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"A Hybrid Model Integrating Feature Selection Methodologies"

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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

In the last ten years, there has been a notable increase in the use of artificial intelligence (AI) applications. This may be attributed to the growing popularity of emerging machine learning algorithms and technologies, particularly deep learning (DL). Since that time, machine learning has reached a level of development that allows it to be used in a wide range of disciplines, including computer vision and machine-type communications. The capacity of this technology to effectively address intricate, multi- dimensional challenges across several domains has positioned it as a significant catalyst within the Industry 4.0 movement, alongside the industrial Internet of Things [1]. With the growing implementation of digitalization in the industry, there is a shift towards converting traditional manufacturing into advanced smart factories that are highly automated. In this context, machine learning techniques play a crucial role in automating various aspects such as product manufacturing, maintenance tasks, logistical processes throughout the supply chain, warehouse management, automated quality management, and production control. These applications are widely recognised and widely adopted within the industry [2]. Numerous multinational corporations with substantial technological and financial expertise have successfully used machine learning-driven solutions to automate certain operations inside warehouses or shop-floors. Notably, these solutions include the deployment of autonomous trucks capable of moving assets without requiring any human intervention from operators.

The steel sector is well recognised for its extensive utilisation as a green material because to its high accessibility, cost-effectiveness in manufacturing, and broad application. These factors contribute significantly to its pivotal position in both everyday life and industrial production within contemporary civilization [3]. As an integral component of the domestic economy, it serves as a crucial source of essential resources for several sectors like construction, transportation, infrastructure, automotive industry, maritime operations, home goods, electrical power, and marine engineering, among others, therefore significantly impacting our everyday existence [4]. Concurrently, the steel sector is confronted with significant carbon dioxide emissions, substandard working conditions, environmental contamination, safety challenges arising from elevated temperatures and toxic gases, labor-intensive demands on workers, and repetitive tasks [5]. In response to the aforementioned concerns, prominent steel corporations have undertaken significant measures such as automation, information alteration, and updating during the last several decades. These initiatives have significantly impacted the steel industry's production efficiency and degree of automation [6].

1.1 Smart manufacturing system

The Smart Manufacturing System (SMS) is the complete digitalization of the manufacturing process, allowing for increased efficiency via such features as interoperability, real-time control and monitoring, flexible production, rapid reaction to market shifts, cutting-edge sensors, and big data

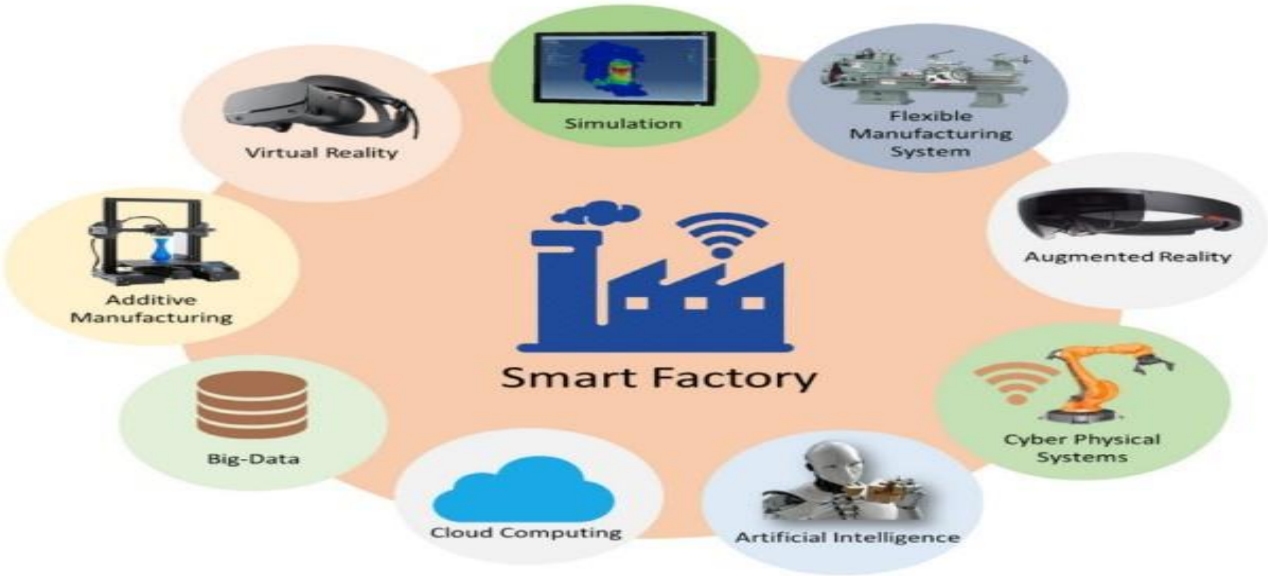


Figure 1. Component of smart manufacturing system

analytics. The SMS may function in either a semi- or completely autonomous mode. The production engineer in a semi-autonomous system establishes the system's objectives and controls its variables. In a completely automated system, the SMS determines the best settings for operation and applies them mechanically across all of the connected machines. Cost-effectiveness, optimum production and delivery time, product quality, and customization flexibility are of paramount importance to manufacturers for survival in today's highly competitive market [8]. The second issue is whether or not a production system can keep its performance at a high level in the face of new data and shifting conditions. Numerous technologies have been created to facilitate the establishment of an intelligent production system. To transform an existing system into a smart manufacturing system, technology selection may be a major challenge.

The breadth of smart manufacturing technologies has expanded as a consequence of the integration of several technologies, leading to cost efficiency, time savings, simplified configuration, enhanced comprehension, prompt responsiveness to market needs, increased flexibility, and remote monitoring capabilities. Figure 1 depicts the foundational framework of the intelligent manufacturing system.

The smart manufacturing ecosystem, as seen in Figure 2, is offered by the National Institute of Standards and Technology (NIST). This diagram illustrates the interconnectedness of many domains within the realm of smart manufacturing and delineates their respective functionalities. The presented schematic diagram illustrates the interrelationship among the enterprise's product (represented by the green arrow), production process (represented by the blue arrow), and business operations (represented by the orange arrow) within the context of their lifetime in the ecosystem.

