International Journal of Engineering Sciences 2022 15(1) 9 - 16

INTERNATIONAL JOURNAL
OF
ENGINEERING SCIENCES

Fault Identification in Investment Casting Process Using Naive Bayes Method

Yatish Subhash Sawant* and S. D. Agashe
College of Engineering Pune , India

(Received 5 July 2021; Accepted 15 February 2022)

DOI: https://doi.org/10.36224/ijes.150102

Abstract
Optimization in the investment casting industry is a difficult task as it contains multiple-stage operations for pro- duction. Although taking care of all the parameters investment casting industry is facing issues due to defects in the final product. This leads to a decrease in production, loss of production resources, and efficiency by analyzing the parameters and defects from the previous batches. We can predict the occurrence of defects for the given batch using a suitable machine learning technique. The Naive Bayes method, a supervised machine learning technique, is introduced to predict defects for the given batch from the model developed for it. Naive Bayes method includes four different models as, Gaussian NB, Multinomial NB, Complement NB, Bernoulli NB. This paper compared results for each model and analyzes which Naive Bayes model is best suitable for the Investment Casting industry and can predict the defect in the final product before it occurs.

Keywords: Machine Learning, Naive Bayes, Gaussian NB, Multinomial NB, Complement NB, Bernoulli NB, prediction

1. Introduction

The investment casting industry involves multiple stage operation, and individual stage affects the final product quality, which increases rejection. It mainly involves three major steps: Wax pattern creation, Ceramic shell preparation, and metal pouring. In the first step of operation, the industrial wax and additives are poured into the dies to prepare wax pattern molds. These wax molds are connected to a tree-like structure and taken to the next step of ceramic shell preparation. In this step, a ceramic slurry solution is used to govern the surface finish of the final casting with a primary coating and then sprayed with coarse particles to get secondary coating whole operation is done under a controlled environment by maintaining temperature and humidity. This process is repeated several times, and then ceramic molds are dried in a controlled environment. To dewax the mold, we will keep the mold in the autoclave and heating the tree arrangement, and the wax will melt out. Ceramic molds are then appropriately baked under high temperatures, which increases the mold's strength and prevents cracking while pouring the molten metal. After pouring the molten metal, it is kept to get cool, and then the ceramic shell is broken, and other processes are done to get the final product. Although maintaining proper operating conditions will often cause defects in the product, which will directly affect the system's efficiency. So, by using the appropriate data analytics technique, we can get an idea about whether the defect will occur before getting the product ready and make possible changes for that batch if required. Data from a different stage of the operation is collected together to analyze, which will increase the process efficiency and decrease the rejection ratio. In the previous work, People have collected the data in different ways like handwritten data entry, Excel sheets, and etc.

*Corresponding author
Email address: sawantys19.instru@coep.ac.in (Yatish Subhash Sawant)
ISSN 0976 – 6693.

This Collected data has been analyzed using a data analytics method named the Bayesian Inference method, where analysis gives the result as the range of operation of the parameters to be avoided in which defect has occurred, which will decrease the occurrence of the defect. After using the Bayesian inference method also there will be defects present in the system. Different supervised and unsupervised machine learning techniques like an artificial neural network, back propagation neural networks, etc., have been used previously to identify the defect. The naive Bayes machine learning model is easy compared to other sophisticated machine learning models with similar performance. So, the author has implemented the Naive Bayes machine learning technique to identify the defect before it occurs using data set of parameters and occurrence and non occurrence of the fault. The author Referred to the paper on which the Bayesian inference method is implemented for the data set.

2. Methodology

2.1.Naive Bayes method

In this method, different parameters and defects that occurred are used as input to the system at a time a single defect can be predicted. For the selection of which defect has to be analyzed, we count which defect occurred for maximum time shrinkage defect occurred for the maximum time that is this defect mainly affected the rejection ratio so selected shrinkage as defect for analysis. The system is divided into three stages pre-processing, processing, and post-processing. The output is the best suitable Naive Bayes model for the investment casting industry from the analysis of results. The whole system is implemented on Python IDE (Jupyter Notebook).

