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Prediction of Sinter Productivity Utilizing Deep Learning Frameworks: A Multivariate Analysis

SVS Raja Prasad, Rambabu Mukkamala*, Vishnu Namboodiri

School of Energy & Clean Technology, NICMAR University of Construction Studies, Shamirpet, Hyderabad, Telangana State, India

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ABSTRACT

The productivity of a sinter machine is a key techno-economic factor in steel plant operations. It depends on the precise composition of several constituents agglomerated to form sinter for blast furnaces. Understanding the interrelationships between these constituents and their effects on sinter productivity presents opportunities for improvement, and innovative methods can enhance impact assessment beyond traditional experimentation. This paper explores the application of deep learning (DL) methodologies to improve sinter plant productivity prediction. By gathering industrial data from an integrated steel plant, this study provides insights for optimizing operational efficiency. The methodology employs Long Short-Term Memory (LSTM), Bi-directional LSTM (BiLSTM), and Convolutional Neural Network BiLSTM (CNN-BiLSTM) to forecast productivity using sixteen input parameters. Results are compared with baseline machine learning (ML) models: Random Forest (RF), Support Vector Machines (SVM), and Extreme Gradient Boosting (XGBoost). The novel CNN-BiLSTM architecture outperforms baseline models, achieving a Mean Absolute Error (MAE) of 0.0239 $T/m^2{\cdot}hr$, Mean Squared Error (MSE) of 0.0009 $T/m^2{\cdot}hr$, Root Mean Squared Error (RMSE) of 0.0301 $T/m^2{\cdot}hr$, and R^2 of 0.8982. Evaluation metrics are statistically validated using the Diebold-Mariano (DM) test.

Keywords: Sinter plant, productivity, deep learning, parameters, evaluation metrics.

1. Introduction

The efficiency of sinter plants critically determines blast furnace productivity, which directly influences overall steel plant efficiency. Enhancing the operations of the sinter plant is essential for improving the comprehensive productivity of steel production facilities. In response to this, many steel producers are proactively integrating cutting-edge automation technologies into their sinter plants as part of their modernization initiatives. This strategic approach not only enhances operational performance but also positions these producers for greater success in the industry. Researchers and engineers are dedicated to improving sinter plant operations, as advancements yield significant techno-economic benefits (Arpit et al. 2021).

One of the primary challenges associated with the sintering process is the degradation of the chemical quality of iron ores, which can have a detrimental effect on the quality of the produced sinter. To address this issue, the parameters of the sintering process have been optimized through the application of ML algorithms and a simulated annealing algorithm with an objective to enhance sinter productivity and improve the overall effectiveness of the process (Karina and Flávio 2024). The ability to predict sinter productivity is a vital resource for identifying potential losses and enhancing the operational efficiency of the sinter plant. It is imperative for sintering plants to minimize fuel energy consumption and carbon emissions while maximizing both the yield and the quality of sinter ore to comply with environmental protection standards. However, the inherent complexity of the sintering process complicates the ability of operators to adjust chemical compositions and process parameters to achieve multiple optimization objectives concurrently. As a result, considerable research efforts have focused on the development of data-driven optimization models for the sintering process (Feng Yan et al., 2023). Consequently, it is essential to develop systematic approaches and tools to facilitate informed decision-making. Such advancements are crucial for effective and environmentally friendly practices. The implementation of ML algorithms offers a valuable approach to predicting sinter productivity and other key parameters that significantly influence the sintering process. This can lead to enhanced efficiency and improved outcomes in production (Singh, et. al 2020). Numerous studies have been conducted to enhance sinter productivity. These investigations have employed are, backpropagation artificial neural network (ANN) models, fuzzy neural networks (FNN), and genetic algorithm (GA) systems to predict the chemical composition of the final sinter product. Additionally, ANN models have been utilized to forecast the burning–through-point,

* Corresponding authors.
E-mail address: rmukkamala@nicmar.ac.in (Rambabu Mukkamala).

