A Meta-Analysis of the Application of Artificial Neural Networks in Accounting and Finance

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Abstract

Artificial Neural Networks (ANNs) have emerged as a robust technique of forecasting and prediction in almost every part of the business. This study explores the development of ANNs over a period of time and provides an extensive and exhaustive literature review on the applications of ANN in various fields of accounting and finance, such as stock market prediction, bankruptcy, and many others. The findings of the study support the superiority of the ANN model over conventional statistical techniques in prediction, such as Linear Discriminant Analysis (LDA), Logit Model, etc. However, determining the optimal architecture of an ANN model is a time consuming and difficult process. The novelty of this study lies in the fact that there is a dearth of literature on applications of ANNs in some sub-areas of accounting and finance, namely time series forecasting, specifically in foreign exchange and commodity markets. Thus, ANN application can be explored in these sub-areas of accounting and finance.

Keywords: *Neural Networks (NNs), Artificial Neural Networks, Meta-Analysis, Bankruptcy, Stock Market Prediction.*

1. Introduction

"Artificial Neural Network is a system of hardware and software patterned after the operation of neurons in the human brain. It builds a relationship in the form of data through a process that mimics the way a human brain operates." Artificial Neural Networks are dynamic in nature as they can adapt to changes in output so that they provide the best possible result without changing the input nodes. ANNs have shown huge potential in the field of finance where they are used for various purposes to enhance the productivity of the business in the global arena. ANN follows a series of algorithms that helps in finding the underlying relationship between the output and input variables. ANN consists of several neurons or nodes that are operated in parallel and arranged in layers or tiers. The layers are highly connected as each node from the tier N is connected to subsequent tiers N+1. The first layer receives raw input and transfers it to the preceding layer to generate the desired output, and the middle layer is called the hidden layer, which is responsible for connecting the first layer, i.e., the input layer and the last layer called the output layer. However, the number of nodes and layers depends on the desired accuracy to be achieved and also the complexity of the problem. Also, there can be a series of nodes in the output layer which forms an image in the readable format. In ANN, each node carries a weight that entirely depends on values that contribute to getting the correct answers. In other words, nodes that contribute to getting the desired results are awarded higher weights in comparison to nodes that don't. Initially, nodes are flooded with huge chunks of data and output is told to the network in advance. With advantages also come drawbacks and ANN is the one that is unaffected by this curse as the assumptions people make that causes bias during training has evolved as the biggest threat for the practitioners. If the data feeding is not neutral – the machine propagates bias.

Many scientists, practitioners and academicians have developed models based on ANNs in the past. The first computational model of Artificial Neural Networks, popularly called threshold logic which was based on mathematics and algorithms, was developed by Warren McCulloch and Walter Pitts in 1943. It splits the ANNs research into two approaches. The first approach was related to the biological process in the human brain, and the second approach was related to the application of ANNs. Later, Minsky and Papert (1969) discovered two critical issues with the Artificial Neural Network technique. The first one was the ability of the machine to solve complex problems, and the second was the incapability of the computers to run large ANN models efficiently. This brought a slowdown in research on ANNs till the machines got fast processing circuit boards.

Due to its ability to learn and model non-linear relationships, its usage has gained popularity in different fields of business. They also allow users to build a strong and reliable model that can help in predicting future events. Nowadays, it is being used to check the reliability of a business plan, recognition of human faces, speech, characters and so on. Also, it is widely used in various areas of finance such as prediction of stocks, evaluation of loan application, analyzing the credit- worthiness of customers and many more. However, there is a dearth of review articles that combines the various applications of the ANN model in accounting and finance. Moreover, the authors believe that there is a great demand for comprehensive review articles that combine the various methods and current studies. Therefore, this study analyzes the various applications of the ANN model in different fields of accounting and finance.

This paper presents a review of articles comparing numerous models of ANN and conventional statistical techniques. Section 1 represents the introduction of the study, and section 2 consists of relevant literature in different areas of accounting and finance. The results of the study have been presented and summarized in section 3; section 4 deals with the future scope for research, and the last section deals with the conclusion part of the study discussing certain issues pertaining to ANN models.

2. A Review of Literature

Over the past few years, the usage of ANN has gained popularity due to its distinct ability to detect the underlying relationship between different sets of data. However, there are various factors that determine the accuracy of ANNs, which include the choice of input variables, architecture selected for a specified problem, training pattern of ANNs, etc. Thus, it becomes significantly important to study these factors before building an Artificial Neural Network. Also, various studies conclude that ANNs have provided a better statistical technique in forecasting when compared with other conventional prediction models. However, some studies also reveal that traditional statistical tools have outperformed ANNs in forecasting. Thus, it becomes important to identify the key areas where ANNs have shown good potential. This section provides a brief overview of applications of ANN in various areas of accounting and finance, namely bankruptcy prediction, stock market prediction and other applications.

