Modeling Volatility in the Stock Market for Accuracy in Forecasting

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Abstract: In this paper, the best GARCH type model was selected and compared with the machine learning models, such as Extreme Learning Machine (ELM) and Multilayer Perceptron Neural Network (MLP-NN) models in modeling and forecasting monthly return of the financial market data. The objective of the study was to compare the best model in forecasting New York and Shanghai Stock Composite indices, for the period 01.01.1996 to 01.09.2019. The GJR-GARCH model outperformed other GARCH type models based on the Schwarz Bayesian Information Criterion (SSBIC). The Monte Carlo simulation carried at 1000, 2000, 3000, 4000 and 5000 finite sample (window) sizes to test the consistency of the GJR-GARCH model parameters has shown perfect results between true and the simulated coefficients. Finally, the GJR-GARCH model was compared with the MLP-NN and ELM machine learning models. The monthly return forecasting of two years (24 months) was done starting from period 01.09.2019 to 01.09.2021. The study found the MLP-NN model as the best in the modeling and forecasting monthly returns of the two composite stock indices for the two years by considering the Root Mean Square Error (RMSE).The study recommends that further research should focus on the formulation of the hybrid model that combines machine learning and the GJR-GARCH models in forecasting stock market volatility.

Keywords: GARCH type models, GJR-GARCH, Extreme Learning Machine (ELM), Multilayer Perceptron Neural Network (MLP-NN), MSE, RMSE.

I. INTRODUCTION

Modeling and forecasting Financial Time Series have become a hot cake almost in all organizations that work with quantifiable data. Financial markets have been affected daily by ongoing social, Economic, Political and other related factors on a day-to-day basis. Statistical models are very essential in solving forecasting problems. In this perspective, the prediction of the volatility with the best precision is significant for stock markets and for the economy of the world in general. The classical method for modeling and forecasting volatility known as Generalized Autoregressive Conditional Heteroscedasticity (GARCH) has been deployed by many researchers, nevertheless, the prediction based on the method often is quite not higher. Furthermore, limitations in modeling methods resulted in greater inadequacies in the financial market.

Currently, financial time series modeling forecasting using GARCH type models have been combined with Machine learning models to produce the exciting accuracy in forecasting with minimum forecasting error. Thus, improved modeling and forecasting methods are continuously required to reduce investment risks and increase the efficiency of the markets. This study will innovate focus on changing the models to improve the capability of the future forecast of the stock volatility. The study by [1] tested a hybrid Neural Networks-GARCH model in forecasting the volatility of the three Latin-American stock indexes. Further, the outcomes of the ANN model revealed an improved performance of the GARCH model for the three stock markets with robust and consistent results at different volatility measures and specifications.

The accuracy in forecasting performance still is an important subject in stock market volatility. The ensemble system of EGARCH-BPNN depicted a wonderful performance in the stock volatility forecasting based on Mean Squared and Mean absolute errors. The results from the experiment proposed that the ensemble model captured the skewness, kurtosis, and normality of the intra-day forecasting of the S&P 500 data [2]. The rest of the work portioned into four further sections. The brief review of literature on modeling and forecasting models with numerous applications evidenced from world-leading stock markets found in China and U.S.A will be done, since recently arguments pertaining bilateral business relationship has brought a huge discussion. The following section will include the detailed methodology and the data used for the analysis. The results will then presented and interpreted. Eventually, summarization and the main conclusions and recommendations will be made.

II. LITERATURE REVIEW

There is a number of researchers who tried their best in the field of financial time series. Researchers such as [3] and [4] developed Autoregressive Conditional Heteroscedasticity (ARCH) and Generalized ARCH symmetric models for stock market modeling and prediction. Furthermore, Exponential GARCH [5], Threshold GARCH [6] and GARCH-M [7] were developed later as an extension that incorporates alternative specifications to the two aforementioned models to capture the asymmetric characteristics in the financial data. These increasing complexity and uncertainty of the financial time series forecasting have resulted in the improvement and modification of the GARCH-type models for accurate forecasting of financial volatility. The Realized GARCH combined returns modeling and measures volatility. Many features were found in the linear or log-linear Realized GARCH models.