strength and quality of sinter demonstrating the potential of these advanced methodologies to optimize the sintering process and improve overall operational efficiency (Liao 2000; Liu 2023; Reihanian, 2011; Song 2020, Zhang 2007). The analysis of datasets related to sinter process variables is critical for optimizing the sintering process. This optimization can lead to enhanced productivity, reduce energy consumption, and minimized waste (Song Liu et al., 2020). The studies in the past were primarily concentrated on the enhancement of sinter production through a detailed experimental analysis of various process parameters. The influence of the physical characteristics of input raw materials on the productivity of sinter machines was not studied in the past. To address this, the study examines the effectiveness and efficiency of these DL architectures in accurately forecasting the productivity of the sinter plant, thereby contributing valuable insights to the steel industry.

This study presents a valuable analysis utilizing a multivariate dataset with sixteen input parameters that influence sinter productivity. It examines the potential of LSTM, Bi LSTM, and CNN Bi LSTM algorithms to enhance our understanding of the various factors affecting productivity in this domain. By comparing the results, the research aims to identify the most effective DL architecture, paving the way for improved outcomes in sinter productivity analysis.

2. Materials and methods

2.1. Data collection

This dataset contains sinter machine productivity as output and sixteen input parameters: iron ore Fines total Fe %, iron ore (IO) Fines SiO_2 %, IO Fines Al_2O_3 %, IO CaO %, flux CaO %, flux MgO %, flux crushing index (CI) %, coke CI %, sinter total Fe %, sinter FeO %, sinter SiO_2 %, sinter Al_2O_3 %, sinter CaO %, sinter MgO %, sinter +40mm Size %, and drum tumbling index (DTI) %. The secondary dataset provides valuable insights into the operations of an integrated steel plant located in India (Rath and Sushant 2021). The dataset analyzed comprised 449 samples, each incorporating sixteen input parameters classified as independent variables. The primary focus of the analysis was to assess sinter productivity as the target variable. To facilitate this evaluation, three distinct deep learning frameworks were implemented, providing a robust approach to the data analysis. The framework outlining the steps involved in the process of DL architecture is illustrated in Figure 1.

The study aimed to evaluate the performance of ML and DL models. This section primarily details the structure of the DL frameworks used in the analysis. Both ML and DL models were employed to assess the effectiveness of various model parameters in predicting sinter productivity. While the ML models were included mainly for comparison purposes, the primary focus of the study is to identify the best DL model that demonstrates high prediction accuracy.

2.2. LSTM model

The LSTM model incorporates memory cells that are regulated by gates. There are three distinct types of gates: the input gate, output gate, and forget gate. These gates govern the flow of information and are integral to the mixing and transformation of data within the LSTM framework illustrated in Figure 2.

The memory module is capable of storing permanent training data, while the cell state memory facilitates the retention of long-term dependencies. The aforementioned gates can be categorized as memory gates, input gates (I/P gates), and output gates (O/P gates). Distinct memory cells are utilized to store both short-term and long-term memories. This architecture can be metaphorically likened to a conveyor belt, pervading the entire system with minimal direct connectivity to the gates. LSTM models are highly effective for classifying processes and making predictions based on time series data. The output generated by the LSTM layer, referred to as the hidden state, serves as input for further processing. The Sigmoid layer produces a value ranging from 0 to 1, indicating the extent to which each segment of data should be transmitted (Memarzadeh and Keynia 2020).

