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Research Article

A Hybrid Convolutional Neural Network and Bidirectional LSTM Architecture for Multi-Sector Export Forecasting: A Macroeconomic Time Series Analysis of Indonesia

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Abstract:

Accurately predicting export values is key for a country in formulating its economic plans. Unfortunately, export data often exhibits complex time series patterns that are difficult to predict, characterized by non-linearity, high volatility, and complex temporal dependencies. This study offers a solution by testing a combined deep learning model, specifically a fusion of Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM), to address the challenges of export time series forecasting. This study uses this approach to forecast Indonesia's monthly export time series data from 2016 to 2023, covering various sectors ranging from oil and gas, non-oil and gas, agriculture, industry, mining, and others. The core idea is to leverage the CNN's ability to identify hidden features within time series patterns, while the BiLSTM is tasked with understanding the temporal flow of data from both directions to capture the inherent long-term temporal dependencies within economic time series data. As a result, this combined model proved to be far superior to the standard BiLSTM model in handling the complexity of export time series. In the Non-Oil and Gas sector, the proposed model achieved a high level of accuracy with an MSE value of 3,330,239.74, an RMSE of 1,824.89, and an average prediction error (MAPE) of only 8.17%, representing a significant improvement of 69% over the baseline BiLSTM model. Similar success was also found in all other sectors, proving that this hybrid approach is highly promising for complex economic time series analysis.

Keywords: Bidirectional LSTM, Convolutional Neural Network, Hybrid Architecture, Export Forecasting, Time Series Analysis
Dataset link: https://bit.ly/dataseteksport

1. Introduction

Export performance is a key pillar of Indonesia's economic growth, directly affecting the stability of the trade balance and national economic resilience [1]. Data from the Central Statistics Agency shows that throughout 2023, Indonesia's total exports reached US$258.82 billion, with the non-oil and gas sector contributing US$242.90 billion [2]. However, export forecasts face significant challenges due to the volatility of macroeconomic time series data, which is influenced by fluctuations in global commodity prices, changes in trade policy, and geopolitical uncertainty [3]. Conventional forecasting methods such as Autoregressive Integrated Moving Average (ARIMA) show limitations in capturing complex non-linear patterns that are characteristic of economic data [4]. This approach assumes linear relationships and stationarity, which are often not fulfilled in the dynamic reality of economics [5]. As a result, prediction accuracy becomes suboptimal, especially when dealing with data featuring multifactorial patterns and complex temporal interdependencies [6].

The deep learning revolution has opened up a new paradigm in economic forecasting through its ability to learn complex patterns without rigid distribution assumptions [7]. Long Short-Term Memory (LSTM) and its variants have demonstrated superiority in handling sequential data with long-term dependencies [8]. Meanwhile, Bidirectional LSTM (BiLSTM) enriches contextual understanding through bidirectional temporal processing [9]. Recent research indicates that integrating LSTM with Convolutional Neural Networks (CNN) yields superior performance across various forecasting domains [10]. CNN, which was initially revolutionary in computer vision, is now adapted for time series analysis through 1D-CNN architecture [11]. The ability of convolutional filters to automatically extract local features has proven effective in identifying hidden temporal patterns [12]. Research shows that the combination of CNN-LSTM produces superior forecasting accuracy compared to individual models [13].

Several studies have explored the application of deep learning for Indonesian economic forecasting. Yulisa et al. [14] demonstrated the effectiveness of deep learning for export prediction with promising accuracy. However, this research has not explored the potential of hybrid architectures for multi-sector forecasting. Meanwhile, Andika et al. [15] proposed the integration of CNN-LSTM with metaheuristic optimization, which showed superior results in time series forecasting of raw material purchases.

This study proposes a novel contribution in the form of a hybrid CNN-BiLSTM architecture that integrates convolutional feature extraction with bidirectional temporal modeling. The research hypothesis is that the synergy of these two approaches will result in forecasting accuracy that significantly surpasses standalone models. The main contributions include the development of a novel hybrid architecture for multi-sector export forecasting, a comprehensive evaluation on the 2016-2023 Indonesian export dataset, and a demonstration of substantial accuracy improvements compared to the BiLSTM baseline. Recent studies show that the implementation of hybrid deep learning models requires careful fine-tuning to optimize performance in specific application domains [16].

