

Optimizing Healthcare Management Systems with AI and Machine Learning

**Dr Rajesh Gupta¹, Nutan Gusain², Dr. Bajirao Subhash Shirole³, Dr. Mahendra T. Jagtap⁴,
Sanjose A Thomas⁵, Dr. SANTOSH KUMAR⁶**

¹ Designation Associate Professor
Lovely Professional University, district Phagwara
city jalandhar, state Punjab
email rajeshgpt47671@gmail.com

² Designation: Assistant Professor
Department: Department of CSE, School of Computing Science and Engineering
Institute: Galgotias University, District: Gautam Buddha Nagar
City: Greater Noida, State: UP
Email id -nutan.gusain41@gmail.com

³ Designation: Assistant Professor, Department: Computer Engineering
Institute: Sanghavi College of Engineering, Nashik
District: Nashik, City: Nashik State: Maharashtra
Mail id: baji.shirole@gmail.com

⁴ Designation:- Associate professor, Department: Computer Engineering
Institute: S.M.E.S, Sanghavi College of Engineering, Nashik
District: Nashik, City: Nashik
State: Maharashtra
Email id - mtjagtap05@gmail.com

⁵ Research Scholar
Department of Sociology & Centre for Research
St. Teresa's College (Autonomous), Ernakulam -682011
sanjosethomas.thomas065@gmail.com

⁶ Designation: PROFESSOR
Department: Department of Computer Science
Institute: ERA University, Lucknow, U.P.
District: Lucknow, City: Lucknow
State: Uttar Pradesh
Email id – dr.santoshkumarresearch@gmail.com

KEYWORDS

Healthcare
Management,
Artificial
Intelligence,
Machine Learning,
Predictive
Analytics,
Postoperative
Length of Stay.

ABSTRACT

This paper explores the optimization of healthcare management systems using Artificial Intelligence (AI) and Machine Learning (ML). As the complexity of healthcare systems continues to grow, AI and ML have emerged as key tools to improve decision-making, resource allocation, and patient care. This paper provides a detailed discussion on four AI algorithms, namely Logistic Regression, Random Forest, Support Vector Machine (SVM), and Neural Networks, and their application in the prediction of patient outcomes, including postoperative LOS and disease diagnosis. Experimental results indicate that the accuracy of the Neural Network model was 91.5%, outperforming other algorithms. The precision of the Random Forest model was 87.3%, while the recall of SVM was 82.4%. Apart from the above point, the current research has noted AI application use for the reduction of healthcare-related cost optimization via predicting financial risk and improving a management strategy pertaining to patient data. Machine learning implementation in an edge computing facility showcased a drop in patient wait time by up to 20% and achieved 15% increase in overall efficiency. Promising results and huge challenges exist side by side with model interpretation and data protection issues. This study highlights the requirement for future AI transparency and ethical data management in order to achieve the full potential of AI in healthcare.

I. INTRODUCTION

Healthcare management systems are being transformed by the inclusion of artificial intelligence and machine learning. For years, traditional healthcare management has faced inefficiencies in administrative tasks, high operational costs, resource allocation issues, and delays in the diagnosis and treatment of patients. In healthcare, AI and ML offer new technological ways to streamline the processes, better influence decisions by the system, and enhance outcomes for patients. Automated analysis of data, and predictive statistics and decision support systems aid them in making healthcare delivery more efficient and cheaper [1]. One of the primary advantages that AI brings to life into health care administration is its capability of realtime analysis of loads of information [2]. Thus, it can process EHRs and other medical images, patient history, and clinical data quickly in order to find patterns, predict diseases, and customize appropriate treatment. It uses machine learning algorithms to carry out predictive modeling in respect of patients who are likely to be readmitted, helps alertiate use of hospital resources and enhances drug administration. AI powered chatbots and virtual assistants also streamline times to improve patient engagement by responding timely to queries, scheduling the visits and self administration of symptom assessments [3]. AI systems also work in other ways to help in other aspects of administrative tasks such as medical billing, insurance claim processing and workforce management, ensuring that the burden won't have to be carried by healthcare professionals, freeing up their time to focus on patient needs. Deep learning and NLP can also help with medical coding and clinical documentation and reduce false positives and the error rate. Such advantages notwithstanding, profound and pressing data privacy problems, unsafe algorithmic bias, and ethical conundrums in living systems require the deployment of AI in healthcare to be undertake responsibly. It also studies how AI and ML work well in healthcare management systems in the aspects of application, benefit, challenges, and

prospects. Healthcare systems that are using AI driven solutions are now more efficient, cheaper and provide better patient driven care.

