Advances in Dynamical Systems and Applications.
ISSN 0973-5321, Volume 16, Number 2, (2021) pp. 1599-1613

https://www.ripublication.com/adsa.htm

Sand Casting Defect Prediction through Probabilistic Modelling

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Abstract

In this paper, discussion about the implementation of Bayesian prediction model based on probabilistic modelling for a grey iron sand casting component for defect reduction and quality assurance is presented. Bayesian modal, the values of posterior probability of each input parameter are computed to identify the avoidable range of their values. The data related to processing parameters and the number of defective castings is collected from a foundry. The Bayesian model gave better results in terms of prediction and accuracy. The systems are favourably tested on real-life data obtained from the foundry, attending to a significant decrease in the rejection rate of cast component. For creating Bayesian inferencing Python is used and the model is presented online to make this modal available for the foundry engineers. The Bayesian prediction system can help foundry engineers to take decisions regarding preventing possible defects in advance in user friendly manner.

Keywords: Bayesian Prediction, Artificial Neural Networks, Sand casting defects

1. INTRODUCTION

Metal casting is a versatile primary manufacturing process. It can produce complex products from a few grams to several tons from molten metal, and the production of castings plays a significant role in the global and local economy. (1). The production of castings plays a significant role in the global and local economy. The yearly casting production around the world from 2015 to 2019 has recognized the remarkable growth from 104.129 million metric tonnes to 109.059 million metric tonnes (2,3).

And India is the second largest producer of castings just after china. Of the various casting processes, the sand-casting process accounts for 90% of the whole casting process. Even though sand casting is a well-established process still defects in casting range from 5-10%; hence control of defects has become an essential issue for the foundry industry. Moreover, it drives the search for the defect reduction and quality assurance through better use of intelligent systems.

Sand casting process generally means pouring molten metal into a refractory mould which contains a cavity of required shape and allows it to solidify, after solidification the desired metal object is taken out from the mould either by breaking the mould or taking mould apart, this solidified object with the designed shape is called casting.

So many process parameters are responsible for defective sand castings and these parameters vary within a wide range, and it is tough to determine the particular range of values which is responsible for the defect. The sand-casting industries have utilized several Artificial Intelligence algorithms and proven its fruitfulness for making decisions, by training AI modals using past available data. Next Literature review about Naïve Bayes one of the Machine learning classifiers for building self-learning ability in the realm of metal sand casting defect reduction is discussed.

2. LITERATURE REVIEW

To improve sand foundry production and quality assurance, researchers have explored different types of Neural Networks. Now a discussion about the application of ANN in foundries for casting defect reduction is presented progressively. To identify and label some small defects like notches and metal balls (4) provided a Neural Network design approach. (5) applied Artificial Neural Network for cause detection of gas porosity defects in sand casting and used process parameters, materials used and workers involved as input variables for the training of the network. (6) Applied a backpropagation neural network to predict some significant defects in sand castings. For shrinkage location recognition(7) trained back propagation neural network with the results of Finite Element Methods.(8) Used artificial neural network-based methodology to the identification of flaws in the aluminium alloy castings by radio graphical image analysis. (9) Offered an Artificial Neural Network based model to foresee collapsibility of CO_2 sand moulds. To assess the green compressive strength of clay bonded moulding sand (10) offered neuro-fuzzy based models and witnessed that the neuro-fuzzy model was more precise than the neural network model. (11) Indicated that the Radial Basis Function Artificial Neural Network (RBFANN) model could adequately estimate the parameter values of phosphate graphite sand. To determine the relationship between input-output parameters of cement-bonded moulding system (12) used propagation algorithm and a genetic algorithm, based neural networks and proved it can be used for both forward and reverse mapping of input and output parameters. (13) apply back-propagation neural networks and genetic neural networks for both forward and reverse modelling of input and output parameters of green sand moulding after that (14) adopted back-propagation as well as genetic neural network for determining the relationship between input-output parameters of sodium silicate bonded carbon dioxide hardened sand moulding. (15) Presented a method of selection of the proper kind of a neural network for prediction a sand moistness on the bases of certain moulding sand properties such as: permeability and friability. To analyse the influence of input variables on compressive strength of Furan No-bake mould system (16) formed ANN modal. Artificial Neural Network has also been applied in the foundry industry to control melting processes in furnaces. (17) presented Artificial Neural Network-based model to determine the active bentonite content in green moulding sand based on sand properties such as permeability, compatibility and the compressive strength, and letter (18) applied Neural Networks for controlling the quality of bentonite moulding sand. ANN has been used in the sand-casting industries for defect identification, quality assessment of the castings, prediction of possible defects, selection and control of sand mould properties and for optimization of casting input parameters.

