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Review

Machine Learning, Mechatronics, and Stretch Forming: A History of Innovation in Manufacturing Engineering

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Abstract: This review focuses on the complex connections between machine learning, mechatronics, and stretch forming, offering valuable insights that can lay the groundwork for future research. It provides an overview of the origins and fundamentals of these fields, emphasizes notable progress, and explores the influence of these fields on society and industry. Also highlighted is the progress of robotics research and particularities in the field of sheet metal forming and its various applications. This review paper focuses on presenting the latest technological advancements and the integrations of these fields from their beginnings to the present days, providing insights into future research directions.

Keywords: autonomous mechatronic system; processing precision; flexible manufacturing systems; digital processing; fracture prediction; self-organizing manipulators

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1. Introduction

The complexity of machine learning, mechatronics, and stretching forming is well known. Combining them was, is, and will be a necessity as they are closely interconnected disciplines within the field of manufacturing. It is a fact that in any industry, high productivity is achieved with the use of automated manufacturing processes. Intensive work was conducted throughout the year, and extraordinary techniques, equipment, and processes were upgraded or developed. Nevertheless, there are still issues that require optimal solutions.

The purpose of this review is to present the beginnings, evolution, and interpenetration of the domains in question. At the same time, this work aims to present a significant part of the research and implementation work as industrial solutions to the various elements that make an autonomous mechatronic system capable of conducting a stretch-forming process. This paper aims to answer questions such as what types of machine learning algorithms are used and in which fields; what are the mechatronic components capable of providing the necessary processing precision; and how can the internal state of tension be understood and predicted within the process of stretch forming? Therefore, knowing the origins and development of each process is essential to grasping their interconnection. This review will look back in time to highlight, as much as possible, the chronological development of each field, as the title suggests.

This review does not provide an in-depth analysis of each field, as there are already numerous scientific works available for each of them. The analysis of the three fields in this work focuses on their interrelationships, intending to present aspects that can serve as a foundation for further research and exploration. Of course, for some research papers,

we provide a comprehensive analysis, while others may be presented in a more concise manner, such as through the use of tables or figures.

Sections 2 and 3 are structured in three subsections, which present the origins and basics of machine learning, mechatronics, and stretch forming. Section 2 highlights the most significant progress that has been made through a series of essential advancements, while Section 3 deals with the advances made after the period presented in the previous section. As the years passed, numerous advancements were made, and this review will provide a classification for each domain. In this third section, the selected scientific studies presented, while not all being directly related to the proposed domains, are considered useful for understanding how ideas can transcend one industry to another. The main topics that are found in these sections are as follows:

- In the case of machine learning, the topics analyzed in this subsection focus on various algorithms, including rough set theory, learning methods, reinforcement learning, fuzzy logic systems, neural force control frameworks, artificial evolution simulations, neural networks, genetic algorithms, pattern recognition, AI in transportation, machine learning's impact on society and industry, the complexity of ML systems, brain–computer interfaces, humanoid control, structural component design, metaheuristics, mineral resource estimation, deep learning frameworks, automatic defect detection in infrastructure, quality inspection in manufacturing, software quality and ML, defect recognition on steel surfaces, and AI implementation challenges;
- In the case of mechatronics, being multidisciplinary, this subsection focuses on various aspects such as robotics research and development, 3D noncontact sensor systems, self-organizing manipulators, collision behavior simulation, robot navigation, robot control and learning techniques, cooperative mobile robotics, motion planning techniques, controllers for acrobots, real-time, hierarchical, sensor-based robotic system architecture, plan-n-scan, and a constructive control approach for legged robots. It also explores disruptions in multi-robotic systems and the development of reconfigurable machines;
- The subsection related to stretch forming focuses on topics about various aspects of sheet metal forming, including material properties and the use of flexible manufacturing systems, the development, and usage of finite element method software, digital processing for sheet forming, fracture prediction, and optimization of process parameters. Additionally, this study explored the formability of aluminum, titanium, and steel alloys and the design of vertical wall manufacturing.

Section 4 highlights the recent technological advancements over the past 5 years, focusing on the work that specifically points out the interrelated nature of machine learning, mechatronics, and stretch forming. It is interesting to follow the route that has been paved up to this moment to observe how each field has evolved and also how they have become intertwined. The fourth section focuses on the merger of these domains and highlights the complexity of the current systems and how they got here. In addition, it presents a comprehensive explanation of the behavior of these systems when advanced algorithms are applied to the data measurement, processing, and control of the industrial processes that it serves.

The next section presents future research directions, while Section 6 presents the discussions and conclusions.

2. Basics and Beginnings

This section presents the history of machine learning, mechatronics, and stretch forming from the beginning to 2010.

In today's context, artificial intelligence and advanced mechatronics systems are not something intangible. But for this to happen, complex algorithms and high-end mechatronic components are needed so that a system can offer solutions in real time. Discussing in this context, real-time actions attributed to a process that uses the properties of the material and process parameters, there must always be a correlation between the input data and

the control algorithm; therefore, the introduction of elements from the area of machine learning, mechatronics, and stretch forming is essential.

2.1. Machine Learning

Machine learning, as shown in Figure 1, is the branch of artificial intelligence [1] that deals with creating systems that can learn from data and perform tasks such as classification, regression, clustering, anomaly detection, and reinforcement learning [2,3].

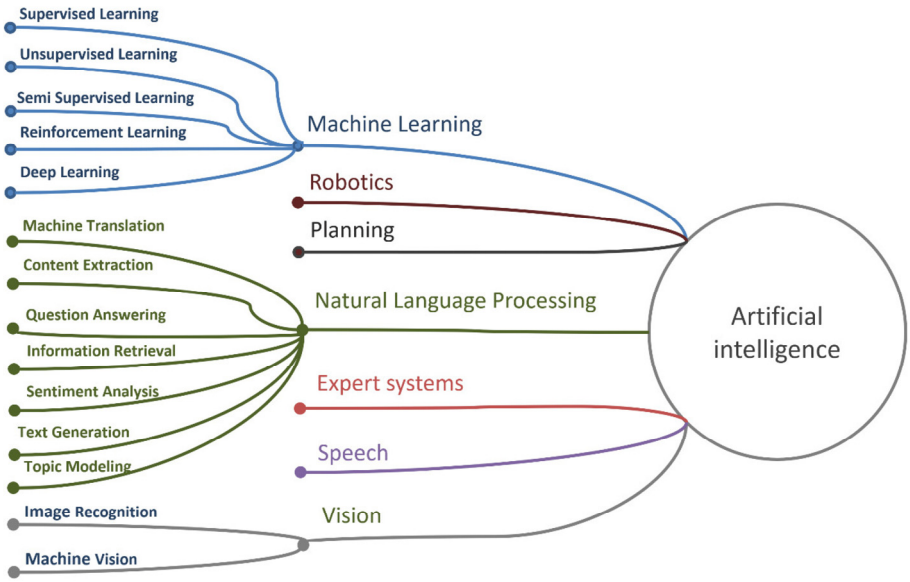

Figure 1. Artificial intelligence subsections [1].

Machine learning has a long and rich history dating back to the mid-20th century when researchers began to explore the possibility of simulating human intelligence and learning with machines. The creation of the first artificial neural network, a mathematical model that drew inspiration from the structure and operation of biological neurons, was one of the earliest achievements in machine learning. In 1943, Warren McCulloch and Walter Pitts proposed a simple neural network with electric circuits that could perform logical operations. They showed that a network of neurons could compute any logical function, laying the foundation for later research on neural computation [4]. Another pioneer in machine learning was Alan Turing, who proposed a test to measure the intelligence of a machine in 1950. The Turing test involved a human interrogator who had to distinguish between a human and a machine based on their responses to questions. Turing also suggested that machines could learn from experience and improve their performance over time [5]. In 1952, Arthur Samuel created one of the first self-learning programs, a computer program that could play checkers. Samuel used a technique called alpha–beta pruning to reduce the number of possible moves and a scoring function to evaluate the board positions. He also implemented a method of reinforcement learning, where the program learned from its own mistakes and improved its strategy by playing against itself [6]. In 1957, Frank Rosenblatt introduced the "Perceptron", a type of neural network that could learn to classify patterns. The Perceptron consisted of an input layer, an output layer, and adjustable weights that connected them. Rosenblatt devised a learning algorithm that updated the weights based on the errors made by the Perceptron. He proved that the Perceptron could learn to recognize simple shapes and letters [7]. In 1967, Peter Hart, Nils Nilsson, and Bertram Raphael developed the nearest neighbor algorithm, a simple but effective method for classification and regression. It is still widely used today for various applications such as image recognition, recommendation systems, and anomaly detection [8]. In 1974, Paul Werbos proposed the backpropagation algorithm, a powerful technique for training multilayer neural networks. The algorithm involved calculating the error at the output layer

and propagating it backward through the network, adjusting the weights accordingly. The backpropagation algorithm enabled neural networks to learn complex nonlinear functions and solve problems that were beyond the capabilities of simpler models [9]. In 1979, Hans Moravec and his team at Stanford University built the Stanford Cart, a self-driving robot that could navigate through obstacles using a camera and a computer. The Stanford Cart used a machine vision system that processed images and generated commands for steering and speed. The Stanford Cart was one of the first examples of machine learning applied to robotics [10]. However, despite these achievements, machine learning faced several challenges and limitations in the following decades. However, overcoming these challenges led to periods of reduced funding and interest in machine learning, known as AI winters [11]. Machine learning research slowed down significantly during these periods until breakthroughs and developments revived it [12].

Rough set theory, introduced by Z. Pawlak in 1982, involves acquiring rules from an information system, which is like a database. This approach falls under the category of learning methods from examples and establishes the taxonomy of expert classifications based on rough set theory [13,14]. In 1988, L. Pau, in the article "Sensor Data Fusion", presented various approaches to representing knowledge in the context of sensor fusion problems. The methods analyze external context information to create a representation, determining if two representations correspond to the same object or entity, combining sensor-based features from multiple representations to generate new attributes, and merging the representations into a unified fused representation. The relevance of sensor fusion arises from the understanding that by combining various sources of information, one can attain enhancements in control law simplicity and robustness, along with improved classification outcomes [15]. V. Tourassis introduced a model-based robot control algorithm in the same year; it provided a combination of discrete time and continuous time implementations for real-time evaluation of robot dynamics. The paper presented a systematic approach to analyzing model-based algorithms and predictors in discrete time, aiming to address inaccuracies caused by modeling and discretization. They proposed to include an additional supervisory module to monitor performance and adjust the command signal as needed. Based on the research simulation experiments, it has been confirmed that predictors that look one step ahead tend to exhibit more consistent performance. These predictors are particularly suitable for trajectory-tracking applications [16].

R. Shoureshi et al. discussed the results of their research on developing an assembly automation system for an automated work cell. This system, first introduced in 1989, integrates a control scheme, a vision module, and an online trajectory planner. The automation system showcases the seamless integration of vision and feedback control, real-time functionality, compensation for uncertainties, and the capability to recover from errors [17]. In 1991, a research paper titled "An Intelligent Controller for process automation" by V. Badami et al. presented a supervisory controller known as the Meta-Controller (MC), which integrates procedural and rule-based language. The system is specifically engineered to effectively manage sensor interruptions in real time, even when they occur at varying intervals. The Meta-Controller utilizes plans to arrange the steps of crystal growth, presented in a structured English-like format that operators can easily follow. The program is capable of promptly handling sensor interruptions and issuing commands to a real-time controller module. The Meta-Controller's language explicitly incorporates the notion of time [18].

