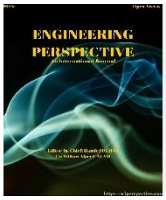

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Research Paper

Classification of Zinc Recovery Quality from EAF Dust Using Machine Learning: A Waelz Process Study

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ABSTRACT

Zinc recovery from Electric Arc Furnace (EAF) dust represents a significant challenge in the iron and steel industry. This study aims to classify zinc quality in slag produced through the Waelz process, where zinc is reduced and volatilized at high temperatures (>1000°C) in rotary kilns, using machine learning techniques. The classification of zinc quality in slag is crucial for process optimization and environmental sustainability, as it directly impacts both resource recovery efficiency and waste management strategies. The dataset utilized for developing classification models was obtained from chemical analyses of Waelz process raw materials and slag samples. Four distinct classification algorithms (Support Vector Machine SVM, Decision Tree - DT, Naive Bayes - NB, and Random Forest - RF) were evaluated on the data labeled by experts according to zinc content in slag. The reliability of the models was assessed through 10-fold cross-validation. In experimental studies, the DT algorithm demonstrated superior performance with 100.0% accuracy, precision, sensitivity, and F1 score. The RF algorithm achieved second-place performance with 96.0-98.0% accuracy and 100.0% precision, followed byNB with 91.0-94.0% accuracy, and SVM with 84.0-88.0% accuracy. The results indicate that the DT algorithm can serve as a reliable tool for quality classification in the zinc recovery process. These findings contribute significantly to the advancement of automated quality control systems in metallurgical processes, potentially enabling real-time monitoring and optimization of zinc recovery operations.

Keywords: Zinc Recovery, Electric Arc Furnace Dust, Waelz Process, Machine Learning Classification, Slag Quality.

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1. Introduction

The extraction of metals worldwide produces a range of goods and services that underpin modern society. This practice has been critical to human survival since the Bronze Age. Later in the 20th century, metals evolved from basic building materials to a versatile resource that influenced many aspects of modern industry and technology [1]. Zinc is a silvery bluish-gray metal with a low melting and boiling point of 420°C and 907°C, respectively. Although zinc is brittle at average temperature, it can be formed at 100°C and rolled quickly. Typically found in brittle form, it transforms into a malleable metal when heated. Globally, zinc is the third most widely used non-ferrous metal after iron, aluminum, and copper, and the most used metal [2]. Zinc can be combined with aluminum to produce the alloy used in die casting. Die casting forces molten metal into a mold cavity by applying high pressure [3]. Zinc demand in global markets includes use in galvanizing steel and iron (50%), alloys (17%), brass and bronze (17%), semi-manufacturing (6%), chemicals (6%) and other applications in various sectors (4%) [2].

2016-2017, overall zinc consumption worldwide increased by approximately 2%. However, there are significant variations from region to region. 2020 global refined zinc production increased to 13.8 million tons. Zinc production is predominantly based on primary resource mining [3-5]. In order to reduce CO_2 emissions by 80% from current levels by 2050 (i.e., to reduce emissions below 2.13 million tons of CO_2 equivalent), the increased demand must be met by recovering zinc from waste, i.e., from secondary sources. Recovering zinc from secondary sources is essential in the current circular economy. Zinc production and consumption are increasing globally, and primary sources of zinc from ore are rapidly depleted. Therefore, effectively extracting zinc from secondary sources can bring several advantages. These advantages include savings in raw resources and fossil resources used to power primary mining processes, increased resource efficiency, reduced resource loss to landfills and dumps, avoided loss of zinc or any metal to landfill, waste treatment, mitigation of environmental and health impacts, and improved economic performance of existing infrastructure. Secondary sources of zinc from waste include zinc in spent batteries, in e-waste, in wastewater, in construction and demolition waste, in scrap steelmaking dust, and in municipal waste [3].

