

Review Article

A Review on Machine Learning Models in Injection Molding Machines

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One of the most suitable methods for the mass production of complicated shapes is injection molding due to its superior production rate and quality. The key to producing higher quality products in injection molding is proper injection speed, pressure, and mold design. Conventional methods relying on the operator's expertise and defect detection techniques are ineffective in reducing defects. Hence, there is a need for more close control over these operating parameters using various machine learning techniques. Neural networks have considerable applications in the injection molding process consisting of optimization, prediction, identification, classification, controlling, modeling, and monitoring, particularly in manufacturing. In recent research, many critical issues in applying machine learning and neural network in injection molding in practical have been addressed. Some problems include data division, collection, and preprocessing steps, such as considering the inputs, networks, and outputs, algorithms used, models utilized for testing and training, and performance criteria set during validation and verification. This review briefly explains working on machine learning and artificial neural network and optimizing injection molding in industries.

1. Introduction

Injection molding is one of the widely used manufacturing processes for manufacturing plastic products [1]. More than 30% of the weight of all plastic products is manufactured using the injection molding process. Besides plastic products, injection molding is mainly used in the automotive, medical, and electronics industries [2]. High production rate and quality are some of the significant advantages of injection molding. The finished products from injection molding require minor finishing operations, which is another advantage [3]. However, the equipment used in injection molding can be quite expensive and sophisticated, so

injection molding is not suitable for small-scale production [4–7].

Injection molding is melting plastic consisting of two types of thermoplastic polymers and thermosetting polymers. The machine injects the pressure onto the mold cavity that fills and solidifies the molten plastic to produce an end product. A whole injection molding process consists of three stages that are filling, postfilling, and mold opening. Some of the interesting properties of plastic are as follows: transparency, ability to make complex sizes and shapes quickly, ability to integrate with other materials easily with an excellent thermal and electrical insulator, lightweight, and anticorrosion. Some of the issues regarding the quality are

flow marks, volumetric shrinkage, jetting, weld lines, flash, sink marks, dimension shrinkage variation, and warpage. Recently, neural network and machine learning have grown drastically to solve problems that will possibly occur in the injection molding process to improve its characteristics [8–11].

Injection molding consists of four stages: filling stage, holding stage, cooling stage, and demolding stage [12]. The material is fed into the injection molding machine and is then heated. The molten material is forced under pressure into the mold and then cooled and hardened inside the mold. It is then ejected out of the mold. The cycle starts from the filling stage and ends at the demolding stage. As shown in Figure 1, a significant portion of the total time is taken by the cooling and recovery stage. Many industries are working on reducing the cooling time by implementing modifications in mold design [13]. Cooling channels in mold helps to reduce the cooling time and decrease the cycle time. More production cycles can be completed by decreasing cycle time, improving the industry's productivity [14]. Injection molding is prone to defects, and some of the common defects are flow lines, weld lines, flash, and sink marks. Injection speed, pressure, and mold design are essential in reducing defects [15]. Most of the defects are caused by improper injection pressure and temperature control. So, control over these parameters is crucial in reducing defects [16]. Traditional methods rely on the operator's expertise and conventional defect detection techniques. These techniques are unreliable and time-consuming, and hence they increase the lead time and reduce the industries' productivity. So, there is a need for faster monitoring [17]. Implementing machine learning techniques in injection molding can be a better alternative to traditional methods. Although establishing a machine learning network can be expensive, it is profitable in the long run. Machine learning techniques can also be used in optimizing the mold design to reduce the cooling rate and improve the quality of the final product [18–20].

Machine learning is an excellent application in the present era, which provides systems the ability to automatically learn and improve from previous training given to them without being explicitly hard coded or programmed. Machine learning explicitly emphasizes the computer program's improvement, which runs the data, using it for their learning.

A significant intention of machine learning is to allow the systems or computers to learn correctly without any human intervention. This review intends to accumulate all the ML models implemented in injection molding.

2. Injection Molding

Injection molding is a manufacturing process in which molten material is injected into a mold to produce parts (Figure 2) [22]. Different materials can be molded into desired shapes using injection molding. Some widely used materials are polyvinyl chloride (PVC) (Figure 3), nylon, polyamide, polyester, and acrylic [23]. Except for aluminum and magnesium, almost all metals can be molded using the

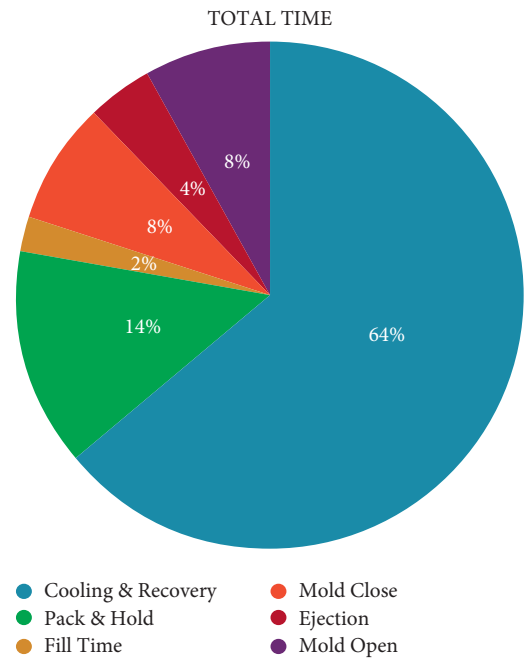


FIGURE 1: Total cycle time in injection molding.

metal injection molding process. The adherent oxide film on the surface of aluminum and magnesium powder hinders the sintering step in the molding process. Titanium alloys, low alloy steels, cobalt alloys, and stainless steel are widely used in metal injection molding. So, injection molding offers an excellent material choice.

One of the significant advantages of injection molding is its higher production rate [24]. The injection process can be automated, and as a result, the production capacity can be tremendously improved. Usually, injection molding is utilized in the production of smaller parts [25]. More extensive parts required more giant molds and more material to fill the mold, impacting its production rate and efficiency. So, the speed of injection molding depends on the size and complexity of the mold. Labor costs are also drastically reduced due to the automation of injection molding. Another advantage of injection molding is that complex parts can also be molded. Thus, injection molding offers design flexibility [26]. Injection molding is capable of producing accurate parts, maintaining good dimensional stability. So, as a result, the scrap resulting from production is meager [27]. Since injection molding is mainly used to produce parts from non-biodegradable materials like plastics and polymers, keeping the scrap rate minimum is essential. The postproduction or finishing work required after production is also low as high dimensional stability is maintained, and surface finish is also good.

2.1. Steps in Injection Molding. The main parts of an injection molding machine are mold, clamping unit, hydraulic system, control system, hopper, cooling channels, injection unit, and drive unit. Injection molding consists of four stages.

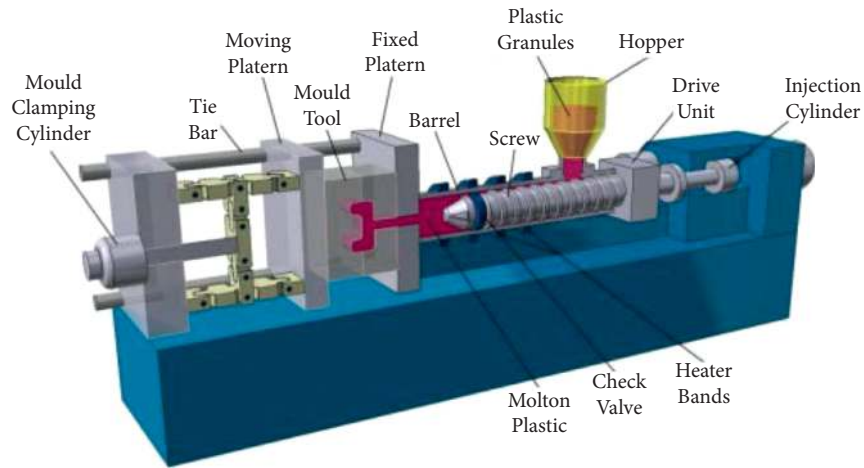
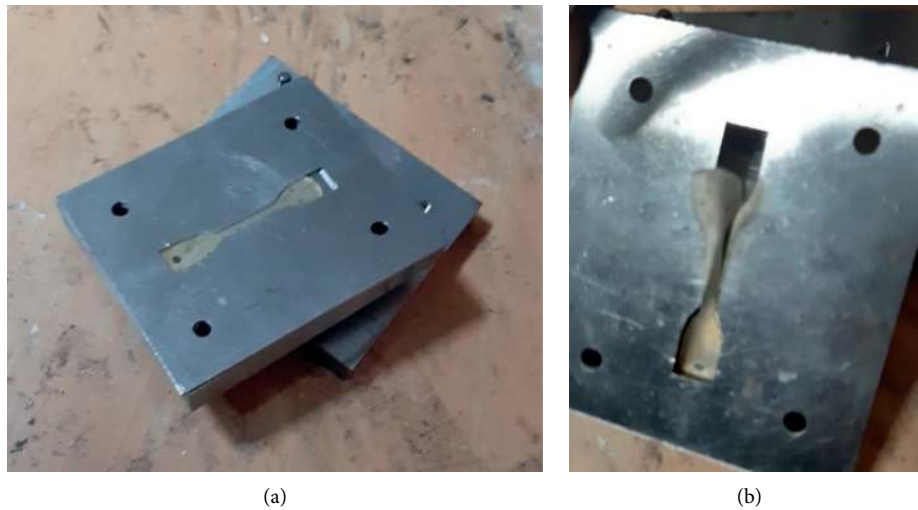


FIGURE 2: Plastic injection molding setup [21].



