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Towards IR4.0 implementation in e-manufacturing: artificial intelligence application in steel plate fault detection

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ABSTRACT

Fault detection is the task of discovering patterns of a certain fault in industrial manufacturing. Early detection of fault is an essential task in industrial manufacturing. Traditionally, faults are detected by human experts. However, this method suffers from cost and time. In this era of Industrial revolution IR 4.0, machine learning (ML) methods and techniques are developed to solve fault detection problem. In this study, three standard ML models: LR, NB, and SVM are developed for the classification problem. The experimental dataset used in this study consists of steel plates faults. The dataset is retrieved from UCI machine learning repository. Three standard evaluation methods: accuracy, precision, and recall are validated on the classification models. Logistic regression (LR) model achieved the highest accuracy and precision scores of 94.5% and 0.756 respectively. In addition, the SVM model had the highest recall score of 0.317. The results showed the significant impact of AI/ML approach in steel plates fault diagnosis problem.

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1. INTRODUCTION

A fault may be defined as an abnormal condition or defect which could lead to a failure. Early detection of fault is an essential task in industry production [1]. Fault detection (or diagnosis) [2] is the task of discovering patterns of a certain fault in industrial manufacturing. These patterns include time, location, and size among others. Over the years, manual fault detection [3, 4] has been the traditional way of finding faults. An expert often acquires information of working equipment, study the manual guiding the equipment maintenance, and finally diagnosed the possible causes of a certain fault. The major setbacks associated with the traditional fault detection (FD) system are timing and cost [4].

With the advancement in industrial manufacturing, the introduction of Industrial Revolution (IR) 4.0 [5, 6], a concept motivated from the digital revolution involving the interconnection between people and technology. In other words, IR 4.0 involves the technological expansion where several ways of demonstrating skills and abilities are discoverable in order to minimize the gap between physical, digital, and biological entities. The digital revolution in manufacturing has led to the development of technologies such as robotics, intelligent systems, human computer interaction, and additive manufacturing. These technologies have had significant impact on manufacturing. The development of autonomous fault detection system could greatly help in achieving the tasks previously done manually with less computational time and cost. The automated system could employ the concept and techniques of artificial intelligence (AI) and machine learning in executing the dedicated tasks.

The field of machine learning (ML) [7] focuses on the study that gives AI system the capability to improve its performance (decision making) over a time period through acquiring new knowledge and skills (learning/training), as well as its ability to reorganize the existing knowledge based on the newly acquired knowledge. The basic concept of ML is typically the goal of modeling machines for critical decision-making purposes. One of the most important and widely studied technique in artificial intelligence and machine learning is data mining [8-10], which is the problem of discovering hidden patterns from data. Data mining (DM) techniques has been extensively studied and applied to solve real world problems such as prediction (or classification), clustering, imaging, cybersecurity, *e*-business, manufacturing, and sports. Furthermore, conventional among machine learning algorithms often implemented in ML tasks include: naïve bayes (NB) [11], decision trees (J48) [12], neural networks [13-19], support vector machines (SVM) [20-23], and *k*-nearest neighbour (*k*-NN) [24-28].

As aforementioned, timely detection of faults is an important task in industrial manufacturing. The steel industry is one of the important areas which has fault detection problem. This study focused on the application of ML approach in steel plates fault detection. To achieve this, standard predictive algorithms (also called classifiers) are implemented. These classifiers include logistic regression, naïve bayes, and support vector machines. The experimental results are validated using three conventional performance metrics: accuracy, precision, and recall.

In [29] experimental work, Support Vector Machines (SVM) method was applied for fault diagnosis. The results showed an effective reduction in the dimensionality of the sample space with high classification accuracy at lower computational time. The findings in [1] highlighted some of the significant importance of fault detection (FD) in steel manufacturing such as errors reduction, minimize loss, and accurate decision-making. The study employed predictive models: Random Forest, Artificial Neural Network (ANN), and SVM, in training and testing industrial data. The models were used to solve some of the complex problems associated with industrial manufacturing. The results showed Random Forest achieved overall highest accuracy of 77.8%.

Furthermore, [30] presented in their research work an intelligent system based on ANN for extracting useful information and predict quality features in multistage manufacturing process. The input data include temperature, material conditions, force, and vibration while the output data include coordinative measurements. The results showed the proposed system achieved high degree of accuracy in predicting the end product quality. From other existing related works include [31-40].

This paper presents the potential of machine learning approach in steel plates faults detection problem. In this work, standard machine learning algorithms are applied. The study employed three ML classification algorithms (or classifiers). These classifiers include Logistic Regression (LR), Naïve Bayes (NB), and Support Vector Machines (SVM). Section 2 documents the methodology employed in executing the classification task.

2. METHODS AND MATERIALS

Experimental Dataset: The Steel plates' faults dataset is used in the experimental work. The dataset (obtained from the UCI machine learning repository) is one of the available datasets utilized to classify steel plate's faults into seven distinct types: Pastry, Z-Scratch, K-Scratch, Stains, Dirtiness, Bumps, and Other_Faults. The dataset consists of 1941 instances with distinct fault types labels. As tabulated in Table 1, each instance of the dataset has 27 independent variables and a fault type.

