ARTIFICIAL NEURAL NETWORKS TO PREDICT SHARE PRICES ON THE JOHANNESBURG STOCK EXCHANGE

by

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Abstract

The use of historical data to build models for stock market prediction has been extensively researched. Artificial Neural Networks (ANNs) bring new opportunities for predicting stock markets, and is now one of the leading techniques used for time series and specifically stock market prediction. This study explored the application of ANNs to predict share prices in the banking sector of the South African Johannesburg Stock Exchange (JSE).

This study used three companies, i.e. Standard Bank, Nedbank and First National Bank, listed on the JSE as case studies for the use of ANNs for predicting the closing share price for the next day, week and month. Historical share price data from the JSE was integrated with datasets of external factors that influence market. The external factors considered in this study include index data from NASDAQ, the JSE top 40 and all share indexes, the exchange rate and the business cycle indicator (BCI) values from the South African Reserve Bank. Comparative analysis were conducted between traditional regression models and ANN models using the lagged share price as input variable. The effect on prediction performance of using external factors as additional input variables was also explored.

The ANN models using only the share price was found in general to perform better than both traditional models and ANNs that used the external factors as additional input variables. The average next month prediction model produced a noticeably smaller prediction error compared to the next week, and next day prediction models for all three banks. The results showed that the introduction of external factors as additional input variables did not lead to an improved prediction performance, over models that used only the share price. This study also highlights the importance of using an appropriate validation method and evaluating model stability for evaluating and developing ANN models for share price prediction in time series data. The results contribute to existing research that indicate that an ANN is more effective than a regression method for predicting banking share prices, and that these predictive models have potential for supporting investment decision making.

Declaration of Own Work

I, Freddie Brenschley Pyon , hereby declare that the work on which this dissertation/thesis is based is my original work (except where acknowledgements indicate otherwise) and that neither the whole work nor any part of it has been, is being, or is to be submitted for another degree in this or any other university.

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Signature: FBPyon

Date: 18 April 2021

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Glossary and Terms

Term	**Meaning**
Share/Stock	A unit of ownership in a publicly traded company that represents a portion of the company’s value.
Stock Market/Exchange	A place where the buying, selling and issuing of stocks/shares of publicly-traded companies occurs.
Johannesburg **S**tock **E**xchange	The main stock exchange in South Africa
National **A**ssociation of **S**ecurities **D**ealers **A**utomated **Q**uotations	An American stock exchange.
South African Reserve Bank	The central bank of the Republic of South Africa

Chapter 1. Introduction

1.1 Background

A stock market, in its simplistic form, consists of buyers and sellers who trade shares or stocks [20,53]. The objective of share trading is to make a profit [20], where buyers become investors and shareholders of a company when buying shares of a public listed company. Various factors influence stock market trends, and has an influence on buying and selling decisions. These factors include economic and financial performance of a company, and the political atmosphere in which the company operate. The ultimate goal of a share trader is to earn a return on their investment, by selling their shares for more than what they paid for them. An even better approach would be to sell shares and earn returns in excess of the market return. Being able to predict the outcome of the share price is the ultimate goal for any successful investor.

Investors study the market outlook and the financial performance of companies in order to make investment decisions. Profit warnings, analyst reports and liquidity are used as measures that inform investors on the performance of companies [7]. Linear regression techniques have traditionally been used for share price prediction and can aid investors in their buying and selling decisions [43]. However machine learning techniques such as Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs) have shown the potential to predict the outcome of the share price and perform with greater magnitude, and with more consistency than traditional statistical techniques[51]. A multi-layered perceptron (MLP), is a type of ANN that is a self-adaptive technique, having the ability to deal with nonlinear trends in stock market data, and can produce more accurate results than traditional linear regression techniques [49]. A recent study show that ANNs can outperform other machine learning techniques such as Support Vector Machines [32].

ANNs use historic time series data to train a model to predict the future share price. The ANN can be trained using either univariate or multivariate approaches. With a univariate approach, only one input and output variable such as the share price is considered in the prediction model. With a multivariate approach the prediction of the output variable, the share price, is done based on multiple input variables that normally include external factors that influence the stock market. Examples of these external factors include general economic conditions, political [11] exchange rate [28], and the composite business cycle index (BCI) that provide an forward outlook on the economy [18].

Building a neural network model is not a straightforward task. A neural network model consists of parameters that need to be suitably optimised to ensure accuracy of the model. If the appropriate parameter values are not set optimally, a neural network can yield poor prediction performance. It is also evident that the same neural network model configuration run multiple times could yield different results [30]. A model will be regarded as unstable if there is a large deviation from the average error across multiple runs of the same model [30]. It is therefore important to evaluate model stability when implementing neural network prediction models. It is also important to validate robustness of a neural network. Fixed partition validation techniques have generally been used, where a validation is done of the entire test data set. However the walk forward validation method where the training set is updated with new values, has been proposed as an alternative to improve model robustness [32]. This method, where the model is updated with data as it become available, considers real world applications where systems are dynamic with datasets that are erratic and non-stationary [30].

Neural network prediction studies have been applied to international stock markets, and to the South Africa Johannesburg Stock Exchange (JSE). The existing studies have used different approaches, with different neural network parameter combinations, and various input and output variables resulting in different outcomes [11,15,40].

1.2 Research aim and objectives

The aim of this research is to explore the use of ANNs for predicting shares in the banking sector on the JSE, in South Africa.

The specific research objectives are:

- Compare the prediction performance of an MLP with a regression model.
- Evaluate the impact of adding external factors on prediction performance.
- Evaluate the impact of adding a forward looking factor on prediction performance.
- Evaluate model stability and robustness.

1.3 Tools and Approach

The research approach involved reviewing the literature on stock market prediction techniques. Applications of neural network prediction methods in financial markets were specifically analysed and compared to other techniques. This revealed that neural networks yielded better performance than other techniques and is one of the leading techniques for predicting share prices. Share price data from the JSE and Google Finance, and exchange rate data from the South African Reserve Bank was collected. This data is exported into .csv format and used for analysis. The code for the study is written in Python (3.7). The Scikit-learn open source machine learning library was used for all experiments. Results were copied to a Microsoft Excel workbook in order to be properly analysed. ANN models using only share price values is compared to ANN models using external factors as additional input variables. The outcomes of both neural network approaches are compared to the Scikit-learn Huber regression statistical prediction technique using the Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) error metrics.

1.4 Contributions

The primary contribution of this work is the application and evaluation of a neural network to prediction the share price of JSE listed companies in the financial sector. This contributed to the field of study by applying a neural network technique to three different banking shares. The research has shown that a neural network using external factors as input variables in addition to the share price does not necessarily improve the performance of a model. This study also highlights the importance of using an appropriate validation technique and evaluating model stability when developing ANN models for time series share price prediction.

1.5 Scope and Constraints

This study is confined to the South African market, and specifically, to Standard Bank, Nedbank and First National Bank shares listed on the JSE.

1.6 Dissertation Layout

1.6.1 Chapter 1 - Research Overview

This chapter provides an overview of the research. The relevance of the research is highlighted and an outline of the research objectives and contributions are provided.

1.6.2 Chapter 2 – Literature Review

This chapter will present an overview of related literature on the use ANN modelling techniques, the use of ANNs for time series prediction, and specifically stock market prediction.

1.6.3 Chapter 3 – Experimental Design

This chapter describes the experimental design decisions made during the course of this research.

1.6.4 Chapter 4 – Results

This chapter describes the results of experiments as designed in chapter 3.

1.6.5 Chapter 5 – Recommendations and Conclusion

This chapter provide a summary of the contributions made by the study. The chapter also provide recommendations and suggestions for future research.

Chapter 2. LITERATURE REVIEW

This chapter is a critical assessment of the related work. It begins with an outline of the stock market, the efficient market hypothesis and decision making. It then briefly introduces the Johannesburg Stock Exchange (JSE), followed by a discussion on artificial neural networks and its application in a number of fields and suitability for stock market prediction. Neural network modelling is examined, with a summary of relevant work and the literature review. This is followed the identification of the research gap, and limitations that exist in the current work.

2.1 The Stock Market

The stock market works through a network of exchanges, for example, the NASDAQ and the Johannesburg Stock Exchange (JSE). The Johannesburg Stock Exchange offers exposure to capital markets in South Africa and Africa [26]. The JSE is the largest stock exchange in Africa and 19th on the list of global stock exchanges for market capitalisation, and provides a market for trading in the local and global economy [26]. The top 40 index consists of the biggest companies on the JSE ranked by market capitalisation [13]. The top 40 index represents 80% of the total market capitalisation of the JSE companies, and is therefore a fair reflection of the South African stock market.

The JSE, and other stock markets enable buyers and sellers to negotiate prices and make trades on listed securities. The goal of an investor would be to predict stocks that would provide greater returns than the market over the long term, by exploiting market inefficiencies. Market inefficiencies are said to arise when all publicly available information regarding the stock is not fully reflected in the price, meaning that the price is not reflective of the stock's true value [38].

The Efficient Market Hypothesises (EMH), proposed in the 1970's, states that current market prices are representative of all information that influence the price [37,38]. This implies that an investor cannot consistently beat the market with an active strategy. The validly of EMH should be questionable if any possibility exist to do reasonably accurate computational prediction of stock market prices [58]. Yoo et al. [58] note that studies exist to show that EMH is invalid, however also point studies have been conducted to show the validity of EMH.

The random walk hypothesis states that any economic time series including stock prices cannot be predicted based on past stocks[10]. Past patterns cannot be used to predict stocks, as it does not reflect the pattern of the current stocks. The random walk theory suggest stocks take a random and unpredictable path that makes all methods of predicting stock prices pointless in the long run. Different viewpoints exist on EMH and the random walk hypotheses, with some in favour of these theories and others against. Cervelló-royo et al. [9] confront the EMH and provide empirical evidence that it is possible to predict the market based on historic data for the US Dow Jones index. Furthermore, Tiwari and Kyophilavong [54] recently found that the South African market does not follow the random walk behaviour. There is a wealth of literature on persistent market inefficiencies in the South African market [31,44,52]. These inefficiencies indicate that a strategy may exist to earn excess returns for a given level of risk. Investors and advisors therefore spend a lot of time and resources on trying to predict market trends to aid decision making that could turn out to be costly if incorrect.

Decision making is generally based on firstly fundamental analysis, and secondly technical analysis [47]. Fundamental analysis is where investors look at the value of the stock, performance in the industry, the current political situations and other general influencing factors [47]. Technical analysis in comparison looks at statistics generated about the market and the stocks, and look at trends and patterns of expected future behaviour of stock prices [47]. These decision making strategies are not mutually exclusive and some investment professionals employ both strategies.

Linear regression techniques have been traditionally used to aid investors in their buying and selling decisions. Machine learning techniques have also been adopted with success, and with potential to outperform the traditional statistical techniques [8]. Machine learning techniques, are self-adaptive and have the ability to capture non-linear trends and patterns in data and can produce more accurate results than traditional linear regression techniques [3]. Machine learning has been used for decision making in areas such as fraud detection, risk management, financial forecasting, classification of SPAM emails, facial and voice recognition as well as in several areas of medical research such as cancer research and DNA testing [33]. Support vector machines and artificial neural networks have shown the potential to predict the outcome of the share price and perform with greater magnitude, and with more consistency than traditional statistical techniques [51].

This research focuses on share price prediction using artificial neural networks (ANNs). The next section introduces artificial neural networks, before discussing how it is used to predict stock market data.

2.2 Artificial Neural Networks

Artificial Neural Networks (ANNs) have been inspired by biological neural networks [4]. The fundamental cell of the brain, the neuron, served as the starting point of the research into neural networks [2]. It can be argued that there is a rough analogy with the behaviour of biological neural networks, and an ANN.

Figure 2.1 shows a model of a neuron and how it connects to an ANN.

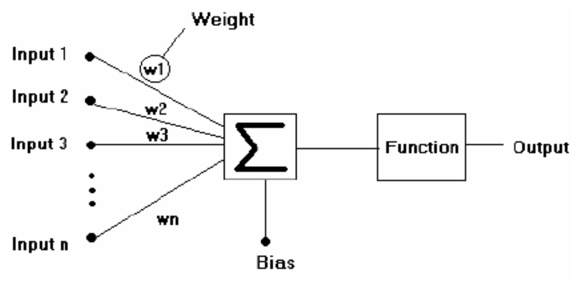

Figure 2.1: Architecture of a Neuron

The input is multiplied by weights along its path. The weighted inputs are then summed and a bias is added. The output of the summation is sent into a function which is called an activation function which the user specifies (linear, logistic). The output of the function forms the output of the neuron.

Figure 2.2 shows a simplified representation of an ANN, with an input layer, hidden layer and output layer. The input layer contain the input variables to the ANN, and output layer the predicted variable. The hidden layer in this case consist of three nodes that represent the neurons. The diagram also shows the weighted connections.

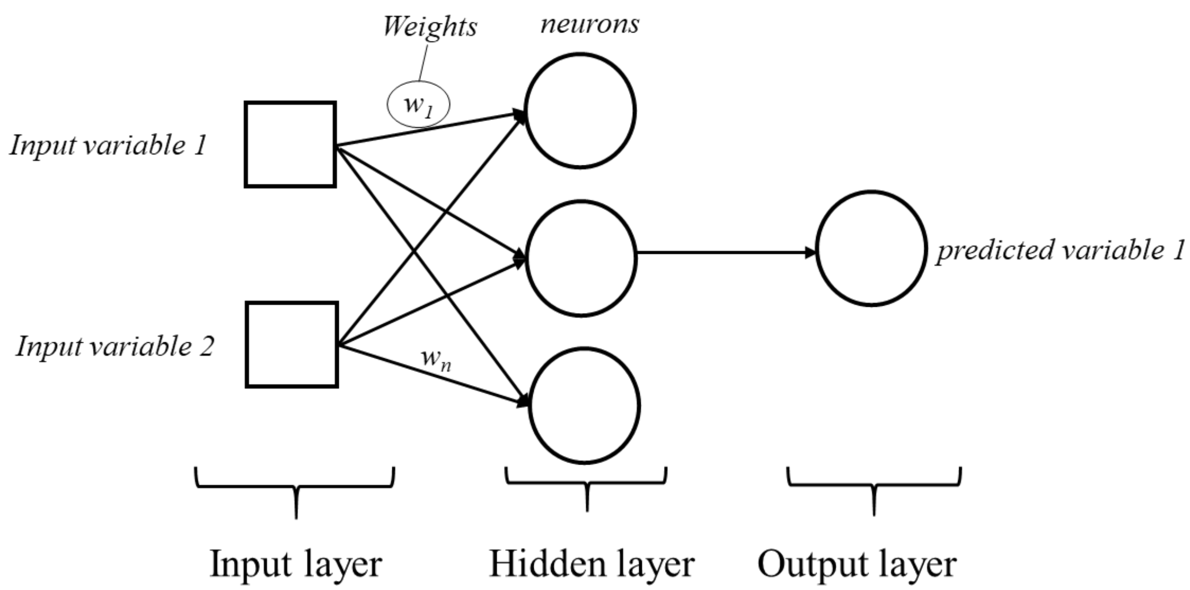

Figure 2.2: Simplified ANN

2.2.1 History

Artificial Neural Network development phases can be divided into four different stages as discussed briefly. At the beginning stage, ANNs gained interest in the 1940's where McCulloch and Pitts developed the first neural network [17]. Hebb also designed the first learning law for ANNs [17,23]. This was followed by the golden age in the 1950s and 1960s where Frank Rosenblatt introduced the perceptron [17]. The quiet years in 1970s has seen some further research in neural networks where Kohonen developed self-organising feature maps with applications to speech recognition [17]. The development of "Brain-State-in-a-Box" by Andersen with applications in medical diagnosis and learning multiplication tables was also seen [17]. The renewed enthusiasm in the 1980 was known for the momentum gained by the discovery of the back propagation algorithm [27]. The renewed area was also characterised by Hopfield who contributed to the development of a number of neural networks based on fixed weights and adaptive activations [17]. The Neocognition, a neural network used for character and other recognition was also developed by Kunihiko Fukushima in the 1980s [17]. This era, at the time, offered improved hardware capabilities, which inspired renewed interest in ANNs. The central idea of the backpropagation algorithm is to determine the errors of the hidden layers of the multilayer perceptron. The late 1990s saw the emergence of the of the deep learning method called the long short-term memory (LSTM) [24], and becoming popular in industry in the 2000's [46].

2.2.2 Types of ANNs

Two common network topologies are distinguished

- A feedforward topology, is where the data flows from the input node(s) to the output node(s). Typical feedforward ANNs can take the form of a single-layer, or a multi-layer network. There is no feedback loop with this topology. The convolution neural network (CNN) and multilayer perceptron (MLP) are examples of a feedforward ANN. A MLP is a fully connected ANN that consists of three or more layers, and uses a nonlinear activation function [27]. A CNN, uses a variation of the MLP. A CCN contains one or more convolutional layers that can either be interconnected or pooled [55]. The CNN uses a convolutional operation on the input before passing the result to the next layers.
- A feedback topology, is where information from an output layer contain feedback connections into the input nodes. Feedback, in a feedback neural network refers to how output signals are sent back as input to other neurons. A feedback neural network however should not be confused with backpropagation which is a training method [35] that is discussed in the next section. A long short-term memory (LSTM) neural network is an example of a feedback neural network [24]. The first layer of an LSTM is formed in the same way as a feedforward network, however with the subsequent layers each node will remember some information that had in the previous time-step. Each node acts as a memory cell while computing and carrying out operations.

2.2.3 Training process and model development

Several algorithms exist to train an ANN, however the choice of algorithm should be based on the type and complexity of the problem to be solved [56]. The backpropagation algorithm has become a preferred algorithm for training MLPs [27]. The weights in the network is initialised to some random values. An error is calculated indicating the difference between the network output, and expected output. This error is propagated back through the network and the weights in each layer are modified so that the error is decreased with the next iteration. The process is repeated until the error is reduced to an acceptable minimum.

It is important to choose the right activation function and parameters to ensure optimal behaviour of a neural network. The main activation functions that can be used in a neural network include [16]:

- Linear function;
- Step function;
- Ramp function;
- Sigmoid function;
- Hyperbolic tangent; and
- Gaussian function.