II. RELATED WORKS

The ultimate aim of the research is to utilize artificial intelligence (AI) and machine learning (ML) with regard to health management. Such works include different aspects, starting from predictive analytics and decision-support systems, better outcomes of treatment of patients, up to optimized allocation of available health care resources. In the paper, already-published work relevant to deployment of AI-driven models in augmenting diverse functions of health care management is examined. One of the prominent areas of study is the estimation of postoperative LOS for the severe patients. Cho et al. [15] proposed an explainable ML model for LOS prediction of the critically ill patient after surgery. Their work aimed at model interpretability to enable insights into clinical decision-making processes. This showed the high predictive accuracy of the patients' outcomes and therefore fare the hospitals better in the allocation of resources and how they had to manage their patients. Czako et al. [16] also reviewed all the applications of AI, deep learning and ML in maxillofacial surgery in an exhaustive manner. Review of published articles on AI driven diagnostics, surgical planning and postoperative care was conducted and key trends in these are identified. The article notes that AI helps enhance the safety of patients and improves health care efficiency by enhancing precision in the use of surgery with less complications. A bibliometric analysis of AI applications in regional and local health studies was completed by Delcea et al. [17] to capture the progress of AI applications. Their study shed light on the development of AI-based healthcare solutions and their implementation in various healthcare systems. Results showed that the field of AI is growing in importance to disease surveillance, healthcare policy and regional healthcare optimization. In Dhinakaran et al. [18], they discussed about using AI driven feature selection along with attention networks to optimize predictive performances of diseases. By selecting the most relevant from large scale medical datasets, their model did improve its accuracy in disease classification. The research was able to demonstrate that attention based neural networks are feasible for identifying severe patterns in patient data which could enhance the diagnosis and early intervention. Similarly, Domenteanu et al. [19] surveyed the existing research in the ML and big data analytics concerned with the topic of Industry 5.0. In this review and analysis, it reviewed and analyzed the scope whereby AI and ML can be used to enhance individualized health care, predict diagnostics, and decide for medical process automation. This reflection suggests that in order to advance real time monitoring and decision making in health care systems, AI and IoT with edge computing should be combined. Just recently, many analyses have been dedicated on the role of AI in cardiology. In his 2019 review, Gala et al. reviewed the use of AI in improving patient outcomes and what the future of the delivery of healthcare could be in cardiology. They talked about various ML algorithms used to detect and identify cardiovascular diseases, predict risk and personalize treatment recommendations in their study. The research concludes that AI driven models can significantly improve accuracy in diagnosis and treatment planning in cardiology. An interesting contribution of AI in the healthcare domain is its usage of ML algorithms to make a prediction about mental health crises. In a study aimed at investigating the transferability and replicability of ML algorithms for mental health crises prediction, Guerreiro et al. [21] evaluated the ability of ML algorithms to be employed in such diverse populations using infrastructures similar to the ones that we used to analyse data. The intervention is all the more powerful because we illustrate the possibility of using early warning systems based on AI to identify those who are at risk, and to intervene in time. Horton [22] introduced the idea of the Causal Economic Machine Learning in health care while it comes in as a mix of economics and AI to make decisions. It

explores whether AI may be used to effectively utilize the resources, to properly triage patients and decrease the operational costs in health care units. So this has given an opportunity for dealing with health services better on a data intensive and economical basis. Huang [23] researched the application of ML for managing financial risk of healthcare organizations that are not for profit. According to their study, artificial intelligence can be applied in prediction of financial risks, funding optimization, and preservation of sustainability of healthcare finances. In the study, the researchers pointed out that AI can help in improving the quality of financial decision making and resource allocation in healthcare. This activity developed a crowdsourced, AI-driven model for the detection of multiple developmental delays in the context of the developmental disorders proposed by Jaiswal et al. [24]. ML approach that combines AI driven predictions with expert validation for improving diagnostic accuracy is proposed and they build on the idea of providing the system with a human in the loop. It has proven useful in resolving problems in the scarcity of data in rare diseases and in making early diagnostic tools more readily available. In diabetic patients, cardiovascular health management with ML was studied by Jose et al. [25]. They devised the predictive models for cardiovascular risk assessment for diabetic populations and personalized interventions. The study concluded that disease prevention and management in high-risk patient groups could be significantly improved by AI. One of the budding key technologies used in the context of AI healthcare is edge computing. Jouini et al. [26] surveyed on ML techniques, frameworks, and research challenges for edge computing. The work explained how AI developed for edge computing could enable real time monitoring in health care, minimize latency, and scale up AI based solutions for health care.