Simple Realized GARCH applied to two indices has shown improvement in the standard GARCH models [8]. The EGARCH and Artificial Neural Networks were combined to form a hybrid model for forecasting S&P 500 index volatility. Hybrid forecasts were compared with the EGARCH model. The study found that the best volatility forecasts were provided by the hybrid model [9]. The study by [10] has shown improvements in forecasting volatility of the oil price using a hybrid model that incorporates financial variables. It further concluded that the hybrid model has increased accuracy in the volatility forecasting by 30% based on Heteroscedasticity Adjusted Mean Squared Error (HMSE). The Simulation made to assess the performance of the finite-sample approach concluded that the estimation conditional quantile on the portfolio returns still an open problem for future further studies[11]. The GARCH model with the student's Innovation was found to perform best on the SSE380 volatility predictions. The bootstrap simulation model has shown that Model Confidence Set (MCS) captures the range of significance levels of the superior models[12]. The performance of the hybrid model that combines GARCH type and Machine learning (Artificial Neural Networks) models in the modeling and forecasting daily log return of the Kenyan Stock Markets. The study found that the ANN-EGARCH hybrid model effectively performs the modeling and forecasting of the stock market price volatility [13].

Over decades now, machine learning has gained momentum in the modeling and forecasting of the financial times series. This provides a platform for researchers to focus on the development of the most performing hybrid models that captures effectively the stock market volatility.

III. METHODOLOGY

A. ARCH-GARCH Models

1. Autoregressive Conditional Heteroscedasticity (ARCH) Model

The introduced $ARCH(p)$ model [14], which is a classical model for stochastic variance modeling. The model changes the assumptions of the variation in the error terms from $var(r_t) = \sigma_t^2$ to random sequence which only depends on the past square values of the time series. Furthermore, r_t can be expressed as a parametric form of σ_t^2 as $r_t = \sigma_t v_t$, where $v_t \sim iid(0,1)$.

Therefore, the $ARCH(p)$ model is given by:-

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^p \alpha_i r_{t-i}^2 \tag{1}$$

Where $\alpha_0 > 0$, $\alpha_i \geq 0$, and $i > 0$. To ensure $\{\sigma_t^2\}$ an asymptotically stationary random sequence $\alpha_1 + \alpha_2 + \alpha_3 + ... + \alpha_p < 1$.

Apart from its useful applications in financial time series forecasting, the introduction of the conditional variance to the ARCH model instead of only considering conditional mean was still useful.

2. Generalized-ARCH (GARCH) model

The drawbacks and limitations of the ARCH model resulted in the development of another model called the Generalized ARCH (GARCH) model. The developed model added a lagged conditional variance $\{\sigma_{t-j}^2\}$ to the ARCH model as the new term in the GARCH model which eventually reduces the estimated number of parameters. The conditional variance in the GARCH model is the linear function of the square its own lags and past observations [15]. The developed $GARCH(p,q)$ model can be written as:-

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^p \alpha_i r_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 \tag{2}$$

Where p and q represents the order of r_t^2 and σ_t^2 respectively, the sufficient condition $\alpha_0, \alpha_i, \beta_j > 0$ for $i = 1,2,3,...,p$ & $j = 1,2,3,...,q$ must be achieved.

The $GARCH(p,q)$ process is weakly stationary if and only if $\sum_{i=1}^p \alpha_i + \sum_{j=1}^q \beta_j < 1$, and the model keeps not only the conditions of the ARCH model but also the condition of the linear function of the lagged conditional variance.

3. Exponential GARCH (EGARCH) Model

The asymmetric EGARCH model expresses the conditional variance as the natural logarithm that varies over time as a function of the logarithm of the lagged conditional variance instead lagged of its squares[16]. The $EGARCH(p,q)$ model can be expressed as:-

$$\log \sigma_t^2 = \alpha_0 + \sum_{i=1}^p \alpha_i \left[\frac{|v_{t-i}|}{\sigma_{t-i}} \right] + \sum_{i=1}^p \gamma_i \left[\frac{|v_{t-i}|}{\sigma_{t-i}} - E\left\{ \frac{|v_{t-i}|}{\sigma_{t-i}} \right\} \right] + \sum_{j=1}^q \beta_j \log(\sigma_{t-j}^2) \tag{3}$$

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Where γ and α measures the leverage effects and volatility clustering respectively. The σ_t^2 always is

negativity constraints. If $\gamma < 1$ it indicates a leverage effect, then the asymmetric effect exponential and not quadratic. The EGARCH model shows volatility impacts

positive irrespective of the parameters sign and non-

on the stock market which can either be good or bad news.