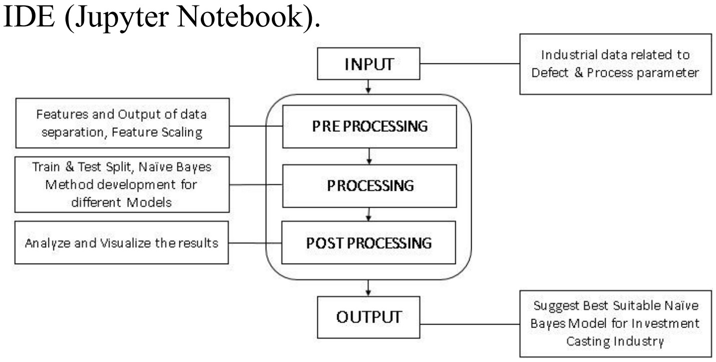

Figure 1: Architecture of the Naive Bayes method analysis

2.1.1. Pre-Processing

We have considered most affecting fourteen parameters related to process and occurrence of Shrinkage defect as input divided into separate data frames as features and defect present from the referred data set. Predicting the occurrence of defect is the task, with two classes as defected and non-defected, given in the data set as 0 and 1, respectively. Attributes used for the analysis have values that are not properly scaled, so performing normalization using feature scaling technique Min Max Scaler get the data properly scaled to process it ahead. Formula for Min Max normalization is as follows

$$N_n = \frac{N_i - min(N)}{max(N) - min(N)} \quad (1)$$

Ni − min(N)
max(N) − min(N)
N_n-New value

N_i-Original Value
Max(N) = Maximum value of column
Min(N) = Minimum value of column

2.1.2. Processing

The normalized data is now used to process using the Naive Bayes method. The Naive Bayes method is a super- vised machine learning technique with simple mathematics, probability, and statistical analysis. Naive Bayes algorithm is a classification technique and is easy to build. The Naive Bayes algorithm is based on the analysis of posterior probability with the simplicity of the build. The Naive Bayes algorithm is known to perform better than many of the sophisticated classification methods.

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \quad (2)$$

n number of parameters are possible as attributes and can also have k number of outcomes to the same system.

$$P(A|x_1, ..., x_n) = \frac{P(x_1, ..., x_n|A)P(A)}{P(x_1, ..., x_n)} \quad (3)$$

This is still a complex equation. It can be simplified by calculating probability P(x1,. . . .,x2) as it is constant, and only numerators are compared from distribution. It is easy to find the probability of class from the data set. So, the only difference remaining is the likelihood that is a conditional probability.

$$P(A|x_1, ..., x_n) \propto P(x_1, ..., x_n|A)P(A) \quad (4)$$

In the Naive Bayes method, first, convert the data set to the frequency table. Next, it creates a likelihood table by calculating the probability of attributes and the probability of defects. Then, for each class, calculate the posterior probability using the Naive Bayes equation. The class that has a higher posterior probability is the predicted class.

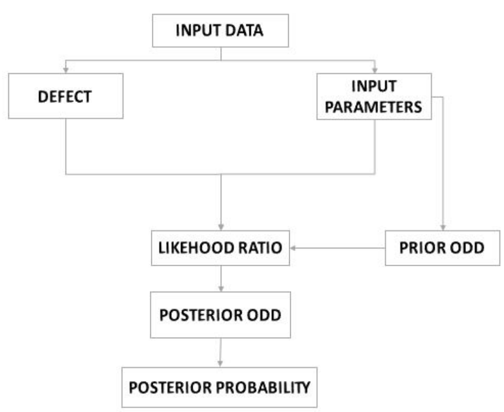

Figure 2: Naive Bayes Method Processing

There are 4 different types of Naive Bayes model,

- Gaussian Naive Bayes

This model is built assuming a normal distribution of probabilities, which means that occurrence and non occurrence of defect classes have frequencies distributed
by Gaussian law,

$$P(x_i|y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} exp(-\frac{(x_i - \mu_y)^2}{2\sigma_y^2}) \quad (5)$$