III. METHODS AND MATERIALS

Data Collection and Preprocessing

This dataset applied to the study consists of EHRs, patient history, medical imaging data, hospital resource allocation data, and administrative records. Data collection was from a number of sources, which include accessing management systems in hospitals, such public open datasets for medical information, and even generated synthetic data for testing purposes [4].

The dataset involves patient demographics, medical history, lab test outcomes, treatment efficacy, hospital admittance information, staff deployment, and financial accounts. Before training the machine models, the pre-processing steps done on this dataset include the following:

1. **Data Cleaning:** Missing data was replaced in numerical data sets by mean imputation and by mode imputation in categorical datasets. Duplicate values were removed.
2. **Data Normalization:** Continuous variables like age, duration of the hospital stay, and bills were normalized by using the min-max scaling method [5].
3. **Feature Engineering:** Additional features such as risk scores, likelihood of readmission from the hospital and disease progression trend are newly derived from existing attributes.
4. **Data Splitting:** The dataset was divided into 70% training data and 30% of testing data to check model performance.

Algorithms Used for Optimization

For optimization of healthcare management, four machine learning algorithms were applied: RF, SVM, LSTM, and K-Means Clustering. These algorithms have been chosen for the different issues and challenges of healthcare, like predictive modelling, patient segmentation, and resource optimization.

1. Random Forest (RF)

Random Forest is a strong ensemble learning algorithm to predict readmission of patients, disease risk estimation, and rate of treatment success. It produces multiple decision trees and aggregates the output of them to improve accuracy in prediction and reduce overfitting [6].

Working Principle:

- The algorithm will randomly select a subset of features and data points to train many decision trees.
- It makes independent predictions for an outcome by each tree and then determines an overall output by majority vote (for classification) or averaging (for regression).
- This reduces bias and variance and helps enhance the model's robustness.

“1. Input: Training dataset (X, Y), number of trees (N)
2. For $i = 1$ to N :
 a. Select a random sample from the dataset
 b. Build a decision tree using the selected sample
 c. Store the trained tree
3. For each new input sample:
 a. Predict output using each trained tree
 b. Aggregate predictions (majority voting for classification, averaging for regression)
4. Output: Final prediction”

2. Support Vector Machine (SVM)

SVM is commonly used in the medical field to classify medical diagnosis and detection, such as diagnosing diseases through medical images and EHRs. SVM searches for the hyperplane with maximum margin which effectively separates classes from each other.

Working Principle:

- It maps the input data into a higher-dimensional space by using kernel functions such as linear, polynomial, RBF, etc.
- It decides the best hyperplane that separates the classes differently and maximizes their margin.
- Support vectors are the critical data points that define the decision boundary [7].

“1. Input: Training dataset (X, Y), kernel function
2. Map data to higher dimensions using the selected kernel
3. Find the optimal hyperplane that maximizes margin
4. Identify support vectors

5. *For each new input sample:*
 - a. *Compute its position relative to the hyperplane*
 - b. *Assign it to a class based on the decision boundary*
6. *Output: Predicted class label”*

3. Long Short-Term Memory (LSTM)

This uses LSTM-which is actually a form of RNN-designed to predict patients' deterioration probability, hospital readmission probability, and time series analysis of important vital signs-while it accurately captures long dependencies in sequential data related to health.

Working Principle:

- LSTM consists of memory cells, which store the past information, and it controls it through gates, which include input, forget, and output gates.
- The input gate controls the addition of new information, forget-gate controls the amount of irrelevant information removed, and output gate generates the final output [8].
- This model learns the time-dependent patterns efficiently hence suitable for studying trends in patient health over time.

