



Artificial Intelligence and Quantum Technology in Multidisciplinary Data Analysis: Applications in Medicine

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Received Date: 15/04/2025

Revised Date: 10/05/2025

Accepted Date: 08/06/2025

KEYWORDS

Eclampsia,
Artificial
Intelligence,
Neuroimaging.

ABSTRACT:

Background: Eclampsia is a severe obstetric complication with high maternal morbidity and mortality, often associated with neurological manifestations. Neuroimaging plays a vital role in assessing disease severity, while Artificial Intelligence (AI) and emerging quantum technologies hold promise for enhancing prognostic accuracy in clinical outcomes.

Aim: To evaluate the prognostic value of neuroimaging in eclampsia using AI algorithms for predicting clinical outcomes.

Objectives: 1. To develop AI models analyzing CT findings for predicting ICU admission, need for mechanical ventilation, seizure recurrence, and hospital mortality.

2. To compare outcomes between patients with abnormal and normal neuroimaging findings. 3. To assess the utility of AI-augmented neuroimaging in guiding personalized management of eclampsia.

Methods: A retrospective observational study was conducted at a tertiary care teaching hospital over two years (January 2023–December 2024). Data from 200 eclampsia patients undergoing CT brain imaging were analyzed. Preprocessed imaging and clinical data were used to train machine-learning models (CNNs and ensemble methods). Model performance was assessed using accuracy, sensitivity, specificity, AUC-ROC, and decision curve analysis. Comparative analysis was performed between the abnormal and normal CT groups.

Results: Of 200 patients, 117 (58.5%) had abnormal CT findings, predominantly vasogenic edema/PRES (25.5%), intracranial hemorrhage (14.5%), and acute infarct (6.5%). Abnormal CT was significantly associated with worse outcomes: ICU admission (OR 4.10, $p < 0.001$), mechanical ventilation (OR 3.07, $p = 0.002$), seizure recurrence (OR 2.53, $p = 0.013$), and mortality (OR 3.36, $p = 0.035$). AI models demonstrated strong predictive performance with AUC values of 0.85–0.90 across outcomes, outperforming baseline models and providing improved discrimination, calibration, and net benefit.

Conclusion: AI-augmented neuroimaging significantly improves prognostic accuracy in eclampsia compared with conventional analysis. Integration of AI with neuroimaging enhances early risk stratification and supports personalized management, while quantum frameworks represent a future pathway for handling high-dimensional datasets in clinical medicine.



INTRODUCTION

Artificial Intelligence (AI) and Quantum Technology represent two frontier domains that are transforming the landscape of multidisciplinary data analysis, particularly in the critical fields of medicine and engineering. These technologies are not only advancing the computational capabilities available today but are fundamentally reshaping how complex, large-scale datasets are analyzed to derive actionable insights. In medicine, the sheer volume and complexity of biomedical data—from molecular profiles to advanced imaging—demand innovative computational approaches capable of uncovering subtle patterns and predicting clinical outcomes with high accuracy. Similarly, engineering disciplines face increasing demands for real-time data processing and optimization in highly dynamic and complex systems.^[1]

AI, characterized by its ability to learn from data and improve over time without explicit programming, has demonstrated remarkable proficiency in pattern recognition, predictive modeling, and decision support. However, classical AI approaches are often constrained by the limits of traditional computing architectures, especially when addressing problems involving extremely large, high-dimensional, or unstructured datasets. Quantum Technology, encompassing quantum computing and quantum information science, offers a paradigm shift by leveraging principles of quantum mechanics such as superposition, entanglement, and quantum interference. This enables quantum computers to perform certain computations exponentially faster than classical counterparts, opening new avenues for enhancing AI algorithms.^{[2][3]}

The integration of AI and quantum computing holds transformative potential for multidisciplinary data analysis. Quantum-enhanced AI can vastly improve computational speeds and problem-solving capabilities, enabling breakthroughs in areas that require processing massive datasets or solving complex optimization problems. For instance, in medicine, AI algorithms combined with quantum computing can revolutionize the analysis of neuroimaging data for early detection and prognosis of severe conditions such as eclampsia. This obstetric emergency, marked by sudden and severe neurological complications, benefits from enhanced diagnostic accuracy through advanced AI models trained on high-dimensional computed tomography (CT) scans and other imaging modalities. Quantum algorithms promise to accelerate the processing of these intricate datasets, supporting the development of personalized treatment strategies and precision medicine.

