SAS Journal of Medicine
Abbreviated Key Title: SAS J Med
ISSN 2454-5112
Journal homepage: https://saspublishers.com

OPEN ACCESS

Gastroenterology

The Role of Artificial Intelligence in Predicting Mortality in Patients with Variceal Gastrointestinal Bleeding: A Retrospective Study

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DOI: https://doi.org/10.36347/sasjm.2026.v12i08.005 | **Received:** 09.06.2026 | **Accepted:** 01.08.2026 | **Published:** 04.08.2026

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Abstract **Original Research Article**

Introduction: Variceal gastrointestinal bleeding is a severe complication of portal hypertension with high in hospital mortality, ***Objective:*** To develop and validate an artificial intelligence (AI) model to predict in-hospital mortality in patients admitted for variceal gastrointestinal bleeding associated with portal hypertension (PH). ***Methods:*** A single-center retrospective study was conducted between 2022 and 2025 on 100 patients with cirrhosis. A supervised learning algorithm of the Random Forest type was trained (90% training, 10% testing) using Python (Pandas, Scikit-learn). To compensate for the small sample size, k-fold cross-validation was applied. ***Results:*** Overall mortality was 22%. The model demonstrated an area under the ROC curve (AUC) of 0.756, a sensitivity of 70%, and a specificity of 66% (overall accuracy: 66%). On the test sample, accuracy reached 80% (specificity of 100%), outperforming the Glasgow-Blatchford and Rockall scores, which are particularly limited by their low variability. The critical variables identified are MELD-Na, creatinine, and the Child-Pugh score. ***Conclusion:*** Artificial intelligence enables superior prognostic stratification compared to nonspecific scores. This exploratory model must now undergo multicenter external validation to confirm its role as a clinical decision-support tool.

Keywords: Artificial intelligence, machine learning, variceal bleeding, mortality prediction, portal hypertension.

INTRODUCTION

Upper gastrointestinal bleeding is a major medical and surgical emergency. Among cases of this condition, variceal bleeding associated with portal hypertension (PH) in patients with cirrhosis is associated with particularly high morbidity and mortality rates, estimated at between 15 and 20% during the first episode [1, 2]. The treatment protocol, strictly guided by the international Baveno VII consensus, is based on a combined strategy that includes immediate hemodynamic stabilization, early administration of medications to reduce portal pressure, systematic prevention of infections, and endoscopic intervention to stop the bleeding [1, 3].

Despite standardized treatment, the clinical course remains difficult to predict. The Child-Pugh and MELD scores, which are essential for assessing the severity of hepatocellular failure, lack accuracy during the acute phase of hemorrhage [4]. These scores are limited by their inability to capture the pathophysiological complexity resulting from the interplay between biological variables and the state of shock.

Artificial intelligence, through machine learning (ML), makes it possible to overcome the limitations of traditional linear statistical models [6]. Random Forest-type algorithms are capable of capturing complex nonlinear relationships, providing personalized risk stratification tailored to the massive amounts of data derived from electronic health records [5, 8].

The goal of this study is to develop and validate an AI model capable of predicting in-hospital mortality following variceal bleeding, in order to optimize triage and the level of care provided.

MATERIALS AND METHODS

1. **Study Framework:** This is a single-center retrospective study conducted in the Department of Hepatology and Gastroenterology at University hospital Mohamed VI of Tangier in Morocco, from 2022 to 2025.

2. Inclusion and Exclusion Criteria:

Inclusion: Cirrhosis with documented portal hypertension, admission for variceal bleeding (confirmed by endoscopy), complete medical record.

Exclusion: Non-variceal bleeding (ulcers, tumors), missing data, early transfers with unknown outcome.

3. Collected Variables:

Demographic: Age, sex.

Clinical: Blood pressure, hepatic encephalopathy, hepatorenal syndrome.

Laboratory: Hemoglobin, platelets, urea, creatinine, bilirubin.

Scores and Treatment: Child-Pugh, MELD-Na, number of red blood cell (RBC) units transfused.

4. Development_of the AI Model: The model was developed using Python (Pandas, Scikit-learn). The Random Forest algorithm was selected for its robustness against overfitting. The data was split into a 90% training set and a 10% test set. To optimize generalization on this sample of n=100, k-fold cross-validation was used.

5. Statistical Analysis: The clinical data were analyzed using SPSS. Predictive performance was quantified using sensitivity, specificity, accuracy, and the area under the ROC curve (AUC-ROC).

