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Article

ROLE OF ARTIFICIAL INTELLIGENCE IN AUTOMATION AND IMPROVEMENT OF EFFICIENCY IN INJECTION MOULDING PROCESSES

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Abstract: - Most of the usable plastics produced across the world involvethe injection moulding process. Improving the efficiency of the injection moulding process can reduce wastages and improve efficiency without affecting the profitability of a manufacturing plant. One of the most important technologies to improve injection moulding efficiency is through Artificial Intelligence (AI). When combining sensors for data acquisition and AI for automation, the improvement opportunities are endless. In order to understand the trends, opportunities, and challenges in AI integration, we designed a narrative-style review in this study. The study uses peer-reviewed research papers that implemented or compared any machine learning algorithm after 2016 are considered for the study. The review focuses on AI models capabilities in process automation, parameter calculation, quality assurance and sustainability in injection moulding manufacturing process. The review mainly distinguished AI models into four categories: supervised learning, unsupervised learning, deep learning, and reinforcement learning algorithm. The review found that most of the research in AI implementation in injection moulding considers either supervised learning algorithms or deep learning algorithms. Many of the implementations are careful in using reinforcement learning as they don't want to include trial and error-based training. But supervised learning like Genetic Algorithm and Particle Swarm Optimization (PSO) have better real-world implementation capability compared to other models. The review highlights the problems and opportunities in existing AI implementations in injection moulding.
Keywords: Artificial intelligence, Injection moulding automation, Supervised learning algorithm, Deep learning algorithms.

1. INTRODUCTION

Injection moulding enables the rapid, large-scale manufacturing of materials, making the entire manufacturing process significantly more efficient. This method will give the ability to produce complex design patterns and shapes while reducing the whole processing cycle for production. All the advanced injection moulding methods reduced the need for post-processing and provide a clear, smooth finish. Additionally, there is a high possibility of cost optimization by reducing the wastage of raw materials and the turnaround time of finished products. This makes Injection moulding contribute to more than 30% of the overall plastic products manufactured worldwide. An annual growth rate of 4.83% injection moulding machine market can increase to $19.72 billion by 2034. Therefore, any optimization and advancement in the injection moulding process can increase the quality and quantity of overall plastic output and disrupt the packaging industry.

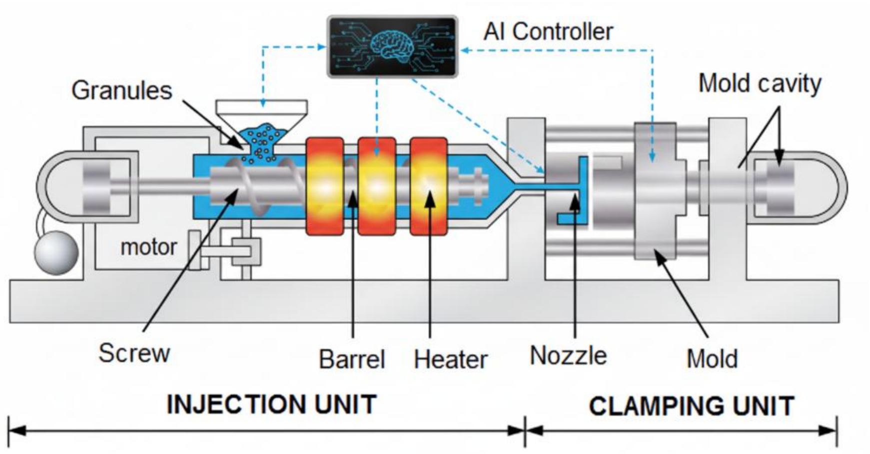

Fig 1: Injection moulding schematic design [1]

This high rate of production makes the plastic materials produced from injection moulding used in food packaging, medical components, electronic parts, and basic consumer goods. The quality and rate of production are determined by the type of materials used, the parameters used in the manufacturing process, the processing environment, and the parameters of mould design. The type of materials used, like polymer type, resin batch variance, additives, and filler material used, can impact the thermal, mechanical, and consistency of the output product. It is important to select the input materials used based on the quality of the output products. The next important consideration should be given to process parameters, as pressure and speed of melted plastic through the mould determine the finish, consistency in filling, and rate of manufacturing of the product. The review starts with a basic question: Is generative AI the answer for all of the problems in manufacturing? But this is not the case for most of the problems in manufacturing.