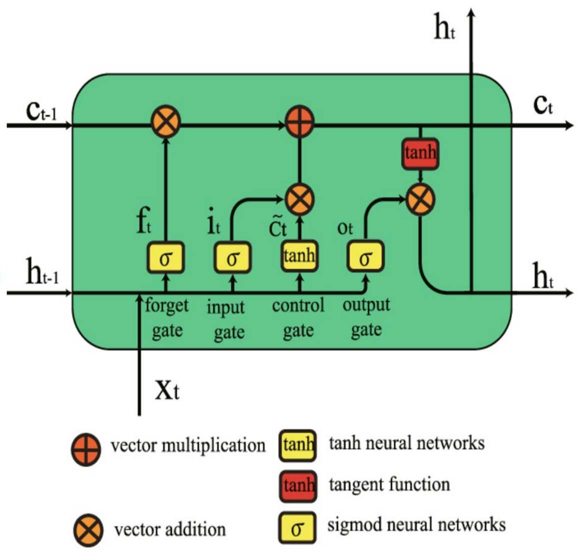

Fig. 2. LSTM cell structure

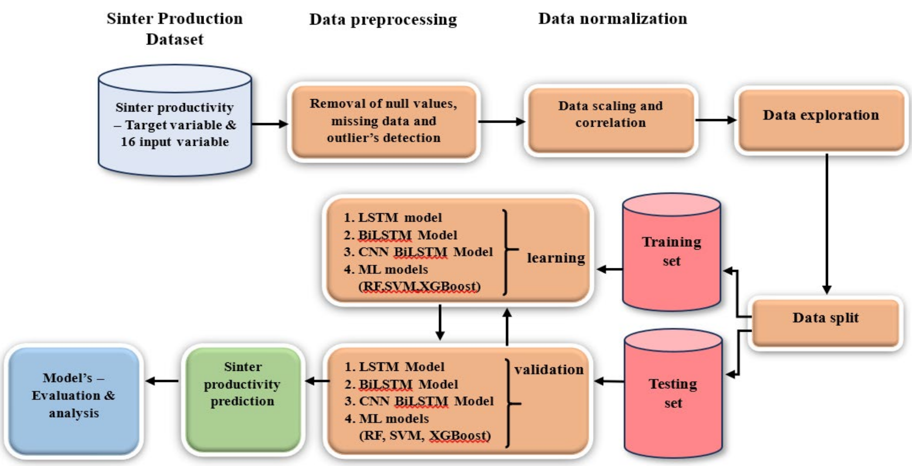

Fig. 1. Framework of DL models

2.3. Bidirectional LSTM model

Bi LSTM is an extension of LSTM that includes both past and future states. Data is processed forward and backward to obtain more accurate predictions compared to the general LSTM model. This is because additional features can be extracted during the recovery phase. The structure of the Bi LSTM model is shown in Figure 3.

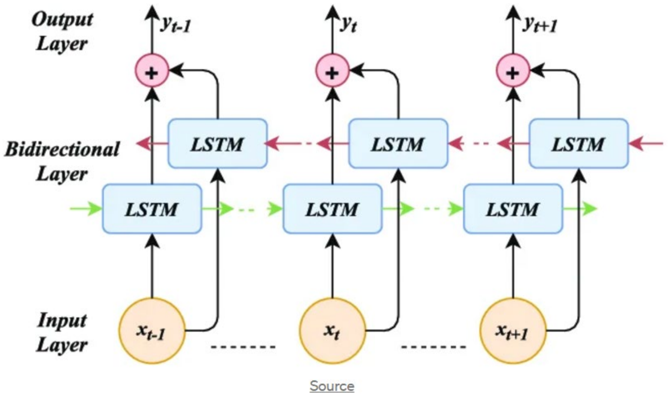

Fig. 3. Schematic diagram of Bidirectional LSTM structure (Isibor Kennedy et al. 2020)

2.4. CNN BiLSTM model

The advantages of CNN and BiLSTM models are good because their performance is better than baseline models. In addition, the improvement of existing models is done by hybridization models (e.g., combining two models to take advantage of both models), and one of the effects is the CNN - BiLSTM model. The performance of CNN-BiLSTM depends on the architecture and hyperparameters. For example, the new CNN-BiLSTM architecture proposed in this paper consists of layers such as convolutional, max pooling, flatten, bidirectional, dropout and the dense layer. The dropout layers in the proposed model help to avoid overfitting scenarios. Whereas the maxpooling layers help sampling operations and flatten layers focuses on the reshape operations. The architecture adopted by the present study is given in the Figure 4.

