Chapter

The Use of Artificial Intelligence in the Management of Intracranial Aneurysms

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Abstract

The use of artificial intelligence (AI) has potential benefits in the management of intracranial aneurysms. Early detection of intracranial aneurysms is critical due to their high risk of complications such as rupture, vasospasm, and ischemia with highly impact on morbidity and mortality. The main findings suggest that AI can improve the accuracy of aneurysm detection, rupture risk prediction, and assist neurointervention in planning and performing procedures. This chapter discusses the potential for AI to improve patient care by enabling earlier diagnosis and timely treatment, reducing medical errors, costs, morbidity, and mortality. However, further validation of AI-based applications is necessary in a real-world clinical setting.

Keywords: intracranial aneurysm, artificial intelligence, machine learning, rupture risk assessment, computer-assisted diagnosis

1. Introduction

The detection and management of unruptured intracranial aneurysms (IAs) is a significant public health concern, affecting an estimated 3–7% of the population [1, 2]. Advances in neuroimaging, such as magnetic resonance angiography (MRA), computed tomographic angiography (CTA), and digital subtraction angiography (DSA), have increased the detection of incidental aneurysms [3, 4]. However, physicians' manual measurements of aneurysm morphology on 2D/3D projections have limitations of subjectivity and inconsistency, leading to interobserver variations [1].

To enhance aneurysm management, it is crucial to strive for greater accuracy and efficacy throughout all stages. Researchers have dedicated significant effort toward identifying risk factors and developing prediction models related to aneurysm initiation, growth, rupture, and intervention assessment [1, 5]. Several scoring systems have been developed and validated, such as PHASES [6] for predicting rupture risk and ELAPSS [7] for predicting growth risk. Additionally, the UIATS [6] score has been developed to balance risks and benefits directly. However, these scoring systems focus mainly on predicting rupture events rather than providing a comprehensive range of objective predictive analytics that may be useful for shared decision-making.

The concept of artificial intelligence (AI) was first introduced by J. McCarthy in the 1950s and involves the development of algorithms that can replicate human cognitive functions, including problem-solving, reasoning, and learning [7]. In essence, it is the ability of a machine to imitate intelligent human behavior and solve complex tasks using a single algorithm or brain [8]. AI includes various subsets, such as computer vision, image processing, artificial neural networks (ANN), convolutional neural networks (CNN), machine learning (ML), and deep learning (DL) [9].

In recent years, AI has become increasingly popular in the medical field, with applications in screening, diagnosis, and risk analysis across various specialties. In the field of neuroscience, AI is used for diverse purposes, such as clinical prediction modeling in intramedullary spinal tumor surgery [10], as well as in the study of neuro-oncology [11], epilepsy [12], Alzheimer's disease [13, 14], schizophrenia [14], and other neurological disorders [15].

AI can identify potential diagnoses, select appropriate treatments based on medical records and imaging data, and make independent decisions based on training data. This technology, which relies on past experiences, has shown promising results in improving patient care by enabling earlier diagnosis and timely treatment, reducing medical errors, costs, morbidity, and mortality [16, 17]. In the 2000s, AI was introduced into the management of intracranial aneurysms, providing an automated morphological 3-D characterization as an alternative to assess the risk of rupture and to determine the most appropriate management without delay [18]. Subsequently, the implementation of artificial intelligence methods allowed for automated morphological calculation, rupture risk stratification, and outcome prediction in aneurysm assessment, demonstrating excellent performance (**Figure 1**) [7].

The goal of using AI in intracranial aneurysm management is to enhance and improve patient health care. However, not all AI studies have been validated in a real clinical setting. In a recent study by Alwalid et al. [5], the clinical feasibility of the most popular AI applications in intracranial aneurysms was evaluated. The study

