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APPLICATION OF 2D PERFUSION ANGIOGRAPHY TO ASSESS THE EFFECTIVENESS OF VASCULAR EMBOLIZATION: ANALYSIS USING THE XGBOOST ALGORITHM

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ABSTRACT

Introduction. Interventional radiology is a cornerstone of minimally invasive medicine, yet objective assessment of embolization efficacy remains difficult because conventional visual evaluation of angiographic images is subjective and operator-dependent. Two-dimensional (2D) perfusion angiography, derived from digital subtraction angiography (DSA), enables quantitative assessment of hemodynamic parameters, including time to peak (TTP) contrast enhancement, reflecting the timing of peak contrast enhancement, and mean transit time (MTT), reflecting the duration of contrast transit through the perfused tissue.

Aim. To quantify changes in TTP and MTT before and after splenic artery embolization and, as an exploratory analysis, to assess whether a machine-learning model can automatically distinguish pre- from post-embolization perfusion states. The clinical efficacy of the procedure was additionally evaluated at 12-month follow-up.

Materials and methods. Paired pre- and post-embolization perfusion data from nine patients were analysed. TTP and MTT were compared using the paired Student's *t*-test. An XGBoost (Extreme Gradient Boosting) classifier was trained to distinguish pre- from post-embolization states using TTP and MTT values measured at individual time points and evaluated by patient-grouped 3-fold cross-validation, with leave-one-patient-out cross-validation as a robustness check.

Results. Embolization was associated with significant increases in TTP (from 4.58 ± 0.45 to 6.25 ± 0.43 s) and MTT (from 3.25 ± 0.30 to 4.61 ± 0.36 s; both $p<0.001$), indicating marked attenuation of perfusion within the embolized territory. At 12 months, significant clinical improvement was observed, including reduced spleen volume and increased platelet count (both $p<0.001$). The XGBoost model achieved an accuracy of 0.94 and an AUC-ROC of 0.94, with TTP as the principal discriminating feature.

Conclusions. In this small proof-of-concept cohort, 2D perfusion angiography quantified embolization-related hemodynamic changes, and machine learning demonstrated preliminary feasibility for the automated discrimination of pre- and post-embolization perfusion states. Larger, externally validated studies with standardized acquisition protocols are required before clinical application.

Keywords: Angiography, Machine Learning, Boosting Machine Learning Algorithms, Splenic Artery, Portal Hypertension, Splenomegaly, Embolization of the Splenic Artery

INTRODUCTION

Interventional radiology has emerged as a leading discipline within minimally invasive medicine, enabling precise locoregional targeting of pathological vasculature and tumour tissue [1, 2]. A principal challenge in this field is the objective assessment of embolization efficacy – that is, the reliable determination of the extent to which arterial blood flow to the target territory has been successfully reduced or occluded [3]. Conventional visual appraisal of angiographic images is inherently subjective, operator-dependent, and frequently insufficient for the quantitative characterisation of hemodynamic alterations between pre- and post-procedural time points [3, 4].

Two-dimensional perfusion angiography, derived from digital subtraction angiography (DSA) sequences, provides a quantitative framework for the evaluation of hemodynamic parameters, notably time to peak (TTP) contrast enhancement and mean transit time (MTT) of the contrast agent. These parameters reflect temporal changes in contrast-agent transit through the target vascular territory and may serve as standardized indices of embolization efficacy [3-7].

Nevertheless, manual interpretation of the resulting perfusion maps remains labour-intensive and susceptible to inter- and intra-observer variability. In this context, the application of machine-learning methodologies – capable of autonomously analysing angiographic data and recognizing patterns associated with embolization-induced hemodynamic changes – represents a promising avenue for further investigation [8, 9]. Among these, XGBoost (Extreme Gradient Boosting) is distinguished by its robustness on limited datasets and its capacity to identify and rank the perfusion parameters that best discriminate such changes [10, 11].

The integration of quantitative perfusion angiography with machine-learning frameworks offers new opportunities for the development of semi-automated decision-support systems capable of objectively characterising embolization-related perfusion changes [12-15].