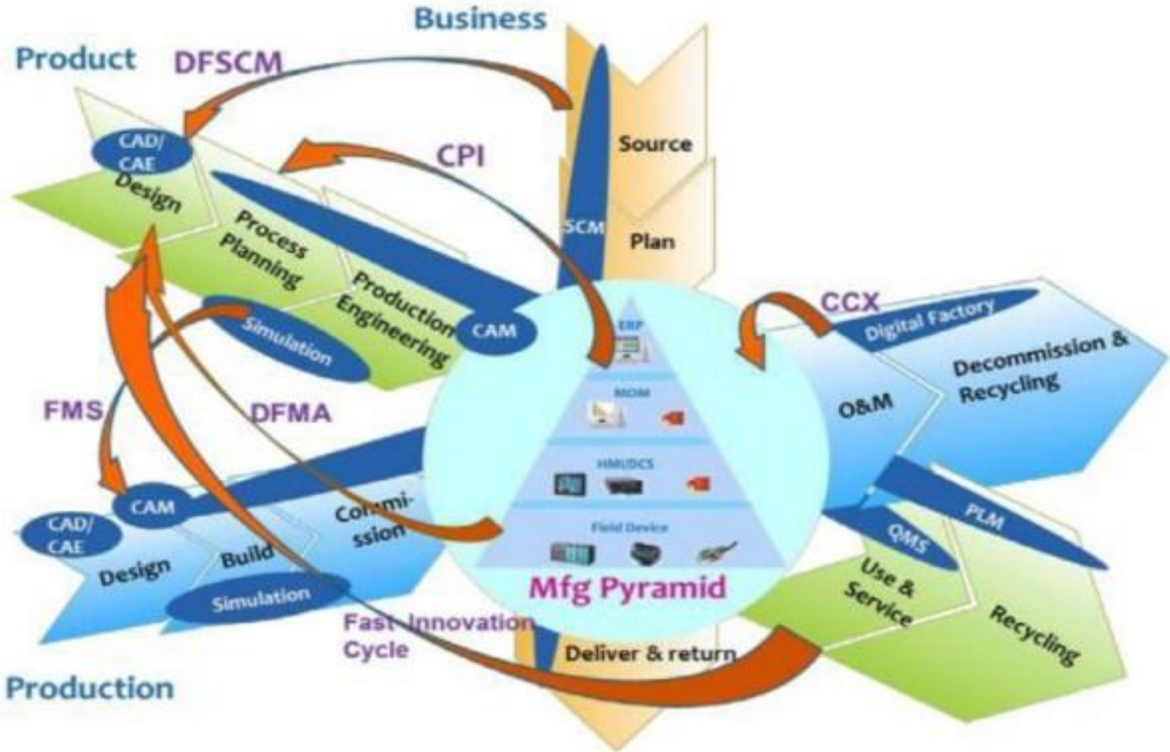


Figure 2. NIST's smart manufacturing eco-system model

The integration of digital transformation and smart technologies, which connect physical things through the internet, is emerging as a fundamental aspect of future industries. The key technological initiatives announced by prominent nations are Industry 4.0 by Germany, Made in China 2025 by China, Industrial Internet by the USA, and Society 5.0 by Japan. These technologies vary in terms of their implementation methods, target industry group, and expected timescale for attainment. However, they have a similar goal of using smart and digital technology to enhance existing production processes globally [9][10].

1.1.1 Machine learning in smart maintenance

Maintenance is a crucial activity inside every sector of the business. Unforeseen failures have the potential to result in unfavourable outcomes, such as the interruption of assemblylines or the need to rearrange logistical activities. These effects might lead to direct or indirect economic losses, such as delays in operations. The process of maintenance seems to be straightforward; nonetheless, effective and efficient maintenance encompasses a multitude of jobs, each of which contributes to enhancing the overall efficiency of the mechanism. Maintenance, in its most fundamental state, is primarily characterised by a reactive approach. Consequently, the act of preserving the optimal condition of certain tools, machinery, or equipment does not fall within the realm of maintenance. In the context of reactive maintenance, the repair of machinery and tools occurs only in response to a failure, rather than being beforehand addressed. However, there are instances when defects may not be readily apparent, resulting in the ongoing deterioration of equipment. Consequently, the use of fault detection systems becomes necessary to identify the need for maintenance. Furthermore, the use of diagnostic techniques and root cause analysis has the potential to augment the overall quality of maintenance procedures, particularly in cases when the underlying reason of failure remains unidentified and necessitates further investigation.

Contemporary maintenance paradigms, including preventive, predictive, and proactive maintenance, use distinct methodologies in contrast to the reactive maintenance approach. Preventive maintenance, as its name implies, is a maintenance strategy that prioritises the preservation of equipment and machines by regularly assessing their state of wear and tear. The optimisation of efficiency in this paradigm is accomplished by the use of telemetry, external sensors, and other condition monitoring systems to gather diagnostic data, hence minimising superfluous inspection and repairs. Predictive maintenance likewise leverages the aforementioned techniques; yet, it serves a distinct objective, namely, to forecast the occurrence of a machinery failure and so facilitate comprehensive planning of the repair process. To get accurate estimates, specific models of the monitored asset are used in order to assess its remaining useful life (RUL) [11]. The integration of proactive maintenance has resulted in the convergence of two paradigms, namely predictive and preventive maintenance. Alongside this development, the toolsets used in both approaches have also been merged. urthermore, the emergence of machine learning and the Industrial Internet of Things (IIoT) has transformed this method into a dynamic and data-centric approach.

The concept of being data-driven entails the utilisation of a substantial volume of data, which is often sourced through interconnected intelligent activities, processes, systems, or records. An illustration of this phenomenon may be seen in the increasing inclination towards the use of technologies such as Manufacturing Execution Systems (MES) like Plant floor automation and information systems (PES). This adoption has the potential to significantly enhance prognostics-based maintenance by creating a substantial volume of data [12]. The Digital Twin, a fundamental component of smart manufacturing, serves as a sophisticated, data-centric, and abstract representation of systems, hence facilitating the process of data collection and analytics. Additionally, it enhances the overall efficiency of preventative maintenance, hence reducing the risk of failure [13]. Figure 3 illustrates the significance of including smart maintenance and smart quality control inside a data-driven smart manufacturing system.

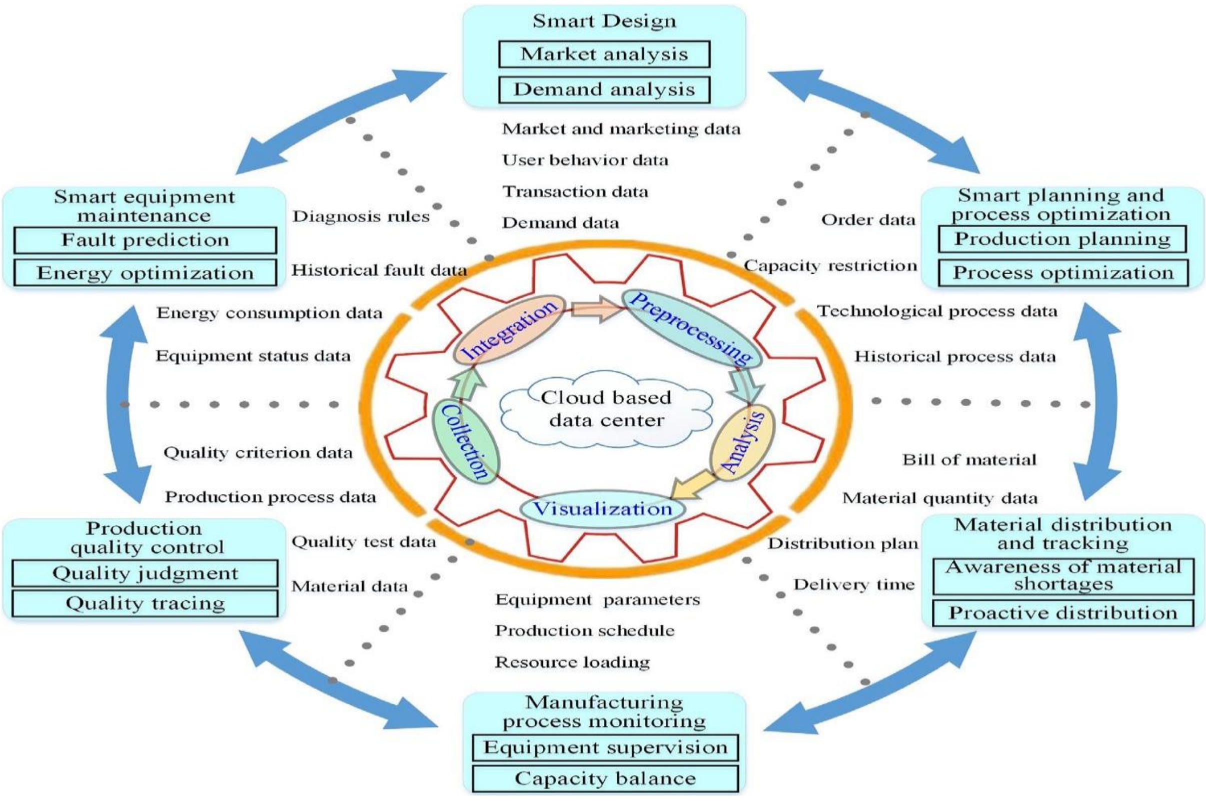


Figure 3. The role of smart maintenance and smart quality control in a data-driven smart manufacturing ecosystem

