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Stock Price Prediction in Indonesia's Mining Sector Using a Hybrid Conv1D-LSTM Model

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Abstract

In the investment world, the ability to predict stock price movements is a key factor for success among investors and analysts. This study introduces a novel approach for forecasting stock prices in Indonesia's mining sector using a hybrid model that combines Convolutional Neural Networks (Conv1D) and Long Short-Term Memory (LSTM) networks. The volatile nature of stock markets and the unique characteristics of the mining industry demand accurate prediction models. Our research demonstrates that the Conv1D-LSTM model can extract patterns from stock price data more effectively than traditional models, thanks to Conv1D's feature extraction capabilities and LSTM's sequence learning strengths. By employing historical stock data from several leading mining companies in Indonesia, our model achieved a 15% higher prediction accuracy compared to conventional methods. These results highlight the significant potential of artificial intelligence in assisting investors to make more precise and informed decisions. We hope this research will pave the way for broader adoption of technology in the financial sector, especially in predicting complex and challenging market dynamics.

Keywords:
Deep Learning, Conv1D, LTSM, Mining Stock Price, Prediction.

1. Introduction

In Indonesia, the mining sector plays a crucial role in the national economy. Abundant natural resources such as coal, gold, nickel, and tin make it a significant economic pillar. According to the Ministry of Energy and Mineral Resources, the mining sector contributes approximately 11% to Indonesia's Gross Domestic Product (GDP) in recent years. In addition to direct financial contributions, the sector also supports related industries and drives regional development [1].

However, stock price volatility in the mining sector remains a major challenge. Global commodity price fluctuations, changes in government regulations, and broader economic conditions often impact stock prices. For example, coal prices, which are one of Indonesia's main exports, can change drastically due to global demand shifts and environmental policies [2]. Regulatory changes, such as mining policies or export restrictions, also add complexity to the financial landscape [3].

Traditional statistical models such as linear regression and ARIMA often struggle to capture the complexities of stock price movements in this sector. These models typically assume linear and stationary patterns, while stock price data often exhibit non-linear patterns and structural changes. Additionally, traditional models may not fully account for

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external factors like macroeconomic indicators and international market trends [4].

To address these limitations, the use of more advanced machine learning techniques is gaining traction. Machine learning models, particularly deep learning approaches, offer advantages due to their ability to learn from large datasets and complex non-linear patterns. Convolutional Neural Networks (CNNs) are effective at identifying spatial hierarchies in data, while Long Short-Term Memory (LSTM) networks excel at capturing long-term temporal dependencies [5]. By combining these models in a hybrid Conv1D-LSTM framework, we can leverage the strengths of both to enhance prediction accuracy.

2. Related Works

Traditional statistical models, such as ARIMA and GARCH, have long been used for stock price prediction. ARIMA models handle linear dependencies in time series data through autoregressive and moving average components. However, these models often struggle to capture non-linear patterns and complex market dynamics. Research indicates that while ARIMA is effective for short-term forecasting, its performance declines over the long term, especially in highly volatile sectors like mining [6], [7]. GARCH models, on the other hand, are robust in modeling volatility clustering but may not fully reflect the complexities of stock price movements influenced by external factors [8].

With technological advancements, machine learning has transformed approaches to stock price prediction. Methods such as Support Vector Machines (SVM) and Random Forests have been employed with varying degrees of success. SVMs are effective in high-dimensional spaces, both for classification and regression, though their performance depends on kernel choice and parameter tuning [9]. Random Forests, as an ensemble method, are resistant to overfitting and effective in handling large datasets, yet may struggle with temporal dependencies in time series data [10].

Deep learning, a subset of machine learning, shows remarkable potential in stock price prediction. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are designed to capture temporal dependencies in sequential data. LSTM networks have demonstrated superior performance in financial time series forecasting compared to traditional models [6]. Convolutional Neural Networks (CNNs), originally developed for image processing, have been adapted for time series analysis, proving effective in identifying local patterns and features important for stock price prediction [11].

Recent research also explores hybrid models that combine various techniques to leverage their complementary strengths. For example, hybrid CNN-LSTM models combine the feature extraction capabilities of CNNs with the sequential learning capabilities of LSTMs. This hybrid approach has proven successful in several domains, including stock price prediction, with the ability to capture both spatial and temporal dependencies. Studies show that hybrid models often outperform single models in terms of accuracy and prediction robustness, highlighting their potential for financial forecasting [12], [13].

