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# Artificial Neural Network Analysis in Finance: Evidence using a Literature Review

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**ABSTRACT**
**Machine language is a sequence of algorithm assign to do a particular task. Neural Networking is inspired by the operation of neurons in the human brain and machine language made possible to use neural networking in data analysis. It identifies a pattern of the desired output by a set of input data. Due to the advancement of technology and its immense benefits, Neutral networking has been a popular tool in the fields of economics and finance for past decades. Instead of traditional methods accurate financial forecasting methods are invented through this technology. The usage of linear as well as the nonlinear transformation in neural networking shows the flexibility in this regard. This paper discusses the utilization of neural networking in the field of Economics and Finance by using the past literature. After providing a brief history on neural networking the paper elaborate simply on how neural network system works. Then, it includes review of relevant past literature on the topic. Finally, the paper discusses some of the limitation of using neural networking. According to the findings of the study neural networking is a powerful tool for financial forecasting which can overpower the advantages of traditional methods.**

**Keywords--** Machine Language, Neural networking, Financial Forecasting

## INTRODUCTION

Machine learning is a set of computer algorithms that are assigned to achieve a specific objective and able to improve automatically using data. It is a branch of Artificial Intelligence that receives an immense amount of popularity due to the advanced technology and time-saving power. Rapid evaluation of digital platforms has made evolve machine learning as the most powerful tool in statistical analysis. Mainly, the capability of data preparation, automation, and iterative processes of machine learning have captured the attention of researchers. In the field of economics and finance, different Machine learning techniques are used to build forecasting models. Further, Hoang & Wiegratz (2020) identified three main application categories of machine learning in financial economics: construction of superior and novel measures, reduction of prediction error in economic prediction problems, and extension of the existing econometric toolset [1]. Neural networking is one of the machine learning techniques gaining more and more popularity as a statistical tool.

Neural Networks can be used to identify a pattern of the desired output by a set of input data. Neural Networks are inspired by the system of neurons that operates in the human brain. This method identifies numerical patterns of data by clustering according to the homogenous characteristics and produces output for new data. It identifies the patterns of the input data set and then predicts the output of a new set of similar data. They are used in a variety of applications in financial services such as forecasting. Due to the availability of open-source programming languages like R and Python, neural networking is becoming a widely used method among researchers. In Neural Networks, there are no any specific rules to begin with that define what to expect from the input data. This is a very useful method when handling complex data leading to nonlinear models.

### History of Neural Networking

The first phase of the Neural Network was initiated in 1943 by Warren McCulloch, a neurophysiologist, and Walter Pitts, a young mathematician. They showed how neurons might work using an electrical circuit. In 1949, Donald Hebb further elaborated on this concept in his book, The Organization of Behavior. In this book, he pointed out that neural pathways strengthen every time they are used and will help to work out complex processes of the brain. With the evolvement of computer systems in the 1950s, researchers tried to model and identify the behavior of Neural Network concepts with the use of computers. As a result, Nathanial Rochester took the first step to simulate a Neural Network. Although Nathanial's first attempts failed with the development of computer systems, he was able to lay some initiatives for neural research in computing. In 1958 Frank Rosenbla proposed the idea of Perceptron which is a system with a simple input-output relationship, modeled on a neuron, and it was an extension of the study done by Warren McCulloch and Walter Pitts [2]. Perceptron was able to calculate the weights of successively passed inputs while minimizing the difference between anticipated and actual output. But still, perceptron had some limitations such as handling linearly separable classes only, making the simple. Marvin Minsky argued that to evaluate the accurate values of the weights of the neurons spread across layers based on the final output would take an infinite number of iterations and a very long time to compute. In 1959, Bernard Widrow and Marcian developed models namely ADALINE and MADALINE. MADALINE which was an adaptive filter that eliminates echoes on phone lines was the first Neural Network to be applied to a real-world problem [3]. Due to the slow rate of advancement in technology during this time researchers could not improvise the importance of the Neural Network.

