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Machine learning-assisted decision support in industrial manufacturing: a case study on injection molding machine selection

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ABSTRACT

Selecting the right injection molding machine for new products remains a challenging task that significantly influences the profitability and flexibility of companies. The conventional approach involves performing theoretical calculations for clamping force, conducting mechanical validations of the mold, and carrying out real trials for new parts. This approach is time-consuming, costly, and requires a high level of expertise to ensure the optimal machine choice. This study explores the use of machine learning (ML) methods for efficient machine selection based on product, material, and mold criteria. Six supervised learning techniques were tested on a dataset comprising 70 plastic parts and five machines. Evaluation metrics like F1-score, recall, precision, and accuracy were used to compare models. The results indicate that ML can provide guidance for predicting machine selection, with a preference for the random forest (RF), decision tree (DT), and support vector machine (SVM) models. The most favorable outcome is demonstrated by the RF model, displaying an accuracy of 93%. In this manner, these findings may be helpful for injection molding businesses that are considering the significance of using classification algorithms in their manufacturing process.

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1. INTRODUCTION

Selecting the appropriate machine for a new product remains a challenging task in the injection molding industry, requiring extensive knowledge and experience [1]. The decision-making process becomes increasingly complex in small and medium-sized industries, especially when managing a diverse range of products with a limited number of available machines. Typically, determining the suitable machine is established during the initial setup through theoretical calculations. The selection is influenced by various factors, including product characteristics such as weight, geometric specifications, and material type, mold specifications including weight and dimensions, and the production rate requested by the customer. The chosen machine should meet these fundamental criteria. However, deviations from theoretical calculations can significantly impact both product margins and the flexibility between machines. Discrepancies in the cost centers of machines mean that selecting the wrong machine can automatically increase the product's cost breakdown [2]. Therefore, considering the importance of this aspect, it is crucial to explore approaches that can help decision-makers accurately assign products to the suitable machine.

In this study, the main objective is to investigate the application of machine learning (ML) classification methods to select the suitable machinery for each specific product. According to the literature, machine selection is categorized as a multi-criteria problem [3]. Various classical methods have been employed to assist decision-makers in selecting the optimal choice. Among the prominent methods are the analytical hierarchy process (AHP) [4], [5] and the technique for order preference by similarity to ideal solution (TOPSIS) [6]. The AHP functions as a framework for structuring and analyzing complex decisions, integrating mathematical principles and psychological factors. It enables the evaluation of these elements concerning the overarching objective, thereby facilitating a systematic decision-making approach. Meanwhile, the TOPSIS method operates on the principle of selecting an alternative that minimizes the geometric distance to the positive ideal solution while maximizing the geometric distance from the negative ideal solution. Alternatives are ranked through the calculation of an overall index based on their distances from these ideal solutions [7]. Both methods involve subjective decisions in ranking criteria and choices, introducing a possible source of bias into the decision-making process.

Therefore, this paper explores an alternative approach based on ML to aid in selecting the appropriate injection-molding machine for a given product. Six classification ML algorithms are utilized, including the support vector machine (SVM), random forest (RF), decision tree (DT), naive Bayes (NB) model, stochastic gradient descent (SGD) classifier, and logistic regression (LR). Evaluation metrics such as accuracy, recall, F1 score, and precision are employed. The study's findings suggest that these classification methods effectively capture feature relationships, enabling predictions of machine selection. The RF, DT, and SVM models can predict the correct machine selection with accuracies of approximately 93%, 87%, even with limited training data. These promising results can provide valuable guidance for selecting new machines for upcoming parts.

The article is divided into four main sections. The first section introduces the injection molding process, emphasizing the conventional approach to selecting machines for new products. The second section reviews existing literature on machine selection processes. The third section discusses the application of classification methods using data gathered from real industry situations. Lastly, the fourth section delves into the results obtained and compares the performance of the methods.

2. SCOPE OF STUDY AND LITERATURE REVIEW

2.1. Injection moldin process

The injection process technique relies on the principle of transforming polymers from a solid state to a molten state by using a press machine and specific tooling [8], [9]. The injection machine comprises two primary components: the injection unit and the closing unit. The injection unit is responsible for converting the plastic from a solid state to a plasticized state before injecting it into the mold. Meanwhile, the closing unit is responsible for sealing the tooling, locking it in place, and overseeing the cooling process of the plastic. The production cycle can be represented by five main sequences, as illustrated in Figure 1.

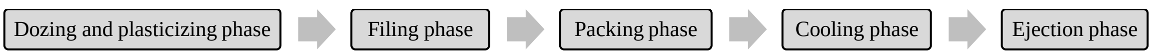


Figure 1. The main steps of the injection molding process

During the dosing and plasticizing phase, the plastic material falls down from the hopper to the injection screw under the influence of gravity. Several materials can be molded, some widely user are polyamide (PA6), polyester, polyvinyl chloride, nylon, and acrylic [10]. Subsequently, the polymer undergoes transformation into a molten state through a dual mechanism: the shearing effect induced by the screw and the heating effect generated by heating resistances surrounding the screw. The molten polymer is then cycled back in front of the screw by metering the total volume for a complete plastic part cycle. In the filling phase, commonly known as the injection phase, the plastic is introduced into the mold through filling channels by the screw. This process typically lasts a few seconds, with the duration influenced by the material's viscosity and the desired injection flow rate. The injection pressure during this phase can range from a few hundred to a thousand bars. During the packing phase, the screw maintains pressure on the plastic to address potential issues arising from material shrinkage as it starts to cool. This additional pressure compensates for any problems that may arise during the cooling process. In the final step, the cooling phase aims to solidify the entire part until the desired rigidity is achieved. The solidification process is facilitated by the thermal transfer applied by the mold. In the ejection phase, after the part has attained sufficient rigidity, the mold opens, and the part is ejected through a designated ejection mechanism. Each step of the process is carefully defined based on specific parameters.

2.2. Machine selection: conventional approach

Selecting the right machine for a particular product remains a task demanding expertise and experience. The molding adjuster allocates machines based on various criteria, including part design, mold design, material specifications, and customer demand [11]. Firstly, mold characteristics, particularly dimensions such as thickness, width, length, height, and weight, are pivotal in assessing the feasibility of mounting the tool on the machine. If the mold surpasses the specified dimensions of the machine, it might require allocation to a larger-sized press to accommodate its size adequately. Secondly, part characteristics, encompassing dimensions, weight, and thickness, constitute the most significant parameters [12]. The part's dimensions directly impact the machine's opening stroke, which is critical for successful part ejection after solidification. If the opening stroke is inadequate for ejection, selecting a machine with a larger opening capacity may be necessary. Furthermore, the part's thickness directly affects the machine's maximum injection pressure capacity; thinner parts necessitate higher injection pressure. Thirdly, material characteristics are pivotal in the process, encompassing various types with diverse chemical compositions [13]. From simple to highly technical and aggressive materials, the chemical composition significantly impacts the selection of the injection unit. The machine selection process must account for the specifications of the screw and barrels, especially their treatment to withstand the chemical aggressiveness of the material being processed. Finally, the production rate signifies the capacity of the chosen machine to meet specific rates aligned with customer demands. This factor facilitates the sizing of the injection unit, ensuring its capacity aligns with the required production rate. The machine selection process can be illustrated by Figure 2. It can be segmented into three primary phases: force calculation, clamping unit validation, and injection unit validation.

