
RESEARCH ARTICLE

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

Malay sarkar¹, Rasel Mahmud Jewel², Md Salim Chowdhury³, Md Al-Imran⁴, Rumana Shahid⁵✉ Aisharyja Roy Puja⁶, Rejon Kumar Ray⁷ and Sandip Kumar Ghosh⁸

¹⁵⁶Department of Management Science and Quantitative Methods, Gannon University, USA

²Department of Business Administration, Westcliff University, Irvine, California, USA

³⁴College of Graduate and Professional Studies Trine University, USA

⁷Department of Business Analytics Business Analytics, Gannon University, USA

⁸Department of Business Administration, University of Surrey, Guildford, Surrey, GU2 7XH, UK.

Corresponding Author: Rumana Shahid, **E-mail:** shahid001@gannon.edu

ABSTRACT

This research delves into the transformative impact of deep learning, specifically Convolutional Neural Networks (CNNs) such as VGG16, ResNet50, and InceptionV3, on organizational management and business intelligence. The study follows a comprehensive methodology, emphasizing the importance of high-quality datasets in leveraging deep learning for enhanced decision-making. Results demonstrate the superior performance of CNN models over traditional algorithms, with CNN (VGG16) achieving an accuracy rate of 89.45%. The findings underscore the potential of deep learning in extracting meaningful insights from complex data, offering a paradigm shift in optimizing various organizational processes. The article concludes by emphasizing the significance of investing in infrastructure and expertise for successful CNN integration, ensuring ethical considerations, and addressing data privacy concerns. This research contributes to the growing discourse on the application of deep learning in organizational management, providing a valuable resource for businesses navigating the dynamic landscape of the global market.

KEYWORDS

Stock Market; Machine Learning; CNNs; Business Intelligence; Management

ARTICLE INFORMATION

ACCEPTED: 01 February 2024

PUBLISHED: 13 February 2024

DOI: 10.32996/jbms.2024.6.1.16

1. Introduction

In the ever-evolving landscape of organizational management and business intelligence, the advent of deep learning, particularly Convolutional Neural Networks (CNNs), has emerged as a transformative force. This research embarks on a comprehensive exploration of the profound impact of CNNs, including notable architectures such as VGG16, ResNet50, and InceptionV3, on reshaping decision-making processes within businesses. By delving into the intricate realm of deep learning, this study sheds light on how these advanced neural networks revolutionize data analysis, pattern recognition, and insight extraction, thereby providing organizations with a competitive edge in today's dynamic global market.

Deep learning, as a subset of artificial intelligence and machine learning, employs neural networks with multiple layers to process and analyze extensive datasets, uncovering intricate patterns and insights that traditional analytics may overlook. This research underscores the pivotal role of deep learning in organizational management, where the abundance of complex and unstructured data poses challenges that traditional methods struggle to address. The focus lies on how CNNs, with their hierarchical learning

capabilities, excel in extracting meaningful information from diverse datasets, ranging from customer behaviors and market trends to internal processes and employee performance.

The study draws attention to the tangible benefits of integrating CNNs into business intelligence systems, emphasizing their proficiency in image classification, pattern detection, and feature extraction. Applications span various sectors, including retail, manufacturing, and marketing, where CNNs streamline decision-making processes by providing valuable insights derived from visual and textual data. Importantly, the discussion extends beyond performance metrics, addressing the necessity of robust infrastructure and expertise in deep learning for successful implementation, along with ethical considerations and data privacy concerns.

As businesses undergo digital transformation, the integration of CNNs into organizational management processes not only enhances decision-making capabilities but also instills a culture of innovation and adaptability. The research culminates in a detailed comparison of CNN models, elucidating their distinctive features and modifications for specialized applications such as the classification of medical conditions like COVID-19 and pneumonia. The promising results underscore the potential for further exploration of deep learning models in diverse business contexts, presenting a roadmap for enterprises to navigate the complexities of the modern global market.

