Application Of Machine Learning Models To Predict Warping Of Plastic Automotive Parts☆

Aplicação De Modelos De Machine Learning Na Previsão Do Empenamento De Peças Plásticas Automotivas

Evandro Menezes de Souza Amarante[1], João Paulo Rios Brandão de Oliveira[1], Pedro Guilherme Carvalho de Souza Marconi[1,†], Armando Sá Ribeiro Júnior[1]

[1] *Universidade Federal da Bahia, R. Prof. Aristídes Novis, 2 - Federação, Salvador - BA, 40210-630, Brasil*
[†] **Autor correspondente:** pedro.marconi@ufba.br

Abstract

In order to manufacture plastic parts with complex geometries on a large scale, injection molding is one of the most widely used manufacturing processes. One of the criteria commonly considered when developing new products is dimensional quality, a factor directly associated with reducing part warpage. In the automotive industry, the manufacture of parts requires high dimensional precision, as many components have an aesthetic purpose or require perfect fits. Therefore, this work employs experimental designs, numerical simulations, statistical methods, and machine learning models to predict the warpage of an automotive cup holder. The polymers used were polypropylene (PP) and acrylonitrile butadiene styrene (ABS). The results indicated that the regression models developed for predicting warpage performed better with the ABS data. Regarding the classification models, both achieved an accuracy rate exceeding 90%. These findings provide useful tools during the mold tryout phase, helping to reduce time, cost, and material waste.

Keywords

Injection molding • Experimental planning • Statistical methods • Machine learning models

Resumo

Para a fabricação de peças plásticas com geometrias complexas e em grande escala, a moldagem por injeção é um dos processos de manufatura mais utilizados. Em relação ao aspecto dimensional, um dos critérios de qualidade comumente levado em consideração no desenvolvimento de novos produtos é a redução do empenamento da peça. Na indústria automotiva, a fabricação de peças exige alta precisão dimensional, pois muitos componentes têm um caráter estético ou necessitam de encaixes perfeitos. Dessa forma, este trabalho faz uso de planejamentos experimentais, simulações numéricas, métodos estatísticos e modelos de *Machine Learning* para a determinação do modelo de predição do empenamento de um porta-copo automotivo. Os polímeros utilizados foram o polipropileno (PP) e a acrilonitrila butadieno estireno (ABS). Os resultados revelaram que os modelos de regressão desenvolvidos para a predição do empenamento tiveram resultados melhores em relação aos dados do ABS. Com relação aos modelos de classificação, ambos atingiram uma taxa de precisão superior a 90%. Estes resultados

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fornecem ferramentas úteis durante a fase de experimentação do molde (*tryout*), ajudando a reduzir tempo, custo e desperdício de material.

Palavras-chave

Moldagem por injeção • Planejamento experimental • Métodos estatísticos • Modelos de *Machine Learning*

1 Introduction

Injection molding (IM) is one of the most common manufacturing processes for mass production of plastic parts, accounting for one-third of plastic product manufacturing [1, 2]. As a high-speed automated process, IM is used to produce plastic parts with complex geometries and demanding dimensional tolerance requirements [3]. In the automotive industry, these characteristics are crucial, as many components serve an aesthetic purpose or require perfect fits. Therefore, to achieve high dimensional quality, it is essential to minimize defects inherent to the manufacturing process.

In this context, according to Marconi et al. [4], the injection molding parameters must be precisely controlled to ensure that the design tolerances are achieved in the manufactured part. In this regard, Amarante et al. [5] emphasize the importance of using design of experiments (DOE) techniques to ensure success in this task. Montgomery [6] points out that these techniques are used to improve the quality characteristics of products and manufacturing processes, reduce the number of tests and optimize the use of company resources (material, employee time, equipment availability, etc.). In addition, it is necessary to simultaneously study the effect of the parameters at different adjustment levels to avoid potential problems related to defects in the parts [7].

Based on the results obtained through numerical simulations conducted using DOE, both industry and the scientific community have adopted optimization methods and machine learning techniques. These approaches are used to determine the best processing conditions in injection molding, as well as to develop predictive models that accurately represent the phenomena studied. Obermeyer and Emanuel [8] point out that data prediction, when related to machine learning, represents the response that a learning algorithm provides after being trained with similar data, in an attempt to respond to a new input stimulus in a manner similar to how it responded during the learning phase.

