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A Hybrid Traditional and Machine Learning-Based Stacking-Based Ensemble Forecasting Approach for Coal Price Prediction

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ABSTRACT
Accurate coal price forecasts are crucial, as volatility in coal prices significantly impacts company performance and profitability. Traditional time series forecasting methods, such as exponential smoothing, are known for their simplicity and low data requirements. In contrast, machine learning techniques, such as random forest and neural network, offer higher accuracy in predictions. However, very few attempts have been made to combine the simplicity of traditional methods with the accuracy of machine learning techniques. This paper presents a novel stacking-based model that integrates both traditional statistical methods and machine learning techniques to enhance coal price predictions. Using Indonesian coal price data from January 2009 to October 2021, we trained the models on various combinations of predictors to generate new predictions. Our findings demonstrate that our stacking-based model outperforms other models, with RMSE and MAPE values of 6.44 and 5.97%, respectively. These results indicate that the model closely forecasts actual coal prices, capturing 94.03% of the price movements. The main contribution of this study is the application of stacking-based models to coal price forecasting in Indonesia, which has not been previously explored, thus enriching the literature on this topic.

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1. INTRODUCTION

Indonesia stands out as one of the largest coal-producing countries globally. According to the Direktorat Jenderal Mineral dan Batubara, coal prices have undergone significant fluctuations over the past decade [1]. In October 2021, prices reached a peak at USD 161.63 per ton, whereas in September 2020, they plummeted to USD 49.42 per ton. Such volatility inevitably impacts company performance and leads to decreased profits [2]. The price of coal, as a commodity, is not solely dictated by regulatory bodies but is also influenced by both domestic and foreign coal markets [3]. Moreover, factors like climate conditions and energy consumption patterns exert a notable influence on coal prices.

Time series forecasting has emerged as a critical practice across various sectors, including the energy industry [4]. Due to the volatility of coal prices, it is essential for every company to conduct forecasting to identify and analyze potential challenges arising from these fluctuations. Forecasting coal prices serves not only as a foundation for decision-making within coal-related businesses but also as a means to safeguard the energy needs of communities reliant on coal-derived resources.

Several studies on coal price forecasting have been conducted previously [3,5–7]. [5] demonstrated forecasting using Support Vector Machine (SVM), Multi-Layer Perceptron (MLP), and a combination of Long-Short Term Memory-Deep Neural Network (LSTM-DNN) models. [6] conducted a coal price forecasting study using the Neural Network (NN) model. [7] proposed using the Long Short Term Memory-Recurrent Neural Networks (LSTM-RNN) model to predict price change trends in coal. [3] forecasted coal prices in China based on a combination of Autoregressive Integrated Moving Average (ARIMA) and SVM models. However, [8] argued that no forecasting model is more dominant than others, as each model has its own advantages and disadvantages. In recent decades, traditional models such as moving average, exponential smoothing, and ARIMA have been frequently used. The application of these models also relies on the assumption of linear data. To address this, machine learning models such as NN, SVM, and random forest are employed. Recently, the use of hybrid models has become popular for forecasting due to their excellent performance and numerous supporting studies [9].

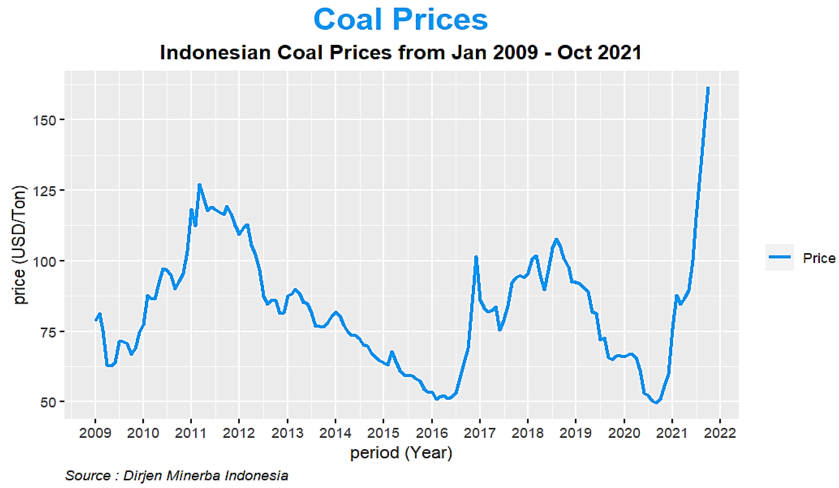

Figure 1. Indonesian coal prices from 2009 to 2021 [1]

