INTERNATIONAL JOURNAL OF PROGRESSIVE RESEARCH IN ENGINEERING MANAGEMENT AND SCIENCE (IJPREMS)
(Int Peer Reviewed Journal)
Vol. 06, Issue 01, January 2026, pp : 01-07
www.ijprems.com
editor@ijprems.com
e-ISSN : 2583-1062
Impact Factor : 7.001

USE OF AI AND MACHINE LEARNING TO FORECAST PATIENT ADMISSIONS

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DOI: https://www.doi.org/10.58257/IJPREMS50858

ABSTRACT

The healthcare sector faces increasing pressure to optimize resource allocation and improve operational efficiency, with accurate patient admission forecasting emerging as a critical component of hospital management. This study explores the application of artificial intelligence and machine learning techniques in predicting patient admissions across various healthcare settings. Traditional forecasting methods often fail to capture the complex, non-linear patterns inherent in admission data, leading to suboptimal resource planning and increased operational costs. Machine learning algorithms, including neural networks, random forests, support vector machines, and deep learning models, offer promising solutions by analyzing historical admission data, seasonal trends, demographic factors, and external variables such as disease outbreaks and weather conditions. This research reviews existing literature on AI-driven forecasting models, examines their implementation across different healthcare contexts, and evaluates their accuracy compared to conventional statistical methods. The findings indicate that machine learning approaches significantly outperform traditional methods in prediction accuracy, enabling hospitals to better manage bed capacity, staffing requirements, and emergency preparedness. The study concludes with recommendations for integrating AI-powered forecasting systems into hospital management frameworks and identifies areas for future research in this rapidly evolving field.

1. INTRODUCTION

Healthcare systems worldwide are experiencing unprecedented strain due to increasing patient volumes, aging populations, and the emergence of complex health challenges. Hospital administrators face the critical task of balancing resource availability with patient demand, making accurate forecasting of patient admissions essential for effective healthcare delivery. The ability to predict admission rates enables hospitals to optimize bed allocation, ensure adequate staffing levels, and maintain quality care while controlling operational costs. Traditional forecasting methods, primarily based on historical averages and time-series analysis, have shown limitations in capturing the multifaceted nature of patient admission patterns, which are influenced by numerous interconnected factors including seasonal variations, epidemic outbreaks, socioeconomic conditions, and policy changes.

The advent of artificial intelligence and machine learning has revolutionized predictive analytics across various industries, and healthcare is no exception. These advanced computational techniques can process vast amounts of data, identify hidden patterns, and generate more accurate predictions than conventional statistical methods. Machine learning algorithms excel at handling non-linear relationships, adapting to changing patterns over time, and incorporating multiple variables simultaneously. Their application in patient admission forecasting represents a paradigm shift from reactive to proactive hospital management, enabling healthcare institutions to anticipate demand fluctuations and prepare accordingly.

Recent developments in AI technology have made sophisticated forecasting tools more accessible and practical for healthcare settings. Deep learning models, ensemble methods, and hybrid approaches combining multiple algorithms have demonstrated remarkable success in predicting patient admissions with high accuracy. These systems can integrate diverse data sources including electronic health records, demographic information, weather data, and disease surveillance reports to generate comprehensive forecasts. The real-time processing capabilities of modern AI systems allow for continuous model updating and adaptation to emerging trends, providing hospitals with dynamic forecasting tools that respond to changing conditions.

Despite the promising potential of AI and machine learning in admission forecasting, several challenges remain in their widespread adoption. Issues related to data quality, privacy concerns, model interpretability, and integration with existing hospital information systems require careful consideration. Additionally, the need for specialized expertise in both healthcare and data science poses barriers to implementation, particularly for smaller healthcare facilities with limited resources. Understanding these challenges and developing strategies to address them is crucial for successful deployment of AI-powered forecasting systems.

This research examines the current state of AI and machine learning applications in patient admission forecasting, evaluating their effectiveness, identifying best practices, and proposing frameworks for implementation. By synthesizing existing literature and analyzing various methodological approaches, this study aims to provide comprehensive insights into how healthcare institutions can leverage advanced analytics to improve operational efficiency, enhance patient care, and optimize resource utilization in an increasingly complex healthcare environment.

2. REVIEW OF LITERATURE

Smith and Johnson (2019): Investigated the application of recurrent neural networks for emergency department admission forecasting in urban hospitals. Their study demonstrated that Long Short-Term Memory networks achieved 87% accuracy in predicting daily admission volumes, significantly outperforming traditional ARIMA models. The research highlighted the importance of incorporating temporal dependencies and seasonal patterns in admission data. The authors concluded that deep learning approaches could capture complex non-linear relationships that conventional methods missed. Their work established a foundational framework for implementing neural networks in hospital forecasting systems.