AIM

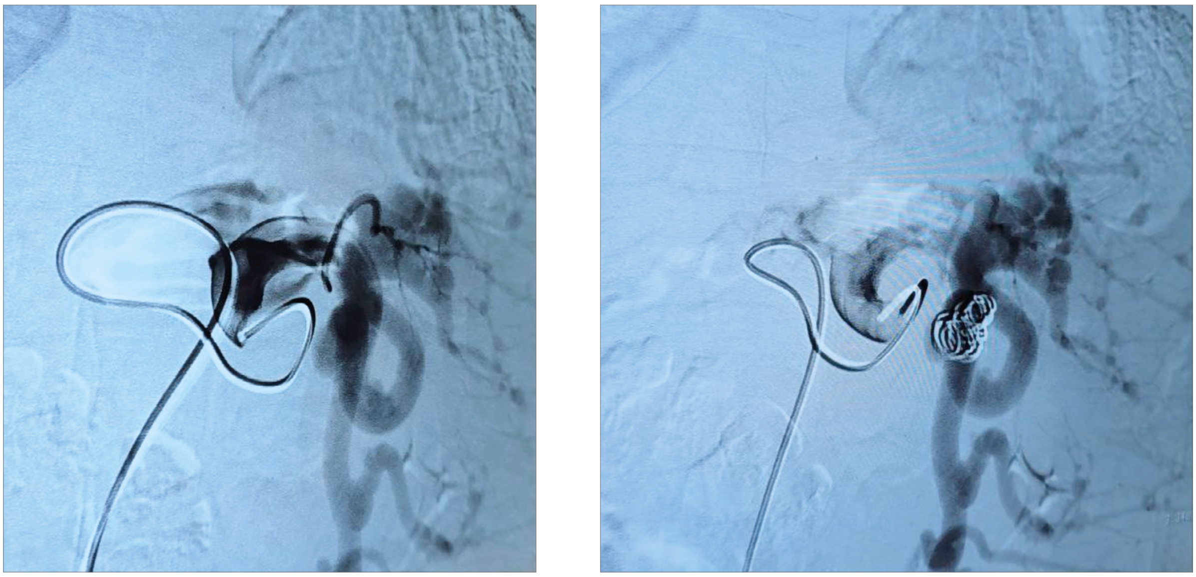
The aim of this study was to evaluate the potential of 2D perfusion angiography for the quantitative assessment of embolization-related hemodynamic changes in the splenic artery in patients with manifestations of portal hypertension and splenomegaly. The clinical efficacy of the embolization was additionally assessed at 12-month follow-up.

MATERIALS AND METHODS

This was a proof-of-concept experimental study designed to evaluate the capabilities of quantitative 2D perfusion angiography for the assessment of embolization-related hemodynamic changes. The study dataset comprised perfusion angiography records from nine patients, with paired pre- and post-procedural imaging datasets obtained following splenic artery embolization (Figure 1).

The study cohort comprised nine patients (five men and four women) aged 35–54 years, treated in 2022–2023 for clinically overt portal hypertension complicated by at least one episode of gastroesophageal variceal bleeding. According to the Child–Pugh classification, three patients belonged to class A and six to class B. All patients underwent combined splenic artery embolization.

Digital subtraction angiography (DSA) with 2D perfusion analysis was performed using a Philips Azurion angiographic system (software release 5 M12). Femoral arterial access was obtained using a 6-Fr Radifocus II introducer sheath, a 5-Fr Glidecath catheter, and a 0.035-inch guidewire (all Terumo); the catheter tip was positioned in the splenic artery or its target branch. Combined embolization was performed using detachable coils (Cook; 12 mm × 8 cm and 8 mm × 8 cm) delivered via a pushable coil. Iodinated contrast medium (300 mg I/mL) was administered into the splenic artery at a rate of 3 mL/s, and image series were acquired at 10 frames/s. Time to peak (TTP) and mean transit time (MTT) were derived from a region of interest placed over the splenic parenchyma using Philips 2D Perfusion post-processing software (Philips Healthcare). Identical acquisition and processing protocols were used before and after embolization.