Existing literature indicates that traditional forecasting methods and machine learning techniques are widely employed for coal price forecasting. Traditional forecasting methods are appreciated for their simplicity and minimal data needs, while machine learning models offer greater accuracy. However, there have been limited attempts to combine the simplicity of traditional methods with the precision of machine learning techniques. Therefore, in this study, we present a novel stacking-based model that integrates both traditional statistical methods and machine learning techniques to enhance coal price predictions in Indonesia by utilizing reference coal prices data spanning from January 2009 to October 2021. The proposed model operates through six main steps, starting with data collection, application of traditional forecasting and machine learning models, generation of initial forecasting results, feature selection, the proposed stacking-based model construction using a metamodel, and generation of new forecasting results using the proposed model. The rest of this paper is divided into several sections: Section 2 comprises a literature review, Section 3 covers the methods, Section 4 introduces our proposed model, addresses performance metrics, and presents the results, while Section 5 presents our conclusion.

2. LITERATURE REVIEW

[10] conducted a study to identify factors influencing coal demand in Poland. The results suggest that the proposed forecasting model offers a potential scenario applicable to the entire coal mining industry. [11] demonstrated the necessity of coal price forecasting by examining numerous variables impacting prices. [3] investigated coal price fluctuations at Qinhuangdao Port, revealing inadequacies in the competitiveness of the domestic coal market and advocating for the development of both coal trading system and coal enterprises themselves. [3] explored coal price forecasting using the ARIMA model, highlighting factors influencing price changes, proposing some prediction models, and offering practical policy recommendations based on their findings. [12] conducted a comparative study between ARIMA and Autoregressive Integrated Moving Average With Exogenous Variable (ARIMAX) models in forecasting china's coal price index, with results favoring the performance of the ARIMAX model. [7] introduced the LSTM-RNN for predicting coal price trends, demonstrating its superior accuracy compared to other models.

In general, traditional models are often utilized for forecasting, as demonstrated by [13], who employed ARIMA to analyze trends in consumption, prices, and investment in Chinese coal from 2016 to 2030. Additionally, [14] proposed an ARIMA-based model to predict the spread of the COVID-19 virus in Italy. The advantage of this model lies in its simplicity and adaptability, facilitating the determination of case trends, estimation of the epidemic's inflection point, and final COVID-19 size. [15] conducted a study using the ARIMA on rabi (a kind of wheat) production in Odisha, India. The results indicated an increase in predicted rabi production due to the projected expansion in planting area. Conversely, [16] proposed a vector exponential smoothing (VETS) model for forecasting mixed-frequency time series. The findings revealed that our proposed model is suitable for short-term and medium-term forecasting.

[9] proposed using machine learning as a forecasting tool. In their research, forecasting of prices for various energy commodities was conducted using machine learning methods such as NN and random forest. [8] proposed various models, including machine learning models, to forecast daily sales using data from social media. It was found that random forest was the best-performing model, producing an out-of-sample MAPE of 7.21% without social media information and 5.73% with it. [5] demonstrated forecasting using SVM, MLP, and a combination of LSTM-DNN models. Their findings indicated that the combination of the LSTM-DNN models yielded better results compared to other models. [17] proposed a Radial Basis Function-Neural Network (RBF-NN) to estimate coal prices, resulting in a minimal error. [18] conducted forecasting on wave conditions using machine learning, obtaining accurate model representations similar to the actual wave conditions, suggesting the efficacy of machine learning models for forecasting. [19] introduced a machine learning model for forecasting the volume of water entering reservoirs in the Iranian region to mitigate flood damage. This forecasting will be highly useful for predicting water volumes to reduce flood damage. [20] proposed a machine learning model for forecasting the availability of electric vehicles for vehicle-to-home services. The study's results underscored the accuracy of a well-performing machine learning model, which can help in reducing vehicle recharging costs. To conclude, both traditional methods and machine learning techniques have unique strengths in coal price forecasting. Combining these approaches leverages their respective advantages. Our proposed model involves using the predictions generated by each model as new variables to create a novel data set. This data set is then used to train a metamodel, specifically a stacking-based model incorporating EN, SVM, and NN. The essence of our proposed model is to consolidate all forecasting results from the utilized models into a new data set, which is then reanalyzed using the same forecasting models to produce enhanced prediction outputs.

