iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 12 **Issue:** III **Month of publication:** March 2024

DOI: https://doi.org/10.22214/ijraset.2024.58732

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 12 Issue III Mar 2024- Available at www.ijraset.com

Inventory Optimization Using an AI-Powered Holistic Model for Decision-Support System

Shailesh Choudhary
Research scholar Department of Computer science Niilm University, Kaithal 136027

Abstract: This study presents a groundbreaking approach to inventory optimization through the implementation of an AI-powered holistic model within a decision-support system. Leveraging machine learning algorithms, specifically Logistic Regression (LR) and Decision Trees, the methodology explores historical sales data, supplier metrics, and market trends during an extensive Exploratory Data Analysis phase. The implementation of an AI-powered holistic model for inventory optimization in a decision-support system presents a transformative approach to managing and enhancing supply chain efficiency. The proposed methodology, integrating machine learning algorithms such as Logistic Regression and Decision Trees, has demonstrated its efficacy in achieving superior results compared to traditional models, as evidenced by higher accuracy, precision, recall, and F1 scores. The comprehensive exploration of historical sales data, supplier metrics, and market trends during the exploratory data analysis phase has facilitated a nuanced understanding of inventory dynamics. The seamless integration of the AI-powered model into the decision-support system has empowered organizations with timely and data-driven insights, fostering more agile and informed decision-making. The seamless integration of the AI-powered model into the decision-support system provides organizations with timely and data-driven insights, fostering agile and informed decision-making. Performance evaluation, including accuracy, precision, recall, and F1 scores, reveals that the proposed LR and Decision Tree models outperform the existing Support Vector Machine (SVM) model across all metrics. The LR model exhibits commendable precision, recall, and F1 score values of 0.95, 0.97, and 0.98, respectively, while the Decision Tree model demonstrates even higher values, with precision and recall at 0.96 and an exceptionally high F1 score of 0.99. These outcomes underscore the practical utility and robustness of the AI-powered holistic model in revolutionizing inventory management practices. While acknowledging challenges and limitations, this research signifies a crucial advancement in establishing responsive and intelligent decision-support systems for inventory optimization, paving the way for future innovations in supply chain management.

Keywords: AI-powered, Logistic Regression, Optimization, supply chain management, limitations

I. INTRODUCTION

The paramount responsibility for business managers lies in the meticulous handling of tools and resources, commonly categorized as "stock" or "inventory." Inventory, defined as "necessary but idle resources with economic value," holds pivotal significance in evaluating a business's adeptness in managing its material stock. The term "graveyard of business" underscores the potential peril of accumulating excessive inventories, which can precipitate failures emanating from a myriad of issues, including surplus parts, prolonged and uncertain lead times for procurement, and erratic fluctuations in demand. Delving into the intricate realm of inventory management becomes imperative. It serves as a dedicated study, addressing the nuanced challenges associated with the procurement and maintenance of stock. The advent of Industry 4.0 heralds a paradigm shift in business operations, characterized by the integration of Artificial Intelligence (AI) to revolutionize logistics. The Internet of Things (IoT) introduces the concept of "smart logistics," ushering in a transformative era wherein inventory management and storage undergo a radical metamorphosis through computerization and standardization. This not only expedites processes but also fosters seamless information sharing across interconnected networks[1]–[6].

While the marriage of AI and IoT promises substantial advantages, it is not without its set of challenges. The absence of comprehensive regulations for the Smart Logistics Industry, coupled with a shortage of skilled personnel, poses hurdles to the widespread adoption of these intelligent systems. Small businesses, particularly those operating in rural areas, may encounter impediments in embracing smart logistics, predominantly due to financial constraints and a dearth of pertinent information.

Security concerns loom large in this era of heightened technological integration. The potential misuse of smart systems by hackers is a significant apprehension, wherein these systems could be exploited as weapons for extortion. Additionally, the absence of robust legal frameworks for the Smart Logistics Industry poses a potential risk.