(a)

(b)

FIGURE 3: Pictures of (a) injection mold and (b) mold made from PVC pellets (taken in Composite Lab, VIT University, Vellore.).



FIGURE 4: Stages of injection molding.

From Figure 4, in the first stage, the material is heated until it is melted, and it is then injected into a mold under pressure. Material is fed from the hopper and is then melted [28]. A screw is used to transfer the molten material to the injection site. The melted material takes the shape of the mold, and it is allowed to cool to solidify the material [29]. Different methods are used in the preparation of ceramic powders and metallic powders. Carbonyl synthesis, high-pressure water atomization, and atomization using gas are standard methods for preparing metal powders. The median particle size obtained from these three processes is shown in Table 1.

The purity of gas atomized powder is superior to those prepared using water atomization [33]. Silicon nitride is obtained by nitriding of silicon, and aluminum oxide is obtained from the leaching of bauxite. Different chemical

TABLE 1: Median particle size obtained from various processes.

Process	Median particle size (in micrometers)	Ref.
Water atomization	100	[30]
Gas atomization	50–300	[31]
Carbonyl synthesis	1–70	[32]

methods are used in the manufacture of ceramic powders. In general, ceramic powders are finer than metal powders. Finer powders offer better strength in comparison to coarse powders. Binders are used to provide easy separation from mold and retain the shape and strength of the part formed [34]. The majority of the defects occur during the molding or injection phase. Injection pressure, mold temperature, and mold complexity are significant factors that affect the quality of the produced parts, so to reduce defects and improve the

quality of the produced parts, reasonable control is required over these parameters. Hardened steel, aluminum, and beryllium-copper alloys are used for manufacturing molds. Steel is used for making molds that require a longer lifespan, but it is comparatively expensive [35]. Ejection gap, cooling circuit design, and allowances are considered while designing the mold. A good surface finish is required in the core, cavity, and runner.

Pressure is applied continuously by the screw, which melts the material and injects the molten material into the mold [36]. The screw of the injection molding machine moves forward at a slower rate, and the injection rate is also slower. As the material starts to cool down and solidify, the gate solidifies. After this, the screw of the injection molding machine moves back to its original position [37]. To compensate for shrinkages and ensure the quality of the final product, the holding pressure is maintained for some time after the material in the mold completely solidifies. About 60% of the total cycle time of injection molding is in the cooling phase, as shown in Figure 1 [38]. Cooling channels are provided in the mold design to accelerate the cooling process. Incomplete cooling produces defective parts and is not suitable for the application.

The mold release or demolding is the next and final stage in injection molding. When the mold reaches a particular value, the mold is opened by the clamping unit for extracting the final product. Improper molding methods result in uneven surface stress and product deformation. So, the method of the demolding has to be chosen carefully. Stripper plate demolding and ejector demolding are the most widely used demolding methods [39]. When ejector pins or pressurized air cannot remove a part from the mold core, a stripper plate is used. A stripper plate is utilized to push the part from the injection mold core, and complete contact is made between the outer parts of the part and the stripper plate for the injection process. It is more reliable than ejector pins or pressurized air, and it is usually used for thin-wall injection molding. Incomplete molding can increase cycle time, incur high costs, and waste material. After demolding, one cycle of injection molding is completed. Usually, a cycle time can vary from a couple of seconds to a couple of minutes.

Many injection molding processes are widely used for different sets of applications, as shown in Table 2 [33]. The most commonly used injection molding techniques are thermoplastic injection molding and metal injection molding [40]. Thermoplastic injection molding plays a vital role in manufacturing products from plastic and polymers, whereas metal injection molding is mainly used for automotive and electronic applications [41]. The other commonly used injection molding processes are gas-assisted injection molding, microinjection, and thin-wall injection molding. These molding techniques find their use in medical, electronics, and telecommunication fields. There are various parameters to consider while choosing the desired injection molding process for a particular application [24]. Some factors to consider are production capacity, product size, design considerations, and cost of operation and materials.

Injection molding also has certain disadvantages [42]. Designing and modeling injection molding components take much time, and it is a complex process. One such complicated process is designing the mold. Mold design is critical to the accuracy and finishing of the final product, and hence much time is invested in this process. So, this leads to a temporary increase in lead time and hence affects the industry's productivity [43]. The equipment and necessary apparatus are pretty expensive compared to other manufacturing processes. So, injection molding is not suitable for small-scale production. Also, there are limitations in the size of the product because it is challenging to manufacture large-size products. High tool cost and design cost are incurred in the manufacture of large-sized products, and hence it is not feasible. So, these are some of the limitations of injection molding.

2.2. Defects in Injection Molding. Injection molding is also prone to defects like any other manufacturing process [44]. The majority of the defects can be mitigated by redesigning the molding process and following design guidelines [45]. Commonly observed defects in injection molding are flow lines, weld lines, flash, and sink marks. The causes and prevention of these defects are listed in Table 3.

From Table 3, it can be seen that most of these defects can be eliminated if we have reasonable control over the operating parameters of the injection molding process. So, to establish a reasonable control on operating parameters, we need to implement specific machine learning techniques into the molding process.

Flow lines are lines or patterns appearing on the final product, and they are usually off-toned in color. Small craters formed in dense areas of the final product are called sink marks [45]. They are mainly caused by the improper gate and runner design and inadequate cooling time. Condition in which thin surface layers form on the surface of the part due to the presence of contaminants is called surface delamination. Weld lines are similar to flow lines, but they appear similar to a plane than a line when compared to flow lines. They are caused by improper bonding and low injection pressure and speed [46]. Non-uniform cooling of mold causes warping, creating internal stresses within the part and resulting in distortions. When mold is subjected to high injection pressure and high screw speed, it can degrade the mold's material, which can cause discolorations in the final product. This type of defect is called a burn mark [16]. Traditional methods of inspection of the parts include visual inspection and various destructive and non-destructive tests. However, the main problem with these techniques is that they are inefficient and rely on the operator's experience. It is time-consuming and increases the product's production cycle, affecting the productivity of the industries [47]. Online monitoring can offer a better alternative than conventional methods. It utilizes machine learning techniques in defect detection, and it is more efficient and improves the industry's productivity. The initial cost of an online monitoring system can be pretty expensive, but they are profitable in the long run [48].

TABLE 2: Applications of different types of injection molding.

Type of injection molding	Applications	Ref.
Metal injection molding	Medical applications, automotive parts, and electronic appliances	[33]
Gas-assisted injection molding	Household appliances and automotive panels	[33]
Microinjection molding	Lens, sensors, and optical instruments	[33]
Thin-wall injection molding	Food packaging, telecommunication applications, and medical applications	[33]
Thermoplastic injection molding	Plastic industry, medical, electronics, and automotive applications	[33]

TABLE 3: Defects in injection molding.

Defect	Causes	Prevention	Ref.
Warping	(i) Inadequate cooling time	(i) Improve mold design and increase cooling time	[44]
Flow lines	(i) A varying flow rate of molten material (ii) Low injection pressure	(i) Maintain optimum injection pressure and rate (ii) Modify the design to avoid sudden changes in mold thickness and direction	[45]
Weld lines	(i) Low injection pressure or speed (ii) Low mold temperature (iii) Gates and runners are not of adequate size	(i) Increase injection pressure and speed (ii) Increase temperature of the mold	[45]
Flash	(i) Low clamping force (ii) High injection pressure	(i) Reduce injection rate (ii) Increase cycle time	[45]
Surface delamination	(i) Presence of contaminants or foreign particles	(i) Preheat the mold before molding (ii) Increase the mold temperature	[45]
Burn marks	(i) High injection pressure (ii) High screw speed	(i) Reduce injection pressure and speed (ii) Reduce mold temperature	[46]
Sink marks	(i) Cooling time is not adequate (ii) Small runners or gates (iii) High mold temperature	(i) Lower mold temperature (ii) Provide a uniform cooling rate by optimizing the thickness of the mold	[47]

3. Machine Learning Models

Machine learning algorithms are mainly categorized into supervised and unsupervised.