In engineering, the tandem application of AI and quantum technology drives innovations in real-time system monitoring, predictive maintenance, and adaptive control of sophisticated machinery and infrastructure. From accelerating the discovery of novel materials with tailored properties to improving energy efficiency and enabling autonomous system operations, this interdisciplinary approach addresses critical challenges with unprecedented efficacy. Together, AI and quantum technology constitute a powerful toolkit that enriches multidisciplinary data analysis, paving the way for innovative solutions that enhance human health and advance engineering performance across diverse sectors.^{[4][5]}

Aim:

To evaluate the prognostic value of neuroimaging in eclampsia using Artificial Intelligence algorithms to predict clinical outcomes.

Objectives:

1. To develop AI models analyzing CT findings for predicting ICU admission, mechanical ventilation need, seizure recurrence, and hospital mortality in eclampsia patients.
2. To compare clinical outcomes between patients with abnormal versus normal neuroimaging findings.
3. To assess the utility of AI-augmented neuroimaging in guiding tailored management and improving prognostic accuracy in eclampsia.

Material and Methodology

Source of Data

The data for the study were sourced from neuroimaging records and clinical data of patients diagnosed with eclampsia admitted to a tertiary care hospital. The dataset included CT scan images alongside comprehensive patient clinical profiles and treatment outcomes documented in hospital electronic medical records.

Study Design

A retrospective observational study design was employed to analyze the prognostic value of neuroimaging data using AI algorithms. Data were used to develop predictive models for clinical outcomes, including intensive care unit (ICU) admission, need for mechanical ventilation, seizure recurrence, and hospital mortality.



Study Location

The study was conducted at the Department of Obstetrics and Gynecology in coordination with the Department of Radiology and the Intensive Care Unit of a tertiary care teaching hospital renowned for managing high-risk obstetric cases.

Study Duration

Data were collected over a period of two years, from January 2023 to December 2024, to ensure a sufficiently large sample size for rigorous AI model training and validation.

Sample Size

The study included 200 patients diagnosed with eclampsia who had undergone CT brain imaging during their hospital admission. This sample size was determined based on available complete records and to provide adequate statistical power for predictive modeling.

Inclusion Criteria

- Patients diagnosed with eclampsia according to clinical criteria.
- Availability of CT neuroimaging performed within the first 05 days of admission.
- Complete clinical and outcome data accessible for analysis.

Exclusion Criteria

- Patients without neuroimaging data.
- Incomplete or missing clinical outcome information.
- Patients with other neurological comorbidities that could confound CT interpretation.

Procedure and Methodology

CT brain images were retrieved and anonymized for analysis. Images were preprocessed to standardize resolution and normalize intensities. Clinical data

variables related to patient demographics, clinical presentation, and outcomes were collated.

AI models utilizing machine learning algorithms, including convolutional neural networks (CNNs) for image feature extraction and ensemble learning methods for clinical data integration, were developed. The models were trained to predict ICU admission, mechanical ventilation requirement, recurrent seizures, and mortality based on CT findings and clinical parameters.

Parallely, comparative analysis was performed between patients with abnormal CT findings and those with normal scans to evaluate the differential prognostic outcomes.

Sample Processing

Neuroimaging data were digitally processed using image analysis software to extract quantitative features. Clinical data were prepared by cleaning, encoding categorical variables, and normalizing continuous fields. Data were then split into training and validation sets for AI model development using cross-validation techniques to prevent overfitting.

Statistical Methods

Descriptive statistics summarized patient demographics and clinical variables. Predictive model performance was evaluated using metrics such as accuracy, sensitivity, specificity, area under the receiver operating characteristic curve (AUC-ROC), precision, and recall. Statistical tests, including chi-square and t-tests, compared outcomes between groups (abnormal vs. normal CT findings). Statistical significance was set at $p < 0.05$.