2. Method

The study used time series data on Indonesia's monthly export values from BPS for the period January 2016 to December 2023, covering six major sectors. The dataset was divided chronologically with an 80:20 ratio for training and testing to maintain temporal order and prevent data leakage [17]. Preprocessing involved Min-Max normalization to stabilize the training process:

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

Where:

x	:	The original or raw value of the data to be normalized
x_{min}	:	The minimum value of all data in that column/feature
x_{max}	:	The maximum value of all data in that column/feature
x_{scaled}	:	The result of the normalized value x x (will be in the range of 0 to 1)

A sliding window transformation with a sequence length of 12 months is applied to convert the data into a supervised learning format suitable for deep learning architecture [18].

Model Architecture

BiLSTM Baseline

The baseline model uses a pure BiLSTM architecture with 50 units that process sequences in two directions to capture bidirectional temporal dependencies [19]. Each LSTM unit implements a standard gating mechanism to address the vanishing gradient problem in long sequential data[20].

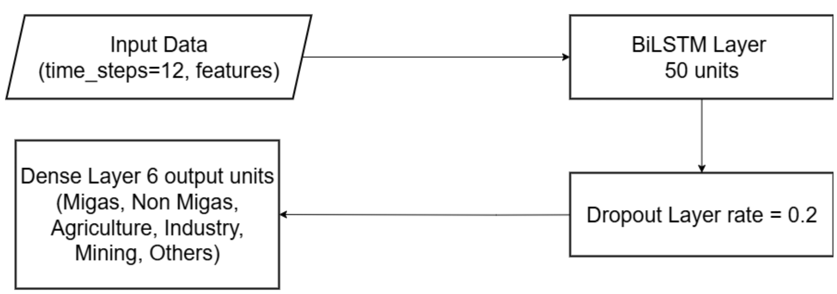


Figure 1: Model-BiLSTM Architecture

CNN-BiLSTM Hybrid

The hybrid architecture integrates a 1D-CNN layer as a feature extractor with 64 filters and a kernel size of 1, followed by a BiLSTM layer for temporal modeling. The CNN performs convolution operations [21]:

$$y[i] = \sum (j = 0\ to\ k - 1)\, x[i + j]\ .\ w[j] + b \tag{2}$$

Where:

$y[i]$	:	Convolution output at position i
$x[i]$	:	Input signal at position i
$w[j]$	:	Filter weight at position j
k	:	Kernel/filter size
b	:	Bias

The CNN output is then processed by BiLSTM to generate the final prediction through a dense layer [22].

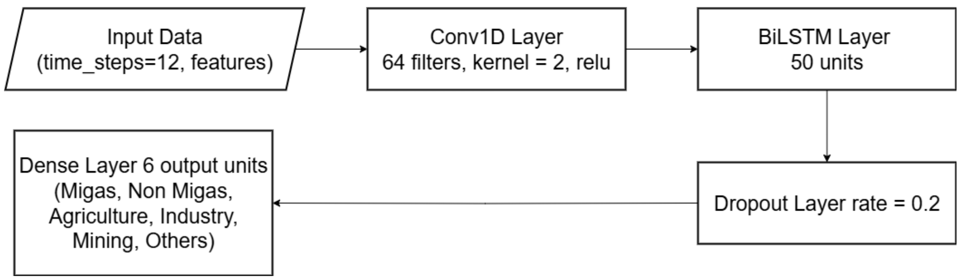


Figure 2: Hybrid CNN-BiLSTM Architecture

Training Configuration

To convert time series data into a format that can be processed by the model, this study uses a sliding window approach with an input sequence length of 12, meaning that the model uses export data from the previous 12 months to predict export values for the following month. The data is split with an 80% training and 20% testing ratio, as this provides sufficient data for the model to learn while leaving a significant portion of the data for objective evaluation. Min-Max normalization was chosen for its ability to scale data to the range [0, 1] without altering the intrinsic distribution, which is highly effective for LSTM and CNN neural networks that use activation functions sensitive to inputs within that scale range.