Thus, in the field of injection molding, Affonso and Sassi [9] used a combination of the Multilayer Perceptron (MLP) artificial neural network and the Radial Basis Function (RBF) artificial neural network, associated with fuzzy logic, to build an inference model that predicted the cycle time of injection processes. Manickam [10] used a Back Propagation (BP) neural network model to predict warpage and optimize plastic parts based on mold temperature, melt temperature, packing pressure, packing time and cooling time. The author concluded that the model was able to predict warpage within an error range of 2%. Additionally, there was a 32.99% reduction in warpage when compared to the initial result. Bensingh et al. [11] used a hybrid methodology based on the combination of Artificial Neural Networks (ANN) and the Particle Swarm Optimization (PSO) algorithm to predict the optimal injection parameters for biospherical lenses. The optimized injection molding process parameters obtained from the ANN-PSO hybrid algorithm were validated with on-machine experiments.

Sedighi et al. [12] combined finite element analysis, artificial neural networks, and a genetic algorithm to find the ideal location of the injection point on a plastic part. A regression model was developed from the neural network to predict the length and position of the weld line on the part, using data obtained from numerical simulations carried out in MoldFlow™ software. The developed model was then used as an objective function in the genetic algorithm to determine the injection parameters that would minimize the length of the weld line. Regarding the assessment of the dimensional aspect, Ogorodnyk et al. [13] explored the application of machine learning methods to predict the quality of plastic parts. They utilized tools such as neural networks and decision trees (DT) to create prediction models. Injection machine parameters, such as pressure, packing time and injection speed were evaluated in the experimental design. The models demonstrated accuracy rates of 99.375% and 97.5% for ANN and DT, respectively.

Therefore, this work seeks to evaluate the feasibility of a machine learning model for predicting the warping of an automotive plastic part made from different classes of thermoplastics (both amorphous and semi-crystalline). The objective is to analyze the performance of models generated from numerical simulation data, taking into account the specified tolerances. This work is organized into four sections: the first presents the methodology adopted in the research; the second addresses data pre-processing; the third presents the results obtained; and finally, the fourth section presents the study's conclusions.

2 Materials and methods

The methodology adopted in this work involves experimental design, numerical simulations, statistical methods and machine learning models to determine the warping prediction model, as well as to classify parts as either pass or fail. The quality criterion used for developing the classification model was warpage. Consequently, plastic parts with warping exceeding the adopted tolerance were considered failures, while those with warping within the tolerance were approved.

The numerical simulations were conducted using MoldFlow™, the DOE development was performed with Minitab™, and the machine learning models were implemented in Google Colab, utilizing the Python programming language and its respective libraries. In this context, the flowchart shown in Fig. 1 illustrates the sequence of the methodology used in this study.

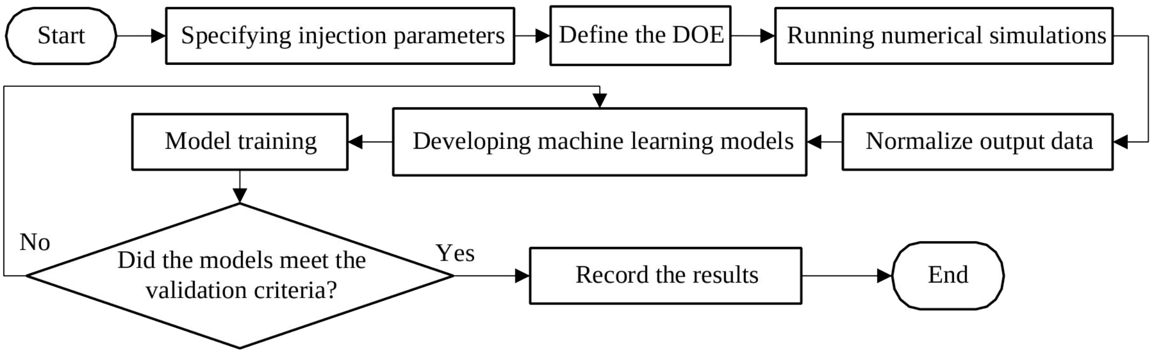


Figure 1: Flowchart of the methodology.

2.1 Case study: Geometry and polymers

The part used as a case study is an automotive cup holder with a nominal thickness of 2 mm, the other dimensions can be seen in Fig. 2.