A Naive Bayes is a simple and robust algorithm of predictive analysis. It is a classification technique of statistics based on Bayes' theorem used to predict the probability for a hypothesis. In the viewpoint of decision theory, it is related to Bayesian probability (19) and uses prior data learning and Bayesian rules to predict the probability of occurrence of specific parameters. Various researchers (20) have raised the potential of Bayesian Networks in the domain of building machine learning ability and less explored in the domain of metal casting. Now a discussion about the Bayesian application in foundries for defect reduction and quality assurance is presented next. (21) Used three-tier structured graphs, chill climbing search technique and Bayesian analysis and made intelligent computer-aided defects identification analysis system for grey iron sand casting defects. (22) Showed Bayesian Networks can be used to modal the casting processes and to predict the values of variables like the ultimate tensile strength of the cast components.

For training and building a machining learning ability, a knowledge cloud was prepared by (23), which was helpful in prediction of the ultimate tensile strength of cast components. After comparing Bayesian networks with artificial neural network and K-nearest neighbour algorithm (24) showed that Artificial Neural Networks are best suited for the prediction of ultimate tensile strength. To predict the presence of micro shrinkage in nodular iron sand castings (25) applied Bayesian network-based approach and developed an expert system to help foundry engineers regarding decision making in the field of sand-casting defect reduction. After that compared artificial neural network and K-nearest neighbour algorithm with Bayesian networks (26) and found Bayesian networks more suitable, and then (27) compared support vector and decision trees with Bayesian networks for the same objective and showed that the decision trees are more suitable for the defect prediction. For detection of micro shrinkages in iron castings (28) employed anomaly-detection based approach and was able to classify the correct or erroneous castings, but being completely supervised learning approach it required labelling of each casting in the dataset. To handle this issue (29) employed another technique called collective-classification approach, it being semi-supervised learning technique required fewer labelled castings only. To study shrinkage incidence variations in cast iron castings (30) used group of

Bayesian networks which was helpful in prediction of one of its input variables. Completely new in the foundry industries it was used in 1995 for identification of some major defects in grey iron and casting. Furthermore, they have also given better results in sand casting quality prediction. The application of Naive Bayes classifiers in the sand-casting industries is at its inclination stage. It needs much attention of the researchers to explore in the field for sand castings quality assurance and defect reduction.

To summarise Both Artificial Neural Networks and Bayesian networks have been used to carry out input-output modelling of the metal sand casting process. That Artificial Neural Networks are excellent in the sand-casting quality and mould quality predictions and for optimization of casting input parameters. However, it has Poor explanation ability of the reported Output. Unlike this, the naive Bayes approach has the potential to give a better explanation of the results because it is based on the probabilistic modelling. Furthermore, it is at its tender stage, which can make foundries more intelligent by probabilistic learning from stored data and relatively less explored approach in the domain of metal casting. In this work, Naïve Bayes Defect prediction system has been developed for grey iron sand casting component. The architecture of Naïve Bayes defect prediction system is presented next followed by its testing with real life data obtained by a sand-casting foundry.

3. DATA COLLECTION AND DEFECT ANALYSIS

Data related to sand properties, metal properties and metal casting process are exhaustively reported in metal casting hand books and some casting related books. American Society of Metals (ASM) published metals handbook (31, 32) that presents experience based extensive knowledge of process capabilities of casting process and the influence of design details on castability along with the benefits of modifying the design and process to achieve compatible inter-relationship. American Foundry men's Association (33) which is considered to be as a standard for many foundries, has listed and described a total of 31 casting Defects which can occur in grey iron castings. These defects can be grouped into two categories Major defects and Minor defects. The presence of Major defects results in rejection of casting, makes it a total scrap otherwise too much of rework is required to reuse it. Minor defects are those defects which can be easily removed by after machining or any other secure manner. Hence to reduce the rejection and improve the productivity of foundries efforts should be made to prevent the occurrence of these major defects. Some major defects observed in a grey iron sand castings are shown in Figure 1.

(a) Blow holes (b) Penetration (c) Erosion

Figure 2. Various defects in sand casting

Many process parameters are liable for defective castings, and they vary in a broad range. Hence, it needs to recognize the safe range of their values during the process, and it is also essential to identify the responsible parameters to reduce defects. AI approaches such as Neural Networks, case-based reasoning and rule-based expert systems have been reported sensible in the context of Quality assurance and defect reduction. To reduce sand casting defect it is essential to identify defect causing parameters and there values. Hence in this work, Naïve Bayes casting defect prediction system was formed to analyze and counter defects in sand castings, by identifying responsible parameters and the avoidable range of their values. Early research work in the field of application of Artificial Neural Networks and Bayesian inferencing in the sand, casting industry for defect analysis is manifested next, followed by the proposed system and its testing in an foundry.

