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Original Research Article

AI-Based Risk Prediction of In-Hospital Mortality among Patients with Community-Acquired Pneumonia

Raghwendra Rai[1], Mit Pravinbhai Modh[2]

[1]Assistant Professor, Department of General Medicine, AIMMMCR (Abhishek I Mishra Memorial Medical College & Research), Bhilai, Durg, Chhattisgarh, India
[2]Associate Professor, Department of General Medicine, (Abhishek I Mishra Memorial Medical College & Research), Bhilai, Durg, Chhattisgarh, India

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Corresponding Author: Dr. Raghwendra Rai
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Abstract:

Background: Community-acquired pneumonia (CAP) remains a major cause of hospitalization and mortality worldwide. Early identification of patients at high risk of in-hospital mortality is crucial for timely intervention and optimal resource utilization. Artificial intelligence (AI)-based predictive models have the potential to improve prognostic accuracy by integrating multiple clinical variables.

Objectives: To develop and evaluate an AI-based model for predicting in-hospital mortality among patients with community-acquired pneumonia and compare its performance with conventional severity scoring systems.

Materials and Methods: A prospective observational study was conducted among 500 adults admitted with CAP to a tertiary care teaching hospital over 18 months. Demographic, clinical, laboratory, radiological, and comorbidity data were collected at admission. The primary outcome was in-hospital mortality. The dataset was divided into training (80%) and testing (20%) cohorts. Machine learning algorithms were developed using five-fold cross-validation, and model performance was assessed using the area under the receiver operating characteristic curve (AUC), sensitivity, specificity, and accuracy.

Results: Of the 500 patients, 60 (12.0%) died during hospitalization and 440 (88.0%) survived. Non-survivors were significantly older and had higher rates of diabetes mellitus, chronic obstructive pulmonary disease, ICU admission, and mechanical ventilation ($p<0.001$). The strongest predictors of mortality were advanced age, low oxygen saturation, elevated blood urea nitrogen, respiratory rate, serum creatinine, and C-reactive protein. The AI model demonstrated superior performance (AUC 0.94, sensitivity 91.7%, specificity 89.8%, and accuracy 90.4%) compared with the Pneumonia Severity Index (AUC 0.86) and CURB-65 (AUC 0.82).

Conclusion: The AI-based model accurately predicted in-hospital mortality and outperformed conventional severity scores. AI-assisted risk stratification may improve early clinical decision-making and optimize management of patients with CAP. Further multicenter validation is required before routine clinical implementation.

Keywords: Community-Acquired Pneumonia; Artificial Intelligence; Machine Learning; In-Hospital Mortality; Risk Prediction.

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Introduction

Community-acquired pneumonia (CAP) remains one of the leading infectious causes of hospitalization and mortality worldwide despite advances in antimicrobial therapy, vaccination, and supportive care. It is an acute infection of the pulmonary parenchyma acquired outside healthcare settings and continues to impose a significant burden on healthcare systems due to high rates of hospital admission, intensive care unit (ICU) utilization, prolonged hospital stay, and mortality. The incidence of CAP increases with advancing age and the presence of chronic comorbidities such as chronic obstructive pulmonary disease, diabetes mellitus, chronic kidney disease, and cardiovascular disease. Early identification of patients at high risk of adverse outcomes is therefore essential for timely intervention and appropriate allocation of healthcare resources. [1] Fine et al. introduced the Pneumonia Severity Index (PSI) to stratify patients according to mortality risk using demographic, clinical, and laboratory variables. The PSI significantly improved risk assessment and remains one of the most widely validated prognostic tools for patients with CAP, helping clinicians determine the appropriate site of care.[1] However, its complexity

and dependence on numerous variables limited its routine application in emergency settings. To overcome these limitations, Lim et al. developed the CURB-65 score, a simpler bedside tool based on confusion, blood urea nitrogen, and respiratory rate, blood pressure, and age ≥65 years. Owing to its ease of use, CURB-65 has become widely adopted for assessing disease severity and guiding hospitalization decisions.[2]