In 1993, H. Kang and G. Vachtsevanos introduced a new tool for intelligent control and identification. This tool utilizes fuzzy set theory and fuzzy associative memories, providing a fresh approach to the field. The system first acquires a knowledge base through approximation learning and then applies this information for identification and control using fuzzy inferencing. This architecture is similar to a well-established approach where memory-related rules are stored in a disjunctive manner. Complex and highly nonlinear systems that are influenced by ambiguity, uncertainty, and incomplete data can be effectively addressed using fuzzy hypercubes [19].

In 1994, C. Wu proposed a technique that employs a sensor-based fuzzy algorithm to navigate a mobile robot through a two-dimensional environment with stationary polygonal obstacles. The sensors analyze the robot's initial position and choose the one with the highest priority. The robot is directed along the line segment that connects these two points, making consecutive navigation decisions until it reaches the destination point [20]. One year later, in 1995, F. Janabi-Sharifi developed a framework that utilizes artificial neural networks (ANNs) to identify collisions in robotic tasks. This framework provides a fast and reliable method for identifying collision attributes. The ANNs are trained using simulation results to generate training data. An architecture based on artificial neural networks was developed to reduce training time and improve accuracy. The test results reveal the successful performance of the collision identification system presented in this study [21].

By 1997, S. Brown and K. Passino conducted a study on controllers designed to enhance the performance of the acrobot. The acrobot is a mechanical device that mimics the movements of a human acrobat hanging from a bar. The objective of the study was to develop intelligent controllers that could assist the acrobot in swinging up to an inverted position and maintaining balance with its hands on the bar. Two genetic algorithms have been developed to optimize the performance of the balancing and swing-up controllers [22]. The effective control of manipulators relies heavily on various factors, including the speed of motion, the configuration of the manipulator, and the desired acceleration. This relationship is non-linear and requires the implementation of intricate control strategies. In 1997, J. Pons et al. introduced the Nonlinear Performance Index (NPI) as a useful tool for identifying and quantifying nonlinear effects that occur during the movement of a manipulator. During the design phase, the NPI can be utilized to analyze and address unwanted nonlinear effects in general motion. Additionally, it can be employed during trajectory planning to identify paths that allow for more precise control [23].

In 1998, O. Buckmann et al. proposed an application platform that enables the development and testing of mobile robot units. The platform consists of various modules, such as a neural network simulator, a simulation and off-line programming system, optical sensor components, a rapid prototyping system, and an experimental work cell. This specialized publication focuses on various aspects of robot development and shows potential for use in healthcare applications [24]. By the same year, Y. Pao examined the viability of employing Rumelhart semi-linear feedforward connectionist networks to learn and implement intelligent system control. The findings indicate that these networks naturally develop redundancy, leading to a distinctive holographic characteristic and a gradual decline in performance due to internal damage [25]. In the same year, C. Ribeiro published the results of a study conducted on temporal differences methods as useful tools for reinforcement learning. Since they are stochastic adaptive algorithms, they often require extensive exploration of the state–action space before reaching convergence. The results demonstrate that the resulting variants can achieve impressive performance when a careful balance is struck between leveraging prior imprecise knowledge and exercising caution in utilizing learning experience [26]. Another approach at the time was the development of fuzzy systems, widely used in industry and science. Neuro-fuzzy systems, which combine fuzzy systems with neural network learning techniques, have been widely used according to A. Nürnberger, D. Nauck, and R. Kruse's work back in 1999. With the help of a reinforcement learning algorithm, neuro-fuzzy systems like the NEFCON model could acquire knowledge and improve the ruleset of a Mamdani-like fuzzy controller in real time [27]. In 1999, T. Lin and S. Tzeng proposed a neural force control framework, which consists of a high-level control system that employs a neural network and a pre-existing motion control system of a manipulator. The neural network takes in inputs consisting of the error in contact force and the estimated stiffness of the touched environment. It then generates outputs in the form of position commands, which are used by the position controller of industrial robots. For object manipulation, the framework has been tested effectively with dual-industrial robot systems and a variety of contact motions [28].

A new conceptual approach for addressing the local navigation and obstacle avoidance problem in industrial 3-dof robotic manipulators was proposed in the year 2000. This approach was based on fuzzy logic. The system proposed by P. Zavlangas and S. Tzafestas is divided into distinct fuzzy units, with each unit responsible for controlling a specific manipulator link. The fuzzy rule base combines a repelling effect determined by the distance between the manipulator and nearby obstacles with an attractive effect based on the angular difference between the actual and final manipulator configuration. This approach has proven to be effective in controlling manipulators in different simulated workspace environments, leading to the generation of paths that are free from collisions [29]. Complex autonomous learning systems often consist of multiple interacting modules or agents, which can be overwhelming and impede debugging. In the same year, a research paper authored by K. End et al. introduced the layered learning system architecture (LLS), which offers various advantages, including incremental development and testing, simplified debugging, and facilitated progressive upgrading. An experiment was conducted to demonstrate the principles of LLS. A hexapod robot was created with the main goal of achieving the highest possible walking speed without any instances of falling [30]. The complex nature of humanoid robots makes traditional analytical methods insufficient for control. Learning techniques are valuable tools for controller design in situations where analytical knowledge is limited. They play a crucial role in achieving complete autonomy in humanoid systems.

In 2001, M. Lee and H. Rhee conducted a study on the utilization of learning behavior in artificial evolution simulation and its impact on the efficiency of evolution. The paper discusses the introduction of learning behavior at the individual level, which has been found to result in accelerated evolution and improved effectiveness in complex environments. The course of evolution is not dependent on learning, and reinforcement learning can influence the patterns of evolution. As a result, artificial life techniques have the potential to be utilized in a wide range of fields [31].

In 2002, S. Vijayakumar et al. published a study that demonstrated the effective use of nonparametric regression and locally weighted learning techniques in solving complex learning problems with high-dimensional data [32].

In 2004, C. Loo et al. conducted a study on the implementation of Active Force Control (AFC) as a control concept for robots. The problem of unidentified friction in the robotic arm is tackled by AFC through the direct measurement of acceleration and force. A neural network known as the growing multi-experts network (GMN) has been developed to estimate the inertia matrix of the robot. The size of the network is adjusted dynamically using a mechanism that allows it to grow and prune as needed. This mechanism ensures that the network performs optimally and has a strong ability to generalize. By utilizing Active Force Control (AFC) and generalized minimum norm, the accuracy of velocity and position tracking is significantly improved, even when the robot's joints experience friction. The embedded generalized minimum norm enables real-time estimation of the inertia matrix, resulting in enhanced performance of the AFC controller. The efficacy and robustness of this novel hybrid neural network-based AFC scheme are showcased through experiments conducted on a two-link articulated robot and a simulated two-degree-of-freedom system [33].

In 2006, B. Samanta et al. made significant advancements in their research paper titled "Artificial neural networks and genetic algorithm for bearing fault detection". They conducted a comprehensive analysis comparing the effectiveness of three distinct types of artificial neural networks (ANNs) in identifying faults in bearings. The study analyzes vibration signals from a rotating machine, comparing those from machines with normal and defective bearings. These signals were then used as inputs for three artificial neural network (ANN) classifiers in a two-class recognition task. Genetic algorithms (GAs) were used to determine the characteristic parameters of the classifiers and the input features [34].

It is important to highlight that extensive work has been conducted in other domains, such as economics, from which the manufacturing sector took advantage. The concept of

rationality holds great importance in the field of economics. Ariel Rubinstein proposed a method to represent bounded rationality by explicitly outlining the decision-making processes of individuals [35]. In 2008, E. Tsang published a paper titled "Computational Intelligence Determines Effective Rationality", where he takes a computational perspective on Rubinstein's approach. Tsang suggests that the agent's level of effective rationality is influenced by its computational capacity. This perspective on bounded rationality enables the examination of economic systems from a computational perspective, even when the assumption of complete rationality is relaxed [36].

In a paper published in 2009, L. Doitsidis et al. discuss the process of selecting fitness function parameters in the evolution of fuzzy logic controllers for mobile robot navigation. The paper, titled "Evolution of Fuzzy Controllers for Robotic Vehicles: The Role of Fitness Function Selection", provides valuable insights into this topic. Many fitness functions are selected based on empirical evidence and specific tasks, making them highly dependent on the choice of the function. A comparison was made between three different types of fitness functions to assess their impact on the navigation performance of a real robot controlled by fuzzy logic. In this study, genetic algorithms were used to evolve membership functions, and a new efficiency measure was introduced to systematically analyze and benchmark the overall performance [37].

2.2. Mechatronics

Mechatronics is a multidisciplinary domain [38] that integrates mechanical engineering, electrical engineering, computer science, and control engineering to develop and construct systems that encompass both physical and computational elements [39]. As can be noted from Figure 2, the design and implementation of a robotic arm are subjected to disciplines such as kinematics, dynamics, digital control, computer-aided design, industrial automation, and advanced manufacturing [38].

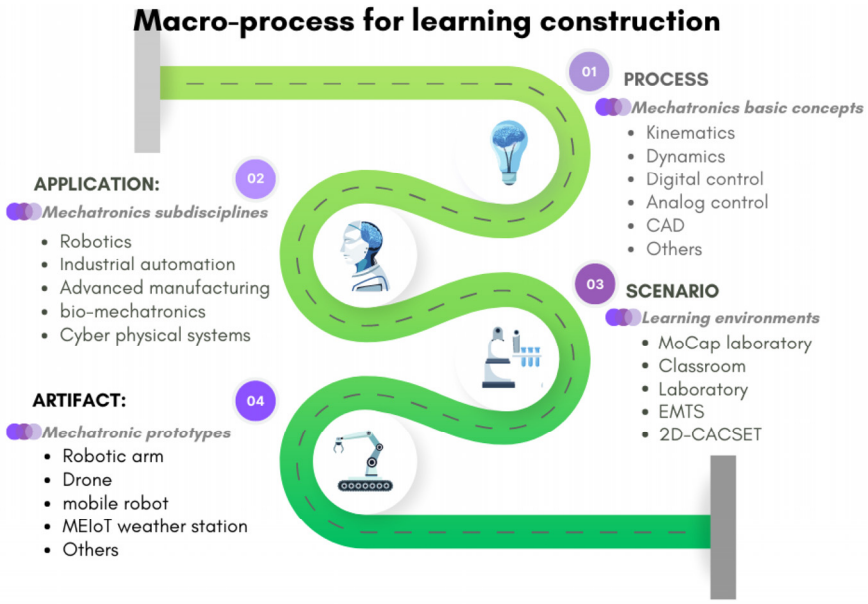

Figure 2. Extended education framework for mechatronics proposed by E. Lopez et al. in 2023 [38].

The history of mechatronics can be traced back to the 1960s when the term was first coined by Tetsuro Mori, an engineer at Yaskawa Electric Corporation in Japan. The term was registered as a trademark by the company from 1971 to 1982 and then released to the public [40]. Mechatronics was initially a fusion of mechanics and electronics but later expanded to include other disciplines as technology advanced. One of the early applications of mechatronics was robotics, which involved the integration of mechanical structures, electronic circuits, control systems, and software [41]. Robotics evolved from

simple and rigid machines to complex and flexible ones, with improved coordination, feedback, and intelligence. Robots are complex systems that combine mechanical actions with interactions with humans or other systems [42]. Mechatronics also contributed to the development of other products and systems, such as vending machines, auto-focus cameras, door openers, anti-lock brakes, photocopiers, disk drives, and more [43]. It is now a multidisciplinary field that covers various domains of science, technology, engineering, and industry and has enabled the creation of smart and innovative devices that can perform multiple tasks and adapt to different environments. It has enhanced the quality, efficiency, and reliability of products and systems, as well as reducing their cost and size. Mechatronics continues to be a dynamic and growing field that offers new challenges and opportunities for engineers [42–47].

