

**CNN LOB: STOCK PRICE MOVEMENT PREDICTION
EXPLOITING SPATIAL FEATURES OF
THE LIMIT ORDER BOOK**

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Sri Lanka

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Thesis submitted in partial fulfillment of the requirements for the degree Master of
Science in Computer Science and Engineering

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Declaration

I declare that this is my own work and this MSc Research Project Report does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or institute of higher learning and to the best of my knowledge and belief, it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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Dr. Uthayasanker Thayasivam

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Abstract

The problem of accurately predicting equity price movements is of high importance to all agents involved in modern financial markets. Price prediction is extremely difficult due to the complex interplay of spatial and temporal dynamics on the limit order book (LOB). Price movement prediction SOTA is still around 80%. We model the price prediction problem as a time series classification problem where we predict if the price will move upwards, downwards or remain in a neutral state after a prediction horizon. The prediction horizon 'k' is a fixed number of timesteps typically taken at intervals of 10, 20, 50 and 100. In recent works, convolutional and recurrent neural networks have been adopted with some success, however, none of these approaches fully exploit the spatial coherence of volumes along the price axis inside a limit order book. We propose CNNLOB, a convolutional neural network (CNN) and gated recurrent unit (GRU) architecture to exploit this property. Our model only uses aggregated volumes, in the ascending order of prices. Recent models like DeepLOB suffer from regime shift of prices, hence requires a dynamic feature scaling based on recent statistics. We eliminate the need for prices. Our main contribution would be to exploit the spatial coherence of aggregated volumes inside LOB. Our second contribution would be to design a ResNet inspired CNN and GRU based deep network, containing residual connections at both convolutional layers and stacked recurrent layers to solve price movement prediction problem. CNNLOB outperforms all the state-of-the-art models on benchmark LOB dataset, FI-2010, while only using volumes. Going beyond a blackbox model, we analyse the sensitivity of features for CNNLOB predictions using Local Interpretable Model-Agnostic Explanation (LIME) technique. Finally, we discuss possible applications and new research opportunities.

Index Terms

CNN, GRU, Stock price movement prediction, Multi class classification, Time Series, Capital markets, Limit order book, Deep Learning.

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LIST OF ABBREVIATIONS

Abbreviation	Description
LOB	Limit Order Book
ANN	Artificial Neural Network
RNN	Recurrent Neural Network
MLP	Multi-Layer Perceptron
LSTM	Long Short Term Memory
GRU	Gated Recurrent Unit
CNN	Convolutional Neural networks
HFT	High Frequency Trading
NYSE	New York Stock Exchange
LSEG	London Stock Exchange Group
NLP	Natural Language Processing
EMF	Efficient Market Hypothesis
TABL	Temporal Attention augmented Bilinear network
BN	Batch Normalization
ROC	Receiver Operating Characteristic curve
AUC	Area Under the Curve
LIME	Local Interpretable Model-Agnostic Explanations