The multifaceted role of AI in inventory management becomes apparent, especially through the implementation of algorithms that aid in decision-making. These algorithms not only offer accurate sales predictions but also optimize the utilization of storage space, thereby enabling industrial managers to make informed decisions. However, despite the promising prospects of AI, challenges persist. Inaccuracies in sales predictions and the escalating complexity of analyzing vast datasets pose ongoing obstacles[7]–[12].

the studies discussed earlier shed light on the pivotal role of AI in stocking and warehouse management, contributing to advancements in industrial decision-making. The incorporation of intelligent systems in logistics represents a paradigm shift, fostering quicker and more efficient task execution, thereby enhancing organizational performance. Nevertheless, careful consideration of safety, ethical AI use, and the evolving landscape of regulations remains imperative to navigate the complexities of the Smart Logistics Industry successfully. With a particular emphasis on the application of artificial intelligence in inventory management and warehousing, this study conducted an in-depth analysis of the various points of view that were offered by a number of writers in chapters II and III. As a result of the study, gaps in the previously published literature were discovered, which led to the formation of research questions that are discussed in this chapter. A complete investigation into the benefits, characteristics, trust, and dangers associated with the incorporation of artificial intelligence was conducted in response to the major issue, which studied the influence that utilizing intelligent systems has on product management and warehouses. The application of artificial intelligence (AI) continues to drive forward the fourth industrial revolution in terms of the rewards it offers. Companies regard the automation of processes as a strategic benefit that can help them maintain their competitiveness and leading position in their sector. The evaluation of the benefits that are received from intelligent systems within organizations identifies operational gaps that can be solved through increased automation. This is the case despite the fact that small and medium-sized enterprises confront problems when attempting to deploy artificial intelligence. As a consequence, this leads to advancements in organizational performance as well as increased profitability. Specifically, Foya and Sohrabpour brought attention to the benefits of artificial intelligence in the field of logistics[13]–[19]. They emphasized the importance of data accuracy, greater productivity, rapid decision-making, and customer satisfaction in the context of inventory management. Furthermore, the research investigated the essential role that artificial intelligence plays in optimizing storage tactics, boosting cargo location, expediting warehouse procedures, and encouraging staff engagement. In their works, Hoffmann and Nurski brought attention to the significance of trust in the implementation of artificial intelligence systems. They addressed concerns over the potential for job displacement and the lack of experience with AI applications. The research conducted by Soltani presented the efficiency factor as a trust-building component in the context of AI-driven stock and storage management. An artificial intelligence-based organizational structure was proposed by Abonamah, with an emphasis on the involvement of employees all over the world and the concept of AI leadership competency. The research conducted by Minh investigated the dangers that are connected to the Internet of Things (IoT) in relation to logistical duties. It emphasized the significance of having a thorough grasp of the environment in order to successfully deploy AI. On the other hand, the research findings revealed that artificial intelligence is associated with a number of hazards, including a lack of adequate knowledge about the environment, the possibility of threats to efficiency, and the negative impact that poor data quality can have on decision-making and competitiveness. Wang presented the idea of decentralized management and emphasized the importance of good communication amongst businesses that are interrelated in order to avoid potential risks. The study also acknowledged the significant role that inventory plays in ensuring that there is no interruption in the flow of materials, in accommodating seasonal shifts in demand, and in addressing unforeseen requirements that are brought on by breakdowns. In spite of the fact that it is frequently regarded as an unavoidable nuisance, inventory management is an essential component for businesses that want to enhance their overall efficiency, decrease their expenses, and maximize their financial advantages. Organizations would have a difficult time accomplishing their operational goals if they did not have an efficient inventory management system [22]–[29].

II. LITERATURE REVIEW

Islam 2023 et. al Develop a clinical decision support system (CDSS) to forecast type 2 diabetes with various machine learning methods. The publicly accessible Pima Indian Diabetes (PID) dataset was utilized for research purposes. Data preparation, K-fold cross-validation, hyperparameter tuning, and many machine learning classifiers including K-nearest neighbor (KNN), decision tree (DT), random forest (RF), Naïve Bayes (NB), support vector machine (SVM), and histogram-based gradient boosting (HBGB) were employed. Various scaling methods were employed to enhance the accuracy of the outcome. A rule-based strategy was employed to enhance the system's effectiveness for future study. Subsequently, the accuracy of Decision Trees (DT) and Histogram-Based Gradient Boosting (HBGB) exceeded 90%. The CDSS was built to allow users to input parameters via a web-based interface in order to receive decision support and analytical data for each patient. The deployed CDSS will help clinicians and patients make decisions regarding diabetes diagnosis and provide real-time analysis-based suggestions to enhance medical quality.