2.1. Bankruptcy Prediction

Much of the research has been done on bankruptcy prediction as detection of accounting frauds, and bankruptcy is an important measure to evaluate a firm's performance. In the study of Odom et al. (1990), an analysis was performed on ratios using both discriminant and artificial neural network techniques. The authors have used the predictive abilities of both the models and the results show that neural networks might apply to this problem. Salchenberger et al. (1992) made a comparative analysis between a logit and ANN model, and to reduce the dimensionality of the model; the authors employed stepwise regression on twenty-nine variables resulting in five significant variables. The findings of the study reveal the ANN model has outperformed the logit model in terms of forecasting bankruptcy. Furthermore, the authors reported a reduction in type I and an increase in Type II error.

Tam and Kiang (1992) introduced a neural network approach to perform Linear Discriminant Analysis (LDA). They compared the performance of the ANN technique with linear classifier, logistic regression, k-Nearest Neighbour and ID3. The results show that ANN is a promising technique having the ability to outperform other traditional statistical models, especially in evaluating bank conditions. However, there are certain limitations too that includes limited interpretation ability of weights and computation time etc. The authors have also quoted that it is necessary to test the on-line capabilities before the full potential of ANNs is asserted.

One year later, Fletcher and Goss (1993) stated that ANN provides a better and accurate view of the given data. The author has used two methods to ascertain the firm's performance and stated that ANNs are more statistically accurate and viable than logit function as it has less variance and lowers forecasting risk as determined by the coefficient of variation. However, both methods failed to predict the performance of the firms implying the presence of missing explanatory variables in the model. After one year, Wilson and Sharda (1994) explained that the ANNs are better at forecasting the bankruptcy of firms in comparison to the traditional discriminant model. The author used five variables and achieved 97% accuracy. The study argued that the number of variables has a direct relation with the accuracy of NNs, i.e. larger the number of variables higher will be the accuracy. However, NNs failed to predict correctly in the case of non-bankrupt firms due to limitations in the data set, methodology, and training. Still, when NNs were provided with balanced data sets, they outperformed discriminant analysis in forecasting non-bankrupt firms.

Later, in the same year, Fanning and Cogger (1994) determined two basic interpretations, ANNs should be viewed as a potential competitor, especially in the area of predicting financial distress of the firms and- ANNs can outperform other existing models that can be used in prediction. ANNs can be capitalized in the arena of forecasting as they are capable of exploring the underlying relationship between different data sets. The authors quoted that NNs have good potential that can be used in several other areas of business. Yang et al. (1999) examined four different methods to predict bankruptcy using financial ratios of the U.S. oil industry. Fisher Discriminant Analysis, back-propagation NN and probabilistic NN with and without patterns were used to determine the bankruptcy of firms, particularly in the oil industry, using deflated and non-deflated data. The authors quoted that the back-propagation NN model managed to achieve the highest accuracy using non-deflated data and the possible reason inferred was it predicted non-bankruptcy only. Another important finding of the study was that the discriminant analysis technique obtained the best results when using deflated data sets in both bankrupt and non-bankrupt firms.

Further, Zhang et al. (1999) explained that ANN techniques are superior to traditional statistical methods of prediction. In his study, the authors used the ANN technique to predict the bankruptcy of firms and also quoted that a better understanding of causes can substantially impact the financial and managerial decision-making process. The findings of the study reveal that ANN is the only known model that makes use of posterior probability to determine the underlying relationship of the unknown population. The study used a cross-validation technique to verify the robustness of neural classifiers, and the results reveal that ANNs are quite robust. The study also compared logistic regression with the ANN technique for classification purpose, and the results were very encouraging as ANNs were significantly superior to logistic regression in determining the classification rate of the unknown population.

Charalambous et al. (2000) proved that ANNs show superior results in comparison to traditional methods of prediction in the current scenario. However, the author also argued that the reliability of the model majorly depends on the complexity of the problem and variables used, but researchers can apply the ANNs to their problems to find whether they indeed provide better results than commonly used statistical methods or not. Atiya (2001) explained that ANNs are better techniques, especially in predicting stock prices. However, the author also said that improvements must be made by way of better training methods, inputs, and architecture. The study showed this by improving the inputs resulting in improved performance of ANNs. Two years later, Lin et al. (2003) stated that Fuzzy Neural Networks (FNNs) outperformed other statistical models, and the performance of FNNs was compared with the logit model using fraudulent and non-fraudulent firm's data set. Both models have proved their potential in classifying non-fraud cases that will, in turn, enhance the validity and efficiency of the audit. However, the authors also quote that the Logit model was slightly better in forecasting non-fraud cases, and at the same time, FNN was substantially better than the Logit model in predicting fraud cases. Overall, when compared with other conventional statistical methods of forecasting, FNN was better in assessing the risk associated with the fraudulent firms. The study also recommends the auditors to implement these techniques as they offer the great potential that can enhance the effectiveness and efficiency of the audit.