In addition to selecting the activation function, additional parameters should be considered when designing a neural network. These parameters include:

- Learning rate:
  The ultimate goal is to find the optimal learning rate for the neural network model being used. The learning values range between 0 and 1. A too small or too large learning rate can result in the optimal not being reached [34]. If the learning rate is too small, the training may be slow, and if the learning rate is too large the optimal network may not be achieved.
- Momentum factor:
  The momentum factor ranges from 0 to 1. The momentum factor determine the weight of the next iteration. If the momentum factor rate is closer to 1, the next iteration would adopt a weight close to or equal to of the previous iteration [34].
- Hidden layers:
  The number of hidden layers and the number of neurons for each layer will also influence the optimal performance of the neural network. One hidden layer can be sufficient for most applications of a neural network [34]. Adding to many layers can result in the neural network memorising the training set. Adjustment of the amount hidden layer can be done based on the training accuracy of the model [34].

2.3 Multi-layered Perceptron (MLP) for Time Series Prediction

2.3.1 Problem formulation

A time series is defined as “a sequence of readings as a function of time” [25]. A time series is noticeable in many real world applications such as weather readings and stock market prices. Time series prediction has many business applications to forecast sales, budgets, yield projects, process control, and whether conditions among others. Financial and specifically stock market prediction using a time series ANN model has been under scrutiny for some time for reasons that are well known (to improve investment returns) [15,41,43,49]. Hence, the focus of this research would be to do stock market time series prediction, predicting x_{t+1} based on past observations $x_{t-w}...x_{t-1}$, x_t where x_t is a real-valued observation at time *t* and *w* the window size.

The standard method of performing time series prediction is using an MLP that uses a set of N-tuples as input and a single output as the target value [19]. This method is illustrated in Figure 2.3 and is called the sliding window technique.

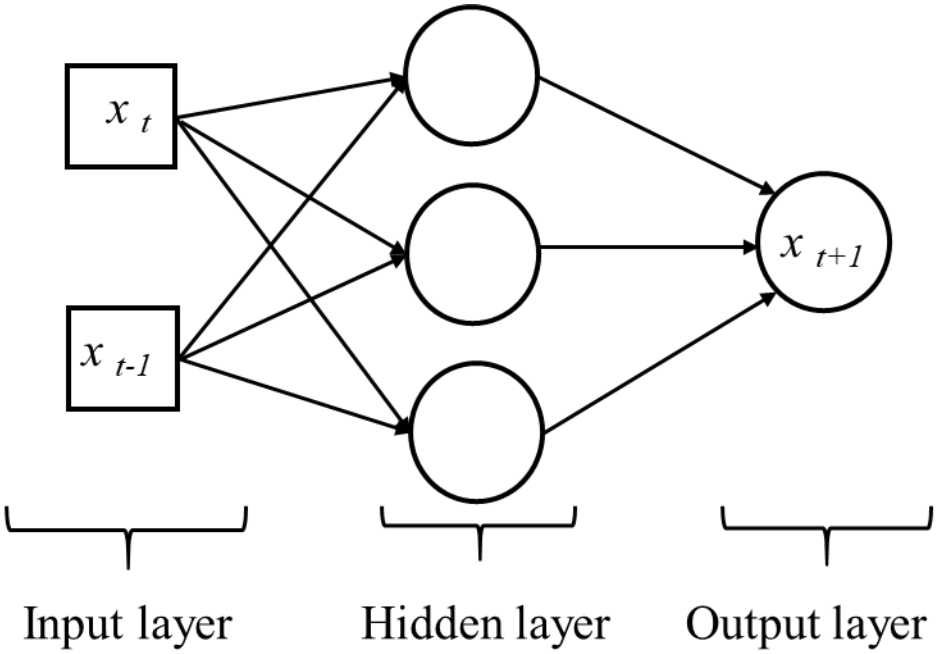

Figure 2.3: Sliding Window: A set of N-tuples as Input and a Single Output

The sliding window technique can be applied in time series prediction with the aim of improved results as it operates over a window of a time series [27]. When using the sliding window technique, the next value in the time window is predicted using a changing starting point from a sample set of observations.

Figure 2.4 depict an example of trained neural network performing time series prediction using the sliding window technique. The window size in the sliding window technique is also referred to as the lag length. The illustration show four equally time spaced input data points, also referred to as a lag length (or window size) of four, sliding over the full training set of input data to predict the next output data point value. Determining the correct lag length when using the sliding window technique is critical for any time series problem [25].

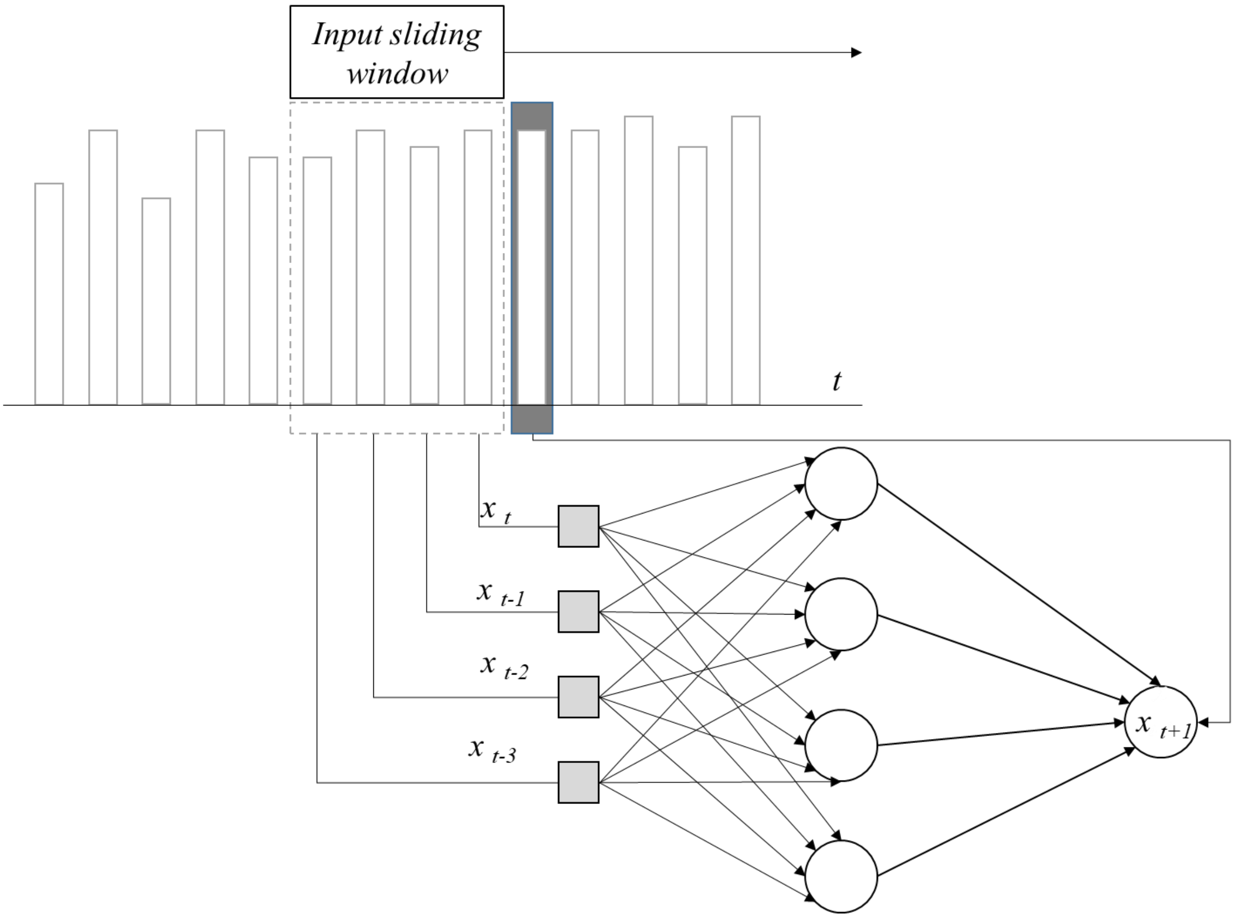

Figure 2.4: Sliding Window Example [45]

2.3.2 Stock market prediction

Stock market data is generally time bound observations which is available in time intervals such a quarterly, monthly, daily and even shorter time interval such as hourly. Stock market data therefore is seen as time series data in the way that the data is collected, stored and analysed. ANNs using an MLP for prediction has been applied with success to stock market time series in the last numbers of years [5,6,15,41,43,58]. The reviewed studies are summarised in **Table 2.1** briefly is discussed next.

Ayankoya et al. [5] used a data set from 02 January 2012 to 31 March 2015 to do real time prediction of the futures contract prices of white maize in South Africa using an MLP. In a similar study also using an MLP, Ayankoya et al. [6] used a data set from 1 Jan 2010 to 31 Mar 2015 to predict prices of grain commodities in South Africa. The input variable selection process was guided by knowledge in the field, and both studies used correlation analysis to refine the input variables [5,6]. The studies, after refinement of the input variables, determined the optimal lag length to use for the predicted variable as input to the model through experiments [5,6]. Both studies split their data into training and test sets, and using the roll-forward technique to update their training set with new available data [5,6]. The sigmoid activation function was used in both studies, however the other parameters varied in the implemented models. The MAPE, RMSE, R^2 metrics were used to validate the model in comparing the predicted values to actual values, and expert predictions. Ayankoya et al. [5], calculated the average values of the validation metrics from six iterations for the same model configuration, and Ayankoya et al. [6] similarly calculated the average for ten iterations for the same model configuration.

Emam [15] used a MLP to predict the FOREX, splitting the data in two fixed partitions, 66% for training and 34% for testing. Input variables were selected by gradually adding them to the models, and evaluating and comparing the results of the models after the addition of new input variable. The short term daily prediction yielded better results, compared to weekly and monthly. This outcome is attributed to the available sample data. This study also used the sigmoid activation function, and the MSE, R^2 evaluation metrics.

Moghaddam et al. [41] used an MLP to predict daily NASDAQ stock exchange rate. The study considered the short-term historical stock prices as well as the day of week as inputs. The data set consist of data from 28 January 2015 to18 June 2015, using 70 days for training and the last 29 days for testing the model prediction ability. Two types of datasets (four prior days and nine prior days) were used as input variables to develop the models for the NASDAQ index prediction. The models were found to be acceptable and validated using MSE and R^2 with no distinct difference between the prediction ability of the four and nine prior working days used as input variable.

Qiu et al. [50] applied ANNs to predict the return of the Japense Nikkei 225 index. This study used a new set of input variable established through experiments in attempt to improve the prediction algorithm effectiveness [50]. While the objective of the study was to compare different algorithms, it found the ANNs to be acceptable to for stock market prediction.

Motiwalla et al. [26] used an MLP to build a prediction model for US equities using a data set from January 1990 to August 1998. The input variable selection was mainly guided by existing literature in the field. The TANH activation function was used in the hidden layer and the sigmoid function in the output layer. The performance of both ANN and regression-based models was compared using the Pesaran and Timmermann (PT) validation test. The validation results showed that the ANN models were more successful.

Table 2.1: Summary of Reviewed Research

Paper	Algorithms Used	Performance	Target Variable and Input Variables	Evaluation Metrics	Data Set
Ayankoya [5]	Feed Forward ANN (MLP) Hidden Layers: 7 Neurons: not specified Activation Function: Sigmoid Momentum Factor: 0.0001 Learning rate: 0.4	ANN model result provide better predictive insights, and perform better than experts.	Target Variable: • Futures contract prices of white maize Input Variables: • Spot price of WMAZ • BID price of December futures • Price of Wheat • OFFER prices of December futures • USD-Rand Exchange Rate • Closing price of Corn on CBOT • Spot price of Brent Crude Oil • Demand for WMAZ • Demand for Wheat • Prime interest rate • Lagged December futures contract prices	MAPE RMSE R^2 ***Model Stability:*** Metrics calculated based on average results of 6 iterations.	JSE: Futures Contract Prices of White Maize 3.2 years 02 Jan 2012 to 31 Mar 2015 93% Training 7% Testing *Roll-forward technique used to update the training set*
Ayankoya [6]	Feed Forward ANN (MLP) Hidden Layers: 7 Neurons: not specified	ANN has minimum MAPE and RMSE error compared predictions from 8 experts.	Target Variable: • End-of-day data for spot prices Input Variables: • Spot price of Wheat	MAPE RMSE R^2 ***Model Stability:***	JSE: Grain Commodities South Africa 5.2 years 1 Jan 2010 to 31 Mar 2015

	Activation Function: Sigmoid Momentum Factor: 0.001 Learning rate: 0.4		• USD-Rand exchange rate • Spot price of Brent Crude oil • Prime interest rate in SA • Price of Corn in USA Volume of Corn Trade in USA • Demand for WMAZ in SA • Demand for Wheat in SA • Lagged End-of-day data for spot prices	Metrics calculated based on average results of 10 iterations	95% Training 5% Testing *Roll-forward technique used to update the training set*
Emam [15]	Feed Forward ANN (MLP) Hidden Layers: 2 Neurons: 2 Activation Function: Sigmoid Momentum Factor: not specified Learning rate: not specified	Short term daily prediction yielded better results, compared to weekly and monthly.	Target Variable: • Next Day Close Input Variables: • Exchange Rate (USD/JPY • GBP/USD • EUR/USD • USD/CHF • NEXT DAY CLOSE, HIGH, LOW	MSE R^2 ***Model Stability:*** Not specified.	FOREX Date range not specified 66% training 34% testing Fixed partitions
Moghaddam et al. [41] (First Model)	Feed Forward ANN (MLP) Hidden Layers: 2 Neurons: 40-40 Activation Function: *TANSIG* Momentum Factor: not specified	No distinct difference between the prediction ability of the four and nine prior working days	Target Variable: • NASDAQ Stock Exchange Rate Input Variables: • Historical stock prices Day of week (9 prior days)	MSE R^2 ***Model Stability:*** Not specified.	NASDAQ Stock Exchange Rate 99 Days 28 Jan 2015 to 18 Jun 2015 Fixed partitions

	Learning rate: not specified				
Moghaddam et al. [41] (Second Model)	Feed Forward ANN (MLP) Hidden Layers: 3 Neurons: 20-40-20 Activation Function: *TANSIG* Momentum Factor: not specified Learning rate: not specified	No distinct difference between the prediction ability of the four and nine prior working days	Target Variable: • NASDAQ Stock Exchange Rate Input Variables: • Historical stock prices • Day of week (4 prior days)	MSE R^2 ***Model Stability:*** Not specified.	NASDAQ Stock Exchange Rate 99 Days 28 Jan 2015 to 18 Jun 2015 Fixed partitions
Motiwalla et al. [43]	Feed Forward ANN (MLP) Hidden Layers: not specified Neurons: not specified Activation Function: *hidden layer:TANH* *output layer:SIGMOID* Momentum Factor: not specified Learning rate: not specified	ANN superior over regression or simple buy-and-hold strategies	Target Variable: stock returns • Stock Market Returns Input Variables: • 90-day Treasury bill rate • One-month Commercial paper rate • Spread between yields on long-term US Treasury bonds & three month Treasury bills • Spread between yields on long-term US Treasury bonds & six-month Treasury bills • Spread between yields on long-term US Treasury	PT (Pesaran and Timmermann) ***Model Stability:*** Not specified.	US equities 8.5 years Jan 1990 to Aug 1998 Training 66.6% Testing: 33.3% Fixed partitions

			bonds & one-year Treasury bills • Spread between yields on long-term Baa corporate bonds & long-term US Treasury bills • Spread between yields on long-term Baa corporate bonds & 90-day US Treasury bills • Spread between yields on long-term Baa corporate bonds & six-month US Treasury bills • Spread between yields on long-term Baa corporate bonds & AAA-rated corporate bonds • Yield on long-term Baa-rated corporate bonds • One-month lag of TERM1 • One-month lag of TERM3 • One-month lag of TERM6 • One-month lag of DEFALT1 • One-month lag of DEFALT3 • One-month lag of DEFALT6 • One-month lag of DEFAULT • Two-month lag of TERM1 • Two-month lag of TERM6 • Two-month lag of spread between yields on long-term Baa corporate bonds & one-year US Treasury bills • Two-month lag of spread between yields on six-month Treasury bills & three-month Treasury bills		

Qiu et al. [50]	Feed Forward ANN (MLP) Hidden Layers: 1 Neurons: 10 Activation Function: *not specified* Momentum Factor: 0.4 Learning rate: 0.1	"A hybrid approach based on Genetic Algorithm (GA) and Simulated Annealing (SA)improve prediction accuracy significantly and outperform the traditional BP training algorithm"	Target Variable: • Return of Nikkei 225 index Input Variables: • Average amounts outstanding of monetary base • Banknotes in circulation of average amounts outstanding of monetary base • Coins in circulation of average amounts outstanding of monetary base • Uncollateralized overnight of call rates at the end of month • Yen spot rate at the end of month of Tokyo market • Yen central rate at the end of month of Tokyo market • Yen lowest in the month of Tokyo market • Percent changes from the previous year in average amounts outstanding of money stock • Percentage changes in average amounts outstanding from the previous year of loans and discounts for total of major and regional banks • Loans and discounts of regional banks • Import price index of all commodities • Real exports • Real imports	MSE ***Model Stability:*** Not specified.	Japanese Nikkei 225 index 19 Years Nov 1993 to Dec 2007 Training 72% Testing 28% Fixed partitions

			• Indices of industrial production • 1-year T-bill rate • 2-years T-bill rate • 3-years T-bill rate • 4-years T-bill rate		

Table 2.1 summarises a number of studies where ANNs were applied with success to do time series stock market predictions. The results show different approaches to the size of the datasets used, and partitioning of the data. It also show different input parameters, and predicted values in the different studies. The lag length for lagged input variables was determined through experimentation in two recent studies [5,6] where a lag length of five was found to be optimal. However to do comparative analysis between two lagged periods (four and nine working day), the lag length was predefined in one study [41]. The ANN models and optimal parameters used in the different studies also vary. More recent studies used the MAPE and R^2 validation metrics [5,6], however some studies has also used the MSE [15,40,50] and the PT test [43]. Fixed partition validation techniques have generally been used, however the walk forward validation method where the training set is updated with new values, has been proposed as a more robust alternative in a recent study [30]. Only two studies [5,6] used a similar type of validation method. It is also noticeable that a few studies used the average error from multiple runs of the same ANN configuration [5,6,30], however this method is not evident in all of the previous studies which could be a limitation.

