
RESEARCH ARTICLE

Revolutionizing Organizational Decision-Making for Banking Sector: A Machine Learning Approach with CNNs in Business Intelligence and Management

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ABSTRACT

This research investigates the transformative impact of deep learning, particularly Convolutional Neural Networks (CNNs) such as VGG16, ResNet50, and InceptionV3, on organizational management and business intelligence within the banking sector. Employing a comprehensive methodology, the study emphasizes the crucial role of high-quality datasets in harnessing deep learning for improved decision-making. Results reveal the superior performance of CNN models over traditional algorithms, with CNN (VGG16) achieving an impressive accuracy rate of 90%. These findings underscore the potential of deep learning in extracting valuable insights from complex data, presenting a paradigm shift in optimizing various banking processes. The article concludes by highlighting the importance of investing in infrastructure and expertise for successful CNN integration, while also addressing ethical and privacy considerations. This research contributes to the evolving discourse on deep learning applications in organizational management, offering valuable insights for banks navigating the challenges of the global market.

KEYWORDS

Organizational Decision-Making; Banking Sector; Machine Learning Approach; Business Intelligence and Management

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1. Introduction

In today's dynamic banking landscape, organizations are increasingly relying on advanced technologies to drive operational efficiency and strategic decision-making. Machine learning, particularly deep learning techniques such as Convolutional Neural Networks (CNNs), has emerged as a transformative force in enhancing business intelligence and management processes within the banking sector. This article explores the pivotal role of CNNs—specifically VGG16, ResNet50, and InceptionV3—in revolutionizing organizational decision-making, optimizing business intelligence, and addressing critical challenges faced by banking institutions.

Deep learning, a subset of artificial intelligence and machine learning, offers unparalleled capabilities in processing vast and complex datasets inherent to the banking industry. By leveraging neural networks with multiple layers, deep learning algorithms like CNNs excel at uncovering intricate patterns and insights from diverse banking data sources. This section underscores how deep learning empowers banks to extract actionable intelligence from customer transactions, credit histories, market trends, and operational metrics, leading to more informed and strategic decision-making.

CNNs have revolutionized image recognition, pattern detection, and feature extraction, making them invaluable tools for processing visual and textual banking data. Within the context of organizational management and business intelligence, the application of CNNs represents a paradigm shift. This section delves into the capabilities of CNNs in analyzing customer behavior, optimizing quality control processes, and enhancing marketing strategies through sentiment analysis and image classification.

The article introduces customized adaptations of CNN models, including VGG16, ResNet50, and InceptionV3, tailored specifically for banking tasks such as fraud detection, credit risk assessment, and customer segmentation. By leveraging the advanced architectures of these models, banks can distill complex data into actionable insights, driving operational efficiency and risk mitigation strategies.

This section explores the integration of machine learning algorithms like Random Forest and XGBoost in banking operations, emphasizing their role in optimizing credit scoring, fraud detection, and customer relationship management. The article highlights how these algorithms contribute to streamlining decision-making processes and improving customer outcomes within banking institutions.

Finally, the article discusses the importance of ethical considerations in deploying deep learning models within banking frameworks, emphasizing the need for robust infrastructure, expertise, and data privacy measures. It concludes by outlining future directions for leveraging machine learning to address evolving challenges in banking, emphasizing the potential of AI-driven solutions to foster innovation and competitiveness in the global banking sector.