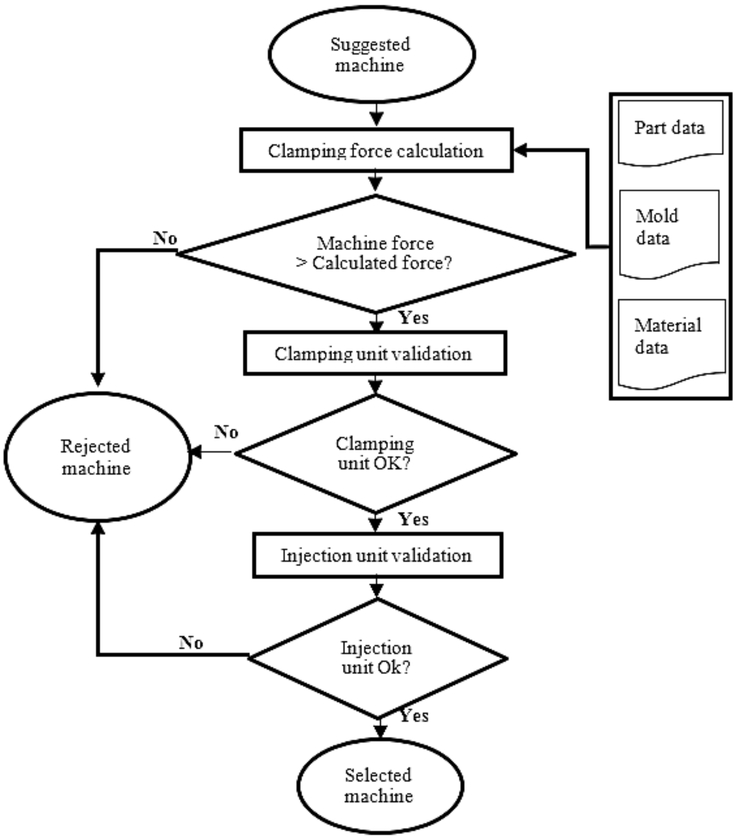


Figure 2. Machine selection flowhchart: conventional approach

In the initial phase, the force calculation involves determining the clamping force required to ensure the proper closing and holding of the mold during the plastic injection, packing, and cooling phases. If the calculated force is within the maximum clamping force capacity of the machine, the machine can be validated based on this force, allowing the process to proceed to the second step. However, if the calculated force exceeds the machine's maximum clamping force, it becomes necessary to consider a machine with a higher closing capacity, and further steps may not be pursued. In the second phase, validating the clamping unit includes confirming whether the mold can be effectively mounted on the machine, considering its size and the allowable spaces within the machine. Additionally, the validation considers also the verification of the mechanical dimensions of the mold and the opening stroke allowing satisfactory ejection of the part during the ejection phase. If these criteria are met, the clamping unit is validated. However, if the requirements are not met, an oversized machine may be necessary, and the selection process may need to be ignored. In such cases, consideration of a different press becomes necessary. The third and final phase is dedicated to validating the injection unit. The unit is considered suitable if it meets the criteria related to the material, dosing volume, part weight, type of screw, maximum injection pressure, and maximum production rate. If any of these criteria is not met, the allocation of the part cannot be assured, and further consideration or adjustments may be required.

2.3. Related works

Many While numerous studies have delved into machine selection allocation, only a limited few have tackled the issue using artificial intelligence methods. In an investigation conducted by Nyanga *et al*. [14], the study explored the application of a multi-agent system for selecting the most suitable machine to optimize production order. The criteria for machine selection were established using the AHP, with quality, time, and cost identified as key parameters. Five criteria—clamping force, distances between tie bars, shot weight, time, and cost—were chosen. A multi-agent system, comprising a managing agent, administrator, and bidding agents, facilitated an auction between machine agents acting as potential contractors representing available machines in the production line. The study demonstrated that the system effectively reduced short shot defects by 10%, sink marks by 5%, and flashing by 30%. Trivedi *et al.* [15] presented an application of multi-criteria decision-making using the optimized TOPSIS method with a fuzzy logic approach. This research focused on 14 electrical molding machines, considering eight criteria: rate of return, risk investment, likely profit, installation cost, similarity to existing business, environmental impact, and expected life. By incorporating fuzzy logic, the fuzzy TOPSIS method provided results oriented toward selected membership functions, thereby making the machine selection process more autonomous. Lin and Yang [5] developed a model employing the AHP to select the most appropriate machine. Their approach centered on choosing a machine from various available options tailored for manufacturing specific types of parts. The researchers introduced a prototype framework and software that utilized AHP for machine selection, integrating the expert-system concept to develop the program and articulate selection criteria. Their primary goal was to optimize machine selection, enhancing both cost-effectiveness and workshop flexibility with existing parts. In a recent study by Dominguez *et al.* [16], multicriteria selection methods such as combinative distance-based assessment (CODAS), TOPSIS, and AHP were investigated in the pastry industry. The study aimed to compare the performance of each method in making the best choice among five machines. Criteria considered included price, capacity, warranty, product weight, and speed. Results indicated that AHP and CODAS provided approximate machine selections, with potential refinement through complementary studies using variance analysis. This study highlighted the effectiveness of these multicriteria selection methods in choosing machines for the pastry industry. ML-assisted decision support in industrial manufacturing can also be considered in relation with deep learning-assisted smart process planning, robotic wireless sensor networks, and geospatial big data management algorithms within the domain of the internet of manufacturing things, as discussed in [17]. Additionally, it relates to artificial intelligence-based decision-making algorithms, internet of things sensing networks, and sustainable cyber-physical management systems in big data-driven cognitive manufacturing, as outlined in [18].

3. IMPLEMENTATION

3.1. Methodology

The suggested approach is based on the traditional concept of ML, it represented on the Figure 3. The methodology comprises five primary steps. Initially, data collection is conducted to gather the requisite information for model application. Following this, the second step involves preprocessing the data, aiming to ascertain correlations and ready it for model implementation. The subsequent step entails the application of ML algorithms. In the fourth step, performance comparison among different methods is carried out to select the optimal approach. Lastly, the fifth step involves analysing the learning process of each model from the provided data. Additionally, a final verification is performed to assess the influence of individual features on the models using the local interpretable model-agnostic explanations (LIME) method.