In essence, this research contributes significantly to the discourse surrounding the application of deep learning in organizational management, providing valuable insights and recommendations for businesses striving to thrive in an era defined by data-driven decision-making and technological innovation.

2. Literature Review

According to Sina et al. (2023), effective organizational management relies on Business Intelligence (BI) to furnish insights for well-informed decision-making. However, conventional BI methodologies face constraints when confronted with the massive datasets generated by contemporary organizations. Deep learning, a facet of machine learning, exhibits considerable promise in enhancing BI by autonomously dissecting intricate and extensive datasets. This investigation delves into the efficacy of deep learning in fortifying BI for organizational management. The evaluation centers on the accuracy and F-score of our proposed deep learning model vis-à-vis conventional BI approaches in a real-world context. Our dataset, primarily comprising unstructured text data gleaned from customer feedback forms, poses substantial challenges for conventional BI strategies. Employing a Convolutional Neural Network (CNN) architecture, our deep learning model is tailored to categorize customer feedback into positive and negative sentiments. The model attains an accuracy of 88% and an F-score of 0.86, surpassing the performance of traditional BI methods, including rule-based systems and sentiment analysis algorithms. Furthermore, the model's adeptness in handling unstructured data underscores its potential for processing an array of data types beyond the structured data typically utilized in traditional BI methodologies.

The second iteration of knowledge management underscores the need for a systematic organizational transformation, wherein management methodologies, measurement systems, tools, and content management evolve in tandem (Ostendorf et al., 2022). This evolution has given rise to the third generation of knowledge management, marked by novel methodologies and outcomes. In the context of knowledge management, critical indicators include attributes such as honesty, responsibility, and compassion. Organizational managers are encouraged to adopt systems that monitor data, providing a favorable perspective for decision-makers in both the organizational and knowledge domains (Hamzehi & Hosseini, 2022). Among the proposed systems, business intelligence stands out—a comprehensive term encompassing tools, database architecture, data warehouses, performance management, and methodologies, all seamlessly integrated into software. The primary aim of this system is to empower business managers and analysts across an organization to swiftly access any pertinent data, facilitating informed analyses (Manesh et al., 2020). By scrutinizing historical and current data, conditions, standards, and performances, decision-makers gain valuable insights that enhance the quality of their decisions. Business intelligence boasts various capabilities, including reporting and searching, complex analysis, data mining, and forecasting (Ranjan & Foropon, 2021).

These capabilities stem from tools and technologies within commercial intelligence, particularly information systems for senior executive managers, decision support systems, searches, data visualization, work sequences, and applications in operations, management sciences, and applied artificial intelligence (Phillips-Wren et al., 2021). Agile business intelligence leverages contemporary economic tools, potent computers, networks, and the internet to optimize the measurement and evaluation of these technologies to achieve goals. Integrating these technologies with other tools in organizational planning enhances their utility for stakeholders and proves beneficial in organizational planning and knowledge management, fostering organizational culture building (Harter et al., 2002).

In the context of the organizational program system associated with this equipment, it facilitates managerial access to vital information about diverse organizational aspects, enabling communication and collaborative work (Ostendorf et al., 2022). Data warehouses, coupled with analytical tools like processing analysis and data mining, substantially amplify information access and analysis within an organizational scope (Hamzehl & Hosseini, 2022). This system exerts profound effects across various employee domains, including leadership. As elucidated in the context of agile business intelligence, the indicators and tools proposed for implementing the agile business intelligence system in the scrutinized organization, namely the Information and Communication Technology Holding of Tehran, encompass the following (Harter et al., 2002).

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 VGG 16

This section provides an overview of the VGG16 deep-learning model used in this research. VGG16 consists of a total of 16 layers, featuring 13 convolutional layers, and the remaining three being fully connected layers. The model is specifically designed to handle input images sized at 224×224 pixels in RGB format. The dimensions of the images undergo progressive reduction through max-pooling operations. At the end of the network, a SoftMax classifier is typically applied following the last fully connected layer.