In 1988, T. Fukuda and S. Nakagawa introduced a dynamically reconfigurable robotic system (DRRS) that provides enhanced flexibility and adaptability for varying working environments, surpassing the limitations of traditional robots with fixed shapes and structures. DRRS has found applications in a wide range of fields, including maintenance robots, advanced working robots, free-flying service robots in space, and more advanced flexible automation [48]. One year later, in 1989, K. Valavanis and P. Yuan presented a methodology in their paper titled "Hardware and Software for Intelligent Robotic Systems" that focused on designing intelligent robotic systems with three interactive levels. The expert system represents the organization level, while the loosely coupled parallel processing system represents the coordination level. The execution level is represented by specific hardware components. The overall system hardware configuration is accomplished through the utilization of microprocessor-based configurations and discrete logic design techniques. The methodology employed in this study ensures the preservation of the system's hierarchical structure while also providing a practical demonstration of its feasibility through a detailed case study [49].

In a research study published in the 1990s, B. Siciliano presented a tutorial on the kinematic control of redundant robot manipulators. The paper offered an intriguing approach to the subject and provided a comprehensive overview of the latest research in controlling redundant robot manipulators with a focus on kinematics. The study aimed to present a global review of commonly employed online control techniques. These techniques encompass utilizing the manipulator's Jacobian, optimizing objective functions within the Jacobian's null space, incorporating additional constraint tasks in the task space (with task priority), and constructing inverse kinematic functions [50].

In 1992, M. Megahed presented a streamlined analytical method for solving the inverse kinematics of a spherical wrist robot arm. This approach divides the problem into two more manageable sub-problems: one concerning the arm's fundamental structure and the other regarding its hand. The proposed approach is used to derive inverse kinematic position models for two different types of robot arms: one that consists solely of revolute joints and another that combines revolute and prismatic joints [51].

In 1992, J. Fiala and A. Wavering conducted a study on the programming of Cartesian stiffness in Cartesian servo control algorithms without the need for explicit force feedback. The study showcases the effectiveness of Cartesian servo algorithms in providing programmability and accurate replication of stiffness across a wide range. These algorithms make use of the transpose of the Jacobian and model-based gravity compensation, resulting in convenient and precise outcomes [52].

A different method for determining the generalized velocities of a robotic manipulator is through the use of a simple asymptotic observer. Proposed in 1993 by S. Nicosia et al., this study provides valuable insights into the stability analysis of error dynamics, employing the singular perturbation theory. The algorithm's accuracy is proven through simulation runs and confirmed by experimental tests [53].

In 1993, E. Castro et al. presented an advanced real-time control system for a robotic filament winding production unit. This system is constructed using a multiprocessor architecture comprising four pressure boards. The system employs a hierarchical control

structure, with task specification taking place at the highest level and robot and winder set point tracking being carried out at the lowest level. The study presents the latest empirical findings on pipe fittings with cylindrical, elbow, and T-shaped designs [54].

In 1994, M. Amirate et al. presented an innovative 3D noncontact sensor system. This system was designed to precisely determine the position and orientation of a robot's end effector. The paper introduces a system that utilizes a unique arrangement of four spheres along a tetrahedral axis, along with three cameras positioned orthogonally. This system is designed for robot applications and aims to provide accurate three-dimensional measurements. The technology has been utilized in two experiments to fine-tune a parallel robot and validate the effectiveness of geometrical control. In a given time frame of 100 ms, the system can accurately determine the position and orientation of the tetrahedron. It achieves an impressive level of precision, with an accuracy of 0.6 mm and 0.2 degrees. This remarkable performance is achieved within a workspace that measured 0.3 m on each side [55].

In 1995, G. Xue et al. proposed the construction of a self-organizing manipulator (SOM) using active sensing. This procedure involved the placement of a six-axis force/torque sensor in the wrist of one manipulator and a CCD camera in the hand of another manipulator. The system aimed to replicate the operation of a human by combining a visual system, a manipulator, and a force/torque sensor into a unified hand–eye working system [56]. In the same year, in his paper titled "A three-dimensional machine-vision Approach for Automatic Robot Programming", D. Tsai explored the representation and simulation of collision behavior in manipulators. This study focused on analyzing collision attributes, such as the properties of the contact surface and the structure of the objects involved in the collision. The simulation results are used to highlight the collision characteristics that affect collision behavior and examine how they affect the safety and performance of the manipulator in its work environment [57].

Another innovative approach for that time was the research conducted by S. Ratering and M. Gini on "Robot navigation in a known environment with unknown moving obstacles". The article presents a novel approach by using a hybrid field to navigate a robot in environments that are mostly known but may contain unidentified and possibly moving obstacles. The evaluation of the technique was conducted using both a physical robot and a virtual one. They also introduce an algorithm for correcting positional errors. The simulation encompassed scenarios that involved up to 50 randomly shifting obstacles [58].

In 1996, M. Racković presented a technique for creating and implementing a translator for robotic programming languages using compiler-compilers. The investigation begins with the commonly employed robotic programming language PASRO. A new robotic language was developed, along with the creation of a translator that can convert programs written in this language into the symbolic robot language utilized by the EDUC-NET robot control system. This article provides a comparative analysis of two different compiler-compilers, COCO-2 and LEX-YACC, and their use in constructing a translator [59]. During that period, researchers were particularly interested in creating robots that could operate effectively in ever-changing and partially familiar surroundings. The integration of learning capabilities empowers the robot with independent intelligence to efficiently navigate such situations. Here is an article for you to read. The study conducted by Abouelsoud et al. provides valuable insights into the subject matter. The study conducted by al. delves into the intersection of robot control and learning techniques, with a specific focus on artificial neural networks. The researchers explore various neural network structures, highlighting important considerations in the field of robotics [60].

In a paper titled "Cooperative Mobile Robotics: Antecedents and Directions", published in 1996, Y. Cao et al. discussed the increasing research interest in systems comprising multiple independent mobile robots that exhibit cooperative behavior. This collection of robots was designed to explore a range of subjects, such as group structure, resource disputes, the roots of collaboration, learning, and geometric obstacles. Nevertheless, information regarding the practical applications of cooperative robotics is scarce, and the

theory behind it is still in its nascent stages of development [61]. In 1996, T. Sobh and R. Bajcsy presented a framework that tackles the broad issue of observation in different visual tasks. The research focuses on the development of advanced control mechanisms that can actively identify and understand various processes within a complex dynamic system. The model utilizes tracking mechanisms to allow the observer to perceive the workspace of the manipulating robot. A novel device is developed to study the dynamics of hand/object interaction over some time, and a sophisticated observer is designed to ensure stability. The design of low-level modules involves the recognition of visual events that prompt state transitions in the dynamic manipulation system in real-time. To achieve a dynamic and purposeful sensing mechanism, a method of roughly quantifying the manipulation actions is employed. The inherent possibility of errors, mistakes, and uncertainties in the manipulation system, observer construction process, and event identification mechanisms are among the bases for developing techniques for representing and analyzing uncertainties, allowing them to develop and be resolved within a defined period. Also, by this time, error recovery mechanisms had been developed [62].

In 1997, J. Lee and H. Cho presented a motion planning technique that enables mobile manipulators to efficiently carry out multiple tasks in a predetermined sequence. The end-effector is guided along a predetermined path within a fixed reference frame. Furthermore, the final configuration of each task is used as the starting configuration for the subsequent task, which is known as a commutation configuration. The motion planning problem is presented as a global optimization problem, and the effectiveness of the proposed approach is supported by simulation results [63]. By the same year, S. Brown and K. Passino conducted a study on controllers designed to enhance the performance of the acrobot. The acrobot is a mechanical device that mimics the movements of a human acrobat hanging from a bar. The objective of the study was to develop intelligent controllers that could assist the acrobot in swinging up to an inverted position and maintaining balance with its hands on the bar. Two genetic algorithms have been developed to optimize the performance of the balancing and swing-up controllers [22].

In 1998, F. Matía and A. Jiménez introduced a self-governing mobile robot that utilized various techniques to merge sensor data. The aim was to demonstrate the efficacy of mathematical and artificial intelligence methods in enabling the robot to navigate dynamic environments while performing designated tasks. This study explores well-established techniques for managing uncertainty and provides a real-world illustration of a mobile robot that employs a range of sensors for navigation and localization [64]. In the same year, T. Hebert et al. proposed an alternative perspective in their paper titled "A Real-Time, Hierarchical, Sensor-Based Robotic System Architecture". This paper presented a robotic system architecture and evaluated its real-time performance in controlling a robotic gripper system for handling delicate materials without causing any deformation. The article explores the advancements in software and hardware protocols and interfaces for effectively managing and coordinating subsystem operations and interactions. The performance of the advanced real-time, hierarchical, sensor-based robotic system architecture effectively fulfills the operational constraints and requirements established by the industry at that time [65].

In 1999, a group of researchers led by P. Renton developed a robotic system known as Plan-N-Scan. This system utilizes a wrist-mounted laser range camera to autonomously navigate and map a workspace, ensuring collision-free exploration. This system utilizes advanced techniques for gaze planning and sensor positioning in a static environment, leading to the creation of a highly accurate 3D map. The system employs two different types of representations: a spherical model of the manipulator and a weighted voxel map of the workspace. The process of target scanning involves a highly efficient A*-based search and a method for choosing optimal viewing positions. This enables the gradual collection of scans and the detection of targets, even if they are not initially visible to the range camera. Volume scanning is carried out iteratively, where the system autonomously chooses to scan targets and explores the designated volume of the workspace [66]. In 2000, N. M'Sirdi

et al. presented a constructive control approach for legged robots with fast dynamic gaits. The method relies on controlled limit cycles (CLCs), which help stabilize the trajectories of periodic systems. The control algorithm produces desired trajectories and control input in real time [67].

S. Gustafson and D. Gustafson seek to understand the disruption that occurs in multi-robotic systems when addressing search and tagging challenges. This study examined the effects of increasing the number of robots and expanding sensor ranges on path and sensor interference, which can lead to negative outcomes [68].

In 2003, A. Orebäck and H. Christensen conducted a comparative analysis of three successful software architectures for mobile robot systems: Saphira, TeamBots, and BERRA. The analysis primarily centers around assessing the portability, user-friendliness, software characteristics, programming capabilities, and run-time efficiency. The study analyzes these architectures and evaluates their performance through a practical evaluation carried out on a standardized hardware robot platform [69].

The paper "Development of reconfigurable machines" by Z. Bi et al. in 2008 provides a comprehensive overview of the advancements made in the field of reconfigurable machines (RMs). The article presents explanations for the development of RMs along with the academic and practical challenges that come with it. It also takes a closer look at the current state of research and development in design methodologies for RMs while identifying potential future research directions that can have a positive impact on the manufacturing industries in the short and long term. The study highlights the benefits of reconfigurable manufacturing systems (RMSs) in effectively responding to changes and uncertainties in a dynamic setting [70].

Complementary metal oxide semiconductors (C) image sensors have a wide range of applications, including industrial automation and traffic systems such as aiming systems, blind guidance, and range finders. The paper titled "Applications of the Integrated High-Performance CMOS Image Sensor to Range Finders—from Optical Triangulation to the Automotive Field" presents the introduction of CMOS image sensor-based active and passive rangefinders in 2008. These range finders have been extensively tested in various applications, including the automotive industry [71].