The electric arc furnace (EAF) method is used to recycle scrap. However, recycling these wastes and iron by-products using EAF is associated with the emission of dust particles, which, according to the United States Environmental Agency, are considered hazardous solid waste. Due to its chemical and physical properties, EAF dust is classified as hazardous waste according to the European Waste Catalogue, where hazardous substances are present above a threshold concentration. EAF dust is produced from the evaporation of heavy metals and silica particles during the melting of steel scrap. During the melting of scrap, volatile components are removed by smoke and collected together with particulate matter in the waste gas cleaning system. During the metal melting process, the EAF can reach temperatures of 1600°C or higher, and many components of the charge, including iron, zinc, and lead, vaporize and enter the gas phase. When the vapor is cooled and collected, a large amount of dust is generated [6-7]. This dust is produced at a rate of 10-20 kg per ton of steel, which could mean that as much as 5-7 million tons of high dust is produced worldwide each year. However, this dust contains a fair amount of heavy metals such as zinc, which contains 20-30 wt% zinc oxide. Given the low production cost, recovering zinc at such a high percentage is an attractive option. Two main technological processes extract zinc from EAF dust: pyrometallurgical and hydrometallurgical methods. The pyrometallurgical method is costly due to the enormous energy consumption and the need for reductants to produce zinc oxides with low commercial value. The hydrometallurgical method is more advantageous than the pyrometallurgical method in terms of process economics and environment [6]. The chemical composition of EAF powder depends mainly on the quality of the steel scrap processed and the type of steel produced. Table 1 shows the chemical composition of EAF powder.

This study aims to make a scientific contribution to the improvement of zinc recovery processes in rotary kilns by using classification methods of the Waelz process. In the study, zinc recovery was performed with the Waelz process, and Support Vector Machines (SVM), Decision Tree (DT), Random Forest (RF), and Naive Bayes (NB) machine learning models were evaluated to classify the zinc quality in the slag and make accurate quality determination using supervised machine learning techniques.

2. Materials and methods

The Waelz process, implemented for zinc recovery from EAF dust in rotary kilns, was utilized to obtain the labeled data for this study. This process is widely employed worldwide, including multiple facilities in Turkey, specifically in the provinces of Izmir, Kayseri, Karabük, and Hatay. The primary equipment in the Waelz process is a rotary kiln with dimensions of 65 meters in length and 4.4 meters in diameter. The kiln operates at a 2% inclination with a rotation speed of 1.1 rpm. Due to operational temperatures exceeding 1200°C, the kiln requires protection against potential structural damage. High-alumina refractory bricks line the inner wall of the rotary kiln for this purpose. The chemical composition of these refractory bricks varies by zone, corresponding to the temperature gradient along the kiln length. In the slag exit zone, where temperatures can reach 1200°C, the refractory bricks contain approximately 70% alumina, while other zones utilize varying brick compositions based on their specific thermal requirements. Figure 1 illustrates the temperature distribution along the kiln's outer shell, with regions 8, 9, and 10 representing the slag zone. The classification data were obtained through chemical analyses of Waelz process raw materials and slag samples, with expert labeling for quality assessment. Four machine learning algorithms - Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and Naive Bayes (NB) - were employed for slag zinc quality classification. Model reliability was ensured through cross-validation techniques and hyperparameter optimization. The experimental results demonstrated that the DT model achieved superior classification performance exceeding 99% accuracy, with other models showing comparable performance levels. [8].

Table 1. Chemical composition of EAF powder [7]

Oxides	Weight (%)
SiO_2	1.145
Al_2O_3	0.519
Fe_2O_3	24.780
CaO	18.600
MgO	3.949
K_2O	1.804
Na_2O	2.440
SO_3	3.214
Cr_2O_3	0.194
PbO	6.016
ZnO	25.290
MnO	2.452
CoO	0.240
CuO	0.454
Cl	3.622
LOI	6.450

The Waelz process starts with adding raw materials (EAF powder, anthracite coal, coke, and lime) to the rotary kiln. However, the rotary kiln temperature must be sufficient for chemical reactions before this process. When the rotary kiln system is commissioned after the planned shutdown (the period determined for periodic maintenance of the rotary kiln), natural gas is used for an average of 3 days to reach sufficient temperature inside the kiln. When the furnace reaches sufficient temperature, raw material is charged, and anthracite and coke coals are used to maintain this temperature until the next shutdown. For this temperature and heat balance, the furnace temperature should be approximately 1200°C.

