Stock Market Prediction Using LSTM Recurrent Neural Network

This article addresses the challenges of predicting future stock market values due to the complexities of financial markets. Leveraging the dominance of machine learning in current scientific research, the study focuses on constructing a model using Recurrent Neural Networks (RNN), specifically the Long-Short Term Memory (LSTM) model. The primary goal is to assess the precision of machine learning algorithms in predicting stock market values and evaluate the impact of epochs on model improvement.

Introduction:

Highlighting the role of machine learning in quantitative finance, the introduction establishes the context for using algorithms to predict asset values. It emphasises the term "machine learning" and its application in revealing patterns solely based on data. Various models are discussed, offering a mechanism to combine diverse information sources efficiently.

Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM):

The section introduces LSTM as a type of RNN capable of capturing data from past stages for future predictions. It outlines the structure of an Artificial Neural Network, emphasising the role of LSTM in predicting future values based on sequential observations. The limitations of RNN's long-term memory are addressed, highlighting the utility of LSTM in handling extended data sequences.

Describing the data used in the study, it consists of daily opening prices of stocks (GOOGL and NKE) from the New York Stock Exchange. The LSTM RNN model is employed, utilising 80% of the data for training and 20% for testing. Mean squared error is chosen for model optimisation, and different epochs are explored to structure the LSTM model.

Results and Discussion:

The results showcase the impact of epochs and data length on testing outcomes. Observing the testing data for NKE stocks, the study discusses the changing nature of assets over time. It emphasises the importance of avoiding significant changes in data nature for accurate predictions. Different epochs and datasets are compared, revealing how training with less data and more epochs can enhance forecasting precision.

Conclusion:

The paper concludes with promising results from the LSTM RNN model for forecasting asset values. It acknowledges the model's capability to trace the evolution of opening prices for both GOOGL and NKE assets. Future work is proposed to optimise data length and the number of training epochs for improved prediction accuracy.