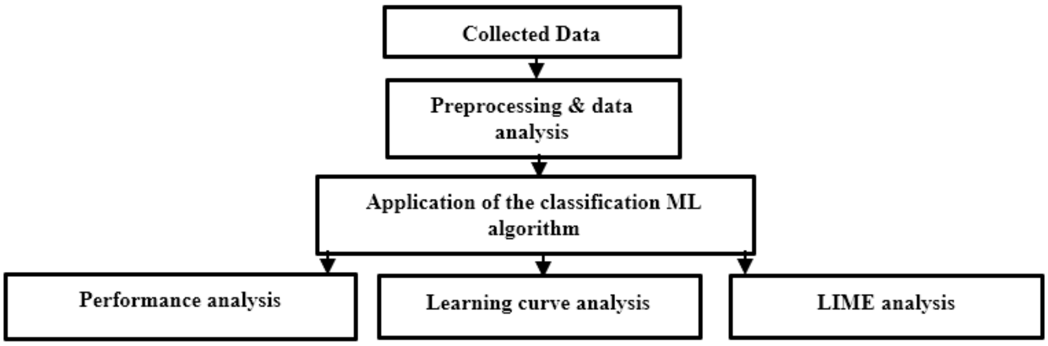


Figure 3. Flow chart of the suggested aproach

3.2. Initial data

The study used dataset collected from actual workshop operating in the automotive industry, the company is located in north of Morocco. The dataset consists of information on 70 unique molds, each with varying sizes and weights. Additionally, it includes five types of machines with different clamping capacities, ranging from 150 tons to 400 tons. Finally, the dataset contains details on 10 different types of plastic materials. Table 1 describes the main used variables on this study. The data is classified into four groups: part_data, material_data, mold_data, and machine_data. The "part_data" consolidates information pertaining to the characteristics of the part. This includes details like the part weight, sprue weight, and the number of parts per cavity. It encompasses tree specific items. The "material_data" focuses on the type of material used, such as PA6, polypropylene (PP), polyethylene (PE), and others. In the final dataset, there are 10 different material types, and Table 1 illustrates three main characteristics of the materials. The "mold data " regroups information related to the dimensions of the mold, including its weight, height, length, and width. The "machine_data" refers to the machine assigned to each product based on the clamping force required, characterized by the maximum force necessary for clamping and holding. The unit of measurement is kilo-newton or tons.

Table 1. Dataset items specifications

Data	Item	Description
Part data	Weight of the part	Weight of the plastic part [g]
	Sprue weight	Number of cavity mold [g]
	Total weight	weight of the part and the sprue [g]
Mold data	Width	Width dimension of the mold [mm]
	Length	Length of the mold [mm]
	Height	Height dimension of the mold [mm]
	Weight	Total weight of the mold [Kg]
Material data	density	Density of material [Kg/m3]
	Rate Flow	Flow rate of material [g/10min]
	Type	Type of material (PP, PE, and PA6)
Machine data	Size	Machine size, 150T, 200T, 250T, 320T, 400T

3.3. Data analysis

The initial step of the investigation involves conducting a correlation study between the classes and their respective features. Correlation, broadly defined, quantifies the relationship between variables. In correlated data, alterations in the magnitude of one variable are linked to changes in the magnitude of another variable, either in the same direction (positive correlation) or in the opposite direction (negative correlation) [19].

The correlation matrix confirms a significant relation between clamping force and features related to mold dimensions, with strong positive coefficients classified as follows: mold weight (0.788), mold height (0.737), mold length (0.741), and mold width (0.761). Indeed, the selection of machine size based on the part is significantly influenced by the dimensions and characteristics of the mold as displayed on the Figure 4 showing the machine allocation according to the size of the mold. It is highly likely that small molds are addressed to smaller machine sizes, while large molds are allocated to larger machine sizes. Furthermore, the correlation coefficient indicates that clamping force is influenced by features associated also with part weight, with a positive coefficient of (0.591) for total part weight and (0.4) for part weight. On the other hand, features related to plastic types, such as density, melt flow, and material type, demonstrate lower correlations.

Specifically, the correlation coefficients for these features are (0.156) for density, (-0.346) for melt flow, and (0.11) for material type. This initial analysis confirms that mold and part features are the most significant contributors to machine selection. This is consistent with the actual plastic molding manufacturing. The visualization in Figure 5 demonstrates the interaction among the variables of the dataset, specifically represented by the parameter "machine clamping force," in relation the mold specfication and part weight.

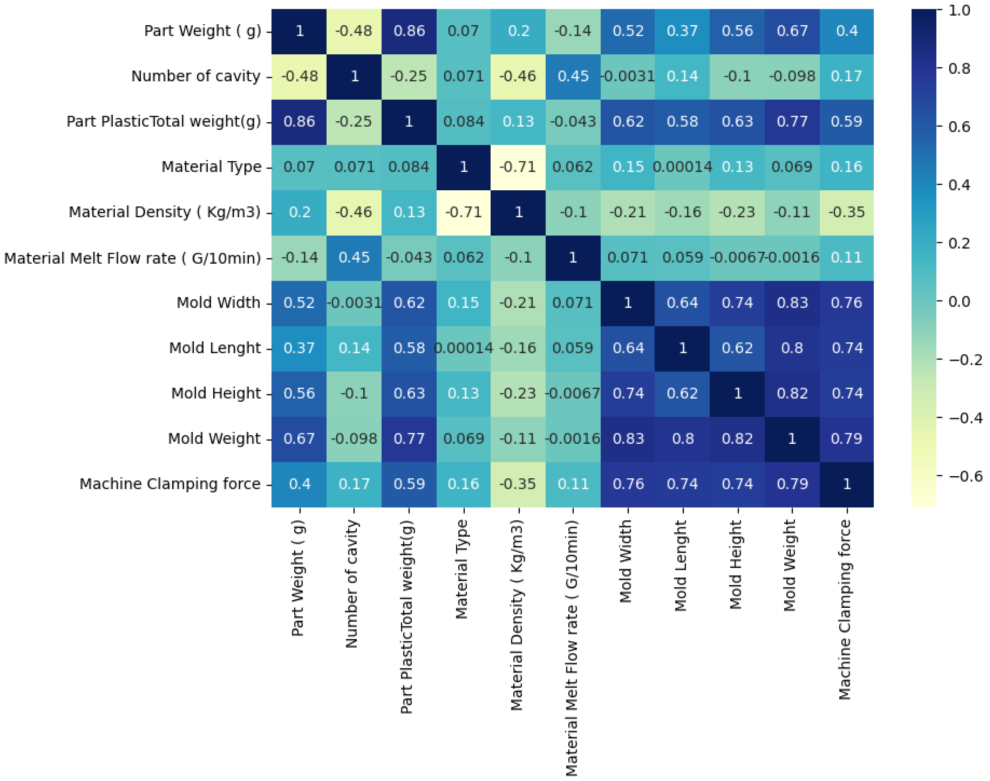


Figure 4. Data correlation matrix (machine clamping force vs dataset features)