2.3. Stretch Forming

Stretch forming is a metal-forming technique where a metal sheet is stretched over a die to achieve a specific shape. At the simplest level, stretch forming requires applying biaxial tension to a metal sheet, as shown in Figure 3. To achieve the desired shape, the material needs to be stretched in the axial direction by a die pushing in a perpendicular direction to draw the metal sheet. Throughout this process, severe plastic deformation (SPD) is generated as a result of the increasing stress, thus the importance of taking strain distribution into account. Consequently, the strain will vary by a specific degree, influenced by the mechanical characteristics of each material. One important consideration is the deformation of materials, as their behavior changes when experiencing elastic or plastic deformation. Materials in the elastic domain exhibit predictable behavior by following Hooke's law, showcasing a constant slope between stress and strain known as Young's modulus. Within the plastic domain, the theory of elasticity reveals the occurrence of more intricate phenomena [72]. The stretch-forming process parameters include information about the material being stretched, the griping jaws' clamping force and orientation, stretching force, die shape, and force [72–76].

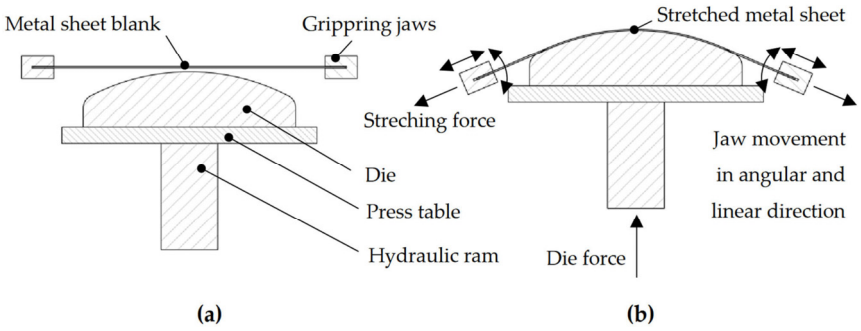

Figure 3. Schematic representation of the transversal stretch-forming process indicating (**a**) the main components, and (**b**) stretching directions, forces, and movements [72].

The beginnings of stretch forming can be traced back to the early 20th century when aircraft manufacturers needed to produce large and curved parts for wings and fuselages. In 1950, the first stretch-forming machine patented was claimed in the US by Landora R. Gray, Manhattan Beach, and Harry P. Smith used hydraulic cylinders and clamps to pull the metal over a curved die [77]. The process was further refined and automated by American companies such as Boeing and Lockheed in the 1940s and 1950s, using servo-controlled systems and computerized controls [78]. Today, stretch forming is widely used in various industries, such as aerospace, automotive, architecture, and shipbuilding. Stretch forming can produce parts with high strength-to-weight ratios, complex geometries, and smooth surfaces [72]. Some examples of stretch-formed products are aircraft skins, car doors, window frames, and boat hulls [73,79–83]. Stretch forming is a common method in the aerospace industry for creating skin parts. However, it often requires costly intermediate heat treatments, especially for complex shapes [84,85]. To improve this process, engineers use FEM simulations to optimize it [86–90]. The accuracy of these simulations depends on material models that accurately describe work hardening during stretching and residual stresses [84].

In 1976, T. Hsu and H. Shang introduced a new approach to the bulge test (a method used to determine the material properties of thin films, such as Young's modulus, Poisson's ratios, and residual stresses [91]). This method enables the examination of the relationship between the shape of a thin shell and the stresses it undergoes when exposed to internal pressure. Prolateness is a quantitative measure that evaluates how much local geometry deviates from a perfectly spherical shape. An analysis is conducted on the forms and stresses of thin shells with continuous prolateness surfaces. The initiative utilizes innovative experimental techniques and presents its discoveries. The metal shell assumes a complete spherical form only in the vicinity of the pole and along a circular path of consistent latitude. The shape of the shell changes from prolate within the circle to oblate beyond it. As the formation process progresses, the circular surface gradually expands until it becomes elongated in shape. The study focuses on the stress distributions observed during various stages of the formation process [92]. A study conducted in 1980 by C. Magee et al. highlighted that the automotive industry had started using high-strength steel instead of mild steel as part of a materials substitution program. As high-strength, low-alloy steel becomes more used in vehicles, a range of new challenges arises. These challenges encompass various aspects, such as improvements in metallurgy, material availability, cost considerations, material properties, sheet steel fabrication methods, vehicle design, crash performance, mechanical durability, and stiffness. One of the key aspects of vehicle design is finding appropriate materials for all components and achieving weight reduction in different applications. The primary challenges to the widespread use of high-strength, low-alloy steels were the limited availability of materials and the complexities involved in sheet metal forming [93]. In 1982, D. Lee created a computer software package that could predict the results of formed sheet metal parts during the design phase. The software described in the paper "Computer-Aided Control of Sheet Metal Forming Processes" provides a visual representation of the major and minor strains calculated at various points

on the formed part. These strain values can then be superimposed on material-specific forming limit diagrams. The analysis code includes programs that define constitutive equations, calculate forming limit diagrams, and perform finite element analysis [94]. Adapting quickly to changes in the manufacturing environment is essential, and flexible manufacturing systems (FMS) play a key role in achieving this. The primary goal of FMS is to provide comprehensive data about the factory, enabling analysis and decision-making across a wide range of scenarios, including product planning, operations, and performance evaluation. In 1988, B. Farah proposed the development of an expert support system (ESS) to assist in the analysis of information needs and the design of information systems for flexible manufacturing [95].

By 1992, a software called SHEET-3 was developed specifically to simulate the process of sheet-metal stretch formation. It utilizes triangular elements to accurately model the process. This algorithm employs an implicit, incremental approach that is grounded in a rigid viscoplastic constitutive equation. It also incorporates adjustments to account for material unloading. The program, proposed by Y. Keum and H. Wagoner, utilizes membrane approximation, assuming plane stress conditions, and incorporates the generalized tool description method to accurately represent tool surfaces of any shape [89]. In a study published in the same year by R. Joshi et al., the focus was on demonstrating the feasibility of using digital processing to analyze stretch-forming sheet metal. The researchers aimed to replace outdated and time-consuming methods of obtaining materials parameters with a computerized process that offered cost-effectiveness, speed, and technical efficiency. An investigation was conducted using a digital image-processing technique to analyze the formability and susceptibility to deformation of cold-rolled 70/30 cartridge brass. A computer interface was developed, and a reliable software package was designed to manage and regulate the digital image processing system, as well as analyze the material flow during uniaxial tension stretching [96].

B. Ren et al. observed that the crystallographic texture has a significant impact on mechanical anisotropy. The presence of texture plays a crucial role in the development of strain localization in a sheet material subjected to biaxial stretching. This study examined the impact of various textures on the ability of aluminum AA5182 to be stretched in two directions. The crystallographic texture was found to have a significant impact on the biaxial stretchability of textured AA5182 sheets. The research results indicate a strong correlation between the Olsen cup values (test method for ball punch deformation of metallic sheet material [97]) and the calculated strain path values and limit strains. When a sheet material has the right texture combination, its biaxial stretchability experiences significant improvement [98].

In 1997, H. Takuda et al. published a research paper titled "Fracture prediction in stretch forming using finite element simulation combined with ductile fracture criterion", where they extensively discuss crucial aspects of stretch forming. A ductile fracture criterion has been integrated into a finite element simulation that focuses on sheet metal forming. A simulation was performed to study the axisymmetric stretch forming of various types of aluminum alloy sheets and their laminates coated with mild steel sheets. Based on the results, it has been concluded that by combining finite element simulation with the ductile fracture criterion, it is possible to make precise predictions regarding the forming limit in various types of sheet metals [90]. Another mathematical approach was analyzed by Y. Huang in 2007; an investigation into sheet stretching under axisymmetric conditions was carried out using the incremental updated Lagrangian elastoplastic finite element method (FEM). The method called the extended Rmin technique is used to calculate the incremental step size. This method relies on the yielding of a Gaussian point within each element and the changes in boundary conditions along the tool–metal interface. The frictional force in the contact region between the sheet and the tools is determined by applying Coulomb's friction law. The experiments employ sheets with low-carbon content (BA-DDQ) and are deformed using a hemispherical punch head [86].

A major setback in the stretch-forming process is fracture, which, unfortunately, is a common occurrence, often caused by tensile instability. An analysis was conducted on experiments and theories utilized in the construction of forming limit diagrams. Integration of finite element simulations and experimentation is used to study the forming limit diagrams when subjected to complex strain paths. Results indicate that the use of finite element simulation can faithfully reproduce intricate strain patterns, which play a significant role in determining the success of sheet metal forming [99].

In a research paper published in 2008, D. Vlahovic and M. Liewald discussed the utilization of stretch forming in the production of slightly curved components, such as aircraft body panels. The authors focused on benchmarking methods for short-cycle stretch forming. Nevertheless, its efficacy and cost-effectiveness have been proven to be lower when applied to car body panels. A new stretch-forming technique called SCS (short-cycle stretch forming) was developed at the Institute for Metal Forming Technology in Stuttgart to tackle these challenges and fulfill economic requirements. The SCS technology allows for the implementation of highly efficient processes that integrate plane stretching and deep drawing, all while utilizing cost-effective tools [84]. The automotive industry places great importance on diversifying its product offerings and requires efficient and affordable manufacturing tools to produce high-quality parts. With the introduction of SCS, which utilizes a combination of plane pre-stretching and deep drawing operations, it was possible to create compact car body panels that presented a superior surface finish. The tool concept functions without the need for a blank holder and is cost-effective thanks to its simple tool design [100].

In their research, V. Paunoiu et al. present a manufacturing technique known as reconfigurable multipoint forming (RMF). This technique utilizes discrete pins to deform a continuous 3D surface, resulting in the desired shape. The authors investigate the impact of different pin networks on the deformation process in RMF with a fixed configuration. The results suggest that the selection of network type is primarily influenced by design considerations [101].

In 2008, A. Yan and I. Klappka proposed an alternative method for stretch-forming usage. The study titled "Springback in Aeronautic Panel Production through Finite Element Simulation" looks into the phenomenon of springback in panel forming processes, specifically focusing on the multi-point stretch forming technique. An investigation was carried out using the SAMCEF/MECANO software, version 12.1, to simulate the stretch-forming process for aeronautical panels. The main objective was to accurately predict and mitigate springback effects that may occur during the manufacturing process [89].

In 2009, S. Panda and D. Kumar conducted a study to explore the boundaries of de-formation for tailor-welded blanks (TWBs) when exposed to plane-strain stretching. The objective was to prevent failure during stamping. Tests were conducted on all three combinations of TWBs to determine the limiting dome height (LDH). Based on the findings, it is evident that there is a higher LDH level in transverse cases compared to longitudinal cases. The characteristics of the welds play a crucial role in the deformation of longitudinal specimens. Variations in properties, thickness, and surface characteristics have a strong influence on the fracture location in transverse specimens [102].

