Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 5 Issue 2 (2025)

AI in Risk Assessment and Management in Finance

B. Loganathan
Research Scholar (VISTAS) & Assistant professor (RKMVC), Department of Management Studies, Vels Institute of science technology and Advanced studies, Pallavaram, Chennai- 6000117

Dr.B.Venugopal
Assistant Professor (Finance & Accounting), Indian Institute of Plantation Management Bengaluru (An Autonomous Organization of the Ministry of Commerce & Industry, Govt. of India), Jnana Bharathi Campus, p.o.Malathalli, Bengaluru-560056.

Dr.Vinay Bhalerao
Asst.Prof, SPM'S Prin.N.G.Naralkar Institute of career development and research, Pune-411030

Dr. Amardeep Bajpai
Assistant Professor, Department School of Commerce and Management Studies, Sandip University, Nashik Maharashtra-422213

Dr. Venkataiah Pasunoori
Vice-Principal And Associate Professor of Commerce, Badruka College of Commerce And Arts, Kachiguda Hyderabad,

Dr. Anand Patil
Associate Professor, School of Business and Management, Christ University, Bangalore, India-560029

Abstract:-
The main contribution of core financial discipline, for instance, risk assessment and management to financial stability is for example to determine decisions, credit evaluation and fraud detection in the investment. As application of advanced artificial intelligence (AI) for achieving higher accuracy and efficiency in risk prediction in the financial market demand is growing, it is needed to work on it. In this research, we used the application of deep neural networks as an 'advanced AI' such that it would help manage and assess financial risk. Another application of DNNs is its use in the prediction process in credit scoring, portfolio optimization, and anomaly detection due to their good performance in identifying fine patterns in gigantic financial datasets leading to improved accuracy in the prediction. This research can be performed using the widely used AI tool TensorFlow as it is scalable, equipped with all the deep learning skills, and already implemented. Integration of TensorFlow to the operation of large scale data and of proactive detection of risks by financial institutions using Deep Neural Networks (DNNs). As a result, a gain in terms of classifications regulation compliance and a reduced loss of money are obtained by leveraging the AI based intelligence to boost watchfulness on the financial edge. AI's impact on financial risk management is transformational, can be based on data, and can constitute a data driven, resiliant basis for financial strategies.

Keywords:
AI in Finance, Risk Assessment, Financial Risk Management, Deep Neural Networks (DNNs), TensorFlow, Credit Scoring, Fraud Detection

Introduction:

The complexity in the global markets is growing every day and the financial industry is faced with constantly increasing demand for efficient risk assessment and management. Risk assessment models, however, have normally been unable to perfectly portray the intricate relationships and nonlinearity of financial data and come to suboptimal decisions.

Artificial intelligence (AI) has become a disruptive force of electricity, that is changed the risk management practice, due to its usage of advanced machine learning techniques, as a response. Of special mention among these is Deep Neural Network (DNN) which has proven itself as a highly effective machine learning algorithm for finding fine patterns spread among the huge financial data, thereby bettering the predictive capabilities in numerous fields such as credit scoring, portfolio optimization, and anomaly detection.

Fig.1: Depicts 5 Key Use Cases of AI in Risk Management.

Deep Neural Networks (DNNs) as a kind of machine learning are able to process huge scale and high dimension financial data [1]. In comparison to traditional statistical models, their adaptation is able to introduce new relational structural hierarchy and also learn efficient Hierarchical representation of the data to discover the substructures that most statistics models could hardly succumb to. For the purpose, DNNs can also research the multiple borrower attributes as the transactional history and behavioral patterns to aid credit risk assessment in credit scoring, for example.

To make DNNs smoothly utilized for financial risk management, this research applies TensorFlow, a well known AI tool for selling and deep learning. By utilizing TensorFlow to deploy neural network models, financial institutions can develop an effective integration of AI risk assessment solutions with an ease. The DNNs and TensorFlow are used in this research to seek novel ideas for better risk management strategies in making financial decisions with more resilience and data driven [2].