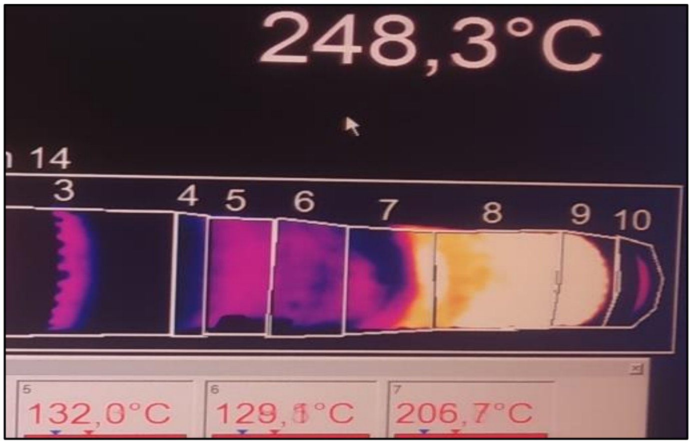

Figure 1. Rotary kiln slag zone outer sheet temperature.

When necessary, in addition to the coals, the flame pipe system is used to provide temperature support and manage the process. Samples are taken regularly from all raw materials to determine the ratio and content of raw materials to be charged into the furnace system. These samples are taken from belt spills or directly from stored raw materials. These raw materials are charged to the preheating zone of the furnace with the help of conveyors in the quantities determined as the final process. At this stage, the primary expectation from the preheating zone of the furnace is to prepare the raw materials for the reduction zone, where chemical reactions take place intensively. Figure 2 schematically shows the Waelz process rotary kiln zones. As a result of the chemical reactions in the furnace, one of the process outputs is slag with high iron content, and the other is zinc oxide. The negative suction system draws the evaporated zinc oxide into the dust chamber unit. The purpose of this unit is to separate the impurities in the zinc oxide drawn from the furnace by density difference. Zinc oxide turns into powder form in this unit. Powders with low zinc content (average 44% and below) are charged back to the rotary kiln, while powders with high zinc content (average above 44%) are sent to other stages of the process.

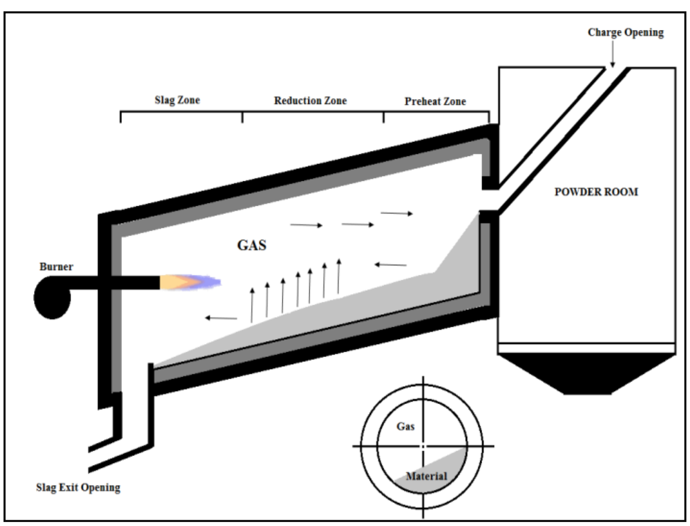

Figure 2. Waelz processes rotary kiln zones

Chemical analyses of raw materials charged to the furnace and furnace outputs are carried out simultaneously. Samples taken from raw materials and outputs are subjected to specific tests and analyses in the factory's accredited laboratory. Since it is the output of the rotary kiln in terms of recovery and does not contribute to production, one of the main targets is to keep the amount of zinc in the slag below 1%. The higher the amount of zinc in the slag, the more zinc recovery in the rotary kiln cannot be done correctly, and the more zinc that can be obtained is lost in the slag. Failure to recover zinc properly can be caused by low zinc content in the raw material charged to the furnace, insufficient temperature and sufficient air for reactions, ring formations, and insufficient oxidation.

