Turkish Journal of Clinical Research

Turk J Clin Res. 2025;1(2):144-149
https://doi.org/10.63909/1453022

REVIEW ARTICLE

Artificial intelligence and machine learning applications in the imaging of cerebral vascular lesions: A narrative review

Serebral vasküler lezyonların görüntülenmesinde yapay zekâ ve makine öğrenmesi uygulamaları: Bir anlatımsal derleme

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Abstract

Challenges in cerebral imaging have been present since the dawn of the modern practice of neurosurgery. Despite leaps of progress, subtle pathologies, especially vascular lesions, are still easily missed. In the recent literature, several authors have utilized artificial intelligence (AI) and machine learning (ML) techniques to automatically detect and segment various vascular lesions, including aneurysms, AVMs, and cavernous malformations. These models have been trained with computerized angiography (CTA), magnetic resonance angiography (MRA), and digital subtraction angiography (DSA). The models reached the highest sensitivity (94–96%) and specificity (92–95%) in aneurysms due to the simple morphological properties and the abundance of large cohort datasets. In AVMs, hybrid models incorporating multimodal imaging improve nidus segmentation and radiosurgical planning, though irregular morphology and limited datasets restrict generalizability; reported Dice scores range from 0.80–0.88. Lastly, for cavernous malformations, the models showed promising results, with Dice scores around 0.74, although they lacked external validation. Despite limitations of these models, they consistently reduced diagnostic time (often <1 second in detection tasks) and supported clinical decision-making in real-life complex clinical scenarios. Following a series of continuous refinements, their integration into real-world neurosurgical practice is inevitable in the future.

Keywords: Cerebrovascular system, artificial intelligence, machine learning.

Özet

Beyin görüntülemesindeki zorluklar, modern beyin cerrahisi pratiğinin başlangıcından bu yana varlığını sürdürmektedir. Kaydedilen büyük ilerlemelere rağmen, özellikle vasküler lezyonlar gibi ince patolojiler hâlâ kolaylıkla gözden kaçabilmektedir. Güncel literatürde, birçok yazar yapay zekâ ve makine öğrenmesi tekniklerini kullanarak anevrizmalar, AVM'ler ve kavernöz malformasyonlar dâhil çeşitli vasküler lezyonları otomatik olarak tespit etmek ve segmentlemek amacıyla çalışmalar yapmıştır. Bu modeller bilgisayarlı anjiyografi (CTA), manyetik rezonans anjiyografi (MRA) ve dijital subtraksiyon anjiyografisi (DSA) ile eğitilmiştir. Basit morfolojik özellikler ve geniş hasta kohortlarına ait veri bolluğu nedeniyle, modeller en yüksek duyarlılık ve özgüllüğe anevrizmalarda ulaşmıştır. AVM'lerde multimodal görüntülemeyi birleştiren hibrit modeller, nidus segmentasyonu ve radyocerrahi planlamasında iyileşme sağlamış olsa da düzensiz morfoloji ve sınırlı veri setleri genellenebilirliği kısıtlamaktadır. Son olarak, kavernöz malformasyonlar için geliştirilen modeller umut verici sonuçlar göstermiştir, ancak harici doğrulama eksiktir. Bu modellerin sınırlılıklarına rağmen, tanı süresini tutarlı biçimde azaltmış ve karmaşık klinik senaryolarda klinik karar verme süreçlerini desteklemiştir. Sürekli iyileştirmelerin ardından, bu teknolojilerin gerçek dünyadaki nöroşirürjik uygulamaya entegrasyonu kaçınılmaz olacaktır.

Anahtar Kelimeler: Serebrovasküler sistem, yapay zekâ, makine öğrenmesi.