RESULTS

1. Description of the Population: The mean age was 58 ± 13 years (63% were male). At admission, 22% of patients had hypotension and 15% had encephalopathy. The in-hospital mortality rate was 22%.

2. Clinical and Biological Comparison: Table 1 highlights significant differences, particularly in renal function and bilirubin levels.

Table 1: Comparison of parameters between survivors and non-survivors

Parameter	Mortality Group (n=22)	Survivor Group (n=78)
Platelets (G/L)	41.8 ± 26.6	130.1 ± 68.1
Hemoglobin (g/dl)	5.0 ± 1.0	6.97 ± 1.27
Child-Pugh Score	10 ± 3	6 ± 2
MELD-Na	21 ± 5	14 ± 4
Transfusions (PRBC)	3 ± 1	0.8 ± 1
Urea (g/L)	1.0 ± 1.0	0.38 ± 0.26
Creatinine (mg/L)	18 ± 11	9 ± 6
Bilirubin (mg/L)	46 ± 40	23 ± 51

3. AI Model Performance: The overall model has an AUC of 0.756, a sensitivity of 70%, and a specificity of 66%. The variable importance analysis identifies, in descending order: MELD-Na, creatinine, the Child-Pugh score, RBC transfusion, and hemoglobin.

4. Comparative Analysis (Test Sample): On the test sample (n=10), the model achieved an accuracy of 80% and a specificity of 100%.

Table 3: Comparison of AI vs. GBS (0 = survival, 1 = death)

Patient	Glasgow-Blatchford (GBS)	AI (Prediction)	Actual mortality
1	2	0	0
2	7	0	0
3	4	0	0
4	1	0	0
5	8	0	0
6	8	0	1
7	15	1	1
8	9	0	1
9	19	1	1
10	10	1	1

The Rockall score showed virtually no variability, rendering it ineffective for individual stratification

Table 4: Comparison of IA and Rockall. The concentration of scores at 3 (80%) limits any discriminatory power

Patient	Rockall (post-endoscopy)	AI (Prediction)	Actual mortality
1 to 10	3 (pour 8/10 patients)	See Table 3	See Table 3

DISCUSSION

The profile of patients included in our cohort (mean age of 58 years, 63% men) is generally consistent with that typically described in variceal gastrointestinal bleeding associated with advanced cirrhosis, where the higher proportion of men is explained by increased exposure to the primary causes and more rapid hepatic decompensation [11].

Our results demonstrate that mortality is not solely determined by the hemorrhagic episode itself, but fundamentally depends on the collapse of overall physiological reserve: marked thrombocytopenia reflecting hypersplenism due to severe portal hypertension, profound anemia correlated with a massive need for red blood cell concentrates, a marked deterioration in Child-Pugh and MELD-Na scores, as well as predominant renal impairment (elevated urea and creatinine) induced by hypovolemia and systemic circulatory dysfunction [12].

To capture this complex pathophysiological triad (liver reserve, renal function, and hemodynamic tolerance), the Random Forest model demonstrated moderate predictive performance consistent with recent literature (AUC = 0,756, sensitivity 70%, specificity 66%), deriving its inherent superiority from its ability to model complex nonlinear interactions between routine variables (MELD-Na, creatinine, Child-Pugh score, hemoglobin, and transfusions) where traditional statistical models fail [9,10].

This algorithmic approach overcomes the structural limitations of conventional scores, such as the Rockall score whose homogeneity (80% of scores equal to 3) negates any discriminatory power or the Glasgow-Blatchford Score (GBS), which overemphasizes immediate hemodynamics without assessing liver function, and thus fails to stratify ambiguous "gray zone" profiles at risk of sudden decompensation.

By offering personalized and early stratification to guide emergency triage (Intensive Care, TIPS), this innovative approach opens the way for future hybrid models, combining the simplicity of standard scores with the predictive power of AI, although the study's retrospective and single-center design, combined with the small size of the overall sample and the test set (n=10) which exposes the study to the risk of overfitting makes prospective, multicenter external validation essential before any integration into clinical decision support systems.

CONCLUSION

Artificial intelligence offers a promising prognostic stratification method, outperforming conventional scores thanks to its multidimensional approach. It does not replace clinical judgment but serves as a critical "second opinion" to identify high-risk patients upon admission. Transforming this model into a routine tool requires prospective, multicenter validation.

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