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NEURAL NETWORKS IN FINANCE: A DESCRIPTIVE SYSTEMATIC REVIEW

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ABSTRACT

Traditional statistical methods pose challenges in data analysis due to irregularity in the financial data. To improve accuracy, financial researchers use machine learning architectures for the past two decades. Neural Networks (NN) are a widely used architecture in financial research. Despite the wider usage, NN application in finance is yet to be well defined. Hence, this descriptive study classifies and examines the NN application in finance into four broad categories i.e., investment prediction, credit evaluation, financial distress, and other financial applications. Likewise, the review classifies the NN methods used under each category into standard, optimized and hybrid NN. Further, accuracy measures used by the research work widely differ, in turn, pose challenges for comparison of a NN under each category and reduces the scope of formalizing a theory to choose optimum network model under each category.

Keywords: Neural Networks, ANN, Analytics, Machine Learning.

JEL Classification Codes: G1, G17, M150.

INTRODUCTION

Financial data are immensely available, yet the innate nature of big data shows uncertainty, incompleteness, and inconsistency which pose challenges in using traditional statistical methods for financial data analysis (Brooks et al., 2019; Hariri et al., 2019). Financial researchers try to overcome the traditional statistical limitations by using machine learning architecture like Neural Networks (NN).

NN imitates the human brain by using nodes and layers of connections, which pass signals with a set of associated weights and bias adjustments (Figure 1). NN results are not easily interpretable and so the analysis is in black-box nature. Irrespective of the non-interpretability of results, NN received importance in financial research due to its computing efficiency in handling financial big data.

For the last two decades, financial researchers are using NN in various analyses like risk classification (Altman, Marco, & Varetto, 1994), bankruptcy and share price prediction (Barr & Mani, 1994). Despite the attention, NN application in finance is yet to be well defined. The last decade saw an increase in the finance research using NN in an analysis like forecasting of *share prices* (Chang, Liu, Fan, Lin, & Lai, 2009; Sapna & Argente, 2003; Safer, 2002), *option prices*

(Lin & Yeh, 2009; Kohler, Krzyzak, & Todorovic, 2010), and the *future prices* (Dunis, Laws, & Evans, 2008; Laws & Dunis, 2013).

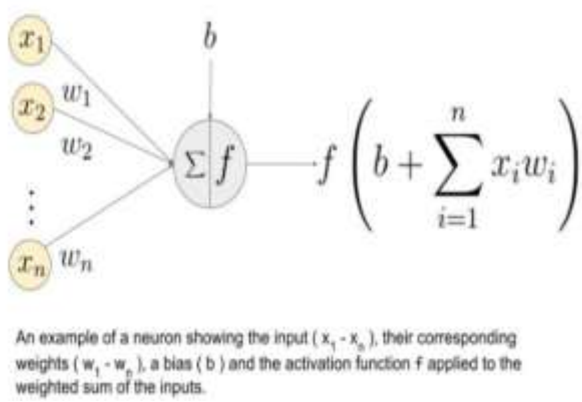


Figure 1. standard Neural Network

The Literature reviews of Feldman and Kingdon (1995), Wong and Selvi (1998), Vellido, Lisboa, and Vaughan (1999), Krishnaswamy, Gilbert, and Pashley (2000), Coakley and Brown (2000), Fadlalla and Lin (2001), Wei, Nakamori, Wang, and Yu (2007), Cavalcante et al. (2016), and Huang, Chai, and Cho (2020) are the existing works in this regard. Yet, the review works show significant limitations. Firstly, no review follows a protocol-based review process which is essential for reproducibility. Secondly, several reviews are not examining financial applications entirely or they focus on aspects like soft computing, and computational intelligence, instead of NN architectures (Table 1). Even though the studies analyze the NN applications to a certain extent, non-reproducibility is a serious concern.

Further, the absence of a systematic review method results in serious drawbacks in the quality of review findings (Karunananthan, Maxwell, & Welch, 2020). Systematic reviews have greater potential than other research designs leading to the reproducibility of research (Shokraneh & Adams, 2019). Since the computing efficiency doubles every two years (Gustafson, 2011) which improves the efficiency of handling complex data sets, exploring the research works to date with the scientific review methods will help to understand the existing status of NN in analyzing the financial data.

Table 1. Summary of existing reviews

Study	**Period of review**	**Nature of study**	**Focus of the study**	**Summary of conclusion**
Feldman and Kingdon (1995)	1988-1996 (*Authors' estimation)	Descriptive, Non-Systematic review.	Advantages of MLP, BPNN, and SOM.	Generalization, architecture selection, and application of selected NN.
Wong and Selvi (1998)	1990 – 1996	Descriptive, Review process disclosed.	Classification of NN application in finance.	The implication to NN developers.
Velido, Lisboa,	1992 – 1998	Descriptive,	Application of	Comprehensively

and Vaughan (1999)		Review process disclosed.	NN in business.	reported the most quoted advantages and disadvantages of NN in various business applications.
Krishnaswamy et al. (2000)	1989 – 1996 (*Authors' estimation)	Descriptive, Non – systematic review	Description of NN and its finance application.	Backpropagation NN has proven robust. Supervised and unsupervised NN is used in finance.
Coakley and Brown (2000)	1988 – 1997 (*Authors' estimation)	Descriptive, Non – systematic review	Financial Application, development of ANN models.	ANN researchers face a challenge that there are no formal theories for determining optimal network model
Fadlalla and Lin (2001)	1986 – 1997	Descriptive, Non – systematic review	Financial Application, focus on feedforward and feed backward NN models.	NN has great promise for financial applications and combinations of two approaches should be investigated.
Calderon and Cheh (2002)	1993 – 1999	Descriptive, sources of review disclosed.	NN in auditing and risk management.	NN shows promising performance in Preliminary analytical procedures in the auditing process.
Wei Huang et al. (2007)	NA	Descriptive, Non – systematic review	Focus on input variables, NN models applied in forex, stock market, and economic forecasting.	The prediction performance of neural networks can be improved by being integrated with other technologies.
Cavalcante et al. (2016)	2009 -2015	Descriptive, review process disclosed	Computational intelligence in finance (NN is a part of the study)	Categorized studies into preprocessing, forecasting, and text mining.
Huang et al. (2020)	2014 – 2018	Descriptive, review collection process disclosed.	Deep learning applications in finance and banking.	Reports about data inputs, preprocessing and evaluation rules of deep learning in finance and banking