2.1. Dataset

In this study, the chemical analysis values of the materials used before the Waelz process and obtained as a result of the process of a zinc recovery company were used and turned into a dataset. These analysis values are the results of the samples given to the accredited laboratory. Therefore, this thesis verifies experimental studies with the machine learning method. The reliability of the numerical verification needs to be addressed in the thesis. Table 2 shows the raw materials charged to the rotary kiln and some values of the labeled data. In the slag, which is the output of the rotary kiln, the data with an average zinc value below 1% is labeled A, and the data with an average zinc value of 1% and above is labeled B. The actual dataset is summarized in Table 2, consisting of 29 columns.

Table 2. Dataset

Dataset	EAF powder (tons)	Lime (tons)	Coal (tons) (anthracite+coke)	A label	B label
Mean	398.26	37.73	142.87	0.63	1.73
Max	458	66	203	0.99	5.34
Min	71	4	102	0.23	1.01
Standard Deviation	40.59	10.57	10.41	0.18	0.77

2.2. Performance Metrics

Different performance metrics are used to measure the classification success rate of machine learning models. More than one machine learning method can be used for the data under study, and each algorithm's performance is measured separately to select the most successful algorithm. Table 3 shows the Confusion matrix used to measure classification performance. Performance metrics are determined according to the values obtained from this matrix. Metrics A and B were used in this study. A represents the average zinc value in slag below 1%, and B represents the average zinc value above 1%.
According to this matrix:
TP: Both positive in actual value and positive predicted value by the model.
TN: The value that is negative both in reality and in the model's prediction.
FP: The value that is negative in reality but predicted positively by the model.
FN: The value that is positive in reality but negative in the machine value.

Table 3. Confusion matrix

Confusion Matrix		Actual	
		Positive (A)	Negative (B)
Prediction	Positive (A)	TP	FP
	Negative (B)	FN	TN

Performance metrics used for classification:
Accuracy, precision, sensitivity, and F1 score. Their formulas are given in Eq. 1-4.
Accuracy is the number of correct predictions divided by the number of all predictions made.

Accuracy = (TP+TN)/(TP+TN+FN+FP) (1)

Precision refers to how many of the positively predicted samples were correctly predicted.

Certainty = TP/(TP+FP) (2)

Sensitivity indicates what proportion of values that should be positively predicted are correctly predicted.

Sensitivity = TP/(TP+FN) (3)

The F1 score is a combination of precision and sensitivity values and is often considered a metric to measure the performance of classification algorithms [9].

F1 score=(2*Accuracy*Sensitivity)/(Certainty + Sensitivity) (4)

Cross-validation is used to determine the performance of the models. One of these methods is the k-layer cross-validation method. This method divides the entire dataset into "k" equal parts. In the k-layer cross-validation method, the training set to be used in the training process is first shuffled and divided into k subsets of equal size. This process is repeated k times, and the subset in each split is removed from the training dataset and used as the test set. This method tests the model's generalization ability, and overfitting problems are minimized [10]. Accuracy is checked by adding data to each partition one by one. This method uses each data point at least once as validation data. If the dataset is decided to be divided into ten parts, the value of k becomes 10. Ten pieces of validation data are created, and the process is repeated 10 times. In each repetition, these ratios are averaged. Accordingly, the higher the value of k, the higher the model's performance and the lower the model's error margin.

3. Results and discussions

This study used four different classification models and four different performance metrics on labeled data, and the best-performing classification models were identified. The dataset was divided into ten equal parts using the k-layer cross-validation method to determine the performance of the models. The results obtained are given in Table 4. When Table 4 and the ROC curves of the models are analyzed, the classification performance of the DT model is 100% at all K-fold values; the NB model is 97% at K-fold 2, the RF model is 100% at K-fold 10, and the SVM model is 94% at K-fold 2. (The performance values given as 100% are accepted as 100% since they are more than 99%).

According to Figure 3, at K-fold 10, the models show similar classification performance. However, when other criteria are considered, the DT model performs better in classification. In the other models, RF, NB, and SVM have the highest classification performance, ranging from highest to lowest.