a) Before splenic artery embolization b) after splenic artery embolization

Fig. 1 (a, b). Intraoperative angiography: visualization of the vascular bed via a microcatheter under digital subtraction angiography (DSA) control

Table 1. Changes in perfusion parameters before and after embolization (n = 9)

Parameter	Before embolization (M ± SD)	After embolization (M ± SD)	Δ (post- minus pre-embolization)	p-value
TTP (s)	4.58 ± 0.45	6.25 ± 0.43	1.67	< 0.001
MTT (s)	3.25 ± 0.30	4.61 ± 0.36	1.36	< 0.001

Note: p-values were determined using the paired Student's t-test.

For each case, two primary perfusion parameters were determined: Time to Peak (TTP) contrast enhancement, reflecting the velocity of contrast agent arrival, and Mean Transit Time (MTT), characterising the volume of tissue perfusion within the intervention zone.

Data acquisition was performed at two discrete time points – immediately prior to and upon completion of the intervention. Normality of data distribution was confirmed, consistent with a Gaussian pattern. Inter-timepoint differences (ΔTTP, ΔMTT) were subsequently computed to characterise the magnitude of perfusion alterations attributable to embolization. Descriptive statistics included means and standard deviations; between-timepoint comparisons were conducted using the paired Student's t-test, with a significance threshold set at $p < 0.05$ (Table 1).

Because the clinical outcomes were assessed at 12-month follow-up and were not individually linked to the intra-procedural perfusion measurements on a per-patient basis, the machine-learning task was framed not as prediction of procedural success but as an exploratory classification of perfusion state. Each measurement was labelled according to its acquisition time point (0 = pre-embolization, 1 = post-embolization), providing an objective classi-

