progress in other areas [60].

4.7. In Garment Packing

AI is transforming garment packing in the apparel industry through automation and improved efficiency. AI-driven computer vision systems automatically categorize garments by attributes like size and color, aiding in organized packing. Robotic systems controlled by AI ensure precise and fast packing, as shown in Figure 20, analyzing historical data to optimize inventory levels. This reduces wasted space in packaging, minimizing shipping costs. AI-equipped systems inspect garments for defects during packing, ensuring high-quality shipments and reducing returns. AI-driven chatbots handle customer inquiries, enhancing satisfaction. Across the supply chain, AI, RFID, and IoT technologies track garment movement, providing real-time visibility. AI algorithms adjust pricing dynamically, optimizing revenue, and personalized packing based on customer preferences enhances the overall packing experience.

Figure 20. AI in garment packing.

4.8. In Garment Shipment

AI revolutionizes garment shipping by optimizing routes, providing real-time tracking, and ensuring a customer-centric experience in the apparel industry. By analyzing historical and real-time data, AI optimizes shipping routes, delivering garments efficiently. Predictive analytics enhance delivery time estimates, considering factors like traffic, weather, and historical data. AI, IoT, and RFID technologies offer real-time tracking, reducing risks and improving transparency, as shown in Figure 21. Automated customs clearance and dynamic cost adjustments enhance international shipping. AI-driven chatbots handle customer inquiries, improving satisfaction, while AI optimizes warehouse operations and mitigates shipping risks. Robotic systems automate sorting and loading, reducing errors and speeding up the shipment process. AI assesses environmental impacts, aligning shipping choices with sustainability goals, and analyses return patterns for efficiency improvements.

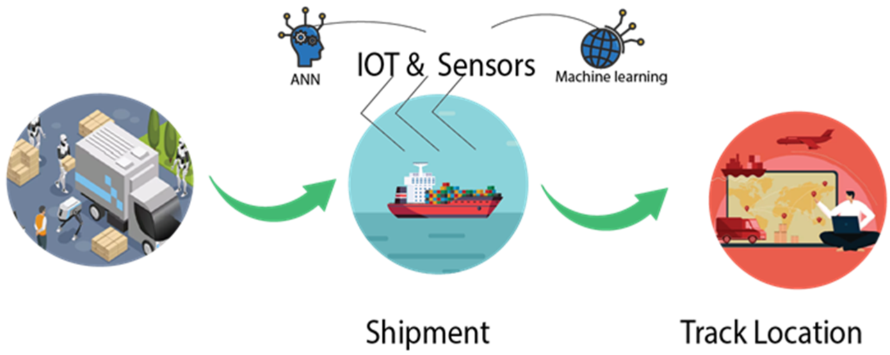

Figure 21. AI in garment shipment.

The integration of artificial intelligence into the garment industry marks a transformative era, redefining traditional processes and unlocking unprecedented efficiency and innovation. From the initial stages of design- and pattern-making to the final steps of quality control and customer engagement, AI is revolutionizing every facet of garment production and retail. Some other comparative studies related to the integration of AI in garment manufacturing have been mentioned below in Table 2.

Table 2. AI in garment manufacturing.

Sr.	AI Type	Method	Application	Ref.
1.	Artificial Neural Network	Statistical analysis, prediction model	This technique was used to predict the seam strength for various stitch types in cotton plain woven fabric, concerning stitch density.	[67]
2.	Artificial Neural Network	ANN parallel computational models(radial-based function and multi-layered perception neural network modeling)	A model based on ANN was developed using this technique; it can accurately predict the values of seam elongation and seam strength.	[68]
3.	Image Processing	Deep learning method, convolutional neural network	This was used for the detection of some sewing defects, like broken stitches.	[69]
4.	Regression Analysis	Statistical multi-linear regression method	The quantity of the sewing thread required for women's undergarments was predicted using this technique.	[70]

Table 2. *Cont.*

Sr.	AI Type	Method	Application	Ref.
5.	Regression Analysis	Geometrical and statistical multi-linear regression method	The quantity of the sewing thread required for over-edge stitch class 500 was predicted using this technique.	[71]
6.	Regression Analysis	Geometrical and statistical multi-linear regression method	The quantity of the sewing thread required for cover stitches class 602, 605, and 607 was predicted using this technique.	[72]
7.	Image Analysis	Geometrical modeling and statistical technique	This was used to analyze the consumption of sewing thread for lockstitches and chain stitches of different classes.	[73]
8.	Image Analysis	Fourier series	This was used to develop a mathematical model for the consumption of sewing thread required for stitch class 301.	[74]
9.	Genetic Algorithms	Data mining technique (fuzzy association rule mining technique)	Using this technique, a genetic-algorithm-based process mining system was developed to improve the level of quality assurance in the garment industry.	[75]
10.	Grouping Genetic Algorithm	GGA-based computational model	This technique was used to solve the line balancing problem by allocating the tasks to each workstation in a way that minimizes the workload imbalance.	[76]
11.	Machine Learning and Deep Learning	QSR NVivo 11 software (11.0) for analyzing the data	This was used to implement AI in the textile and apparel industry, specifically in agile manufacturing.	[77]
12.	Regression Analysis	Statistical regression method	This was used to predict the tendency of a fabric to pucker, concerning fabric thickness, compressibility, shear and bending properties, tear strength, and air permeability.	[78]
13.	Artificial Neural Network	Back propagation neural network model with 21 input units and 16 output units	This technique was used to predict the sewing performance of apparel, concerning fabric weave structure, yarn count, fabric weight, formability, and extensibility.	[79]

4.9. AI for Garment Properties

In 2017, Mihriban Kalkanci and Gulseren Kurumer used artificial neural networks to predict the dimensional properties of t-shirts made from single jersey and interlock fabrics. Using ANN, a solution was developed for estimating the garment pattern size and dimensional change problems experienced in garment manufacturing facilities, which cause a waste of time and quality-related problems. A total of seventy-two t-shirt variations were produced using six distinct materials with three varying densities and employing two different knitting techniques. The ANN system proved to be exceedingly effective in estimating pattern measures of garments; its co-efficient of determination was found to be greater than 0.99 ($R^2 > 0.99$) [80].