2.4 Model development and validation

ANN model development broadly consist of the same steps. These steps are collecting the data, preparing the data, partitioning the data, training the model, testing the model and evaluating the results.

2.4.1 Data collection

Appropriate data need to be collected to develop the ANN model. Previous studies, as shown in **Table 2.1**, collected relevant historical stock market data for periods that varied between 5 month and 10 years [5,6,15,40,43,50]. When collecting data, consideration is given to the input variables that are needed to build a prediction model. While the majority of previous studies relied on previous knowledge to select input variables [5,6,15,41,43,50], some studies used correlation analysis [5,6], experiments [15] and fuzzy curve analysis [50] to refine the input variables. Some studies also used lagged values of the input variables [5,6,41].

The collected data often need to be cleaned and prepared. This is the data pre-processing step.

2.4.2 Pre-processing

Data does not always come in formats ready for analysis and prone to inconsistencies. These characteristics can lower the quality of the results that will be produced if the data is not pre-processed [5,6,50]. Data pre-processing involves data cleaning, data transformation, data integration, and data reduction. Missing data points can be replaced with the closest preceding non-missing value.

After cleaning the data, it is often necessary to normalise the data into a format ranging between -1 and 1 or 0 and 1 [6,50]. This process helps training algorithms when dealing with input variables with different ranges. There may however be cases where normalisation is not required, as normalisation may generate “undesired results” in certain situations [5]. It is also possible to allow the ANN modelling software to automatically apply normalisation techniques [6,43].

The data, after cleaning, is transformed and integrated into a time sequenced set of data, and reduced to the required set of data. The input variables are selected as discussed in section 2.5.1 and the data is partitioned into training and testing sets.

2.4.3 Data Partitioning

Data is required for both the training and testing of a time series ANN, and thus the data must be partitioned into a training set and a test set. The objective is to train a model with part of the data, and keeping ‘unseen’ data to test and verify the model. As shown in **Table 2.1**, often the data is split into fix partition sets with approximately 66.6% for training and 33.3% for testing [15,43], or approximately 71-72% for training and 28-29% for testing [41,50]. An alternative approach applied in two studies, is where the training partition is updated with new data , with a 93% training and a 7% test set split [5], or a 95% training and a 5% test set split [6]. In a recent study, Kouassi and Moodley [30] used different approaches with the different data sets used: The voltage dataset used a 20% training and 80% test split, methane a 90% training and 10% test split, NYSE a 50% training and 50% test split and JSE a 90% training and 10% test split. The training sets were also updated with new data in this study for all datasets, and the first value dropped from the training set after each iteration [30].

2.4.4 Model Training

The model parameters, as discussed in section 2.2.3, are selected to train the model in an iterative process using the training set of data. As summarised in **Table 2.1**, the sigmoid function [5,6,15,43] and the hyperbolic tangent (tanh) activation function [41,43] were mostly used in previous studies. Some studies did not report the activation function used [50]. The summary in **Table 2.1** also show that the momentum factor, learning rate, number of hidden layers, and neurons varied for the different studies. These parameters are iteratively adjusted until error is reduced to a minimum. Validation metrics are used to evaluate the accuracy of the model after each iteration.

2.4.5 Model Evaluation

Once the model has been developed and tested, the results need to be evaluated for accuracy. Depending on the nature of the task, different metrics may be utilised. As shown in **Table 2.1** the most commonly used measue are MAPE, RMSE, R2 and MSE. These are described below.

The mean absolute percentage is a summary metric using the absolute error and is denoted as follow[21]:

$$MAPE = \frac{\sum_{i=1}^{n} \frac{|e_t|}{y_t}}{n}$$

where e_t is the prediction error in the time period t;

y_t is the actual value in time period t;

n is the number of prediction observations in the estimation period.

The mean square error and the root mean square error are summary metric using the squared error and are denoted as follow [21]:

The mean square error

$$MSE = \frac{\sum_{t=1}^{n} e_t^2}{n}$$

The root mean square error

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n} e_t^2}{n}}$$

where e_t is the prediction error in time period t;

n is the number of prediction observations in the estimation period

The coefficient of determination (R^2) is used to analyse how differences in one variable can be explained by a difference in a second variable [21].

$$R^2 = 1 \frac{RSS}{TSS}$$

where TSS = total sum of squares

$$TSS = \sum_{i=1}^{n} (y_i - \bar{y})^2$$

$n = number\ of\ observation$

$\bar{y} = mean\ value\ of\ a\ sample$

$y_i = value\ in\ a\ sample$

where RSS = sum of squares of residual

$$RSS = \sum_{i=1}^{n} (y_i - f(x_i))^2$$

$n = upper\ limit\ of\ summation$

$f(x_i) = predicted\ value\ of\ y_i$

$y_i = i^{th}\ valueof\ the\ variable\ to\ be\ predicted$

While the MAPE, RMSE, R2 and MSE have been used in related work as shown in **Table 2.1**, only two studies indicated that an average of the metrics were calculated across multiple model runs [5,6]. It must be noted that the calculated metrics may vary for the same model configuration due to the random initialisation of weights in the training process as discussed in section 2.2.3. An approach to address the differing results is to run the model multiple times and report on the average error [5,6]. According to a more recent study, a model would be regarded as stable if the minimum and maximum values of the different runs are close to the average across the specified number of runs of the same model [30].

2.5 Research gap and limitations of current work

This section focuses on identification of the research gap, and limitations that exist in the current work. It will first describe the input variables selected for this study. This is followed by a discussion on the gaps and limitation in validation approaches in the reviewed literature.

2.5.1 Selection of input variables

The selection of input variables involves choosing the variables that will contribute to the model. In stock market prediction the input variables are selected from historic data [5,6,15,41,43,50], and different approaches have been used as discussed in section 2.3.2. Share price prediction is the objective of this research. The input variables in this study will be determined by the two aspects, the lagged share price values determined by the sliding window method as described in section 2.3.1, and factors influencing the stock mark.

Stock markets are influenced by various factors. Factors influencing global stock markets include political events, general economic conditions, traders' expectations [11], corporate policies, the commodity price index, bank and exchange rates, the psychology of investors, investors' choices and expectations, the direction of other stock markets [48], oil prices, terms of trade, term premiums, risk premiums, and growth rate [28]. Factors identified to specifically influence the JSE include interest and exchange rates, risk premiums and foreign stock markets [39,42], also the prime overdraft rate, total mining production and the interest rates of the USA [39].

These factors contribute to the non-linear effect of stock market, and should ideally to be considered in the input variable selection when predicting stock market prices.

2.5.2 Model validation

While previous studies have successfully been used to predict the share prices, it can be argued that there are limitations in the validation approaches. In some studies, validation was applied where the data was divided into single training and test sets, and the error was estimated on a fixed partition [15,41,43,50]. This approach has a limitation in that it assumes that the system under consideration is static. These approaches may not be suitable for datasets that are erratic and non-stationary. In real world applications where systems are often dynamic, models become outdated and must be updated as new data becomes available.

A roll-forward or walk forward approach as adopted in recent studies can overcome this limitation [5,6,30]. The roll-forward method can be in the form of adding one future step ahead [30] or, a predefined set of multiple steps or data points ahead [5,6]. The roll-forward method ensures that the most recent and relevant data points are available. In the studies of Ayankoya et al. [5,6], the starting point of the training set was not shifted into the future. This could result in a limitation where unwanted trends and relationships not relevant to the immediate prediction task, and an approach to shift the starting point may be more robust [30].

It must however be noted that the roll-forward approach requires many updates where new data is introduced by rolling forward and including new data points. This can slow the training of the ANN. However a model update with warm start initialisation can be used to reduce the training time of the neural network based algorithms [30].

It is also evident that an MLP with the same parameter configuration could yield substantially different results when rerun, however it is important to ensure model stability [30]. Model stability refers to the "minimal deviation from the mean test loss across multiple runs" [30]. In order to provide a measure of stability, it is recommended to run the same model configuration multiple times, and obtain the average of the evaluation metrics applied. The minimum and maximum values of the metrics is also recorded to measure how stable the models are. If the minimum and maximum values of the recorded metrics are erratic across multiple runs it would indicate that the models are not very stable. The models would be regarded as more stable if the minimum and maximum values are close to the average of the evaluation metrics applied. Evidence of evaluating model stability is limited in the reviewed literature. However the same model configuration was run six times and an average of RMSE, MAPE and R^2 was obtained in a recent study [5]. Similar approaches were followed where the same model configuration was run ten times and an average of RMSE [6,30] and MAPE and R^2 was obtained [6].

2.6 Summary

Previous studies in the literature have shown that ANNs can provide improved prediction accuracy compared to traditional statistical techniques. While ANNs has been applied in previous studies, limitations in the validation techniques and model stability have been highlighted. Validation techniques using fixed training and test sets can have limitations, however this can be addressed by using the roll-forward validation method. ANNs can also suffer from model stability. This can be addressed by running the same model configuration multiple times, and obtaining the average error that is compared to the minimum and maximum error values across the multiple runs of the model. A smaller deviation would indicate that the model is more stable. This research will therefore focus on testing the robustness of ANNs through model validation and model stability. This research will also evaluate the effect of adding more information through using a combination of input variables derived from the external factors that influence the market. This will be done through rigorous experiments.

Chapter 3. EXPERIMENTAL DESIGN

This chapter describes the experimental design decisions made during the course of this research and the experiments performed to evaluate the neural network models. Section 3.1 describes the dataset used in the experiments. Section 3.2 describes the machine learning process, and section 3.3 the software tool used. Sections 3.4, 3.5 and 3.6 describe the three experiments that were conducted.

3.1 The Dataset

Section 2.3.2 has shown that recent research to predict stock markets using ANN approaches used data for periods that varied between 5 month and 10 years [5,6,15,40,43,50]. Historical data was obtained from the JSE for the period of just over 2 years between 01 April 2016 to 04 June 2018. The core data set contained the end of day closing prices for Standard Bank (SB), Nedbank (NED) and First National Bank (FNB). Additional data obtained from the JSE included the daily values for the JSE top 40 and all share indices.

Various factors that may influence stock markets were identified in section 2.5.1. The conducted experiments focus on the following external factors that may influence the stock market prices:

- Exchange Rate(South African Rand per United States Dollar)
- NASDAQ Composite Index
- JSE Top 40 Index
- JSE All Share Index
- Composite Business Cycle Indicator (BCI)

The South African Rand(ZAR) per United States Dollar(USD) exchange rate data was obtained from the South African Reserve Bank website [59]. The stock market data for the NASDAQ composite index end of day closing price was obtained from Google Finance [60]. The data is available in a daily frequency for all variables except for the composite business cycle indicators which are available in a monthly frequency.

The target values for the experiments are the following closing share prices.

- next day closing price(CP)
- average CP for the next week (5 days)
- average CP for the next month (21 days)

3.2 Machine Learning Process

ANN modelling is discussed in detail in section 2.4. Figure 3.1 shows the typical ANN machine learning pipeline where the process start with the collection of historical data. The data is cleaned, variables selected and formatted correctly in a time series sequence in the pre-processing step. The data is partitioned in training and test sets. The model is than trained followed by validation of the model. The training process is adjusted to ensure the error obtained in the validation process is minimised. This is done by adjusting the weights in the training process. The model training and validation is an iterative process until a minimum error is obtained, and the accuracy of the model is satisfactory.

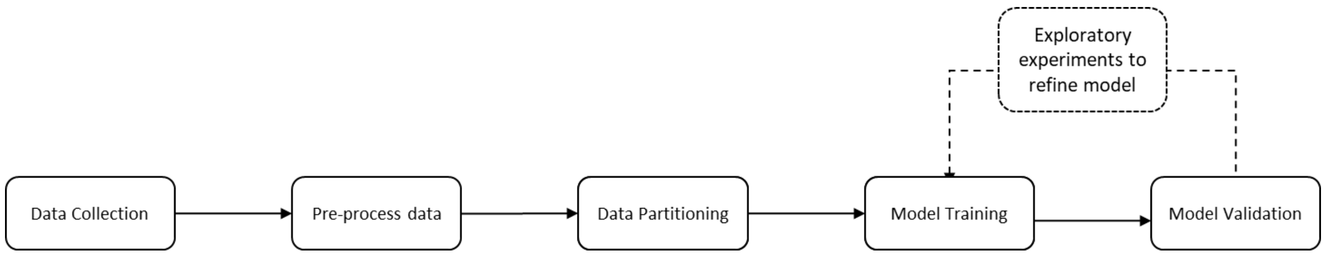

Figure 3.1: Artificial Neural Network Machine Leaning Process

3.2.1 Neural Network Design

A typical feedforward ANN is discussed in section 2.2. Figure 3.2 depicts a feedforward ANN with three hidden layers to illustrate the neural network design that was applied in this research.

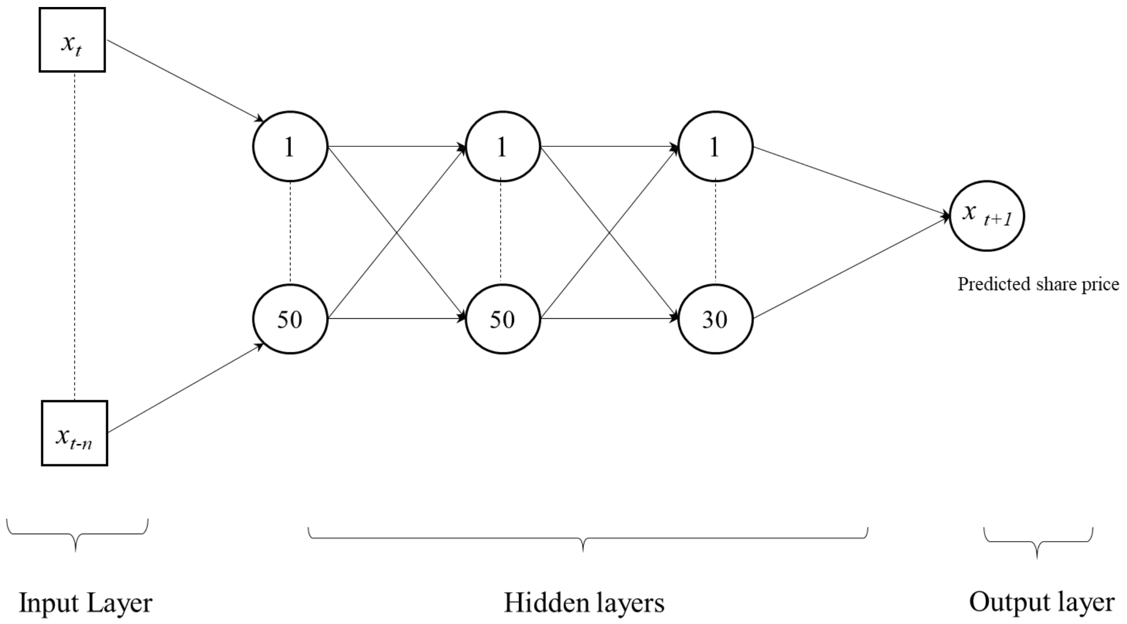

Figure 3.2: Implemented Neural Network

Let x (x_t ...x_{t-n}) represent the input variables, which are passed on to the next layer in the network. x_{t+1} shows the output as predicted by the neural network. In-between the input and output layers are three fully connected hidden layers which apply transformations including a bias to the input received. Weights which represent the strength of the connection between neurons are applied as the inputs move from one layer to the next. Each neuron in the hidden layer transforms the values from the previous layer with a weighted linear summation $w_1x_1 + w_2x_2 + \cdots + w_mx_m$ followed by a non-linear activation function such as $g(.): R \rightarrow R$. The output layer receives the values from the last hidden layer and transforms them into output values.

During the training process, an error is calculated, and the process start with an initial set of parameters. Table 3.1 shows the initial parameter values used to start the iterative process to conduct the three experiments. The process is repeated with adjustments to the neural network model parameters until a minimum error and most accurate prediction is obtained as discussed in section 2.4.4 and depicted in Figure 3.1

Table 3.1: Initial Experimental Values

Parameter and options	**Description**
activation	Identity Logistic Tanh Relu *Activation function for hidden layers*
Learning_rate	0,1 0,001 0.0001
momentum	0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9
solver	lbfgs *The solver for weight optimization*
shuffle	False *Whether to shuffle samples in each iteration*
verbose	True *Print progress messages to stdout*.
early_stopping	True *If set to true, it will automatically set aside 10% of training data as validation and terminate training when validation score is not improving by at least*
random_state	None
alpha	0.1e-9 *Regulation parameter to prevent overfitting*
warm_start	True *When set to True, reuse the solution of the previous call to fit as initialization*

The end-goal of an ANN is to identify an optimum learning option that minimises the error in the network as discussed in section 2.2.3. The learning rate is the number and size of the steps taken to update the weights towards determining the output. Selecting the correct learning rate size is therefore an important consideration as a too small or to large learning rate can determine how long it takes to train the neural network. The consequence of a too small learning rate could be a longer time for the neural network to train and a too large can result in not achieving the correct output [14]. The momentum factor is a value ranging from 0 - 1 and determines the influence of the weight from the previous learning iteration on the current learning iteration. A value of close to 1 imply the weight of the current iteration is close to or equal to the previous iteration [14].

The number of neurons in the hidden layer can be decreased or increased, and additional hidden layers can be added. The activation function typically used is the logistic sigmoid and hyperbolic tan (tanh)function as discussed in in section 2.4.4, however the, identity and rectified linear unit (relu) functions were also tested during the experimental process to ensure the most optimal ANN was built with the least error.

Section 2.3.2 has shown that the optimal lag length can be determined through experiments, and a lag lengths of five, was determined to be optimal through experimentation in two recent studies [5,6]. The approach of determining lag length through experimentation was adopted in this study, where the lag length was varied between one and twenty to determine the optimal.

3.2.2 Data Pre-Processing

Data pre-processing is an important step to ensure data is normalised, as discussed in section 2.4.2. Experiments should ideally be conducted with a normalised format ranging from -1 and 1 or 0 and 1 [29]. Experiments can however be conducted successfully without normalising the data [5]. This research did not use normalised data, as the results was more desirable without normalisation.