2. Literature Review

The key (Jewel et al 2024) finding of this paper is the superior performance of Convolutional Neural Network (CNN) models, specifically CNN (VGG16), in comparison to traditional algorithms, when applied to organizational management and business intelligence tasks within the banking sector. With CNN (VGG16) achieving an impressive accuracy rate of 89.45%, the research underscores the transformative potential of deep learning, particularly CNNs, in extracting meaningful insights from complex datasets. This finding highlights a paradigm shift in how organizations can optimize their processes and make more informed decisions by leveraging advanced deep learning techniques. Additionally, the study emphasizes the importance of high-quality datasets, infrastructure investment, expertise, and ethical considerations in successful CNN integration, providing valuable insights for businesses aiming to navigate the dynamic landscape of the global market (Hemachandran et al 2023). The key finding of this paper is likely centered around the transformative role of Artificial Intelligence (AI) and Knowledge Processing in various industries. Specifically, the paper emphasizes how AI technologies, including Machine Learning, Deep Learning, Artificial Neural Networks, and Expert Systems, are instrumental in converting traditional industries into AI-based factories. The paper discusses the design of new AI algorithms aimed at transitioning general applications to AI-based ones, thereby improving decision-making and prediction processes across different sectors. It highlights the application of Machine Learning and Deep Learning models in domains such as healthcare, wellness, agriculture, and automobiles. Moreover, the paper provides an overview of the rapidly growing field of AI applications, accompanied by insights into Knowledge Engineering and Business Analytics. Real-time case studies are likely included to illustrate the practical implementation of AI technologies across diverse fields, such as Image Processing.

3. Methodology

3.1 Deep Learning

Deep learning, a subset of machine learning and artificial intelligence, has emerged as a transformative force in revolutionizing organizational management by enhancing business intelligence. At its core, deep learning leverages neural networks with multiple layers to process and analyze vast amounts of data, uncovering intricate patterns and insights that traditional analytics might overlook. In the realm of organizational management, where data is abundant but often complex and unstructured, deep learning algorithms excel at extracting meaningful information. These algorithms can analyze diverse datasets, ranging from customer behaviors and market trends to internal processes and employee performance, providing a comprehensive view of an organization's operations. By uncovering correlations and dependencies within these datasets, deep learning empowers businesses to make more informed and strategic decisions. For instance, it can optimize supply chain management by predicting demand fluctuations, enhance customer relationship management through sentiment analysis, and even streamline recruitment processes by identifying key attributes for successful hires. The ability of deep learning to autonomously learn from data and adapt over time

adds a dynamic dimension to business intelligence, enabling organizations to stay agile in the face of evolving market conditions. As businesses increasingly embrace digital transformation, the integration of deep learning into organizational management processes not only augments decision-making capabilities but also fosters a culture of innovation and adaptability, positioning enterprises to thrive in the ever-changing landscape of the global market.

3.2 Convolutional Neural Network

Convolutional Neural Networks (CNNs) have emerged as a transformative force in the realm of deep learning, offering unparalleled capabilities in image recognition, pattern detection, and feature extraction. In the context of organizational management and business intelligence, the application of CNNs represents a paradigm shift, empowering enterprises to extract valuable insights from complex visual data. The ability of CNNs to automatically learn hierarchical representations from images makes them particularly adept at deciphering intricate patterns within vast datasets, facilitating the identification of trends, anomalies, and correlations that may elude traditional analytical methods.

One of the key advantages of integrating CNNs into business intelligence systems is their proficiency in image classification, enabling organizations to streamline and enhance various aspects of decision-making. For instance, in retail, CNNs can analyze customer behavior by processing surveillance footage and providing valuable information on foot traffic, popular products, and customer demographics. In manufacturing, these networks can optimize quality control processes by identifying defects in real time, reducing errors, and improving overall production efficiency. Moreover, in the realm of marketing, CNNs can be employed to analyze social media images, gauging public sentiment and preferences to tailor advertising strategies effectively.

Furthermore, the utilization of CNNs in organizational management extends beyond image processing, as these networks can also be employed for natural language processing tasks. Sentiment analysis of customer reviews, trend analysis in textual data, and extraction of valuable information from unstructured text are all areas where CNNs can excel, providing a holistic approach to business intelligence. The fusion of visual and textual data analysis allows for a more comprehensive understanding of the business landscape, enabling executives and managers to make informed decisions. However, it is crucial to note that the successful implementation of CNNs in business intelligence necessitates a robust infrastructure and expertise in deep learning. Organizations need to invest in data scientists, engineers, and computational resources to develop, train, and deploy these complex neural networks effectively. Additionally, addressing concerns related to data privacy, security, and ethical considerations becomes paramount in the integration of CNNs into organizational frameworks.