1.1 Review Objectives and Scope

Despite growing research activity, the field lacks a comprehensive synthesis of ML methodologies, their comparative performance, implementation considerations, and practical limitations specific to injection molding contexts. Existing reviews either focus narrowly on specific algorithms, lack critical evaluation of industrial applicability, or fail to address recent advances in deep learning and hybrid approaches. This review aims to bridge these gaps by providing a systematic, critical analysis of ML applications in injection molding from both algorithmic and application perspectives.

1.2 Overview of Artificial Intelligence in Injection Moulding

Optimization of the injection moulding process can take place during the cooling and ejection phases of plastic production. This phase constitutes up to 90% of the whole time; therefore, optimizing this process can save most of the processing time [2].The machine learning process can reduce cycle time and optimize the whole process planning. These algorithms can detect product defects, optimize moulding parameters, and control the mould design to reduce cooling time. These changes can also help in reducing the wastage from the manufacturing process.

2. RELATED WORKS

Introducing deep learning algorithms in injection moulding can outperform traditional methods by optimizing parameter tuning, abnormality detection, designing the mould, and process monitoring. Machine learning algorithms reduced the need for expert individuals and their experience, and make predictions completely based on real-time data collected from IoT devices. The machine learning models are divided into three major categories supervised learning, unsupervised learning, and reinforcement learning (RL). The most commonly used method in injection moulding process is supervised learning. This method involves both training data as well as data labels to train the models. Supervised learning is very effective for classification and prediction problems, the linear relationship between data availability and accuracy makes these algorithms improve over time. Pierleoni et al. (2020) compared different decision trees, KNN, and logistic regression model performance on different types of injection moulding processes. In this study based on non-linearity in data machine learning algorithms performed differently for each input. Therefore, choosing the machine learning model for a specific task is very important [3]. In case of unlabelled data, classification and prediction can be done with the help of an unsupervised learning algorithm. There are many different methods used to classify unlabelled datasets effectively; one of those techniques is clustering. Costa et al. (2025) used Principal Component Analysis (PCA) to reduce dimensionality, a clustering algorithm to identify states of these machines, this clustering allows supervised algorithms like

XGBoost to classify the dataset effectively. This type of hybrid approach of combining supervised and unsupervised learning can make the model learn faster with fewer resources, instead of unsupervised learning algorithms [4]. Instead of these hybrid methods, many studies use reinforcement learning, which can optimize for a long period of time. Recent research papers used a Deep-Q-Network, a Reinforcement learning algorithm for scheduling and analyzing the sequential jobs that are processed in multiple machines in injection moulding. This type of reinforcement learning algorithm can be scaled effectively for large-scale operations without changing the underlying operations and model performance.

3. RESEARCH METHODOLOGY

To find the impact of AI on injection moulding, we analysed recent research papers published in high-impact journals over the last 7 years. The whole study was structured into four different clusters: process optimization using deep learning, quality control using AI, machine maintenance, and design and optimization using AI. The papers are analysed and compared based on their performance metrics to understand the basic structure behind all these studies. The study also includes initial simulated research papers and, at the end, compares the performance of industrial adoption and understands the problem with real-world adaptability.

3.1 Process Optimization using AI

The closed-loop process control uses AI to identify the quality of the product and optimize the parameters such as temperature, speed, and pressure in the moulding machine. The injection moulding can be optimized using AI, which reduces the cycle time, scrap rate, process setup time, and power usage by the machine. The review on various deep learning networks found that convolutional and recurrent neural networks have the most potential to optimize the process because of their simplicity and complex pattern recognition capability [5]. One of the major advantages of AI in manufacturing is predicting the optimal parameters for the injection moulding process. Liu et al. (2024) proposed the use of multi-layered neural networks to predict the optimal parameters, temperature, and cooling time based on historical records from manufacturing plants. The deep learning algorithms are not only capable of producing optimal values, but they are also capable of generalising the data for new types of input designs [6]. The basic machine learning algorithm that has faster inference time and easy to train is ANN (Artificial Neural Network) algorithm represented by formula (1).

$$\hat{y} = f\left(\sum_{i=0}^{n} w_i x_i + b\right) \qquad (1)$$

Where the predicted output (y) is processed in multiple neurons (x_i), weights (w_i) and activation functions (f).These types of deep learning algorithms are often stuck with a problem called interpretability; it is very hard to know what is the reason for a particular output, which makes them harder to implement in high-stakes industries where accuracy is of the utmost importance.