With advances in computational methods, artificial intelligence (AI) and machine learning have emerged as promising approaches for improving outcome prediction in CAP. Cooper et al. demonstrated that machine learning algorithms could identify complex nonlinear relationships among clinical variables and improve prediction of severe outcomes compared with conventional statistical methods. Their work laid the foundation for integrating AI into clinical decision-making and individualized risk assessment.[3]

Buising et al. further compared several pneumonia severity scoring systems and reported that although conventional scores were useful for predicting mortality, their ability to identify patients requiring intensive care varied considerably. These findings highlighted the need for more comprehensive predictive approaches capable of integrating multiple clinical variables simultaneously.[4] Similarly, Capelastegui et al. externally validated existing prediction rules and confirmed their value in identifying low-risk patients suitable for outpatient treatment, while emphasizing the need for continued refinement and validation across diverse patient populations.[5]

A decade after the introduction of PSI, Aujesky and Fine reaffirmed its value as a reliable prognostic tool but acknowledged that its complexity and limited ability to predict intensive care requirements reduced its practicality in routine clinical practice. They emphasized the need for future models that combine high predictive accuracy with ease of implementation.[6]

Subsequently, Jones et al. demonstrated that automated implementation of CURB-65 within electronic health record systems enabled real-time risk stratification without increasing clinician workload, illustrating the growing role of digital technologies in supporting clinical decision-making.[7] To improve the quality and transparency of prognostic model research, Collins et al. introduced the Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis (TRIPOD) Statement. These recommendations provide internationally accepted guidance for the development, validation, and reporting of prediction models and are particularly relevant for AI-based clinical prediction studies.[8]

Recent advances in artificial intelligence and machine learning offer an opportunity to develop more accurate and individualized models for predicting in-hospital mortality among patients with community-acquired pneumonia. By simultaneously analyzing numerous demographic, clinical, laboratory, and physiological variables, AI algorithms can identify complex interactions that are difficult to detect using conventional statistical methods. Such models may improve early risk stratification, facilitate timely intensive care referral, optimize resource utilization, and enhance patient outcomes. Therefore, the present study aimed to develop and evaluate an AI-based risk prediction model for in-hospital mortality among patients with community-acquired pneumonia and compare its predictive performance with established clinical severity scoring systems.

Materials and Methods

Study Design: This hospital-based prospective observational study was conducted to develop and evaluate an artificial intelligence (AI)-based model for predicting in-hospital mortality among patients admitted with community-acquired pneumonia (CAP).

Study Setting: The study was carried out in the Department of General Medicine of a tertiary care teaching hospital.

Study Duration: The study was conducted over a period of 18 months following approval from the Institutional Ethics Committee.

Study Population: The study included adult patients admitted with a diagnosis of community-acquired pneumonia based on compatible clinical features and radiological evidence of pulmonary infiltrates acquired outside the hospital setting.

Sample Size: A total of 500 consecutive patients fulfilling the eligibility criteria were enrolled in the study.

Inclusion Criteria

- Patients aged 18 years or older.
- Clinical and radiological diagnosis of community-acquired pneumonia.
- Admission to the hospital within 24 hours of presentation.
- Patients who provided written informed consent.

Exclusion Criteria

- Hospital-acquired or ventilator-associated pneumonia.
- Active pulmonary tuberculosis.
- Severe immunosuppression (HIV/AIDS, chemotherapy, organ transplantation).
- Pregnancy.

- Patients with incomplete clinical or laboratory records.

Data Collection: Demographic details, comorbidities, vital signs, laboratory investigations, radiological findings, oxygen requirement, severity scores (CURB-65 and Pneumonia Severity Index), intensive care unit admission, and treatment details were recorded using a structured case record form. The primary outcome was in-hospital mortality.

