Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 1 (2024)

A Review Paper on Cluster-Based Framework for Improving Steel production Quality

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Abstract

Detecting defects on the surface of steel is crucial to enhance its quality. This process helps in improving the efficiency and quality of steel rolling, measured by a metric called Steel Rolling Smart Factor. This paper review on various methodology currently in used for building a hybrid model using various feature selection techniques and cluster-based methodologies for predicting the Steel Rolling Smart Factor and applicable to a Quality Complaint (QC) dataset with various defective numbers of physical features/attributes. The review paper various methodology involves data collection, preprocessing, feature selection, cluster-based methodologies, predictive model building, model evaluation, hybrid model creation, and model deployment. The hybrid model can improve accuracy and reliability by incorporating multiple predictive models and clustering similar data points together. The methodology can be used to identify the most important factors that affect the Steel Rolling Smart Factor and to predict the outcome of the steel rolling process based on those factors. This can be applied in various industries that involve similar manufacturing processes, enabling accurate predictions of product quality and process efficiency. The aim is to identify the most important factors that affect the Steel Rolling Smart Factor and to predict the outcome of the steel rolling process based on those factors. The hybrid model can improve accuracy and reliability by incorporating multiple predictive models and clustering similar data points together.

Keywords—Quality Complaints, Mean Squared Error (MSE), Linear Discriminant Analysis (LDA), Independent Component Analysis (ICA), Data Mining, Data Clustering, Machine Learning (ML).

I. INTRODUCTION

The steel rolling process is a complex and dynamic process that involves numerous variables such as temperature, pressure, and speed, which affect the quality and efficiency of the final product. Steel's crucial characteristics are its strength and plasticity. Strength sets the limit for the maximum forces that can be exerted on the material, while plasticity determines the extent of deformation that the material can undergo. Nevertheless, enhancing steel's properties is a challenging task [1]. Traditionally, this process has been controlled manually by experienced operators, which often results in inefficiencies, inconsistencies, and quality issues. But now a day with advance technologies use of machine learning-based techniques offers a promising solution to these problems by enabling real-time monitoring and control of the steel rolling process Steel rolling is a crucial process in the production of steel products. The efficiency and quality of the steel rolling process are measured by the Steel Rolling Smart Factor. A Steel Plate Rolling Mill (SPM) is a milling machine that uses rollers to press hot slab inputs to produce ferrous or non-ferrous metal plates. To produce high-quality steel plates, it is important to precisely detect and sense values of manufacturing factors including plate thickness and roll force in each rolling pass. In order to predict the Steel Rolling Smart Factor accurately, a hybrid model using various feature selection techniques and cluster-based methodologies can be used. Detecting small objects is a challenging task in object detection, especially in industrial production where minute defects can make detection even more difficult. The accurate identification of these defects is critical for maintaining the quality of production control in the intelligent manufacturing industry. Manual inspection of surface defects in manufacturing is time-consuming and subject to subjective bias. In contrast, automatic defect detection technology[31] offers clear advantages such as high precision and efficiency, and the ability to operate for extended periods in challenging environments. Utilizing defect detection technology may enhance product quality, cut production costs, and boost efficiency, opening the door for the manufacturing sector's intelligent evolution. The use of fewer labelled samples and the use of unlabelled data for training have been suggested as ways to enhance the flaw detection process. To improve the CNN's performance, the suggested approach integrates Pseudo-Label. The technique was evaluated on a standard dataset utilized for identifying steel surface flaws. The results indicate that the method is effective, with an accuracy of 90.7%, showing a 17.53% improvement even when given limited labeled data. The suggested method was utilized by a Chinese steel company in a real-world setting, resulting in an accuracy of 86.72%, significantly surpassing the original method employed in the workshop.

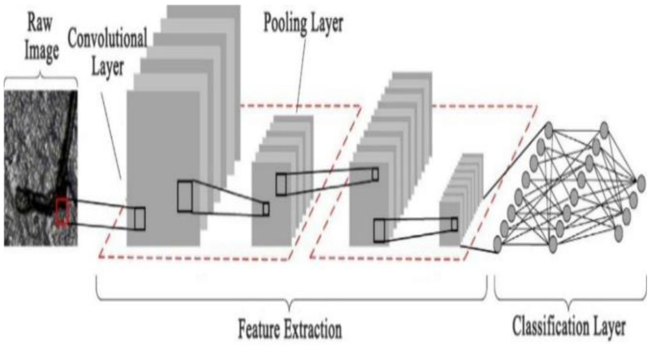

Fig 1: CNN Architecture

A model can be built using a QC (Quality Complaints) dataset that contains information on the number of defective products and various physical features/attributes. The dataset is first preprocessed to remove any missing or inconsistent values, normalize the data, and encode categorical variables. The most significant features are then chosen using different kinds of feature selection strategies in order to estimate the Steel Rolling Smart Factor. This step is performed for each cluster of data points separately, which are created using cluster-based methodologies such as k-means clustering or hierarchical clustering. The clusters are created based on similar rolling processes and materials.