West et al. (2005) explained ensemble ANNs are better predictors than "Single best" multilayer perceptron models, and this fact was supported by examples of three real-world financial data sets where generalization error was reduced by 3-4%, which is a significant reduction statistically. The author evaluated bagging and boosting strategies on the same data set and found bagging was more effective than boosting with the fewest number of variables and least noise. Later, Alfaro et al. (2008) compared two classification methods and showed improvement in accuracy that AdaBoost achieved against ANNs. The authors used these technologies to ascertain the corporate bankruptcy using financial ratios, and the results of the study indicate that the AdaBoost algorithm outperformed the ANN technique both in the cross-validation and test set estimation in the classification error because AdaBoost makes use of a modified version of the training set to build consecutive classifiers. Also, the authors used accounting-based variables, the size of the firm, the industry and the organizational structure as inputs to evaluate the financial performance of the firm.

Celik and Karatape (2007) examined the performance of ANN in forecasting banking crises. The authors indicated by using a 25 input neurons ANN model that ANN is capable of forecasting banking crises, and ANN can be used for developing effective policies for the banking sector. Kim and Kang (2010) proposed an ensemble neural network for enhancing the performance of conventional ANN models for predicting bankruptcy. The results of the study indicate that the bagged and boosted ANN is a better predictor than traditional ANN models. Particularly, bagged ANN produced better accuracy than other classifiers. Also, the authors recommended more algorithms for future research. Rafiei et al. (2011) made the comparison of ANN, GA, and MDA for bankruptcy prediction. The results of the study indicate that the ANN is better than the other two models. However, the Genetic Algorithm has also evolved as a powerful technique of prediction. Olson et al. (2012) compared the forecasting ability of decision tree algorithms, artificial neural networks and support vector machines. The results of the study indicate that decision trees are more powerful predictors than ANN and SVM. Also, the authors indicate there were more rule modes than desired.

Lee and Choi (2013) analyzed the performance of ANN and MDA for a "multi-industry bankruptcy prediction model". The results indicate an ANN model outperformed the traditional MDA technique. Also, the authors quote the results will partially overcome the limitations of ANNs. Bredart (2014) developed a model to predict the bankruptcy of small and medium enterprises by using three financial ratios that are easily available and achieved 80 percent accuracy. Iturriaga and Sanz (2015) proposed a model based on ANNs to predict the bankruptcy of U.S. banks. The authors took into consideration some specific features of the financial crisis of 2014. Also, they combined multilayer perceptrons and self-organizing maps that can access the insolvency up to three years before bankruptcy occurs. The results reveal the proposed model to be more accurate due to the following reasons. First, the developed model has outperformed other statistical tools. Second, it provides a better visualization of the complex structures. Third, it is simpler than other models proposed in the previous studies. However, the authors have also explained certain limitations that limit its usage.

Duan (2019) quoted that NNs can outperform traditional statistical tools. The author used Multi-Layer Perceptron (MLP) consisting of three hidden layers trained by the back-propagation algorithm to predict loan default. The study classifies the loan application into three categories: safe loan, risky loan and bad loan. The results of the study reveal that the accuracy level of MLP was much better than the conventional logistic model and the commonly used MLP with one hidden layer.

2.2. Stock Market Prediction

During the past few decades, a precise prediction of the stock price has become a significant issue. Thus, ANN models are used extensively to predict stock price movement more precisely and accurately. Yoon et al. (1991) quoted that the precise forecasting of a stock price is a difficult and complex preposition. The findings revealed that artificial neural networks are capable of learning a function that maps input to output and encoding it in the magnitudes of the weights in the network's connection. The number of hidden layers employed in the model contributed to achieving a certain amount of viability. Also, the increase in the number of hidden units resulted in higher performance. However, additional hidden units beyond the point impaired the model's predictive performance. Furthermore, the results of the comparison reveal a superior performance of the ANN model than the MDA approach.

Chen et al. (2001) proposed that Probability Neural Networks (PNNs) have shown great potential in forecasting stock price movement as compared to the GMM-Kalman filter and the random walk model. The results of the study reveal that PNN guided trading strategies have obtained higher returns in comparison to strategies suggested by other models. The authors also recommend that Probability Neural Networks (PNNs) capability can be increased by including the threshold levels. Three years later, Cao et al. (2004) explained the superiority that ANNs have established over a period of time in predicting stock prices. ANNs indeed do provide an opportunity for the investors to enhance their predictive ability that can, in turn, increase profitability. The findings of the study also suggest that the univariate model has shown more potential than multivariate models in predicting stock prices and also recommends using macroeconomic variables like volume; economic indicators can significantly enhance the accuracy estimates of NNs.

