ISSN 2616-5902 Vol. 6, Issue 1: 119-126, DOI: 10.25236/AJBM.2024.060117

Research progress on the influence of deep learning models on bank credit management

Huang Mingyu

Guangxi Normal University, Guilin, China
18378957109@139.com

Abstract: *With the continuous advancement of the "3.0 era" of financial technology and the innovation of bank credit function, deep learning has once again become a hot issue in the formulation, implementation and effect evaluation of bank credit policy. This paper combed through the relevant literature on the impact of deep learning models on bank credit, and found that: in terms of the development path of deep learning models, most of the articles choose the optimal model by comparing machine learning and deep learning. These studies explore and act as new derivative models on the basis of the applicability of deep learning, so that the deep learning model is constantly revised and improved in the test and criticism; in terms of the impact of deep learning on bank credit risk management, the existing literature mainly focuses on the three parts of risk identification, early warning and avoidance. This paper tries to put forward reasonable suggestions recommendations on the basis of reviewing the existing research.*

Keywords: *Deep learning model; Bank credit; Risk management*

1. Introduction

Ensuring the security of the financial system is the basis for maintaining the national economy and social stability, and strengthening the prevention and control of bank credit risks is an important element in avoiding systemic risks in the financial market[1]. The risks of banking financial institutions and financial market vulnerability follow each other, and in the context of global financial liberalization, they are highly hidden, multi-dimensional infectious and extremely destructive. For example, the subprime mortgage crisis in 2008 dragged the world economy into a sustained recession; the credit risk incident of the China Baoshang Bank in 2019 and its chain reaction once again aroused widespread public concern about the capital turnover and loan quality of commercial banks, especially urban commercial banks; and the credit risk of banking financial institutions is an important factor in avoiding systemic risks in the financial market. The credit risk incident of Baoshang Bank in China in 2019 and its chain reaction have once again aroused widespread public concern about the liquidity of commercial banks, especially city banks, and the quality of their loans; the myth of "too big to fail" of banking financial institutions went bankrupt due to the closure of Silicon Valley Bank in the United States in 2023, which led to the collapse of its share price by more than 60%, and dealt a severe blow to the banking industry and even to the global financial environment. Undoubtedly, the financial crisis and the frequent outbreak of credit risk events have posed a great challenge to banks in terms of risk measurement and credit strategy management.

In recent years , big data, artificial intelligence and other emerging technologies continue to emerge. In this context, the coupling of financial development and Internet technology in the process of coordinated development of financial technology, and the most representative of which is the application of deep learning[2]. The concept of "deep learning" was proposed by Geoff Hinton in 2006, which was developed from the neural network theory of psychologist McCulloch and mathematical logician Pitts (1943) and the inductor theory of Frank Rosenblat (1957) containing binary classification linear, which simulates the human mind and is based on the training set. Since the 21st century, there has been an explosive growth in the research of deep learning models, and MIT Technology Review even listed deep learning as one of the top ten breakthrough technologies in 2013. As a new field in machine learning research, deep learning models inherit both the methodology of logistic regression and the unsupervised nature, which makes it more unique in terms of algorithmic complexity, decision accuracy, and interpretability. Specifically, compared with traditional machine models, deep learning models have greater advantages: first, the expression ability is stronger, and more latent patterns in the data can be

ISSN 2616-5902 Vol. 6, Issue 1: 119-126, DOI: 10.25236/AJBM.2024.060117

mined; second, the structure is very flexible according to the business scenarios and data characteristics, the model structure can be flexibly adjusted, so that the model and the application scenarios are perfectly suited to each other.

Therefore, based on the deep learning model to analyze the influencing factors of bank credit risk and adopt corresponding prevention and control strategies, it is of great significance to the risk prevention of the banking industry, the institutional reform of the financial field, and the improvement of the level of financial services. In this paper, we will systematically elaborate the current research status of deep learning models and their problems, review the existing research on the application of deep learning models in bank credit risk management, and finally discuss the relevant countermeasures for deep learning models to empower the healthy development of banking financial institutions and financial ecology.

