ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAY2125

An Overview of AI and Advanced Algorithmic Applications in Financial Risk

Moussab El khair Ghoujdam*[1]; Rachid Chaabita[2]; Salwa idamia[3]; Oussama El khalfi[4]; Hicham El Alaoui[5]; Kamal Zehraoui[6]
[1]Doctor in Economic Sciences, University Hassan II Casablanca, Maroc
[2]Professor of Higher Education at the Faculty of Legal, Economic and Social Sciences - University Hassan II and Director of the Laboratory Business Intelligence Governance of Organizations, Finance and Financial Crime. University Hassan II Casablanca, Maroc
[3]Doctor in Economic Sciences, University Hassan II Casablanca, Maroc
[4]Research Professor, University Sidi Mohamed Ben Abdallah de Fes, FSJES, Maroc
[5]Doctor in Economic Sciences, University Hassan II Casablanca, Maroc
[6]Research Professor, University Hassan II Casablanca, Maroc

Abstarct:- This article delves into the transformative effects of Artificial Intelligence (AI) and Machine Learning (ML) on the realm of risk management. AI and ML technologies have revolutionized risk assessment, mitigation, and management across various sectors by offering advanced analytical capabilities and automated decision-making processes. In the financial sector, for instance, these technologies have facilitated improvements in loan decision processes, fraud detection, and compliance. Partnerships like ZestFinance and Baidu exemplify the successful application of AI in enhancing loan decisions based on vast data analysis. Despite the evident benefits, challenges such as model-related risks, data availability and protection, and the need for skilled personnel persist. This article aims to provide a comprehensive overview of the current applications of AI and ML in risk management while identifying opportunities for further research and development in this rapidly evolving field.

Keywords:- *Artificial Intelligence (AI) ; Machine Learning (ML); Risk Management; Credit Risk; Market risk; Operational Risk.*

I. INTRODUCTION

The integration of artificial intelligence (AI) and machine learning (ML) techniques into risk management is significantly transforming various sectors by offering advanced methods for assessing, mitigating, and managing risks. These technologies enable precise data analysis and automated decision-making, essential for navigating complex risk environments.

In the financial sector, AI and ML are revolutionizing risk management by enhancing loan decision processes, detecting fraud, and improving compliance. For instance, ZestFinance leverages AI to analyze vast amounts of data for quick and accurate loan decisions. In collaboration with Baidu, ZestFinance improved loan decisions in China by using data points such as customers' search and purchase histories [1]. This system led to a 150% increase in small loans granted by Baidu without an increase in credit losses within just two months. Machine learning is also applied to assess credit risks, optimize investment strategies, and enhance overall risk management. An examination of annual bank reports highlights the areas where ML techniques have been implemented and the algorithms used [2]. Nevertheless, certain aspects of risk management require further exploration and research to fully understand the potential and limitations of AI and ML technologies [3,4].

As new financial technologies and digital banking emerge, risk management practices are evolving accordingly. AI research and solutions are expected to make significant contributions to this evolution [5]. However, despite the numerous positive effects of AI, ML, and deep learning (DL), it is essential to consider the challenges and open questions. These challenges include model-related risks ("black box"), data availability, collection, and protection, transparency, ethics, and the need for skilled personnel to develop and implement new techniques (Financial Stability Board, 2017).

The objective of this article is to provide an overview of the current applications of AI and ML in risk management, highlighting their advantages and identifying opportunities for future research and development. Exploring the integration of AI and ML techniques in risk management is of major interest for several reasons. Firstly, AI and ML have the potential to radically transform how risks are identified, assessed, and managed, enabling faster, more accurate, and more comprehensive analyses than traditional methods. Secondly, the adoption of AI and ML in risk management addresses the growing need to handle increasingly large and complex data volumes. This leads us to pose the question: How can the integration of AI and ML techniques into risk management improve the efficiency and accuracy of risk management processes?

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAY2125

To answer this question, we began our discussion by establishing a foundational understanding of risk management and machine learning, setting the stage for a comprehensive exploration of their integration. Subsequently, we delved into the practical application of machine learning techniques within the realm of risk management.

II. BACKGROUND

A. Risk Management

Managing risk in the banking sector is a significant challenge for financial institutions, given their pivotal role in economic systems. The main goal of risk management in banks is to maintain financial stability while maximizing shareholder returns. However, striving for profitability naturally leads to greater exposure to various risks, which can threaten the institution's long-term sustainability.