4.   Threshold GARCH(TGARCH) Model

The TGARCH model measures the asymmetric effect by augmenting the dichotomous dummy variable into the GARCH model [17]. The TGARCH (p, q) model is given by:-

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i r_{t-i}^2 + \sum_{j=1}^{q} \beta_i \sigma_{t-j}^2 + \sum_{i=1}^{p} \gamma_i \psi_{t-i} \, y_{t-i}^2 \qquad (4)$$

Where

$$\psi_{t-i} = \begin{cases} 1 & if \ r_{t-i} < 0 \quad \rightarrow Negative \ news \\ 0 & if \ r_{t-i} \geq 0 \quad \rightarrow Positive \ News \end{cases}$$

The parameter $\psi(.)$ stands for the indicator function. This can either indicate negative or positive stock market news. The leverage effects exist if $\gamma > 0$, this is equivalent to the

GARCH (p, q) model. The other important required conditions are $\alpha; \beta; \alpha + \gamma \geq 0$.

B.   Machine learning Models

1.   Multilayer Perceptron Neural Network (MPL-NN)

The MLP-NN has become a famous Artificial Neural Network (ANN) model in forecasting [18]. The single hidden layer was used in the modeling and forecasting of the

two giant stock market returns by Market capitalization found in China and the USA.
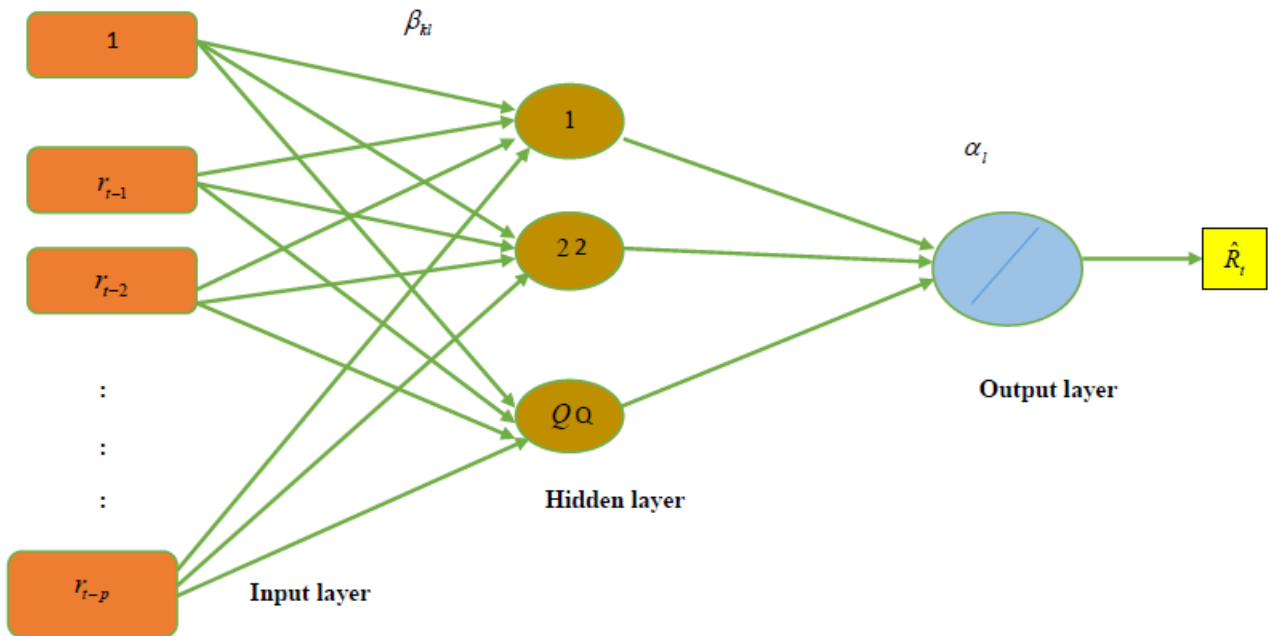

Figure 1: The Architecture of MLP-NN

Mathematically, the MLP-NN model can be expressed by the following:-

$$r_t = \alpha_0 + \sum_{l=1}^{q} \alpha_l f \left(\beta_{0l} + \sum_{k=1}^{p} \beta_{kl} r_{t-k} \right) + \varepsilon_t \qquad (5)$$

Where Q are the hidden layers, while r_{t-k} and $\hat{R}_t$ are the inputs output layers respectively. The p and q are the inputs and hidden layers respectively. $\alpha_l (l = 0,1,2,...,q)$ and $\beta_{kl} (k = 0,1,2,...,p; l = 0,1,2,...,q)$ are the

connection weights and ε_t is the error term; f is the transfer function, it is applied as the nonlinear activation function, the sigmoid transfer function employed is given by

$$f(x) = \frac{1}{1+e^{-x}} \; ; \; \alpha_0 \; and \; \beta_{0j} \; \text{are the bias terms.}$$

