



Artificial Intelligence for Management of Esophagogastric Varices: Applications in Screening, Diagnosis, and Risk Prediction

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Abstract

Esophagogastric varices (EGV) represent a major complication of liver cirrhosis, with variceal hemorrhage constituting a life-threatening event in patients with clinically significant portal hypertension. Early identification of high-risk varices is critical, and esophagogastroduodenoscopy remains the gold standard for diagnosis and hemorrhage risk stratification. However, routine endoscopic screening results in numerous unnecessary procedures, highlighting the need for effective non-invasive tools. Furthermore, objective methods are needed to accurately classify variceal severity and predict bleeding risk, enabling optimized treatment strategies and personalized care. The rapid advancement of artificial intelligence (AI) has generated growing interest in its application to EGV management. This review synthesizes current AI-based screening models for EGV, examines AI applications in non-invasive and endoscopic diagnostic approaches, and evaluates its potential in predicting variceal bleeding risk. Overall, we critically point out key limitations and outline future directions for developing AI tools that augment human expertise in EGV management.

Keywords: Artificial intelligence; Esophagogastric varices; Machine learning; Deep learning; Variceal bleeding

Abbreviations: EGV: Esophagogastric Varices; EGD: Esophagogastroduodenoscopy; HVPG: Hepatic Venous Pressure Gradient; AI: Artificial Intelligence; ML: Machine Learning; DL: Deep Learning

Introduction

Portal hypertension, a critical pathophysiological consequence of liver cirrhosis, leads to life-threatening complications including variceal hemorrhage, ascites, and hepatic encephalopathy [1]. Esophagogastric varices (EGV) represent one of the most prevalent and lethal manifestations, present in 40–60% of patients with compensated advanced chronic liver disease and up to 85% of those with decompensated cirrhosis [2,3]. Despite therapeutic advances, variceal hemorrhage remains catastrophic, with six-week mortality rates of 15%–25% [2,4], underscoring the critical importance of early identification and risk stratification. Esophagogastroduodenoscopy (EGD) remains the gold standard for EGV diagnosis and bleeding risk assessment. Current guidelines recommend screening endoscopy at cirrhosis diagnosis, with surveillance intervals determined by initial findings [5]. However, this universal screening paradigm faces significant challenges: approximately 50%–60% of endoscopies reveal no high-risk features, representing substantial procedural overutilization [6].

Besides, endoscopic grading exhibits considerable inter-observer variability, and bleeding risk prediction remains imprecise. Hepatic venous pressure gradient (HVPG) measurement, though accurate for detecting clinically significant portal hypertension (≥ 10 mmHg), is invasive and available only in specialized centers [7–10].

These limitations highlight the urgent need for non-invasive screening tools, objective diagnostic methods, and personalized risk prediction models to optimize EGV management. Artificial intelligence (AI), encompassing machine learning (ML) and deep learning (DL), has demonstrated remarkable potential in medical image analysis and clinical decision support. ML algorithms excel at identifying complex patterns in structured clinical data, while DL models, particularly convolutional neural networks (CNNs), have achieved expert-level performance in image recognition tasks. In the context of EGV management, AI offers several advantages: (1) development of non-invasive screening models to

reduce unnecessary endoscopies; (2) automated detection and grading of varices from endoscopic images to minimize inter-observer variability; (3) integration of multimodal data for personalized bleeding risk prediction; and (4) real-time decision support during endoscopic procedures. Here, we synthesize current evidence on AI applications across the EGV management pathway—from screening and diagnosis to risk prediction—critically evaluate their clinical performance and potential impact, and discuss key challenges and future directions for translating these technol-

ogies into routine practice.

AI in Esophageal and Gastric Varices

AI applications in EGV management can be categorized into three clinical domains: non-invasive screening to reduce unnecessary endoscopies, automated diagnostic systems to improve grading consistency, and prognostic models to predict bleeding risk and guide treatment. Table 1 summarizes representative studies in each domain [11-24].

Table 1: Overview of Artificial Intelligence Applications in the Management of Esophageal Varices in Cirrhosis