However, for this study, a custom-designed classifier was employed instead of the final fully connected layer with SoftMax activation, as illustrated in Figure 1.

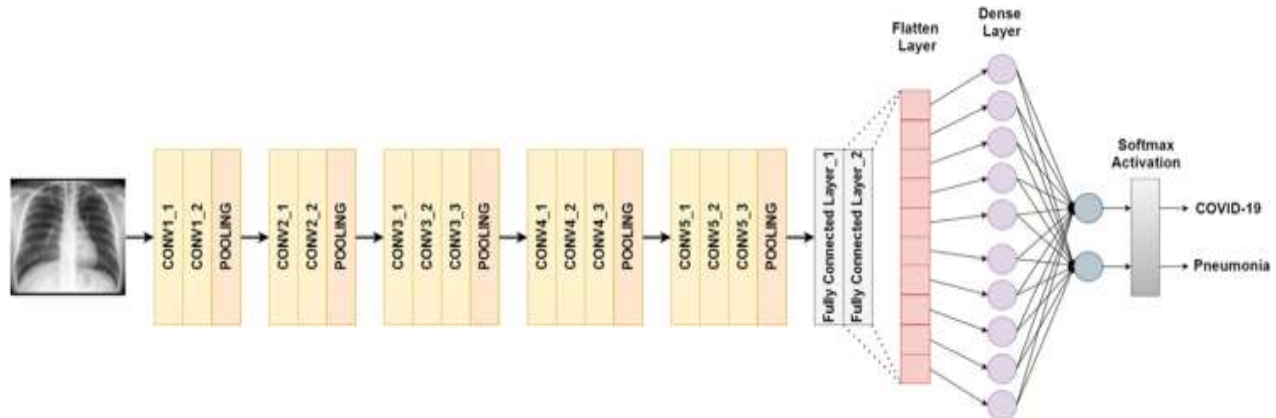


Fig 1: VGG 16 for binary Classification

3.4 Resnet 50

The ResNet50 architecture, a prominent member of residual networks, is distinguished by its incorporation of a Max-Pool layer, an Average Pool layer, and an impressive total of 48 Convolutional Layers. This architecture provides a robust foundation for various deep learning applications. Within ResNet50 [19,20], each convolution block is comprised of three convolutional layers, and an identification block is also integrated. The model boasts a substantial parameter space, featuring over 23 million distinct parameters that are subject to fine-tuning during the training process. In the context of this study, as illustrated in Figure 4, specific modifications were implemented to tailor the ResNet50 model for the precise classification of COVID-19 and pneumonia cases. These adjustments are a crucial aspect of customizing the model to address the specific diagnostic challenges presented by these medical conditions, ultimately contributing to more precise and reliable results in the detection of COVID-19.