Table 1. Final Hyperparameter Configuration

Parameter	BiiLSTM Model	Hybrid CNN-BiLSTM Model
CNN Layer		
Filters	-	64
Kernel Size	-	1
Activation	-	ReLU
BiLSTM Layer		
Units	50	50
Training		
Optimizer	Adam	Adam
Learning Rate	0.001	0.001
Loss Function	Mean Square Error (MSE)	Mean Square Error (MSE)
Epochs	50 (dengan early stoppping)	50 (dengan early stoppping)
Baatch Size	32	32

The final hyperparameters presented in **Table 1** were determined through a series of systematic experimental processes. We used a structured trial-and-error approach, focusing on the parameters that most significantly impact model performance. For the CNN layers, the number of filters was tested within the range [32, 64, 128], and the kernel size was tested at [1, 2, 3]. For training parameters, the learning rate was explored at values [0.01, 0.005, 0.001], while the batch size was tested at [16, 32, 64]. The final configuration was selected based on the combination that consistently produced the lowest RMSE and MAPE values on the validation dataset (a subset of the training data) across all sectors. This approach ensures that the selected hyperparameters not only perform well on a single sector but demonstrate strong generalization across various export data dynamics.

Performance Evaluation Metrics

Mean Squared Error (MSE)

MSE calculates the average of the squared differences between the actual values (Y_i) and the predicted values (hatY_i). This metric imposes a greater "penalty" for large prediction errors due to the squaring process, making it highly sensitive to outliers or predictions that are significantly off target [23].

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \mathcal{Y}_i)^2 \tag{3}$$

Where:

n	:	Total amount of data (number of samples/predicted vs. actual pairs)
y_i	:	Actual value in data i
$\mathcal{Y}_i$	:	Predicted value in data i

Root Mean Squared Error (RMSE)

RMSE is the square root of MSE. Its main advantage is that its units are the same as the original data units (in this case, millions of US dollars). This makes it easier to interpret directly as the average magnitude of prediction errors [24].

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \mathcal{Y}_i)^2} \tag{4}$$

Where:

$RMSE$	:	Root Mean Squared Error, or the root of the mean square error
MSE	:	Mean Squared Error, which is the average value of the square difference between the actual value and the prediction
n	:	Total number of data (samples)
y_i	:	Actual value in data i
$\mathcal{Y}_i$	:	Predicted value in data

Mean Absolute Percentage Error (MAPE)

MAPE presents error as a percentage of the actual value. This makes it a very intuitive metric for communicating the level of error to non-technical stakeholders. MAPE shows how large, on average, the prediction error is relative to the actual value [25].

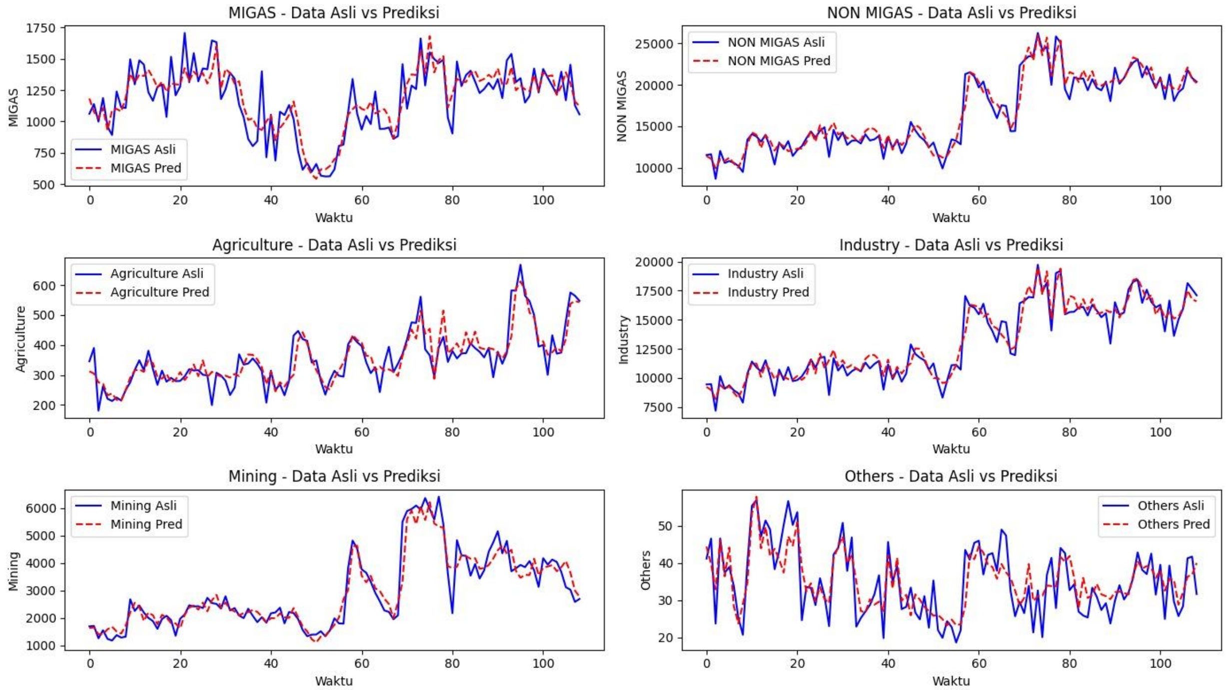
$$MAPE = \left(\frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \mathcal{Y}_i}{y_i}\right|\right) \text{x } 100\% \tag{5}$$