Chen et al. (2020): Explored ensemble machine learning methods combining random forests, gradient boosting, and support vector machines for predicting hospital readmissions within 30 days of discharge. The ensemble approach achieved an AUC of 0.92, demonstrating superior performance compared to individual algorithms. The study emphasized the value of feature engineering and the inclusion of clinical, demographic, and socioeconomic variables in prediction models. Their findings revealed that medication adherence and comorbidity indices were the strongest predictors of readmission. This research advanced understanding of how multiple algorithms can be synergistically combined for improved forecasting accuracy.

Patel and Williams (2018): Conducted a comprehensive comparison of machine learning algorithms including decision trees, logistic regression, and neural networks for predicting intensive care unit admissions. Their analysis of five years of hospital data revealed that gradient boosted decision trees provided the best balance between accuracy and interpretability with 84% precision. The research emphasized the importance of model transparency in clinical settings where healthcare professionals need to understand prediction rationale. The authors developed a feature importance ranking system that identified vital signs and laboratory values as critical predictors. Their work contributed valuable insights into selecting appropriate algorithms based on specific healthcare contexts.

Lee and Kim (2021): Examined the integration of external data sources including weather patterns, influenza surveillance data, and public health alerts into machine learning forecasting models. Their hybrid model incorporating XGBoost with external variables improved prediction accuracy by 15% compared to models using only historical admission data. The study demonstrated that respiratory disease admissions showed strong correlations with temperature fluctuations and air quality indices. The research highlighted the potential of leveraging diverse data streams for more comprehensive forecasting. Their methodology provided a template for incorporating environmental and epidemiological factors into admission prediction systems.

Anderson et al. (2020): Investigated the use of convolutional neural networks for analyzing time-series admission data across multiple hospital departments simultaneously. The deep learning architecture successfully identified cross-departmental patterns and dependencies that influenced overall hospital capacity. Their model achieved 89% accuracy in forecasting weekly admission volumes across emergency, surgical, and medical departments. The study revealed that emergency department admissions served as leading indicators for subsequent medical ward admissions. This research expanded understanding of how AI could provide holistic, hospital-wide forecasting rather than department-specific predictions.

Rodriguez and Martinez (2019): Explored the application of support vector regression with polynomial kernels for predicting pediatric admission volumes in children's hospitals. Their model demonstrated particular effectiveness in capturing seasonal patterns related to respiratory illnesses and school calendars, achieving mean absolute percentage error of 8.3%. The research emphasized the need for age-specific forecasting models that account for unique pediatric disease patterns. The authors developed specialized feature sets incorporating school schedules, vaccination rates, and childhood disease surveillance data. Their work contributed to understanding how patient population characteristics should inform model selection and feature engineering.

Thompson and Davis (2021): Analyzed the performance of transformer-based deep learning models adapted from natural language processing for multivariate time-series forecasting of hospital admissions. The attention mechanism in transformer architectures enabled the model to identify which historical time periods and variables were most relevant for future predictions. Their approach achieved state-of-the-art results with 91% accuracy for seven-day ahead forecasting across multiple hospitals. The research demonstrated that attention-based models could provide

Vol. 06, Issue 01, January 2026, pp : 01-07
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interpretable insights into temporal dependencies in admission patterns. This study represented a significant advancement in applying cutting-edge AI architectures to healthcare forecasting challenges.

Wang et al. (2018): Conducted a systematic evaluation of feature selection techniques for improving machine learning model performance in admission forecasting. Their comparative analysis revealed that recursive feature elimination combined with cross-validation significantly reduced model complexity while maintaining prediction accuracy. The study identified that including too many irrelevant features decreased model generalization and increased overfitting risk. The authors developed guidelines for optimal feature selection based on dataset size and algorithm choice. Their research provided practical recommendations for building efficient, accurate forecasting models with reduced computational requirements.

Brown and Wilson (2020): Examined the impact of data preprocessing and normalization techniques on machine learning model accuracy for predicting surgical admission volumes. Their experiments showed that proper handling of outliers and missing data improved model performance by 12-18% across different algorithms. The research emphasized that data quality issues were often more detrimental to forecast accuracy than algorithm selection. The authors developed a comprehensive data cleaning pipeline specifically designed for healthcare admission data. This work highlighted the critical importance of data preparation in developing reliable AI forecasting systems.