In 2010, Tomsilav Rolich and Anica Husra used artificial neural networks for predicting fabrics' extensibility, which is crucial in the field of clothing technology. The researchers investigated the influence of fabric properties on clothing item appearance and the importance of knowing fabric properties during the clothing manufacturing process and clothing items' usage. The values of experimental measurement of extensibility using a KES-FB1 measuring device were compared with predicted values computed with ANN. The ANN model was successful in predicting the fabrics' extensibility, and the predicted values were in good agreement with the experimental measurements; the prediction of fabrics' extensibility can be used in computer simulations for clothing design [81].

In 1999, R.H. Gong and Y. Chen used artificial neural networks to predict fabric effectiveness in garment manufacturing based on some mechanical properties of fabric, including tensile, compression, shearing, bending, and surface properties. A feed-forward multi-layer perception neural network in Neu frame was used for this work, and 32 fabrics with a variety of fiber compositions and fabric weaves, all made by the industrial KES-FB system, were selected. Artificial neural networks were found to be very accurate in predicting fabric performance and identifying potential manufacturing problems. AI also has the capability to enhance efficiency and lower expenses [82].

4.10. AI in Industrial Engineering

In 2021, Hueqing Cao and Xiaofin Ji used machine learning algorithms and an ANN model to predict production cycle time in the garment manufacturing industry. A neural network model was established to accurately predict production cycle time, allowing for better control of the production process. A back propagation neural network was used for clothing production cycle time prediction. The neural network structure consists of three layers: the input layer, hidden layer, and output layer. The input layer receives data related to production quantity, GST per capita, and initial cycle time. The hidden layer processes the data using the tansig formula, and the output layer predicts the cycle time for different production quantities using the Relu function. They concluded that the neural network model can predict the production cycle time, which allows manufacturers to arrange production plans more accurately, avoid imbalances in order accumulation or production waiting, and improve production efficiency. Although the neural network showed promising results in predicting garment production cycle time, there is still room for improvement. Factors such as complex styles and bottleneck processes can affect the actual cycle time, which may deviate from the predicted values [83].

In 2022, Yibing Shau and Xiaofin Ji used a combination of particle swarm optimization and support vector machine (PSO-SWM) techniques to predict standard time in the sewing process. Accurate standard time prediction is crucial for manufacturing plans, cost management, and resource optimization, and the use of advanced techniques can improve efficiency and profitability. The researchers collected data on the sewing process from the apparel manufacturing industry and then these data were used to train the PSO-SVM model. The model was then used to predict the standard time required for the sewing process. The performance of the PSO-SVM model was compared with that of a BP neural network, and the results showed that the PSO-SVM model outperformed the neural network in terms of mean square error and R^2 values. The researchers also compared the prediction results with different parameter optimization methods [84].

4.11. AI for Optimizing Production Processes

In 2020, Yani Xu and Sebastien Thomassay used machine learning algorithms for the estimation of marker length for efficient cutting of fabric. The researchers employed two widely used software programs, Modaris Lectra and Diamino Lectra, to create patterns and markers. Numerous benefits were discovered in using neural networks for estimating marker length, including enhanced efficiency and accuracy in the cutting process. They also discussed the impact of modern garment mass customization on marker making workload and the use of mixed and group markers in lean production [85].

In 2014, Ranga Parasad Abeysoriya proposed a new method of calculating thread consumption using regression analysis and geometrical modeling techniques. This method was proposed for calculating thread consumption of lockstitch 301 and chain-stitch 401 by incorporating thread tension into existing formulae of thread tension, thread consumption, and stitch formation in sewing operations. The researchers used regression analysis and geometrical modeling techniques to optimize their formulae and compare them to existing methods through error analysis. Their proposed method was found to be more efficient because it optimized the consumption of sewing thread, which consequently decreased thread wastage [86].

4.12. AI for Detection of Fabric and Production Defects

In 2021, Taner Ersoze and Hamza Zahoor used data mining algorithms for detecting fabric and production defects in the apparel industry. Data mining classification algorithms, specifically "decision tree" algorithms, image processing techniques, and simulation methods were used to determine the core causes of defective products. The model takes into consideration factors such as the types of products, sizes of the defective products, types of defects, and explanations to determine the main reasons for defective products. The study found that the main reasons for defects were production-induced defects and fabric defects. The occurrence of defects was determined according to the defect type, model number, production size, and product type. The accuracy rates of the model were compared, and it was seen that "decision tree" algorithms had higher accuracy rates than other classifier algorithms that were used [87].