- Multinomial Naive Bayes

Multinomial classification is best suitable for discrete values. Distribution of probability is based on the following formula in the case of multinomial Naive Bayes model.

$$\theta_(yi) = \frac{N_(yi) + \alpha}{N_y + \alpha n} \quad (6)$$

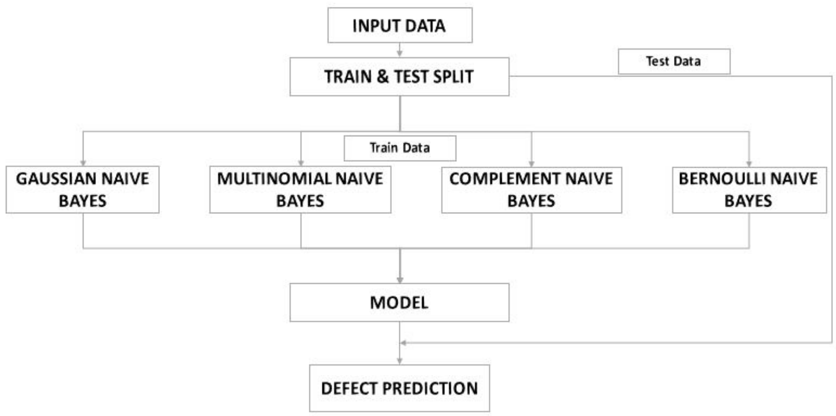

Figure 3: Naive Bayes model algorithm

where,
Ny = Total number of features of the event y
N(yi) = Count of each feature
n = Number of features
∞ = Smoothing Laplace parameter

- Complement Naive Bayes

The complement Naive Bayes method is the same as the multinomial model, but the occurrence of a defect in the form of compliment to the class is counted. This is done using the following formula,

$$\theta_(ci) = \frac{N_(ci) + \alpha_i}{N_c + \alpha n} \quad (7)$$

where,
Nc = Total number of defects in the opposite class
N(ci) = Repetitions of a defect in the opposite class

- Bernoulli Naive Bayes

Bernoulli's Naive Bayes method is the same as the multinomial model, where input is the set of Booleanvalues instead of frequencies,

$$P(x_i|y) = P(i|y)x_i + (1 - P(i|y)(1 - x_i) \quad (8)$$

While the multinomial Naive Bayes uses the smoothing parameter for the absent values, the Bernoulli algorithm binaries input values, so no additional actions are required.

C. Post Processing

From Naive Bayes models for analysis, we will extract parameters like accuracy, sensitivity, specificity, kappa coefficient, and f1-score and form a performance metrics also plotting and comparing test and predicted data to analyze and visualize the results. Performance Metrics parameters,

$$accuracy = \frac{T_P + T_N}{T_P + T_N + F_P + F_N}$$

$$sensitivity = \frac{T_P}{T_P + F_N}$$

$$specificity = \frac{T_N}{T_N + F_P}$$

$$f1_{(score)} = 2\left(\frac{Precision \times Recall}{Precision + Recall}\right)$$

$$kappa_{(coeff)} = \frac{Accuracy_{(observed)} - Accuracy_{(expected)}}{1 - Accuracy_{(expected)}}$$

accuracy, sensitivity, specificity are drawn
using confusion
matrix where,
TP = True Positive
TN = True Negative
FP = False Positive
FN = False Negative

Precision and recall are used to calculate the f1 score, which ranges between 0 and 1. Kappa coefficient also ranges between 0 and 1 if kappa coefficient is near to 1, it shows high reliability in observed and expected value.