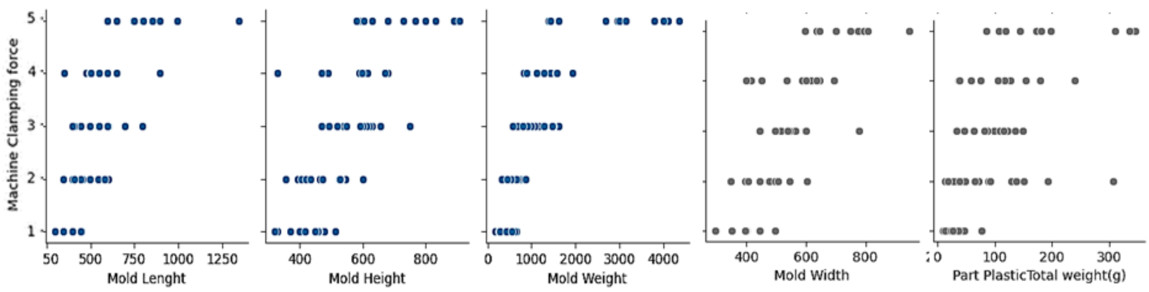
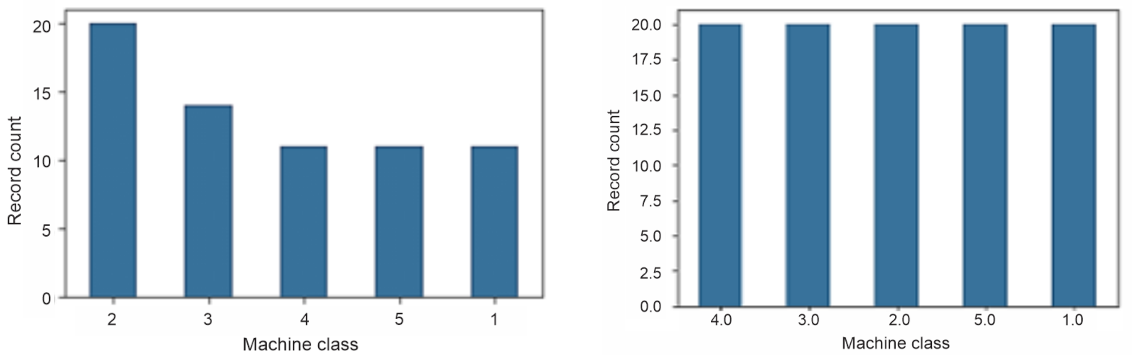


Figure 5. Classification of the machine size according to the mold specfication and part weight

The distribution of classes based on the main features mold and part weight is illustrated in Figure 5. The distributions are distinctly represented by five classes: Class 1 (150 t), Class 2 (200 t), Class 3 (250 t), Class 4 (320 t), and Class 5 (400 t). The machine distribution follows a normal distribution, with the average centered on machines 200 t and 250 t. The trend observed indicates that smaller molds are more likely to be assigned to smaller machines. For instance, molds with a height less than 400 mm tend to be assigned to Class 1 and 2 machines, while molds with a height exceeding 700 mm are associated with Class 5 machines. This correlation underscores the impact of mold dimensions on the allocation of machines. Moreover, the parameter "Mold Width" significantly influences the selection of the machine. Specifically, machines with a width less than 400 mm are assigned to smaller machine classes (Class 1 and 2), while machines with a width exceeding 600 mm are allocated to machines of 250 t, 320 t, and 400 t. This parameter is directly linked to the tie bar of the machine and serves as a critical characteristic determining whether the mold can fit the machine. Logically, if the mold has substantial width dimensions, it is assigned to a machine with a higher distance between tie bars. Concerning the total weight of the part, this feature exhibits a significant impact on the choice of the machine. Parts with a weight exceeding 300 g are typically assigned to Machine 5, while parts with weights ranging between 200 g and 300 g are allocated to machine 2 and machine 4. This indicates a clear correlation between the total plastic weight and the selection of specific machines, highlighting the importance of this feature in the decision-making process. The initial cross-check of the dataset reveals compelling evidence indicating that features associated with both the size of the mold and the total weight of the plastic part exert a significant impact on the decision-making process regarding machine allocation.

The data used in this study exhibits non-equitable distribution among machines, as depicted in Figure 6. Notably in Figure 6(a), machine 200 t (Class 2) has the highest representation with 20 records, followed by Machine 3 with 14 records, and the remaining machines each having 12 records. Machine 200 t stands out as the majority class, while Machines 4, 5, and 1 are considered minority classes. To address this imbalance, the first step involved equilibrating the dataset using the oversampling technique [20]. Additional records were generated for the minority machines, ensuring that each machine now has 20 records. Consequently, the final dataset has been expanded to [100×11] as shown in Figure 6(b).



(a) (b)

Figure 6. Data balancing: (a) imbalancing dataset and (b) balanced dataset

3.4. Machine learning methods and multicriteria problem

The problem of machine selection is considered as a multi-criteria problem, with its multiple criteria and parameters, aligns well with the capabilities of classification algorithms. These algorithms are designed to handle multi-criteria problems by learning from diverse sets of input features and making predictions or classifications based on the learned patterns. In the context of this study, the classification algorithms were applied to predict the "clamping force machine" by considering various parameters related to machine, material, mold, and part characteristics. This approach allows for a systematic and data-driven decision-making process in the complex domain of machine selection. Six algorithms were applied: RF, DT, SVM, NB, SGD classifier, and LR. The goal is to anticipate the "clamping force machine.

3.4.1. Random forest

RF is considered a crucial ML algorithm for pattern recognition, primarily because of its cost-effectiveness. The fundamental principle behind its training strategy is bagging [21]. This suggests that RF is built upon ensemble sampling without replacement from subsets of the dataset. The remaining data, termed out-of-bag, are used for assessing the model's performance. Many boosting or bagging algorithms are centered around DT. The initial node's state generates additional nodes containing features directed upward. As a result, multiple DT are employed to classify each dataset with sampling this method, individual DT may exhibit lower accuracy compared to a DT constructed using the entire dataset. Therefore, it is advantageous to aggregate the results of each tree, as they can collectively classify trained data in a complementary manner.

3.4.2. Decision tree

This model classifies data or predicts outcomes by splitting a dataset based on responses to questions [22]. As a supervised learning method, it is trained on a dataset with known target classifications. This training allows the model to make accurate predictions on new data.

3.4.3. Naives Bayes model

The naïve Bayes algorithm is a supervised learning method based on Bayes' theorem, used for classification problems [23]. It acts as a probabilistic classifier, predicting the likelihood of an object belonging to a specific class. This makes it efficient for handling large datasets.

3.4.4. Stochastic gradient descent classifier

SGD is a powerful algorithm used to find parameter values that minimize a cost function [24]. It is widely applied in discriminative learning tasks involving linear classifiers. Its effectiveness is particularly notable with convex loss functions such as SVM and LR.

3.4.5. Logistic regression

The moldel is used for forecasting the values of a specific variable by considering the values of other variables. Any change in prediction is termed as the dependent variable [25]. An independent variable is one that is used to predict the values of other variables. For instance, in the context of linear regression, we utilize independent variables to understand how changes in them relate to changes in the dependent variable.