Deep learning and machine learning algorithms are used in conditions where a complete change of design is expensive. In those cases, they are used to update or change the parameters and improve the outcome of the manufacturing process. They can be used either to increase production speed or to improve the quality of the output product from the manufacturing process. Parameter optimization can be done in real-time using Deep reinforcement learning (DRL) algorithms, which update the parameters based on performance metrics [7]. Machine learning models like CNN are used to identify defectsin the objects, and are used to estimate the percentage of defect in the output. These values are used to tweak the parameters of injection moulding [8]. Instead of image as a predictive medium, many techniques use sensor signals as inputs and predict defective objects. This data is then fed to classification models like kNN, naïve Bayes, and decision trees, which classify good vs default outputs based on input parameters. This classification model doesn't require a huge training dataset, which makes it highly adaptable to new input samples. These classification models can be good to improve the speed of optimization, but most of the models have an accuracy of more than 90%. A 10% loss in accuracy can be a significant drawback in the injection moulding space, potentially impacting the model's real-world adaptability [9]. The usage of a sensor inside the mould cavity can cause damage which can lead to noise and deviation in outputs. This noise in sensor output can harm the whole prediction process by classification algorithms [10]. The industrial sensor noise is unstable and difficult to distinguish between the sources of noise, such as vibration, thermal noise, electromagnetic interference, and material degradation. This noise is non-gaussian in nature and can be cleaned using self-supervised algorithms like Denoising Auto-Encoder (DAE) which shows better performances for industrial sensor outputs [11].

Table 1: Synthesis of studies

Algorithm	What It Optimises / Application	Performance

Decision Tree (DT) [12]	Uses cavity pressure and temperature to detect faults.	*Accuracy=90%*
Artificial Neural Network (ANN) [13]	Uses stress, weight, and dimensions to calculate quality outputs.	*Accuracy=90% to 95%.*
Particle Swarm Optimization (PSO) [14]	Uses warpage, shrinkage values to optimise melt temperature, pressure and time.	*The examined warpage errors are less than 3.5%.*
Genetic Algorithm (GA) [15]	Uses process parameters to predict defect.	Reduces warpage by ~10–15%, shrinkage ~8%, and cycle time by ~5–10%.
ANN and GA [16]	Uses optimization to reduce material loss, cycle time and power consumption.	Material consumption down by 2%, cycle time down by 12%, power reduced by 16%.
RSM and GA [17]	Optimises warpage, cycle time and power consumption using output.	50% low power, cycle time consumption using optimisation.
Soft Actor–Critic (SAC), PPO [18]	Uses surrogate models to optimise parameters for process control.	135 times faster inference than traditional heuristic algorithms.
Intelligent Optimisation Frameworks [19]	Improves performance using shrinkage and warpage as predictor.	*Accuracy 95%*