Table 1: Steel plate's faults dataset with class distribution and predictive attributes

Output class	# of Cases	Predictive attributes			
Pastry	158	Attribute 1	X_Minimum	Attribute 14	Steel_Plate_Thickness
Z_Scratch	190	Attribute 2	X_Maximum	Attribute 15	Edges_Index
K_Scratch	391	Attribute 3	Y_Minimum	Attribute 16	Empty_Index
Stains	72	Attribute 4	Y_Maximum	Attribute 17	Square_Index
Dirtiness	55	Attribute 5	Pixels_Areas	Attribute 18	Outside_X_Index
Bumps	402	Attribute 6	X_Perimeter	Attribute 19	Edges_X_Index
Other_Faults	673	Attribute 7	Y_Perimeter	Attribute 20	Edges_Y_Index
		Attribute 8	Sum_of_Luminosity	Attribute 21	Outside_Global_Index
		Attribute 9	Minimum_of_Luminosity	Attribute 22	LogOfAreas
		Attribute 10	Maximum_of_Luminosity	Attribute 23	Log_X_Index
		Attribute 11	Length_of_Conveyer	Attribute 24	Log_Y_Index
		Attribute 12	TypeOfSteel_A300	Attribute 25	Orientation_Index
		Attribute 13	TypeOfSteel_A400	Attribute 26	Luminosity_Index
				Attribute 27	SigmoidOfAreas

Classification models: The overall goal of this study is to evaluate the potential of machine learning approach in steel plate's faults detection. To achieve this, three ML classifiers: logistic regression (LR), Naïve Bayes (NB), and Support Vector Machine (SVM) will be implemented on the steel plate's faults dataset. The classifiers are trained to predict or classify the faults.

Logistic Regression (LR) [41-44] is a multivariate statistical method that can be used to evaluate the inter-relationship between dependent and independent variables. The technique works by classifying records based on values of input attributes. For each record, a probability of membership is computed for all possible output categories. The target category with the highest probability is assigned as the predicted output value. LR is an efficient approach which helps both in prediction of data classification sample as well as the calculation of the probability of classification. Given the probability of $y = 1$, logistic regression model is built using (1).

$$logit\,(y) = C_0 + C_1x_1 + C_2x_2 + \cdots + C_nx_n \tag{1}$$

where $x_1, x_2,\ldots, x_n$ are predictions while y is the output to predict. Furthermore, $logit\,(y)$ could be expressed as:

$$logit\,(y) = \ln\left(\frac{y}{1-y}\right) \tag{2}$$

Naïve bayes classifier greatly simplify learning by assuming that features are independent given class and has proven effective in many practical applications, including data classification [45]. The classification method is a simple probabilistic model based on the Bayes rule. To determine the probability of a document d belonging to a class C, the naive bayes model follows (3).

$$P(C_i|\ d) = \frac{P(d|\ C_i)*P(C_i)}{P(d)} \tag{3}$$

Support vector machines (SVM) algorithm is typically used for learning classification, regression, or ranking function. The algorithm works by searching a seperating hyperplane to seperate between samples with a maximal margin. The equation for hyperplane is:

$$w^Tx + b = 0 \tag{4}$$

where w is the weight vector and b is the threshold.

Performance Metrics: The study validated the experimental results using accuracy, precision, and recall performance. These are among the conventional evaluation methods [45] used in prediction or classification. Given a confusion matrix, the accuracy, precision, and recall metrics are calculated as:

$$accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{5}$$

$$precision = \frac{TP}{TP+FP} \tag{6}$$

$$recall = \frac{TP}{TP+FN} \tag{7}$$

where TP = True positive
TN = True negative
FP = False positive
FN = False negative

The steel plate's faults dataset is divided into training set and testing set using percentage ratio 70:30% respectively. The training set is used to build and estimate the model parameters, while the test set is used to independently validate the trained prediction model. As earlier mentioned, the dataset consists of 1941 instances distinctly labeled into one of 7 fault types: Pastry, Z-Scratch, K-Scratch, Stains, Dirtiness, Bumps, and Other_Faults. Each of the 1941 instances owns 27 independent variables and one fault type. The experimental dataset is explored for incorrect, inconsistent, and missing data. The predictive attributes are of numeric type: flag or range, while the target class is of type nominal.

3. EXPERIMENTAL RESULTS AND ANALYSIS

The classification performance of the predictive models was evaluated using three conventional performance measures: classification accuracy, precision, and recall which are described in (4), (5), and (6) respectively. Figures 1 to 3 show the interface of the experiment using the LR, NB, and SVM on Azure Machine Learning software. The metrics are calculated using the confusion matrix table comprising of true positive (TP), true negative (TN), false positive (FP), and false negative (FN). The classifiers were implemented using the entire steel plate's faults dataset. The classification results obtained established the significant influence of machine learning approach to faults detection problem.