3. Proposed Method

3.1. Hybrid Conv1D-LSTM Model

1. Basic Concept

The Hybrid Conv1D-LSTM model combines Convolutional Neural Networks (Conv1D) with Long Short-Term Memory (LSTM) networks to predict stock prices. Conv1D extracts spatial features, while LSTM handles long-term temporal dependencies. This combination leverages the strengths of both architectures in handling spatial and temporal information in stock price time series data [14].

2. Strengths and Weaknesses of This Model

a. Strengths:

1. Multiscale Feature Extraction: Conv1D captures spatial features at various levels, while LSTM handles complex temporal patterns.
2. Model Flexibility: This model can adapt to the complexity of stock price data, accommodating both spatial and temporal changes.

b. Weaknesses:

1. Careful Parameter Tuning: The effectiveness of this model depends on accurate parameter tuning, and its performance may vary depending on data complexity and market conditions [14], [15].

By explaining recent developments in the mining sector, factors influencing stock prices, and the concepts, advantages, and limitations of the Hybrid Conv1D-LSTM Model, this study aims to enhance stock price prediction accuracy in the mining sector.

3. Convolutional Neural Network 1D (Conv1D) Conv1D processes one-dimensional data, such as time series data, through convolution with filters (kernels) to extract patterns and features.

Conv1D Formula: $y(t)=f(W*x(t)+b)$

- $y(t)$: Output at time t
- f : Activation function (e.g., ReLU)
- W : Kernel (filter) with parameters learned during training
- $x(t)$: Input at time t
- b : Bias

4. Long Short-Term Memory (LSTM) The LSTM layer handles time series data by "remembering" past information and "forgetting" irrelevant information.

LSTM Formula:

$$ft = \sigma(Wf \cdot [ht-1,xt]+bf)$$
$$it = \sigma(Wi \cdot [ht-1,xt]+bi)$$
$$C\sim t = \tanh(WC \cdot [ht-1,xt]+bC)$$
$$Ct = ft \cdot Ct-1+it \cdot C\sim t$$
$$ot = \sigma(Wo \cdot [ht-1,xt]+bo)$$
$$ht = ot \cdot \tanh(Ct)$$

- f_t : Forget Gate
- i_t : Input Gate
- $C\sim_t$: New Cell Content
- C_t : Cell State
- o_t : Output Gate
- h_t : Hidden State

5. Model the Hybrid Conv1D-LSTM Model combines Conv1D and LSTM layers, either in series or parallel, depending on the design.

Hybrid Conv1D-LSTM Model Formula: Output=LSTM(Conv1D(Input)) The input data first passes through the Conv1D layer for feature extraction and then through the LSTM layer for further processing.

4. Experimental Setup

4.1. Dataset

This study aims to predict stock prices of mining companies using the Hybrid Conv1D-LSTM model. The model leverages Conv1D for short-term patterns and LSTM for long-term patterns in time series data. Data is obtained from Yahoo Finance for the period from January 1, 2020, to January 1, 2024.

4.2. Methodology

1. Data Daily closing price data for mining company stocks from January 1, 2020, to January 1, 2024, is used.
2. Preprocessing Data is normalized using the Min-Max Scaler from scikit-learn to ensure features are within the same range.

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_data = scaler.fit_transform(data)
```

3. Dataset Preparation Data is divided into training and testing sets, with an 80:20 ratio. The dataset is transformed into a format suitable for Conv1D and LSTM using the create_dataset function.

```
def create_dataset(data, time_step=1):
    X, y = [], []
    for i in range(len(data) - time_step):
        X.append(data[i:(i + time_step), 0])
        y.append(data[i + time_step, 0])
    return np.array(X), np.array(y)

time_step = 10
X_train, y_train = create_dataset(train_data, time_step)
X_test, y_test = create_dataset(test_data, time_step)

X_train = X_train.reshape((X_train.shape[0],
X_train.shape[1], 1))
X_test = X_test.reshape((X_test.shape[0], X_test.shape[1],
1))
```

4. Model Training the Hybrid Conv1D-LSTM model is built using Keras. The model is trained for 10 epochs with a batch size of 32 and a 20% validation split.

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv1D, MaxPooling1D,
LSTM, Dense
model = Sequential ()
model.add(Conv1D(filters=64, kernel_size=3,
activation='relu', input_shape=(time_step, 1)))
model.add(MaxPooling1D(pool_size=2))
model.add(LSTM(50))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mean_squared_error')
history = model.fit(X_train, y_train, epochs=10,
batch_size=32, validation_split=0.2)
```

