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Data Mining Approach for Quality Prediction and Fault Diagnosis of Injection Molding Process

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Abstract

Objectives: To implement data mining approach to diagnose the causes of faults occurring in the injection molding product and to predict the quality of product for a particular setting of process parameters. **Methods and Statistical Analysis:** Decision Tree, k-Nearest Neighbor (k-NN) and Polynomial by Binomial classification techniques are used to build the data mining models by training them on dataset collected during the injection molding of a cap for 25 ml container. **Findings:** These models are evaluated on test dataset and their prediction accuracy is found to be 95%. Sink marks are caused by low injection speed, nozzle temperature and injection pressure. Low nozzle and mould temperatures and injection pressure resulted in short shot. High barrel temperature at Zone 2 and injection speed are responsible for burn marks in the product. **Applications/Improvements:** The higher prediction accuracy of these models is helpful in predicting the quality of product before its manufacture and thereby avoiding the production of defective parts. This approach can be further extended for injection molded parts made out of various plastic materials and process conditions.

Keywords: Data Mining, Fault Diagnosis, Injection Molding, Quality Prediction

1. Introduction

Injection molding is the most widely used method for manufacturing complex shaped plastic products at an affordable cost. The polymer pallets are fed in the solid state through the hopper and subsequently melted in the barrel. The plastic material is thoroughly mixed and moved to the front by the screw motion, and then forced into the mould through nozzle under high pressure[1].The part is cooled in the mould until it becomes rigid enough for ejection. Back Propagation Neural Networks (BPNN), Support Vector Machine and Genetic Algorithm, Dynamic Model Turning Minimum Variance (DMTMV), Least Squares Support Vector Machines (LSSVM), Rough Set Theory (RST), Neural-Fuzzy approaches were implemented for optimization of parameter settings, fault diagnosis and quality control of injection molding process[2-7].

Most of the times, the vast amount of data generated in manufacturing processes are only partially utilized. Data mining approach has emerged as a prominent tool to extract hidden patterns in process data and in discovering relationships existing between process parameters. Data mining techniques are being used for manufacturing process characterization, fault diagnosis, defect prediction[8]. Barrel temperature, injection pressure, time and speed, hold pressure and time, nozzle and mould temperatures, cooling time, clamping force, screw speed are considered as the input process attributes for the injection molding process. These attributes are continuously monitored and controlled to improve the quality of the product. In the proposed work, data mining approach has been used to create data mining models by applying Decision Tree, k-Nearest Neighbor, and Polynomial by Binomial Classification techniques in Rapid Miner software and trained on the process dataset.

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The causes of sink marks, short shot, burn marks and flash in the product are identified by the decision tree.

2. Decision Tree Model

Decision Tree model has the advantage of ease of interpretation over other techniques. The goal of the tree model is to predict target attribute/class. The path from the root to leaf node in the tree represents values of input attributes, whereas the leaf or terminal node represents target attribute for the given values of input attributes. Pre-pruning is carried out parallel to the tree building process to avoid over fitted tree on the other hand post-pruning is done after construction of the tree[9].

Decision Trees are built using recursive partitioning by splitting on the values of attributes. The gain ratio is set as the criterion in order to split the attributes. Confidence level and minimal gain values are set as 0.25 and 0.1 respectively as shown in Figure 1. Maximal depth parameter, which can restrict the size of tree, is set as 20. Pre-pruning and pruning options are invoked to build a tree in a more general form so as to improve its predictive power on unseen datasets. The minimal leaf size, minimal size for split and number of pre-pruning alternatives are set as 2, 4 and 3 respectively.

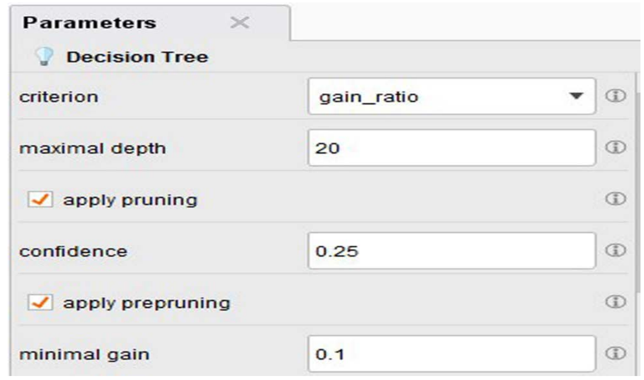

Figure 1. Decision tree parameters.