2. Deep learning model research development status

2.1. Artificial neural network model and its defects

In early research, Artificial Neural Network (ANN) models are widely used for the internal restructuring of adaptive systems by simulating the flow of information processing in the human brain [3]. The neural network is composed by the connection between "neurons", and each node represents a specific activation function. During the learning or training process, researchers reduce the difference between the network output value and the target value in an iterative loop in order to get a higher accuracy target network model [4]. In the continuous network optimization, a target network model with higher accuracy is obtained [5]. In the learning and training mode, some scholars divided the neural network into two kinds: one is supervised learning, that is, through the given sample information criteria for classification, imitation, and target value characterization; the second is unsupervised learning [6], that is, given the learning mode or certain rules, but the specific learning content depends on the input signal situation, which is highly flexible.

However, artificial neural network (ANN) models use the training mechanism of back-propagation feedback, which is flawed by the problems of vanishing network gradients and the inability of the network to converge when the number of network layers increases [7]. The emergence and application of deep learning model (DNN) solves the above problems. Compared with the traditional ANN model, the advantages of DNN are: more network layers, stronger modeling or abstraction ability of the information of the thing, better simulation effect of the complexity of the information processing, and this kind of heterogeneity extraction through the multilayer network and thus make the lower-level features oriented to the function of the higher-level features [8], which makes the depth of the learning is widely used in bank credit risk analysis, such as risk identification matrix image analysis, target detection, etc [9].

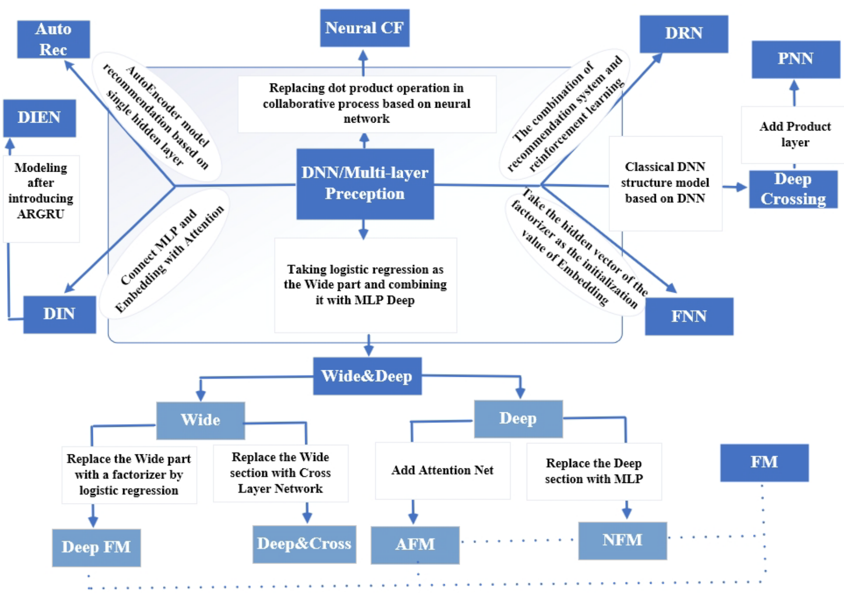

Figure.1: Deep learning model relationship mapping

As a result, many studies and project analyses are keen on deep dataset training for deep learning

ISSN 2616-5902 Vol. 6, Issue 1: 119-126, DOI: 10.25236/AJBM.2024.060117

models. From the perspective of financial technology, deep learning can be seen as an improvement of the traditional artificial neural network model. With the development of deep learning algorithms, large-scale datasets get efficient training and good model fitting. In other words, deep learning models are promising in promoting the integration and development of fintech in financial risk information aggregation and training, and policy effect optimization. In this paper, we sort out the relationship between deep learning models and other models, as shown in Figure 1.

2.2. Deep learning model development and extension

In the process of promoting the development of fintech, deep learning models are themselves constantly innovating. For example, the AutoRec model is based on autoencoder and collaborative filtering ideas, and introduces single hidden layer training. Specifically, the AutoRec model first utilizes the co-occurrence matrix in collaborative filtering (CF) to complete the self-encoding, and then utilizes the results of the self-encoding to perform recommendation ranking, which has some applications in assessing the customer's satisfaction level of bank financial management [10]. However, the structure of AutoRec model is relatively simple, and there are problems of insufficient expression ability [11]. Faced with the dilemma of more complex information judgment and expression. The Deep Crossing model designed on the basis of Embedding+MLP architecture has completed the revolution of feature crossing methods. It has been shown that the Deep Crossing model has a high complexity of the feature crossing layer, which requires deep crossing between features by adjusting the depth of the neural network [11]. In view of the difficulty of fitting and convergence in overly complex interchanges, some scholars have combined CF and deep learning to obtain a NeuralCF model with stronger feature combination and nonlinear ability [12]. In terms of improving training efficiency, through the linear and product of features and the full-layer connection [13], some studies have realized efficient training with three-dimensional vectors of width, height and depth (channel) through PNN model and CNN model, and captured cross-information of features [14].