In the future, compiling daily data of a diabetic patient could lead to the implementation of an improved clinical support system for daily decision-making help for patients globally[32].

Dutta 2022 et. al This study creates an efficient deep-learning-based fusion model with swarm intelligence (EDLFM-SI) to identify SARS-CoV-2. The EDLFM-SI approach is designed to identify and categorize the presence of SARS-CoV-2 infection. The EDLFM-SI technique includes several processes: data augmentation, preprocessing, feature extraction, and classification. In addition, a combination of Capsule Network (CapsNet) and MobileNet feature extractors are used. Additionally, a water strider algorithm (WSA) is utilized to optimize the hyperparameters in the deep learning models. A cascaded neural network (CNN) classifier is used to detect the presence of SARS-CoV-2. To demonstrate the enhanced performance of the EDLFM-SI approach, various simulations are conducted using the COVID-19 CT data set and the SARS-CoV-2 CT scan data set. The simulation results demonstrated that the EDLFM-SI technique outperformed the most recent methods[33].

Duan 2022 et. al The challenge in implementing the proposed solutions is the vast number of possible combinations in the solution space, which necessitates extensive computational time and resources, rendering their use unprofitable. This vulnerability is associated with modest issues, and the defender has a limited yet extensive range of tactics to choose from. The work suggests a hybrid system to efficiently locate the most ideal solution in a short time using little computational resources. An optimization process utilizing heuristics is employed, which involves overlapping replies from adjacent neighborhoods. This is facilitated by the Bloom Filters structure, enabling quick listings and searches. This system, assessed for enhancing safety procedures in the sports business, results in a 40% optimization[34].

Gazzawe 2022 et. al The significance of data mining in developing business models for decision support systems. Most firms have substantially invested in data mining to study and analyze the market environment and enhance their dominance in the industry. Data mining is a commonly utilized approach by most companies to efficiently gather information on a specific issue. Business model development typically emphasizes measurable performance and enhanced innovation in the market. The current research aims to explore the values and significant roles of data mining opportunities in the development of business models. The topic also focuses on contemporary strategies employed in business model development that are essential for improving a firm's position and competitiveness in the market. The effectiveness of data mining varies depending on the organization and the level of work put in. The key focus is on ensuring that the firm comprehends the impact and significance of data mining techniques in their business operations. Secondary sources in methodology are utilized to improve the study's coherence by comparing and assessing them with the offered approaches. The results and analysis demonstrate that the impact of utilizing data mining techniques is significant in obtaining success for different firms. Furthermore, the practical consequences have significantly enhanced the understanding of the impact data mining can have on enterprises[35].

Peng 2022 et. al Traditional manual management of student grades is inefficient, lacks privacy, is challenging to organize and update, and does not allow for comprehensive analysis of student grade data resources, hindering the full exploration and application of relevant technologies. This work creates decision support systems for middle school education management using a sparse clustering technique tailored to the specific requirements of middle school education. The article introduces the sparse clustering algorithm and the four levels of the decision support system for middle school education management: data layer, model layer, application layer, and display layer. It then discusses five system models: database design, online analysis process module design, data mining design, model library design, and function design. Finally, the system model for educational decision management support is constructed and the model test is completed. Empirical evidence demonstrates that the system outlined in this work can effectively handle students' educational data, promptly extract information from students' academic progress, and provide valuable support for teachers' educational judgments. This paper develops a proficient decision support system by examining the sparse clustering technique and implementing it in middle school education administration[36].