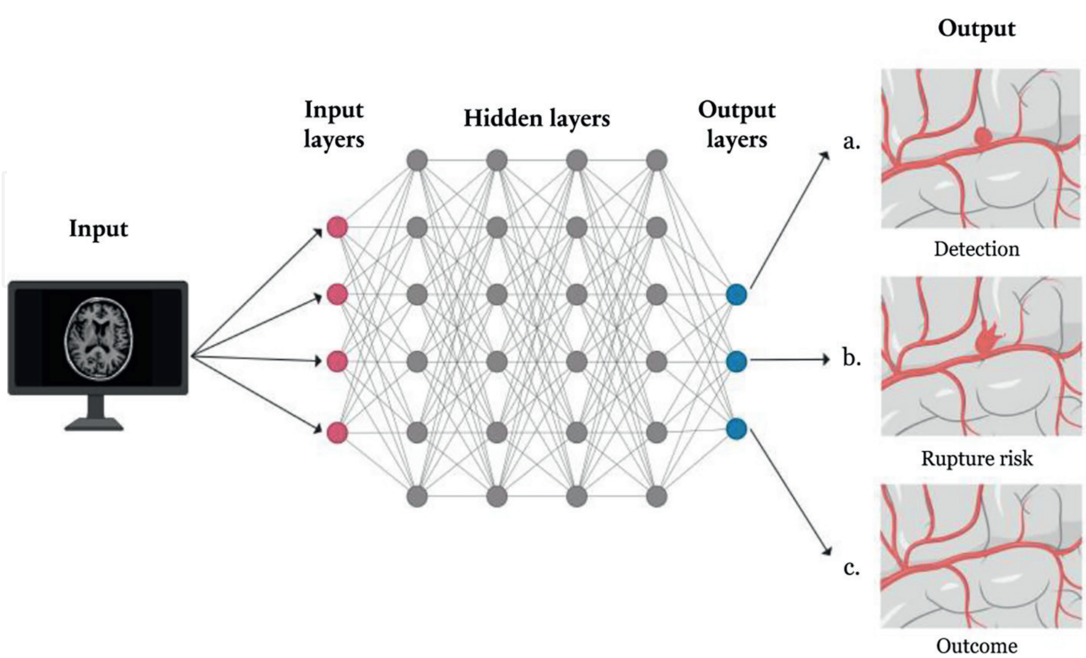

Figure 1.
Schematic representation of the use of DL-based algorithms in intracranial aneurysm management. The main applications include a. detection of intracranial aneurysms, b. assessing the risk of rupture, and c. predicting prognosis and risk of recurrence.

demonstrated that AI-based applications, particularly aneurysm detection, can potentially improve radiologists' clinical performance and shorten interpretation time. However, further validation is necessary in a real-world clinical setting [1, 5].

This chapter will discuss AI's main applications in managing intracranial aneurysms and its limitations and potential for future development.

2. Intracranial aneurysm detection

Artificial intelligence has become a significant focus in neurology for the detection of intracranial aneurysms. Early detection of aneurysms is critical due to their high risk of rupture, morbidity, and mortality. Computer-assisted diagnosis (CAD) is an AI-based technology that has emerged as a valuable tool for aneurysm detection based on imaging features. There are two types of CAD algorithms: conventional-style and deep learning-based models [19].

CAD systems have proven to be useful tools for faster, more accurate, objective, and consistent diagnoses of intracranial aneurysms by reducing intra and interobserver variability. Conventional-style CAD systems utilize quantitative analysis of predetermined imaging characteristics to detect aneurysms automatically [10]. The first CAD system developed for aneurysms using this method was created by Arimura et al. [20], which showed high sensitivity but could not detect small or fusiform aneurysms. Additionally, digital subtraction angiography (DSA) as an outside reference standard did not verify the aneurysms in the study.

Yang et al. [21] developed a fully automated algorithm for aneurysm detection that overcomes some of the limitations of conventional-style CAD systems. Their algorithm utilizes two complementary techniques: automatic intracranial artery segmentation and detecting points of interest from the segmented vessels, verified by DSA. This system demonstrated high sensitivity, especially for small aneurysms, and outperformed human detection in some cases. However, conventional-style CAD systems have a high false positive rate and low sensitivity, which limits their reliability and widespread adoption in clinical practice [19].

DL-based models for intracranial aneurysm detection have shown significant improvements in sensitivity and specificity compared to conventional-style CAD systems. These models can detect aneurysms of various shapes and sizes and can differentiate them from normal vessels and other intracranial structures with high accuracy. Furthermore, DL-based CAD systems can segment and quantify aneurysms, providing valuable information for treatment planning. DL models for aneurysm detection can be trained on a large dataset of radiological images, allowing for the identification of subtle imaging features that may be missed by human observers. For example, DL models can identify aneurysms in regions of the brain that are difficult to visualize or differentiate small aneurysms from normal vasculature [22, 23].

DL-based CAD systems have shown promising results in intracranial aneurysm detection. In 2018, Hua et al. developed a DL-based system that achieved a sensitivity of 96.4% and a specificity of 91.1% for aneurysm detection on MRA images. In another study, Zhang et al. developed a DL-based system that achieved a sensitivity of 92.3% and a specificity of 95.2% for aneurysm detection on CTA images [24]. These DL-based CAD systems have the potential to improve the accuracy and efficiency of aneurysm detection greatly. These models can be classified according to whether they have been developed for MRA, CTA, or DSA. REF.