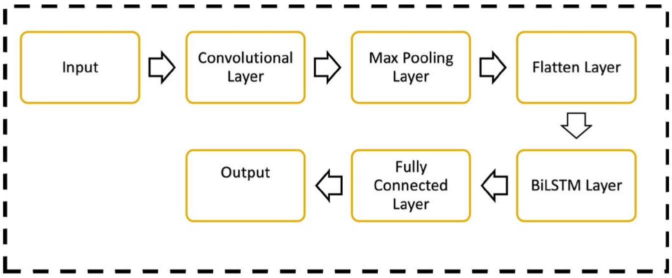

Fig. 4. Proposed novel architecture of CNN-BiLSTM

2.5. Performance metrics

The performance of the proposed models is evaluated using the error metrics such as MAE, MSE, RMSE and R^2, as shown in Equations (1) – (4).

Where, A represents the actual value, represents the predicted value, represents the mean of actual value and n is the number of observations.

$$MAE = \frac{1}{n}\sum_{k=1}^{n}|A-P| \quad 1$$

$$MSE = \frac{1}{n}\sum_{k=1}^{n}(|A-P|)^2 \quad 2$$

$$RMSE = \frac{1}{n}\sqrt{\sum_{k=1}^{n}|A-P|} \quad 3$$

$$R^2 = 1-\frac{\sum_{i=1}^{n}|A-P|}{\sum_{i=1}^{n}|\overline{A}-\overline{P}|} \quad 4$$

2.6. Validation

The most effective model identified in the analysis was subjected to statistical validation through the Diebold-Mariano (DM) test. This test serves as a robust tool for assessing the statistical outcomes of the models and for comparing their predictive accuracy. The primary objective is to examine the variability in prediction errors by utilizing metrics such as DM statistics and p-values. This analysis enables the determination of whether the observed differences in model performance are statistically significant (Mariano and Preve 2012).

DM test enables analysts to evaluate whether one predictive model demonstrates a statistically significant improvement over another model or whether the observed differences in performance can be attributed to random fluctuations within the data (Mohammed and Mousa 2019).

The following outlines the steps and equations employed in the DM test:

- In order to define the forecast errors, denote er1t and er2t as the forecast errors associated with Model 1 and Model 2 at time t, respectively. These errors represent the discrepancies observed during the testing phase.
- To calculate the loss differential ldt, one must consider the difference in forecasted errors through the application of a loss function LF, which is designated as the squared error. The expression for the differential is delineated in Equation (5):

ldt = LF (er1t) – LF (er2t) = (er1t2 – e2t2) 5

- To calculate the mean loss differential, the mean value, referred to as , is obtained through the application of Equation (6).

$$\overline{ld} = \frac{1}{T}\sum_{t=1}^{T} ld_t \quad 6$$

The DM statistics (DM_st) test is generally computed utilizing Equation (7).

$$\text{DM\_st} = \frac{\overline{ld}}{\sqrt{\frac{\sigma^2 ld}{T}}} \quad 7$$

where σld2 signifies the estimate of variance associated with ldt, and T denotes the number of forecasted periods.

Hypothesis Testing: This analysis begins with the assumption of the null hypothesis (H0), which asserts that the forecasting accuracy of both models is equivalent. The DM_st is asymptotically distributed according to a standard normal distribution. A rejection of H0 is warranted when the absolute value of the DM_st is notably high, thereby indicating a significant discrepancy in the forecasting performance between the two models.

3. Results and discussion

The study involved the collection of sample data pertaining to sixteen input parameters and one output parameter, specifically sinter productivity, resulting in a total of 449 samples. The data underwent standardization following the removal of extreme and null values. Subsequently, a dataset comprising 371 samples was utilized for analysis through the implementation of RF, SVM, XGBoost, LSTM, BiLSTM, and CNN BiLSTM models. The statistical characteristics of the dataset, including metrics such as minimum (min), maximum (max), standard deviation, and the number of data points are delineated in (Table 1).