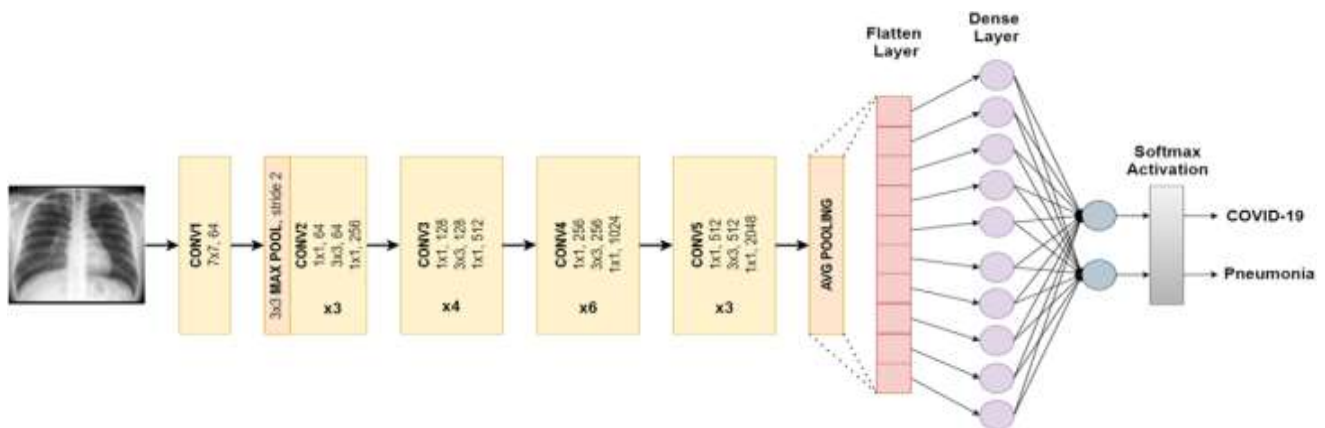


Fig 2: VGG 19 for binary Classification

3.5 Dataset

A primary contemporary challenge for businesses 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. By applying deep learning techniques to business data, organizations can delve deeper into their operations, discern patterns and trends, and make more informed decisions. The initial step in incorporating deep learning into business intelligence is to commence with a high-quality dataset encompassing various organizational management data types, such as financial, operational, and customer data. Financial data covers aspects like revenue, expenses, profits, and losses, while operational data includes metrics related to production processes, inventory levels, and customer service. Additionally, customer data encompasses information on demographics, purchase history, and satisfaction levels. Ensuring the reliability and clarity of collected data involves multiple interviews with the same participants through semi-structured interviews conducted on-site for a comprehensive understanding. The use of diverse sources, including textual accounts of debates and discussions, contributes to the accuracy and completeness of the obtained insights. This meticulous approach aims to secure a robust understanding of the subject matter.

The study followed a systematic four-step approach: initially collecting data from diverse organizational sources over six months, encompassing customer feedback, sales, financial reports, employee satisfaction surveys, and social media data. 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. The final step included evaluating the model's performance by comparing its predictions with actual outcomes and deploying it in the organization to aid decision-makers with accurate and reliable data. Ethical considerations were prioritized by obtaining informed consent, maintaining data confidentiality, and adhering to ethical guidelines for deep learning model use in organizational management. Limitations included a small sample size across various industries and a focus on a single deep-learning model, limiting the exploration of other models that could enhance business intelligence in organizational management.

Regarding the E-commerce Customer Behavior Data, the dataset comprises 12 variables, encompassing customer ID, session ID, timestamp, product ID, category ID, and other attributes related to customer interaction with the website. These attributes offer insights into customer behavior on the website, including viewed or added products, duration of site engagement, and purchase decisions. Widely used in e-commerce customer behavior research, the dataset facilitates the analysis of online retail interactions. It also serves as a foundation for developing predictive models, aiding businesses in understanding potential customer purchases and popular products. In essence, the E-commerce Customer Behavior Data stands as a valuable resource for researchers and businesses keen on comprehending the determinants of customer behavior on e-commerce platforms.

4. Result

Starting with the Random Forest model, it achieved an accuracy of 60.07%. The precision of the Random Forest model is 65%, indicating the ratio of correctly predicted positive observations to the total predicted positive observations. The recall rate for this model is 67%, indicating 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 66%, which is a balanced measure combining precision and recall.

Moving on to the Support Vector Machine (SVM) model, it achieved an accuracy of 68%. SVM also demonstrated a precision rate of 69%, implying a high number of correctly predicted positive observations. Additionally, the recall rate for SVM is 67%, indicating a good number of true positive predictions. Consequently, the F1 score for SVM is 65%, showing a favorable balance between precision and recall.