Hence, this structured review reveals an interpretable pattern of NN architectures and their application in finance research. The study follows the systematic review process provided by Moher, Liberati, Tetzlaff, Altman, and The PRISMA Group (2009) and Gupta, Chauhan, and Jaiswal (2019). The primary aim of the study is to classify the research papers based on their NN application in finance research. This is done by,

- Classification of major topics and sub-topics, and
- Identification of various NN architectures used in the classified subtopics.

METHOD

A literature review starts with searching for quality research papers from prominent journals (Ngai & Wat, 2002). Further collecting research papers from the online database has become an emerging culture in the information era (Petter & Lean 2009). So, this study uses the EBSCO Business Elite database, which is a repository of 525 peer-reviewed research journals, to collect research papers. The systematic review process prescribed by Moher et al. (2009) comprises defining a protocol for literature search, exclusion criteria of research papers, and final selection of papers (Figure 2).

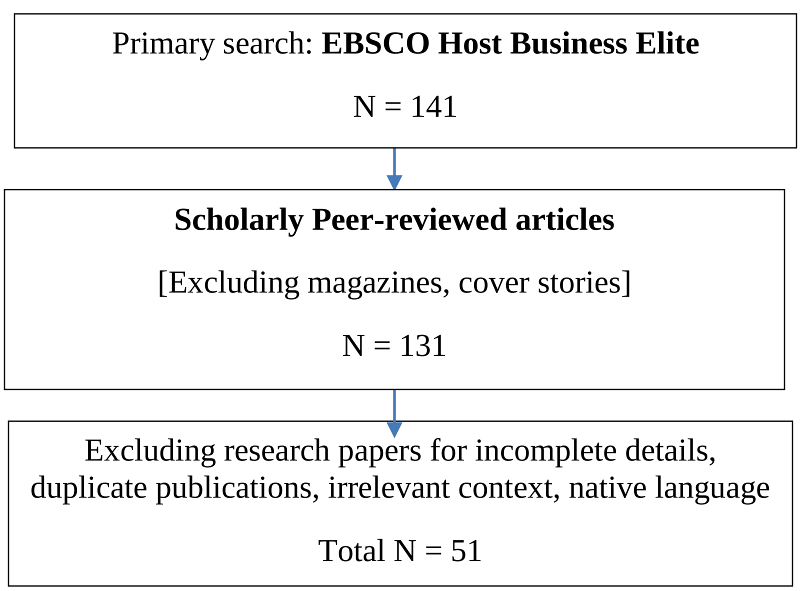


Figure 2. Selection process of research papers (Moher et al., 2009)

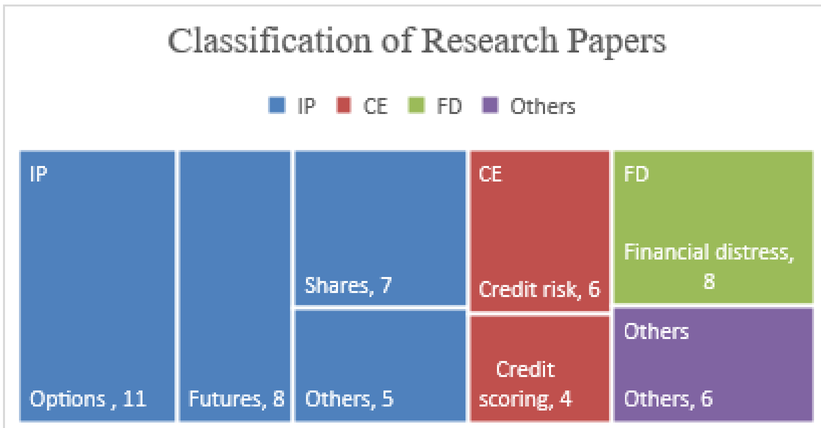
Protocol directs the research paper selection based on the criteria. To obtain research papers the study followed an advanced search option in the EBSCO Business Elite database and used two keywords ‘Neural Networks’ and ‘Finance’. Research studies published in English under the subject areas of business, management, and finance are only considered. Empirical articles that are published in peer-reviewed academic journals are collected at the first level.

Restricting the review only to published articles can strengthen quality control since many of the academic journals follow meticulous publishing criteria in terms of research contribution and robustness of the results (Light & Pillemer, 1984). The protocol process has helped to collect papers with high research quality. After collection, the studies with incomplete details, irrelevant context, and duplicate publications are excluded.

After exclusions, data extraction is done by carefully considering the title, abstract, and overall theme of the paper focuses on applying NN in finance. 141 papers are collected from the EBSCO Business Elite database and during the first level of screening 77 research papers are excluded. Finally, 51 research papers are considered for review.

RESULTS

The researcher scrutinized the collected research articles for their relevancy and suitability to be considered as a part of this review paper. When research papers fulfill the established criteria, the author read the full paper to find its contributions. Figure 3 represents the broader classification of research papers under major topics and sub-topics.



IP – Investment Prediction; CE – Credit Evaluation; FD – Financial Distress.
Figure 3. Classification of research papers based on major topics and sub-topics

Based on the reading the author identified four main topics and several subtopics (Table 2). The next section discusses each main topic, inferences of the research work carried in the subtopics based on the NN methods. Further, NN with statistical and architectural advancements is classified as 'Optimized NN'. NNs incorporating financial theories and knowledge are classified under 'Hybrid NN'. A model-free NN is classified as 'Standard NN'.