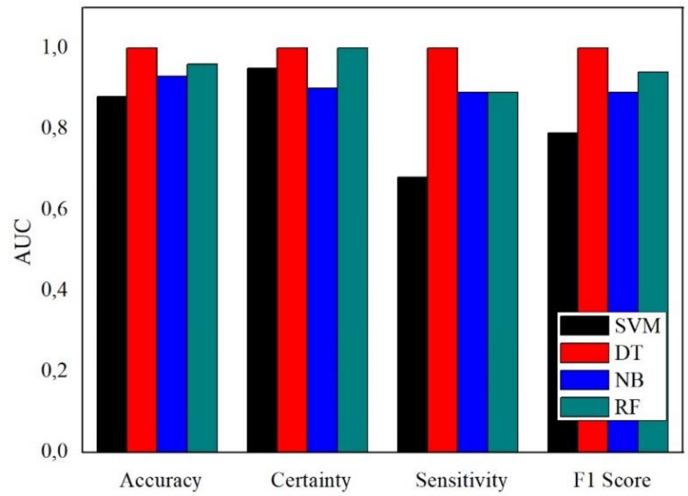

Figure 3. Classification performance comparison for k-fold 10

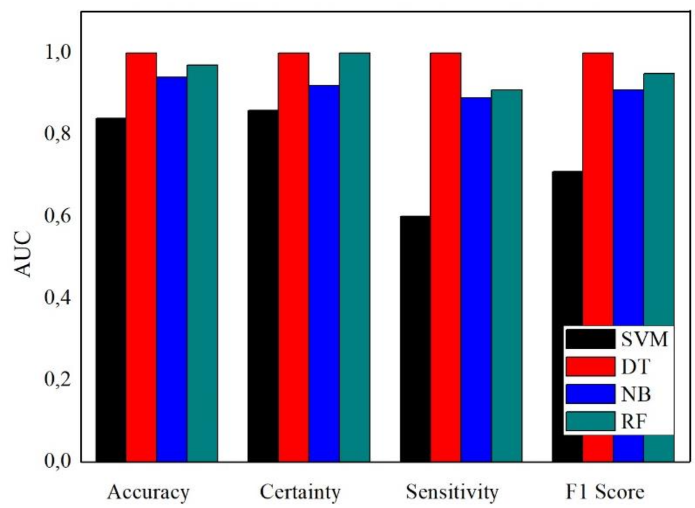

Figure 4. Classification performance comparison for K-fold 2

Considering Figure 4, the classification models perform close to each other according to the K-fold 2 value. However, when other criteria are considered, the DT model has a higher classification performance than the others. In the other models, RF, NB, and SVM have the highest classification performance, with the highest being the lowest, respectively. Figure 5-8 shows the ROC curves of the classification models.

Table 4. Results

K-fold	Performance Metrics	Models			
		SVM	DT	NB	RF
K-fold 2	Accuracy	0.84	1	0.94	0.97
	Certainty	0.86	1	0.92	1
	Sensitivity	0.6	1	0.89	0.91
	F1 Score	0.71	1	0.91	0.95
K-fold 3	Accuracy	0.87	1	0.93	0.97
	Certainty	0.92	1	0.9	1
	Sensitivity	0.67	1	0.89	0.91
	F1 Score	0.77	1	0.89	0.95
K-fold 4	Accuracy	0.88	1	0.94	0.96
	Certainty	0.94	1	0.90	1
	Sensitivity	0.67	1	0.90	0.88
	F1 Score	0.78	1	0.90	0.93
K-fold 5	Accuracy	0.88	1	0.94	0.97
	Certainty	0.94	1	0.91	1
	Sensitivity	0.68	1	0.90	0.90
	F1 Score	0.79	1	0.90	0.95
K-fold 6	Accuracy	0.88	1	0.92	0.98
	Certainty	0.95	1	0.89	1
	Sensitivity	0.66	1	0.89	0.94
	F1 Score	0.78	1	0.89	0.97
K-fold 7	Accuracy	0.88	1	0.92	0.97
	Certainty	0.96	1	0.89	1
	Sensitivity	0.67	1	0.89	0.91
	F1 Score	0.79	1	0.89	0.95
K-fold 8	Accuracy	0.87	1	0.91	0.96
	Certainty	0.93	1	0.87	1
	Sensitivity	0.65	1	0.88	0.90
	F1 Score	0.76	1	0.87	0.94
K-Fold 9	Accuracy	0.88	1	0.92	0.96
	Certainty	0.95	1	0.88	1
	Sensitivity	0.69	1	0.89	0.90
	F1 Score	0.79	1	0.88	0.95
K-fold 10	Accuracy	0.88	1	0.93	0.96
	Certainty	0.95	1	0.90	1
	Sensitivity	0.68	1	0.89	0.89
	F1 Score	0.79	1	0.89	0.94