In 1982, John Hopfield presented a paper to the National Academy of Sciences which showed that the studies of the human brain could be helpful in creating useful devices [4]. This was a turning point and was able to reopen the interest in the concept of Neural Networks. Several parties invested in conducting researches in this field. In 1985 American Institute of Physics, established an annual meeting named "Neural Networks in Computing" and in 1987 the first International Conference on Neural Networks was organized by the Institute of Electrical and Electronics Engineers (IEEE). With these activities, numerous people were aware about Neural Networks and computer technology reached a peak of its advancement during this period. Around 1990s Neural Network was back in track compared to a decade back.

Today, the Neural Network is used everywhere and with the vast development of computer systems, it is further expanding. With the development of Artificial Intelligence (AI) Neural Network is growing more towards the commercial applications.

### How Neural Network works

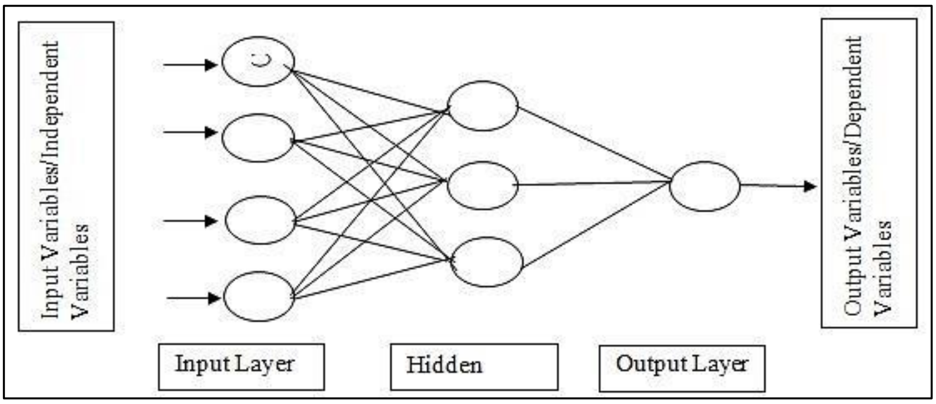


***Figure 1:*** *Neural Network System*

The process of a Neural Network can be simply described as following. The Neural Network is made up of layers of neurons which are the core processing unit of the network. As shown in Figure 01, at the beginning, the input layer receives the input of the data set and at the end, the output layer predicts the final output. In between the two layers, there is a hidden layer that performs the computational part required for the network. The number of nodes in the hidden layer will be unique to each Neural Network. The researchers are still in a debate about choosing the best method for this purpose. For example, Hwang (1988) found that the number of neurons in a single hidden layer should be equal to the number of distinct training patterns [5]. Arai, (1989) suggested that N-1 number of neurons in a single hidden layer is essential for N number of inputs [6]. Each data point is fed as input to each neuron in the first layer and the neurons of a particular layer are connected to the neurons of the next layer through channels.

