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Develop A Novel Cluster-Based Framework For Improving Steel Production Quality

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Abstract

The steel sector has had difficulties in finding solutions for quality control of goods using data mining methods, notwithstanding recent progress. This study presents a steel quality prediction system that integrates real-world data with in-depth data analysis conclusions. The main process is carefully designed as a regression problem, which is therefore best handled by integrating various learning algorithms with their huge repository of historical production data. A comprehensive examination and comparison of the characteristics of the most often utilized learning models in regression problem analysis has been conducted. The efficacy of our steel quality control prediction system, which utilizes an ensemble machine learning model, showcases promising outcomes. This system offers great usability for local businesses in addressing production problems via the use of machine learning methods. Moreover, the practical implementation of this system is shown and analyzed. The proposed method attained high accuracy, precision, recall and f1 score, mean absolute error, root mean square error as compared to other different technique. Lastly, this study highlights the future prospects and sets out the anticipated level of performance.

Keywords: *Steel production quality, data mining, intelligent manufacturing.*

Introduction

The steel industry's level serves as a significant gauge for assessing a country's degree of industrialization. Currently, several industries have more strict demands for iron and steel goods. The mechanical characteristics of steel may significantly determine whether it will have a prolonged and efficient lifespan in highly abrasive and wear-intensive scenarios, or whether it will have frequent or even catastrophic breakdowns [1]. Comprehending these characteristics is crucial since all manufacturing operations are ultimately aimed at fulfilling the specific quality criteria. In order to uphold and enhance the quality, energy efficiency, and economic gains of the product, it is crucial to forecast and manage the quality based on certain mechanical qualities. This area of study has been intensively explored in recent years [2]. Tensile strength, yield strength, and elongation are widely used metrics to assess the mechanical propert[1]ies of a product. These

measurements are influenced by several variables [3]. Nevertheless, the manufacturing of steel products involves sophisticated physical and chemical transformations together with complex technical procedures, making the prediction and control of properties a persistent challenge in the metallurgical sector [4]. Traditionally, property prediction relies on experiential knowledge and destructive testing, both of which are expensive, time-consuming, and labor-intensive [5]. If the forecast incorporates the pertinent process factors and subsequently optimizes the metal composition and process technology, it has the potential to significantly decrease testing time and enhance the production efficiency of iron and steel firms [6]. There are two primary ways for this idea: empirical and statistical

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models. However, there is still room for improvement in terms of forecast accuracy. This is mainly due to the fact that these approaches heavily rely on experience and mechanism, while disregarding the significance of data. The chosen criteria are insufficient to accurately depict the real scenario.

Clustering techniques may be used for the purpose of feature selection. These techniques partition all the nodes in the network into distinct subgroups based on correlation measures [7]. In the field of complex network theory, an actor's strength is derived from its interconnectedness with other actors. Thus, it may be inferred that the nodes within a cluster possess comparable "power" or "importance", and the nodes with the highest centrality can be chosen as the representatives of each partition [8]. The demand for high-quality steel has never been more paramount, with industries relying on the resilience, strength, and consistency of this material for a diverse array of products. However, the pursuit of optimal steel production quality is fraught with challenges, as the intricate interplay of numerous variables during the manufacturing process can introduce variations that impact the final product's characteristics.

In the competitive landscape of the global steel market, the ability to consistently deliver steel of superior quality is not only a strategic advantage but a prerequisite for meeting stringent industry standards and customer expectations. As technology advances, the steel production sector is poised to leverage cutting-edge methodologies to refine and elevate the quality control processes inherent to its operations. This quest for enhanced steel production quality is the focus of the following exploration. This initiative recognizes the complexity of the steel manufacturing process, where factors such as temperature, pressure, raw material composition, and manufacturing parameters intertwine in a delicate dance. These multifaceted processes, while essential, present a formidable challenge in ensuring that each batch of steel meets the required specifications, avoiding defects, and achieving uniform quality.

The remaining structure of this paper are followed as; section 2 discussed the related work, section 3 &4 presented problem formulation and methodology while section 5 indicated the results of this study. Section 6 described the conclusion of this study.