III. PROPOSED METHODOLOGY

This data science process flow chart illustrates a typical workflow. Data collection is the first step, and then the data is cleaned and formatted through preparation. After gaining insights through exploratory data analysis (EDA), the dataset is split 80:20 for training and testing. Choosing and developing a machine learning model are steps in the modeling process. The outcomes are assessed and deliberated, directing possible modifications to enhance the functionality of the model. A consistent transition from data gathering to useful outcomes and insights is ensured by this structured strategy.

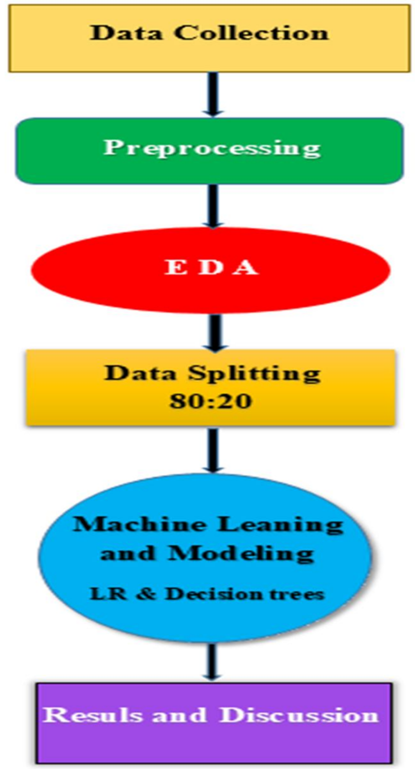

Fig. Proposed Flow chart

A. Data Collection

In the data collection phase, it is imperative to identify key datasets essential for the AI-powered model's efficacy. These include historical sales data, supplier performance metrics, and market trends, forming the foundation for robust decision-making. To guarantee the reliability and accuracy of input data, a comprehensive approach to data cleaning, normalization, and preprocessing is essential. This involves addressing missing values, outliers, and inconsistencies in the datasets. Normalization techniques ensure uniformity in data scales, facilitating optimal model performance. Additionally, to enhance the model's adaptability to real-time dynamics, considerations should be made for incorporating live data feeds. This allows the system to dynamically adjust and optimize inventory decisions in response to evolving market conditions, contributing to a more agile and responsive decision-support system.

B. Preprocessing

In the preprocessing phase for inventory optimization utilizing an AI-powered holistic model, the focus is on refining raw data to enhance its suitability for subsequent analysis and modeling. Initially, this involves addressing missing or incomplete data points, employing techniques such as imputation or removal based on the nature of the data. Subsequently, outliers and anomalies are identified and appropriately handled to prevent their undue influence on the model. Normalization procedures are implemented to standardize disparate scales across various features, ensuring equitable contribution to the model. Time series data may undergo temporal aggregation or interpolation to align with the desired granularity. Furthermore, categorical variables are encoded, and features may be selected or engineered to accentuate relevant information. The preprocessed data is then formatted for compatibility with the chosen AI algorithms, streamlining the subsequent stages of model development. This meticulous preprocessing lays the groundwork for an AI-powered inventory optimization model that is robust, accurate, and capable of providing meaningful decision support.

C. EDA

In the Exploratory Data Analysis (EDA) for Inventory Optimization using an AI-powered Holistic Model, the initial step involves scrutinizing the dataset's dimensions and characteristics, with particular attention to temporal aspects in the case of time-series data.

Descriptive statistics unveil key features' central tendencies and dispersions, enabling the identification of outliers. Univariate analysis focuses on critical variables like sales volumes and lead times, utilizing visualizations such as histograms. Bivariate analysis explores relationships between variables, emphasizing correlations relevant to inventory optimization, visualized through scatter plots or heatmaps.