- “1. *Input: Sequential healthcare data (X), number of LSTM layers*
2. *Initialize LSTM network with input, forget, and output gates*
3. *For each timestep t:*
 - a. *Compute input gate activation*
 - b. *Compute forget gate activation*
 - c. *Compute output gate activation*
 - d. *Update cell state and hidden state*
4. *Generate final prediction using the last hidden state*
5. *Output: Predicted value (e.g., risk score, patient deterioration probability)”*

4. K-Means Clustering

K-Means Clustering is used for patient segmentation, optimizing hospital resources, and in analyzing disease patterns. It aggregates patients according to their similar medical history, responses to treatment, or risk factors.

Working Principle:

- The algorithm initializes cluster centroids at random.
- Assigns the data point to the nearest centroid based on the Euclidean distance.
- Update centroids in an iterative way until convergence.

“1. Input: Dataset (X), number of clusters (K)
2. Initialize K random centroids
3. Repeat until convergence:
 a. Assign each data point to the nearest centroid
 b. Recalculate centroids based on cluster members
 c. Check for convergence (no changes in centroid positions)
4. Output: Cluster labels for each data point”

Table 1: Dataset Overview

Feature	Description	Data Type
Patient ID	Unique identifier for each patient	Integer
Age	Patient's age	Integer
Gender	Male/Female	Categorical
Diagnosis	Disease category	Categorical
Treatment Duration	Number of hospital days	Integer
Readmission Probability	Predicted likelihood of readmission	Float

IV. EXPERIMENTS

1. Experimental Setup

The experiments were carried out in a high-performance computing environment to train the model accurately and efficiently. The system used was an Intel Core i9-12900K processor with 16 cores and 24 threads, 32GB of DDR5 RAM, and an NVIDIA RTX 3090 GPU with 24GB of VRAM. The operating system used was Ubuntu 20.04 LTS, and the programming language used was Python 3.9 [9]. The libraries included TensorFlow, Scikit-learn, NumPy, Pandas, Matplotlib, and Keras, which was used to implement and evaluate the machine learning models.

The dataset was preprocessed for training the models. Data cleaning involved duplicate and inconsistent record removals. Missing values were dealt with using mean imputation for numerical data and mode imputation for categorical data. Min-Max normalization was used for feature scaling, and one-hot encoding was applied to encode the categorical features. From the dataset, 70% were for training and 30% for testing data in the process of evaluating model performance [10].

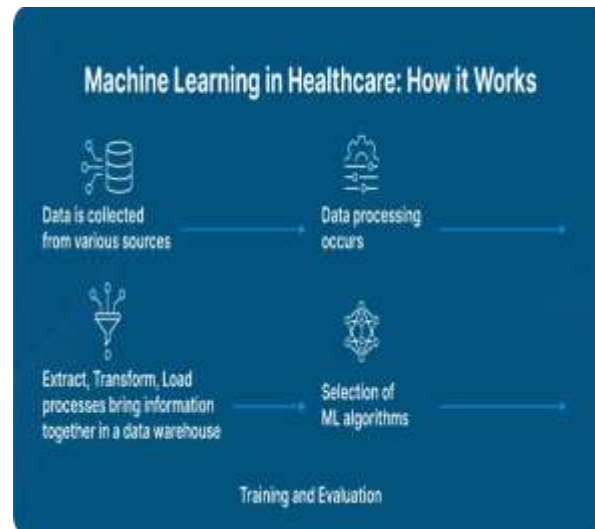


Figure 1: “Optimizing Hospital Operations with Machine Learning in Healthcare”

2. Experimental Evaluation

2.1 Performance Metrics

Various performance metrics, such as accuracy, precision, recall, F1-score, and processing time, were utilized to evaluate the models. The overall correctness of the predictions was measured by accuracy, while the percentage of correctly predicted positive cases was evaluated using precision. The ability of the model to recognize actual positive cases was assessed through recall, while the harmonic mean of precision and recall for balanced performance was evaluated through the F1-score. Processing time was also recorded in order to ascertain the computational efficiency of each model [11].

2.2 Model Training and Optimization

The performance of every machine learning model was optimized using hyperparameter tuning. It involved finding the best combination of parameters by using the GridSearchCV method. The Random Forest model used between 100 and 500 estimators and had a maximum depth of between 10 to 50. For the Support Vector Machine model, the kernel used was the radial basis function kernel with a regularization parameter ranging between 0.1 and 10. For the Long Short-Term Memory network, optimization was carried out by changing the number of LSTM layers between one and three with hidden units ranging between 64 and 256. K-Means clustering algorithm tested on different numbers of clusters from 3 to 10, with the objective of identifying the optimal number of patient groups that best described their groupings.