3. Summary of the 2010s—More Industrial Processes Require Improved Algorithms

3.1. Machine Learning Advances

Machine learning algorithms have become essential in modern technology, providing robust tools for data processing and extracting valuable insights across various domains. The algorithms behind the machine learning umbrella are divided into four categories, as indicated in Table 1. The classification takes into consideration each class's ability to analyze the input data as being labeled or not labeled. Supervised learning, which uses labeled datasets for classification and prediction tasks, includes methods like linear regression, logistic regression, decision trees, Naïve Bayes, support vector machines (SVM), k-nearest neighbors (kNN), and ensemble learning techniques [103–110]. Semi-supervised learning,

which uses both labeled and unlabeled data, includes techniques like pseudo-labeling and semi-supervised generative adversarial networks (SGAN), which can revolutionize tasks like image classification and interpreting unfiltered data streams [111–113]. Unsupervised learning, on the other hand, uses algorithms that independently analyze and group unlabeled data, uncovering concealed patterns without human involvement. These algorithms include K-means clustering, hierarchical agglomerative clustering (HAC), Density-Based Spatial Clustering of Applications with Noise (DBSCAN), and principal component analysis (PCA) [114–118]. Reinforcement learning, a framework for sequential decisions in uncertain situations, uses algorithms like Q-learning, SARSA, Deep Q-Network (DQN), and Deep Deterministic Policy Gradient (DDPG) in applications like traffic control, algorithmic trading, and intelligent robotics [119–123]. Machine learning algorithms have a profound influence across various sectors, fostering creativity and enabling us to address complex problems with better effectiveness and insight.

Table 1. Machine learning algorithms, purpose, and applicability.

Machine Learning Algorithms		Purpose	Applicability
Supervised Learning (uses labeled datasets to train algorithms to classify and predict outcomes [103])	linear regression [104]	finds a linear relationship between one or more predictor(s)	traditional method for evaluating trends and making predictions
	logistic regression [105]	analysis and classification of binary and proportional response data sets	widely used in data mining
	decision tree [106]	repeatedly performing tests on the input x, where the outcome of each test determines the next test until f(x) is known with certainty	mostly used in statistics and data mining
	Naïve Bayes [107]	finds the probability of an event occurring considering the probability of another that occurred	mostly used for text classification, spam filtering
	support vector machines (SVM) [108]	classification strategy minimizes the classification errors of the training data and obtains a better generalization ability	mostly used for data mining, pattern recognition
	k-nearest neighbors (kNN) [109]	classify unlabeled observations by assigning them to the class of the most similar labeled examples	mostly used for intrusion detection, financial market prediction
	ensemble learning techniques [110]	generated by multiple datasets by bootstrapping the training data and then developing models based on the individual datasets and making predictions using these models	mostly used for predicting crop yield, mapping natural hazards, or land surface temperature

Table 1. *Cont.*

Machine Learning Algorithms		Purpose	Applicability
Semi-supervised Learning (uses both unlabeled and labeled data [111])	pseudo labeling [112]	applying pseudo-labels to samples in the unlabeled set by using a model trained on the combination of the labeled samples and any previously pseudo-labeled samples and iteratively repeating this process in a self-training cycle	mostly used for image classification
	semi-supervised generative adversarial network (SGAN) [113]	extract useful information from the unlabeled process data	used in interpreting unfiltered, noise data
Unsupervised Learning (analyses and clusters unlabeled data to discover hidden patterns or data grouping without human intervention [114])	K-means clustering [115]	categorized as a partitional clustering algorithm; partitioning given datasets into clusters involves finding the minimum squared error between the various data points in the data set and the mean of a cluster and then assigning each data point to the cluster center nearest to it	used in medical science, manufacturing, robotics, the financial sector, privacy protection, artificial intelligence, urban development, aviation, industries, sales, marketing
	hierarchical agglomerative clustering (HAC) [116]	can yield impressive and rather easily readable results concerning clustering and classification of general building information/dataset	business intelligence, image pattern recognition, web search, biology, and security
	Density-Based Spatial Clustering of Applications with Noise (DBSCAN) [117]	performs clustering by finding different density regions that depart from each other	used in data analysis and pattern recognition
	principal component analysis [118]	versatile statistical method for reducing a cases-by-variables data table to its essential features, called principal components	population genetics, market research, quantitative finance
Reinforcement Learning (sequential decision-making problems that are typically under uncertainty, mimicking how we, as humans, learn [119])	Q-learning [120]	a simple way for agents to learn how to act optimally in controlled Markovian domains	used in news recommendations, online web system auto-configuration, traffic control signal
	state–action–reward–state–action (SARSA) [121]	has faster convergence characteristics but not lower final performance than Q-learning	robotics, artificial intelligence, and mechatronics control
	Deep Q-Network (DQN) [122]	combines reinforcement learning with deep neural networks	used for algorithmic trading
	Deep Deterministic Policy Gradient (DDPG) [123]	explores the environment and makes action decisions	intelligent robotics

In a paper published in 2010, R. Smith et al. introduced a learning classifier system (LCS) called MILCS ("my LCS"). This system utilizes mutual information as a measure of fitness feedback. MILCS is designed for supervised learning and has been compared to other LCSs such as XCS (accuracy-based classifier system), UCS (unconfined compressive strength), GAssist (machine learning genetic algorithm), BioHEL (evolutionary learning

system designed to handle large-scale bioinformatic datasets), C4.5 (used in data mining as a decision tree classifier), and Naïve Bayes in various studies. MILCS can assist in identifying default hierarchies, a unique characteristic of LCSs [107]. In the same year, G. Jeong et al. contributed with a novel approach to pattern recognition. His work explores the utilization of feature feedback, with a specific emphasis on its implementation in face recognition. Conventional approaches in pattern recognition utilize methods such as PCA (principal components analysis) and LDA (linear discriminant analysis) to extract features for classification purposes. On the other hand, this approach examines the extracted characteristics in the original space through the use of feature feedback. Through the process of mapping the extracted features back to the original space, it becomes feasible to pinpoint the essential elements of the original data that play a significant role in classification. The results of this study indicate higher accuracy rates in classification, along with the possibility of decreased complexity and a decreased requirement for sensors [124].

In 2011, advanced algorithms were developed to address transportation challenges. In their study, C. Dai et al. thoroughly investigated the traction system of a permanent magnet electrodynamic suspension (EDS) train. This particular train operates in synchronous traction mode and makes use of long stators and track cables. A proposed system aims to detect the speed and position of the train's feedback end. The EDS train's method of measurement produces position signals that may be affected by vibrations and track connections, resulting in irregular and noisy data. To address this issue, a new algorithm is presented that focuses on the filtering properties of a specific type of track differentiator. This algorithm, known as the linear discrete track-differentiator filtering algorithm, aimed to analyze and optimize the performance of the track differentiator and its associated group [125]. Another approach in the field of transportation was conducted by H. Hou et al., who explored a novel approach for its time to enhance the efficiency of an intelligent transportation system (ITS) by accurately identifying the intentions of drivers. Three models have been developed using the continuous hidden Markov model (CHMM) to distinguish between the intention to change lanes to the left or right and the intention to continue driving in the current lane. Participants engage in lane change maneuvers and lane-keeping maneuvers using driving simulators while collecting and analyzing various parameters associated with lane change behavior [126].

In 2012, A. Nebot et al. conducted research that led to the development of a genetic fuzzy system (GFS). This system is designed to learn discretization parameters using the fuzzy inductive reasoning (FIR) methodology and the linguistic rule FIR (LR-FIR) algorithm. The goal of the GFS is to obtain precise predictive models and decision support models by learning the fuzzification parameters of FIR and LR-FIR approaches [127].

A creative strategy that integrates functional neurophysiology with elements of distributed computing to investigate the state of consciousness. In 2015, S. Bagchi presented a model that handles the intricacies of consciousness and memory development, node classification, and the hierarchical structure of distributed computing nodes. The model showcases its adaptability to bio-inspired distributed computing structures through numerical simulations using various choice functions. His work suggests that the model shows promise in its application to bio-inspired structures and that the development of consciousness is influenced by various environmental stimuli [128]. Understanding and addressing classification problems is a crucial focus in the field of machine learning [129].

Utilizing image-based control, also known as point-and-click control, offers a wide range of advantages in human–robot interactive applications such as telerobotics, remote supervisory, and unmanned systems. This control mode is designed to provide users with a seamless experience, allowing them to effortlessly issue commands without any concerns. It is especially effective for remote applications [130].

In a recent publication, Z. Liu et al. introduced a method for accurately measuring the size of sizable objects through the utilization of a mobile vision system. This technique, introduced in 2015, utilizes a binocular vision sensor and a wide-field camera to develop a 3D scanning sensor. To conduct the measurements, several planar targets are strategically

placed around the object. The collected local 3D data are then combined and aligned within a global coordinate system [131].

In 2017, M. Lepot et al. published an in-depth review that has been carried out on various interpolation techniques used to fill gaps in time-series data. The paper focused on evaluating their efficacy and measuring the associated uncertainties. Although numerous techniques are available, the computation of uncertainties for interpolated values is rarely carried out. The work presents algorithms that deal with the estimation of uncertainties surrounding interpolated and extrapolated data [132].

Machine learning techniques were also being used in surveillance systems for pipeline monitoring. In 2017, J. Tejedor et al. thoroughly examined the difficulties involved in implementing and evaluating DAS+PRS for monitoring pipeline threats. The combination of distributed acoustic sensing (DAS) and a pattern recognition system (PRS) is increasingly being used in pipeline surveillance systems to detect and classify potentially dangerous incidents [133]. These advancements have resulted in numerous practical uses in both industry and society. In 2018, C. Chang et al. published a review-type paper titled "A Review of Artificial Intelligence Algorithms Used for Smart Machine Tools". The paper discusses various aspects related to the current state of AI algorithms and their applications in smart machine tools. The AI methods are classified into different types of learning algorithms, including deep learning, meta-learning, unsupervised learning, supervised learning, and reinforcement learning. These algorithms were a part of models that were able to detect issues in mechanical components. AI techniques are beginning to be used in various applications, including smart machine tools, intelligent manufacturing, cyber–physical systems, mechanical components prognosis, and smart sensors. Several AI algorithms are used to operate advanced machine tools and achieve accurate results [134].

In 2019, S. Lui et al. proposed a solution that explores autonomous machine reading comprehension (MRC). The paper highlights the importance of autonomous systems in addressing environmental unpredictability [135]. "Machine Learning and Deep Learning Methods for Intrusion Detection Systems: A Survey" by H. Liu et al. examines, a year later, an intrusion detection system (IDS) classification system that employs data objects as the main metric for classification. This framework has been developed with a focus on assisting cybersecurity researchers in gaining a comprehensive understanding of IDSs, their concepts, and their classification [136]. Machine learning systems were progressively gaining prevalence at this juncture, leading to an increased societal dependence on algorithms. Nevertheless, the precision of decision support systems remains highly intricate, with their internal reasoning remaining opaque. Even the most knowledgeable individuals struggle to comprehend the mechanisms behind these systems' predictions, which is briefly presented in Figure 4. With the emergence of new regulations and stringent industries, it has become imperative to have the ability to question, comprehend, and have confidence in machine learning systems. Understanding these systems is essential, and scientists have been dedicated to creating models and techniques to elucidate their functioning [137].

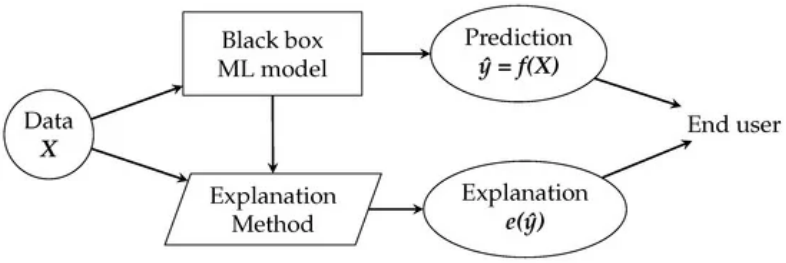

Figure 4. Machine learning pipeline [137].