3.4.6. Support vector machine

SVM possess versatility in handling both regression and classification tasks. However, their performance tends to excel particularly in classification problems. SVM gained widespread popularity upon their creation and remain a prominent choice for high-performing algorithms, often requiring minimal tuning to achieve excellent results. It's a supervised ML approach where the objective is to determine a hyperplane that effectively segregates two classes in the dataset. Both SVM and LR aim to identify the optimal hyperplane for classification tasks. However, LR is a probabilistic approach, estimating the probability that a given instance belongs to a particular class, while SVM is rooted in statistical principles, focusing on maximizing the margin between classes for effective separation [26].

3.4.7. Performance metrics and confusion matrix

The technique employed for assessing the performance of the six machines involves the use of a confusion matrix [27]. This matrix provides a tabular representation of various outcomes in a classification problem, aiding in the visualization of prediction results. It outlines a table with the predicted and actual values of a classifier, following the standard representation illustrated in Table 2.

– True positive: this is also known as the count of true positives, which signifies the number of instances where the model's prediction of a positive outcome aligns with the actual positive outcome.
– False positive: this is termed as false positive in binary classification. It represents the instances where the model incorrectly predicts the positive class when the actual class is negative.
– True negative: it represents the instances where the model correctly predicts the negative class when the actual class is also negative.
– False negative: it signifies the instances where the model incorrectly predicts the negative class when the actual class is positive.

a) Accuracy: the accuracy, which measures the proportion of correct predictions out of all predictions made by the model. We can calculate the mean absolute error (MAE) using the (1).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

b) Precision: Precision is a measure of the accuracy of the positive predictions made by a model. The formula is (2).

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

c) Recall/Sensitivity: Recall, also known as sensitivity, quantifies the proportion of positive cases correctly identified by the classifier among all actual positive cases in the dataset. Its formula is expressed as (3).

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

d) F1-score: The F1-score, a measure that combines precision and recall, is often defined as the harmonic mean of the two metrics. Harmonic mean is favored for ratios, like precision and recall, as it balances extreme values more effectively than the arithmetic mean. The formula for calculating the F1-score is given by (4).

$$F1 - Score = \frac{2*Recall*Precision}{Reclall*Precision} \quad (4)$$

Table 2. Confusion matrix representation

		Actual	
		Positive	Negative
Predicted	Positive	True positive	False positive
	Negative	False negative	True negative

4. MAIN RESULTS

The six models underwent training using 85% of the dataset and were subsequently tested with the remaining 15%. This signifies that the models were exposed to 85 molds and parts for training and later applied to predict outcomes for 15 additional parts. The results of these predictions are detailed in Table 3. The methodology followed to analyze the obtained result is structured into three sections. Firstly, a comprehensive table is employed to aggregate metrics such as accuracy, precision, recall, and F1-score. This first result serves as a consolidated summary of the performance indicators of the six models. Secondly, a confusion matrix is explored to examine the alignment between the actual and predicted values, offering insights into the model's classification outcomes. Finally, the evaluation includes the examination of learning curves [28] to assess the training approaches adopted by each model over the course of their training.

Table 3. Performance analysis

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
RF	93	96	95	95
DT	87	90	90	90
SVM	87	90	90	90
NB	73	67	63	64
LR	53	42	50	45
SGD classifier	27	12	40	18

4.1. Metric report (precision, recall, F1, and accuracy)

In terms of accuracy, the RF model exhibits the highest performance, achieving a 93% accuracy rate in true predictions. Following closely are the DT and SVM models, both demonstrating a comparable accuracy of 87%. The NB model shows an accuracy around 73%, while the remaining models, LR and SGD, display lower accuracy rates at 53% and 27%, respectively. In terms of precision, the RF algorithm once again demonstrates the best result with a weighted average of 95%. This indicates that the RF model has only a 5% error rate in correctly selecting the right machine. The DT and SVM models exhibit similar precision results, both achieving a weighted average of 87%. The NB model shows a precision of 73%. However, the precision for the remaining models, specifically the SGD classifier and LR, is notably lower, with values below 44%, indicating poorer performance in correctly identifying relevant instances. In terms of recall, the ranking remains consistent, with the RF model leading the list with an average of 93%, followed by the DT model and SVM, both achieving 87%. This indicates that these models have a strong ability to predict both true positives and true negatives effectively. On the other hand, SGD, LR, and NB exhibit mediocre scores in recall, with values of 63%, 50%, and 40%, respectively. These lower scores suggest a relatively lower capability to accurately predict both true positive and false negative instances for these models. In terms of F1-score, the order of performance remains consistent, with the RF model leading at 93%, followed by SVM and the SGD classifier, both achieving 87%. The F1-score is a harmonic mean of precision and recall, reflecting a balance between the two metrics. The rest of the models exhibit F1-scores below 64%, indicating a lower balance between precision and recall for these models compared to the top-performing ones. As evident from the results, all metrics consistently favor optimistic predictions for RF, DT, and SVM, with a preference for RF. This suggests that ML exhibits the ability to select machines even with limited data. However, it's important to note that this situation may introduce bias. This will be further investigated in this paper through learning curves to assess overfitting in models with good predictions and under fitting in models with lower scores [29].

4.2. Confusion matrix

The confusion matrix serves to visualize both true and erroneous predictions made by each machine across different classes. Figure 7 summarizes the confusion matrices for each model trained is this study, providing a comprehensive overview of their performance. Additionally, the figure illustrates the distribution of the 15 predicted machines across the five classes, offering a visual representation of how well each model classified instances within specific categories.