1.2 Steel rolling

Steel rolling is a metalworking process that involves reducing the thickness or changing the cross-sectional shape of a metal sheet or plate by passing it through a pair of rotating rolls. This process is commonly used to produce various forms of steel products, including sheets, plates, bars, and structural shapes. Steel rolling is essential in manufacturing industries, construction, automotive, aerospace, and more. The primary goals of steel rolling are to improve material properties, achieve precise dimensions, and enhance surface finish [14].

1.2.1 Challenges in Steel Rolling

Energy Efficiency: Steel rolling is an energy-intensive process, and optimizing energy consumption while maintaining product quality is a significant challenge.

Material Variability: Variations in raw material quality can impact the rolling process, leading to defects or inconsistencies in the finished product.

Maintenance and Downtime: Rolling mills require regular maintenance, and unexpected downtime can disrupt production schedules and increase costs.

Quality Control: Ensuring product quality and detecting defects during rolling is critical but challenging due to the high-speed nature of the process.

1.2.2 Recent Trends in Steel Rolling:

Automation and Industry 4.0: Integration of automation, IoT devices, and data analytics is transforming steel rolling plants into smart factories. Real-time monitoring and predictive maintenance help reduce downtime and improve efficiency.

Advanced Materials: The demand for high-strength, lightweight steel for automotive and aerospace applications is driving the development of advanced steel alloys and rolling techniques.Energy Efficiency: Steel manufacturers are adopting more energy-efficient processes and technologies, such as electric arc furnaces and regenerative heating systems, to reduce carbon emissions.

Digital Twins: Digital twin technology allows manufacturers to create virtual models of their rolling processes, enabling better simulation, optimization, and predictive maintenance.

Hybrid and Additive Manufacturing: Hybrid manufacturing combines traditional steel rolling with additive manufacturing techniques, allowing for the creation of complex and customized steel products.

Environmental Sustainability: Steel rolling plants are focusing on reducing their environmental footprint by implementing eco-friendly practices and recycling materials.

1.2.3 Future of Steel Rolling:

The future of steel rolling holds several exciting possibilities:

Advanced Automation: Further automation and robotics will increase efficiency, reduce labor costs, and enhance safety in steel rolling plants.

Materials Innovation: Continued research into high-strength, lightweight steel alloys will lead to the development of innovative products for industries like automotive, aerospace, and renewable energy.

Green Technologies: Adoption of green and sustainable technologies, such as hydrogen-based steel production, will help reduce the environmental impact of steel rolling.

Digitalization: The use of AI, machine learning, and big data analytics will become more prominent in optimizing steel rolling processes and improving quality control.

Customization: Steel rolling plants may offer more customization options for clients, enabling the production of tailored steel products for specific applications.

Circular Economy: The steel industry will increasingly focus on recycling and reusing steel products to minimize waste and energy consumption.

In conclusion, the steel rolling industry is undergoing significant changes driven by technology, sustainability concerns, and the need for innovation. These changes are expected to result in more efficient, environmentally friendly, and customized steel products in the future.

1.2.4 Steel rolling smart factor using machine learning

Steel rolling is a critical process in the manufacturing industry, used to transform raw steel into various shapes and sizes, such as sheets, bars, and coils. The efficiency and quality of this process are essential for the final product's performance and cost-effectiveness. Implementing machine learning (ML) and data-driven approaches can enhance the steel rolling process by creating a "Smart Factory." In this context, a Smart Factory leverages real-time data, automation, and ML to optimize production, reduce waste, and improve overall efficiency [15][16].

Here's a detailed explanation of how machine learning can be applied to create a Smart Factory for steel rolling:

Data Collection: The first step is to gather data from various sources within the steel rolling facility. This data can include temperature sensors, pressure sensors, speed sensors, motor data, operator logs, and more. Historical data is also essential, as it provides insights into past process performance and can be used for training ML models.

Data Preprocessing: Raw data collected from sensors may contain noise, outliers, and missing values. Data preprocessing techniques are applied to clean and prepare the data for analysis. Feature engineering can be performed to extract relevant features from the raw data, such as rolling speed, temperature differentials, and hydraulic pressure.

Anomaly Detection: Machine learning models can be trained to detect anomalies in real-time sensor data. Anomalies might indicate equipment malfunctions, deviations from optimal conditions, or potential quality issues. Algorithms like Isolation Forests, One-Class SVMs, or deep learning-based approaches can be used for anomaly detection.

Predictive Maintenance: ML models can predict when machinery is likely to fail or require maintenance by analyzing historical maintenance records and real-time sensor data. Predictive maintenance can help reduce downtime, extend equipment lifespan, and prevent costly breakdowns.

Quality Control: Machine learning models can be trained to monitor and control product quality by analyzing sensor data during the rolling process. For instance, image recognition techniques can be used to detect surface defects in the steel, and predictive models can adjust rolling parameters to minimize defects.

Process Optimization: ML models can optimize the steel rolling process by adjusting parameters like temperature, pressure, and rolling speed in real-time to maximize efficiency and minimize energy consumption. Reinforcement learning algorithms can be employed to find the best control policies.

Energy Efficiency: Smart factories can reduce energy consumption by using ML models to optimize equipment operation, reduce waste, and schedule energy-intensive tasks during off-peak hours.

Human-Machine Collaboration: While ML automates many tasks, human operators still play a crucial role in a Smart Factory. ML can provide real-time recommendations and alerts to operators, helping them make informed decisions.

Continuous Improvement: Data collected from the steel rolling process and the performance of ML models can be used for continuous improvement. Feedback loops ensure that the system gets better over time.

Integration: ML models and data-driven insights should be seamlessly integrated into the existing manufacturing process, with proper communication and control systems in place.

Security: Given the importance of data in a Smart Factory, robust cybersecurity measures are essential to protect against potential threats and breaches.

Creating a Smart Factory for steel rolling using machine learning is a complex endeavor that requires interdisciplinary collaboration between engineers, data scientists, and domain experts. It can lead to significant improvements in productivity, product quality, and resource efficiency in the steel manufacturing industry. However, it's crucial to carefully plan and implement these technologies to ensure they meet safety, quality, and regulatory standards.