Table 1. Descriptive statistics of the input and output parameters

Statistic	SP (T/m2-hr)	I/O Fine Total Fe %	I/O Fine SiO2 %	I/O Fine l2O3%	I/O Fine CaO %	Flux CaO %	Flux MgO %	Flux CI	Coke CI	Total Fe %	FeO %	SiO2 %	Al2O3 %	CaO %	MgO %	+40mm Size, %	(DTI) %
count	371	371	371.	371	371	371	371	371	371	371	371	371	371	371	371	371	371
mean	1.14	60.6	4.6	2.7	0.7	36.2	9.3	88.1	81.2	54.9	8.67	6.01	2.59	10.4	2.6	10.2	72.3
std	0.08	0.36	0.47	0.23	0.15	0.51	0.46	3.88	0.85	0.82	0.08	0.51	0.17	0.54	0.10	2.34	1.83
min	0.93	59.8	3.59	2.17	0.39	34.7	8.35	77.2	78.8	53.5	8.47	4.96	2.16	9.25	2.44	4.80	68.00
25%	1.08	60.3	4.06	2.60	0.69	35.8	8.88	84.4	80.6	54.2	8.62	5.50	2.46	10.1	2.61	8.70	71.30
50%	1.14	60.6	4.80	2.78	0.80	36.2	9.50	90.1	81.0	54.7	8.66	6.30	2.59	10.5	2.69	9.70	72.00
75%	1.19	60.9	4.95	2.95	0.89	36.6	9.72	91.2	81.6	55.7	8.71	6.41	2.71	10.9	2.75	11.5	73.30
max	1.31	61.5	5.68	3.37	1.10	37.5	10.0	93.3	83.3	56.6	8.86	6.81	2.94	11.5	3.00	20.0	76.70

The data underwent normalization to a range of 0 to 1 using the MinMax scaler prior to the division of the dataset into training and testing subsets. Specifically, 80% of the data, comprising 297 samples, was designated for training purposes, while the remaining 20%, totaling 74 samples, was allocated for testing. The predictive capability of the model was evaluated through the application of five metrics: MAE, MSE, RMSE, and R^2. These metrics were utilized to compare the actual values against the predicted outcomes.

3.1. Parameters and the experimental models

In this study, the performance of multivariate RF, SVM, XGBoost, LSTM, BiLSTM, and CNN-BiLSTM models was systematically compared using various evaluation metrics. To ensure a valid comparison, the model architecture and training parameters were standardized across all models. The Adam optimizer was utilized to compute an adaptive learning rate, which is derived from the means of the first and second moments of the gradient. The learning rate was established at 0.01, and the MAE was employed as the loss function. MAE is particularly effective as it quantifies the average magnitude of errors in predictions without regard to their direction, thereby demonstrating robustness against outliers.

A series of experiments were conducted by varying the key parameters, including batch size, number of epochs, learning rate, time step, and window length. The most favorable outcomes were achieved with a batch size of 32 and a total of 75 epochs. The training process incorporated sixteen input parameters along with the output, which represents the productivity of sinter for the samples after preprocessing. Following the completion of training, the test dataset was utilized for predictive analysis.

The evaluation indicators utilized in this analysis—MAE, MSE, RMSE, and R^2 are employed to compare the results of ML and DL models. These indicators serve to quantify the discrepancies between the predicted and actual values of sinter productivity, with the corresponding metrics presented in Table 2. The CNN BiLSTM model achieved an R^2 score of 0.8982, which is superior to that of the baseline models. Moreover, the MAE, MSE, and RMSE scores for the CNN BiLSTM model are reported as 0.0238, 0.0009 and 0.0301 respectively. These findings clearly demonstrate that the CNN BiLSTM approach exhibits enhanced performance in relation to the evaluation metrics.

The CNN Bi LSTM model's plot comparing actual and predicted values for the last 71 samples is illustrated in Fig. 5 and Fig . 6.