4.13. AI for Seam Strength Assessment

Stitches and seams play crucial roles in the basic structure of apparel products. Stitches are employed to connect various components of the apparel, while seams contribute to shaping the apparel for comfortable wear. Both of these elements, along with their performance characteristics, significantly contribute to the overall quality of the apparel [88]. Seam assembly stands as the most commonly employed technique in garment construction. To form a seam, fabric is divided into segments and then interconnected using stitching. By altering aspects such as fabric cutting, joining methods, and stitching parameters, a range of diverse seams can be achieved, resulting in significant differences in the way the fabric drapes and performs [89].

Seam strength is a measure of the force needed to rupture a seam, serving as an indicator of the seam's overall robustness and durability [90]. Seam strength refers to the inherent strength of a seam as evaluated in a sewn garment. Various factors can lead to seam failure, such as the sewing thread breaking, fabric tearing, excessive seam slippage, or a combination of these issues. In the garment industry, fabric and sewing thread are fundamental raw materials. The quality of these raw materials significantly impacts the total seam quality of the garment [91]. A garment's quality is determined not just by its visual aesthetics but also by its technical characteristics [92]. High-quality seams are crucial for ensuring the durability, overall quality, and visual appeal of garments [91]. When assessing seam quality, one of the pivotal factors to consider is seam strength, which plays a key role in evaluating the durability of seams. Given that these seam characteristics are closely tied to the overall quality of the garment, it is imperative that the chosen seam meets the specified criteria, including sufficient strength, proper appearance, and durability [93].

Seams play a pivotal role in improving the functionality and durability of fabric in apparel. Both the functional and visual appeal of an apparel item are significantly influenced by the strength of its seams. Quality seams in apparel significantly enhance the overall functionality of the clothing when worn. Conversely, a low-quality seam can render apparel unusable, even if the fabric itself is in good condition. The presence of a defect in a purchased product renders it unfit for use, and poor seam quality is a prevalent defect in the lifespan of sewn garments [94].

Determining seam strength is essential to ensure that these seams can withstand the stresses and forces they will encounter during use. Seam strength can be determined through various testing methods, with the most common method being the use of a universal testing machine, such as the one depicted in Figure 22. It is essential to follow relevant testing standards and guidelines when conducting seam strength tests to ensure consistency and accuracy in the results. A universal testing machine, as shown in figure, is composed of five main parts, including the main frame, moveable crosshead, drive system, load cell, and load indicator. The main frame is composed of a table, a rectangular base, upper cross head, and two vertical columns. The drive system contains a motor, which provides motion to the moveable crosshead to which test specimen has been clamped. The load cell is used to place weight if needed, depending upon the testing requirements, and the load indicator represents tensile strength value [95].

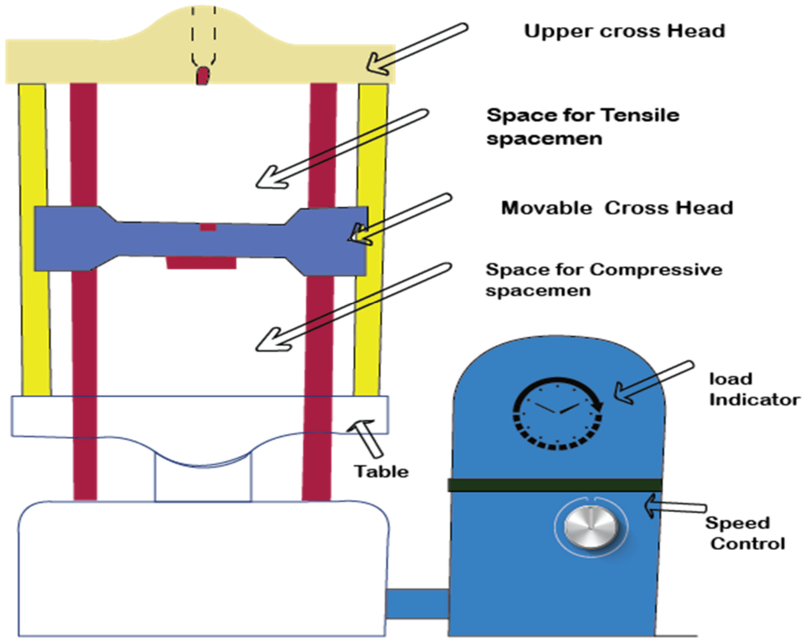

Figure 22. Universal tensile strength tester.

The UTM works on the principle of applying controlled forces/load to a test specimen and measuring its response, which typically involves deformation, strain, and, in some cases, failure. The process begins with the preparation of a sample of the material to be tested. For example, in the case of seam strength testing, firstly, samples of specific dimensions as per the selected testing standard are prepared, and then the samples are securely clamped within the jaws or clamps of the UTM, ensuring proper alignment to uniformly transmit the applied force. The UTM begins to apply a controlled force/load to the sample as the moveable crosshead starts to move downward. The load can be applied steadily at a constant rate, incrementally, or at specific load intervals, depending on the test requirements. The UTM measures and records the force continuously as it is applied. When the test specimen faces failure, the load indicator represents its seam strength value [96].

Several factors influence the strength of seams. The visual appeal and functionality of seams rely on the fabric type, thread type, stitch type, seam type, and sewing terms, which comprise stitch density, needle size, and the appropriate operation and maintenance of the sewing machines [97].