3. METHOD

3.1. Study Design

The data used in this study consists of 154 months of observations of the Indonesian coal prices in USD/ton from January 2009 to October 2021. The entire data set is then divided into training and testing data. [21] stressed the importance of splitting the data for estimating and evaluating the accuracy of forecasting models. Typically, the test data size is 20% of the total available data; therefore, in this study, the training and testing data are divided in an 80:20 ratio, respectively comprising 130 initial observations (80% of the data) and the last 24 observations (20% of the data). Coal price data sourced from Direktorat Jenderal Mineral dan Batubara are provided at monthly intervals [1]. To create multivariate data, a new variable is formed by including each price up to 12 months prior.

3.2. Traditional Forecasting Methods

3.2.1. Moving Average

One of the most well-known traditional forecasting methods is the Moving Average (MA). A moving average is obtained by summing and averaging values over a certain number of periods, then replacing the oldest value with a new one. MA forecasting is a systematic method for analyzing time series. MA is widely used to extract or reduce uncertainty in time series [22]. The equation form of the MA model is as follows [23].

$$Y_{t+1} = \frac{Y_t + Y_{t-1} + \cdots + Y_{t-m+1}}{m} \tag{1}$$

where Y_{t+1} is the forecasted value for the next period, Y_t is the actual value in period t, and m is the number of periods for forecasting.

3.2.2. Exponential Smoothing

The exponential smoothing (ES) method is characterized by an exponential decrease in the weight of the previous observation value. This model forecasts by exponentially averaging past values of a time series data. ES provides an estimate of future demand as a final level. This forecasting method assigns weighted values to a series of previous observations to predict future values [24]. The equation form of the ES model is as follows [23].

$$Y_t = Y_{t-1} + \alpha(A_{t-1} - Y_{t-1}) \tag{2}$$

where Y_t is the forecasted value in period t, Y_{t-1} is the forecasted value one period before t, A_{t-1} is the actual value one period before t, and α is the constant value of alpha smoothing.

3.3. Machine Learning-Based Forecasting Methods

3.3.1. Elastic Net

The Elastic Net (EN) is a forecasting model that combines ridge and Least Absolute Shrinkage and Selection Operator (LASSO) regression techniques. Ridge regression is a modification of the Ordinary Least Squares (OLS) method that reduces bias. LASSO is a shrinkage method, similar to ridge regression, used to address multicollinearity issues. EN operates similarly to LASSO, performing variable selection and coefficient shrinkage [25].

3.3.2. Support Vector Machine

Support Vector Machine (SVM) employs a nonlinear mapping technique to project input prototypes onto optimal separation boundaries within a high-dimensional feature space. SVM identifies the optimal separation hyperplane by maximizing the distance between separable classes. It can handle nonlinear data through the kernel function, where the kernel function maps the initial data set dimensions from a lower to a higher dimension [26][31]. The equation representing the SVM model is as follows [23]

$$f(x) = W^T\Phi(x) + b \tag{3}$$

where x is the input vector, W represents the weight parameter, $\Phi(x)$ denotes the basis function, and b is the bias term.