3.2.3 Partitioning and Training

The data was divided into training and test data sets where the latest observations were used for training. The dataset contained data from 01 April 2016 to 04 June 2018 and was partitioned as shown in Figure 3.3 where 66% of the dataset was used for training, and 34% used for testing to initiate the training process.

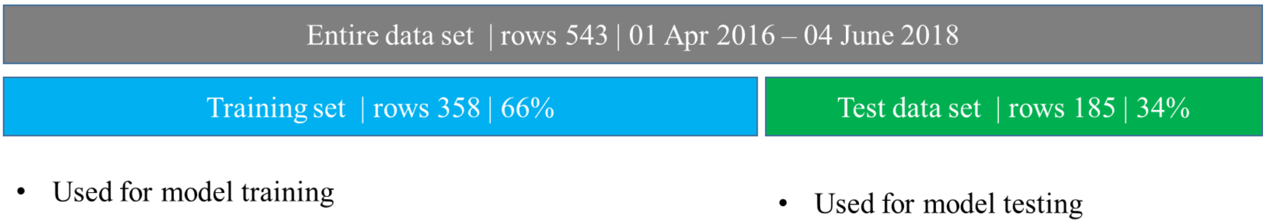

Figure 3.3: Initial Training and Test Data Split

The model was retrained after each prediction iteration with the roll-forward method described in section 2.5.2. For the first iteration, rows 0 to 357 is used for training and the model is used to predict the value in position 358. In the next iteration, the training set is adjusted by dropping a single value at the beginning, at position 0, and advancing the training set by one to include the value at position 358. The retrained model is now used to predict the value at position 359. This iterative training process continues up to the end of the available test set resulting in a total of 185 different training/test cycles. **Table 3.2** illustrates the training and prediction process.

Table 3.2: Training Process

Iteration	**Training**	**Prediction**
1	0 - 357	358
2	1 -358	359
3	2 -359	360
	…	…
185	Continue iteratively until the end of the test set	

The roll-forward method requires many model updates that can be computationally very expensive. Thus, in this work, model update with warm start initialisation is used as shown in **Table 3.1** to reduce the training time of the neural network based algorithms.

3.2.4 Evaluation

The default Scikit-learn Huber regressor was used as a baseline to compare the prediction of the share prices with the Scikit-learn Multi Perceptron regressor. Both the Huber regressor and the Multi Perceptron regressor was compared to the last value prediction model for further robustness of the experiments. The last value prediction model, also referred to as the naïve time series model [12,22], use the last actual value in the time series to predict next future value. The last value model can be represented as $Y_{t+1} = Y_t$.

This study used the MAPE and RMSE validation metrics that were identified as two of the commonly used metrics for ANN time series prediction in in section 2.4.5:

$$\textit{Mean Absolute Percentage Error } (MAPE) = \frac{\sum_{t=1}^{n} \frac{|e_t|}{Y_t}}{n}$$

$$\textit{Root Mean Square Error } (RMSE) = \sqrt{\frac{\sum_{t=1}^{n} e_t^2}{n}}$$

Model stability, as highlighted in section 2.5.2, can be regarded as a limitation if not considered adequately as the same ANN parameter configuration of a model could yield substantially different results when repeated. This study addressed model stability by running the same model configuration six times, and calculate the average MAPE and RMSE. The variance of the minimum and maximum MAPE achieved across six runs is compared to average MAPE to report on the stability of the model. If the minimum or maximum MAPE do not deviate erratically from the average, it would indicate the model is stable.

3.3 Software Tools

Two software tools were evaluated to create the neural network, i.e. Waikato Environment for Knowledge Analysis (WEKA) and Scikit-learn [36]. The objective is to use the standard functionality as provided by the software tools as far as possible to achieve the research objectives.

3.3.1 WEKA

WEKA is an open source software data mining and machine learning tool that contain ANN libraries for predictive analytics using the back propagation algorithm. WEKA is installed and configured with minimal effort, thus allowing the researcher to focus on the core research tasks.

WEKA 3.8.1 was evaluated in this research as it contain a dedicated time series environment to model prediction models and allow for visualisation and evaluation of models. WEKA was used to conduct experiments with the selected data to determine the feasibility to configure and build the optimal neural network.

3.3.2 Scikit-Learn

Scikit-learn is an open source tool available for data mining and analysis. It contain machine learning algorithms and have access to the python libraries[1]. The regression multi-perceptron method was explored in this research to determine the feasibility to configure and build the optimal neural network.

Scikit learn was selected after conducting a number of initial tests. The tests found that Scikit-learn offered more flexibility and customisation to adjust the ANN parameters as required to fulfil the research objectives.

3.4 Experiment 1: Share Price Only

The objective of the first experiment is to design and implement a basic MLP to predict the closing share price over three time frames, i.e. next day, average next week and average next month. The experiment uses only lagged closing share price values as the input to the MLP and predicts the closing share price for the next day share price, average next week share price, and average next month share price for Standard Bank (SB), Nedbank (NED) and First National Bank (FNB) respectively.

The experiment explores the impact of varying the different parameter values of the MLP parameters, shown in Table 3.1, and the lag length. The sliding window technique as illustrated in section 2.3.1 was used to add lagged share prices values. The experiment started with a lag length of one, and the length was increased gradually up to twenty as discussed in section 3.2.1, while keeping the neural network parameters static. Figure 3.4 illustrates how the lag length was applied to the share price values. A lag length of 3 is illustrated for the section marked as “x_train” and the target values in “y_train. “x_test” is used to predict the next value “x_{t+1}”.

x_train = rows 0 -9, columns 0-2 | y_train = row 0-9, column 3

Time(t)	Lagged share price values 0	1	2	y 3
0	18910	19100	18561	18000
1	19100	18561	18000	17635
2	18561	18000	17635	18000
3	18000	17635	18000	17595
4	17635	18000	17595	18025
5	18000	17595	18025	18306
6	17595	18025	18306	18267
7	18025	18306	18267	18136
8	18306	18267	18136	18200
9	18267	18136	18200	18396
10	18136	18200	18396	**18826**

x_test = row 10, columns 0-3 | x_{t+1}

Figure 3.4: Training Concept with Lagged Share Price Values

The iterative process was followed using the initial MLP parameters as described section 3.2.1. This process was followed by a validation process conducted using the metrics in section 3.2.4 to test the reliability of predictions made by the model, and the assessment of model stability. This experiment sets a baseline performance for experiments 2 and 3, so that the impact of adding other input variables can be analysed.

3.5 Experiment 2: Impact of External Factors

The objective of this experiment is to design and implement a neural network model to assess the impact of other external factors to predict the share price. The external factors considered are the four input variables numbered 1 – 4 in **Table 3.3.**

Table 3.3: Experiment 2: Input Variables

No.	Variable	Description
1	Exchange rate	End of day exchange rate (ZAR/ USD)
2	NASDAQ	NASDAQ daily closing value
3	JSE top 40 Index	JSE top 40 daily closing value
4	JSE All Share Index	JSE all share daily closing value

Similarly to experiment 1, Figure 3.5 illustrate the lagged share price values, and selected external variables used as input to the ANN. A lag length of three for the share price is illustrated for the section marked as "x_train" and the target values in "y_train. "x_test" is used to predict the next value "x_{t+1}"

x_train = rows 0 -9, columns 0-6

y_train = rows 0-9, column 7

	Lagged Share Price Values			External Variables				y
Time(t)	0	1	2	3	4	5	6	7
0	18910	19100	18561	14.9157	45112.97	51226.09	4843.93	18000
1	19100	18561	18000	15.179	45084.42	51184.32	4920.72	17635
2	18561	18000	17635	15.1191	45024.17	51146.82	4848.37	18000
3	18000	17635	18000	15.0808	45252.36	51424.48	4850.69	17595
4	17635	18000	17595	14.8226	45206.33	51428.08	4833.4	18025
5	18000	17595	18025	14.692	45751.08	52059.76	4872.09	18306
6	17595	18025	18306	14.7577	46617.72	52938.24	4947.42	18267
7	18025	18306	18267	14.6402	46551.55	52848	4945.89	18136
8	18306	18267	18136	14.4954	46763.08	53038.91	4938.22	18200
9	18267	18136	18200	14.6705	46879.92	53166.59	4960.02	18396
10	18136	18200	18396	14.4027	47025.18	53380.94	4940.33	**18826**

x_test = row 10, columns 0-6

x_{t+1}

Figure 3.5: Training Concept with Lagged Share Price Values and External Variables

Experiment 2 further followed the same process as Experiment 1 to determine optimal MLP parameters, and lag length with the least error. Three different prediction models were also implemented for the next day share price, average next week share price, and average next month share price for Standard Bank (SB), Nedbank (NED) and First National Bank (FNB) respectively.

3.6 Experiment 3: Impact of a Forward Looking Variable.

The objective of this experiment is to design and implement a neural network model to assess the impact of a forward looking variable to predict the share price. This experiment followed the same process as experiment 2, however the BCI input variable was added in addition to the variables described in section 3.5. The BCI is an indicator of the future economic outlook of the country [18]. It is a measure of the future direction of real economic movement. A number of key economic indicators are included in the calculation [14]. The leading business cycle indicator that provide an outlook on the economic future was used for this research. This experiment determined the influence of the BCI on the neural network.

3.7 Implementation

Data for all input variables were collated in individual .csv files. The files were combined per banking share, and the chronological order of the share information were maintained through the process. The result was three files for each bank containing the end of day share prices joined with all input variables. The average 5 day (next week) share price and the average 21 day (next month) share price were calculated for each bank using the end of day share price. This process resulted in a total 3 files per banking share. All null values related to non-trading days were removed when preparing the data.

The test procedure depicted in Figure 3.6 is as follows:

1. Programmatic pre-processing was performed on the data to format the data appropriately for a time series problem as required. The data was then partitioned into the initial training and test sets.
2. The lag length was varied between one to a maximum of twenty lags during test iterations.
3. The parameters in section 3.2.1 was varied during the iterations. Additional parameters were added as required based on the results obtained, and the required optimisation to improve the results.
4. Error metrics were calculated and recorded for each iteration in the process of predicting the next day share price for Standard Bank. To ensure the neural network perform optimally,

random weights were assigned at each time the model was initialised. This improves robustness where the model is not forced to initialise based on the same values. Not assigning random weights would produce the same result every time when executing the model, hence limiting the capabilities of the neural network. The average of six MLP regressor prediction iteration results was used to calculate the error metrics, as different results and error metrics were produced with each execution of the model.

5. Step 1 - 4 was repeated and applied to predicting the target values for Standard Bank until the optimal neural network is achieved for:
    a. average CP for the next week (5 day average price)
    b. next month/30 days (21 day average price)
6. A similar process was applied with the Nedbank and FNB shares using the optimal neural network obtained through 1 - 5 as a starting point.

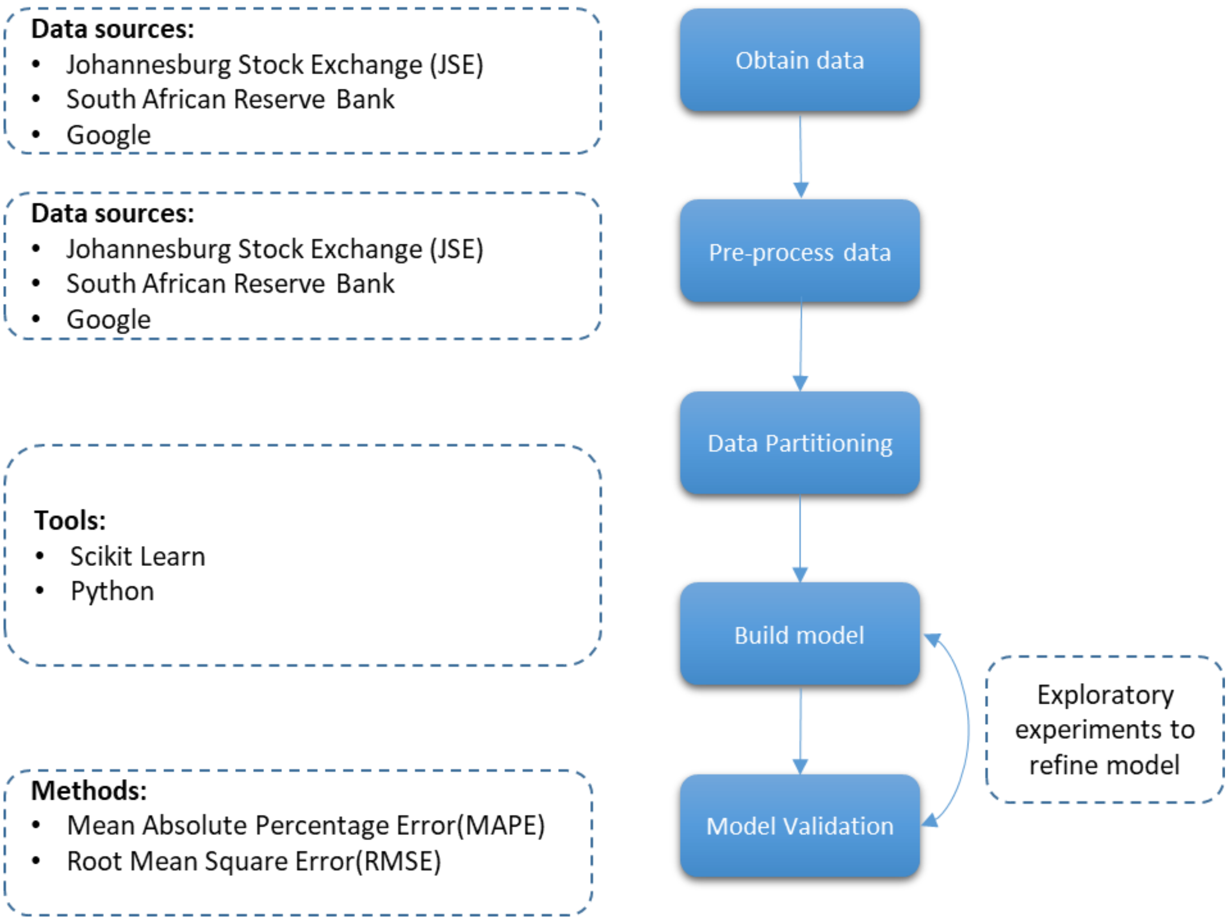

Figure 3.6: Summary of the Experimental Process

3.8 Summary

The experimental design process allows for the assessment of the individual experiments using evaluation metrics. It further allows for comparison between experiments. Experiment 1 informs us on the performance of the optimal neural network when using only the lagged share price values as input variable to predict the share price. Experiment 2 informs us on the impact of adding four additional external variables to the lagged share price values. Experiment 3 allows us to assess the impact of adding a forward looking variable. The results and evaluation metrics of the experiments are presented in the next chapter.

Chapter 4. RESULTS

This chapter reports on the results of the experiments described in Chapter 3. The results for experiment 1, 2 and 3 are presented for each banking share by comparing the MAPE and RMSE achieved for the Huber regressor to the MLP regressor from the Scikit learn library. The results achieved for the Huber regressor and MLP regressor are further compared to the last actual value prediction model.

4.1 Experiment 1: Share price only

The objective of this experiment was to design and implement a neural network model using only the share price as the input variable to predict the share price. Predictions were performed for the next day share price, average next week share price, and average next month share price for Standard Bank (SB), Nedbank (NED) and First National Bank (FNB) respectively. The experiment uses only lagged closing share price values as the input to the ANN model and predicts the closing share price for the next day share price, average next week share price, and average next month share price as described in section 3.4.

The parameters as described in section 3.2.1 in Chapter 3 were varied and adjusted with each iteration until reaching the best MAPE, and the values of optimal parameters recorded. **Table 4.1** shows the optimal neural network parameters found for the three different prediction targets. All experiment 1 neural network prediction models had the same number of hidden layers, activation and solver. The alpha regulation parameter is 0.1e-9 for predicting the next day share price, and 0.1e-1000 for the average next week and average next month prediction. The shuffle parameter was set to FALSE for all experiments, implying that the values fed to the neural network will not be randomly shuffled. Early stopping was set to TRUE. When setting early stopping to TRUE, 10% of the training set is used for validation, and training is terminated when the validation score do not improve further. The random state was set to NONE for all experiments, allowing for the random allocation of neural network weights.

Table 4.1: Experiment 1: Optimal MLP Parameters

		Next Day	Next Week	Next Month
Parameter	**hidden_layer_sizes**	50,50,30	50,50,30	50,50,30
	activation	identity	identity	identity
	solver	lbfgs	lbfgs	lbfgs
	shuffle	FALSE	FALSE	FALSE
	early_stopping	TRUE	TRUE	TRUE
	random_state	None	None	None
	alpha	**0.1e-9**	**0.1e-1000**	**0.1e-1000**
	warm_start	TRUE	TRUE	TRUE

Table 4.2 and **Figure 4.1** show the summary results for experiment 1. The results show that the MLP achieved a better average MAPE across six iterations for predicting the share price for Standard, Nedbank and First National Bank. The deviation across the six runs is also shown to provide an indication of the stability of the models across the runs. The deviation reported is minimal, suggesting the model is relatively stable. The results also show the optimal lag length achieved. The result imply it is possible to predict the share price using a neural network using one input variable, as it mostly outperformed the Huber regressor except for predicting the next day and average next week share price for First National Bank. The detailed results for experiment 1 are shown in Tables A.1 to A.9 in Appendix A.

