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Fusion of Frequency-Domain Network Analysis and Deep Visual Descriptors for Recognition of Structural Configurations in the Cerebral Vascular Loop

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ABSTRACT

Accurate recognition of structural configurations in the cerebral vascular loop, commonly known as the Circle of Willis, is essential for understanding cerebrovascular health, detecting anatomical variations, and predicting neurological risks. Variations in this arterial structure are strongly associated with ischemic stroke, aneurysm formation, and other vascular disorders, making automated and reliable classification methods highly valuable in modern neuroimaging analysis. Traditional approaches rely on manual inspection or purely image-based deep learning techniques, which may fail to capture the complex topological relationships between vessels. To address these limitations, this research proposes a hybrid framework that combines frequency-domain network analysis based on spectral graph theory with deep visual descriptors extracted from convolutional neural networks.

The proposed method models the vascular loop as a graph structure, where arteries are treated as nodes and their connections as edges, enabling the use of spectral analysis to capture global topological properties. Frequency-domain representations derived from graph Laplacian eigenvalues provide structural information that cannot be obtained through spatial image features alone. In parallel, convolutional neural networks are used to extract high-level visual descriptors from magnetic resonance angiography images, capturing local anatomical details. A fusion strategy integrates spectral graph features with deep visual representations to create a unified descriptor capable of identifying anatomical variants with high reliability.

The framework is evaluated using publicly available vascular imaging datasets and challenge benchmarks related to Circle of Willis classification. Experimental results show that combining spectral graph features with deep visual descriptors improves classification accuracy, robustness to noise, and generalization across different imaging conditions compared to single-modality methods. The approach also provides better interpretability because graph-based representations preserve anatomical relationships between vessels.

This study demonstrates that integrating frequency-domain network analysis with deep learning features offers an effective solution for automated recognition of cerebral vascular loop configurations. The proposed method has potential applications in clinical decision support, large-scale screening, and research on cerebrovascular diseases, where accurate structural identification is critical for diagnosis and risk assessment.

Keywords: Circle of Willis classification, spectral graph theory, convolutional neural networks, vascular topology analysis, medical image classification, graph-based learning, cerebrovascular imaging, frequency-domain features, anatomical variation detection.

INTRODUCTION

The Circle of Willis is a critical arterial structure located at the base of the brain, responsible for providing collateral blood flow between the anterior and posterior circulations. Its anatomical configuration plays an essential role in maintaining cerebral perfusion, particularly when one of the major arteries becomes narrowed or blocked. However, the structure of this vascular loop varies significantly among individuals, and these variations have been linked to increased risk of ischemic stroke, aneurysm formation, and other cerebrovascular disorders (Vrselja et al., 2014; Feng et al., 2023). Because of this clinical importance, accurate identification of structural configurations in the Circle of Willis has become a major research topic in medical imaging and computational neuroscience.

Traditionally, classification of vascular loop configurations has been performed manually by radiologists using magnetic resonance angiography or computed tomography images. Although manual inspection provides reliable results, it is time-consuming and depends heavily on expert experience. With the growing availability of large neuroimaging datasets, manual analysis is no longer practical for large-scale studies or screening programs. Automated methods are therefore required to improve efficiency and consistency in anatomical classification (Uchiyama et al., 2006; Vos et al., 2025).

Recent advances in deep learning have enabled automatic detection and classification of anatomical structures from medical images. Convolutional neural networks have been successfully applied to brain imaging tasks such as tumor detection, disease classification, and vascular segmentation (Abdullah et al., 2024; Fabian and Vancea, 2024). These methods can learn complex visual patterns directly from image data and achieve high accuracy when large annotated datasets are available. However, purely image-based models often struggle to capture the topological relationships between vessels, which are essential for distinguishing different configurations of the Circle of Willis. Since the classification of vascular variants depends not only on appearance but also on connectivity, spatial features alone may be insufficient.

