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Volatility Forecasting Using Asymmetric EGARCH Model with Neural Network Models and Fuzzy Inference System: The Case of Nairobi Securities Exchange

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136946

A Thesis Submitted in Total Fulfillment of the Requirements for the Degree of Master of Science in Mathematical Finance and Risk Analytics at Strathmore University.

Institute of Mathematical Sciences

Strathmore University

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Abstract

This research undertook a comparative analysis of volatility prediction models, with a particular emphasis on asymmetric EGARCH model with Artificial Neural Networks and Fuzzy Inference system. The rationale was to produce more accurate volatility forecasts for the Nairobi Security Exchange (NSE). To this end, we combined the EGARCH model with artificial neural networks in two distinct ways. Firstly, we modeled the return series of the stock index with an asymmetric EGARCH model using the Augmented Dickey Fuller (ADF) test and Jacque-Bera test. In the next phase, we estimated an ANN model and then developed two hybrid models, the Fuzzy-EGARCH-ANN and the EGARCH-ANN models. The forecasts generated by each of the four models (asymmetric EGARCH model, ANN model, and the two hybrid models) were compared in terms of their proximity to the realized volatility. The research utilized daily time series data from the NSE-all Share Index, spanning from April 1st, 2011 to July 31st, 20220. Out of these, 940 observations (approximately 90% of the total observations) were used for estimations (training set), and 100 observations (approximately 10% of the total observations) were used for out-of-sample forecasts (test set). The parameters for the asymmetric EGARCH model were determined through maximum likelihood estimation (MLE). The asymmetric EGARCH model was evaluated using AIC and BIC to ascertain the best-fitting model. The RMSE and MAE measures were employed to assess the forecasting abilities of the models. The results from the RMSE and MAE indicated that the artificial neural networks surpassed the asymmetric EGARCH models.

Key words: NSE, MLE, EGARCH-ANN.

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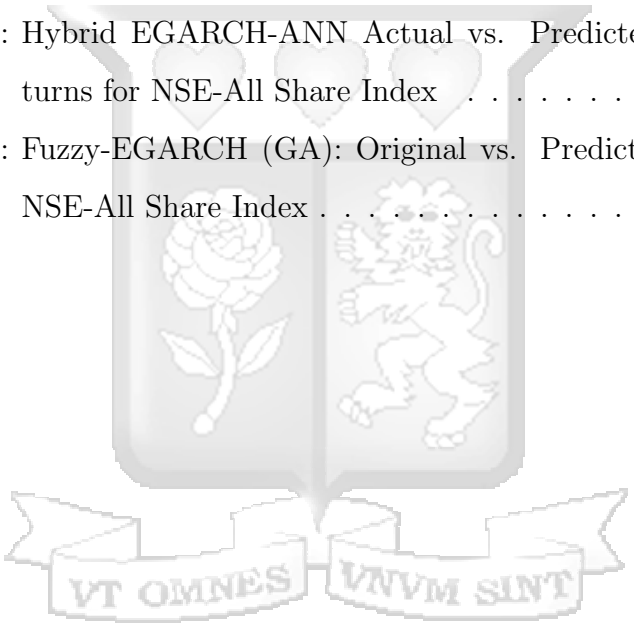
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VT OMNES VNVM SINT

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Dedication

This is for my mother, for trusting and believing in me and being a pillar of strength throughout my education. I similarly dedicate this to my late mother, who planted the passion for education at a much younger age. Thank you, mum. Finally, I would like to thank my brothers and sisters for always believing in my skills and ability and their encouragement that has been a pillar for my success. May the good Lord bless you all.



List of Abbreviations

ADF	Augmented Dickey Fuller
ANN	Artificial Neural Networks
ARMA	Autoregressive Moving Average
ASEA	African Securities Exchanges Association
EASEA	East African Securities Exchanges Association
EGARCH	Exponential Autoregressive Conditional Heteroscedasticity Model
EMH	Efficient Market Hypothesis
MLE	Maximum Likelihood Estimation
NSE	Nairobi Securities Exchange
NYSE	New York Stock Exchange
TSE	Tokyo Stock Exchange
TSX	Toronto Stock Exchange



Chapter 1

Introduction

1.1 Background to the study

A study by (Akgiray, 2019) notes that modelling and forecasting the volatility of the stock market has been a significant area of focus for both researchers and participants. This is due to its critical role in various financial outcomes, ranging from the pricing of assets and options to the evaluation of risk. Volatility, in the context of financial indices, can be viewed as a risk indicator, or alternatively, as the extent to which a stock's price varies from its mean value. Forecasting volatilities and asset returns is vital for making informed investment choices in financial markets. Market players use various techniques to forecast the volatility of financial metrics (Alagidede and Panagiotidis, 2010).

(Dash and Dash, 2016) categorize these techniques into three unique groups: the classical method, the neural network, and the fuzzy inference method. One of the classical techniques is the application of time series modelling to financial data with time-varying conditional variance, which has ideally received much attention from researchers such as (Esman Nyamongo and Misati, 2010) and (Fleming et al., 2013). (Glosten et al., 2013) was the pioneer who introduced the Autoregressive Conditional heteroskedasticity (ARCH) model, while (Hansen and Lunde, 2005) generalized these models and provided the exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model. (Hynd-

man and Athanasopoulos, 2018) adds that these models have found widespread applications in the field of financial markets since they incorporate heteroscedastic errors. These errors have been used to predict the high volatility in the financial data (Lee et al., 2001). Although these classical methods, also known as structural models, have shown some success in predicting a range of variables, their ability to accurately predict financial data leaves much to be desired. This is largely because they rely heavily on information already derived from historical events. Considering these intricate relationships and non-linear patterns in stock markets, it is possible that these time-series models might fall short of encapsulating these attributes (Dash and Dash, 2016). For this reason, non-linear and more flexible models, such as neural networks and fuzzy inference systems, can produce better results in modeling and forecasting than linear models (Glosten et al., 2013). Additionally, (Kristjanpoller and Minutolo, 2016) proposes a combination of classic method and neural networks (hybrid models) methods such as ANN model, the Fuzzy-EGARCH and EGARCH-ANN hybrid models.

1.1.1 Volatility Forecasting

Over recent years, there has been an increased focus from scholars and industry professionals alike on the measurement and prediction of stock market volatility. Market volatility seeks to make sense of financial market uncertainties by observing fluctuations in security values. This is typically quantified using the standard deviation, which assesses the dispersion around a mean value. A larger standard deviation indicates higher volatility, and vice versa. The forecasting of volatility is of paramount

importance in risk management, asset valuation, and investment management for investors and participants in the financial market. Consequently, this field has seen a surge in research aimed at discovering effective models for volatility prediction.

EGARCH models are frequently utilized in academic studies for volatility forecasting due to their ability to account for fluctuations in volatility over time. However, the conventional EGARCH model has its limitations, particularly in accurately predicting distributions, which could be attributed to the potentially non-linear relationship between present and past variances. To address these shortcomings and capture the volatility asymmetries that the standard EGARCH model could not, asymmetric EGARCH models have been introduced.

EGARCH models operate on certain foundational assumptions, such as the normality of error distributions. In contrast, artificial neural networks (ANNs) and fuzzy inference systems have been designed to establish and predict the relationships between variables without heavily depending on these assumptions. ANNs possess the ability to learn and model complex and non-linear relationships, which is a significant advantage. This research will concentrate on asymmetric EGARCH models, fuzzy inference systems, and ANNs. The objective is to compare the predictive capabilities of asymmetric EGARCH models, ANNs, and fuzzy inference systems and determine which model is more effective at forecasting volatility.

1.1.2 The Nairobi Securities Exchange (NSE)

The Nairobi Securities Exchange, previously referred to as the Nairobi Stock Exchange, was established in 1954 as a voluntary organization of stockbrokers under the Societies Act. Its primary responsibilities in-

cluded the growth of the securities market and the regulation of trading operations. It offers a world class trading facility for local and international investors looking to gain exposure to Kenya's and Africa's economic growth. The NSE market is characterized by three primary indices, namely:

- The NSE 20-Share Index, which is designed to represent the average prices of the leading 20 companies listed on the exchange,
- The NSE 25-Share Index, which is designed to represent the performance of Kenyan companies listed in the NSE,
- NSE All Share Index designed to represent all companies listed in the NSE. This is the overall indicator of the markets performance.

The Nairobi Securities Exchange (NSE) is significantly contributing to Kenya's economic expansion by promoting investment and savings, and by assisting both domestic and global firms in obtaining affordable capital. The NSE functions under the regulatory oversight of Kenya's Capital Markets Authority. It holds full membership in the World Federation of Exchanges, and is a founding member of both the African Securities Exchanges Association (ASEA) and the East African Securities Exchanges Association (EASEA). Additionally, the NSE is part of the Association of Futures Markets and collaborates with the Sustainable Stock Exchanges initiative led by the United Nations.

1.2 Problem Statement

Forecasting market volatility is a vital task in financial markets, playing a significant role in risk management, pricing, and other areas. It is

therefore essential to pinpoint a model that can effectively and accurately forecast these market fluctuations. The body of research specific to the Kenyan market is somewhat sparse. While studies have been conducted to explore the existence of stylized facts in the Kenyan market, there's a lack of substantial evidence regarding the models used for volatility forecasting. For example, it's unclear whether the asymmetric EGARCH model outperforms the symmetric model or how neural network techniques fare in forecasting stock market volatility. This study aims to bridge the gap in literature concerning asymmetric EGARCH models and neural network techniques and to determine which model can most accurately predict volatility.