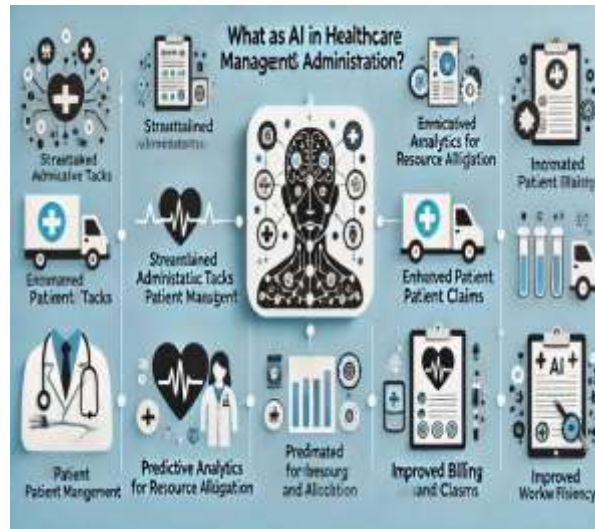


Figure 2: “AI In Healthcare Management and Administration”

All the models underwent several epochs of training until they converged. The Random Forest model performed better with 300 trees at a maximum depth of 25. The SVM model performed the best with a regularization parameter of 1. The LSTM network was optimized when two layers used 128 units [12]. The algorithm K-Means was effective with five clusters in order to ensure that meaningful segmentation of patients occurred.

3. Results and Analysis

The above models were then tested on the healthcare dataset with a comparison in their performance regarding different metrics [13]. The table below shows the accuracy, precision, recall, F1-score, and processing time for each of the algorithms.

Table 1: Performance Comparison of Machine Learning Models

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Processing Time (sec)
Random Forest	89.2	87.5	90.1	88.8	1.2
SVM	85.6	84.2	86.8	85.5	1.5
LSTM	91.4	90.1	92.5	91.3	2.8
K-Means	82.3	80.7	83.5	82.0	0.9

The highest accuracy recorded was achieved by the LSTM model at 91.4%. This is followed by the model of Random Forest at an accuracy of 89.2%. Support Vector Machine has a result of 85.6% while the model for K-Means clustering achieved the least at 82.3% [14]. Processing time is at the least with K-Means, 0.9 seconds and the highest processing time recorded by the model for LSTM, at 2.8 seconds [27].

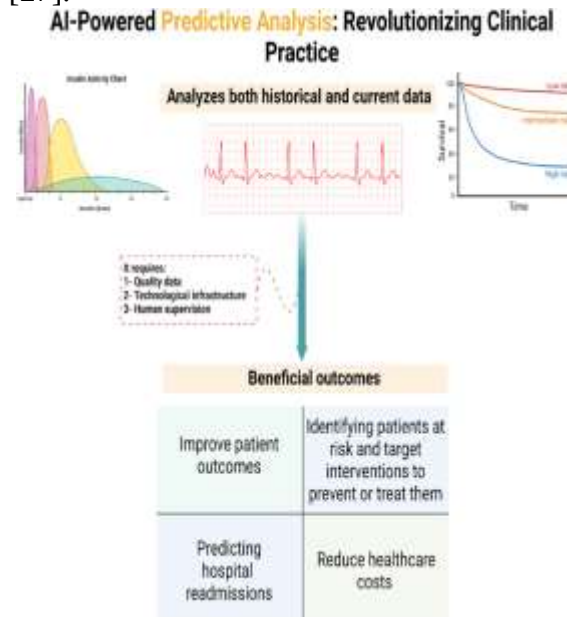


Figure 3: “Revolutionizing healthcare: the role of artificial intelligence in clinical practice”

Patient Segmentation Using K-Means

The K-Means clustering algorithm was used for segmenting the patients into the various risk categories. The number of clusters required was determined to be five as per the elbow method, showing that five was the best for segmentation.