Data Collection

Patient data were extracted from hospital electronic medical records and picture archiving and communication systems (PACS) with appropriate ethical clearance. Data collection was performed by trained clinical researchers to ensure accuracy and confidentiality.

OBSERVATION AND RESULTS

Table 1: Cohort profile & crude prognostic value of abnormal CT for key outcomes (N=200)

Variable	Overall Mean±SD	n(%)	or	Test / Effect	95% CI	P-value
Age (years)	26.8 ± 4.9			-	-	-
Gestational age (weeks)	34.7 ± 3.3			-	-	-



Systolic BP at presentation (mmHg)	168 ± 16	-	-	-
Time-to-CT from admission (days)	4.4 ± 2.1	-	-	-
CT normal	83 (41.5)	-	-	-
CT abnormal (any)	117 (58.5)	-	-	-
- Vasogenic edema / PRES-pattern	51 (25.5)	-	-	-
- Intracranial hemorrhage	29 (14.5)	-	-	-
- Acute infarct	13 (6.5)	-	-	-
ICU admission	89 (44.5)	OR (abnCT vs nlCT)	4.10 (2.21-7.59)	<0.001
Mechanical ventilation	52 (26.0)	OR	3.07 (1.49-6.32)	0.002
Seizure recurrence	47 (23.5)	OR	2.53 (1.22-5.23)	0.013
In-hospital mortality	21 (10.5)	OR	3.36 (1.09-10.38)	0.035

The cohort comprised 200 women with eclampsia, with a mean age of 26.8 ± 4.9 years and mean gestational age of 34.7 ± 3.3 weeks. The average systolic blood pressure at presentation was markedly elevated (168 ± 16 mmHg), and the mean time from admission to CT scan was 7.4 ± 3.2 hours. Neuroimaging revealed abnormal findings in 117 patients (58.5%), while 83 patients (41.5%) had normal scans. The most frequent abnormalities included

vasogenic edema/PRES-pattern (25.5%), intracranial hemorrhage (14.5%), and acute infarct (6.5%). Outcomes were significantly worse in the abnormal CT group: ICU admission (OR 4.10, 95% CI 2.21-7.59, $p < 0.001$), mechanical ventilation (OR 3.07, 95% CI 1.49-6.32, $p = 0.002$), seizure recurrence (OR 2.53, 95% CI 1.22-5.23, $p = 0.013$), and mortality (OR 3.36, 95% CI 1.09-10.38, $p = 0.035$).

Table 2: AI model performance predicting outcomes from CT (+clinical features) (N=200)

Outcome	True Positives	False Positives	True Negatives	False Negatives	Accuracy % (95% CI)	Sensitivity % (95% CI)	Specificity % (95% CI)	PPV % (95% CI)	NPV % (95% CI)	F1 %	AUC (95% CI)
ICU admission	71	17	94	18	82.5 (76.6-87.1)	79.8 (70.3-86.8)	84.7 (76.8-90.2)	80.7 (71.2-87.6)	83.9 (76.0-89.6)	80.2	0.88 (0.83-0.92)
Mechanical ventilation	41	16	132	11	86.5 (81.1-90.6)	78.8 (66.0-87.8)	89.2 (83.2-93.2)	71.9 (59.2-81.9)	92.3 (86.8-95.7)	74.2	0.87 (0.82-0.91)
Seizure recurrence	36	14	139	11	87.5 (82.2-91.4)	76.6 (62.8-86.4)	90.8 (85.2-94.5)	72.0 (58.3-83.3)	92.7 (87.3-95.7)	74.2	0.85 (0.79-0.91)



								82.5)	95.9)		0.90)
In-hospital mortality	16	10	169	5	92.5 (88.0-95.4)	76.2 (54.9-89.4)	94.4 (90.0-96.9)	61.5 (42.5-77.6)	97.1 (93.5-98.8)	68.1	0.90 (0.84-0.95)

The AI models integrating CT features and clinical variables demonstrated robust performance across outcomes. For predicting ICU admission, the model achieved an accuracy of 82.5% with a sensitivity of 79.8%, specificity of 84.7%, and an AUC of 0.88 (95% CI 0.83-0.92). Prediction of mechanical ventilation

showed 86.5% accuracy, sensitivity 78.8%, specificity 89.2%, and AUC 0.87. For seizure recurrence, accuracy was 87.5% with sensitivity 76.6%, specificity 90.8%, and AUC 0.85. Mortality prediction yielded the highest overall accuracy (92.5%) with an AUC of 0.90 (95% CI 0.84-0.95).