Where:

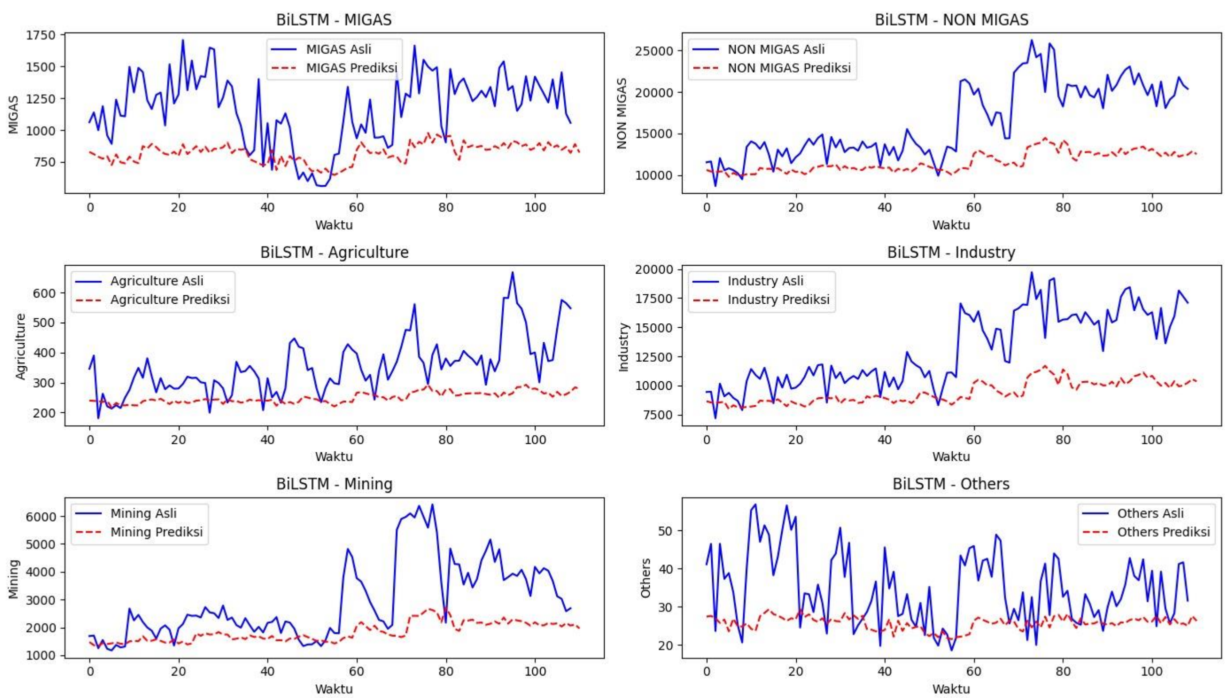
$MAPE$	:	Mean Absolute Percentage Error – average error in percentage form
x 100%	:	Convert the average value to percentage form (%)
n	:	Total number of data (samples)
y_i	:	Actual value in data i
$\mathcal{Y}_i$	:	Predicted value in data i

