A HYBRID MODEL FOR INTEGRATING LONG SHORT TERM MEMORY NETWORKS WITH TRADITIONAL APPROACHES FOR STOCK MARKET FORECASTING

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Dissertation submitted in partial fulfilment of the requirements for the degree Master of Science in Computer Science

Department of Computer Science and Engineering

University of Moratuwa Sri Lanka **DECLARATION**

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ABSTRACT

Stock market prediction has become a vital task as investing in the stock market involves a high risk. It would be appealing if the stock market behaviour can be predicted accurately to support investors' decision of time and place to invest money. However, due to high unpredictability of the laws of the financial time series, building an adequate forecasting model is not an easy task.

Classical time series forecasting models come with inherent assumptions of normality, stationarity and linearity assumptions of data. However, it is not guaranteed that financial time series such as stock market data will follow such assumptions.

This research focuses on combining classical time series models with neural network models. It is presumed that the ability of neural networks to handle noisy and volatile data will help overcome the complications of classical time series models. With the advances of deep learning methods around the world, it is believed that applying those findings for high frequency time series modelling will open up new opportunities in financial data analysis.

Colombo Stock Exchange (CSE) data will be used for the model implementation and model adequacy will be identified by several accuracy measures and model adequacy tests for residuals. The research will discuss the time series components that can be captured by neural networks and further improvement areas of using deep learning for financial time series data.

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