Study	Algorithm	Training Cohort	Validation Cohort	Test Cohort	Key Features	Performance
Screening Models						
Dong et al. [11]	RF	multi-center (n=238)	multi-center (n=109)	/	INR, AST, PLT, UN, Hb, ascites	reduced 30.5% EGDs with 2.8% VNT missed
Huang et al. [12]	LightGBM	multi-center (n=1154)	multi-center (n=129)	multi-center (n=1511)	LSM, PLT, TBIL	reduced 41.1-58.1% EGDs
Reiniš et al. [13]	LR, MLP, RF, SVM, XGBoost, Lasso	multi-center (n=163)	multi-center (n=1232)	/	PLT, TBIL, APTT, GGT, CHE	AUC 0.813 for CSPH; AUC 0.887 for severe PH
Bayani et al. [14]	Catboost, XGBoost	single-center (n=490)	/	/	Child-Pugh score, WBC, vitamin K, INR, MCV	accuracy 100% for EV grade prediction
Dong et al. [15]	LR, XGBoost	multi-center (n=268)	multi-center (n=200)	multi-center (n=34)	FIB-4 index, LSM, SSM	AUC 0.927 (training); AUC 0.919, 0.902 (validation)
Diagnosis Models						
Yan et al. [16]	SVM	single-center (n=391)	single-center (n=405)	/	contrast-enhanced abdominal CT features	AUC 0.736 (outperformed Baveno VI)
Yan et al. [17]	LR, LDA, SVM, et al.	single-center (n=155)	/	multi-center (n=78)	radiomics features from spleen CT images	AUC 0.85 for high-risk esophageal varices
Wang et al. [18]	FCN, DCNN	multi-center (n=1020)	multi-center (n=136)	single-center (n=161)	endoscopic features	12.31% improvement in appropriate intervention
Prediction Models						
Agarwal et al. [19]	XGBoost	single-center (n=497)	single-center (n=331)	/	demographic data, laboratory parameters, LSM	accuracy 85.7-98.7% for variceal bleeding prediction
Wang et al. [20]	DL, XGBoost, GLM, et al.	single-center (n=275)	single-center (n=66)	single-center (n=161)	endoscopic images, clinical structured data	accuracy 93.2%; sensitivity 95.2% (12-month EGVb)
Hou et al. [21]	ANN	single-center (n=999)	single-center (n=101)	/	demographic data, laboratory parameters	AUC 0.959 for 1-year EGVb risk prediction
Gao et al. [22]	FCN, MLP, LR, et al.	multi-center (n=169)	multi-center (n=71)	single-center (n=90)	106 radiomics features of liver and spleen	AUC 0.782-0.789 (outperformed clinical scores)
Wan et al. [23]	ViT network, RL	multi-center (n=126)	multi-center (n=58)	/	CTA and clinical data	AUC 0.985 for FVH prediction
Zheng et al. [24]	HGB, MLP, RF, SVM, XGB	single-center (n=107)	multi-center (n=149)	/	Hb, PVT, superior mesenteric vein diameter, PLT, minimum shunt diameter, splenic vein diameter	AUC 0.814 (internal validation); AUC 0.776 (external validation)

Table Abbreviations: RF: random forest; LightGBM: light gradient-boosting machine; LR: logistic regression; MLP: multilayer perceptron; SVM: support vector machine; XGBoost: eXtreme Gradient Boosting; LDA: linear discriminant analysis; FCN: fully convolutional network; DCNN: deep convolutional neural network; DL: deep learning; GLM: general linear model; ANN: artificial neural network; ViT: Vision Transformer, RL: reinforcement learning; HGB: hierarchical gradient boosting; INR: international normalized ratio; AST: aspartate aminotransferase; PLT: platelet counts; UA: urea nitrogen; Hb: hemoglobin; LSM: liver stiffness measurement; TBIL: total bilirubin; APTT: activated partial thromboplastin time; GGT: gamma-glutamyl transferase; CHE: serum cholinesterase; WBC: white blood cell; MCV: mean corpuscular volume; PVT: portal vein thrombosis; EGD: esophagogastroduodenoscopy; VNT: varices needed treatment; CSPH: clinically significant portal hypertension; EGVb: esophagogastric variceal bleeding; FVH: first variceal hemorrhage; SVD: splenic vein diameter

Non-invasive Screening for High-Risk Varices

Routine endoscopic screening of all cirrhotic patients is resource-intensive and often yields negative findings. ML-based screening models offer a promising solution by stratifying patients according to their likelihood of having high-risk varices, thereby reducing unnecessary endoscopies while maintaining diagnostic sensitivity. These models typically leverage readily available clinical parameters including demographic data, routine laboratory values, and non-invasive assessments of liver fibrosis and portal hypertension. Ensemble learning methods have demonstrated superior performance compared to traditional risk scores, with multi-center validations confirming their robustness across diverse patient populations.

AI-Enhanced Diagnosis of EGV

DL models applied to cross-sectional imaging and ultrasound provide non-invasive alternatives for EGV detection and severity grading. CNN-based systems can analyze CT scans to identify varices and assess bleeding risk, while radiomics approaches extract quantitative imaging features that correlate with portal pressure measurements. Ultrasound-based AI models show promise for point-of-care screening, though standardization of image acquisition protocols remains essential for consistent performance. Beyond non-invasive imaging, AI-assisted endoscopy addresses the significant inter-observer variability in variceal assessment during direct visualization. Real-time CNN models can detect varices, classify their severity according to established grading systems, and identify high-risk stigmata such as red color signs. These systems achieve expert-level diagnostic accuracy while processing images at speeds compatible with clinical workflow, enabling immediate decision support during procedures. AI models also demonstrate ability to detect subtle findings that may be overlooked by less experienced endoscopists.