Kim and Lee (2004) proposed a genetically transformed ANN for stock market prediction. The results reveal that the proposed methodology is significantly better than the models considered for comparison in this study. Zhang and Wu (2009) proposed an integrated model consisting of IBCO and BPNN for the prediction of various stock indices. The authors used the IBCO algorithm to adjust the weights of the BPNN network and achieved better results than the traditional BPNN model. Further, Hadavandi et al. (2010) proposed a novel methodology based on the Genetic Fuzzy System and SOM Clustering for predicting stock price. In their study, the authors used the three-stage method to model the proposed structure. In the first stage, they used stepwise regression to choose significant variables, then in the second stage, they categorized the data into k clusters by SOM method, and in the last stage, they fed the clusters into a genetic fuzzy network to build the proposed model and validated the results using real-life datasets. In the end, the authors concluded that the proposed method outperforms all other models held for comparison. One year later, Guresen et al. (2011) compared simple MLP, DAN2 and Hybrid models that used GARCH to define input variables and reported that simple MLP outperforms the other two models in predicting NASDAQ stock exchange prices and recommended focusing on improving the architecture of DAN2 and hybrid models to improve accuracy measures.

Kara et al. (2011) analyzed the performances of ANN and Support Vector Machines (SVM) to predict the stock price movement. The results of the study clearly reveal the potential of the ANN model in determining the stock price movement in comparison to SVM with an average accuracy of 75.74%. Ticknor (2013) introduced a novel technique that combined the Bayesian regularization and ANN for predicting stock prices. The results of the study reveal the proposed methodology solves the problem of overfitting and local minima than commonly used ANNs. Later, Qiu et al. (2016) examined the NN approach to predict the return on

NIKKEI 225. The authors selected seventy-one variables with respect to the Stock Index of Japan, and then they made new combinations of eighteen input variables by fuzzy surfaces. The results showed that eighteen selected variables were capable of successfully predicting stock prices on NIKKEI 225. For selecting the best model, the authors conducted an experiment of nine hundred parameter combinations using the Back Propagation (BP) Algorithm. Also, the authors used a hybrid approach based on the Genetic Algorithm (GA) and Simulated Annealing (SA) that significantly enhanced the prediction ability of ANNs and outperformed the traditional BP algorithm.

Moghaddam et al. (2016) evaluated different architectures to predict the NASDAQ stock index. The results reveal that the network with 20-40-20 neurons has produced the highest level of accuracy. Inthachot et al. (2016) proposed a hybrid methodology for predicting the stock prices of Thailand's stock index. The results of the study indicate the proposed model is better than the previous model in terms of predicting stock prices. Ghasemieh et al. (2017) analyzed the performance of the ANN model using metaheuristic algorithms, and the results suggest that particle swarm optimization outperforms all other algorithms considered for a study that is cuckoo search, improved cuckoo search, improved cuckoo search genetic algorithm, and genetic algorithm.

Later, Alonso et al. (2018) explained the benefits of deep learning and the advantages that users can take while using it. The authors evaluated different ANN models to achieve the highest level of accuracy in time series and Long Short Term Model (LSTM) to be best suited because of the fact that autocorrelations, cycles, and non-linearity are present in time series. Furthermore, time-series data exhibits other challenging features such as estimations and non-stationarity. However, Eltman ANNs are also good candidates, but LSTMs have performed better in non-financial problems. Also, the authors have quoted it is not the performance of the LSTM, which is significant; the LSTMs have shown consistency in their predictions. In the end, the authors have concluded that LSTMs are powerful techniques in forecasting time series. Menon et al. (2018) stated that CNN outperformed all other models considered for the study. Furthermore, the author concluded that there exist underlying dynamics between the National Stock Exchange (NSE) and the New York Stock Exchange (NYSE).

2.3 Other Applications in Accounting and Finance

Other applications include time series forecasting, foreign exchange prediction, etc., which is a relatively new area of application for ANN as much of the research has focused on bankruptcy and stock market prediction. Jensen (1992) examined "the making and training of ANN to analyze the creditworthiness of the loan applicants is the practical and easy approach" The Author used 100 sample loan applications to train them and still achieved around 75-80% accuracy. The research has also highlighted the effectiveness of ANNs in forecasting. It is economically viable against other statistical methods of prediction. Later, Leung et al. (2000) examined the forecasting ability of a specific ANN architecture called the general regression neural network (GRNN) and compared its performance with numerous forecasting techniques, including a multi-layered feedforward network (MLFN), multivariate transfer function, and random walk models. The findings of the study reveal that GRNN achieved a higher degree of prediction accuracy but also performed significantly better than other models considered for the study. Later, West (2000) analyzed the prediction accuracy of ANN models for credit scoring applications by considering two real financial data sets. The results of the study suggest that ANN credit scoring models can enhance their accuracy level ranging from 0.5 to 3% by using advanced training methods and improved modelling skills. The author also suggests that radial basis ANNs and the mixture of experts are more accurate than other prevailing models in predicting the credit score of the applicant.