3.1 Analysis of Industrial Data

The shop floor data employed to carry out the present researches have been collected from a metal casting foundry located at Chhattisgarh, this foundry is involved in making casting components for Mining sector, cement sector and steel plants. The significant defects confronted by these industry are blowholes, Porosity Penetration and erosion as shown in figure 2. Hence, an effort has been made to prepare prediction system for these major defects for grey cast iron components using Bayesian approach. A grey cast iron component of (FG 250, Composition: C 3.3-3.7, Si 2.2-2.6, Mg 0.65-0.67, S 0.00-0.04, P 0.03-0.05, Induction furnace) produced in the foundry was taken up to implement and test the proposed approach for casting defect analysis (Fig. 3.1.5). It has an overall size of 1000 × 550 × 113 mm and weighs 200 kg; its wood pattern weighs 27kg. The yield is between 70 and 75 %. The detailed drawing of the component is shown in figure 2.

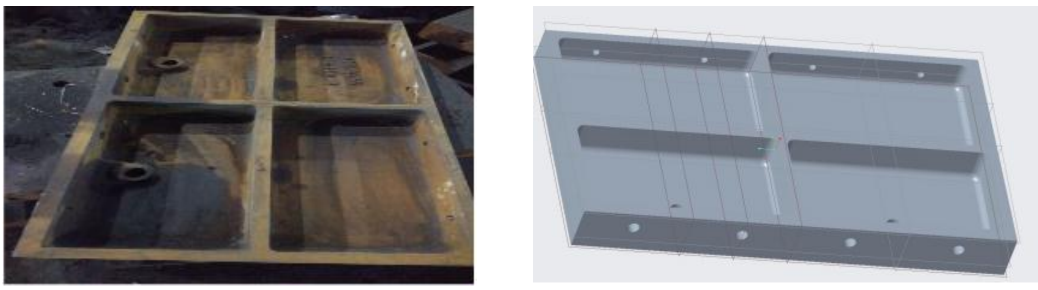

Figure 2. Sand casting component considered in the study

The foundry typically carried out 4–5 heats (cycles of melting and pouring) on each working day, each heat being used to pour 4-5 castings. For each heat, 7 data items were identified for collection included Moisture percentage, Permeability, Binder Percentage, Pouring Temperature, Grain Fineness Number, Mould Hardness, Green Strength and assurance of the three defects. The data from 493 heats (approximately 1590 castings) were collected over six months. Table 1 contains the sample dataset of 494 data entry which contains the total seven parameters for evaluation propose from that we can predict the output variables like blow, Penetration and Erosion. Each record has a class value that indicate whether the casting suffered any defect or not within six-month measurements.

Table 1. Sample dataset of sand-casting model.

S. no	Heat No	Process Parameters							Output		
		Moisture %	Permeability (AFS unit)	Binder %	Pouring Temp. °C	GFN	Mould Hardness	Green Strength	Blow	Pen	Erosion
1.	DM004	3.3	95	8.6	1385	50	75	13.5	0	0	0
2.	DM005	3.3	95	8.6	1370	47	69	13.5	0	1	0
3.	DM010	3	100	8	1390	56	74	13.5	0	0	0
4.	DM054	3.2	92	8.6	1350	56	75	10	0	0	1
5.	DM069	3.5	91	8.8	1350	52	75	12.5	0	0	0
6.	DM088	3.7	81	9.5	1325	42	70	13.5	1	1	1
7.	DM089	3.5	92	8.8	1350	52	75	12.5	0	0	0
8.	DM273	3.2	81	9.5	1320	56	75	13.5	1	0	0
9.	DM285	3.3	95	8.5	1390	50	75	13.5	0	0	0
10	DM342	3.3	95	8.6	1370	50	75	13.5	0	0	0

The created sand-casting data has certain characteristics that makes the analysis very challenging and attractive as well. Statistical algorithms that can learn from the data and figure any relevant information out is now the scientists' significant helpers. And in past various statistical methods have been used for modelling in the area of sand-casting defect diagnosis these methods should be capable of dealing with massive and complicated nonlinear and dependent data. The sand-casting industries have utilized several Artificial Intelligence algorithms and proven its fruitfulness for making decisions, by training networks using past available data. Bayesian Belief Networks also has good potential in the domain of building machine learning ability in manufacturing and less explored in the realm of metal casting.