Review of Literature

Zhang et al., (2023)[9] studied that the presence of surface defects has a substantial role in determining the quality of steel products. The present research primarily emphasises the identification and categorization of defects by algorithms based on machine vision. However, these approaches are limited in their ability to identify the underlying causes of defects and make use of experience knowledge. In this study, a novel technique based on policy-based reinforcement learning is proposed to address the route reasoning issue within the context of defect identification and diagnosis in an industrial knowledge graph. The proposed methodology involves the utilisation of two agents to effectively navigate a path from opposite directions. This approach incorporates a comprehensive reward function that takes into account various factors such as the direction of the path, the length of the path, and the distance to entities in order to make informed decisions on action selection. Additionally, the methodology incorporates a path sharing mechanism and prior knowledge to update the selection policy. The efficacy of the suggested methodology is further assessed using an actual dataset of steel surface defects. The findings indicate that our technique demonstrates proficiency in knowledge inference inside the surface defect graph. The proliferation of industrial IoT and Cyber-physical system (CPS) technologies has led to the accumulation of a significant amount of industrial data. Consequently, machine learning techniques have been devised and implemented to facilitate the identification and detection of problems. Consequently, our system achieves a notable level of accuracy in knowledge reasoning tasks when compared to other current algorithms, as shown by its performance on two benchmark datasets and a real steel surface defect dataset. Therefore, this approach may be easily used in practical scenarios involving the identification of surface defects, therefore enabling the advancement of intelligent manufacturing in the steel production industry.

Wang et al., (2023)[10] studied that the presence of flatness variations during the tandem cold-rolling process of steel strips has a significant influence on the overall quality and form of the final product. These deviations may result in various negative consequences such as strip breakage, decreased working speed, and potential damage to the equipment used in the process. Nevertheless, traditional numerical models based on physics lack the capability to effectively forecast the levelness under the intricate operating circumstances and variables encountered in tandem rolling situations. The suggested technique efficiently predicts the profiles of flatness by combining various factors, eliminating the need for extra data pre-processing procedures. Furthermore, a comprehensive examination is conducted to explore the impact of network width, depth, and topology on the performance of flatness prediction. The Inception-ResNet model, which has been constructed, has exceptional predictive capabilities while using a reduced number of model parameters and demonstrating lower computational complexity in comparison to other network topologies. The Inception-ResNet-39 model, which is composed of 39 layers of trainable parameters, has exceptional predictive performance, surpassing current benchmarks in the field. The accuracy of our technique, which is based on deep learning, enables the precise prediction of flatness in tandem cold-rolling. This is achieved by end-to-end modeling, which encompasses the whole process and ensures the efficient deployment of comprehensive pipelines for model transfer creation.

Pal et al., (2023)[11] stated that age and natural disasters like earthquakes and storms are major causes of damage to structures throughout their useful lives. Timely damage detection is crucial for ensuring the building's continued integrity and safe use. Subsurface damage (SSD) may result in extensive interior damage and perhaps premature structural collapse if not addressed. In this research, we used surface strain data to train a Convolutional Neural Network (CNN) for SSD identification. The network design that was used can segment images down to the pixel level, labeling each strain measurement point as damaged or undamaged. A 256x256 input picture of full-field strain measurements is used to project the SSD onto a 256x256 output image. The training data for the network is created via numerical simulations of damaged aluminum bars with randomised position, direction, length, and thickness. The validation set IoU score for the trained network is 0.790, while the testing set value is 0.794. The trained network is evaluated using a steel dataset that was created numerically to ensure it can be used to materials other than aluminum. With an IoU of 0.793, identical to that of the aluminum dataset, we may be certain that the network will be effective when applied to other materials with a similar stress-strain relationship. The network's generalizability is evaluated by testing it on triple damage scenarios, where it achieves an IoU score of 0.764, indicating that it performs well even for previously encountered damage patterns. Real experimental data from Strain Sensing Smart Skin (S4) was also successfully predicted by the network. This demonstrates the network's capacity to use innovative full-field strain sensing techniques, such as S4, to their fullest extent in practical applications. The effectiveness of the suggested network as a non-destructive testing strategy for detecting and localising cracks in the subsurface is confirmed.