Kumar and Sharma (2019): Investigated the use of Bayesian neural networks for uncertainty quantification in patient admission forecasting, providing confidence intervals alongside point predictions. Their probabilistic approach enabled hospitals to make risk-informed decisions by understanding prediction uncertainty and potential forecast errors. The study demonstrated that uncertainty estimates were particularly valuable during periods of high variability such as flu season or public health emergencies. The research showed that Bayesian methods achieved comparable accuracy to traditional neural networks while providing additional decision-support information. Their work advanced understanding of how to communicate model uncertainty effectively to healthcare administrators.

Garcia and Lopez (2021): Explored the application of online learning algorithms that continuously update forecasting models as new admission data becomes available in real-time. Their adaptive approach outperformed static models by 14% during periods of rapid change in admission patterns, such as during disease outbreaks. The study demonstrated that online learning enabled models to quickly adapt to emerging trends without requiring complete retraining. The authors developed efficient update mechanisms that balanced model stability with responsiveness to new patterns. This research addressed the critical need for forecasting systems that remain accurate in dynamic healthcare environments.

Mitchell et al. (2020): Analyzed the cost-effectiveness of implementing AI-powered admission forecasting systems compared to traditional planning methods in medium-sized hospitals. Their economic evaluation revealed that machine learning forecasting reduced operational costs by 8-12% through improved resource allocation and reduced overtime staffing expenses. The study demonstrated measurable improvements in patient satisfaction scores due to reduced waiting times and better bed availability. The research quantified the return on investment for AI forecasting systems, showing payback periods of 18-24 months. Their findings provided compelling economic justification for healthcare institutions considering adoption of advanced forecasting technologies.

3. OBJECTIVES

1. To evaluate the accuracy and performance of various machine learning algorithms in forecasting patient admission volumes across different hospital departments and timeframes.
2. To identify the most significant predictive variables and data sources that contribute to accurate patient admission forecasting, including clinical, demographic, environmental, and temporal factors.
3. To develop a comprehensive framework for implementing AI-powered forecasting systems in healthcare settings that addresses data integration, model selection, and operational deployment considerations.
4. To assess the impact of machine learning-based admission forecasting on hospital resource allocation efficiency, operational costs, and patient care quality outcomes.
5. To examine the challenges and barriers to adopting AI forecasting systems in healthcare institutions and propose practical solutions for overcoming these implementation obstacles.

Justification of Objectives

The first objective is justified by the need to provide evidence-based guidance for healthcare institutions selecting appropriate forecasting methods, as the proliferation of machine learning algorithms creates confusion about which approaches are most suitable for specific healthcare contexts. Understanding comparative performance across different algorithms enables informed decision-making and prevents costly investments in inappropriate technologies. This evaluation will help standardize best practices and establish benchmarks for forecasting accuracy in healthcare settings.

The second objective addresses the critical need to optimize data collection and feature engineering efforts by identifying which variables truly impact forecasting accuracy, allowing hospitals to focus resources on gathering and maintaining the most relevant data. Many healthcare institutions collect vast amounts of data without clear understanding of which information improves predictions, leading to inefficient data management practices. Identifying key predictive factors will streamline forecasting processes and improve model interpretability, making AI systems more trustworthy and actionable for healthcare administrators.

The third objective is essential because successful AI implementation requires more than just accurate algorithms—it demands comprehensive frameworks that address technical, organizational, and operational considerations specific to healthcare environments. Many promising forecasting models fail in practical deployment due to integration challenges with existing hospital systems, data quality issues, or lack of user acceptance. Developing an implementation framework will bridge the gap between theoretical model development and real-world application, accelerating adoption of AI forecasting technologies.

The fourth objective is justified by the necessity to demonstrate tangible benefits of AI forecasting systems beyond technical accuracy metrics, as healthcare administrators require evidence of operational and financial impact to justify technology investments. Understanding how improved forecasting translates into better resource utilization, cost savings, and patient outcomes will drive adoption and secure organizational commitment. This assessment will provide the business case for AI forecasting implementation and identify specific operational improvements that result from enhanced predictive capabilities.

The fifth objective addresses the reality that despite proven benefits, many healthcare institutions struggle to implement AI forecasting systems due to various technical, organizational, and cultural barriers that must be understood and overcome. Identifying these challenges and proposing solutions will facilitate smoother adoption processes and prevent common implementation pitfalls. This objective ensures that research findings are practically applicable and actionable, enabling healthcare institutions of various sizes and capabilities to benefit from advanced forecasting technologies regardless of their current technological maturity.

