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* **Corresponding author**.

kavitasaini_2000@yahoo.com

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Data Mining and Predictive Analytics for Injection Molding: An Analysis

Rani Kumari[1], Kavita Saini[2]*

1 Research Scholar, SCSE, Galgotias University, NCR, Delhi, India
2 Professor, SCSE, Galgotias University, NCR, Delhi, India

Abstract

Objectives: The objective of the research is to focus on the quality product of injection molding for the automobile industry. The root cause of the defects in the product needs to be understood in order to improve the product quality. **Method:** The research represents an industry Standard Process for Data Mining (CRISP-DM) framework for molding quality improvement. The Logistic Regression, AI ML algorithm has been used to develop the model. Because Logistic Regression is a classification supervised algorithm and our dependent variable also belongs to classification so used this algorithm. Splits the data set for training (66.66%) and testing (33.33%) of the model. **Findings:** During the literature review, it was found that some of the researchers focused on minimizing the variation in the product quality by considering the filling and packing stage, but only these parameters' impact on product quality is not sufficient. Considering the limitation as done by many researchers, the presented research work on molding parameters. The presented research considers multiple process-independent variables and their range as mould weight, the temperature of mold and material, injection time, hold time, plastification time, cooling time, and total cycle time and one dependent variable like quality. **Novelty:** The novelty of this research is that it is detailing and focus on the quantity of molded items and all independent parameters that impact the dependent parameter (quality) of molded items during the injection molding process. Therefore, this model performs the prediction of the molded items' quality based on their parameter values and sends an alarm or notification to the respective teams. The analysis has been done based on a pattern they find from a machine or database, and it returns the outcome, which can be a prediction.

Keywords: Predictive Analytics; Predictive Injection Molding; Data Mining; Machine Learning; Descriptive Data Mining; Predictive Data Mining

1 Introduction

Customers in today's competitive market place a higher priority on product quality than price [1]. This is one of the motivational points and objectives of the research. The presented research work is focused on quality improvement process parameters of the

Injection Molding process [1].

The paper, proposes a novel approach to a predictive injection molding model that makes use of data mining and predictive analytics [2,3]. The work reported in the research, carried out the facilities of the injection molding process in the automated industry with the help of data mining and predictive analytics [4]. The paper implements the Predictive Injection Molding predictive model for the Injection Molding process. The exploratory data analysis (EDA) work has been done to collect the data from the process of the domain, conforming to their type. After that finding the central tendency of the data like mean, median, mode and standard deviation. Through graphical presentation understand the data and avoid their noise. The Classification logistic regression algorithm of machine learning has been used to develop the PIM predictive model.

CISP–DM has been used as a framework in this paper [1,4,5]. This framework is one of the most reliable, robust, and user-friendly. This framework provides a structured approach to processing their research work phase-wise. The CISP-DM has six phases. Clearly stated, the research reported in this paper predicts molded items' quality based on the value of their parameters. The developed model also helps to understand the root cause of defects in the molded product.

The Logistic Regression Supervised Machine Learning algorithm has been used to develop the model. The Sigmoid Function which is widely used in other machine learning logistic applications need to set the threshold value (0.5). That threshold value helps to determine whether the quality may belong to a good or bad area. Splits the data set for training (66.66%) and testing (33.33%) of the model. During the development of the model the supervised machine learning logistic algorithm was used.

During the research, also found that few researchers divided the data set into 80:20 ratios to train and test the model. Sometimes if more data is used during the training of the model time it suffers from overfitting the model and testing with very few data sets then the model doesn't behave well in the real-time environment. So this research tries to justify the division of the data into the train (66.66%) and test (33.33%) set. Hence, the chance the overfitting the model is very low here.

The problems that can be addressed by the proposed mode are predicting the quality of molded items on the basis of process parameter variables. Identify the cause of defects in quality during the injection process. Feature selection (Independent variable) that should be meaningful. Algorithm selection from machine learning that will suit my research problem. However, this study is not concerned with other facts of molding, such as energy consumption, polymer recycling and sensor uses during the injection process. These are the future scopes and limitations of this paper.