Gharagoz et al., (2023)[12] presented a design approach for a novel seismic retrofit system using machine learning techniques. The effectiveness of the proposed system in enhancing seismic retrofit capabilities is shown via rigorous seismic studies. The retrofit system comprises a steel frame that incorporates rotational friction dampers (RFD) at the beam-column joints and linear springs at the corners. This configuration enables the existing structures to possess both energy dissipation and self-centering capabilities. The development of the performance-based seismic design technique for the retrofit system of the spring-rotational friction damper (SRFD) involves the use of a genetic algorithm (GA) and an artificial neural network (ANN). The evaluation of the retrofit system's performance and its optimal design approach is conducted via the examination of seismic fragilities, life-cycle cost (LCC), and seismic Resilience Index (RI) for multi-limit states. This evaluation is carried out by using case study models, both before and after the retrofit process. Based on the findings of the investigation, it was determined that the use of the SRFD retrofit system yielded significant reductions in story drifts, seismic fragility, and life cycle costs (LCC) of the retrofitted buildings. The retrofitted models have enhanced resilience and exhibit superior post-earthquake recovery compared to the un-retrofitted versions. The efficacy of the performance-based design method in seismic retrofitting of case study structures to meet multiple design goals has been shown.

Ji et al., (2022)[13] examined that the assessment of width deviation has significant importance as a measure in the evaluation of the overall quality of a hot-rolled strip within steel manufacturing systems. This study examines the issue of predicting width deviation and introduces a hybrid technique called MGH, which combines machine learning and genetic algorithms, to develop a prediction model. The current body of research primarily on achieving high levels of prediction accuracy, sometimes at the expense of interpretability. The objective of this study is to develop a predictive model that effectively balances two essential characteristics demanded by the business, namely, prediction accuracy and interpretability. The first step involves the collection of process variables inside a hot rolling process, which are then included with built variables into a feature pool. We suggest the use of the Minimum Group Heterogeneity (MGH) method to identify representative variables from the dataset and then construct a predictive model. The findings of MGH are derived from the amalgamation of hierarchical clustering, genetic algorithm, and generalised linear regression techniques. Hierarchical clustering is used to partition variables into clusters, using a detailed approach. The integration of genetic algorithm and generalised linear regression is used in a novel manner to effectively identify a representative variable from each cluster and construct a predictive model. The computational tests performed on datasets from both industry and public domains demonstrate that the suggested strategy successfully achieves a balance between prediction accuracy and interpretability in its resultant model. The performance of this model surpasses that of the state-of-the-art models being compared.

Deng et al., (2022)[14] analyzed that the process of strip rolling is a commonly used industrial technique that often employs traditional control methods. The development of control algorithms necessitates the formulation of a mathematical representation of the underlying process, either via the use of fundamental principles or empirical models. Nevertheless, the task of enhancing traditional control techniques to adapt to dynamic demands and changing environmental circumstances is a challenge due to the need of possessing expertise in control engineering, mechanical engineering, and material science. Reinforcement learning is a machine learning technique that enables an agent to acquire knowledge via iterative interactions with its environment, hence obviating the need of using the aforementioned mathematical framework. This study presents an innovative methodology that integrates ensemble learning techniques with reinforcement learning algorithms for the purpose of strip rolling control. A multi-actor PPO framework is presented, building upon the proximal policy optimization (PPO) algorithm. Every actor, which is initialized randomly, interacts with the environment simultaneously. However, only the experience gained by the actor that achieves the greatest reward is used for updating all the actors. The findings obtained from the simulation demonstrate that the suggested technique exhibits superior performance compared to traditional control methods and state-of-the-art reinforcement learning techniques, specifically in terms of process capacity and smoothing.

Chen et al., (2022)[15] studied that hot rolled steel fault checks and judgments are often conducted manually at present, with reference to a predetermined set of guidelines. However, because of human error, the evaluations' quality varies. As a result, it's crucial to create an automated inspection system that can determine the level of rust on hot rolled steel and decide whether or not to retain it. Lately, artificial intelligence has been a hot issue in the research and development of automated systems to detect manufacturing flaws. The purpose of this work is to create a decision-support system for detecting rust in hot-rolled steels using deep learning. The detection procedures may be broken down into three distinct phases: identifying hot rolled steel, identifying rust, and reaching a final determination. In the model, object detection is used to identify hot rolled steel, while colour detection is used to identify rust. The SSD MobileNetv2 was selected as the deep learning architecture for object recognition, while the HSV colour model was used for colour detection due to its superior accuracy and inference speed. The image's rust detection % is used as input for a hold/release decision. For both the hold and release states, simulation findings show an accuracy of 96.05% and 97.92%, respectively, for rust defect identification.