The training dataset is fed to decision tree operator as depicted in Figure 2. The decision tree model is extracted from the model port of Decision Tree operator is fed as one of the inputs to Apply Model operator. Test dataset is given as other input through unlabeled port of Apply Model operator. The labeled dataset is fed to Performance Operator to evaluate the performance of Decision Tree for the classification task. The decision tree built by the model is presented in Figure 3. The classification matrix in Figure 4 shows prediction accuracy of Decision Tree model along with class recall and precision.

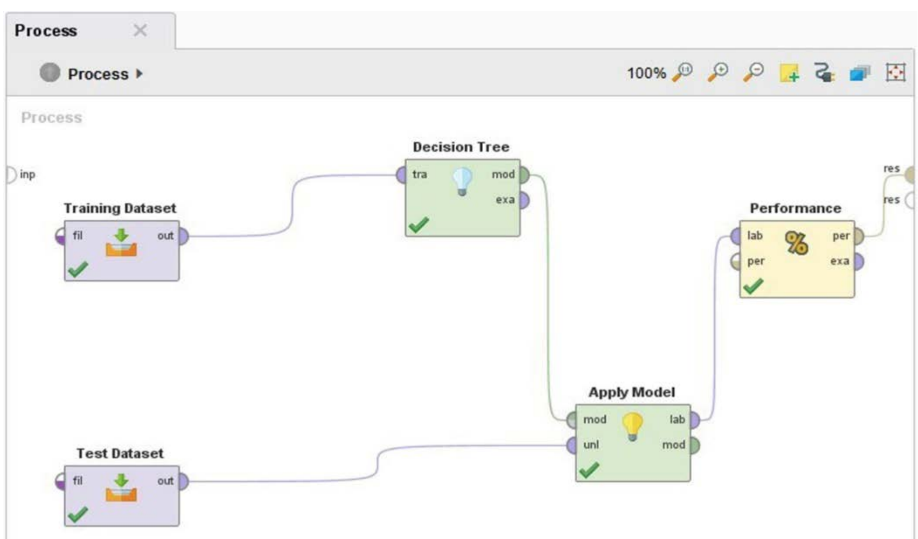

Figure 2. Rapid miner process with decision tree operator.