ROC curves are one of the most valuable methods for evaluating and comparing the performance of classification models [11]. Figure 5 shows the ROC curve and the AUC area of the curve for the DT classification model. According to this curve, the DT classification model performed best at a K-fold ten value and an AUC value 1. K-fold ten means that the dataset is divided into ten equal parts. A high K-fold value in ROC curves is preferred because it can eliminate problems such as overfitting. An AUC value of 1 is considered as 100% performance. It means that a 100% correct classification is made for the values given for this model. This rate means that the model can distinguish the data well, and the accuracy rate is relatively high.

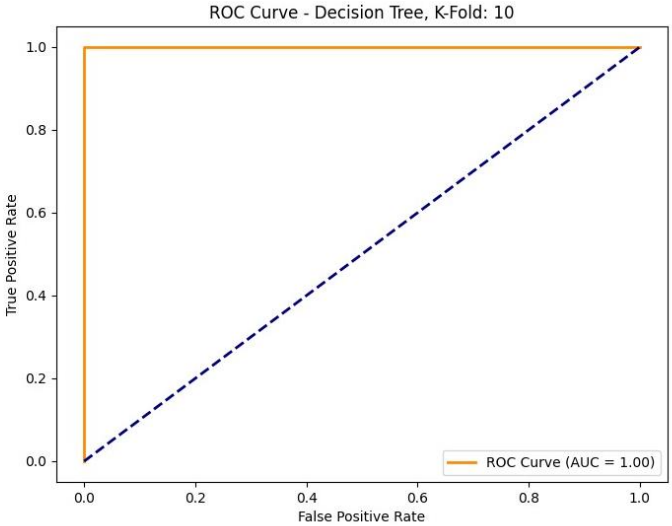

Figure 5. ROC curve DT model

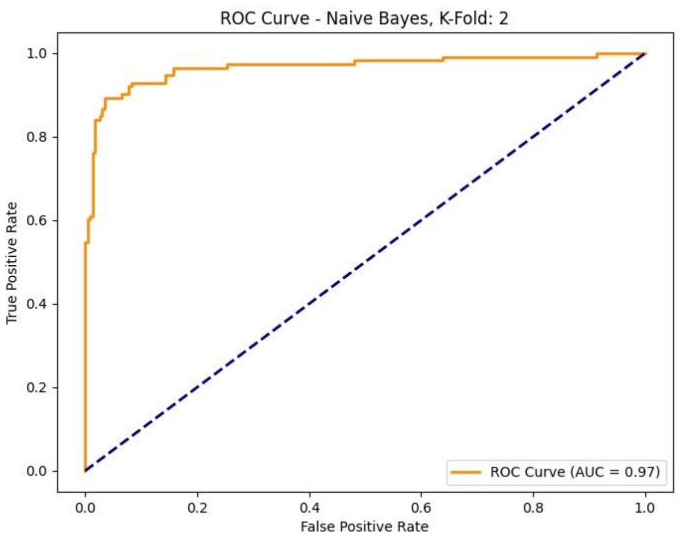

Figure 6. ROC curve NB model

Figure 6 shows the ROC curve and AUC area for the NB classification model. According to this curve, the NB classification model performed best at K-fold 2. The AUC value is 0.97. The higher the AUC value, the higher the classification success of the model [10]. For this reason, in the ROC curve divided into ten equal parts, the K-fold value closest to AUC 1 was taken as the basis. In this case, the only value close to AUC 1, i.e., 100%, is the K-fold 2 value. As a result of this curve, the NB model made 97% correct classification.

The ROC curve shown in Figure 7 was used to evaluate the performance of the RF classification model. The area under the curve, AUC, takes a value between 0 and 1. A value of 0.5 is equivalent to random guessing, while 1 indicates perfect prediction [12]. According to the ROC curve in Figure 7, the RF classification model gave the highest accuracy value with K-fold 10. The AUC value is 1. This indicates 100% correct classification and that the model works very well.