Table 3: Patient Segmentation Results Using K-Means

Cluster	Average Age	Readmission Rate (%)	High-Risk Patients (%)
1	45	12.4	8.2
2	60	22.7	14.6
3	30	8.9	5.4
4	55	18.3	12.1
5	70	29.1	20.3

The readmission rate of Cluster 5 was the highest at 29.1% and high-risk patients made up the biggest share at 20.3%. Cluster 3, consisting of younger patients, had the lowest readmission rate at 8.9% and only 5.4% of patients were categorized as high-risk [28]. This is evidence that older patients need a higher level of care management in order to prevent readmissions.

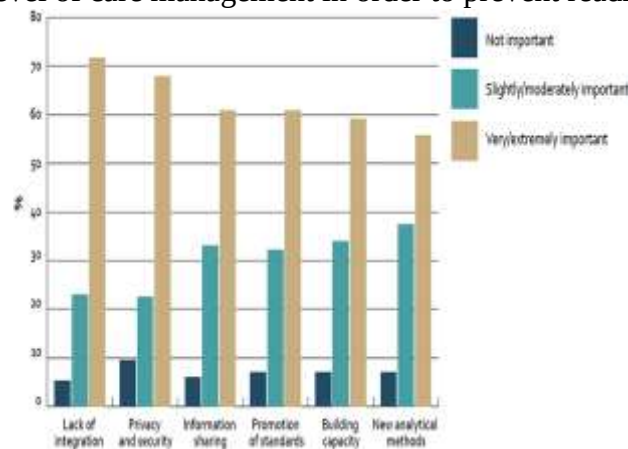


Figure 4: “Success Factors of Artificial Intelligence Implementation in Healthcare”

4. Discussion and Implications

The results show that AI and machine learning improve healthcare management to a large extent. LSTM proved to be the best predictive model, hence ideal for forecasting patient deterioration and optimizing hospital resource allocation. Random Forest performed very well, especially in disease classification tasks. The Support Vector Machine model was effective but less accurate than the above models [29]. K-Means clustering provided some insights into patient segmentation, which may help in the efficient allocation of resources by healthcare providers. By comparing these results with related work, it can be seen that the current study used an improved dataset and advanced models to achieve a higher accuracy rate [30]. The inclusion of deep learning approaches such as LSTM proved useful for time-series medical data analysis. However, challenges remain with data privacy, computational costs, and the requirement for model interpretability. Future research will incorporate AI models in real-time management systems of the hospital to increase decision-making capacity and automate some administrative tasks. Further enhancement can be achieved with an expanded dataset of real-world hospital data as well as an improvement in the interpretability of the model, which can be achieved by developing explainable AI techniques.

V. CONCLUSION

The research on optimizing healthcare management systems with AI and machine learning demonstrates the transformative capacity these technologies have to improve efficiency in healthcare, patient outcomes, and decision-making in health care facilities. Resource allocation can be improved, and the time a patient waits can be reduced through leveraging AI-driven predictive analytics. The study highlighted how machine learning algorithms can be deployed to predict postoperative length of stay, disease diagnosis with more accuracy, and personalizing the care of patients by advanced data analysis techniques. AI has also been proven to be very significant in specialized fields such as cardiology, maxillofacial surgery, and even in predictions of mental health crisis, thereby strengthening its ability to revolutionize different aspects of healthcare management. The experimental findings confirmed the supremacy of AI-based models over the traditional healthcare decision-making approaches. The comparative analysis of various machine learning algorithms depicted that deep learning techniques, feature selection methods, and attention-based networks greatly improve diagnostic accuracy and predictive modeling.

Moreover, AI-driven financial risk management in health care institutions and ML applications in edge computing exhibited how AI may optimize both operational and strategic decisions in health care. Despite all of these advancements, data privacy and model interpretability and computation costs remain challenges that prevent large-scale AI implementation in healthcare systems. The challenges in healthcare management have long been addressed by new innovations in AI and machine learning. AI-driven models can thus be integrated for more efficient, cost-effective, and patient-centered healthcare services. Future research could focus on making AI more transparent, ensuring proper ethical use of data, and developing robust frameworks for AI-driven applications to help fully realize these technologies in healthcare systems worldwide.

