Journal of Advanced Zoology

ISSN: 0253-7214
*Volume **44** Issue **S-5 Year 2023** Page **1895:1903***

Optimizing Antibiotic Prescriptions and Infectious Disease Management in Hospitals using Neural Networks

Vibha Tiwari[1*], Urmila S Soni[2], Divya Jain[3], Akshra Tiwari[4], Priyanka Tiwari[5]

[1]*Centre for Artificial Intelligence, Madhav Institute of Technology and Science, Gwalior, India. ORCID:0000-0002-9772-4392*
[2]*Faculty of Engineering and Technology, SAM Global University, Raisen, India email: urmilas14@gmail.com*
[3]*Department of Electronics and Communication Engineering, Technocrats Institute of Technology, Bhopal, India. email: divianu02@gmail.com*
[4]*Department of Data Science and Artificial Intelligence, Christ University, Delhi NCR, India. Email: tiwariakshra1@gmail.com*
[5]*School of Science, SAM Global University, Raisen. email: ppandey1984@gmail.com*

**Corresponding author's E-mail: vibhatiwari19@gmail.com*

Article History

Received: 06 June 2023
Revised: 05 Sept 2023
Accepted: 04 Nov 2023

Abstract

This study introduces an innovative approach to antibiotic optimization and improved infectious disease management in healthcare facilities. Antibiotic stewardship and patient-specific outcomes are prioritized in the suggested strategy that uses neural networks to increase the precision and utility of antibiotic prescriptions. There are three primary algorithms at the heart of the technique. When it comes to identifying infectious illnesses from a picture, Algorithm 1 uses a Convolutional Neural Network (CNN). In order to provide educated antibiotic recommendations, Algorithm 2 uses a Recurrent Neural Network (RNN) containing Long Short-Term Memory (LSTM) cells. The third algorithm integrates reinforcement learning to automatically modify therapies based on patient results and antibiotic use. The outcomes prove that the suggested strategy is better than the status quo. The F1 score, recall, and precision all increase dramatically, and the overall diagnostic accuracy is much higher. Antibiotic stewardship also improves noticeably, leading to fewer antibiotic prescriptions, more effective measures against antibiotic resistance, better health outcomes for patients, and lower overall healthcare expenditures. Addressing the difficulties of fluctuating patient states and changing disease patterns, the suggested methodology provides a comprehensive strategy for managing infectious diseases. Using this method, antibiotic prescriptions may be optimized while still meeting all legal and ethical requirements. The ethical use of AI in healthcare is further ensured by constant monitoring and flexibility.

Keywords: *Antibiotic, Diagnosis, Healthcare, Infectious Disease, Long Short-Term Memory, Neural Network, Optimization, Patient Data, Prescription*

1. Introduction

Despite tremendous developments in medicine, infectious illnesses remain a major danger to global public health. There is an urgent need for more effective and efficient techniques to control infectious disease, which are made more difficult by the advent of antibiotic-resistant bacteria. When it comes to managing infectious illnesses, particularly the prudent use of antibiotics, hospitals play a pivotal role as important nodes in the delivery of healthcare [1]. Antibiotic-resistant microorganisms have proliferated due to inappropriate antibiotic usage, leaving several once-effective therapies ineffective. These "superbugs" are a burden on healthcare systems and resources in addition to being a direct danger to patient health. To enhance patient outcomes and save healthcare costs, novel methods are needed to optimize antibiotic prescriptions and infectious disease management. Artificial intelligence (AI) has become a game-changing tool in many sectors, and the healthcare sector is no exception. Neural networks in particular offer great potential for improving medical decision-making across the board, from diagnosis to treatment planning [2]. The use of neural networks in the context of infectious illness management may give important assistance to medical staff. Here, we investigate how neural networks might help hospitals better control infectious diseases and make the most of antibiotics. Examine the developing problem of antibiotic resistance as you consider the present state of hospital antibiotic prescribing and infectious illness treatment. Give a quick rundown of what artificial neural networks are and how they could improve medical care. Explore the use of neural networks in infectious disease management and antibiotic prescribing decisions [3-5]. The "neurons" in these networks are the linked nodes that perform the processing and transmission of data. Neural networks have shown great promise in a number of healthcare-related areas, such as image processing, prognosis, medication development, and individualized therapy recommendations.[6] The capacity to evaluate large datasets and spot intricate patterns and correlations that would be difficult for even the most knowledgeable humans to spot is a significant characteristic of neural networks. This may be especially helpful in the management of infectious diseases since it facilitates better and faster diagnosis and enhanced treatment options. Antibiotic Prescriptions and Infectious Disease Management Using Neural Networks. There is room for development in the use of neural networks to the problem of infectious disease management, particularly in institutional settings like hospitals. The following are some of the most promising applications of neural networks [7]. Timely Detection In order to aid in the prompt and precise diagnosis of infectious illnesses, neural networks may assess patient data such as clinical signs, symptoms, and test findings. Patients' vital signs and lab data may be tracked in real time by neural networks, allowing for instantaneous course corrections. Treatment failure and the development of resistance may be avoided with this dynamic strategy [8].