The selection of a manufacturing process to achieve the desired geometry of a metal part currently lacks structure and is heavily dependent on human expertise. Furthermore, the automation of metal forming process classification and design is still an ongoing challenge. In the following study, machine learning was used to determine the manufacturing

process that could manufacture a part solely based on its final shape. Different configurations of neural networks were evaluated using different methods to represent geometric data. Mapping the geometric properties, a highly effective classifier achieved an accuracy of 89% using a deep convolutional neural network. Due to its exceptional precision, automated systems have the potential to perform this step between design and manufacturing, eliminating the requirement for human knowledge in selecting the most suitable forming method for each product [138].

3.2. Mechatronics

Mechatronics subsystems include mechanical and electrically powered systems consisting of a range of components designed to fulfill specific functions, as indicated in Table 2. Various mechanisms provide linear and rotational movements in mechanically powered subsystems. These include cylinders that use pneumatic or hydraulic power, motors that run on air or hydraulic power, and engines that rely on combustion or steam. These systems utilize various mechanical components, including rolling-element bearings, cams, gears, belts, and springs, to ensure accurate operation and efficient force transmission. Electrically powered subsystems utilize various mechanisms for both linear and rotational motion. In addition, a variety of sensors, including proximity, photoelectric, and pressure sensors, are combined with control hardware like switches, relays, and PLCs to effectively manage and regulate operations [139]. The control software, along with the human–machine interfaces, enhances the functionality of these hardware components, ensuring efficient interaction and control [140].

Table 2. Mechatronics subsystems classification [139,141].

	Subsystems	Global Component	Particular Component
Electrotechnical components	Mechanically powered subsystems	linear movement	pneumatic/hydraulic cylinders
		rotational movement	air/hydraulic motors, combustion/steam engines
		motion machine parts	rolling-element bearings (ball, roller, needle linear bearings), plain bearings, ball joints, leadscrew, ball screw, cams, gears, belts, pulleys, chains, sprockets, springs,
	Electrically powered subsystems	linear movement	electric actuators, solenoids, shape memory alloys
		rotational movement	servo/stepper motors
		sensors	proximity, photoelectric, temperature, pressure sensors, limit switch, rotary encoders, machine vision
	Control subsystems	control hardware	switches, relays, PLCs, power management hardware (PMH)
		control software	human–machine interface
	End effector	parallel mechanisms, unfolding mechanisms, and series-parallel mechanisms	

In 2012, S. Chen et al. investigated the utilization of model-free variable structure control in sensor–actuator systems. In this method, the system relies solely on the online input and output without any reliance on the mathematical model of the system. The issue is addressed from a perspective of optimal control, and the control law is derived through analytical methods based on the principle of optimality. Simulations were performed to showcase the efficacy and efficiency of the suggested approach [142].

In 2013, a group of researchers, M. Fontana, F. Salsedo, and M. Bergamasco, introduced a new technique for determining the rotation angle of a shaft without the need for direct physical contact. The technique utilizes affordable components that can be seamlessly

incorporated into a rotary joint. The principle is based on the rotation of a small magnet and the use of at least one Hall effect sensor. Extensive efforts were made to optimize the parameters, ensuring that the model exhibits linearity within a specific range of angles [143].

Z. Liu et al. introduced a methodology for accurately measuring the size of sizable objects through the utilization of a mobile vision system. This technique, introduced in 2015, utilizes a binocular vision sensor and a wide-field camera to develop a 3D scanning sensor. To conduct the measurements, several planar targets are strategically placed around the object. The collected local 3D data are then combined and aligned within a global coordinate system [144].

In 2019, J. Chen et al. provided a comprehensive overview of the most recent advancements in autonomous systems. The exploration starts with an analysis of the definition, modeling, and system structure of autonomous systems. The article presents the possible incorporation of autonomous systems with cutting-edge technologies like the Internet of Things, Big Data, Over-the-Air, and federated learning. Following the attainment of complete autonomy, this article presents a brief analysis of the subsequent steps that ensue [145].

The identification of linear systems is described in detail by L. Ljung. This article explores the traditional methods used in scientific research, including parametric methods such as maximum likelihood and prediction error methods, as well as non-parametric methods like spectral analysis [146]. In a research paper titled "Experimental Investigations on Self-Bearing Motors with Combined Torque and Electrodynamic Bearing Windings", V. Kluyskens et al. discusses the ability of multifunction windings to generate electrodynamic centering forces and driving torque without the need for additional electronics. An investigation was conducted to measure the electromotive force (EMF) of a prototype device operating under controlled conditions. The measured radial forces generated by the electrodynamic bearing and the drive torque closely align with the predictions of the model. The research demonstrates the simultaneous generation of passive guidance forces and torque using a single winding [147].

The enhancement in accuracy of the roboforming process is essential, as it is utilized for the production of sheet metal components in limited quantities and prototypes. It utilizes two collaborating industrial robots for the kinematic shaping of sheet metal workpieces. Eliminating workpiece-specific tooling and dies is a significant advancement. The geometrical design of sheet metal workpieces offers a significant amount of flexibility. The precision of incremental sheet-forming methods is a significant constraint that restricts their widespread use in industrial applications. To overcome these limitations, a potential solution was put forward: utilizing a machine learning approach to enhance the precision of geometric measurements in incremental sheet manufacturing processes. An innovative approach was implemented, utilizing a cutting-edge learning strategy that leverages reinforcement learning techniques [148–150].

3.3. Stretch Forming as a Computer-Aided Manufacturing Process

The stretch-forming processes include a range of techniques designed to meet specific needs and achieve desired results, at it is indicated in Table 3. A common method in the field of scientific research involves the use of stationary gripping jaws while the forming block or die is pushed into the material [75,79,81,151,152]. In tangential stretch forming, both gripping jaws and die can move; this results in a biaxial process [72–74,82,153]. With remarkable flexibility and improved formability, incremental stretch forming allows for the production of intricate three-dimensional shapes [148–150,154–157]. Multi-point stretch forming, or flexible die stretch forming, involves the use of adaptable dies and elastic cushions, enabling the manufacturing of intricate 3D sheet metal components [158–165].

In a study published in 2011 by S. Kurukuri et al., a physically based material modeling approach is proposed to simulate stretch forming with intermediate heat treatments and predict the resulting outcomes. The Vegter yield function is used to consider the anisotropic and biaxial behavior of the aluminum sheet. The simulation of stretching air-craft skins with

intermediate heat treatments using the FEM model and experimental findings produces favorable results. Through the application of physics-based material modeling, researchers have discovered a more effective approach compared to other methods [84].

Table 3. Stretch-forming classification and particularities.

Stretch-Forming Process Types	Particularities
Tangential stretch forming [72]	the gripping jaws and forming block/die can move
	the sheet is pre-strained, after which it is stretched
	it is considered a two-step biaxial process
Multi-point stretch forming/ flexible die stretch forming [101,165]	it uses reconfigurable dies and elastic cushions to manufacture 3D sheet metal parts
	it is considered a flexible manufacturing process
	stress and strain are distributed more uniformly, as the elastic cushions help to a certain degree
Incremental stretch forming (incremental sheet forming) [150,154,165]	it offers flexibility and increased formability, resulting in complex 3D shapes
	it is a hybrid manufacturing process, combining classical stretch forming with incremental sheet forming
	the sheet experiments only localized plastic deformation
Simple stretch forming [162–164]	the gripping jaws are stationary; only the forming block/die moves it has a large contact area; only tensile load has to be largely considered it can be used in large parts, such as airplane fuselage

Springback is a common issue in sheet metal forming, especially during stretching and bending operations. It occurs due to the elastic behavior of materials and can lead to shape inaccuracies. In their study, H. Schilp et al. focus on three crucial factors: the stretching technique, the stretching direction, and the duration of stretching. The springback factor is commonly used as a benchmark to assess swing and v-bending processes in finite element simulations [153].

Multi-point stretch forming (MPSF) is a method employed in the shaping of outer skin parts for aircraft. This technique utilizes a multi-point stretching die (MPSD) in place of the conventional fixed shape stretching die. The sheet metal is shaped over the MPSD, which includes a punch element. A study was conducted to compare the results with those obtained from conventional stretch forming by S. Wang et al. in 2012. The research examined how variations in the thickness of the elastic cushion and the size of the punch element affected stress concentration and local strain. Based on the results, it has been noted that using a smaller punch element in conjunction with an elastic cushion can effectively affect stress concentration and minimize local deformation. This facilitates the stress distribution on the sheet and aids in the prevention of dimple defects [166].

In a study conducted by E. Odenberger et al. in 2013, the focus was on evaluating suitable constitutive models for the thermo-mechanical forming of the titanium alloy Ti-6Al-4V. Additionally, it introduces a new approach for fabricating curved sheet metal parts with Ti-6Al-4V. The virtual tool's design was analyzed with finite element (FE) analyses, which assess two different anisotropic yield criteria to forecast a range of factors, including global forming force, draw-in, springback, and strain localization. The significance of the yield surface's shape is highlighted, and the accuracy of predicting shape deviation can be slightly improved by including the cooling procedure [167].

A study on the multi-point forming (MPF) process of polycarbonate (PC) sheets emphasizes the importance of the connection between the objective surface and punch element. A simple calculation method for determining the punch height is proposed. A series of numerical simulations were performed using dynamic explicit finite element analysis to investigate the deformation process of spherical and saddle-shaped components.

This study explores the effects of various factors, such as temperature, pressure, punch matrix, and punch radius, on the overall quality of the forming process [159].

Multiple die stretch forming (MDSF), a versatile fabrication method, can be used to manufacture single or double-curved surfaces [120]. In 2014, J. Park et al. published a research paper titled "Study on multiple die stretch forming for curved the surface of sheet metal". The paper presents a systematic numerical simulation that evaluates the behavior of elastic deformation and assesses the formability of an atypical double-curved surface formed by MDSF. The results suggest that MDSF proves to be a suitable process for creating curved surfaces of ships and architectural skin structures of buildings [168]. In 2016, a group of researchers led by D. Shim conducted a study on the tension force involved in the stretch-forming process of doubly curved aluminum alloy sheets. Aluminum alloys are being used in various industries, particularly in the automotive, shipbuilding, and aerospace sectors, due to their lightweight properties. However, the process of shaping aluminum sheets with double curvatures poses a significant challenge due to the springback effect. Hence, the stretch-forming process plays a crucial role in attaining accurate outcomes and reducing product flaws. This study investigates the deformation of the Al5083 aluminum alloy sheet and proposes an optimal tension force, considering the variations in the mechanical properties of the formed material. Through the use of finite element simulations and experiments, it has been shown that the tension force plays a crucial role in the creation of doubly curved aluminum surfaces. This process allows for minimal reduction in thickness while achieving exceptional accuracy [169].

In 2016, J. Fend et al. put forward a different approach that involved studying the stretching and deforming properties of Al–Li–S4–T8 Al–Li alloy sheets to analyze their critical orange peel state. Several specimens with varying notches underwent stretching experiments to analyze the forming limit diagram and establish the equation for the forming limit curve of the suggested alloy [170].

The Swift and Hill criteria, which are derived from the maximum force criteria, have been extensively used in the investigation of sheet formability. In their study, D. Morales-Palma et al. present stretch-bending conditions and explore the application of the maximum force principle. They present two different approaches that can be used to predict necking. One method involves adjusting the traditional maximum force criteria to account for stretch-bending processes, while the other method builds on prior studies that utilized critical distance concepts. A deformation model is proposed to analyze the stretch-bending process under plane-strain conditions. This model considers various parameters, including the reduction in thickness, the variation of variables throughout the thickness of the sheet, the stress caused by thickness, and the anisotropy of the material. [152].