Stitch density, measured as "stitches per inch", determines the number of stitches in a sewing row per unit length of the seam. Higher SPI values indicate better quality stitching, resulting in a stronger seam due to increased thread usage. The specified SPI is crucial in garment construction, influencing seam strength, aesthetic appeal, and fabric stretchiness. The relationship between SPI, thread strength, and stitch type determines overall seam durability. Opting for a higher SPI standard enhances seam strength and stretch but requires more time and thread for each inch of the seam, impacting overall garment production [98].

The **thread count** in a seam can have a direct impact on its strength. The term 'count' is a numerical value that serves to describe the yarn's coarseness or fineness. It also signifies the correlation between the yarn's length and weight, which can be expressed as either the mass per unit length or the length per unit mass [99]. Generally, a higher thread count, which means more stitches per inch, tends to result in a stronger seam. This is because the threads are more closely packed, providing better support and resistance to stress.

A **sewing thread** with greater strength is more likely to result in a stronger seam, which in turn enhances the functional performance of the seam [100]. An ideal sewing thread, made from filament, staple yarn, or core-spun yarns, should possess high tensile strength, consistent twisting, a smooth texture, and be treated for increased wear resistance to maintain garment seams through multiple wash cycles [101]. The seam performance is influenced by various other factors related to the sewing thread, including the thread type, the number of plies, the type of finish, the twist, and the thread size [102]. It is essential to ensure that the sewing thread's strength is in line with the fabric's strength, without the thread being stronger than the fabric [103].

GSM, which stands for grams per square meter, measures the weight of one square meter of fabric in metric units. Fabrics with higher GSM values are generally denser and heavier. The GSM of the fabric can influence seam strength. Thicker fabrics can provide more support to the seam, potentially resulting in increased seam strength. The specific effect of GSM on seam strength depends on aspects such as fabric type, sewing techniques, and the intended use of the garment.

The **size of the needle** used in sewing can impact seam strength. A larger needle size, typically indicated by a higher number, can create larger holes in the fabric as it penetrates because the larger needle size increases the surface area of contact with the material, and this can weaken the fabric and the seam. On the other hand, a smaller needle size may create smaller, less damaging punctures. The choice of needle size should be appropriate for the fabric being used. Using the right needle size for the fabric helps ensure a stronger and more durable seam.

When creating a garment, it is essential to make appropriate choices regarding the **seam types** used. Incorrect selections can have an adverse impact on the sewing process. The tensile properties of seamed fabric are influenced by variations in the bias angle of stitching and stitch densities. Certain seams in a garment, such as those along the shoulders of a jacket, do not experience significant stress or stretching during use. Conversely, seams like those found at the arm joints and in the crotch area of trousers undergo considerable stretching during wear. Consequently, it is advisable to use high-strength seams in these high-stress areas [104].

As per BS 3870:1991, there are eight different classes of seams, which are: superimposed seam, lapped seam, flat seam, bound seam, edge neatening, decorative stitching, applied seam, and single-ply construction [90]. In this review, as mentioned below in Table 3, only six types of seams, including superimposed seam, bound seam, lapped seam, flat seam, edge finishing, and ornamental stitching have been discussed.

The **superimposed seam**, as shown in Figure 23a, is created by overlaying two or more layers of fabric and then using one or more rows of 301 or 401 stitches at a defined gap from the edges to secure them together. The superimposed seam encompasses a total of 55 distinct subcategories. The **lapped seam**, as depicted in Figure 23b, is produced by layering two or more layers of fabric at a designated gap and then securing them with one or more rows of stitches. The lapped seam encompasses a total of 101 unique subcategories. The **bound seam**, as presented in Figure 23c, is created by creasing a binding strip along the border of the layers of the main body material and then stitching the binding strip and body material together using one or more rows of stitches. The bound seam encompasses a total of 18 distinct subcategories. The **flat seam**, as displayed in Figure 23d, is achieved by flipping and aligning the turned edges of two layers of material and then joining them with a row of stitches that spans across and conceals the turned edges of the material. The flat seam encompasses a total of six unique subgroups. **Edge finishing**, as shown in Figure 23e, is created by folding the edge of the fabric and sewing the folded section to the main body of the fabric using one or more rows of stitches. The edge finishing seam encompasses a total of 32 distinct subcategories. **Ornamental stitching**, as depicted in Figure 23f, is achieved through the use of one or more straight rows of stitches. The ornamental stitching seam encompasses a total of eight unique sub-categories [104].

Table 3. Seam types.

Seam Class	Seam Type	Subgroup No. of Seam Type
SS	Superimposed seam	55
LS	Lapped seam	101
BS	Bound seam	18
FS	Flat seam	6
EF	Edge finishing	32
OS	Ornamental finishing	8