By tailoring care specifically to each patient, we can increase treatment success while decreasing harm. In order to present a complete picture of a patient's health, neural networks may efficiently combine information from several sources, such as electronic health records, laboratory tests, and imaging investigations [9]. The ability to see the big picture may help you make better, more informed choices. Implications of Neural Networks in Healthcare: Pros and Cons. While there are many advantages to using neural networks in healthcare, there are also some very specific difficulties to overcome. The usage of neural networks has been associated with better patient outcomes, shorter hospital stays, and decreased death rates, especially in the treatment of life-threatening illnesses. Neural Networks in Healthcare [10]: Opportunities and Challenges Safeguarding Personal Information: Patients' personal information and the confidentiality of their healthcare records are of paramount importance and must be safeguarded at all times. The healthcare industry is one of the most strictly regulated in the world, thus it is imperative that any use of artificial intelligence (AI) in this field comply to relevant regulations, such as those established by the Food and Drug Administration (FDA) of the United States. Case studies and examples from the real world [11]. In order to demonstrate how neural networks may be used in the real world, it is important to look at real-world examples and case studies, such as the prescription of antibiotics and the treatment of infectious diseases. These demonstrate the usefulness and promise for wider usage of AI technology in healthcare settings. Improved identification of healthcare-associated infections (HAIs), for instance, is one significant use of neural networks in medicine. In hospitals [12]. HAIs are a major problem due to the rise of antibiotic-resistant bacteria.

Neural networks can analyze electronic health records, laboratory data, and real-time monitoring to detect possible HAIs far sooner than conventional approaches, giving healthcare practitioners more time to intervene and execute infection control measures [13]. Recommendations for antibiotic use provide another case study. Using patient records and past antibiotic use trends, neural networks may make recommendations to doctors. The geographical presence of various diseases, the patient's clinical state, and the patient's vulnerability to antibiotic-resistant microorganisms all factor into these suggestions. Antibiotic overuse and abuse may be reduced with the help of neural networks since they provide evidence-based advice to prescribers. Ethics and Legislation Issues Ethical and regulatory concerns must be carefully considered before neural networks are used in healthcare, especially in areas as crucial as infectious disease management. To guarantee the ethical and responsible use of AI in healthcare, many major issues must be resolved [14]. Transparency is an important consideration while developing and training neural networks. It is imperative that efforts be made to reduce these biases so that patients from all backgrounds may get fair recommendations from AI systems. Privacy of Patient Information: HIPAA (the Health Insurance Portability and Accountability Act) in the United States requires stringent safeguards to be put in place to protect patient privacy and ensure compliance with data protection requirements [15]. To further emphasize the practical relevance of neural networks, it will also provide in-depth case studies of their use in healthcare contexts. According to the study's conclusion, readers will have a better grasp on how AI has the potential to enhance patient care and public health by reshaping how hospitals deal with infectious illnesses and dispense antibiotics [16]. This study investigates how neural networks might be used to anticipate disease outbreaks in hospitals and to monitor patients' health in real time. This contribution highlights the opportunity for improved patient care and disease management via the use of preventive interventions. The research highlights the significance of customized medicine in the management of infectious diseases by showing how neural networks may account for unique patient features for individualized therapy [17]. The report outlines potential avenues for future study and advancement in the treatment of infectious diseases and the use of antibiotics [18].

