Big Data Mining in Financial Risk Management

P. Kaushik
Dept of CSE(AIML-CSE)
Chandigarh University
Chandigarh, India
gazalkaushik17@gmail.com

N.Girija
Dept. of Business Administration
Dhanalakshmi Srinivasan college of Engineering
Coimbatore , India
girijantn@gmail.com

S.Malarvizhi
Dept. of Commerce
Meenakshi A.H.E.R
Chennai, India

Arvind Hans
Dept.of Mangement
Usha Martin University
Jharkhand, India
arvind@umu.ac.in

Ankur Kumar
Dept. of CSE
Manglayatan University
Aligarh, India
ankur.kumar@mangalayatan.edu.in

Jaideep Singh
Dept.of Mangement
J.S. University,
Shikohabad, India
jaideep0612995@gmail.com

***Abstract*—Big data mining is transforming financial risk management by enabling the analysis of vast and diverse datasets to identify, assess, and mitigate risks with unprecedented accuracy. This research explores the integration of big data analytics into financial risk management practices, focusing on techniques such as machine learning, natural language processing, and predictive modeling. By leveraging data from market trends, financial statements, social media, and economic indicators, financial institutions can gain deeper insights into potential risks and make informed decisions. The study highlights case studies where big data mining has been successfully applied to detect fraud, forecast market movements, and assess credit risk. The findings demonstrate significant improvements in risk prediction, early warning systems, and decision-making processes. This research underscores the importance of big data mining in enhancing the resilience and stability of financial systems, advocating for its adoption to proactively manage and mitigate financial risks.**

***Index Terms*—Random Forest, Data Mining, Bagging, Support Vector Machine, Financial Risk, Credit risk**

I. Introduction

Technology plays an essential role in financial risk analysis by highlighting future trends using data mining to gather and analyze valuable data. Big data models, which incorporate machine learning and artificial intelligence, parse vast datasets to identify crucial trends in managing various financial risks such as operational, liquidity, market, legal, and credit risks. Effective models are developed to handle real-time challenges, combining statistical analysis, AI, and machine learning. These models employ both unsupervised and supervised learning to aid in decision-making, allowing organizations to handle diverse scenarios effectively. Data mining, efficient in processing information across multiple platforms, is vital for profiling, trend identification, and real-time insight acquisition in financial risk management.

A. Motivation of the Research:

The financial sector faces increasing challenges in predicting and managing risks due to the growing complexity and volatility of global markets. Traditional risk management methods often fall short in handling the vast amounts of data available, leading to poor risk assessment and unexpected financial losses. The emergence of big data mining offers a novel approach to utilize extensive datasets for more accurate and proactive risk management. This research is motivated by the potential of big data analytics to enhance risk identification, assessment, and mitigation processes, contributing to the stability and robustness of financial institutions.

B. Statement of the Problem:

Current financial risk management strategies are hindered by reliance on outdated analytical methods that cannot keep pace with the rapid influx of data and the complexities of modern financial markets. These limitations result in inadequate risk forecasting and slow response times, making institutions vulnerable to significant risks. This research aims to address the challenge of integrating big data mining techniques into financial risk management to improve the accuracy and timeliness of risk assessment and mitigation strategies. The goal is to develop more robust and effective risk management frameworks that leverage the capabilities of big data to safeguard financial institutions.

II. REVIEW OF LITERATURE

Hassani et al. (2018) explored the role of digitalization and big data mining in banking, emphasizing its transformative potential for operational efficiency and decision-making in financial services [1]. H. Cui (2021) presented a credit risk control framework for commercial banks using data mining, demonstrating its utility in enhancing risk prediction and management in the financial sector [2]. M. Pejić Bach et al. (2019) reviewed text mining applications for big data

979-8-3503-5681-6/24/$31.00©2024 IEEE

analysis in finance, identifying its importance in extracting insights and supporting strategic decision-making [3]. J. Sun et al. (2021) designed a big data-based enterprise financial risk management system, highlighting how data mining improves the accuracy of risk identification and mitigation strategies [4]. P. Cerchiello and P. Giudici (2016) discussed the application of big data in financial risk management, showcasing its role in predictive modeling and informed decision-making for minimizing risks [5]. H. Wang et al. (2024) proposed a family financial risk management system leveraging AI and big data, enabling proactive and precise financial planning and risk control [6]. V. Sharma (2022) examined data scaling methods in machine learning, focusing on their impact on enhancing model performance and ensuring accurate data processing [7].