Table 2. Major research topics and subtopics

Main topics	**Sub-topics**
Investment prediction	Prediction of options prices, futures prices, share prices, Forex, indexes, bond yields, commodity spreads, trading patterns, shareholder wealth, and portfolio performance.
Credit evaluation	Predicting credit risk, and Estimating credit rating.
Financial distress	Evaluating financial distress
Other financial applications	Development of financial intelligent system, Detecting fraudulent financial reporting, Assessment of systematic risk, Evaluating operating performance, Assessing project portfolio performance.

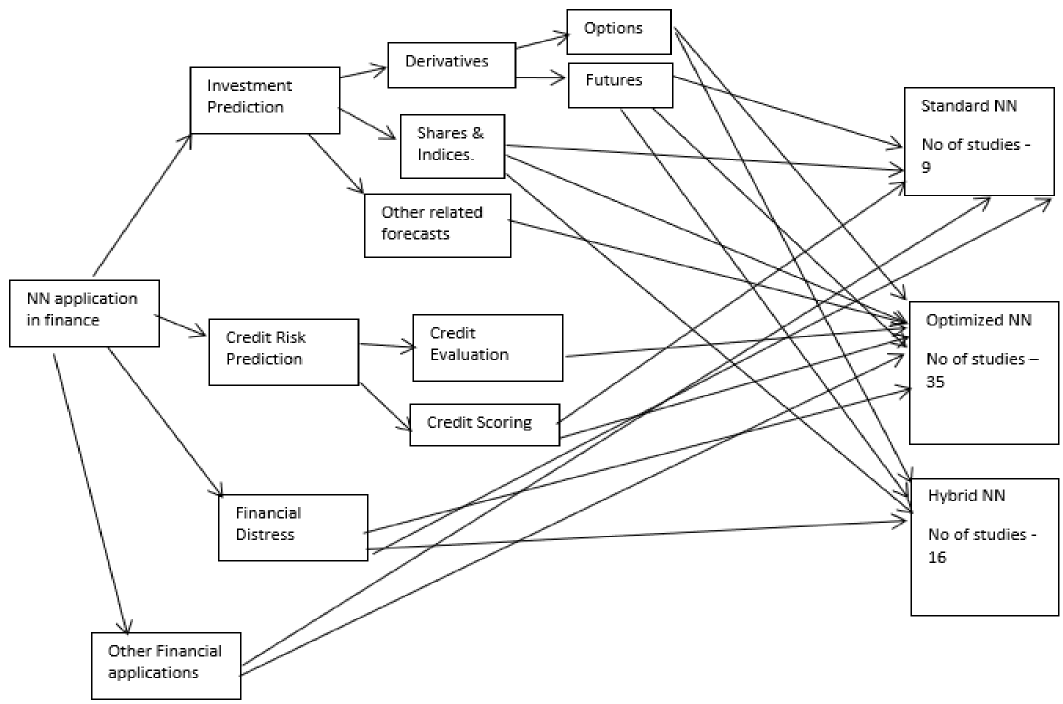


Figure 4. Framework of NN application in finance

DISCUSSION

Investment Prediction:

Derivatives -

a) Options

Optimized NN –

Back Propagation NN (BPNN) – BPNN minimizes the prediction error by giving the nodes with higher error rates lower weights and vice versa. Hence, BPNN is found to be more suitable for derivative prediction (Kaastra & Boyd, 1995). When used to predict Taiwan stock index options, BPNN demonstrated improved accuracy in support of hedging at in-the-money option (Lin & Yeh, 2009).

Likewise, the research study of Hutchison et al. (1994) used BPNN to predict the prices of S & P 500 futures and options, yet the result is that BPNN did not show significantly better accuracy than other linear models like ordinary least squares.

NN with Monte Carlo simulation **–** Monte Carlo, is a simulation technique to understand the impact of risk and uncertainty in prediction. It is used with linear NN for predicting American options (Kohler et al., 2010). Since it is a simulation based NN, the accuracy would widely differ in empirical prediction.

Advanced Modular NN (AMNN) **–** AMNN is a series of independent NN which serves as a module and operates on separate inputs to accomplish a subtask. AMNN gives more accuracy than the standard NN when predicting European call option prices (Gradojevic et al., 2009).

***Feed forward NN (FFNN)* –** FFNN is used when the nature of financial data is neither sequential nor time-dependent. FFNN predicts European Index options and S&P 500 European call options more accurately than standard NN (Gencay & Gibson, 2007).

Hybrid NN -
NN with Black Scholes - The research study by Blynski, and Faseruk (2006) compared the effectiveness of option price forecasting using the traditional Black Scholes model with NN (hybrid NN) and standard NN. Likewise, the research study by Chen and Sutcliffe (2012) confirms that a hybrid NN along with Black Scholes predicts accurately than the standard NN or Black Scholes model individually. Similarly, Sperckelsen et al. (2014) used Black Scholes model variables in predicting option prices of currency futures (EUR/USD and concluded that the hybrid model is better than the theoretical option pricing model and MLP.

NN with Black Scholes & Wavelet – Zapart (2003) in his research study uses Wavelet along with NN and Black Scholes. Wavelet is a mathematical advancement that addresses oscillations that decays quickly in a data set. The study found that Black Scholes NN with Wavelet predicts superior when analyzing option prices.

Hybrid Black Scholes NN with stochastic volatility - Stochastic volatility represents the nature of volatility fluctuating over time. The research study by Gencay and Gibson (2007) found that the hybrid NN model with stochastic volatility predicts better than the standard NN Model while predicting European stock index options.

b) Futures –
Standard NN – Model-free NN, without the attributes of financial theories, also performs significantly in the case of predicting currency futures prices. A model-free NN is used to predict the high-frequency currency futures and the predictability power is better than the closed-form financial model (Sperckelsen et al., 2014).

