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Research Article

Comparison Analysis of Machine Learning Algorithms for Steel Plate Fault Detection

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ABSTRACT

Metals are one of the most important building materials of modern times. Especially the production and metalworking process of flat metal sheets is very sensitive. Control of the manufacturing process affects not only the intermediate products but also the quality of final products. Early detection of defects on steel plate surfaces is an important task in industrial production. Process control and mistake detection have traditionally been done manually by experts. However, this method is not proper in terms of both time and cost. With the industrial revolution IR 4.0, machine learning (ML) techniques have been developed to solve fault detection problems in products. This study focuses on developing basic machine learning methods for the detection of six different error classes that may occur during production on steel surfaces. Five standard ML models: LD, KNN, DT, SVM, RF, and deep learning (DNN) model: one-dimensional DNN was developed for the classification problem. The UCI steel plate deformation data set was used as the experimental data set. Five performance criteria: Accuracy, Sensitivity, Specificity, Precision, and F1 value were used to determine the success of the methods. The success rates of LD, KNN, DT, SVM, RF and DNN classification methods were 90.136%, 91.7880%, 93.013%, 93.287%, 95.479%, 96.986%, respectively. The results show the significant impact of the machine learning approach on the steel plate fault diagnosis problem.

Keywords: *Steel Plate Defect, Fault Detection, Machine Learning*

Çelik Levha Arıza Tespiti için Makine Öğrenimi Algoritmalarının Karşılaştırmalı Analizi

ÖZET

Metaller, modern zamanların en önemli yapı malzemelerinden biridir. Özellikle yassı metal sacın üretim ve işleme süreci oldukça hassastır. Üretim sürecinin kontrolü sadece ara ürünlerin değil, aynı zamanda son ürünlerinde kalitesini etkiler. Çelik levha yüzeylerinde oluşan hataların erken tespiti, endüstriyel üretimde önemli bir görevdir. Geleneksel olarak süreç kontrolü ve hata tespiti uzman kişiler tarafından manuel olarak yapılmaktadır. Ancak bu yöntem hem zaman hem de maliyet açısından uygun değildir. Sanayi devrimi IR 4.0 ile ürünlerde hata tespit problemlerini çözmek için makine öğrenimi (ML) teknikleri geliştirilmiştir. Bu çalışma, çelik yüzeyde üretim esnasında oluşabilecek altı farklı hata sınıfının tespiti için temel makine öğrenme yöntemleri geliştirmeye odaklanmıştır. Sınıflandırma problemi için beş standart ML modeli: LD, KNN, DT, SVM, RF ve bir derin öğrenme (DNN) modeli: tek boyutlu DNN geliştirilmiştir. Deneysel veri seti olarak UCI çelik plaka deformasyon veri seti kullanılmıştır. Yöntemlerin başarısını tespit etmek için beş performans kriteri: Doğruluk, Duyarlılık, Özgüllük, Kesinlik, F1 değeri kullanılmıştır. LD, KNN, DT, SVM, RF ve DNN sınıflandırma yöntemlerinin başarı oranları sırasıyla 90.136%, 91.780%, 93.013%, 93.287%, 95.479%, 96.986% olarak elde edilmiştir. Sonuçlar, makina öğrenmesi yaklaşımının çelik levha arıza teşhis problemindeki önemli etkisini gösterilmiştir.

Anahtar Kelimeler: *Çelik Levha Arızası, Arıza Tespiti, Makine Öğrenimi*

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I. INTRODUCTION

A. BACKGROUND

Steel is one of the most widely used and most important buildings/industrial producing materials. However, flat steel sheet production and processing are very difficult and demanding. In many steps, from casting to drawing, pressing, cutting, and folding into rolls, machines come into contact with the steel surface, which can cause some deformations on the steel plate surface. These defects on the steel surface not only reduce the production quality but also affect the corrosion and wear resistance of the product during the use phase [1]. Detection of defects and malfunctions in metal materials is an important research topic in materials science [2], [3]. Early detection of manufacturing defects and malfunctions is an important task in industrial production and can save time and money [4], [5]. Traditional methods have been used for many years to detect errors such as pastry, Z-scratch, K-scratch, stains, and pollution, which are some of the defects that may occur in steel plates during production. The experts would manually examine the plates according to the characteristics of the product to be released and create a malfunction report [6], [7]. However, this method is both time-consuming and costly, as it is possible that defects could be overlooked [7].