Almasabha et al., (2022)[16] stated that the increasing use of short links in steel buildings, driven by their notable shear strength and rotational capacity, has garnered the interest of structural engineers who want to examine the performance of these components. Nevertheless, there has been a lack of major focus on the efficient development of a complete model for predicting the shear strength of short connections, which has the potential to improve the constructability of steel structures. ML techniques have been effectively used in many domains of structural engineering. This work aims to address the existing research gap by using advanced machine learning methods to estimate the shear strength of short linkages. This research examined many key elements, including the slenderness ratios of the web and flange, the ratio of flange area to web area, the stresses acting on the web and flange, and the ratio of link length. These factors are crucial for developing a comprehensive prediction model. Therefore, the objective of this research employs sophisticated ML algorithms to provide precise predictions for the shear strength. This work used publically accessible datasets for the purposes of training, testing, and validation. Various assessment metrics were used to assess the efficacy of the utilized models in making predictions. Hence, the comprehensive results indicated that the Logic GBM model exhibited superior performance compared to the XGBOOST model. The use of established models is crucial for practitioners in properly forecasting shear strength, hence facilitating the broader implementation of automation in steel structures.

Dissanayake et al., (2022)[17] discussed the application of many well-known machine learning techniques to the problem of predicting the shear resistance of steel channel sections by making use of both practical and numerical data. In order to prevent over-fitting, the procedure of training has included the cross-validation with 10 folds that was carried out. The hyper parameter tuning technique included identifying the optimal the hyper parameter combination for each machine learning model. Four performance indicators were used to assess the effectiveness of the trained models. The examination revealed that all of the machine learning models used in the study correctly predicted the shear strength of stainless-steel lipped channel segments and carbon steel Lite Steel sections. Nevertheless, the SVR algorithm exhibited exceptional performance compared to the other models used. Furthermore, empirical evidence demonstrates that the deployed machine learning models exhibit superior predictive accuracy compared to the presently available design equations for assessing the shear capacity of steel channel sections.

Xie et al., (2021)[18] intended that the internal structure and mechanical qualities of steel generated in industrial steel plate manufacture are greatly influenced by process parameters and steel grade composition. However, establishing the precise correlation between process parameters and mechanical qualities poses a formidable challenge. The model was designed to incorporate process parameters and raw steel composition as input variables. Furthermore, the model was intended to be implemented online in a real steel manufacturing plant. The resulting model achieved a high level of accuracy, with an R2 value of 0.907. By means of conducting a comparison study, it was determined that the precision of the Deep Neural Network (DNN) model surpassed that of traditional machine learning techniques. In order to comprehend the model's hypotheses and conclusions, a number of local linear models were constructed and examined to determine the relationship between process parameters and mechanical qualities. The DNN model that had been optimized was ultimately used in an operational steel factory to facilitate the real-time monitoring and control of steel mechanical characteristics. Additionally, it was utilized to provide guidance for the manufacturing of specific steel plates with customized mechanical properties.

Zhao et al., (2021)[19] presented as a direct result of the unceasing advancement of deep learning in recent years, an increasing number of academics have focused their attention on the investigation of algorithms for target recognition. Among these challenges, one that has yet to be conquered is the detection and identification of objects that are both tiny and complicated. The writers of this paper have gained an understanding of the weaknesses of the deep learning detection method in terms of recognizing tiny and complicated defect targets, and as a result, they would like to offer a new enhanced target identification technique in steel surface defect detection with the readership. The surface flaws in the steel will have a significant impact on the overall quality of the steel. Because we found that the majority of the currently available detection methods for the NEU-DET dataset have a poor detection accuracy, we have decided to validate a steel surface defect detection algorithm based on machine vision using this dataset in order to solve the issue of defect identification in steel manufacturing. The conventional Faster R-CNN method goes through a number of different enhancement steps, such as recreating the network structure of Faster R-CNN, in order to increase its performance. We train the network via multi scale fusion, taking into account both the large and the tiny properties of the target. We use a deformable convolution network to substitute some of the traditional one's nodes so that it can better handle the complicated characteristics of the target. The results of the experiments reveal that the deep learning network model that was trained using the suggested technique has strong detection performance, and the mean average accuracy is 0.752, which is 0.128 points greater than the methodology that was originally used. In this group, the average accuracy of crazing, inclusion, patches, pitted surface, rolled in scale, and scratches is 0.501, 0.791, 0.792, 0.874, and 0.649, respectively, while the precision of rolled in scale is 0.905. The technique of detection is able to efficiently identify minor target flaws on the steel surface, which may serve as a reference for the automated identification of steel defects.