Prognostic Assessment in Variceal Hemorrhage Management

Accurate prediction of variceal bleeding enables personalized prophylaxis strategies and optimal resource allocation. Traditional clinical scoring systems have limited predictive accuracy, prompting development of ML models that integrate multi-modal data including clinical parameters, laboratory values, endoscopic findings, and imaging features. These models demonstrate superior discriminative ability for predicting both first bleeding episodes and rebleeding events. Advanced approaches incorporating time-varying covariates and survival analysis methods enable dynamic risk assessment over extended follow-up periods. Feature importance analyses have identified novel risk factors beyond conventional predictors, potentially revealing new insights into bleeding pathophysiology. For secondary prophylaxis, predictive models may guide clinical decisions regarding endoscopic surveillance intervals and timing of interventional procedures.

Limitations and Future Direction

Several barriers impede clinical translation of AI in EGV management. Model heterogeneity with disparate input features creates diagnostic inconsistency [11,14,19,25], while deep learning's "black box" nature undermines clinician trust [26]. Methodological weaknesses constrain generalizability: small, single-center datasets cause overfitting [25,27], etiological imbalances limit global applicability [12], and retrospective designs introduce selection bias. Additionally, AI cannot replicate patient-centered decision-making, and legal ambiguity necessitates regulatory frameworks [25]. Addressing these challenges requires prospective, multicenter trials with diverse populations. Integration of explainable AI and multimodal data fusion will enable comprehensive risk stratification. Successful implementation depends on developing tools that enhance rather than replace human expertise, ensuring AI augments clinical judgment in EGV management.

Conclusion

Artificial intelligence has demonstrated significant potential across the clinical pathway of esophagogastric variceal management. Machine learning models enable non-invasive screening to identify low-risk patients, reducing unnecessary endoscopies and healthcare costs. AI-assisted systems show robust performance in variceal detection and classification through advanced image analysis, while prognostic models enhance bleeding risk stratification. These advances support an integrated AI framework spanning screening, diagnosis, and therapeutic decision-making. However, clinical implementation requires prospective multicenter validation and development of explainable, multimodal systems that augment rather than replace clinical expertise in EGV management.

References

1. Qi X, Berzigotti A, Cardenas A, Sarin SK (2018) Emerging non-invasive approaches for diagnosis and monitoring of portal hypertension. *The Lancet. Gastroenterology & Hepatology* 3(10): 708-719.
2. De Franchis R, Bosch J, Garcia-Tsao G, Reiberger T, Ripoll C (2022) Baveno VII - Renewing consensus in portal hypertension. *J Hepatol* 76(4): 959-974.
3. Lv Y, Yang Z, Liu L, Li K, He C, et al. (2019) Early TIPS with covered stents versus standard treatment for acute variceal bleeding in patients with advanced cirrhosis: a randomised controlled trial. *The Lancet. Gastroenterology & Hepatology* 4(8): 587-598.
4. Garcia-Tsao G, Abraldes JG, Berzigotti A, Bosch J (2017) Portal hypertensive bleeding in cirrhosis: Risk stratification, diagnosis, and management: 2016 practice guidance by the American Association for the study of liver diseases. *Hepatology* (Baltimore, Md.) 65(1): 310-335.
5. (2018) EASL Clinical Practice Guidelines for the management of patients with decompensated cirrhosis. *J Hepatol* 69(2): 406-460.
6. Augustin S, Pons M, Maurice JB, Bureau C, Stefanescu H, et al. (2017) Expanding the Baveno VI criteria for the screening of varices in patients with compensated advanced chronic liver disease. *Hepatology* (Baltimore, Md.) 66(6): 1980-1988.