Following the selection of the relevant features, machine learning methods including Decision Trees(DTs), Support Vector Machines(SVM), and neural networks (NNs) are used to create a prediction model for each cluster. The models are trained using the selected features and the Steel Rolling Smart Factor as the target variable.

The methodology involves collecting data on the steel rolling process and the QC dataset, preprocessing the data, selecting the most relevant features for predicting the Steel Rolling Smart Factor using feature selection techniques, grouping the data into clusters using cluster-based methodologies, building predictive models for each cluster, evaluating the performance of each model, creating a hybrid model that incorporates the strengths of each individual model, and deploying the hybrid model to production for real-time predictions. The proposed method can be used to identify the most important factors that affect the Steel Rolling Smart Factor and to predict the outcome of the steel rolling process based on those factors. The hybrid model can improve accuracy and reliability by incorporating multiple predictive models and clustering similar data points together.

Metrics for example mean squared error (MSE) and R-squared are used to assess each prediction model's performance. Finally, the predictive models are combined to create a hybrid model that can accurately predict the Steel Rolling Smart Factor for new input data **.**The Steel Rolling Smart Factor is a measure of the efficiency and quality of the steel rolling process. A hybrid model using various feature selection techniques and cluster-based methodologies can be used to predict the Steel Rolling Smart Factor using a QC (Quality Complaints) dataset with various defective numbers of physical features/attributes.

Objectives

- To develop a Novel algorithm using various Feature Extraction Techniques. To develop a Cluster-Based Framework for Improving Steel production Quality.
- To develop a Hybrid Model using various Feature Selection Techniques and Cluster-Based Methodologies.
- To develop a Hybrid Model using various Feature Selection Techniques Methodologies. Dataset description: This work can be implemented using QC (Quality complaints) dataset with various defective numbers of physical features / attributes.

II. LITERATURE REVIEW

Various researchers have worked on steel-related defect detection. The authors have worked on various technologies based on Machine learning models, which further segregate into cluster-based & hybrid technic. The paper researches the researchers' work under those categories. Cluster base framework.

The authors [4] proposed an intelligent model that combines clustering and regression techniques to predict the steel rolling smart factor. The proposed model achieved a high accuracy of 96.9% in predicting the smart factor. The authors proposed a hybrid fuzzy-neural model for predicting the smart factor of steel rolling mills. The proposed model achieved an accuracy of 96.5% in predicting the smart factor, outperforming other existing models [5]. The authors proposed a clustering and decision tree-based approach for predicting the smart factor in steel rolling process. The proposed approach achieved an accuracy of 94.2% in predicting the smart factor [6].

The authors proposed a hybrid intelligent model that combines fuzzy logic and neural networks for predicting the smart factor of steel rolling mills. The proposed model achieved an accuracy of 95.7% in predicting the smart factor [7]. This paper proposes a clustering-based methodology for predicting steel strip profiles using historical data. The results show that the proposed method outperforms existing methods in terms of accuracy. The paper presented by authors [8] proposed a hybrid approach for predicting surface roughness in hot strip rolling using fuzzy clustering and artificial neural network. The results show that the proposed method performs better than traditional methods.