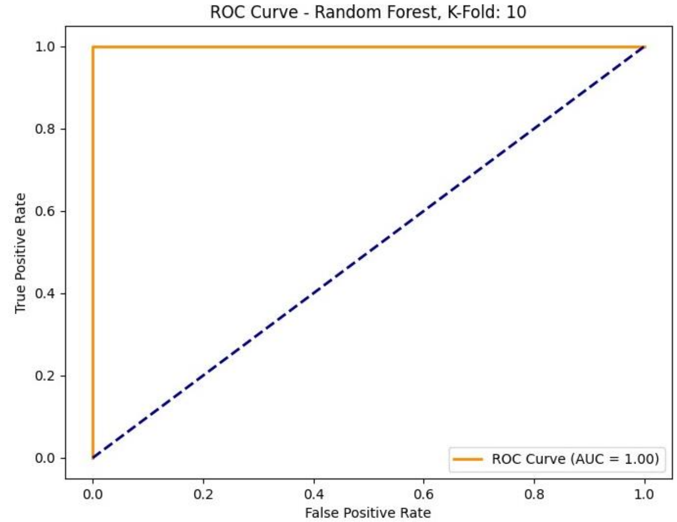

Figure 7. RF model of the ROC curve

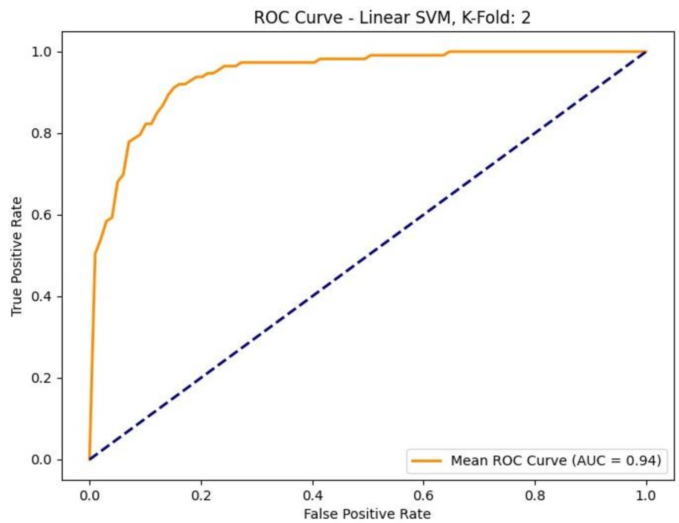

Figure 8. ROC curve SVM model

Figure 8 shows the ROC curve and the AUC area of the curve for the SVM classification model. If the AUC area is between 0.5 and 0.7, it indicates poor performance, between 0.7 and 0.9 indicates moderate performance, and above 0.9 indicates good performance of the model [13]. The best performance for the SVM classification model was obtained at K-fold 2, and the AUC value was 0.94. This value indicates that the model performs 94% correct classification. This shows that the model learns the dataset effectively and correctly classifies it.

4. Conclusion

This study explored the application of machine learning techniques to classify zinc quality in slag generated through the Waelz process, addressing a key challenge in the iron and steel industry. Among the algorithms evaluated, the Decision Tree (DT) model demonstrated exceptional performance, achieving

100% accuracy, precision, sensitivity, and F1 score, establishing itself as a highly reliable tool for quality control in zinc recovery. Other models, such as Random Forest (RF) and Naive Bayes (NB), also delivered high accuracy, highlighting the potential of machine learning in this domain. The findings of this study contribute significantly to advancing automated quality control in metallurgical processes by offering accurate and efficient classification models. Furthermore, integrating these models into real-time monitoring systems has the potential to optimize zinc recovery operations, improve resource efficiency, and support sustainable waste management practices.