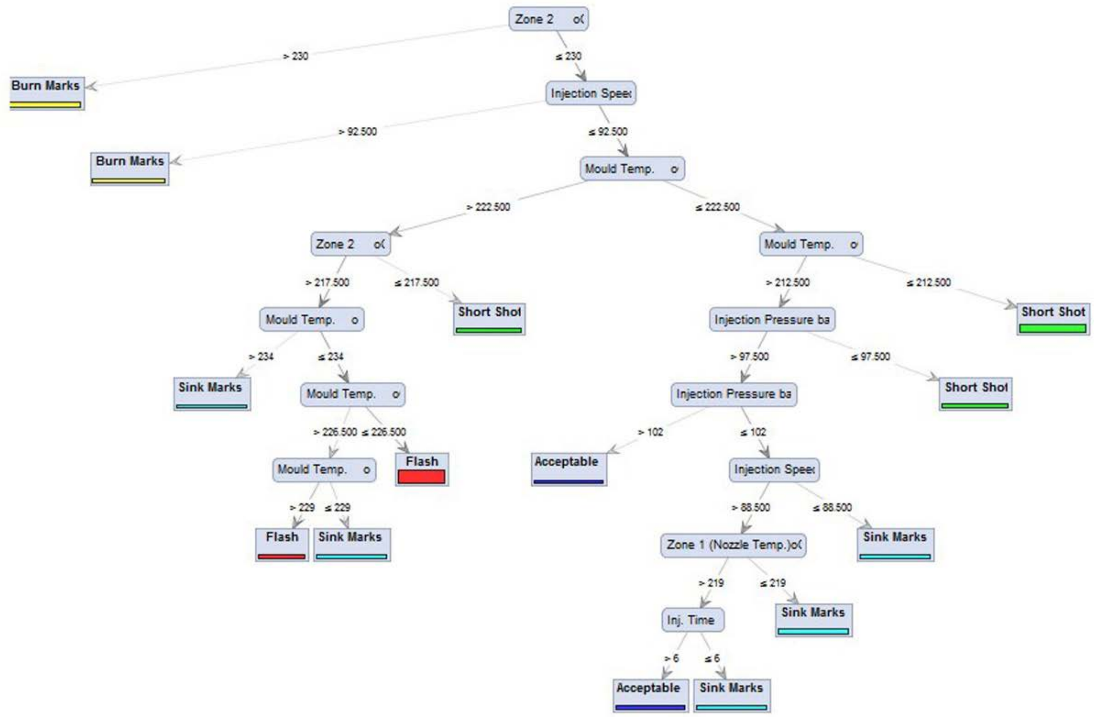

Figure 3. Decision tree.

Table View Plot View

accuracy: 95.00%

	true Acceptable	true Sink Marks	true Short Shot	true Burn Marks	true Flash	class precision
pred. Acceptable	3	0	0	0	0	100.00%
pred. Sink Marks	0	4	0	0	0	100.00%
pred. Short Shot	0	0	4	0	0	100.00%
pred. Burn Marks	0	0	0	3	0	100.00%
pred. Flash	0	1	0	0	5	83.33%
class recall	100.00%	80.00%	100.00%	100.00%	100.00%	

Figure 4. Classification matrix – decision tree model.

3. K-Nearest Neighbor (k-NN) Model

K-Nearest Nearest Neighbor algorithm learns by comparing a given test example (case) with examples available in test dataset that are similar to it. This algorithm is implemented in two steps. K training examples that are closest to the unseen example (test case) are found in the first step. Next unseen example is labeled as the most commonly occurring class of k examples i.e. an example is classified by a majority vote of its neighbors. An odd integer value is usually considered as k value. It is set as 3. Weighted vote parameter is set to provide weight to the contributions of neighbors. The type of measure for finding nearest neighbor is set as "MixedMesures"[9,10].

The process and its sequence using k-NN operator

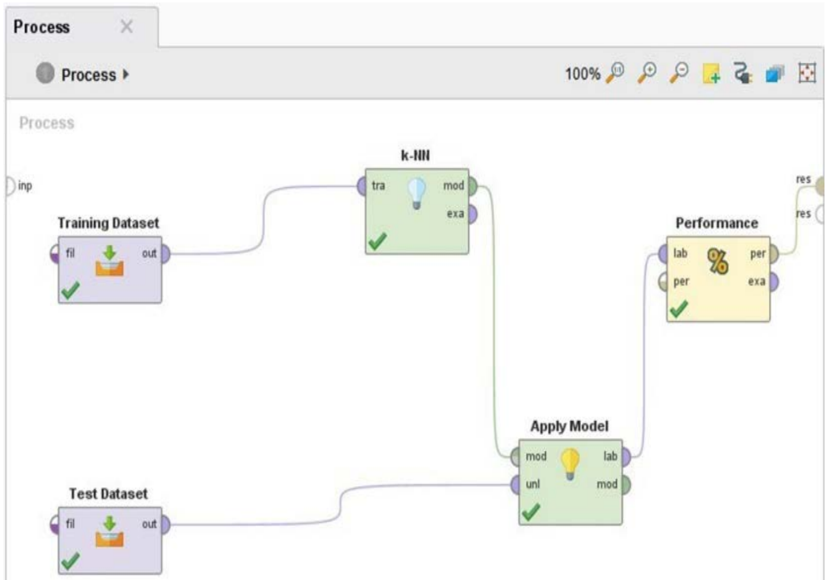

Figure 5. Rapid miner process with k-NN operator.

