Temporal Analysis of Microsoft Stock: Integrating Statistical and Deep Learning Models for Forecasting and Insights

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GitHub: https://github.com/mahmoudg32/Temporal-Analysis-of-Microsoft-Stock.git

Abstract— This report explores the application of various forecasting models, including CNN-LSTM, TCN, CNN, SARIMAX, and ARIMAX, to predict Microsoft stock prices based on historical data. Each model's performance is evaluated using metrics such as Root Mean Squared Error (RMSE), with a focus on understanding their effectiveness in capturing stock price dynamics.

1. *Introduction and Problem Statement*

Stock price prediction is a crucial aspect of financial analysis and trading strategies. Accurately forecasting stock prices can greatly benefit investors and traders, but it's a challenging task due to the volatile nature of stock markets and numerous influencing factors. This project aims to tackle the challenge of predicting stock prices using deep learning classifiers. By analyzing historical stock price data, including opening and closing prices along with date and time information, we aim to determine the most effective deep learning model for predicting future stock prices.Use the enter key to start a new paragraph. The appropriate spacing and indent are automatically applied.

2. *Data Description and Preprocessing*

The dataset 'MicrosoftStocks.csv' acquired from Kaggle contains daily historical stock prices of Microsoft the data set contains nearly 9.5K rows and 6 columns. Data preprocessing includes converting dates to DateTime format and extracting additional time-related features such as year, month, day, hour, and quarter. The 'Price' column is normalized using MinMaxScaler.

3. Methodology

Models Used

- **TCN**: Temporal Convolutional Network with configurable depth and kernel size.
- **CNN**: Convolutional Neural Network with varying architectures and kernel sizes.
- *CNN-LSTM: Convolutional Neural Network followed by Long Short-Term Memory Network*
- **SARIMAX**: Seasonal AutoRegressive Integrated Moving Average model with exogenous variables.
- **ARIMAX**: AutoRegressive Integrated Moving Average model with exogenous variables.

Each model is trained and evaluated using the same dataset and performance metrics.

4. Results and Performance Evaluation

1) Training and Validation

Each model is trained and validated to assess its predictive accuracy. Training details and validation results are summarized for each model.

2) Prediction Results

Predicted vs. actual stock prices are plotted for visual comparison across all models. The effectiveness of each model in capturing stock price trends is analyzed.

3) Model Performance Metrics

RMSE values for each model:

- **CNN-LSTM**: 1.615
- **TCN**: 0.919
- **CNN**: 2.558
- **SARIMAX**: 4.66543
- **ARIMAX**: 4.63959

5. Discussion and Interpretation of Results

1) Model Comparison

Models are compared based on their RMSE values and ability to forecast Microsoft stock prices. Strengths and limitations of each model are discussed, highlighting their applicability in different scenarios.

6. Conclusion

In this study, we evaluated several models for predicting Microsoft stock prices: CNN-LSTM, TCN, CNN, SARIMAX, and ARIMAX. Each model offered unique strengths in forecasting accuracy and interpretability.

The CNN-LSTM model, combining convolutional and LSTM layers, achieved an RMSE of 1.615, demonstrating strong predictive performance by capturing both spatial and temporal patterns in the data.

Comparatively, TCN excelled with an RMSE of 0.919, leveraging temporal convolutional layers to model long-range dependencies effectively.

Traditional models like SARIMAX and ARIMAX provided insights into seasonal and exogenous factors but showed higher RMSE values of 4.665 and 4.640, respectively.

CNN models, with diverse architectures, achieved an RMSE of 2.558, highlighting their ability to learn complex data patterns through convolution.

In conclusion, model selection should consider the data characteristics and forecasting requirements. The CNN-LSTM model offers robust performance, complemented by TCN for

capturing intricate temporal dynamics. Future research could explore hybrid approaches for enhanced predictive accuracy in financial forecasting.

This study underscores the importance of model diversity and evaluation metrics in designing effective forecasting systems for financial markets.

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THE DATASET :
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