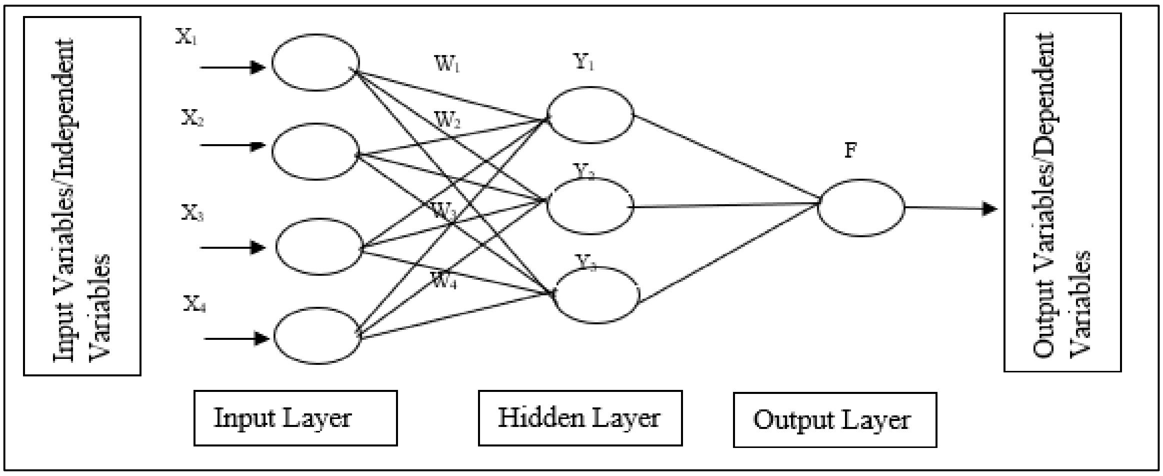


***Figure 2:*** *Hidden layer of Neural Network system*

As shown in Figure 02, each of these channels has assigned a numerical value which is known as weight ($W_i$). The given inputs are multiplied by the corresponding weights and the weighted sum of the corresponding connected neuron is send as input for the next layer ($W_1X_1+W_2X_2+W_3X_3+W_4X_4$).

Each of the neurons in the hidden layer is associated with a numerical value and the input sum from previous layer is added to this value.

Net input to a node (sum): $Y_i + \sum_j w_{ij} \times Output_j$

Here $w_{ij}$ is the weights connecting neuron j to neuron i and $Output_j$ is the output from node j, and $Y_i$ is a threshold for neuron i. The threshold is the input to a neuron in the absence of any other input [7]. Inputs and generated outputs in neural networking are in the form of vectors and hence net input is the dot product of the input and weight vectors.
Then, the final sum passes through a function called the Activation function which comprises of logical expressions, F(sum). The results of the Activation function decide whether a particular neuron will be activated or not. Usually, the Activation function has a bounded range, often 0 to 1 or –1 to 1. Only the activated neurons will be transmitting the data to the next layer through the channels. If a network comprises of a linear transfer function, then multiple layers can be represented as a single-layer network. In the study of Harrington (1993), he mentioned that nonlinear transfer functions let multiple layers to deliver newmodeling abilities [8]. Further Stern, (1996) revealed that most of the Activation functions used in neural networking are monotonic functions [9]. Some of the common Activation functions are as follows.

$$F(x) = x, \quad F(x) = tanhx, \quad F(x) = xe^{\frac{-x^2}{2}}, \quad F(x) = \frac{1}{1+e^{-x}}$$

The procedure will continue, and data will transmit forward until the last layer and this is called Forward Propagation. At the last layer or the output layer, the neurons with the highest value will determine the output and those values are probability values.

To identify the correct predictions, the network will be subjected to a training process. In machine learning, this is known as supervised learning. In this process input and its corresponding output is inserted. That is a set of inputs with known results are inserted into the process. Then the predicted output will be compared against the actual output and prediction error will be calculated. The numerical value of the calculated error will give both direction and the magnitude of the error. This information is transferred backward through the network to adjust the weights according to the error and this is called Backward Propagation. In this process, the main objective is to minimize the squared error. If the error is not minimized the process will continue until it achieves its objective. The forward and backward process is iteratively performed with multiple inputs until the network can perform the predictions correctly and which is the end of the training process.

## NEURAL NETWORK IN THE FIELD OF FINANCE AND ECONOMICS

Most of the statistical analysis, parametric and nonparametric regression, linear and nonlinear models can be easily produced using neural networking. The statistical models generated using neural networking have more predictive power compared to general methods. Further neural networking can handle the nonlinear transformations and discontinuations of data very effectively. Neural networking becoming a very popular method among economists. Numerous researches have been conducted in the field of finance and economics using Neural Network due to less time allocated for the whole process. From a very broad perspective, Artificial Neural Networks (ANN) can be used for financial prediction in one of the three ways; It can be provided with inputs, which enable it to find rules relating the current state of the system being predicted to future states, It can have a window of inputs describing a fixed set of recent past states and relate those to future states and It can be designed with an internal state to enable it to learn the relationship of an indefinitely large set of past inputs to future states, which can be accomplished via recurrent connections [10]. Moreover, neural networking can be used as a semiparametric method in econometrics due to the incorporation of nonparametric methods and the interpretability of parameters of parametric methods [11]. Financial researchers use neural networking in various analyses such as risk classification [12], bankruptcy, and share price prediction [13]. Further, the use of neural networking has a big potential as it represents the modern tool of using ICT in business with many advantages [14]. Qi (1996) suggests that the abundance of high-quality financial data and the paucity of testable financial models make the Neural Network more attractive in the financial area [15]. Since Neural Networks can obtain useful information from a large set of data, it is very useful for predicting world stock markets [16]. Neural network systems achieve a higher rate of success in resolving particular financial problems and some of these applications of neural networking have already resulted in dramatic increases in productivity [17].