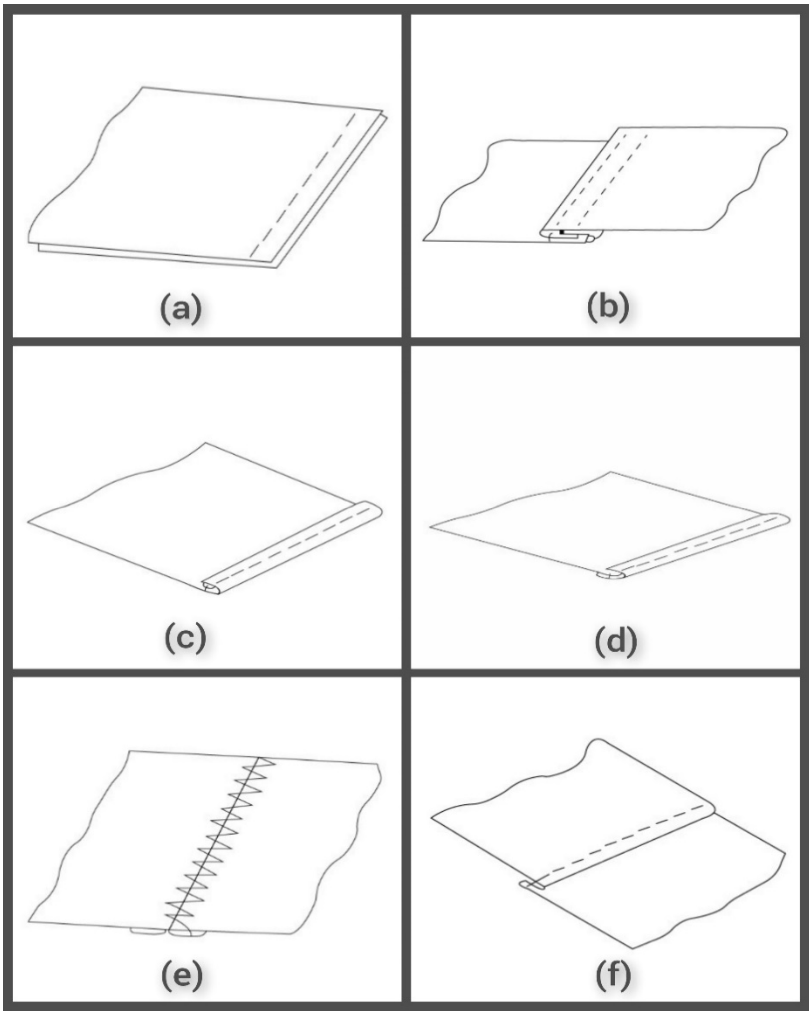

Figure 23. Seam types: (**a**) superimposed seam, (**b**) lapped seam, (**c**) bound seam, (**d**) flat seam, (**e**) edge finishing, (**f**) ornamental stitching.

The choice of stitch class in sewing has a direct impact on seam strength. Different stitch classes offer varying levels of strength and durability. The selection of the appropriate stitch class depends on factors like fabric type, garment application, and the desired balance between seam strength and other considerations, like stretch or aesthetics. Making the right choice in stitch class is essential to achieve the desired level of seam strength for a specific sewing project.

As per British Standard 3870: Part 1:1991, there are six different classes of stitch, which are: Class-100 Chain Stitch, Class-200 Hand Stitch, Class-300 Lock Stitch, Class-400 Multi-Thread Chain Stitch, Class-500 Overedge Chain Stitch, and Class-600 Covering Chain Stitch [90]. These six stitch classes have been mentioned below in Table 4.

Table 4. Stitch classes.

Stitch Class	Stitch Type	Subgroup Numbers of Seam Types	Subgroups of Stitch Types
100	Chain Stitch with one needle thread	5	101–105
200	Hand Stitch	5	201–205
300	Lock Stitch	16	301–316
400	Multi-Thread Chain Stitch	11	401–411
500	Overlock Stitch	22	501–522
600	Covering Chain Stitch	10	601–622

The formation of **Class 100—Chain Stitch**, illustrated in Figure 24a and known as Type 101, utilizes one or more needle threads and is distinguished by the intra-looping process. This process involves threading a loop or loops through the material and subsequently securing them through intra-looping with successive loops after their passage through the material, ultimately creating the stitch. The **Class 200—Hand Stitch,** illustrated in Figure 24b and known as Type 201, is made by hand, utilizing one or more needle threads. Its distinctive trait involves each needle thread moving across the material as an independent thread line, securing the stitch either by this single thread line weaving in and out of the material or by the threads forming loops within themselves. When multiple threads are utilized, they traverse the same perforation in the material. The **Class 300—Lock Stitch** type, illustrated in Figure 24c and known as Type 301, is produced by utilizing two or more sets of threads and is primarily characterized by the interweaving of these two groups. Loops from the first group are threaded through the material and then anchored in place by the thread or threads from the second group, ultimately resulting in the formation of a stitch. The **Class 400—Multi-Thread Chain Stitch,** illustrated in Figure 24d and known as Type 401, is created by using two or more groups of threads and is distinguished by its general characteristic of intertwining and inter-looping the loops from these two groups. The loops and threads from the first group are threaded through the material and are firmly tied by interweaving and inter-looping with the loops from the second group, resulting in the formation of a stitch. The **Class 500—Overlock Stitch,** illustrated in Figure 24e and known as Type 504, is composed of one or more sets of threads and is primarily characterized by loops from at least one group of threads encircling the material's edge. Loops from one group of threads are passed through the material and are anchored in place through self-intra-looping before subsequent loops pass through the material. Alternatively, they may be secured through inter-looping with loops from one or more other inter-looping groups of threads, followed by the subsequent threads from the first group passing through the material. The **Class 600—Covering Chain Stitch,** illustrated in Figure 24f and known as Type 601, consists of three sets of threads. Its key feature involves one set of threads spanning the butted join on the fabric's front, while the second set spans the butted join on the fabric's back. The connection between these two sets is established through the fabric by a third group, which consists of the needle threads [105].