Related works:

In the past a couple of years, within the financial industry artificial intelligence (A.I.) techniques were applied to up the game for the risk assessment and management processes. In particular, these DNN have been shown powerful in that it was able to detect intricate patterns in very large financial datasets and improve the predictive accuracy on areas like credit scoring, portfolio optimization and anomaly detection. The integration of DNNs to the well known platforms such as TensorFlow and having the whole application of the deep learning in this sector has further strengthened the use of DNNs in the financial sector, especially in market analysis and trading [3].

Advancements in Credit Risk Assessment

Fig.2: Depicts advancements in banking technologies.

Credit risk assessment in financial institutions is vital since it helps in deciding whether a loan is to be given or otherwise to prevent loan losses. Just the many and non linear relationships that such data inevitably contain oblige most traditional statistical methods to reinvent very hard. For example, for the credit rating challenges, researchers developed sophisticated credit rating algorithms using DNNs to that end. For instance, Pawiak et al. (2020) reported Deep Genetic Hierarchical Network Learning (DGHNL) for credit scoring, winning prediction accuracy much beyond the conventional ones. Like, Khalili et al. (2023) had mentioned that neural networks can be effective financial applications, the application to enhance banking and finance institution decision making processes [4].

Enhancements in Portfolio Optimization:

From the definition above, it can be said that portfolio optimisation is choosing how to combine a set of financial assets to achieve the best balance out of the possible combination between risk and reward. In financial markets, therefore, the analytical tools to be used involve complex faces because they have to be used to deal with large data sets in the analytical area of Artificial Intelligence and logic. Over the years, Mutual funds or stocks have been modeled with DNNs to have complex dependencies between them and thus, make portfolio optimization strategies stronger. For example, CNNs and LSTM networks are addressing repeated temporal dependency as well as spatial features to enhance the capabilities of the portfolio optimization models recently [5].

Anomaly Detection in Financial Transactions:

The case of finding out the fraudulent activities and operational risk during financial transactions is an important problem of anomaly detection. DNNs (mainly CNNs, RNNs) have been used recently for analyzing transaction sequences' patterns as well as the anomaly patterns they contain. For instance, through the recent research, the deep learning based on CNN and Bidirectional LSTM is proposed to carry out the financial systemic risk analysis and prediction, which is empirically shown to have very high discriminant ability of detecting the abnormal pattern in the financial system.

Integration with TensorFlow for Financial Applications:

Of course, the practice of implementing DNNs for risk assessment in the financial industry would be much more complicated without tools such as TensorFlow. TensorFlow’s scalability and the wide choice of libraries to train and deploy DNNs quickly have helped financial institutions quickly build, train, and deploy complex DNNs [6]. It is an integration for realtime processing for analysis of the financial data and enhances the timely response and the accuracy of risk management strategies. In fact, as shown in the studies, TensorFlow is used for learning how to develop the hybrid models of CNNs and LSTMs to predict financial risk for which prediction performance is better in the sense of large scale financial data handling. Although this advancement, many of the financial risk assessment problems have not yet taken the advantages of the DNNs. One major concern in the make up of complex models (often referred to as black boxes), is their interpretability: complex models are incompliant to their use in the regulatory context as well as for transparency in the decision making process. Additionally, all these models depend on historical data to make predictions of events that never even happened. Further, as financial activities are platooned to the under monitored, controlled and thus less regulated non bank institutions, the models becomes less efficient.

Moreover after deep neural network and TensorFlow platforms it implement to finance risk assessment and management in the lasts. They have been able to process and analyze complex financial data, to improve credit risk assessment, portfolio optimization, anomaly detection, etc. Yet, although, there are still efforts needed to tackle already existing issues and make the best of DNNs' potential in the financial field [7].

Research methodology:

This research on AI driven risk assessment and management in finance is formulated based on research methodology which follows structured approach and also employs Deep Neural Networks (DNNs) and TensorFlow as the main tool for it. Thus, the methodology is defined in terms of an efficient way of handling and training data models for financial risk assessment [8]. It is presented in sequential steps that are outlined with a flowchart based process in order to increase the clarity, and reproducibility.