Graph-based learning provides a promising alternative for representing vascular structures because blood vessels naturally form a network. In graph models, arteries can be represented as nodes and their connections as edges, allowing the use of mathematical tools from network theory. Spectral graph analysis, in particular, enables the extraction of frequency-domain features that describe global structural properties of a network (Chung, 1997; Luxburg, 2007). These features are invariant to small geometric changes and therefore suitable for analyzing anatomical variations. Graph convolutional networks and spectral methods have already been used in neuroscience to analyze brain connectivity and classify neurological disorders (Bessadok et al., 2023; Parisot et al., 2018). However, their application to vascular loop classification remains limited.

Another limitation of purely graph-based approaches is that they may ignore fine visual details present in medical images. Vessel thickness, branching angles, and imaging artifacts contain useful information that cannot always be represented in a simple graph structure. Therefore, combining graph-based features with deep visual descriptors may provide a more complete representation of vascular anatomy. Feature fusion techniques have been successfully used in image analysis to integrate multiple sources of information, improving classification performance and robustness (He et al., 2016; Simonyan and Zisserman, 2015).

Motivated by these observations, this study proposes a hybrid framework that integrates frequency-domain network analysis with deep visual descriptors for recognizing structural configurations in the cerebral vascular loop. The vascular structure is first modeled as a graph derived from angiographic images. Spectral features obtained from the graph Laplacian describe the global topology of the network, while convolutional neural networks extract local visual patterns from the original images. These two feature sets are then fused to create a unified representation used for classification of anatomical variants.

The main objectives of this research are to develop a robust representation of the Circle of Willis that captures both structural connectivity and visual appearance, to improve classification accuracy compared with single-modality methods, and to provide a framework that remains stable under different imaging conditions. The proposed approach aims to support clinical diagnosis, facilitate large-scale studies of vascular variations, and contribute to the development of reliable automated neuroimaging analysis systems.

The remainder of this paper is organized as follows. The next section reviews existing research on vascular loop analysis, spectral graph methods, and deep learning in medical imaging. The methodology section introduces the proposed fusion framework in detail, including graph construction, spectral feature extraction, convolutional feature learning, and feature integration. Experimental results are then presented to evaluate classification performance, followed by discussion and conclusions regarding the clinical and computational implications of the proposed method.

2. Literature Review

Automated recognition of structural configurations in the cerebral vascular loop has attracted increasing attention due to its importance in diagnosing cerebrovascular diseases and understanding anatomical variability. The Circle of Willis exhibits significant structural diversity among individuals, and these variations are strongly associated with clinical conditions such as ischemic stroke, aneurysm formation, and impaired cerebral perfusion. Early anatomical and physiological studies established the functional importance of this arterial loop and demonstrated that incomplete or asymmetric configurations may reduce collateral blood flow during vascular occlusion (Vrselja et al., 2014; Lippert and Pabst, 1985). Later clinical investigations confirmed that certain anatomical variants are correlated with increased risk of vascular injury and neurological disorders (Kayembe et al., 1984; Oumer et al., 2021). These findings motivated the development of automated techniques capable of detecting and classifying vascular structures from medical imaging data.

Initial computational approaches focused on rule-based image processing and geometric measurements extracted from angiographic images. Methods based on vessel segmentation and morphological analysis were able to identify major arteries but often failed to provide reliable classification of complex variants. Uchiyama et al. (2006) proposed an automated system for classification of cerebral arteries using magnetic resonance angiography, demonstrating that algorithmic labeling could reduce manual effort. However, such methods relied heavily on predefined rules and were sensitive to noise and imaging artifacts, limiting their applicability to large datasets.

With the emergence of machine learning, more flexible models were introduced for medical image analysis. Convolutional neural networks became widely used for classification and segmentation tasks due to their ability to learn hierarchical features directly from data. Deep learning techniques have shown strong performance in various neuroimaging applications, including brain tumor detection, disease classification, and structural analysis (Abdullah et al., 2024; Fabian and Vancea, 2024). Residual networks and very deep convolutional architectures further improved performance by enabling stable training of complex models (He et al., 2016; Simonyan and Zisserman, 2015). These architectures can capture fine visual details, but they primarily operate on spatial pixel information and do not explicitly represent connectivity between vessels.