1.3 Objectives of the Study

The main objective of this study is to forecast stock market volatility at the Nairobi Securities Exchange (NSE).
The supporting objectives are:

1. Perform a comparative analysis between the best-fit asymmetric EGARCH model, the Artificial Neural networks, and Fuzzy Inference system;

2. Investigate the best-fit asymmetric EGARCH model.

1.4 Value of the Study

The study will:

- Demonstrate which model is more accurate at predicting stock market volatility, and this will be beneficial to financial market players.
- Contribute to the limited literature available for forecasting stock volatility in emerging and developing markets

1.5 Organization of the study

Chapter 1 provides a background to the study, discusses volatility forecasting, and provides an overview of the Nairobi Securities Exchange. It spells out the problem statement and outlines the research objectives. Chapter 2 reviews the existing literature related to asymmetric EGARCH models, artificial neural networks, and fuzzy inference systems. It also provides a model approach to understanding the effects of volatility clustering in the financial data series. Chapter 3 outlines the research methodology adopted in carrying out the study. Chapter 4 scopes the data analysis and discussions conducted to complement the proposal and addresses the study's objectives. Chapter 5 concludes the research findings and outlines the recommendations arrived at due to the research study. It also highlights areas of further research that the researcher recommends.

Chapter 2

Literature Review

2.1 Introduction

2.1.1 Volatility Forecasting

The concept of the efficient security market is often linked to (Fama, 1965), who proposed that a market is considered "efficient" if the prices of every security fully reflect all available public and private information and hence are equal to its true investment value. This implies that subsequent price changes are independent and identically distributed. (Dash and Dash, 2016) cited in (Fama, 1965) that the idea of market efficiency is tied to the random walk theory, which suggests that new information randomly influences the current stock price, which in turn affects future stock prices.

Econometric models, as discussed by (Zhang and Sanderson, 2009), have previously been applied in the examination of the efficient market hypothesis (EMH), which claims that market prices already incorporate the relevant information. The market price mechanism is such that the active trading patterns of a small number of informed analysts can lead to accurate market prices. Uninformed (or'cost-conscious', since actively trading incurs potentially unnecessary costs), investors can then take a free ride, in the knowledge that the research of others is keeping the market efficient (Zhang et al., 2018). Fundamental analysis uses information

concerning the issuer of the security, such as asset turnover, profitability, liquidity, level of gearing, and general economic and investment conditions such as real interest rates and inflation, in order to determine the 'true' or 'fundamental' value of a security and hence whether or not it is cheap or expensive. However, the dependency of share prices tested by some of these models contradicts the efficient market hypothesis (Mandelbrot and Mandelbrot, 2017). Different stock exchanges have different levels of required disclosure of information. Hence, it would be reasonable to expect different markets to have different levels of efficiency. For example, the New York Stock Exchange (NYSE), which requires a high level of disclosure, should be more efficient than a market with limited disclosure requirements (Hyndman and Athanasopoulos, 2018).

(Fama, 1965) highlighted that certain recurring patterns, known as stylized facts, are evident in financial time series. These patterns are crucial for model estimation and forecasting. Stylized facts, as defined by (Alagidede and Panagiotidis, 2010), are empirical observations so consistently found across markets that they are widely accepted as truth in economics. In order to produce reliable future volatility forecasts, it's essential to consider these stylized facts. These include phenomena such as volatility clustering, fat tails, leverage effects, long memory, skewness, and leptokurtic distributions.

2.2 Theoretical Review of Literature

2.2.1 EGARCH Family Models

The Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model, introduced by (Nelson, 2011), was designed to consider the impact of price volatility on conditional variance, a phenomenon known as leverage effects. (Maqsood et al., 2017) emphasized the significance of constructing models that account for leverage effects in the second-order moments over time, permitting the conditional variance to evolve based on historical errors.

(Mekoya, 2013) observed that the EGARCH model, which accounts for long-term memory, exhibited a decreasing lag structure in the conditional variance. To address this, he adapted the EGARCH-MIDAS (mixed data sampling) into the EGARCH model, which introduces a more adaptable lag structure. The task of predicting market volatility has garnered considerable research interest, leading to numerous applications of the GARCH models.

(Monfared and Enke, 2014) provided fresh insights into the time-series dynamics of stock prices by analyzing US stock data, demonstrating the superiority of forecasts generated through the EGARCH model. In a study by (Wagala et al., 2012) examining volatility forecasting in the Tokyo exchange market, three models were assessed, including the Standard EGARCH and EGARCH-MIDAS models. Contrary to (Monfared and Enke, 2014)'s findings, (Wagala et al., 2012)'s study determined that the Standard EGARCH and EGARCH-MIDAS models exhibited greater accuracy than the other GARCH models. Similarly, (Wei, 2013) conducted a comparable investigation within the Singapore stock market, reaching the same conclusion that the EGARCH models outperformed

the other GARCH models.

(Youssef and Rowe, 2022) conducted a study to forecast the volatility of the S&P 500 stock index utilizing EGARCH models. Their findings indicated that the asymmetric EGARCH models exhibited superior performance compared to the symmetric GARCH models. This conclusion was further supported by (Zhang and Sanderson, 2009), (Wei, 2013), and (Wagala et al., 2012), who also observed that asymmetric EGARCH models outperformed symmetric GARCH models in estimating stock market volatility. Subsequent studies have consistently corroborated these findings, demonstrating the superior performance of asymmetric EGARCH models over traditional GARCH models.

(Whitelaw, 2004) highlights the skewed distribution of stock market returns, which poses a challenge for the linear EGARCH models. Their study, which focused on forecasting volatility in emerging stock markets, compared linear and non-linear EGARCH models. Despite the skewed distribution of stock market returns, the study concluded that the linear model outperformed the non-linear model in emerging markets.

(Whitelaw, 2004) and (Schwert, 2008) conducted a study on modeling stock returns in Africa's emerging markets. They examined and refuted the random walk hypothesis. Utilizing the standard EGARCH and EGARCH-MIDAS models to model conditional variance, they identified volatility clustering, autocorrelation, and leverage effects in African stock index returns(Gatuhi et al., 2015). Moreover, their findings suggested insufficient evidence to reject weak form efficiency in these markets.

(Godfrey and Ismail, 2020) examined EGARCH-MIDAS modeling in monthly foreign exchange and share prices for specific companies in Kenya, observing that EGARCH-MIDAS (1,1) effectively captures volatility clustering and can be adapted to accommodate other stylized facts.

(Olweny, 2011) corroborated these findings in her research, concluding that EGARCH-MIDAS (1,1) adequately encapsulates the stylized characteristics of financial time series. (Schwert, 2008) investigated volatility in the emerging equity markets of Kenya and Nigeria using the EGARCH model. They observed asymmetric volatility akin to that in the U.S. and other developed countries in the Nigerian stock market. However, in the Kenyan market, they found positive asymmetric volatility, indicating that positive shocks had a greater impact on volatility compared to negative shocks of the same magnitude. Given that the effects of such a downward volatility effect are both systematic and non-diversifiable, it resulted in numerous hitches around predicting market volatility (Olweny, 2011).

The study conducted by (Dash and Dash, 2016) and (Zhang et al., 2008) used the jump-diffusion process to redefine the alterations in stock prices, with the latter research indicating that negative and positive innovations have significant impacts on market volatility. (Lee et al., 2001) from the American Risk and Insurance Association published a paper on volatility forecasting using a dataset of around 1000 stock price data given in a volatility forecasting challenge. They found that stock price data exhibits serial correlation and an infinitely increasing variance that the Black (Esman Nyamongo and Misati, 2010) and GBM (Refenes et al., 2004) failed to capture. Several researchers have addressed the above problems. (Wei, 2013), and (Hajizadeh et al., 2012) presented a generalized artificial neural network (ANN) model with the two hybrid models, the fuzzy-EGARCH and EGARCH-ANN hybrid models, which challenged the setbacks raised against the standard EGARCH and EGARCH-MIDAS models.

2.2.2 A case for Artificial Neural Networks (ANN)

The concept of artificial intelligence, a term first introduced by (Donaldson and Kamstra, 2007), revolves around the idea of developing machines capable of exhibiting human-like intelligence. This broad field of study encompasses various sub-disciplines, including but not limited to machine learning, neural networks, robotics, fuzzy logic, expert systems, and natural language processing.

(Hornik, 2003) suggested in their publication that machine learning can be perceived as an extremely effective method of data compression. It is designed to offer predictors in intricate scenarios where the relationships between the input and output variables are non-linear and the input space is frequently high-dimensional. They further elaborated that machine learning aims to strike a balance between data filtering and the objective of making precise and resilient decisions, which are often discrete and function categorically based on input data. They pointed out that this is distinct from maximum likelihood estimators (MLE) utilized in conventional statistical models. These estimators presume that the data was produced by the model and usually struggle with overfitting, particularly when dealing with high-dimensional datasets.

This research will concentrate on neural networks, a collection of algorithms designed to identify fundamental relationships within large sets of data by mimicking the way the human brain functions. A neuron, in this context, is a mathematical function that collects and sorts information based on a specific architecture and employs a variety of methods to complete a task. Applications of this technology span various fields, including market research, risk assessment, and stock market forecasting, among others (Hyndman and Athanasopoulos, 2018).

Neural networks hold significant value in forecasting due to their ability

to carry out nonlinear modeling without the need for prior knowledge about the relationship between input and output variables (Kristjanpoller and Minutolo, 2016). Their capacity to generalize makes them a versatile and adaptable tool for forecasting. Furthermore, numerous scholars have integrated neural networks with GARCH models in their studies on volatility forecasting (Donaldson and Kamstra, 2007).