3.3.3. Neural Network

A Neural Network (NN) is an imitation of neurons in the form of a complex nonlinear model, developed with characteristics similar to regression models. Each neuron is connected to other neurons by a connection link, represented by a weight. Each neuron uses an activation function on the net input to determine the predicted output. The neurons in NN are organized into groups called layers [27]. The equation form of the NN model is as follows [28]

$$Y_t = f(Y_t - 1,\ Y_t - 2, \dots, Y_t - p, w) + e_t \tag{4}$$

where W is a vector of all parameters, and f is a function of the network structure and connection weights.

3.4. Proposed Model

[29] introduced the stacking technique for forecasting, an ensemble-based machine learning algorithm that entails training multiple models and amalgamating their outcomes through a metamodel to produce new predictions. Constructing a stacking-based model necessitates two components: a base model and a metamodel to amalgamate the outcomes. The framework structure of our proposed model is depicted in Figure 2. The initial phase of this research comprised several steps. The steps are detailed as follows:

1. Coal price data for the period January 2009 to October 2021 was collected. The data set was compiled by including each actual price and its values up to 12 months back. The data set was then divided into a training set (80%) and a test set (20%) for forecasting.
2. Traditional models (MA and ES) and machine learning models (EN, SVM, and NN) were applied to the first 130 data points (80% of the data) and the last 24 data points (20% of the data), respectively.
3. The forecast from all the models we utilized earlier have been gathered.
4. The prediction results obtained from each model were used as new variables to produce additional predictions and appraise the performance metrics with the proposed model.
5. A stacking-based model was built using metamodel, integrating the predictions from past models like EN, SVM, and NN.

6. The forecasting results from each model were compared to evaluate using root mean square error (RMSE) and mean absolute percentage error (MAPE) to assess the performance concerning the case study, which is the forecasting of Indonesian coal prices.