Table 4.2: Experiment 1: MAPE Summary

	Closing Share Price	Last Value	HUBER Regressor	MLP Regressor	Huber Lag	MLP Lag
Standard Bank	Next Day	1.253	1.251	**1.244** ± 0.003	2	1
	Average Next Week	0.560	0.315	**0.314** ± 0.002	8	7
	Average Next Month	0.261	0.088	**0.087** ± 0.003	2	2
Nedbank	Next Day	1.327	1.322	**1.321** ± 0.002	1	1
	Average Next Week	0.614	0.337	**0.336** ± 0.002	9	7
	Next Month	0.325	0.096	**0.095** ± 0.001	2	2
First National Bank	Next Day	1.559	1.546	**1.557** ± 0.005	1	1
	Average Next Week	0.668	0.386	**0.402** ± 0.011	12	7
	Average Next Month	0.301	0.111	**0.088** ± 0.001	9	2

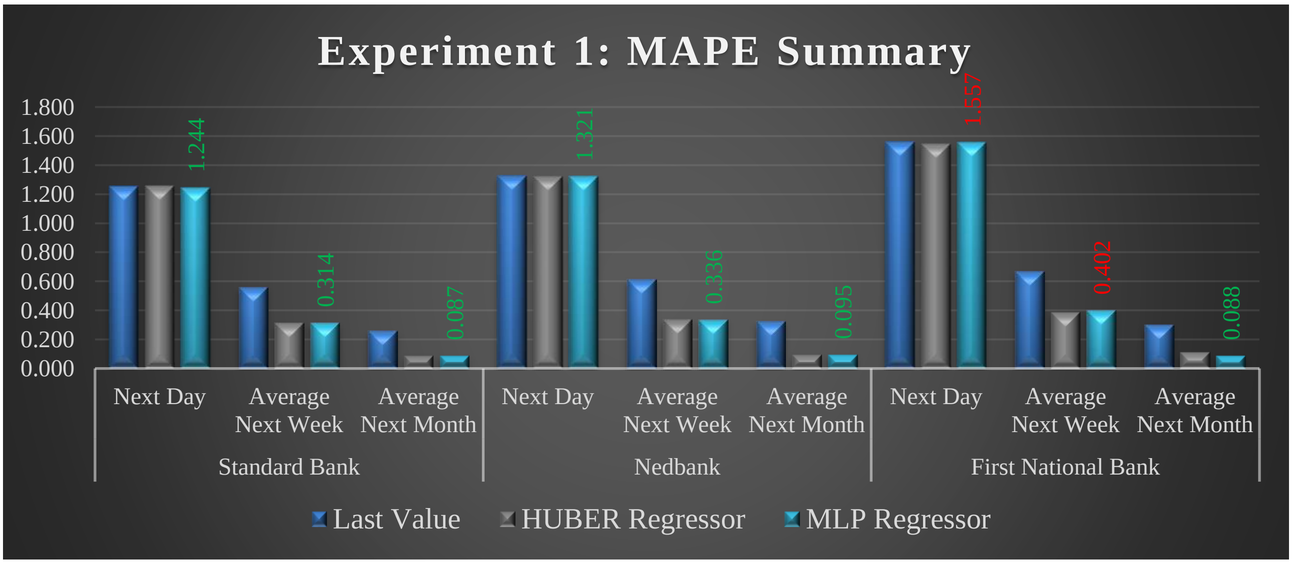

Figure 4.1: Experiment 1: MAPE Summary

4.2 Experiment 2: Impact of External Factors

The objective of this experiment was to design and implement a neural network model to assess the impact of other external factors to predict the share price. In addition to the lagged share price, four input variables as depicted in **Table 4.3** were introduced as input to the prediction model. Predictions were performed for the next day, average next week, and average next month share price for each of the three banking shares.

Table 4.3: Experiment 2: Four Input Variables

NO.	VARIABLE	DESCRIPTION
1	Exchange rate	End of day exchange rate (ZAR /USD)
2	NASDAQ	NASDAQ daily closing value
3	JSE top 40 Index	JSE top 40 daily closing value
4	JSE All Share Index	JSE all shares daily closing value

Table 4.4 shows the optimal neural network parameters used for the experiment 2 predictions. The parameters were varied and adjusted as described in Section 3.2.1 in Chapter 3 with each iteration until reaching the best MAPE, and the values of optimal parameters recorded. All experiment 2 neural network prediction models had the same number of hidden layers, activation and solver. The alpha regulation parameter is 0.1e-9 for predicting the next day share price, and 0.1e-1000 for the average next week and next month prediction. The shuffle parameter was set to FALSE for all experiments, implying that the values fed to the neural network will not be randomly shuffled. Early stopping was also set to TRUE the same as experiment 1. The random state was kept at NONE for all experiments, allowing for the random allocation of neural network weights. The optimal parameter values were obtained by adjusting the parameters iteratively, and were found to be the same as for experiment 1.

Table 4.4: Experiment 2: Optimal MLP Parameters

		Next Day	Next Week	Next 30 Days
Parameter	**hidden_layer_sizes**	50,50,30	50,50,30	50,50,30
	activation	identity	identity	identity
	solver	lbfgs	lbfgs	lbfgs
	shuffle	FALSE	FALSE	FALSE
	early_stopping	TRUE	TRUE	TRUE
	random_state	None	None	None
	alpha	**0.1e-9**	**0.1e-1000**	**0.1e-1000**
	warm_start	TRUE	TRUE	TRUE

Table 4.5 and Figure 4.2 show the summary of the experiment 2 results. The results show that the MLP achieved a better average MAPE across six iterations for predicting the share price for Standard Bank, Nedbank and First National Bank. The MAPE deviation across the six runs is also shown to provide an indication of the stability of the model across the runs. The deviation reported for experiment 2 is also minimal, suggesting the models are relatively stable. The result imply it is possible to predict the share price using a neural network with four external factors as input variables, as it mostly outperformed the Huber regressor except for predicting the next day and average next month share price for Nedbank, and the average next week share price for First National Bank. The detailed results for experiment 2 are shown in Tables A.10 to A.18 in Appendix A.

Table 4.5: Experiment 2: MAPE Summary

	Closing Share Price	Last Value	HUBER Regressor	MLP Regressor	Huber Lag	MLP Lag
Standard Bank	Next Day	1.253	1.251	**1.240** ± 0.003	8	1
	Average Next Week	0.563	0.362	**0.358** ± 0.006	2	2
	Average Next Month	0.261	0.089	**0.088** ± 0.001	2	2
Nedbank	Next Day	1.327	1.333	**1.339** ± 0.018	2	1
	Average Next Week	0.614	0.392	**0.384** ± 0.002	6	6
	Next Month	0.325	0.097	**0.103** ± 0.004	2	2
First National Bank	Next Day	1.559	1.563	**1.556** ± 0.001	4	1
	Average Next Week	0.668	0.425	**0.461** ± 0.020	2	2
	Average Next Month	0.301	0.113	**0.112** ± 0.011	2	2

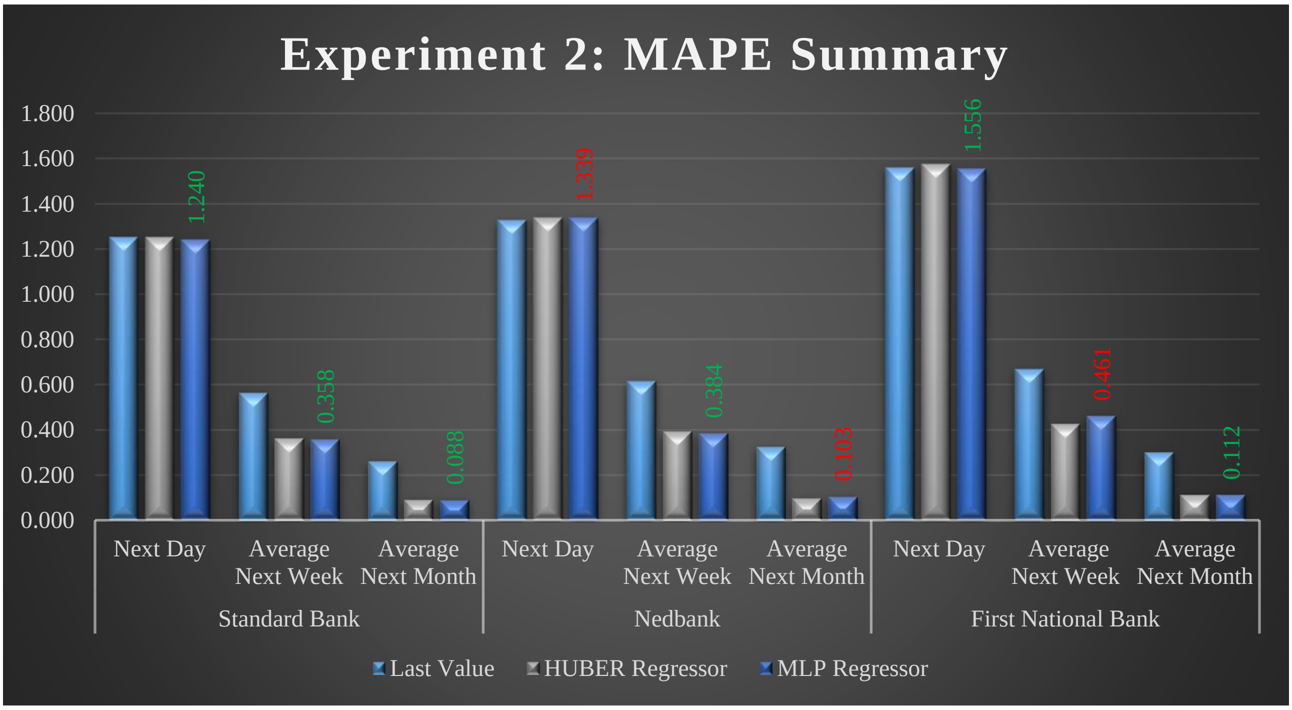

Figure 4.2: Experiment 2: MAPE Summary

4.3 Experiment 3: Impact of a Forward Looking Variable.

The purpose of this experiment was to test what the impact of introducing a forward looking variable would have on the prediction model. The business cycle indicator (BCI) is a forward looking economic indicator as introduced in section 3.6.

In addition to the lagged share price, the five input variables used in experiment 3 is depicted in **Table 4.6**. The next day, the average next week, and the average next month share prices were predicted for Standard Bank (SB), Nedbank (NED) and First National Bank (FNB) respectively.

Table 4.6: Experiment 3: Five Input Variables

No.	**Variable**	**Description**
1	Exchange rate	End of day exchange rate (ZAR /USD)
2	NASDAQ	NASDAQ daily closing value
3	JSE Top 40 Index	JSE top 40 daily closing value
4	JSE All Share Index	JSE all shares daily closing value
5	Business Cycle Indicator (BCI)	BCI Leading Indicator (Monthly Value)

Table 4.7 shows the optimal neural network parameters used for experiment 3. The parameters were varied and adjusted as described in Section 3.2.1 in Chapter 3 with each iteration until reaching the best MAPE, and the values of optimal parameters recorded. All experiment 3 neural network prediction models used in this section had the same number of hidden layers, activation and solver. The alpha regulation parameter is 0.1e-9 for prediction the next day share price, and 0.1e-1000 for the average next week and next month prediction. The shuffle parameter was set to FALSE for all experiments, implying that the values fed to the neural network will not be randomly shuffled. Early stopping was set to TRUE, similar to experiment 1 and experiment 2. The random state was kept at NONE for all experiments, allowing for the random allocation of neural network weights. The optimal parameters are consistent with experiment 1 and experiment 2 prediction models.

Table 4.7: Experiment 3: Optimal MLP Parameters

		Next Day	Next Week	Next 30 Days
Parameter	**hidden_layer_sizes**	50,50,30	50,50,30	50,50,30
	activation	identity	identity	identity
	solver	lbfgs	lbfgs	lbfgs
	shuffle	FALSE	FALSE	FALSE
	early_stopping	TRUE	TRUE	TRUE
	random_state	None	None	None
	alpha	**0.1e-9**	**0.1e-1000**	**0.1e-1000**
	warm_start	TRUE	TRUE	TRUE

Table 4.8 and Figure 4.3 shows the summary results of experiment 3 using lagged share and five external factors as input variables. Predictions were performed for the next day, average next week, and average next month for each of the three banking shares. The results show that the MLP achieved a better average MAPE across six iterations for predicting the share price for Standard Bank, Nedbank and First National Bank. The deviation across the six runs is also shown to provide an indication of the stability of the model across the runs. The deviation reported for experiment 3 is also minimal, suggesting the model is relatively stable. The results imply it is possible to predict the share price using a neural network with five independent variables, as it mostly outperformed the Huber regressor except for predicting the next day share price for Nedbank and average next week share price for First National Bank. The detailed results for experiment 3 are shown in Tables A.19 to A.27 in Appendix A.

Table 4.8: Experiment 3: MAPE Summary

	Closing Share Price	Last Value	HUBER Regressor	MLP Regressor	MLP Lag	MLP Lag
Standard Bank	Next Day	1.253	1.247	**1.240** ± 0.003	1	1
	Average Next Week	0.563	0.363	**0.358** ± 0.002	3	2
	Average Next Month	0.261	0.091	**0.090** ± 0.001	2	2
Nedbank	Next Day	1.327	1.339	**1.351** ± 0.008	2	1
	Average Next Week	0.614	0.394	**0.388** ± 0.002	2	2
	Next Month	0.325	0.096	**0.095** ± 0.001	3	2
First National Bank	Next Day	1.559	1.559	**1.556** ± 0.004	5	1
	Average Next Week	0.668	0.425	**0.461** ± 0.021	3	2
	Average Next Month	0.301	0.115	**0.114** ± 0.001	2	3

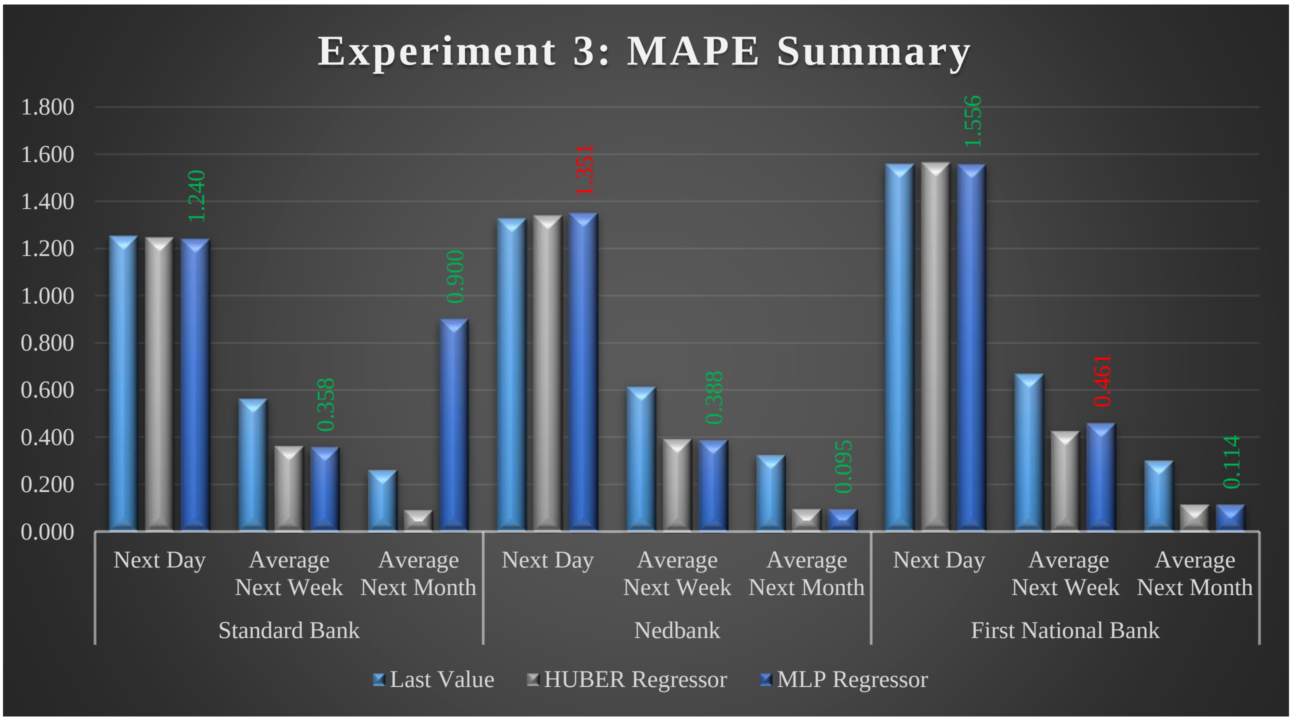

Figure 4.3: Experiment 3: MAPE Summary

4.4 Analysis

4.4.1 Summary and results

Table 4.9 and Figure 4.4 show the average MAPE across six iterations for Experiment 1, 2 and 3.

The ANN models using only the share price was found in general to perform better than the ANNs that used the external factors as additional input variables, except for the next day closing share predictions for both Standard Bank and First National Bank. The average next month prediction model noticeably produced a smaller prediction error compared to the next week, and next day prediction models for all three banks. **Table 4.10** shows how the MLP results compare to Huber regressor. The First National Bank average next week and average next month Huber regressor prediction models performed better than the MLP regressor, however the overall result was more consistent for the MLP regressor models. It is evident that the average next month prediction model yielded better prediction accuracy compared to the average week and one day prediction models. This could be attributed to less volatility in the in the average next month share price, compared to the daily share price or average next week share price.