3.1. Supervised Learning. These algorithms can predict the future or unknown data based on their learning in the previous training. The comparison will be made with the expected output and output that the machine has generated, and then the model can be changed accordingly [49].

3.2. Unsupervised Learning. These algorithms are quite the opposite of the supervised learning algorithms, where they will not be trained to classify, but these will get inference from a function and describe the unlabelled dataset [50].

The following is the list of widely used machine learning algorithms. The following algorithms can be used for most of the data problems.

3.3. Linear Regression. It is used to predict the values of one variable based on the values based on other variables. A variation in guessing is called a dependent variable. A variable that we use to predict other variables' values is called an independent variable. For example, we use linear regression for understanding that test performance could be predicted based upon the updated timing of how to use tobacco based on smoking time [51].

3.4. Logistic Regression. Logistic regression is a supervised learning set of rules using binary type troubles. Though "regression" contradicts classifying the point of interest here in the phrase, logistic refers to the logistic feature doing the classification assignment on these algorithms. Logistic regression is an easy and productive algorithm, and that is why it is usually utilized as much as binary class obligation. Customer churns, e-mail spamming, and website and advert click prediction are few examples wherein logistic regression offers a practical answer. A base about logistic regression is the logistic function, also known as sigmoid function, which takes into any of the actual value numbers, mapping it to the values between zero and one [52].

3.5. Decision Tree. A decision tree classifier is a nonparametric supervised learning algorithm that can be used for classification and regression. A tree is a piecewise constant approximation. The main element of the decision tree classifier is its ability to separate intricate, complex, and dynamic decision-making processes into an assortment of less complex decisions and, along these lines, provides a solution that is simpler to interpret [53].

3.6. SVM. Support vector machine intakes data points and generates the maximum marginal hyperplane (MMH) that best separates the tags. A line can be an example of MMH in 2 dimensions which can be called as the decision boundary. This decision boundary classifies both sides of lines with different classes [54].

3.7. *Naive Bayes*. Naive Bayes is a supervised set of rules used for type responsibilities. Therefore, it is known as the Naive Bayes classifier.

Naive Bayes assumes that capability is independent of each difference; there is no correlation among features. However, that is not the case in actual lifestyle. The naive assumption about capabilities is not correlated which is why the set of rules is called naive [55].

3.8. *KNN*. The K -nearest neighbor (KNN) is a nonparametric classification method, which is easy yet powerful in the vast majority of the cases. The algorithm has a significant dependency on the value of K . In practice, for every unseen instance, its K -nearest neighbors within the training set are first of all recognized. From that point forward, the dominant occurring class on this produced neighborhood set of K elements is recognized as a label set for the unseen instance. Predicting was achieved consistently with most of the people classes. Similarly, KNN regressions take mean values about five close factors.

3.9. *K-Means*. K -means clustering is a vector quantization method that seeks to partition n observations into k clusters, with each observation belonging to the cluster with the closest mean cluster centres, which serves as the cluster's prototype. As a result, the data space is partitioned into Voronoi cells. Squared Euclidean distances are minimised by K -means clustering within cluster variances [57].

3.10. *Random Forest*. In this machine learning algorithm, a combination of tree predictors is used to predict the output data. These trees depend on the value of a random vector which is sampled independently and with similar distribution for all the trees in the forest. These are also called decision forests for classification and regression by constructing a multitude of decision trees at training time [58].

A neural network is a subset of machine learning (ML) and is the core of deep learning. Neural networks are also called artificial neural networks or SNN. This neural network is mainly inspired by the human brain and how the neurons send the signals to each other. The artificial neural networks consist of three components: the input layer, the hidden layer, and finally the output layer. The neural networks mainly rely on the training data for learning and improving their accuracy over time [53, 59–62].

- (1) Single-layer feed-forward network: in the single-layer feed-forward network, there will be two layers: the input layer and the output layer. In the input layer, computations are not done, so they will not be counted. When different weights are applied to the input nodes, the cumulative effect for each node is taken, and the output layer is formed.
- (2) Multilayer feed-forward network: the multilayer feed-forward network has a hidden layer and does

not directly contact external layers. Having more hidden layers makes the neural network computationally stronger.

- (3) Single node with its feedback: in the single node with its feedback, the output could be directed back like input to the same layers or the preceding layer node resulting in a feedback network. Recurrent networks are the feedback networks with a closed loop.
- (4) Single-layer recurrent network: recurrent neural network is a subset of an artificial neural network in which the connections between the nodes form a directed graph with sequence. The neural network will exhibit dynamic behavior for a time sequence. The single-layer recurrent network will use the internal state or memory to process the input sequences.
- (5) Multilayer recurrent network: the processing output element may be directed to the processing element in the same and preceding layers in the recurrent multilayer network. The same task is performed for all sequence elements, and the output depends on previous computations. The main feature of RNN is the hidden state that captures information about the sequence.

4. Discussion: ML Implementations and Outcomes

As technology advances, more advanced injection molding types are invented. Some of the examples include metal injection molding and ceramic injection molding. In metal injection molding, powdered metals are fused with alloys of relatively softer metals injected into the mold. Gas-assisted injection molding and water-assisted injection molding are used when the molding parts are very thick and in cases where making hollow parts is necessary to save both cycle time and maintain high product quality. Even existing injection molding processes are also developed to improve performance. For example, in plastic injection molding, new resin formulations are developed to improve the strength and decrease the weight of the product. Many injection molding tools are also developed, which can improve the quality of the products. These tools use machine learning to improve the precision and accuracy of the final products.

The paper's main focus was on the algorithm used, AI model taxonomy, depth layer sizes, training time, testing time, dataset, framework, core language, interface, advantages, and disadvantages. Based on the algorithm used, classification was done if it was a supervised or unsupervised algorithm. Depth layer size is found to determine the number of layers and the number of neurons in the hidden layers for the most optimized result. Dataset size is also considered to determine if the amount of input training data was sufficient or not to the model to give the most accurate results and predictions. The framework and software also considered which software gives the best visualization and correct prediction of the results. It was found that the most used software programs were MATLAB and

C-MOLD. At last, the advantages and disadvantages of the model proposed in the research works are given to date to help the future models to be analyzed accurately and chosen for the right task based on the requirements met by their advantages and disadvantages.

In machine learning, supervised learning (Figure 5) is when the machine will be trained on input data using labels to be given or predict the output with the required accuracy. The scheme like the supervisor or a teacher first teaches the student how to solve and then makes the student more accurate. After training, the model is then tested on test data, which is a part or subset of the training data in different ratios. Since the machine is already trained, it gives the output more reliability. The method in [63] gave the best output by predicting the perfect time when the machine should be changed to minimize damage cost by getting trained using multiple supervised algorithms, compared with other obtained results from various research works shown in Table 4.

Unsupervised learning (Figure 6) is a section of machine learning used in many real-world problems in which the labels are not mentioned, and the hidden patterns from the dataset should be found out. The model by itself tries to generate a pattern from all the datasets without supervision. Based on the similarities in the dataset, the machine tries to find common elements and group or cluster those data together. This method is similar to how a normal human being learns on his or her own. The method in [72] shows the best results using unsupervised cluster analysis that finds the molds wearing out and predicts in real-time, and it has an excellent early warning system which predicts before they wear out and cause trouble. The comparison of such models with other obtained results from various research works is given in Table 5.

Reinforcement learning (Figure 7) is a segment of machine learning where the machine learns the classification of the dataset by the trial and error method like getting rewards for giving correct output and penalties for wrong output to the machine. Using this concept, the model finds how it should be doing a task to maximize rewards and minimize penalties by starting with random data trials. The paper [77] used reinforcement learning by predicting the operating conditions and molding conditions in a short period and performing molding with less consumption power, compared with other obtained results from various research works shown in Table 6.

The artificial neural network (Figure 8) is a segment of artificial intelligence used to simulate or replicate the working of human brain functionality. The ANN consists of processing units that contain inputs and outputs. Through the input, the ANN learns and then produces the required output. The method in [43] gives the best result using ANN by predicting high accuracy and recommending the injection molding process condition on the real and correct time in fix material condition. Table 7 compares research works done in ANN implementation in injection molding.