1.1 Literature Review

The literature review helps in research to find out the existing knowledge and gaps on the same topic. It also helps to select the framework, tool & technology that will be used in the research. The below section describes some literature review papers, that are referred to in this research paper.

• Párizs, R. D., Török, D., Ageyeva, T., & Kovács, J. G. [6], purposed Multiple In-Mold Sensors for Quality and Process Control in Injection Molding. The sensors and applying technique is the volume-controlled method, the sensors are built in the cavity of the mold capable of finding the limit of the filling.

Research Gap: The researcher focuses on the suitability of Utilising in-mold pressure sensors. To control multi-cavity molds while injecting the material into the mold but only these parameters' impact on product quality is not sufficient.

• Silva, B., Marques, R., Faustino, D., Ilheu, P., Santos, T., Sousa, J., & Rocha, A. D. [7] , employing Enhance the Injection Molding Quality Prediction with Artificial Intelligence to Reach Zero-Defect Manufacturing and applying techniques are Methodologies used are data are fetched from the actual-time classification environment, such as Data Augmentation

Research Gap: Real-time quality Prediction Methodology and divide the data set into 80:20 ratio to train and test the model. If train data is bigger in size then sometimes the model suffers from the problem of overfitting.

• Tripathi, S., Mittermayr, C., & Jodlbauer, H. [8] , purpose Exploring the time-lagged causality of process variables from injection molding machines and applying the technique is variable lagged transfer entropy measure.

Research Gap: The researcher analyzes the process variable data and their interaction with the dependent variable and discusses the time lags. Discuss the time lag during the process but only these parameters' impact on product quality is not sufficient.

• Su, C. W., Su, W. J., Cheng, F. J., Liou, G. Y., Hwang, S. J., Peng, H. S., & Chu, H. Y [9] , purpose Optimization process Parameter and adaptive quality monitoring injection molding process for materials with different viscosity and applying techniques are the variables to quality monitoring used are peak pressure and clamping force.

Research Gap: The process parameters such as the viscosity index, peak pressure, and clamping force peak are monitored during the injection process to minimize the product weight but only these parameters' impact on product quality is not sufficient.

• Gim, J., & Turng, L. S[10] purposed a review of current advancements in high surface quality injection molding: Measurement, influencing factors, prediction, and control and applying techniques are thermal analysis, Machine learning and machine vision were used for surface quality control.

Research Gap : This paper talked about the influencing factors, prediction, and control for injection moulding. Researchers cover very few influencing factors like temperature and pressure.

• Plotnikova, V., Dumas, M., & Milani, F. P.[4] purposed Applying the CRISP-DM data mining process in the financial services industry: Elicitation of adaptation requirements. Data and Knowledge Engineering and applying techniques are The CRISP-DM techniques applied.

Research Gap : The findings show alleged inadequacies in CRISP-DM. It is not suitable for management activities. The research helps to identify the framework to apply in the research.

• J.Mendikute, J.Plazaola, M.Baskaran, E.Zugasti, L.Aretxabaleta and J.Aurrekoetxea[11] purposed an impregnation quality diagnosis in Resin Transfer Moulding by machine learning. This paper uses a Supervised machine Learning binary classification algorithm to train model with synthetic data set. The developed ML model allowed not only to predict the quality of the part but also to locate the areas where the defect was generated.

Research Gap: The present paper analyses the quality after the injection stage of RTM parts by Machine Learning not during the injection process being.

This paper is further organized as Section 2 discusses the background of the research and explains the descriptive data mining and predictive data mining techniques. Section 3 talks about problem statements and elaborates on the problems in existing systems. Section 4 defines the objective of the research.

Section 5 illustrates the framework, and provides the overall functionality, methodology, tools, and other approaches used to achieve the mentioned objectives. Business understanding, data understanding, data preparation, molding, evaluation, and deployment phases in detail. Further, exploratory analysis is discussed in Section 6. Section 7 mentions discussion and section 8 includes a conclusion and future scope.