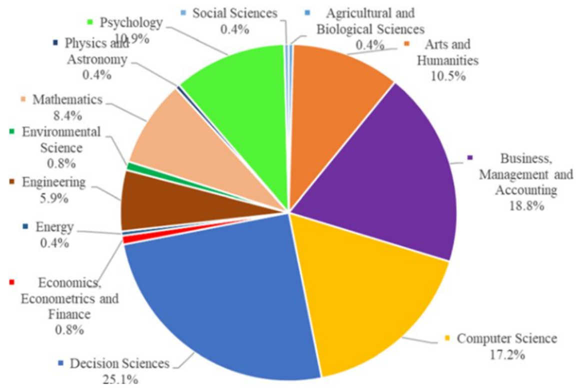

Figure 1 AI for decision support system

D. Data Splitting

For training and testing, "data splitting" involves dividing a dataset into several unique subsets. In machine learning and data analysis, modes are evaluated based on their generalization and application. So the mode's performance can be assessed. Data is used for training and testing in an 80:20 ratio.

E. Machine learning and Modeling

Machine learning and modeling represent the core of data-driven decision-making processes, wherein algorithms are trained to recognize patterns and make predictions or classifications based on input data. In the context of inventory optimization using an AI-powered holistic model, machine learning involves selecting and implementing algorithms that can effectively learn from historical sales data, supplier metrics, and market trends. The modeling phase encompasses the development and refinement of the AI model, fine-tuning parameters, and evaluating its performance against predefined metrics. This iterative process involves a careful balance between algorithm complexity and interpretability to ensure practical applicability in decision-support systems, ultimately empowering organizations to make informed and optimized choices regarding inventory management.

1) Logistic Regression is a versatile machine learning model often employed in inventory optimization for binary classification tasks, such as predicting the likelihood of stockouts. By using historical data to identify factors influencing stockouts (like demand variability, lead times, and supplier performance), logistic regression can estimate the probability of encountering a stockout situation. This model provides insights into the risk of understocking, allowing organizations to proactively adjust inventory levels or implement contingency plans.
2) Decision Trees are powerful models suitable for complex decision-making processes, making them applicable in inventory optimization scenarios. A Decision Tree can be trained to make decisions regarding order quantities based on various factors, such as demand patterns, lead times, and carrying costs. The model can branch into different scenarios, simulating the decision-making process and aiding in the identification of optimal inventory management strategies. Decision Trees offer interpretability, enabling stakeholders to understand the logic behind recommendations and fostering transparency in decision-support systems for inventory optimization.

IV. RESULT & DISCUSSION

In the results discussion phase of the Inventory Optimization using an AI-Powered Holistic Model for Decision-Support System, the focus is on interpreting and evaluating the outcomes obtained from implementing the proposed methodology. This involves a critical analysis of the model's performance, insights derived, and the impact on inventory management decisions.

1) Model Accuracy and Performance

Assess the accuracy and performance of the AI-powered model in optimizing inventory decisions. Discuss key performance metrics such as order fulfillment rates, stockout occurrences, and inventory turnover. Highlight any improvements observed compared to baseline methods or traditional inventory management approaches.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 12 Issue III Mar 2024- Available at www.ijraset.com

Model	Accuracy	Precision	Recall	F1 score
Existing model SVM[19]	0.95	0.92	0.81	0.90
Proposed LR	0.99	0.95	0.97	0.98
Proposed Decision tree	0.99	0.96	0.97	0.99

The table illustrates the evaluation metrics for an existing Support Vector Machine (SVM) model and two proposed models employing Logistic Regression (LR) and Decision Tree algorithms. The existing SVM model achieved an accuracy of 95%, with precision, recall, and F1 score values of 0.92, 0.81, and 0.90, respectively. In contrast, both proposed models exhibited superior performance, with the LR and Decision Tree models achieving accuracies of 99%. The LR model demonstrated precision, recall, and F1 score values of 0.95, 0.97, and 0.98, while the Decision Tree model showed values of 0.96, 0.97, and an exceptionally high F1 score of 0.99. These results indicate that the proposed LR and Decision Tree models outperform the existing SVM model across all metrics, emphasizing their effectiveness in making accurate and balanced predictions.