Park et al., (2020)[20] examined a SPM refers to a milling apparatus that employs a series of rollers to exert pressure on heated slab inputs, therefore generating ferrous or non-ferrous metal plates. In order to ensure the production of steel plates of superior quality, it is necessary to accurately detect and measure the values of various manufacturing parameters, such as plate thickness and roll force, throughout each rolling pass. The estimate or forecast of the thickness throughout the manufacturing process is used to determine the appropriate control values, such as the roll gap, for the subsequent rolling pass. Nevertheless, the presence of unfavorable production circumstances may impede the precise identification of manufacturing variables. The use of the advanced gamma-ray camera for thickness measurement is subject to the effect of unfavorable production circumstances, including elevated plate temperatures and subsequent evaporation of lubricating water. Hence, the presence of noise in the calculation of thickness is unavoidable. Moreover, the implementation of such thickness measurements for every individual step incurs significant expenses. The accuracy of the thickness calculation has a substantial impact on both the cost and quality of the end product. The aim is to minimize the expense associated with measuring the in-process thickness and enable the manufacturing of high-quality steel plates. In order to do this, we examine well recognized technology inside this application.

The present study introduces Data Clustering based Machine Learning (DC-ML), which involves the integration of clustering methods with supervised learning algorithms. Two tests were done to assess the effectiveness of DC-ML in predicting issues in the SPM operation, and the results indicate that DC-ML is highly suitable for this task.

Problem formulation

The current state of steel production processes faces challenges in ensuring consistent and high-quality output. Variability in production parameters, raw material characteristics, and operational conditions can lead to defects and deviations in steel quality. To address these issues, there is a need to implement a robust methodology that leverages clustering methods to identify patterns within the production data, allowing for the categorization of distinct process conditions and their impact on steel quality.

Key Issues:

Quality Variability: The existing steel production processes exhibit fluctuations in product quality due to multiple factors such as temperature variations, chemical composition deviations, and equipment malfunctions.

Process Complexity: The complexity of steel manufacturing involves numerous interdependent parameters, making it challenging to pinpoint specific factors contributing to variations in product quality.

Data Overload: Large volumes of data are generated during the steel production process, including information on temperature profiles, chemical compositions, and production line settings. Analyzing this vast dataset manually is time-consuming and may not reveal hidden patterns.

Defect Detection and Prevention: Timely identification of potential defects and the ability to prevent their occurrence is crucial for enhancing overall steel quality. Current methods may not efficiently detect subtle patterns leading to defects.

Operational Efficiency: Optimizing production efficiency is essential for minimizing waste, reducing energy consumption, and improving overall resource utilization. Clustering methods can aid in identifying optimal operational conditions.

Research methodology

The steel manufacturing process is known for its inherent complexity. The comprehensive technique generally involves five separate stages of activities, including iron-making, steel-making, hot-rolling, cold-rolling, and heat-treatment. The quality control of steel manufacturing is a complex undertaking that encompasses several stages throughout the process. In terms of steel quality control, neither system-level design nor the deployment of computational models provides a particularly elegant answer. The paucity of on-site actual data and the lack of domain expertise from sustained involvement in the steel sector are two of the most significant challenges. In this study, we approach the issue of forecasting steel quality control from both perspectives and provide a complete solution. The industrial system may benefit from better decision-making when large volumes of data are transformed into useful information and knowledge via the use of predictive analytics and the discovery of hidden linkages in the data.