3.2 Quality control using AI

Instead of just collecting temperature, pressure, and time values during process control, there are IoT devices that are available to collect solidification time, filling completion, flow velocity, and cavities in the finished products. These metrics can be collected through ultrasound, mold visualization through X-rays, magnetic levitation devices, and capacitive sensors. These are non-destructive methods for closed-loop process control, which can be used to adjust the parameters in real-time to control the quality of the finished product [20].Ke, K. et al. (2020) analysed the melt flow inside the Mold using the sensor and predicted the quality of the product using a Multi-Layered Perceptron (MLP) Neural Network. This is automatic quality control that reduces material waste and the need for manual quality checks after production [21]. The complexity of quality check increases with an increase in the number of cavities in the Mold design. Párizs, R. et al. (2022) used sensor inputs from cavity pressure sensors to predict the defect in quality. After comparing four different machine learning algorithms decision tree algorithm was found to be efficient in finding defects in the produced product [22]. These simple and faster classification techniques are useful to increase the overall cycle time in manufacturing. But doing individual-level quality checks can consume time and power, which is critical for any high-volume manufacturing facility. The speed and accuracy of the quality checking process can be increased by batch processing. Lee, J. et al. (2025) used 76 types of recipe models based on predefined settings and used autoencoders to classify the data for known data. Unknown data are trained and classified using the Adaptable Learning algorithm by calculating the KL-Divergence score [23]. This type of adaptive learning model can learn up to 76 types of defects instead of two defects, which is much superior compared to other algorithms. To compare the working of each model to a particular input, explainable AI can be applied to those models. Hong, J. et al. (2025) implemented XGBoost and LightGBM to detect faults in the process dataset. This algorithm is combined with explainable AI algorithms to find the most important variables that contribute to a particular output. The use of XAI helps to find almost 70% of the most important features that contribute to the output [24].

Image-based quality control systems are much faster and more reliable when combined with sensor-based quality control methods. Aminabadi, S. S. et al. (2022) implemented quality control in plastic injection mouldingby predicting defaults using a CNN (ResNet) algorithm. The study also uses a heuristic algorithm to simulate various changes in design based on parameters such as injection speed and pressure [25]. In-line measurement doesn't consider material type and design; therefore, a strong prediction machine that predicts quality problems before designing the Mold is necessary. Kaulen, N. et al. (2025) uses a pre-trained ResNet algorithm and divides the input images into patches based on edges and other low-level features ashigh-frequency semantics. The distance between the input image and the normal distribution is used to find the anomaly in product images. This is a simple but effective implementation of an image-based quality control mechanism [26].

Table 2: Algorithm performance on quality control

Author	**Algorithm**	**Variable measured**	**Accuracy / Detection Rate**	**Cycle Time Impact**	**Defect Rate**
Ke & Huang (2020)[21]	MLP	Melt flow	High	Lower	Lower
Párizs et al. (2022)[22]	Decision Tree	Cavity pressure	High	Faster inference	Lower
Lee et al. (2025) [23]	Autoencoder	76 Different variables	High	Low overhead	76 quality issues detected
Hong et al. (2025)[24]	XGBoost and XAI	Feature importance	70% identification	N/A	Significantly reduced
Aminabadi et al. (2022)[25]	CNN	Image sensors	High	Faster inference	Significantly reduced
Kaulen et al. (2025)[26]	ResNet (CNN)	Image sensors	Low false positivity	Faster inference	Significantly reduced

3.3 Machine maintenance using AI

The profit margin of a manufacturing company that invests a huge sum of money in buying these injection moulding machines relies on the entire manufacturing life cycle and total production time. Therefore, protecting against machine breakdown, as well as increasing the total life of a machine part, is important for a successful manufacturing company. Existing reactive maintenance strategies can be applied to machines that have reserves and can be replaced immediately without interrupting the production cycle [27]. High-priority machines in a production line can be maintained effectively using predictive maintenance methods. Predictive maintenance methods use various input signals across the production cycle and process them to get useful insights about the current condition of machines. Predictive maintenance uses a machine learning algorithm to understand the underlying pattern across the data, which can be missed by a human agent. A simple rule-based predictive maintenance approach uses an if-then condition to determine the possibility of repair. One of the rule-based algorithms is fuzzy rule-based networks. These algorithms offer interpretability, which is lacking in many fully connected neural networks. Lv, Y. et al. (2021) used fuzzy rules with a back-propagation neural network for multi-granularity prediction in machine maintenance. These rule-based algorithms are simple, interpretable, and highly scalable compared to other machine learning algorithms [28]. Theseknowledge-based models are not suitable for highly complex failure patterns and are harder to scale for different areas of manufacturing. This problem can be solved by data-driven prediction models, which use historic sensor data for training and use real-time sensor data to provide probability output. They usually have high accuracy and scalability compared to knowledge-based models [29].