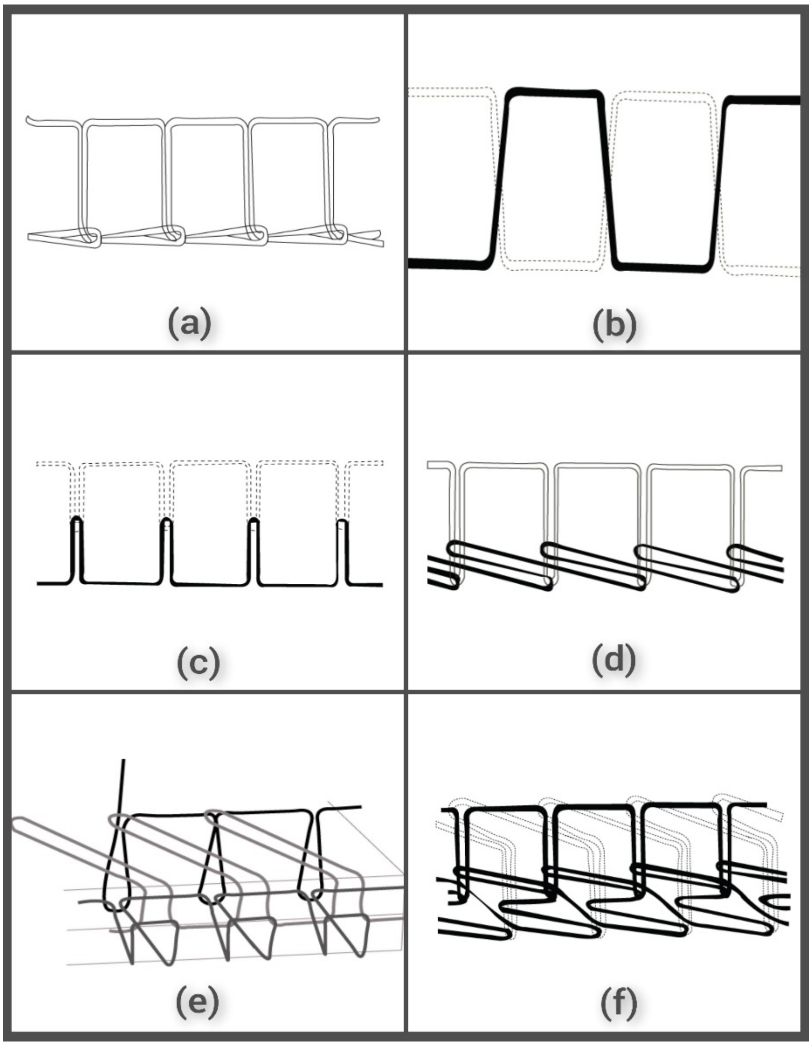

Figure 24. Stitch classes: (**a**) Class 100—Chain Stitch, (**b**) Class 200—Hand Stitch, (**c**) Class 300—Lock Stitch, (**d**) Class 400—Multi-Thread Chain Stitch, (**e**) Class 500—Overlock Stitch, (**f**) Class 600—Covering Chain Stitch.

4.13.1. Mathematical Model for Prediction of Seam Strength

In 2012, Belkis Zervant Unal developed a mathematical equations model for predicting the seam strength of denim fabrics. Researchers analyzed the effects of sewing parameters, such as thread type, stitch density, and number of sewing threads, on seam strength and used regression analysis to predict weft and warp seam strengths before beginning actual production. Four different denim fabrics with varying properties were selected as samples and subjected to prewashing treatments; seam strength tests were conducted according to the ASTM standard testing method. The validity of the equations was tested by calculating seam strength values for denim fabrics with different properties and comparing them with experimentally measured values. A high correlation was found between the calculated values and the measured values, supporting the validity of the equations [106].

4.13.2. Logic Expert System for Prediction of Seam Strength

In 2021, Joy Sarkaar and Mohd Abdullah used a fuzzy logic expert system to develop a prediction model for the seam strength of denim garments. The researchers explained the importance of seam strength in denim garments and the factors that affect it, such as thread linear density and stitches per inch. The fuzzy expert system was developed to provide a decision-making tool for setting proper seam strength in the superimposed seams of denim garments. It consisted of four major components: fuzzification interface, rule bases, decision-making logic, and defuzzification interface. Two variables, tex and SPI, were used as the input parameters, and seam strength was used as the output parameter for the construction of the fuzzy logic system. Both experimental and predicted results were compared. The determination coefficient yielded a value of 0.98, indicating a high level of explanatory power in predicting seam strength for denim garments. Additionally, the mean relative error falls within acceptable limits, further affirming the model's strong performance in predicting seam strength for denim garments [107].

Proper seam strength is essential to ensure that seams can withstand the stresses and forces they will encounter during the daily use of apparel products. The seam strength of apparel products depends on several factors, including fabric GSM, stitch density, sewing thread type, and sewing thread count, as explained earlier. A mathematics computational model, based on artificial intelligence and advanced machine learning algorithms, can be developed that can accurately predict the seam strength of apparel products considering these factors. A mathematics computational model is a mathematical representation or algorithm that uses numerical methods and computer simulations to solve complex real-world problems. These models involve the application of mathematical concepts to analyze and predict outcomes, making them invaluable tools in various fields, including engineering, science, finance, and manufacturing. AI-based mathematics computational models can be used to simulate sewing operations to optimize seam placements, sewing machine settings, and sewing path planning for efficient and high-quality production, and to predict the seam strength of garments, concerning all the factors that influence seam strength.