2. *Extreme Machine Learning (ELM)*

The ELM model has been purposely introduced to improve the learning speed of the feedforward neural networks[19]. The ELM with **S**ingle hidden **L**ayer **F**eedforward Neural **N**etworks (SLFNs) selects randomly the number of hidden nodes and eventually the SLFNs output weights. Then, arbitrary separate N samples of Size $(r_k, v_k), 1 \le k \le N$,

$$r_k = [r_{k1}, r_{k2}, r_{k3}, ..., r_{kn}]^T \in \mathbb{R}^N;$$

$v_k = [v_{k1}, v_{k2}, v_{k3}, ..., v_{km}]^t \in \mathbb{R}^m$; Mathematical formula for the activation function $f(r)$ and $\tilde{N}$ hidden nodes is written as:-

$$\sum_{k=1}^{\tilde{N}} \pi_k f_k (\phi_k \bullet r_l + c_k) = 0_l \; , l = 1, 2, 3, ..., N \qquad (6)$$

Where $\phi_i \bullet r_j$ is the inner product of $\phi_k \; and \; r_l$; $\phi_k = [\phi_{k1}, \phi_{k2}, \phi_{k3}, ..., \phi_{kn}]^T$ is the weight vectors connecting the ith hidden and the input nodes; $\pi_k = [\pi_{k1}, \pi_{k2}, \pi_{k3}, ..., \pi_{kn}]^T$ is the weight vectors connecting the kth hidden and the output nodes and c_k is the threshold for the kth hidden node.

C. *Performance Measure*

Numerous statistical measures stand to be used to estimate model accuracy with the lowest error [20]. The most famous measures for forecasting performance employed in the study **Process flow Diagram**
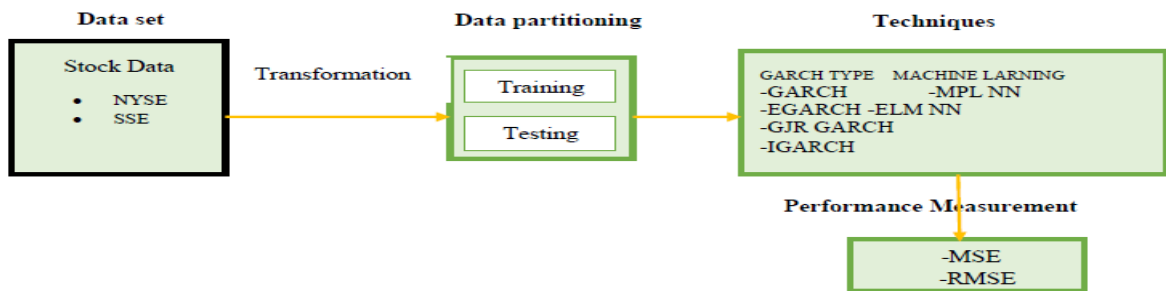
are MSE and RMSE. Based on the aforementioned, let $r_1, r_2, r_3, ... , r_n$ represents the time series observations, then the $\hat{y}_i$ represents the kth predicted values, where $k \le n$. For $k \le n$, the kth error e_k is then given by $e_k = r_k - \hat{r}$.

Now,

$$MSE = \frac{1}{n} \sum_{i=1}^{n} e_k^2 \qquad (7)$$

$$RMSE = \sqrt{MSE}$$

D. *Data Description and Process Flow Diagram*

In order to perform modeling and forecasting on financial time series data, historical financial time series monthly data of twenty-three years from http://www.yahoofinance.com was extracted starting from January 1996 to August 2019. The stock indices employed are the New York Stock Exchange (NYSE) in the U.S.A and Shanghai Stock Exchange (SSE) in China. The selected stock markets are among the top ten stock markets and globally dominates in terms of market capitalization. Thus, there is a need to make a critical statistical analysis of the two countries' financial markets to see if there are impacts in bilateral trading. The extracted dataset is partitioned into training (80%) and testing (20%) datasets. The raw data is normalized using a normalization equation in which each sample value of data is divided by maximum value among all data samples. Normalization is a technique that is applied as part of data preparation for machine learning techniques. The monthly stock returns transformed into monthly log returns as follows:-

$$r_t = \log(P_t) - l \, og(P_{t-1}) \qquad (8)$$

Where, r_t is the monthly log return, while $P_t \; and \; P_{t-1}$ are the stock prices for time $t \; and \; t-1$ respectively.