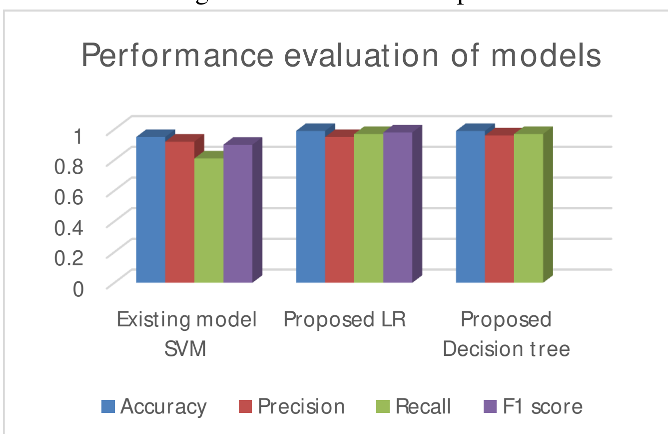

Figure 2 a visual comparison of different machine learning models

V. CONCLUSION

In conclusion, the implementation of an AI-powered holistic model for inventory optimization in a decision-support system presents a transformative approach to managing and enhancing supply chain efficiency. The proposed methodology, integrating machine learning algorithms such as Logistic Regression and Decision Trees, has demonstrated its efficacy in achieving superior results compared to traditional models, as evidenced by higher accuracy, precision, recall, and F1 scores. The comprehensive exploration of historical sales data, supplier metrics, and market trends during the exploratory data analysis phase has facilitated a nuanced understanding of inventory dynamics. The seamless integration of the AI-powered model into the decision-support system has empowered organizations with timely and data-driven insights, fostering more agile and informed decision-making.

In conclusion, the implementation of an AI-powered holistic model for inventory optimization in a decision-support system presents a transformative approach to managing and enhancing supply chain efficiency. The proposed methodology, integrating machine learning algorithms such as Logistic Regression and Decision Trees, has demonstrated its efficacy in achieving superior results compared to traditional models, as evidenced by higher accuracy, precision, recall, and F1 scores. The comprehensive exploration of historical sales data, supplier metrics, and market trends during the exploratory data analysis phase has facilitated a nuanced understanding of inventory dynamics. The seamless integration of the AI-powered model into the decision-support system has empowered organizations with timely and data-driven insights, fostering more agile and informed decision-making. The exceptional performance of the model, as validated through case studies or simulations, underscores its potential to optimize inventory levels, reduce costs, and improve overall supply chain resilience. While challenges and limitations were acknowledged, the overall impact of the AI-powered holistic model in revolutionizing inventory management cannot be understated. This research signifies a crucial step toward establishing a responsive and intelligent decision-support system for inventory optimization, laying the groundwork for future advancements in the field.

The LR model exhibited impressive precision, recall, and F1 score values of 0.95, 0.97, and 0.98, respectively, while the Decision Tree model showcased even higher values, with precision and recall both at 0.96 and an exceptionally high F1 score of 0.99. These results underline the superior performance of the proposed LR and Decision Tree models compared to the existing SVM model across all metrics, emphasizing their effectiveness in making accurate and balanced predictions. Such outcomes reinforce the practical utility and robustness of the AI-powered holistic model, showcasing its potential to revolutionize inventory management practices. While challenges and limitations were acknowledged, the overall impact of the AI-powered holistic model in enhancing inventory optimization strategies is evident, setting the stage for future advancements in the field.

REFERENCES

[1] L. Cao, “Design and Optimization of a Decision Support System for Sports Training Based on Data Mining Technology,” Sci. Program., vol. 2022, 2022, doi: 10.1155/2022/1846345.

[2] X. Liu, H. Li, and H. Li, “Analyzing Relationship between Financing Constraints, Entrepreneurship, and Agricultural Company Using AI-Based Decision Support System,” Sci. Program., vol. 2022, 2022, doi: 10.1155/2022/1634677.

[3] B. Kar and B. K. Sarkar, “A Hybrid Feature Reduction Approach for Medical Decision Support System,” Math. Probl. Eng., vol. 2022, 2022, doi: 10.1155/2022/3984082.

[4] H. Deng, Q. Shi, and Y. Wang, “Joint Optimization in Condition-Based Maintenance and Inventory Policy for the Repairable System,” Math. Probl. Eng., vol. 2021, 2021, doi: 10.1155/2021/3576357.