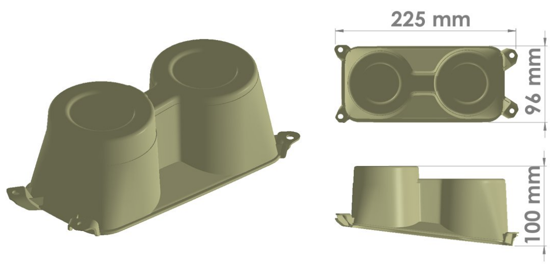


Figure 2: Automotive cup holder.

The thermoplastics selected were polypropylene (PP) and acrylonitrile butadiene styrene (ABS), both of which are widely used in injection molding processes and the automotive industry. Additionally, it is important to note that the material selection considered the differences in their processing conditions. Table 1 presents the processing conditions provided by the polymer manufacturers.

Table 1: Technical specifications of polymers

Polymer information	ABS	PP
Manufacturer	Kingfa Sci & Tech	Kingfa Sci & Tech
Trade name	HR-527A	ABP-2036 GT
Melt temperature (^{o}C)	210 – 260	190 - 245
Mold temperature (^{o}C)	40 – 80	20 - 50
Maximum shear stress (MPa)	0.3	0.25
Maximum shear rate (1/s)	50000	100000

2.2 Setup of numerical simulations: Experimental design

According to Kazmer [14], it is crucial to consider the effect of various processing conditions on polymer shrinkage, particularly those related to melt temperature, pressure, and process timing. In this context, the injection parameters were selected to map and investigate the key combinations related to the filling and packing phases. Jayapalan [15] highlighted that the most influential factors in reducing warpage include melt temperature, injection pressure, and packing pressure and time. Additionally, Barghash and Alkaabneh [16] demonstrated that filling time and mold temperature also play a significant role in warping behavior.

Given the wide range of mold and melt temperatures, as well as the number of decision variables and levels to be explored, the Generalized Space Design (GSD) was used as a DOE to determine the solution space for the injection parameters, which consists of 174 different configurations. It should be noted that 74 of these simulations correspond to the initial combination determined by the GSD (initial population), while the remaining 100 simulations result from the generation of new parameters. Consequently, the configuration used in the NSGA-II algorithm had crossover and mutation probabilities of 0.9 and 1/number of parameters, respectively.

Thus, six injection parameters were used to configure the experimental plan: melt temperature (T_{mt}), mold temperature (T_{md}), injection time (t_i), percentage of volume filled (V_f), packing time (t_p), and packing pressure (P_p), the latter being a percentage of the maximum injection pressure. The combination of factors and levels for each polymer is presented in Tables 2 and 3.

Table 2: Factors and levels of the GSD matrix for PP

Level	Factors					
	T_{mt} (°C)	T_{md} (°C)	t_i (s)	V_f (%)	t_p (s)	P_p (%)
1	190	20	1	97	2	50
2	218	35	2	98	4	73
3	245	50	3	100	7	96
4	-	-	4	-	10	120

Table 3: Factors and levels of the GSD matrix for ABS

Level	Factors					
	T_{mt} (°C)	T_{md} (°C)	t_i (s)	V_f (%)	t_p (s)	P_p (%)
1	210	40	1	97	2	50
2	235	60	2	98	4	73
3	260	80	3	100	7	96
4	-	-	4	-	10	120

The six injection parameters were selected to map and investigate the key combinations during the filling and packing stages. These parameters were chosen because of their significant influence on the warpage of the parts [4]. The data obtained from the numerical simulations were used to develop the prediction and classification models. Since the same type of experimental design and algorithm configuration were applied to both polymers, the aim of this procedure was to determine which dataset yielded the best results in terms of fit quality according to the evaluation metrics.

3 Data pre-processing

3.1 Development of the machine learning model

To address the varying scales of the injection parameters (such as temperatures, pressures, and times) used in the study, the first step was to normalize the data. To achieve this, the correlation matrix was employed, as recommended by Johnson and Wichern [17]. Standardizing the data is essential to prevent any single variable from exerting a disproportionate influence on the others due to differences in units of measurement. In this context, Mustaffa and Yusof [18] mention that pre-processing is the stage in which the input and/or output variables of a learning model are transformed to improve performance. Amarante *et al.* [19] highlight that one normalization strategy is the use of StandardScaler. This technique adjusts any range of values to have a zero mean and a unit standard deviation, as shown in Eq. (1).

$$z = \frac{x-u}{s}, \tag{1}$$

where z represents the transformed range, x the original range of values, u and s the mean and standard deviation of x, respectively.