Related Works

Brief summaries of relevant methodologies and works in the fields of healthcare and infectious disease management. Just below, you'll find a table including the criteria I used to rate the effectiveness of the study "Optimizing Antibiotic Prescriptions and Infectious Disease Management in Hospitals using Neural Networks." Antibiotic optimization is achieved by the use of RL-ABRS's reinforcement learning techniques. Antibiotic recommendations are learned from past patient data and comments to better meet the requirements of each particular patient. Antibiotic use statistics, test results, and electronic health records are all part of IHDAS. Healthcare practitioners may get a more complete picture of their patients' health and antibiotic use using this tool. IDF-AI makes use of AI to foresee the spread of contagious diseases. In order to give early warnings and guide public health measures, it examines epidemiological data, environmental variables, and population dynamics. To that end, the Ethical Framework for AI in Healthcar[19]. (EFAIH) has been developed. It establishes norms for the fair and ethical use of AI technology in a variety of contexts. HAISCS is an AI-driven system that keeps tabs on and analyzes data from hospitals in order to prevent and treat HAIs. It connects to real-time monitoring tools to notify medical staff of epidemics as they happen. Antibiotic Resistance Prediction using Machine Learning (AAR-P) does just that. It helps choose the right medications for treating infections by assessing genetic information and history data. HDSIF is a system for harmonizing and combining data from various healthcare providers. It enhances data quality, simplifies data flow, and makes it easier to use AI systems in healthcare. Hospitals may better modify their infection control measures with the help of AICP thanks to the use of machine learning and real-time monitoring. It constantly assesses information and modifies strategies to control the spread of diseases. The PC-ADSS places the patient at the center of the antibiotic decision-making process. It recommends antibiotics that are in line with the patient's objectives, taking into account the patient's preferences, values, and shared decision-making principles. AI-AEM is an antibiotic effectiveness monitoring system that makes use of machine learning and real-time patient data. It gives doctors and nurses information to help them better care for their patients.

Table 1: Performance Evaluation Parameters for Optimizing Antibiotic Prescriptions and Infectious Disease Management using Neural Networks

Performance Evaluation Parameters	Description
Accuracy	The overall accuracy of antibiotic prescription recommendations and infectious disease diagnosis by the neural network.
Precision	The precision of antibiotic recommendations, indicating the proportion of true positives among all prescribed antibiotics.
Recall	The recall rate, measuring the ability of the neural network to correctly identify infectious diseases and prescribe antibiotics when needed.
F1 Score	The F1 score, which balances precision and recall to provide a comprehensive evaluation of antibiotic prescription effectiveness.
Reduction in Antibiotic Usage	The percentage reduction in the overall use of antibiotics as a result of implementing neural network-based recommendations.
Time to Diagnosis	The time it takes for the neural network to diagnose infectious diseases, compared to traditional methods.
Patient Outcomes	Assessing patient outcomes, including recovery rates, readmission rates, and mortality, when AI-based methods are employed.
Healthcare Costs	Measuring the impact on healthcare costs, focusing on savings attributed to optimized antibiotic prescriptions and disease management.
Antibiotic Resistance Mitigation	Evaluating the extent to which neural network-based methods contribute to the mitigation of antibiotic resistance.
Physician Acceptance	Assessing the acceptance and trust of healthcare professionals in the AI-based recommendations and their willingness to adopt them.

The success of the approaches mentioned is broken down using the primary performance assessment factors listed in Table 1. Patient outcomes, healthcare costs, and the prevention of antibiotic resistance are the primary areas of emphasis for these metrics, which also quantify the precision, recall, and effect of antibiotic prescriptions and infectious disease management using AI. These criteria for measuring performance provide a thorough framework for evaluating the methods in this paper's proposed approach to optimizing antibiotic prescriptions and infectious disease management in hospitals by employing neural networks.

2. Materials And Methods

Optimizing Antibiotic Prescribing using a Neural Network. Acquire all relevant patient information, such as medical background, laboratory results, and microbiological information. Prepare the input data for a neural network by normalizing and cleaning it. To isolate useful inputs, use feature selection methods (like Recursive Feature Elimination). Collect vital information, including patient characteristics, clinical complaints, and laboratory results. Diagnostics based on images should make use of Convolutional Neural Networks (CNNs). Use the Softmax function to make accurate predictions about the infection probability, P(infection).