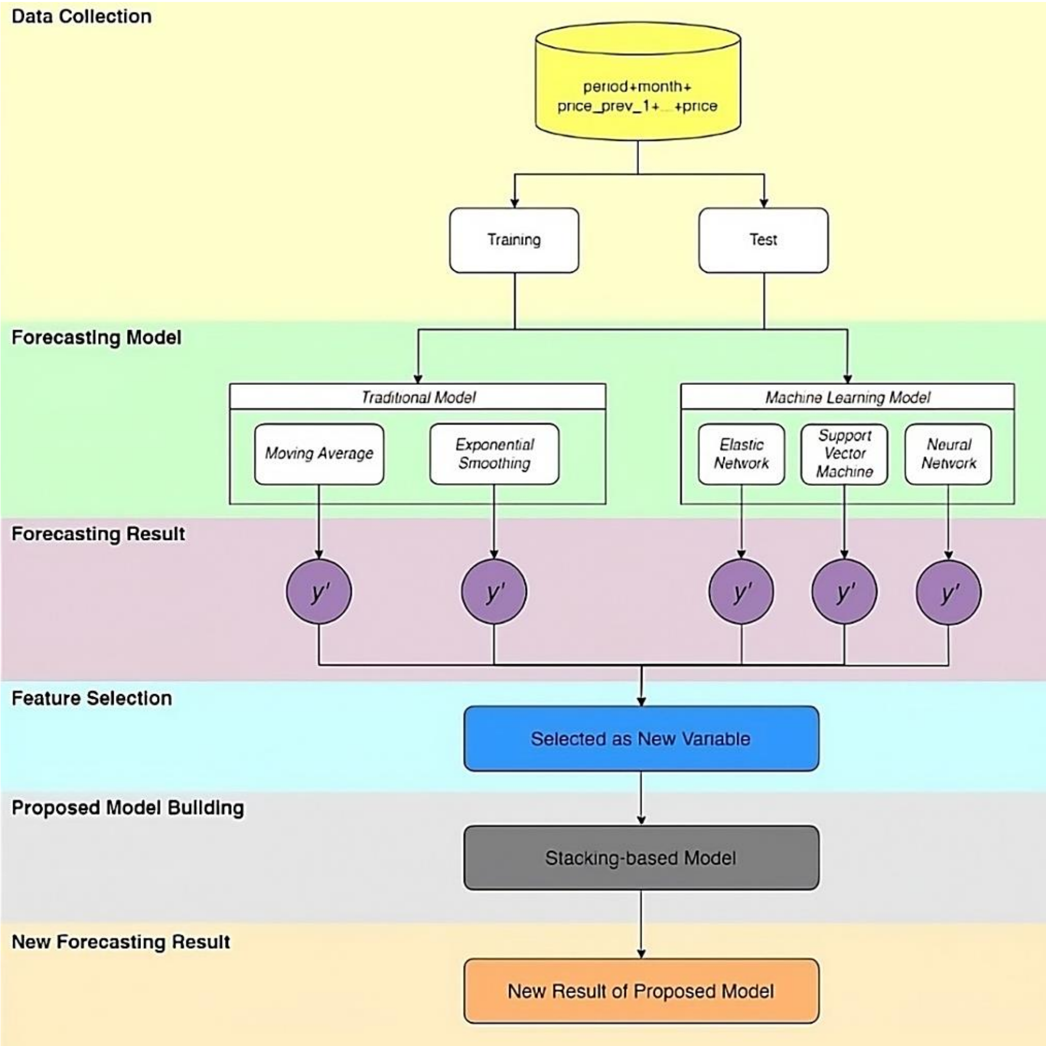

Figure 2. The framework of the proposed model

4. RESULTS

4.1. Case Study

This research focuses on forecasting coal prices in Indonesia, necessitating the collection of reference data on coal prices to derive prediction results. The objective is to forecast coal prices using various models, comparing them based on RMSE and MAPE values, and determining the most effective forecasting model among several. The data utilized comprises secondary data, specifically the price of coal in Indonesia over the past 10 years (January 2009 – October 2021), sourced from Direktorat Jenderal Mineral dan Batubara [1]. A total of 154 records and 15 different variables were collected.

4.2. Data

The data used in this study consists of 154 months of observations of the Indonesian coal prices in USD/ton from January 2009 to October 2021. The entire observational data set is then divided into training and testing sets. [21] emphasizes the importance of dividing data into training and testing sets for estimating and evaluating the accuracy of forecasting models. Generally, the test set size is 20% of the total available data. Therefore, in this study, the training and testing data are divided in an 80:20 ratio, comprising the first 130 data points (80% of the data) and the last 24 data points (20% of the data), respectively.

The coal price data, sourced from Direktorat Jenderal Mineral dan Batubara [1], is provided with monthly intervals. To convert it into multivariate data, a new variable is formed by including each price up to 12 months prior. The attributes of the data set formed in this study are as follows.

Table 1. The variables used in this study

No.	Name	Type	Description
1	period	Input	Numeric: time period
2	month	Input	Nominal: 1 - January, 2 - February, up to, 12 - December
3	price_prev_1	Input	Numeric: price of month 1
4	price_prev_2	Input	Numeric: price of month 2
5	price_prev_3	Input	Numeric: price of month 3
6	price_prev_4	Input	Numeric: price of month 4
7	price_prev_5	Input	Numeric: price of month 5
8	price_prev_6	Input	Numeric: price of month 6
9	price_prev_7	Input	Numeric: price of month 7
10	price_prev_8	Input	Numeric: price of month 8
11	price_prev_9	Input	Numeric: price of month 9
12	price_prev_10	Input	Numeric: price of month 10
13	price_prev_11	Input	Numeric: price of month 11
14	price_prev_12	Input	Numeric: price of month 12
15	price	Output	Numeric: current coal price

4.3. Performance Metrics

4.3.1. Root Mean Square Error

In forecasting, the performance evaluation of forecasting models typically utilizes the root mean square error (RMSE). RMSE has been employed in various recent studies, demonstrating its effectiveness in achieving accurate forecasts [5,9,30]. RMSE represents the average value of the squared errors, indicating the deviation of predicted values from observations. A lower RMSE value indicates that the predicted values closely match the actual values. RMSE can be formulated as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y'_i - Y_i)^2} \tag{5}$$

with N being the number of data points, while Y'_i and Y_i representing the predicted and actual values, respectively.