Banking institutions face numerous risks, including interest rate risk, market risk, credit risk, off-balance sheet risk, technological and operational risk, foreign exchange risk, sovereign risk, liquidity risk, and default risk (Figure 1) [6]; [7]. Each type of risk has distinct characteristics and origins. For instance, interest rate risk arises from market interest rate fluctuations, while credit risk pertains to the potential default by borrowers. Liquidity risk, which is treated separately from other risks, manifests in two forms: asset liquidity risk and funding liquidity risk. Asset liquidity risk occurs when a transaction cannot be completed at current market prices, often due to the transaction size relative to typical market lots. Funding liquidity risk, also known as cash flow risk, refers to the inability to meet cash flow obligations [8].

According to the Basel Committee on Banking Supervision (BCBS), operational risk involves losses resulting from internal processes, human or system failures, or external events. This risk is a critical component of risk management within banks, encompassing legal risks but excluding strategic and reputational risks. Operational risk is inherent in all banking products, activities, processes, and systems (Basel Committee on Banking Supervision, 2011).

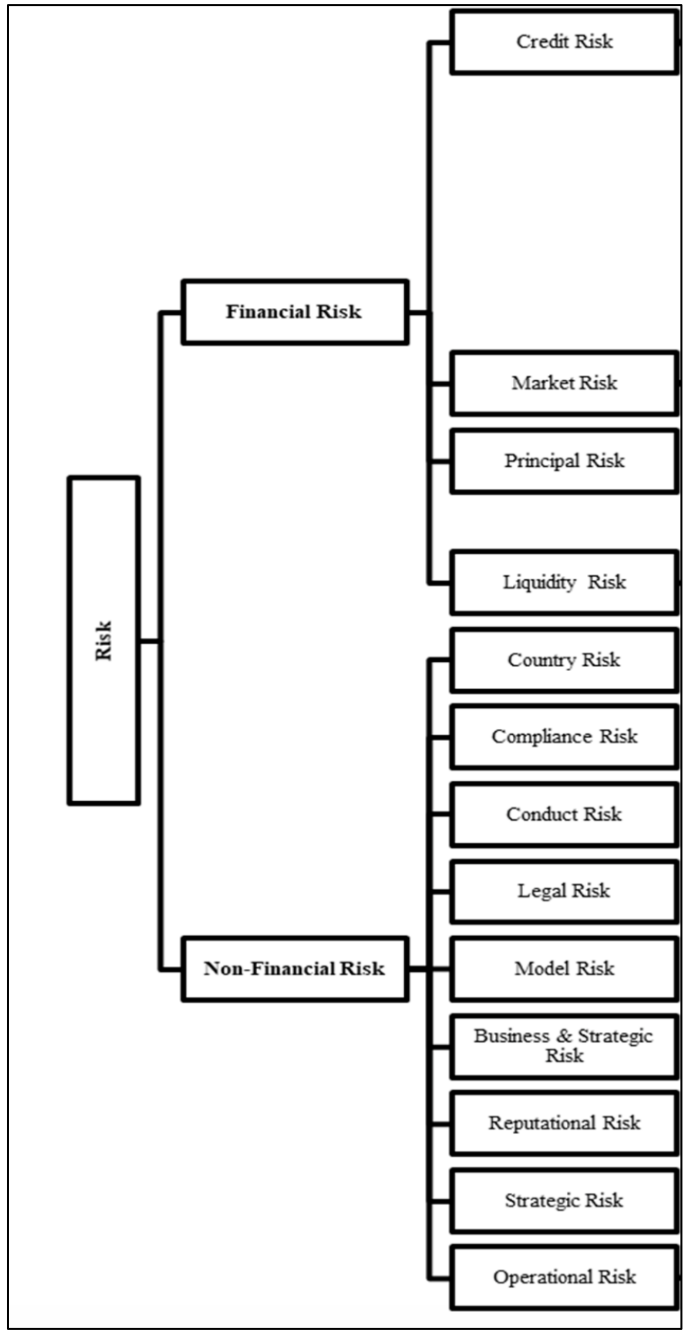

Fig 1: Taxonomy of Risks
Source: Leo, M., Sharma, S., & Maddulety, K. (2019)

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAY2125

To address this complexity, regulators have established standards and guidelines to oversee bank risk management. The Basel Accords, initiated in 1998 and updated since then, provide a crucial regulatory framework for determining banks' capital requirements based on the risks they face [9]; (Basel Committee on Banking Supervision, 2008). These accords establish methods for calculating capital requirements for each type of risk, enabling banks to measure and effectively manage their risk exposure. Effective risk management also requires constant monitoring of market conditions and regular assessment of risk portfolios. Banks must be able to identify emerging trends and potential vulnerabilities, adjusting their strategies accordingly. This often involves the use of sophisticated forecasting models and data analysis techniques to anticipate market movements and assess risk scenarios. Additionally, banks must also ensure adequate levels of liquidity to meet fund withdrawal demands and potential market shocks. Liquidity risk, manifested by a bank's inability to honor its financial obligations, can have serious consequences on its financial stability if not managed appropriately. Therefore, banks must develop robust liquidity management policies and implement monitoring mechanisms to ensure effective risk management.