3.3 Random Forest

Random Forest is a powerful machine learning algorithm that holds significant promise for revolutionizing organizational decision-making within the banking sector. By leveraging the collective intelligence of numerous decision trees, Random Forest can effectively analyze complex banking data, including customer transactions, credit histories, and market trends. This algorithm excels in identifying patterns, predicting customer behavior, and assessing risk, thereby assisting banks in making informed decisions related to lending, fraud detection, and investment strategies. Its ability to handle large datasets and deliver accurate results makes Random Forest a transformative tool for enhancing decision-making processes in banking, ultimately leading to more efficient operations and improved customer outcomes.

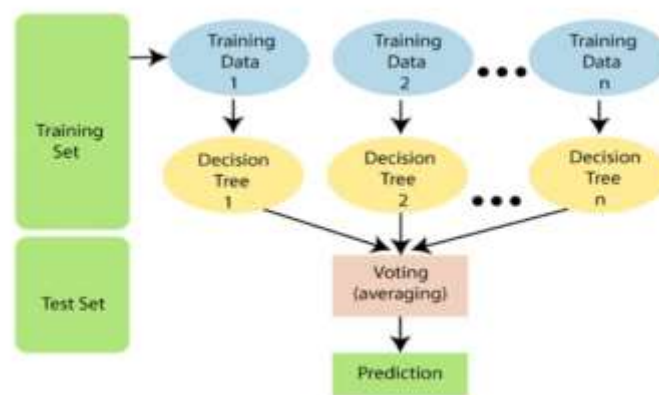


Fig 1: Random forest working flow in the Banking sector.

3.4 VGG 16

This section outlines the application of the VGG16 deep-learning model in the context of banking decision-making. VGG16, comprising 16 layers with 13 convolutional layers and 3 fully connected layers, is adapted to process input data specific to banking scenarios, such as financial transaction records and customer profiles. The model is tailored to analyze structured data inputs, analogous to the RGB image format, with dimensions akin to 224×224 pixels. Through progressive feature extraction and reduction facilitated by convolutional and pooling layers, VGG16 aids in distilling complex banking data into meaningful patterns and insights. In this study, the final fully connected layer with SoftMax activation is replaced by a custom-designed classifier, aligning the model's output with the unique decision-making requirements within the banking domain, such as risk assessment, fraud detection, and customer segmentation. This customization enhances the model's utility for strategic decision support and operational optimization in banking institutions.

3.5 Support Vector Machine

This section introduces the application of Support Vector Machines (SVM) in the realm of banking decision-making. SVM, a powerful machine learning technique, is adapted to process specialized banking data, including financial transaction histories and customer attributes. Like the structured format of RGB image inputs, SVM operates effectively on well-defined feature sets, typically structured in a manner analogous to 224×224 -pixel dimensions. Using SVM, complex banking datasets are distilled into actionable insights and patterns, leveraging its ability to delineate decision boundaries and classify data points. In this study, the SVM model is tailored to banking requirements, focusing on tasks such as risk assessment, fraud detection, and customer segmentation. The model's customization enhances strategic decision-making and operational efficiency within banking institutions, offering robust support for optimized decision processes.