Table 2. Evaluation parameters of sinter productivity data of ML and DL models

Model	MAE	MSE	RMSE	R2
RF	0.1368	0.0144	0.1200	0.7644
SVM	0.1084	0.0126	0.1120	0.7766
XGBoost	0. 0976	0.0098	0.0990	0.8086
LSTM	0.0824	0.0086	0.0926	0.8341
BiLSTM	0.0576	0.0052	0.0721	0.8563
CNN-BiLSTM	0.0238	0.0009	0.0301	0.8982

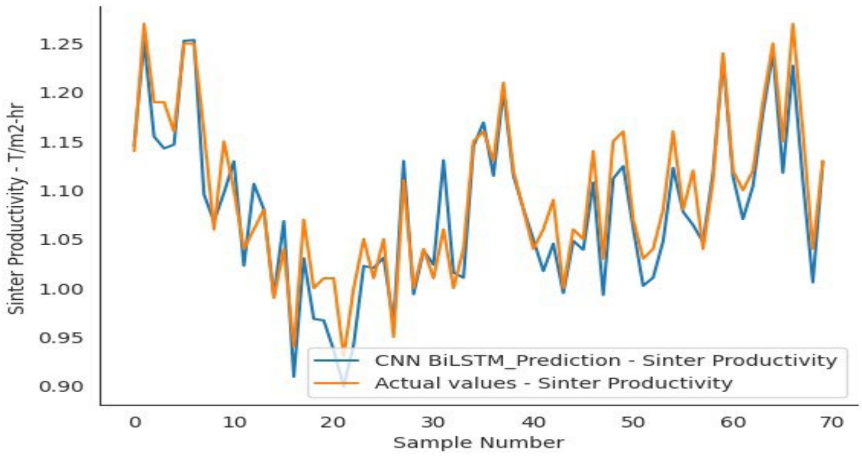

Fig. 5. Plot of Actual vs predicted values of test data

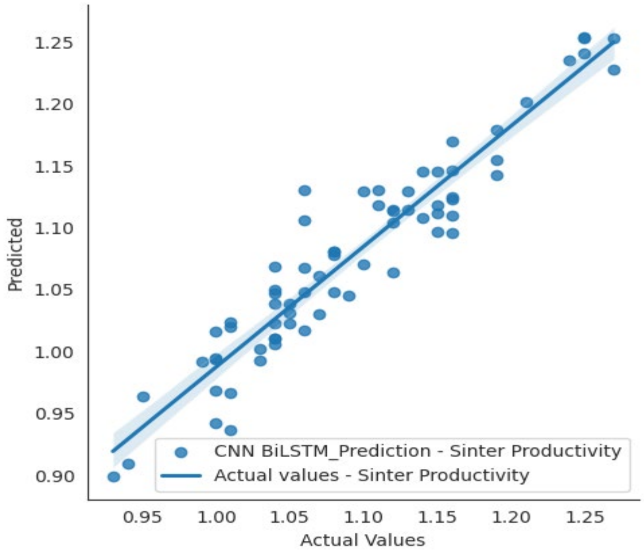

Fig . 6. Plot between Actual and Predicted values

To validate the results of the predictions, the DM test was employed. The CNN BiLSTM model, noted for its superior performance, served as the baseline for comparison against other models, specifically RF, SVM, XGBoost, LSTM, and BiLSTM. The null hypothesis (H_0) asserts that there is no significant difference between the CNN BiLSTM model and the other models. In contrast, the alternative hypothesis (H_1) posits that the predictive power of the CNN BiLSTM model is superior, while hypothesis H_2 suggests that the other models exhibit higher output power in comparison to CNN BiLSTM. Mean Squared Error (MSE) was utilized as the error metric for model comparisons (Harvey et., al 1997). A confidence level of 95% was established for this investigation, indicating that a p-value exceeding 0.05 would lead to the non-rejection of the null hypothesis. Conversely, a p-value below 0.05 would necessitate the selection of either H_1 or H_2. If the DM_ st is negative, H_1 will be accepted; otherwise, H_2 will be endorsed. The results of the DM Test is presented in Table 3. The results of the DM test indicate that the p-value is less than 0.05 for all analyzed models, including RF, SVM, XGBoost, LSTM, and BiLSTM. Consequently, the null hypothesis is rejected. In this situation, the decision should be based on the DM_ st, which substantiates the superior predictive accuracy of the CNN BiLSTM model compared to the other models**.**