INTRODUCTION

Since the start of the practice of neurosurgery, imaging of the central nervous system (CNS) has been a cornerstone in the diagnosis, management, and subsequent follow-up of patients with various neurological pathologies. The invention of the X-ray and cranial radiographs started a long line of imaging modalities. Although only bony structures were visible, this new modality at that time gave surgeons an idea of any fractures and dislocations following any trauma. This modality was followed by pneumoencephalograms, computerized tomographies (CT), and lastly Magnetic resonance imaging (MRI) (1). MRI gave a detailed report on the ıntracranial and extracranial components of CNS as well as other structures residing intracranially and aiding CNS, such as vessels, Dura mater, and cerebrospinal fluid (CSF) (2). Other special sequences, including CT angiography and MR angiography, have followed in subsequent years to better visualize vessels intracranially, to get an idea

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Cite as: Yurtluk MD. Artificial intelligence and machine learning applications in the imaging of cerebral vascular lesions: A narrative review. Turk J Clin Res. 2025;1(2):144-149

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Received: 24 August 2025 | **Accepted:** 4 September 2025 | **Published:** 30 September 2025

Turk J Clin Res. 2025;1(2):144-149
https://doi.org/10.63909/1453022

of cerebrovasculature and the pertaining pathology. Although these modalities provided a good amount of imaging, they need the trained eye of a physician, a radiologist, or a neurosurgeon to capture the full gravity of the situation. Despite a certain amount of training, subtle pathologies still can be missed and have detrimental consequences for the patients. The emergence of artificial intelligence (AI) and machine learning (ML) methods has started to accommodate this problem, and many studies to date have demonstrated their utility in diagnosing cerebrovascular pathologies (3). Although these methods do not catch up to physician-level proficiency in diagnosis, they have helped streamline initial phases of management. Recent reviews and meta-analyses from 2023–2024 further highlight the potential and challenges of AI in vascular neuroimaging (4–6).

In our review, we aim to report up-to-date results of such models and show their efficacy in patient diagnosis.

The use of Artificial Intelligence and Machine Learning in Arteriovenous Malformations

The Arteriovenous malformations are congenital or de novo lesions encompassing the brain parenchyma, consisting of feeding arteries, draining vein, and a nidus (7). Although their MRI scan shows a typical "bag of worms" appearance in simple, unruptured lesions, the segmentation of these lesions is time-consuming, and identifying feeding arteries and draining venous structures is crucial. Furthermore, ruptured lesions show similar properties to hemorrhagic lesions, including brain metastasis and cavernous malformations. There is a substantial body of data within the literature to streamline the process of segmentation for intervention planning, such as surgery and stereotactic radiosurgery (SRS) (8). In one of the early studies, the authors investigated several machine learning models, including YOLOv5 and v8, U-NET, nnU-NET, and fuzzy c-means clustering, to detect and segment AVM nidus from T2 and time-of-flight MRI sequences to significantly decrease diagnosis time and increase precision at nidus segmentation (8–11). Dong et al in their study showed that 3D reconstruction of the AVM nidus from TOF MRI images was possible, while applying a standardized demarcation principle with a threshold-based approach to overcome inconsistent nidus boundary delineation (11). In another study by Forkert et al, the authors achieved near manual level segmentation quality in AVM segmentation using support vector machines trained on unruptured AVM images while also integrating hemodynamic analysis to differentiate arteries and veins (12). Hong et al. in their study used a random forest model to detect and segment ruptured AVMs with superior sensitivity and specificity compared to radiologists while generating segmentation in less than 1 second (13). The authors improved their results in their further studies, enhancing their model with pretraining, augmentation, and semi-automatic workflows (10).

One of the areas for ML utilization was SRS planning, which is a time-consuming endeavor and most times requires an invasive procedure, namely digital subtraction angiography, the gold standard for AVM diagnosis. Several authors investigated and compared ML models, including DeconvNET, U-Net, PSPNet, and V-Net DeepMedic (8, 14–18). The authors found that multiple sequence inputs improved automatic segmentation of the AVMs, while clinically negligible dose differences between manual vs automatic plans were found. These studies show promising utilization of these programs; however, these models are not without limitations. Small sample size limits the generalizability of these results and may enhance the biases in the cohorts. The current literature lacks a benchmark model, which prevents more robust comparisons. Also, Dice score, which is the prominent metric used in the evaluation of the models, lacks clinical interpretability, making these models less sensitive in clinical interpretation. Lastly, previously treated lesions, such as embolization, decrease the sensitivity and specificity of the models by introducing artifacts.