Optimized NN -
***Multilayer perceptron* (MLP)** – MLP commonly represents a feed-forward NN with three layers. MLP is used to predict the commodity futures to hedge against corn and ethanol spreads and found to be accurate in prediction (Dunis et al., 2015). Likewise, Karathanasapoulos et al. (2016) used MLP in gasoline futures contracts.

***Higher-order NN (HONN)* -**HONN utilizes a higher combination of NN inputs. The research study of Dunis et al. (2015) compared the performance of HONN with MLP. The study concludes that MLP and HONN are superior in predicting with leveraging option. Sermpinis et al. (2013) tested HONN in predicting index futures. Likewise, Karathanasapoulos et al. (2016), in their research study used HONN to predict gasoline futures contracts.

Radical base function neural network (RBFNN)– Karathanasapoulos et al. (2016) used a radical basic function neural network (RBFNN) to improve the trading performance of futures. RBFNN transforms the input signal into another form, which can be then feed into the network to get linear separability. The study concludes that RBF NN is superior in both trading performance and statistical accuracy.

Hybrid NN -

***Feature transformed NN* –** Kim (2004) used feature transformed NN, including domain-specific factors like relative strength index to predict the futures prices and found that feature transformed NN predicts accurately than the linear models and concludes that incorporating domain knowledge in NN architecture improves performance.

***Shares & Indices* –**

Standard NN –

Haefke and Helmenstien (2002) used NN in forecasting indices and inferred that applicability of information criteria is important in the selection of NN. In contrast, Moreno and Olmeda (2007) claim that NN is not superior in predicting the stock markets to the linear models.

Optimized NN -

NN with Statistical optimization – LV D et al. (2020) used principal component analysis (PCA), Least absolute shrinkage and selection operators (LASSO), classification and regression trees (CART), and Piecewise linear representation methods (PLR) to optimize NN. As a result, there no significant improvement in NN incorporating the features, however, NN with PLR, resulted in an improvement in profit through better forecast ability.

Back propagation (BPNN) and Piecewise linear representation (PLR) – In a research study by Chang et al. (2009), it is found that BPNN along with PLR consistently created good results for predicting upward, steady, and downward trends of stock prices.

Hybrid NN –

NN with Fama French five-factor model - Besides customizing the NN, researchers have used financial models like Fama and French five-factor model with NN and found improvement in the profitability of investors in both linear and nonlinear data (Jan & Ayub, 2019).

NN with GARCH model– Ozbey and Paksoy (2020) combined GARCH with NN and compared the performance of the hybrid model with the classic GARCH model. The study found that the hybrid model is superior in predicting volatility to the classic GARCH.

***NN with Top-down theory, technical analysis, and dynamic time series methods* –**Huang, G.,Huang,GB., Shiji, and Youa (2014) used integrated models using conventional top-down trading theory, technical analysis, and dynamic time series methods and concludes that the hybrid system gives remarkable investment returns and demonstrates promising potential tools for stock market forecasting.

***Other related financial forecasts* –**

Optimized NN –

Back propagation NN (BPNN) –Chiang et al. (1996) used BPNN to predict the Net Asset Value (NAV) of mutual funds and found that BPNN outperforms the regression model. Jain and Nag (1995) predicted the prices of initial public offering (IPO) using BPNN and found significant economic benefits in BPNN.

Multi-layer perception (MLP) **–** Indroa et al. (1999) used MLP and compared it with stepwise linear regression. The results show that MLP is superior to the linear model.

General regression NN (GRNN) –Barnes and Lee (2009) used GRNN in analyzing the effect of macroeconomic and firm-specific factors in determining shareholder wealth.

Multivariate NN -Wie et al. (2004) used Multivariate NN to predict earning per share in comparison with univariate and multivariate linear models incorporating fundamental accounting variables and found that NN along with accounting variables predicts more accurately than linear forecasting models.

Table 3. NN research in Investment prediction

	Author(s)	**Purpose**	**NN Model**	**Sample**	**Period**	**Predictors**	**Comparison**	**R Squared Value**	**Accuracy**
1	Kaastra and Boyd (1995)	Forecasting Economic time-series data	Back Propagation NN	Conceptual Paper	-	-	-	-	-
2	Lin and Yeh (2009)	Forecasting Option Prices	Back Propagation NN	15 582 call option price data points	2003 - 2004	Black Scholes variables		-	MAPE 5.2534
3	Hutchison et al. (1994)	Pricing and Hedging derivative securities	Ordinary Least squares, Radical Basis functions network, Multi-layer Perceptron, Projection Pursuit	S&P 500 Future and options	1987 - 1991	Black Scholes variables	No significant difference between models	84.76	-
4	Kohler et al. (2010)	Pricing of American Options	Least square NN	Monte Carlo Simulated Data	-	-	-	-	-
5	Gradojevic et al. (2009)	Pricing European Call options	Modular NN & Black Scholes NN	S&P-500 index European call option prices, Chicago Board Options Exchange	1987 - 1994	Black Scholes variables	BS NN Model > Modular NN	-	MAPE 1.87
6	Gencay and Gibson (2007)	Pricing European Stock Index options	Feedforward NN	S&P 500 index9 options from the Berkeley	1989 - 1991	Price of the underlying, strike price, volatility, interest	FFNN > Stochastic volatility (SV) and stochastic	-	-