For the time series or data autocorrelation problem, RNN model facilitates the sequence data modeling by hiding the state input and recursive output. However, it has been found that RNN training is prone to gradient vanishing and explosion phenomenon [15], i.e., when the initial weight value of the model does not match the activation function, it will not be able to converge to the optimal solution or the parameter update is slow. Suppose the RNN model activation function is:

$$f_1(x)=\tanh(x) \tag{1}$$

Then we can derive its derivative as:

$$f_2(x)=1-\tanh^2(x) \tag{2}$$

The images of the above two functions are shown in Figure 2 below.:

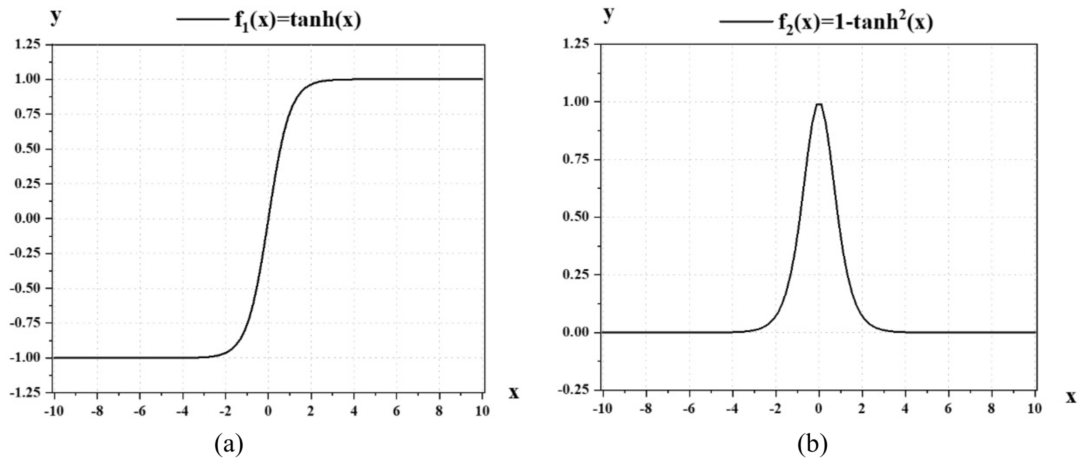

Figure 2: Examples of functions for gradient vanishing and gradient explosion

Now, we consider the case where the initialization weights are much smaller than the threshold. Since the peak value of f does not exceed 1, the activation function gradient exhibits an exponential decrease until the gradient disappears for very small values of the weights. On the contrary, a gradient explosion occurs when the weights are initialized much larger than the threshold. In order to avoid the phenomenon of gradient vanishing and explosion in RNN training, some scholars have optimized the model. For example, one study created the Wide&Deep model based on memorizing the information in the user's behavioral characteristics and creating the Wide&Deep model based on the information recommendation results, which in turn deepened the level of development and application of deep algorithms. [16]. In addition, Deep Belief Networks (DBN) proposed unsupervised greedy layer-by-layer training algorithms, which brought hope for solving optimization challenges related to deep structures, followed by multilayer autoencoder deep structures [17].

In conclusion, with the continuous development of FinTech, deep learning models have derived various research models for different fields and problems, in addition to the above models, there are also AFM models [18], NFM models [19] and so on. The evolution of deep learning models has also led to the continuous penetration of their applications into other fields such as graphic design, natural sciences as well as economic and financial research, in this regard, this paper will further analyze the relationship between deep learning models and bank credit risk management.