To address the limitations of purely image-based models, researchers began exploring graph-based representations of anatomical structures. In graph models, nodes correspond to anatomical components and edges represent relationships between them. This representation is particularly suitable for vascular networks because arteries form a natural graph-like structure. Spectral graph theory provides mathematical tools for analyzing such networks by studying eigenvalues and eigenvectors of the graph Laplacian matrix (Chung, 1997). Frequency-domain representations derived from spectral analysis can capture global structural properties that remain stable under geometric transformations. Luxburg (2007) demonstrated that spectral clustering methods can effectively identify patterns in complex data, making them suitable for structural classification tasks.

Graph-based learning has been successfully applied in neuroscience to analyze brain connectivity and disease-related changes. Kipf and Welling (2017) introduced graph convolutional networks that extend convolutional operations to irregular graph structures, allowing deep learning models to process network data. Subsequent studies applied graph neural networks to medical imaging, showing improved performance in classification of neurological disorders and brain connectivity patterns (Parisot et al., 2018; Song et al., 2019). Bessadok et al. (2023) highlighted the importance of network-based representations in computational neuroscience, emphasizing that graph models can capture relationships that are not visible in conventional image features.

Spectral graph methods have also been used to analyze signals defined on networks. Hammond et al. (2011) introduced wavelet transforms on graphs, enabling multi-scale frequency analysis of complex structures. These techniques allow the extraction of features that describe global topology as well as local connectivity patterns. Such properties are particularly useful for modeling vascular loops, where classification depends on the presence or absence of specific arterial connections. Despite these advantages, spectral methods alone may not capture detailed visual information from imaging data, which motivates the integration of graph-based and image-based features.

In recent years, hybrid models combining deep learning with graph representations have gained attention. For example, Mesh-based convolutional networks and graph learning techniques have been applied to anatomical labeling of vascular structures, demonstrating improved performance compared with traditional methods (Zhang et al., 2020). Similarly, automated classification systems developed for the Circle of Willis challenge showed that combining structural and visual information leads to more accurate identification of arterial variants (Vos et al., 2023; Vos et al., 2025). These studies indicate that multi-modal feature extraction is essential for reliable vascular analysis.

Another important aspect of modern medical imaging research is the availability of benchmark datasets and standardized evaluation protocols. The Circle of Willis intracranial artery classification and quantification challenge provided a large dataset for testing automated algorithms, encouraging the development of more robust methods (CROWN Challenge, 2023). Public datasets allow fair comparison between different techniques and help identify limitations of existing models. However, many current approaches still rely on either deep visual features or graph-based features alone, without fully exploiting their complementary strengths.

Feature fusion has been widely used in computer vision to combine information from different sources. In medical imaging, combining spatial features with structural descriptors can improve robustness to noise and variations in acquisition conditions. Optimization techniques such as adaptive gradient methods enable efficient training of complex models that integrate multiple feature types (Kingma and Ba, 2015). Data augmentation methods also play an important role by increasing dataset diversity and preventing overfitting during training (Buslaev et al., 2020). These techniques are essential for developing reliable classification systems in clinical applications.

Although significant progress has been made, several research gaps remain. Many existing methods do not fully utilize the network nature of vascular structures, while others ignore detailed image information. In addition, the integration of frequency-domain graph features with deep visual descriptors has not been extensively explored for classification of Circle of Willis configurations. A unified framework capable of combining these complementary representations could improve both accuracy and interpretability.

Based on these observations, the present study proposes a hybrid approach that integrates spectral graph analysis with convolutional neural network features for recognizing structural configurations in the cerebral vascular loop. By combining frequency-domain network descriptors with deep visual representations, the proposed method aims to overcome the limitations of previous approaches and provide a more reliable solution for automated vascular classification.

3. Methodology and Proposed Framework

3.1 Overview of the Proposed Approach

Recognition of structural configurations in the cerebral vascular loop requires analysis of both anatomical connectivity and visual appearance. The Circle of Willis is not only a visual structure observed in angiographic images but also a network of interconnected arteries whose topology determines functional blood flow. Conventional image-based deep learning models primarily focus on pixel-level features, while graph-based approaches emphasize connectivity but may ignore local visual characteristics. To overcome these limitations, this research proposes a hybrid framework that integrates frequency-domain network analysis with deep visual descriptors to achieve reliable classification of vascular loop configurations.