Backpropagation algorithms (Figure 9) are rules used to guide artificial neural networks (ANNs). It is the most basic block in the neural network. This algorithm can effectively train the neural network by chain rule technique. The backpropagation performs a back pass after every forward pass, which adjusts the model parameter. Here, the method

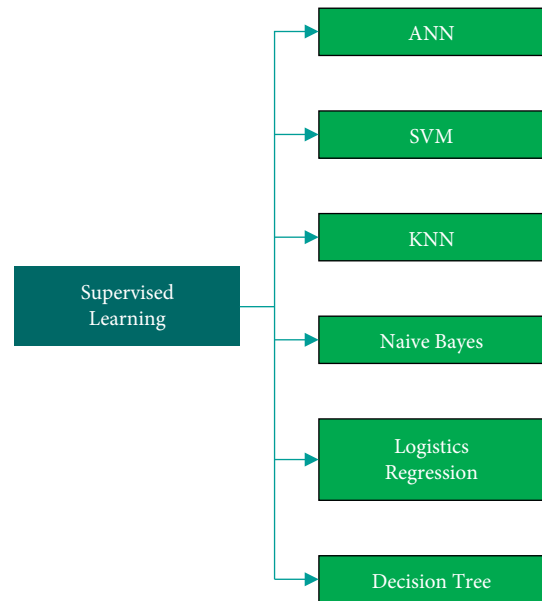


FIGURE 5: Supervised learning.

in [13] using the backpropagation algorithm predicts the faults even with less important variables than desired, causing an ANN system to diagnose faults that can be successfully built, compared with other obtained results from various research works shown in Table 8.

The hybrid algorithms in the artificial neural network use different algorithms like swarm optimization, greedy gradient, and backpropagation and combine them to get an improved hybrid algorithm for prediction. The research works have shown that using the hybrid algorithm for ANN gave high process reliability.

They are cost-effective due to reduced production costs and high-quality parameters. Here, the method in [18] gave the best result by predicting the parameters ideally at the test run without consuming and wasting many resources, compared with other obtained results from various research works shown in Table 9.

A genetic algorithm (Figure 10) is a segment of neural network algorithms which are based on nature-inspired property of natural selection. It is a subset of evolutionary computation. This tedious process follows the Darwinian theory. This algorithm's main advantage is that it is faster and efficient than many traditional methods and has an excellent list of solutions rather than just one solution. In the papers using many parameters and increasing the search space, the genetic algorithms fit the best. The method in [108] gives the best result using genetic algorithms by taking the time needed to determine the starting process parameter for injection molding which could be significantly reduced compared with other obtained results from various research works shown in Table 10.

Recurrent neural networks (Figure 11) are a subset of neural networks mainly used for their sequential data algorithm in the famous Apple Siri and the Google search by voice. It contains an internal memory due to which it can remember its inputs that help significantly solve the

TABLE 4: Supervised learning cases in injection molding.

Algorithm used	AI model taxonomy	Depth layer sizes, training time, and testing time	Dataset	Framework, core language, and interface	Advantages	Disadvantages	Ref.
Polynomial regression techniques	Supervised learning	NA	Simulation data, actual data	CADMOULD 3DF of SIMCON kunststofftechnische Software	The simulation predicts the direction of influence correctly	All factors' interactions are not modeled properly	[64]
The artificial intelligence algorithm used is based on random forest	Supervised learning	Time of the molding press (approximately 55 seconds).	Data were collected from a worker for hours which were later tested by other datasets	Collaborative human-robot framework light interface	Cobot's repeatability and precision, mixed with the operator's flexibility, gives the capability to manage unpredictable conditions effortlessly	Cobot does not have bumpy behavior; for that reason, an employee is forced to adapt to a cobot's advent, coping along with its pace	[65]
Artificial neural network gradient descent optimization approach, which iteratively tries to reduce the mistake	Supervised learning	Cooling time, holding pressure level, injection time, mold temperature, holding pressure time	Large image datasets	The underlying neural networks adjust themselves from the simulation to the real data between the transfer learning phases	Covers the space between simulation and real statistics in the manufacturing process plan. Accurately predicts the quality criteria from the process parameter.	Requires continuous improvement in learning version by automatic triggering of a new experiment	[66]
Each dataset is trained on 7 classification models: medium tree, medium KNN, fine KNN, logistic regressions, and coarse KNN	Supervised	The model training utilizes the 10-fold cross-validation	Sensor data are extracted through an injection molding machine	Classification models are used. Python language is used to find the accuracy of the classification models.	Predicts the time when machine should be changed exactly which makes damage cost minimum	There is a lack of fault relating to the data	[63]
Naive Bayes classifier and classification by decision trees and SVM	Supervised, unsupervised	Ten-fold cross-validation method was used, with a complete database of two hundred and thirty-seven samples	A signal dataset was used with 152 correct and 85 faulty pieces	Classification models were used, and Python language was used	SVM predicted and detected the fabrication with good accuracy of the plastics part	Samples from the databases did not adapt to the distribution of Gaussian. The same good and lousy part examples are not present.	[67]
Support vector machine (SVM)	Supervised learning	NA	36 test series are used, with 80% used for training and 20% used for testing	NA	The quality components are produced from the first shot onwards	The recommendation and classifier are not optimized	[68]

TABLE 4: Continued.

Algorithm used	AI model taxonomy	Depth layer sizes, training time, and testing time	Dataset	Framework, core language, and interface	Advantages	Disadvantages	Ref.
The linear regression technique was used	Supervised learning	Cycle time was 45 seconds, including 15 seconds for packing time and 20 s for cooling time	Dataset consisted of various points in a part and a part of the weight	ML-based framework	Minimized the number of physical experiments. Predicted the quality characteristics of the injection molding processes about various process parameters' values by utilizing the intelligence combination for the simulation data and measurement.	A considerable amount of data is required for training these models reasonably	[69]
6 various machine learning methodologies are utilized. The first three were based upon the decision tree: AdaBoost, ID3, and random forests. The other 3 were K-nearest neighbors (KNN), artificial neural network, and Naive Bayes	Supervised learning	The six classifiers are tested by using five-fold ten-time cross-validation.	Sensor dataset like pressure transducers, thermocouples, velocity, and flow sensors. Position sensors.	A human-machine graphical interface creation on Python by utilizing library PyQT graph and PyDaqmx along with standard Python libraries like NumPy	Improves overall performance according to the target productivity goal, for example, extending manufacturing equipment life and reducing area rejection, extending manufacturing equipment life, and improving energy management	Overall processing performance is not optimized	[70]
ARIMA model	Supervised learning	NA	Data consist of 100000 measurements for all machines and 53767 for machine 2605 Data are split into training and development sets using an 80:20 ratio	Used Python for graphical and predictive analysis	Models have relatively low MAPEs and hence can be considered as good	Verification of results was not present since there were no ground truths.	[71]

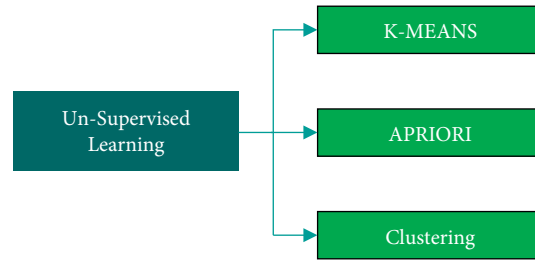


FIGURE 6: Unsupervised learning.

TABLE 5: Unsupervised Learning Cases in Injection Molding.

Algorithm used	AI model taxonomy	Depth layer sizes, training time, and testing time	Dataset	Framework, core language, and interface	Advantages	Disadvantages	Ref.
Xception and Inception V3, d Resnet-50	Unsupervised	71 layers deep. Twenty % testing and eighty % training data.	ImageNet dataset	TensorFlow Python language	Imaging models may be helpful to come across faults in injection molding, along with weaving, which is tough to become aware of with the naked eyes. Model testing performs the best at detecting short forming, with good precision, recall, and high F1 score.	It is required to make a dedicated neural network to bring images and the sensor data that could carry required information on the internal faults.	[73]
SMOTE algorithm is chosen as the training algorithm	Supervised	The cycle time is 21.84 seconds, and inject time is 1.35 seconds	The dataset is imbalanced and stored in a NoSQL database, and preprocessing is done using significant data methods	An extensive data framework is used, and machine classification and prediction models are used	The faults are estimated before occurrence and also provide an expert interpretation that can give insight into the main problem of the mistakes	Quality rates are very excessive for most types of synthetic parts. Much data are required before the overall performance of the model can become handy.	[74]
Artificial neural networks (ANNs) and decision tree	Unsupervised	Has three layers (hidden layer, input layer, and output layer), where twenty two neurons were on a hidden layer	Data include forty-one machines and process parameters from one hundred and sixty machine runs based on difference about holding of pressure time, holding off pressure, back pressure, injection speed, cooling time, barrel temperature, screw speed, and temperature of the tool parameter	Python Language and classification model	The model can differentiate good or bad parts with 99.375% accuracy	No chance to categorize the type of defect that occurs	[44]
Cluster analysis	Unsupervised learning	NA	Datasets related to the molds are used in the production	NA	Finds the molds wearing out and predicts in real-time which has an excellent early warning system	Complete data are not fed into models	[72]

TABLE 5: Continued.