J. Jemai et al. (2022) developed a big data mining approach for credit risk analysis, emphasizing advanced predictive models for assessing creditworthiness and financial stability [8]. H. Zhou et al. (2019) introduced a PSO-based BP neural network for financial risk management using IoT and big data mining, achieving higher precision in risk assessment [9]. M. Al Malki (2023) reviewed challenges faced by SMEs in achieving sustainable growth, stressing the importance of technological adoption and financial strategy optimization [10]. M. S. Murugan and S. K. T (2023) proposed large-scale data-driven financial risk management using machine learning, highlighting its effectiveness in detecting anomalies and predicting market trends [11]. Y. Zhang (2021) applied data mining technology to financial risk management, focusing on its capabilities for risk assessment and improved decision-making in financial institutions [12]. S. P. S. Rathore et al. (2024) introduced ”Ease Delivery,” a next-gen delivery management solution leveraging advanced technology, enhancing operational efficiency and service optimization [13]. L. Wan (2023) developed an early financial risk warning system using big data analytics, emphasizing the importance of proactive strategies in mitigating potential financial crises [14]. H. Yue et al. (2021) proposed a financial risk management model using information fusion and big data mining, demonstrating enhanced precision in risk evaluation and decision-making [15]. Z. Zuo (2023) explored risk management for internet finance using big data, emphasizing tailored risk control measures for digital financial platforms [16].

W. Peng (2022) investigated the use of big data in financial investment risk management, showcasing improved risk identification and strategic investment planning [17]. L. Jiang (2021) presented an early warning mechanism for enterprise financial risks in the big data era, highlighting actionable countermeasures for sustainable financial stability [18]. P. Kaushik et al. (2024) introduced ”PneumoAI,” an advanced machine learning system for pneumonia detection, setting a benchmark for accuracy in medical diagnosis [19]. R. Deng (2022) examined value mining in management accounting non-financial data using association rule algorithms, offering new insights into data-driven decision-making [20]. Omolara Patricia Olaiya et al. (2024) reviewed the transformative impact of big data analytics on financial risk management, focusing on its ability to improve predictive accuracy and strategic decisions [21]. R. Rathore and S. P. S. Rathore (2024) explored machine learning applications in HR management, specifically in predicting employee turnover and performance, enhancing organizational decision-making [22].

Rathore et al. (2024) introduced a pioneering approach to skin cancer detection within smart ecosystems. Utilizing advanced image processing techniques and AI, their system enhances early diagnosis accuracy, which is crucial for effective treatment planning [23]. In the realm of digital marketing and e-commerce, understanding consumer behavior through sentiment analysis is vital. Priyanka et al., 2024 have developed a novel framework for analyzing consumer sentiments, which leverages natural language processing to provide deeper insights into consumer preferences and market trends [24]. Addressing the need for more intuitive human-computer interactions, Anand et al. (2024) designed a smart AI-based volume control system. By integrating OpenCV and Mediapipe, their system recognizes gestures, thereby offering a user-friendly interface for managing volume without physical contact (Anand et al., 2024). This innovation is particularly relevant in contexts requiring sterility or where users' mobility is impaired [25]. Sikarwar et al. (2024) tackled the urban challenge of parking management. Their research utilizes the Internet of Things (IoT) to optimize parking space usage, thereby reducing traffic congestion and enhancing urban mobility. This study exemplifies how IoT can empower smart city environments and improve urban living standards [26].

III. METHODOLOGY

Data mining is the systematic extraction of valuable knowledge from massive datasets by identifying and analyzing patterns. Data mining is advantageous for various industries, such as manufacturing, advertising, risk management, and others. Hence, there is a need for a standardized data mining procedure. The data mining method must have a high level of reliability. Furthermore, this process should be replicable by entrepreneurs with minimal to no knowledge or skills in the field of data science.