				Option Database		rate, time to maturity	volatility random jump (SVJ),		
7	Blensky and Fasurek (2006)	Comparing Option prices forecast of NN with Black Scholes model	Back Propagation NN	64, 280 OEX 100 Index call option	1986 – 1993	-	NN > Black Scholes model	-	-
8	Chen and Sutcliffe (2012)	Pricing and hedging short sterling options	Standard NN, Modified Black Model NN, and Hybrid NN	Short sterling futures traded on NYSE	2012 (Quarterly expiry cycle)	Ask, bid, trade, spread trade, and block trade,	Hybrid NN > Modified Black model, Standard NN	r = 98.6864	-
9	Sperckelsen et al. (2014)	Realtime pricing of options on currency futures	Model-free option pricing NN, Multi-Layer Perceptron	EUR/USD option on currency future from Chicago Mercantile Exchange (CME)	2012	Futures price, Strike price, Expiration time, Risk-free rate, Asset volatility	Hybrid NN > theoretical option pricing model	99%	MAPE 0.3146
10	Zapart (2003)	Pricing European and American Call options	NN with Binomial trees and Wavelets, NN with Genetic algorithm and Black Scholes model	Options prices as quoted on the Chicago Board Options Exchange are used	2003	Time to expiry, current stock price, risk-free rate	-	-	-
11	Dunis et al. (2015)	Modeling corn/ethanol crush spread	MLP, HONN, GPA	Ethanol futures contract traded in Chicago Board	2005 - 2010	Leverage	GPA > HONN, MLP	-	-
13	Sermpinis et al. (2013)	The forecasting FTSE 100 futures	Higher-order NN, Multi-Layer Perceptron, Recurrent neural networks	FTSE 100 futures	2007 - 2008	Realized daily returns (21 days)	HONN> MLP, RNN	-	18.85%
14	Karathanasopoulos et al. (2016)	Modeling crack spread	RBF, PSO, MLP	-	2005 - 2015	20 ARIMA and 10 GARCH models	PSORBF > MLP	-	-
1	Kim (2004)	Future	Feature	Korean	May to	Positive	Feature	-	-

5		price prediction	transformed ANN based on domain knowledge	stock index (KOSPI)	November 1996	volume index, Rate of Change, Momentum, etc.	transformed ANN > Linear ANN		
16	Haefke and Helmenstien (2002)	Index Forecasting and Model Selection	Feedforward NN	Austrian Traded Index (ATX)	2 November 1992 to 14 October 1994	Geometric mean, arithmetic mean	The proposed integrated model shows significant performanc	0.041	AMAPE = 1.862
17	Moreno and Olmeda (2007)	Predictability of emerging and developed stock markets using NN	Standard NN	49 MSCI (Morgan Stanley Capital International) indexes	March 1995 to March of 2001 (1560 daily observations)	index returns, daily and weekly	NN is not superior to the linear models	-	-
18	LV D et al. (2020)	Dimensionality reduction in stock trading	MLP, Deep Belief Network (DBN), Stacked Auto-Encoders (SAE), RNN, LSTM, Gated Recurrent Unit (GRU)	US SPICS and the Chinese CSICS	Past 2000 trading days of SPICS and CSICS before December 31, 2017	44 technical, Volatility, Psychological, cash flow indicators.	LASSO NN	-	-
19	Chang et al. (2009)	Stock Trading Points Prediction	BPNN, GA, PLR	Stock Prices	2004/01/02 to 2006/04/12	Moving average, Bias, RSI, ninety days stochastic line, etc.	PLR +GA improves Profitability	-	-
20	Jan and Ayub (2019)	Improving the predictability of Fama French five-factor model	Standard NN	Manufacturing companies in Pakistan Stock Exchange	2000 to 2015	Market cap, BV/MV ratio, % in total assets, and EBIT	NN improves FF model	r = 0.99989	MSE = 0.0012
21	Ozbey and Paksoy (2020)	Estimation of index returns with GARCH and NN	Hybrid NN, Exp GARCH, and Nor. Distrn	Borsa Istanbul 100 price Index	2017 - 2018	Borsa Istanbul 100 Index value	Hybrid NN + GARCH > Hybrid NN + normal distribution	-	MSE = 0.015926
22	Huang, Huang, Shiji, and Youa (2014)	Integrated data mining in stock	Top-down trading theory + ANN + technical	Taiwan Semiconductor Manufact	2011 - 2013	Stochastic KD, William %R, RSI,	Integrated NN model improves stock	-	True positive = 98.50%

		forecasting	analysis + dynamic time series + and Bayesian probability	uring Company and Evergreen Marine Corporation		PSY line, ADX, MA, MACD	forecasting		
23	Chiang et al. (1996)	Mutual Fund NAV forecasting	BPNN	6 Year economic variables and 101 US mutual funds	1981 - 1986	GNP, Consumption, Investment, CPI, Money supply, unemployment, T-bill, Long term rate	BPNN > Linear & Non-Linear regression	0.989	MAPE = 8.76
24	Jain and Nag (1995)	Predicting IPO pricing	FFNN	552 IPOs in the United States	1980 - 1990	11 variables [Size, Underwriter, sales, ROA, ROI, Assets turnover, etc.]	-	-	-
25	Indroa et al. (1999)	Predicting mutual fund performance	MLP	Morningstar Mutual Funds On-Disc database	1993 - 1995	Annualized return, turnover, P/E, P/B, Mar.Cap	MLP > Linear models	-	MAPE = 4.88
26	Barnes and Lee (2009)	Effects of Macroeconomic-Firm-Specific Factors on Shareholder Wealth	General regression NN (GRNN)	Miscellaneous Industrials in the Australian Stock Market	2007	D/E, Gross margin, Debt to cash, EVA, EPS, WACC funds, ROIC	ANN is effective in the prediction	0.0548	MAE = 37.649
27	Wie et al. (2004)	NN model for EPS forecasting	Univariate-NN and multivariate NN	Quarterly EPS of 283 companies in SEC	1992 – 2002	Inventory, A/R, capital expenditure, gross margin, Sel.Adm exp, Tax rate, labour force	NN models > Linear models	-	MAPE = 0.362

Credit Risk Prediction:
Credit evaluation –
Optimized NN –
Bayesian regularized NN (BRNN) - Sariev and Germano (2020) used BRNN to Predict the Probability of Default and found BRNN superior in prediction.