Algorithm used	AI model taxonomy	Depth layer sizes, training time, and testing time	Dataset	Framework, core language, and interface	Advantages	Disadvantages	Ref.
Control algorithm	Unsupervised algorithm	NA	PVT (pressure, specific volume, and temperature) data are used	Plotter for plotting the curve and graph	Consistent quality of the molded part is maintained	Many training data are required to be acquired	[75]
AI models are used	Supervised learning	Cycle time is 37 seconds, and inject time is 3 seconds	Data are generated from many injection molding cycles by using temp sensors and pressure caused by the cavity.	Python language	Implements the control system for good quality for product generated by the injection molding through real-time monitoring.	The whole artificial intelligence-based control system is not ready	[76]

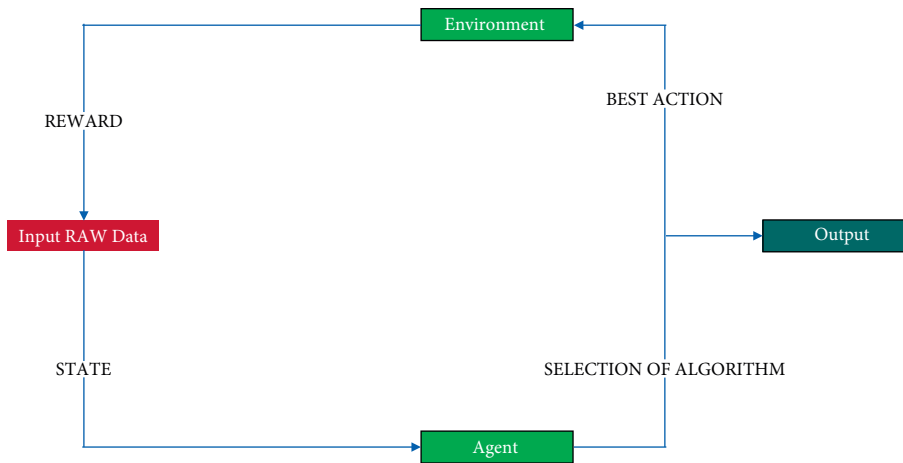


FIGURE 7: Reinforcement learning.

TABLE 6: Reinforcement learning models in injection molding.

Algorithm used	AI model taxonomy	Depth layer sizes, training time, and testing time	Dataset	Framework, core language, and interface	Advantages	Disadvantages	Ref.
Reinforcement learning	Reinforcement learning	NA	Sensor dataset	NA	Easily possible to adjust operating conditions and molding conditions in a short period and perform molding with less consumption power	NA	[77]

sequential data problems. In the research by Nagorny et al. [113], the recurrent network gave the best result by showing the best performance about the LSTM layer architectures, compared with other obtained results from various research works shown in Table 11.

5. Summary and Conclusions

For reducing defects in injection molding, control on operating parameters is required [48]. These operating parameters include injection speed and pressure, mold

temperature, and mold design [16]. Traditional defect detection methods are unsuitable for detecting defects and controlling operating parameters. They mostly rely on the operator’s expertise, and they are unreliable at times and are not efficient [47]. We can establish reasonable control over the operating parameters with machine learning techniques and reduce errors. One such application of machine learning techniques is in mold design [14]. The mold design takes a great deal of time, and it is a very complex process. Mold design can affect the quality and strength of the final product. Machine

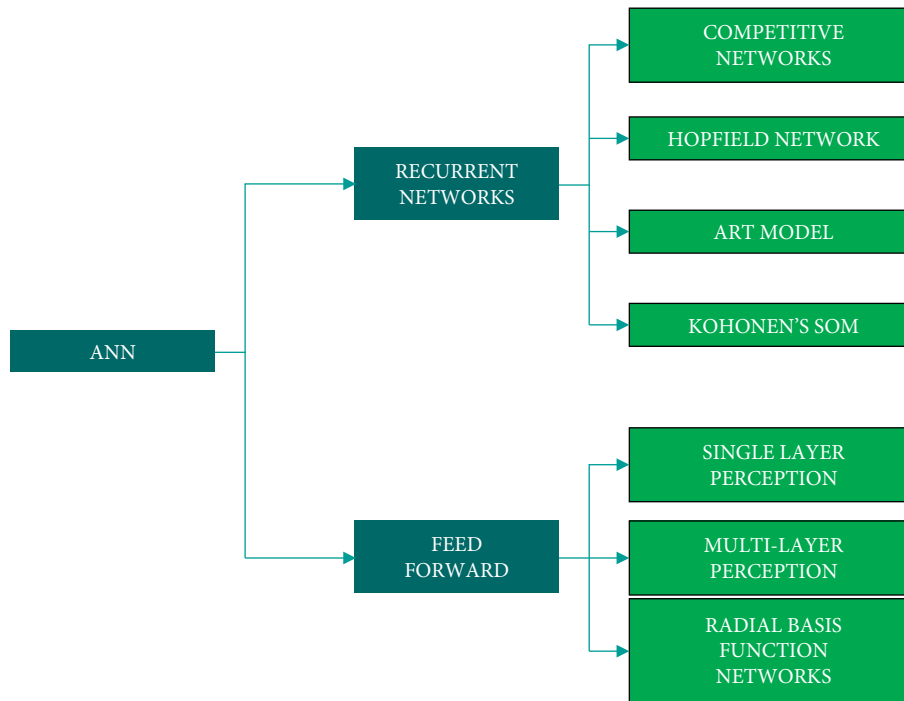


FIGURE 8: Artificial neural networks.

TABLE 7: ANN models in injection molding.

Algorithm used	AI model taxonomy	Depth layer sizes, training time, and testing time	Dataset	Framework, core language, and interface	Advantages	Disadvantages	Ref.
Adaptive neural networks, feed-forward backpropagation	Supervised learning	NA	Mold position sensor, nozzle pressure sensor, and screw position sensor data are used	BCI framework	Robustness and adaptivity for general purpose application for an injection molding machine	An accurate mathematical model has not been obtained	[36]
ANN backpropagation algorithms	Unsupervised	The network consisted of two hidden layers: two neurons from the 2nd hidden layer and two neurons from the 1st hidden layer	Training dataset consists of position about a motor of the velocity of injections profile and valve pin position profile	MATLAB Simulink	Molding precision is high because of smooth injection, better molding repeatability, and lesser power energy consumption	The training dataset is not always distributed upon the entire length for available input value to confirm the best approximate level about networks	[2]
Artificial neural network	Supervised learning	ANN with 3 hidden layers of neuron	The output data for ANN refer to the second-order fiber orientation tensor. The input data refer to a normalized level comparative to the starting charging sizes.	Keras library, Python 3.6	Reliably predicts the fiber orientation of the long fiber compression molded composite	NA	[78]

TABLE 7: Continued.

Algorithm used	AI model taxonomy	Depth layer sizes, training time, and testing time	Dataset	Framework, core language, and interface	Advantages	Disadvantages	Ref.
Artificial neural network (ANN)	Supervised learning	It consists of three layers	The dataset consists of 3600 simulation and 476 experiments from 36 various molds	3D files using Python and STL extension	With high accuracy, it recommends injection molding process condition on the real and correct time in fix material condition	The quantity of data is not sufficient. The system does not respond very quickly to new products.	[43]
A multilayer perceptron (MLP) neural network	Supervised learning	It consists of three layers	Dataset consists of temperature, pressure, and position	MLP framework	Outstanding performances in terms of the predicted accurate cost deduction	NA	[45]