Bayesian prediction based on the Bayes theorem of probability where posterior probability is estimated to predict the desired output. It is useful when a high number of prior data associated with various process parameters is easily available. It is a probabilistic model that relies on the Bayesian rule to predict the probability based on the evidence. Next, a framework for Bayesian inference based sand-casting defect analysis system is discussed.

4. BAYESIAN MODAL FOR SAND CASTING DEFECT PREDICTION

The primary architecture of the sand-casting defect prediction system comprises three modules: - pre-processing, processing, and post-processing, as shown in Figure 3.

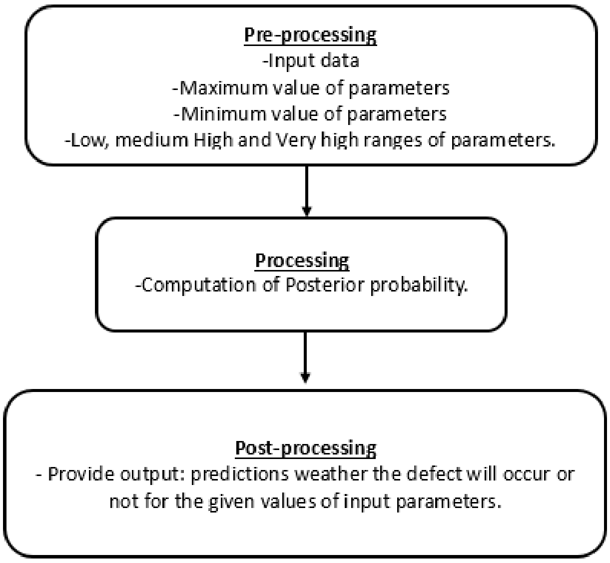

Figure 3. Architecture of Bayesian-based sand casting prediction system

4.1 Pre-Processing

In the pre-processing, the shop floor data related to processing parameters (Moisture%, Permeability, Binder%, Pouring Temp, Grain Finesse Number, Mould Hardness and Green Strength) and along with the occurrence of defects (Blow, Penetration and Erosion) of all 493 observations (heats) is fed in the Excel sheets. And then the wide range of all seven input parameters are categorized into four ranges as Range1, Range2, Range3 and Range4 depending on its minimum and maximum values. The maximum and minimum values of each parameter along with their four ranges is shown in table 2.

Table 2. Pre-processing of input data.

Parameters	Min. value	Max. value	Range1	Range2	Range3	Range4
Moisture %	3	3.8	(M1) 3-3.2	(M2) 3.3-3.4	(M3) 3.4-3.6	(M4) 3.6-3.8
Permeability (AFS unit)	80	100	(Pr1) 80-85	(Pr2) 86-90	(Pr3) 91-95	(Pr4) 96-100
Binder %	8	9.5	(Bi1) 8-8.38	(Bi2) 8.39-8.75	(Bi3) 8.76-9.125	(Bi4) 9.13-9.5
Pouring Temp. °C	1300	1400	(Pt1) 1300-1325	(Pt2) 1325-1350	(Pt3) 1350-1375	(Pt4) 1375-1400
GFN	40	60	(GF1) 40-45	(GF2) 45-50	GF3 50-55	GF4 55-60
Mould Hardness	70	80	(MH1) 70-72.5	(MH2) 72.5-75	(MH3) 75-77.5	(MH4) 77.5-80
Green Strength	10	14.5	(GS1) 10-11.1	(GS2) 11.1-12.3	(GS3) 12.3-13.38	(GS4) 13.38-14.5

Where M1 is for the moisture value 3 to 3.2, M2 is for the moisture value 3.3 to 3.4, M3 is for the moisture value 3.5 to 3.6, M4 is for the moisture value 3.7 to 3.8, Pr1 is for the permeability value 80 to 85, Pr2 is for the permeability value 86 to 90, Pr3 is for the permeability value 91 to 95, Pr4 is for the permeability value 96 to 100, Bi1 is for the binder% value 8 to 8.38, Bi2 is for the binder% value 8.39 to 8.75, Bi3 is for the binder% value 8.76 to 9.125, Bi4 is for the binder% value 9.13 to 9.5, GF1 is for the pouring temperature value 1300 to 1325, Pt2 is for the pouring temperature value 1326 to 1350, Pt3 is for the pouring temperature value 1351 to 1375, Pt4 is for the pouring temperature value 1376 to 1400, GF1 is for the grain finesse number value 40 to 45, GF2 is for the grain finesse number value 46 to 50, GF3 is for the grain finesse number value 51 to 55, GF4 is for the grain finesse number value 56 to 60, MH1 is for the mould hardness value 70 to 72.5, MH2 is for the mould hardness value 70 to 72.5, MH3 is for the mould hardness value 72.6 to 75, MH4 is for the mould hardness value 75.1to 77.5, GS1 is for the mould hardness value 10 to 11.1, GS2 is for the mould hardness value 11.2 to 12.3, GS1 is for the mould hardness value 12.4 to 13.38, GS1 is for the mould hardness value 13.38 to 14.5.