Ensemble method

Ensemble techniques refer to learning algorithms that integrate numerous distinct machine learning models in order to enhance the accuracy of predictions. The assemblage of machine learning models may be referred to as either basic learners or weak learners. Overall, using an ensemble method has been shown to improve the overall capacity to generalize compared to using a single model. Bagging, boosting, and layered generalisation (stacking) are three often used techniques for creating ensemble systems to tackle various problem areas. Stacking is a strategy where a set of initial individual learners are combined as input for a meta-learner in order to enhance prediction accuracy and resilience.

System flowchart for Iron and steel company

The Iron and Steel Company has incorporated the ensemble approach, together with its associated data flow, into a comprehensive system under its management and operation. The design of this machine learning-based performance prediction system consists of four major layers: raw datasets, data extraction and preprocessing, data modeling and analysis platform, and steel quality control integrated systems. This architecture is shown in Figure 1.These layers are listed in descending order from the bottom to the top of the figure.

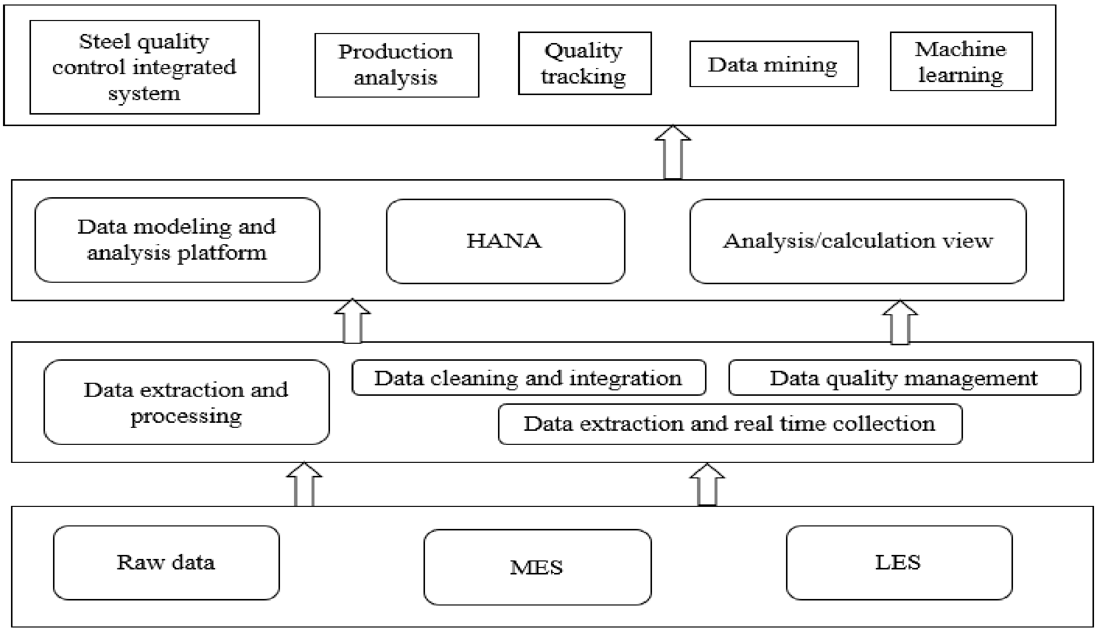


Figure1. Flowchart of system

The raw datasets consist of both historical observations and data from a manufacturing execution system (MES) and a Lab Execution System (LES). Data extraction and preparation include the scrutiny and modification of abnormal data, filling in missing information, and removing duplicate data. In order to enhance the speed at which the model converges, it is advisable to rescale the feature variables of the datasets to a range of 0 to 1, owing to the variations seen among these variables. For the purpose of extracting information from a historical dataset, the process of data modeling and analysis requires the use of Extract Transform Load (ETL) tools in conjunction with real-time gathering capabilities. After the information has been retrieved, it is then moved into a data warehouse that is based on the high-performance analytic appliance known as .

The whole steel quality control layer is formed by numerous important components, including data modeling and analysis platform, manufacturing process analysis, quality tracking, data mining, and machine learning.

