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Cognitive Computing

Report on

Mini Project
Stock Price Prediction

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Experiment 10 : Mini Project : Stock Price Prediction.

Introduction :

Stock price prediction is a critical task in the financial sector, with applications ranging from investment strategies to risk management. Recent advancements in deep learning, particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, have shown promising results in predicting stock prices. This report outlines a project that leverages cognitive computing to predict upcoming stock prices using LSTM and GRU models, with a focus on preprocessing data from an uploaded dataset and integrating financial news sentiments for enhanced forecasting accuracy.

Background :

The financial market is characterized by its volatility and unpredictability, making stock price prediction a challenging task. Traditional methods, such as time series analysis and statistical models, have limitations in capturing the complex dynamics of stock prices. Deep learning models, including LSTM and GRU, have emerged as powerful tools for time series forecasting due to their ability to learn from sequential data and capture long-term dependencies [1].

Problem Definition :

The primary challenge in stock price prediction is to accurately forecast future prices based on historical data and external factors, such as financial news. The project aims to address this challenge by developing a model that combines the strengths of LSTM and GRU networks, along with sentiment analysis of financial news, to predict stock prices with high accuracy.

System Description :

The proposed system consists of two main components:

- Data Preprocessing Module: This module is responsible for cleaning and preparing the dataset, which includes historical stock prices and financial news. The data is preprocessed to ensure it is in a suitable format for model training.
- Prediction Module: This module integrates LSTM and GRU models for stock price prediction. The models are trained on the preprocessed data.

Methodology and Technology Used :

- Data Preprocessing

The dataset includes features such as date, open, last traded price (LTP), high, low, and quantity for historical stock prices, and date, news headline, and news body for financial news. Sentiment analysis of news headlines and bodies is performed to gauge the overall sentiment of the news towards the stock, which is then used as an additional feature for the LSTM and GRU models [1].

- Model Architecture

Two deep learning models are employed for stock price prediction: LSTM and GRU. Both models are designed to handle sequential data, making them suitable for time series forecasting tasks like stock price prediction. The LSTM model is known for its ability to learn long-term dependencies, while the GRU model is a simplified version of LSTM that has fewer parameters, making it computationally efficient [1].

Implementation :

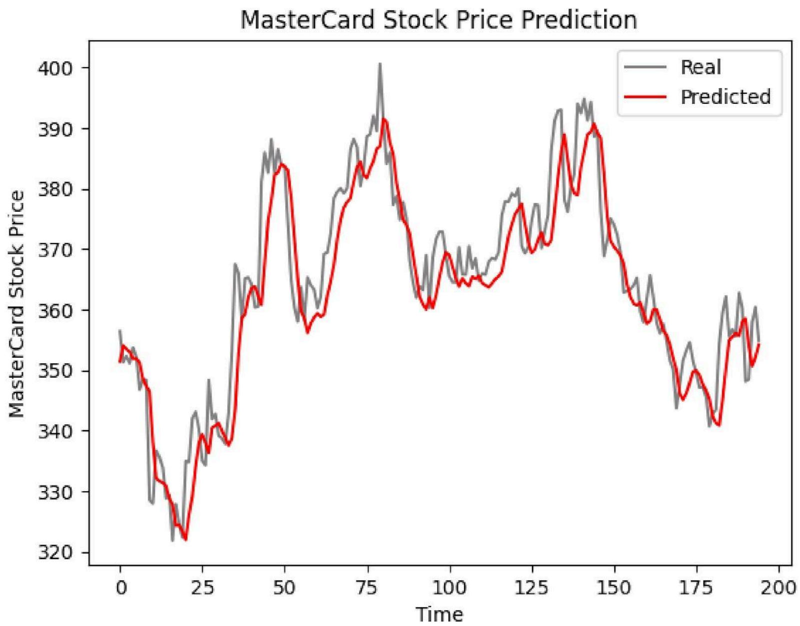
The implementation of the project involves several steps:

- Data Collection and Preprocessing: Historical stock price data and financial news are collected and cleaned. Sentiment analysis is performed on the news to extract sentiment scores.
- Model Training: The LSTM and GRU models are trained on the preprocessed data, with financial news sentiments incorporated as additional features.
- Prediction: The trained models are used to predict future stock prices based on the input features.