In a study conducted by (Refenes et al., 2004), the effectiveness of a semi-parametric EGARCH model was examined to understand its capability in identifying nonlinear associations. The focus of this research was to assess the model's predictive power for stock return volatility in major financial markets, including the London Stock Exchange (LSE), New York Stock Exchange (NYSE), Tokyo Stock Exchange (TSE), and Toronto Stock Exchange (TSX). The findings from this study suggested that the Artificial Neural Network (ANN) model outperformed all other models in terms of forecasting accuracy.

(Taylor, 2009) and (Vortelinos, 2017) conducted a comprehensive review of various forecasting techniques used in the stock market, with an emphasis on soft computing methods. Their review encompassed 100 distinct articles that utilized neural networks and neuro-fuzzy models for forecasting purposes. The review highlighted the suitability of these models for predicting stock market trends and their superior performance compared to traditional models. In a separate study, (Zhang et al., 2008) and (White, 2008) conducted an analysis of neural networks for forecasting financial time series, comparing their performance with conventional EGARCH models. Their research spanned across North American, European, and Brazilian stock markets. The conclusion drawn from their research was that neural networks demonstrated superior performance compared to EGARCH models.

(Santamaría-Bonfil et al., 2015) conducted research on the application of neural networks for forecasting realized volatility. The conclusion from (Su, 2021)'s research was that neural networks surpassed the performance of traditional econometric methods. (Zhang et al., 2018) also carried out a comparative study between the EGARCH models and neural networks. Their findings indicated that neural networks had better performance than the GARCH model.

(Alberg et al., 2018) conducted a study specifically on the South African stock market. The findings from (Alberg et al., 2018)'s research suggested that neural networks demonstrated superior forecasting capabilities compared to traditional forecasting models.

2.2.3 The Hybrid Models

(Dash and Dash, 2016) presented a novel approach that combines a neural network with a semi-nonparametric non-linear EGARCH model. This approach was designed to assess the influence of volatility on stock returns. They tested its forecasting capabilities for stock return volatility in several major markets, including Toronto, New York, Tokyo, and London. The results from their out-of-sample forecasts indicated that their Artificial Neural Network (ANN) model outperformed the GARCH, EGARCH, and GJR-GARCH models.

(Esman Nyamongo and Misati, 2010) demonstrated an enhancement in prediction using a neural network model in a linear regression setup for forecasting stock prices. Their findings were largely consistent, even in out-of-sample tests. In a separate study, (Hung, 2011) developed a semi-non-parametric model using a neural network structure to estimate con-

ditional density. His recurrent mixture density network was inspired by the fundamental concepts of EGARCH-type models, but it also had the capability to model any continuous conditional density, accommodating higher-order time-dependent moments. When they applied their model to the returns of the FTSE100, the results indicated that their out-of-sample forecast marginally surpassed those of the EGARCH models.

(Kristjanpoller and Minutolo, 2016) introduced hybrid models that combined time-series and neural network models for forecasting stock price index volatility in two aspects: direction and deviation. This model was applied to the South Korean stock market, and the results underscored the effectiveness of combining neural network forecasting with time-series models. (Hung, 2011), on the other hand, employed fuzzy-EGARCH models and augmented them with neural networks to study the volatility of daily returns in the Istanbul stock market. Their hybrid models demonstrated enhanced forecasting capabilities.

(Donaldson and Kamstra, 2007) sought to enhance the forecasting capabilities of GARCH-type models in predicting return volatility. They introduced two hybrid models that integrated neural networks and the EGARCH model. Their findings indicated that the second hybrid model yielded superior volatility forecasts in terms of alignment with actual volatility. A separate study conducted by (Dash and Dash, 2016) applied a hybrid model that combined neural networks and GARCH to predict the volatility of three Latin American stock markets: Brazil, Chile, and Mexico. Their research affirmed that the ANN models could enhance the forecasting performance of the GARCH-type models. Furthermore, they found that the results were consistent across various ANN configurations and volatility measures.

In a study conducted in 2009, (Hung, 2009) evaluated the precision of

volatility predictions by juxtaposing two hybrid models. These models were a fusion of artificial neural networks (ANN) and asymmetric EGARCH models, specifically EGARCH-MIDAS and GJR-GARCH. The outcome of their research suggested that the hybrid model of EGARCH and ANN surpassed other models in predicting the volatility of the energy market in China. In a similar vein, (Esman Nyamongo and Misati, 2010) employed a hybrid model of ANN and GARCH, integrating financial variables like exchange rates and stock market indices. Their objective was to enhance forecasts of oil price volatility. The results of their research indicated that the hybrid model augmented the accuracy of volatility forecasting by 30%, as gauged by HMSE. This demonstrates the potential of such hybrid models in financial forecasting.

(Hajizadeh et al., 2012) conducted a comparative study on the predictive capabilities of two GARCH models (GARCH and EGARCH), two hybrid models (GARCH-ANN and EGARCH-ANN), and a neural network that incorporated a set of technical indicators. The study found that the neural network, with its straightforward approach, was more accurate in predicting the volatility of two exchange rates (U.S./Canada and U.S./Euro) when compared to the other models, as measured by MAE, MSE, and Theil's inequality coefficient.

(Donaldson and Kamstra, 2007) analyzed the volatility of crude oil in India. Their findings favored hybrid models over GARCH models. They attempted to forecast oil volatility by comparing various GARCH-type models with hybrid GARCH-ANN models. According to the MSE index, the EGARCH-ANN model demonstrated the best predictive ability among all the models. However, adding an exchange rate (Indian Rupee/Saudi Arabia Riyal) as an input to the hybrid model did not result in any further improvements.

(El-Mihoub et al., 2006) used data from 2000 to 2017 for the S&P 500 to construct a hybrid model for predicting its volatility. This model was based on machine learning techniques and was compared with two GARCH-type ANN models, (Rouah, 2013)'s model, and a neural network. The findings, based on the RMSE index, indicated that their model was superior in all five sub-periods into which the sample was divided. This highlights the potential of machine learning techniques in financial forecasting.

2.3 Conclusion

The literature reviewed highlighted the milestones made in developing tools for forecasting stock market volatility. Nevertheless, it appeared that each of these prior studies failed to assess the forecasting abilities of the models. We, therefore, aim to fill this gap within the exact literature by considering these factors. More specifically, we estimate an ANN model and then developed two hybrid models, the fuzzy-EGARCH and EGARCH-ANN hybrid models. We then compare the forecasts generated by each of the four models (the asymmetric EGARCH model, the ANN model, and the two hybrid models).

To improve the model fit, we follow the research by (Rouah, 2013) and (Zhang et al., 2018) and consider that the volatility effects are stochastic in nature with time-varying conditional parameters.

Chapter 3

Methodology

In this chapter, we present the computational models used in this research. We also compare our modelling method with the asymmetric EGARCH models, specifically the standard EGARCH and EGARCH-MIDAS approaches, and the results of the hybrid models obtained with our simulation methods.

3.1 Data Collection Methods

The research utilized daily time series data from the NSE-All Share Index, designed to represent all companies, spanning from April 1st, 2011, to July 31st, 2020. Out of these, 940 observations (approximately 90% of the total observations) were used for estimations (training set), and 100 observations (approximately 10% of the total observations) were used for out-of-sample forecasts (test set).

3.2 Data Analysis

In time series analysis, a fundamental premise is that the series being studied is stationary. To verify this, the Augmented Dickey Fuller (ADF) test statistics will be utilized. Before this, a preliminary test was conducted on the data to check for normality. This was done using

the Jacque-Bera test, in line with the efficient market hypothesis, which posits that returns should follow a normal distribution with zero skewness and a kurtosis of three. This ensures the robustness of the subsequent analysis.

This research will concentrate on two analytical models: the asymmetrical EGARCH model and two hybrid models, the fuzzy-EGARCH-ANN and EGARCH-ANN models. The forecasts generated by each of the four models (asymmetric EGARCH model, ANN model, and the two hybrid models) were compared in terms of their proximity to the realized volatility.

3.2.1 Augmented Dickey Fuller (ADF)

The Dickey Fuller examination is a type of unit root test that scrutinizes the coefficient of the initial lag of Y_t, symbolized by ϕ. The corresponding formula was represented as follows:

$$Y_t = C + \alpha_t + \phi Y_{t-1} + \theta_1 \Delta Y_{t-1} + \vartheta_t \tag{3.1}$$

The Augmented Dickey-Fuller test enhances the original Dickey-Fuller test by incorporating higher-order autoregressive processes in the model.

$$Y_t = C + \alpha_t + \phi Y_{t-1} + \theta_1 \Delta Y_{t-1} + \theta_2 \Delta Y_{t-2} + \theta_{p-1} \Delta Y_{t-p+1} + \vartheta_t \tag{3.2}$$

Where C is a constant, α_t is the coefficient on a time trend, and p is the lag order of the autoregressive process. This test is designed to evaluate the base assumption of a unit root existing within a sample of stock price data, with the null hypothesis Φ=0 and the alternative hypothesis Φ <0. A unit root is a feature of time series data that results in non-

stationary condition. The test statistic is calculated, and if it falls below the critical value within a certain confidence level, the null hypothesis is then rejected.