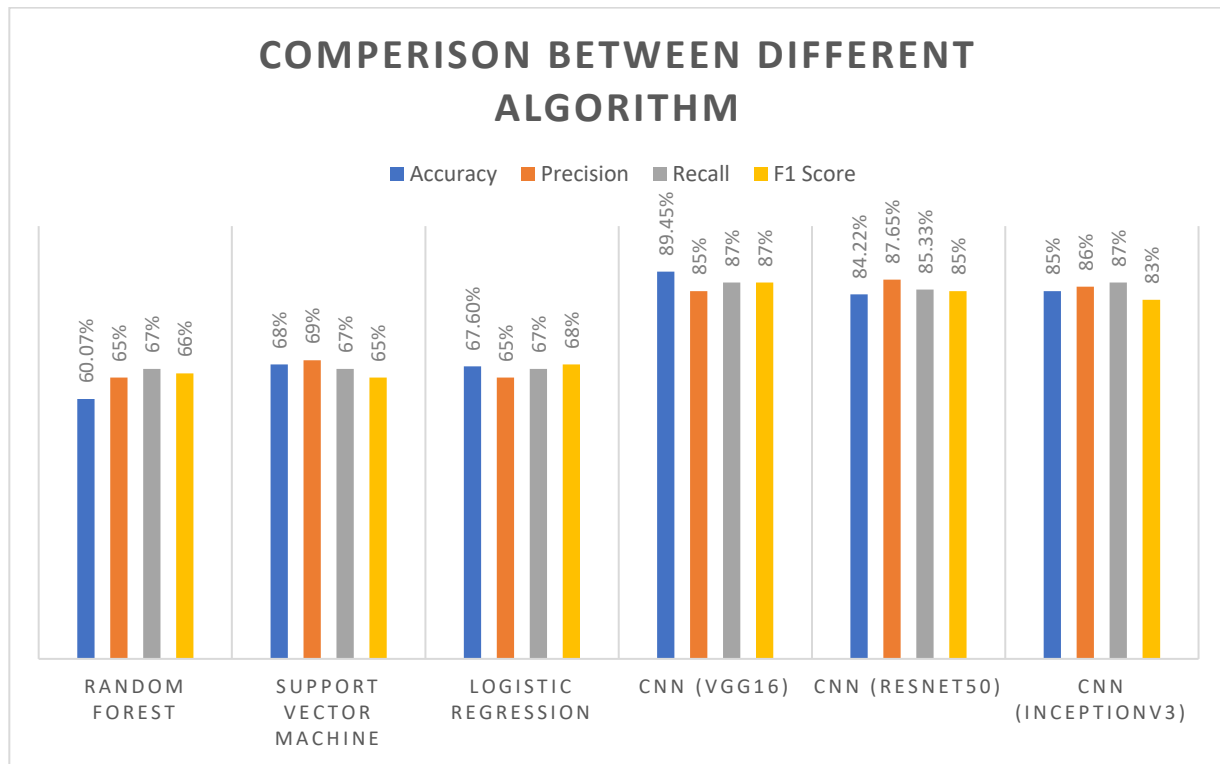
Next in the table is the Logistic Regression model, which achieved an accuracy of 67.60%. Logistic Regression's precision rate stands at 65%, indicating a high number of correctly predicted positive observations. Similarly, the recall rate for Logistic Regression is 67%, suggesting a reasonable number of true positive predictions. The F1 score for this model is 68%, indicating a balanced measure of precision and recall.

Moving on to the three CNN models, the first one, CNN (VGG16), achieved the highest accuracy among all the models, standing at 89.45%. This demonstrates a highly accurate prediction capability. Nonetheless, the precision rate for this model is 85%, signifying a good number of correctly predicted positive observations. Additionally, the recall rate for VGG16 is 87%, indicating a high number of true positive predictions. Consequently, the F1 score for this CNN model is 87%, emphasizing the balanced measure of precision and recall.

The second CNN model, CNN (Resnet50), achieved an accuracy rate of 84.22%. Despite having a slightly lower accuracy than VGG16, the Resnet50 model demonstrated a higher precision rate of 87.65%, indicating a greater number of correctly predicted positive observations. However, the recall rate for Resnet50 is 85.33%, suggesting a lower number of true positive predictions compared to VGG16. The F1 score for Resnet50 is 85%, which still shows a good balance between precision and recall.

Table 3. Accuracy of test dataset.