Further, Yao and Tan (2000) used the ANN technique to forecast the movement of exchange rates of the American dollar with respect to five major currencies "Japanese Yen, Deutsch Mark, British Pound, Swiss Franc, and Australian Dollar". The results are very encouraging for most currencies except Yen, and the reason could be the market of Japanese Yen is vaster and developed in comparison with other currencies selected for reference. The authors also recommend that ANNs can be best used when dealing with the real trading dataset. The findings of the study suggest using a more robust approach than Mean of Squared Errors (NMSE) for evaluating the performance of Neural Networks. However, sometimes it is important to have a small NMSE for testing and validation purpose. Later, Walczak (2001) analyzed that Neural Network incurs cost. It can be in the form of money, time and effort. During his study, the author focused on training ANNs and argued that typically a Neural Network takes around 1 to 2 years to produce the best results through the back-propagation algorithm.

One year later, Nag and Mitra (2002) explained that ANNs had proved superiority over traditional statistical models in forecasting exchange rates in the past few decades. However, researchers argue that there is no theory available on the model building process as it depends on the decision of the model builder to choose an optimal number of hidden layers and a number of neurons in hidden and input layers to find the best solution. Therefore, the authors used a genetic algorithm optimization technique to overcome the shortcomings of traditional ANN models. The findings of the study revealed the potential of the proposed approach over conventional ANNs in forecasting foreign exchange rates. The researchers also quote that the proposed model is best suited to find the optimal topology of NNs, and further Malhotra and Malhotra (2003) compared the performance of Multiple Discriminant Analysis (MDA) and Artificial Neural Network in identifying potential loans. The findings of the study show that the ANN techniques consistently perform better than the MDA models in identifying potential loans and alleviating the problem of bias in the training set, and to examine the robustness of the model in identifying bad loans, the authors cross-validate the results through seven different samples of the data. In the same year, Zhang (2003) used a hybrid methodology consisting of ARIMA for linear modelling and ANN for non-linear modelling. The author concludes that the proposed hybrid methodology is significantly better than the traditional ANN model. Also, the authors validated the results by considering real-life data sets.

Later, Kumar and Bhattacharya (2006) stated ANNs outperformed Linear Discriminant Analysis (LDA) in both training and tests partition as they are capable of handling complex data sets and can be even employed to unseen data as it has the potential to determine the underlying relationship between the target and input variables. However, the author employed both techniques to check the credit score of companies by using financial statements and found NNs achieved a 79% accuracy level and the LDA technique achieved a 60% accuracy level which is very low statistically. Also, the findings of the study suggest carefully choosing the variables after addressing the problem of multicollinearity in order to enhance the validity and reliability of the model. Weizhong (2012) proposed an automatic ANN modelling scheme that made use of a special type of network called GRNN. The author introduced several design parameters to automate the process of modelling ANN for time series forecasting. In the end, the results of the study conclude that GRNNs are robust and potentially good candidates for the automatic ANN modelling process.

Later, Wang et al. (2015) proposed the ADE-BPNN model to enhance the prediction accuracy of traditional BPNN. In their study, the authors concluded that ADE-BPNN outperforms conventional BPNN and statistical tools such as ARIMA in time series forecasting. Also, the authors validated the results by using two real-life cases. Khandelwal et al. (2015) proposed a novel methodology for time series forecasting that combines the unique features of Discrete Wavelet Transform (DWT), ARIMA and ANN. The results of the study were compared with Zhang's hybrid model and found to be significantly better. Parot et al. (2019) analyzed the performance of the hybrid model to forecast EUR/USD returns. The results of the model indicate that the proposed methodology is better than the traditional and classical forecasting models. Also, the authors recommend that post-processing is significant for increasing forecasting accuracy. Cao et al. (2019) introduced a novel methodology by combining the CEEDMAN and LSTM neural networks, and the results of the study indicate that the proposed method is better than other models used for comparison. Also, the authors say the proposed model can also be used for predicting other time series such as traffic and weather.

3. Findings

This paper presents a review of the application of ANN models in accounting and finance. The authors have reviewed 50 papers that have used ANN and other models to forecast in various areas of accounting and finance, namely bankruptcy prediction, stock market prediction and other applications such as time series forecasting, etc. An attempt is made to look at the literature more critically with respect to various criteria such as the number of variables, sample size chosen for the study, error measure, the model used in the study and the findings.