Figure 2: Modeling process flow

IV. EMPIRICAL RESULTS AND DISCUSSIONS

Table I below shows log-returns summary statistics for NYSE and SSE stock indices. An upward shift of the monthly return shows a negative loss. Besides, it shows that the indices faced a negative shock. The excess kurtosis for the two indices indicates a fat tail for return distribution. The J-B test (p-value<0.05) provides strong evidence that the returns of the closing stock prices for the two indices are non-normally distributed. Based on the result the study opted for in the GARCH model the student's t innovations.

Table I: Summary Statistics

Statistics	Log return for closing Prices	
	New York Stock Index	Shanghai Stock Index
Size	284	284
Mean	0.0054	0.006063
Min	-0.22303	-0.282782
Max	0.12878	0.278057
SD	0.04656449	0.07858687
Skewness	-0.8269198	-0.1936297
Kurtosis	5.759658	4.789212
JB Statistic	122.49	39.656
JB(P-value)	< 2.2e-16	<2.447e-09

Figure 3 below shows the plot for both original and log return series for the NYSE and SSE stock indices respectively.

The plot has evidenced that for the two indices there is sharp decline and upward movements of the stock indices evidencing the existence of the volatility.
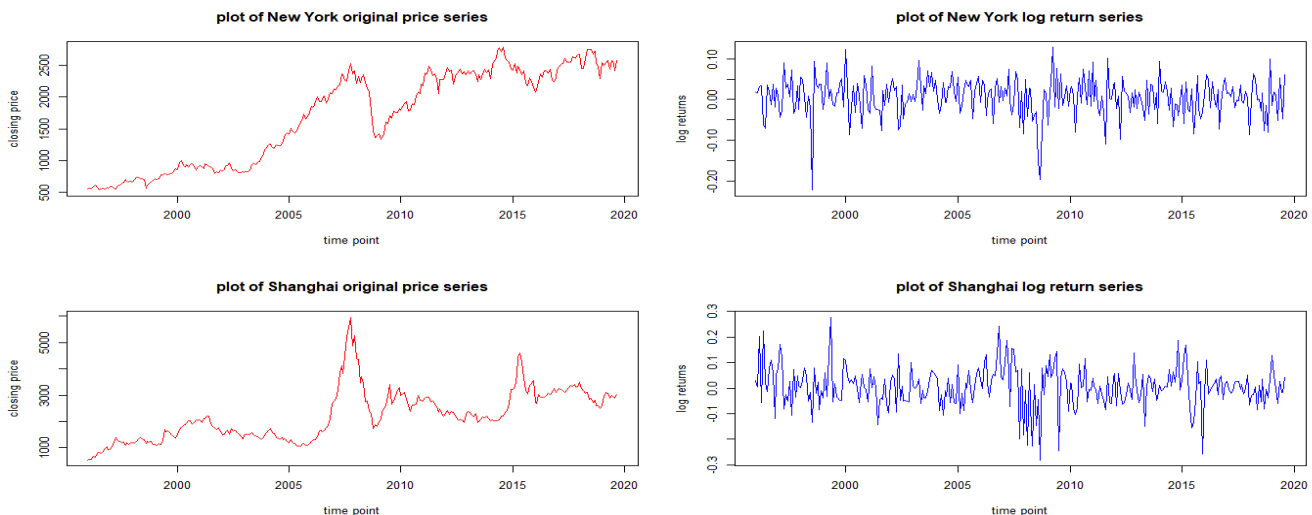

Figure 3: Plots of the Original and the return series

Table II below presents the optimal variance GARCH (1, 1) type models for the stock price return for the two stock indices. The optimal model selection was made based on the Minimum value of the SBIC. The optimal selected GARCH type model for both indices is the GJR-GARCH (1, 1) model with the student's t innovations.

Table II: SBIC Results for GARCH type models

GARCH MODEL	NYSE-SBIC	SSE-SBIC
GARCH(1,1)	-3.2678	-2.299
EGARCH(1,1)	-3.2937	-2.299
GJR-GARCH(1,1)	-3.2497	-2.2912

This results in table III below confirms the existence of the volatility in the two market indices since $\alpha + \beta + \gamma < 1$. However, the negative sign in the GJR- GARCH model implies that there exist no leverage effects.