Table 4.9: MLP Average MAPE Comparison

	Closing Share Price	**Experiment 1:** **Lagged Share Price**	**Experiment 2:** **Impact of External Factors**	**Experiment 3:** **Impact of a Forward Looking Variable**
Standard Bank	Next Day	1.244 ± 0.003	**1.240** ± 0.003	**1.240** ± 0.003
	Average Next Week	**0.314** ± 0.002	0.358 ± 0.006	0.358 ± 0.002
	Average Next Month	**0.087** ± 0.003	0.088 ± 0.001	0.090 ± 0.001
Nedbank	Next Day	**1.321** ± 0.002	1.339 ± 0.018	1.351 ± 0.008
	Average Next Week	**0.336** ± 0.002	0.384 ± 0.002	0.388 ± 0.002
	Average Next Month	**0.095** ± 0.001	0.103 ± 0.004	**0.095** ± 0.001
First National Bank	Next Day	1.557 ± 0.005	**1.556** ± 0.001	**1.556** ± 0.004
	Average Next Week	**0.402** ± 0.011	0.461 ± 0.020	0.461 ± 0.021
	Average Next Month	**0.088** ± 0.001	0.112 ± 0.011	0.114 ± 0.011

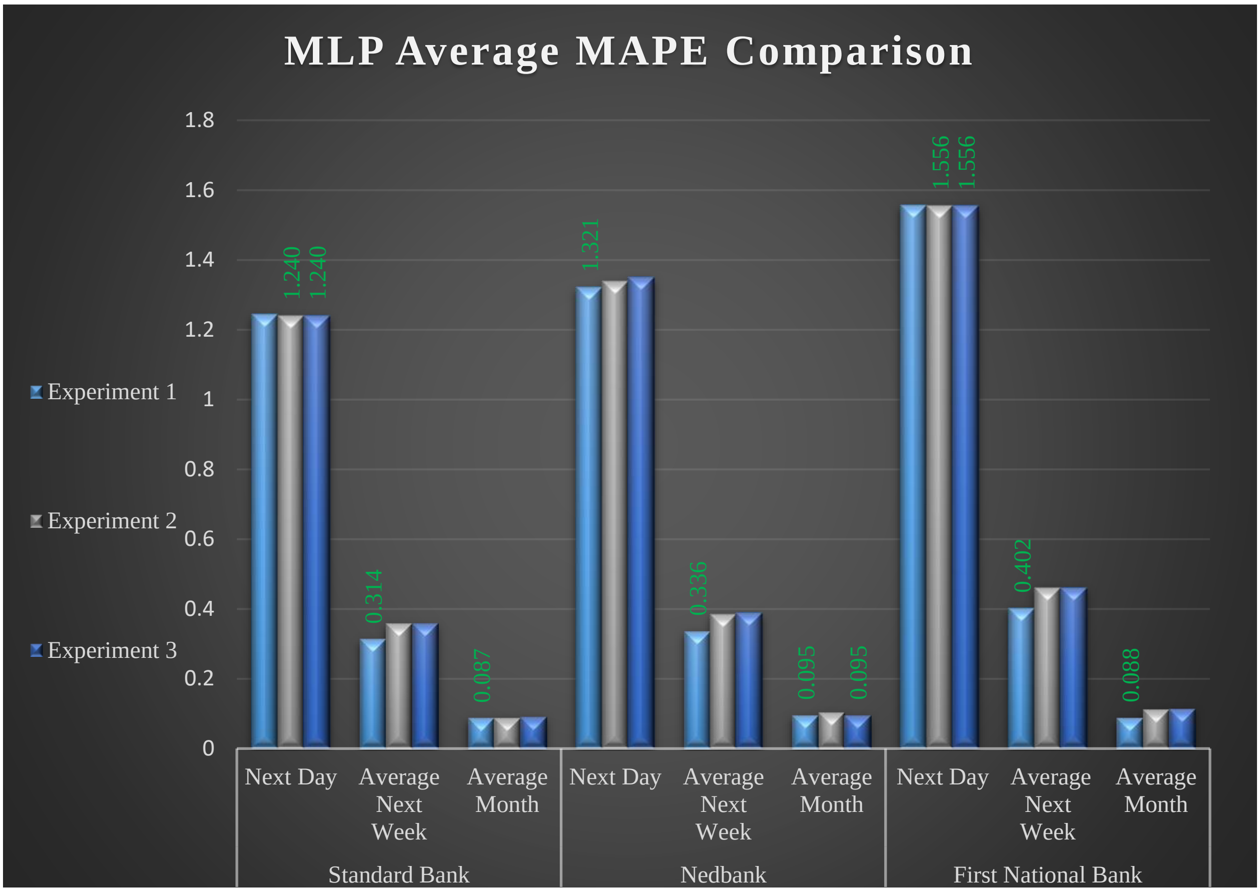

Figure 4.4: MLP Average MAPE Comparison

Table 4.10: All Results: MAPE Comparison

		Experiment1: Input variables: Lagged Share Prices		**Experiment 2: Impact of External Factors**		**Experiment 3: Impact of a Forward Looking Variable**	
	Closing Price	**HUBER Regressor**	**MLP Regressor**	**HUBER Regressor**	**MLP Regressor**	**HUBER Regressor**	**MLP Regressor**
Standard Bank	**Next Day**	1.251	1.244 ± 0.003	1.251	**1.240** ± 0.003	1.247	1.240 ± 0.003
	Average Next Week	0.315	**0.314 ± 0.002**	0.362	0.358 **± 0.006**	0.363	0.358 ± 0.002
	Average Next Month	0.088	**0.087 ± 0.003**	0.089	0.088 ± 0.001	0.091	0.090 ± 0.001
Nedbank	**Next Day**	1.322	**1.321 ± 0.002**	1.333	1.339 ± 0.018	1.339	1.351 ± 0.008
	Average Next Week	0.337	**0.336 ± 0.002**	0.392	0.384 ± 0.002	0.394	0.388 ± 0.002
	Average Next Month	0.096	**0.095** ± 0.001	0.097	0.103 ± 0.004	0.096	0.095 ± 0.001
First National Bank	**Next Day**	**1.546**	1.557 ± 0.005	1.563	1.556 ± 0.001	1.559	1.556 **± 0.004**
	Average Next Week	**0.386**	0.402 ± 0.011	0.425	0.461 ± 0.020	0.425	0.461 ± 0.021
	Average Next Month	0.111	**0.088** ± 0.001	0.113	0.112 **± 0.011**	0.115	0.114 ± 0.001

4.4.2 The impact of the additional input variables

The prediction models, using only the share price as input variable, in general outperformed the models using external factors as additional input variables. This shows that the external factors found to typically influence the share price, does not necessarily improve the accuracy of prediction models. The forward looking input variable had largely a negative impact on the models.

It must be noted that the share price is however not only influenced by external factors, but also factors originating internal to the corporate environment [57]. Internal factors specific to the individual banks can therefore potentially contribute to the observation where the next day and next week share prediction for First National Bank is not consistent with the same prediction for Standard Bank and Nedbank.

4.4.3 Model robustness and stability

Section 2.5.2 reports on the limitations in the validation approaches in some of the previous studies, and also highlighted an alternative approach to overcome these limitations by using the roll-forward validation approach. This study focussed on improving robustness of the model by using the roll-forward approach. The study updated the model with new data while training to ensure the model does not become outdated. The starting point of the training set was also updated to prevent unwanted trends in the training data.

This study also evaluated model stability to further emphasise the robustness of the models. The deviation of the minimum and maximum MAPE values from the average across the six runs are shown in **Table 4.9** and **Table 4.10** to provide an indication of the stability of the model across the runs. The deviation values shown in red text indicate that the Huber regressor can outperform some individual prediction runs of the MLP regressor. This result highlight the importance of obtaining the average of multiple runs of the same model, and measuring the model stability.

4.4.4 Comparison to related work

While the previous work as highlighted in Chapter 2 successfully built time series neural networking prediction models, this study specifically focussed on predicting end of day closing next day, average next week and average next month shares for the for three banks listed on the JSE. It further evaluated the impact of a new combination of external variables on the prediction accuracy. The study than also introduced a forward looking external factor, to assess whether it would impact the prediction accuracy. A robust experimental process was followed with a focus on the walk-forward validation approach. This validation approach was highlighted by a few studies [5,6,30], however a number of previous studies [15,41,43,50] used fixed partition validation. The ANN models were compared to the Huber regressor, and the general outcome is a better performance by the ANN model, using the MLP regressor. Evidence of evaluating model stability in most previous studies was lacking [15,41,43,50]. Two previous studies [5,6] realised the importance of calculating the average evaluation metrics across multiple model runs, and one clearly highlighted the importance of evaluating model stability [30]. This study evaluated and reported on model stability.

This study aimed for rigorous and robust experiments applied to the three banks, i.e. Standard Bank, Nedbank and First National Bank. The MLP regressor performed in general better than Huber regressor. This result is promising and show that there is a benefit in using ANNs to predict the share price on the JSE.

Chapter 5. Conclusion.

This study aimed to explore the prediction of share prices in the banking sector of the South African JSE using artificial neural networks. It dealt with the effect of adding more information through using a combination of input variables derived from the external factors that influence the market. The study also focused on robustness through using an appropriate validation method, i.e. walk-forward validation and also tested model stability.

The performance of the ANN models were compared to a traditional regression method. The study found that all ANN prediction models can be used for predicting the share price with accuracy, and with general improved accuracy compared to the traditional models. The models using only the share price as input variable performed better, indicating that the additional variables selected for analysis did not improve the accuracy of the models. The study also tested for model stability across six iterations of the same model configuration. The ANN models across all experiments were found to be relatively stable.

The theoretical and practical contributions include additions to the body of knowledge on the application of artificial neural networks to build a validated model to do financial predictions in the banking sector on the JSE. The outcome of the study contributes to the theories on whether it is possible to predict the stock market, and the factors influencing predicting the stock market. A practical implementation is available to evaluate and build on in future research.

Future studies may include different algorithms other than MLPs. The input variables can also be adjusted to include other factors that can influence the outcome of the share price.

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Appendix A

Experiment 1: Detailed Results

Table A.1, **Table A.2** and **Table A.3** show the detailed result achieved for predicting the next day for **Standard Bank (SB), Nedbank (NED)** and **First National bank (FNB).** The results include the Mean Absolute Percentage Error (MAPE) and the Root Mean Squared Error (RMSE) for both the Huber regressor and the MLP regressor from the Scikit-learn machine learning library, as well as the last value prediction (LV).

Table A.1: Experiment 1: SB - Next Day Closing Share Price

	Last Value		**Huber Regressor**		**MLP Regressor**	
LAG	**MAPE(%)**	**RMSE**	**MAPE(%)**	**RMSE**	**AVG MAPE(%)**	**RMSE**
1	1.253	327.032	1.257	330.338	**1.244**	**326.303**
2	1.253	327.032	**1.251**	327.777	1.255	327.520
3	1.382	621.783	1.257	**326.491**	1.258	329.073
4	1.260	327.032	1.278	335.415	1.265	331.021
5	1.260	327.929	1.273	334.181	1.267	329.274
6	1.260	327.929	1.269	331.350	1.265	329.489
7	1.264	328.784	1.278	332.489	1.274	329.824
8	1.264	328.784	1.276	334.075	1.274	331.191
9	1.264	328.784	1.260	332.549	1.280	332.224
10	1.271	329.693	1.275	333.080	1.282	333.956
11	1.271	329.693	1.290	341.481	1.281	332.636
12	1.271	329.693	1.278	340.755	1.289	334.006
13	1.271	329.693	1.265	333.376	1.303	336.588
14	1.264	329.337	1.288	343.495	1.312	336.411
15	1.264	330.103	1.302	344.663	1.316	339.310
16	1.266	330.103	1.295	336.777	1.302	341.064
17	1.453	709.004	1.279	340.725	1.311	369.815
18	1.266	330.103	1.270	331.648	1.317	340.158
19	1.270	330.942	1.289	338.587	1.324	348.632
20	1.270	330.942	1.315	338.587	1.311	339.821

Table A.2: Experiment 1: NED - Next Day Closing Share Price

	Last Value		Huber Regressor		MLP Regressor	
LAG	**MAPE(%)**	**RMSE**	**MAPE(%)**	**RMSE**	**AVG MAPE(%)**	**RMSE**
1	1.327	472.057	**1.322**	470.780	**1.321**	**471.194**
2	1.327	472.057	1.326	472.036	1.334	472.811
3	1.327	472.057	1.325	**470.630**	1.340	474.289
4	1.333	472.045	1.337	474.576	1.347	477.159
5	1.333	473.340	1.349	477.306	1.352	478.201
6	1.333	473.340	1.359	477.896	1.359	478.736
7	1.339	474.634	1.364	479.743	1.368	481.858
8	1.339	474.634	1.369	483.595	1.360	482.282
9	1.339	474.634	1.364	482.635	1.352	477.727
10	1.343	475.892	1.356	481.566	1.362	479.797
11	1.343	475.892	1.357	480.003	1.363	480.914
12	1.343	475.892	1.372	488.034	1.369	483.825
13	1.340	476.282	1.372	487.944	1.382	489.408
14	1.340	476.282	1.365	485.901	1.387	486.903
15	1.340	477.525	1.360	482.855	1.386	487.255
16	1.344	477.525	1.358	481.951	1.405	497.824
17	1.344	477.525	1.368	484.705	1.398	489.729
18	1.344	477.525	1.376	487.624	1.408	497.795
19	1.350	478.852	1.385	489.937	1.411	489.507
20	1.350	478.852	1.361	485.285	1.388	494.295

Table A.3: Experiment 1: FNB - Next Day Closing Share Price

	Last Value		Huber Regressor		MLP Regressor	
LAG	**MAPE(%)**	**RMSE**	**MAPE(%)**	**RMSE**	**AVG MAPE(%)**	**RMSE**
1	1.559	132.881	**1.546**	**132.038**	**1.557**	**132.709**
2	1.559	132.881	1.562	133.195	1.583	133.159
3	1.559	132.881	1.570	133.079	1.590	133.839
4	1.565	132.863	1.572	133.866	1.599	134.817
5	1.565	133.227	1.591	134.879	1.604	135.434
6	1.565	133.227	1.596	134.148	1.607	135.782
7	1.572	133.593	1.573	133.650	1.613	135.730
8	1.572	133.593	1.582	133.698	1.617	135.775
9	1.572	133.593	1.581	133.141	1.616	135.109
10	1.578	133.950	1.586	133.464	1.626	135.234
11	1.578	133.950	1.596	134.059	1.633	135.451
12	1.578	133.950	1.597	134.591	1.633	135.877
13	1.585	134.313	1.614	135.569	1.650	137.135
14	1.585	134.313	1.617	136.788	1.646	136.520
15	1.585	134.642	1.601	134.899	1.662	136.958
16	1.589	134.642	1.629	136.222	1.670	138.188
17	1.589	134.642	1.625	136.473	1.661	135.693
18	1.589	134.642	1.626	136.667	1.663	138.162
19	1.585	134.740	1.630	137.638	1.671	139.430
20	1.585	134.740	1.626	137.522	1.659	139.626

The experiment 1 results for predicting the next week average share price for **Standard Bank (SB)**, **Nedbank (NED)** and **First National Bank (FNB)** are presented in **Table A.4**, **Table A.5** and **Table A.6** respectively. The results include the Mean Absolute Percentage Error (MAPE) and the Root Mean Squared Error (RMSE) for both the Huber regressor and the MLP regressor from the scikit-learn machine learning library, as well as the last value prediction (LV).

Table A.4: Experiment 1: SB - Next Week Average Closing Share Price

	Last Value		Huber Regressor		MLP Regressor	
LAG	**MAPE(%)**	**RMSE**	**MAPE(%)**	**RMSE**	**AVG MAPE(%)**	**RMSE**
1	0.563	142.541	0.565	141.210	0.568	142.314
2	0.563	142.541	0.355	91.461	0.354	91.585
3	0.563	142.541	0.350	90.130	0.351	90.428
4	0.562	142.240	0.356	90.514	0.358	90.931
5	0.562	142.630	0.350	88.008	0.350	88.569
6	0.562	142.630	0.344	88.019	0.346	87.578
7	0.560	142.620	0.323	83.220	**0.314**	**80.578**
8	0.560	142.620	**0.315**	**81.699**	0.334	84.929
9	0.560	142.620	0.323	83.398	0.342	87.065
10	0.561	142.960	0.331	84.272	0.347	86.953
11	0.561	142.960	0.339	86.465	0.353	89.923
12	0.561	143.010	0.334	83.947	0.350	88.293
13	0.562	143.292	0.336	84.353	0.357	88.778
14	0.562	143.292	0.349	85.827	0.363	95.017
15	0.562	143.619	0.368	93.817	0.374	100.905
16	0.563	143.619	0.376	96.953	0.400	98.143
17	0.563	143.619	0.409	104.323	0.409	100.308
18	0.563	143.619	0.427	111.123	0.414	99.555
19	0.565	143.985	0.426	109.845	0.435	110.032
20	0.565	143.985	0.435	113.016	0.434	117.098

Table A.5: Experiment 1: NED - Next Week Average Closing Share Price

	Last Value		Huber Regressor		MLP Regressor	
LAG	**MAPE(%)**	**RMSE**	**MAPE(%)**	**RMSE**	**AVG MAPE(%)**	**RMSE**
1	0.614	206.645	0.611	207.851	0.611	208.514
2	0.614	206.645	0.383	130.369	0.383	130.157
3	0.614	206.645	0.388	130.748	0.388	131.152
4	0.615	206.571	0.392	131.772	0.390	131.271
5	0.615	207.138	0.380	128.685	0.377	127.258
6	0.615	207.138	0.359	121.334	0.362	122.614
7	0.616	207.588	0.338	115.585	**0.336**	**114.781**
8	0.616	207.588	0.347	118.586	0.354	120.406
9	0.616	207.588	**0.337**	**115.206**	0.351	120.563
10	0.619	208.163	0.342	118.321	0.363	125.272
11	0.619	208.163	0.348	119.663	0.367	122.327
12	0.619	208.163	0.356	121.005	0.373	126.868
13	0.621	208.724	0.354	119.962	0.381	128.581
14	0.621	208.724	0.363	124.347	0.386	132.796
15	0.621	209.024	0.392	131.218	0.403	139.512
16	0.621	209.024	0.410	138.468	0.405	131.210
17	0.621	209.024	0.424	142.058	0.421	144.811
18	0.621	209.024	0.461	151.683	0.422	142.140
19	0.623	209.590	0.440	153.384	0.447	138.450
20	0.623	209.590	0.442	152.740	0.458	158.130

Table A.6: Experiment 1: FNB - Next Week Average Closing Share Price

	Last Value		Huber Regressor		MLP Regressor	
LAG	**MAPE(%)**	**RMSE**	**MAPE(%)**	**RMSE**	**AVG MAPE(%)**	**RMSE**
1	0.672	59.137	0.670	59.377	0.674	60.134
2	0.668	58.859	0.425	36.431	0.426	36.475
3	0.668	58.859	0.432	36.266	0.432	36.376
4	0.670	58.853	0.431	36.343	0.432	36.409
5	0.670	59.014	0.430	35.515	0.429	35.892
6	0.670	59.014	0.420	34.510	0.420	34.690
7	0.670	59.101	0.407	32.916	**0.402**	**32.655**
8	0.670	59.101	0.391	**32.086**	0.413	34.136
9	0.670	59.101	0.393	32.351	0.410	34.136
10	0.673	59.261	0.393	32.923	0.414	34.115
11	0.676	59.260	0.392	32.867	0.415	35.816
12	0.673	59.261	**0.386**	32.487	0.427	35.872
13	0.675	59.421	0.396	33.872	0.427	34.634
14	0.675	59.421	0.408	35.093	0.445	38.955
15	0.679	59.588	0.408	34.267	0.448	35.993
16	0.679	59.588	0.432	37.365	0.466	40.300
17	0.679	59.588	0.442	37.558	0.481	41.184
18	0.679	59.588	0.452	39.156	0.492	40.144
19	0.681	59.749	0.480	40.880	0.503	42.519
20	0.681	59.749	0.486	41.538	0.517	44.364

The experiment results for predicting the next month average share price for **Standard Bank (SB)**, **Nedbank (NED)** and **First National Bank (FNB)** are presented in **Table A.7**, **Table A.8** and **Table A.9** respectively. The results include the Mean Absolute Percentage Error (MAPE) and the Root Mean Squared Error (RMSE) for both the Huber regressor and the MLP regressor from the Scikit-learn machine learning library, as well as the last value prediction (LV).