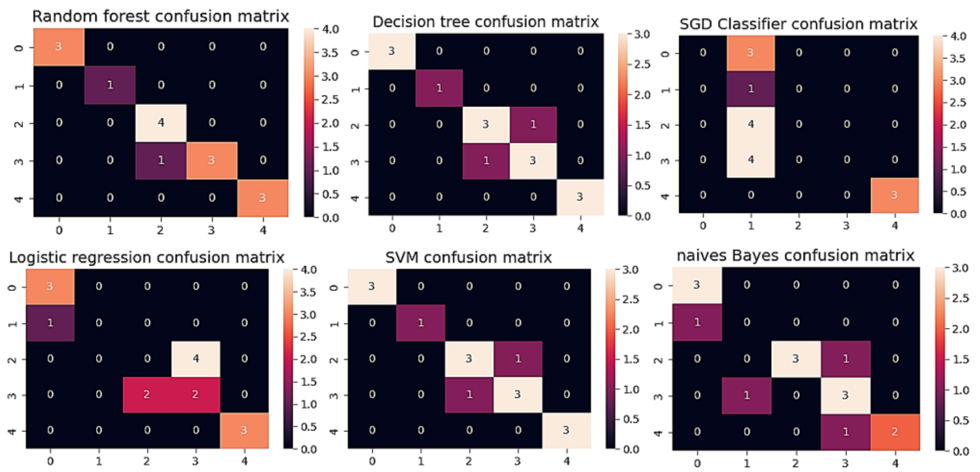


Figure 7. Matrix confusion analysis for the six models

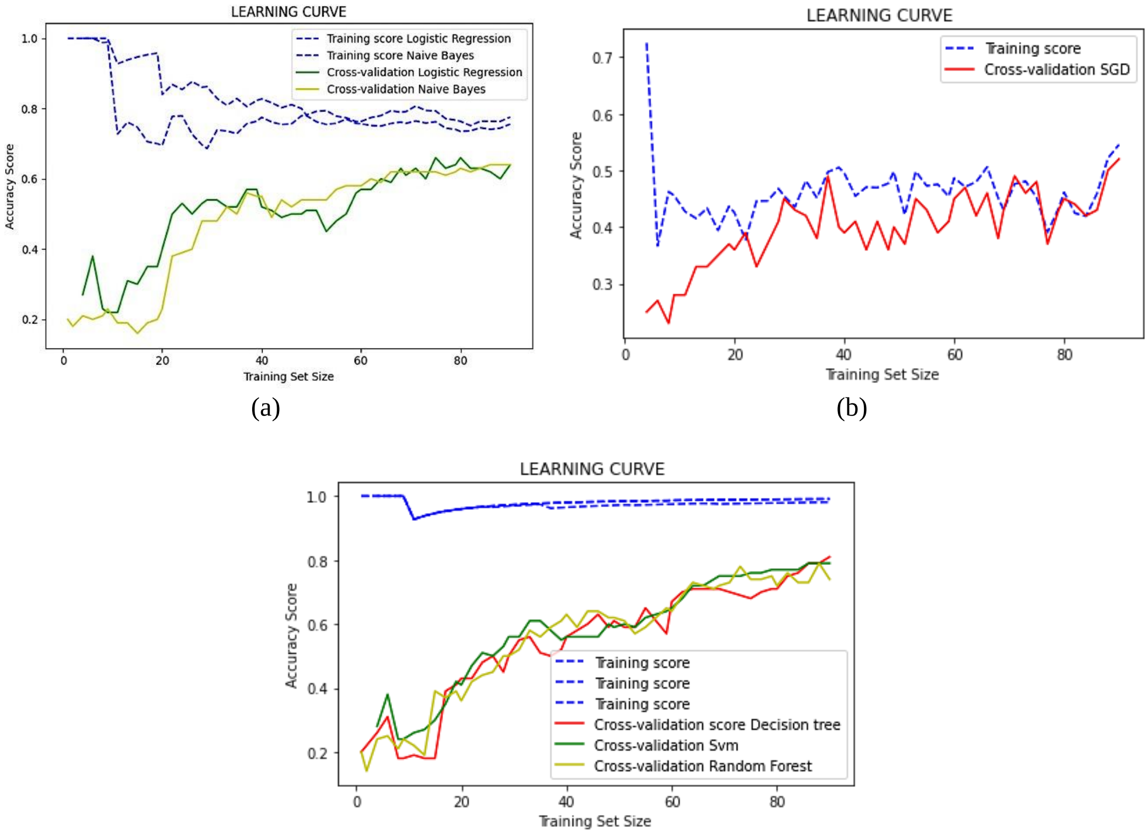
The confirmation from the confusion matrix of the RF model reinforces the accuracy of predictions for all the machines. The instances were effectively classified and distributed among the five classes, indicating the model's proficiency in making precise predictions for each machine category. Nevertheless, the unique instance of inaccurate prediction occurred within class 4 (machine 320 t), where one out of the four machines was erroneously assigned to class 3 (machine 250 t). Regarding SVM and DT, they exhibited identical outcomes by correctly predicting classes 1, 2, and 5. However, both models made inaccurate predictions for one machine in class 4 (1 out of 4) and one machine in class 3 (1 out of 4). The tree models demonstrated a commendable ability to distinguish between true positives, false negatives, and false positives. In contrast, the NB model exhibited incorrect predictions for classes 2, 3, and 4, leading to fewer true predictions (neither for true positives nor false negatives). Consequently, this impacted the recall, which stands at 63%. The NB model appears to have limited capability in distinguishing between false negatives and false positives.

4.3. Learning curve

To conduct a comprehensive evaluation of the models based on their learning experiences, we employed learning curves analysis [30] as shown in the Figure 8. This approach provided a detailed insight into how each model gained knowledge and proficiency over time. Learning curves serve as a widely adopted diagnostic tool in the field of ML, particularly for algorithms that progressively acquire knowledge from an expanding training dataset. In this paper, the accuracy score is employed as metric for evaluating the performance of the model on both the training set and the validation set. The six algorithms are categorized based on their trends into three visualizations for analysis.

Regarding the Figure 8(a), it illustrates the progression of NB and LR models. Both models exhibit a similar evolutionary trend, showcasing improvements in performance. However, these enhancements are insufficient to match the training model, leading to a situation of under fitting. The model struggles to grasp the intricacies of the training dataset, evident in the training curve maintaining an accuracy around 70%. Examining the learning curve, there exists a substantial gap between the training and validation sets initially. This gap gradually diminishes with the addition of training examples, starting from a dataset size of 20. Nevertheless, the accuracy plateaus at 60%, indicating a limitation in the model's ability to generalize to unseen data. Even with the continuous addition of training examples, there is no discernible improvement in performance. This predicament is mirrored in the SGD model (Figure 8(b)), where the training model faces challenges in learning from the dataset, resulting in a comparable inability to improve performance.

Figure 8(c) illustrates the progression of the SVM, RF, and DT models. Notably, all three exhibit a similar trend, showcasing consistent performance improvement over time. This implies that the models are undergoing experiential learning, evident within the interval [0:20]. The accuracy is at its minimum for the models, primarily attributed to the limited training experience accessible during this phase. However, within the range [20:70], the models exhibit a progressive enhancement, gradually approaching the accuracy of the training set. The models can generate predictions for novel data that has never been encountered before. In the interval [70:100], both the RF and SVM exhibit a combination of variation and stability. This suggests that despite the introduction of new training data, these two models are unable to achieve significant further improvement. However, in the case of the DT model, the situation is different. It continues to demonstrate a positive trend of improvement, indicating that providing more training data could enhance its learning experience and performance. In conclusion, considering the training score's high accuracy, it suggests low bias and high variance in the model. Indeed, it appears that the models start overfitting the data, given that the cross-validation score is comparatively lower and shows a gradual increase as the training set size grows, which means adding training data proves beneficial in this scenario as it enhances performance when dealing with previously unseen data.



(a) (b)

(c)

Figure 8. Model learning curve comparison: (a) LR and NB, (b) SGD, and (c) SVM, DT, RF

4.4. Interpretability of the model's predictions

To interpret the model's predictions, we explore the LIME method, which stands for local interpretable model-agnostic explanations, renowned as one of the prominent techniques in explainable artificial intelligence (XAI) [31]. This approach is regarded as accessible. It'is designed to provide explanations for individual predictions made by ML models. It works by taking any ML model as input and generating explanations about the contributions of different features in making a prediction for a specific example. It presupposes that the model operates as a black box, indicating a lack of awareness regarding its internal mechanisms, and consequently produces explanations under this premise. It enables the generation of explanations for individual data examples. The interpretation outcomes for one example may differ from those of others. The underlying principle of the LIME method is based on two key principles:

– Model agnosticism refers to LIME's capability to provide explanations for any supervised learning model by treating it as a 'black box' separately. This implies that LIME possesses the ability to handle virtually any existing model encountered in real-world scenarios.
– Local explanations denote that LIME provides explanations that are faithful and relevant to the specific context or vicinity of the observation or sample being explained.