Table III: GJR-GARCH Model Summary

Stock Index	Optimal Parameter	Estimator	p-value
NYSE	μ	0.0078	0.000649
	ω	0.00001	0.00000
	α1	0.0000	0.999636
	β1	1	0.00000
	γ1	-0.007081	0.00000
	Shape	6.35737	0.000159
	Volatility persistence	0.4964595	
SSE	μ	0.003269	0.401732
	ω	0.000391	0.05154
	α1	0.1958	0.030474
	β1	0.806456	0.00000
	γ1	-0.1321	0.08363
	Shape	7.523359	0.029511
	Volatility persistence	0.4350635	

E.   Monte Carlo Simulation of Parameter Distribution

It is important after the model identification to see the consistency estimated model parameters using the underlying density. The ugarchdistribution function enables the performance of the Monte Carlo experiment. This method enables the simulation and fitting multiple times a model at different sample (window) sizes. In this paper, we tried to use 1000, 2000, 3000, 4000 and 5000 sample (window) sizes to test the consistency of the GJR-GARCH model parameters. The results at different windows were approximately the same as the true coefficients of the model. This implies that the Monte Carlo simulation has reflected the true parameters of the fitted GJR-GARCH model. Table IV below shows the results of the true versus Monte Carlo simulated GJR-GARCH model parameters.

Table IV: True Vs Monte Carlo Simulation parameters

Stock Index	Coefficients	μ	ω	α1	β1	γ1	Shape
NYSE	True-Coefficient	0.0078431	9.56E-06	8.83E-09	1	-0.00708	6.3574
	Window-1000	0.007996	1.2E-05	0.001658	0.99891	-0.00986	6.7512
	Window-2000	0.0078261	8.96E-06	0.001327	0.99946	-0.00819	6.4883
	Window-3000	0.0078697	8.87E-06	0.001235	0.99942	-0.0079	6.4075
	window-4000	0.0077843	8.19E-06	0.001304	0.99924	-0.00716	6.4078
	window-5000	0.0078306	8.18E-06	0.001154	0.99932	-0.00699	6.3555
SSE	True-Coefficient	0.0032693	0.000391	0.19577	0.80646	-0.1322	7.5234
	Window-1000	0.0034506	0.000424	0.18645	0.80548	-0.12654	8.4503
	Window-2000	0.0032778	0.000413	0.19803	0.80083	-0.13494	7.8605
	Window-3000	0.0030309	0.000416	0.19736	0.80066	-0.13335	7.6074
	window-4000	0.0033828	0.000404	0.19024	0.80721	-0.1296	7.6037
	window-5000	0.0031951	0.000409	0.19679	0.80305	-0.13201	7.5827

F.   Stock Market Data Partitioning into Training and Testing Sets

Table V below, two composite stock data were partitioned into 227(80%) training and 57(20%) testing set respectively. The MSE for both the train and test data was obtained by getting MSE between fitted and actual values and the forecast and the test values respectively. The MSE for both training and testing data is acceptable.

Table V: The MSE for the Training and Testing data

Forecasting Method	Stock Index	Layers		MSE
MLP-NN	NYSE	Number of inputs	10	Total Train=0.0011
		Number of hidden layers	1	
		Number of Neurons	5	Total Test=0.0023
		Number of outputs layer	1	
	SSE	Number of inputslayers	8	Total Train =0.0030
		Number of hidden layers	1	
		Number of Neurons	5	Total Test =0.0188
		Number of the output layer	1	
ELM	NYSE	Number of input layers	10	Total Train =0.0029
		Number of hidden layers	1	
		Number of Neurons	100	Total Test =0.0020
		Number of the output layer	1	
	SSE	Number of input layers	8	Total Train =0.0072
		Number of hidden layers	1	
		Number of Neurons	100	Total Test =0.0194
		Number of the output layer	1	

G. Modeling and Forecasting Comparisons

The forecasting comparison of different models was used in this paper. The machine learning MLP-NN and ELM and statistical GARCH model performance were compared. Based on the previous findings, the combined EGARCH and ANNs hybrid model was found to provide the best forecasting of stock market volatility[21]. In addition, the ANN-GJR-GARCH model found to outperform other GARCH type models in volatility forecasting[22]. For the case of the two stock indices, the RMSE was used in the forecasting performance assessment. In the two stock indices, the MLP-NN model performed the best compared to ELM and GJR-GARCH models. Table VI below evidenced MLP-NN has the minimum RMSE in both NYSE and SSE stock indices.