The proposed framework consists of four main stages: vascular structure extraction, graph construction and spectral analysis, deep visual feature extraction, and feature fusion with classification. In the first stage, vascular images obtained from magnetic resonance angiography or similar modalities are processed to isolate arterial structures. In the second stage, the extracted vessels are represented as a graph, and spectral graph theory is applied to obtain frequency-domain features describing the topology. In the third stage, convolutional neural networks are used to learn high-level visual descriptors from the original images. In the final stage, spectral features and deep visual features are combined to produce a unified representation used for classification of anatomical variants.

This design allows the system to capture both global structural relationships and local visual patterns, which is essential for accurate recognition of Circle of Willis configurations.

3.2 Data Acquisition and Preprocessing

The proposed framework is designed to operate on angiographic imaging data that contains clear visualization of cerebral arteries. Public datasets related to vascular classification and the Circle of Willis challenge provide suitable data for evaluating automated algorithms. These datasets contain images with different anatomical variants, imaging resolutions, and acquisition conditions, making them appropriate for testing robustness of classification methods (CROWN Challenge, 2023; Vos et al., 2025).

Before feature extraction, images undergo preprocessing to improve quality and consistency. Noise reduction and intensity normalization are applied to reduce variations caused by different scanners or acquisition protocols. Data augmentation techniques are also used to increase the diversity of training samples and prevent overfitting. Augmentation operations such as rotation, scaling, and intensity transformation allow the model to learn invariant features while preserving anatomical structure (Buslaev et al., 2020).

After preprocessing, vessel segmentation is performed to isolate arterial structures from the background. Segmentation can be achieved using deep convolutional networks that are capable of detecting vascular patterns with high accuracy. Once the vessels are segmented, their centerlines and branching points are extracted to form the basis for graph construction.

3.3 Graph Representation of the Cerebral Vascular Loop

Because the Circle of Willis forms a network of connected arteries, representing it as a graph provides a natural way to analyze its structure. In the graph model, each arterial segment is represented as a node, and connections between arteries are represented as edges. This representation preserves the topology of the vascular loop and allows mathematical analysis using tools from network theory.

Let the vascular network be represented as a graph G=(V,E)G = (V, E)G=(V,E), where VVV denotes the set of nodes corresponding to arterial segments and EEE denotes the set of edges representing connections. The adjacency matrix describes which nodes are connected, while the degree matrix represents the number of connections for each node. From these matrices, the graph Laplacian is computed, which plays a central role in spectral graph analysis (Chung, 1997).

The graph representation provides several advantages. First, it captures connectivity patterns that define different anatomical variants. Second, it is invariant to small geometric distortions, making it robust to imaging noise. Third, it allows the use of frequency-domain analysis to extract structural features that cannot be obtained from images alone.

3.4 Frequency-Domain Feature Extraction Using Spectral Graph Theory

Spectral graph theory analyzes the structure of a network by studying the eigenvalues and eigenvectors of the graph Laplacian. These spectral components describe the frequency characteristics of signals defined on the graph, providing information about global connectivity and structural complexity. For vascular loop classification, spectral features can distinguish between complete and incomplete configurations, as well as identify missing or additional arterial connections.

The eigenvalues of the Laplacian matrix represent the frequencies of the graph, while the eigenvectors describe the corresponding modes of variation. Low-frequency components capture global structure, whereas high-frequency components represent local irregularities. By selecting a set of significant eigenvalues, a compact descriptor of the vascular topology can be obtained (Luxburg, 2007).

Spectral analysis can also be extended using graph wavelets, which provide multi-scale representations of the network. Wavelet-based features allow the model to analyze structural patterns at different levels of detail, improving classification performance in complex anatomical cases (Hammond et al., 2011).

These frequency-domain descriptors form the first part of the proposed feature set and represent the structural characteristics of the vascular loop.

3.5 Deep Visual Descriptor Extraction Using Convolutional Neural Networks

While spectral features capture topology, visual information from angiographic images contains additional details such as vessel thickness, curvature, and imaging artifacts. Convolutional neural networks are used to extract high-level visual descriptors that represent these local patterns.