Table A.7: Experiment 1: SB - Next Month Average Closing Share Price

	Last Value		Huber Regressor		MLP Regressor	
LAG	**MAPE(%)**	**RMSE**	**MAPE(%)**	**RMSE**	**AVG MAPE(%)**	**RMSE**
1	0.261	61.811	0.245	56.30	0.250	58.06
2	0.261	61.811	**0.088**	**21.970**	**0.087**	**21.949**
3	0.261	61.811	0.090	22.31	0.088	22.00
4	0.261	61.795	0.088	22.19	0.089	22.22
5	0.261	61.965	0.089	22.37	0.088	22.24
6	0.261	61.965	0.089	22.30	0.092	23.23
7	0.262	62.130	0.091	22.73	0.092	23.25
8	0.262	62.130	0.089	22.54	0.093	23.48
9	0.262	62.130	0.093	23.19	0.099	25.13
10	0.263	62.295	0.093	23.70	0.101	25.02
11	0.263	62.295	0.095	24.29	0.108	27.24
12	0.263	62.295	0.098	24.79	0.112	28.96
13	0.264	62.454	0.095	23.98	0.113	28.27
14	0.264	62.454	0.103	25.81	0.119	29.54
15	0.264	62.531	0.109	27.06	0.123	30.52
16	0.264	62.531	0.112	27.98	0.142	35.51
17	0.264	62.531	0.112	28.41	0.135	33.67
18	0.264	62.531	0.120	30.15	0.136	33.09
19	0.263	62.536	0.126	31.87	0.130	33.60
20	0.263	62.536	0.129	32.06	0.136	34.51

Table A.8: Experiment 1: NED - Next Month Average Closing Share Price

	Last Value		Huber Regressor		MLP Regressor	
LAG	**MAPE (%)**	**RMSE**	**MAPE (%)**	**RMSE**	**AVG MAPE (%)**	**RMSE**
1	0.325	100.217	0.304	93.167	0.313	96.193
2	0.325	100.217	**0.096**	**32.920**	**0.095**	**31.786**
3	0.325	100.217	0.096	32.932	0.096	32.769
4	0.326	100.214	0.097	33.012	0.096	32.969
5	0.326	100.489	0.098	33.254	0.097	33.045
6	0.326	100.489	0.097	33.302	0.098	33.604
7	0.328	100.760	0.097	33.334	0.098	34.710
8	0.328	100.760	0.101	34.434	0.100	33.681
9	0.328	100.760	0.097	33.803	0.101	34.017
10	0.328	101.001	0.102	35.191	0.104	35.947
11	0.328	101.001	0.103	35.236	0.109	38.663
12	0.328	101.001	0.102	35.214	0.112	38.549
13	0.329	101.179	0.103	35.534	0.116	38.908
14	0.329	101.179	0.103	35.856	0.120	42.321
15	0.329	101.289	0.110	36.985	0.122	41.738
16	0.328	101.289	0.114	38.048	0.126	41.311
17	0.328	101.289	0.118	39.455	0.127	45.252
18	0.328	101.289	0.123	41.379	0.131	43.893
19	0.328	101.435	0.124	40.638	0.136	45.920
20	0.328	101.435	0.126	41.725	0.140	45.912

Table A.9: Experiment 1: FNB - Next Month Average Closing Share Price

	Last Value		Huber Regressor		MLP Regressor	
LAG	**MAPE (%)**	**RMSE**	**MAPE (%)**	**RMSE**	**AVG MAPE (%)**	**RMSE**
1	0.301	24.028	0.303	24.169	0.248	24.138
2	0.301	24.028	0.111	9.233	**0.088**	**9.222**
3	0.301	24.028	0.114	9.372	0.088	9.231
4	0.301	24.016	0.112	9.208	0.088	9.248
5	0.301	24.082	0.113	9.301	0.089	9.226
6	0.301	24.082	0.112	9.284	0.090	9.456
7	0.302	24.141	0.116	9.491	0.093	9.291
8	0.302	24.141	0.114	9.411	0.095	9.435
9	0.302	24.141	**0.111**	**9.139**	0.097	9.762
10	0.303	24.204	0.115	9.481	0.101	9.995
11	0.303	24.204	0.118	9.825	0.106	10.401
12	0.303	24.204	0.117	9.588	0.111	10.980
13	0.305	24.271	0.121	9.694	0.111	10.367
14	0.305	24.271	0.122	9.923	0.118	11.095
15	0.305	24.335	0.129	10.336	0.125	12.153
16	0.306	24.335	0.128	10.464	0.130	11.569
17	0.306	24.335	0.132	10.921	0.133	11.816
18	0.306	24.335	0.138	11.182	0.135	12.396
19	0.307	24.403	0.137	11.366	0.135	12.364
20	0.307	24.403	0.141	11.539	0.142	13.178

Experiment 2: Detailed Results

The experiment 2 results for predicting the next day share price for **Standard Bank (SB)**, **Nedbank (NED)** and **First National Bank (FNB)** are presented in **Table A.10**, **Table A.11** and **Table A.12** respectively. The results include the Mean Absolute Percentage Error (MAPE) and the Root Mean Squared Error (RMSE) for both the Huber regressor and the MLP regressor from the Scikit-learn machine learning library, as well as the last value prediction (LV). The results show the MAPE and RMSE achieved for lag lengths 1 – 20.

Table A.10: Experiment 2: SB - Next Day Closing Share Price

	Last Value		Huber Regressor		MLP Regressor	
LAG	**MAPE(%)**	**RMSE**	**MAPE(%)**	**RMSE**	**AVG MAPE(%)**	**RMSE**
1	1.253	327.032	1.257	330.466	**1.240**	**325.395**
2	1.253	327.032	1.254	327.295	1.249	326.526
3	1.382	621.783	1.259	**326.789**	1.260	328.036
4	1.260	327.032	1.279	335.339	1.266	330.684
5	1.260	327.929	1.264	329.832	1.265	328.844
6	1.260	327.929	1.285	333.673	1.265	330.388
7	1.264	328.784	1.273	329.448	1.274	335.017
8	1.264	328.784	**1.251**	330.772	1.267	338.095
9	1.264	328.784	1.278	336.921	1.282	331.678
10	1.271	329.693	1.266	333.862	1.276	330.708
11	1.271	329.693	1.292	339.318	1.289	332.722
12	1.271	329.693	1.264	335.347	1.280	337.247
13	1.271	329.693	1.271	338.029	1.312	350.567
14	1.264	329.337	1.292	337.447	1.315	335.448
15	1.264	330.103	1.302	340.011	1.340	331.247
16	1.266	330.103	1.269	332.593	1.315	340.012
17	1.453	709.004	1.292	338.844	1.310	359.245
18	1.266	330.103	1.295	339.983	1.308	355.731
19	1.270	330.942	1.297	341.267	1.324	339.989
20	1.270	330.942	1.317	347.193	1.295	349.944

Table A.11: Experiment 2: NED - Next Day Closing Share Price

	Last Value		Huber Regressor		MLP Regressor	
LAG	MAPE(%)	RMSE	MAPE(%)	RMSE	AVG MAPE(%)	RMSE
1	1.327	472.057	1.338	473.098	**1.339**	**474.027**
2	1.327	472.057	**1.333**	**472.836**	1.351	476.093
3	1.327	472.057	1.350	476.039	1.361	479.074
4	1.333	472.045	1.356	481.697	1.367	481.576
5	1.333	473.340	1.353	481.199	1.372	483.045
6	1.333	473.340	1.365	484.118	1.372	481.785
7	1.339	474.634	1.365	481.799	1.387	487.297
8	1.339	474.634	1.365	484.637	1.372	483.652
9	1.339	474.634	1.365	486.432	1.373	478.119
10	1.343	475.892	1.366	486.001	1.369	483.257
11	1.343	475.892	1.373	490.773	1.384	498.590
12	1.343	475.892	1.386	492.078	1.387	491.788
13	1.340	476.282	1.363	489.247	1.403	500.044
14	1.340	476.282	1.384	495.857	1.398	489.261
15	1.340	477.525	1.397	498.778	1.412	500.774
16	1.344	477.525	1.395	496.420	1.423	496.732
17	1.344	477.525	1.416	503.360	1.420	503.073
18	1.344	477.525	1.411	495.264	1.424	506.739
19	1.350	478.852	1.431	505.365	1.427	501.600
20	1.350	478.852	1.408	499.628	1.413	499.796

Table A.12: Experiment 2: FNB - Next Day Closing Share Price

	Last Value		Huber Regressor		MLP Regressor	
LAG	**MAPE(%)**	**RMSE**	**MAPE(%)**	**RMSE**	**AVG MAPE(%)**	**RMSE**
1	1.559	132.881	1.575	134.179	**1.556**	**132.854**
2	1.559	132.881	1.579	**133.507**	1.582	133.052
3	1.559	132.881	1.613	135.775	1.592	133.777
4	1.565	132.863	**1.563**	134.168	1.608	134.898
5	1.565	133.227	1.572	135.454	1.611	135.823
6	1.565	133.227	1.600	136.502	1.621	136.422
7	1.572	133.593	1.604	136.878	1.628	138.036
8	1.572	133.593	1.590	136.967	1.643	137.601
9	1.572	133.593	1.573	136.956	1.637	136.322
10	1.578	133.950	1.609	136.555	1.675	137.571
11	1.578	133.950	1.593	137.271	1.671	138.441
12	1.578	133.950	1.618	136.618	1.670	137.426
13	1.585	134.313	1.654	140.737	1.671	137.692
14	1.585	134.313	1.648	141.216	1.697	139.829
15	1.585	134.642	1.673	144.193	1.684	137.219
16	1.589	134.642	1.698	145.554	1.763	141.633
17	1.589	134.642	1.708	143.169	1.748	143.449
18	1.589	134.642	1.666	142.843	1.767	141.939
19	1.585	134.740	1.691	143.628	1.787	141.939
20	1.585	134.740	1.689	145.532	1.761	142.552

The experiment 2 results for predicting the average next week share price for **Standard Bank (SB)**, **Nedbank (NED)** and **First National Bank (FNB)** are presented in **Table A.13**, **Table A.14** and **Table A.15** respectively. The results include the Mean Absolute Percentage Error (MAPE) and the Root Mean Squared Error (RMSE) for both the Huber Regressor and the MLP Regressor from the Scikit-learn machine learning library, as well as the last value prediction (LV). The results show the MAPE and RMSE achieved for lag lengths 1 – 20.

Table A.13: Experiment 2: SB - Next Week Average Closing Share Price

	Last Value		Huber Regressor		MLP Regressor	
LAG	**MAPE(%)**	**RMSE**	**MAPE(%)**	**RMSE**	**AVG MAPE(%)**	**RMSE**
1	0.563	142.541	0.557	139.978	0.571	120.52
2	0.563	142.541	**0.362**	**93.271**	**0.358**	**92.22**
3	0.563	142.541	0.366	96.415	0.371	93.46
4	0.562	142.240	0.373	94.612	0.383	108.30
5	0.562	142.630	0.398	98.502	0.386	98.72
6	0.562	142.630	0.387	99.540	0.391	97.28
7	0.560	142.620	0.406	103.631	0.399	105.38
8	0.560	142.620	0.405	99.174	0.416	104.55
9	0.560	142.620	0.437	108.936	0.422	107.69
10	0.561	142.960	0.434	110.111	0.447	108.27
11	0.561	142.960	0.490	121.656	0.444	108.27
12	0.561	143.010	0.484	123.960	0.466	119.18
13	0.562	143.292	0.495	129.530	0.478	121.14
14	0.562	143.292	0.553	144.319	0.479	130.75
15	0.562	143.619	0.560	149.267	0.497	128.16
16	0.563	143.619	0.562	142.106	0.517	123.38
17	0.563	143.619	0.559	146.476	0.524	132.88
18	0.563	143.619	0.570	147.523	0.526	140.35
19	0.565	143.985	0.541	140.691	0.524	137.13
20	0.565	143.985	0.590	157.466	0.537	147.15

Table A.14: Experiment 2: NED - Next Week Average Closing Share Price

	Last Value		Huber Regressor		MLP Regressor	
LAG	**MAPE(%)**	**RMSE**	**MAPE(%)**	**RMSE**	**AVG MAPE(%)**	**RMSE**
1	0.614	206.645	0.643	222.15	0.626	217.01
2	0.614	206.645	0.395	**132.49**	0.388	132.60
3	0.614	206.645	0.402	136.45	0.392	131.58
4	0.615	206.571	0.421	139.24	0.405	137.40
5	0.615	207.138	0.401	138.61	0.396	136.34
6	0.615	207.138	**0.392**	134.17	**0.384**	**129.11**
7	0.616	207.588	0.421	143.03	0.388	134.50
8	0.616	207.588	0.402	134.87	0.401	129.16
9	0.616	207.588	0.428	141.83	0.404	141.71
10	0.619	208.163	0.438	146.20	0.412	139.86
11	0.619	208.163	0.459	151.58	0.438	142.76
12	0.619	208.163	0.462	153.91	0.445	154.20
13	0.621	208.724	0.469	158.68	0.449	164.11
14	0.621	208.724	0.492	163.76	0.466	160.56
15	0.621	209.024	0.514	168.72	0.477	170.25
16	0.621	209.024	0.496	167.04	0.482	170.18
17	0.621	209.024	0.511	176.30	0.495	163.52
18	0.621	209.024	0.514	173.22	0.476	153.32
19	0.623	209.590	0.533	180.30	0.509	152.85
20	0.623	209.590	0.532	185.20	0.512	175.92

Table A.15: Experiment 2: FNB - Next Week Average Closing Share Price

	Last Value		**Huber Regressor**		**MLP Regressor**	
LAG	**MAPE(%)**	**RMSE**	**MAPE(%)**	**RMSE**	**AVG MAPE(%)**	**RMSE**
1	0.672	59.137	0.673	59.456	0.673	59.299
2	0.668	58.859	**0.425**	**36.044**	**0.461**	43.296
3	0.668	58.859	0.442	36.743	0.480	**42.664**
4	0.670	58.853	0.446	38.422	0.502	43.490
5	0.670	59.014	0.470	38.635	0.516	46.627
6	0.670	59.014	0.479	39.951	0.537	56.098
7	0.670	59.101	0.517	43.688	0.566	49.639
8	0.670	59.101	0.573	47.702	0.584	49.298
9	0.670	59.101	0.650	54.423	0.600	51.142
10	0.673	59.261	0.622	53.261	0.623	52.701
11	0.676	59.260	0.682	55.190	0.661	61.233
12	0.673	59.261	0.695	60.496	0.664	54.740
13	0.675	59.421	0.726	59.362	0.701	58.184
14	0.675	59.421	0.713	60.556	0.725	64.304
15	0.679	59.588	0.769	67.330	0.750	61.346
16	0.679	59.588	0.811	65.608	0.761	62.629
17	0.679	59.588	0.783	66.203	0.758	67.206
18	0.679	59.588	0.782	66.191	0.778	65.984
19	0.681	59.749	0.808	68.373	0.820	68.953
20	0.681	59.749	0.824	70.297	0.796	77.311

The experiment 2 results for predicting the average next month share price for **Standard Bank (SB)**, **Nedbank (NED)** and **First National Bank (FNB)** are presented in **Table A.16**, **Table A.17** and **Table A.18** respectively. The results include the Mean Absolute Percentage Error (MAPE) and the Root Mean Squared Error (RMSE) for both the Huber regressor and the MLP regressor from the Scikit-learn machine learning library, as well as the last value prediction (LV). The results show the MAPE and RMSE achieved for lag lengths 1 – 20.