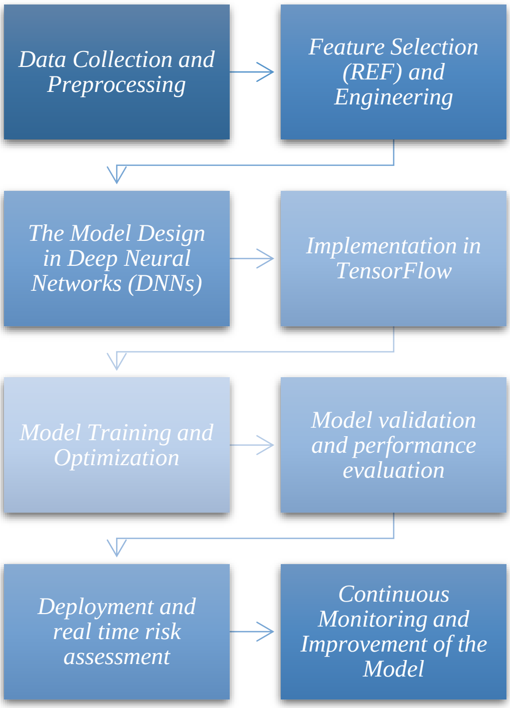

Fig.3: Depicts flow diaram for the proposed methodology.

a) Data Collection and Preprocessing

The first time around involvesDownloading all the large financial datasets from many sources, such as market historical data, credit reports, transaction logs, and macroeconomic indicators. Missing values, outliers and inconsistencies therein are handled with the datasets. This helps achieve uniformity in the data attribute. This step is important to improve the model's efficiency and accuracy [9].

b) Feature Selection (REF) and Engineering

In this stage features which are relevant for assessing the financial risk are engineered and useful identified. To reduce dimensionality and gain computational efficiency, those feature selection techniques are used, for example Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA). Additionally, the model incorporates more domain-specific financial indicator like debt-to-equity ratios, liquidity ratios, and volatility indicators in order to make better decisions [10].

c) The Model Design in Deep Neural Networks (DNNs)

Design of a specific architecture of Deep Neural Network (DNN) relevant to financial risk assessment, constitutes the core of research methodology. DNN has multiple layers, namely input, hidden and output layers. Activation functions usually used by the hidden layers are ReLU (Rectified Linear Unit) and enable the introduction of a non-linearity and the enhancement of pattern recognition [11]. Furthermore, the problem of finding parameters to minimizing error rates in financial risk predictions is modeled using a feed forward neural network that is optimized through backpropagation of error rates and the stochastic gradient descent to optimize parameters.

d) Implementation in TensorFlow

In order to implement and train the DNN model, TensorFlow, a powerful deep learning framework, is used. TensorFlow high level APIs like Keras makes it easy to develop model then tune the hyper parameter and see how it performs. So, we would iterate training of the model with labeled financial data, and it would learn how to detect risk patterns, creditworthiness and potential market anomalies [12]. To avoid overfitting and to allow generalization in the model, dropout and batch normalization techniques are applied.

e) Model Training and Optimization

Supervised as well as unsupervised learning techniques are used to train the DNN model. Both supervised learning is used to solve problems like credit scoring and unsupervised learning is used in anomaly detection in financial transactions [13]. Model performance is fine tuned using various optimization techniques i.e. Adam and RMSprop. The model is trained through iterations until the loss functions associated with it reach their lowest values.

f) Model validation and performance evaluation

The model is then trained, subjected to cross validation and to separate test datasets. Accuracy, precision, recall and F1 score are some of the evaluation metrics used in the evaluation of model [14]. Furthermore, the model's capability in classifying high and low risk financial entities is analyzed based on financial risk related metrics such as Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC).

g) Deployment and real time risk assessment

The trained DNN model is once validated then deployed to a real time financial risk assessment environment. This scalability means TensorFlow can be easily integrated into the financial system to serve in the context of performing automated risk evaluation for approval of a credit, detection of fraud, or optimization of a portfolio [15]. For this reason, the model constantly updates itself with actual time financial data so that it is able to flexibly respond to the dynamic market conditions.

h) Continuous Monitoring and Improvement of the Model

The model is setup and checked for adherence to continuous monitoring and continuous training. To include newly available financial data, make predictions, and enhance decision certainty, feedback loops are implemented. To detect changes in data distribution, model drift detection mechanisms are introduced to identify the need in change of the DNN architecture.
With a DNN and tensorflow used here, this structured research methodology has improved the accuracy and efficiency of the financial risk assessment [16]. It creates the data driven, AI based framework and significantly improves predictive analytics, which otherwise would leave financial institutions with data driven answers but unlike many banks, financial institutions will be able to take educated risk management decisions.