3. Results and Discussion

Used Performance evaluation matrix to evaluate the Naïve Bayes Machine Learning models in that considered accuracy, sensitivity, specificity, f1-score and kappa coefficient

3.1. Performance evolution matrix

TABLE I
PERFORMANCE EVOLUTION MATRIX

Parameters	*Gaussian NB*	*Multinomial NB*	*Complement NB*	*Bernoulli NB*
ACCURACY	*0.89*	*0.83*	*0.89*	*0.67*
SENSITIVITY	*0.78*	*0.90*	*0.90*	*1.00*
SPECIFICITY	*1.00*	*0.75*	*0.88*	*0.0*
F1 SCORE	*0.88*	*0.82*	*0.89*	*0.0*
KAPPA CO-EFFICIENT	*0.78*	*0.66*	*0.78*	*0.0*

It is found that, the accuracy of 89% for the Gaussian Naïve Bayes model and the Complement Naive Bayes model is the highest in all the models from this performance evolutionmatrix. In contrast, the Multinomial Naive Bayes model has an accuracy of 83%, which is satisfactory. Bernoulli's Naïve Bayes model has 67% accuracy, which is the lowest of all of the models.

Sensitivity of 100% is highest for Bernoulli Naive Bayes model, Multinomial Naive Bayes model and Complement Naive Bayes model has a sensitivity of 90% whereas, Gaussian Naive Bayes model has a sensitivity of 78%, which is satisfactory but lowest among all the models. In terms of specificity, the Gaussian Naive Bayes modelis best among them with 100% evolution, Multinomial Naïve Bayes model and Complement Naive Bayes model has the specificity of 75% and 88%, respectively. The specificity for the Bernoulli Naive Bayes model is 0% which is the lowest value possible. We have also evaluated precision for all the models which came to be 100%, 75%, 88%, 0%for Gaussian Naive Bayes model, Multinomial Naive Bayes model, Complement Naive Bayes model and Bernoulli Naïve Bayes model respectively.

In the evaluation we found that, Gaussian Naive Bayes model and Complement Naive Bayes model has almost samef1 score with 88% and 89% respectively whereas, Multinomial Naive Bayes model has f1 score of 82% which is also good score and Bernoulli Naive Bayes model has 0% f1 score. We know that a higher Kappa coefficient will have high reliability in observed and expected value. Our analysis found that the Gaussian Naive Bayes model and Complement Naïve Bayes model have a 78% Kappa coefficient, which is the best among them. The multinomial Naive Bayes model has a kappa coefficient of 66% whereas, the Bernoulli Naive Bayes model is 0% which is the lowest value possible.

3.2. Graphical analysis

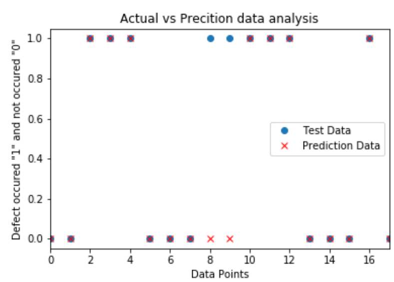

Figure 4: Gaussian Naive Bayes plot

Author has compared the test and predicted data graphically by plotting the discrete plot for the same number of data points with different symbols as blue dot for test data and red cross for predicted data. As a result, we will be able to visualize the data.

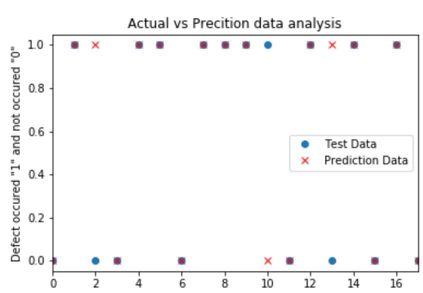

Figure 5: Multinomial Naive Bayes plot

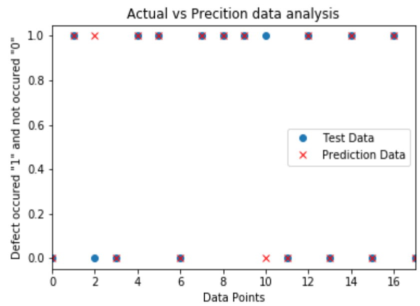

Figure 6: Complement Naive Bayes plot

From the graphs, we can visualize that most of the test data points and predicted data points overlap each other in the Gaussian Naive Bayes model and Complement Naive Bayes model, implying that prediction was good using Gaussian Naive Bayes model and Complement Naive Bayes model. Moreover, they also had similar performance evaluation matrix parameters whereas, for the Multinomial Naive Bayes model prediction and performance evaluation matrix parameters were satisfactory and average in case of Bernoulli Naive Bayes model.