B. Machine Learning,

A sub-discipline of artificial intelligence, is a self-learning process based on algorithms (Figure 2). It has the ability to analyze data and detect patterns without requiring explicit programming for each task. For example, by exposing the system to different types of data, it can learn and adapt, thereby improving its performance over time [10]. This field of artificial intelligence aims to develop models and techniques that enable computers to learn from data, generalize knowledge, and make decisions or formulate autonomous predictions [11].

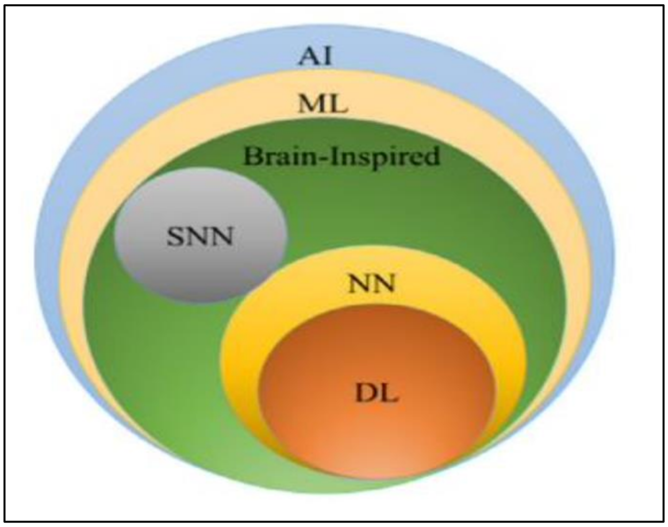

Fig 2: The Correlation between Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), Neural Networks (NN), and Spiking Neural Networks (SNN). Source: (Shinde &al,2018)

Advancements in machine learning have paved the way for the emergence of intelligent systems that rival human cognition. These systems are now ubiquitous in both our professional and personal lives, influencing our interactions in electronic markets in various ways. They contribute to improving decision-making in businesses, thereby enhancing productivity, employee engagement, and retention [12]. They also power personalized assistance systems tailored to individual user preferences [13], as well as trading agents that disrupt traditional financial markets [14].

Over the past few decades, the field of machine learning has witnessed significant advancements, particularly in the development of sophisticated algorithms and effective preprocessing techniques. One such major advancement has been the transition from Artificial Neural Networks (ANNs) to deeper neural network architectures, characterized by enhanced learning capabilities, collectively referred to as Deep Learning (DL) [15]. In specific environments, DL already demonstrates performance surpassing that of humans [16]; [17].

In machine learning, three primary types are generally recognized: supervised learning, unsupervised learning, and reinforcement learning. While many applications in electronic markets utilize supervised learning, such as stock market prediction, understanding customer perceptions, analyzing customer needs, and product recommendation, other methodologies like unsupervised learning and reinforcement learning are also being explored [18]; [19]; [20].

- **Supervised Learning:** This approach involves training a computer program on labeled data to establish the relationship between inputs and outputs. The process requires manual labeling of data, making it particularly useful when there is sufficient knowledge of the dataset. Feature engineering, parameter tuning, and algorithm selection must be performed by an expert. Supervised learning algorithms are used to address regression and classification tasks, optimizing parameters and minimizing errors to predict continuous values or discrete classes from input variables.
- **Unsupervised Learning:** Unlike supervised learning, unsupervised learning operates on unlabeled data, removing the need for manual labeling. It is mainly applied when there is insufficient knowledge of the input data, aiming to group the data into different patterns. Unsupervised learning algorithms are employed for tasks like clustering, dimensionality reduction, and anomaly detection.
- **Semi-Supervised Learning:** Combining aspects of both supervised and unsupervised learning, semi-supervised learning leverages a small amount of labeled data alongside a larger pool of unlabeled data to enhance the accuracy and robustness of machine learning algorithms, reducing the need for extensive manual labeling.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAY2125

- **Reinforcement Learning:** This method depends on a trial-and-error process and a feedback mechanism to refine previous states and actions, optimizing the developed function. In reinforcement learning, agents observe and interact with an environment, receiving rewards or punishments based on their actions, which helps in updating the machine learning model. This technique is especially beneficial for decision-making processes, such as deriving optimal policy solutions.