Table View Plot View

accuracy: 95.00%

	true Acceptable	true Sink Marks	true Short Shot	true Burn Marks	true Flash	class precision
pred. Acceptable	3	0	0	0	0	100.00%
pred. Sink Marks	0	4	0	0	0	100.00%
pred. Short Shot	0	0	4	0	0	100.00%
pred. Burn Marks	0	0	0	3	0	100.00%
pred. Flash	0	1	0	0	5	83.33%
class recall	100.00%	80.00%	100.00%	100.00%	100.00%	

Figure 6. Classification matrix – k-NN model.

have been shown in Figure 5. The k-Nearest Nearest Neighbor model is delivered from output port of k-NN operator is given as input to Apply Model operator to predict the class label of test dataset. The labeled dataset delivered by Apply Model operator is given as input to Performance operator for performance evaluation of the model to carry out the classification task. The classification matrix in Figure 6 shows prediction accuracy of k-NN model along with class recall and precision.

4. Polynomial by Binomial Classification Model

Polynomial by Binomial Classification operator applies Support Vector Machine (SVM) as its sub process. It can be used for classification and regression tasks and aggregates the responses of binomial classification models for classification of polynomial label. The values of parameters that are set for SVM are shown in Figure 7. SVM maps the examples as points in space in such a way that different categories are separated by a wide gap. The categories of new examples are predicted by locating which side of gap them fall[9,10]. The process and its sequence using Polynomial by Binomial Classification operator have been shown in Figure 8. The SVM as sub process of Polynomial by Binomial Classification operator is shown in Figure 9. The Polynomial by Binomial Classification model is delivered from model port of Polynomial by

Binomial Classification Operator is given as input to Apply Model operator to predict the class label of test dataset. The labeled dataset delivered by Apply Model operator is given as input to Performance operator for performance evaluation of the model to carry out the classification task. The classification matrix in Figure 10 shows prediction accuracy of Polynomial by Binomial Classification model along with class recall and precision.

5. Conclusion

Decision Tree, K-Nearest Neighbor (k-NN) and Polynomial by Binomial Classification models are having the prediction accuracy of 95% in predicting the category of the examples in the test dataset. The causes of defects are identified by interpreting the rules derived from the Decision Tree. Sink marks are caused by low

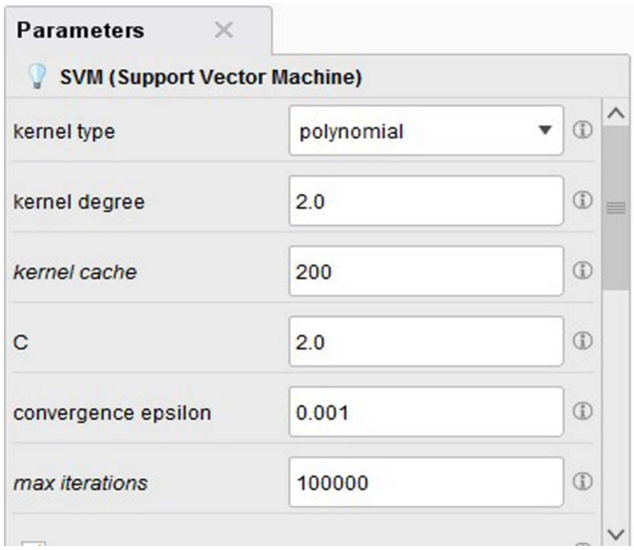

Figure 7. SVM parameters.