1.2.5 Problem statement

The steel industry operates within a dynamic and highly competitive market, where accurate demand forecasting is crucial for optimizing production, inventory management, and overall operational efficiency. However, existing forecasting methods often struggle to capture the complex patterns and fluctuations in demand, leading to suboptimal resource allocation, excess inventory, and potential revenue loss. Traditional forecasting techniques, such as time series analysis and regression models, often fall short in accurately predicting demand due to their inability to capture non- linear relationships, seasonal variations, and sudden market shifts. Additionally, the inherent uncertainties and volatility in steel demand, influenced by factors like economic conditions, geopolitical events, and technological advancements, pose significant challenges for accurate forecasting. Therefore, there is a pressing need to develop a robust and adaptive forecasting framework tailored to the specific requirements of the steel industry. This framework should leverage the power of ensemble learning, a machine learning technique that combines multiple models to improve predictive accuracy and robustness. By integrating diverse forecasting algorithms, such as decision trees, random forests, gradient boosting, and neural networks, an ensemble approach can effectively capture the complex patterns and dependencies in steel demand data. Furthermore, the ensemble learning approach offers the flexibility to adapt and evolve with changing market dynamics, incorporating new data sources, and refining prediction models over time. By harnessing the collective intelligence of multiple models, the proposed framework aims to enhance the accuracy, reliability, and actionableinsights derived from demand forecasts in the steel industry. Overall, the development of an ensemble learning approach for demand forecasting in the steel industry represents a critical step towards addressing the challenges of uncertainty, volatility, and complexity inherent in predicting demand patterns. By leveraging advanced machine learning techniques, this framework has the potential to revolutionize demand forecasting practices, enabling steel manufacturers to make informed decisions, optimize resource allocation, and maintain a competitive edge in the market.

1.2.6 Research methodology

This section provides a brief overview of the materials and methodology used. No information provided. The proposed framework is shown in Figure 4. These are the main stages in our proposed framework: 1. Gathering industrial environmental data for the framework. 2. Preprocessing the data by filling missing values, and standardization. 3. Removing irrelevant and redundant features to prevent overfitting. 4. Using grid search algorithm with cross validation to tune hyperparameters for each machine learning model. 5. Creating a two-level stacking ensemble method using machine learning models with optimal hyperparameters as the baseline. 6. Utilising evaluation metrics to assess the proposed framework. The blocks will be detailed in the subsequent sections.

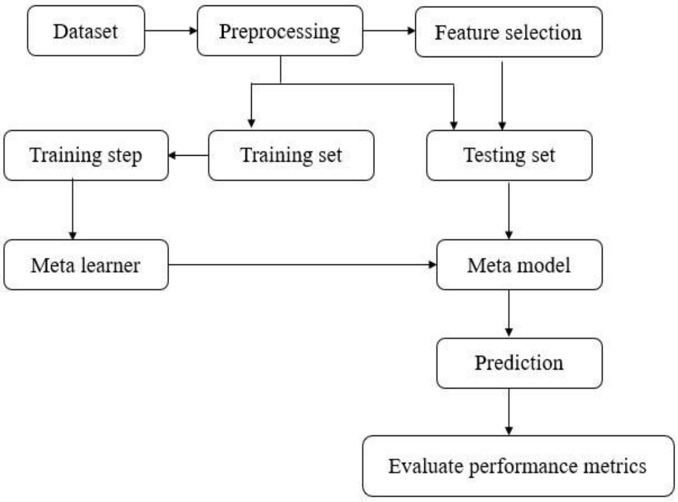


Figure 4. Proposed framework

1.3 Typical models for Intelligent manufacturing of steel industry

1.3.1 Rolling Process Intelligent Manufacturing Model

The presence of information islands in the country's rolling steel production lines is primarily attributed to the inadequate implementation of big data technologies and the absence of a comprehensive big data control system that encompasses the entire production process. This deficiency can be attributed to the lack of inspection and testing technology, automation, and intelligent manufacturing equipment. Consequently, the rolling process exhibits little automation and intelligence, leading to elevated labour expenses and reduced labour productivity. Additionally, the quality control, testing, and traceability systems are inefficient, contributing to a significant number of defective products.

Taking consideration of the aforementioned problems, the following aspects are prioritised in intelligent manufacturing for the rolling process. To begin, the rolling mode uses cutting-edge tools like intelligent robotics and data integration from the industrial Internet's hybrid model and data analysis. Then, they used technologies like robots, unmanned storage for slabs, and sophisticated inspection and monitoring of the whole process. The major goal was to maximise material and energy efficiency, process control, and employee output. An increase in the use of intelligent control, predictive and early-warning forward-looking reaction, and multi-objective optimisation in business cooperation has led to improved manufacturing stability and flexibility of the hot-rolled production line, as well as decreased manufacturing costs.

1.3.2 Steelmaking and Rolling Process Intelligent Manufacturing Model

A smart manufacturing model for steelmaking and rolling encompasses not just the rolling procedure but also the smelting and refining of steel as well as continuous casting. Currently, the primary concerns that require resolution in relation to the country's steelmaking and rolling processesare outlined below. Insufficient automation, informatization, and intelligence are seen in the steelmaking system due to the presence of an inaccurate regulating model throughout the smelting process. In addition, it should be noted that several crucial operational parameters, including the composition of flue gas, temperature of molten steel, billet temperature, composition of molten steel and slag, and presence of internal impurities in the casting blank, are not promptly and accurately detected in real-time. As a result, the refining models fail to establish an effective closed-loop control system.

The online detection of essential operational parameters and the quality of hot and cold rolled components is currently inadequate, which poses challenges for unmanned or less humanised equipment and workshops. The lack of intelligent packing, smart grind roller room, intelligent slab storage, and intelligent final product storage systems is the main contributing factor to this issue. Furthermore, the achievement of intelligent robot operation in situations characterised by high repeatability, high risk, and labour loss has not yet been realised. Furthermore, it should be noted that the process of product development is characterised by its extensive duration and substantial expenses. A significant portion of these endeavours heavily relies on trial-and-error methodologies. Additionally, it is worth mentioning that there is a limited availability of simulation systems and tools that effectively integrate various simulation techniques. In summary, the equipment management information system encompasses many date islands and exhibits a degree of data and function overlap among its various systems.

The implementation of the intelligent manufacturing project is recommended for the steelmaking and rolling model in order to facilitate industrial structure adjustment. This approach emphasises innovation-driven development and aims to achieve the seamless integration of informatization and industrialization. By addressing the issue of data isolation among different procedures, it is anticipated that the project will enhance the global standard of quality control and production management.**Intelligent sensing system:** The surveillance of crucial process parameters, such as those pertaining to steelmaking converters, refining furnaces, continuous casting ladles, and continuous casting machines, plays a vital role in enhancing the control model's optimisation and augmenting its level of intelligence. Commonly utilised in manufacturing processes are sensors, intelligent cameras, radio-frequency identification, and gateways. These technologies are integrated with key advancements such as high-temperature heat pipes, image recognition, and voice recognition. This integration enables the creation of a comprehensive compilation of production data, encompassing equipment data, product identification data, and factory environmental data. The purpose of this compilation is to fulfil the need for real-time awareness of the manufacturing process, operating data, and the status of critical equipment. In order to enhance the transmission of real-time sensor data, it is imperative to equip the system with high-performance network equipment that possesses a substantial system capacity, a high transmission rate, multiple fault-tolerant mechanisms, and low latency. Additionally, the utilisation of decentralised industrial control networks, the establishment of software-defined agile networks, and the achievement of network optimised resource allocation are crucial steps towards achieving this object.