Back propagation NN (BPNN) – Loss-given default (LGD) is used in credit risk assessment. LGD is the share of an asset that is lost if a borrower default. Loterman et al. (2012) compared the nonlinear techniques with the linear counterparts in predicting LGD of major international banks.

Feed forward NN (FFNN) – Qi and Zhao (2011) found that nonparametric method like FFNN and regression tree predicts the LGD accurately both in and out of sample than their parametric counterparts. Cifter et al. (2009) investigated the relationship between industrial production and credit defaults (nonperforming loans) using FFNN based on wavelet decomposition.

Fuzzy mathematical model **–**Aiqun et al. (2020) applied NN in risk assessment of logistic finance using back propagation NN and Fuzzy mathematical model. The study found that NN with the fuzzy mathematical model is accurate in risk assessment. Further, Baesens et al. (2003) provided a table with a graphical format that facilitates easy consultation to interpret the NN results.

Credit Scoring –
Standard NN -
Chikolwa and Chan (2008) compared NN with ordinal regression (OR) to study the determinants of Commercial Mortgage-Backed Securities (CMBS) and concluded that NN is superior in prediction to OR. Trinkle and Baldwin (2007) applied NN in credit evaluation for loan finance and concluded that NN can be used in the credit scoring process with caution because of its hidden nature.

Optimized NN –
Backpropagation NN– Hajek (2011) applied NN to rate the United States municipalities in the state of Connecticut and found a higher accuracy of NN in classifying the municipalities with a limited subset of variables. Zan et al. (2004) compared the performance of Support vector machines (SVM) with back propagation NN (BPNN) on the credit rating of companies and found that both SVM and BPNN have the same accuracy in predicting the credit rating.

Table 4. NN literatures in Credit Risk analysis

	Author(s)	**Purpose**	**NN Model**	**Sample**	**Output Variable**	**Predictors**	**Comparison**	**R Squared Value**	**Accuracy**
1	Sariev and Germano (2020)	Estimation of the probability of default	BRNN, BPNN	East European, German, and Polish	2007 - 2012 (EE), 2007 - 2013 (P)	Payables turnover, ROA, cash ratio, sales/total assets,	BRNN > BPNN	-	-

				data		LA/TA, interest coverage			
2	Lotterman et al. (2012)#	Benchmarking regression algorithms for loss given default modeling	NN, SVM, and OLS.	six LGD datasets from international banks	-	-	SVM, NN > Linear Models	0.1295	MAE = 0.3118
3	Qi and Zhao (2011)#	Comparison of modeling methods for Loss Given Default	OLS, fractional response regression (FRR), inverse Gaussian regression (IGR), and inverse Gaussian regression with beta transformation (IGR-BT), and regression tree (RT), NN	3751 defaulted securities in the US, Moody's Ultimate Recovery Database	1985 to 2008	-	NN, regression tree > linear regression, fractional response, OLS	0.576	-
4	Cifter et al. (2009)	Examine the relationship between industrial production and credit defaults	FFNN using Wavelet decomposition	83 monthly observations Industrial production and credit default rates are from Central Bank of Turkey	2001 to 2007	Industrial production, Credit defaults all sectors, Wholesale, and retail trade	Industrial cycle affects the sectoral credit-default cycles at different. time scales	-	MSE = 0.00022
5	Aigun et al. (2020)	Risk assessment of logistic finance	BPNN and Fuzzy mathematical	-	2019	-	NN +Fuzzy is accurate in the prediction	-	-
6	Baesens et al. (2003)	Rule Extraction and Decision Tables	MLP, Neuro rule, Trepan, and Nef	German credit dataset from UCI	-	Term of loan, Purpose, savings account	Extract very compact rule sets and trees for all data sets	-	-

		for Credit-Risk Evaluation	class.	repository, Bene1 and Bene2 datasets from Beneluex financial institutions		balance, income, property, No. of years as a client, Economical sector			
7	Chikolwa and Chan (2008)	Determinants of credit ratings	Standard NN Vs Ordinal regression	MBS credit ratings of Standard and Poor	1999 - 2005	Loan to value; Debt Service Coverage Ratio; issue size; bond tenure, property diversity, geographical diversity, CMBS rating	ANN > Ordinal regression	Pseudo R squared = 0.018	Classification accuracy = 80%
8	Trinkle and Baldwin (2007)	Interpretable credit model development using NN	ANN models created from previous research studies	Two German consumer credit data sets, SAS data repository	-	Age, car, cards, Cash, etc.	ANN > General credit models	-	Accuracy rate = 0.63084
9	Hajek (2011)	Municipal credit rating modeling by neural networks	FFNN, RBFNN, Probabilistic NN, Cascade correlation NN, Group method of data handling (GMDH) polynomial NNs, Support Vector Machines.	Credit information's of r 169 US municipalities (located in the State of Connecticut)	2003 - 2007	Population. Population growth, median family income, unemployment rate, total revenue to total expenditure, tax revenue to total revenue, tax collectibles, debt service, total debt to the total population, tax	An accurate credit rating classification	-	PNN, Classification Accuracy test = 98.8%

						collection rate, form of income.			
10	Zan et al. (2004)	Credit rating analysis with support vector machines and neural networks	backpropagation neural network (BNN) Vs Support vector machines	Taiwan Ratings Corporation, Securities and Futures Institute, S&P Compustat data set.	1991 to 2000	TA, TL, DE, CR, ROA, ROE, EPS, NOI, NII, etc.	BNN, SVM >Linear regression	-	Accuracy rate = 80%

Cross validation

Financial Distress:

Optimized NN –

***Multi-layer perceptron (MLP)* –**Loukeris and Eleftheriadis (2015) used MLP, hybrid MLP with neurogenetic, and voted perceptron algorithm (VPA). VPA is a method that linearly separates data with a larger margin to predict financial distress. Manel (2012) used five MLP and compared them with traditional financial analysis to predict financial distress and found that the MLP is superior in accuracy.