With the Industrial Revolution (IR) 4.0, digital transformation has taken place and computerized support software based on image processing has been used in fault diagnosis and quality control stages, as in many areas (robotics, intelligent systems, human-computer interaction, and additive manufacturing, etc.) [8], [9]. Thanks to computer vision and automatic fault detection systems, the product can be analyzed quickly at every stage on the production line, and even the smallest defects can be detected with fault diagnosis algorithms. [10]. Error detection algorithms are basically based on data mining techniques [11]. It uses historical fault databases to develop algorithms, which can detect surface errors and classify them by type. However, variations of defects on steel surfaces (pastry, Z-Scratch, K-Scratch, Stains, etc.) are also most variable, making it difficult to develop high-performance classification algorithms. Researchers continue to work to develop software that will provide high performance on small datasets.

This study focuses on the development of feature selection and machine learning algorithms for the detection of six surface defects in steel plates. LD, KNN, DT, SVM, RF, and DNN methods were used for classification. The performances of the classifiers were compared by calculating five performance evaluation parameters: Accuracy, Sensitivity, Specificity, Precision, and F1 score.

B. RELATED WORKS

Halawani [1] used the Random Subspace and AdaBoost method, one of the Decision Tree (DT) ensembles, for the estimation of steel plate errors and achieved a success rate of over 80%. It also showed that removing unimportant features from datasets improves the performance of the classifier. Abdullahi et al. [4] used ML, LR, NB, and SVM models for the classification problem of steel surface deformations. And they tested the success of their method with three criteria. These are accuracy, precision, and recall values. They achieved the highest success with the Logistic regression (LR) model and reported an accuracy rate of 94.5% and a precision score of 0.756. Nkonyana et al. [5] in their studies, made the fault classification of real steel surface data obtained from the industry environment by using RF, ANN, and SVM methods. They used 27 features to detect seven different surface defects and presented the results as a confusion matrix. They reported that the RF model was more successful than the other two models. They achieved the accuracy of 0.778 with RF. Zhao et al. [12] proposed a back propagation neural network (BPNN) to classify steel plate faults. Also, they analyzed the effect of eliminating outliers with the LOF method. They achieved 94.57% accuracy rate using LOF+BPNN. Kharal et. al. [13], performed the classification of faults on steel surfaces by using the optimized RF and LR models. With these methods, they achieved success of 94.18% and 89.13%, respectively.
Tian et al. [14] used the SVM method for the classification problem of seven types of failures of steel surfaces. They used GA, GS and PSO optimization methods in their studies and stated that they reached

a maximum classification accuracy of 94.6%, 95.2% and 88% with each method. They showed that the GS method was more effective than GA and PSO. Jain et al. [15] developed a predictive analysis method using data mining. In their study, they used decision tree, neural network model and linear regression classifiers. They reported that the decision tree model produced higher accuracy. With DT, NN, LR models, 94.38%, 83.87% and 72.64% classification success were obtained, respectively. Chen [16] used a set of classical machine learning algorithms based on decision trees (Decision Tree, Adaboosting, Bagging, Random Forest). They used 10-fold cross-validation rate in analysis. The used dataset includes 6 different types of steel plate defects Pastry, Z_Scratch, K_Scatch, Stains, Dirtiness, Bumps. It is reported that the bagging algorithm outperformed other methods and achieved 96.30% and 90% accuracy in the training and test set, respectively. Jui-Sheng Chou et al. [17] combined five methods. These were firefly algorithm (FA), metaheuristic intelligence, decomposition approaches, one-to-one (OAO) method and least squares support vector machine (LSSVM) methods. With this method, they performed multi-class error detection in steel plates with an accuracy of 91.085%. Mohamed Gamal et al. [18] multilayer perceptron (MLP), Recurrent Neural Networks (RNN), Decision Trees, Random Forest (RF), k-Nearest Neighbor (KNN) Support Vector Machine (SVM), Naive, Bayes and Logistic Regression (LR) methods were used to detect anomaly problem in steel plate production. They reported that they achieved the highest classification success with the DT method with 91.14%.