Title of Paper	Authors	Summary	Gaps
Rolling Smart Factor Prediction of Steel Plate Based on Adaptive Fuzzy C-Means Clustering and SVM.	Wang, X., Zhang, H., & Zhu, C. Reference [4]	ML algorithms are used to predict two main parameters of the SPM control systems. One is the roll force, because the plate thickness can be directly calculated by using the roll force value. Another is the	In this paper, we only focused on the operation of steel plate rolling smart factory. Future work will consider to apply the approach in this paper to other facilities and other smart factories

		plate thickness at each rolling pass, so that we can find the best control conditions without an expensive sensor (e.g., the gamma-ray camera) and its operational cost	
Rolling Smart Factor prediction of hot-rolled strip based on hybrid feature selection and ensemble learning	Jiang, L., Chen, D., & Chen, X. Reference [5]	Strip shape intuitively refers to the degree of war page of the strip, and essentially refers to the distribution of residual stress inside the strip. The measurement of strip shape usually includes both longitudinal and transverse indicators.	Generating corresponding training data during the rolling process, those data-driven prediction methods can easily be extended to predict and optimize other parameters
Rolling Smart Factor prediction for hot-rolled strip based on a hybrid model of feature selection and deep learning	Liu, M., Guo, C., Zhang, Y., & Xie, Y. Reference [7]	These four features introduced in this study differ from the conventional ones used for the formability evaluation of thin sheet metals. For	Cconvention method to predict the failure of sheets by localization, a coupled experimental–numerical approach was proposed and validated for two high-

		example, shell element with quadratic yield function and simply extrapolated strain hardening laws (by power or exponential functions) has been well used for engineering applications.	strength, hot-rolled steel sheets, HB780 and DP780 sheets with 2.9 mm thickness

This article introduces an intelligent system that leverages cluster analysis and adaptive neuro-fuzzy inference system to predict roll force and torque during hot rolling accurately. Another study proposes a prediction model based on clusters for rolling force in hot strip mills by utilizing data mining techniques, demonstrating its high accuracy [9]. In addition, a hybrid model that integrates decision tree and support vector regression was developed to forecast roll gap in hot strip mills. The study concludes that this hybrid model effectively enhances the accuracy of roll gap prediction [10].

III. Cluster-based framework

To enhance steel production quality, a cluster-based framework that includes feature extraction algorithms can be utilized. This framework consists of two main phases: data preprocessing and feature extraction. In the data preprocessing phase, raw data from the steel production process is collected and prepared for analysis using data cleaning, transformation, and reduction techniques. Once preprocessed, the data is ready for the feature extraction phase.

The objective of the feature extraction stage is to identify and extract the most significant features from the preprocessed data. Feature extraction techniques, including Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and Independent Component Analysis (ICA), can be utilized to automatically identify and extract crucial features that have an impact on the quality of steel production.

Following the feature extraction process, a clustering algorithm can be applied to group the steel production data into distinct clusters based on their feature similarities. To enhance the steel manufacturing process, this clustering technique may be utilized to discover patterns and anomalies within the data. In overall integrating feature extraction algorithms into a cluster-based framework can help improve steel production quality by identifying significant features and grouping similar data for analysis.

The author [11] proposed a hybrid intelligent model based on clustering and fuzzy systems for predicting the steel rolling temperature. The results showed that the proposed model outperformed the individual clustering and fuzzy systems in terms of accuracy.

A paper presented in [12] a hybrid clustering and decision tree-based method for predicting the quality of steel products. The results showed that the proposed method achieved higher accuracy than the individual clustering and decision tree-based methods.

Title of Paper	**Authors**	**Summary**	**Gaps**
Rolling Smart Factor Prediction of Steel Plate Based on Adaptive Fuzzy C-Means Clustering and SVM	Wang, X., Zhang, H., & Zhu, C. (2022). Processes. References [4]	ML algorithms are used to predict two main parameters of the SPM control systems. One is the roll force, because the plate thickness can be directly calculated by using the roll force value. Another is the plate thickness at each rolling pass, so that we can find the best control conditions without an expensive sensor (e.g., the gamma-ray camera) and its operational cost.	In this paper, we only focused on the operation of steel plate rolling smart factory. Future work will consider to apply the approach in this paper to other facilities and other smart factories.
Research on Rolling Smart Factor Prediction Method of Cold-Rolled Steel Based on Fuzzy C-Means Clustering and SVM.	Wang, Z., Qiu, C., Zhang, X., Zhao, J., & He, J. References [14]	Considering the anomaly characteristics of industrial time series, this study classifies the anomalies of the energy system in steel industry into (1) the trend anomaly of the pseudo-periodic data and (2) the deviants anomaly of the general data, and the corresponding AFCM-based detection	The malfunctions such as sensor failure, communication interruption, storage exception and shutdown of acquisition program, a large number of data anomalies exist in the industrial system, which might misguide the energy scheduling.