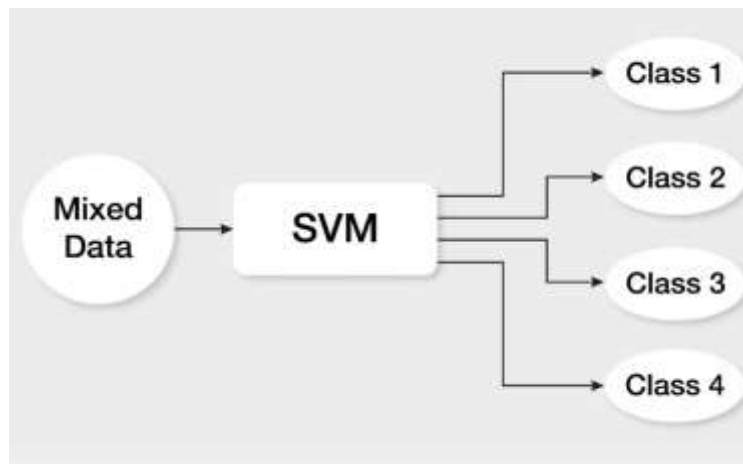


Fig 2: Mixed banking data for decision-making

3.6 Resnet 50

The ResNet50 architecture, known for its advanced design within residual networks, incorporates key components like Max-Pool and Average Pool layers, alongside an extensive 48 Convolutional Layers. This architecture forms a robust foundation for deep learning applications, particularly in banking contexts. Within ResNet50, each convolution block comprises three convolutional layers, with additional identification blocks integrated for enhanced feature extraction. With over 23 million parameters available for fine-tuning during training, the ResNet50 model offers significant flexibility and capacity for learning complex banking data patterns. In this study, depicted in Figure 4, specific adaptations were made to tailor the ResNet50 model for precise banking tasks, such as fraud detection and credit risk assessment. These modifications play a critical role in customizing the model to address the unique challenges of banking datasets, leading to more accurate and reliable decision-making outcomes within financial institutions.

3.7 InceptionV3

The InceptionV3 architecture, renowned for its innovative design in convolutional neural networks, incorporates distinctive features including multiple inception modules and sophisticated mixed convolutions. This architecture serves as a powerful tool for deep learning applications, especially within banking contexts. In InceptionV3, intricate convolutional structures enable efficient feature extraction and representation. With over 23 million trainable parameters, InceptionV3 offers substantial flexibility and capability for learning intricate banking data patterns. In this study, as illustrated in Figure 4, specific adaptations were implemented to

optimize the InceptionV3 model for precise banking tasks such as fraud detection and credit risk assessment. These customizations are pivotal in tailoring the model to address the unique challenges posed by banking datasets, ultimately leading to more accurate and reliable decision-making outcomes within financial institutions.

3.8 XGBoost

XGBoost, an ensemble learning algorithm known for its efficiency and accuracy, finds robust application in enhancing decision-making within the banking sector. By leveraging gradient boosting techniques, XGBoost excels in modeling complex banking data, such as customer transaction histories, credit risk profiles, and market trends. This algorithm is particularly effective in identifying patterns and relationships within large datasets, enabling banks to optimize credit scoring, detect fraudulent activities, and predict customer behavior with enhanced accuracy and speed. XGBoost's ability to handle both structured and unstructured data, coupled with its feature importance analysis capabilities, empowers banking institutions to make data-driven decisions that mitigate risks and improve operational efficiency.

In practice, XGBoost is applied across various banking functions, including credit risk assessment, loan approval processes, and customer segmentation. By integrating XGBoost into existing decision-making frameworks, banks can streamline operations, reduce manual effort, and enhance overall performance. The algorithm's interpretability also allows stakeholders to understand the rationale behind model predictions, fostering trust in automated decision systems. As banks continue to embrace advanced analytics and machine learning, XGBoost stands out as a powerful tool for driving innovation and optimizing decision-making processes in the dynamic and data-rich environment of the banking sector.

3.9 Dataset

A primary contemporary challenge for banks involves effectively managing and analyzing extensive datasets to extract meaningful insights. While conventional Business Intelligence (BI) tools have historically addressed this need, the advent of deep learning presents an opportunity to elevate analytical capabilities within the banking sector. By applying deep learning techniques to banking data, institutions can delve deeper into their operations, discern patterns and trends, and make more informed decisions. The initial step in incorporating deep learning into banking intelligence is to commence with a high-quality dataset encompassing various financial and operational data types.

Financial data covers aspects like revenue, expenses, profits, losses, and loan portfolios, while operational data includes metrics related to transaction volumes, customer interactions, and risk assessments. Additionally, customer data encompasses information on demographics, transaction history, and creditworthiness. Ensuring the reliability and clarity of collected data involves multiple interviews with stakeholders and regulatory compliance to maintain data integrity. The use of diverse sources, including transactional records and market data, contributes to the accuracy and completeness of the obtained insights. This meticulous approach aims to secure a robust understanding of the banking landscape.