Despite challenges, these models show promising results and, with larger data studies, enhance their detection and segmentation capability.

The Utilization of Artificial Intelligence and Machine Learning in Aneurysm Detection

Intracranial aneurysms are a prominent source of morbidity and mortality in the general population. While going asymptomatic in many cases, they can rupture unexpectedly and cause subarachnoid or intraparenchymal hemorrhage and herniation. Detection

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of the aneurysm requires a trained eye, and in small aneurysms is a big challenge. AI and ML techniques have advanced, and several studies have investigated these models to decrease detection time and reduce interobserver variability. These models can utilize several imaging including Computerized Angiography (CTA), Magnetic Resonance Angiography (MRA), and Digital Subtraction Angiography (DSA). In a recent literature review of diagnostic performance of ML and AI models on cerebral aneurysm detection by Din et al., models included showed a pooled specificity of 95% (CI 0.92-0.97) and sensitivity of 94% (CI 0.92-0.96) with an AUC value OF 0.98 in more than 15000 aneurysms from CTA, MRA, and DSA images (19). Furthermore, false positive detection rates were decreased as the models were trained with more images. For the smaller lesions, detection sensitivity dropped significantly in the range of 0.80-0.88 for aneurysms smaller than 3mm. The authors also underscored the importance of independent datasets, where these studies reported a slight drop in the sensitivity, implying an overfitting risk. In the subgroup analysis, models that were treated with CTA had higher sensitivity compared to models that were trained with MRA. Although DSA studies were fewer, DSA-trained models showed excellent efficacy for small aneurysm detection. Models that were trained with multiple imaging modalities often had reduced false positive rates. The emphasis of these meta-analyses was that these models used as secondary readers, significantly reduce reading times and improve training for junior radiologists or residents. Naturally, these models are not without limitations; first of all, most studies were single-center studies that can reproduce the center biases, and in the current workflow, these models lack prospective validation in real clinical environments. In another meta-analysis by Shi et al., the authors also examined AI-derived aneurysm risk stratification, treatment planning, and follow-up (20). In the literature, the 3D Convolutional Neural Networks (CNN) trained by the MRA and CTA images dominate the deep learning detection techniques. Several studies used support vector machine and random forest teaching methods, as well as handcrafted vessel curvature and intensity profiles that provided lower accuracy rates. In their analysis, the detection sensitivity ranged from 90-98% for aneurysms >3mm on CTA images. However, for the <3mm group, CNN models outperformed radiologists in some studies, reaching up to 94% sensitivity when trained with a large dataset. The authors underscored the feasibility of integration into real-world everyday clinical apps that are commonly used in clinics, which can greatly reduce the reading time and streamline the patient management. However, small aneurysms remain a challenge, even with highly trained CNNs. Multi-center large databases are a must for highly sensitive and specific models to decrease overfitting and reduce biases.

The use of Artificial Intelligence and Machine Learning in Cavernous Malformations

The Cerebral Cavernous Malformations are among the four major hemorrhagic lesions of the CNS, besides AVMs, Arteriovenous fistulas, and capillary telangiectasias. They account for approximately 10-15% of these lesions (21). They are generally angiographically occult lesions due to low intralesional pressure. They have a characteristic appearance on MRI imaging with hemosiderin deposition from repetitive bleeding and a classic berry appearance on Macroscopic examination. Studies estimate a 1.5-2.4% annual bleeding risk, which is influenced by cortical involvement and overall lesion location (22).