3. Results and Discussion

After the training process was completed, both models were used to predict export values in the test data. The predictive capabilities of the CNN-BiLSTM hybrid model can be visually observed in Figure 3 These plots directly compare actual export values (blue line) with values predicted by the model (orange line) for each sector. Visually, it is evident that the model is able to capture general trends and fluctuation patterns in the actual data fairly well across most sectors.



(a)



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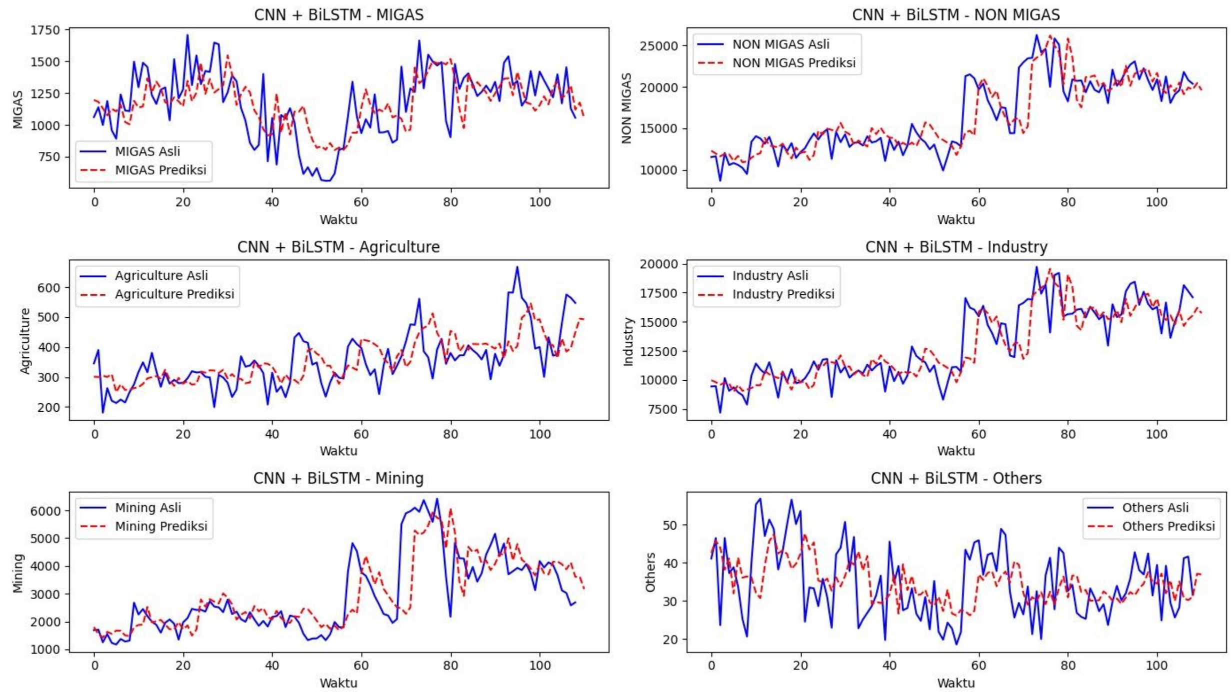

(c)

Figure 3: Visualization of Forecasting Results on Test Data (a) Actual export data for six sectors (b) Comparison of actual data (blue) with BiLSTM model predictions (red) (c) Comparison of actual data (blue) with hybrid CNN-BiLSTM model predictions (red)

This bar chart presents a direct comparison of RMSE values between BiLSTM (blue bars) and hybrid CNN-BiLSTM (orange bars) across six export sectors. The visual evidence clearly shows that the orange bars are consistently much shorter than the blue bars in all categories, providing strong evidence that CNN-BiLSTM produces much lower absolute prediction errors.