Based on the experimental results and analyses, the following conclusions can be drawn:

- The proposed machine learning approach successfully classified zinc content in Waelz process slag, with the Decision Tree (DT) algorithm achieving 100.0% accuracy, precision, sensitivity, and F1 score across all validation sets.
- Cross-validation results demonstrated that the DT and Random Forest (RF) algorithms outperformed other tested methods, with RF achieving 96.0-98.0% accuracy and 100.0% precision. This confirms the robustness and reliability of tree-based methods for this classification task.
- The developed classification system enables rapid assessment of slag quality, thereby potentially optimizing the zinc recovery process through real-time monitoring and control.
- Chemical composition analysis of input materials combined with the classification model provides predictive insights for process optimization, potentially reducing operational variability and improving resource efficiency.
- The methodology demonstrates potential for industrial implementation, offering a data-driven approach to quality control in metallurgical processes.

Future Research Directions:

- Implementation of real-time monitoring systems
- Investigation of deep learning approaches for process optimization
- Development of integrated control systems based on classification outputs
- Extension of the methodology to similar metallurgical processes

This research contributes to the industrial application of machine learning in metallurgical processes, providing a systematic approach for zinc recovery optimization through accurate quality classification.

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Conflict of Interest Statement

The authors declare that there is no conflict of interest in the study.

CRediT Author Statement

Didem Özcan: Conceptualization, Data curation, **M. Kürşat Karaoğlan:** Conceptualization, Data curation, Original draft writing, Validation, **Mehmet Çelik:** Original draft writing, Validation, Formal analysis, Supervision

References

1. Mudd, G. M., Jowitt, S.M., & Werner, T. T. (2017). The world’s lead-zinc mineral resources: Scarcity, data, issues and opportunities. Ore Geology Reviews, 80, 1160–1190.
2. Avachat, H., Sabnavis, M., & Jagasheth, U. H. (2018). Zinc industry: the unsung metal of the economy-industry research report. CARE Ratings: Professional Risk Opinion, 1-11
3. Ng, K. S., Head, I., Premier, G. C., Scott, K., Yu, E., Lloyd, J., & Sadhukhan, J. (2016). A multilevel sustainability analysis of zinc recovery from wastes. Resources, Conservation and Recycling, 113, 88–105.
4. Goodwin, F.E. (2017). Current status anf future expectations for the zinc market. International Zinc Association for Presentation at InterZAC 2017, Toronto.
5. Jia, Y., Zhang, T., Zhai, Y., Bai, Y., Ren, K., Shen, X., Cheng, Z., Zhou, X. & Hong, J. (2022). Exploring the potential health and ecological damage of lead–zinc production activities in China: A life cycle assessment perspective. Journal of Cleaner Production, 381(1), 135–218.
6. Shawabkeh, R. A. (2010). Hydrometallurgical extraction of zinc from Jordanian electric arc furnace dust. Hydrometallurgy, 104(1), 61–65.
7. Oustadakis, P., Tsakiridis, P. E., Katsiapi, A. & Agatzini-Leonardou, S. (2010). Hydrometallurgical process for zinc recovery from electric arc furnace dust (EAFD): Part I: Characterization and leaching by diluted sulphuric acid. Journal of Hazardous Materials, 179(1-3), 1-7.
8. Özcan, D. (2024). Classification and regression analysis of zinc recovery in rotary kilns using machine learning. Published Master's Thesis, Karabük Üniversitesi, Karabük.
9. Polatgil, M. (2023). Investigation of the effects of data scaling and imputation of missing data approaches on the success of machine learning methods. Duzce University Journal of Science & Technology, 11, 78–88.
10. Başer, B. Ö., Yangın, M., & Sarıdaş, E. S. (2021). Classification of diabetes mellitus with machine learning techniques. Süleyman Demirel University Journal of Natural and Applied Sciences, 25(1), 112–120.
11. Tomak, L., & Bek, Y. (2010). The analysis of receiver operating characteristic curve and comparison of the areas under the curve. Journal of Experimental and Clinical Medicine, 27(2), 58–65.
12. Yiğit, P. (2011). Yapay sinir ağları ve kredi taleplerinin değerlendirilmesi üzerine bir uygulama. Published Master's Thesis, İstanbul Üniversitesi, İstanbul.
13. Pintea, S., & Moldovan, R. (2009). The receiver-operating characteristic(roc) analysis: Fundamentals and applications in clinical psychology. Journal of Cognitive and Behavioral Psychotherapies, 9(1), 49–66.