Background: The term DM first appeared in the 1990s. Before that, technical statisticians used data fishing or dredging to analyze data without a pre-concluded hypothesis. One of the most important goals of the DM tool process is to easily extract conclusions or patterns from a large set of datasets. Each business problem is handled differently by different DM techniques. First, identify the problem, then make a good strategic plan to implement the proper DM technique to get the best result. DM analyzes big data to give a business solution, customer satisfaction, and business growth. Two data analysis methods can be used to extract information and develop the model.

The automotive sector makes extensive use of data mining for knowledge discovery in databases (KDD). This is a widely used data mining technique process. It includes several steps: gaining knowledge of the industrial industry, gathering data, using machine learning, data mining, and predictive analytics, evaluating the results, and presenting[12].

The first phase is called understanding the manufacturing domain. In this phase, understand and determine the problem, available resources, constraints, overall process, quality prediction, cost, and benefit of the developments[6]. The second data preparation phase, includes collection, fusion, cleansing, compression, and transformation of data[13]. The data is collected from different machines (about machine parameters), process data (like time, temperature, sort size, pressure, etc.), product data (size, shape, weight, etc.), quality-related data, etc. Generally, sensors are used to collect data from machines and processes. The data integration combines the data that comes from different resources[14]. The data cleaning handles the noisy data, filling in missing values by using some pattern, making consistency in data, removing the outliers from the data set, and making it an improved version of data.

To acquire the target dataset from the original data without suffering a major loss of information, data reduction is used, for example, in feature selection. The Data transformation converts data into a suitable form, such as normalization so that easily used. The set of data is stored in a private cloud or data warehouse following data preparation. To create the model, the third stage involves choosing the machine method of learning based on the type of problem.

In the fourth step, after developing the model check the accuracy of the model by using the evaluation method. During the evaluation, it might use precision, recall, f-measure, mean and R square value, etc. The last step is interpretation and visualization. Where check the performance of the model, by using product quality, process optimization, etc. The KDD steps are iterated several times until they get a satisfactory result. Finally, deploy the developed model in the running stage of production. Hence, discovered knowledge from the KDD process in data mining helps the managers in their decision-making and gives an improved version of the manufacturing system[1,5].

In a machine learning system, a developed model predicting the quality of the molded items. Predictive Analytics (PA) is an integral part of ML. The PA works based on a pattern they find from a machine or database, and after further analysis, they return the outcome, which can be a prediction[5]. The predictive analysis used in this paper predicts the molded items' product quality. Product quality is more important than cost, so they are essential for the success of the company and its reputation in customer markets [2]. That's why companies have more focus and spend a lot of time and money on it.

Problem Statement: When talking about solving anything, first need to identify the problem and its causes. After identifying, the respective team members make changes to improve the product quality. Some of the identification of this research problem is

1) Predicting the quality of molded items on the basis of process parameter variables.

2) Identify the cause of defects in quality during the injection process and send the recommendation to the respective team member.

3) Feature selection (Independent variable) that should be meaningful.

4) Algorithm selection from machine learning that will suit my research problem.

Objective: The primary area of this paper is to focus on quality products, minimizing wasting raw materials, and how to achieve this [2]. Product quality is essential for the company and its reputation in customer markets. Some of the important objectives of this paper are

1. The objective of the research is to focus on the quality product of injection molding products for the automobile industry.

2. This research aims to understand the root cause of the defects in the product and send the recommendation to the respective team.

3. Selection of all meaningful independent parameters (Co-relation-based feature selection) that affect the dependent parameter, i.e., output.

4. Implement of CRISP-DM framework.

2 Methodology

The literature review helps in selecting the methodology, tool and technique used in this research. The research presented in this paper uses the framework is Cross Industry Standard Process for Data Mining [5]. CRISP-DM methodology provides a structured approach to planning a data mining project, and it is one of the most reliable, robust, and user-friendly frameworks in DM . The CRISP-DM framework has six phases.