In 2017, researchers M. Abosaf et al. shared their findings in a published research paper titled "Optimisation of multi-point forming process parameters". The authors observed a rise in the demand for sheet metal forming with reconfigurable dies, which can be attributed to the fast-evolving part design, particularly in the automotive sector. Reconfigurable dies provide a more cost-effective manufacturing solution compared to solid dies, allowing for easy adjustments to produce a variety of parts. Prior studies have predominantly concentrated on avoiding defects, overlooking the influence of the forming process on the quality attributes of manufactured components. The study focused on investigating the impact of different factors, including the thickness of the elastic cushion, coefficient of friction, size of the pin, and radius of curvature, on the overall quality of parts produced using a flexible multi-point stamping die. A study utilized finite element modeling to simulate the multi-point forming of hemispherical parts. The effects of process parameters on wrinkling, deviation from the target shape, and thickness variation were analyzed using the response surface method [158].

More and more, numerical simulation was becoming the go-to method for investigating intricate engineering issues. When it comes to simulating sheet metal forming processes, the primary techniques used are the finite difference method (FDM) and finite element method (FEM). The paper "Numerical simulation of sheet metal forming: a review"

by M. Ablat and A. Qattawi presents developments in simulation techniques, weighing the advantages and disadvantages of numerical methods, emphasizing advancements in solution strategies and formulation, as well as the selection of elements, historical evolution of anisotropy and yield criteria, material springback and simulation techniques for cutting-edge sheet metal forming methods such as laser forming and incremental sheet forming (ISF) [171].

4. Recent Developments—Using Autonomous Processes

In the current era of the Internet of Things, cyberspace, mobile devices, businesses, social media platforms, and healthcare systems, there is a vast amount of online data. To effectively analyze and use these data, it is crucial to understand machine learning (ML). ML enables intelligent analysis and automation of applications using these data. There exist various types of machine learning problems, each needing specific machine learning algorithms for their solution [172]. Big manufacturers or startup companies understand that metal forming is a complex process that has to be augmented or fully controlled by complex algorithms. This level of process automation has been moving in this direction for several years, with companies such as Machina Labs (vertical collaborative robo-forming), Rios Intelligent Machines and Aqrose Technology (visual intelligence collaborative robots), BMW (humanoid robots for their production lines), or Figure AI (integrating humanoid robots into labor force) integrating high-end software solutions into industrial or humanoid robots.

Advancements in the control of sheet metal forming processes through computer-aided techniques have revolutionized the manufacturing industry.

By the year 2020, the algorithms were reaching higher and higher levels of complexity. Extensive research has been conducted, as highlighted in a review paper titled "Brain-Computer Interface-Based Humanoid Control: A Review" by V. Chamola et al. The application of brain–computer interface (BCI) technology is being researched for enabling communication and control of external devices for individuals with severe motor impairments. Traditional BCI systems have typically used brain signals captured through electroencephalography (EEG) and translation algorithms based on rules. Nevertheless, the accuracy of these systems has been significantly improved with the recent integration of machine learning-based translation algorithms and multi-sensor data fusion. This is achieved by including telepresence, object grasping, and navigation, with the help of multi-sensor fusion and machine learning techniques to control humanoid robots, as indicated in Figure 5 [173].

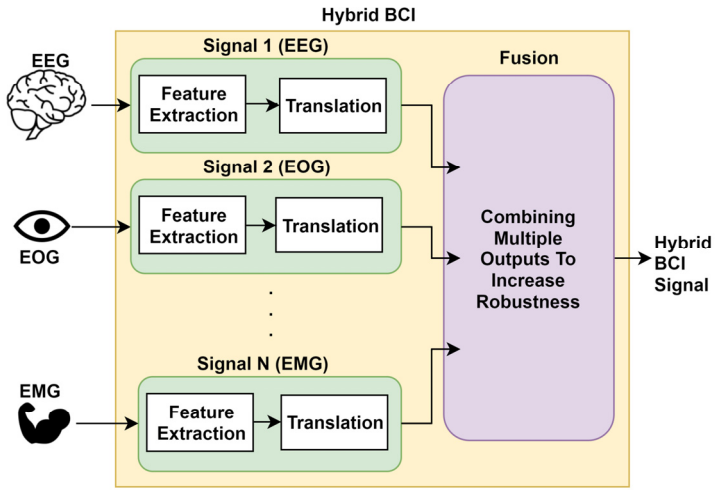

Figure 5. Block diagram of BCI [173].

In 2020, Y. Boon et al. proposed using machine learning for several aspects of structural component design. The research was centered around the development of materials with specific microstructures. Furthermore, machine learning models were being utilized to

analyze stress patterns, while efforts were being undertaken to enhance the performance of fiber-reinforced polymer composites. A framework for automating the design and optimization process of these components is proposed, with a strong emphasis on achieving optimal performance [174]. Mineral resource estimation includes assessing the characteristics of a mineral deposit, such as its geological attributes, to determine its quality and quantity. Conventional estimation methods, such as geometric and geostatistical techniques, continue to be widely used. Nevertheless, the latest developments in computer algorithms have empowered researchers to explore the potential of employing machine learning techniques for mineral resource estimation [175]. In the same year, A. Raza published a paper on fault diagnosis techniques in power transmission systems. The focus of the study was on fault detection, classification, and localization, with an emphasis on exploring effective methods. The article explores various techniques such as feature extraction, dimensionality reduction, fault classification, and localization. These methods heavily rely on artificial intelligence (AI) and signal processing. The study assesses the advantages and disadvantages of different AI and machine learning algorithms, conducting a comparison of various methods based on their features, inputs, complexity, system used, and results [176].

Research has predominantly centered around the development of novel algorithms, with less emphasis on integrating and building upon established knowledge. The absence of strictness and structure in the classification, design, and development of combinatorial optimization problems and metaheuristics presents a significant obstacle to the progress of this field. In the article "Combinatorial Optimization Problems and Metaheuristics: Review, Challenges, Design, and Development", F. Perez et al. discuss the key concepts and challenges in this field. They also propose a formal framework for classifying, designing, and implementing combinatorial optimization problems [177].

In 2021, C. Shen and T. Hsu proposed a cutting-edge method using a deep learning framework to enhance driving safety. Their research focuses on accurately predicting and determining the path of a vehicle. The study is organized into three main sections: lane line identification, car object detection, and car trajectory prediction. Utilizing authentic images and videos, researchers were able to accurately detect cars with a precision of 0.91, effectively simulating real-world situations, and a loss of 0.00024, costing 12 ms of computational time [178]. In 2023, S. Budzan et al. conducted research on the utilization of 2D hand gesture recognition (HGR) to control the automated guided vehicle (AGV). It indicates that RGB images might produce better results than grayscale images in real-world situations. Utilizing advanced 3D imaging techniques and incorporating a depth map can significantly improve the outcomes [179]. Computer vision algorithms were also used to examine critical infrastructure, like roads, bridges, and buildings, for flaws, which is a labor-intensive process that necessitates routine visual inspections after natural calamities. Identifying cracks poses a significant challenge, requiring substantial resources and frequently leading to cracks going unnoticed. To guarantee the efficiency and dependability of infrastructure, the implementation of automated defect detection is essential. An effective approach involves utilizing image processing techniques to analyze images of infrastructure components, as proposed in a recent publication by H. Munawar et al. in 2021. More and more, machine learning techniques are being used to improve the accuracy and reliability of fracture detection [180]. Returning to the manufacturing area, where inspection operations are essential, and considering the progress of this industry, it becomes crucial to improve the quality inspection of industrial products. In their research, Y. Chen et al. present a comprehensive review of the current studies focused on machine learning methods used in identifying surface defects. This is a crucial aspect of ensuring high-quality inspection in the manufacturing of industrial products. The research looks into the application of traditional machine vision techniques for identifying surface defects in industrial products. The emphasis is placed on analyzing texture, color, and shape characteristics [181]. Identifying imperfections on steel surfaces is a critical component of detecting flaws in industrial products. There has been a surge of interest in this field before this time. Y. Matsuzaka and R. Yashiro delve into the crucial hardware components utilized

in systems designed to identify imperfections on steel surfaces. The publication "AI-Based Computer Vision Techniques and Expert Systems", released in 2023, thoroughly examines the algorithms employed in identifying imperfections on steel surfaces. These algorithms encompass a range of machine learning techniques, including traditional approaches that utilize texture and shape features, as well as advanced deep learning algorithms that can be supervised, unsupervised, or weakly supervised [182].

In the age of digital transformation, the integration of interconnected computers and software systems has become indispensable in people's daily lives. There has been a growing interest in studying software quality, and numerous endeavors have been made to consolidate the knowledge acquired in this domain. Publications on software quality were gathered from the Scopus bibliographic database and examined using synthetic content analysis. A comprehensive analysis from 2022 by P. Kokol indicates a significant surge in research publications focused on software quality. Notably, the United States emerges as the leading contributor in this domain. Key areas of focus revolve around optimizing software engineering practices to enhance the overall quality of software, implementing advanced techniques for software testing, and harnessing the power of machine learning and data mining to predict defects and faults more effectively [183].

As indicated so far, machine learning (ML) is a branch of artificial intelligence (AI) that specializes in developing algorithms that can learn from data and apply their knowledge to new situations through statistical techniques. Nevertheless, ML algorithms do not adhere to the methodology typically associated with scientific disciplines. Although they excel at making precise predictions, they fall short of providing a causal explanation for these predictions. As an example, an artificial neural network (ANN) that has undergone training using a vast amount of consumer financial data can predict creditworthiness. Nevertheless, understanding the intricate and complex structure of the model poses a challenge when trying to determine the specific factors or combinations of factors it utilizes to reach its decisions. The lack of transparency in this situation can be problematic, especially when a credit application is rejected, and the applicant wants to understand the specific reasons for the denial. Recent developments in machine learning, including reinforcement learning and imitation learning, suggest a growing resemblance to the cognitive skills used in human learning. [184]. The potential of artificial intelligence (AI) and machine learning (ML) for solving practical problems is immense. So far, their adoption in various sectors and communities remains limited. The complexities of integrating AI applications must be tackled from various angles, encompassing both technical and societal considerations [185].

In a recent publication by P. Gupta et al. in 2021, a new approach to vertical wall manufacturing was introduced. The design involves the use of a die that closely resembles the concept of two-point incremental forming but without the need for actuators. The authors present their results and discuss the potential applications of this technique. The geometry is created through a series of six passes, with the toolpath being generated using state-of-the-art computer-aided manufacturing software. Applying this method in manufacturing significantly decreases errors in critical areas and improves the evenness of thickness distribution [155].

In their publication, J. Bressan et al. examine the predictions of formability for Ti6Al4V titanium alloy sheets under deformation conditions at both room temperature and 600 °C. The predictions were made utilizing D-Bressan's shear stress rupture criterion and the critical strain gradient macroscopic modeling. The application of a specific criterion for shear stress rupture showed a strong correlation with the experimental limit strain results. This suggests that the behavior of the specimens, deformed at different temperatures, was accurately reproduced [186].

Stretch bending is a common method used to shape long products by curving their axis while maintaining a consistent cross-section. Optimizing the forming path is a highly effective and straightforward method to prevent common issues in stretch bending, including axial springback and cross-sectional distortion. This paper presents a representation of the forming path using a function that considers the stretch length and bending angle.

To further enhance the understanding of the impact of the forming path on forming quality, two additional variables, total stretch length and distribution ratio, are introduced. A machine learning model has been developed using data obtained from finite element simulation to efficiently predict the quality of rail formation with a hat-shaped section. An optimization strategy based on the NSGA-II algorithm is employed to efficiently optimize the formation path. Based on the findings, it is clear that the overall stretch plays a crucial role in determining the quality of stretch bending. However, the distribution of stretch in various forming processes, such as pre-stretch, bend stretch, and post-stretch, has a relatively minor impact on stretch bending quality, with only a few exceptions. As the overall stretch increases, the forming angle goes through a significant initial increase before reaching a stable state. However, the cross-sectional distortion continues to increase without stopping. Based on the analysis conducted, it has been determined that the optimal forming path indicates a balanced combination of post-stretch and bending stretch during the forming process [187].