4.2 Processing

In processing Module computation of probability of each defects (blow, penetration and erosion) at given level of input parameters is done. The computation of probability for Blow defect at given level of input parameters is demonstrated next.

First the Probability of Moisture level given blow and no blow is determined in the excel sheet using pivot table. The estimated values of Probability of Moisture Level given Blow [P (ML|B)] and Probability of Moisture Level given Blow No Blow [P (ML|NB)] are shown in table 3.

Table 3: Probability of Moisture Level given Blow and No Blow

<table>
<tr><th>Probability Table</th><th>Values</th></tr>
<tr><td>
<table>
<tr><td>Moisture Labels</td><td>Blow</td><td>No Blow</td><td>Grand Total</td></tr>
<tr><td>M1</td><td>18.68%</td><td>13.64%</td><td>16.43%</td></tr>
<tr><td>M2</td><td>12.82%</td><td>86.36%</td><td>45.64%</td></tr>
<tr><td>M3</td><td>28.94%</td><td>0.00%</td><td>16.02%</td></tr>
<tr><td>M4</td><td>39.56%</td><td>0.00%</td><td>21.91%</td></tr>
<tr><td>Grand Total</td><td>100.00%</td><td>100.00%</td><td>100.00%</td></tr>
</table>
</td><td>
<table>
<tr><td>Probability of Moisture Level given Blow</td></tr>
<tr><td>P (M1|B)=0.1868</td></tr>
<tr><td>P (M2|B)=0.1282</td></tr>
<tr><td>P (M3|B)=0.2894</td></tr>
<tr><td>P (M4|B)=0.3956</td></tr>
<tr><td>Probability of Moisture Level given No Blow using</td></tr>
<tr><td>P (M1|NB)=0.1364</td></tr>
<tr><td>P (M2|NB)=0.8636</td></tr>
<tr><td>P (M3|NB)=0.0</td></tr>
<tr><td>P (M4|NB)=0.0</td></tr>
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Similarly probability of permeability level given blow [P (PrL|B)], no blow [P (PrL|NB)], probability of Binder% level given blow[P (BiL|B)], no blow [P (BiL|NB)], probability of Poring Temperature level given blow [P (PtL|B)], no blow [P (PtL|NB)], probability of GFN level given blow [P (GFNL|B)], no blow [P (GFNL|NB)], probability of Mould Hardness level given blow[P (MHL|B)], no blow[P (MHL|NB)], probability of Green Strength level given blow [P (GSL|NB)], no blow [P (GSL|NB)] is determined in the excel sheet using pivot table.

Next Computation of Probability of Blow with each input parameter level P (9): P(B, ML, PrL, BiL,PtL,GFL, MHL, GSL) = .5538* P(ML|B)* P(PrL|B)* P(BiL|B)* P(PtL|B) * P(GFL|B)* P(MHL|B)*P(GSL|B). The calculated values for each observation are shown in table 4.

Computation of Probability of No Blow with each input parameter level P (10) :P(NB, ML, PrL, BiL,PtL,GFL, MHL, GSL) = .4462* P(ML|NB)* P(PrL|NB)* P(BiL|NB)*P(PtL|NB)* P(GFL|NB)*P(MHL|NB)* P(GSL|NB). The calculated values P (10) for each observation are shown in table 4.

Computation of Probability of Blow given level of input parameters: P(B| ML, PrL, BiL,PtL,GFL, MHL, GSL) = P(B, ML, PrL, BiL,PtL,GFL, MHL, GSL)/[P(B, ML, PrL, BiL,PtL,GFL, MHL, GSL) +P(NB, ML, PrL, BiL,PtL,GFL, MHL, GSL)]. The calculated values P (11) for each observation are shown in table 4. The P (11) is the final probability for blow defects under the given input parameter values which will decide whether the defect will occur or not, its value is ranging from 0 to 1. If the value of P (11) is between 0 - 0.45 then the system will predict that there will be no blow in the casting, and the value is greater than 0.45 the system will predict blow for the particular input parameters values.

Similarly, probability for penetration and erosion of all the given values if input parameters is calculated following the above-mentioned steps.