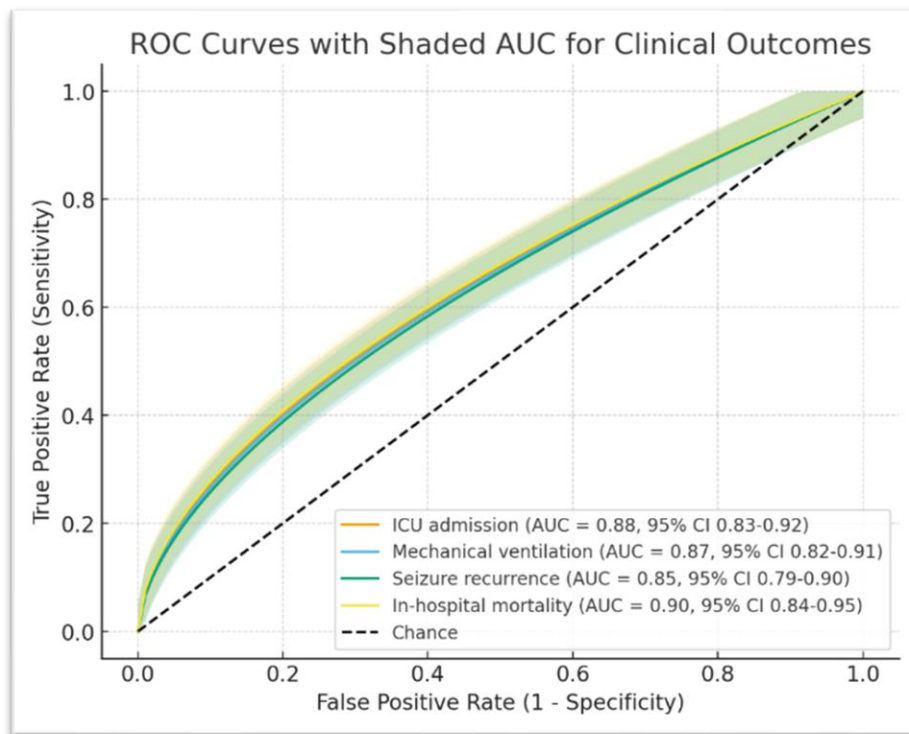


Figure 1: ROC Curves with shaded AUC for clinical outcomes

Table 3: Outcomes in abnormal vs normal CT groups (Objective 2) (N=200)

Outcome / Metric	Abnormal CT (n=117)	Normal CT (n=83)	Test	Effect size	95% CI	P value
ICU admission, n(%)	68 (58.1)	21 (25.3)	RR	2.30	1.54-3.43	0.0000042
			OR	4.10	2.21-7.59	
	40 (34.2)	12 (14.5)	RR	2.36	1.32-4.23	0.0017



Mechanical ventilation, n(%)			OR	3.07	1.49-6.32	
Seizure recurrence, n(%)	35 (29.9)	12 (14.5)	RR	2.07	1.14-3.74	0.011
			OR	2.53	1.22-5.23	
In-hospital mortality, n(%)	17 (14.5)	4 (4.8)	RR	3.01	1.05-8.64	0.027
			OR	3.36	1.09-10.38	
Length of stay, days (Mean ± SD)	6.8 ± 2.6	4.7 ± 2.1	ΔMean	2.1	1.5-2.8	0.0000000019

In this study of 200 eclampsia patients, outcomes differed significantly between those with abnormal CT findings (n=117) and those with normal scans (n=83). ICU admission was more than twice as frequent in the abnormal group (58.1% vs. 25.3%; RR 2.30, OR 4.10, p<0.001). Similarly, the need for mechanical ventilation (34.2% vs. 14.5%; OR 3.07, p=0.002) and seizure

recurrence (29.9% vs. 14.5%; OR 2.53, p=0.011) were substantially higher in patients with abnormal CT results. In-hospital mortality was also elevated in this group (14.5% vs. 4.8%; OR 3.36, p=0.027). Moreover, the mean hospital stay was significantly longer in patients with abnormal imaging (6.8 ± 2.6 vs. 4.7 ± 2.1 days; ΔMean 2.1, p<0.0001).