II. MATERIAL AND METHOD

A. STEEL FAULT DATASET

In this study, the "Faulty Steel Plates" dataset shared with the researchers in the Kaggle and UCI Machine Learning dataset bank was used to determine the type of surface defects in stainless steel plates. This dataset was obtained from the studies of the Semeion Research Sciences Center. The dataset contains the numerical values of 27 features that express the geometric shape and outline of the surface defects. Data for the classification of seven defects on steel plates are not labeled. The class set is in Table 1 and the feature set is summarized in Table 2 [19].

Table 1. *Faults class and account of subject* [19].

Fault Class	Pastry	Z_Scratch	K_Scatch	Stains	Dirtiness	Bumps	Common Fault
Data Number of Class	158	190	391	72	55	402	673

Table 2. *Features in Sakar's dataset* [19].

Features No	Feature	Features No	Feature
1	X_Minimum	15	Edges_Index
2	X_Maximum	16	Empty_Index
3	Y_Minimum	17	Square_Index
4	Y_Maximum	18	OutsideXIndex
5	Pixels_Areas	19	EdgesXIndex
6	X_Perimeter	20	EdgesYIndex
7	Y_Perimeter	21	Outside Global Index
8	Sum of Luminosity	22	LogOfAreas
9	Minimum of Luminosity	23	LogXIndex
10	Maximum of Luminosity	24	LogYIndex
11	Length of Conveyer	25	Orientation_Index
12	Type Of Steel_A300	26	Luminosity_Index
13	Type Of Steel_A400	27	Sigmoid Of Areas
14	Steel Plate Thickness		

After the analyzing dataset, it was seen that the number of data in each class was numerically out of proportion (Table 1). And also, it has been stated that fault class 7 is not a specific type of fault in the dataset description file. It is a combination of many different faults from fault classes 1 to 6. For this reason, it is difficult to select examples of class 7 (a common fault) from other types of faults. In addition, the examples in class 7 faults do not share certain characteristics. Since some of the samples in class 7 fault have similar characteristics to the samples from other classes, it reduces the classification success. For this reason, in some studies in the literature, class 7 (common fault) studies were excluded to increase the classification success [14]. Similarly, class 7 data (a common fault) was left out within the scope of this study. After the analyzing dataset, it was seen that the dataset contains outliner values. The boxplot provides a visualization of the statistics for the four features(Figure1). The bottom and top of each rectangular box represent the border of the 25th and 75th percentiles of the data for that sample, respectively, and the data in this range in the rate. The red line in the middle of the box is the median value of that feature. The dashes at the top and bottom of the box and the horizontal line at the end represent the normally distributed maximum and minimum values of the data. The red '+' symbols outside this horizontal line indicate the outliner values. The outliner values seen in Figure 1 were excluded from the data set as they would reduce the classification success. But any feature selection method didn't use, all features in the dataset were given as input to the classification algorithm.