The most common category of machine learning model used for predictive maintenance is a supervised learning algorithm. Heuristic algorithms like SVM and RNN algorithms have high performance in maintenance planning for highly noisy datasets [30]. Supervised learning algorithms like RNN, LSTM, and GRU are good in predicting time series input data from sensors. Brahimi et al. (2024) used a hybrid of LSTM and fuzzy models for machine maintenance prediction to increase prediction accuracy, scalability, and also to reduce false positives in the results [31]. These sequential algorithms, like RNN, LSTM, and GRU algorithms, can accumulate error, which can increase the false positive rates in prediction [32]. This evolving problem can be solved by using hybrid algorithms, which have two different abilities. Liu et al. (2022) used a CNN for extracting spatial patterns and an LSTM algorithm to extract temporal patterns from the IoT data. However, these hybrid algorithms still struggle with the issue of data quality; any sequential training data collected from a real industrial floor is prone to environmental noise, which affects data quality [33]. Noisy input data problem can be tackled by using a multi-modal approach, where input from multiple input sources is processed to extract useful insights without depending on a single data source.

3.4 Mould design and testing using AI

Some of the most important factors in manufacturing, such as Product quality, wastage, material usage, and cooling time, are directly impacted by Mold design. Complexity in design often can lead to increased design errors and wastage, which can increase the cooling time and cost of manufacturing. Optimal cooling can reduce the cycle time and increase productivity in manufacturing. Cooling time is directly proportional to the thickness of ribs and the complexity of the design. The cooling time in injection moulding can be represented using formula (2).

$$t_c = \frac{T^2}{\pi^2 \alpha} \ln\left(\frac{4}{\pi} \cdot \frac{T_m - T_w}{T_e - T_w}\right) \quad (2)$$

Where, cooling temperature (T) is determined by the thickness of the mould, melt (T_m), wall (T_w), and ejection temperatures (T_e). There controlling the design and parameters of the mould can drastically reduce the cooling temperature. Torres-Alba, A. et al. (2020) created a clustering-based approach to group the regions in the design with the highest temperature to create a design that reduces cooling time. This cooling method uses a change in material flow, thickness, and distance metrics in a genetic algorithm to find optimal parameters [34]. This parameter-based optimization can lack nuances for complex 3D models. Redeker, J. et al. (2025) used a gradient-based topology optimization method to control mass/volume ratio in the design. This algorithm uses finite element analysis (FEA) to measure the points in design that consume more materials and tries to penalise overhangs to reduce unnecessary volume in the design [35]. Optimizing model parameters can lead to shrinkage in volume and warpage to completed products. The Mold design not only should consider performance factors, but it also should consider the quality of the finished product. Hong, T. et al. (2025) solved this multi-objective problem by implementing a hybrid between Back-propagation and genetic algorithms. The hybrid algorithm simulates many different scenarios and picks the best values suitable for all the parameters [36].

The cooling time and flow of the material are determined by the location of the gate in the Mold. Manual methods consider the thickness of the material as an indicator to decide the gate location in the Mold. This method is not consistent and can often lead to wastage of material and production time. Therefore, machine learning algorithms are employed for gate location estimation based on past simulation data and material properties. To reduce defects in weld lines,Sedighi, R. et al. (2017) introduced a hybrid algorithm using Artificial Neural Network (ANN) and Genetic Algorithm (GA)to test different gate locations based on variables like strength, temperature, and speed [37]. This method of weld line optimisation reduces wastage, the cost of manufacturing, and increases the quality of products. An automation algorithm for single and multiple gate position estimation is done by Perin, M. et al. (2023). The method uses 3D mesh to find the possible places in the design that can increase the stiffness and strength of the product. The Gradient Boosting algorithm used in this method is non-interpretable making it very hard to scale [38]. The gate positioning methods can reduce the wastage and increase the strength of the finished products.