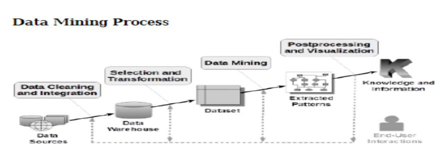

Fig. 1. Data mining process

The data mining process is divided into two stages:

1) data preparation/data preprocessing, and
2) data mining. The data preparation process encompasses data cleansing, data integration, data selection, and data transformation. The second stage encompasses the processes of data mining, pattern interpretation, and knowledge representation.

1) Data Cleaning Empirical evidence has shown that real-world data, sometimes referred to as raw data, often

exhibits inconsistencies or unreliability. The initial phase involves cleansing the target data, which entails addressing any missing values and calculating the necessary parameters or values.

2) Data Integration The unprocessed data, obtained from many sources, is often found in diverse formats and locations, such as multiple databases, spreadsheets, or documents. In order to minimize errors in the data integration process, it was necessary to format the data from all these sources using a standardized metadata or data dictionaries. Data integration aims to minimize duplication of data while ensuring that no data is lost.
3) Data Selection During the data selection step, data that is pertinent to the study is extracted from the data sources. This technique examines the stored big data or historical data and generates a subset of data in order to accomplish the predetermined objectives of the study.
4) Data Transformation Data transformation is the systematic procedure of extracting data from multiple sources, consolidating it, and preparing it in a manner that is appropriate for data mining.
5) Data Mining This is the process of identifying and extracting patterns that are present in the target data set. Data mining involves a series of procedures, including classification, prediction, and grouping, among others.
6) Patterns Evaluation Pattern evaluation is the procedure of identifying strictly ascending patterns that represent knowledge based on provided measurements. A pattern is considered fascinating if it has the potential to be beneficial and can be easily understood.
7) g. Knowledge Representation Knowledge representation is the organized and visually appealing presentation of material to the intended audience.

Standardized Procedure for Data Mining in the Industry The Industry Standards Process comprises four phases that occur in a cyclical manner:

1) Data Sources: After identifying user requirements, the focus shifts to pinpointing available data and its sources. This phase ensures that all relevant data sources are identified and assessed to meet the project's needs, setting the foundation for effective data utilization.
2) Data Exploration and Preparation: Data is loaded, integrated, and explored using querying, reporting, and visualization tools to address data mining objectives. The quality of data is rigorously assessed to ensure completeness and accuracy, preparing it for further analysis.
3) Modeling: A suitable modeling technique is selected to align with business goals, and a test scenario is created to evaluate the model's effectiveness. The model is developed using appropriate tools and presented to project stakeholders to confirm its alignment with business objectives.
4) Deployment Model: The insights derived from modeling are communicated to stakeholders to aid in informed decision-making. This phase includes report writing and potentially extensive data mining applications across the company, complemented by a maintenance strategy to ensure data integrity and continuous improvement.

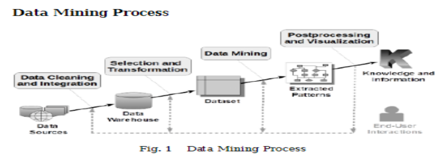

Fig. 2. Data Mining Process in Financial Industry

Data mining involves various techniques for gathering and preparing data. The decision tree is a popular technique for data classification and prediction, utilizing inductive learning algorithms to handle irregular and disorganized data. It improves precision in data sets and streamlines data integration. The Association Rules Technique detects associations between datasets, producing precise results and aiding in indirect data extraction. Clustering analysis, also known as unsupervised classification, enhances precision and promotes similarity by classifying data and making decisions for each category. It uses algorithms like BIRCH, k-medoids, k-means, ROCK, and CURE for organizing and categorizing data.

IV. DATA MINING FOR MARKET RISK MANAGEMENT

Machine learning and data mining are integral in managing market risk within financial markets, enhancing portfolio stability and model accuracy. These techniques perform stress tests, analyze trading behaviors, and improve risk management strategies. They are particularly useful for large corporations and in trading illiquid markets by identifying relationships between asset movements and market responses, thereby refining trading algorithms and predictive models.