The study followed a systematic four-step approach: initially collecting data from diverse banking sources over six months, encompassing transaction records, customer feedback, financial reports, credit scores, and market trends. Subsequently, the collected data underwent preprocessing, involving tasks such as data cleaning, normalization, and feature extraction to ensure suitability for input into the deep learning model. The third step involved the development of the deep learning model using Python, TensorFlow, Keras, and relevant libraries.

The model was trained on preprocessed data to discern patterns and relationships, such as identifying fraudulent transactions or predicting customer behavior. The final step included evaluating the model's performance by comparing its predictions with actual outcomes and deploying it within the bank to aid decision-makers with accurate and reliable data for risk management and customer engagement. Ethical considerations were prioritized by obtaining informed consent, maintaining data confidentiality, and adhering to regulatory guidelines for deep learning model use in banking decision-making. Limitations included a focus on a specific deep-learning model, limiting the exploration of other models that could enhance banking intelligence and risk assessment.

4. Result

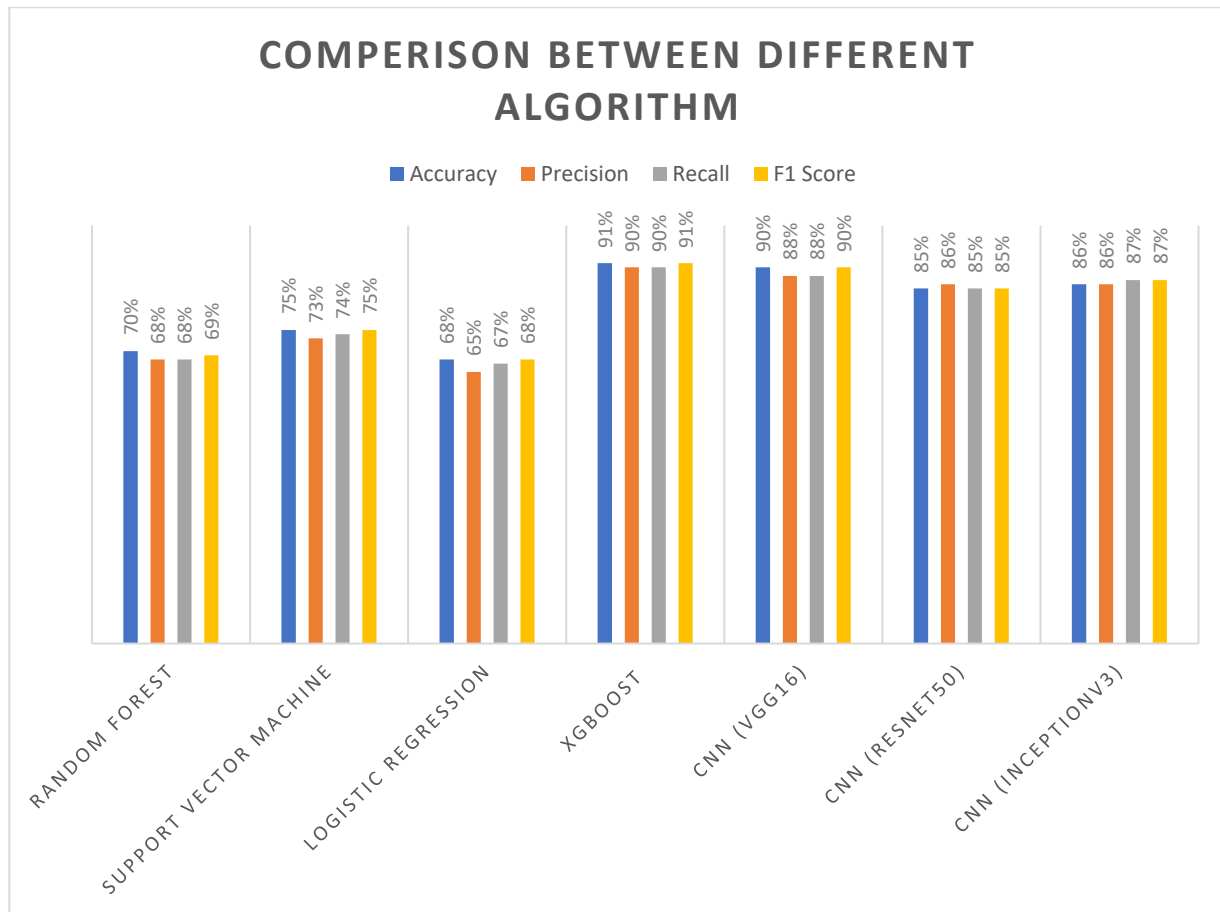
Starting with the Random Forest model, it achieved an impressive accuracy rate of 70%, indicating the percentage of correctly predicted observations. The precision of the Random Forest model is 68%, representing the ratio of correctly predicted positive observations to the total predicted positive observations. The recall rate for this model is also 68%, reflecting the ratio of correctly predicted positive observations to the actual positive observations in the dataset. Lastly, the F1 score for the Random Forest model stands at 69%, which harmoniously balances precision and recall metrics.