To develop the machine learning model, a dense Multilayer Perceptron (MLP) neural network was used, consisting of three fully connected layers. The input layer contains 6 neurons (input variables), the first hidden layer has 64 neurons followed by a dropout layer, the second hidden layer has 32 neurons, and the output layer has 1 neuron (regression result). For the first two hidden layers, the Rectified Linear Unit (ReLU) function was used as the activation function, as described in Eq. (2).

$$f(x) = max \ (0,x). \tag{2}$$

ReLU was chosen for its simplicity and computational efficiency, as it replaces negative values with zero and leaves positive values unchanged. This approach helps mitigate the problem of vanishing gradients while introducing non-linearities into the network, enabling the model to learn and capture complex patterns in the data.

For the output layer, a linear activation function was used, as shown in Eq. (3). This function was chosen for its ability to predict continuous values that are not restricted to a specific range, making it ideal for predicting the maximum warping value.

$$f(x) = x. \tag{3}$$

where x is the input value of the function.

For the dropout layer, a deactivation rate of 0.3 was used. This means that during each training epoch, 30% of the neurons in the previous layer are deactivated, helping to prevent overfitting. This layer is only active during the training phase and is deactivated during predictions.

For a more accurate comparison of the results, the same network structure was used for both polymers. Figure 3 presents a schematic of the neural network employed, where the injection parameters, detailed in Tables 2 and 3, serve as input data, and warpage is the output variable.

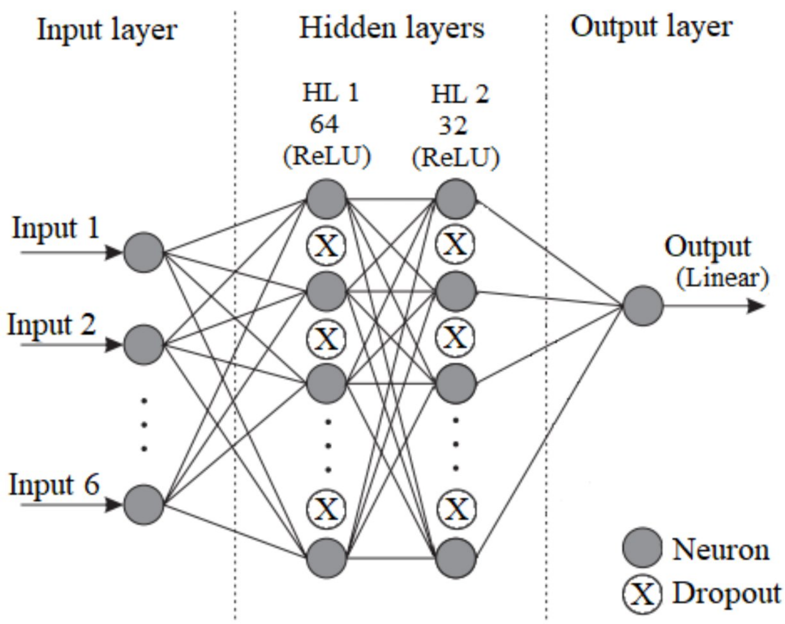


Figure 3: General architecture of the neural network. Adapted from Bre et al. [20].

3.2 Model training and validation

After the pre-processing stage, the databases were divided into two sets: training and test. This approach ensures that the model is not only tuned to the training data but is also capable of generating accurate predictions for new inputs. The training algorithm used in the MLP neural network is error backpropagation [21]. The operation of this network involves presenting a pattern to the input layer, which is then processed through successive layers until the output layer produces the final result.

Since neural network training is an iterative process, during each epoch (iteration), the neural network is fed a set of training data. In this process, the network calculates its outputs and evaluates them using a loss function. The metric chosen to evaluate the model was the coefficient of determination R^2, described in Eq. (4), due to its robustness, ease of interpretation, and popularity in the field of neural networks and deep learning. This performance indicator is commonly used to assess the quality of predictions [22, 23, 24, 25, 26].

$$R^2(y,\hat{y}) = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{\sum_{i=1}^{n}\left(Y_i - \overline{y}\right)^2}, \quad (4)$$

where Y_i are the output values of the numerical simulation, $\hat{Y}_i$ are the values predicted by the model, $\overline{y}$ is the average of the values obtained from the simulations and n is the amount of data used.