Table VI1: RMSE for the two Stock Indices

Stock Index	Forecasting Method	RMSE
NYSE	MLP-NN	0.035741
	ELM	0.051179
	GJR-GARCH	0.041942
SSE	MLP-NN	0.035854
	ELM	0.051171
	GJR-GARCH	0.066964

Figure 4 below presents the MLP-NN with 9 input nodes, 1 hidden layer with 5 neurons and 1 output layer. Likewise, figure 5 shows the forecasting two years (24 months) for the SSE stock index from September 2019 to September 2021. The forecasting results show an upward shift in the NYSE stock index in the next two years.
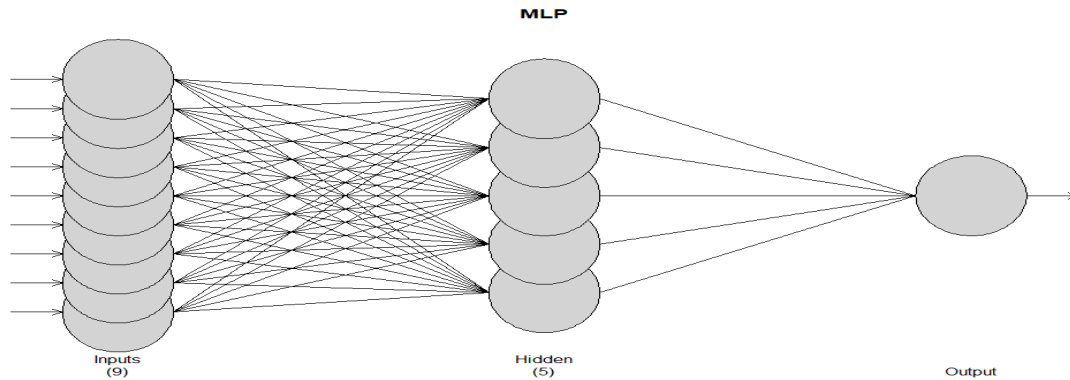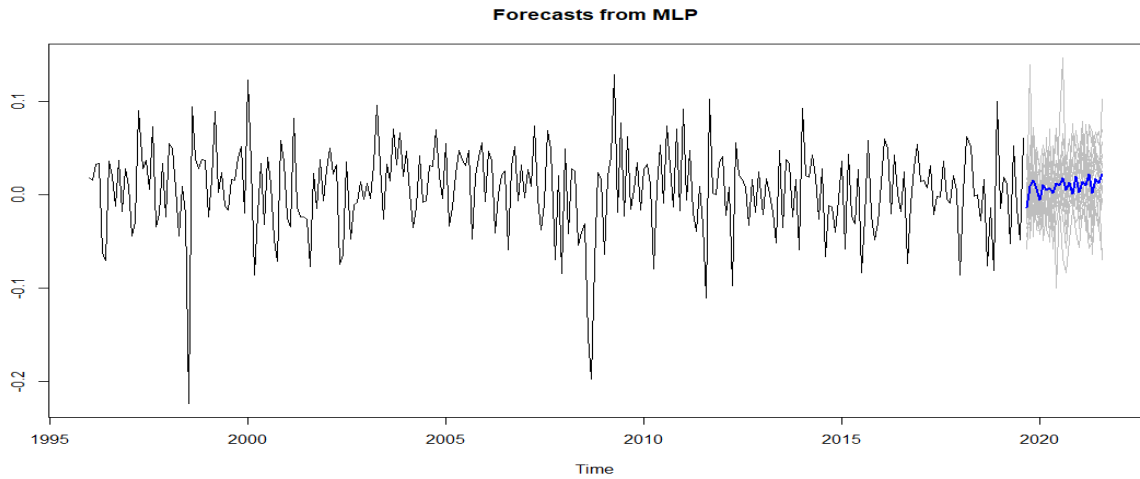