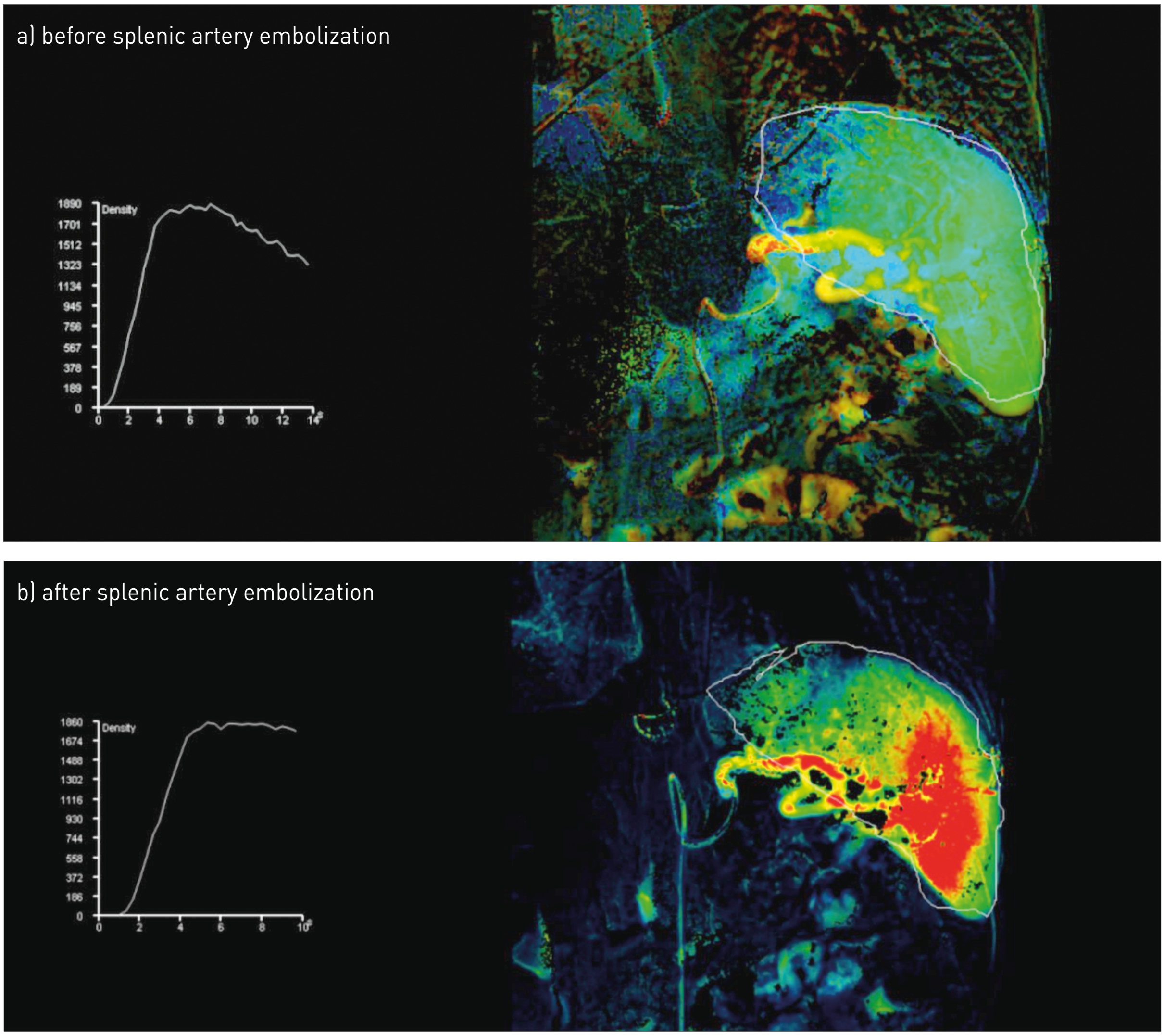


Fig. 2 (a, b). 2D perfusion angiography

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Table 2. Individual patient data before and after embolization (n = 9)

ID	TTP pre (s)	TTP post (s)	ΔTTP (s)	MTT pre (s)	MTT post (s)	ΔMTT (s)
1	4.84	6.28	1.44	3.12	4.91	1.79
2	4.41	6.61	2.20	3.37	4.53	1.16
3	4.75	5.86	1.11	3.16	4.45	1.29
4	5.23	6.68	1.45	3.62	4.82	1.20
5	4.48	5.56	1.08	3.27	4.17	0.90
6	4.01	6.83	2.82	2.74	5.17	2.43
7	5.09	6.09	1.00	3.58	4.12	0.54
8	3.87	6.49	2.62	2.90	4.92	2.02
9	4.55	5.89	1.34	3.46	4.38	0.92

Note: ΔTTP and ΔMTT denote the post- minus pre-embolization differences.

fication target independent of the perfusion features themselves.

For this exploratory analysis, the XGBoost (Extreme Gradient Boosting) algorithm – an ensemble learning method based on sequential decision-tree boosting – was employed to distinguish pre- from post-embolization states. The feature set comprised TTP and MTT values at each time point, yielding two paired measurements per patient.

Model training and evaluation were performed using patient-grouped 3-fold cross-validation (*StratifiedGroupKFold*), in which all measurements from a given patient were assigned to the same fold to prevent information leakage between paired pre- and post-embolization measurements while preserving class distribution across folds. Given the small sample size, leave-one-patient-out cross-validation was additionally performed as a robustness check, with comparable results. Model performance was characterised using AUC-ROC, accuracy, precision, and recall, and feature-importance analysis was conducted to identify the relative contribution of each perfusion parameter.

All data processing and modelling procedures were implemented in Python 3.12, utilising the pandas, scikit-learn, and xgboost libraries. Findings are reported as means ± standard deviations and presented in tabular and graphical formats, including ROC curves and feature-importance plots.

RESULTS

Perfusion angiography data from nine patients demonstrated that splenic artery embolization was associated with statistically significant changes in hemodynamic parameters reflecting regional perfusion within the intervention zone (Figure 2). Mean TTP increased from 4.58 ± 0.45 s to 6.25 ± 0.43 s following embolization ($p<0.001$), indicating delayed contrast-medium transit consistent with reduced arterial perfusion. A concurrent and significant increase in MTT was observed, from 3.25 ± 0.30 s to 4.61 ± 0.36 s ($p<0.001$), further supporting prolonged contrast transit within the embolized territory (Table 2).