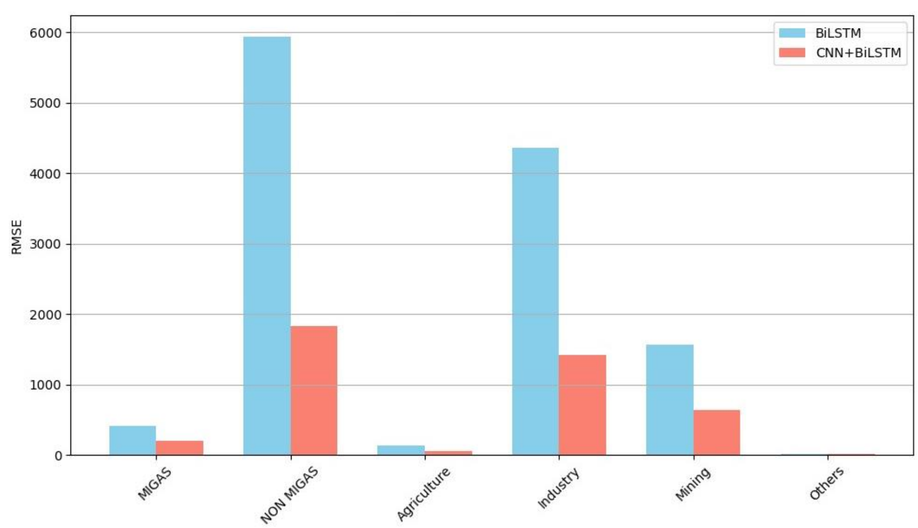

Figure 4: Comparison Chart of RMSE Values between BiLSTM and CNN+BiLSTM Models

While RMSE provides a clear picture of the absolute magnitude of error in US dollar units, this metric is not always intuitive for measuring relative accuracy, especially when comparing performance across sectors with vastly different value scales. To address this, the evaluation continues using Mean Absolute Percentage Error (MAPE), which normalizes errors based on actual values. This metric presents errors as percentages, enabling a more balanced and easily understood comparison of accuracy among various stakeholders, regardless of the export value scale of each sector.