Figure 4: MLP-NN Plot for NYSE Index

Figure 5: MLP-NN Forecasting for NYSE Index

Figure 6 below presents the MLP-NN with 9 input nodes, 1 hidden layer with 5 neurons and 1 output layer. Figure 7 shows the forecasting of two years (24 months) for the SSE stock index from September 2019 to September 2021. The forecasting results show a stable stock index for SSE in the next two years.
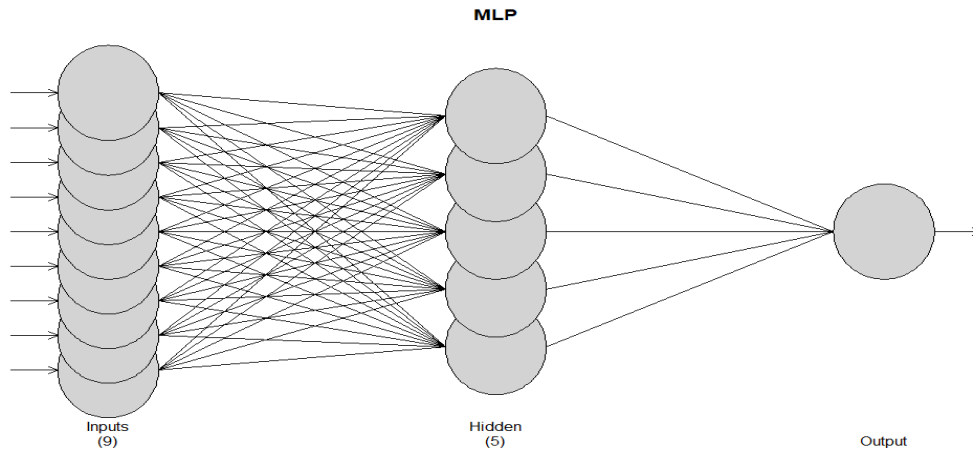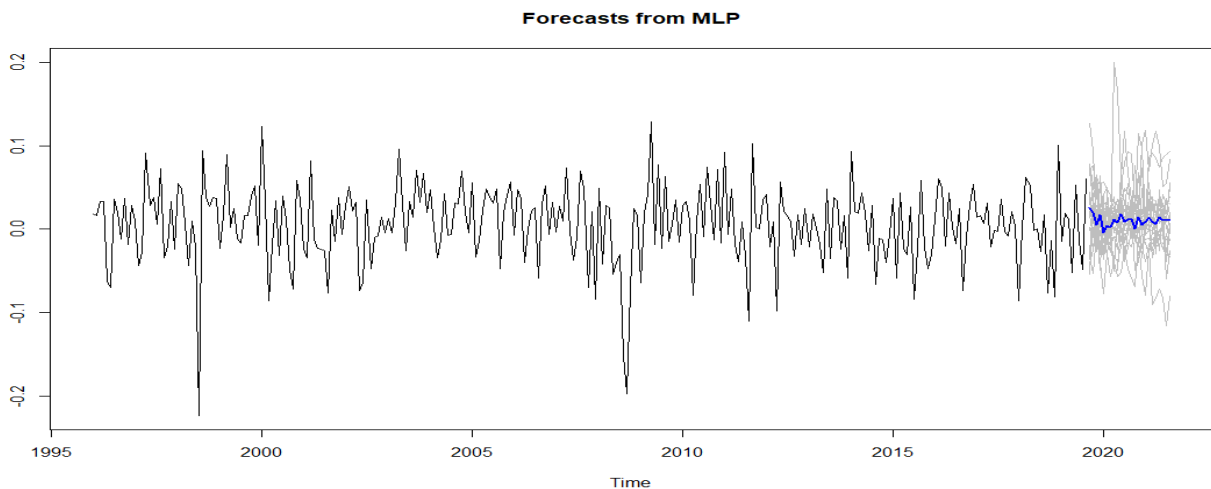

Figure 6: MLP-NN plot for SSE Index

Figure 7: MLP-NN Forecasting for SSE Index

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V. CONCLUSION AND RECOMMENDATIONS

The purpose of the paper was to come up with the best GARCH type model and then compare it with the Machine Learning models. The GJR-GARCH Model was found to outperform other GARCH models in modeling NYSE and SSE composite monthly stock returns. The Monte Carlo simulation is done at 1,000, 2,000, 3,000, 4,000 and 5,000 finite sample (window) sizes have shown consistency in the estimated GJR-GARCH model parameters. Then, the modeling and forecasting comparison was made between GJR-GARCH, MLP-NN, and ELM. The study found the MLP-NN model to be the best performing model in both estimating and forecasting volatility for the NYSE and SSE composite stock market indices. Moreover, the forecasting results for the two stock markets for the next two years have shown price volatility in NYSE which is found in the U.S.A compared to SSE which in China. This has great implications in the economic stability and competition of these global leading stock markets and countries in terms of economy. Further research should focus on the formulation of the hybrid model that combines machine learning and GARCH type models in forecasting stock market volatility.

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