2.1 Working principle and data flow in system

The development and implementation of a steel quality control system employing ensemble learning techniques has addressed the regression issue. The flowchart shown in Figure 2 provides a visual representation of the operating concepts used by the ensemble learning system. A set of tasks is performed to analyse, and engineer the data after obtaining the MES and LES data from the steel quality management system. The objective of these activities is to choose 57 specific attributes that will be used as inputs for the estimation models.

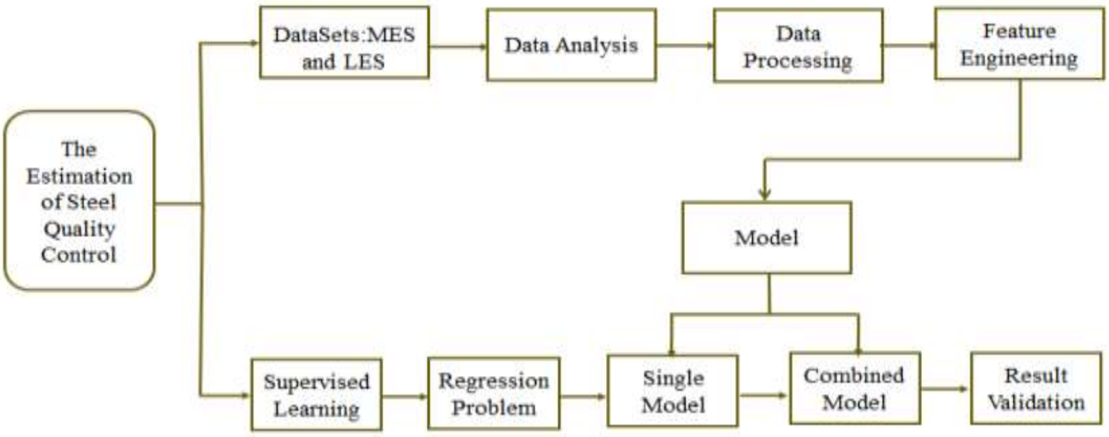


Figure 2. Flowchart of Ensemble learning system

Result and discussion

Figure 3 illustrates a comparison table that showcases the suggested approach alongside several techniques. According to the data shown in Figure 3, the Support Vector Regression (SVR) techniques achieved an accuracy of

	SVR	ELM	MLP	RFR	GBR	XGBR	STACK2	STACK1 \
Accuracy	0.931	0.942	0.961	0.966	0.969	0.974	0.977	0.977
MAE	0.202	0.183	0.149	0.133	0.125	0.120	0.112	0.112
RMSE	0.246	0.226	0.186	0.172	0.164	0.151	0.143	0.144
MAPE	0.902	0.880	0.569	0.517	0.401	0.619	0.463	0.445

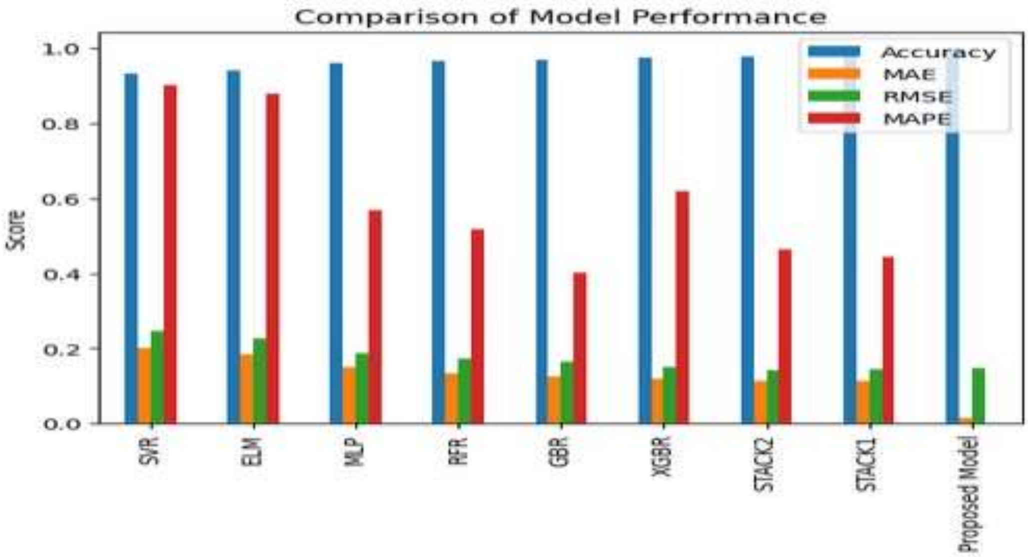
	Proposed Model
Accuracy	0.993988
MAE	0.014258
RMSE	0.148487
MAPE	NaN