A. Centralized monitoring and controlling system: The aim of this study is to develop a complete monitoring system for the production line by combining the control systems of crucial stages in the steelmaking and continuous casting processes. These stages include the converter area, refining area, continuously casting area, heating furnace region, and rolling area. This system will be built upon data collecting and analysis. This system offers the capability to monitor the production process in real-time, enabling remote centralised control of equipment and providing alerts for abnormal situations. As a result, it reduces the need for on-siteoperators and inspection employees, therefore decreasing labour intensity and ensuring product safety.

B. Production management and intelligent scheduling system: In order to achieve real-time monitoring, balance cooperation, and decision-making capabilities, it is necessary to establish a production organisation and intelligent scheduling system. This system should be based on factors such as raw and fuel conditions, equipment status, and field-of-view requirements. It should encompass various functions including plan execution, resource utilisation, statistical analysis of output and quality, optimal scheduling of stable operating conditions, dynamic scheduling of abnormal operating conditions, as well as additional scheduling of production and decision-making functions.

C. Intelligent device administration system: The monitoring, tracking, and maintenance of equipment life-cycle states should be initiated from the outset of equipment planning, design, manufacture, procurement, installation, operation, maintenance, upgrading, transformation, and scrapping phases. Subsequently, a comprehensive database pertaining to equipment status should be established by the use of advanced technologies such as big data analysis, artificial intelligence, and virtual reality. The primary objective of this endeavour is to develop a simulation model centred on the core equipment, enabling the timely detection, alerting, and prediction of equipment failures. In conclusion, it is imperative to establish a universally standardised system for gathering and managing information, as well as implementing an automated diagnostic system. Additionally, the development of a fault prediction model, using an expert system, and the creation of a comprehensive knowledge base consisting of fault indexes are essential components of this endeavour. The proposed system aims to achieve remote unmanned control, early detection of hazardous working conditions, monitoring of operational status, fault analysis, and self-repair capabilities.

D. Quality controlling system: The concept of quality management pertains to handling of information, necessitating the establishment of a quality management system that encompasses the maintenance of quality standards, monitoring of quality, conducting inspections and laboratory testing, doing statistical analysis, and optimising quality. The integration of product quality and operation parameters across the whole product production process is achieved via the use of big data analysis and machine-learning techniques. This enables the online assessment of product quality and facilitates the study of quality traceability throughout the entire process. This study aims to examine the key quality features in the steelmaking and rolling processes. By using online statistics, diagnosis, prediction, analysis, and optimisation techniques, it is possible to enhance the stability of the final product quality.

E. Process simulation and prediction system: The substantial output variation and challenging exact control make it hard to coordinate this process, which is already complicated by the current state of the steelmaking technique. First and foremost, when paired with experienced knowledge of the smelting process and on-site operating experiences, the value of the production database is profoundly dug. Statistical analysis, machine learning, big data analysis, and other technical means are used to establish an empirical model of the metallurgical process; the model generalisation ability is continuously improved through model training; the smelting production experience is mathematically expressed; and the artificial intelligence ingredients related to the decision optimisation system are built to achieve the operation guidance and prediction of the actual production. The equipment involved in the converter method of steelmaking is then subjected to extensive simulation calculations including fluid mechanics, chemical reaction, heat and mass transport, and other simulation calculations utilising a combination of a mechanism model and a data model. Similar attention should be paid to developingsimulation models for the melting, continuous casting, and rolling stages of production. Finally, the real-world steel process communicates with the virtual system in real time, which has the potential to optimise the parameters of production operations throughout steelmaking and rolling.

F. An early warning system for employee safety: The comprehensive procedure for monitoring and overseeing workers' visits to the production regions should be established via the utilisation of satellite location, Wi-Fi, 5G, and other communication technologies, alongside intelligent wearable devices. A personnel management system ought to be developed with the capability to autonomously perceive and acquire fundamental personnel information, personnel whereabouts, safety status, operational details of the surrounding environment, statistical analysis of operational data, and real-time monitoring of personnel location trajectory and position status. The system may run without human intervention and show alarm data and related monitoring panels. As soon as it detects that you've entered a potentially dangerous region, it may send a notification to your phone or any predetermined locations. With online monitoring, intelligent analysis, and linked alerts, it may also identify irregularities in critical equipment, significant danger sources, and other scenarios, helping to keep workers safe.

1.4 Key technologies for intelligent manufacturing in steel industry

1.4.1 Online Detection Technologies

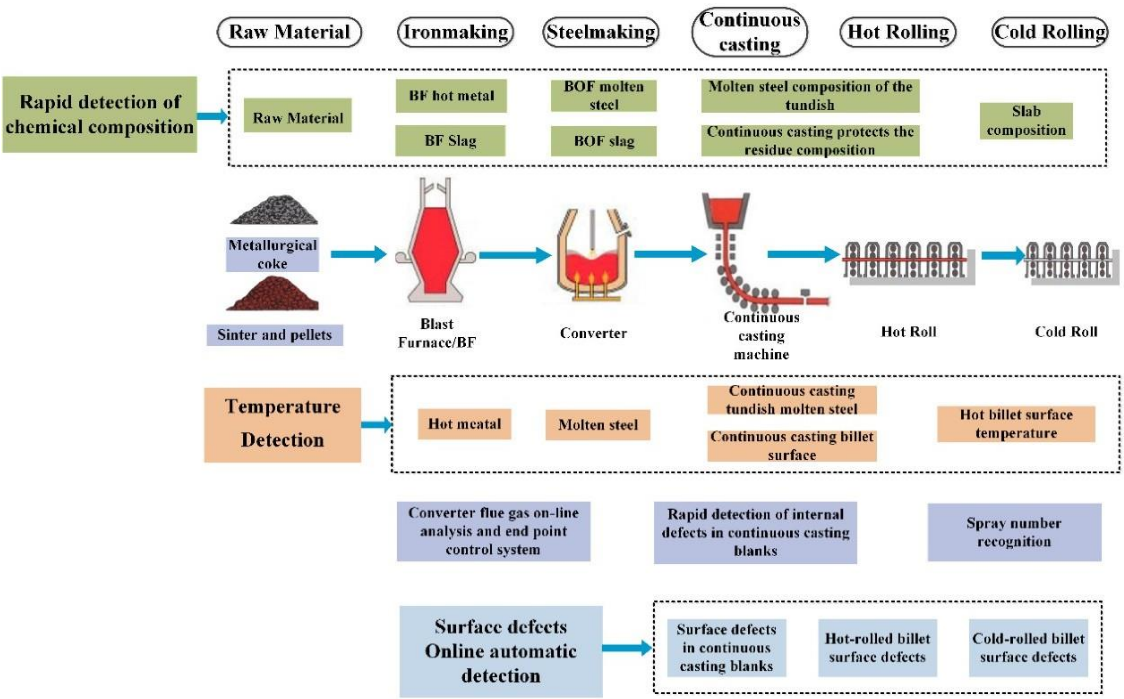
Online detection in steel firms has an impact on accuracy and intelligence control [17]. One primary concern is to the timely identification of essential parameters within the production process, necessitating a dependence on expert knowledge and occasional reliance on batch-quality occurrences for smelting control. One of the primary concerns is to the absence or outdated nature of terminal product quality detection systems. Consequently, this inadequacy leads to diminished productivity and challenges

in effectively guaranteeing the quality of intermediate or semi-finished steel products [18][19]. One notable concern is to the timeliness or absence of fundamental data detection for the purpose of intelligent transformation. This deficiency leads to a dearth of essential parameters inside both the quality control system and the big data platform.