2.1 MRA-based models

In recent years, several DL-based computer-assisted diagnosis (CAD) algorithms that use deep learning and magnetic resonance angiography (MRA) have emerged. One such algorithm, called DeepMedic, was developed by Sichtermann et al. [25] for automated detection of intracranial aneurysms using 3D time-of-flight MRA. The algorithm achieved a sensitivity rate of 90%, with higher sensitivity rates of 96% and 100% for aneurysms measuring between 3 and 7 mm and >7 mm, respectively. However, the algorithm showed poor specificity due to the limited sample size. The study also compared the performance of two clinicians in detecting aneurysms with and without augmentation from the DeepMedic algorithm, revealing improved sensitivity when the human reader was combined with the algorithm [19, 25].

Stember et al. [26] machined a convolutional neural network (CNN) algorithm for detecting intracranial aneurysms (IA) on both time-of-flight MRA and contrast-enhanced MRA. Their algorithm achieved a high sensitivity rate of 98.8%, but during the learning process, it only incorporated two-dimensional maximum intensity projection (MIP) images, resulting in false positives due to vascular curvatures that mimic aneurysms. In another study, Ueda et al. [27] developed an 18-layer CNN algorithm that utilized imaging data from multiple MRI units from various institutions. The algorithm achieved a sensitivity rate of 91–93% for aneurysms that are smaller than 5 mm. However, due to the heterogeneous internal signals of large aneurysms that are greater than 5 mm, the sensitivity rate was not satisfactory for this type of aneurysm [28]. Algorithms that use deep learning and magnetic resonance angiography (MRA) have shown promising results for the automated detection of intracranial aneurysms.

2.2 CTA-based models

Compared to MRA-based models, fewer studies have proposed AI algorithms for detecting intracranial aneurysms on CT angiography. In 2019, Park and colleagues introduced a DL-based CAD system called HeadXNet, which was applied to CTA images and outperformed clinicians in aneurysm detection [29]. Another study by Yang et al. [30] proposed an 18-layer CNN DL algorithm on CTA, which had a high sensitivity of 97.5% but a high false positive rate. Nevertheless, this algorithm helped improve the detection rate of IAs smaller than 3 mm, which are often missed by humans.

The DeepMedic algorithm developed by Sichtermann and colleagues in 2019 has also been applied to CTA images for aneurysmal subarachnoid hemorrhage, with a sensitivity of 87% and false positives of 0.42 for aneurysms larger than 30 mm and a sensitivity of 96% and a false positive of 0.14 for aneurysms larger than 100 mm [19].

2.3 DSA-based models

Several AI models have been developed to automatically detect intracranial aneurysms on 2D and 3D-DSA. In 2020, Jin and colleagues [31] developed a U-shaped deep neural network for aneurysmal detection and segmentation on 2D-DSA, which showed a high lesion-level sensitivity and low false-positive rate, making it a useful clinical tool for prompt diagnosis with less risk of errors. Duan and colleagues in 2019 [32] developed the regional average grayscale suppression (RAGS) algorithm for dual-input 2D DSA images, achieving a sensitivity of 100%, but with 11 false positives per case. However, combining dual-input images with the RAGS algorithm reduced false positives to 1.8 per case [19].

In summary, computer-aided detection of intracranial aneurysms using deep learning and medical imaging techniques has shown promising results for improving diagnostic accuracy and reducing false negatives. MRA-based models have been extensively studied and have demonstrated high sensitivity rates but poor specificity. CTA-based models have shown comparable sensitivity rates to MRA-based models, with fewer studies reported in the literature. DSA-based models have also shown high sensitivity rates, with low false positives, but require more invasive imaging procedures [19].

However, the performance of these algorithms can be affected by various factors, such as the quality and quantity of training data, machine learning approach, and image processing techniques. Further research is necessary to optimize these algorithms and develop reliable and efficient tools for detecting and diagnosing intracranial aneurysms [5].

3. Treatment outcomes

Aneurysms can be treated using surgical or endovascular techniques. However, there is still a risk of stroke or death, ranging from 3 to 10%, even with proper treatment [33].

Size, location, and morphology must be considered to determine the best treatment for an aneurysm [5]. For aneurysms located in distal segments or at the middle cerebral artery trifurcation, surgical therapy may be preferred. On the other hand, endovascular treatment has shown better results for proximal intracranial carotid and posterior circulation aneurysms. In some cases, very large or complex aneurysms may require a combination of endovascular and surgical techniques [34].