5. Evaluation Prediction results are compared with actual data to evaluate model performance.

```
predictions = model.predict(X_test)
predictions = scaler.inverse_transform(predictions)

plt.figure(figsize=(12, 6))
plt.plot(data.index[-len(y_test):],
scaler.inverse_transform(test_data[time_step:]),
label='Actual Price')
plt.plot(data.index[-len(y_test):], predictions,
label='Predicted Price')
plt.legend()
plt.show()
```

5. Result and Analysis

5.1. Evaluation Metrics

1. Mean Absolute Error (MAE):
   $$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\mathrm{Actual}_i - \mathrm{Predicted}_i|$$
2. Mean Squared Error (MSE):
   $$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\mathrm{Actual}_i - \mathrm{Predicted}_i)^2$$
3. Root Mean Squared Error (RMSE):
   $$\mathrm{RMSE} = \sqrt{\mathrm{MSE}}$$
4. R-squared (R^2):
   $$R^2 = 1 - \frac{\sum_{i=1}^{n}(\mathrm{Actual}_i - \mathrm{Predicted}_i)^2}{\sum_{i=1}^{n}(\mathrm{Actual}_i - \overline{\mathrm{Actual}})^2}$$

5.2. Comparison with Traditional Models

- ARIMA: MAE = 0.45, MSE = 0.35, RMSE = 0.59, R^2 = 0.65
- GARCH: MAE = 0.43, MSE = 0.32, RMSE = 0.57, R^2 = 0.68
- Hybrid Conv1D-LSTM: MAE = 0.37, MSE = 0.29, RMSE = 0.54, R^2 = 0.72

The comparison of ARIMA, GARCH, and Hybrid Conv1D-LSTM models highlights significant differences in predictive performance. ARIMA, a traditional time series model, has the highest error rates, with an MAE of 0.45, MSE of 0.35, and RMSE of 0.59, while explaining 65% of the variance (R^2 = 0.65). GARCH performs slightly better, reducing errors to an MAE of 0.43 and improving R^2 to 0.68, indicating its effectiveness in capturing volatility patterns. However, both models struggle compared to deep learning-based approaches, as their reliance on linear assumptions limits their ability to model complex relationships in the data.

The Hybrid Conv1D-LSTM model outperforms both traditional methods, achieving the lowest errors (MAE = 0.37, MSE = 0.29, RMSE = 0.54) and the highest R^2 value (0.72), indicating superior predictive accuracy. This suggests that deep learning models, which leverage convolutional layers for feature extraction and LSTMs for sequential dependencies, are more effective at capturing intricate time series patterns. Given its higher explanatory power and lower error rates, the Hybrid Conv1D-LSTM model presents a more reliable solution for forecasting tasks where non-linear dependencies play a crucial role.

6. Conclusion

The Hybrid Conv1D-LSTM model demonstrates strong predictive capabilities for stock price forecasting in the mining sector by leveraging the strengths of both convolutional and recurrent neural networks. The Conv1D layer efficiently extracts essential patterns and trends from historical stock price data, capturing short-term dependencies and fluctuations that may not be easily identifiable through traditional statistical models. Meanwhile, the LSTM component processes these extracted features over time, preserving long-term dependencies and accounting for the sequential nature of stock price movements. By combining these two deep learning architectures, the Hybrid Conv1D-LSTM model significantly enhances forecasting accuracy, as reflected in its lower error metrics (MAE = 0.37, MSE = 0.29, RMSE = 0.54) and higher coefficient of determination (R^2 = 0.72), outperforming conventional time series models like ARIMA and GARCH.

The study underscores the potential of hybrid deep learning models in financial forecasting, particularly in volatile sectors such as mining, where price fluctuations are influenced by multiple factors, including global demand, commodity prices, and geopolitical events. The superior performance of the Hybrid Conv1D-LSTM model suggests that deep learning-based approaches can provide more reliable and data-driven insights for investors and financial analysts. By reducing forecasting errors and improving predictive accuracy, this model aids stakeholders in making informed decisions, optimizing investment strategies, and mitigating risks associated with stock price volatility. As financial markets become increasingly complex, integrating AI-driven models into predictive analytics could revolutionize traditional forecasting methodologies, paving the way for more advanced and adaptive financial modeling techniques.

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