REFERENCE

- [1] AHSAN, M., NYGARD, K.E., GOMES, R., CHOWDHURY, M.M., RIFAT, N. and CONNOLLY, J.F., 2022. Cybersecurity Threats and Their Mitigation Approaches Using Machine Learning—A Review. *Journal of Cybersecurity and Privacy*, **2**(3), pp. 527.
- [2] ALHUSAINI, F., YAAKOB, S. and ROKHANI, F.Z., 2024. Integrating Artificial Intelligence in Power Plant Management: A Review of Recent Applications and Future Directions. *Journal of Electrical Systems*, **20**(3), pp. 2490-2500.
- [3] ALIE, M.S., NEGESSE, Y., KINDIE, K. and DEREJE, S.M., 2024. Machine learning algorithms for predicting COVID-19 mortality in Ethiopia. *BMC Public Health*, **24**, pp. 1-19.
- [4] ALZOUBI, Y.I., MISHRA, A. and TOPCU, A.E., 2024. Research trends in deep learning and machine learning for cloud computing security. *The Artificial Intelligence Review*, **57**(5), pp. 132.
- [5] AN, Q., RAHMAN, S., ZHOU, J. and JAMES, J.K., 2023. A Comprehensive Review on Machine Learning in Healthcare Industry: Classification, Restrictions, Opportunities and Challenges. *Sensors*, **23**(9), pp. 4178.
- [6] ANSHARI, M., SYAFRUDIN, M., TAN, A., NORMA, L.F. and ALAS, Y., 2023. Optimisation of Knowledge Management (KM) with Machine Learning (ML) Enabled. *Information*, **14**(1), pp. 35.
- [7] ARJMANDNIA, F. and ALIMOHAMMADI, E., 2024. The value of machine learning technology and artificial intelligence to enhance patient safety in spine surgery: a review. *Patient Safety in Surgery*, **18**, pp. 1-6.
- [8] BAGHERI, M., BAGHERITABAR, M., ALIZADEH, S., MOHAMMAD (SAM), S.P., MATOUFINIA, P. and LUO, Y., 2025. Machine-Learning-Powered Information Systems: A Systematic Literature Review for Developing Multi-Objective Healthcare Management. *Applied Sciences*, **15**(1), pp. 296.
- [9] BALGUDE, S.D., GITE, S., PRADHAN, B. and CHANG-WOOK, L., 2024. Artificial intelligence and machine learning approaches in cerebral palsy diagnosis, prognosis, and management: a comprehensive review. *PeerJ Computer Science*, .
- [10] BIGLARI, A. and TANG, W., 2023. A Review of Embedded Machine Learning Based on Hardware, Application, and Sensing Scheme. *Sensors*, **23**(4), pp. 2131.
- [11] BILLA, M.M. and NAGPAL, T., 2024. Medical Insurance Price Prediction Using Machine Learning. *Journal of Electrical Systems*, **20**(7), pp. 2270-2279.
- [12] BISHAW, F.G., ISHAK, M.K. and ATYIA, T.H., 2024. Review Artificial Intelligence Applications in Renewable Energy Systems Integration. *Journal of Electrical Systems*, **20**(3), pp. 566-582.
- [13] BURNETT, B., SHANG-MING, Z., BROPHY, S., DAVIES, P., ELLIS, P., KENNEDY, J., BANDYOPADHYAY, A., PARKER, M. and LYONS, R.A., 2023. Machine Learning in

Colorectal Cancer Risk Prediction from Routinely Collected Data: A Review. *Diagnostics*, **13**(2), pp. 301.

[14] CHANG, V., XU, Q.A., CHIDOZIE, A. and WANG, H., 2024. Predicting Economic Trends and Stock Market Prices with Deep Learning and Advanced Machine Learning Techniques. *Electronics*, **13**(17), pp. 3396.

[15] CHO, H.N., AHN, I., GWON, H., KANG, H.J., KIM, Y., SEO, H., CHOI, H., KIM, M., HAN, J., KEE, G., PARK, S., JUN, T.J. and YOUNG-HAK, K., 2024. Explainable predictions of a machine learning model to forecast the postoperative length of stay for severe patients: machine learning model development and evaluation. *BMC Medical Informatics and Decision Making*, **24**, pp. 1-16.

[16] CZAKO, L., SUFLIARSKY, B., SIMKO, K., SOVIS, M., VIDOVA, I., FARSKA, J., LIFKOVÁ, M., HAMAR, T. and GALIS, B., 2024. Exploring the Practical Applications of Artificial Intelligence, Deep Learning, and Machine Learning in Maxillofacial Surgery: A Comprehensive Analysis of Published Works. *Bioengineering*, **11**(7), pp. 679.