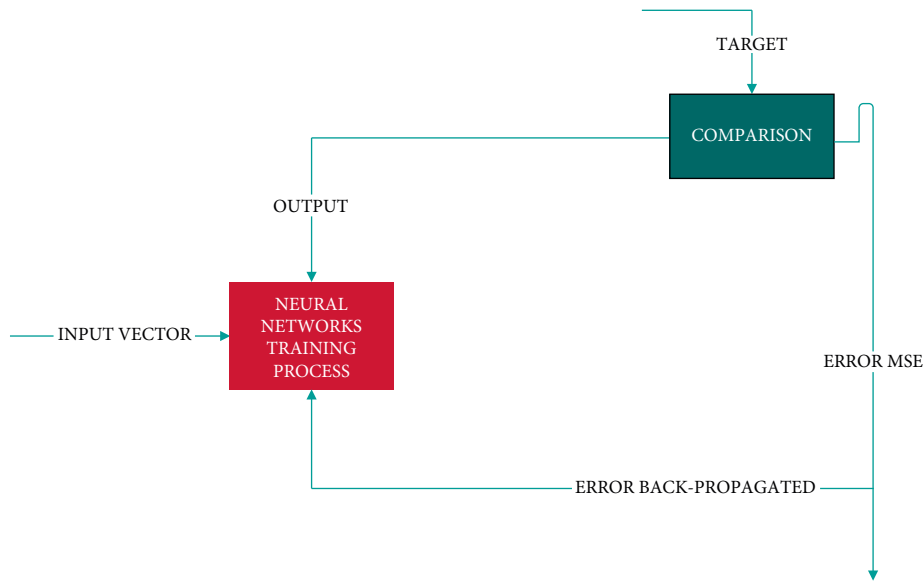


FIGURE 9: ANN backpropagation algorithm.

learning can be applied in designing and optimizing mold design. It helps to save a lot of time and preproduction delays [47]. The initial setup cost for implementing machine learning to injection molding can be costly, and it is not suitable in low production applications [2]. However, in high production, applications can be profitable in the long run and improve productivity [118–123]. However, in injection molding, there is a constraint on the size of the product. For manufacturing large products, the equipment required is costly and takes a lot of floor space. So, it is not feasible for the manufacture of large products [20, 124–127].

These are some of the significant conclusions that can be drawn from the recent research works which may benefit researchers:

- (1) Machine learning algorithms can be used in injection molding processes, starting from the molding process until the final step stages.
- (2) Multiple regression equations that were obtained through design of experiments can help the requirement of many train datasets for ANN.
- (3) Machine learning counters the drawback of the simulation by reducing repetitive processes significantly and reducing substantial computational power, amount, and time, which replaces the need for professionals to interpret results that again help in the implementation.
- (4) The most commonly used simulation programs were MATLAB and C-MOLD.

TABLE 8: Cases of ANN backpropagation algorithms in injection molding.

Algorithm used	AI model taxonomy	Depth layer sizes, training time, and testing time	Dataset	Framework, core language, and interface	Advantages	Disadvantages	Ref.
An artificial neural network trained with a backpropagation algorithm	Supervised learning	It consists of a two-layer network, and cycle time is 43.77 seconds	Dataset consists of 6 quality variables (part length, spot, stains, burn marks, flash, and unfilled parts)	NA	All the parameters have high coefficients, which shows that the network performs well	There is a small amount of redundancy among all the observation variables	[79]
ANN coupled with an improved PSO algorithm like hybrid ANN-PSO	Supervised learning	Multilayer feed-forward backpropagation ANN	The dataset consists of forty-four sets, where forty sets are utilized as the training set, and four sets are utilized as test set	Python	There is an excellent agreement between measured radii about curvature about a bi-spheric lens with less than 1% deviation and the predicted ones	There are strain and volumetric shrinkage variations in the lens	[80]
A backpropagation neural network algorithm	Supervised learning	It consists of input and output layers	Test data as 2 models, respectively, consisting of 120 samples and 40 samples	NA	Increasing the predicted performance on a product quality	NA	[81]
A simulated annealing (SA) optimization algorithm	Supervised algorithm	Three-layer abductive networks	The datasets consisted of various runner diameters, cavities, volumes, and gate lengths, searching for max warp and gate diameter.	Moldflow/MPI system	Accurately predicts the warp of multijection mold	There is an error of 8.6%, valuing optimally selective values about results in prediction of neural models	[14]
Backpropagation neural network algorithm	Supervised learning	Two layers	Data consisted of input conditions: CaCo3%, MnO3%, dwell time, and temperature	MATLAB 7.0	Predicts the output range which is lesser than ten percentage errors that correspond to the noticed value	NA	[82]
Artificial neural networks, trained with the backpropagation algorithm	Supervised learning	Three-layer network	Data were obtained from 126 production cycles	QwikNet	Even with less important variables than desired, an ANN system to diagnose faults can be successfully built	Only one topology was considered	[13]
Multilayer perceptron (MLP) backpropagation algorithm	Supervised learning	It consists of three layers	Dataset consists of injection speed and holding pressure	Integrated circuit (IC)	Reduces the size of data, which improves the training time	Prediction of the quality is good if more datasets are used	[26]
Non-binary genetic algorithm	Supervised learning	Three-layer neural network with a 4-12-1-neuron configuration	There are 54 training datasets and 10 testing datasets	Simulation studies were done utilizing Moldflow software systems.	The process operating parameters were determined correctly	The training dataset size should be increased	[83]

TABLE 8: Continued.

Algorithm used	AI model taxonomy	Depth layer sizes, training time, and testing time	Dataset	Framework, core language, and interface	Advantages	Disadvantages	Ref.
Error backpropagation algorithm and the Levenberg \pm Marquardt approximation algorithm	Supervised learning	Two-stage multilayered feed-forward neural network	114 total data points in which 94 are used to train	C-MOLD simulation software and MATLAB	Have the ability to predict injection time while presenting new operating condition with high accuracy	Slow convergence and a tendency about the networks from becoming stuck locally, making a gradient in a descent methodology not suitable or applicable for applications of this type	[84]
Backpropagation artificial neural network algorithm	Supervised learning	The 2-hidden-layer architecture was utilized for every network	Dataset consisted of process parameters	Software simulation. Using a PC with spreadsheet input.	Able to process and train in time using the single network just for monitoring multiple products, qualities, and parameters	Case study of real-life manufacture problems was not considered	[24]
Error backpropagation algorithm and Levenberg-Marquardt algorithm	Supervised learning	3-layer network	Dataset consists of process parameters	C-MOLD simulation and MATLAB	Overall error is significantly less than 0.93%	NA	[17]
Backpropagation (BP) algorithm	Supervised learning	Two-layer network	Data consist of process parameters	PLASFIL	Increase of accuracy of a process	The number of process parameters was less	[85]
Scale conjugating gradients and Levenberg-Marquardt (LM) learning algorithm	Supervised learning	Three-layer neural network	Some experimental data were utilized for testing data; that value is not utilized as train. MAPE and R2 for testing data were 1.849 and 0.9995	TOOL-TEMP TT-157 E MATLAB	Predicts the yield lengths of plastic in the mold	NA	[86]
Backpropagation learning algorithm	Supervised learning	Three or more layers	Dataset consists of mold, constant pressure, melt, gas injection, injection speed, gas delay, and gas distance.	NETS simulator	Improved through reducing residual stress, warpage, shrinkage, and sink mark	Limited testing projects were used	[42]
Backpropagation algorithm	Supervised learning	Three layers	The data consist of powder blending parameters and are randomly split into test set and train set	MATLAB	Found out optimal solids loading of feedstocks consisting of blends	Not able to detect a critical solid loading enabling the attainment of a significant reduction in lead times for a particular feedstock	[37]

TABLE 8: Continued.

Algorithm used	AI model taxonomy	Depth layer sizes, training time, and testing time	Dataset	Framework, core language, and interface	Advantages	Disadvantages	Ref.
Backpropagation algorithm	Supervised learning	Three-layer network	The data consist of coolant flow rate, coolant flow temperature, and CTP	National Instruments simultaneous DAQ boards are used in combination with LabWindows CVI software	Excellent prediction about polymeric surface cavities' temperature profiles based upon different process conditions	ANN size is not optimized	[87]
Backpropagation algorithm	Supervised learning	Three-layer network. The hidden layer is considered with 2 nodes. A value of 0.9 was utilized to reduce overfitting.	Data consist of MFR, Pinj, Tmold, and Tmelt	PartAdviser CAE	The model developed can predict standard injected part as a shortage of otherwise known about weld line defects or short shots	Process parameters are not integrated	[88]
Backpropagation algorithm	Supervised learning	3-layer feed-forward backpropagation with ten neurons in the hidden layer	Data are extracted from the factory databases utilizing MATLAB	MATLAB environment	Reported through applying the intelligent system technique for improving downstream performances predicting in range of manufacturing environment	Several measurements are inadequate	[89]
Backpropagation algorithm	Supervised learning	Three-layer networks, where the hidden layers had 3 neurons, and the neurons are L-neuron, D-neuron, and P-neuron, respectively	Dataset consists of temperature	Visual Basic software platform	Train timing about the PIDNN was relatively small, and the last controlled results are excellent	It was computationally costly and time-consuming to train with traditional CPUs	[41]
Backpropagation-learning algorithm	Supervised learning	Three-layer network	Data are collected through rotation viscometry continued through the non-linear regression	NA	Reducing a quantity for the experiment needed for determination for practicing constantly	NA	[90]
Backpropagation-learning algorithm	Supervised learning	Three-layer network	Product cost data	MATLAB	Complete info in the process timing was no requirement. The neural networks help us improve concept design by evaluating costs on the various process and design alternatives.	Determines the total number as hidden layers; the neuron on every hiding layer was the trial-error process. The selected neural network might be the best and may not be the best. Sensitive studies about a cost relating feature in a product the cost might be challenging.	[91]

TABLE 8: Continued.