III. APPLICATIONS OF MACHINE LEARNING AND AI IN RISK MANAGEMENT

A. Applications of machine learning and AI in credit risk

Credit risk refers to the potential economic loss from a counterparty's failure to meet contractual obligations, such as timely payments of interest or principal, or an increased default risk during the transaction period. Traditionally, financial institutions used methods like linear regression, logit, and probit models to assess credit risk [21]. However, there is a growing interest in employing artificial intelligence and machine learning techniques to enhance credit risk management practices, due to the limitations of traditional methods. AI and machine learning have proven to significantly improve credit risk management by effectively interpreting unstructured data.

The use of AI and machine learning in credit risk modeling is not new but is expanding. In 1994, Altman and colleagues conducted a comparative analysis of traditional statistical methods and a neural network algorithm for predicting distress and bankruptcy, finding that a combined approach improved accuracy [22]. The increasing complexity of credit risk assessment has led to the adoption of machine learning, particularly in the context of credit default swaps (CDS). Analyzing daily CDS data from January 2001 to February 2014, non-parametric machine learning models, including deep learning, were shown to outperform traditional models in forecast accuracy and practical coverage measures [23].

In the domains of consumer and SME lending, vast amounts of data are increasingly utilized with machine learning to enhance lending decisions. Companies like ZestFinance operate in this area, demonstrating the effectiveness of machine learning. For example, a technique based on decision trees and Support Vector Machines (SVM) resulted in significant cost savings when applied to real lending data [24]. Similarly, Figini et al. (2017) found that a multivariate outlier detection machine learning technique improved credit risk estimation for SME loans [25]. SVM, a supervised learning algorithm used for classification, has been applied in various forms to design credit risk assessment and scoring models [26]. Studies have shown that models with a broader definition of credit risk are more accurate [27]-[32].

Galindo and Tamayo (2000) conducted a comparative analysis of statistical classification and machine learning techniques on credit portfolios, ranking the performance of over 9000 models. They found that CART decision tree models provided the best default estimates, with neural networks ranking second [33]. Hamori et al. (2018) compared the forecast accuracy and classification ability of various machine learning methods, concluding that boosting was superior [34]. Hybrid techniques and ensemble methods have also been explored for credit scoring, where one technique is used for final predictions after employing several others in the analysis [35]-[38]. For instance, an ensemble learning method using regularized logistic regression, clustering, and bagging algorithms outperformed many popular credit scoring models [39].

B. Application of machine learning in market risk

Risk is quantified by the standard deviation of unexpected outcomes, often referred to as volatility. Value at Risk (VaR) estimates the maximum loss over a target period that will not be exceeded with a specified level of confidence, capturing both underlying volatility and financial risk exposure. Accurately forecasting market volatility is essential for risk management and asset pricing. Neural network models have been shown to improve volatility estimation methods. For example, Zhang et al. (2017) developed a model combining the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and the Extreme Learning Machine (ELM) algorithm to predict volatility. This model uses GELM-RBF to forecast time series volatility and extrapolates these predictions to calculate VaR more accurately and efficiently. It employs a stochastic mapping method that is nonlinear and does not require Gaussian probability assumptions.

Market risk also encompasses interest rate risk and exchange rate risk. Interest rate curves, depicting the relationship between interest rates and debt maturity for a specific borrower in a particular currency, are crucial in financial engineering and market risk management. The "Gaussian Mixture Model" clustering method can be used to create nonlinear models of parameter evolution and predict interest rate curves, improving interest rate visualization. Machine learning clustering techniques designed for stochastic differential equations can help develop anticipatory VaR models, crucial for managing risk during market regime changes.