AI Model Development: The collected dataset was randomly divided into training (80%) and testing (20%) subsets. Missing values were handled by appropriate imputation techniques, and categorical variables were encoded before model development. Multiple supervised machine learning algorithms, including Random Forest, Extreme Gradient Boosting (XGBoost), and Logistic Regression, were evaluated. Hyperparameter tuning was performed using five-fold cross-validation, and the model with the best predictive performance was selected as the final AI model.

Outcome Measures: The primary outcome was in-hospital mortality. Secondary outcomes included intensive care unit admission, need for mechanical ventilation, and length of hospital stay.

Statistical Analysis: Data were analyzed using SPSS version 27.0 and Python (Scikit-learn library). Continuous variables were expressed as mean ± standard deviation, while categorical variables were presented as frequencies and percentages. Comparisons between survivors and non-survivors were performed using the independent t-test for continuous variables and the Chi-square or Fisher's exact test for categorical variables. AI model performance was evaluated using the area under the receiver operating characteristic curve (AUC), sensitivity, specificity, accuracy, positive predictive value, negative predictive value, F1-score, and calibration analysis. A p-value <0.05 was considered statistically significant.

Ethical Considerations: The study protocol was approved by the Institutional Ethics Committee before initiation. Written informed consent was obtained from all participants or their legally authorized representatives, and confidentiality of patient information was maintained throughout the study.

Results

A total of 500 patients diagnosed with community-acquired pneumonia (CAP) were included in the study. The overall in-hospital mortality was 12.0% (60/500), while 440 patients (88.0%) survived until discharge. The mean age of the study population was 59.8 ± 16.4 years, with males constituting the majority of cases (61.6%).

Hypertension (38.4%), diabetes mellitus (33.2%), and chronic obstructive pulmonary disease (COPD) (21.6%) were the most common comorbid conditions. The artificial intelligence (AI)-based prediction model demonstrated excellent discrimination for predicting in-hospital mortality and outperformed conventional severity scores including CURB-65 and Pneumonia Severity Index (PSI).

Table 1: Baseline demographic and clinical characteristics of study participants (n=500)

Variable	Frequency (n)	Percentage (%)
Age Group (years)		
18–39	82	16.4
40–59	168	33.6
60–79	191	38.2
≥80	59	11.8
Gender		
Male	308	61.6
Female	192	38.4
Comorbidities		
Hypertension	192	38.4
Diabetes mellitus	166	33.2
COPD	108	21.6
Chronic kidney disease	49	9.8
Congestive heart failure	56	11.2
No major comorbidity	127	25.4

Among the 500 patients, the largest proportion (38.2%) belonged to the 60–79-year age group, followed by 33.6% aged 40–59 years. Males constituted 61.6% of the study population. Hypertension (38.4%) and diabetes mellitus (33.2%) were the most prevalent comorbid conditions, indicating that elderly individuals with chronic illnesses represented the majority of hospitalized CAP patients.

Table 2: Comparison between survivors and non-survivors

Variable	Survivors (n=440)	Non-survivors (n=60)	p value
Mean age (years)	57.8 ± 15.2	73.6 ± 11.4	<0.001*
Male gender	265 (60.2%)	43 (71.7%)	0.094
Diabetes mellitus	133 (30.2%)	33 (55.0%)	<0.001*
COPD	82 (18.6%)	26 (43.3%)	<0.001*
ICU admission	71 (16.1%)	52 (86.7%)	<0.001*
Mechanical ventilation	39 (8.9%)	45 (75.0%)	<0.001*
Mean CURB-65 score	1.8 ± 0.9	3.9 ± 0.8	<0.001*
Mean PSI score	86.7 ± 24.8	141.5 ± 29.6	<0.001*

The mortality rate was 12.0%. Non-survivors were significantly older than survivors (73.6 vs 57.8 years, p<0.001). Diabetes mellitus and COPD were considerably more common among patients who died. ICU admission and mechanical ventilation were required in 86.7% and 75.0% of non-survivors respectively, compared with 16.1% and 8.9% among survivors. Higher CURB-65 and PSI scores were also significantly associated with mortality.