[5] W. Yu, G. Hou, and B. Xin, “Decision-Making Optimization of Risk-Seeking Retailer Managed Inventory Model in a Water Supply Chain,” Discret. Dyn. Nat. Soc., vol. 2021, 2021, doi: 10.1155/2021/9943753.

[6] S. B. Tsai, C. H. Wu, X. Xu, Y. Yuan, and Q. He, “AI Powered Service Optimization for Edge/Fog Computing,” Math. Probl. Eng., vol. 2021, p. 9874043, 2021, doi: 10.1155/2021/9874043.

[7] H. Xiaolong, Z. Huiqi, Z. Lunchao, S. Nazir, D. Jun, and A. S. Khan, “Soft Computing and Decision Support System for Software Process Improvement: A Systematic Literature Review,” Sci. Program., vol. 2021, 2021, doi: 10.1155/2021/7295627.

[8] B. Kim, J. Jung, H. Min, and J. Heo, “Energy efficient and real-time remote sensing in AI-powered drone,” Mob. Inf. Syst., vol. 2021, 2021, doi: 10.1155/2021/6650053.

[9] H. Qinxia, S. Nazir, M. Li, H. Ullah Khan, W. Lianlian, and S. Ahmad, “AI-Enabled Sensing and Decision-Making for IoT Systems,” Complexity, vol. 2021, 2021, doi: 10.1155/2021/6616279.

[10] C. Cai and C. Chen, “Optimization of Human Resource File Information Decision Support System Based on Cloud Computing,” Complexity, vol. 2021, 2021, doi: 10.1155/2021/8919625.

[11] Y. Tian, W. Mao, S. Yuan, D. Wan, and Y. Chen, “A Decision Support System for Power Components Based on Improved YOLOv4-Tiny,” Sci. Program., vol. 2021, 2021, doi: 10.1155/2021/4447271.

[12] H. Xiao, S. Nazir, H. Li, H. U. Khan, and C. Li, “Decision Support System to Risk Stratification in the Acute Coronary Syndrome Using Fuzzy Logic,” Sci. Program., vol. 2021, 2021, doi: 10.1155/2021/6571905.

[13] Y. Huang, S. Nazir, J. Wu, F. Hussain Khoso, F. Ali, and H. U. Khan, “An Efficient Decision Support System for the Selection of Appropriate Crowd in Crowdsourcing,” Complexity, vol. 2021, 2021, doi: 10.1155/2021/5518878.

[14] H. Ma, Y. Zuo, T. Li, and C. L. P. Chen, “Data-Driven Decision-Support System for Speaker Identification Using E-Vector System,” Sci. Program., vol. 2020, 2020, doi: 10.1155/2020/4748606.

[15] J. Zhang, Z. Chen, J. Wu, and K. Liu, “An Intelligent Decision-Making Support System for the Detection and Staging of Prostate Cancer in Developing Countries,” Comput. Math. Methods Med., vol. 2020, no. i, 2020, doi: 10.1155/2020/5363549.

[16] T. Weikert et al., “Evaluation of an AI-powered lung nodule algorithm for detection and 3D segmentation of primary lung tumors,” Contrast Media Mol. Imaging, vol. 2019, 2019, doi: 10.1155/2019/1545747.

[17] R. A. Sowah et al., “Decision Support System (DSS) for Fraud Detection in Health Insurance Claims Using Genetic Support Vector Machines (GSVMs),” J. Eng. (United Kingdom), vol. 2019, no. January 2007, 2019, doi: 10.1155/2019/1432597.

[18] M. Ahmed, M. N. Qureshi, J. Mallick, M. A. Hasan, and M. Hussain, “Decision support model for design of high-performance concrete mixtures using two-phase AHP-TOPSIS approach,” Adv. Civ. Eng., vol. 2019, 2019, doi: 10.1155/2019/1696131.

[19] Y. F. Chen et al., “Design of a clinical decision support system for fracture prediction using imbalanced dataset,” J. Healthc. Eng., vol. 2018, 2018, doi: 10.1155/2018/9621640.