One of the strategies used to reduce the possibility of failures is to use carefully selected data [27]. A simple approach in this context is to separate the data into training and validation sets, which can later be used in model construction and performance analysis [28]. Regarding the adopted strategy, Kohavi [29] explains that cross-validation involves randomly partitioning a given dataset into k subsets of approximately equal size. Amarante *et al.* [19] further clarify that, in this method, once a subset is selected for validation, the remaining subsets are used to train the model, with the procedure repeated k times. Ultimately, the model's performance is calculated as the arithmetic mean of the individual performances from each combination of training and validation sets.

For the developed model, cross-validation was performed with 5 subsets, a value recommended in the literature [30] as it balances the need to evaluate different combinations with the computational resources required. It is important to note that this study used 80% of the data for training and 20% for testing.

In addition, a classification layer was added to the regression model results. For the evaluated case study, based on the tolerances specified in the part design, warping below 0.7 mm is considered acceptable, while values above 0.7 mm are rejected. This classification layer enables a binary assessment of part quality, simplifying the decision-making process for accepting or rejecting products based on the established tolerance.

To evaluate the performance of the regression models with the classification layer, an accuracy score was used. This score represents the proportion of correct predictions (both true positives and true negatives) relative to the total number of cases evaluated. Additionally, a confusion matrix was employed.

4 Results

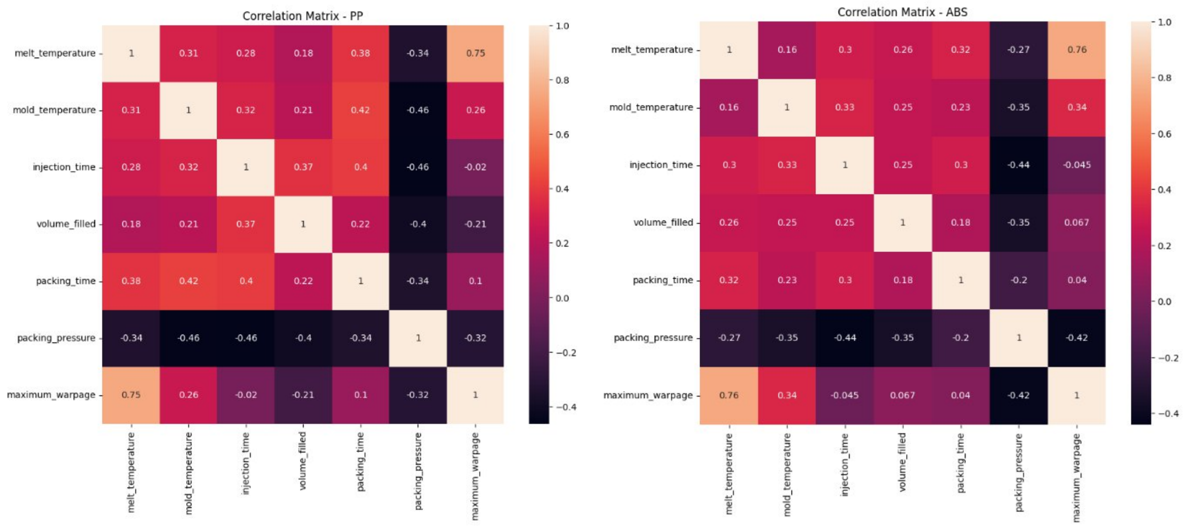
4.1 Simulation results

Table 4 displays the injection parameter settings that minimized part warping for each polymer, as determined through the developed DOEs.

Table 4: Filling and packing parameters that minimized warping

Polymer	T_{md} (°C)	T_{mt} (°C)	t_i (s)	V_f (%)	t_p (s)	P_p (%)	Warpage (mm)
ABS	210	40	4	97	2	90	0.4007
PP	190	20	4	97	2	90	0.4609

As shown in Table 4, divergence in the injection parameters that minimized warping, as well as the warping values themselves, was expected due to the differing processing conditions and the nature of the evaluated polymers. To assess the degree of correlation between the parameters, a correlation matrix (Fig. 4) was created for the data of each polymer.