The use of artificial intelligence (AI) has enabled the determination of the most suitable intervention therapy based on patient characteristics and aneurysm features. Through the analysis of large datasets, AI models can assist in the decision-making process. Moreover, incorporating objective data on aneurysm flow and morphological characteristics can further enhance the process, improving occlusion rates and potentially reducing the risk of recanalization [35].

3.1 Surgery

The application of artificial intelligence (AI) in neurosurgery has generated considerable interest in recent years, mainly due to the large amounts of data produced by modern diagnostic methods that require quantitative analysis. In conjunction with advancements in microsurgical techniques, the use of surgical management involving the placement of a clip across the neck of a cerebral aneurysm has proven to be an effective and safe procedure for patients with unruptured cerebral aneurysms or subarachnoid hemorrhage (SAH) [36].

Certain factors could influence prognosis, and studies have indicated that patients treated at specialized neurosurgical centers with high volumes of cerebral aneurysm procedures tend to experience better outcomes than those treated at lower-volume centers. Numerous studies have shown that machine learning (ML) can be utilized in surgical procedures, including presurgical planning, intraoperative guidance, and outcome prediction [34, 36, 37].

Staartjes and colleagues used various ML models, including support vector machines, decision trees, random forests, generalized linear models, generalized additive models, and stochastic gradient boosting machines, to achieve a peak accuracy of 91% during internal validation of the gradient boosting machine [8].

Neurosurgeons can incorporate AI and ML into their daily clinical practices and use these models for intraoperative and postoperative care, thereby creating superior medical care and research tools and techniques [38].

3.2 Endovascular therapy

The techniques used for endovascular therapy for cerebral aneurysms have evolved, with coil systems being introduced in the early 1990s [39], and newer techniques, including stent-assisted coiling, balloon-assisted coiling, flow diverters (FD), disruptors, and new embolic materials, such as liquids, showing promising results [33]. However, complications can occur, such as intraprocedural aneurysm rupture and thromboembolism, which are more frequent in the setting of SAH compared to unruptured aneurysms [40].

Flow diverters have emerged as an alternative to coil embolization for treating wide-neck and challenging aneurysm morphologies, but 25% of FD-treated intracranial aneurysms still fail to reach complete occlusion even after six months, increasing the risk of rupture and thromboembolic complications. Factors such as aneurysm ostium size, pre- and post-treatment inflow rates, shear rate, and averaged velocity are analyzed to assess the effectiveness of FD treatment [40].

For coil embolization, recanalization has been shown to correlate with aneurysm morphometrics such as size, neck-to-dome ratio, and neck size, which have been used to gauge coil treatment outcomes [41]. On the other hand, the FD treatment of IAs does not correlate to these morphological features; instead, hemodynamic metrics are analyzed [42].

Mut et al. [43] found that specific hemodynamic metrics, such as pre-and post-treatment inflow rates, shear rate, and aneurysm velocity, significantly differed between occluded and non-occluded intracranial aneurysms following six months of FD treatment.

Paliwal et al. used computational image analysis to extract information on morphology, hemodynamics, and FD-device characteristics from FD-treated aneurysms [44]. They used this data to train machine learning algorithms to predict 6-month clinical outcomes after FD treatment, finding that a neural network performed best (AUC = 0.967) and that the G-SVM with NN was able to predict occlusion outcomes with 90% accuracy.

Guedon et al. [45] utilized ElasticNet penalized logistic regression for developing a predictive score consisting of aneurysm diameter, treatment indication, parent artery diameter ratio, neck ratio, side-branch artery, and sex to forecast aneurysm occlusion following FD treatment at a follow-up of six months or longer, achieving an accuracy of 86%.

Endovascular therapy for cerebral aneurysms has undergone significant advancements over the years, with newer techniques, such as flow diverters showing promising results for treating challenging aneurysm morphologies. However, complications can still arise, and effective treatment outcome assessment requires considering various factors such as hemodynamic metrics and morphological features.

4. Prediction of aneurysm complications

The cornerstone of prediction modeling in aneurysm is to predict rupture, and statistical models such as logistic regression have been widely used for this purpose [35]. However, recent studies have demonstrated that machine learning (ML) models perform better than traditional statistical methods because they can process massive amounts of data and model nonlinear relationships [46].