The study of White (1988) applied Neural Network modeling to identify and interpret nonlinear symmetries in asset price movements [18]. A day rate of return to holding IBM common stock with a sample of 1000 days which was categorized as 500 days before and after the training period utilized in the study to evaluate the network. The investigations revealed that according to time-series plots simple networks are capable of extremely rich dynamic behavior. Further, it was found that although the least squares method (equivalently, back-propagation) is adequate for testing the efficient markets hypothesis, it is not the best to create a network for market trading purposes if interest is attached. The authors suggested to train using profit and loss from generated trades rather than the squared forecast error to overcome this problem. In general, this study concluded that neural networking incorporated with high technology is a very powerful tool in econometrics.

Schierholt & Dagli (1996) predicted the behavior of S&P 500 Index using different Neural Network algorithms [19]. Multilayer perceptron algorithm and a probabilistic Neural Network were applied in the study and the results revealed that the probabilistic

Neural Network performed slightly better than the multi-layer perceptron in forecasting.

Yoon & Swales (1991) investigated the predicting power of the Neural Network method and multivariate analytical techniques using two separate sets of data [20]. It was revealed that the Neural Network method can learn a function that maps input to output and encoding it in the magnitudes of the weights in the network's connection. Further, the number of hidden units in the network contributed to its viability and by increasing the number of hidden units it can increase the performance up to a certain point. The comparison results between the Neural Network method and multivariate analytical techniques discovered that the Neural Network approach can significantly improve the predictability of stock price performance.

Kryzanowski at el., (1993) conducted a study to determine the accuracy of neural networking in forecasting future return performance as positive or negative, or as negative, neutral, or positive [21]. The study used company's stock return one year forward and the most recent four years of financial data for the company and its industry, also data for seven macroeconomic variables. The model of the study correctly categorizes 72% of the positive/negative returns.

Tan (1997) compared some ANN models with AR models in predicting exchange rate. The results revealed that ANN models provide better results by improving the robustness and the profitability of trading systems relative to those based on AR models. Also, it was revealed that the best ANN model in the study was a network with one hidden layer [22].

Moshiri & Cameron (2000) compared the performance of Back Propagation Artificial Neural Network (BPN) models with the traditional econometric approaches for forecasting the inflation rate with the use of a sample of twenty-one years with 252 observations for the estimation period and a sample of four years with 48 observations for the forecasting period [23]. Traditional econometric models used for the comparison are, an ARIMA model, a vector autoregressive model, and a Bayesian vector autoregression model. Root mean squared errors and mean absolute errors are used to compare the quality of forecasts. The results revealed that the performance of the BPN and econometric models are almost the same in one- and three-periods-ahead in dynamic forecasting, but BPN outperforms all other models in one-period-ahead and twelve-periods-ahead in dynamic forecasting.

Jasic & Wood (2004) investigated the statistical significance and potential profitability of one-step-ahead forecasts of stock market index returns provided by univariate Neural Network models by using daily returns of S&P 500, DAX, TOPIX, and FTSE stock market indices over the period 1965–1999 [24]. In the study single hidden layer models are constructed for input units with a varying number of nodes, according to accepted rules of thumb. The results showed the significant predictability power of stock market data using non-linear modeling. Further, they discussed that the method adopted in the study show predictability, with straightforward methods involving no subjective elements. They also suggest that the comparative advantage of Neural Network models could also be discovered further by expanding the range of technical analysis models used for comparison.

Zhang at el., (2004) used a multi-layer Back-Propagation (BP) Neural Network, in financial data mining. The study developed a Neural Network forecasting model and an intelligent mining system with aim of forecasting the buying and selling signs according to the prediction of future trends to the stock market and providing decision-making for stock investors [25]. The study concluded that applying Neural Networks to forecast financial time series is beneficial for investors.