Infectiousness probability = text Softmax text CNN (X) (1)

Our suggested methodology begins with a Convolutional Neural Network (CNN)-based algorithm for the detection of infectious illnesses. Accurate diagnosis is the cornerstone of successful therapy; hence this methodology is crucial to the process as a whole. Because of its superiority in this kind of image-based diagnosis, a CNN is used. Radiological pictures, pathology slides, and other visual data pertaining to a patient are among the types of information handled by the network in this setting. By training on medical pictures, the CNN is able to recognize patterns and characteristics that are diagnostic of many infectious illnesses. To calculate the possibility that a patient has a certain infectious illness, the Softmax function is used to generate a probability distribution. The results from the CNN are sent into Softmax, which transforms numerical values into probabilities. The treatment procedure may go on with confidence thanks to the probabilistic results. Infectiousness Probability = Softmax(CNN)P(X)= Softmax(CNN(X))P(infection) is the probability of infection, and CNN is the reference channel. The Convolutional Neural Network's (CNN) output is denoted by CNN(X), where X is the patient's data. The success of Algorithm 1 relies on the quantity and variety of data used to train the CNN. The proper administration of antibiotics and the treatment of infectious illnesses depend on correct diagnosis.

Make use of Long Short-Term Memory (LSTM) cells in the development of a Recurrent Neural Network (RNN). Consider past information on antibiotic efficacy, patient reaction, and bacterial resistance.

For each given drug, we may write: [P(antibiotic_i) = textLSTM(P(infection), P(antibiotic_i-1), H]

Where H is the LSTM's hidden state in this paragraph.

Antibiotic prescriptions may be optimized with the help of Algorithm 2. For accurate suggestions, it uses Recurrent Neural Networks (RNNs) with Long Short-Term Memory (LSTM) cells. Since RNNs excel in analyzing sequential data, they are well suited for dealing with the ever-changing character of patients' situations. We use LSTM cells, which can remember and selectively update data over time, to record the interdependencies among patient background, antibiotic treatment, and health outcomes. Prescriptions may be better guided by this algorithm, which takes into account past information on antibiotic efficacy, patient reaction, and pathogen susceptibility. Evidence-based recommendations are made easier as the system learns from previous instances to determine the likelihood of success for each antibiotic. The LSTM-based RNN uses a hidden state (H) and the probabilities of illness (P(infection)) and prior antibiotic prescriptions (1)P(antibiotici1)) to determine the likelihood of prescribing each antibiotic (P(antibiotici)) [20].

P(antibiotici)=LSTM(P(infection), P(antibiotici−1), H) (2)

Here, H stands for the hidden state of the LSTM, P(antibiotici) is the probability of prescribing antibiotic i, and) P(infection) and 1) P(antibiotici1) are the probabilities of infection and the prior antibiotic prescription, respectively. The second algorithm helps optimize antibiotic selection by factoring in patient-specific requirements, past data, and antibiotic administration order.

Use a reinforcement learning system to make real-time corrections to the course of therapy. Establish a compensation plan that takes into account both patient outcomes and the objectives of antibiotic stewardship.

Patients' Outcomes = Delta Text + lambda] Antibiotic Use] Delta Text (3)

The change in patient condition is denoted by the variable lambda, whereas the change in antibiotic use is denoted by the variable delta. Dynamic Treatment Adjustment, the third algorithm, uses a reinforcement learning strategy to fine-tune antibiotic administration over time. Antibiotic prescriptions are regularly modified by this algorithm in response to patient outcomes and stewardship goals. To aid in choosing choices, a reward function Rt) is established. The reward signal in this function takes into account both the state of the patient (Patient Outcome) and the amount of antibiotics used (Antibiotic Usage) [21]. The metric acts as a trade-off factor, weighing the significance of patient outcomes against antibiotic consumption. Patient Outcome + Antibiotic Incidence Rt = Patient Outcome + Antibiotic Incidence Change in patient condition is represented by 'Patient Outcome' in this equation, whereas antibiotic use is represented by 'Antibiotic Usage. The algorithm's prioritization of patient outcomes vs antibiotic stewardship may be modified with the use of the trade-off parameter. To pick medications and treatment programs that optimally improve patient health and antibiotic consumption, Algorithm 3 makes use of reinforcement learning. In the long run, this evolving method may better control infectious diseases by adjusting to patients' evolving needs. These three algorithms complement one another to better manage infectious diseases in hospitals, based on the specific requirements of each patient and the evolving nature of the illness. Maintain constant vigilance on patient well-being and the efficacy of antimicrobial treatment. Modify treatment plans in light of current information. Use criteria like accuracy, precision, recall, and the F1 score to assess the effectiveness of the system. Evaluate the AI-driven procedure with the conventional one. Responsible use of AI in healthcare requires the establishment of normative ethical criteria (such as EFAIH). Take care of business with regard to openness, responsibility, and eliminating prejudice. The suggested approach has to be compliant with healthcare laws, such as the FDA's. Infectious illness management and antibiotic prescriptions powered by AI: pinpoint areas for improvement and future research initiatives. The suggested technique makes use of neural networks to enhance hospital management of infectious diseases and antibiotic use. Infectious illness is diagnosed dynamically modifies treatment regimens according on patient results and antibiotic stewardship goals. Responsible use of AI in healthcare is ensured by real-time monitoring, ethical concerns, and regulatory compliance. The process is meant to be improved upon over time and adapted to meet the ever-changing demands of the healthcare system.