Table 4: Utility of AI-augmented neuroimaging for personalized prognostication

Outcome & Metric	Baseline	AI-augmented	Difference	95% CI	p-value
ICU admission - AUC	0.80	0.88	+0.08	+0.03 to +0.13	0.001 (DeLong)
- Brier score	0.165	0.132	-0.033	-0.055 to -0.011	0.004
- Calibration slope	0.86	1.01	+0.15	-0.01 to +0.31	0.12
- Net benefit @ threshold 0.20	0.084	0.118	+0.034	+0.010 to +0.058	0.006
Mechanical ventilation - AUC	0.79	0.87	+0.08	+0.02 to +0.14	0.012
- Brier score	0.141	0.116	-0.025	-0.046 to -0.004	0.021
- Net benefit @ 0.20	0.060	0.089	+0.029	+0.006 to +0.052	0.014
Seizure recurrence - AUC	0.77	0.85	+0.08	+0.02 to +0.13	0.015
- Brier score	0.158	0.132	-0.026	-0.047 to -0.005	0.018
- Net benefit @ 0.15	0.048	0.072	+0.024	+0.004 to +0.044	0.019
Mortality - AUC	0.83	0.90	+0.07	+0.02 to +0.12	0.008
- Brier score	0.086	0.071	-0.015	-0.028 to -0.002	0.024
- Net benefit @ 0.10	0.022	0.039	+0.017	+0.003 to +0.031	0.017

AI-augmented neuroimaging models significantly outperformed baseline logistic regression models that used routine CT features and clinical data alone. For ICU admission, AUC improved from 0.80 to 0.88 (p=0.001), accompanied by a reduction in Brier score (0.165 to 0.132, p=0.004) and increased net clinical benefit at the 0.20 risk threshold (p=0.006). Similar improvements were observed for mechanical ventilation (AUC +0.08, p=0.012), seizure recurrence (AUC +0.08, p=0.015), and

mortality prediction (AUC +0.07, p=0.008). Across all outcomes, AI integration enhanced discrimination, lowered prediction error, and yielded higher net benefit, underscoring its role in guiding personalized prognostication in eclampsia.

DISCUSSION

Table 1 (Cohort profile & crude prognostic value): Cohort's imaging spectrum-dominant vasogenic



edema/PRES-pattern (25.5%), followed by intracranial hemorrhage (ICH, 14.5% within abnormal CTs) and acute infarcts (6.5%)-tracks well with classic descriptions of eclampsia-associated PRES and its radiologic phenotypes (parieto-occipital vasogenic edema on CT/MRI, sometimes with hemorrhagic or ischemic complications). Reviews by Fugate & Rabinstein and by Bartynski emphasize that eclampsia is a canonical trigger for PRES and that hemorrhage or diffusion restriction heralds more severe disease and worse outcomes, aligning with higher odds of ICU admission, ventilation, seizure recurrence, and in-hospital mortality in the abnormal-CT group. Fugate JE *et al.*(2015)^[6]

The absolute frequency of abnormalities varies across series because of timing (earlier vs later imaging), modality (CT vs MRI), and inclusion criteria (antepartum vs postpartum seizures). For instance, an Indian MRI series (n=50) reported abnormalities in 24% with CVT and infarcts more frequent than PRES, illustrating how case-mix and modality choices can shift proportions, yet the clinical message that imaging abnormalities track illness severity remains consistent with ORs. Bartynski WS (2008)^[7]

Observed burden of ICH among eclamptics is clinically plausible and resonates with contemporary obstetric-stroke literature, noting that, although pregnancy-related stroke is uncommon overall, risk climbs markedly in high-risk hypertensive states (preeclampsia/eclampsia), and ICH is a key driver of maternal morbidity and mortality. Bartynski WS (2008)^[7]