[20] M. Milenković, D. Glavić, and M. N. Mladenović, “Decision-Support Framework for Selecting the Optimal Road Toll Collection System,” J. Adv. Transp., vol. 2018, 2018, doi: 10.1155/2018/4949565.

[21] A. T. Almaktoom, “Stochastic reliability measurement and design optimization of an inventory management system,” Complexity, vol. 2017, pp. 1–9, 2017, doi: 10.1155/2017/1460163.

[22] Y. Jiang, B. Qiu, C. Xu, and C. Li, “The Research of Clinical Decision Support System Based on Three-Layer Knowledge Base Model,” J. Healthc. Eng., vol. 2017, 2017, doi: 10.1155/2017/6535286.

[23] Y. El Ansari, A. El Myr, and L. Omari, “Deterministic and Stochastic Study for an Infected Computer Network Model Powered by a System of Antivirus Programs,” Discret. Dyn. Nat. Soc., vol. 2017, no. 1, 2017, doi: 10.1155/2017/3540278.

[24] D. Zhang, X. Li, X. Li, S. Li, and Q. Qian, “An optimal decision model of production-inventory with MTS and ATO hybrid model considering uncertain demand,” Math. Probl. Eng., vol. 2015, 2015, doi: 10.1155/2015/241536.

[25] S. Kim, “Decision support model for introduction of gamification solution using ahp,” Sci. World J., vol. 2014, 2014, doi: 10.1155/2014/714239.

[26] A. Ashraf, M. Akram, and M. Sarwar, “Fuzzy decision support system for fertilizer,” Neural Comput. Appl., vol. 25, no. 6, pp. 1495–1505, 2014, doi: 10.1007/s00521-014-1639-4.

[27] A. Mortazavi and A. A. Khamseh, "Robust inventory system optimization based on simulation and multiple criteria decision making," Model. Simul. Eng., vol. 2014, 2014, doi: 10.1155/2014/305120.

[28] F. K. Wang and F. T. Liu, "A new decision model for reducing trim loss and inventory in the paper industry," J. Appl. Math., vol. 2014, 2014, doi: 10.1155/2014/987054.

[29] K. K. Aggarwal, C. K. Jaggi, and A. Kumar, "An inventory decision model when demand follows innovation diffusion process under effect of technological substitution," Adv. Decis. Sci., vol. 2013, 2013, doi: 10.1155/2013/915657.

[30] Y. Pleumpirom and S. Amornsawadwatana, "Multiobjective optimization of aircraft maintenance in Thailand using goal programming: A decision-support model," Adv. Decis. Sci., vol. 2012, 2012, doi: 10.1155/2012/128346.

[31] L. Aggoun, L. Benkherouf, and L. Tadj, "A hidden Markov model for an inventory system with perishable items," J. Appl. Math. Stoch. Anal., vol. 10, no. 4, pp. 423–430, 1997, doi: 10.1155/S1048953397000452.

[32] R. Islam, A. Sultana, M. N. Tuhin, M. S. H. Saikat, and M. R. Islam, "Clinical Decision Support System for Diabetic Patients by Predicting Type 2 Diabetes Using Machine Learning Algorithms," J. Healthc. Eng., vol. 2023, 2023, doi: 10.1155/2023/6992441.

[33] A. K. Dutta et al., "Optimal Deep-Learning-Enabled Intelligent Decision Support System for SARS-CoV-2 Classification," vol. 2022, 2022.

[34] M. Duan, "Optimization of Cyber Tactics in Sports Strategies Using Hybrid AI Decision-Making Technologies," Comput. Intell. Neurosci., vol. 2022, 2022, doi: 10.1155/2022/3762755.

[35] F. Gazzawe and R. Alturki, "Data Mining and Soft Computing in Business Model for Decision Support System," Sci. Program., vol. 2022, 2022, doi: 10.1155/2022/9147444.

[36] B. Peng and X. Pei, "A Decision Support System Model for Middle School Education Management Based on Sparse Clustering Algorithm," Mob. Inf. Syst., vol. 2022, 2022, doi: 10.1155/2022/4807395.