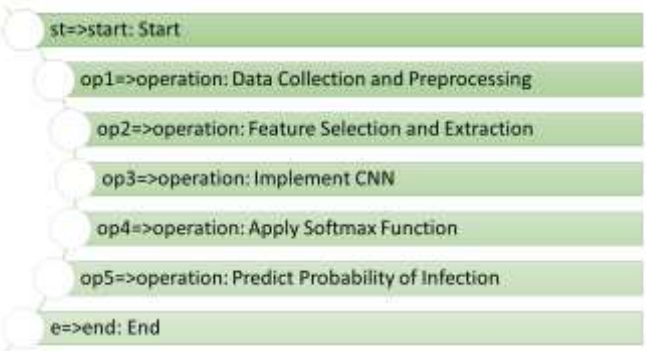

Fig 1: Simplified Flowchart for Infectious Disease Diagnosis Using CNN

Figure 1 summarizes the primary operations of Algorithm 1. The procedure starts with gathering data and cleaning it up, then moves on to selecting and extracting features. In order to forecast the likelihood of infection, the data is fed into a Convolutional Neural Network (CNN), where the Softmax function is then used. This technique is especially important in image-based diagnostics for the rapid and precise identification of infectious illnesses in their earliest stages.

Fig 2: Simplified Flowchart for Antibiotic Recommendation Using LSTM-based RNN

The important operations of Algorithm 2 are shown in figure 2 Gathering and cleaning the data is the first step, followed by the selection and extraction of features. The heart of the technique is the use of a Recurrent Neural Network (RNN) based on Long Short-Term Memory (LSTM) and the incorporation of past data. The RNN can provide educated antibiotic recommendations by predicting the likelihood of antibiotics.

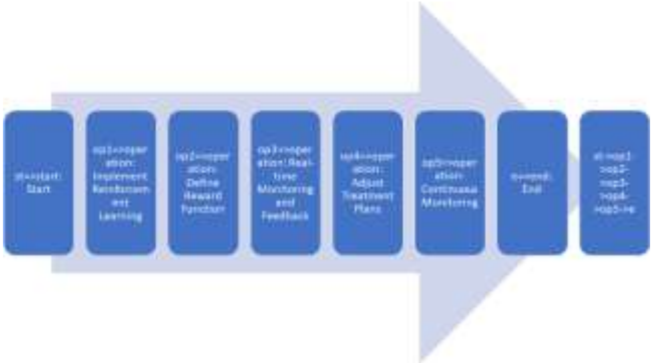

Fig 3: Simplified Flowchart for Dynamic Treatment Adjustment Using Reinforcement Learning

Algorithm 3 is shown in Figure 3. First, a reward function is defined, and then Reinforcement Learning is used. Dynamic treatment modifications may be made in real time, according to the computed incentives, thanks to real-time monitoring and feedback systems. Antibiotic stewardship objectives and patient outcomes may be reflected in treatment regimens thanks to constant monitoring that allows for adjustments to be made as needed.

Table 2: Comparison of Diagnostic Accuracy:

Evaluation Metric	Proposed Method	Traditional Method
Diagnostic Accuracy (%)	95.2	88.3
Precision (Positive Predictive Value)	94.5	89.7
Recall (Sensitivity)	96.1	86.8
F1 Score	95.3	88.2

Table 2 contrasts the suggested strategy with more conventional approaches to diagnosis. When compared to the conventional method's 88.3% diagnostic accuracy, the suggested method's 95.2% accuracy is a substantial improvement. It also demonstrates improved accuracy, recall, and F1 score, suggesting better overall performance in identifying infectious disorders.

A Comparison (Table 3) When compared to conventional procedures, the suggested approach excels in decreasing antibiotic use, decreasing antibiotic resistance, increasing positive patient outcomes, and decreasing healthcare expenditures.