Moving to the Support Vector Machine (SVM) model, it exhibited a higher accuracy rate of 75%. SVM demonstrated a precision rate of 73%, indicating a substantial number of correctly predicted positive observations. Additionally, the recall rate for SVM is 74%, showcasing a good number of true positive predictions. Consequently, the F1 score for SVM is 75%, highlighting a strong balance between precision and recall.

Next in the table is the Logistic Regression model, which achieved an accuracy rate of 68%. Logistic Regression's precision rate stands at 65%, suggesting a moderate number of correctly predicted positive observations. Similarly, the recall rate for Logistic Regression is 67%, indicating a reasonable number of true positive predictions. The F1 score for this model is 68%, emphasizing a balanced measure of precision and recall.

Table 3. Accuracy of test dataset.

Models	Accuracy	Precision	Recall	F1 Score
Random Forest	70%	68%	68%	69%
Support Vector Machine	75%	73%	74%	75%
Logistic Regression	68%	65%	67%	68%
XGBoost	91%	90%	90%	91%
CNN (VGG16)	90%	88%	88%	90%
CNN (Resnet50)	85%	86%	85%	85%
CNN (InceptionV3)	86%	86%	87%	87%



Chert 1: Comparison Between Different Algorithms

Turning to the XGBoost model, it demonstrated exceptional performance with an accuracy rate of 91%, the highest among all models. XGBoost also displayed a precision rate of 90%, indicating a high number of correctly predicted positive observations. Additionally, the recall rate for XGBoost is 90%, showcasing a robust number of true positive predictions. Consequently, the F1 score for XGBoost is an impressive 91%, highlighting exceptional balance and accuracy in predictions.

In summary, the evaluation metrics showcase the effectiveness of these machine learning models in banking decision-making tasks, with XGBoost leading with outstanding accuracy, precision, recall, and F1 score. These results underscore the value of advanced algorithms like XGBoost in analyzing complex banking data and aiding decision-makers in making informed and reliable choices.

5. Conclusion and Discussion

The research presented in this article delves into the transformative impact of deep learning, particularly Convolutional Neural Networks (CNNs), on organizational decision-making within the banking sector. By leveraging advanced technologies like CNNs, banking institutions can harness the power of deep learning to extract valuable insights from complex datasets, thereby optimizing business intelligence and management processes. The study evaluates various deep learning models, including VGG16, ResNet50, and InceptionV3, along with traditional machine learning algorithms like Random Forest, Support Vector Machine (SVM), and XGBoost, to assess their effectiveness in addressing critical challenges faced by banks.