Dutta at el., (2006) modeled Indian stock market (price index) data using ANN. The study developed two networks with three hidden layers and used weekly closing values as inputs [26]. Root mean square error and mean absolute error was used to evaluate the performance of the networks. The comparison results using RMSE, and MAE has revealed that one of the models is quite estimable than the other. The study concluded that building ANN models in predicting the security prices give higher levels of accuracy, however, the error increases gradually during the validation period.

The study of Huang, & Nakamori (2007) compared the performance of Neural Network models, for the prediction of foreign exchange rates, stock market index, and economic growth [27]. Multi-Layer Perceptron (MLP), Recurrent Neural Networks (RNNs), General Regression Neural Networks (GRNNs), Modular, Learning Vector Quantization (LVQ), Radial Basis Function Networks (RBFNs), fuzzy ARTMAP network were the types of networks the study compared. The study revealed that most Neural Network inputs for exchange rate prediction are univariate, while for stock market index prices and economic growth predictions are multivariate. Furthermore, nonlinear combining forecasting by Neural Networks provides accurate results, and the performance of Neural Networks can be improved by integrating with other technologies.

Li & Ma (2010) conducted a survey with the aim of finding the use of ANN in forecasting financial market prices [10]. The study used a non-linear Neural Network model to forecast stock prices and option pricing and further emphases the application of neural networking in predicting exchange rates. The results of the study reveal the following facts: ANN has the ability to extract useful information from a large set of data. Therefore, ANN plays a very important role in stock market prediction, ANNs are significantly more accurate than other competitive models and algorithms such as multiple linear regression analysis models for stock market prediction. In general, it concluded that ANN is a valuable forecast tool in financial economics due to its learning, generalization, and nonlinear behavior properties.

Brédart (2014) developed a model that predicts bankruptcy using three financial ratios that are simple and easily available incorporating Neural Network analysis [28]. The findings of the study indicated that the Neural Network methodology based on three financial ratios is simple and easily available as explanatory variables show a good classification rate of more or less 80%.

Falat & Pancikova (2015) used Radial Basis Neural Network in the process of forecasting financial data [14]. Radial Basis Function (RBF) Neural Network is an upgrade of multilayer perceptron network which is a real-valued function whose values depend only on the distance from the origin or some other point, called a center. In the study, the authors combined the standard algorithm for adapting weights of the Neural Network with K-means clustering which is an unsupervised algorithm. All the methods used in the study are compared with the standard approach using real economic data and the results implied that comparatively ANN models showed a high accuracy than the standard models such as regression models. Also, it was concluded that this approach has many other advantages such as flexibility, automatization as well.

Riyazahmed (2021) conducted a descriptive systematic review to find the applications of Neural Networks in the field of finance [29]. The results revealed that about 53% of the collected research studies applied Neural Networks in investment prediction, 20% in credit evaluation, 17% in financial distress topics, and only about 10% found on other financial aspects.

Torres-Pruñonosa at el., (2021) used ANNs, Quantile Regressions (QRs), and Semi-Log Regressions (SLRs) for a comparison between different real estate valuation methods in Catalonia from 1994 to 2013 [30]. The results of the study revealed that the ANNs and SLRs obtained similar and better performances than the QRs and that the SLRs performed better when the datasets were smaller. Further, QRs were not found to be an alternative to ANNs, and the study could not be validated that ANNs performed better than SLRs when assessing properties in Catalonia.

Neural networking vs GARCH type models Guresen at el., (2011) evaluated the effectiveness of Neural Network models in stock-market predictions by using real exchange daily rate values of the NASDAQ Stock Exchange index [31]. The models used in the study were Multi-Layer Perceptron (MLP), Dynamic Artificial Neural Network (DAN2), and the hybrid Neural Networks which use in Generalized Autoregressive Conditional Heteroscedasticity (GARCH) to extract new input variables. According to the findings of the study of the classical Neural Network model, MLP outperforms DAN2 and GARCH-MLP with a little difference. Further, the study revealed that the MLP model accurately forecasted the first movement as down and hence MLP is a powerful tool for forecasting stock movements.