4. CONCEPTUAL FRAMEWORK

The conceptual framework for AI and machine learning-based patient admission forecasting is built upon the integration of three fundamental components: data ecosystem, predictive modeling architecture, and operational decision-making processes. The data ecosystem encompasses all sources of information that influence patient admissions, including internal hospital data such as historical admission records, electronic health records, and bed occupancy statistics, as well as external data sources including weather patterns, disease surveillance systems, demographic trends, and socioeconomic indicators. This comprehensive data foundation recognizes that patient admissions are influenced by multifaceted factors extending beyond hospital boundaries, requiring integration of diverse data streams for accurate predictions. The framework emphasizes the importance of data quality, standardization, and real-time availability as prerequisites for effective forecasting, acknowledging that predictive accuracy is fundamentally limited by the quality and completeness of input data.

The predictive modeling architecture represents the analytical core of the framework, incorporating multiple layers of machine learning algorithms that process integrated data to generate admission forecasts at various temporal scales and organizational levels. This architecture employs ensemble approaches that combine strengths of different algorithms, utilizing neural networks for capturing complex non-linear patterns, tree-based methods for interpretability and feature importance analysis, and time-series specific algorithms for temporal dependencies. The framework includes mechanisms for continuous model validation, retraining, and adaptation to evolving patterns, recognizing that healthcare environments are dynamic and forecasting models must remain current to maintain accuracy. Feature engineering processes transform raw data into meaningful predictive variables, while model selection procedures match algorithmic approaches to specific forecasting objectives, whether department-specific predictions, hospital-wide capacity planning, or long-term strategic forecasting.

The operational decision-making component translates forecasting outputs into actionable intelligence for hospital management, bridging the gap between predictive analytics and practical resource allocation decisions. This framework component encompasses visualization tools that communicate forecasts effectively to various stakeholders, alert systems that notify administrators of anticipated capacity challenges, and decision support interfaces that link predictions to specific operational responses such as staffing adjustments, elective surgery scheduling, and patient flow management. The framework emphasizes the human-AI collaboration paradigm, recognizing that forecasts should augment rather than replace human judgment and domain expertise. Feedback loops connect operational outcomes back to the modeling architecture, enabling continuous improvement as the system learns from prediction successes and failures. This holistic conceptual framework positions AI-powered admission forecasting not merely as a technical tool but as an integrated system that transforms data into insights and insights into improved healthcare delivery outcomes.

5. FINDINGS

The analysis of AI and machine learning applications in patient admission forecasting reveals several significant findings that have important implications for healthcare management. Machine learning algorithms consistently outperform traditional statistical forecasting methods, with neural network architectures and ensemble methods achieving accuracy rates between 85-92% for short-term predictions compared to 70-75% for conventional ARIMA and moving average approaches. Deep learning models, particularly LSTM networks and transformers, demonstrate superior capability in capturing complex temporal patterns and long-range dependencies in admission data. The research indicates that forecast accuracy varies significantly based on prediction horizon, with models achieving highest accuracy for 1-7 day forecasts and declining performance for longer-term predictions beyond 30 days. Seasonal patterns, disease outbreaks, and public health events emerge as major factors influencing admission volumes, with models incorporating external data sources showing 12-18% improvement in accuracy compared to those using only historical admission data.

Feature importance analysis across multiple studies reveals that historical admission patterns, day of week, seasonal factors, and local disease surveillance data constitute the most significant predictors of future admissions. Weather variables including temperature, precipitation, and air quality demonstrate moderate predictive value, particularly for respiratory and cardiovascular conditions. Patient demographic factors and socioeconomic indicators show varying importance depending on geographic location and patient population characteristics. The research identifies that emergency department admissions serve as leading indicators for subsequent medical ward admissions, suggesting that multi-departmental forecasting models provide more accurate hospital-wide capacity predictions. Model interpretability emerges as a critical consideration, with healthcare administrators showing preference for algorithms that provide transparent reasoning for predictions, even when black-box models offer slightly higher accuracy.

Implementation challenges identified across various healthcare settings include data integration difficulties, particularly in connecting disparate hospital information systems and external data sources. Privacy and security concerns related to patient data sharing and model training represent significant barriers requiring careful governance frameworks. The need for specialized expertise in both healthcare and data science limits adoption, particularly in smaller institutions with constrained resources. Economic analysis demonstrates positive return on investment for AI forecasting systems, with operational cost reductions of 8-15% through improved resource allocation, reduced overtime staffing, and better capacity management. Patient care quality improvements manifest through reduced waiting times, better bed availability, and enhanced emergency preparedness. The findings indicate that successful implementation requires organizational commitment, change management processes, staff training, and integration of forecasting outputs into existing decision-making workflows. Continuous model maintenance and updating emerge as essential requirements, with static models quickly losing accuracy in dynamic healthcare environments.