Zhao et al. developed and trained a deep learning model from non-contrast CT scans for non-traumatic intracranial hemorrhages (21). The main goal of the model is to identify the etiology of AVMs, aneurysms, cavernous malformations, hypertensive hemorrhage, and moyamoya disease. They have trained their model on 1868 non-contrast CT images and then tested on two independent sets with cavernous malformation prevalence of 7% and 1% respectively. The model performed AUC values of 0.83 and 0.979 in these two datasets separately, respectively, showing discriminative power between aneurysms and AVMs. Although cavernous malformation-related bleeding detection is harder than aneurysm-related bleeding detection, radiologist-aided detection increased specificity by 0.028 when clinicians were complemented by the models. In another study by Chou et al., wanted to reduce manual labor work for cavenous malformation manual segmentation and reduce inter-observer variability in Gamma Knife radiosurgery planning (22). They have created a mask CNN to extract brain parenchyma, then a 3D CNN performed the segmentation from MRI volumes. The post-contrast T1 and T2 sequences were used for

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the model training and segmentation, which reduced the precision overall, so the final training was done with T2-weighted images. The model reached a dice score of 0.741 with only T2W input; furthermore, the dice scores were decreased with more inconspicuous lesions. Overall, AI and mL methods were effective in segmenting even smaller cavernous malformations. Naturally, these models need multi-center large datasets for further refinements (Table 1).

Table 1. AI in cerebrovascular imaging

Focus Area	AI Methods	Main Application	Key Findings
AVM Detection and Segmentation	CNNs, UNet++, YOLO, Deep V-Net, DenseUNet	Automated nidus/lesion detection and segmentation from MRI, CT, angiography	High Dice scores (0.8–0.9) achievable; AI feasible for precise delineation and treatment planning
Tissue and Vascular Classification	SVM, Fuzzy C-means, Random Forest	Differentiation of AVM tissue, vessel extraction, treatment plan evaluation	Automated classification comparable to manual; supports treatment planning (e.g., radiosurgery)
Diffuseness and Risk Prediction	CNNs, Machine Learning classifiers	Prediction of AVM diffuseness, surgical risk factors, functional outcomes	Models identify diffuseness and risk features, aiding in patient stratification
Functional Imaging Integration	fMRI + DTI + AI-based analysis	Mapping eloquent areas (motor, language, visual)	Helps predict neurological deficits, optimizes surgical/radiosurgical planning
Outcome Prediction Models	AI-enhanced grading scales (HDVL, fS-M, CLAD)	Predicting postoperative neurological deficits and outcomes	AI-based scales outperform classical Spetzler-Martin in predictive accuracy
Angiography and Radiation Reduction	AI-enhanced imaging (angiography reconstruction)	Visualization with reduced radiation exposure	Comparable to digital subtraction angiography; reduces patient risk
Generalizability and Large Datasets	Multi-model deep learning	Mixed lesion types, large-scale validation	Demonstrates potential for broader cerebrovascular applications, but variability in lesion types remains a limitation

Nevertheless, current cavernous malformation studies are limited by small sample sizes, reliance on single-center cohorts, and inconsistent imaging protocols. Moreover, external validation is almost always lacking, which limits its generalizability. Compared to aneurysms and AVMs, cavernous malformations are less studied, highlighting the need for future multicenter collaboration.

DISCUSSION

The integration of artificial intelligence and machine learning models in the modern neurosurgery practice will be a giant leap in terms of data and patient management. The proposed model has the potential to greatly aid in diagnosis, both in the clinic and emergency settings.

In the current literature, the AVMs, cavernous malformations, aneurysms, and non-traumatic intracranial bleeding are the most commonly investigated vascular pathologies (Table 2). The current literature consistently demonstrates the efficacy of AI and ML models in aiding diagnosis and decreasing the diagnosis times, which is valuable in the early emergency bleeding setting.