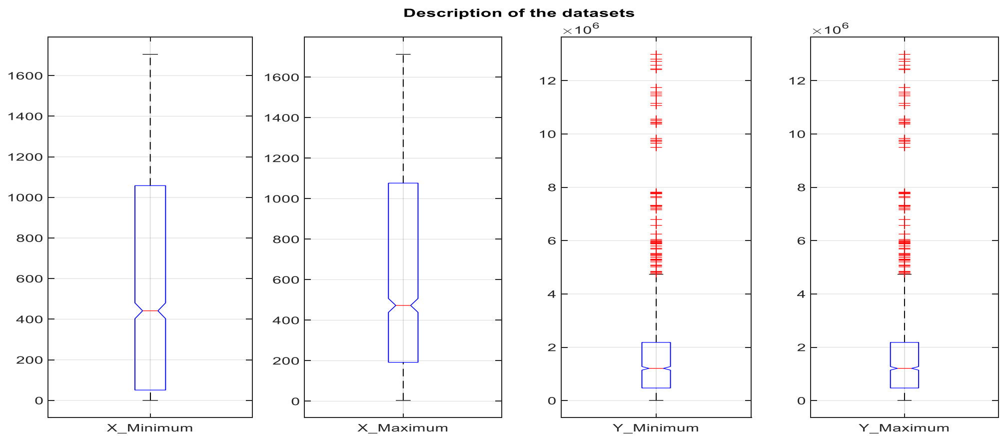

Figure 1. *Description of Xmin, Xmax, Ymin, Ymax values, and outliers.*

The balance value calculated with the help of Equation 1, considering the number of elements in the classes of the original data set, is 12,236. C_i expression in Equation (1) represents the decision class in the data set. $Max_i\{|C_i|\}$ and $Min_i\{|C_i|\}$ expressions represent the classes with the most and least tags among the examples of the decision class [20, 21]. After excluding class 7 from the original dataset and removing outliers with reference to the first four features in the first six classes, the calculated balance value of the remaining dataset is 7.21 (Table 3). Calculated ρ value is greater than 1. This situation is not ideal, but the Dirtiness class has very few data compared to other classes. Therefore, it is necessary to make the data set very small in order to reach equilibrium level 1. This was not preferred because it would negatively affect training success.

$$Balance\ Level\ (\rho) = \frac{Max_i\{|C_i|\}}{Min_i\{|C_i|\}} \tag{1}$$

Table 3. *Faults class and account of subject.*

Dataset	Number of Dataset Attributes	Number of Samples	Number of Classes	Balance Level
Original dataset	27	1650	7	12.236
Dropout outliner and balanced dataset	27	730	6	7.21

B. CLASSIFICATION METHODS

Support Vector Machines (SVMs) are learning machines that use the inductive principle of Structural Risk Minimization (SRM) to achieve a high level of generalization over a small number of learning patterns. SVM is an effective learning method for identifying patterns in complex data sets that are difficult to evaluate [22]. The support vector machine algorithm seeks a hyperplane in an N-dimensional space (N — the number of features) that clearly classifies the data points. There are numerous possible hyperplanes that could be used to separate the classes of data points. The goal is to find planes with the greatest margin, that is, the greatest distance between data points in each class [22].

Decision Tree (DT) is a type of supervised machine learning in which data is continuously split based on a specific parameter. Two entities can be used to explain the tree: decision nodes and leaves. Decision trees are one of the most extensively used methods in classification models. Because it is a simpler technique to configure and comprehend, gives model transparency, and has a visual presentation [23].

K-Nearest Neighborhood (KNN) The K-Nearest Neighbor (KNN) method is a non-parametric classification algorithm. The KNN model is easy as it is based on basic mathematical foundations. And it is widely used in many industries. The basic principle is based on the assumption that the class of an unknown variable will be the same as that of its nearest neighbors. The average of the current states of the k nearest elements in the training dataset is used to calculate the prediction result. The number of neighbors is indicated by the letter "k" in the method name. The k number is very important when it comes to determining the optimum categorization or estimation. It can use trial-and-error or cross-validation approaches to choose the correct k number [24]. The class of data is determined by averaging the k data points calculated as the closest distance of the training set. The threshold value is calculated before the found value is interpreted.

Linear Discriminant (LD) is to define a relationship between a categorical dependent variable and more than one independent variable. Two-group problems are relatively easy in LD analysis. A linear discriminant function passing through the means of the two groups is defined to distinguish the subjects between the two groups. When there are more than two groups, the number of groups minus one function definition is made for the classification problem. Linear discriminant analysis is evaluated separately for each of the groups. Explanatory variables are assumed to have a normal distribution with equal covariance matrices. The estimated coefficient for an independent variable in each case is multiplied by the event's score on that variable, and these results are added to the constant. The result gives the discriminant score for the condition [4].

Random Forest - Boosted Tree (RF) The RF model is a method of creating a decision ensemble (forest) consisting of multiple decision trees. The RF model is a combination of hundreds of decision trees, and to obtain a comprehensive result, the decision results from all trees are evaluated with a majority voting method to produce the final result of the decision tree [13].