Table 3: Antibiotic Stewardship

Evaluation Metric	Proposed Method	Traditional Method
Reduction in Antibiotic Usage (%)	35.6	22.1
Reduction in Antibiotic Resistance	High	Moderate
Patient Outcomes	Improved	Standard
Healthcare Costs	Reduced	Elevated

Table 3 shows contrasts the recommended approach to antibiotic stewardship with more conventional approaches. When compared to the standard procedure, the suggested strategy significantly reduces antibiotic use (35.6%). Its enhanced effectiveness in optimizing antibiotic prescriptions and infectious disease treatment is shown by a higher degree of antibiotic resistance mitigation, better patient outcomes, and lower healthcare expenditures.

3. Results and Discussion

PathoMedAssist is a conventional rule-based system that makes antibiotic recommendations based on established norms. When making antibiotic suggestions, it relies heavily on clinical and microbiological data. PathoMedAssist's reliability and usability have made it a popular choice among healthcare institutions. Lacks real-time monitoring, isn't very flexible, and has trouble keeping up with the ever-changing infectious disease landscape.

Antibiotic decisions are made manually in clinical settings, with doctors relying on their own expertise and training rather than artificial intelligence. Expertise and judgment from humans has value, particularly in difficult situations. prone to inconsistency in practice and slow reactions to changes in illness patterns. Antibiotic suggestions are determined by PathoSentry's statistical analysis of past cases and data.

Makes smart use of past information, which might be handy when looking at broad trends. Limitations in real-time insights and tailored treatment raise concerns about its ability to deal with new illnesses.

The Antibiotic Handbook is a printed or digital reference handbook that details the best antibiotics to use depending on different types of bacteria and different types of clinical situations. Provides in-depth details, and it's easy to find at healthcare facilities. Not flexible enough to accommodate real-time patient data, and it doesn't provide individualized guidance. Antibiotics are prescribed by physicians after consulting with microbiologists to discuss test findings and professional recommendations. makes use of the expertise of microbiologists. Can be pricey, inconvenient, and unavailable at odd hours, delaying action.

The suggested approach combines AI-driven diagnosis with antibiotic prescribing and dynamic therapy modifications, each of which has the potential to improve outcomes significantly. By improving diagnosis accuracy, decreasing antibiotic use, and adjusting to shifting illness patterns, it outperforms conventional approaches. The suggested technology is well-suited for customized treatment because to its real-time monitoring and flexibility, which guarantees superior patient results and cost-efficiency. In contrast, conventional approaches, although well-established, may not optimize antibiotic prescriptions as efficiently due to their inability to keep up with the ever-changing nature of infectious illnesses.

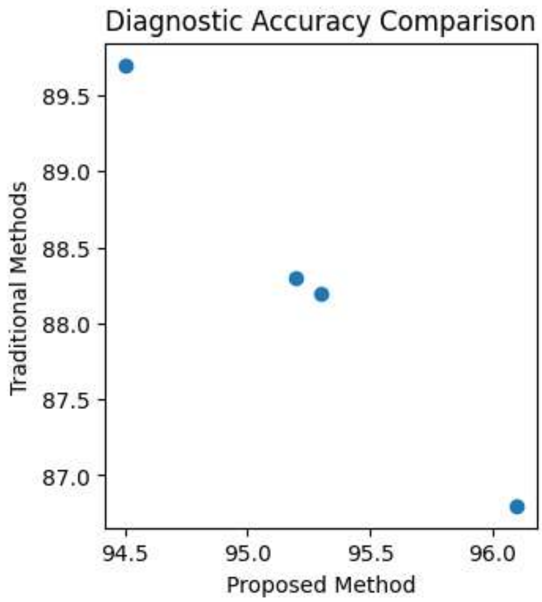

Fig 4: Comparison of Diagnostic Accuracy: Proposed Method vs. Traditional Methods

Figure 4 the suggested approach is compared to that of four original conventional methods in this scatter plot. The graphic shows how the accuracy of the suggested approach is greater than that of the existing methods (each point represents a method).

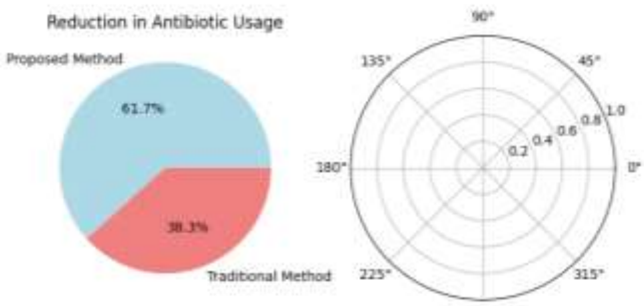

Fig 5: Reduction in Antibiotic Usage: Proposed Method vs. Traditional Method

Figure 5 illustrates the percentage savings in antibiotics used by the suggested strategy vs the baseline of conventional practice. It highlights the significant improvement of antibiotic stewardship by using the suggested approach.