3.2.2 Jacque-Bera Test

The Jarque-Bera test is a statistical procedure employed to verify if a dataset follows a normal distribution. It's a type of goodness-of-fit test that checks if the data's skewness and kurtosis align with those of a normal distribution. The test statistic of the Jarque-Bera test is utilized in this process.

$$JB = \frac{n}{6}\left(S_t^2 + \frac{1}{4}(k-3)^2\right) \tag{3.3}$$

where n is the total observations, K is the kurtosis of the sample and S is the sample skewness.

The test is designed to evaluate the null hypothesis, which posits that the data's skewness is zero, akin to a kurtosis of 3, indicating that the data's kurtosis is also zero. Any divergence from this escalates the Jacque-Bera metric, leading to the null hypothesis being dismissed and the inference that the error terms do not follow a normal distribution.

3.3 Model Specification

3.3.1 Asymmetric EGARCH Model

The EGARCH framework reduces a large set of macroeconomic time series to a small number of common components, which are then used

to forecast stock market volatility (Akgiray, 2019). We followed (Nelson, 2011) and allow the natural logarithm of the condition variance to vary over time as a function of the lagged error terms rather than lagged squared errors. EGARCH(p,q) was then specified as:

$$ln\delta_t^2 = C + \sum_{j=1}^{p} \alpha_j \left| \frac{U_{t-j}}{\sqrt{\delta_{t-j}^2}} \right| + \sum_{j=1}^{p} \phi_j \left| \frac{U_{t-j}}{\sqrt{\delta_{t-j}^2}} \right| + \sum_{j=1}^{q} \beta_i ln\delta_{t-i}^2 \qquad (3.4)$$

where $ln\delta_t^2$ is the natural logarithm that transforms the leverage effect from quadratic to exponential, guaranteeing that the estimates remain positive. The constant is denoted by C, while α_j signified the influence of ARCH (Autoregressive Conditional Heteroskedasticity). The symbol ϕ_j stands for the asymmetric impacts, and β_i indicated the effects of GARCH (Generalized Autoregressive Conditional Heteroskedasticity). The parameter ϕ_j also played a crucial role in examining asymmetries. The hypothesis posits that if $\phi_j > 0$, then then positive shocks led to higher volatility compared to negative shocks. whereas if $\phi_j = 0$, then the model exhibits symmetry. This was a fundamental concept in volatility modeling (El-Mihoub et al., 2006).

3.3.2 Artificial Neural Networks

Neural Networks employ a forecasting method that is non-parametric. This implies that there is no predetermined nonlinear function, allowing the model to go beyond a limited set of nonlinear functions. The single-layer feed-forward network is among the most commonly used Artificial Neural Networks (ANN). In this Feed-Forward Neural Network (FNN), appropriately weighted information is transferred from an entry point to an additional layer of concealed neurons. These hidden neurons are

also given a weight. The information ultimately arrives at the output layer, which signifies the forecast. This process allows for a flexible and dynamic approach to forecasting.

Let $P_t, t = 1, 2, 3, 4, 5, ...$ be the daily stock price. The daily stock returns can then be determined by

$$r_t = log(p_t) - log(p_{t-1}) \tag{3.5}$$

The output y of a single layer FNN is then given by

$$Y_t = C\left|\phi_0 + \sum_{j=1}^{\phi} \phi_i.g_t, i\right|, \tag{3.6}$$

where $g_{t,i} = G(bio + \sum_{j=1}^{n} b_{ijrt-j} + \sum_{k=0}^{p} {}_{ik}\Delta_{t-k}^{\frac{1}{2}}, (i = 1, 2, 3, 4, 5, ...q)$, Functions C and G employ the hyperbolic tangent activation function and the linear activation function, respectively. The hyperbolic tangent activation function scales the neuron values within the range of (-1, +1). On the other hand, the linear activation function in the output layer allows the network to generate values beyond this range.

In the context of the error-back propagation technique, the neural network processes all the input data during an initial "learning" phase, resulting in a series of outputs. Following this, the weights are adjusted using an iterative gradient descent approach to minimize the mean squared error between the actual output and the network's prediction. This process ensures the network learns from the discrepancies between its predictions and the actual data.

Once the neural network has been trained, it is then tested on a separate data set known as the "validation" period. This process is crucial for assessing the network's capability to prevent overfitting. To account

for dynamic changes, Feedforward Neural Networks (FNN) incorporate lagged variables as predictors. Recurrent Neural Networks address this issue by incorporating feedback from the hidden neurons,g, to the input layer with a certain delay. This allows the network to retain information over time and adapt to changes in the data.

The Recurrent Neural Networks (RNNs) have the ability to retain information because their output is influenced by both the current input and previous inputs. Our discussion will primarily revolve around a variant of RNN that has a single hidden layer and includes a feedback loop from the output of the hidden layer back to its input.

Therefore, the Recurrent Neural Network (RNN), the formula can be rephrased as follows:

$$g_{t,i} = G(bio + \sum_{j=1}^{n} b_{ijrt-j} + \sum_{k=0}^{p} {}_{ik}\Delta_{t-k}^{\frac{1}{2}} + \sum_{l=1}^{m} \delta_{ilgl,t-1}, (i = 1, 2, 3, 4.....q) \quad (3.7)$$

By employing the method of backward substitution, it can be demonstrated that the resultant output, denoted as y_t, is influenced by the comprehensive historical data of the inputs, represented as r and $\Delta h^{\frac{1}{2}}$.

The research will employ the Recurrent Neural Network (RNN) model, specifically utilizing the Long-short-Term Memory (LSTM) technique. The LSTM model, originally proposed by (Rouah, 2013) and (Zhang et al., 2018), operates by limiting the flow of information in extended sequences. LSTMs possess a distinct cell memory, denoted as C_t, alongside a hidden state h_t. The cell memory undergoes an update process involving a forget gate ($\hat{f}_t$), an input gate ($\hat{z}_t$), and a cell gate ($\hat{c}_t$). The update equation for the cell memory is given by:

$$c_t = \hat{f}_t c_{t-1} + \hat{z}_t \hat{c}_t \quad (3.8)$$

(Zhang et al., 2018) notes that the cell memory is solely dependent on the cell memory gate update, denoted as $\hat{c}_t$, when the forget gate $\hat{f}_t$ is set to zero. The term $\hat{f}_t c_{t-1}$ implies that the cell memory possesses a long-term memory, which is only forgotten beyond a certain lag ϕ if $\hat{f}_t$ equals zero. The hidden state, represented as h_t, is determined by the equation:

$$ht = \hat{r} \tanh(c_t) \tag{3.9}$$

(El-Mihoub et al., 2006) argues that if $\hat{r}$ equals zero, the hidden state is reset. Conversely, if $\hat{r}$ equals one, the cell memory is influenced by the hidden state. This interpretation provides a nuanced understanding of the dynamics of the hidden state and cell memory in the model.

3.3.3 The EGARCH-ANN Model

We follow the notation of (El-Mihoub et al., 2006) and develop the EGARCH-ANN (p, q, m, s) representing a hybrid model derived from the integration of the EGARCH model and Artificial Neural Networks (ANN):

$$y_t = \sigma_t \vartheta_t, \tag{3.10}$$

$$\ln \sigma_t^2 = C + \sum_{j=1}^{q} \beta_j \ln \sigma_{t-j}^2 + \sum_{i=1}^{p} c_i \frac{y_{t-i} - C y_{t-i}}{\sigma_{t-i}} + \sum_{i=1}^{p} \alpha_i \frac{y_{t-i}}{\sigma_{t-i}} + \sum_{h=1}^{s} \xi_h G(h_t W_h + w_{h,0}), \tag{3.11}$$

where

$$G(h_t W_h + w_{h,0}) = \tanh(h_t W_h + w_{h,0}), \tag{3.12}$$

$$W_h = [w_{h,1}, ..., w_{h,m}] \tag{3.13}$$

and

$$h_{t-d} = \frac{y_{t-d} - E(y)}{\sqrt{E(y^2)}}, d = 1 : m, \tag{3.14}$$

$$C = \xi_0 + w, \tag{3.15}$$

In which, σ_t^2 is the asymmetric function of y_t and $G(Z_t W_h + w_{h,0})$. The in-sample mean and the in-sample variance are represented by $C(y)$ and $C(y^2)$ respectively. Both $w_{h,0}$ and the elements of W_h are generated by a uniform random number generator, and they lie between -1 and 1 (Donaldson and Kamstra, 2007). After obtaining the values of p, q, m, and s, the EGARCH-ANN (p, q, m, s) model can be estimated using Maximum Likelihood Estimation (MLE), taking into account the chosen distribution of ϑ_t. The EGARCH-ANN model, a hybrid of the EGARCH and ANN models, is capable of addressing the leverage effect, a feature that the EGARCH model alone may not fully capture. This is made possible by the universal approximation characteristic of the ANN component (Alagidede and Panagiotidis, 2010). The ANN component enhances the EGARCH model by enabling it to manage the nonlinear relationship between past return innovations and future volatility. Therefore, this hybrid model outperforms the asymmetric EGARCH models in volatility modeling and forecasting. This is largely due to the ANN's ability to

manage the leverage effect, a stylized fact of volatility that the EGARCH model may not fully account for (Donaldson and Kamstra, 2007).

3.3.4 The Fuzzy-EGARCH-ANN Model

Based on (Esman Nyamongo and Misati, 2010), we introduce the fuzzy-EGARCH-ANN model by defining a set of fuzzy rules articulated as if-then statements. These rules aim to capture stock market fluctuations that exhibit volatility clustering, a feature not fully captured by the standard EGARCH-ANN model. By incorporating fuzzy rules into the EGARCH-ANN model, it can better account for the asymmetric reactions of volatility to both positive and negative market shocks. The k^th rule of the fuzzy system for this model, which we denote as EGARCH-ANN (p, q, m, s), is outlined below.