A one-dimensional Deep Neural Network (DNN) model was created for the classification of the steel fault feature dataset. The network consists of 7 layers in total. The input layer is the layer where selected steel fault features are entered. Data were normalized using Z-score normalization in the input layer. Next, a fully connected layer with output size 50 followed by a batch normalization layer and a ReLU layer was added. The batch normalization layer stabilizes the learning process and significantly decreases the number of training cycles required to form deep networks [25]. For classification, another fully connected layer with an output size corresponding to the number of included classes 6 is added to the network. And finally, the network is completed with one softmax layer and one classification layer.

__Table 4.__ Algorithm parameters that are employed in the suggested method's classification algorithms.

DT	LD
Model Type: Medium Tree Max. number of split: 20 Split Criterion: Gini's diversity Surrogate: off	Model Type: Linear Discriminant Covariance structure: Full
SVM	**RF**
Type: Linear Kernel Function: Polynomial Polynomial Order: 3 Kernel Scale: Auto Box Constraint Level : 1	Number of neurons in the ith layer :100 Activation function: ReLu The solver weight optimization: Adam Penalty parameter: 0.0001 Batch size :200 Output Function: Majority Voting
KNN	**DNN**
Type: Fine Distance: City block Number of Neighbors: 1 Distance Weight: Equal Standardize: True	Feature Input Layer(numFeatures,'Normalization', 'zscore') Fully Connected Layer :50 Batch Normalization Layer Relu Layer Fully Connected Layer :numClass Softmax Layer Classification Layer

D. PERFORMANCE EVALUATION METHODS (PEM)

To compare the performance of machine learning algorithms, a variety of standard evaluation methodologies such as precision, sensitivity, accuracy, and F1 score were used. The number of successfully predicted cases is known as true positives (TP), whereas the number of incorrectly predicted instances is known as false negatives (FN). True negatives (TN) are the number of negative cases that were successfully predicted, while false positives (FP) are the number of negative instances that were wrongly predicted. And also, we use the confusion matrix to show how our methods predict our data. The confusion matrix is a numerical table used to demonstrate the classification model output effects on the test data known from the goal labels. Performance evaluation metrics used in this study is given in Table 5 [23].

__Table 5.__ Lookup table of performance evaluation metrics used in this study.

Performance Metric	Acronym	Equation	
Positive Predictive Value	PPV Precision	$\frac{TP}{TP+FP}$	The ratio of positive samples that are predicted correctly out of all the samples predicted to be positive.
Negative Predictive Value	NPV	$\frac{TN}{TN+FN}$	The ratio of negative samples that are predicted correctly out of all the samples that are predicted to be negative.
True Positive Rate	TPR Sensitivity	$\frac{TP}{TP+FN}$	The ratio of TP outcomes to the total number of actual positive samples.
True Negative Rate	TNR Specificity	$\frac{TN}{TN+FP}$	The ratio of TP outcomes to the total number of actual negative samples.
Single class Accuracy	ACC	$\frac{TP}{TP+FN}$	The ratio of TP outcomes to the total number of actual positive samples.
Multi class Accuracy	ACC	$\frac{TP+TN}{TP+TN+FP+FN}$	The ratio of the number of correct predictions made by the method out of the total number of predictions made.
F1-Score	F1	$2x\frac{PPV*TPR}{PPV+TPR}$	The weighted average between the PPV and TPR scores.

III. EXPERIMENTAL RESULTS AND DISCUSSION

For this task, we used a PC, which has a 3.60 GHz Intel i7-7700 CPU and 16 GB of RAM. This PC runs Windows 10.1. We used the Matlab 2022a trial use version program. In the proposed method, 10-fold cross-validation was used to obtain validation results from classifiers. Accuracy, Sensitivity, Specificity, Precision, and F1 were calculated after the classifiers ran 100 iterations.

The average accuracy values obtained for each surface deformation class are listed in Table 6. For each classification algorithm, the highest success was obtained in the detection of Stains failure and the lowest success in the detection of Pastry failure. Confusion matrices for each classifier showing the number of correct and incorrect predictions of our classification model were calculated and presented in Figure 2.