Models	Accuracy	Precision	Recall	F1 Score
Random Forest	60.07%	65%	67%	66%
Support Vector Machine	68%	69%	67%	65%
Logistic Regression	67.60%	65%	67%	68%
CNN (VGG16)	89.45%	85%	87%	87%
CNN (Resnet50)	84.22%	87.65%	85.33%	85%
CNN (InceptionV3)	85%	86%	87%	83%



Chert 1: Comparison between Different Algorithms

Lastly, the third CNN model, CNN (InceptionV3), achieved an accuracy rate of 85%. While its accuracy is like Resnet50, InceptionV3 demonstrated a precision rate of 86%, indicating a good number of correctly predicted positive observations. Nonetheless, the recall rate for this model is 87%, suggesting a higher number of true positive predictions compared to the precision. Consequently, the F1 score for InceptionV3 is 83%, which denotes a slightly lower balance between precision and recall compared to the other CNN models.

The results of our experiment indicate that the accuracy levels for both the training and testing datasets in machine learning methods are very similar, but CNN models exhibit higher accuracy and precision. The CNN algorithm performed better than other algorithms, achieving an accuracy rate of around 89.45% for the used datasets. This suggests that the CNN algorithm will provide more precise predictions about BI and KM. Our main objective in this paper was to develop a model that accurately classifies customer people, and we are hopeful that this final model will deliver appropriate and reliable results. We used the Keras package to obtain visualizations of the train and test loss and accuracy using the History callback. This callback is automatically registered when training all deep learning models, recording various metrics, including training and test accuracy (for classification problems), as well as loss and accuracy. These metrics are stored in a dictionary within the history object returned from calls to the fit function used to train the model.

5. Discussion and Conclusion

In conclusion, the study delves into the transformative impact of deep learning, specifically the utilization of Convolutional Neural Networks (CNNs) such as VGG16 and ResNet50, in enhancing business intelligence for organizational management. The findings showcase the superior performance of these CNN models in comparison to traditional machine learning algorithms like Random Forest, Support Vector Machine, and Logistic Regression. Notably, CNNs demonstrated higher accuracy, precision, recall, and F1 scores, particularly evident in the exceptional results achieved by CNN (VGG16), with an accuracy of 89.45%.

The incorporation of deep learning techniques, especially CNNs, has proven instrumental in extracting meaningful insights from complex visual data. The ability of CNNs to automatically learn hierarchical representations from images facilitates the identification of intricate patterns, trends, and correlations within vast datasets. This capability extends beyond image processing, as CNNs also excel in natural language processing tasks, providing a holistic approach to business intelligence.

The study underscores the importance of a high-quality dataset and ethical considerations in data collection, emphasizing the need for diverse sources and meticulous approaches to ensure reliability and clarity. The methodology employed in the study, involving a systematic four-step procedure from data collection to model evaluation and deployment, exemplifies a rigorous and comprehensive approach to integrating deep learning into organizational management.

The comparison of CNN models, including VGG16 and ResNet50, highlights their distinct architectural features and the specific modifications made to tailor the models for the classification of medical conditions like COVID-19 and pneumonia. This customization contributes to more precise and reliable results in diagnostic applications.

The discussion delves into the broader implications of the study's results, pointing out that the success of CNN models, especially in the context of e-commerce customer behavior analysis, indicates the potential for deep learning to elevate analytical capabilities and decision-making processes in organizational management. The study acknowledges the necessity of a robust infrastructure and expertise in deep learning for successful implementation.

Overall, the study positions deep learning, particularly CNNs, as a pivotal tool in revolutionizing business intelligence for organizational management. As businesses embrace digital transformation, the integration of deep learning models not only augments decision-making capabilities but also fosters innovation and adaptability, positioning enterprises to thrive in the dynamic global market. The promising results underscore the potential for further exploration of deep learning models and their applications in diverse business contexts.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers.