3. Research on the relationship between deep learning and bank credit

The 2017 Financial Stability Board (FSB) report shows that the use of artificial intelligence and deep learning in financial services with loan risk management is growing rapidly. Research closely related to the topic of deep learning has seen an increasing number of publications in some of the top international conferences, as shown in Figure 3.

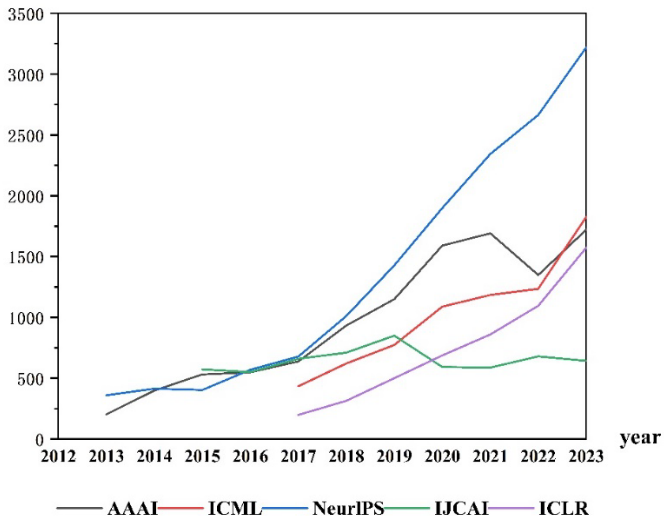

Figure 3: Number of Manuscript Acceptances in Selected Top International Conferences on Artificial Intelligence and Deep Learning from 2013 to 2023

Figure 3 shows the paper acceptance of the top international conferences on deep learning in the past ten years, including the International Association for Advanced Artificial Intelligence(AAAI), the International Conference on Machine Learning(ICML), the Conference on Neural Information Processing Systems(NeurIPS), the International Confederation of Artificial Intelligence(IJCAI), and the International Conference on Representation Learning(ICLR). From the data in the figure, it can be seen that the number of accepted papers in the three major conferences NeuralPS, ICML and ICLR shows an increasing trend year by year, in which the number of accepted papers in NeuralPS in 2023 reaches 3,221, and the corresponding acceptance rate is 26.1%. In addition, the acceptance rate of manuscripts from AAAI and IJCAI has been decreasing in recent years, which may be due to the fact that these two conferences tend to be stricter on the quality of incoming manuscripts. As a matter of fact, the number of manuscripts from the above five top conferences has been increasing year by year. It also demonstrates that deep learning is highly favored by both practice and academia due to its unique actuarial and simulation learning advantages.

The increasing richness of deep learning modeling research brings opportunities for the development of commercial banks. Currently, the credit risk of the banking industry is becoming increasingly complicated globally, including liquidity risk caused by the lack of compensation for the capital chain, the substitution risk of third-party payment "disintermediation" caused by financial technology, and the technical risk of the lack of specialized processing of risk screening and early warning, etc. The increase

ISSN 2616-5902 Vol. 6, Issue 1: 119-126, DOI: 10.25236/AJBM.2024.060117

in the level of risk-taking will deteriorate the bank's operating environment, and may even cause a bank run and credit crises. It may even trigger bank runs and credit crises. Studies have introduced deep learning models to make bank credit risk identification, early warning, processing and response more accurate and scientifically rationalized.

3.1. Deep learning models and credit risk identification

In the early stage of combining credit risk and training models in the banking sector, it is mainly the identification of indicators and the standardization of financial data, which is an important link in the identification of bank credit risk. Gandrud and Hallerberg (2015) constructed a financial market stress indicator through machine learning and text analysis, which provided the idea of credit continuity indicator measurement in the banking sector[20]. In order to improve the accuracy of assessing bank credit risk, some scholars have proposed residual useless information based on deep learning models, which are trained by combining banking sector data and macrofinancial data [21]. Other scholars have reduced misreporting and underreporting of risk in out-of-sample testing of models through deep learning model training, and they mine quantitative summary statistics to improve the effectiveness of systematic risk assessment [22]. Deep learning models bred in financial technology to be China's bank credit risk identification research provides a broad idea. On the one hand, based on Baidu search big data, RNN is used to construct financial risk perception indicators, which effectively predicts the information state during the period of rising risk [23]; on the other hand, crawler technology is used to obtain financial data and construct bank credit risk pressure indicators, which can accurately identify the potential risks brought by factors such as customer profiles, policy dynamics, and market sentiments through DNN clustering and training [24].