V. EXPERIMENTAL CONSIDERATION

This section provides an overview of the effectiveness and precision of the algorithm that has been proposed. The F-measure, correctness, MCC, and ROC were calculated and utilized to assess the correctness of the suggested method, based on the parameters provided in Table 1 of the confusion matrix.

TABLE I
CCONFUSION MATRIX

	Defected	Non-Defective
Devective	TP	FP
Non-Defective	FN	TN

Within the provided confusion matrix: TP = A true positive instance was observed. FP = A false positive was identified. FN refers to a positive instance that is incorrectly classified as negative by the algorithm. TN refers to a negative instance identified by the algorithm. Below is a concise overview of the performance metrics employed to assess the precision of the algorithms: The F-Measure is computed by assessing the

Precision (the ratio of True Positive (TP) instances to the total number of instances classified as positive) and Recall measure (the ratio of True Positive (TP) instances to the total number of positive instances).

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F^{N}OW - Measure = \frac{Precision * Recall * 2}{Precision + Recall}$$

Accuracy is the proportion of cases that are correctly classified out of the total number of examples.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

The AUC metric quantifies the ability of an algorithm to differentiate between faulty and non-defective classes.

$$\text{AUC} = \frac{1 + TP_{\gamma} - FP_{\gamma}}{2}$$

VI. EXPERIMENT

The study utilized the Kaggle German Credit dataset from https://www.kaggle.com/uciml/german-credit, featuring 1000 entries with 20 attributes each, to classify individuals as favorable or unfavorable credit risks. Classification techniques used included Gaussian Naïve Bayes, Random Forest, J48, and MLP as base learners for bagging, implemented in a Python environment via Pycharm. The classifiers were evaluated on accuracy, precision, recall, ROC, and F-score, employing a weighted average for metric computation. A 10-fold cross-validation method was applied during the experiments to ensure reliable training and testing, with performance metrics averaged over multiple datasets and iterations.

```
Input: Data-set, Classifiers
Results: AvgAccuracy, AvgPrecision, AvgF-Score, and AvgAUC
1: Data set: Kaggle Dataset for Fake News
2: Classifies ←— {RF,NB,MLP,J48,
      Bagging(RF,NB,MLP,J48),Smooteddataset(RF,NB,MLP,J48)}
3: All Accuracy Scores ←— {}.
4: All Recall Scores ←— {}.
5: All Precision Scores ←— {}.
6: All F– Scores ←— {}.
7: All AUC Scores ←— {}.
for DS ∈ Datasets do
    for Xtrain, Xtest ∈ KFold (nsplits = 10, shuffle = True).split(DS) do
        (Xtrain, Xtest) ← PerformStandardScaler(Xtrain, Xtest);
        ResampledXtrain, ResampledYtrain ← SMOTE(Xtrain, Ytrain);
        for clf ∈ Classifiers do
            clf ← TrainClassifier(clf, ResampledXtrain, XtrainLabels);
            predictions ← predict(cls, Xtest);
            Accurecy ← ComputeAccurecy(predictions, XtestLabels);
            Recall ← ComputeRecall(predictions, XtestLabels);
            Precision ← ComputePrecision(predictions, XtestLabels);
            F-score ← ComputeFmeasure(predictions, XtestLabels);
            AUC ← ComputeAUC(predictions, XtestLabels);
            AllAccuracyScores ← AllAccuracyScores ∪ Accurecy;
            AllRecallScores ← AllRecallScores ∪ Recall;
            AllPrecisionScores ← AllPrecisionScores ∪ Precision;
            AllFScores ← AllFscoreScores ∪ F-score;
            AllAUCScores ← AllAUCScores ∪ AUC;
        end
    end
    AvgAccurecy ← ComputeAvgAccurecy(AllAccuracyScores);
    AvgRecall ← ComputeAvgRecall(AllRecallScores);
    AvgPrecision ← ComputeAvgPrecision(AllPrecisionScores);
    AvgF-score ← ComputeAvgFmeasure(AllFScores);
    AvgAUC ← ComputeAvgAUC(AllAUCScores);
end
return AvgAccurecy,AvgRecall,AvgPrecision,AvgF-score,AvgAUC
```