Liquidity risk is another significant concern that can be addressed with machine learning. Techniques like artificial neural networks (ANNs) and genetic algorithms can be used to measure liquidity risk, analyze key factors, and study the interconnections between these factors. ANNs can estimate general risk trends and identify the most influential factors, while Bayesian networks can predict the probability of liquidity risk events.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAY2125

Market risk, arising from investments, transactions, and overall financial market exposure, is another area where machine learning can be impactful. According to [46], machine learning can enhance market risk management at various stages, including data preparation, modeling, stress testing, and model validation. Trading in financial markets carries the risk that the trading model may be incorrect, incomplete, or outdated, known as model risk management. Machine learning is particularly effective for stress testing market models to identify emerging risks in trading behaviors. Woodall (2017) discusses how machine learning is currently used in model validation, such as Natixis's use of unsupervised learning to discover new asset connection patterns. An exciting future application is the integration of reinforcement learning into market trading algorithms, allowing them to learn from market reactions and adapt their trading strategies accordingly. Additionally, [50] suggest combining neural networks and decision tree techniques to provide real-time alerts to traders about changes in trading patterns.

C. Application of Machine Learning in Operational Risk

Machine learning is also applied in operational domains to enable risk mitigation, specifically in risk detection and/or prevention. In terms of operational risk, aside from cybersecurity cases, machine learning primarily focuses on issues related to fraud detection and suspicious transactions. Operational risk management involves the identification by businesses of potential risks of direct or indirect financial loss resulting from various operational failures [51]. These risks can be internal to institutions (e.g., inadequate or failing internal processes, human errors, or system failures) or can originate from external events (such as fraud, vulnerable computer systems, control failures, operational errors, neglected procedures, or natural disasters). The increase in the quantity, variety, and complexity of operational risk exposures, particularly for financial firms, has led to the adoption of AI and machine learning-based solutions [52]. AI can assist institutions at various stages of the risk management process, from identifying risk exposure to measuring, estimating, and evaluating their effects [53]. It can also help in choosing an appropriate risk mitigation strategy and finding instruments to transfer or negotiate risk. Thus, the use of AI techniques for operational risk management, which began with preventing external losses such as credit card frauds, now extends to new areas involving analyzing vast collections of documents, executing repetitive processes, and detecting money laundering by analyzing large amounts of data.

Financial fraud detection is another commonly referenced use case of machine learning and AI in risk management. Banks attempt to control financial fraud by evaluating the best ways to protect their systems, data, and ultimately, their clients. The ability of AI to automate processes can speed up routine tasks, minimize human errors, process unstructured data to filter relevant content or negative news, and determine connections between individuals to assess at-risk clients and networks. This network analysis can also be used to monitor employees and traders. Clustering and classification techniques can be employed to establish trader behavior profiles, where combining trading data, electronic and vocal communications records allows banks to observe emerging behavior patterns to predict latent risks and detect connections between employees. This also enables banks to generate and prioritize alerts based on types of suspicious activities and the level of involved risk. Ngai et al. (2011)[54] provide an excellent overview of the main AI techniques used for financial fraud detection, noting that the main applied techniques are decision trees and neural networks. For instance, five of the largest Nordic banks recently joined forces to establish a common infrastructure for combating money laundering, known as the Nordic KYC Utility. AI-based infrastructure will aid in complying with KYC (Know Your Customer) regulations and requirements and avoiding fines imposed by regulators. Similarly, HSBC is introducing AI technology, developed by data analytics firm Quantexa, to monitor their anti-money laundering processes. There are also practical efforts in fraud prevention. For example, a joint venture of the Royal Bank of Scotland and Vocalink in the UK is creating a machine learning system to analyze transactions from commercial clients, both large and small, to identify and circumvent false invoices and potential frauds. A study by Colladon and Remondi (2017) [55] using real data from 33,000 transactions of an Italian factoring company demonstrates the effectiveness of such analyses in fraud detection (see also Demetis, 2018)[56]. In terms of money laundering, criminals route money through various transactions, mixing them with legitimate transactions to conceal the true source of funds. Funds usually originate from criminal or illegal activities and can be used in other illegal activities, including financing terrorist activities. There has been extensive research on financial crime detection using traditional statistical methods and, more recently, machine learning techniques. Clustering algorithms identify customers with similar behaviors and can help find groups of people working together to commit money laundering [57]. A major challenge for banks, given the large volume of transactions per day and the non-uniform nature of many transactions, is to be able to sort through all transactions and identify those that are suspicious. Financial institutions use anti-money laundering systems to filter and classify transactions based on degrees of suspicion. Structured processes and intelligent systems are needed to enable the detection of these money laundering transactions [58].