2.1 Business Understanding

Any research/project starts with the first phase of business understanding, which focuses on determining the business/research objectives. After gathering the knowledge, they try to get the preliminary stage of data and then plan to proceed with the research. In this research, the objectives are listed below-

i. The objective of the research is to focus on the quality product of injection molding products for the automobile industry.

ii. This research aims to understand the root cause of the defects in the product and send the recommendation to the respective team.

iii. Selection of all meaningful independent parameters (Co-relation-based feature selection) that affect the dependent parameter, i.e., output.

iv. Implement of CRISP-DM framework.

2.2 Data Understanding

This phase starts with initial data collection and proceeds with activities to familiarize the injection molding affecting parameters [6]. Try to understand the meaning of each parameter range during the injection molding. Here also understand the importance of each parameter's value on the quality of molded items.

2.3 Data Preparation

In the third phase, data preparation, after gathering data from different sources, like run time from the machine, a database, the cloud, or various cyber experiments, etc., performs cleaning, construction, and integration of the data. The initially gathered data was messy and unstructured, so data cleaning must be done . The Null value treatment was used for the data cleaning process in this paper, and the skewness treatment of the data along with the data types was checked before moving to the next step.

2.4 Modeling

The fourth phase is selecting the algorithm to develop the model and splitting the data set into train and test sets for training and testing the model. In this research paper, the problem is related to the binary classification problem, so logistic regression classification supervised machine learning (LRCSML), i.e., the logistic regression algorithm, will be used to develop the PIM model to predict the molding items. The research paper data set is divided into 66.66% and 33.33% rules for training and testing the developed PIM model.

2.5 Evaluation

In the evaluation phase, after developing the model and training the model, it needs to test the model before deploying it in the real environment. After evaluation of the results and satisfaction, the model is ready to deploy in the real environment. Finding out if there are any important objective that have not been fully examined is one of the phase's main goals.

2.6 Deployment

The last phase is the deployment of the CRISP-DM framework. After training and testing the model's performance, it is ready to deploy in the real environment to predict the molding of the products. The product development and product support teams are alert at deployment time. If any problem or recommendation comes up, the respective team modifies the parameter value to achieve quality.

3 Result and Discussion

The Purposed research, implements the PIM (Predictive Injection Molding) predictive model for the Injection Molding process by using a very famous classification Logistic Regression algorithm of Machine Learning has used. The dependent variable (quality) is binary (Success / Failure). 7 independent process variables and 1 dependent process variable were used. During the model implementation, Null value treatment, skewness treatment, and outlier treatment work was done for cleaning data. After doing these things found that the data was mostly balanced and next did some exploratory data analysis (EDA) work through a count plot, distribution plot and correlation plot. The model was trained using 66.66 % of data and 33.33 % of data was used for testing the model. The data's specifics are in Table 1.

Table 1. Data Overview

Max	75%	50%	25%	Min	Std	Mean	Count	
4.55	4.19	4.07	3.96	3.85	0.132485	4.073648	12485	WM_kg
227	218	208	198	188	11.652	207.64	12485	Temp_c
121	116	111	106	101	6.007	111	12485	TCt_sec
18	17	15	13	12	2.0074	14.999	12485	Issac
11	10	8	7	6	1.715	8.512	12485	Ht_sec
53	44	34	24	15	11.32	34.1	12485	Pt_sec
52	47	41	35	30	6.606	40.99	12485	Ct_sec
1	1	1	1	0	0.35489	0.85222	12485	WaitTimeImpact
1	1	1	1	0	0.3845	0.8196	12485	TemparutuImpact
1	1	1	1	0	0.1486	0.9774	12485	TCImpact
1	1	1	1	0	0.262	0.926	12485	ITImpact
1	1	1	1	0	0.2339	0.9419	12485	HTImpact
1	1	1	1	0	0.1639	0.9724	12485	PTImpact
1	1	1	1	0	0.143	0.979	12485	CTImpact
1	1	1	1	0	0.298	0.901	12485	Quality