4.3.2. Mean Absolute Percentage Error

Mean absolute percentage error (MAPE) is commonly used in evaluating the performance of forecasting models. As a performance metric that can provide information on the percentage error rate in forecasting, it forms the basis of various studies conducted in recent years, especially those related to energy commodity price forecasting [8,9,30]. MAPE measures the level of forecasting error in percentage terms. The lower the MAPE value, the closer the variation in the predicted value to the variation in the actual value. MAPE can be formulated as follows:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Y_i - Y'_i}{Y_i}\right| \tag{6}$$

where N is the number of data points, while Y'_i and Y_i are the predicted and actual values, respectively.

4.4. Performance Comparison

Following forecasting with the predetermined model, the subsequent step involves assessing its performance through graphical visualization to offer a comprehensive overview of the results. This process entails comparing seven forecasting models to ascertain the most effective one for addressing the studied problem. The forecasting outcomes spanning 24 periods (2 years) are outlined in Table 2.

Table 2. Actual vs. forecasted coal prices for the last 24 months (testing data) across different methods (USD/ton)

Month	Actual	MA	ES	EN	SVM	NN	PM
1	66.27	65.29	64.80	63.83	72.08	64.05	66.24
2	66.3	65.53	66.26	66.41	71.24	65.71	68.37
3	65.93	66.28	66.30	66.40	74.75	66.37	68.79
4	66.89	66.11	65.93	64.45	69.77	63.56	66.40
5	67.08	66.41	66.88	67.34	74.61	66.76	69.53

Month	Actual	MA	ES	EN	SVM	NN	PM
6	65.77	66.98	67.08	62.10	70.70	61.55	64.82
7	61.11	66.42	65.78	62.84	71.68	62.64	65.37
8	52.98	63.44	61.16	59.16	63.45	59.28	60.86
9	52.16	57.04	53.06	51.98	56.83	54.29	53.74
10	50.34	52.57	52.17	51.72	56.62	54.40	54.04
11	49.42	51.25	50.36	51.14	55.33	54.26	53.27
12	51	49.88	49.43	50.11	54.89	53.30	52.37
13	55.71	50.21	50.98	51.65	56.34	54.62	54.07
14	59.65	53.35	55.66	58.83	63.49	59.98	60.95
15	75.84	57.68	59.61	60.76	65.83	60.58	62.80
16	87.79	67.74	75.68	77.56	85.71	76.86	81.04
17	84.47	81.81	87.67	89.52	94.98	88.24	92.59
18	86.68	86.13	84.50	79.74	87.85	77.59	82.19
19	89.74	85.57	86.66	83.36	89.67	81.70	86.09
20	100.33	88.21	89.71	91.41	96.60	91.59	94.22
21	115.35	95.03	100.22	101.26	107.85	100.37	104.83
22	130.99	107.84	115.20	115.70	122.21	114.70	119.99
23	150.03	123.17	130.83	132.41	139.90	126.77	136.02
24	161.63	140.51	149.84	151.16	159.91	134.07	152.84

After completing the forecasting process, the performance metrics for each model are assessed. Table 3 outlines these performance metrics for each forecasting model, while Figure 3 visually represents the RMSE and MAPE values for each forecasting model, organized from largest to the smallest error rates.

Table 3. Performance comparison across different methods on the testing set

Method	RMSE	MAPE
Moving average (MA)	11.66	8.7%
Exponential smoothing (ES)	8.35	6.5%
Elastic net (EN)	7.82	6.46%
Support vecto machine (SVM)	6.59	8.02%
Neural network (NN)	10.22	7.63%
Proposed model (PM)	6.44	5.97%

Table 3 displays the categorized forecasting models, showcasing each obtained performance metric value. The table compares six different forecasting methods based on two metrics: RMSE and MAPE. The methods listed are MA, ES, EN, SVM, NN, and our proposed model. For each method, there are corresponding RMSE and MAPE values. The RMSE values range from 6.44 to 11.66, while the MAPE values range from 5.97% to 8.7%. The lowest RMSE is for our proposed model at 6.44, and it also has the lowest MAPE at 5.97%, indicating it may be the most accurate forecasting method among those listed in this context. Consequently, visualizing these performance metric values through a bar chart sorted from largest to smallest is imperative. The RMSE and MAPE graphs for the models are depicted in Figure 3.