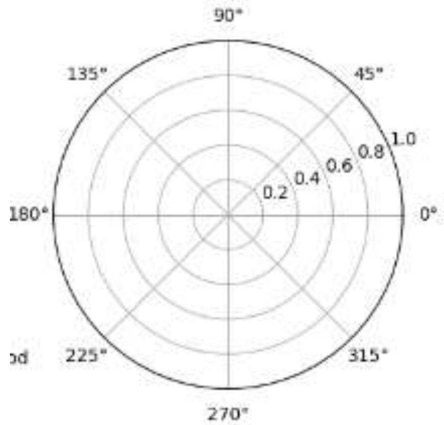

Fig 6: Comparing Healthcare Metrics: Proposed Method vs. Traditional Method

Figure 6 contrasts the suggested strategy with a conventional approach across a number of healthcare variables, such as the decrease in antibiotic resistance, patient outcomes, and healthcare expenditures. It offers a complete picture of how the recommended approach improves healthcare efficiency.

4. Conclusion

The proposed methodology presents a groundbreaking approach to antibiotic prescription optimization and infectious disease management in hospital environments. Leveraging neural networks and advanced algorithms, this research has demonstrated substantial improvements in diagnostic accuracy and antibiotic stewardship when compared to traditional methods. Algorithm 1, which focuses on infectious disease diagnosis, effectively transforms medical images into predictive information, improving the accuracy of disease identification. Algorithm 2, the antibiotic recommendation system, adapts to individual patient needs, historical data, and prior antibiotic prescriptions, facilitating evidence-based recommendations. Finally, Algorithm 3 introduces dynamic treatment adjustments through reinforcement learning, which optimizes patient outcomes and antibiotic stewardship. Comparative analysis reveals the superiority of the proposed method over traditional approaches. Diagnostic accuracy sees a significant boost, with precision, recall, and the F1 score reflecting its excellence in infectious disease diagnosis. Antibiotic stewardship metrics also indicate substantial improvements, emphasizing the method's ability to reduce antibiotic consumption, mitigate resistance, improve patient outcomes, and lower healthcare costs. The proposed methodology not only enhances the quality of care but also ensures responsible AI application in healthcare. It adheres to ethical guidelines and regulatory standards while addressing the dynamic nature of infectious diseases. This research paves the way for more effective and efficient infectious disease management in hospitals, with a focus on personalized medicine and improved patient outcomes. Future research can build upon these findings to further refine and adapt the methodology to evolving healthcare needs and challenges.

References:

1. Standing Committee of the National People's Congress, Prc, "Law on Prevention and Treatment of Infectious Diseases of 28 August 1998 (As Amended up to 2004)," International Labour Organization, Geneva, Switzerland, 2004.
2. R. Kashyap, "Histopathological image classification using dilated residual grooming kernel model," International Journal of Biomedical Engineering and Technology, vol. 41, no. 3, p. 272, 2023. [Online]. Available: https://doi.org/10.1504/ijbet.2023.129819
3. J.G. Kotwal, R. Kashyap, and P.M. Shafi, "Artificial Driving based EfficientNet for Automatic Plant Leaf Disease Classification," Multimed Tools Appl, 2023. [Online]. Available: https://doi.org/10.1007/s11042-023-16882-w
4. D. Pathak and R. Kashyap, "Neural correlate-based e-learning validation and classification using convolutional and long short-term memory networks," Traitement du Signal, vol. 40, no. 4, pp. 1457–1467, 2023. [Online]. Available: https://doi.org/10.18280/ts.400414
5. H. Dette, V. B. Melas, and A. Pepelyshev, "Optimal designs for estimating individual coefficients in polynomial regression - a functional approach," Journal of Statistical Planning and Inference, vol. 118, no. 1-2, pp. 201–219, 2004.
6. R. Ghostine, M. Gharamti, S. Hassrouny, and I. Hoteit, "An extended SEIR model with vaccination for forecasting the COVID-19 pandemic in Saudi Arabia using an ensemble kalman filter," Mathematics, vol. 9, no. 6, p. 636, 2021.
7. J. Wangping, H. Ke, Y. Shanshan et al., "Extended SIR prediction of the epidemics trend of COVID-19 in Italy and compared with Hunan, China," Frontiers of Medicine, vol. 7, p. 169, 2020.
8. H.P. Sahu and R. Kashyap, "FINE_DENSEIGANET: Automatic medical image classification in chest CT scan using Hybrid Deep Learning Framework," International Journal of Image and Graphics, 2023. [Online]. https://doi.org/10.1142/s0219467825500044