7. Abraldes JG, Bureau C, Stefanescu H, Augustin S, Ney M, et al. (2016) Noninvasive tools and risk of clinically significant portal hypertension and varices in compensated cirrhosis: The "Anticipate" study. *Hepatology* (Baltimore, Md.) 64(6): 2173-2184.
8. Bosch J, Abraldes JG, Berzigotti A, García-Pagan JC (2009) The clinical use of HVPG measurements in chronic liver disease. *Nat Rev Gastroenterol Hepatol* 6(10): 573-582.
9. Ramakrishnan R, Kuang K, Rajput V, Benson M, Mohan S (2024) Esophageal varices detection and bleeding risk assessment with artificial intelligence: a systematic review. *iGIE* 3(4): 478-486.
10. Wang QC, Jiao J, Zhang CQ (2025) Application of artificial intelligence in portal hypertension and esophagogastric varices. *World J Gastroenterol* 31(24): 108508.
11. Dong TS, Kalani A, Aby ES, Le L, Luu K, et al. (2019) Machine Learning-based Development and Validation of a Scoring System for Screening High-Risk Esophageal Varices. *Clinical Gastroenterology and Hepatology : the Official Clinical Practice Journal of the American Gastroenterological Association* 17(9).
12. Huang Y, Li J, Zheng T, Ji D, Wong YJ, et al. (2023) Development and validation of a machine learning-based model for varices screening in compensated cirrhosis (CHESS2001): an international multicenter study. *Gastrointest Endosc* 97(3).
13. Reiniš J, Petrenko O, Simbrunner B, Hofer BS, Schepis F, et al. (2023) Assessment of portal hypertension severity using machine learning models in patients with compensated cirrhosis. *J Hepatol* 78(2): 390-400.
14. Bayani A, Hosseini A, Asadi F, Hatami B, Kavousi K, et al. (2022) Identifying predictors of varices grading in patients with cirrhosis using ensemble learning. *Clin Chem Lab Med* 60(12): 1938-1945.
15. Dong B, He R, Ju S, Chen Y, Grgurevic I, et al. (2025) Fibrosis-4plus score: a novel machine learning-based tool for screening high-risk varices in compensated cirrhosis (CHESS2004): an international multicenter study. *Clin Mol Hepatol* 31(3): 881-898.
16. Yan Y, Li Y, Fan C, Zhang Y, Zhang S, et al. (2022) A novel machine learning-based radiomic model for diagnosing high bleeding risk esophageal varices in cirrhotic patients. *Hepatol Int* 16(2): 423-432.
17. Yan C, Li M, Liu C, Zhang Z, Zhang J, et al. (2024) Development of a non-invasive diagnostic model for high-risk esophageal varices based on radiomics of spleen CT. *Abdom Radiol (NY)* 49(12): 4373-4382.
18. Wang J, Wang Z, Chen M, Xiao Y, Chen S, et al. (2022) An interpretable artificial intelligence system for detecting risk factors of gastroesophageal variceal bleeding. *NPJ Digital Medicine* 5(1): 183.
19. Agarwal S, Sharma S, Kumar M, Venishetty S, Bhardwaj A, et al. (2021) Development of a machine learning model to predict bleed in esophageal varices in compensated advanced chronic liver disease: A proof of concept. *J Gastroenterol Hepatol* 36(10): 2935-2942.
20. Wang Y, Hong Y, Wang Y, Zhou X, Gao X, et al. (2023) Automated Multimodal Machine Learning for Esophageal Variceal Bleeding Prediction Based on Endoscopy and Structured Data. *J Digit Imaging* 36(1): 326-338.
21. Hou Y, Yu H, Zhang Q, Yang Y, Liu X, et al. (2023) Machine learning-based model for predicting the esophagogastric variceal bleeding risk in liver cirrhosis patients. *Diagn Pathol* 18(1): 29.
22. Gao Y, Yu Q, Li X, Xia C, Zhou J, et al. (2023) An imaging-based machine learning model outperforms clinical risk scores for prognosis of cirrhotic variceal bleeding. *Eur Radiol* 33(12): 8965-8973.
23. Wan S, Gao Y, Li T, Tian X, Liu M, et al. (2025) Deep Learning-Enhanced CTA for Noninvasive Prediction of First Variceal Haemorrhage in Cirrhosis: A Multi-Centre Study. *Liver Int* 45(9): e70274.
24. Zheng L, Shi N, Li P, Ge H, Tu C, et al. (2025) Development and validation of machine learning models to predict esophagogastric variceal rebleeding risk in HBV-related cirrhosis after endoscopic treatment: a prospective multicenter study. *EClinicalMedicine* 87: 103436.
25. Ruffle JK, Farmer AD, Aziz Q (2019) Artificial Intelligence-Assisted Gastroenterology- Promises and Pitfalls. *The American Journal of Gastroenterology* 114(3): 422-428.
26. Kulkarni S, Seneviratne N, Baig MS, Khan AHA (2020) Artificial Intelligence in Medicine: Where Are We Now? *Acad Radiol* 27(1): 62-70.
27. Bayani A, Asadi F, Hosseini A, Hatami B, Kavousi K, et al. (2022) Performance of machine learning techniques on prediction of esophageal varices grades among patients with cirrhosis. *Clin Chem Lab Med* 60(12): 1955-1962.



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