The identification of crucial characteristics within the steel industry is essential for steel manufacturers to ensure the quality of their products and enhance the efficiency of production processes. At now, the existing detection methods are limited to assessing the aesthetic attributes of steel goods, namely their dimensional accuracy, plate form, and surface imperfections. The analysis of hot metal and slag compositions in ironmaking and steelmaking processes has traditionally been conducted offline. However, the evaluation of tissue performance and internal quality of steel products has been challenging due to the absence of a complete cycle of quality control. Simultaneously, several crucial characteristics within the steel industry elude online detection, including the particle size and compositions of raw materials, the temperature and compositions of high- temperature liquid slag, and temperature measurements [20], surface and internal defects of high-temperature plate strip, gas composition, automated detection of billet spraynumber characters, and product size. Moreover, a significant portion of detection tests lack standardization, and the steel sector, like other domestic steel industries, has the challenge of meeting specific production standards and ensuring product quality characteristics in relation to testing technology.

Figure 5 depicts the various online detection systems that are used within the steel sector. The current trend in the development of detection technology involves the utilisation of sophisticated modern detection technologies, such as machine vision [21][22][23], laser-induced breakdown spectroscopy (LIBS), ultrasonic microscopy technology, and others. These technologies are combined with deep-learning algorithms and statistical modelling theory to enable the application or advancement of intelligent perception technology in the production line. This allows for the online or rapid detect [24][25]. The primary objectives of online detection technologies in the steel industry are to facilitate intelligent management and optimise processes, enhance the of end products, augment labour productivity, minimise labour expenses, and furnish essential foundational data for quality control and big data platforms.

Figure 5. Online detection technologies used in steel industry



1.4.2 Quality Controlling Technology for the Entire Procedure of Steel Industry

The quality control system in the steel sector serves as a platform for enhancing quality, design, research, and optimisation. It effectively integrates various processes involved in steel production, captures comprehensive data throughout the manufacturing process, and performs other functions. The achievement of capturing production process data in a high-precision and real-time manner is facilitated, ensuring that the data collection variables and frequency requirements align with the expectations set by the corporate entity. This is made possible via the integration of the firm's current data acquisition system. The following are some of the most important advantages of quality control technologies across the board in modern steel production [26]. To begin, the steel sector will have access to online product quality grading, digital scoring values, and product quality grades, as well as a crucial production process parameter and product quality monitoring [27]. By developing a model for predicting product quality, it becomes conceivable to notice and get notifications about prospective quality issues that may be difficult to uncover using online means. Additionally, this enables the timely implementation of pre-control measures. In addition, it is imperative to promptly propose flow control recommendations for steel goods exhibiting potential quality issues or procedural deficiencies. This proactive approach is crucial in preventing the inclusion of substandard products in subsequent production lines, thereby ensuring consistent product quality throughout each production phase via effective quality control measures [28]. The present system is capable of gathering data from many stages of themanufacturing process, as well as collecting different process data from related processes. Furthermore, it has the ability to automatically identify and recognise such data. Ultimately, it is essential to initiate data analysis and process improvement efforts, using sophisticated algorithms to evaluate the efficacy of both the method and the quality of the final output. This approach enables the identification of vulnerable areas within the control and process, thus establishing a comprehensive framework for optimising and enhancing the whole process.

Figure 6 illustrates a schematic representation of the architectural framework used for quality control systems within the steel sector. The comprehensive architectural layout of the system entails the division of the full process quality control system into online and offline applications. The web programme mainly serves the purpose of collecting, monitoring, issuing early warnings, and doing analysis, with specific features tailored towards on-site quality inspectors and process personnel. This highlights the significance of the system's ability to analyse data in real- time and its timeliness. It offers near real-time manufacturing process parameters, determination of quality parameters, and early warning information to operators and quality inspectors present on-site, hence enhancing operational efficiency. In contrast, offline application entails the utilisation of sophisticated analysis and application methods that are rooted in the product manufacturing process. This approach places emphasis on comprehensively integrating and analysing quality data throughout the manufacturing process, taking into account various factors such as product manufacturing procedure parameters, quality target parameters, quality inspection, and traceability. The ultimate goal is to address challenges related to cross-process issues, product manufacturing process systems, and technical specifications.

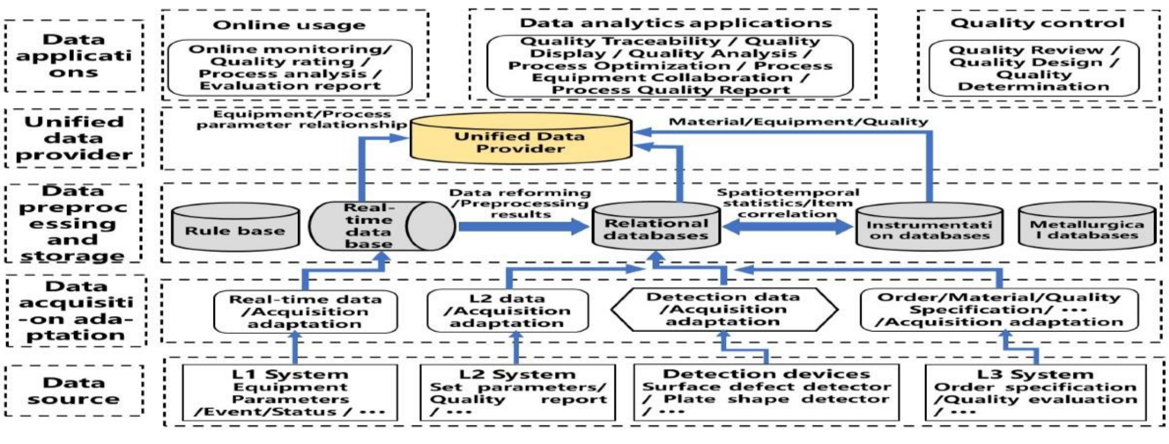


Figure 6. Architecture of quality control technologies in steel industry

1.4.3 Intelligent machinery

The widespread adoption of intelligent machinery, equipped with self-detection, self-diagnosis, and self-regulation capabilities, is highly recommended [29][30][31]. This is particularly crucial in hazardous positions characterised by high temperature, high coal gas, and repetitive labour, in order to ensure precise control during ironmaking and steelmaking processes. By doing so, it is possible to reduce the physical strain on workers, enhance production efficiency, and maintain consistent quality. The intelligent equipment used in the steel sector primarily focuses on four key factors [32].

A. Intelligent logistics equipment, such as an AGV (automated guided transport vehicle), unmanned elevators, intelligent roller rooms, intelligent three- dimensional factories, and flat storage facilities;

B. Industrial robots including automatic slag fishing robots, automatic slag cleaning robots, intelligent temperature measurement robots, intelligent inspection robots, automatic baling robots, automatic coding robots, automatic alignment devices, automatic loading and unloading devices, and automatic welding devices;Intelligent detection equipment, which includes, in addition to the previously mentioned key component detection technology, intelligent monitoring of personnel safety, intelligent monitoring of safety facilities, and intelligent monitoring of equipment operational status; eddy current flaw detector; particle detector; thickness gauge; convexity meter; plate roller; and product contour detection device;

C. Advanced control technology, one-key intelligent control technology of steelmaking, converter automatic steel production technology, refining process automatic control system, plate-type intelligent control

Technology and other process intelligence and refined control technology.