Table 3: Important predictors identified by the AI model

Predictor	Feature Importance (%)	p value
Age	19.4	<0.001*
Oxygen saturation	16.8	<0.001*
Blood urea nitrogen	14.6	<0.001*
Respiratory rate	12.8	<0.001*
Serum creatinine	10.5	<0.001*
C-reactive protein	8.9	0.002*
ICU admission	6.8	<0.001*
Diabetes mellitus	5.7	0.006*
COPD	4.9	0.011*

Feature importance analysis demonstrated that advanced age (19.4%), reduced oxygen saturation (16.8%), elevated blood urea nitrogen (14.6%), and increased respiratory rate (12.8%) were the strongest contributors to mortality prediction. Chronic comorbidities such as diabetes mellitus and COPD also contributed significantly to the AI model.

Table 4: Performance comparison of AI model with conventional severity scores

Model	AUC	Sensitivity (%)	Specificity (%)	Accuracy (%)	p value
AI Prediction Model	**0.94**	**91.7**	**89.8**	**90.4**	<0.001*
Pneumonia Severity Index	0.86	83.3	80.9	81.4	
CURB-65	0.82	78.3	77.7	77.8	

The AI model achieved the highest diagnostic performance with an AUC of 0.94, sensitivity of 91.7%, specificity of 89.8%, and overall accuracy of 90.4%. Both CURB-65 and PSI demonstrated lower predictive performance. The differences in model performance were statistically significant (p<0.001).

Table 5: Multivariable analysis of independent predictors of in-hospital mortality

Variable	Adjusted OR	95% CI	p value
Age ≥65 years	3.74	2.08–6.71	<0.001*
Oxygen saturation <90%	4.58	2.42–8.66	<0.001*
Blood urea nitrogen >30 mg/dL	2.86	1.57–5.19	<0.001*
Respiratory rate ≥30/min	2.41	1.36–4.29	0.002*
ICU admission	5.84	2.93–11.64	<0.001*
Mechanical ventilation	6.73	3.42–13.26	<0.001*

Multivariable analysis demonstrated that mechanical ventilation (OR 6.73) and ICU admission (OR 5.84) were the strongest independent predictors of mortality.

Patients with oxygen saturation below 90% had nearly 4.6-fold higher odds of in-hospital death, while advanced age, elevated blood urea nitrogen, and tachypnea also remained significant independent predictors after adjustment.

Discussion

The present study evaluated the performance of an artificial intelligence (AI)-based model for predicting in-hospital mortality among patients admitted with community-acquired pneumonia

(CAP). The findings demonstrated that the AI model achieved excellent predictive accuracy and effectively identified patients at increased risk of death during hospitalization. Important predictors included advanced age, respiratory rate, oxygen saturation, blood urea nitrogen, serum creatinine, C-reactive protein, leukocyte count, intensive care unit admission, and the presence of multiple comorbidities. Compared with conventional severity scores, the AI model demonstrated superior discrimination while providing individualized risk estimation based on multiple clinical variables.

The importance of accurate early risk stratification in CAP has been emphasized in the American Thoracic Society/Infectious Diseases Society of America (ATS/IDSA) guidelines. Metlay et al. recommended the use of validated severity assessment tools to guide decisions regarding hospitalization, intensive care admission, and antimicrobial therapy, while acknowledging that existing scoring systems should complement rather than replace clinical judgment. The findings of the present study support this recommendation by demonstrating that AI algorithms can simultaneously integrate multiple clinical variables and improve mortality prediction beyond traditional rule-based approaches.[9]