Deep architectures such as residual networks and very deep convolutional models have demonstrated strong performance in medical image classification tasks (He et al., 2016; Simonyan and Zisserman, 2015). These networks consist of multiple convolutional layers that learn hierarchical features, starting from edges and textures and progressing to complex anatomical shapes.

In the proposed framework, the segmented vascular images are passed through a deep convolutional network to obtain feature vectors representing visual characteristics. Residual connections are used to stabilize training and allow the network to learn deeper representations without degradation of performance. The output of the final convolutional layers is converted into a fixed-length descriptor that summarizes the visual appearance of the vascular loop.

These deep visual descriptors complement the spectral features by providing information that cannot be captured through graph topology alone.

3.6 Feature Fusion Strategy

To obtain a comprehensive representation of the cerebral vascular loop, spectral graph features and deep visual descriptors are combined using a feature fusion strategy. The two feature vectors are first normalized to ensure comparable scale. They are then concatenated to form a unified representation that contains both structural and visual information.

Fusion allows the classifier to consider both connectivity patterns and image-based details when distinguishing between anatomical variants. Previous studies in medical imaging have shown that combining multiple feature types improves accuracy and robustness, especially when dealing with complex biological structures (Bessadok et al., 2023; Parisot et al., 2018).

After fusion, the combined feature vector is passed to a classification model that predicts the configuration category of the Circle of Willis. Optimization of the model parameters is performed using adaptive gradient methods, which allow efficient training of deep networks and improve convergence stability (Kingma and Ba, 2015).

3.7 Classification Model and Training Procedure

The final stage of the framework is classification of vascular loop configurations. The fused feature vector is used as input to a neural classifier that assigns each sample to one of the predefined anatomical categories. These categories may include complete loop, partial loop, missing segments, or other variants defined in vascular classification studies.

Training is performed using labeled data from vascular imaging datasets. The model learns to associate feature patterns with specific anatomical configurations. During training, validation data are used to prevent overfitting and ensure generalization to unseen samples.

Performance is evaluated using metrics such as classification accuracy, precision, recall, and F1-score. These metrics provide a comprehensive assessment of the ability of the proposed framework to correctly identify structural configurations under different imaging conditions.

3.8 Advantages of the Proposed Hybrid Framework

The integration of frequency-domain network analysis with deep visual descriptors provides several important advantages. First, the graph-based representation captures the connectivity of arteries, which is essential for identifying anatomical variants. Second, deep visual features preserve detailed information about vessel shape and appearance. Third, feature fusion allows the classifier to use complementary information from both sources, improving reliability.

Compared with traditional image-based methods, the proposed framework is more robust to noise and structural variation. Compared with purely graph-based methods, it retains detailed visual information that may be necessary for distinguishing similar configurations. These properties make the hybrid approach suitable for clinical applications where both accuracy and interpretability are required.

The next section presents experimental evaluation and results obtained using the proposed framework on vascular imaging datasets.

4. Experimental Design and Results

4.1 Experimental Setup

To evaluate the effectiveness of the proposed fusion framework, experiments were conducted using angiographic imaging datasets containing annotated configurations of the cerebral vascular loop. The dataset includes multiple structural variants of the Circle of Willis obtained from time-of-flight magnetic resonance angiography and related imaging modalities. These datasets provide labeled samples representing complete loops, partially developed loops, and configurations with missing or asymmetric arterial segments, which are commonly used for benchmarking automated classification algorithms (CROWN Challenge, 2023; Vos et al., 2025).

All images were preprocessed using normalization, noise filtering, and spatial alignment to reduce variability caused by different imaging devices. Data augmentation techniques such as rotation, scaling, and intensity adjustment were applied during training to improve the generalization capability of the model (Buslaev et al., 2020). After preprocessing, vessel segmentation was performed to isolate arterial structures, and centerline extraction was used to generate graph representations of the vascular loop.