(a) (b)

Figure 4: Correlation matrix for polymer data: (a) PP and (b) ABS.

The correlation matrices reveal significant relationships between the injection process parameters. There is a strong positive correlation between melt temperature and maximum warpage. Additionally, a moderate negative correlation exists between mold temperature and packing pressure, as well as between injection time and packing pressure.

4.2 Results related to prediction and classification models

The effectiveness of the regression models developed for predicting and classifying part warping was evaluated using the coefficient of determination (R^2) and the accuracy score metrics. Table 5 presents the results for each polymer.

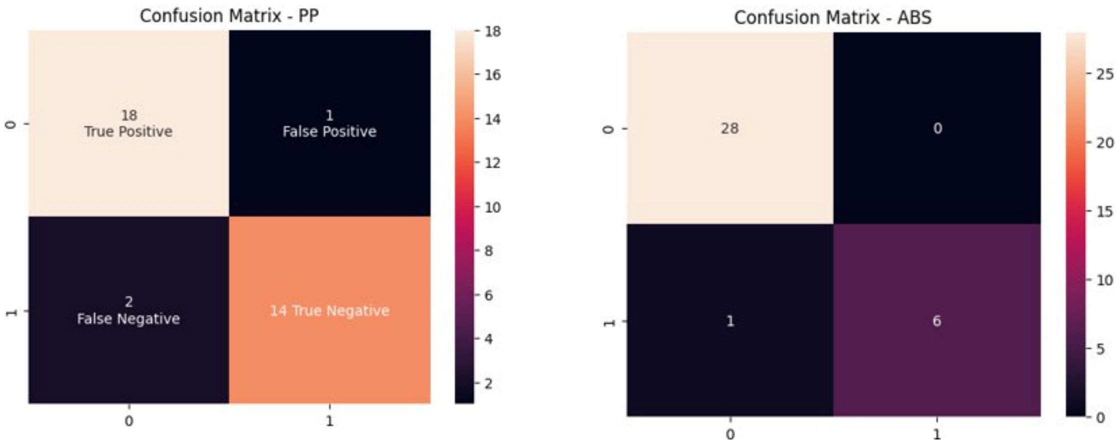
Table 5: Results of the model evaluation metrics

Polymer	Accuracy Score	R^2 Score
ABS	0.9714	0.9630
PP	0.9142	0.8854

Based on the results in Table 5, the regression model developed for predicting ABS warping demonstrated the best performance indicators. This result may be attributed to the properties of ABS. Amorphous materials generally exhibit lower shrinkage and a more linear change in specific volume during solidification compared to semicrystalline materials [31, 32]. These characteristics enable more accurate predictions of part warping behavior.

Additionally, analyzing the confusion matrix was crucial for evaluating model performance, as it detailed the distribution of classifications. In the PP model, out of 35 predicted cases, there were 18 true positives (where the model correctly classified the part as approved), 1 false positive (where the model incorrectly classified a part that did not meet the tolerance as approved), 2 false negatives (where the model failed to identify an approved part), and 14 true negatives (where the model correctly identified a failed part). For the ABS model, which also had 35 predictions, there were 28 true positives, 0 false positives, 1 false negative, and 6 true negatives.

These results demonstrate the effectiveness of the models in accurately identifying the classes for their respective tasks. The absence of false positives in the ABS model underscores its accuracy in avoiding critical errors. Thus, the confusion matrix proved to be an essential tool for assessing the accuracy and robustness of the classifications, as illustrated in Figure 5.



(a) (b)

Figure 5: Confusion matrix for polymer data: (a) PP and (b) ABS.

5 Conclusions

Injection molding of plastic parts requires a detailed evaluation of the process parameters to minimize warping. In this study, machine learning techniques were applied to classify the dimensional quality of parts made from polymers of different classes.

The results demonstrated the effectiveness of the method, as evidenced by high coefficient of determination values. In the case study, the model developed for ABS exhibited the best predictive performance, highlighting the specific characteristics of the amorphous polymer in relation to injection parameters, particularly its linear volumetric contraction profile compared to semicrystalline materials. For classification, the PP model achieved an accuracy rate of 91.43% (32/35), while the ABS model achieved an accuracy rate of 97.14% (34/35).

These results underscore the importance of ensuring high dimensional quality in plastic parts within an industrial environment. They provide valuable tools for the mold tryout phase, helping to reduce time, costs, and material waste.

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