IV. CONCLUSION

Machine learning and artificial intelligence have transformed financial risk management, covering credit, market, and operational risks. Our study has explored how these technologies offer innovative and effective solutions for identifying, assessing, and mitigating various types of risks.For credit risk, AI and ML significantly improve the accuracy of prediction models, surpassing traditional techniques like linear

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAY2125

and logistic regressions. Financial institutions can thus better assess the probability of borrower default and optimize lending decisions. For example, techniques like neural networks and decision trees have shown promising results in reducing losses and managing loan portfolios. Regarding market risk, AI is used to enhance volatility forecasting and value-at-risk (VaR) assessment. Models based on deep learning and non-parametric methods often outperform traditional models in terms of accuracy and efficiency. These advancements enable institutions to better manage their exposure to interest rate fluctuations, currency risks, and stock price changes, while meeting increasingly complex regulatory requirements.Lastly, in operational risk management, AI and ML focus on fraud detection and prevention of suspicious transactions. Clustering and classification techniques help identify abnormal behaviors and fraudulent activities, while neural networks and logistic regression algorithms are used to analyze large amounts of data and detect potential risks. These tools are also applied in combating money laundering and cybercrime, thereby strengthening the security and compliance of financial institutions.

Despite these advancements, our research has also highlighted certain limitations. Integrating AI and ML into risk management requires significant investments in infrastructure and training. Moreover, ML models can introduce algorithmic biases and modeling errors, necessitating robust governance and oversight frameworks. Transparency and interpretability of models remain major challenges that need to be addressed to ensure effective and ethical adoption of these technologies.

REFERENCES

[1]. Technology Review. (2017). "An AI-fueled credit formula might help you get a loan." Retrieved from https://www.technologyreview.com/s/603604/an-ai-fueled-credit-formula-might-help-you-get-a-loan/.

[2]. Westengen, O.T., Haug, R., Guthiga, P., and Macharia, E. (2019). "Global climate risk management: The role of agribusiness." *Climate Risk Management*, 23, 18-28.

[3]. Taneja, S., Awasthi, A., and Arora, P. (2020). "A heuristic machine learning approach for agriculture supply chain risk assessment." *Computers and Electronics in Agriculture*, 168, 105130.

[4]. Zhong, R.Y., and Zhou, Q. (2020). "The application of artificial intelligence in smart agriculture: A survey." *IEEE Transactions on Industrial Informatics*, 16(4), 2978-2987.

[5]. Kolanovic, M., and R. T. Krishnamachari, 2017, “Big Data and AI Strategies, Machine Learning and Alternative Data Approach to Investing”, Technical Report, JP Morgan.

[6]. Saunders, Anthony, Marcia Millon Cornett, and Patricia Anne McGraw. 2006. Financial Institutions Management: A Risk Management Approach. New York: McGraw-Hill.

[7]. Apostolik, Richard, Christopher Donohue, Peter Went, and Global Association of Risk Professionals. 2009. Foundations of Banking Risk: An Overview of Banking, Banking Risks, and Risk-Based Banking Regulation. New York: John Wiley.

[8]. Jorion, Philippe. 2007. Value at Risk: The New Benchmark for Managing Financial Risk. New York: McGraw-Hill

[9]. Hull, John. 2012. Risk Management and Financial Institutions. New York: John Wiley and Sons, vol. 733.

[10]. Bishop, C. M. (2006). Pattern recognition and machine learning. Springer google schola, 2, 1122-1128.

[11]. Hastie, T., Tibshirani, R., Friedman, J. H., & Friedman, J. H. (2009). The elements of statistical learning: data mining, inference, and prediction (Vol. 2, pp. 1-758). New York: springer.

[12]. Shrestha, U., Alsadoon, A., Prasad, P. W. C., Al Aloussi, S., & Alsadoon, O. H. (2021). Supervised machine learning for early predicting the sepsis patient: modified mean imputation and modified chi-square feature selection. Multimedia Tools and Applications, 80(13), 20477-20500.

[13]. Al-Dury, N., Ravn-Fischer, A., Hollenberg, J., Israelsson, J., Nordberg, P., Strömsöe, A., ... & Rawshani, A. (2020). Identifying the relative importance of predictors of survival in out of hospital cardiac arrest: a machine learning study. Scandinavian journal of trauma, resuscitation and emergency medicine, 28, 1-8.

[14]. Balaji, A. J., Balaji, G. T., Dinesh, M. S., Nair, B. B., & Ram, D. H. (2018, December). A machine learning based approach to crack detection in asphalt pavements. In 2018 15th IEEE India Council International Conference (INDICON) (pp. 1-4). IEEE.