Rule k: If the first variable, x_1^t, is F_k1..... and the x_d^t, is F_kd, then the following conditions apply:

$$y_k t = \sigma_t \vartheta_t, \tag{3.16}$$

$$ln\sigma_{kt}^2 = C_k + \sum_{j=1}^{q} \beta_{kj} \ln \sigma_{t-j}^2 + \sum_{i=1}^{p} c_{ki} \frac{y_{t-i} - C(y_{t-i})}{\sigma_{t-i}} + \sum_{i=1}^{p} \alpha_{ki} \frac{y_{t-i}}{\sigma_{t-i}} + \sum_{h=1}^{s} \xi_{kh} G(h_t W_h + w_{h,0}), \tag{3.17}$$

where $G(h_t W_h + w_{h,0}) = \tanh(h_t W_h + w_{h,0})$,

and $W_h = [w_{h,1}, ..., w_{h,m}]'$,

$h_{t-d} = \frac{y_{t-d} - E(y)}{\sqrt{E(y^2)}}, \quad d = 1 : m$, $x_t = [y_{t-1}, y_{t-2}, ..., y_{t-p}, \sigma_{t-1}^2, \sigma_{t-2}^2, ..., \sigma_{t-q}^2]'$,

$T = [x_{t1}, x_{t2}, ..., x_{td}]'$,

where, x_t is the input vector with $d = (p + q)$ at instance t, F_kl is the

fuzzy set used to describe the stock market return and volatility for l = 1, 2, 3, ..., d, and R is the number of rules. Additionally, x_{tl} is the premise variable. The study assumes that the distribution of the residual series follows either the Gaussian normal or Student's t-distribution. If it does not follow the Gaussian normal distribution, then it directly follows the Student's t-distribution (Donaldson and Kamstra, 2007).

Further adopting (Alagidede and Panagiotidis, 2010) and letting the premise variables include both the previous value of the stock market return and the previous volatility of the stock market return. The "then" part clearly expresses a local input and output relation by considering the EGARCH-ANN model parameters. As in the previous EGARCH-ANN hybrid model, this fuzzy-EGARCH-ANN hybrid model's σ_t^2 is not only an asymmetric function of y_t but also an asymmetric function of $G(h_t W_h + w_{h,0})$. (Wang et al., 2002) stated that a fuzzy system with the Gaussian membership function has been shown to be a universal approximation of any nonlinear function on a compact set.

The final output of this fuzzy-EGARCH-ANN model is the weighted average output of each individual rule output and is obtained by using FIS fundamental steps as follows:

- Fuzzification layer: Using the Gaussian membership function, the grade of membership of the input x_{tl} in F_{kl} is found as follows:

$$F_{kl}(x_{tl}) = \exp\left(-\frac{1}{2}\left(\frac{x_{tl} - c_{kl}}{a_{kl}}\right)^2\right), \tag{3.18}$$

  where C_{kl} represents the center and a_{kl} denotes the spread of the k^th rule membership function, which corresponds to the l^th premise variable.

- Firing strength layer: the firing strength of the k^th rule is calcu-

lated. This is done by assuming the product T-norm of the antecedent fuzzy sets. The formula for this is:

$$u_k(x_t) = \prod_{l=1}^{d} F_{kl}(x_{t_l}) = \prod_{l=1}^{d} \exp\left(-\frac{1}{2}(x_{t_l} - c_{kl})^2/a_{kl}^2\right), \quad (3.19)$$

where x_{t_l} is the l^th input variable at time t, c_{kl} is the center of the l^th Gaussian membership function in the k^th rule, and

$$a_{kl}$$

is the width of the l^th Gaussian membership function in the k^th rule. The product takes over all input variables. The result is the firing strength of the k^th rule. This value is used in the subsequent layers of the fuzzy system.

- The normalization layer: we calculate the normalized firing strengths. This is the ratio of the firing strength of the k^th rule to the sum of the firing strengths of all rules:

$$w_k = \frac{u_k(x_t)}{\sum_{k=1}^{R} u_k(x_t)}. \quad (3.20)$$

- Consequent and defuzzification layer: we combined the normalized firing strengths with the corresponding rule to produce the model output. This was done by taking the weighted average of each individual rule:

$$\ln \sigma_t^2 = \sum_{k=1}^{R} w_k f_k \quad (3.21)$$

where f_k is the output of the k^th rule. That is, $f_k = E_k + \sum_{j=1}^{q} \beta_{kj} \ln \sigma_{t-j}^2 + \sum_{i=1}^{p} c_{ki} \frac{y_{t-i}}{\sigma_{t-i}} - E \frac{y_{t-i}}{\sigma_{t-i}} + \sum_{i=1}^{p} \alpha_{ki} \frac{y_{t-i}}{\sigma_{t-i}} + \sum_{h=1}^{s} \xi_{kh} G(Z_t W_h +$

$w_{h,0}$).

Implying that $\ln \sigma_t^2 = \sum_{k=1}^{R} w_k f_k = \frac{\sum_{k=1}^{R} u_k(x_t) f_k}{\sum_{k=1}^{R} u_k(x_t)}$

The fuzzy-EGARCH-ANN model, which is a combination of local R models, is assembled using a set of R rules. Each local model adds a value to the total output of the fuzzy-EGARCH-ANN model. This contribution is proportional to the normalized intensity of each rule's activation. Consequently, the exponential of this weighted mean value provides the forecasted volatility of stock market returns, as per the recently introduced model. This is achieved by taking into account the firing strength of each rule.

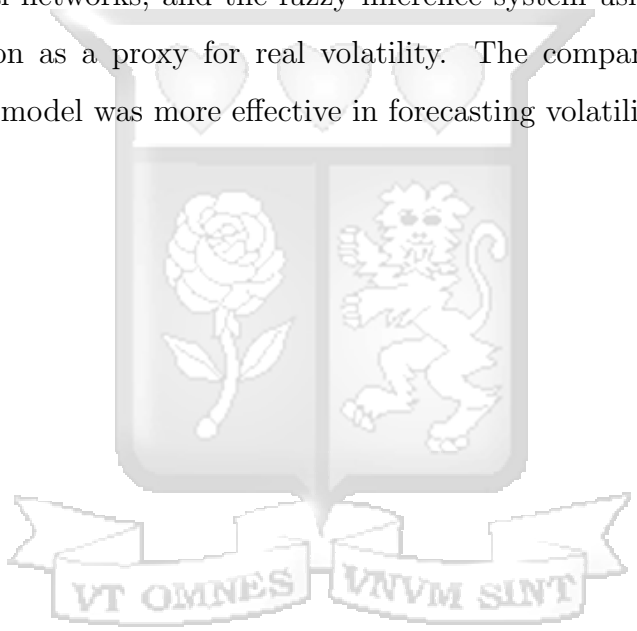
3.4 Parameter Estimation

The asymmetric EGARCH model parameters were determined by employing the maximum likelihood method, utilizing the student t likelihoods. The parameters were identified in a way that optimizes the likelihood of the observed data being generated by the model's described process. The Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were used to identify the model that provided the best fit. Both AIC and BIC are utilized because AIC is more suitable when a false negative result would be more misleading than a false positive, while BIC is more appropriate when a false positive is equally or more misleading than a false negative.

3.5 Simulation

The parameters that have been determined were employed to carry out a simulation of the model, utilizing data spanning from June 1st, 2014, to July 31st, 2023. The predictive performance of these models were evaluated using two key metrics: the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE).

We evaluated the predictive power of both the asymmetric EGARCH model, neural networks, and the fuzzy inference system using the standard deviation as a proxy for real volatility. The comparison was to reveal which model was more effective in forecasting volatility.



Chapter 4

Data Analysis, Results and Discussions

4.1 The Nairobi Stock Exchange System Data

We focus on the Nairobi stock exchange system database (https://www.nse.co.ke/). Precisely, we utilized daily time series data from the NSE-All Share Index, designed to represent all companies, spanning from April 1st, 2011, to July 31st, 2020. Out of these, 940 observations (approximately 90% of the total observations) were used for estimations (training set), and 100 observations (approximately 10% of the total observations) were used for out-of-sample forecasts (test set).

4.2 Data Analysis

In the research, we used the stock return formulae denoted by:

$$Y_t = \log\left(\frac{St}{St-1}\right) \tag{4.1}$$

where S_t represents the price, while Y_t represents the stock return.
The descriptive analysis of the data is described in Table 1 below.

Table 4.1: Descriptive Statistics for the NSE-All Share Index from April 1st, 2011 to July 31st, 2020

Variables	**Mean**	**Std. Dev**	**Min**	**Max**	**Skewness**	**Kurtosis**
Pt	0.00016697	0.00821138	1723.9600	5499.6400	-0.7136689	-6.37704143
rt	-0.0236	0.7226	-8.6022	8.6344	-0.3755	21.8080

Table 4.1 above shows the NSE-All Share Index from April 1st, 2011, to July 31st, 2020. The prices reached a maximum of 5499.64 and a minimum of 1723.96. Both the share index price and the return exhibit non-zero and negative skewness, suggesting a non-normal distribution that leans towards the left. The kurtosis of the share index price is below 3, indicating a platykurtic distribution, which means it has tails that are thinner compared to a normal distribution. On the other hand, the kurtosis of the share index return exceeds three, signifying a leptokurtic distribution, which implies it has thicker tails relative to a normal distribution.