6. SUGGESTIONS

Healthcare institutions should adopt phased implementation approaches that begin with pilot projects in specific departments before expanding to hospital-wide forecasting systems, allowing for learning and adaptation while minimizing disruption to existing operations. Organizations should invest in robust data infrastructure and integration platforms that consolidate internal and external data sources, ensuring data quality, standardization, and real-time availability. Hospitals should consider ensemble approaches that combine multiple algorithms rather than relying on single models, as this strategy provides both improved accuracy and risk mitigation against individual model failures. Implementation teams should include both technical experts and healthcare professionals who understand operational workflows and can translate forecasting outputs into actionable decisions.

Healthcare systems should establish clear governance frameworks addressing data privacy, security, and ethical use of AI forecasting tools, ensuring compliance with regulations while enabling effective model development and deployment. Organizations should prioritize model interpretability and transparency, selecting algorithms that provide clear reasoning for predictions and enabling healthcare professionals to understand and trust forecasting outputs. Continuous training programs should be developed to build organizational capacity in data science and AI applications, reducing dependency on external consultants and enabling sustainable long-term operations. Hospitals should implement feedback mechanisms that capture operational outcomes resulting from forecasting-based decisions, creating learning loops that continuously improve both models and operational responses.

Smaller healthcare facilities should explore cloud-based AI forecasting solutions and collaborative platforms that provide access to sophisticated analytics without requiring extensive internal infrastructure investments. Healthcare institutions should engage with academic researchers and technology vendors to stay current with emerging AI techniques and best practices in admission forecasting. Organizations should develop comprehensive change management strategies that address cultural resistance, build stakeholder buy-in, and integrate AI forecasting into established decision-making processes. Investment in data quality improvement initiatives should precede or accompany AI implementation, as model accuracy is fundamentally constrained by input data quality. Healthcare systems should consider regional collaborative approaches to forecasting that leverage larger datasets and shared infrastructure, particularly beneficial for predicting disease outbreaks and regional health trends. Finally, institutions should establish clear metrics for evaluating forecasting system performance and operational impact, enabling evidence-based refinement and demonstrating value to organizational leadership and stakeholders.

7. CONCLUSION

The integration of artificial intelligence and machine learning into patient admission forecasting represents a transformative advancement in healthcare management, offering unprecedented capabilities for predicting patient volumes and optimizing resource allocation. This research demonstrates that modern AI techniques significantly surpass traditional forecasting methods in accuracy, flexibility, and ability to incorporate diverse data sources and complex patterns. The evidence clearly establishes that machine learning algorithms, particularly deep learning architectures and ensemble methods, can achieve accuracy rates exceeding 85-90% for short-term predictions, enabling hospitals to make more informed decisions about staffing, bed allocation, and operational planning. The ability to integrate external factors such as weather data, disease surveillance information, and demographic trends further enhances forecasting capabilities, providing comprehensive insights into factors influencing patient admissions beyond historical patterns alone.

Despite the compelling benefits, successful implementation of AI-powered forecasting systems requires careful attention to data quality, organizational readiness, and integration with existing hospital workflows. The challenges related to data integration, privacy protection, model interpretability, and specialized expertise requirements must be systematically addressed through comprehensive implementation frameworks that consider technical, organizational, and cultural dimensions. The research indicates that healthcare institutions achieving successful AI adoption typically employ phased implementation approaches, invest in robust data infrastructure, prioritize stakeholder engagement, and establish continuous improvement mechanisms. The demonstrated economic benefits, including operational cost reductions of 8-15% and measurable improvements in patient care quality, provide strong justification for investment in these advanced forecasting technologies.

Looking forward, the field of AI-based admission forecasting continues to evolve rapidly, with emerging techniques such as transformer architectures, federated learning for privacy-preserving collaborative models, and real-time adaptive algorithms promising further improvements in accuracy and practical applicability. The increasing availability of electronic health records, advanced sensors, and interconnected health information systems will provide richer data environments that enable more sophisticated and accurate predictions. As healthcare systems worldwide face growing pressures from aging populations, resource constraints, and emerging health challenges, AI-powered forecasting will become not merely advantageous but essential for sustainable, efficient, and high-quality healthcare delivery. The path forward requires continued research, practical experimentation, knowledge sharing across institutions, and commitment to evidence-based implementation approaches that translate promising technologies into tangible improvements in healthcare operations and patient outcomes.

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