In the current literature, several models showed high sensitivity and specificity, particularly in the detection and segmentation of these lesions. The sensitivity levels of up to 94% to 96% show promising potential of these models for aneurysms. Although for AVMs, the results are less robust, several authors have achieved modest levels of diagnostic accuracy in models trained with hybrid imaging techniques, including CTA and MRA. The

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Table 2. Comparing for different pathologies

Pathology	Imaging Modalities Used	Key Models	Reported Performance	Limitations
Aneurysms	CTA, MRA, DSA	CNNs, SVM, Random Forest	Sensitivity: 90–98% (>3 mm), 80–88% (<3 mm); Specificity: ~95%; AUC up	Small aneurysms remain challenging; single-center biases; risk of overfitting
AVMs	MRI (TOF, T2), CTA, DSA	U-Net, nnU-Net, YOLO, SVM	Dice ~0.80; near-manual segmentation quality; detection <1 s in some models	Limited sample sizes; artifacts after embolization; no benchmark model
Cavernous Malformations	MRI (T1, T2, post-contras), CT	3D CNN, Mask CNN	Dice ~0.74 (best with T2W input); AUC 0.83–0.97 in etiology classification	Under-investigated; fewer datasets; lack of external validation

current results, although not perfect, can be improved with larger, multi-institutional datasets that will reduce overfitting and prevent internal biases within single-center datasets. Cavernous malformations remain under-investigated compared to aneurysms and AVMs; however, current studies show potential in these models for cavernous malformations (23,24). Besides AI and ML models, pathologies also pose certain challenges. While aneurysms have a circumscribed anatomy, AVMs have irregular and heterogeneous morphologies, making them very difficult to distinguish from normal brain vasculature. Therefore, the segmentation model must differentiate between healthy vasculature and the feeding arteries, the nidus, and the draining veins. This explains the lower dice scores seen in AVM-trained models compared to those for aneurysms. Moreover, AVMs are rarer than aneurysms, which hampers the formation of large datasets needed to develop robust ML algorithms. For cavernous malformations, these lesions lack a conformal vascular lumen like aneurysms and AVMs, and smaller, more subtle lesions can be mistaken for healthy brain tissue. Current models are limited by several factors. First of all, most conducted studies are retrospective and comprise only single-center datasets, which limits generalizability. Due to scanner, acquisition parameter, and patient population differences, these models may not show efficacy at an outside institution. For AVMs and cavernous malformations, sample sizes remain limited, decreasing the robustness of the models significantly. Secondly, the lack of interpretability of the results is still a matter of debate. The clinical correlation and the flagged lesion are at the discretion of the clinician. On a technical standpoint point smaller vessels can be flagged as aneurysms, and for the AVMs, previous treatment by embolization will leave artifacts in the image that will greatly decrease the diagnostic accuracy (25).

In the future, multi-center clinical trial initiatives hold promise for accelerating model training application development. By gathering diverse imaging datasets across different institutions and patients, we will be able to reduce bias, improve generalizability.

CONCLUSION

Artificial intelligence and machine learning models have already proven efficacy in doing certain tasks that will enhance the clinical decision-making of a given clinician. Future studies will surely address the gaps and limitations of these models with collaborative, multi-center, multi-modal, large cohort studies to enhance the efficacy of these models, but for now, they remain as high-potential tools to be used in certain clinical scenarios.

Acknowledgement: None.

Ethical Approval: None.

Author Contributions: Idea/Concept: M.D.Y.; Design: M.D.Y.; Supervision: M.D.Y.; Resources: M.D.Y.; Materials: M.D.Y.; Data Collection and/or Processing: M.D.Y.; Analysis and/or Interpretation: M.D.Y.; Literature Review: M.D.Y.; Written: M.D.Y.; Critical Reviews: M.D.Y.

Turk J Clin Res. 2025;1(2):144-149
https://doi.org/10.63909/1453022

Conflict of Interest: There is no conflict of interest.

Financial Disclosure: There is no financial support or funding for this study.

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