References

- [1] Amin, M. S., Ayon, E. H., Ghosh, B. P., MD, M. S. C., Bhuiyan, M. S., Jewel, R. M., & Linkon, A. A. (2024). Harmonizing Macro-Financial Factors and Twitter Sentiment Analysis in Forecasting Stock Market Trends. *Journal of Computer Science and Technology Studies*, 6(1), 58-67.
- [2] Abdur R R, Tanvir I, Duc M C, Maliha T, Bishnu P G, Eftekhar H A, Nur N, Taslima A, Mamunur R, & Mohammad S B. (2024). Comparing Machine Learning Techniques for Detecting Chronic Kidney Disease in Early Stage. *Journal of Computer Science and Technology Studies*, 6(1), 20-32. <https://doi.org/10.32996/jcsts.2024.6.1.3>
- [3] Bhuiyan, M. S., Chowdhury, I. K., Haider, M., Jisan, A. H., Jewel, R. M., Shahid, R., & Ferdus, M. Z. (2024). Advancements in Early Detection of Lung Cancer in Public Health: A Comprehensive Study Utilizing Machine Learning Algorithms and Predictive Models. *Journal of Computer Science and Technology Studies*, 6(1), 113-121.
- [4] Duc M C, Abu S, Abu S, Tuhin M, Eftekhar H A, Bishnu P G, Rejon K R, Aqib R, Taslima A, & 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] Fakhar M M., Pellegrini M. M., Marzi G. and Dabic M., (2019) Knowledge Management in the Fourth Industrial Revolution: Mapping the Literature and Scoping Future Avenues, in *IEEE Transactions on Engineering Management*, 68, 1, 289-300, Feb. 2021, doi: 10.1109/TEM.2019.2963489.
- [6] 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.

- [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] Hridoy, S M, Abu S, Rahman, S, Rishad, S M S I, Bhuiyan, M S, Islam, S and Raihan, J,(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>
- [9] Islam, M. T., Ayon, E. H., Ghosh, B. P., MD, S. C., Shahid, R., Rahman, S., & Nguyen, T. N. (2024). Revolutionizing Retail: A Hybrid Machine Learning Approach for Precision Demand Forecasting and Strategic Decision-Making in Global Commerce. *Journal of Computer Science and Technology Studies*, 6(1), 33-39.
- [10] 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.
- [11] Nosrati S (2015). The role of business intelligence on the productivity of the Iranian banking industry. *Int Conf on Manag, Eco, and Fin Sys*.
- [12] Ostendorf S, Meier Y and Brand M (2022) Self-disclosure on social networks: More than a rational decision-making process. *Cyberpsycholog* 16: 27. <https://doi.org/10.5817/CP2022-4-2> doi: [10.5817/CP2022-4-2](https://doi.org/10.5817/CP2022-4-2)
- [13] Ranjan J and Foropon C (2021). Big data analytics in building the competitive intelligence of organizations. *Int J of Infor Manag* 56: 102231. <https://doi.org/10.1016/j.ijinfomgt.2020.102231> doi: [10.1016/j.ijinfomgt.2020.102231](https://doi.org/10.1016/j.ijinfomgt.2020.102231)
- [14] 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)
- [15] 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.
- [16] Sarkar, M., Ayon, E. H., Mia, M. T., Ray, R. K., Chowdhury, M. S., Ghosh, B. P., ... & Puja, A. R. (2023). Optimizing E-Commerce Profits: A Comprehensive Machine Learning Framework for Dynamic Pricing and Predicting Online Purchases. *Journal of Computer Science and Technology Studies*, 5(4), 186-193.
- [17] 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*, 2023, 3(4): 337-353. doi: [10.3934/DSFE.2023020](https://doi.org/10.3934/DSFE.2023020)
- [18] Tayaba, M., Ayon, E. H., Mia, M. T., Sarkar, M., Ray, R. K., Chowdhury, M. S., ... & Puja, A. R. (2023). Transforming Customer Experience in the Airline Industry: A Comprehensive Analysis of Twitter Sentiments Using Machine Learning and Association Rule Mining. *Journal of Computer Science and Technology Studies*, 5(4), 194-202.