The articles discussed in the survey are summarized in tables 1-3. Each table provides a summary of each area in accounting and finance in order bankruptcy prediction, stock market prediction and other applications in accounting and finance. Each table consists of seven columns. Column 1 represents the year in which the study was conducted, column 2 represents the names of the authors, column 3 illustrates the models used for the study, column 4 shows the number of variables, column 5 represents the sample size selected for the study, column 6 gives the error measure, and column 7 represents the findings of the respective studies.

Table1: Applications of ANN in Bankruptcy Prediction

Year	Author	RM	No. of Variables	Sample Size	Error Measure	Findings
1990	Odom and Sharda	NN and MDA	5	129	Confusion Matrix	NNs are better than MDA
1992	Salchenberger et al.	BPNN and LM	29	3479	Confusion Matrix	NNs outperformed Logit Model
1992	Tam and Kiang	NN, Linear Classifier, kNN, ID3 and LR	19, LR-14	236	Confusion Matrix	NN outperforms all three other statistical techniques
1993	Fletcher and Goss	BPNN and LM	3	36	Confusion Matrix, MSE	NN are better predictors than LM
1994	Wilson and Sharda	NN and MDA	5	129	Confusion Matrix	NN outperformed MDA
1994	Fanning and Cogger	GANNA, BPNN and LR	3	230	Confusion Matrix	GANNA outperformed the other two models
1999	Yang et al.	BPNN, PNN, FDA and MDA	5	122	Confusion Matrix	PNN is better than the other three models
1999	Zhang et al.	NN and LR	6	220	Confusion Matrix	NN outperforms LR
2000	Charamlambous et al.	LVQ, RBF and FFNN	7	139	Confusion Matrix	LVQ is better than the other two models
2001	Atiya	NN	5 and 6	911	Confusion Matrix	Proposed novel Indicators to improve performance of NNs
2003	Lin et al.	FNN and Logit	8	200	Confusion Matrix	Mixed Results
2005	West et al.	MLP, Cross-validation, Boosting, Bagging	24, 5	1000, 329	Confusion Matrix	Ensembles are better than single best MLP
2007	Celik and Karatape	ANN	25	350	RMS	ANN performs reasonably well.

2008	Alfaro et al.	AdaBoost and NNs	16	590	Confusion Matrix	AdaBoost outperforms NNs
2010	Kim and Kang	NN, Bagged NN, Boosted NN	32	1458	Type I and Type II	Bagged and Boosted NN is better than traditional NN.
2011	Rafiei et al.	ANN, GA and MDA	17	180	Confusion Matrix	ANN outperforms other models
2012	Olson et al.	Decision Tree, MLP, RBF, BPNN and SVM	18	1321	NA	Decision trees outperformed neural networks and SVM
2013	Lee and Choi	BPNN and MDA	46,40 and 58	6767	t-test	BPNN outperforms MDA
2014	Bredart	NN	3	3728	Confusion Matrix	NN achieves 80% accuracy
2015	Iturriaga and Sanz	MLP and SOM	32	386	ROC	The proposed model is better than other statistical techniques
2019	Duan	MLP and LM	28	887383	MSE, Confusion Matrix	MLP outperforms LM

Table 1 illustrates the application of ANN models in bankruptcy prediction. In most of the cases, the ANN model outperformed the other statistical models except for two. Olson et al. (2012) showed that decision tree algorithms are better predictors than ANN models and Alfaro et al. (2008) showed the Adaboost algorithm is better than an artificial neural network. However, there are studies that compare the different kinds of ANN models. Also, it is clear from the table that the majority of the studies have used the confusion matrix as the most common error measure.

Table 2: Applications of ANN in Stock Market Prediction

Year	Author	RM	No. of Variables	Sample Size	Validation Method	Findings
1991	Yoon and Swales	NN and MDA	9	58	Confusion Matrix	NNs are better than MDA
2003	Chen et al.	PNN, RWM and GMM-kalman filter	4 and 6	128	Confusion Matrix	PNN outperformed the other two models
2004	Cao et al.	ANN and Fama and French's Model Fuzzy Transformation Model, Genetic	1 and 3	367	MAD, MAPE, SD, MSE	ANN is better than other statistical models
2004	Kim and Lee	Transformation Model, Linear Transformation Model	12	2348	Confusion Matrix	GTM outperform all other models
2009	Zhang and Wu	IBCO-BPNN and BPNN	1	2350	MSE	IBCO-BPNN outperformed BPNN