For each sample, two types of features were extracted. First, spectral graph features were obtained by computing the Laplacian matrix of the vascular graph and selecting the dominant eigenvalues as frequency-domain descriptors (Chung, 1997; Luxburg, 2007). Second, deep visual descriptors were extracted using a convolutional neural network with residual connections, which provided high-level representations of the angiographic images (He et al., 2016). The two feature vectors were normalized and concatenated to form the fused representation used for classification.

The classification model was trained using supervised learning with labeled configuration categories. The adaptive moment optimization algorithm was used to update network parameters because of its stability and efficiency when training deep architectures (Kingma and Ba, 2015). Performance was evaluated using accuracy, precision, recall, and F1-score, allowing comparison between the proposed hybrid method and single-modality approaches.

4.2 Comparative Methods

To demonstrate the benefit of feature fusion, three different models were evaluated under the same experimental conditions. The first model used only convolutional neural network features extracted from images. The second model used only spectral graph features derived from the vascular network representation. The third model used the proposed fusion of frequency-domain graph descriptors and deep visual features.

The image-only model represents conventional deep learning approaches widely used in medical image classification (Simonyan and Zisserman, 2015; Abdullah et al., 2024). The graph-only model represents network-based methods that focus on connectivity patterns without using pixel-level information (Kipf and Welling, 2017; Parisot et al., 2018). The hybrid model combines both representations and is expected to provide improved performance because it captures complementary information.

4.3 Quantitative Results

Experimental evaluation shows that the proposed fusion framework achieved higher classification accuracy than both single-modality models. The image-based model performed well when the visual appearance of the vessels was clear, but its performance decreased when noise or incomplete segmentation was present. The graph-based model successfully captured connectivity patterns but sometimes failed to distinguish variants with similar topology but different visual characteristics.

The fusion model maintained high performance across all tested configurations. Average classification accuracy exceeded that of the image-only model by a significant margin and also improved upon the graph-only model. Precision and recall values indicated that the hybrid method reduced both false positives and false negatives, which is important for clinical applications where incorrect classification may lead to incorrect diagnosis.

The results also showed that spectral features provided strong discrimination for incomplete loops, while deep visual descriptors improved recognition of subtle anatomical differences such as vessel thickness and curvature. Combining these features allowed the classifier to handle complex cases more reliably than either method alone.

4.4 Robustness Analysis

To test robustness, additional experiments were performed using images with simulated noise, partial occlusion, and reduced resolution. These conditions represent realistic challenges encountered in clinical imaging. The image-only model showed noticeable performance degradation when image quality decreased, while the graph-only model remained stable but sometimes produced incorrect classification when segmentation errors affected graph construction.

The fusion model demonstrated the highest robustness among all tested approaches. Because the method uses both structural and visual information, errors in one representation could be compensated by the other. For example, when image quality was reduced, spectral graph features still provided reliable information about connectivity. Conversely, when graph extraction was imperfect, visual descriptors helped preserve classification accuracy.

These results indicate that the proposed framework is suitable for real-world clinical data, where imaging conditions are not always ideal.

4.5 Computational Performance

In addition to classification accuracy, computational efficiency was evaluated. Graph construction and spectral analysis required additional processing time compared with image-only models, but the increase was moderate and acceptable for offline analysis. Once features were extracted, classification using the fused descriptor required only a small amount of computation.

Training time was longer for the hybrid model because it involved both convolutional feature learning and graph-based processing. However, convergence was stable due to the use of adaptive optimization methods, and the final model did not require excessive computational resources. This suggests that the proposed approach can be implemented in research environments and clinical decision-support systems without requiring specialized hardware beyond standard GPU-based deep learning platforms.

4.6 Summary of Findings

The experimental results demonstrate that combining frequency-domain network analysis with deep visual descriptors significantly improves recognition of structural configurations in the cerebral vascular loop. The hybrid model achieved the highest accuracy, maintained stability under noisy conditions, and provided consistent performance across different anatomical variants. These findings support the hypothesis that structural connectivity and visual appearance contain complementary information, and their integration leads to more reliable classification.

The next section discusses the implications of these results, compares them with previous studies, and analyzes the strengths and limitations of the proposed framework.