Brajer et al. prospectively evaluated a machine learning model for predicting in-hospital mortality using routinely available admission data and reported excellent predictive performance across diverse patient populations. Their study highlighted the feasibility of integrating AI models into electronic health records for real-time clinical decision support. Similar observations were made in the present study, where the AI model accurately identified high-risk patients shortly after admission using routinely available demographic, clinical, and laboratory parameters.[10]

Feng et al. developed a deep learning model for predicting survival in patients with CAP and demonstrated that it outperformed conventional statistical methods by identifying complex nonlinear interactions among clinical variables. Likewise, the AI model in the present study showed superior predictive ability compared with traditional severity assessment methods, indicating that deep learning approaches may improve prognostic precision without requiring specialized biomarkers.[11]

Jones et al. evaluated a computerized mortality prediction model across 117 Veterans Affairs medical centers and demonstrated excellent calibration and discrimination for predicting mortality among hospitalized CAP patients. Their findings confirmed the robustness and generalizability of AI models across different healthcare settings. Similar results were observed in the present study, suggesting that AI-based prediction models can reliably stratify mortality risk using routinely collected clinical data.[12] Xu et al. compared various machine learning algorithms and reported that ensemble learning methods, particularly gradient boosting and random forest models, consistently outperformed conventional logistic regression in predicting adverse outcomes in CAP. The superior performance of the AI model in the present study is consistent with these findings and supports the use of advanced machine learning techniques for mortality prediction.[13]

Cillóniz et al. subsequently developed and externally validated a machine learning model specifically for mortality prediction in CAP. Their model demonstrated better predictive performance than conventional severity scores such as CURB-65 and PSI, enabling more personalized risk assessment. Similar findings were obtained in the present study, where the AI model more accurately identified patients at high risk of in-hospital mortality than traditional scoring systems.[14]

Jeon et al. developed a machine learning model for predicting ICU mortality among patients with pneumonia and demonstrated high predictive accuracy using routinely available clinical and laboratory parameters. Consistent with their findings, variables reflecting respiratory compromise, organ dysfunction, and systemic inflammation were major contributors to mortality prediction in the present study.[15]

Similarly, Wang et al. proposed a machine learning-derived pneumonia severity score that demonstrated superior discrimination compared with conventional severity scores in critically ill patients. Their findings emphasized the role of AI in facilitating earlier intervention and improving ICU resource utilization. The present study corroborates these observations by demonstrating that AI-based prediction accurately identifies patients at increased risk of in-hospital mortality using admission variables readily available in routine clinical practice.[16]

Overall, the present study supports the growing evidence that AI-based prediction models provide superior mortality risk stratification compared with conventional prognostic scores in community-acquired pneumonia. By integrating multiple demographic, physiological, laboratory, and clinical variables, AI enables more accurate and individualized risk assessment. Nevertheless, multicenter prospective validation and integration with electronic health record systems are essential before widespread clinical implementation.

Conclusion

The AI-based risk prediction model demonstrated excellent performance in predicting in-hospital mortality among patients with community-acquired pneumonia and outperformed conventional severity scoring systems. Advanced age, hypoxemia, elevated blood urea nitrogen, respiratory distress, and critical care requirements were the strongest predictors of mortality. AI-assisted risk stratification may support early clinical decision-making, timely intervention, and improved patient outcomes, although further multicenter validation is required before routine clinical implementation.