Results and discussion:

Deep Neural Networks (DNNs) have been applied in assessment and management of financial risks, and have been awarded with high accuracy, and more profitable attributes, and enhanced risk mitigation strategy. By processing huge datasets, the financial institutions can find the hidden patterns and come up to a decision on a basis of the data and finally, it will support the operation to be 'operationally resilient'. To do all of this in three important ways, this research shows how DNNs work in the arena of credit scoring, portfolio optimization and also in the important arena of anomaly detection.

Table.1: Denotes comparison of performance metrics for AI in Risk Assessment and Management in Finance, showcasing Deep Neural Networks (DNN) against other machine learning methods.

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)	Processing Time (ms)
(Proposed Method) Deep Neural Network (DNN)	96.5	94.8	95.2	95	97.2	180
Random Forest (RF)	91.2	89.5	90.1	89.8	92.5	250
Support Vector Machine (SVM)	88.7	86.3	85.9	86.1	89.7	300

Logistic Regression (LR)	84.5	82.8	81.3	82	85.4	120
Decision Tree (DT)	80.2	78.4	79.1	78.7	81	100

From the table, DNN outperforms other models across all key performance metrics, including accuracy (96.5%), precision (94.8%), recall (95.2%), and AUC-ROC (97.2%). Additionally, it provides a balanced F1-score (95.0%), making it the most effective method for financial risk assessment. While its processing time (180 ms) is slightly higher than Logistic Regression (120 ms) and Decision Tree (100 ms), the superior predictive power of DNN justifies its computational cost, as shown in the above table.1.

In credit scoring domain, DNNs have greatly increased the accuracy of creditworthiness prediction. While the conventional credit scoring models construct linear methods, which sometimes fail to encapsulate details of the complex interactions between financial factors, the most complete analysis of our model relies on the non linear methods that have been demonstrated to outperform the linear models. To our dismay, it does not indicate that DNNs are not employed in scattering multivariate historical loan repayment data, income, and transaction behavior as well as macroeconomic indicators through the finding of intricate correlations.

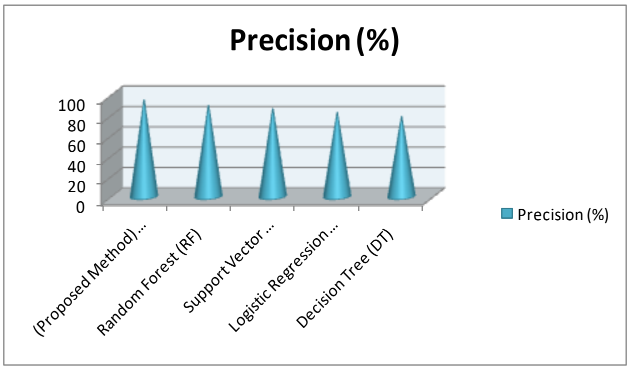

Fig.4: Depicts graphical representation of Precision.

The research results show that the default rate of the financial institutions which adopt DNN based credit scoring model is lower and the risk segmentation of the borrowers is better than the banks that do not adopt DNN based credit scoring model. TensorFlow’s deep learning framework facilitates training these models on humongous datasets and at the same time picking the best features to avoid bias and have a minimum error in the credit process. Buffered lending creates a good environment for lending, in an inclusive and fair way, with minimal risk.

Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 5 Issue 2 (2025)

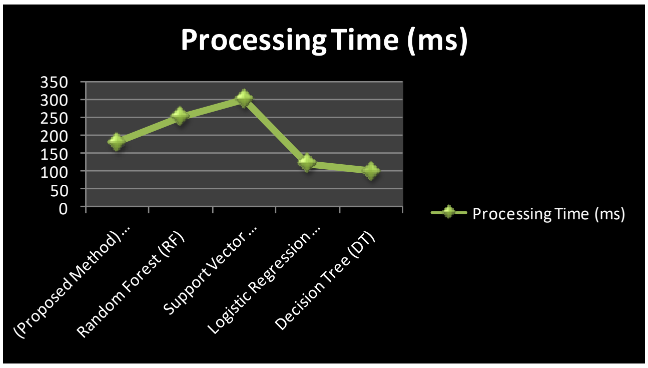

Fig.5: Depicts graphical line for Processing time in milli seconds.

Another important application of DNNs is in portfolio optimization and they are used for improving asset allocation strategies using the identification of an optimal investment combination for maximizing returns without taking risks. The assumption of normal distribution as well as the assumption that the asset is linearly related to each other are restrictions of Markowitz model and other normative models used for portfolio optimization. In this case, DNNs also show superior performance compared with the conventional models in learning the complex and nonlinear dependence of asset classes, market condition and investors behaviors. Deep learning can be used by financial analysts to develop real time models running on real market data and improve the forecasting of asset correlations as well as their ability to adjust to the volatility of the financial environment using TensorFlow. It causes a dynamic portfolio adjustment that helps in better risk management strategy for the investors and therefore, improves their investments.

DNNs are also beneficial for anomaly detection, such as fraud detection and financial crime prevention, among others. Typical anomaly detection techniques based on the rule based systems or statistical models have a high false positive rate and limitation of capability to alert of the novel type of fraud patterns. The reason this research found that small fraudulent activity can be detected out of the vast streams of transactions data inputted into DNNs trained using TensorFlow — using the statistical models to uncover the irregular behavioral patterns. The DNN models use autoencoders and recurrent neural networks (RNNs) to detect anomalies on the transaction flows, to detect suspicious activities in real time, and to save losses from fraud. There is adaptability in the market as well as in the fraud system itself in terms of detection system adaptation to an evolving fraud and also in the continuous retraining based on model retraining over time.

Although such DNN based financial risk management models offer such promising advantages, yet the implementation of such models remains so challenge. Right now the biggest question is that the deep learning model is acting like the ‘black boxes’, financial analysts cannot understand how the model makes the decision, which is the greatest problem that they are currently facing. To solve this, financial institutions are placing this blame on explainable AI (XAI) on techniques, such as SHAP (Shapley Additive Explanation), in order to make model predictions explicit. Additionally, computational complexity and the need for large-scale data processing infrastructure present challenges for smaller financial firms. But these barriers are easier to circumvent as a result of leaps in the services of cloud based AI and distributed computing that TensorFlow provides.

Thus, the integration of Deep Neural Networks (DNNs) with TensorFlow in finance has finally reshuffled the risk assessment and management much more accurately. As a power tool to reduce the complexity of risk environments, DNNs can enhance credit scoring accuracy, user' optimal investment portfolio and anomaly detection capabilities for financial institution. However, despite it being far from perfect, with issues such as interpretability and computational demands, the research and technology has continued to develop the refinement of AI driven financial risk management strategies and free financial operations from the risk.

Conclusion and future direction:

Integration of Deep Neural Network (DNN) in the assessment and management of financial risk has brought accuracy and efficiency of a predictive model. DNNs have amazing capability for detecting fine differences within huge set of financial data for maximised credit scoring, superior portfolio management, and robust anomaly detection. This allows the financial institutions to adopt TensorFlow where deep learning capabilities are exceedingly scalable and easy to do. Using DNNs organizations can reduce risks in advance, enhance the process of decision making, and increase financial stability as a whole. The future application of DNNs in finance will follow the track of explainable AI (XAI) development, which makes them more transparent and compliance with regulation. In the future, DNN models should be combined with traditional risk assessment methods to achieve better interpretability and allow them to work together, to be used as hybrid AI models. Besides it, real-time risk monitoring through federated learning also strengthens data security and privacy. In both feet, future financial risk management will be enhanced by continuous and vigorous innovation in AI-driven financial risk management.