Another important part of injection moulding that can be improved using AI models is the runner systems. Effective design of runner systems using AI can reduce cycle time, control the material temperature, and protect the products from cavities. The most effective algorithms are also aware of the dynamics between material flow and design aspects. One of those algorithms is Physics-Informed Neural Networks (PINNs), which is implemented by Pieressa, A. et al. (2025). The PINN algorithm uses Partial Differential Equation (PDE) values of temperature conducted across the product to find a suitable design. These physics-aware algorithms are used to simulate multiple variations of the design based on physics equations, eliminating the need for a larger number of iterations [39].

Many existing design techniques use one or two important parameters for optimizing the design. This can harm other parameters; for example, a design to optimise warpage can increase the overall cycle time. Therefore, many research studies are introduced in optimising multiple objectives at the same time. Guo et al. (2024) used three major variables such as fiber orientation tensor flow (FOT), warpage, and strain values, for design optimization. The study also used an industrial standard algorithm called theNon-Dominated Sorting Genetic Algorithm II (NSGA-II) for optimization.NSGA-II uses Mult-objective optimization to find the optimal parameters.

$$F(x) = f(p_1, p_2, p_3) \quad (3)$$

The parameters can be cooling time, pressure, and power consumption, which can be optimized using multi-objective machine learning algorithms. This algorithm implementation shows a reduction in wastage and material cost compared to other design methods [40]. Another study that completely focuses on quality aspects of finished products was done by Mukras et al. (2025). In this study, shrinkage in volume and surface roughness are the two parameters considered for optimization. The study uses a Kriging model to find the non-linear patterns, and a pattern search algorithm is used to generate Pareto front values to find the best suitable value of shrinkage and roughness [41].

3.5 Sustainability improvements using AI

The next important area in which AI can add a lot of value is improving sustainability. AI can be implemented to predict the demand of a product and reduce deadstock, accurately measure the faults in manufacturing, reducing wastages, and newer process optimization models can optimize critical parameters like temperature, pressure, and cycle time, reducing the power consumption during the injection moulding process. Detecting the defect in the product by monitoring parameters like temperature, pressure, and volume is a proven technique. Jung, H. et al. (2021) compared different machine learning algorithms performance on the classification of defects using an industrial IoT sensor database. When comparing machine learning algorithms autoencoder algorithm have near perfect recall score compared to tree-based and regression-based algorithms [42].

Waste and energy control can be done by optimizing the process of manufacturing. Instead of optimizing the manufacturing process based on a single parameter, multi-objective optimization in manufacturing can be very effective. Hashimoto et al. (2020) [43]control injection velocity to control defects in the produced products using multi-objective optimization. The optimization uses an RBF model to simulate and predict the correct injection flow. These methods can reduce overall wastage and defective products inthe supply chain. Real-time monitoring and control of the injection molding process is done by Kumar, S. et al. (2020) [44]. The machine learning model creates the best molding window, and during the manufacturing process, if any of the process cycle goes beyond the window is considered defective. The process both finds defects as well as controls the manufacturing parameters to reduce defects and wastages. Making any adjustment for sustainability doesn't necessarily increase the cost of operations. Ouaomar, Y. et al. (2025) [45] used cost as a parameter for optimization while using machine learning applications like the ANN algorithm. The hyperparameters in the ANN algorithm are tuned with the help of a genetic algorithm. This implementation of cost as a parameter reduces the total number of defects from manufacturing. The next sustainable approach is to reduce energy consumption while manufacturing through injection molding.

Another main contributor to environmental pollution is high energy usage; machine learning algorithms can predict energy usage by considering multiple different input variables. Huang, J. et al. (2024) implemented a transformer-based informer model, which are designed to predict the pattern in complex datasets. These algorithms forecast energy usages and usage can be adjusted to limit high energy wastage. Transformers are complex algorithms, but they outperform time series prediction algorithms like GRU and LSTM ona large scale [46].