This study is related to the seam strength of five-pocket denim pants. In the manufacturing of five-pocket denim pants, flat seams and overlock seams are preferred for their durability and ability to withstand the stresses of everyday wear. AI-based mathematics computational models can help manufacturers in optimizing the design of seams and the selection of materials. By inputting parameters, such as fabric type, thread type, and stitch density, the model can suggest ideal combinations that meet the desired strength requirements. It can help manufacturers to predict and analyze the seam strength of different seams that will be used on denim pants before starting the actual production of denim pants at mass level. By predicting seam strength, manufacturers can avoid costly trial and error during production. They can select the most cost-effective materials and seam configurations that meet quality standards, reducing material wastage and production costs. It can help them to identify potential weaknesses in seam strength early in the design phase, reducing the risk of seam failures in the final product.

5. Future Trends

Envisioning the trajectory of computational models for predicting seam strength in five-pocket denim jeans based on cellulosic polymer reveals a dynamic landscape with several discernible future trends. One key trend anticipates a more profound integration of advanced machine learning techniques, particularly delving into the realms of deep learning and neural networks. This type of evolution, based on ANN, will support and enhance the accuracy and efficiency of seam strength predictions by allowing models to discern intricate patterns and relationships within vast and diverse datasets. The ANN is very important and one of the most effective AI tools. Beyond the multi-layer perceptron, as mentioned in Figure 25, ANNs encompass convolutional and recurrent networks optimized for computer vision and sequence modeling tasks. Additionally, the future of predictive modeling appears geared towards the incorporation of multi-dimensional data. While traditional parameters such as stitch density and fabric GSM remain crucial, upcoming models are likely to broaden their scope to include factors like environmental conditions, wearer behavior, and real-world usage scenarios, providing a more holistic understanding of seam performance. Ensuring the longevity and quality of clothing is crucial for producers, designers, and consumers in the current clothes industry. Seam strength is a critical component of garment quality that directly affects the wearability and durability of clothes, especially pants. The creation of an artificial intelligence (AI) model for forecasting the strength of a pant seam has great potential to improve production procedures, raise product standards, and satisfy customers. The process of model construction begins with data collection. Analyzing these data with methods like the z-score and the interquartile range helps to identify outliers. Removing these outliers cleans the data for further processing. The linear dependence among predictors, quantified by linear correlation, can significantly impact the performance of artificial neural network (ANN) models. When predictors exhibit high correlations, reducing the data's dimensionality can enhance the efficiency of ANN models. Beyond basic multi-layer perceptron neural networks, more advanced ANN architectures such as convolutional neural networks (CNNs) and generative adversarial networks (GANs) exist. CNNs have demonstrated exceptional performance in tasks like image recognition. Specifically, in the context of denim fabrics, CNNs can significantly contribute to assessing structural integrity, texture, and weaving patterns. They can predict seam strength by evaluating material quality, thus identifying potential weaknesses prior to the commencement of the manufacturing process [108,109]. Conversely, in scenarios where acquiring real-world data is prohibitively expensive, GANs are at the forefront of generating synthetic data for training AI models [110,111]. The integration of AI models with big data is transformative [112,113]. Big data enable the consideration of an extensive array of variables affecting seam strength, including environmental factors, material characteristics, and historical performance data. In practical applications, reinforcement learning algorithms can optimize the manufacturing process through continuous feedback. AI models are instrumental in determining the optimal settings for each fabric type and design by predicting the impact of various sewing parameters on seam strength. This approach helps to reduce waste and enhance efficiency [114,115]. Thus, AI plays a crucial role in maintaining the quality of denim products, from the selection of raw materials to final garment production [116,117]. In this research, we present a complete framework that makes use of industry knowledge and machine learning techniques to develop such a model.

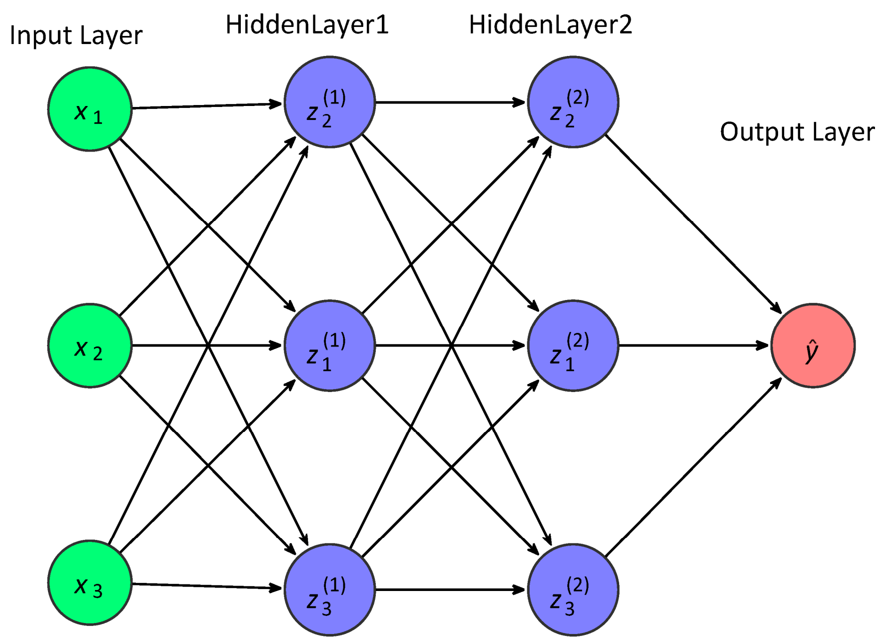

Figure 25. Artificial neuron model.