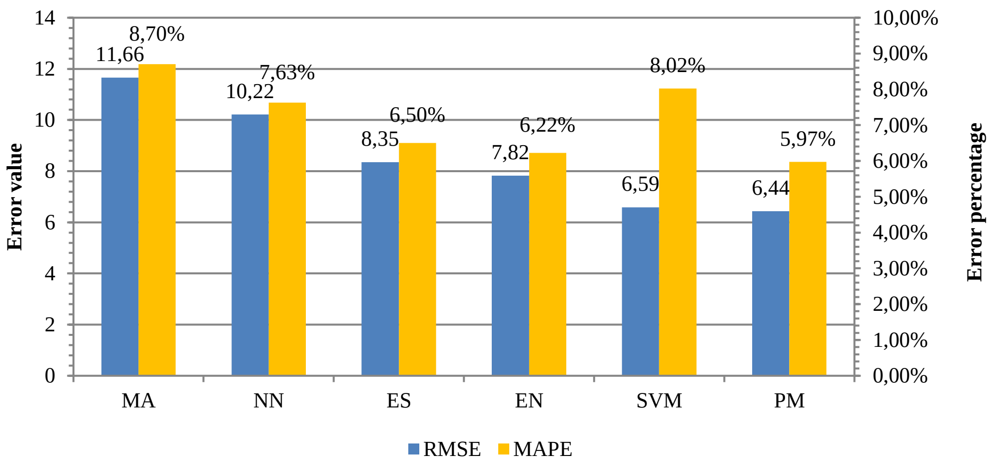

Figure 3. Performance comparison across different methods on the testing set, visualized with a bar chart

Figure 3 illustrates that the traditional model with the largest RMSE is MA, at 11.66, while ES has the smallest error value, at 8.35. In machine learning models, NN exhibits the largest error value of 10.22, while SVM has the smallest error value, at 6.59. For our proposed model, the RMSE value is 6.44. By comparing all existing forecasting models, it is evident that the largest error value belongs to MA, while the smallest error value is associated with our proposed model.

The performance metric values of each forecasting model used have been presented. It is evident that the best performance among the traditional models is achieved by ES. In contrast, for the machine learning models, prioritizing the RMSE value as the best tool for displaying deviation and fully describing the error distribution of the forecasting model, the best performance is observed with SVM. Figure 3 shows that the smallest value and percentage error are in our proposed model. Then, our proposed model, with RMSE and MAPE values of 6.44 and 5.97%, respectively, is the best-performing forecasting model and can be used as an alternative in forecasting coal prices.

Lastly, a visualization in the form of a graph is necessary, displaying the actual data of coal prices combined with forecasting results from the best-performing traditional model (ES), the best-performing machine learning model (SVM), and our proposed model. The graph depicting actual coal price data and forecasting results is presented in Figure 4.