3.1 Logistic Regression Algorithm

The research implements the Logistic Regression using Python. Below are the steps:

Step 1: Exploratory Data Analysis (EDA) work and splitting the data in training (66.66 %) and testing (33.33%) data set

Step 2: Apply the Logistic Regression algorithm and Training set
Step 3: The Model Prediction
Step 4: Test the accuracy
Step 5: Visualizing the result (Classification Report and Correlation Matrices)

3.2 Data Cleaning

Before continuing to the next phase, first, the null value treatment and then the skewness treatment of the data were examined.

3.3 Detecting Outliers and Their Treatment

Detecting outliers indicates an experimental error or heavy skewness in the data sets. The outlier figure has found a heavy-tailed distribution of parameters. During the implementation, we selected a mean of +1.5 sigma for the parameter's right-hand limit and a mean of -1.5 sigma for its left-hand limit. Any points that deviate from these guidelines are marked as problems, and they are ultimately handed to the proper team with the quality parameter marked as inadequate. This technique is used to establish the value range based on the data distribution. As we have shown, most of the data is symmetric.

3.4 Implementation of Exploratory Analysis

3.4.1 Representation of Count Plot for The Molding Items

The count plot is used to show how many times an observation appears in a categorical variable. The good and bad molded items in the given dataset where 0 represent bad quality and 1 good quality of moldeded item. Hear; see that there is a ratio of 10 to 90 for good and bad molded items and our data is biased to some extent. This research used samples of data from the internet for the current analysis.

- Less than 2000 data support bad quality and
- More than 10000 data support good quality of molded items

3.4.2 Study on Distribution Plot for Parameters

Figure 1 describes the Total cycle time vs. Density whereas Figure 2 describes the Temperature vs. Density

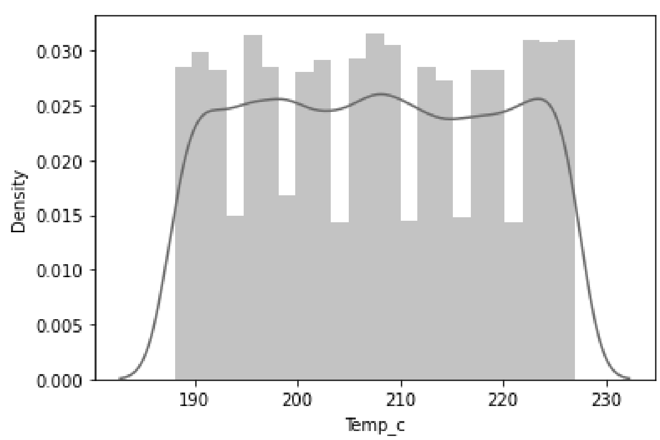

Fig 1. Total cycle time vs. Density

3.4.3 Implementation of Correlation Plot

We can learn about the relationship between two parameters from the correlation plot and values. Its value is between -1 and 1. The parameters are said to be inversely related when the value is negative, directly related when the value is positive, and unrelated when the value is zero. The results of this study can be used to establish a feature cut-off to reduce the number of parameters. Contrarily, any association between an independent parameter and a dependent variable would suggest that the making a significant contribution to the output variable and can be disregarded. A graph depicts Figure 3 the relationship between the data sets. After preparing our dataset, we trained the model using the training set and import the Logistic