Table 6. *Each Class Self Accuracy of classification methods after running 100 iterations.*

Class / Self	LD	KNN	DT	SVM	RF	DNN
Pastry	**0.6667**	0.8167	**0.7500**	0.7000	0.8000	0.900
Z_Scratch	0.8994	0.7673	0.9497	0.9497	0.9623	0.974
K_Scatch	**0.97729**	**0.9729**	**0.9910**	0.9789	0.9940	0.997
Stains	0.9677	0.8387	0.9516	**0.9839**	**1.000**	**1.00**
Dirtiness	0.8261	0.6522	0.8478	0.9348	0.9130	0.913
Bumps	0.7606	**0.6479**	0.8169	**0.6761**	**0.8732**	**0.9014**

For the 100 iterations, the maximum accuracy of the LD, KNN, DT, SVM, RF, and DNN classification methods were obtained respectively 90.136%, 91.780%, 93.013%, 93.287%, 95.479%, and 96.986%. F1 score, Specialty, Sensitivity, and Precision values for each method are given in Table 7. As can be seen from the results, the highest success percentage was obtained with the RF method.

Table 7. *Performance values for each classification after running 100 iterations.*

Classifier	Metric	Accuracy	Sensitivity	Specificity	Precision	F1
LD	**Best**	90.136	83.267	84.888	84.134	84.070
	Min	88.767	81.375	83.097	82.328	82.227
	Mean	89.397	83.007	84.637	83.927	83.814
	Std	0.302	0.257	0.205	0.196	0.223
KNN	**Best**	91.780	87.159	87.055	86.002	87.107
	Min	90.684	86.647	86.585	85.394	86.616
	Mean	91.386	87.075	86.991	85.922	87.033
	Std	0.199	0.169	0.131	0.166	0.150
DT	**Best**	93.013	89.302	88.827	88.472	89.064
	Min	91.369	87.648	87.713	87.226	87.680
	Mean	92.082	89.054	88.655	88.205	88.854
	Std	0.378	0.242	0.166	0.238	0.204
SVM	**Best**	93.287	89.289	88.449	88.024	88.867
	Min	92.328	88.103	87.467	86.923	87.784
	Mean	92.782	89.135	88.328	87.888	88.730
	Std	0.227	0.333	0.266	0.300	0.299
RF	**Best**	95.479	93.179	92.375	92.093	92.775
	Min	93.561	91.973	91.343	90.969	91.657
	Mean	94.395	93.053	92.275	91.986	92.662
	Std	0.338	0.363	0.298	0.324	0.329
DNN	**Best**	96.986	95.546	94.871	94.753	95.157
	Min	96.164	94.494	93.476	93.313	93.982
	Mean	96.575	95.106	94.522	94.401	94.813
	Std	0.223	0.453	0.494	0.515	0.453