3.2. Deep learning models and credit risk warning

For the liquidity mismatch problem, some scholars based on the dynamic empowerment factor for binary label setting and input LightGBM model for training. The results show that the early warning effect of commercial bank credit accuracy, recall, and precision is improved [25].In terms of operational risk, many scholars have combined deep learning models with anomaly detection, such as credit card fraudulent transaction sequence detection based on long and short-term memory neural networks [26], and using convolutional selfencoder to realize bank credit network intrusion detection [27]. Huang (2021) based on network embedding and deep learning for abnormal trading behavior detection method, found that the core index value of LSTM model is greater than 0.7, and the deep learning model can improve the accuracy of operational risk detection in the interbank bond market[28].

In recent years, more and more deep learning algorithms have been applied to the problem of bank credit risk assessment. Specifically, many scholars have launched a series of research on credit risk assessment models by applying methods based on statistics, machine learning and deep learning. For example, Sirignano and others used deep neural networks to predict the risk of late and early repayment of real estate loans in the U.S., and its effect is better than that of logistic regression and artificial neural network models[29]. Deep learning is suitable for high-dimensional data learning ability, so that it can effectively mine personal big data characterizing the combination of personal credit features, and thus improve the effect of risk assessment [30]. Domestic related research mostly draws on foreign experience and expands its application, such as the improvement of the stack noise reduction self-coding neural network model, which makes the user credit image richer and thus improves the credit risk warning and assessment of banks [31]. In addition, Zhao Xuefeng (2020) formed a WV-CNN credit assessment model using Word2Vec and convolutional neural network (CNN) in response to the problems of complex feature preprocessing, subjective interference, and low accuracy in the current loan assessment process[32]. The above model design idea is based on the neural network with embedded gradient, and its basic credit risk simulation and testing process can be shown in Figure 4 below.

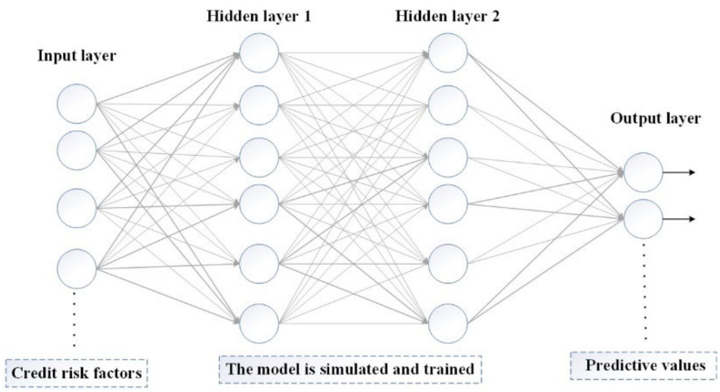

Figure 4: Deep learning neural network with credit factor training process

3.3. Deep Learning Models and Credit Risk Avoidance

Risk avoidance is an important part of credit risk management in banks, and it is also the focused mission of deep learning models. For risk transfer, some scholars use Word2vec to convert loan text into vectors and use LSTM network to predict the probability of user default; a feasible path for credit risk transfer is effectively fitted [33]. For risk reduction, Pang et al constructed a loan default customer early warning model based on C5.0 decision tree, CART decision tree and CHAID decision tree from the perspective of loan customer type and defaulted loan[34]. In addition, some scholars use Pytorch deep learning framework, combine Bag-of-Words and multi-attention mechanism in Bert to get BM-Linear assessment model, overcome the word vector curing problem due to the correspondence between bag-of-words and credit words, and realize the dynamic word vector process, which in turn improves the assessment accuracy rate, and provides support for credit institutions to efficiently assess and quickly lend money [35]. It can be seen that deep learning can reduce the default probability through the channel in order to realize bank credit risk avoidance.

To sum up, the deep learning model mainly analyzes its role in bank credit risk early warning from the aspects of liquidity risk, operational risk, credit risk, an so on, and improves its applicability and the level of bank credit risk early warning through continuous revision and improvement of the model.