1. Data Collection and Preprocessing

To begin building our AI-based model, we must first collect a representative and diversified dataset that includes details on the several parameters affecting trousers' seam strength. Variables including fabric type, thread type, seam type, stitch density, and seam strength measures are included in this dataset. Strict data preprocessing methods are used to ensure the quality and dependability of the dataset by cleaning, normalizing, and encoding categorical variables. Furthermore, an attempt is made to achieve dataset balance in order to effectively represent the variability that exists in actual clothing manufacturing.

2. Feature Selection and Engineering

Next, from the dataset, pertinent features that are probably going to influence seam strength are carefully chosen. These characteristics could include seam construction methods, fabric type, stitch density, and thread type. Moreover, new features that capture intricate relationships and interactions between variables are created via feature engineering. This procedure uses additional information obtained from the data to improve the model's capacity to forecast seam strength.

3. Model Selection

Selecting the right machine learning methods is essential to getting precise seam strength estimates for pants. Regression methods such as random forest, gradient boosting machines (GBM), support vector regression (SVR), and neural networks are evaluated according to how well suited they are for the given dataset and situation. To find the best-performing strategy, various algorithms are tested, and models are assessed using cross-validation techniques.

4. Training and Validation

To train the chosen model and evaluate its efficacy, the dataset is divided into training and validation sets. The training data are used to train the model and to maximize performance; grid search or random search methods are used to fine-tune the hyperparameters. The performance of the model is then assessed using the validation data and suitable regression assessment measures, including mean squared error (MSE), root mean squared error (RMSE), or r-squared (R2) score.

5. Model Evaluation

To determine the trained model's efficacy and accuracy in forecasting pants seam strength, a thorough evaluation is conducted. To improve predictive capabilities, performance analysis is conducted, and feature selection, engineering, and model tuning are repeatedly improved as needed.

6. Deployment and Integration

The model is launched into production as an API or integrated into a software program for easy accessibility once its performance satisfies predetermined requirements. To aid in the comprehension and use of the model in practical situations, users are furnished with extensive documentation and support.

7. Continuous Improvement

The work involved in creating an AI-based model to forecast trousers' seam strength is ongoing and aims to be better every time. To find areas for improvement, the model's performance is tracked over time and user input is gathered. Additionally, the model is periodically retrained using updated data to enhance accuracy and adjust to changes in the market.

However, in the garment manufacturing industry, the integration of AI poses several limitations and risks that warrant careful consideration. One significant risk is the potential displacement of human labor, leading to job loss and socioeconomic impacts, especially in regions heavily reliant on the textile industry for employment. Additionally, the complexity of AI systems and algorithms introduces the risk of errors or biases in decision-making processes, which could result in defective products or compromised safety standards. Furthermore, the reliance on AI for various tasks, such as design optimization or supply chain management, may create vulnerabilities to cyber threats and data breaches, compromising sensitive information and intellectual property. The challenge of imitating human workers' complex decision-making abilities, especially in jobs demanding imagination, intuition, and subjective judgment, is one of AI's limitations in the apparel business.

While AI algorithms are great at processing massive amounts of data and conducting repetitive activities, they could have trouble with complicated visual or tactile judgments, like choosing fabrics or fitting clothes, which largely depend on human senses and aesthetic sensibilities. Furthermore, adopting AI technology in the apparel industry necessitates a substantial upfront investment in software development, infrastructure, and training for staff members, which could present difficulties for smaller businesses or those located in less technologically developed areas. Furthermore, biases or errors in training data might provide less-than-ideal results or reinforce already-existing inequities in the business. AI systems are only as good as the data they are taught on. As a result, even if AI presents many chances for innovation and efficiency in the clothing industry, its proper and moral application depends on identifying and resolving these constraints. Addressing these risks requires comprehensive risk assessment frameworks, transparent deployment practices, and ongoing monitoring and regulation to ensure responsible AI implementation in the garment manufacturing industry.

6. Conclusions

In the era of the industrial revolution 4.0 and 5.0, artificial intelligence is increasingly being integrated into the fields of management science and operational research. It can be used in all fields of life, especially in the textile and polymer industry, which fulfills the second largest need of human beings. AI-based tools can be used to enhance the production, quality, and accuracy level of products. Moreover, these tools can be used for manufacturing, testing, inspection, and evaluation of the products. In this study, the authors tried to present the future trends for research on AI-based studies. The authors focused on and introduced the best tool for the evolution of seam strength, and a prediction model which is likely to embrace continuous learning and adaptability. This type of model may refine their predictions over time, incorporating feedback from the actual performance of garments and adjusting parameters based on evolving industry standards and consumer expectations. Overall, these future trends signal a dynamic and exciting future for the intersection of ANN modeling for seam strength prediction and the production of five-pocket denim jeans based on cellulosic polymer. An ANN-based model will support and enhance the accuracy and efficiency of seam strength predictions by allowing models to discern intricate patterns and relationships within vast and diverse datasets. In the garment manufacturing industries, there are many risks associated with the integration of AI, one very significant risk being job loss for human beings, which involves huge potential displacement, among other risks. It requires comprehensive risk assessment frameworks, transparent deployment practices, and ongoing monitoring and regulation to ensure responsible AI implementation in the garment manufacturing industry.

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