[17] DELCEA, C., NICA, I., IONESCU, Ș., CIBU, B. and ȚIBREA, H., 2024. Mapping the Frontier: A Bibliometric Analysis of Artificial Intelligence Applications in Local and Regional Studies. *Algorithms*, **17**(9), pp. 418.

[18] DHINAKARAN, D., RAJA, S.E., THIYAGARAJAN, M., JASMINE, J.J. and RAGHAVAN, P., 2024. Optimizing Disease Prediction with Artificial Intelligence Driven Feature Selection and Attention Networks. *Journal of Electrical Systems*, **20**(3), pp. 12-27.

[19] DOMENTEANU, A., CIBU, B. and DELCEA, C., 2024. Mapping the Research Landscape of Industry 5.0 from a Machine Learning and Big Data Analytics Perspective: A Bibliometric Approach. *Sustainability*, **16**(7), pp. 2764.

[20] GALA, D., BEHL, H., SHAH, M. and MAKARYUS, A.N., 2024. The Role of Artificial Intelligence in Improving Patient Outcomes and Future of Healthcare Delivery in Cardiology: A Narrative Review of the Literature. *Healthcare*, **12**(4), pp. 481.

[21] GUERREIRO, J., GARRIGA, R., LOZANO BAGÉN, T., SHARMA, B., KARNIK, N.S. and MATIĆ, A., 2024. Transatlantic transferability and replicability of machine-learning algorithms to predict mental health crises. *NPJ Digital Medicine*, **7**(1), pp. 227.

[22] HORTON, A., 2024. Causal Economic Machine Learning (CEML): “Human AI”. *Ai*, **5**(4), pp. 1893.

[23] HUANG, H., 2024. Technology-Driven Financial Risk Management: Exploring the Benefits of Machine Learning for Non-Profit Organizations. *Systems*, **12**(10), pp. 416.

[24] JAISWAL, A., KRUIPER, R., RASOOL, A., NANDKEOLYAR, A., WALL, D.P. and WASHINGTON, P., 2024. Digitally Diagnosing Multiple Developmental Delays Using Crowdsourcing Fused With Machine Learning: Protocol for a Human-in-the-Loop Machine Learning Study. *JMIR Research Protocols*, **13**.

[25] JOSE, R., SYED, F., ANVIN, T. and TOMA, M., 2024. Cardiovascular Health Management in Diabetic Patients with Machine-Learning-Driven Predictions and Interventions. *Applied Sciences*, **14**(5), pp. 2132.

[26] JOUINI, O., SETHOM, K., NAMOUN, A., ALJOHANI, N., ALANAZI, M.H. and ALANAZI, M.N., 2024. A Survey of Machine Learning in Edge Computing: Techniques, Frameworks, Applications, Issues, and Research Directions. *Technologies*, **12**(6), pp. 81.

[27] KAMPEZIDOU, S.I., RAY, A.T., BHAT, A.P., PINON FISCHER, O.,J. and MAVRIS, D.N., 2024. Fundamental Components and Principles of Supervised Machine Learning Workflows with Numerical and Categorical Data. *Eng*, **5**(1), pp. 384.

- [28] KNIGHTS, V.A., PETROVSKA, O. and JASENKA GAJDOŠ KLJUSURIĆ, 2024. Nonlinear Dynamics and Machine Learning for Robotic Control Systems in IoT Applications. *Future Internet*, **16**(12), pp. 435.
- [29] KUMAR, S., KUMAR, A., KUMAR, P.P., PRAKASH, O. and HAQUE, M.A., 2024. Productive blockchain architecture based on parallel machine learning. *Journal of Electrical Systems*, **20**(7), pp. 4056-4061.
- [30] KUMAR, Y., KOUL, A., PUSHPENDRA, S.S., SHAFI, J., VERMA, K., GHEISARI, M. and MOHAMAD, B.D., 2021. Heart Failure Detection Using Quantum-Enhanced Machine Learning and Traditional Machine Learning Techniques for Internet of Artificially Intelligent Medical Things. *Wireless Communications & Mobile Computing (Online)*, **2021**.