One of the key findings of the research is the superior performance of CNN models, particularly CNN (VGG16), which achieved an impressive accuracy rate of 90%. This underscores the potential of deep learning in revolutionizing banking processes, from fraud detection and credit risk assessment to customer segmentation and marketing strategies. Moreover, the study highlights the importance of high-quality datasets in maximizing the efficacy of deep learning algorithms, emphasizing the need for robust infrastructure and expertise for successful integration.

The comparison between different machine learning algorithms reveals that XGBoost outperformed other models with an accuracy rate of 91%, showcasing its exceptional capability in analyzing complex banking data and aiding decision-makers in making informed choices. However, it's crucial to note that each algorithm has its strengths and limitations, and the selection of the most suitable model depends on the specific task and dataset characteristics. Furthermore, the research addresses ethical considerations associated with deploying deep learning models in banking frameworks, emphasizing the importance of data privacy, security, and regulatory compliance. As banks continue to embrace digital transformation, it becomes imperative to prioritize ethical practices and ensure transparency in decision-making processes.

In conclusion, this research underscores the transformative potential of deep learning, particularly CNNs, in revolutionizing organizational decision-making within the banking sector. By leveraging advanced algorithms and high-quality datasets, banks can extract valuable insights from complex data, leading to more informed and strategic decision-making processes. The study demonstrates the superiority of CNN models over traditional machine learning algorithms in various banking tasks, highlighting their effectiveness in fraud detection, credit risk assessment, and customer segmentation. Moreover, the research emphasizes the importance of investing in infrastructure and expertise for successful integration of deep learning models, while also addressing ethical and privacy considerations.