Examining the share price index from Table 4.1 above, it is evident that there was a steady growth in share prices from 2012 until the end of 2015. This was followed by a continuous decline until the end of 2016. Subsequently, there was a price surge from 2018 to 2019 followed by a consistent drop towards the end of 2020 and the early part of 2021. The peak price of the share index during the observed period was recorded in mid-2018.



Figure 4.1: NSE-All Share Index Daily Prices

A series of daily price returns were calculated from the daily prices of the share index. It can be observed from Figure 4.1 above that the peak volatility was observed in 2015. To identify the distinct attributes of the share index, we plotted a time series graph of the daily returns, as illustrated in Figure 4.2. The figure showed a slight spike in the returns of the share index for the examined period.

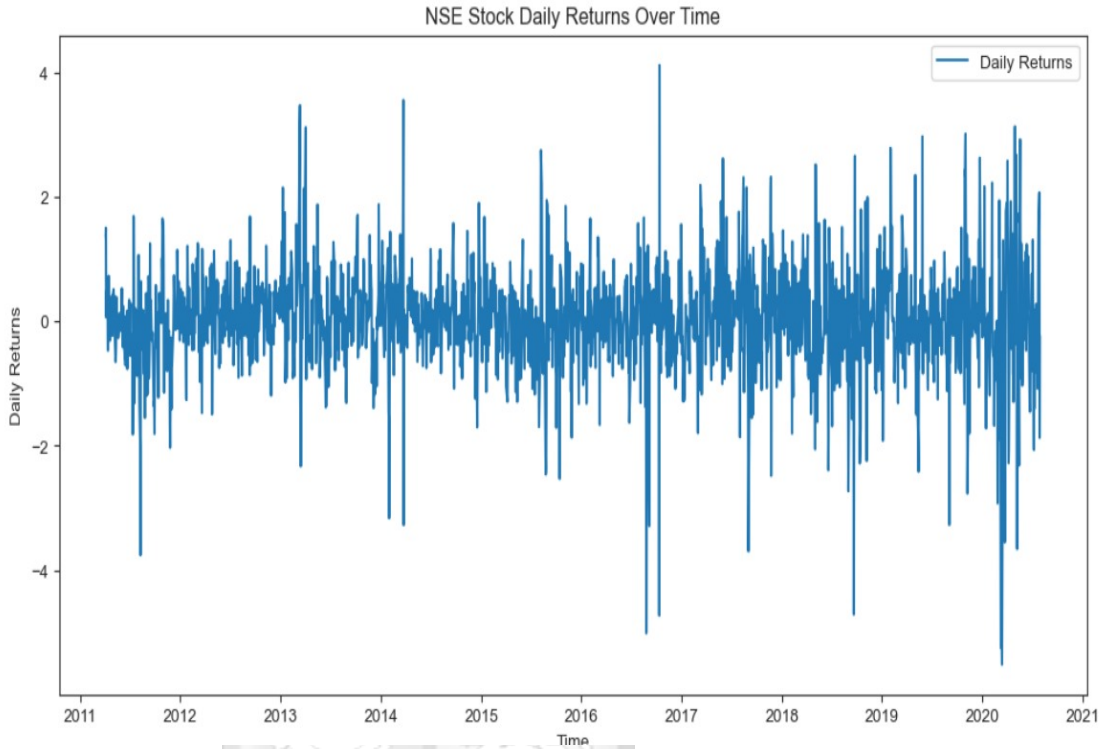


Figure 4.2: NSE-All Share Index Daily Prices

4.2.1 Results of Normality test

In this research, we used the Jarque-Bera test to assess the goodness of fit to a normal distribution. This test examines whether the skewness and kurtosis of the data align with those of a normal distribution. The outcomes of the Jarque-Bera test applied to the daily returns of the share index were presented in Table 4.2. Given that the test statistic significantly deviates from zero, we reject the null hypothesis, leading us to conclude that the daily returns do not follow a normal distribution.

Table 4.2: Results of Jarque-Bera Test to Assess the Goodness of Fit

Variables	**Test-Statistics**	**P-Value**
Jarque-Bera	44866.9458	0.0000

4.2.2 Results of Stationarity test

The test of stationarity was conducted using the Augmented Dickey Fuller test and the result indicates that there may be presence of trend in the data. The results of the stationarity test is summarized in Table 4.3 below.

Table 4.3: Augmented-Dickey Fuller Test for Stationarity for the NSE-All Share Index

		T-Statistics	**P-Values**
ADF Test	Test-Statistics	-19.912	0.0000
Tets Critical Values	1%	-3.4223	
	5%	-2.8628	
	10%	-2.6684	

The null hypothesis posits the existence of a unit root in the time series data, an attribute that renders it non-stationary. Given that the test statistic falls below the critical values at confidence intervals of 1%, 5%, and 10%, we rejected the null hypothesis, thereby concluding that the dataset exhibits stationarity.

4.3 Empirical Results

4.3.1 Asymmetric EGARCH Models

The research concentrated on two distinct types of asymmetric GARCH models. The standard EGARCH was applied to the daily returns of the NSE-All Share Index to account for volatility asymmetries and guarantee that the estimates remain positive. Conversely, the GJR-GARCH model was utilized to examine the leverage effect and the correlation between

stock market returns and volatility. A summary of the findings can be found in Table 4.4 below.

Table 4.4: Parameter Estimation Results for the NSE-all Share Index

Variables	**Standard EGARCH**	**GJR-GARCH**
C	-0.3466	0.1787
α	0.2367	0.2226
ϕ	-0.0133	-0.0327
β	0.7210	0.3158
AIC	3243.21	3250.38
BIC	3276.24	3283.41
Log-Likehood	-1615.60	-1619.60

The leverage effect, symbolized by α, exhibits a negative value and is statistically significant in the context of the EGARCH model. This leads to the rejection of the null hypothesis, implying that negative shocks will induce greater volatility than positive ones. In the case of the GJR-GARCH model, α is also negative and statistically significant. However, considering the non-negativity conditions, we infer that the leverage effect for the GJR-GARCH model is positive and statistically significant. Therefore, the null hypothesis is accepted, indicating that negative shocks will have a more substantial impact on δ_t^2 than positive shocks, i.e., the higher the volatility at the NSE, the lower the returns. Both the EGARCH and GJR-GARCH models are effective in fitting the actual data. Nevertheless, the EGARCH model outperforms the GJR-GARCH model in terms of fitting the actual data, as evidenced by its lower AIC and BIC values.

4.3.2 Hybrid EGARCH Model and Artificial Neural Network Analysis

In this research, the Recurrent Neural Network (RNN) was chosen due to its unique ability to handle time series predictions more effectively than other machine learning techniques. The dataset was split into a training set, comprising 80% of the data, and a testing set, making up the remaining 20%. Out of 2305 total data points, 1,819 were allocated for training and 486 for testing. The model was trained on the 1,818 data points and used to forecast the 1,820th data point. This predicted value was then incorporated into the training set, while the first data point was removed. This process was repeated, with the model predicting the next data point based on the updated training set, until all data points in the testing set were covered. Finally, the model's accuracy was evaluated by comparing the predicted values with the actual values from the testing set. This approach ensured a robust and iterative prediction process, enhancing the model's performance on time series data.

Following the division of data into training and testing subsets, the MinMaxScaler was employed to normalize the data for training purposes. The model was set up with a specific number of neurons and timestamps. The Adam optimizer, which implements gradient descent through backpropagation over time, was utilized for optimization. This approach was chosen to expedite convergence, despite the time cost. The Mean Absolute Error (MAE) served as the loss function, aiming to reduce the discrepancy between the actual and predicted values. This comprehensive process ensured the effective training and optimization of the model. Figures 4.3 below provide a visual illustration of the training data, predictions from the test set, and the actual data that was not part of the

sample.

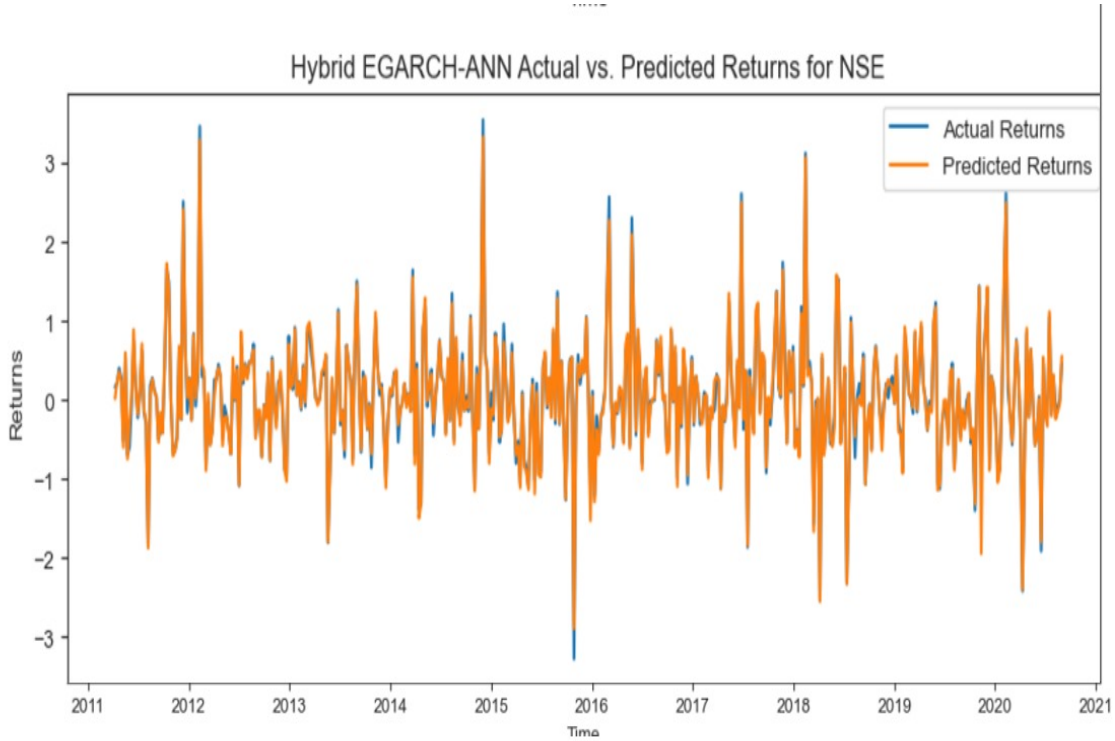


Figure 4.3: Hybrid EGARCH-ANN Actual vs. Predicted Returns for NSE-All Share Index