Working with machine learning classification models in the steel plate's faults detection problem had promising results as could be seen from the result in Table 2. Remarkably, the three classification methods achieved above 90% accuracy result. Logistic Regression model had the overall accuracy result of 94.5% while naïve bayes had the result of 94% accuracy. This possibly is due to the sensitivity of the methods to the features (attributes set). Furthermore, LR had the highest precision value while Support vector machine had the highest recall value. This shows how difficult it is to conclude on which particular model is the best. Classification models are highly competitive with varying strengths and weaknesses. Overall, the experimental results showed the significant impact of applying AI/ML approach in detecting faults in industrial manufacturing.

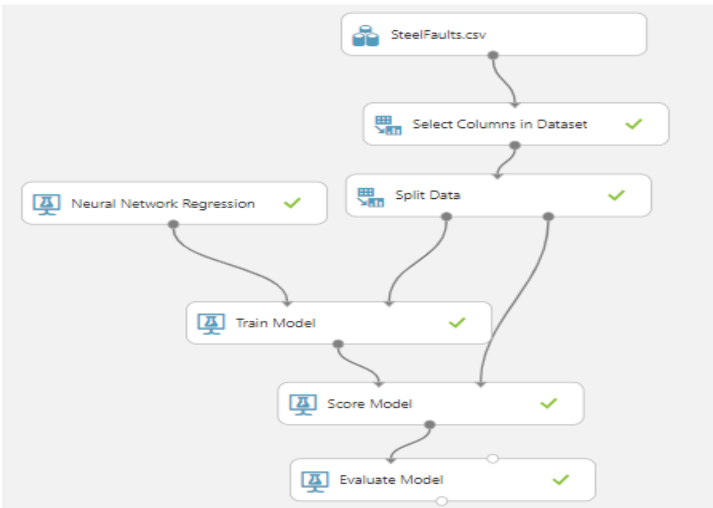

Figure 1. Interface of experiment using logistic regression on azure machine learning software

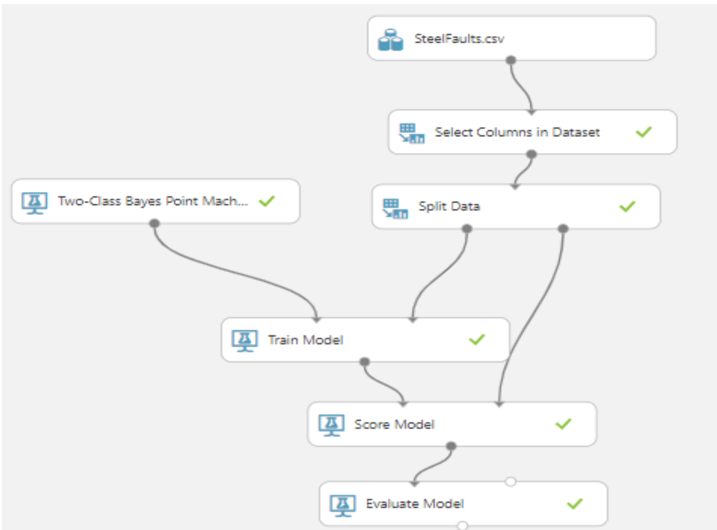

Figure 2. Interface of experiment using naïve bayes on azure machine learning software

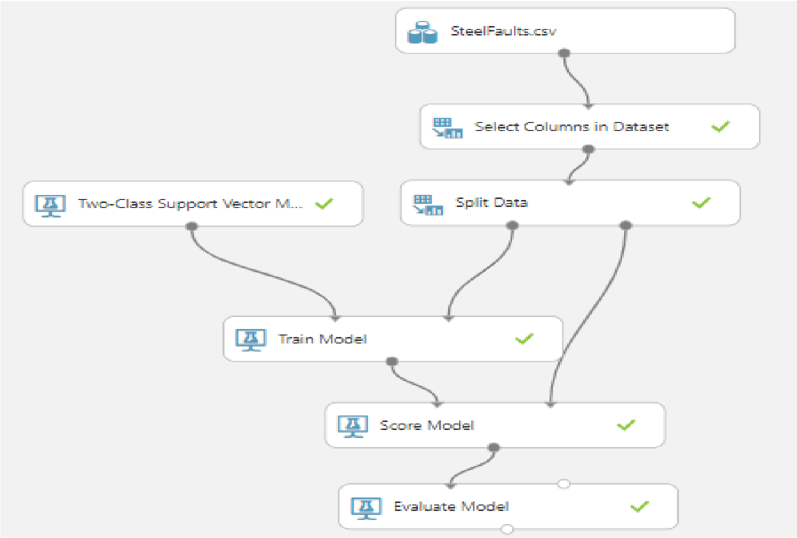

Figure 3. Interface of experiment using support vector machine on azure machine learning software

Table 2. Classification performance of the predictive models on the steel plate's faults dataset

Classification models	ACC (%)	Precision	Recall
LR	94.5	0.756	0.2
NB	94	0.688	0.268
SVM	94.2	0.684	0.317

4. CONCLUSION

This study has successfully implemented the comparative analysis on the automated fault diagnostic application in steel manufacturing problem domain. We found that the AI or machine learning techniques have the potential to detect problems in steel manufacturing industry. Such findings may be extended to other applications in manufacturing industry, towards fulfilling Industry Revolution 4.0 requirements.

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