Fig. 5 Experiment for classification

Fig. 3. Experiment for classification

VII. RESULTS

The experimental results are presented in Tables 2-5 and Figures 6-8. The tables display a range of classification metrics. The Random Forest classifier got the highest accuracy in recognizing good credit in banks, with a score of 73.5% for Bagging Random Forest and 75.3% for Random Forest. The Random Forest classifier also performed the best on the smoothed dataset, with an accuracy of 74.1%. The Random Forest algorithm has superior performance in terms of Recall and F-Measure, achieving values of 72.2%, 74.1%, and 75.4% for Recall, and 72.6%, 74.1%, and 75% for F-Measure. Typically, an AUC value of 0.5 indicates a lack of discrimination, whereas a range of 0.7 to 0.8 is considered highly favorable, and a value beyond 0.9 is exceptional. The Random Forest algorithm consistently achieves high performance, with accuracy values of 74.0%, 74.8%, and 75.8%.

Base Learner				Smoothed Dataset				Bagging Smoothed dataset			
RF	NB	MLP	J48	RF	NB	MLP	J48	RF	NB	MLP	J48
72.2	69.8	68.1	70.4	74.1	69.7	69.1	72.9	75.4	71.3	70.8	73.5

Fig. 4. Recall

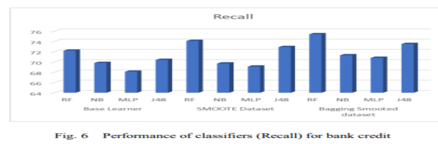

Fig. 5. Performance Of Classifiers (Recall) For Bank Credit

Base Learner				SMOOTE Dataset				Bagging Smoothed dataset			
RF	NB	MLP	J48	RF	NB	MLP	J48	RF	NB	MLP	J48
72.6	70	68.4	71.3	74.1	70.3	69.5	72.4	75.3	70.5	71	73.2

Fig. 6. F-measure

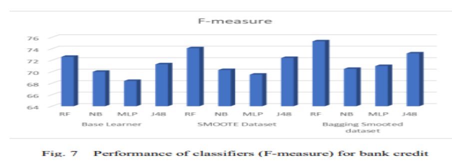

Fig. 7. Performance Of Classifiers (Recall) For Bank Credit

VIII. CONCLUSION

Data mining plays a pivotal role in financial risk management, integrating with statistical regression, machine learning, and AI to enhance processes such as credit risk assessment, client profiling, and credit rating determination. It utilizes various models and algorithms like SVM and hybrid models to boost classification accuracy. In operational risk, it helps develop controls against fraud and forecasts financial crises. For market risk, it analyzes real-time patterns to advise on asset implications. Data mining also supports legal risk management by ensuring compliance and addressing social injustices, thereby minimizing legal breaches and associated costs. The Random Forest classifier is noted for its superior performance across multiple metrics.

Base Learner				Smoothed Dataset				Bagging Smoothed dataset			
RF	NB	MLP	J48	RF	NB	MLP	J48	RF	NB	MLP	J48
74	74.6	66.1	69	74.8	73.4	70.3	69.2	75.8	73.6	72.1	74.6

Fig. 8. AUC

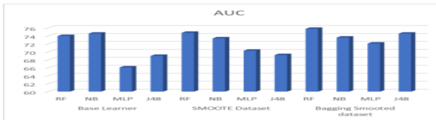

Fig. 8 Performance of classifiers (AUC) for bank credit

Fig. 9. Performance Of Classifiers (AUC) For Bank Credit

Base Learner				Soothed Dataset				Bagging Smoothed dataset			
Random forest	NB	MLP	J48	RF	NB	MLP	J48	RF	NB	MLP	J48
73.5	72	68.8	70.4	74.1	69.7	69.1	72	75.3	70	70.8	73

Fig. 10. Accuracy

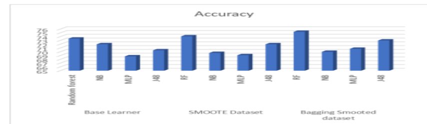

Fig. 9 Performance of classifiers (Accuracy) for bank credit

Fig. 11. Performance Of Classifiers (Accuracy) For Bank Credit

REFERENCES

[1] H. Hassani, X. Huang, and E. Silva, "Digitalisation and Big Data Mining in Banking," Big Data and Cognitive Computing, vol. 2, no. 3. MDPI AG, p. 18, Jul. 20, 2018. doi: 10.3390/bdcc2030018.