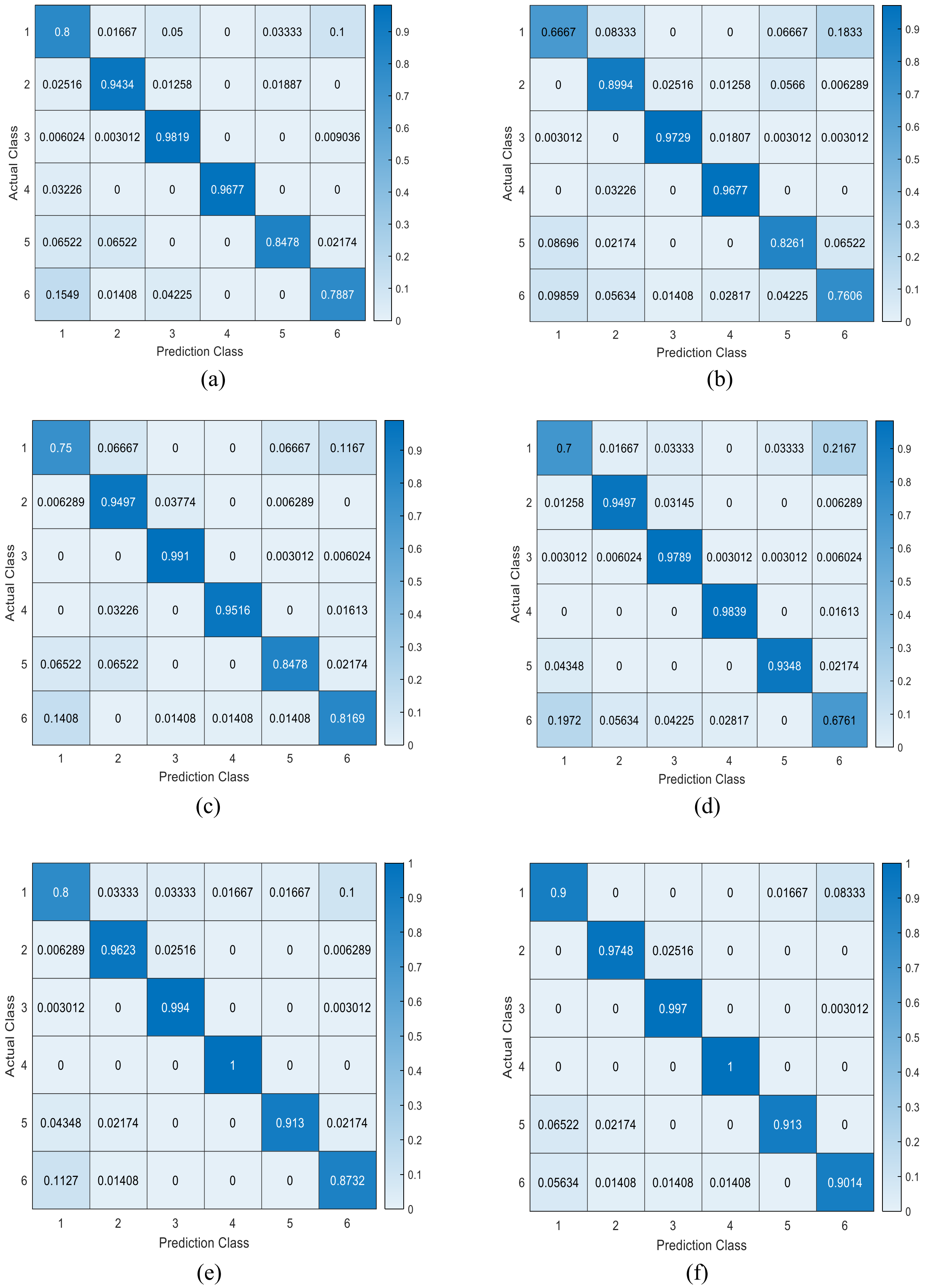

Figure 2. *Validation Confusion matrices of the classification methods after running 100 iterations a) DT b) LD c) SVM d) KNN e) RF f) DNN.*

The results of the classification algorithm studies using the same steel surface deformation dataset in Table 8 were compared with the results of this study. It is seen that the proposed RF and DNN model outperforms the more successful than Tian's optimized SVM model, also without the need for any optimization method. The reason for this is that in Tian's study, 7 classes that contain common data are considered as a class with separate features. In addition, the estimation of outliers applied before the classification step in this study and their removal from the dataset significantly increased the success.

Table 8. *Comparison of this study classification performance with related works.*

References	Classification Method	Accuracy (%)
Sami M. Halawani [1]	DT	80
Abdullahi et al. [4]	LR	94.5
Zhao et al.[12]	Back Propagation Neural Network	94.57
Kharal [13]	RF	94.18
	LR	89.13
Tian et al. [14]	GA with SVM	94.6
	GS with SVM	95.2
	PSO with SVM	88
Sanjay Jain [15]	DT	94.38
	MLP	83.87
	LR	72.64
Chen [16]	DT	90
Chou et al. [17]	LSSVM	91.085
Gamal et al.[18]	DT	91.14
This study	LD	**90.136**
	KNN	**91.780**
	DT	**93.013**
	SVM	**93.287**
	RF	**95.479**
	DNN	**96.986**

IV. CONCLUSION

In this study, LD, KNN, DT, SVM, RF, and DNN classification methods were developed. Twenty-seven geometric features for automatic detection of deformations on steel surfaces were used. As a result of the study, it was analyzed that the LD classifier had the lowest classification accuracy at 90.136%. The highest classification accuracy was obtained with the DNN classifier as 96.986%. It has been shown that the developed methodical approach has achieved such high success that it can be a decision support mechanism that helps experts in product quality control units in steel plate production facilities.

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