Algorithm used	AI model taxonomy	Depth layer sizes, training time, and testing time	Dataset	Framework, core language, and interface	Advantages	Disadvantages	Ref.
Backpropagation algorithm	Supervised learning	Three-layer network	Dataset is split into a training set, validation set, and testing set	MATLAB tool	Able to model almost any data	Relies on discrete measured process parameters as inputs to the model	[92]
Backpropagation algorithm	Supervised learning	Entry layer with five process variables, a hidden layer with 33 neurons, and an exit layer with eight variables.	Dataset consists of process variables like injection, temperature, and switch over.	Specific software not mentioned	The precision of the model of a neural network is perfectly valid	Very few process variables are considered	[93]
Backpropagation algorithm	Supervised learning	4-2-3 (4 neurons of an input layer, two neurons of the hidden layer, three neurons of output layer)	Data were obtained experimentally based on the Taguchi test schedule	C-MOLD software	Reduces the number of experiments and has adaptive learning ability	Requires a lot of training process before a BPANN can be used for prediction and optimization	[94]
Backpropagation algorithm	Supervised learning	Three-layer network	Powdered metals, compaction pressure, powder composition, and sintering condition are important input parameters	MATLAB neural network toolbox	Demonstrated method is about advising the best selection of material as earlier as possible onstage about design in a component	Design geometries about commonly occurring component were not considered	[95]
Backpropagation algorithm	Supervised algorithm	The network had 3 core layers and output layers, a hidden layer, and an input layer	Data consist of pattern lines (two hundred micrometer nozzle), feed rates, pressure, and standoff distance (millimeter)	MATLAB simulation model	The approach adopted in this paper is applicable for different printable materials having a different composition and viscosity along with another printable technology about providing the incentive about optimizing	Dispensement in materials affects the volume of air in syringe barrels and the viscosity of the material	[96]
Backpropagation algorithm	Supervised learning	Three-layer backpropagation neural network	Data consist of surface finish, number type lines, part size, cavity material, tolerance, number of cavities, plating, mold material, number of cavities per mold, insert, and mold base type	CAD modeling software	Helps in increasing the efficiency of the product developing process by reducing the number of mold design iteration designed by the designer	Many input parameters are considered and it is sensitive to noisy data	[1]
Feed-forward type neural network	Supervised learning	3-layer network, and the hidden layer was determined through the trial and error method	Injection time data were utilized for training a neural network system	MATLAB environment	Solves the real-world problem of the MIM process and Moldflow software	NA	[23]

TABLE 9: Hybrid algorithms in injection molding.

Algorithm used	AI model taxonomy	Depth layer sizes, training time, and testing time	Dataset	Framework, core language, and interface	Advantages	Disadvantages	Ref.
Self-designed learning algorithm	Supervised learning	NA	The dataset consists of process control parameters	MATLAB toolbox	It provides real-time control. Effective in the controlled injection molding machine.	NA	[97]
A hybrid learning algorithm is used	Supervised learning	Two-layer network	Dataset consists of peak melt temperature, cushion, dosage time, cycle time, injection time, and ram velocity	NA	High process reliability. Cost-effective due to reduction in production costs.	Automatic tuning of machine setups	[98]
NA	Supervised learning	Three-layer network	Data from experimental investigations	Product design workbook	Quality of the model is very high for the parameter space investigated, allowing plausible formulation-property correlations to be readily presented	NA	[99]
An efficient algorithm, reliable in detecting the presence of the location of weld lines	Supervised learning	3-4-1 three-layer BPN is modeled for evaluating weld line properties	Experimental data for open literature simulates results about self-development (CAE)-system HSCAE	MATLAB neural network toolbox	Detecting the location about weld lines with good accuracy	NA	[100]
Multiple learning algorithms	Supervised learning	One or two hidden layers	Review of literature on injection molding, casting, and applications through ANN	Fluent, CALCOSOFT, and Magmasoft	Provides a comprehensive exploration of types of research performed on injection molding parameters to obtain the best result	NA	[101]
Bee colony algorithm	Semisupervised learning	Packing time is 6.6 s, and cooling time is 3.4 s	Dataset consists of packing pressure (Pack_P), mold temperature (Mold_T), and melt temperature (Melt_T), Data were melt temperature levels mold temperature levels, holding pressure levels, packing time, and cooling time	FE analysis software Moldflow	Has advantages in terms of quality and costs and efficiently supports engineers to determine the optimal process parameter	Many design variables related to machine settings and mold conditions were not considered	[102]
Simple SOM model	Unsupervised learning	One or two-dimensional network		NA	Efficient method to find an optimal parameter for the injection molding process	The amount of needed data is large	[103]

TABLE 9: Continued.

Algorithm used	AI model taxonomy	Depth layer sizes, training time, and testing time	Dataset	Framework, core language, and interface	Advantages	Disadvantages	Ref.
Particle swarm optimization algorithm	Supervised learning	A factor with a significant impact is time for cooling. It tells about shrinkage about HDPE.	Data consist of input parameters: mold temperature, packing pressure, packing time, and melting temperature	NA	Results accurately show melting of the temperature of 190°C, injective pressures about 70 MPa, and refill pressures of 85 MPa, and minimum shrinkage is found within eleven seconds of cooling	NA	[34]
Multiple response optimization models	NA	3-layer network, where input layer has 5 nodes and output layer has 3 nodes	Data consist of 5 process parameters: values cooling time, mold temperature, the melt, the injection flow rate, and holding pressure	MATLAB software	Improves the amount about proposing multiple responses and optimizes the problem about multiple responses optimized in the enterprise	NA	[104]
Neural network model, an integrated simulation program	NA	Three-layer adductive network	Data consist of the length and diameter of the runner system	FEM simulation	Rapidly and efficiently gives the result for determining the optimal runner-system parameter about injection molding	NA	[12]
Levenberg-Marquardt algorithm	Supervised learning	Multilayer FFN Frequency fs = 200 Hz, oil temperature toil = 30 ~ 40°, and maximum supply pressure pS max = 21 MPa.	Data consist of temperature in the melting zone, the pressure of molten plastic, and mold tolerance	MATLAB/Simulink software environment	Significantly less overshoot and faster transience	Has a larger quantity of neurons	[105]
DFSMC algorithm	NA	The total control system is coupled with 2-input 2-output system		NA	Counteracts a coupling effect, reducing a fuzzy rule number	NA	[106]
Fuzzing sets and neural networks	Supervised learning	Input and output layers have 45 and 81 neurons, respectively.	Dataset consists of short-shot, sink-mark, ash, ow-mark, weld line, warpage, and cracking	MATLAB neural network toolbox was used for system implementation	Predicts the parameters perfectly at the test run itself without wasting many resources	The neural network should be trained with exceptional white rules to encounter the sudden unexpected problems	[107]

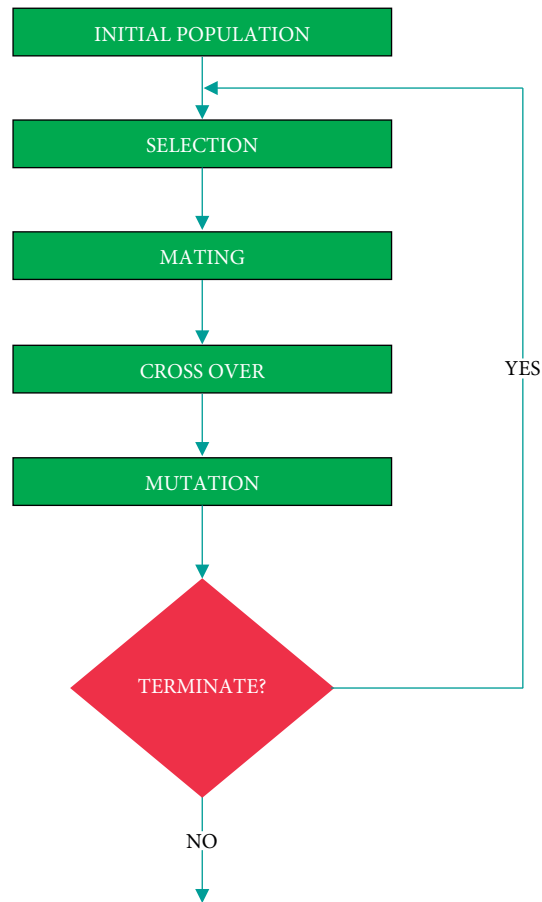


FIGURE 10: ANN genetic algorithm.