Any of the energy, cost, or wastage reduction efforts are not meant to reduce the quality of products manufactured. The combination of providing low defect rates sustainably is discussed by Jou, Y. T. et al. (2025) [47]. The study uses a hybrid method of the back propagation algorithm and the PSO algorithm to find the suitable parameters for sustainable manufacturing. The PSO algorithm uses different variables like melt temperature, pressure, and time for cooling, to find an optimal parameter (v_i). In manufacturing it can be nozzle pressure, cooling time, and flow rate, depending on particular use cases, which can be measured using formula (4).

$$v_i^{t+1} = w.v_i^t + c_1r_1\left(p_i^{best} - x_i^t\right) + c_2r_2\left(g_i^{best} - x_i^t\right) \quad (4)$$

The next value of parameters is estimated using inertia values, memory of previous best values, and overall best values during the iteration. The PSO algorithm is used to predict optimal parameters, and the BPNN algorithm is used to find the most suitable parameter without any practical implementation of the parameters.

4.RESULTS AND DISCUSSION

The narrative review discussed the recent studies done on AI role in improving the quality of manufacturing, predictive maintenance, parameter optimization and sustainability improvements in injection moulding. There is a clear shift seen after researching all the recent studies in injection moulding. The advantages of using AI in injection moulding 4.0 make it inevitable to be implemented across all the processes in manufacturing. Predictive maintenance has the most important effect in manufacturing as it reduces total downtime and production failures which is the most important concern for all the manufacturers. AI is employed to predict the current state and possible failures in the future making the whole production cycle uninterrupted. In place of regular maintenance where a spare part is replaced regularly, AI can predict the potential lifespan of a spare part and increase the overall life. This reduces the cost and wastage associated with regular change of spare parts. The main failures that can be detected by sensor inputs are cracks (using acquistic data), cooling system fault, thermal drifts and micro to macro failures. Machine learning algorithms uses sensor inputs to measure both system-level and component level health of machine parts.Hybrid algorithm of combining supervised machine learning algorithm (BP, ANFIS) with time series algorithm (GRU, LSTM) for sensor data classification seems to work best for predictive maintenance. The machine learning algorithms in predictive maintenance reduces the manufacturing line downtime by 40% to 50% for hybrid networks with fuzzy and time series networks. The main limitation in machine learning and its predictive capacity in injection molding industry is lack of interpretability; there are many research that uses explainable AI algorithms to find the most important features that contribute to particular output. But this research is still in early stages for predictive maintenance.

The main way researchers tried to control defects, cycle time, and improve the efficiency of manufacturing is through optimizing the parameters set for injection moulding devices. The parameter optimization in some studies is conducted using reinforcement learning algorithms by setting optimal conditions as input and rewarding the model every time a correct prediction is made. In conditions where there is high training inefficiency and training data constraints. In those situations, evolutionary algorithms like genetic algorithms are employed. They have low data and computational requirements. Similarly, algorithms like PSO generates lot of parameters, with that many different scenarios are calculated to find global maxima and global minima values. These simulation-based parameter optimization methods reduce the errors and defects that arise with real-world implementations. The review clearly suggests the use of multi-objective optimization algorithm using cost, energy, quality and performance factors together for evaluating parameters is very effective for real-world implementation. But it is important to note the total dimensions of input parameters are higher the number of parameters the complexity of the system also increases.

Quality control in manufacturing can be automated and made effective with the use of AI. Sensors and image-capturing devices are used to monitor and control defective products from entering the supply chain. Main algorithms like random forest and SVM are common ML models for quality control using sensor input data. For finding defects in the product through images, Convolutional algorithms is the most common choice. In case of noisy input data, autoencoders are used, which have the ability to detect abnormalities from noisy sensor data. This real-time processing of quality control needs a lot of input data for training, and accuracy of the algorithm improves over time. The comparison of predictive performance of different machine learning models is shown in Figure 2 below.