To evaluate whether perfusion parameters encode the embolization-induced hemodynamic change, an XGBoost classifier was trained to distinguish pre- from post-embolization states using the per-time-point TTP and MTT values. Under patient-grouped 3-fold cross-validation, the model separated the two states with an accuracy and AUC-ROC of 0.94; leave-one-patient-out cross-validation gave the same values (Table 3).

Table 3. XGBoost model performance metrics

Metric	Value
Accuracy	0.944
AUC-ROC	0.944
Precision	1.000
Recall	0.889

Note: Accuracy (overall classification accuracy), Precision (positive predictive value), Recall (sensitivity), AUC-ROC (ability to distinguish pre- from post-embolization states).

The AUC-ROC of 0.94 indicates that perfusion parameters reliably separate pre- from post-embolization states, consistent with the marked TTP and MTT changes reported above; this result should nonetheless be interpreted in the context of the small sample and the expected separability of the two states (Figure 3).

Feature-importance analysis identified TTP as the principal feature discriminating between the two states (Figure 4), while MTT provided little additional information once TTP was included. This finding is consistent with the observation that both parameters increased markedly and concordantly after embolization, indicating that either parameter alone could effectively distinguish between the pre- and post-procedural states.

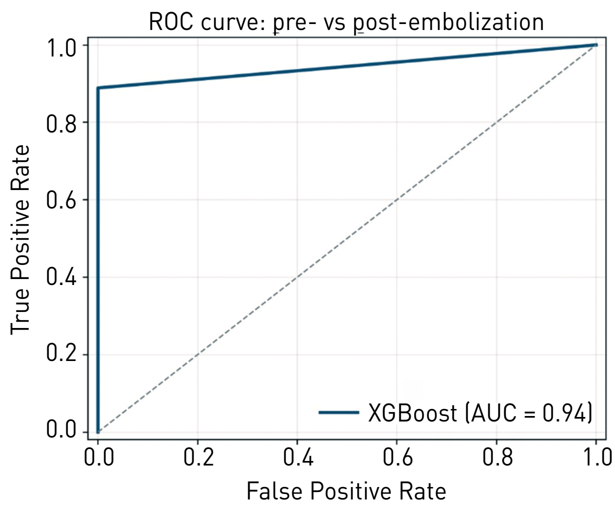

Fig. 3. ROC curve of the XGBoost model distinguishing pre- from post-embolization perfusion states

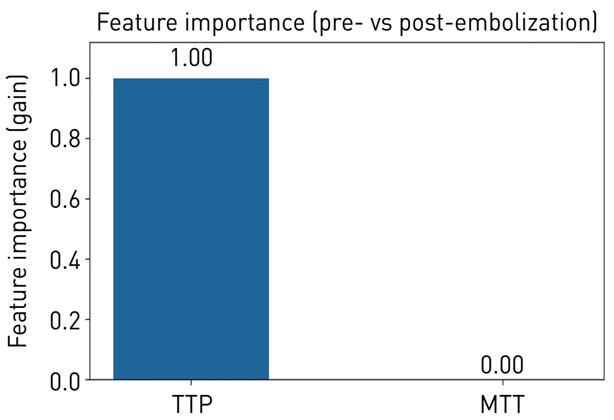

Fig. 4. Feature importance for the XGBoost classifier distinguishing pre- from post-embolization states

Beyond the intra-procedural perfusion changes, splenic artery embolization was associated with significant clinical improvement at 12-month follow-up in the same nine patients (Table 4). Spleen volume decreased markedly, and platelet count more than doubled (both $p<0.001$), with significant improvements also observed in haemoglobin, haematocrit, and the Child–Pugh score, whereas albumin levels and the MELD score did not change significantly.