Table 4: Computed values of Permeability of each input parameter levels given Blow or No Blow

Heat No	$P(ML \mid B)$	$P(ML \mid NB)$	$P(PrL \mid B)$	$P(PrL \mid NB)$	$P(BiL \mid B)$	$P(BiL \mid NB)$	$P(PtL \mid B)$	$P(PtL \mid NB)$	$P(GFL \mid B)$	$P(GFL \mid NB)$	$P(MHL \mid B)$	$P(MHL \mid NB)$	$P(GSL \mid B)$	$P(GSL \mid NB)$	P(9)	P(10)	P(11)	**Decision**
DM006	0.1282	0.8636	0.3223	0.8364	0.2015	0.1364	0.1832	0.2955	0.1026	0.2773	0.0733	0.3	0.5714	0.1364	0.0000	0.0001	0.0240	Safe from Blow
DM067	0.3956	0	0.5788	0	0.5421	0	0.1832	0.2955	0.2198	0.4273	0.2198	0.0682	0.5714	0.1364	0.0003	0.0000	1.0000	Blow
DM106	0.1282	0.8636	0.3223	0.8364	0.2308	0.8045	0.1722	0.1818	0.2198	0.4273	0.674	0.6139	0.1392	0.4727	0.0000	0.0058	0.0032	Safe from Blow
DM114	0.1282	0.8636	0.3223	0.8364	0.2308	0.8045	0.1722	0.1818	0.1026	0.2773	0.033	0.0182	0.0806	0.2273	0.0000	0.0001	0.0046	Safe from Blow
DM140	0.1282	0.8636	0.3223	0.8364	0.2308	0.8045	0.1722	0.1818	0.6007	0.164	0.674	0.6139	0.5714	0.1364	0.0002	0.0006	0.2453	Safe from Blow
DM198	0.1282	0.8636	0.3223	0.8364	0.2015	0.1364	0.3626	0.2955	0.6007	0.164	0.2198	0.0682	0.0806	0.2273	0.0000	0.0000	0.3501	Safe from Blow
DM206	0.1282	0.8636	0.3223	0.8364	0.2015	0.1364	0.3626	0.2955	0.2198	0.4273	0.2198	0.0682	0.5714	0.1364	0.0000	0.0001	0.4720	Blow
DM214	0.2894	0	0.3223	0.8364	0.2015	0.1364	0.3626	0.2955	0.1026	0.2773	0.674	0.6139	0.5714	0.1364	0.0001	0.0000	1.0000	Blow
DM387	0.1282	0.8636	0.3223	0.8364	0.2308	0.8045	0.2821	0.2273	0.2198	0.4273	0.674	0.6139	0.1392	0.4727	0.0000	0.0073	0.0042	Safe from Blow
DM408	0.1282	0.8636	0.3223	0.8364	0.0256	0.591	0.1832	0.2955	0.2198	0.4273	0.674	0.6139	0.1392	0.4727	0.0000	0.0070	0.0003	Safe from Blow
DM431	0.1282	0.8636	0.3223	0.8364	0.2308	0.8045	0.1722	0.1818	0.6007	0.164	0.674	0.6139	0.5714	0.1364	0.0002	0.0006	0.2453	Safe from Blow
DM493.	0.1282	0.8636	0.5788	0	0.5421	0	0.3626	0.2955	0.2198	0.4273	0.674	0.6139	0.5714	0.1364	0.0007	0.0000	1.0000	Blow

P(9)-- P(B,ML,PrL,BiL,PtL,GFL,MHL,GSL)
P(10)-- P(NB,ML,PrL,BiL,PtL,GFL,MHL,GSL)
P(11)-Final probability for blow- P(B|ML,PrL,BiL,PtL,GFL,MHL,GSL).

4.3 Post-Processing

Finally to show the results from Bayesian based defect prediction System a graphical user interface is created. The front page of the Bayesian based defect prediction system shown in Figure 4 is made in HTML and flask is used as a backend. To get the predictions from the system the user hast to select the predict option in this front page, then it will go to next page shown in figure 5. Here the user has to fill the values of input variables for which the predictions is needed to be done, and select the predict option and finally the system will retrieve which defect is most likely to occur (shown in figure 6) for the given values of input variables. This way the Bayesian based prediction system can help foundry engineers to take decisions regarding preventing possible defects in a user friendly manner