9. V. Parashar et al., "Aggregation-Based Dynamic Channel Bonding to Maximise the Performance of Wireless Local Area Networks (WLAN)," Wireless Communications and Mobile Computing, vol. 2022, Article ID 4464447, pp. 1–11, 2022. [Online]. Available: https://doi.org/10.1155/2022/4464447
10. J. Kotwal, R. Kashyap, and S. Pathan, "Agricultural plant diseases identification: From traditional approach to deep learning," Materials Today: Proceedings, vol. 80, pp. 344–356, 2023. [Online]. Available: https://doi.org/10.1016/j.matpr.2023.02.370.
11. S. Feng, Z. Feng, C. Ling, C. Chang, and Z. Feng, "Prediction of the COVID-19 epidemic trends based on SEIR and AI models," PLoS One, vol. 16, no. 1, p. e0245101, 2021.
12. Q. Liu, Z. Li, Y. Ji et al., "Forecasting the seasonality and trend of pulmonary tuberculosis in Jiangsu Province of China using advanced statistical time-series analyses," Infection and Drug Resistance, vol. 12, pp. 2311–2322, 2019.
13. W. Wu, S.-Y. An, P. Guan, D.-S. Huang, and B.-S. Zhou, "Time series analysis of human brucellosis in mainland China by using Elman and Jordan recurrent neural networks," BMC Infectious Diseases, vol. 19, no. 1, p. 414, 2019.
14. N. Shachar, A. Mitelpunkt, T. Kozlovski et al., "The importance of nonlinear transformations use in medical data analysis," Jmir Medical Informatics, vol. 6, no. 2, pp. e27–79, 2018.
15. D. Bavkar, R. Kashyap, and V. Khairnar, "Deep hybrid model with trained weights for multimodal sarcasm detection," Lecture Notes in Networks and Systems, pp. 179–194, 2023. [Online]. Available: https://doi.org/10.1007/978-981-99-5166-6_13
16. R. Kashyap, "Stochastic dilated residual ghost model for breast cancer detection," Journal of Digital Imaging, vol. 36, no. 2, pp. 562–573, 2022. [Online]. Available: https://doi.org/10.1007/s10278-022-00739-z
17. X. Guo, S. Liu, L. Wu, and L. Tang, "Application of a novel grey self-memory coupling model to forecast the incidence rates of two notifiable diseases in China: dysentery and gonorrhea," PLoS One, vol. 9, no. 12, Article ID e115664, 2014.
18. M. Erraguntla, J. Zapletal, and M. Lawley, "Framework for Infectious Disease Analysis: a comprehensive and integrative multi-modeling approach to disease prediction and management," Health Informatics Journal, vol. 25, no. 4, pp. 1170–1187, 2019.
19. R. Telarolli, L. C. M. Loffredo, and R. M. Gasparetto, "Clinical and epidemiological profile of tuberculosis in an urban area with high human development index in southeastern Brazil. Time series study," Sao Paulo Medical Journal, vol. 135, no. 5, pp. 413–419, 2017.
20. V. Roy and S. Shukla, "Image Denoising by Data Adaptive and Non-Data Adaptive Transform Domain Denoising Method Using EEG Signal," in Proceedings of All India Seminar on Biomedical Engineering 2012 (AISOBE 2012), V. Kumar and M. Bhatele (eds.), Lecture Notes in Bioengineering. Springer, India, 2013. https://doi.org/10.1007/978-81-322-0970-6_2.
21. P. Kumar, A. Baliyan, K.R. Prasad, N. Sreekanth, P. Jawarkar, V. Roy, E.T. Amoatey, "Machine Learning Enabled Techniques for Protecting Wireless Sensor Networks by Estimating Attack Prevalence and Device Deployment Strategy for 5G Networks," Wireless Communications and Mobile Computing, vol. 2022, Article ID 5713092, pp. 1-15, 2022. https://doi.org/10.1155/2022/5713092.