[15]. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. The MIT Press

[16]. Madani, A., Arnaout, R., Mofrad, M., & Arnaout, R. (2018). Fast and accurate view classification of echocardiograms using deep learning. Npj Digital Medicine, 1(1)

[17]. Silver, D., Hubert, T., Schrittwieser, J., Antonoglou, I., Lai, M., Guez, A., Lanctot, M., Sifre, L., Kumaran, D.,

[18]. Brynjolfsson, E., & McAfee, A. (2017). The business of artificial intelligence. Harvard Business Review, 1–20

[19]. Ramaswamy, S., & DeClerck, N. (2018). Customer perception analysis using deep learning and NLP. Procedia Computer Science, 140, 170–178

[20]. Kühl, N., Mühlthaler, M., & Goutier, M. (2020). Supporting customeroriented marketing with artificial intelligence:Automatically quantifying customer needs from social media. Electronic Markets, 30(2), 351–367

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAY2125

[21]. Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. The Journal of Finance, 23(4), 589–609.
[22]. Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. The Journal of Finance, 23(4), 589–609.
[23]. Son, Y., Byun, H., & Lee, J. (2016). Nonparametric machine learning models for predicting the credit default swaps: An empirical study. Expert Systems with Applications, 58, 210–220.
[24]. Khandani, Amir E., Adlar J. Kim, and Andrew W. Lo. 2010. Consumer credit-risk models via machine-learning algorithms. Journal of Banking & Finance 34: 2767–87.
[25]. Figini, S., Bonelli, F., & Giovannini, E. (2017). Solvency prediction for small and medium enterprises in banking. Decision Support Systems, 102, 91–97.
[26]. Ray, Sunil. 2015. Understanding Support Vector Machine Algorithm from Examples (along with Code). Available online: https://www.analyticsvidhya.com/blog/2017/09/understaing-support-vector-machine-example- code
[27]. Bellotti, Tony, and Jonathan Crook. 2009. Support Vector Machines for Credit Scoring and Discovery of Significant Features. Expert Systems with Applications.
[28]. Cao, Jie, Hongke Lu, Weiwei Wang, and Jian Wang. 2013. A Loan Default Discrimination Model Using Cost-Sensitive Support Vector Machine Improved by PSO. Information Technology and Management 14: 193–204.
[29]. Van Gestel, Ir Tony, Bart Baesens, Ir Joao Garcia, and Peter Van Dijcke. 2003. A support vector machine approach to credit scoring. In Forum Financier—Revue Bancaire Et Financiaire Bank En Financiewezen. Bruxelles: Larcier, pp. 73–82. Available online: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10. 1.1.93.6492&rep= rep1&type=pdf
[30]. Huang, Cheng Lung, Mu Chen Chen, and Chieh Jen Wang. 2007. Credit Scoring with a Data Mining Approach Based on Support Vector Machines. Expert Systems with Applications 33: 847–56.
[31]. Lai, Kin Keung, Lean Yu, Ligang Zhou, and Shouyang Wang. 2006. Credit risk evaluation with least square support vector machine. In International Conference on Rough Sets and Knowledge Technology. Berlin/Heidelberg: Springer, pp. 490–95.
[32]. Harris, Terry. 2013. Quantitative credit risk assessment using support vector machines: Broad versus Narrow default definitions. Expert Systems with Applications 40: 4404–13.
[33]. Galindo, Jorge, and Pablo Tamayo. 2000. Credit Risk Assessment Using Statistical and Machine Learning: Basic Methodology and Risk Modeling Applications. Computational Economics 15: 107–43.
[34]. Hamori, Shigeyuki, Minami Kawai, Takahiro Kume, Yuji Murakami, and Chikara Watanabe. 2018. Ensemble Learning or Deep Learning? Application to Default Risk Analysis. Journal of Risk and Financial Management 11: 12.
[35]. Bastos, João A. 2014. Ensemble Predictions of Recovery Rates. Journal of Financial Services Research 46: 177–93
[36]. Hamori, Shigeyuki, Minami Kawai, Takahiro Kume, Yuji Murakami, and Chikara Watanabe. 2018. Ensemble Learning or Deep Learning? Application to Default Risk Analysis. Journal of Risk and Financial Management 11: 12.
[37]. Raei, Reza, Mahdi Saeidi Kousha, Saeid Fallahpour, and Mohammad Fadaeinejad. 2016. A Hybrid Model for Estimating the Probability of Default of Corporate Customers. Iranian Journal of Management Studies 9: 651–73.
[38]. Chen, Ning, Bernardete Ribeiro, and An Chen. 2016. Financial Credit Risk Assessment: A Recent Review. Artificial Intelligence Review 45: 1–23.
[39]. Wang, Hong, Qingsong Xu, and Lifeng Zhou. 2015. Large Unbalanced Credit Scoring Using Lasso-Logistic Regression Ensemble. PLoS ONE 10: e0117844.
[40]. Jorion, Philippe. 2007. Value at Risk: The New Benchmark for Managing Financial Risk. New York: McGraw-Hill.
[41]. Monfared, Soheil Almasi, and David Enke. 2014. Volatility Forecasting Using a Hybrid GJR-GARCH Neural Network Model. Procedia Computer Science 36: 246–53.
[42]. Zhang, Wenhao. 2017. Machine Learning Approaches to Predicting Company Bankruptcy. Journal of Financial Risk Management 6: 364–74.
[43]. Kanevski, Mikhail F., and Vadim Timonin. 2010. Machine learning analysis and modeling of interest rate curves. Paper presented at the 18th European Symposium on Artificial Neural Networks ESANN, Bruges, Belgium, April 28–30; Available online: https://www.elen.ucl.ac.be/Proceedings/esann/esannpdf/es2010-17.pdf.
[44]. Mahdavi-Damghani, Babak, and Stephen Roberts. 2017. A Proposed Risk Modeling Shift from the Approach of Stochastic Differential Equation towards Machine Learning Clustering: Illustration with the Concepts of Anticipative and Responsible VaR. SSRN Electronic Journal.
[45]. Tavana, Madjid, Amir Reza Abtahi, Debora Di Caprio, and Maryam Poortarigh. 2018. An Artificial Neural Network and Bayesian Network Model for Liquidity Risk Assessment in Banking. Neurocomputing 275: 2525–54.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAY2125