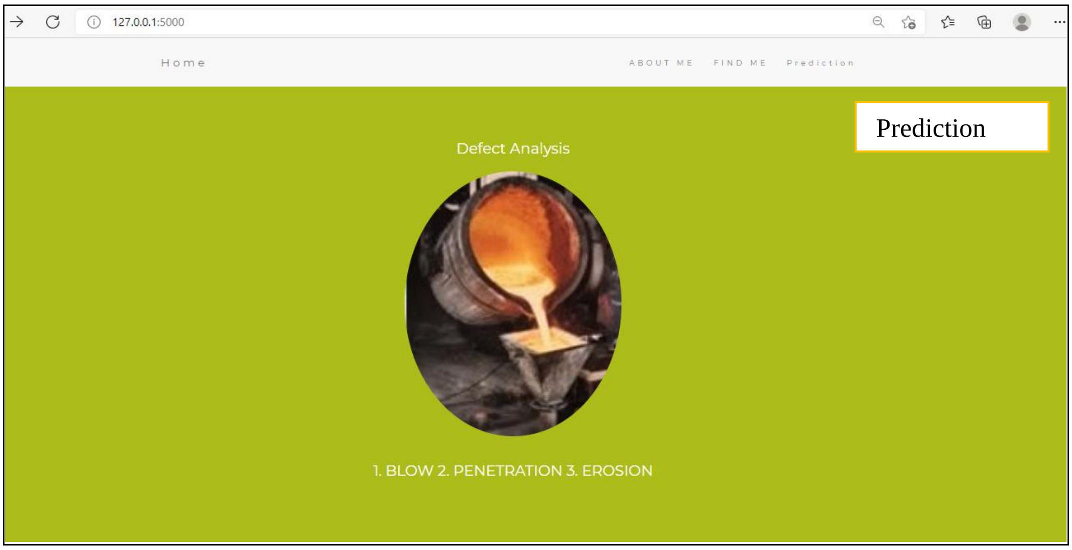

Figure 4: Front Page of Bayesian based defect prediction System

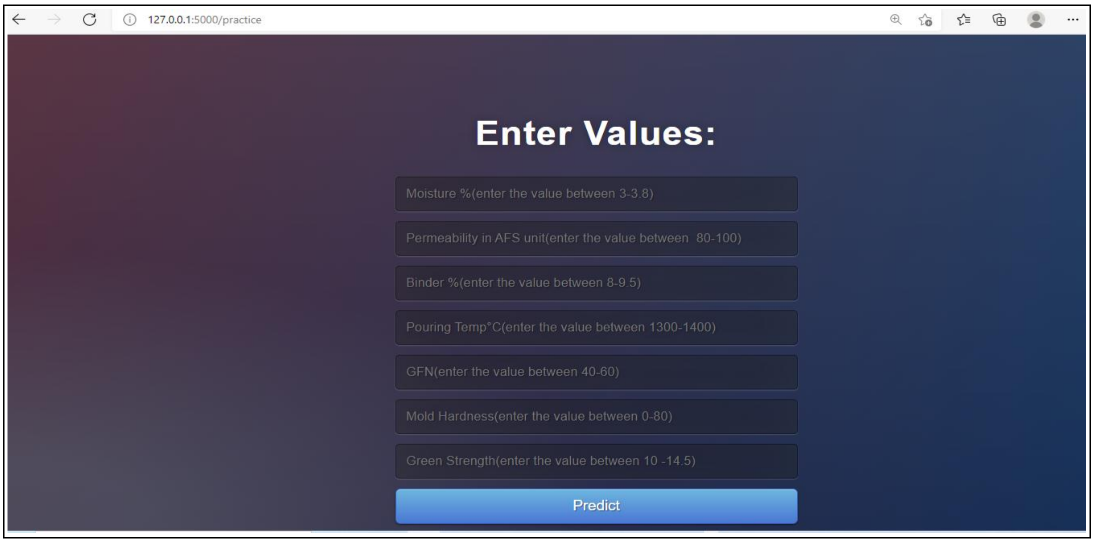

Figure: 5 Input Page for defect prediction

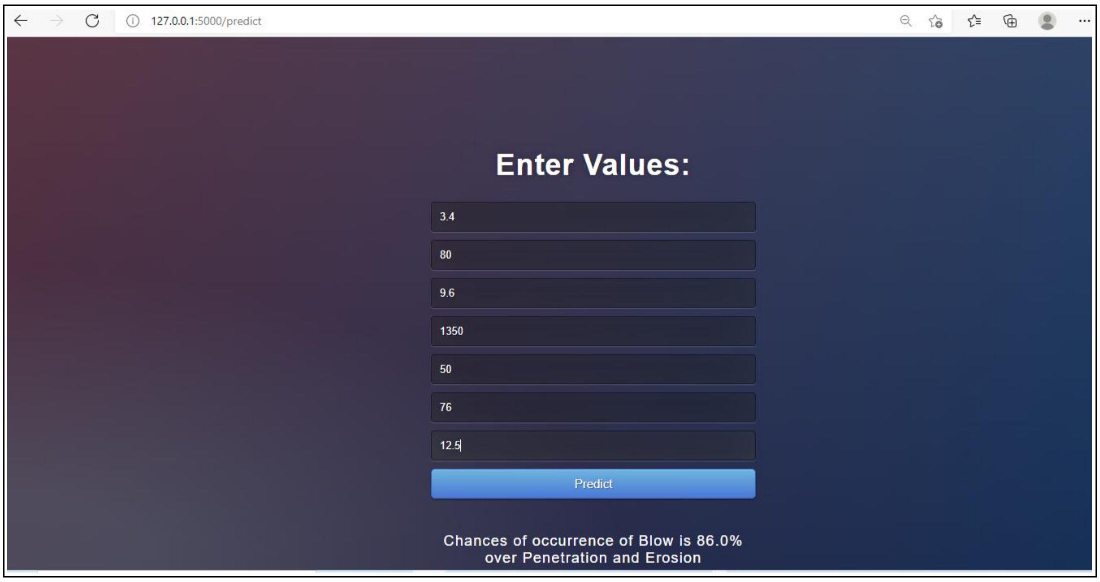

Figure 6: Analysis report by the Naïve Bayes prediction system

4.4. Result and Discussion

In Naive Bayes modal, the values of posterior probability of each input parameter are computed to identify the avoidable range of their values, and to identify the most influencing parameters Gaussian Naive Bayes approach is used. The implementation has done using Python and to present this models online the Djago web framework software as backend is used. The approach found to be simple to implement in industrial usage, and expertise knowledge of defects and their causes can be easily spread making it available online.

Our objective is to predict whether the casting will be defective or not? Furthermore, the data comprises 390 observations of garay cast iron sand castings. The record describes instantaneous measurement taken during the sand casting processing and casting inspection such as the Moisture %, Pouring temperature, Mould Hardness, Green Strength the composition of the Gray iron is considered uniformed due to negligible percentage changes in its components. All the attributes are numeric, and the units vary from attribute to attribute. Each record has a class value that indicates whether the casting had the defect or not, hence classified as zero and one.

Step 1. Data Handling: after loading the data is divided into two parts the training dataset (70% of the total dataset) used to make the prediction, and test dataset (70% of the total dataset) used to evaluate the accuracy of the model. And then the training data set instances is separated by class value so that statistical calculations can be done for each class.

Step 2. Summarizing the data: The Naive Bayes modal constitutes a summary of the data in the training data set for making predictions. The summary comprises the mean, standard deviation of each attribute by class value. Now for the problem of