- (5) Neural network is a perfect model that can be used in the modeling complex interactions among many inputs and outputs along with high prediction with excellent accuracy.
- (6) The only drawback is the need for a good amount of training data and computational power, time, and cost.
- (7) The best selection of the hidden layer architecture is not correctly decided because it fails for other applications.
- (8) A minimal quantity of datasets has been used by many during training. Large datasets should be used to avoid overfitting.
- (9) The neural networks can be applied for many applications like control, identification, modeling prediction, optimization, monitoring, and classification.
- (10) ANN can be used to develop a reverse process model effectively.
- (11) The best predictor was Gaussian process regression with the highest coefficient of determination of 0.995.
- (12) Even the multiple linear regression is a simple model structure, and it did not perform worst on many datasets.

- (13) *K*-nearest neighbor astonishingly produced results below expectation as compared to rest of the algorithms studied
- (14) Some other algorithms like neural networks, support vector machine, and decision tree have average predictive quality.

6. Future Directions

The future directions to guide the researchers ahead are as follows:

- (1) The future work for this review concentrates on applying the different methodologies in machine learning and neural networks to many different types of machine data comprising contrasting values. In the future, more machine learning techniques may be made which are best suited for a particular injection molding machine for corresponding variables that gives the best results after analyzing with different test datasets. The self-made customized learning model might give a better result for a particular injection molding machine and its parameters. In this manner, future work might be continued on this review.
- (2) In the future, the model's scalability should be taken into consideration. The study's main aim was to find the prediction models that can find out good and bad

TABLE 10: ANN genetic algorithms in injection molding.

Algorithm used	AI model taxonomy	Depth layer sizes, training time, and testing time	Dataset	Framework, core language, and interface	Advantages	Disadvantages	Ref.
ANN genetic algorithm	Supervised learning	Model structure with 1 hidden layer, where 7 neurons in the layer were chosen	Dataset by a combination of native (MT) and substitutionary (MS, i) data from other data domain	All implementations were done in Python. TensorFlow, Keras, and scikit-learn Hybrid NN. GA systems are implemented on Visual Basic programming languages. Validation tests were performed in desktop computers for PII-three hundred processors and one hundred and twenty-eight Mbytes about memory as utilizing commercial mold flow simulation packages C MOLD	Reduces the requirement of many training data	Experiments have not been designed with geometrically different parts	[29]
Artificial neural network genetic algorithm	Supervised learning algorithm	A 3-layered backpropagation network (BPN) with a supervised learning algorithm was employed for producing required output-input layers	Dataset consisted of parameters of mold design, part design, and process		Time needed for the determination of starting process parameter for injection molding could be significantly reduced	The effectiveness of that system is not verified and validated	[108]
Genetic algorithm	Supervised learning	Three-layer network	Two datasets: one of them was from Petronas Penapisan (Melaka) and the second dataset was XOR common problem dataset Dataset consists of parameters like cooling time, back pressure, screw rotation speed, injection pressure, injection rate, holding pressure, nozzle temperature, holding time, and open stroke The dataset was sixty from the GDC plant in Universiti Teknologi PETRONAS, and five hundred datasets from the Sdn Bhd in PETRONAS Penapisan and sixty-four experiment datasets from flank wear for the drilling process were used in developing the newly proposed architecture	MATLAB	The performance of the proposed ANN-GA approach was compared with existing 5 approaches in terms of the prediction effectiveness	Optimum ANN parameters into a broader search space are not determined	[109]
Genetic algorithms	Supervised learning	NA		ENGEL injection molding machine (USA) was equipped with EC88/CC90 and A02 controllers	Different sized simplexes were the apt methods for online optimization of the situation	The percentage of reject was also susceptible to half pressure level and cool time	[110]
Genetic algorithm	Supervised learning	A three-layer network, the hidden layer contains six nodes.		MATLAB function	Process of designing ANN is less dependent on humans and is more sophisticated	The training data used are not sufficient	[111]

TABLE 10: Continued.

Algorithm used	AI model taxonomy	Depth layer sizes, training time, and testing time	Dataset	Framework, core language, and interface	Advantages	Disadvantages	Ref.
Genetic algorithm	Supervised learning	Two-layer network where a hidden layer contains the radial basis neuron and the output layer contains the linear neuron	A dataset used in this study consists of 102 sets.	Moldflow software	The proposed approach can effectively be helpful for the engineer's determination of optimal gate, locations, and other designing elements for achieving competition profits about product cost and quality	During detection in the optimum location of the gate, many parts have not been considered	[44]
Genetic algorithm	Supervised learning	Three-layer network	Experimental data of Taguchi's parameter design method are utilized for effectively training and testing the BPNN model	Integrated numerical simulation software	Effectively helps engineers determine the final optimal process parameter setting	Multiresponse process parameter design problems	[112]

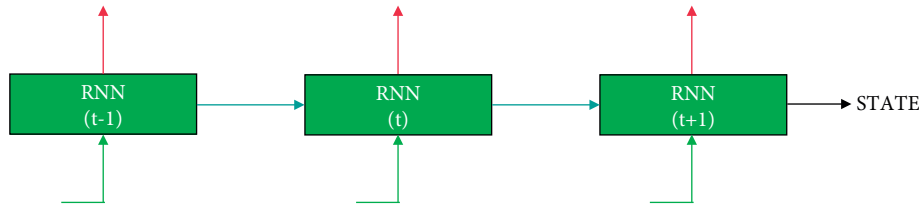


FIGURE 11: Recurrent neural networks.

TABLE 11: Recurrent neural networks in injection molding.

Algorithm used	AI model taxonomy	Depth layer sizes, training time, and testing time	Dataset	Framework, core language, and interface	Advantages	Disadvantages	Ref.
Regression and neural network	Supervised learning	Three-layer MLP architectures	Dataset comes from inline industrial measurements	Scikit-learn library, Python,	Shows the best performance about one and only LSTM layer architectures	Recurrent network architecture was also complex	[113]
The real-time adaptive control algorithm	Supervised learning	Three-layer neural network	NA	Computer simulations	Proposed control strategy is effective under setpoint change and bounded disturbance	For example, a considerable fixed learning rate was considered, so RNNM might suffer from instability	[114]
Training algorithm	Supervised	Two-layer neural network	Dataset consists of plasticizing stroke, holding pressure, injection velocity, metering stroke, mold opening speed, RPM, injection pressure, cooling time, cushion, and nozzle temperature	Computational tool (DPTNN)	Online monitoring and diagnosis system on false detection of the injection molding machine	Only single network architecture was used	[115]
TDNN and Elman networks	Supervised learning	NA	NA	MATLAB	TDNN exhibits lesser train time comparatively for the wanted performance	Temporal dependency is large	[116]
Genetic algorithms	Supervised learning	Three layers. Hidden layers do not interact with the outside world but help in non-linear feature extraction about data providing the output-input layer.	Data consisted of injection velocity, melt temperature, packing pressure, and mold temperature	NA	Parameters were optimized for minimum dimensional shrinkage. Reduces a good amount of cost and time.	Few results of reverse mapping deviation which is more significant than 10%	[117]

values for injection molding parameters. Many different parameters have been taken into consideration while feeding the models with data, and multiple machine learning models, including supervised and unsupervised learning, have been considered. Their outputs were compared with respect to the best and worst predictions to find the best models that give the most accurate results.

While feeding and training the model, the dataset ratio should be balanced between several good and bad parts. The data size should also be considered; it should not cause overfitting or underfitting, which might result in wrong predictions in the future.

- (3) For the future, the work can concentrate mainly on integrating more and more factors or parameters affecting the performance of injection molding

machines. It is strongly believed that the optimization strategy is effective. Many materials might be included in the future, and different molds might also be used for the workpieces to give a great application where automated machines are primarily used in the industries. More stress can be given on the parameter optimization and the tolerance design, which are essential activities related to quality; by considering different molds, the scalability of the model increases.

- (4) In the future, the work corresponding to this review study can prepare or generate various kinds of learning models and algorithms. It includes the complete implementation of machine learning-based models or artificial intelligence-based models or control systems to manufacture different objects using injection molding. It should also involve the validation part of the injection molding machine with different kinds of data (including the edge cases and exceptions) and experiments that make the model complete for usage in terms of prediction and validation of the injection molding machine output using given process control parameters.

Disclosure

Senthil Kumaran Selvaraj and Aditya Raj are first authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Senthil Kumaran Selvaraj and Aditya Raj contributed equally to this study.

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