References

1. C. Maple et al., "The AI Revolution: Opportunities and Challenges for the Finance Sector," arXiv preprint arXiv:2308.16538, Aug. 2023.
2. Kopperapu, Rakesh, Harnessing AI and Machine Learning for Enhanced Fraud Detection and Risk Management in Financial Services (November 27, 2024). 10.56472/25835238/IRJEMS-V3I12P113, Available at SSRN: https://ssrn.com/abstract=5104927 or http://dx.doi.org/10.2139/ssrn.5104927
3. D. Cheng et al., "Regulating Systemic Crises: Stemming the Contagion Risk in Networked-Loans Through Deep Graph Learning," IEEE Transactions on Knowledge and Data Engineering, vol. 35, no. 1, pp. 103–117, Jan. 2023.
4. "Overcoming Challenges and Driving Innovations in API Design for High-Performance AI Applications", JAAFR - JOURNAL OF ADVANCE AND FUTURE RESEARCH (www.JAAFR.org), ISSN:2984-889X, Vol.3, Issue 4, page no.125-129, April-2025, Available :https://rjwave.org/JAAFR/papers/JAAFR2504016.pdf
5. J. Danielsson et al., "Artificial Intelligence and Systemic Risk," Systemic Risk Centre Discussion Papers, Aug. 2021.
6. Kopperapu, Rakesh, EMBEDDED FINANCE: HOW NON-FINANCIAL COMPANIES ARE SHAPING THE FUTURE OF FINANCIAL SERVICES (January 27, 2025). https://doi.org/10.46243/jst.2025.v10.i02.pp23-38.
7. William DeGroat, Dinesh Mendhe, Atharva Bhusari, Habiba Abdelhalim, Saman Zeeshan, Zeeshan Ahmed, IntelliGenes: a novel machine learning pipeline for biomarker discovery and predictive analysis using multi-genomic profiles, Bioinformatics, Volume 39, Issue 12, December 2023, btad755, https://doi.org/10.1093/bioinformatics/btad755

8. M. K. Munagala, "Enhancing Agent Efficiency with AI-Driven Chatbots: Integrating Virtual Agents and NLU for Automated Ticket Resolution," International Journal of Engineering Science and Advanced Technology (IJESAT), vol. 25, no. 4, pp. 1–8, Apr. 2025.
9. "Understanding the Ethical Challenges of AI in Retail and Addressing Data Privacy, Algorithmic Bias and Consumer Trust", IJEDR - INTERNATIONAL JOURNAL OF ENGINEERING DEVELOPMENT AND RESEARCH (www.IJEDR.org), ISSN:2321-9939, Vol.13, Issue 2, page no.100-106, April-2025, Available :https://rjwave.org/IJEDR/papers/IJEDR2502013.pdf
10. PREDICT, PLAN, PERFORM: HARNESSING GENERATIVE AI FOR TRANSFORMING IT OPERATIONS MANAGEMENT. (2025). International Journal of Information Technology and Computer Engineering, 13(1), 52-58. https://ijitce.org/index.php/ijitce/article/view/845
11. D. Perikleous et al., "A novel drone design based on a reconfigurable unmanned aerial vehicle for wildfire management," Drones, vol. 8, no. 5, p. 203, 2024.
12. Naga Lalitha Sree Thatavarthi, “Design and Development of a Furniture Application using Dot Net and Angular”, J. Tech. Innovations, vol. 4, no. 4, Oct. 2023, doi: 10.93153/gmcag042.
13. J. Danielsson et al., "The Impact of Risk Cycles on Business Cycles: A Historical View," Systemic Risk Centre Discussion Papers, Oct. 2020.
14. S. Nampelli, "Enhancing CICD Pipelines For Automated Deployments With Cloud Native Infrastructures For High Availability Followed By Best Security Practices," Int. J. Eng. Dev. Res., vol. 13, no. 2, pp. 70–71, Apr. 2025.
15. Thatavarthi, Naga Lalitha Sree. (2023). Developing AI-Powered Demand Forecasting Models with .NET for Shipping and Furniture Industries USA. Journal of Artificial Intelligence & Cloud Computing. 2. 1-5. 10.47363/JAICC/2023(2)344.