Blow prediction, there is two class value that is Blow or No-blow, and four numerical attributes (moisture %, Permiaility, Binder % and Poring temperature) hence the total of eight attribute summaries for each class value needs to be created. The mean and standard deviation was computed for each attribute of the class value of the training dataset. The mean is the central tendency of the data, and we use it as the middle of Gaussian distribution while calculating the probabilities. The standard deviation is calculated as a square root of the variance. And (n-1) method for calculating the variance. This way summaries for the training data is prepared, and comparison on the mean and standard deviation for each attribute can be performed very easily. These summaries are to make predictions.

Step 3. Making a prediction: after getting mean and the standard deviation of the attributes the probability of a given attribute is determined using Gaussian probability density function.

Step 4. Making all the Predictions: after getting the predictions for each attributes final prediction for the class is performed. We combine the probabilities of all the attributes and come up with the probability of the entire data instance belonging to a class.

Step 5. Accuracy of the model: the accuracy of the model is estimated by making predictions for each data instances in our test data, the accuracy of this Gaussian Naive Bayes modal is reported as 83%. To check the performance of the model the root mean square error, Mean square error and Mean absolute error values asr also shown in Table 5.

Table 5: Performance of Bayesian Regresser models

	For Blow	For Penetration	For Erosion
RMSE	0.1365	0.1123	0.13279
MSE	0.0186	0.0126	0.0176
MAE	0.0975	0.0940	0.1167
R square	0.7565	0.5993	0.7235
Adjusted R2	0.7377	0.5729	0.6942

5 CONCLUSION

The Naive Bayes prediction system first requires the operator to enter the value of seven input parameter like value of moisture% in sand mixture, Permeability, Binder %, poring temperature, GFN, mould hardness and green strength of the mould. The program then identifies the range of these parameter as low, medium, high and very high and calculate the posterior probability for the given input values. And on the bases of calculated posterior probability does the prediction regarding the defects in the casting. Such type of prediction reports can be generated by the operator by simply putting the values of their input variables. The web based system developed can thus predict the possibility of occurrence of the major sand casting defects for the given condition. This can help foundry engineers to decide the values of their input parameters well in advance.

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