Results and Discussions :

- Performance Comparison

The performance of LSTM and GRU models in stock price forecasting was found to be circumstantial, with neither model consistently outperforming the other when only stock market features were used as input. However, when financial news sentiments were incorporated into the input features, both models demonstrated improved forecasting accuracy [1].



```
[ ]: return_rmse(test_set,predicted_stock_price)
```

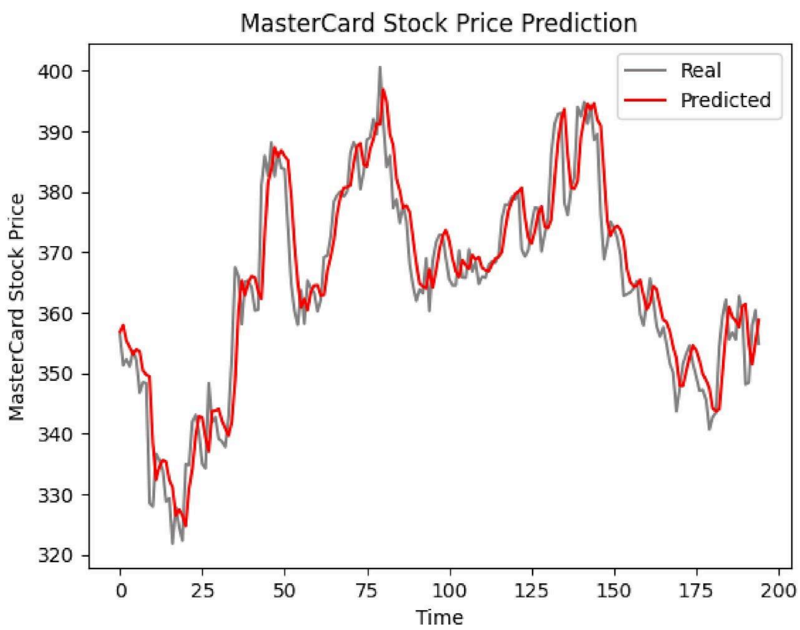
```
The root mean squared error is 6.70.
```

```
[ ]: from sklearn.metrics import r2_score

accuracy = r2_score(test_set,predicted_stock_price)
print(accuracy)
```

```
0.8419888705231202
```

LSTM Architecture




```
[ ]: return_rmse(test_set,GRU_predicted_stock_price)
```

```
The root mean squared error is 5.93.
```

```
[ ]: from sklearn.metrics import r2_score

accuracy = r2_score(test_set,GRU_predicted_stock_price)
print(accuracy)
```

```
0.8764566641268986
```

GRU Architecture

- Computational Considerations

Despite the enhanced accuracy, both the LSTM-News and GRU-News models require more computational power and take longer to complete the prediction process. This trade-off between accuracy and computational efficiency is a common challenge in deep learning applications [1].

- Cooperative Deep-Learning Architecture

The study proposes a cooperative deep-learning architecture that combines both the LSTM-News and GRU-News models. This architecture acts as an expert system, dynamically recommending the best possible forecast based on the performance of both models. This approach aims to leverage the strengths of both models to achieve more accurate and reliable stock price predictions [1].

Conclusion and Future Scope :

The project successfully demonstrates the potential of LSTM and GRU models in stock price prediction, particularly when enhanced with financial news sentiments. While both models offer competitive performance, the integration of news sentiments significantly improves forecasting accuracy. The proposed cooperative deep-learning architecture represents a promising direction for future research and application in the field of stock price prediction.

Annexure :

```
[ ]: # The LSTM architecture
model_lstm = Sequential()
model_lstm.add(LSTM(units=125, activation="tanh", input_shape=(n_steps,␣
  ↪features)))
model_lstm.add(Dense(units=1))
# Compiling the model
model_lstm.compile(optimizer="RMSprop", loss="mse")

model_lstm.summary()
```

```
Model: "sequential"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 125)               63500

 dense (Dense)               (None, 1)                 126

=================================================================
Total params: 63626 (248.54 KB)
Trainable params: 63626 (248.54 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

LSTM Architecture

```
[ ]: model_gru = Sequential()
model_gru.add(GRU(units=125, activation="tanh", input_shape=(n_steps,␣
  ↪features)))
model_gru.add(Dense(units=1))
# Compiling the RNN
model_gru.compile(optimizer="RMSprop", loss="mse")

model_gru.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 gru (GRU)                   (None, 125)               48000

 dense_1 (Dense)             (None, 1)                 126

=================================================================
Total params: 48126 (187.99 KB)
Trainable params: 48126 (187.99 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

References :

[1] Li, C.; Qian, G. (2023). Stock Price Prediction Using a Frequency Decomposition Based GRU Transformer Neural Network. Applied Sciences, 13(1), 222. [Source 3](https://www.mdpi.com/2076-3417/13/1/222)

[2] A Technical Guide on RNN/LSTM/GRU for Stock Price Prediction. [Source 0](https://medium.com/swlh/a-technical-guide-on-rnn-lstm-gru-for-stock-price-prediction-bce2f7f30346)

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Correction Parameters	**Formative Assessment [40%]**	**Timely completion of Practical [40%]**	**Attendance / Learning Attitude [20%]**	**Total**
Marks Obtained				