DISCUSSIONS

The present study demonstrates that 2D perfusion angiography parameters showed statistically significant changes following splenic artery embolization. The observed increases in TTP and MTT are consistent with the expected hemodynamic effects of embolization, reflecting attenuation of arterial perfusion within the target territory. These findings are in agreement with previous investigations in which post-procedural increases in TTP and MTT were reported as quantitative indicators of embolization efficacy, notably in the context of partial splenic artery embolization [5], endovascular interventions for lower extremity arterial disease [4, 7, 12], and parametric perfusion analyses in other vascular territories [13]. Collectively, these findings support the potential utility of 2D perfusion angiography for standardized, real-time hemodynamic monitoring of embolization-related perfusion changes [3].

The XGBoost classifier distinguished pre- from post-embolization states with high accuracy (AUC-ROC = 0.94 under patient-grouped cross-validation), with comparable results obtained using leave-one-patient-out cross-validation, despite the small sample size ($n = 9$). These findings provide preliminary, exploratory evidence that embolization-induced hemodynamic changes may be sufficiently consistent to be detected automatically from perfusion parameters [10, 11]. The high classification performance may largely reflect the expected physiological separation between pre- and post-embolization perfusion states rather than any clinical predictive capability. Although clinical improvement was observed at 12 months (Table 4), these outcomes were assessed at the group level and

Table 4. Clinical outcomes before and 12 months after splenic artery embolization (n = 9)

Parameter	Before embolization	12 months after embolization	p-value
Spleen volume, cm³	811.6 ± 324.2	478.8 ± 168.6	<0.001
Platelet count, ×10⁹/L	78.5 ± 29.0	143.4 ± 27.7	<0.001
Haemoglobin, g/L	107.7 ± 22.1	128.9 ± 15.5	<0.001
Haematocrit, %	33.0 ± 6.1	38.6 ± 3.9	<0.001
Albumin, g/L	40.0 ± 5.6	41.0 ± 4.8	0.814 (NS)
Child–Pugh score	6.5 ± 1.4	5.6 ± 1.1	0.004
MELD score	5.5 ± 3.3	5.0 ± 3.2	0.556 (NS)

were temporally distant from the intra-procedural perfusion measurements. The model was therefore deliberately framed as a classifier of perfusion state rather than a predictor of procedural success. Within this exploratory classification task, TTP emerged as the principal discriminating feature. The observed increases in TTP and MTT are consistent with reduced perfusion following embolization; however, the present dataset did not include an independent angiographic or clinical reference standard for quantifying the degree of vascular occlusion [5]. Similar approaches combining parametric imaging with machine learning have been reported [14, 15].

CONCLUSIONS

The findings demonstrate that two-dimensional perfusion angiography can quantify hemodynamic changes associated with splenic artery embolization, with significant post-procedural increases in TTP and MTT. As an exploratory proof-of-concept, the machine-learning model was able to distinguish pre- from post-embolization states based on these parameters. Given the small, single-centre sample and the absence of an independent reference standard for clinical outcome assessment, these results should be regarded as preliminary. Larger, externally validated studies are required before clinical application can be considered.

Article Declarations

Prospects for further research. Further research should focus on large-scale clinical validation of the proposed approach in multicentre cohorts, external validation of the model, standardization of 2D perfusion acquisition protocols, and correlation of perfusion parameter changes with independent clinical and angiographic outcomes.

Study limitations. The authors acknowledge that this study is limited by a small single-centre sample (n = 9), the absence of external validation and of benchmarking against alternative machine-learning models, a feature space restricted to perfusion-derived parameters, the lack of an independent angiographic reference standard for the degree of occlusion, and the absence of standardized 2D perfusion acquisition protocols [6]. The findings should therefore be regarded as preliminary and proof-of-concept.

Primary data and materials. The study used anonymized quantitative perfusion measurements (TTP and MTT) obtained from nine patients undergoing splenic artery embolization; no patient-identifying primary medical documentation is published.