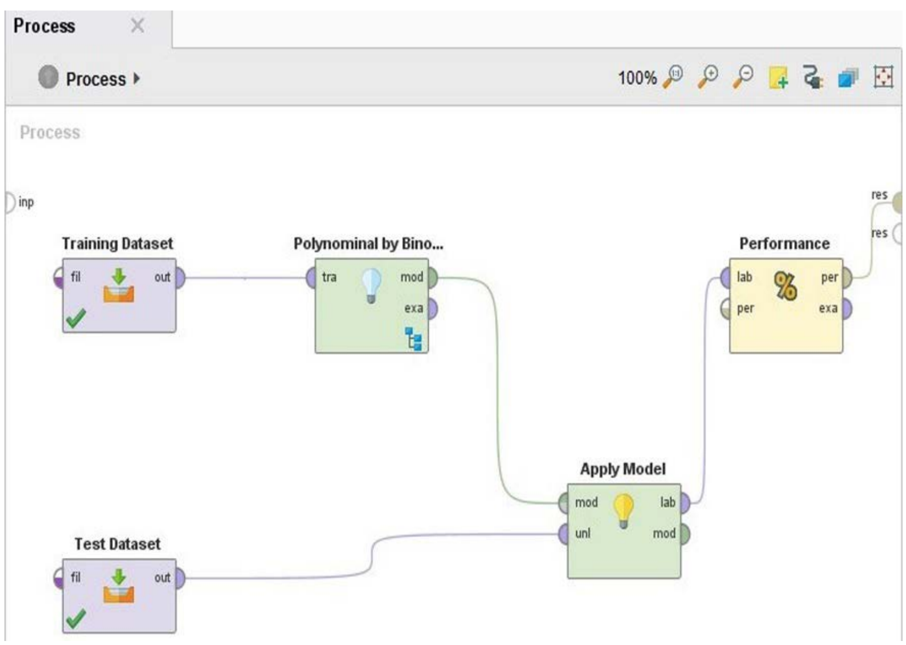

Figure 8. Polynomial by binomial classification model.

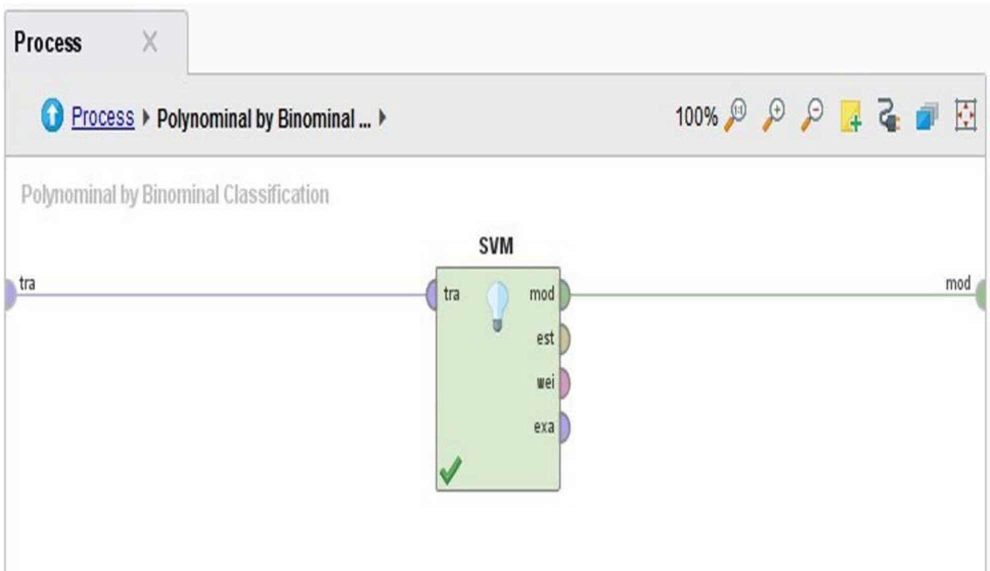

Figure 9. SVM as a sub process of polynomial by binomial classification.

Table View Plot View

accuracy: 95.00%

	true Acceptable	true Sink Marks	true Short Shot	true Burn Marks	true Flash	class precision
pred. Acceptable	3	0	0	0	0	100.00%
pred. Sink Marks	0	4	0	0	0	100.00%
pred. Short Shot	0	0	4	0	0	100.00%
pred. Burn Marks	0	0	0	3	0	100.00%
pred. Flash	0	1	0	0	5	83.33%
class recall	100.00%	80.00%	100.00%	100.00%	100.00%	

Figure 10. Classification matrix – polynomial by binomial classification model.

injection speed (≤ 85%), nozzle temperature (≤ 219^{0}C) and injection time (≤ 6 s) in the product. Short shot are resulted by low nozzle temperature (≤ 217.5^{0}C), molding temperature (≤ 212.5^{0}C) and low injection pressure (≤ 97.5 bar). High barrel temperature at Zone2 (> 230^{0}C) and injection speed (> 92.5%) are responsible for burn marks in the product. Flash is mainly caused by high mold temperature (> 229^{0}C). The quality of the product shall be predicted for a particular setting of process parameters by using Decision Tree, K-Nearest Neighbor (k-NN) and Polynomial by Binomial classification models.

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