2010	Hadavandi et al.	Hybrid Model, ANN, ARIMA and CGFS	4	2047	MAPE	CGFS outperformed all other models
2011	Guresen et al.	MLP, DAN2, Hybrid models with GARCH	2	182	MSE and MAD	MLP outperform all other models
2011	Kara et al.	ANN and SVM	10	2733	RMS	ANN outperformed SVM
2013	Ticknor	Bayesian Regularized Artificial Neural Network (BRANN), ARIMA	6	734	MAPE	BRANN outperformed ARIMA
2016	Qiu et al.	BPNN and BPNN with GA and SA	18	180	MSE	The hybrid model outperformed traditional BPNN
2016	Moghaddam et al.	BPNN	5,10,20,40, 50,100,200	99	R-Square and MSE	Evaluated different architectures
2016	Inthachot et al.	ANN and GA	44	1464	MSE and MAPE	The hybrid Model outperformed the previous model.
2017	Ghasemieh et al.	ANN	28	1609	MSE	Particle Swarm Optimization Algorithm performs better than other algorithms
2018	Alonso et al.	NN and LSTM	50 and 53	560	MSE	LSTM is better than traditional NN
2018	Menon et al.	MLP, RNN, CNN, LSTM, ARIMA	NA	4861	MAPE	CNN outperform all other models

Table 2 illustrates the application of ANN in forecasting stock price. Over a period of time, different ANN models have been used for stock market prediction, and a comparative analysis is done with the other statistical models and traditional ANN models. It is clear from the table that in recent times a hybrid model that combines two or more techniques has outperformed the traditional statistical techniques and conventional ANN models.

Table 3: Other Applications of ANN

Year	Author	RM	No. of Variables	Sample Size	Validation Method	Findings
1992	Jensen	NN	8	125	Confusion Matrix	NNs are quite practical and easy.
2000	Leung et al.	GRNN, MLFN, RWM	6	259	MAE and RMSE	GRNN outperformed all three models
2000	West	MOE, RBF, LVQ, FAR, MLP, kNN, LR, LDA, KD and CART	2 and 5	1000 and 690	Confusion Matrix	Mixed results

2000	Yao and Tan	NN and ARIMA	5 and 6	510	NMSE	NN outperformed ARIMA
2001	Wakczak	BPNN	2 and 3	125	Confusion Matrix	BPNN incurs cost
2002	Nag and Mitra	GANN, FGNN, ARCH, GARCH, EGARCH, AGARCH	NA	250	AAE, MAPE, Max AE, RSQ, MSE	GANN is better than other models
2003	Malhotra and Malhotra	MDA and NNs	6	1078	Confusion Matrix	NN outperformed MDA
2003	Zhang	NN and Hybrid Model	4	1133	MAD and MSE	Hybrid model outperformed NNs
2006	Kumar and Bhattacharya	LDA and ANN	25 and 8	129	Confusion Matrix	ANN is better than LDA
2012	Weizhong	GRNN	12	111	sMAPE	GRNNs performed well
2015	Wang et al.	BPNN and ADE-BPNN	12	168	RMSE, MAPE, MSE	ADE-BPNN outperforms BPNN
2015	Khandelwal et al.	DWT, ARIMA, ANN and Zhang's Hyrbid Model	4	1133	MSE and MAPE	Proposed model outperformed all other techniques
2019	Parot et al.	ANN, VAR, VECM	20	4242	RMSE, MAE, MAPE	Proposed model is better than classical models
2019	Li et al.	CEEDMAN, LSTM, SVM and MLP	9951	128	MAE, RMSE and MAPE	The Proposed model is better than other models

Table 3 illustrates the application of ANN models in other areas of accounting and finance which includes time series forecasting and exchange rate prediction. Various models have been studied by the researchers and a comparison is made with other ANN models. The table shows a recent trend of using hybrid models instead of traditional ANN models.

Table 4: Frequency of error measures used

Error Measure	No. of Papers
Confusion Matrix	24
MSE/RMSE/NMSE	16
MAPE/MAE/MAPE/AAE	12
MAD	3
RMS	2
R square	2
ROC	1
Type I and Type II	1
t-test	1
SD	1
Max AE	1

Table 4 illustrates the error measures used in the studies to compare the performance of different techniques. Confusion matrix has been used most frequently, followed by MSE/RMSE/NMSE.

4. Future Scope and Limitations

The present study has further scope for more comprehensive results. It can be explored in other areas of accounting and finance as there is a dearth of literature on applications of ANNs in other areas of accounting and finance such as time series forecasting, foreign exchange rate prediction and commodity market prediction. Furthermore, a comparative analysis can be done by comparing the forecasting accuracy of traditional ANN models and the hybrid models that combines two or more techniques. Also, the current study can be performed using different techniques such as the PRIMA method, bibliometric analysis, systematic analysis, etc.