Hemodynamics is considered the most valuable parameter in exploring intracranial aneurysm behavior. Promising AI tools, such as computational fluid dynamics, have been developed to assess hemodynamics [47]. Morphological features, including size and shape, have shown great potential in identifying aneurysms at risk of rupture, while geometric features that describe the 3D characteristics of the aneurysm can be automated to evaluate aneurysm formation, growth, and risk of rupture. Integrating clinical, morphological, and hemodynamic parameters can improve rupture prediction, but limited clinical use is still observed due to complexity, cost, and expertise requirements [5].

Several studies have used ML methods to predict complications arising from aneurysm rupture, such as vasospasm, delayed cerebral ischemia, and infarction [48]. Dumon et al. [49] developed an ANN prediction model that had a higher predictive value (AUC of 0.960) for symptomatic cerebral vasospasm than two multiple logistic regression models (AUC = 0.933 and 0.897). In another study, ML methods such as SVM, random forest, and multilayer perceptron outperformed logistic regression models in predicting delayed cerebral ischemia.

Tanioka et al. [47] used random forests to develop early prediction models for delayed cerebral ischemia, angiographic vasospasm, and cerebral infarction using clinical variables and matricellular proteins. The proteins osteopontin, periostin, and galectin-3 had prediction accuracies of 95.1%, 78.1%, and 3.8%, respectively. These studies demonstrate that ML methods have shown excellent performance in predicting complications that arise from aneurysm rupture.

Another application is the use of clinical data and CT perfusion from hospital admissions to predict outcomes of aneurysmal SAH. A random forest model was trained to predict dichotomized mRS (<2 and >2), and the accuracy was 84.4% in the training folds and 70.9% in the validation folds. However, it cannot be introduced into clinical practice because of small population size [50].

5. Limitations and challenges of AI on intracranial aneurysm

The use of artificial intelligence in the analysis of intracranial aneurysms has been expanding rapidly. While numerous algorithms and techniques have been developed for managing these aneurysms, certain challenges and limitations must be addressed.

Kim and colleagues [51] suggested certain standards to assess the clinical effectiveness of AI algorithms. These include obtaining external validation, conducting a diagnostic cohort study, involving multiple institutions, and performing prospective studies. However, most of the studies on AI in managing intracranial aneurysms lack external validation and are retrospectively designed, which can lead to selection bias and variability. To achieve reliable results, it is necessary to conduct prospective studies and externally validate the available algorithms for their clinical feasibility [5].

DL-based algorithms have exhibited positive outcomes, along with other AI techniques. However, the time taken to train them and their cost-effectiveness are still questionable. The intricate structure of neural network algorithms poses a challenge known as the "black box" problem, where the process of data processing within the layers is not completely understood. This leads to skepticism regarding the results generated from a "black box." [19].

In addition, these systems may introduce new kinds of errors, particularly automation bias, which is defined as the inclination to use automated cues as a substitute for vigilant information-seeking and processing [52]. Automation bias has been highlighted as one of the potential drawbacks and ethical issues of AI-based applications. It reflects the dependence of the user on the machine, ignoring the contradictory information that may exist without automation, leading to decreased self-confidence and loss of human input [5].

Nowadays, a legal consensus is lacking regarding AI regulations, and no clear guidelines are available regarding the independent mathematical interrogation and validation of outputs generated by AI systems [52].

6. Future perspectives

AI has promising potential in the management of intracranial aneurysms in the future, including prescreening triage systems for emergency medicine physicians to prioritize high-risk patients, automated detection and intelligent outcome prediction, prediction of treatment strategies during follow-up, automated detection of recurrence after treatment, and prediction of rupture risk [1].

For an AI tool to effectively manage aneurysms, it must accurately identify true-positive cases with high confidence. This level of reliability can only be achieved through a significant number of annotated imaging studies, which are necessary before the tool can be widely implemented in real-world scenarios [53].

7. Conclusions

In conclusion, the use of artificial intelligence in managing intracranial aneurysms offers higher accuracy and efficacy than manual measurements and can potentially augment the clinical performance of radiologists and shorten interpretation time. While some studies need to be validated in a clinical setting, AI-based applications should be viewed as a tool to assist and not replace human decision-making in health care. Although implementing new technology may initially be costly, the long-term cost-effectiveness of AI can potentially reduce the cost of unnecessary diagnostic testing. Further studies are required to explore other AI applications in intracranial aneurysms and to validate the findings in a real-world clinical setting.

Acknowledgements

This work would not have been possible without the financial support of Fundación Amigos de la Juventud, A.C. (FUNDAJU).

Conflict of interest

The authors declare no conflict of interest.

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