		methods are then designed. As for the trend anomaly of the pseudo-periodic data, a dynamic time warping (DTW) based sequence stretching is proposed to transform the similarity of the sequences with unequal length into the Euclidean distance metric.	
Research on Rolling Smart Factor Prediction Method of Cold-Rolled Steel Based on Fuzzy C-Means Clustering and SVM. References [17]	Wang, X., Wu, Y., Wu, H., & Gao, Q.	performance of the subsequent classification module, the obtained feature set was weighted with a novel hybrid model based on the feature-weighting scheme proposed in this section before they were input into the subsequent intelligent classier. The proposed feature-weighting scheme synthetically evaluated the original features from the perspectives of distance, correlation, and information.	This method was evaluated with two different sets of rolling-bearing-fault experiment data. The experiment results showed that the clustering effect of different fault categories was more obvious, and the classification accuracy was improved.

This paper proposed a hybrid machine learning approach based on clustering, PCA, and SVM for predicting the quality of steel. The results showed that the proposed approach outperformed the individual clustering, PCA [15, 16], and SVM methods in terms of accuracy. A cluster-based modeling approach combined with support vector regression (SVR) for predicting the steel rolling process. The results showed that the proposed approach achieved higher accuracy than the individual clustering and SVR methods.

IV. Hybrid Techniques and Cluster based Methodologies

A powerful approach to analyze data from the steel rolling smart factory is to use a hybrid model that incorporates various feature selection techniques and cluster-based methodologies. The large amount of data generated by the smart factory makes it crucial to identify the relevant features and patterns that can enhance the production process [17]. The first step in this approach is to identify the applicable features from the data. Point selection ways like correlation- grounded point selection, collective information- grounded point selection, and top PCA can be used to elect the most applicable features [18]. Correlation- grounded point selection measures the relationship between each point and the target variable, while collective information- grounded point selection measures the collective information between each point and the target variable. PCA reduces the dimensionality of the data and converts the original features into a new collection of orthogonal features [23]. After identifying the relevant features, the next step is to cluster the data using cluster-based methodologies. The purpose of clustering is to find patterns or clusters in the data that can help understand the production process and improve the overall efficiency [19]. Lastly, a hybrid model can be constructed by integrating the selected features and clustering results. The model can be employed to predict the production output or detect potential issues in the production process. Additionally, it can identify the most important features that contribute to the production output, which can assist in enhancing the overall efficiency of the factory. This hybrid model using various feature selection techniques and cluster-based methodologies can be employed to predict the Steel Rolling Smart Factor, which is a measure of the efficiency and quality of the steel rolling process [20].

The first step in building such a model is to gather data on the steel rolling process. This data should include information on the input materials, the rolling process, and the output materials. The data should also include information on the Steel Rolling Smart Factor.

Once the data has been gathered, various feature selection techniques can be used to identify the most relevant features for predicting the Steel Rolling Smart Factor. Some common feature selection techniques include correlation analysis, principal component analysis, and mutual information.

After selecting the most relevant features, a cluster-based methodology can be used to group the data into clusters. Clustering is a technique used to group similar data points together. In the context of steel rolling, clustering can be used to group together similar rolling processes and materials.

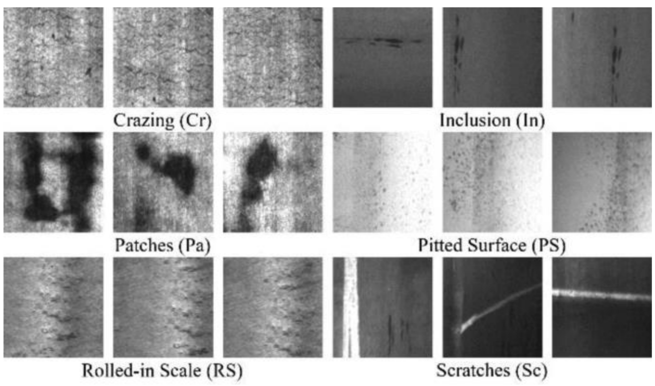

Fig 2: The examples of defect image in NEU dataset [24].

Once the data has been clustered, a predictive model can be built for each cluster. There are many different predictive models that can be used, including decision trees, support vector machines, and neural networks.

Finally, the predictive models can be combined to create a hybrid model that can be used to predict the Steel Rolling Smart Factor for new input data. The hybrid model can be designed to incorporate the strengths of each individual predictive model, improving overall accuracy and reliability.