2. Feature selection

Feature selection or reduction eliminates unnecessary, redundant, or partly significant information that might lead to inaccurate model predictions, since the performance of a machine learning model is influenced by the features it has been trained on. Feature reduction decreases the risk of over fitting by eliminating duplicate features and simplifying the model. Various feature selection or reduction approaches are available. We used PCA, ICA, and correlation-based feature selection methods in our strategy to eliminate irrelevant characteristics [44]. PCA is often used because of its

versatility and simple implementation. PCA operates by transforming data into an orthogonal space where the eigenvectors with the highest eigenvalues retain the most data variance. PCA is a method that emphasises the covariance matrix and second-order statistics. ICA breaks down observed data into linearly independent components.

Algorithm 1: Steps for the implementation of principal component analysis (PCA).

Input: m– dimensional input data matrix $X \in \mathbb{R}^m$ with number of samples N, and variance threshold T_{var}
Output: reduced L– dimensional data matrix $Y \in \mathbb{R}^L L < m$,
Load $X \in \mathbb{R}^m$, and calculate mean for each feature, $\mu_j = 1/N \sum_{i=1}^{N} X_{ij}$ for $j = 1, 2, \ldots, m$; subtract the mean from each corresponding dimension, $X_{ij} = X'_{ij} - \mu_j$ for $j = 1, 2, \ldots, m$ and $i = 1, 2, \ldots, N$;
/ * Make each signal uncorrelated to each other * /
Calculate covariance matrix of X', $\sum_{m\times m} 1/N - 1[X']^T = X'$;
Solve the $\sum_{m\times m}$ as $\sum_{m\times m} = V^{-1}DV$, where $V \in \mathbb{R}^m$ is the matrix of eigenvector and $D_{m\times m}$ is the diagonal matrix containing eigenvalues on both sides of the diagonal matrix ;
Sort the eigenvector matrix V in the descending order to the first L– eigenvector that have variance $\geq T_{\text{val}}$ and form a projection matrix $P_{m\times L}$;
Finally, project on the PCA space, $Y = P^T X$;

Algorithm 2: Steps for the implementation of independent component analysis (ICA).

Input: m- dimensional input data matrix $X \in \mathbb{R}^m$ with number of samples N, and variance threshold T_{var}
Output: reduced L- dimensional data matrix $Y \in \mathbb{R}^L L < m$,
Select a nonquadratic nonlinear function g;
Initialize W as $X = WH$, where $W \leftarrow$ ratio of source during mixing, $H \leftarrow$ matrix contains different components, and $X \leftarrow$ mixed output;
Perform PCA on X, as $X \leftarrow \text{PCA}(X)$ as in Algorithm 1;
while W changes **do**
  Update $X \leftarrow E\{Xg(W^T X)\} - E\{g'(W^T X)\}$;
  Normalize $X \leftarrow W/\|W\|$;
Derive the new dataset by taking $Y = W^T X$, where $Y \in \mathbb{R}^L$;

2.1 Hyperparameter determination

Hyperparameters are variables that directly influence the learning process of machine learning algorithms and may be changed by the user before training begins. Choosing the right values is crucial for creating the optimal and high- quality model. Optimizing the model by selecting the appropriate values is referred to as hyperparameter

optimization or hyperparameter tuning. Grid search and random search are popular methods for optimizing the hyperparameters of an estimator. The research used the grid search approach with cross-validation to get very accurate predictions [45]. The method divides the range of parameter values to be updated into a grid and calculates the best parameters at each location. Various parameter combinations were assessed for each model, and they were separated into training and test sets using the cross-

validation technique.

2.2 Cross-validation in time series

Cross-validation is a commonly used method for optimizing hyperparameters and evaluating the performance of machine learning algorithms [46]. Various parameters need to be specified for each scenario based on the dataset. Utilizing a grid search strategy together with cross-validation is efficient in determining the best hyperparameter

combination for each model. Therefore, reducing forecasting errors in test samples may help identify the optimal set of hyperparameters that improve predictive accuracy while reducing model overfitting [47]. Leave-one- out cross-validation is suitable for handling time series data in this context. This approach may also be seen as a sequential block cross-validation process, which is a subset of K-fold cross-validation. The training set is incrementally built while using both the training and validation sets simultaneously, a technique referred to as rolling cross- validation. The technique is repeated several times, with each iteration including an increase in the number of observations in the training set and a decrease in the validation set. The training set consists of observations that occurred before to the observation in the test set. The dataset is divided into training and test sets, with 70% of the data allocated for training and model validation. The time series split involves dividing the training set in half at each iteration, with the validation set positioned ahead of the training split. The model is first trained on a small portion of data to predict the next data point. The predicted data points are added to the next training dataset, and then more data points are forecasted. This technique is iterated until the whole training set has been used. Estimate the training result by evaluating iteration performance evaluations.

2.3 STACK Ensemble method

STACK modelling included two stages: level 0 where predictions from the base learner are made, and level 1 where these predictions are coupled with the meta-learner. Previous research have shown the usage of support vector regression (SVR) and selection operator (LASSO) regression as the meta-learner. SVR, particularly layer-1 in

he STACK approach, offers significant benefits by detectingpredictor nonlinearities and using them to enhance demand projections. We used a Support Vector Regression (SVR) model with a linear kernel and the selection operator LASSO for meta-learning in our experiment at level 1.

Support vector regression (SVR) method

SVR is a machine learning algorithm used for regression tasks, particularly in cases where traditional linear regression models may not be effective due to non-linear relationships between variables or noisy data [48]. SVR is an extension of Support Vector Machines (SVM) and is mostly used for classification purposes. SVR aims to identify a hyperplane (or several hyperplanes in higher dimensions) that optimally fits the data by maximising the margin between the hyperplane(s) and the data points. SVR differs from standard regression models by focusing on minimising the departure of predicted values from a given margin, rather than minimising the error between predicted and actual values.

Extreme learning machine (ELM)

ELM is a machine learning method designed as a rapid and effective learning procedure for single-hidden layer feedforward neural networks (SLFNs). ELM differs from conventional neural networks by randomly setting the weights between input and hidden layers and then determining the weights between hidden and output layers by analytical calculations, instead of adjusting them repeatedly using techniques like backpropagation [49]. This unique approach makes ELM particularly fast and efficient for training, as it does not involve iterative optimization processes.

The working procedure of the stacking ensemble in this

Input: Input dataset $D = \{X_i, y_i\}_{i=1}^{m}$, where $(X \in \mathbb{R}, y \in Y), \Theta_{set}$ is the set of optimal hyperparameter for each based regression model, M is number of based model T.
Output: final forecast demand level $\hat{Y}_f$ and performance indices.
Step 1: learn first-level base regression models;
/ * Loop for train and evaluate the first-level individual /regressor *
for $t \leftarrow 1$ **to** T do
  Divide the dataset D into D^{train} and D^{test};
  / * 70% data for training and validation, 30% for test set * /
  / * Leave-One-Out Cross-Validation * /
  for $i \leftarrow 1$ **to** K ($K \leftarrow$ size of D^{train}) **do**
    $D_i^{val} = D^{train}(i, :) \Rightarrow D_i^{train} = D^{train} / D_i^{val}$;
    Train M_t with optimal hyperparameter set Θ_{set} on D_i^{train};
    Predict the demand level for M_t with D_i^{val}: $h_t \leftarrow M_t(D_i^{val})$;
Step 2: create a new dataset from D;
for $t \leftarrow 1$ **to** T **do**
  Create a new dataset $D'_{m \times l} = \{X'_i, y_i\}$ for meta-regressor,
  Where $X'_i = \{h_1, h_2, \ldots, h_t\}, h_t \leftarrow$ output of i^{th} model, $l \leftarrow$ number of based model;
Step 3: learn second-level regressor model;
/ * Loop for train and evaluate the final-level meta-regressor model
* /**for** $j \leftarrow 1$ **to** K ($K \leftarrow$ size of D^{train}) **do**
  $D_j'^{val} = D'^{train}(j, :) \Rightarrow D_j'^{train} = D'^{train} / D_j'^{val}$;
  Train the meta-model H_{meta} with $D_j'^{train}$ using Θ_{set};
  Predict the demand level for H_{meta} with $D_j'^{val}$;
Test set D'^{test} are used for the prediction and performance measure $(P_{H_{meta}})$ using H_{meta}
return $P_{H_{meta}}$;

paper is described in algorithm 3.