[46]. Kumar, P. P. (2018). Machine learning for model development in market risk. GARP Institute. Available at:https://www.garp.org/#!/riskintelligence/all/all/a1Z1W000003fM0yUAE?utm_medium=social&utm_source=face-book&utm_content=org_whitepaper&utm_term=machinelearning&utm_campaign=sm_riskintelligence.
[47]. Financial Stability Board. (2017). Artificial intelligence and machine learning in financial services. Available at: http://www.fsb.org/wp-content/uploads/ P011117.pdf.
[48]. Woodall, L. (2017). Model risk managers eye benefits of machine learning. Risk.net. Available at: https://www.risk.net/risk-management/4646956/model-risk-man- agers-eye-benefits-of-machine-learning. Last
[49]. Hendricks, D., & Wilcox, D. (2014). A reinforcement learning extension to the Almgren-Chriss framework for optimal trade execution. In IEEE Conference on Computational Intelligence for Financial Engineering & Economics (CIFEr) (pp. 457–464).
[50]. Chandrinos, S. K., Sakkas, G., & Lagaros, N. D. (2018). AIRMS: A risk man- agement tool using machine learning. Expert Systems with Applications, 105, 34–48.
[51]. Moosa, I. A. (2007). Operational risk management. New York: Palgrave Macmillan.
[52]. Choi, T. M., Chan, H. K., & Yue, X. (2017). Recent development in big data analytics for business operations and risk management. IEEE Transactions on Cybernetics, 47(1), 81–92.
[53]. Sanford, A., & Moosa, I. (2015). Operational risk modelling and organizational learning in structured finance operations: A Bayesian network approach. Journal of the Operational Research Society, 66(1), 86–115.
[54]. Ngai, E. W., Hu, Y., Wong, Y. H., Chen, Y., & Sun, X. (2011). The application of data mining techniques in financial fraud detection: A classification framework and an academic review of literature. Decision Support Systems, 50(3), 559–569.
[55]. Colladon, A. F., & Remondi, E. (2017). Using social network analysis to prevent money laundering. Expert Systems with Applications, 67, 49–58.
[56]. Demetis, D. S. (2018). Fighting money laundering with technology: A case study of Bank X in the UK. Decision Support Systems, 105, 96–107.
[57]. Sudjianto, Agus, Sheela Nair, Ming Yuan, Aijun Zhang, Daniel Kern, and Fernando Cela-Díaz. 2010. Statistical Methods for Fighting Financial Crimes. Technometrics 52: 5–19.
[58]. Kannan, Somasundaram, and K. Somasundaram. 2017. Autoregressive-Based Outlier Algorithm to Detect Money Laundering Activities. Journal of Money Laundering Control 20: 190–202.