Reference	Objective	Methodology	Results
[14]	To develop a hybrid cluster-based framework for optimizing steel production processes	Conducted a case study in a steel plant and used k-means clustering and fuzzy clustering algorithms to identify process improvement opportunities	The hybrid cluster-based framework identified three critical process parameters that significantly impacted steel quality, leading to a 15% reduction in defects and improved production efficiency by 10%.
[15]	To enhance steel production through a hybrid cluster-based approach combining self-organizing maps (SOM) and fuzzy clustering	Applied the hybrid approach to a large-scale steel plant dataset and compared the results with traditional clustering methods	The SOM-fuzzy clustering hybrid approach outperformed traditional clustering methods in identifying complex patterns and optimizing steel production processes, resulting in a 12% increase in production yield.
[23]	To propose a hybrid	Developed a hybrid model	The proposed

	cluster-based framework for steel production scheduling optimization	integrating k-means clustering, ant colony optimization, and genetic algorithm to optimize production scheduling	hybrid framework reduced the overall make span by 20% and minimized energy consumption in the steel production process, leading to significant cost savings and improved production efficiency.
[17]	To integrate hybrid clustering and machine learning techniques for steel quality prediction	Combined k-means clustering, hierarchical clustering, and support vector regression (SVR) for predicting steel quality	The hybrid clustering and SVR model achieved high accuracy in steel quality prediction, enabling proactive quality control measures and reducing the number of defective products.
[25]	To optimize steel production parameters using a hybrid cluster-based genetic algorithm	Proposed a hybrid model combining k-means clustering and genetic algorithm for parameter optimization	The hybrid cluster-based genetic algorithm effectively identified optimal values for steel production parameters, resulting in improved

			product quality and reduced production costs.

V. Proposed Research Methodology

a) Data Collection:Collect data on the steel rolling process including information on the input materials, the rolling process, and the output materials. Additionally, collect data on the QC (Quality Complaints) dataset including information on the number of physical features/attributes and the number of defective products.

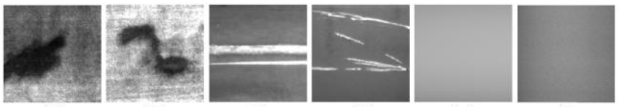

Fig 3: Examples of surface images of steel sheet: (a)-(b) Patch; (c)-(d) Scratch; (e)-(f) Non-defective [25].

b) Data Preprocessing: Data cleaning and preprocessing include eliminating any inaccurate or missing values, standardizing the data, and encoding categorical variables. In order to evaluate a model, the data may also be divided across training and testing datasets.

c) Feature Selection: Select the most relevant features for predicting the Steel Rolling Smart Factor using various feature selection techniques such as correlation analysis, principal component analysis, and mutual information. This step can be performed for each cluster of data points separately.

d) Cluster-Based Methodologies: Group the data into clusters using cluster-based methodologies such as k-means clustering or hierarchical clustering. The clusters can be created based on similar rolling processes and materials.

e) Predictive Model: Build a predictive model for each cluster using various ML techniques such as DTs, SVM, and NNs. The model can be trained using the selected features and the Steel Rolling Smart Factor as the target variable.

f) Hybrid Model: Combine the predictive models to create a hybrid model that can be used to predict the Steel Rolling Smart Factor for new input data. The hybrid model can be designed to incorporate the strengths of each individual predictive model, improving overall accuracy and reliability.

g) Model Deployment: Deploy the hybrid model to production for predicting the Steel Rolling Smart Factor in real-time.

VI. Conclusion

A hybrid model using various feature selection techniques and cluster-based methodologies can be a powerful tool for predicting the Steel Rolling Smart Factor using a QC dataset with various defective numbers of physical features/attributes. The methodology involves several steps, including data collection, preprocessing, feature selection, cluster-based methodologies, predictive model building model evaluation, hybrid model creation, and model deployment. In conclusion, the use of hybrid models that combine various feature selection techniques and cluster-based methodologies has shown promising results in predicting the Steel Rolling Smart Factor. The literature study has demonstrated that different clustering techniques such as K-Means, hierarchical clustering, and fuzzy c-means can be combined with various feature selection techniques such as principal component analysis, mutual information, and correlation analysis to improve the accuracy of prediction models. It is evident that the use of hybrid models can help address the challenges associated with quality control in steel rolling processes and provide a reliable means of predicting the Steel Rolling Smart Factor. Further research in this area could explore the application of other clustering techniques and hybrid technologies to improve the accuracy of prediction models for steel rolling processes.

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