Learning vector quantization (LVQ) – LVQ is a NN method with a supervised algorithm to let choose the number of training instances to hang on to. Brockett et al. (2006) compared the multiple discriminant analysis (MDA) and logistic regression with LVQ to analyze the solvency of life insurance companies and found NN architectures are superior in predictions.

Hidden layer learning vector quantization – Like LVQ, hidden layer LVQ (HDLVQ) outperforms the traditional NN methods and financial techniques while evaluating the corporate solvency of life insurance companies. The research study by Neves and Vieira (2006) integrated HDLVQ to correct the outputs of MLP and found the technique is superior to traditional techniques like z core models and standard NN.

Hybrid NN –

Fuzzy analytical hierarchy and CAMEL model – CAMELS framework is the most widely applied methodology to study the financial position of banks. Wanke et al. (2016) used NN with a fuzzy analytical hierarchical model along the CAMELS framework to predict the financial distress of banks.

***Z score model* –**Z score model is a financial technique to evaluate the financial distress of a company. Pradhan (2011) used NN along with Z score and found it classifies accurately.

***Profitability index and capital structure variables* –**Willer et al. (2020) created a business insolvency forecasting model using NN and found that the predictable power of NN shows significant accuracy. Yang et al. (1998) and Atiya (2001) confirms the accuracy.

Table 5. NN literatures in Financial distress

	Author(s)	Purpose	NN Model	Sample	Output Variable	Predictors	Comparison	R Squared Value	Accuracy
1	Loukeris and Eleftheriadis (2015)	Credit portfolio selection process	MLP, hybrid MLP with neurogenetic, and voted perceptron algorithm	1411 companies from Greek commercial bank	1994 to 1997	16 Financial ratios	-	-	MSE 0.034
2	Manel (2012)	Prediction of financial distress	BPNN	528 Tunisian firm (Central bank of Tunisia report)	1999 - 2006	26 financial ratios predicting distress	-	-	Classification accuracy – 98.9%
3	Brockett et al. (2006)	Comparison of NN and statistical models for life insurers' financial distress prediction	back-propagation and learning vector quantization (LVQ) Vs multiple discriminant analysis and logistic regression analysis	Texas Department of Insurance data	1991 to 1995	IRIS variables	BNN, LVQ > MDA, Logistic Regression	-	Correct rate (1994) = LVQ (1.00), BP (0.971)
4	Neves and Vieira (2006)#	Improving Bankruptcy Prediction with Hidden Layer	Learning vector quantization + Multi-layer perceptron	780,000 financial statements of French companies, Industri	1998 - 2000	Input consists of 30 financial ratios			Generalisation error: MLP = 8.8%, HLVC-Q = 7.3%

		Learning Vector Quantization		al French firms, 583 bankrupt firms					
5	Wanke et al. (2016)	Predicting performance in ASEAN banks	Fuzzy analytic hierarchy process NN	Financial ratios of 88 Association of Southeast Asian Nations bank	2010 to 2013	CAMELS ratios	Possible to explain the causes of inefficiency using NN	-	RMSE = 0.0248
6	Pradhan (2011)	Prediction of financial distress	BPNN	State Bank of India	2001 – 2010	Z score variables	-	-	-
7	Willer et al. (2020)	Forecasting business insolvency	Standard NN	-	-	Profitability index, capital structure	-	-	91% Accuracy Dynamic Model
8	Yang et al. (1998)	Probabilistic Neural Networks in Bankruptcy Prediction	Fisher discriminant analysis, BPNN, PNN, PNN without patterns normalized.	122 companies U.S. oil and gas industry	1984 to 1989	Net cash flow to total assets, TD/TA, CL/TD, etc	Fischer discriminant analysis, PNN normalized> BP NN, Probabilistic NN without a pattern	-	Fisher discriminant analysis = 87% correct classification,
9	Atiya (2001)	Bankruptcy Prediction for Credit Risk	Standard NN	Defaulted and from solvent US firms, 716 solvent firms and 195 defaulted firm	-	Merton's asset-based model	-	-	Correct rate = 85.50%

Cross validation

Other Financial Applications:

Standard NN

Apart from the major topics of research, researchers have found NN is efficient to detect fraudulent reporting (Koskivaara & Back, 2007; Omar et al. 2017) and project portfolio management (Costantino et al., 2015).

Optimized NN –
A fuzzy analytical model is used for creating a financial information system (Wang et al., 2020).

A self-organization map algorithm**,** an unsupervised learning NN that produces a low-dimensional, discretized representation of the input space of the training samples, is called a map. SOM is used to analyze the integration of EU capital markets (Horobet 2014), differences in world economies (Cimpoeru 2015).

Hybrid NN –
NN with *the Ohlson model* is used to predict operating performance (Ying-Hua & Shih-Chin, 2013).

CONCLUSION

A descriptive systematic review was conducted to find the application of neural networks in financial research. The study found a keen research interest to use NN for predicting financial data. This is obvious from the statistic that about 53% of the collected research studies applied NN in investment prediction. Credit evaluation and financial distress topics contribute to 20% and 17% of each of the collected papers. There are very few works (10%) found on other financial aspects.

The following are the reflections of the review. First, it is observed that the researchers have used arbitrary data partition and architecture selection in all the research works. Besides, the performance or evaluation metrics widely differ among the collected research studies, giving less scope for comparing the accuracy of an NN architecture in a particular subtopic. Hence, in this study, a meta-analytic comparison to generalize the NN architectures and formalizing a theory to choose a suitable NN method under a topic has serious limitations.