4. Summary and Outlook

4.1. Summary

On the one hand, the rapid development of fintech has brought about the booming development of artificial intelligence. Among them, from machine learning models to deep learning models, relevant domestic and foreign literature continues to amend and improve the classical analysis models in empirical evidence and criticism, providing a theoretical framework for deepening fintech. On the other hand, bank credit risk prevention needs fintech sharp tools to realize. This paper collects and categorizes the existing literature into three parts, i.e., discussing the existing research in the three major segments of deep learning models and bank credit risk identification, early warning and prevention respectively. In general, 1) research in each of these three segments focuses on and is richer in empirical analysis at home and abroad; 2) most studies take the approach of empirical analysis or summarizing the experience of model application at home and abroad, and then discover the marginal contribution of deep learning models to credit risk management of banks; 3) the existing research focuses more on providing differentiated strategies for commercial banks to cope with the complexity of risk-taking.

4.2. Outlook

Deep learning models have important policy implications for bank credit risk management. First, it is necessary to combine the big data platform to promote the continuous development and improvement of the deep learning model. Secondly, deep learning ideas and integration with bank credit risk identification, early warning and avoidance should be realized. Once again, it should focus on heterogeneity analysis, and make comprehensive consideration based on factors such as bank credit risk characteristics, the investment and financing environment faced, and competitors' pressure. Finally, appropriate deep learning models should be selected to promote the precision and efficiency of risk

ISSN 2616-5902 Vol. 6, Issue 1: 119-126, DOI: 10.25236/AJBM.2024.060117

management.

References

[1] Guangyao Li. (2023). Research on Credit Risk Contagion of Commercial Banks Based on Copula Model. International Business & Economics Studies,(4).
[2] Bin, Y., Shaozi, L., Suxia, X. and Rongrong, J. (2014). Deep learning: a key of stepping into the era of big data. Journal of Engineering Studies, 06(03), 233-243.
[3] Sultan Mohamad T, Sayed Hesham El & Khan Manzoor Ahmed.(2023). An Intrusion Detection Mechanism for MANETS based on Deep Learning. Artificial Neural Networks (ANNS). (01),01-15.
[4] Zirbel, E., Johnson, L. P. and Austin, S. A. (2003). A technique to promote deep learning. Nasa Oss.
[5] Masters, T. (1993). Multilayer feedforward networks. Practical Neural Network Recipies in C++.
[6] Barlow, H. B. (1989). Unsupervised learning. Neural Computation, 1(3), 295-311.
[7] Bosse, T. and Griewank, A. (2012). The relative cost of function and derivative evaluations in the cuter test set. Springer Berlin Heidelberg.
[8] Widrow, B. and Lehr, M. A. (2002). 30 years of adaptive neural networks: perceptron, madaline, and backpropagation. Proceedings of the IEEE, 78(9), 1415-1442.
[9] Tingdan Luo and Yiming Li. (2022). Deep learning in single-molecule localization microscopy. China Laser, 49(24), 15.
[10] Chen, Z. J., Li, J., Yue, S. J. and Zhao, Z. F. (2021). A hybrid recommendation model based on self-encoder and attribute information. Frontiers in Data and Computing Development, 3(3), 8.
[11] Rodavia, M. R. D., Ballera, M., Clemente, G., and Ambat, S. (2017). Autorec: a recommender system based on social media stream. IEEE, 1-6.
[12] Zhou, W., Du, Y., Duan, M., Haq, A. U., and Shah, F. (2022). Ntcf: neural trust-aware collaborative filtering toward hierarchical recommendation services. Arabian journal for science and engineering(2), 47.
[13] Aljunid, M. F. and Huchaiah, M. D. (2022). Integratecf: integrating explicit and implicit feedback based on deep learning collaborative filtering algorithm. Expert Systems with Application.
[14] Zhou, W., Du, Y., Duan, M., Haq, A. U. and Shah, F. (2022). Ntcf: neural trust-aware collaborative filtering toward hierarchical recommendation services. Arabian journal for science and engineering(2), 47.
[15] Sharif Razavian, A., Azizpour, H., Sullivan, J., and Carlsson, S. (2014). Cnn features off-the-shelf: an astounding baseline for recognition. arXiv e-prints.
[16] Mao, J., Xu, W., Yang, Y., Wang, J., Huang, Z. and Yuille, A. (2014). Deep captioning with multimodal recurrent neural networks (m-rnn). Eprint Arxiv.
[17] Hua, J. and Tao, S. (2022). Evaluation algorithm of skilled talents' quality based on deep belief network model. Journal of Interconnection Networks.
[18] Chaliha, D., Josè F. Gomes, Smith, P., and Jones, F. (2022). In situ atomic force microscopy (afm) investigation of kaolinite dissolution in highly caustic environments. CrystEngComm, 24(11), 2042-2049.
[19] Montané, Antonin, Buffin-Bélanger, Thomas, Vinet, F., and Vento, O. (2017). Mappings extreme floods with numerical floodplain models (nfm) in france. Applied Geography, 80, 15-22.
[20] Gandrud, C. and Hallerberg, M. (2015). What is a financial crisis? Efficiently measuring real-time perceptions of financial market stress with an application to financial crisis budget cycles. Mark Hallerberg.
[21] Cerchiello, P., Nicola, G., Samuel Rönnqvist and Sarlin, P. (2017). Deep learning bank distress from news and numerical financial data. Dem Working Papers.
[22] Nyman, R., Kapadia, S. and Tuckett, D. (2021). News and narratives in financial systems: exploiting big data for systemic risk assessment. Journal of Economic Dynamics and Control(4), 104119.
[23] Zaheer Shahzad, Anjum Nadeem, Hussain Saddam, Algarni Abeer D., Iqbal Jawaid, Bourouis Sami and Ullah Syed Sajid. (2023). A Multi Parameter Forecasting for Stock Time Series Data Using LSTM and Deep Learning Model. Mathematics (3),590.
[24] Ahmad, H. O, and Umar, S. U. (2023). Sentiment analysis of financial textual data using machine learning and deep learning models. Informatica (Slovenia), 47.
[25] Tan Benyan and Gan Ziqi. (2022). Liquidity risk measurement and early warning of commercial banks based on BO-LightGBM. Wuhan Finance (11), 21-32.
[26] de Lange Petter Eilif, Melsom Borger, Vennerød Christian Bakke and Westgaard Sjur.(2022). Explainable AI for Credit Assessment in Banks. Journal of Risk and Financial Management(12),556.
[27] Yang Yu, Jun Long, Zhiping Cai and Wojciech Mazurczyk. (2017). Network Intrusion Detection through Stacking Dilated Convolutional Autoencoders. Security and Communication Networks,1-10.
[28] Huang Liangyu, Wang Yiting, Zhan Hanglong and Jin Jian. (2021). Deep learning-based detection