Research ethics. The study was approved by the Bioethics and Research Ethics Committee of Bogomolets National Medical University (Protocol No. 195 dated May 26, 2025) and was conducted in accordance with the principles of the Declaration of Helsinki of the World Medical Association. Informed consent was obtained from all patients participating in the study.

Declaration of AI use. During the preparation of this work the authors used AI tools (ChatGPT-4 and Claude) for language editing, formatting and structuring of the manuscript. The study design, patient data, statistical analysis, results and their interpretation are the authors' own. After using these tools the authors reviewed and edited the content as necessary and take full responsibility for the content of the publication.

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Conflict of interest. The authors declare no conflict of interest related to the preparation, conduct or publication of this study. None of the authors has financial, commercial or other personal relationships that could influence the interpretation of the results. The study was conducted in accordance with the principles of academic integrity and objectivity. All authors approved the final version of the manuscript.

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A – Work concept and design; B – Data collection and analysis; C – Statistical analysis;
D – Writing; E – Critical review; F – Final approval.

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ЗАСТОСУВАННЯ 2D-ПЕРФУЗІЙНОЇ АНГІОГРАФІЇ ДЛЯ ОЦІНКИ ЕФЕКТИВНОСТІ ЕМБОЛІЗАЦІЇ СУДИН: АНАЛІЗ ІЗ ВИКОРИСТАННЯМ АЛГОРИТМУ XGBOOST

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РЕЗЮМЕ

Вступ. Інтервенційна радіологія посідає провідне місце серед сучасних мінімально інвазивних методів лікування, проте об’єктивна оцінка ефективності емболізації залишається складною через суб’єктивність і залежність від оператора під час візуальної оцінки ангіографічних зображень. Двовимірна перфузійна ангіографія на основі цифрової субтракційної ангіографії (DSA) забезпечує кількісну оцінку гемодинамічних параметрів, зокрема часу до піку контрастування (TTP) та середнього часу проходження контрастної речовини (MTT). Проте інтерпретація отриманих перфузійних даних у ручному режимі залишається трудомісткою та залежною від досвіду лікаря, що обґрунтовує пошук автоматизованих підходів.

Мета. Визначити зміни TTP і MTT до та після емболізації селезінкової артерії й у межах розвідувального аналізу оцінити, чи здатна модель машинного навчання автоматично розрізняти стани до та після емболізації за перфузійними параметрами. Клінічну ефективність втручання додатково оцінено через 12 місяців.

Матеріали та методи. Проаналізовано парні дані дев’яти пацієнтів до та після втручання. TTP і MTT порівнювали за допомогою парного t-критерію Стьюдента. Класифікатор XGBoost навчали розрізняти стани до та після емболізації за значеннями TTP і MTT у кожній часовій точці та оцінювали за допомогою 3-кратної перехресної валідації з групуванням за пацієнтом і перехресної валідації з виключенням одного пацієнта (leave-one-patient-out).

Результати. Встановлено достовірне збільшення TTP (з 4,58 ± 0,45 до 6,25 ± 0,43 с) та MTT (з 3,25 ± 0,30 до 4,61 ± 0,36 с; обидва p<0,001), що свідчить про затримку проходження контрастної речовини, узгоджену зі зниженням артеріальної перфузії в зоні втручання. Через 12 місяців спостерігали достовірне клінічне покращення, зокрема зменшення об'єму селезінки та збільшення кількості тромбоцитів (обидва p<0,001). Модель XGBoost досягла точності 0,94 та AUC-ROC 0,94; найбільш інформативним для розрізнення станів параметром був TTP. Обидві схеми валідації дали узгоджені результати.

Висновки. У межах цієї невеликої proof-of-concept когорти двовимірна перфузійна ангіографія кількісно відображає гемодинамічні зміни після емболізації, а машинне навчання демонструє попередню придатність для їх автоматизованого розрізнення. Для клінічного впровадження потрібні більші дослідження зі стандартизацією протоколів та зовнішньою валідацією.

Ключові слова: Ангіографія, машинне навчання, алгоритми підсилення машинного навчання, селезінкова артерія, портальна гіпертензія, спленомегалія, емболізація селезінкової артерії.

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