Based on the results obtained from the previous learning curve analysis, we choose to focus only on models demonstrating satisfactory performance. These selected models include the RF, DT, and SVM. The application of the LIME model depends on randomly sampled values from the validation dataset. The observation number selected in this section is the sample number N°4 which is allocated in reality to the machine number 3. Figures 9 to 11 present visualizations illustrating the contributions of individual features.

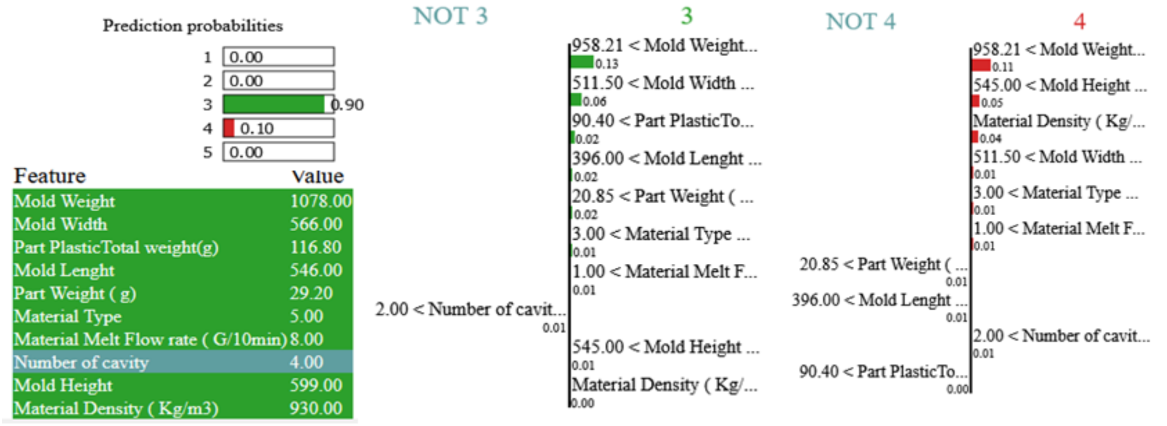


Figure 9. LIME analysis for RF with sample n°4

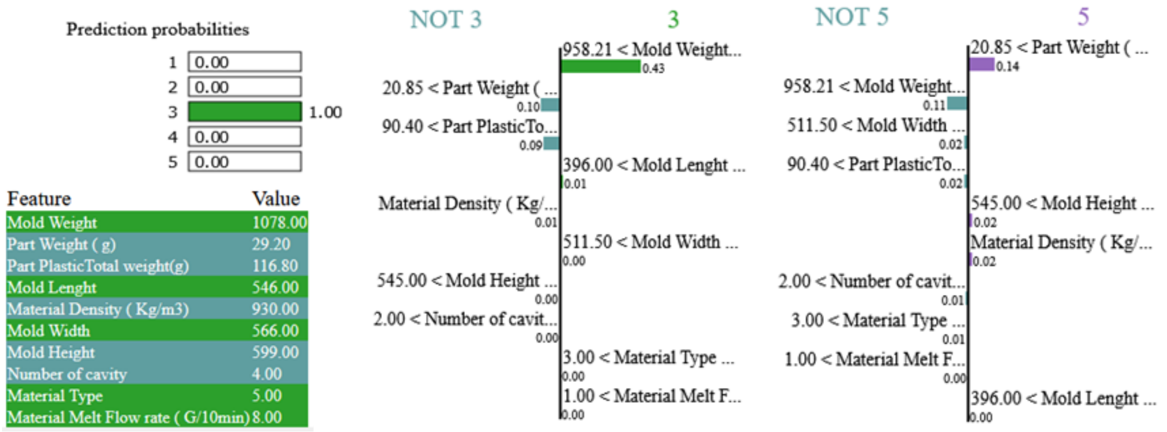


Figure10. LIME analysis for DT with sample n°4

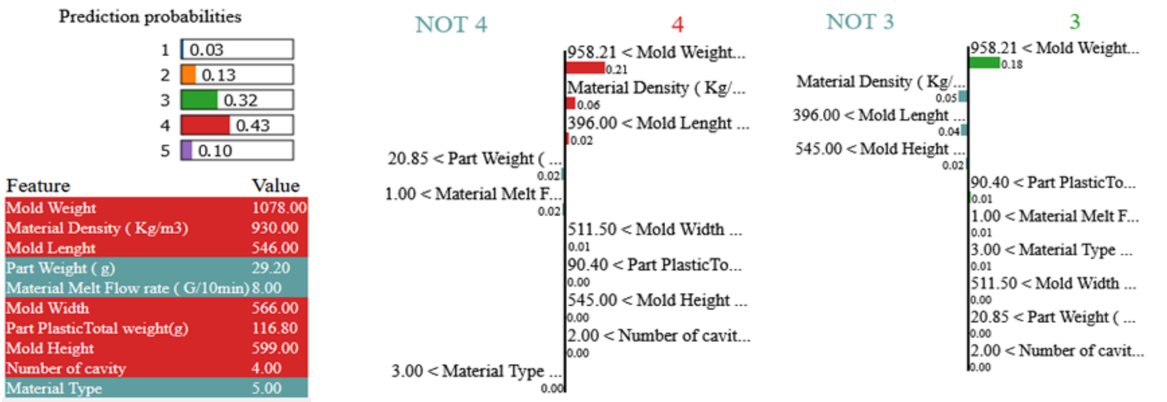


Figure 11. LIME analysis for SVM with sample n°4

Only the two models, DT and RF, assign a higher probability to class 3, which corresponds to the actual value. However, the probabilities assigned by the models range from 0.9 to 1, with the DT model assigning the highest probability. On the other hand, the SVM model's prediction suggests allocation to class 3 and class 4 with distinct probabilities, specifically 0.32 for class 3 and 0.42 for class 4. Regarding the RF model, the table "NOT 3|3" presents the weights assigned to various features of the algorithm. Specifically, it assigns a coefficient of 0.13 to the mold weight feature and a coefficient of 0.02 to both mold width and plastic part weight features. Concerning the DT model, the feature "mold weight" takes the highest coefficient of 0.43, followed by "mold length" with coefficient of 0.01. Regarding the SVM model, the features “mold weight” and “material density” take respectively the weight of 0.21 and 0.06. The feature-value table provides the actual values of each features for that specific record. Overall, based on the LIME Analysis, the features highlighted in the color-coded table confirm that mechanical dimensions of the mold play a more significant role in making predictions, in addition, the plastic weight of the part also influences the allocation decision. The probability values for each class differ across algorithms due to variations in the computed feature weights by each algorithm. Based on the actual values of the features for a particular record and the weights assigned to those features, the algorithm calculates the class probability and predicts the class with the highest probability. The results obtained from the LIME analysis provide increased visibility into the predictions made by the models, as the features impacting the predictions are now more evident.