ISSN 2616-5902 Vol. 6, Issue 1: 119-126, DOI: 10.25236/AJBM.2024.060117

of abnormal trading behavior in the interbank bond market. Computer Applications and Software, (09), 78-85.
[29] Sirignano, J., Sadhwani, A., and Giesecke, K. (2018). Deep learning for mortgage risk. Social ence Electronic Publishing.
[30] Hayashi Yoichi.(2022).Emerging Trends in Deep Learning for Credit Scoring: A Review. Electronics (19),3181.
[31] Mohan Jeyakarthic and Varadharajan Veeramanikandan.(2021). Parameter-Tuned Deep Learning Model for Credit Risk Assessment andScoring Applications. Recent Advances in Computer Science and Communications,(9),2958-2968.
[32] Zhao Xuefeng, Wu Weiwei and Shi Huining. (2020). A credit loan assessment model based on natural language processing and deep learning. Journal of Systems Management (04), 629-638.
[33] Chongren Wang, Dongmei Han, Qigang Liu & Suyuan Luo.(2019).A Deep Learning Approach for Credit Scoring of Peer-to-Peer Lending Using Attention Mechanism LSTM. IEEE Access, 2161-2168.
[34] Sulin Pang, Min Wei, Jinmeng Yuan, Bangzhu Zhu & Zhiming Wen. (2021).WT combined early warning model and applications for loaning platform customers default prediction in smart city. Journal of Ambient Intelligence and Humanized Computing,(3),1-12.
[35] Paszke, A., Gross, S.,Massa, F., Lerer, A. and Chintala, S. (2019). Pytorch: an imperative style, high-performance deep learning library. Computer Science.