Table A.16: Experiment 2: SB - Next Month Average Closing Share Price

	Last Value		Huber Regressor		MLP Regressor	
LAG	**MAPE(%)**	**RMSE**	**MAPE(%)**	**RMSE**	**AVG MAPE(%)**	**RMSE**
1	0.261	61.811	0.223	54.974	0.219	53.29
2	0.261	61.811	**0.089**	**22.171**	**0.088**	**21.84**
3	0.261	61.811	0.096	23.622	0.101	25.27
4	0.261	61.795	0.095	24.382	0.110	28.38
5	0.261	61.965	0.104	26.528	0.113	28.88
6	0.261	61.965	0.112	28.208	0.125	31.14
7	0.262	62.130	0.125	31.185	0.126	34.30
8	0.262	62.130	0.131	32.499	0.133	33.66
9	0.262	62.130	0.146	35.932	0.141	35.68
10	0.263	62.295	0.150	38.160	0.150	37.94
11	0.263	62.295	0.155	39.082	0.158	40.72
12	0.263	62.295	0.170	42.018	0.159	40.72
13	0.264	62.454	0.180	46.062	0.168	40.97
14	0.264	62.454	0.189	47.639	0.174	45.57
15	0.264	62.531	0.197	49.915	0.184	48.88
16	0.264	62.531	0.195	48.975	0.196	52.04
17	0.264	62.531	0.197	48.773	0.197	48.79
18	0.264	62.531	0.217	53.216	0.197	49.77
19	0.263	62.536	0.215	54.101	0.209	48.41
20	0.263	62.536	0.213	52.494	0.218	58.11

Table A.17: Experiment 2: NED - Next Month Average Closing Share Price

	Last Value		Huber Regressor		MLP Regressor	
LAG	**MAPE(%)**	**RMSE**	**MAPE(%)**	**RMSE**	**AVG MAPE(%)**	**RMSE**
1	0.325	100.217	0.289	99.40	0.266	90.29
2	0.325	100.217	**0.097**	**33.45**	**0.103**	**33.14**
3	0.325	100.217	0.100	34.54	0.105	35.31
4	0.326	100.214	0.100	34.74	0.109	37.88
5	0.326	100.489	0.108	37.31	0.114	37.63
6	0.326	100.489	0.119	39.58	0.120	39.66
7	0.328	100.760	0.125	41.10	0.126	46.30
8	0.328	100.760	0.140	46.38	0.130	46.62
9	0.328	100.760	0.136	46.18	0.134	46.05
10	0.328	101.001	0.155	51.04	0.138	45.64
11	0.328	101.001	0.154	51.65	0.150	49.37
12	0.328	101.001	0.154	52.49	0.154	53.21
13	0.329	101.179	0.164	55.63	0.158	58.37
14	0.329	101.179	0.169	58.13	0.166	64.81
15	0.329	101.289	0.163	55.28	0.166	57.71
16	0.328	101.289	0.167	56.98	0.169	57.24
17	0.328	101.289	0.166	56.84	0.173	57.59
18	0.328	101.289	0.177	61.52	0.181	63.89
19	0.328	101.435	0.180	59.98	0.182	59.43
20	0.328	101.435	0.192	63.98	0.196	72.39

Table A.18: Experiment 2: FNB - Next Month Average Closing Share Price

	Last Value		Huber Regressor		MLP Regressor	
LAG	**MAPE(%)**	**RMSE**	**MAPE(%)**	**RMSE**	**AVG MAPE(%)**	**RMSE**
1	0.301	24.028	0.268	22.770	0.256	20.627
2	0.301	24.028	**0.113**	**9.294**	**0.112**	**9.124**
3	0.301	24.028	0.121	10.123	0.147	15.560
4	0.301	24.016	0.124	10.161	0.157	15.786
5	0.301	24.082	0.140	11.325	0.167	12.148
6	0.301	24.082	0.142	11.622	0.171	14.341
7	0.302	24.141	0.148	12.591	0.171	12.580
8	0.302	24.141	0.158	13.068	0.182	15.885
9	0.302	24.141	0.169	13.961	0.188	14.799
10	0.303	24.204	0.179	14.889	0.199	19.474
11	0.303	24.204	0.170	14.325	0.212	18.520
12	0.303	24.204	0.187	15.776	0.220	19.194
13	0.305	24.271	0.202	16.912	0.223	17.408
14	0.305	24.271	0.220	18.182	0.222	21.275
15	0.305	24.335	0.222	18.654	0.236	20.201
16	0.306	24.335	0.221	18.305	0.250	22.504
17	0.306	24.335	0.253	20.555	0.258	22.232
18	0.306	24.335	0.253	21.056	0.263	22.562
19	0.307	24.403	0.260	22.284	0.279	24.432
20	0.307	24.403	0.272	22.630	0.284	24.805

Experiment 3: Detailed Results

The experiment 3 results for predicting the next day share price for **Standard Bank (SB)**, **Nedbank (NED)** and **First National Bank (FNB)** are presented in **Table A.19**, **Table A.20** and **Table A.21** respectively. The results include the Mean Absolute Percentage Error (MAPE) and the Root Mean Squared Error (RMSE) for both the Huber regressor and the MLP regressor from the Scikit-learn machine learning library, as well as the last value prediction (LV). The results show the MAPE and RMSE achieved for lag lengths 1 – 20.

Table A.19: Experiment 3: SB - Next Day Closing Share Price

	Last Value		Huber Regressor		MLP Regressor	
LAG	**MAPE(%)**	**RMSE**	**MAPE(%)**	**RMSE**	**AVG MAPE(%)**	**RMSE**
1	1.253	327.032	**1.247**	328.743	**1.240**	**326.525**
2	1.253	327.032	1.253	327.966	1.249	326.559
3	1.382	621.783	1.258	**326.018**	1.261	327.392
4	1.260	327.032	1.276	334.012	1.264	331.006
5	1.260	327.929	1.273	332.162	1.266	329.031
6	1.260	327.929	1.274	331.512	1.267	331.635
7	1.264	328.784	1.278	331.327	1.276	334.897
8	1.264	328.784	1.256	330.583	1.271	330.608
9	1.264	328.784	1.262	333.691	1.285	334.596
10	1.271	329.693	1.256	331.601	1.294	333.769
11	1.271	329.693	1.274	333.999	1.281	336.629
12	1.271	329.693	1.274	336.999	1.312	344.104
13	1.271	329.693	1.276	338.908	1.322	348.302
14	1.264	329.337	1.294	337.117	1.321	341.534
15	1.264	330.103	1.307	341.967	1.309	343.165
16	1.266	330.103	1.285	335.054	1.322	346.872
17	1.453	709.004	1.272	335.253	1.331	346.480
18	1.266	330.103	1.314	342.549	1.323	348.300
19	1.270	330.942	1.308	340.701	1.330	343.961
20	1.270	330.942	1.315	345.018	1.335	351.356

Table A.20: Experiment 3: NED - Next Day Closing Share Price

	Last Value		Huber Regressor		MLP Regressor	
LAG	**MAPE(%)**	**RMSE**	**MAPE(%)**	**RMSE**	**AVG MAPE(%)**	**RMSE**
1	1.327	472.06	1.349	476.14	**1.351**	**477.21**
2	1.327	472.06	**1.339**	**474.02**	1.359	477.74
3	1.327	472.06	1.348	475.94	1.368	479.09
4	1.333	472.05	1.352	481.60	1.373	481.98
5	1.333	473.34	1.351	480.86	1.375	482.44
6	1.333	473.34	1.361	482.20	1.376	481.97
7	1.339	474.63	1.372	486.39	1.391	488.15
8	1.339	474.63	1.366	485.68	1.374	485.00
9	1.339	474.63	1.372	487.40	1.374	483.42
10	1.343	475.89	1.351	484.74	1.381	481.42
11	1.343	475.89	1.366	488.05	1.387	487.14
12	1.343	475.89	1.393	498.28	1.390	484.92
13	1.340	476.28	1.382	491.16	1.391	495.57
14	1.340	476.28	1.377	493.05	1.413	499.22
15	1.340	477.53	1.379	494.14	1.410	489.57
16	1.344	477.53	1.398	495.18	1.415	487.02
17	1.344	477.53	1.402	498.26	1.402	496.97
18	1.344	477.53	1.415	498.29	1.405	503.12
19	1.350	478.85	1.403	496.92	1.420	495.48
20	1.350	478.85	1.411	497.18	1.410	499.93

Table A.21: Experiment 3: FNB - Next Day Closing Share Price

	Last Value		**Huber Regressor**		**MLP Regressor**	
LAG	**MAPE(%)**	**RMSE**	**MAPE(%)**	**RMSE**	**AVG MAPE(%)**	**RMSE**
1	1.559	132.881	1.563	134.214	**1.556**	**133.363**
2	1.559	132.881	1.578	133.816	1.585	133.521
3	1.559	132.881	1.613	135.450	1.587	134.470
4	1.565	132.863	1.565	134.222	1.613	139.421
5	1.565	133.227	**1.559**	135.565	1.627	137.349
6	1.565	133.227	1.568	134.998	1.622	135.389
7	1.572	133.593	1.559	**133.737**	1.608	135.796
8	1.572	133.593	1.593	137.081	1.644	139.332
9	1.572	133.593	1.595	137.733	1.631	140.347
10	1.578	133.950	1.610	136.556	1.666	139.309
11	1.578	133.950	1.631	138.934	1.670	139.657
12	1.578	133.950	1.570	136.559	1.664	138.687
13	1.585	134.313	1.637	140.017	1.711	144.871
14	1.585	134.313	1.662	139.706	1.705	150.085
15	1.585	134.642	1.609	139.661	1.711	147.848
16	1.589	134.642	1.685	144.744	1.737	142.738
17	1.589	134.642	1.649	141.151	1.736	146.008
18	1.589	134.642	1.676	142.252	1.763	147.254
19	1.585	134.740	1.687	144.119	1.788	153.800
20	1.585	134.740	1.729	145.557	1.732	150.802

The experiment 3 results for predicting the average next week share price for **Standard Bank (SB)**, **Nedbank (NED)** and **First National Bank (FNB)** are presented in **Table A.22**, **Table A.23** and **Table A.24** respectively. The results include the Mean Absolute Percentage Error (MAPE) and the Root Mean Squared Error (RMSE) for both the Huber regressor and the MLP regressor from the Scikit-learn machine learning library, as well as the last value prediction (LV). The results show the MAPE and RMSE achieved for lag lengths 1 – 20.

Table A.22: Experiment 3: SB - Next Week Average Closing Share Price

	Last Value		Huber Regressor		MLP Regressor	
LAG	MAPE(%)	RMSE	MAPE(%)	RMSE	AVG MAPE(%)	RMSE
1	0.563	142.541	0.561	141.84	0.574	142.57
2	0.563	142.541	0.369	94.64	**0.358**	**92.22**
3	0.563	142.541	**0.363**	**94.33**	0.369	92.70
4	0.562	142.240	0.372	94.96	0.376	96.01
5	0.562	142.630	0.391	97.61	0.389	98.58
6	0.562	142.630	0.396	98.44	0.389	100.35
7	0.560	142.620	0.408	103.93	0.403	103.83
8	0.560	142.620	0.408	103.58	0.412	107.99
9	0.560	142.620	0.427	112.64	0.439	112.77
10	0.561	142.960	0.472	118.52	0.446	110.23
11	0.561	142.960	0.469	119.42	0.445	127.24
12	0.561	143.010	0.493	125.63	0.463	119.44
13	0.562	143.292	0.523	133.31	0.477	121.24
14	0.562	143.292	0.509	129.44	0.493	114.85
15	0.562	143.619	0.529	138.56	0.475	117.89
16	0.563	143.619	0.540	136.11	0.511	131.57
17	0.563	143.619	0.571	145.33	0.528	128.44
18	0.563	143.619	0.558	140.98	0.541	139.62
19	0.565	143.985	0.575	149.61	0.522	146.06
20	0.565	143.985	0.589	151.95	0.536	123.89

Table A.23: Experiment 3: NED - Next Week Average Closing Share Price

	Last Value		Huber Regressor		MLP Regressor	
LAG	**MAPE(%)**	**RMSE**	**MAPE(%)**	**RMSE**	**AVG MAPE(%)**	**RMSE**
1	0.614	206.645	0.664	231.61	0.626	216.42
2	0.614	206.645	**0.394**	**133.22**	**0.388**	**131.59**
3	0.614	206.645	0.403	135.41	0.397	138.50
4	0.615	206.571	0.415	137.78	0.405	140.81
5	0.615	207.138	0.404	139.99	0.399	133.66
6	0.615	207.138	0.396	135.89	0.389	134.58
7	0.616	207.588	0.414	141.02	0.400	133.26
8	0.616	207.588	0.416	142.39	0.397	137.65
9	0.616	207.588	0.433	141.34	0.406	141.24
10	0.619	208.163	0.426	143.41	0.410	136.53
11	0.619	208.163	0.454	151.72	0.430	136.53
12	0.619	208.163	0.462	150.11	0.444	143.58
13	0.621	208.724	0.485	162.94	0.462	154.05
14	0.621	208.724	0.494	161.80	0.459	167.10
15	0.621	209.024	0.480	167.71	0.469	160.82
16	0.621	209.024	0.517	174.56	0.481	161.63
17	0.621	209.024	0.505	174.04	0.481	168.78
18	0.621	209.024	0.527	175.34	0.488	165.24
19	0.623	209.590	0.513	173.83	0.488	162.17
20	0.623	209.590	0.546	188.42	0.513	170.80

Table A.24: Experiment 3: FNB - Next Week Average Closing Share Price

	Last Value		Huber Regressor		MLP Regressor	
LAG	**MAPE(%)**	**RMSE**	**MAPE(%)**	**RMSE**	**AVG MAPE(%)**	**RMSE**
1	0.672	59.137	0.667	58.485	0.673	58.973
2	0.668	58.859	0.432	36.397	**0.461**	**38.204**
3	0.668	58.859	**0.425**	**35.885**	0.464	41.097
4	0.670	58.853	0.446	37.852	0.481	42.908
5	0.670	59.014	0.459	38.111	0.524	43.581
6	0.670	59.014	0.467	39.807	0.531	44.823
7	0.670	59.101	0.517	42.722	0.541	41.993
8	0.670	59.101	0.521	44.938	0.594	44.329
9	0.670	59.101	0.590	49.615	0.611	52.755
10	0.673	59.261	0.627	52.658	0.612	53.713
11	0.676	59.260	0.694	59.167	0.663	59.304
12	0.673	59.261	0.707	59.385	0.676	61.125
13	0.675	59.421	0.666	56.837	0.697	57.790
14	0.675	59.421	0.738	60.398	0.704	61.862
15	0.679	59.588	0.715	61.029	0.739	59.079
16	0.679	59.588	0.793	65.002	0.739	67.927
17	0.679	59.588	0.802	67.745	0.769	65.990
18	0.679	59.588	0.798	67.036	0.751	68.740
19	0.681	59.749	0.849	74.717	0.795	63.690
20	0.681	59.749	0.855	72.026	0.814	63.250

The experiment 3 results using five input variables for predicting the average next month share price for **Standard Bank**, **Nedbank** and **First National Bank** are presented in **Table A.25**, **Table A.26** and **Table A.27** respectively. The results include the Mean Absolute Percentage Error (MAPE) and the Root Mean Squared Error (RMSE) for both the Huber regressor and the MLP regressor from the Scikit-learn machine learning library, as well as the last value prediction (LV). The results show the MAPE and RMSE achieved for lag lengths 1 – 20.

Table A.25: Experiment 3: SB - Next Month Average Closing Share Price

	Last Value		Huber Regressor		MLP Regressor	
LAG	**MAPE(%)**	**RMSE**	**MAPE(%)**	**RMSE**	**AVG MAPE(%)**	**RMSE**
1	0.261	61.811	0.227	56.777	0.225	53.915
2	0.261	61.811	**0.091**	**22.596**	**0.090**	**24.896**
3	0.261	61.811	0.095	23.615	0.103	25.420
4	0.261	61.795	0.097	24.380	0.112	28.272
5	0.261	61.965	0.104	25.759	0.113	29.784
6	0.261	61.965	0.108	27.152	0.122	31.695
7	0.262	62.130	0.122	30.749	0.131	33.493
8	0.262	62.130	0.140	34.543	0.131	35.053
9	0.262	62.130	0.150	36.715	0.145	38.355
10	0.263	62.295	0.154	38.379	0.151	38.003
11	0.263	62.295	0.174	43.053	0.155	39.896
12	0.263	62.295	0.171	43.280	0.161	40.369
13	0.264	62.454	0.193	47.986	0.170	41.434
14	0.264	62.454	0.182	47.108	0.182	43.907
15	0.264	62.531	0.186	47.863	0.178	42.968
16	0.264	62.531	0.196	49.090	0.195	47.567
17	0.264	62.531	0.192	47.443	0.198	50.325
18	0.264	62.531	0.204	50.890	0.200	47.432
19	0.263	62.536	0.218	53.518	0.205	52.233
20	0.263	62.536	0.214	53.165	0.206	51.859

Table A.26: Experiment 3: NED - Next Month Average Closing Share Price

	Last Value		Huber Regressor		MLP Regressor	
LAG	**MAPE(%)**	**RMSE**	**MAPE(%)**	**RMSE**	**AVG MAPE(%)**	**RMSE**
1	0.325	100.217	0.292	100.31	0.271	90.72
2	0.325	100.217	0.097	33.41	**0.095**	**32.70**
3	0.325	100.217	**0.096**	**33.04**	0.104	33.78
4	0.326	100.214	0.101	35.17	0.108	36.12
5	0.326	100.489	0.107	37.00	0.117	40.33
6	0.326	100.489	0.118	39.77	0.126	41.93
7	0.328	100.760	0.129	42.72	0.128	42.56
8	0.328	100.760	0.132	46.44	0.127	43.69
9	0.328	100.760	0.140	50.18	0.137	47.61
10	0.328	101.001	0.153	50.18	0.142	52.97
11	0.328	101.001	0.154	51.40	0.150	47.93
12	0.328	101.001	0.146	49.35	0.152	48.96
13	0.329	101.179	0.161	54.59	0.159	57.68
14	0.329	101.179	0.167	56.91	0.164	50.95
15	0.329	101.289	0.160	54.53	0.167	56.41
16	0.328	101.289	0.177	60.22	0.171	59.07
17	0.328	101.289	0.180	61.79	0.174	56.59
18	0.328	101.289	0.179	61.51	0.180	61.76
19	0.328	101.435	0.179	59.49	0.181	61.77
20	0.328	101.435	0.194	64.81	0.190	64.19

Table A.27: Experiment 3: FNB - Next Month Average Closing Share Price

	Last Value		Huber Regressor		MLP Regressor	
LAG	**MAPE(%)**	**RMSE**	**MAPE(%)**	**RMSE**	**AVG MAPE(%)**	**RMSE**
1	0.301	24.028	0.288	24.269	0.259	21.066
2	0.301	24.028	**0.115**	**9.432**	0.140	13.041
3	0.301	24.028	0.115	9.679	**0.114**	**11.857**
4	0.301	24.016	0.126	10.446	0.148	12.089
5	0.301	24.082	0.149	12.555	0.169	17.392
6	0.301	24.082	0.142	11.857	0.169	13.968
7	0.302	24.141	0.150	12.462	0.178	16.872
8	0.302	24.141	0.167	13.886	0.198	17.502
9	0.302	24.141	0.164	13.722	0.194	17.819
10	0.303	24.204	0.181	14.771	0.207	16.839
11	0.303	24.204	0.187	15.477	0.210	18.107
12	0.303	24.204	0.192	16.051	0.201	18.896
13	0.305	24.271	0.207	17.374	0.212	17.074
14	0.305	24.271	0.209	17.393	0.236	21.849
15	0.305	24.335	0.235	19.751	0.238	21.529
16	0.306	24.335	0.233	19.749	0.246	24.506
17	0.306	24.335	0.256	21.587	0.263	23.596
18	0.306	24.335	0.250	21.231	0.267	20.416
19	0.307	24.403	0.282	22.882	0.278	23.596
20	0.307	24.403	0.295	25.110	0.275	22.686