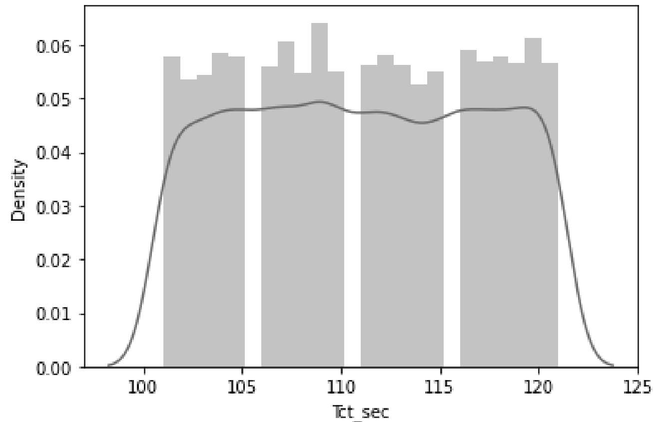

Fig 2. Temperature vs. Density

Regression class of the sklearn library to provide training for the model. After importing the class, we have created an object and used it to fit the model to the logistic regression.

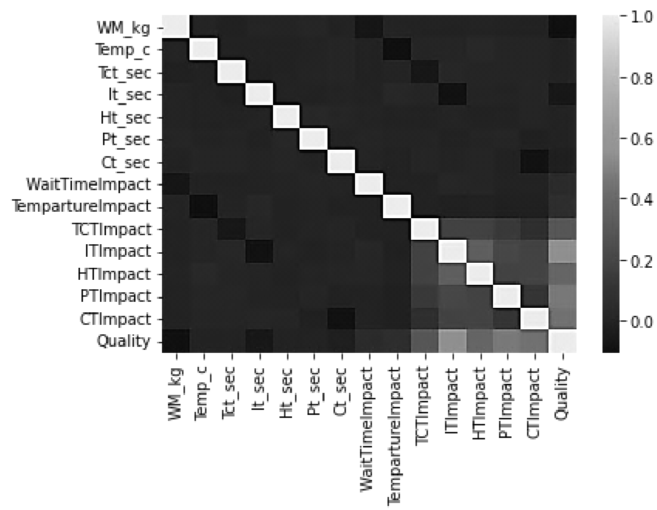

Fig 3. Correlation Plot of Data Set

During implementation, the data is divided into train and test by 66.66 - 33.33 rule. 66.66 % of the data has been used to train the model, and 33.33 % of the data has been used for testing the model. To provide a sufficient amount of data for the model during the training phase, the research provided 66.66% of the data for that. 30% of the data was provided to the PIM predictive model during the testing phase to check its performance. Figure 4 depicts the logistic regression plot. When a model is well trained on the training set, so now predicts the result by using test set data.

3.5 Confusion Matrix and their Classification Report

During implementation, the model has few metric performances

3.5.1 Implementation of Classification Report using Confusion Matrix parameters

The confusion matrix is a tool used in machine learning to assess how well a classification model is performing. A matrix that sums up how well a machine learning model performed on a set of test data is called the confusion matrix. It is frequently used to gauge the effectiveness of categorical label prediction models, which seek to predict a categorical label for each input event. The matrix shows the total amount of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) that

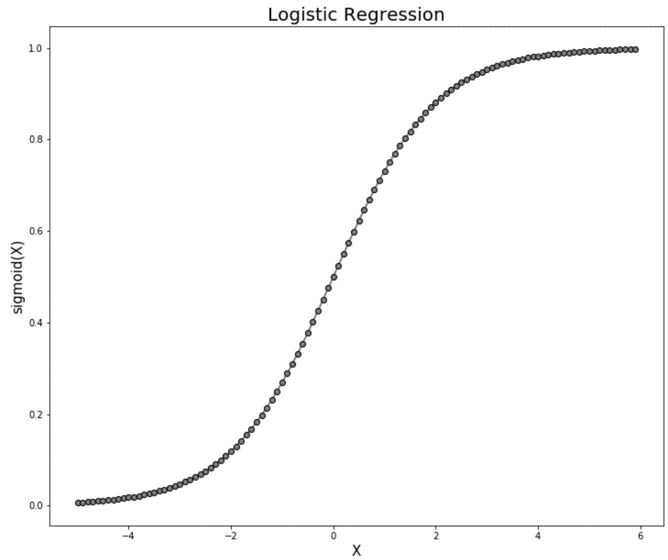

Fig 4. Logistic Regression Plot

the model on the test data has produced. The matrix will be a 2X2 table for binary classification

- **Accuracy:** - the percentage of all correct predictions that were made that were correct.