Second, there are few studies (Neves & Vieira, 2006; Qi & Zhao, 2011) that have performed the cross-validation in NN models. Cross-validation increases efficiency in using financial data as every observation is used for both training and testing which results in a more accurate estimate of out-of-sample prediction. Further, overfitting and underfitting of data will be managed efficiently through cross-validation.

Third, unlike prediction, in the research studies of classifying financial data, there is a scope for a meta-analysis based on generalizing Area Under Curve (AUC) that help to estimate the accuracy of classification on a particular topic. Further, the study observed NN architectures including domain-specific knowledge performs with more accuracy. Hence, more domain-based Hybrid NN architectures can be trained.

Besides, the review has the following limitations. The descriptive systematic review has examined only the research papers published and available under the EBSCO database. Consequently, the works of the literature review are prone to publication bias, which occurs with publishing only statistically significant results. Beyond, the research works in conference proceedings and working papers are not reviewed. Hence some sub-topics and main research topics might have been remaining uncovered. Systematically including more research papers from other sources will improve the chance of a meta-analysis of NN in financial research. Since meta-analysis on machine learning by Krittanawong et al. (2020) and Roelofs et al. (2019) are the only works available, that too in the medical domain, a meta-analysis of NN architectures in financial research will be a significant contribution to the existing financial and NN literature.

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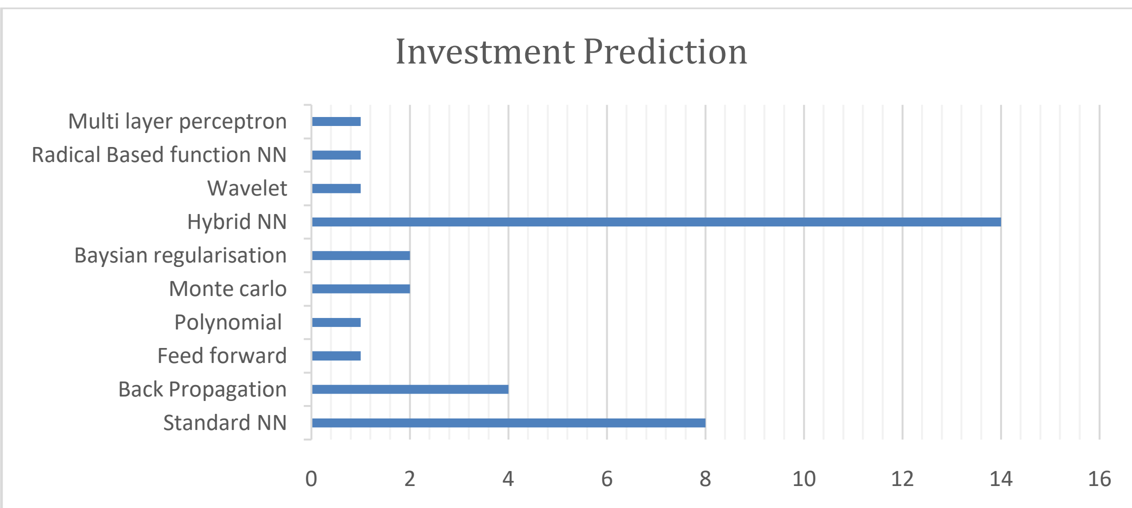
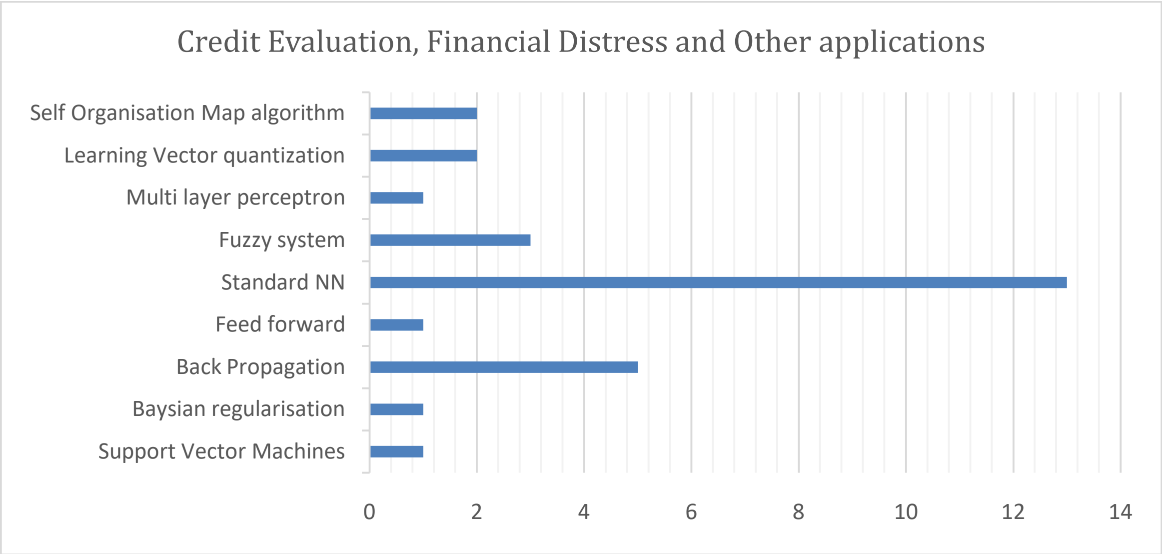
APPENDICES

Appendix A. Figure depicting NN architectures in Investment Prediction



**__Hybrid NN__ methods are developed by incorporating the financial theories (Black Scholes option pricing, Fama French five-factor model), advanced statistics (GARCH, PCA, LASSO, CART, PLR), advanced NN architectures (HONN, GPA, MLP), and domain-specific factors.*

Appendix B. Figure depicting NN architectures in credit evaluation, financial distress, and other applications



*Support Vector Machine is a similar machine learning algorithm like NN.

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