[2] H. Cui, "Research on Credit Risk Control of Commercial Banks Based on Data Mining Technology," 2021 International Conference on Computer, Blockchain and Financial Development (CBFD), Nanjing, China, 2021, pp. 383-386, doi: 10.1109/CBFD52659.2021.00083.

[3] M. Pejić Bach, Ž. Krstić, S. Seljan, and L. Turulja, "Text Mining for Big Data Analysis in Financial Sector: A Literature Review," Sustainability, vol. 11, no. 5. MDPI AG, p. 1277, Feb. 28, 2019. doi: 10.3390/su11051277.

[4] J. Sun, S. Wang and F. Yuan, "Design of an Enterprise Financial Risk Management System Based on Big Data Mining," 2021 IEEE International Conference on Industrial Application of Artificial Intelligence (IAAI), Harbin, China, 2021, pp. 269-274, doi: 10.1109/IAAI54625.2021.9699945.

[5] P. Cerchiello and P. Giudici, "Big data analysis for financial risk management," Journal of Big Data, vol. 3, no. 1. Springer Science and Business Media LLC, Oct. 01, 2016. doi: 10.1186/s40537-016-0053-4.

[6] H. Wang, L. Chen, L. Chen and Y. Wu, "Construction of Family Financial Risk Management System Based on Artificial Intelligence and Big Data Analysis," 2024 Asia-Pacific Conference on Software Engineering, Social Network Analysis and Intelligent Computing (SSAIC), New Delhi, India, 2024, pp. 121-125, doi: 10.1109/SSAIC61213.2024.00029.

[7] V. Sharma, "A Study on Data Scaling Methods for Machine Learning," International Journal for Global Academic & Scientific Research, vol. 1, no. 1. International Consortium of Academic Professionals for Scientific Research, Feb. 23, 2022. doi: 10.55938/ijgasr.v1i1.4.

[8] J. Jemai, M. Chaieb, and A. Zarrad, "A Big Data Mining Approach for Credit Risk Analysis," 2022 International Symposium on Networks, Computers and Communications (ISNCC). IEEE, Jul. 19, 2022. doi: 10.1109/isncc55209.2022.9851809.

[9] H. Zhou, G. Sun, S. Fu, J. Liu, X. Zhou and J. Zhou, "A Big Data Mining Approach of PSO-Based BP Neural Network for Financial Risk Management With IoT," in IEEE Access, vol. 7, pp. 154035-154043, 2019, doi: 10.1109/ACCESS.2019.2948949.

[10] M. Al Malki, "A Review of Sustainable Growth challenges faced by Small and Medium Enterprises," International Journal for Global Academic & Scientific Research, vol. 2, no. 1. International Consortium of Academic Professionals for Scientific Research, pp. 53–67, Mar. 30, 2023. doi: 10.55938/ijgasr.v2i1.39.

[11] M. S. Murugan and S. K. T, "Large-scale data-driven financial risk management & analysis using machine learning strategies," Measurement: Sensors, vol. 27. Elsevier BV, p. 100756, Jun. 2023. doi: 10.1016/j.measen.2023.100756.

[12] Y. Zhang, "Application of Data Mining Technology in Financial Risk Management," 2021 IEEE Conference on Telecommunications, Optics and Computer Science (TOCS), Shenyang, China, 2021, pp. 319-323, doi: 10.1109/TOCS53301.2021.9689039.

[13] S. P. S. Rathore, P. Kaushik, M. Poonia, S. S. Sikarwar, D. Singh and D. Jain, "Ease Delivery: A Next-Gen Delivery Management Solution," 2024 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI), Gwalior, India, 2024, pp. 1-6, doi: 10.1109/IATMSI60426.2024.1050323

[14] L. Wan, "Financial Risk Early Warning Based on Big Data Analysis," 2023 International Conference on Ambient Intelligence, Knowledge Informatics and Industrial Electronics (AIKIIE), Ballari, India, 2023, pp. 1-5, doi: 10.1109/AIKIIE60097.2023.10390274.