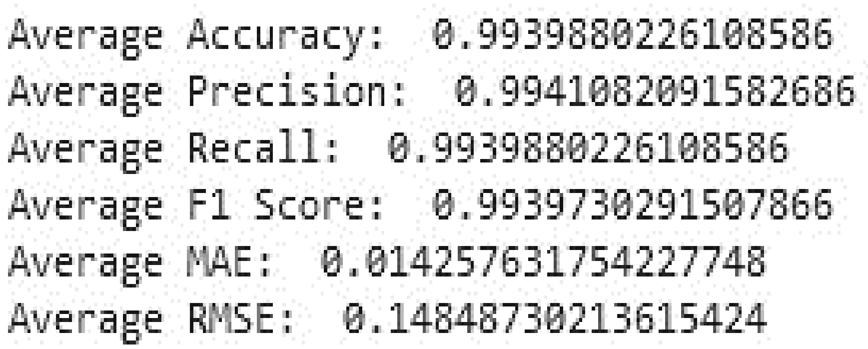
Figure 4 illustrates the comparative graph. According to the 0.931. The Mean Absolute Error (MAE) was 0.202, the Root Mean Square Error (RMSE) was 0.246, and the Mean Absolute Percentage Error (MAPE) was 0.902. The ELM approach achieved an accuracy of 0.942, significantly surpassing that of SVR. The Mean Absolute Error (MAE) is 0.183, the Root Mean Square Error (RMSE) is 0.226, and the Mean Absolute Percentage Error (MAPE) is 0.880. The MLP approach achieved an accuracy of 0.961, a mean absolute error (MAE) of 0.149, a root mean square error (RMSE) of 0.186, and a mean absolute percentage error (MAPE) of 0.569. Among the several techniques, STACK 1 achieved the highest accuracy of 0.977.

Additionally, it had a mean absolute error (MAE) of 0.112, a root mean square error (RMSE) of 0.144, and a mean absolute percentage error (MAPE) of 0.445. Hence, it is evident that the suggested approach attained a maximum accuracy of 0.993, surpassing all previous techniques and demonstrating superior performance across all parameters, as seen in Figure 4.

data shown in Figure 2, the suggested approach outperforms all existing techniques, including SVR, MLP, ELM, BR, XGBR, STACK2, and STACK1, in terms of accuracy, MAE, RMSE, and MAPE.

Figure 4. Comparison graph





Average Accuracy: 0.9939880226108586
Average Precision: 0.9941082091582686
Average Recall: 0.9939880226108586
Average F1 Score: 0.9939730291507866
Average MAE: 0.014257631754227748
Average RMSE: 0.14848730213615424

Figure 5. Outcomes of proposed method.

Figure 5 illustrates the results of the suggested strategy, as shown below. In Figure 3, the suggested technique achieves an accuracy of 0.993, precision of 0.994, recall of 0.993, and an F1 score of 0.993, as seen below.

Conclusion and future scope

This work presents a pragmatic prediction method for steel quality surveillance, using machine learning and historical observation data. The proposed method for steel quality control outperforms other baseline techniques, providing strong evidence that our prediction system is superior and more resilient in predicting steel quality. As a result of the present deployment of the steel quality prediction system, a foundation has been successfully constructed for the incorporation of technologies such as machine learning and data analytics into the actual production process. The architecture of this system has been designed to take use of advantages such as the collection of data, the creation of domain expertise, and the application of machine learning technologies. As a result, there is a substantial possibility of discovering and using a more sophisticated machine learning method in order to improve the accuracy of steel quality prediction in light of the fast accumulation of data. In the future, we will explore other approaches to combining models, including neural networks integrated with fuzzy systems. Furthermore, in the next phase, advanced machine learning techniques like deep learning will be included, taking use of the extensive data sources available. Using deep neural networks has the ability to uncover hidden information and reduce the need for manual feature engineering.

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