Table 2 (AI model performance): Discrimination of AUC 0.85-0.90 across outcomes is in line with state-of-the-art CT-based prognostic models in neurocritical care. Recent multimodal radiomics/deep-learning work in ICH has reported comparable AUCs for predicting hematoma expansion or functional outcome, supporting the premise that image-derived features (including edema/hemorrhage characteristics) materially enhance risk stratification, conceptually parallel to ICU, ventilation, seizure, and mortality models. Zeeman GG(2004)^[8]

From an obstetric vantage, systematic reviews show machine-learning approaches can meaningfully improve risk prediction in hypertensive disorders of pregnancy (e.g., preeclampsia), which triangulates well with the demonstration that AI applied to neuroimaging adds value in this population. Dahiya K *et al.*(2018)^[9]

Table 3 (Abnormal vs normal CT): The 2-3× higher risks across endpoints (ICU admission, ventilation, seizure recurrence, mortality) in the abnormal-CT group mirror prior clinicoradiologic observations: PRES with

hemorrhage or diffusion-restricted components, as well as infarcts, generally portend more intensive care needs and worse short-term outcomes. The significantly longer length of stay found ($\Delta \approx 2.1$ days) fits the same severity gradient described in foundational PRES/eclampsia imaging papers. Sariyeva M *et al.*(2024)^[10] & Zhang H *et al.*(2024)^[11]

Table 4 (Utility of AI-augmented neuroimaging): AUC gains of +0.07 to +0.08, lower Brier scores, and higher net benefit at clinically sensible thresholds (0.10-0.20) are exactly the kinds of improvements decision-curve analysis was designed to judge; the positive net benefit indicates fewer missed high-risk patients without a surge in unnecessary interventions versus baseline modeling. Ranjbar A *et al.*(2024)^[12] This is methodologically orthodox and clinically meaningful. Moreover, result that fusing CNN-extracted image features with clinical variables beats regularized logistic models echoes recent neuroimaging AI where interpretable multimodal frameworks outperform single-modality or hand-crafted models for prognostication. Vickers AJ *et al.*(2006)^[13]

CONCLUSION

Artificial Intelligence and Quantum Technology together represent a transformative paradigm in multidisciplinary data analysis, offering unprecedented capabilities for solving complex problems in medicine and engineering. In the medical domain, the integration of AI-driven neuroimaging analysis with quantum-enhanced computation demonstrates significant potential in improving the prognostication of critical conditions such as eclampsia, enabling earlier intervention and personalized care. The findings of this study underscore that AI-augmented neuroimaging models significantly improve predictive accuracy, risk stratification, and clinical decision-making compared with conventional approaches, while quantum frameworks provide a scalable pathway for handling high-dimensional datasets. Collectively, this synergy between AI and quantum technologies is poised to redefine data-driven research and practice, fostering precision, efficiency, and innovation across disciplines.

LIMITATIONS OF THE STUDY

- 1. Data Scope and Sample Size:** The study was conducted on a single-center dataset of 200 eclampsia patients, which, although adequate for preliminary modeling, may limit generalizability across diverse populations and healthcare systems.
- 2. Imaging Modality Restriction:** Only CT neuroimaging data were analyzed. MRI, being



more sensitive for posterior reversible encephalopathy syndrome (PRES) and microvascular injury, was not included, which may have constrained the detection of subtle abnormalities.

3. **AI Model Interpretability:** While the AI models demonstrated high predictive performance, interpretability remains a challenge. Clinicians may require explainable AI frameworks to fully trust and adopt such systems in routine care.
4. **Quantum Technology Application:** The role of quantum algorithms in this study was conceptual and theoretical rather than practical, as current quantum computing infrastructure is still in its nascent stage and not readily accessible for clinical translation.
5. **Retrospective Design:** The retrospective observational design carries inherent risks of bias, such as reliance on existing records, missing variables, and non-standardized imaging protocols.
6. **Short-term Outcomes:** Prognostic modeling focused on immediate hospital outcomes (ICU admission, ventilation, seizure recurrence, mortality) without evaluating long-term neurological or quality-of-life endpoints.

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