Liu & So (2020) included a GARCH model into an ANN for financial volatility modeling and mean absolute errors are used to evaluate the performance of the models [32]. The findings revealed that the ANN model outperformed the standard GARCH (1,1) model with standardized Student's t distribution. Further, the study identified that proposed models are easy to implement because proposed models can be run in Tensorflow, a Python package that is an open-source software.

Arnerić at el., (2014) used returns of the CROBEX index daily closing prices for the period of January 2011 to September 2014 to construct a parsimonious Neural Network model, which can capture the nonlinear relationship between past return and conditional variance [11]. The study used Jordan Neural Network (JNN) to achieve this objective. The findings revealed that the JNN (1,1,1) model performs better compared to the standard GARCH (1,1) model.

The study of Yim (2002) used Brazilian daily index returns to compare neural networking model with a GARCH model and a Structural Time Series model (STS) [33]. RMSE, MAE, and the Chong and Hendry encompassing test were used to evaluate the predictability power of the models. The results discovered that Neural Networks are superior to GARCH models and STS models. However, volatility derived from the GARCH model is useful as an input to a Neural Network.

Matías at el., (2010) conducted a study to developed new algorithms based on GARCH models, Neural Networks, and boosting techniques and evaluated their performances using simulated data over the S&P 500 Index returns series [34]. The investigation revealed that the proposed new algorithm incorporated neural networking performed better than the GARCH models.

Lu at el., (2016) investigated the performance of hybrid ANN model and GARCH-type models using Chinese energy index in Shanghai Stock Exchange from 31st of December 2013 to 10th of March 2016 for a total of 534 observations [35]. The study developed two types of models: Type 1 built by inputting the outcome of the preferred GARCH-type models into ANN, called ANN-GARCH model, and Type 2 built by studying the output layer of ANN as a variable of GARCH-type models, called the GARCH-ANN model. The forecasting performance is evaluated using RMSE and the results revealed that the EGARCH-ANN model performs better than other models.

Mademlis and Dritsakis (2021) Studied the weekly prices of the Italian stock market index, namely, FTSE MIB from January 7, 1998, to January 6, 2016, to evaluate the forecasting power of asymmetric GARCH model and a Neural Network [36]. The findings revealed that the Neural Network model's predicting power is better than the EGARCH model.

Lahmiri (2017) built a method to predict the historical volatility of currency exchange rates using ANN. The performance of the construction was evaluated using US/Canada and US/Euro exchange rates volatilities and the results revealed that hybrid GARCH and EGARCH which incorporated neural networking performed better in terms of mean absolute error, mean of squared errors, and Theil's inequality coefficient. Further, it was concluded that because of the simplicity and effectiveness of this new approach, it makes the prediction of US currency volatility easier [37].

## LIMITATIONS OF NEURAL NETWORK

Even though neural networking incorporates high technology and advanced algorithms still it contains some limitations compared to the traditional methods.

Although increasing the number of hidden units in a Neural Network result in a better performance up to a certain point, adding more and more hidden units to the system may generate mislead outputs causing overfitting [18, 20] Further, Tan (1997) revealed that ANNs are not transparent and hence interpreting them is difficult [22].

Zhang at el., (2004) revealed that there are many factors that impact the performance of Neural Networks [25]. These factors include the processing of data, the size of the input and hidden layers, the learning rate, the momentum factor, the initial weight, and the error function. Hence when developing models using Neural Network, these factors should be given close attention. Since GARCH models are more parsimonious they contain a smaller number of parameters than neural networking models. This will make GARCH easier for forecasting [38].

## CONCLUSION

Neural Network which is inspired by the structure of the human brain is rapidly gaining popularity due to the incorporation of the newest technology. This paper mainly focused on the use of neural networking in Finance and Economics. After analyzing all the past literature, it can be concluded that neural networking is a powerful tool for financial forecasting. Further neural networking outperforms traditional forecasting such as GARCH. But combining Neural Networks with GARCH and developing hybrid models also have significant predicting power.

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