Accuracy=TP+TN/TP+TN+FP+FN

- **Precision :** - precision tells, what percent of positive prediction is done correctly.

Precision = T p/T p + F p

- **Recall :** - Recall assesses a classification model's ability to correctly identify each pertinent instance within a dataset. It is the proportion of incidences of true positives (TP) to instances of both true positives and false negatives (FN).

Recall = T P/T P + F N

- F1 score: - is also known as the F Measure. A classification model's overall performance is assessed using the F1-score. It represents the harmonic mean of recall and precision

F1- score = 2(Precision*Recall)/Precision + Recall

The below Figure 5 depicts the classification report of the developed model. Once deployed, the model and connected molding machines will feed in data to the IoT core and further from the IoT core to the analytics engine, which will analyse the current dataset and then send guidance to the concerned team to spot the error in the current manufacturing process. This model tries to achieve this. After deploying the model in the runtime environment, it will loaded with some input dataset (Process independent value) with their range and perform the runtime operation on that model.

	precision	recall	f1-score	support
0	0.85	0.65	0.74	401
1	0.96	0.99	0.98	3761
accuracy			0.96	4162
macro avg	0.90	0.82	0.86	4162
weighted avg	0.95	0.96	0.95	4162

Fig 5. Classification report of the Model

During the literature review, we found that some of the researchers only talked about meeting the production goal and maintenance schedule but they didn't talk about the product quality and the parameters that affect the product during the injection process. This research gap we had found, so decided to work on that.

Some of the researchers had worked on the number of cars to be manufactured by a car manufacturing company by using the previous year's data they had achieved through linear regression analysis. But in the linear regression, we need to draw a line each time to check so sometimes it becomes so lengthy to maintain this process. Here we also found that they talk about the quantity of the items not the quality of the items.

In the presented research we have implemented the Predictive Injection Molding (PIM) predictive model for the Injection Molding process by using a very famous classified Logistic Regression algorithm of Machine Learning. The PIM predictive model tells about the chances of defect on the basis of parameter value and it also sends the recommendation to the respective team to make changes accordingly. During the development, 8 independent parameters and 1 dependent parameter were used.

The classified Binary Regression algorithm in this research has used because the predicted output product quality might be good (1) or bad (0) it belongs to the binary type so use this algorithm. This algorithm is also suitable for linearly separate data sets means a data set refers to a graph where a straight line separates the two different data sets**.**

4 Conclusion

In the presented research we have implemented the Predictive Injection Molding (PIM) predictive model for the Injection Molding process by using a very famous classified Logistic Regression algorithm of Machine Learning. The PIM predictive model tells about the chances of defect on the basis of parameter value during the development, 7 independent parameters and 1 dependent parameter were used.

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The framework Cross Industry Standard Process for Data Mining (CISP – DM) has been used. During analysis, work is done on different processing parameter conditions like mold temperature, melt temperature, injection time, injection speed, injection pressure, screw rotation speed, etc., to provide quality improvement parameters. It tells how to improve or control these parameters of IM. So that develops a fine quality product with high repeatability and fast speed. This research aims to discover the elements that affect product quality in order to improve it. It offers the distinguished group a suggestion for a solution. However, this study is not concerned with other facets of molding, such as energy consumption, polymer recycling and type of sensors use during the injection process. These are the future scopes and limitations of this paper. The polymer industry is one of those with the highest energy use. A lot of energy is needed for molding. The polymer recycling process, where energy conservation is the top goal in the automotive industry, is another restriction or limitation on this paper. As more plastic components are utilized on a regular basis, the amount of plastic trash likewise increases. Recycled plastic is used in a variety of products, including brushes, non-food containers, and oil funnels. Recycling, though, must be both.

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