HYBRID APPROACH FOR FINANCIAL FORECASTING WITH SUPPORT VECTOR MACHINES

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

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Declaration

I declare that this is my own work and this thesis 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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The above candidate has carried out research for the Master's thesis under our supervision.

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Dedicated To my parents



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Abstract

Financial markets are the biggest business platforms in the world. Therefore, financial forecasting is getting a lot of attention in today's economic context. Accurate forecast is beneficial to broker firms, governments, individuals etc.

Vast range of forecasting methods, models have introduced by the research community. However, the risk involved with trading on those markets are very high. Such complexity makes a difficulty of making consistent profit. Building an accurate forecasting model is still an active and interesting research area for the academic community.

Recently, nonlinear statistical models such as neural network, support vector machine have shown greater capability to forecast financial markets over conventional methods. This dissertation proposed a hybrid support vector machine model which consists of wavelet transform and k-means clustering for foreign exchange market forecasting. The proposed model analyzes the trends and makes a forecast by entirely depending on the past exchange data. Wavelet transform is used to remove the noise of the time series. K-means clustering cluster the input space according to the similarities of the input vectors and finally support vector models make a forecast for the relevant cluster.

The proposed hybrid forecasting system was tested on real market environment to check the forecasting capability. Auto trading algorithm developed on 'metatrader4' platform used the forecast of the model to trade on the real conditions. Results confirmed that the proposed model can forecast price movements with greater accuracy that leads to profitable trades on foreign exchange market



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List of abbreviations

ABC - Artificial Bee Colony Algorithm

APE - Absolute Percentage Error

ARIMA - Auto Regression Integrated Moving Average

BP - Back Propagation

CD - Correct Down Trend

DS - Directional Symmetry

DWT - Discrete Wavelet Transform

EA - Expert Advisor

EKF - Extended Kalman Filter

EMA - Exponential Moving Average

EUR - Euro

FFT - Fast Fourier Transform

FLNN - Functional Link Neural Network

FOREX - Foreign Exchangersity of Moratuwa, Sri Lanka.

GA - Genetic Algorithmectronic Theses & Dissertations

GARCH - Generalized Autoregressive Conditional Heteroskedasticity

GLAR - Generalized Auto Regression

IBCO - Improved Bacterial Chemotaxis Optimization

ICA - Independent Component Analysis

ICA - Independent Component Analysis

JPY – Japan Yen

MAD – Mean Absolute Deviation

MAE - Mean Absolute Error

MLP - Multilayer Perceptron

MSE - Mean Squared Error

NMSE - Normalized Mean Squared Error

PCA - Principal Component Analysis

PCA - Principal Component Analysis

PSNN - Pi-Sigma Neural Network

PSO - Particle-Swarm Optimization

RBF - Radial Basis Functions

RMSE - Root Mean Square Error

RNN - Recurrent Neural Network

RPNN - Ridge Polynomial Neural Network

RW - Random Walk

SOM - Self-Organizing Maps

SVM - Support Vector Machine

SVR - Support Vector Regression

SWT - Stationary Wavelet Transforms

TAIEX - Taiwan Capitalization Weighted Stock Index

TEMA - Triple Exponential Moving Average

USD - US Dollar

VC - Vapnik-Chervonenkis University of Moratuwa, Sri Lanka.

WT - Wave Fransferm Electronic Theses & Dissertations www.lib.mrt.ac.lk

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