4.5. Validation with new parts

As the concluding step, we executed the six trained algorithms on the two new plastic parts obtained from another workshop. The objective is to check whether these models could generate accurate predictions or, at the very least, offer valuable insights to guide decisions regarding machine allocation. The parts in question are characterized by ten features, as outlined in Table 4.

Table 4. Specification of the two new parts

Item	Description	Part_1	Part_2
Part_ Number	Article reference	1	2
Part_ Weight	Part weight	74.5	37.75
Part_ Cavity_ Number	Number of cavity of the mold	2	2
Part_ Total_ Weight	Part weigh and sprue weight	154.9	89.25
Mold_ Width	Dimension of mold width	395	445
Mold_ Length	Dimension of mold length	676	727
Mold_ Height	Dimension of mold height	429	512
Mold_ Weight	Total weight of the mold	722	1044
Material_ density	Type of material (PP and PA6)	9	8
Material_ Rate Flow	Type of material (PP and PA6)	950	900
Material_ Type	Type of material (PP and PA6)	4	4
Machine_ Type	Machine size, 150t and 250t)	250t	320t

As shown on Table 5, the SVM algorithm demonstrated the highest accuracy among the six models in predicting the first part. Remarkably, the algorithm's prediction aligned with reality, correctly identifying the production association with machine 250 t. In the case of the second part, manufactured by machine 320 t, the SGD model exhibited precise predictions. Intriguingly, among the six models, only the SGD model correctly identified the association with machine 320 t. The remaining five models erroneously selected machine 250 t. In practice, all the models consistently predict machines within the classes 2, 3, and 4. This alignment with these specific machine classes is noteworthy and can be considered satisfactory as results. Notably, the models systematically exclude predictions related to machines of large and small sizes. This behavior can be viewed positively as a reasonable initial approximation in the prediction process. On the other hand, considering the characteristics of the parts, an optimization in real production allocation suggests that both parts could potentially be manufactured using machines with a size of 250 t. Therefore, based on the outcomes generated by the models, it is reasonable to conclude that their results can be regarded as valuable indications and supportive information for making decisions regarding the selection of machines for future production of new parts. These models can serve as useful tools in guiding the decision-making process for optimal machine allocation in upcoming scenarios.

Table 5. Predictions of the new parts

	RF (t)	DT (t)	SVM (t)	SGD (t)	LR (t)	NB (t)	Real (t)
Part_1	200	200	250	320	200	320	250
Part_2	250	250	250	320	250	250	320

5. DISCUSSION

In this research, various supervised ML algorithms were employed to forecast optimal machine selection for new plastic parts. The algorithms utilized included RF, DT, SVM, SGD classifier, LR, and NB. The performance of each model was assessed using precision, accuracy, recall, and F1-score metrics. Additionally, we examined the learning curve of each algorithm to validate how effectively each model learned from the provided training dataset. The dataset was gathered from an actual production workshop and includes information on 70 different parts, involving five categories of machines and 10 varieties of plastic materials. The main outcomes from this study can be summarized as follows:

- The RF, DT, and SVM models exhibited favorable performance compared to SGD, LR, and NB. Among these, the RF model demonstrated the highest performance, achieving an accuracy of 93% and an F1 score of 95%. In contrast, SGD and LRyielded the least favorable results, with accuracy values of 27% and 53% respectively. Compared with other studies, our models show acceptable performance. For instance, other studies report RF metrics like an accuracy of 99.88%, recall of 99.88%, precision of 99.93%, and F1 score of 99.88% [32]; and precision of 95.86, recall of 95.71, and F1 score of 95.73 [33].
- The dataset's size significantly influences the training of models, leading to the under fitting phenomenon observed in SGD, logistic regression, and NB models. Increasing the dataset size, even though oversampling to 100 sets, did not yield satisfactory results. These models show potential for improvement, emphasizing the necessity for a more substantial dataset. This conclusion is further supported by the discernible trends in the learning curve, underscoring the importance of a larger dataset to enhance the performance of these specific models.
- Despite the challenges posed by data size constraints and variations in metric values, ML models demonstrate the capability to predict outcomes for previously unseen data points. This ability proves valuable for decision-makers in selecting appropriate machines. The simulations involving new parts underscored the models' effectiveness in providing approximate results, helping to eliminate machines with oversize and undersized capacities. This positive outcome contributes significantly to the final decision-making process for machine selection in a real production workshop.

Finally, this study is constrained by three specific limitations, outlined below:

- Data limitation: The findings stem from a dataset featuring 70 distinct molds, oversampled to a total of 100 records. The models underwent training using 85 molds 85% and were subsequently tested on 15 molds 15%. The relatively small quantity of molds used for machine training may be deemed insufficient, owing to challenges in acquiring a larger dataset from real-world workshops due to non-availability and complexity. Undoubtedly, enhancing the results could be achieved through access to a more extensive set of records.
- Model optimization: The hyper parameters were not fine-tuned using optimization algorithms such as grid search or random search [20], [21]. Exploring these methods to systematically search for the best parameters tailored to each model could be a promising avenue. This approach aims to enhance the accuracy of each model by identifying and fine-tuning the most suitable set of hyper parameters.
- Technical limitation: The models were exclusively tested on two new parts with similar characteristics and machine assignments (250 t and 320 t). It would be advantageous to extend the testing to various machine sizes encompassing all five classes and a broader range of part characteristics. This broader testing scope can contribute to the validation and evaluation of the models across a more diverse set of unseen data, thereby enhancing their reliability and generalizability.

6. CONCLUSION

Classifying the appropriate machine for a given product remains one of the most challenging tasks in the injection molding process. This article addresses this issue by proposing the application of ML methods for machine selection in the production of new products. The results indicate that the selected models effectively capture the complex relationships between features and accurately predict suitable machines. Specifically, the RF, DT, and SVM algorithms demonstrate promising accuracy levels, highlighting their potential in optimizing the machine selection process. The study was conducted using a dataset comprising 70 different parts distributed across five machines, collected from a real-world industry operating in the automotive sector. The analysis of this data revealed that ML models could significantly enhance the decision-making process in machine selection, potentially leading to more efficient and accurate production setups. However, the relatively limited size of the dataset poses several challenges, such as the risk of underfitting or overfitting the models. These issues could undermine the generalizability and robustness of the model predictions. To address these challenges and enhance the realism and flexibility of the models, it is recommended to increase the size of the dataset. A larger dataset would provide a more comprehensive representation of the various scenarios encountered in the injection molding process, thereby improving the models' predictive performance. Additionally, optimizing the models through techniques such as hyperparameter tuning, cross-validation, and feature selection could further refine their accuracy and reliability. Future research endeavors in this domain could benefit from these recommendations, as they would help in developing more robust and adaptable ML models for machine selection in injection molding. By leveraging a larger and more diverse dataset, researchers can gain deeper insights into the intricate dynamics of the production process, ultimately leading to more effective and efficient manufacturing practices.

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