4.3.3 The Fuzzy-EGARCH-ANN Model

To improve the forecast of the Hybrid EGARCH-ANN, we employed Fuzzy-EGARCH-ANN Model statistical model. The first step involves applying the EGARCH-ANN test to the Mean Squared Forecasting Error (MSFE) with the Fuzzy Computationally Efficient EGARCH model serving as the reference model, and the other models as contenders. The test's p-value at a significance level of 5% was then documented. This approach provided a more comprehensive assessment of the models' predictive capabilities. Figures 4.4 below provides an illustration of the result of this combiantion.

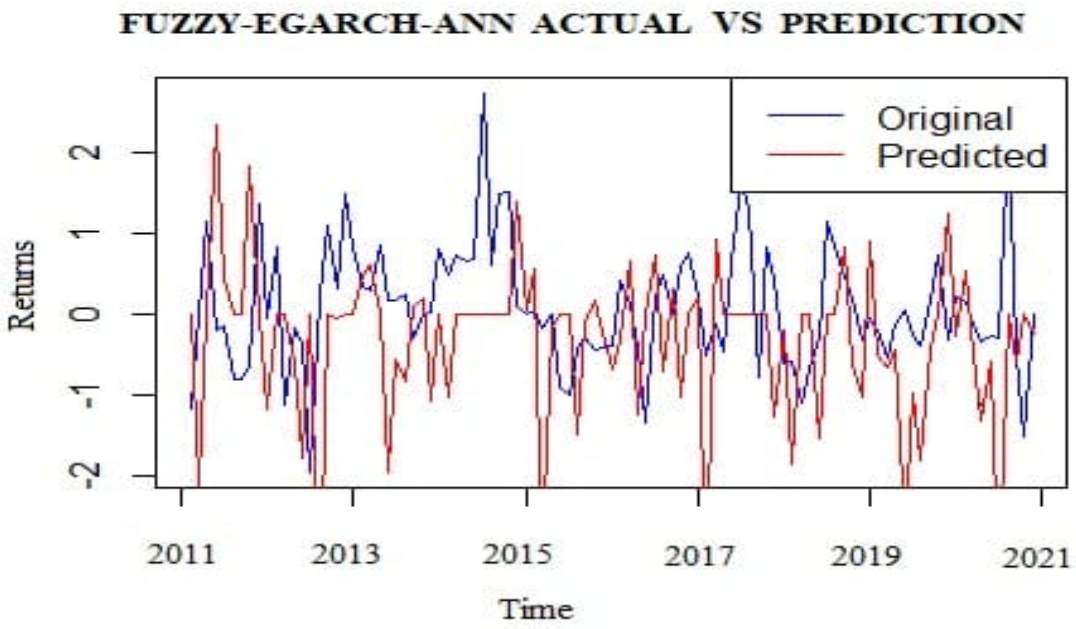


Figure 4.4: Fuzzy-EGARCH (GA): Original vs. Predicted for NSE-All Share Index

From the Figure 4.4, we observed that the recently introduced fuzzy-EGARCH-ANN model has produced values that closely mirror those from its own simulated data.

4.3.4 Forecast Evaluation

In addition to modeling volatility, this study also aimed to predict volatility and determine the most effective model for such predictions among the EGARCH, GJR-GARCH, and Artificial Neural Networks. The Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) metrics were utilized to ascertain the superior model. These measures helped in comparing the performance of the models and identifying the one that

best forecasts volatility. The Root Mean Square Error (RMSE) is derived from the square root of the residual variance, serving as an indicator of the proximity between the observed data points and the values predicted by the model. On the other hand, the Mean Absolute Error (MAE) quantifies the average size of the errors in a set of forecasts, disregarding the direction of the errors. These metrics provide a comprehensive understanding of the model's predictive performance.

Table 4.5: Forecast Metrics for Different Models

Parameter	**MAE**	**RMSE**
EGARCH	1.422611	0.956863
EGARCH-ANN	0.00964	0.06230
Fuzzy-EGARCH-ANN	1.111956	0.729812

The lower the value of the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) the better the model is at forecasting. Based on the results in Table 4.5 above, it can be inferred that among the three models, the EGARCH-ANN model outperforms all other models in terms of forecasting, with the Fuzzy-EGARCH model closely following, as evidenced by its minimal MAE and RMSE values. This observation underscores the continued relevance of machine learning models in volatility forecast modeling. Furthermore, the EGARCH-ANN model demonstrates lower errors compared to the Fuzzy-EGARCH model.

Chapter 5

Conclusion and Recommendations

5.1 Conclusion

This research analysed the volatility patterns at the Nairobi Securities Exchange (NSE) by employing the NSE-All share Index data from January 3, 2012, to February 22, 2021. The computation of daily returns was done using the logarithmic formula

$$\log\left(\frac{S_t}{S_{t-1}}\right)$$

. To ascertain the market efficiency, different tests were applied, including the Augmented-Dickey Fuller test for stationarity and the Jarque-Bera test for normal distribution of the daily returns of the share index during the specified period. The study utilized asymmetric GARCH models, specifically the Exponential GARCH (EGARCH) and the Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) models. The outcomes of these models were then compared with the results derived from Hybrid EGARCH-ANN and the Fuzzy-EGARCH-ANN Model.

The analysis of the NSE-All Share Index during the specified period reveals that it exhibits fat tails and a left skew, indicating a deviation from normal distribution. The returns, upon examination, were found to be

stationary, suggesting a mean-reverting behavior in their first-differenced form. The parameter estimation results from the EGARCH and GJR-GARCH models revealed that the ARCH coefficients were positive and statistically significant, indicating the presence of volatility clustering and market persistence. The EGARCH model demonstrated that the market's response varied to positive and negative shocks of equal magnitude. In contrast, the GJR-GARCH model detected a leverage effect, suggesting an inverse relationship between volatility and returns. A comparison of the two asymmetric GARCH models was conducted using the AIC and BIC criteria to determine the best fitting model. The EGARCH model emerged as the superior model, as evidenced by its lower AIC and BIC values compared to the GJR-GARCH model.

In this study, we utilized Artificial Neural Networks (ANNs) and specifically implemented the Recurrent Neural Network (RNN) with Long Short Term Memory (LSTM) technique. The model was developed and trained using the TensorFlow library in Python. The model's training phase resulted in the generation of predicted values. These predictions were subsequently compared with out-of-sample data. The comparison was based on three key metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Square Error (MSE). The forecasting capabilities of the ANNs were then compared with those of the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) and the Fuzzy inference models. The results, particularly from the RMSE and MAE metrics, indicated that the ANNs demonstrated superior performance over both the EGARCH and Fuzzy inference models.

A significant challenge encountered in this study pertains to the interpretability of the neural networks. Given their structure, which includes numerous hidden layers of nodes, these networks are capable of recogniz-

ing and leveraging highly intricate relationships within the data. However, the complexity of this process renders it less transparent, making it challenging to elucidate how the predictions were derived. For stakeholders to place their trust in a model, they need to comprehend and endorse the decision-making process of the model. This becomes a daunting task when there is a lack of clarity on how these decisions were arrived at.

5.2 Recommendations for Further Research

The primary aim of this research was to predict the volatility of the stock market at the NSE. Several key findings emerged from the data analysis. Initially, the financial time series data exhibited certain characteristics, including leptokurtosis, volatility clustering, volatility persistence, and a leverage effect. These stylized facts must be considered to ensure the reliability of future volatility forecasts. In the realm of asymmetric GARCH models, the EGARCH model demonstrated superior parameter estimation compared to the GJR-GARCH model. Finally, in terms of volatility forecasting, Artificial Neural Networks proved to be more effective than both the EGARCH and hybrid EGARCH-ANN models, according to the results.

In the realm of computer vision and natural language processing, significant strides have been made in the field of explainability. However, the application of these methods to time series data still requires extensive exploration. The concept of Explainable Artificial Intelligence (XAI) presents a promising avenue for future research, particularly in addressing the explainability limitations of Neural Networks. One potential solution could be the utilization of the Layer-wise Relevance Propagation technique, which could enhance the trustworthiness of machine learning

models and facilitate more effective troubleshooting. This study primarily concentrated on technical analysis for modeling and predicting volatility, with a focus on historical stock market return data. Future research could expand this approach to include fundamental analysis, providing investors with a more comprehensive understanding of a stock's intrinsic value in conjunction with technical analysis. This could offer a more holistic view of market dynamics and investment strategies.

Bibliography

Akgiray, V. (2019). Conditional heteroscedasticity in time series of stock returns: Evidence and forecasts. *Journal of business*, pages 55–80.