Table 3. Results of DM test

MSE	RF	SVM	XGBoost	LSTM	BiLSTM
DM_st	-11.251	-9.582	-9.654	-6.923	-3.733
p	0.0006	0.0004	0.0001	0.0000	0.0000

The implementation of predictive analytics facilitates the identification of trends in input parameters that exert a direct influence on sinter quality. This methodology provides a robust framework for ongoing improvement. The variability associated with the quality of raw materials presents considerable challenges to the maintenance of sinter productivity. This study employs multivariate analysis to clarify the intricate interactions among various input parameters. By harnessing these insights, operators are equipped to make proactive adjustments to both raw material compositions and processing settings, thereby alleviating the impact of variability. This systematic approach ensures the stability of both sinter productivity and quality, even amidst fluctuations in raw material characteristics. The results of the study were compared with prior research related to the prediction of sinter productivity. . The application of a multi-layer perceptron framework, consisting of one hidden layer with nine neurons, resulted in a correlation coefficient of 0.77 between the predicted values and the actual measurements of sinter productivity (Thiago et., al 2021). To forecast the productivity of the sinter plant, linear regression and a back-propagation algorithm were utilized. In this context, the productivity of the sinter plant was designated as the output variable, while 16 additional parameters were treated as input variables. The results indicated a correlation coefficient of 0.522 for the linear regression model, in contrast to 0.764 for the back-propagation algorithm (Arpit, Subhra, and Sushant 2021). Importantly, the results from the CNN BiLSTM model in the present study exceeded those of the ML and ANN models applied in earlier research, achieving a correlation coefficient of 0.9477 (R^2 = 0.8982). Furthermore, the CNN BiLSTM model demonstrated enhanced predictive capabilities, with its predicted values closely aligning with the trend of the original dataset when compared to the LSTM and BiLSTM models.

The findings of this research present actionable strategies for the enhancement of sinter plant operations through the implementation of real-time adjustments to input variables and the establishment of optimal production conditions. Furthermore, the predictive insights function as a decision-support tool for plant managers, facilitating informed interventions to maximize the quality of the sinter produced. The study effectively establishes a connection between theoretical models and practical applications within the metallurgical industry through the application of predictive methodologies. The observed improvements in sinter quality, fuel efficiency, and process stability underscore the significant transformative potential of deep learning in the steel sector.

4. Conclusion

The objective of this study is to predict sinter productivity based on sixteen input variables derived from a sinter plant. The outcomes of this research are pertinent to all stakeholders associated with steel manufacturing. Sinter plant productivity represents a crucial techno-economic parameter that is influenced by numerous factors, which are challenging to evaluate through physical experimentation to determine their interrelationships. It serves as an indicator of the efficiency of the sintering process, functions as a parameter for monitoring the performance of the sinter plant, and acts as a benchmarking tool for such facilities. In order to predict sinter productivity, three ML algorithms and three DL frameworks were employed. Among these frameworks, the CNN-BiLSTM model exhibited superior R^2 scores, demonstrating enhanced predictive capabilities for sinter productivity compared to the other models. The innovative architecture of CNN-BiLSTM has been shown to deliver improved performance for sinter productivity data. The predicted and actual values of sinter productivity from the CNN-BiLSTM model were statistically validated against the results of the ML and DL models using the DM test, thereby establishing that the CNN-BiLSTM model significantly outperforms the other models. Future research may expand upon this study by incorporating a larger dataset of sinter productivity along with related variables to yield improved results and enhance the overall performance of sinter plants.

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