Though ANN models find applications in a wide spectrum of areas like geo-engineering, marketing, operations etc., but the scope of this study is limited to applications of ANNs in the finance and accounting domain. Another limitation of this study is that it reviews research articles published over the last three decades. Despite this limitation, the present study covers the entire gamut of applications of ANNs in accounting and finance.

5. Conclusion

In this study, we have carried out a comprehensive literature review on the evolution of artificial neural networks over a period of time and the application of ANN models in various domains of accounting and finance. Since artificial neural networks have gained popularity over the last three decades due to which they have been applied to different domains. The review clearly points out the superiority of artificial neural networks over the conventional statistical models for classification and prediction problems. However, there have been studies where traditional statistical models outperformed the artificial neural network technique. One of the biggest advantages of this technique is it can model any non-linear function. This aspect is particularly useful where the relationship between the variables is unknown, as in the case of prediction of stock prices. However, the determination of various parameters like the number of hidden layers, number of nodes within the layers, the number of input variables is not straight forward and finding the optimal architecture is a time-consuming process.

Another disadvantage highlighted in most of the studies is the lack of interpretability of the weights obtained during the model building process. In this respect, the traditional statistical model stands out as they offer an interpretation of variables, and inferences can be drawn based on these variables. Further, most of the studies have compared the neural network with other statistical models such as logistic regression, linear discriminant analysis and artificial found neural networks to be more effective as they were capable of handling non-linear datasets and establish a relationship between them more precisely. This is particularly so because the performance of these conventional statistical models depends on the validity of the assumptions, which is not considered in the majority of the studies. Also, in most of the articles, the architecture of artificial neural networks is selected by trying out various models on the training data set, which is not done in the case of traditional statistical techniques. Furthermore, various studies have combined the artificial neural network technique with other statistical models and algorithms to enhance the predictive and classification ability of artificial neural networks, and results are very encouraging as they help in lowering down the error rate by 3 to 5%, which is significant statistically. Therefore, the authors conclude that ANN has shown potential in the field of prediction, specifically in accounting and finance and outperforms the traditional statistical techniques. However, the predictability or accuracy level depends on the understanding of the problem statement. Thus, utmost care should be taken while designing the ANN model for a given problem.

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Appendix

The abbreviations used in tables 1 - 4 are described below:

Notation	Meaning
LR	Logistic Regression
MDA	Multivariate Discriminant Analysis
k-NN	k-Nearest Neighbour
NN	Neural Network
ANN	Artificial Neural Network
LM	Logit Model
BPNN	Back Propogation Neural Network
GANNA	Generalized Adaptive Neural Network Architectures
PNN	Probability Neural Networks
FDA	Fisher Discriminant Analysis
LVQ	Learning Vector Quantization
FFNN	Feed Forward Neural Network
FNN	Fuzzy Neural Network
RBF	Radial Basis Function
GA	Genetic Algorithm
MLP	Multilayer Perceptron
SVM	Support Vector Machine
SOM	Self-Organizing Maps
BRANN	Bayesian Regularized Artificial Neural Network
LSTM	Long Short Term Memory
CNN	Convolutional Neural Network
ARIMA	Auto Regressive Integrated Moving Average
GARCH	Generalized AutoRegressive Conditional Heteroskedasticity
RNN	Recurrent Neural Network
GFS	Genetic Fuzzy Systems
RWM	Random Walk Model
GMM	Generalized Methods of Moments
IBCO	Improved Bacterial Chemotaxis Optimization
DAN2	Dynamic Artificial Neural Network
GRNN	General Regression Neural Network
MLFN	Multi Layered Feed forward Network
MOE	Mixture of Experts
FAR	Fuzzy Adaptive Resonance

KD	Kernel Density estimation
GANN	Genetic Algorithm Neural Networks
FGNN	Fixed Geometry Neural Networks
EGARCH	Exponential Generalized AutoRegressive Conditional Heteroskedasticity
AGARCH	Asymmetric Generalized AutoRegressive Conditional Heteroskedasticity
VECM	Vector Error Correction Model
CEEDMAN	Complete Ensemble Empirical Mode Decomposition with Adaptive Noise
ADE	Adaptive Differential Evolution
VAR	Vector AutoRegression
DWT	Discrete Wavelet Transformation
LDA	Linear Discriminant Analysis
MSE	Mean Sqaured Error
RMSE	Root Mean Sqaured Error
NMSE	Normalized Mean Squared Error
MAPE	Mean Absolute Percentage Error
MAE	Mean Absolute Error
ROC	Receiver Operating Characterstic Curve
SD	Standard Deviation
Max AE	Maximum Absolute Error
MAD	Mean Absolute Deviation
AAE	Average Absolute Error
sMAPE	Symmetric Mean Absolute Percentage Error

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