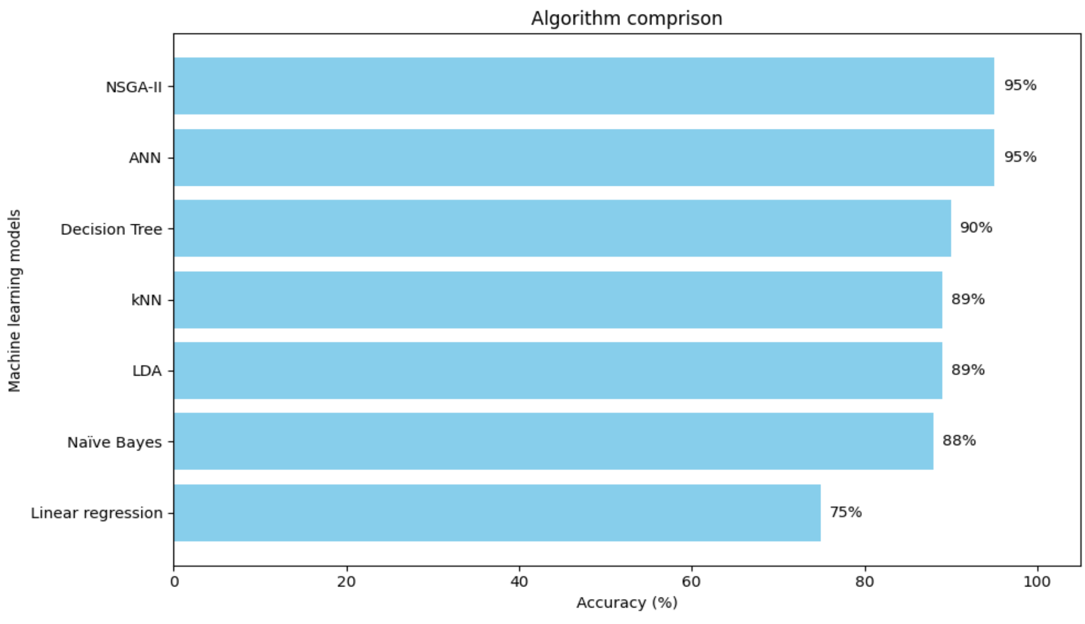

Fig 2: Machine learning models performance in prediction.

There is also increased interest to use transfer learning algorithm across different machines which can improve the overall efficiency of base models. Introducing transfer learning algorithm can increase the efficiency up to 20%. The study also proposes using hybrid architecture were integrating sensor-based data acquisition techniques along with camera-based quality control techniques. This hybrid architecture can increase the detection accuracy and recall for machine maintenance and parameter estimation as well. Any optimization in injection moulding can benefit from integrating explainable AI algorithms into the training process in order to understand the importance of each of the factors in the manufacturing process. For parameter optimization, evolutionary algorithms or SVM, PSO algorithms are best suited to find the most appropriate parameter. This reduces the complexity and data reliability of the model. The study strongly proposes use of a hybrid algorithm instead of single algorithm and there no single best algorithm for the whole injection moulding manufacturing process.

5. CONCLUSION AND FUTURE WORK

The study shows the importance of AI in injection moulding manufacturing, and with advanced data acquisition methods and machine learning architecture, the productivity from injection moulding will grow exponentially. The study found that the evolutionary algorithm and supervised learning algorithm have higher ability in automating injection moulding manufacturing. Evolutionary algorithms have the ability to deliver solid forecasts and parameter predictions compared to other traditional models. While deep learning and reinforcement learning algorithms can be implemented in applications where the input is a time series and is dependent on other parameters. Deep learning algorithms like GRU and LSTM are found to have better prediction accuracy when the input is linear and time series. The proposed study also found that, instead of using two or three objectives, multi-objective-based neural networks are good at predicting anomalies and forecasting parameters. These multi-objectives can be cost and energy as well, which ensures the sustainability aspect of injection moulding manufacturing. The review study also emphasises using hybrid algorithms; the choice of the model can be dependent on the specific domain expertise of the algorithm and the particular problem statement. No universally effective AI model can be implemented for all problems; each neural network model has a particular benefit, making it suitable for different applications. The review also found a very small number of studies that are focused on real-world applications and their results. The results of those studies indicate that the performance of a particular algorithm in a simulation background is different and higher than the actual implementation output. The study found that AI can reduce 40% to 50% of maintenance wastage after implementation. Implementation of AI can significantly reduce warpage, wastage, weld lines, and shrinkage in the product compared to other manual models. The study also found that AI suffers from an interpretability problem, which is somewhat solved by using explainable AI frameworks, but a more effective strategy needs to be implemented to understand AI better so that it can be implemented across the manufacturing sector.

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