[15] H. Yue, H. Liao, D. Li, and L. Chen, "Enterprise Financial Risk Management Using Information Fusion Technology and Big Data Mining," Wireless Communications and Mobile Computing, vol. 2021, no. 1. Wiley, Jan. 2021. doi: 10.1155/2021/3835652.

[16] Z. Zuo, "Risk Management for Internet Finance Based on Big Data," 2023 International Conference on Algorithms, Computing and Data Processing (ACDP), Qingdao, China, 2023, pp. 187-191, doi: 10.1109/ACDP59959.2023.00037.

[17] W. Peng, "Research on the Application of Big Data in Financial Investment Risk Management and Control," Proceedings of the 2022 3rd International Conference on Big Data and Informatization Education (ICBDIE 2022). Atlantis Press International BV, pp. 1139–1147, Dec. 23, 2022. doi: 10.2991/978-94-6463-034-3_117.

[18] L. Jiang, "Early Warning Mechanism and Countermeasures of Enterprise Financial Risk in the Era of Big Data," 2021 7th Annual International Conference on Network and Information Systems for Computers (ICNISC), Guiyang, China, 2021, pp. 652-654, doi: 10.1109/ICNISC54316.2021.00123.

[19] P. Kaushik, M. Arora, Y. Sharma, M. Poonia, P. Kumawat and R. S. Charak, "PneumoAI : Redefining Accuracy in Pneumonia Detection using Advanced Machine Learning," 2024 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI), Gwalior, India, 2024, pp. 1-6, doi: 10.1109/IATMSI60426.2024.1050305.

[20] R. Deng, "Research on Value Mining of Management Accounting Nonfinancial Data Based on Association Rules Algorithm," 2022 2nd International Conference on Networking, Communications and Information Technology (NetCIT), Manchester, United Kingdom, 2022, pp. 175-178, doi: 10.1109/NetCIT57419.2022.00051.

[21] Omolara Patricia Olaiya, Agwubuo Chigozie Cynthia, Sarah Onyeche Usoro, Omotoyosi Qazeem Obani, Kenneth Chukwujekwu Nwafor, and Olajumoke Oluwagbemisola Ajayi, "The impact of big data analytics on financial risk management," International Journal of Science and Research Archive, vol. 12, no. 2. GSC Online Press, pp. 821–827, Jul. 30, 2024. doi: 10.30574/ijsra.2024.12.2.1313.

[22] R. Rathore and S. Pratap Singh Rathore, "Machine Learning Applications in Human Resource Management: Predicting Employee Turnover and Performance," International Journal for Global Academic & Scientific Research, vol. 3, no. 2. International Consortium of Academic Professionals for Scientific Research, pp. 48–59, Jul. 02, 2024. doi: 10.55938/ijgasr.v3i2.77.

[23] R. Rathore, H. Yennapusa, S. Kumar, M. Mahawar, S. Miglani and G. Sharma, "Cutting-Edge Skin Cancer Detection in a Smart Ecosystem," 2023 International Conference on Smart Devices (ICSD), Dehradun, India, 2024, pp. 1-5, doi: 10.1109/ICSD60021.2024.10751528.

[24] S. P. S. Rathore, J. Patole, G. Tilak, R. Lenka, J. C. Lopez and Priyanka, "Consumer Sentiment Analysis," 2023 International Confer-

ence on Smart Devices (ICSD), Dehradun, India, 2024, pp. 1-5, doi: 10.1109/ICSD60021.2024.10751293.

[25] Anand, A. Pandey, S. Mehndiratta, H. Goyal, P. Kaushik and R. Rathore, ”Smart AI basedVolume Control System: Gesture Recognition with OpenCV & Mediapipe Integration,” 2023 International Conference on Smart Devices (ICSD), Dehradun, India, 2024, pp. 1-6, doi: 10.1109/ICSD60021.2024.10751362.

[26] S. Sikarwar, M. F. Afzal, S. Kumar, S. Kumar, S. P. S. Rathore and G. Kaur, ”Improving Parking Management: Leveraging IoT to Empower Smart Environments,” 2023 International Conference on Smart Devices (ICSD), Dehradun, India, 2024, pp. 1-7, doi: 10.1109/ICSD60021.2024.10751449.