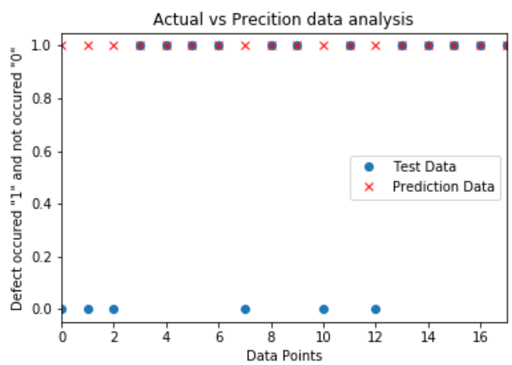

Figure 7: Bernoulli Naive Bayes plot

4. Conclusion

The author has suggested a way of identifying the most affecting fault in the investment casting industry, which will drastically reduce the rejection ratio. The present study gives an idea about different Na¨ıve Bayes models for analysis as Gaussian NB, Multinomial NB, Complement NB, Bernoulli NB. The Performance evolution matrix and graphical analysis conclude that the Gaussian Naive Bayes model and Complement Naive Bayes model are the most suitable models for analysis in the investment casting industry. Real-time identification of fault for a golden batch using the data set of parameters and occurrence of defects in previous batch is possible using this study.

References

[1] Sata, A. and Ravi, B., Bayesian inference-based investment casting defect analysis system for industrial application. The International Journal of Advanced Manufacturing Technology, 2017, 90(9), pp.3301- 3315

[2] Karunakar, D.B. and Datta, G.L., Prevention of defects in castings using back propagation neural networks. The International Journal of Advanced Manufacturing Technology, 2008, 39(11-12), pp.1111-1124

[3] Dabade, U.A. and Bhedasgaonkar, R.C., Casting defect analysis using design of experiments (DoE) and computer aided casting simulation technique. Procedia Cirp, 7,2013, pp.616-621.

[4] Li, B., Han, T. and Kang, F., Fault diagnosis expert system of semiconductor manufacturing equipment using a Bayesian network. International Journal of Computer Integrated Manufacturing, 2013, 26(12), pp.1161-1171.
[5] Hamilton, R.W., See, D., Butler, S. and Lee, P.D., Multiscale modelling for the prediction of casting defects in investment cast aluminum alloys. Materials Science and Engineering: A, 2003, 343(1-2), pp.290-300.
[6] Guharaja, S., Haq, A.N. and Karuppannan, K.M., Optimization of green sand-casting process parameters by using Taguchi's method. The International Journal of Advanced Manufacturing Technology, 2006, 30(11), pp.1040-1048.
[7] Dwivedi, S.N. and Sharan, A., Development of knowledge-based engineering module for diagnosis of defects in casting and interpretation of defects by non destructive testing. Journal of materials processing technology, 2003, 141(2), pp.155-162.
[8] Zheng, J., Wang, Q., Zhao, P. and Wu, C., Optimization of high pressure die-casting process parameters using artificial neural network. The International Journal of Advanced Manufacturing Technology, 2009, 44(7- 8), pp. 667-674.
[9] Jin, S., Liu, C., Lai, X., Li, F. and He, B., Bayesian network approach for ceramic shell deformation fault diagnosis in the investment casting process. The International Journal of Advanced Manufacturing Technology, 2017, 88(1-4), pp. 663-674.
[10] Liu, C., Jin, S., Lai, X. and Wang, Y., Dimensional variation stream modeling of investment casting process based on state space method. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 2015, 229(3), pp. 463-474