The data analysis of the adaptive stretch forming process reveals the algorithm's ability to identify the shift from elastic to plastic deformation. This finding has important implications for future development as it shows that the current form can be effectively used in the elastic domain. However, it may need an upgrade to accurately analyze real-time plastic deformation. Based on the statistical data, it is evident that optimal outcomes are achieved when the initial values for the R^2 are at an average level, indicating the significance of process parameters. When these parameters vary, the radius diverges. Additionally, the outcome is influenced by how often the die speed is adjusted. Another crucial aspect is that the algorithm reaches the most accurate conclusion in the event of unforeseen changes [72].

Shape memory materials, including shape memory alloys (SMAs), have found innovative applications in various industries, spanning from sensors and actuators to robotics, aerospace, civil engineering, and medicine. Traditional methods, such as the finite element method, have been utilized to study the properties of shape memory alloys, their models, and their wide range of applications. However, these materials exhibit non-linear behavior, posing a challenge for the application of conventional methods and increasing the computational time needed to accurately model their diverse shapes and applications. A promising approach involves developing innovative methodological strategies that leverage the power of artificial intelligence (AI) to achieve optimal computational efficiency and accurate results. Artificial neural networks (ANNs), a subset of deep learning, have been employed to analyze shape memory alloys (SMAs). The authors of a recent publication highlight the importance of artificial intelligence in the modeling of shape memory alloys (SMAs). They explore the deep connection between artificial neural networks (ANNs) and SMAs in various fields such as medicine, robotics, engineering, and automation [188].

Identifying imperfections on steel surfaces is a vital component of detecting flaws in industrial products. In their study published in 2023, X. Wen et al. investigated crucial hardware components of systems utilized in the detection of defects on steel surfaces. An extensive analysis of algorithms employed in the identification of imperfections on steel surfaces. These algorithms encompass a range of machine learning approaches, including traditional methods that utilize texture and shape features, as well as advanced deep learning algorithms that can be supervised, unsupervised, or weakly supervised [189].

Navigating through unstructured environments poses a significant challenge, requiring intelligent agents to detect and react to potential obstacles. The challenges can range from vehicles, pedestrians, or stationary objects in controlled settings to unpredictable stationary and moving obstacles in natural environments like forests. In 2024, C. Ginerica et al. put forth a new approach to path determination and navigation for quadruped robots on forest roads. Their research focuses on utilizing a recurrent neural network, which is based on an RGB-D sensor, to analyze vision dynamics. This approach generates sequences of previous depth sensor observations and predicts future observations within a specified

period. The results indicate outstanding performance in designing collision-free trajectories for the intelligent agent [190].

The growing need for accurate analysis and control in manufacturing processes has led to a greater emphasis on utilizing industrial data rather than relying solely on simplified physical models and human expertise. The rapid increase in data volume has significantly transformed the methods of data collection and analysis in the age of data-driven production. This paper offers a comprehensive overview of the technological advancements in data gathering and analysis in the field of in-process manufacturing. Given the challenges and lack of certainty associated with indirect measurement, it is worth noting that there is a notable and promising trend towards the development of advanced sensor technology that enables direct measurement. This technology has the potential to greatly enhance data collection methods. When analyzing data using physical models, it is important to acknowledge that simplifications are necessary and that the answers obtained may not always be well-defined. This is because these models have limitations when it comes to describing complex industrial processes. When provided with a wealth of data, machine learning, especially deep learning methods, holds great potential for improving decision-making and automating processes. In contrast, recent data-driven manufacturing techniques have achieved comparable or even superior results by using less data. These patterns can be demonstrated by analyzing certain typical manufacturing process applications [191].

Ferritic stainless steels are commonly used as replacements for austenitic steels because they are more cost-effective and have improved deep drawing capabilities. However, instances of failure, like shear fracture, have been observed in components with small radii during the drawing process when both bending and stretching occur. Conventional approaches, including failure criterion analysis, finite element method, and forming limit diagram, have proven insufficient in predicting this specific type of fracture, which hinders the progress of innovative processes and products. In a recent study conducted by V. Luiz et al., the researchers looked into the effects of tool radius, direction, and test speed on the structural integrity of an AISI 430 stainless steel sheet. The study aimed to understand the sheet's resistance to bending and stretching, specifically focusing on its ability to withstand these forces without fracturing. A test was conducted using specialized equipment to subject the sheet to bending while under tension, allowing for analysis of the draw-bend fracture (DBF). The experimental outcomes were directly influenced by the relationship between the tool radius and the sheet thickness of the process parameters [192].

5. Future Directions of Research

The future of this particular intertwining holds immense potential. Stretch forming with advancements in mechatronics and machine learning convergence offers possibilities for the following:

- Integrating machine learning algorithms into mechatronic systems enables real-time monitoring and control of stretch-forming processes. By incorporating sensor data from different stages, such as force, strain, and temperature, the machine learning model can be enhanced. Machine learning is essential for advancing material characterization and design in the context of stretch forming;
- By predicting material properties trained on extensive datasets of material properties and forming data, machine learning models can predict the behavior of new materials under stretch-forming conditions;
- By utilizing large amounts of manufacturing and real-time sensor data to predict material behavior during forming, it is possible to anticipate material performance, thus enabling fine-tuning the process parameters for desired outcomes;
- It is also possible to explore the potential of machine learning in structural component design, such as stress pattern analysis and material performance optimization, particularly in fiber-reinforced polymer composites. Through the use of machine learning algorithms, engineers can uncover intricate connections between material properties

and structural behavior, resulting in components that are not only more efficient but also lighter;

- By utilizing anomaly detection algorithms, sensor data can be analyzed to detect defects early on, allowing for timely corrective measures to be implemented;
- By using machine learning, it is possible to enhance process parameters such as tool path, forming speed, and blank holder pressure. This optimization can result in higher product quality, waste reduction, and improved efficiency;
- Developing smart and adaptive tooling for stretch forming can be achieved through the use of mechatronic systems; possible approaches include embedding sensors in the tooling to enable real-time feedback on the forming process, facilitating adjustments to the tool shape for precise forming of complex geometries, such as utilizing piezoelectric actuators or modular and reconfigurable tooling systems controlled by mechatronic systems could push a step forward the development of tools for various part geometries, enhancing flexibility and minimizing downtime;
- Creating products with ease of manufacturing in mind. Designers can enhance component optimization for functionality and manufacturability by integrating machine learning with CAD software;
- Exploring the potential of integrating machine learning algorithms into industrial robots opens up possibilities for complex tasks such as metal forming and production line automation and communication. Through the utilization of machine learning, industrial robots can enhance their ability to analyze intricate data patterns, resulting in heightened accuracy and efficiency across a range of manufacturing procedures;
- Research on enhancing brain–computer interface (BCI) technology has the potential to revolutionize communication and control of external devices. By the integration of advanced machine learning algorithms and multi-sensor data fusion techniques, BCI systems have the potential to enhance human–machine interaction across a wide range of domains;
- It is essential to thoroughly examine the ethical and societal consequences of incorporating AI applications to promote responsible technological progress. By addressing both technical obstacles and societal effects, researchers and developers can establish frameworks and guidelines to guarantee the ethical implementation of AI systems. This will help cultivate trust and accountability in their utilization across different domains.

6. Discussion and Conclusions

Advancements in machine learning are rapidly improving various aspects of human life, including decision making, scientific research, content creation, personalized healthcare, and robotics. Machine learning models can be enhanced using federated learning, lifelong learning, and human-in-the-loop systems. The analysis of intricate data, the anticipation of material characteristics (identifying defects on steel surfaces with advanced computer vision algorithms are significant applications), and the creation of innovative content are all achievable. When considering the robustness and reliability of mechatronic systems, it is important to acknowledge that machine learning algorithms often demand significant data and processing resources to attain optimal accuracy, which can pose challenges for real-time applications; therefore, machine learning plays a crucial role in analyzing large volumes of data, revolutionizing various sectors and improving both safety and productivity. Several companies like Machina Labs, Rios Intelligent Machines, and BMW are integrating cutting-edge software solutions into industrial or humanoid robots to improve or fully automate complex metal-forming procedures.

In the 1960s, mechatronics emerged as a fusion of mechanics and electronics. It has evolved into a multidisciplinary field that has enhanced robotics, product quality, efficiency, and reliability. System size and cost have been decreased by mechatronics. Highlighting the precision, autonomy, and ability to replicate human actions, cutting-edge robotic systems like the dynamically reconfigurable robotic system (DRRS), 3D noncontact sensor system, and self-organizing manipulator (SOM) are at the forefront of technological advancements.

With their versatility and precision, CMOS image sensors play a crucial role in industrial automation and automotive systems. Studying adaptive machines and manufacturing systems is crucial for enabling multi-robotic systems to navigate through path and sensor interference challenges (over time, mechatronic components experience wear and tear, noise, and interference; this can impact their performance and functionality, ultimately affecting the compatibility and interoperability of machine learning and mechatronic systems).

Emphasizing the seamless integration of mechanics, electronics, and control systems is a key focus in mechatronics research. The progress includes the miniaturization of mechatronic systems for micro- and nano-applications, the development of systems tailored for specific fields, the exploration of smart materials, and self-healing mechanisms. Investigating the capabilities of interconnected and intelligent mechatronic systems involves dealing with the Internet of Things (IoT). Enhancements to autonomous mechatronic systems are being pursued by researchers through the creation of advanced control algorithms, enhancements in human–computer interaction, and the integration of energy harvesting methods. Research is currently underway to explore how cyber–physical systems can improve the security and reliability of mechatronic systems.

Computer-aided techniques have revolutionized sheet metal forming processes. Research efforts continue to focus on enhancing automation and optimization, resulting in further advancements in the field. Significant progress has been made in stretch-forming techniques, particularly within the aerospace and automotive sectors. Recent advancements in software, finite element simulations, short-cycle stretch forming (SCS), and reconfigurable multipoint forming techniques have significantly progressed the field. These advancements enhance effectiveness, accuracy, and affordability. Research into material properties and springback effects is propelling advancements in manufacturing processes. Research on stretch forming highlights the progress in lightweight materials, tool design improvement, and the integration of sensor technology for monitoring and control. By incorporating sophisticated numerical simulations and employing multi-material stretch-forming techniques, operational efficiency can be improved while reducing material wastage.

Before achieving full integration of machine learning and mechatronics into stretch forming, it is crucial to address the existing challenges and limitations. All solutions presented have been outstanding; however, certain critical issues require additional investigation. One of the crucial factors to consider involves the availability and quality of data for training and testing machine learning models. Engaging in stretch forming presents a multifaceted procedure with numerous variables and uncertainties to consider. It is challenging to gather adequate and diverse data for various scenarios, considering the computational expenses and the time required to create and execute machine learning models.

Machine learning and mechatronic systems have distinct architectures, protocols, and standards that can present obstacles to their integration into a unified system. However, history has shown that despite facing similar challenges in the past, through dedicated research, viable solutions have been discovered. Machine learning and mechatronics show great potential in enhancing industrial processes by boosting quality and efficiency.

The combination of machine learning, mechatronics, and stretch forming is already transforming the manufacturing industry by allowing for the production of intricate, high-quality parts in a more efficient manner while also minimizing waste and optimizing material usage.

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