Algorithm 3: Demand forecasting using Stacking Ensemble techniques using cross-validation.

2.4 Performance metrics

Assessing the accuracy of a model is essential in developing machine learning models to determine the effectiveness of the model's predictions. The study's performance indicators, including MAE, RMSE, R2, and MAPE, are outlined below.

Mean absolute error (MAE)

MAE stands for mean absolute error. Because the prediction error can be positive or negative, the average total value of the error is used to avoid the cancellation of positive and negative mistakes.variable. R^2 is used to evaluate the scattered data about a fitted regression line.

$$R^2 = 1 - \frac{SS_{res}}{SS_{total}} = \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \mu)}$$

(3)

As shown in Equation (3), where SS_{res} is the sum of squares of residuals, SS_{total} is the total sum of the square, y_i is the true value, $\hat{y}_i$ is the prediction value, and μ is the mean.

Mean Absolute percentage error (MAPE)

The accuracy is often expressed as a ratio using the formula: At/Ft, where At is the actual value and Ft is the prediction value. Their discrepancy is calculated by dividing the difference by the actual value At. Calculate the total of the absolute values of this ratio for each projected time point and then divide by the number of fitted points, $MAE = \left(\frac{1}{n}\right)\sum_{i=1}^{n}|(|x_i - \hat{x}_i|$

(1)

$$M = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$

As can been seen in Eq.1, where n is the number of observations, xi represent the true value, while $\hat{x}_i$ represent the prediction value.

3. Result and discussion(4)

Root mean square error (RMSE)

In order to predict performance more accurately, we use the root-mean-square error (RMSE) evaluation model determine the standard error through the prediction results as shown in Eq. 2:

(2) $$RMSE = \sqrt{\frac{\sum(x_i - \hat{x}_i)^2}{N}}$$

Generally, RMSE is commonly used for evaluating the quality of predictions. As we can see in Eq.2, where n is the number of the participating samples, x_i is the real value while $\hat{x}_i$ is the predicted value.

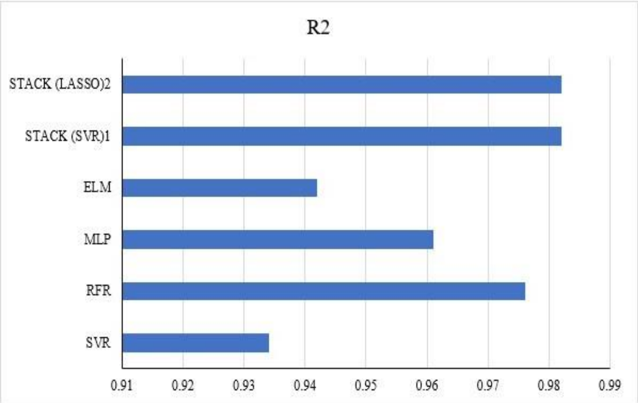
R^2 score

It is also known as the coefficient of determination which expresses the amount of variance in the dependentTable 1 outlines each model's ability to achieve the greatest R2 utilizing the recommended pipeline, as well as shown in Figure 2. Table 1 displays the optimized hyperparameters determined by grid search. SVR method attained the R2 is 0.934, RFR method achieved R2 is 0.976, MLP method obtained R2 is 0.961, which is higher than to SVR, but STACK (SVR)1 and STACK(LASSO)2 achieved maximum R2 is 0.982 and it is higher than to other methods.

Table 1. Performing ML model and preprocessing with the highest possible accuracy (R2).

Models	R2
SVR	0.934
RFR	0.976
MLP	0.961
ELM	0.942
STACK (SVR)1	0.982
STACK (LASSO)2	0.982

Figure 7 depict the comparison of various algorithms based on R2, as shown below. In Figure 7, the suggested



technique achieved maximum an R2 of 0.988, as compared to all other methods.

Figure 7. Comparison of various method based on R2

Table 2 outlines the performance indicators, such as R2, MAE, RMSE, and MAPE, used to assess each model. Table

2 indicates that the ensemble learning methodologies yielded results aligned with the goal of minimizing error during the test phase.

Table 2. Comparing stacking ensemble model with the best performing ML models

Models	R2	MAE	RMSE	MAPE
SVR	0.931	0.202	0.246	0.902
ELM	0.942	0.183	0.226	0.880
MLP	0.963	0.149	0.193	0.579
GBR	0.972	0.138	0.173	0.524

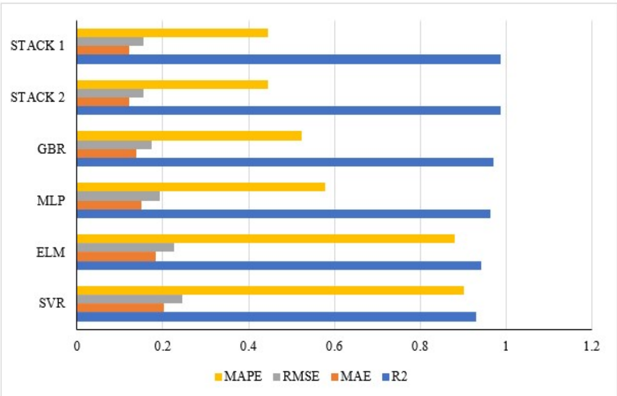


Figure 8 illustrates the results of the suggested strategy, as shown below. In Figure 8, the suggested technique achieves an R2 of 0.988, MAE of 0.122, RMSE of 0.154, and an F1 MAPE of 0.446, as seen below

Figure 8. Comparison of stacking methods

4. Conclusion

This research concludes that an ensemble learning technique is beneficial for demand forecasting in the steel sector. Through ensemble approaches, we have enhanced accuracy and dependability by leveraging the capabilities of several forecasting models, surpassing the performance of individual models. The ensemble learning architecture adeptly captures the intricate and ever-changing demand patterns in the steel sector. This study provides steel makers with a valuable tool to enhance inventory management, production scheduling, and resource allocation by using more precise and dependable demand projections. The suggested preprocessing approach enhances the quality of the raw dataset by addressing missing values and standardizing the data. PCA and ICA reduce duplication between features, whereas correlation-based feature

selection may increase correlation between features. Hyperparameters are fine-tuned to find the optimal configuration for each machine learning technique using a grid search algorithm. The best-performing models are combined in STACK1 to generate level 0. SVR with linear kernels and LASSO regressions are used as meta-learners in the first stage. Ensemble approaches, especially the STACK model, outperform individual models in forecasting steel industry demand, as shown by the test set outcomes.

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