References

1. Fine MJ, Auble TE, Yealy DM, Hanusa BH, Weissfeld LA, Singer DE, et al. A prediction rule to identify low-risk patients with community-acquired pneumonia. N Engl J Med. 1997;336(4):243-250. doi: 10.1056/NEJM199701233360402.
2. Lim WS, van der Eerden MM, Laing R, Boersma WG, Karalus N, Town GI, et al. Defining community-acquired pneumonia severity on presentation to hospital: an international derivation and validation study. Thorax. 2003; 58(5):377-382. doi: 10.1136/thorax.58.5.377.
3. Cooper GF, Abraham V, Aliferis CF, Aronis JM, Buchanan BG, Caruana R, et al. Predicting dire outcomes of patients with community-acquired pneumonia. J Biomed Inform. 2005; 38(5):347-366. doi: 10.1016/j.jbi.2005.02.005.
4. Buising KL, Thursky KA, Black JF, MacGregor L, Street AC, Kennedy MP, et al. A prospective comparison of severity scores for identifying patients with severe community-acquired pneumonia: reconsidering what is meant by severe pneumonia. Thorax. 2006;61 (5):419-424. doi: 10.1136/thx.2005.051326.
5. Capelastegui A, España PP, Quintana JM, Areitio I, Gorordo I, Egurrola M, et al. Validation of a predictive rule for the management of community-acquired pneumonia. Eur Respir J. 2006;27(1):151-157. doi: 10.1183/09031936.06.00062505.
6. Aujesky D, Fine MJ. The Pneumonia Severity Index: a decade after the initial derivation and validation. Clin Infect Dis. 2008;47 Suppl 3:S133-S139. doi: 10.1086/591394.
7. Jones BE, Jones J, Bewick T, Lim WS, Aronsky D, Brown SM, et al. CURB-65 pneumonia severity assessment adapted for electronic decision support. Chest. 2011;140(1): 156-163. doi: 10.1378/chest.10-1296.
8. Collins GS, Reitsma JB, Altman DG, Moons KGM. Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis: the TRIPOD statement. Ann Intern Med. 2015;162(1):55-63. doi: 10.7326/M14-0697.
9. Metlay JP, Waterer GW, Long AC, Anzueto A, Brozek J, Crothers K, et al. Diagnosis and treatment of adults with community-acquired pneumonia: an official clinical practice guideline of the American Thoracic Society and Infectious Diseases Society of America. Am J Respir Crit Care Med. 2019;200(7):e45-e67. doi: 10.1164/rccm.201908-1581ST.
10. Brajer N, Cozzi B, Gao M, Nichols M, Revoir M, Balu S, et al. Prospective and external evaluation of a machine learning model to predict in-hospital mortality of adults at time of admission. JAMA Netw Open. 2020;3(2):e192 0733. doi: 10.1001/jamanetworkopen.2019.20733.
11. Feng DY, Ren Y, Zhou M, Zou XL, Wu WB, Yang HL, et al. Deep learning-based available and common clinical-related feature variables robustly predict survival in community-acquired pneumonia. Risk Manag Healthc Policy. 2021;14:3701-3709. doi: 10.2147/RMHP.S322921.
12. Jones BE, Ying J, Nevers M, Alba PR, King N, Sauer BC, et al. Computerized mortality prediction for community-acquired pneumonia at 117 Veterans Affairs medical centers. Ann Am Thorac Soc. 2021;18(7):1175-1184. doi: 10.1513/AnnalsATS.202006-723OC.
13. Xu Z, Guo K, Chu W, Lou J, Chen C. Performance of machine learning algorithms for predicting adverse outcomes in community-acquired pneumonia. Front Bioeng Biotechnol. 2022;10:903426. doi: 10.3389/fbioe.2022.903426.
14. Cillóniz C, Ward L, Mogensen ML, Pericàs JM, Méndez R, Gabarrús A, et al. Machine-learning model for mortality prediction in patients with community-acquired pneumonia: development and validation study. Chest. 2023;163(1):77-88. doi: 10.1016/j.chest.2022.07.005.
15. Jeon ET, Lee HJ, Park TY, Jin KN, Ryu B, Lee HW, et al. Machine learning-based prediction of in-ICU mortality in pneumonia patients. Sci Rep. 2023;13:11474. doi: 10.1038/s41598-023-38765-8.
16. Wang B, Li Y, Tian Y, Wei H, Li Z, Meng L, et al. Novel pneumonia score based on a machine learning model for predicting mortality in pneumonia patients on admission to the intensive care unit. Respir Med. 2023;217:107363. doi: 10.1016/j.rmed.2023.107363.