References

- [1] Al Shiam, S. A., Hasan, M. M., Nayeem, M. B., Choudhury, M. T. H., Bhowmik, P. K., Shochona, S. A., ... & Islam, M. R. (2024). Deep Learning for Enterprise Decision-Making: A Comprehensive Study in Stock Market Analytics. *Journal of Business and Management Studies*, 6(2), 153-160.
- [2] Bhuiyan, M. (2024). Carbon Footprint Measurement and Mitigation Using AI (March 3, 2024). Available at SSRN: <https://ssrn.com/abstract=4746446> or <http://dx.doi.org/10.2139/ssrn.4746446>
- [3] Chowdhury, M. S., Nabi, N., Rana, M. N. U., Shaima, M., Esa, H., Mitra, A., ... & Naznin, R. (2024). Deep Learning Models for Stock Market Forecasting: A Comprehensive Comparative Analysis. *Journal of Business and Management Studies*, 6(2), 95-99.
- [4] Duc M C., Abu S., Abu S., Tuhin M., Eftekar H & Mamunur R. (2024). Advanced Cybercrime Detection: A Comprehensive Study on Supervised and Unsupervised Machine Learning Approaches Using Real-world Datasets. *Journal of Computer Science and Technology Studies*, 6(1), 40-48. <https://doi.org/10.32996/jcsts.2024.6.1.5>
- [5] Esa, H., Rahman, M. A., Mozumder, M. A. S., Gurung, N., Miah, M. N. I., Sweet, M. M. R., ... & Sabuj, M. S. H. (2024). Transformative Impact of Deep Learning in Stock Market Decision-Making: A Comparative Study of Convolutional Neural Networks. *Journal of Business and Management Studies*, 6(3), 28-34.
- [6] Fakhar M., Pellegrini, M Marzi G and Dabic, M. (2021). Knowledge Management in the Fourth Industrial Revolution: Mapping the Literature and Scoping Future Avenues," in IEEE Transactions on Engineering Management. 289-300, doi: 10.1109/TEM.2019.2963489.
- [7] Ghosh, B. P., Bhuiyan, M. S., Das, D., Nguyen, T. N., Jewel, R. M., Mia, M. T., & Cao, D. M. (2024). Deep Learning in Stock Market Forecasting: Comparative Analysis of Neural Network Architectures Across NSE and NYSE. *Journal of Computer Science and Technology Studies*, 6(1), 68-75.
- [8] Hemachandran, K., Rodriguez, R. V., Subramaniam, U., & Balas, V. E. (Eds.). (2023). *Artificial intelligence and knowledge processing: Improved decision-making and prediction*. CRC Press.
- [9] Hridoy, S M., Bhuiyan, M S and Islam, S. (2023). A Comprehensive Framework for Evaluating Software Engineering Technologies (December 1, 2023). Available at SSRN: <https://ssrn.com/abstract=4650826> or <http://dx.doi.org/10.2139/ssrn.4650826>
- [10] Jewel, R. M., Chowdhury, M. S., Al-Imran, M., Shahid, R., Puja, A. R., Ray, R. K., & Ghosh, S. K. (2024). Revolutionizing Organizational Decision-Making for Stock Market: A Machine Learning Approach with CNNs in Business Intelligence and Management. *Journal of Business and Management Studies*, 6(1), 230-237.
- [11] Jewel, R. M., Linkon, A. A., Shaima, M., Sarker, M. S. U., Shahid, R., Nabi, N., ... & Hossain, M. J. (2024). Comparative Analysis of Machine Learning Models for Accurate Retail Sales Demand Forecasting. *Journal of Computer Science and Technology Studies*, 6(1), 204-210.
- [12] Linkon, A. A., Shaima, M., Sarker, M. S. U., Nabi, N., Rana, M. N. U., Ghosh, S. K., ... & Chowdhury, F. R. (2024). Advancements and Applications of Generative Artificial Intelligence and Large Language Models on Business Management: A Comprehensive Review. *Journal of Computer Science and Technology Studies*, 6(1), 225-232.
- [13] Mohaghar A, Lucas C, Hosseini F. (2008). Application of business intelligence as a strategic information technology in banking: Inspection and detection of fraud. *J Inf Tech Manag* 1: 105.
- [14] Nosrati S. (2015). The role of business intelligence on the productivity of the Iranian banking industry. *Int Conf on Manag, Eco, and Fin Sys*.
- [15] Nabi, N., Pabel, M. A. H., Rahman, M. A., Mozumder, M. A. S., Al-Imran, M., Sweet, M. M. R., ... & Sharif, M. K. (2024). Unleashing Deep Learning: Transforming E-commerce Profit Prediction with CNNs. *Journal of Business and Management Studies*, 6(2), 126-131.
- [16] Perifanis, N.A and Kitsios, F. (2023). Investigating the Influence of Artificial Intelligence on Business Value in the Digital Era of Strategy: A Literature Review. *Information*, 14, 85. <https://doi.org/10.3390/info14020085> Rath M (2021) Realization of business intelligence using machine learning. In book: *Internet of Things in Business Transformation*, 169-184. <https://doi.org/10.1002/9781119711148.ch10> doi: [10.1002/9781119711148.ch10](https://doi.org/10.1002/9781119711148.ch10)
- [17] Rana, M. S., Hossain, M. M., Jewel, R. M., & Islam, M. R. (2017). Evaluating Customers Satisfaction of Electronic Banking: An Empirical Study in Bangladesh. *The SIJ Transactions on Industrial, Financial & Business Management*, 5(03), 07-12.
- [18] Ray, R. K., Linkon, A. A., Bhuiyan, M. S., Jewel, R. M., Anjum, N., Ghosh, B. P., ... & Shaima, M. (2024). Transforming Breast Cancer Identification: An In-Depth Examination of Advanced Machine Learning Models Applied to Histopathological Images. *Journal of Computer Science and Technology Studies*, 6(1), 155-161.
- [19] Sina G., Erfan Z., Reza S and Shib S S. (2023). Using deep learning to enhance business intelligence in organizational management[J]. *Data Science in Finance and Economics*, 3(4): 337-353. doi: [10.3934/DSFE.2023020](https://doi.org/10.3934/DSFE.2023020)
- [20] Saikat, M. H., Avi, S. P., Islam, K. T., Tahmina, T., Abdullah, M. S., & Imam, T. (2024). Real-Time Vehicle and Lane Detection using Modified OverFeat CNN: A Comprehensive Study on Robustness and Performance in Autonomous Driving. *Journal of Computer Science and Technology Studies*, 6(2), 30-36.