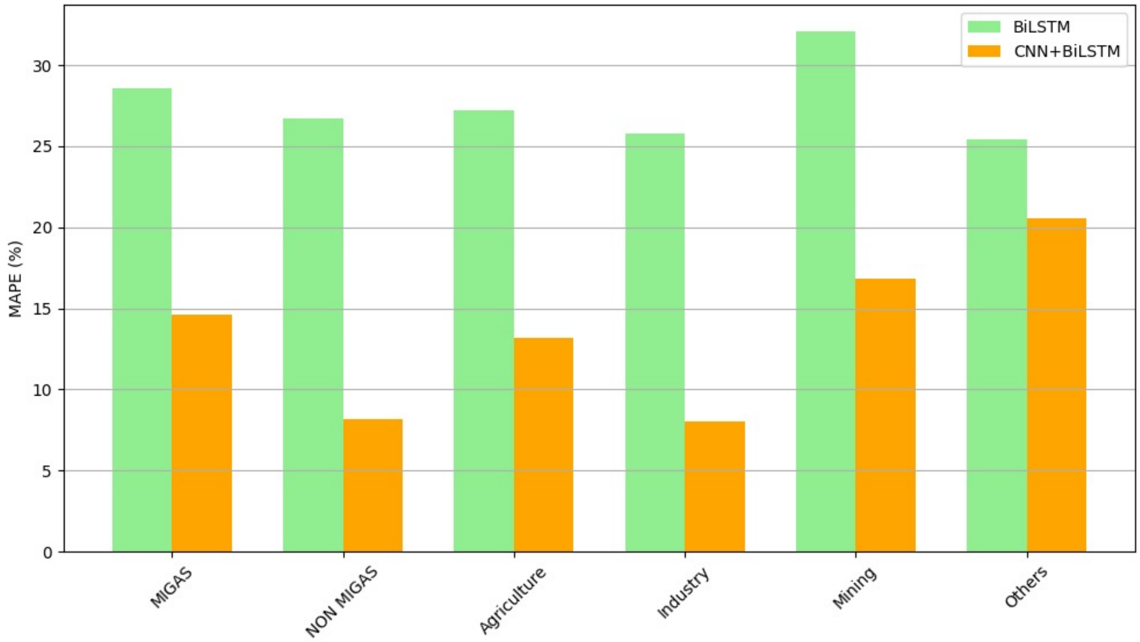

Figure 5: Comparison Chart of MAPE Values between BiLSTM and CNN+BiLSTM Models

The bar chart in **Figure 5** confirms the superiority of the hybrid model from the perspective of relative error. The orange bars (CNN-BiLSTM) consistently show a much lower error rate across all sectors compared to the green bars (BiLSTM). This visualization is highly effective in illustrating the significant relative accuracy improvement achieved by the proposed model, a finding that is highly relevant for business interpretation and policy formulation.

Table 2. Performance Evaluation Results of BiLSTM Model vs Hybrid CNN+BiLSTM

Model	Variable	MSE	RMSE	MAPE (%)
BiLSTM	Migas	175,139.36	418.50	28.57
	Non Migas	35,266,133.90	5,938.53	26.68
	Agriculture	17,361.75	131.76	27.18
	Industry	19,012,001.84	4,360.28	25.74
	Mining	2,431,882.25	1,559.45	32.10
	Others	160.35	12.66	25.42
CNN+BiLSTM	Migas	38,094.57	195.18	14.63
	Non Migas	3,330,239.74	1,824.89	8.17
	Agriculture	3,488.39	59.06	13.16
	Industry	2,010,863.35	1,418.05	8.01
	Mining	403,175.18	634.96	16.83
	Others	63.97	8.00	20.52

The results show that in the non-oil and gas sector, the hybrid model achieved a MAPE of 8.17% with a 69% reduction in error compared to BiLSTM (MAPE 26.68%). Similar performance was seen in the industrial sector with a MAPE of 8.01%, demonstrating superior ability to capture complex patterns in macroeconomic data.

Discussion

The advantage of hybrid architecture lies in the synergistic division of tasks between CNN and BiLSTM components. The CNN layer functions as a feature extractor that identifies hidden local patterns in time series data, while BiLSTM models the long-term temporal dependencies of the extracted features. This synergy enables the model to understand not only “what” (important local patterns) but also ‘when’ and “how” these patterns are temporally interconnected. Achieving a MAPE < 10% in the non-oil and gas sector and industry indicates the model's ability to distinguish important signals from random noise, a crucial characteristic in economic analysis.

However, relatively lower performance in the mining and other sectors (MAPE 16.83% and 20.52%) indicates a strong influence from exogenous factors that were not modeled in this study. The mining sector, for example, is highly vulnerable to global commodity price volatility, such as nickel and coal, as well as sudden changes in domestic mineral downstreaming policies that can drastically alter export volumes and values in a short period of time. On the other hand, the “others” category is an aggregation of various heterogeneous commodities, each with unique market dynamics, making it difficult for the model to capture a dominant pattern. This suggests that for sectors heavily influenced by external variables, future models need to integrate this additional data to achieve higher accuracy.

4. Conclusion

This study successfully demonstrated the superiority of the CNN-BiLSTM hybrid architecture for forecasting Indonesia's multi-sector exports. The developed model achieved a significant improvement in accuracy with a MAPE of 8.17% in the non-oil and gas sector, representing a 69% improvement over the BiLSTM baseline. The main contributions of this research include the development of a novel hybrid architecture that integrates convolutional feature extraction with bidirectional temporal modeling, comprehensive empirical validation on the Indonesian export dataset for the period 2016-2023, and demonstration of consistent accuracy improvement across all economic sectors. The practical implications of this research are highly significant for the formulation of trade policies and national economic planning. A more accurate model can enhance the quality of foreign exchange revenue projections and optimize international trade strategies. Future research could explore the integration of exogenous variables such as global commodity prices and macroeconomic indicators to improve accuracy in volatile sectors. Additionally, to provide a broader comparative context, future research could compare the performance of this hybrid architecture with classical statistical models such as ARIMA or SARIMA. The implementation of the attention mechanism in the BiLSTM architecture also has the potential to yield better interpretability for economic analysis.

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