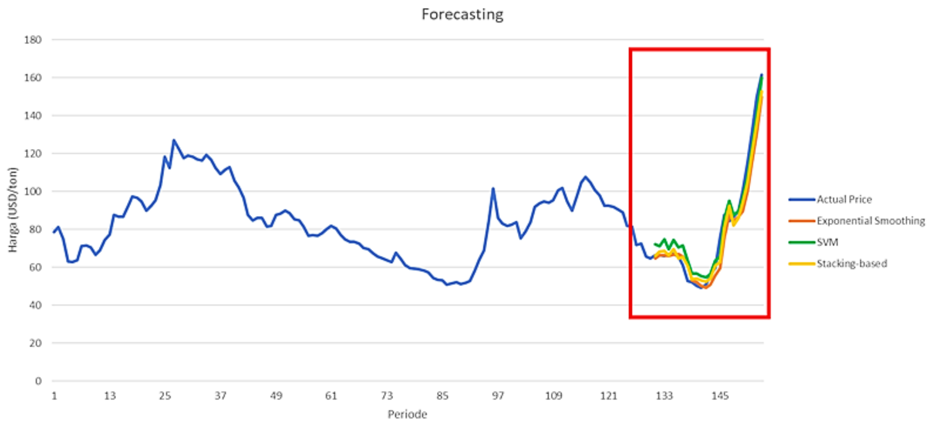

Figure 4. Actual vs. forecasted coal prices for the last 24 months (testing data) across different methods (USD/ ton), visualized with a line chart

Based on figure 4, it is evident that our proposed model provides predictive results that most closely aligned with the actual values compared to traditional and machine learning models. This is indicated by the smaller RMSE and MAPE values of our proposed model.

4.5. DISCUSSION

Traditional forecasting methods are classic but still widely used today due to their simplicity and low data requirements. These methods are easy to implement and interpret, making them accessible for many practitioners. They perform well with short-term forecasts and small data sets but struggle with capturing complex patterns and relationships, leading to lower accuracy in dynamic and intricate environments. In contrast, the complexity of today's data has made machine learning more frequently relied upon due to its ability to handle complex and extensive data sets with higher accuracy. Machine learning models are adept at identifying intricate patterns and interactions within large data sets and can adapt to various types of data, significantly improving prediction accuracy. However, machine learning methods are data-exhaustive, requiring a large number of observation points, making them unsuitable when data availability is limited. They also tend to be more complex and computationally intensive, requiring substantial expertise and resources to develop and maintain. This limitation makes machine learning impractical for certain applications where data is scarce or where simplicity and ease of use are paramount.

The results have been shown that the proposed model performed better than all traditional and machine learning models used for comparison. By balancing the strengths of both approaches, the proposed model, which integrates traditional and machine learning methods, offers a promising solution. It leverages the simplicity and interpretability of traditional models while enhancing accuracy with the capabilities of machine learning. However, this level of accuracy comes at a cost, as the proposed model is not the most efficient and requires greater computational power than standard traditional or machine learning models. Therefore, we suggest that the proposed model is particularly promising for practitioners when accuracy is the top priority and data requirements are met.

5. CONCLUSION

In this study, we explored a new forecasting concept by combining the results from traditional models and machine learning techniques. Traditional forecasting methods are appreciated for their straightforwardness and minimal data needs, whereas machine learning is trusted for its capability to manage intricate and extensive data sets with heightened accuracy. By merging the strengths of both methods, the proposed model, which integrates traditional and machine learning approaches, provides a compelling solution. It utilizes the simplicity and clarity of traditional models while boosting accuracy through machine learning capabilities. Our findings indicate that the proposed model is the best-performing forecasting model, with RMSE and MAPE values of 6.44 and 5.97%, respectively. An RMSE value of 6.44 shows that our proposed model provides the closest forecasting of actual coal prices, while a MAPE value of 5.97% suggests that it can mimic 94.03% of the actual price movement. Therefore, we conclude that our proposed model can serve as an effective alternative for forecasting coal prices.

In this research, we assessed the performance of traditional, machine learning, and proposed model in forecasting coal price in Indonesia. However, our analysis was limited to predicting coal prices without considering additional variables such as government export-import policies, coal supply and demand dynamics, and fluctuations in the stock market. Future research should incorporate these factors to provide deeper insights into coal price forecasting. Additionally, exploring newer machine learning models could improve predictive accuracy. Furthermore, as mentioned previously, achieving this level of accuracy comes with a trade-off, as the proposed model is less efficient and requires greater computational resources compared to standard traditional or machine learning models. The exhaustive nature of our approach has resulted in reduced efficiency relative to conventional methods. Hence, exploring alternative frameworks that can integrate traditional and machine learning more effectively presents a promising direction for future research.

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