Alagidede, P. and Panagiotidis, T. (2010). Modelling stock returns in africa's emerging equity markets. *International review of financial analysis*, 18(1-2):1–11.

Alberg, D., Shalit, H., and Yosef, R. (2018). Estimating stock market volatility using asymmetric egarch models. *Applied Financial Economics*, 18(15):1201–1208.

Dash, R. and Dash, P. K. (2016). An evolutionary hybrid fuzzy computationally efficient egarch model for volatility prediction. *Applied Soft Computing*, 45:40–60.

Donaldson, R. G. and Kamstra, M. (2007). An artificial neural network-garch model for international stock return volatility. *Journal of Empirical Finance*, 4(1):17–46.

El-Mihoub, T. A., Hopgood, A. A., Nolle, L., and Battersby, A. (2006). Hybrid genetic algorithms: A review. *Eng. Lett.*, 13(2):124–137.

Esman Nyamongo, M. and Misati, R. (2010). Modelling the time-varying volatility of equities returns in kenya. *African Journal of Economic and management studies*, 1(2):183–196.

Fama, E. F. (1965). The behavior of stock-market prices. *The journal of Business*, 38(1):34–105.

Fleming, J., Kirby, C., and Ostdiek, B. (2013). The economic value of volatility timing using "realized" volatility. *Journal of Financial Economics*, 67(3):473–509.

Gatuhi, S., Gekara, M., and Muturi, D. (2015). Effect of macroeconomic environment on stock returns of firms in the agricultural sector in kenya. *International Journal of Management & Business Studies*, 5(3):9–23.

Glosten, L. R., Jagannathan, R., and Runkle, D. E. (2013). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The journal of finance*, 48(5):1779–1801.

Godfrey, J. and Ismail, B. (2020). Modeling volatility in the stock market for accuracy in forecasting. *International Journal of Recent Technology and Engineering*, 8(5):41–49.

Hajizadeh, E., Seifi, A., Zarandi, M. F., and Turksen, I. (2012). A hybrid modeling approach for forecasting the volatility of s&p 500 index return. *Expert Systems with Applications*, 39(1):431–436.

Hansen, P. R. and Lunde, A. (2005). A forecast comparison of volatility models: does anything beat egarch (1, 1)? *Journal of applied econometrics*, 20(7):873–889.

Hornik, K. (2003). Some new results on neural network approximation. *Neural networks*, 6(8):1069–1072.

Hung, J.-C. (2009). A fuzzy garch model applied to stock market scenario using a genetic algorithm. *Expert Systems with Applications*, 36(9):11710–11717.

Hung, J.-C. (2011). Adaptive fuzzy-egarch model applied to forecasting the volatility of stock markets using particle swarm optimization. *Information Sciences*, 181(20):4673–4683.

Hyndman, R. J. and Athanasopoulos, G. (2018). *Forecasting: principles and practice*. OTexts.

Kristjanpoller, W. and Minutolo, M. C. (2016). Forecasting volatility of oil price using an artificial neural network-egarch model. *Expert Systems with Applications*, 65:233–241.

Lee, C. F., Chen, G.-m., and Rui, O. M. (2001). Stock returns and volatility on china's stock markets. *Journal of Financial Research*, 24(4):523–543.

Mandelbrot, B. B. and Mandelbrot, B. B. (2017). *The variation of certain speculative prices*. Springer.

Maqsood, A., Safdar, S., Shafi, R., and Lelit, N. J. (2017). Modeling stock market volatility using egarch models: A case study of nairobi securities exchange (nse). *Open Journal of Statistics*, 7(2):369–381.

Mekoya, M. W. (2013). *Modeling and forecasting stock market volatility at Nairobi securities exchange*. PhD thesis, University of Nairobi.

Monfared, S. A. and Enke, D. (2014). Volatility forecasting using a hybrid gjr-garch neural network model. *Procedia Computer Science*, 36:246–253.

Nelson, D. B. (2011). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of the econometric society*, pages 347–370.

Olweny, T. (2011). Modelling volatility of short-term interest rates in kenya. *International Journal of Business and Social Science*, 2(7):289–303.

Refenes, A. N., Zapranis, A., and Francis, G. (2004). Stock performance modeling using neural networks: a comparative study with regression models. *Neural networks*, 7(2):375–388.

Rouah, F. D. (2013). *The Heston model and its extensions in Matlab and C*. John Wiley & Sons.

Santamaría-Bonfil, G., Frausto-Solís, J., and Vázquez-Rodarte, I. (2015). Volatility forecasting using support vector regression and a hybrid genetic algorithm. *Computational Economics*, 45:111–133.

Schwert, G. W. (2008). Why does stock market volatility change over time? *The journal of finance*, 44(5):1115–1153.

Su, J.-B. (2021). How to promote the performance of parametric volatility forecasts in the stock market? a neural networks approach. *Entropy*, 23(9):1151.

Taylor, J. W. (2009). A quantile regression neural network approach to estimating the conditional density of multiperiod returns. *Journal of forecasting*, 19(4):299–311.

Vortelinos, D. I. (2017). Forecasting realized volatility: Har against principal components combining, neural networks and egarch. *Research in international business and finance*, 39:824–839.

Wagala, A., Nassiuma, D., Islam, A., and Mwangi, J. (2012). Volatility modeling of the nairobi securities exchange weekly returns using

the arch-type models. *International Journal of Applied Science and Technology*, 2(3):165–174.

Wang, L.-X., Mendel, J. M., et al. (2002). Fuzzy basis functions, universal approximation, and orthogonal least-squares learning. *IEEE transactions on Neural Networks*, 3(5):807–814.

Wei, L.-Y. (2013). A ga-weighted anfis model based on multiple stock market volatility causality for taiex forecasting. *Applied Soft Computing*, 13(2):911–920.

White, H. (2008). Economic prediction using neural networks: The case of ibm daily stock returns. In *ICNN*, volume 2, pages 451–458.

Whitelaw, R. F. (2004). Time variations and covariations in the expectation and volatility of stock market returns. *The Journal of Finance*, 49(2):515–541.

Youssef, N. and Rowe, S. (2022). Comparative study of modelling and forecasting volatility: the case of egypt, and japan.

Zhang, J., Chung, H. S.-H., and Lo, W.-L. (2008). Chaotic time series prediction using a neuro-fuzzy system with time-delay coordinates. *IEEE Transactions on Knowledge and Data Engineering*, 20(7):956–964.

Zhang, J., Li, D., Hao, Y., and Tan, Z. (2018). A hybrid model using signal processing technology, econometric models and neural network for carbon spot price forecasting. *Journal of Cleaner Production*, 204:958–964.

Zhang, J. and Sanderson, A. C. (2009). Jade: adaptive differential evolu-

tion with optional external archive. *IEEE Transactions on evolutionary computation*, 13(5):945–958.

Appendix A

Similarity Report

Bessie Kuri DISSERTATION

ORIGINALITY REPORT

24%	6%	13%	15%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Strathmore University Student Paper	12%
2	Jui-Chung Hung. "A fuzzy GARCH model applied to stock market scenario using a genetic algorithm", Expert Systems with Applications, 2009 Publication	4%
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4	Rajashree Dash, P.K. Dash. "An evolutionary hybrid Fuzzy Computationally Efficient EGARCH model for volatility prediction", Applied Soft Computing, 2016 Publication	2%
5	www.researchgate.net Internet Source	1%

Appendix B

Ethical Clearance

Strathmore UNIVERSITY

10th July 2023

Ms Kuri Bessie Dorinah,
bessie.kuri@strathmore.edu

Dear Ms Kuri,

RE: Volatility Forecasting using EGARCH with Neural Network Models andFuzzy Inference System: The Case of the Nairobi Securities Exchange

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU-masters** research proposal. Your application reference number is **SU-ISERC1789/23.** The approval period is from **10th July 2023 to 9th July 2024.**

This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, MTA) will be used.
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 72 hours of notification.
iv. Any changes anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 72 hours.
v. Clearance for the export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

Before commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology, and Innovation (NACOSTI) https://research-portal.nacosti.go.ke/ and obtain other clearances needed.

Yours sincerely,

for: **Mr Ambrose Rachier,**
Chairperson; SU-ISERC

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Appendix C

Parameter Estimate Codes

```
NSE_data.head()
```

	Days	Date	Close	Net	%Chg	Open	Low	High
0	1	4/1/2011	90.33	NaN	NaN	90.33	90.33	90.33
1	2	4/4/2011	91.55	1.22	1.35%	91.55	91.55	91.55
2	3	4/5/2011	92.92	1.37	1.50%	91.55	91.55	92.92
3	4	4/6/2011	92.98	0.06	0.06%	92.98	92.98	92.98
4	5	4/7/2011	93.29	0.31	0.33%	93.29	93.29	93.29

Pandas has the percentage change 'pct_change' method to calculate the percentage of changes in the daily r

```
NSE_data['daily_return']=(NSE_data['Close'].pct_change())*100
```

```
NSE_data.dropna(inplace=True)
```

```
fig,ax=plt.subplots(figsize=(12,6))
ax.spines[['top','right','left','bottom']].set_visible(False)
plt.plot(NSE_data['daily_return'], label = 'Daily Returns')
plt.legend(loc='best')
plt.title('NSE Stock Daily Returns Over Time')
ax.spines['top'].set_visible(True)
ax.spines['right'].set_visible(True)
ax.spines['bottom'].set_visible(True)
ax.spines['left'].set_visible(True)
# Add axis labels
plt.xlabel('Time')  # Label for the x-axis
plt.ylabel('Daily Returns')  # Label for the y-axis
plt.show()
```