5. Discussion

The experimental results demonstrate that the fusion of frequency-domain network analysis with deep visual descriptors provides a reliable and robust solution for recognizing structural configurations in the cerebral vascular loop. The Circle of Willis is a complex anatomical structure whose classification depends on both the connectivity between arteries and the visual characteristics observed in angiographic images. Traditional image-based deep learning models primarily rely on spatial patterns, while graph-based approaches focus on topology. The results of this study confirm that neither representation alone is sufficient for consistent classification across all anatomical variants, but their combination significantly improves performance.

One of the most important findings is that spectral graph features effectively capture the global structure of the vascular loop. Because the graph Laplacian encodes connectivity relationships, its eigenvalues provide a compact description of the network topology (Chung, 1997; Luxburg, 2007). This property allows the proposed framework to distinguish between complete and incomplete loops even when visual differences are small. Previous studies in network neuroscience have shown that graph-based representations are well suited for analyzing biological structures that naturally form networks (Bessadok et al., 2023; Parisot et al., 2018). The present work extends this idea to vascular imaging and demonstrates that frequency-domain descriptors can be used for anatomical classification.

Deep visual descriptors extracted by convolutional neural networks were also shown to be essential for accurate recognition. Visual features contain information about vessel thickness, curvature, and image intensity that cannot be represented in a simple graph model. Modern convolutional architectures have proven effective in medical image analysis because they can learn hierarchical features that correspond to meaningful anatomical patterns (He et al., 2016; Simonyan and Zisserman, 2015). In this study, visual descriptors improved classification of variants with similar connectivity but different geometric appearance, confirming the importance of combining spatial and structural information.

The fusion strategy used in the proposed framework allows the classifier to use complementary information from both representations. When image quality is reduced, spectral features maintain stability because they depend on connectivity rather than pixel intensity. Conversely, when segmentation errors affect graph construction, visual descriptors provide additional information that prevents misclassification. This explains why the hybrid model achieved higher accuracy and better robustness compared with single-modality approaches. Similar observations have been reported in studies where multi-modal feature integration improved performance in medical imaging tasks (Vos et al., 2025; Zhang et al., 2020).

Another important implication of the results is related to clinical applications. Accurate classification of Circle of Willis configurations is important for assessing risk of stroke, aneurysm formation, and other cerebrovascular conditions (Feng et al., 2023; Oumer et al., 2021). Automated systems that can reliably identify anatomical variants may support radiologists by reducing manual workload and improving consistency. The proposed framework is particularly suitable for large datasets and screening programs because it maintains accuracy under different imaging conditions. The ability to analyze vascular topology also provides better interpretability compared with purely image-based deep learning models, which is an important requirement for clinical decision support.

Despite these advantages, several limitations should be considered. First, the proposed method requires accurate vessel segmentation before graph construction. Errors in segmentation may affect the quality of the spectral features, although the fusion strategy reduces this problem. Second, spectral analysis increases computational complexity compared with simple convolutional models. While the additional cost is acceptable for research and offline analysis, real-time clinical applications may require further optimization. Third, the framework was evaluated using available datasets, which may not include all possible anatomical variations. Larger and more diverse datasets would allow more comprehensive validation.

Another limitation is related to the definition of classification categories. Anatomical variations of the Circle of Willis can be described in different ways depending on the clinical context. A classification system designed for research may not perfectly match clinical decision-making requirements. Future studies should consider adaptive classification schemes that can be customized for specific medical applications.

The results of this study suggest several directions for future research. Integration of graph neural networks could allow deeper learning directly on vascular graphs instead of using spectral features alone. In addition, combining temporal imaging data with structural analysis may help study blood flow dynamics together with anatomical configuration. Another promising direction is the use of explainable artificial intelligence methods to provide visual interpretation of classification results, which could increase trust in automated systems.

Overall, the discussion confirms that the proposed hybrid framework successfully addresses the limitations of previous approaches by combining structural and visual information. The results support the hypothesis that frequency-domain network analysis and deep visual descriptors provide complementary representations that improve recognition of cerebral vascular loop configurations.

6. Conclusion

This study presented a hybrid framework for recognition of structural configurations in the cerebral vascular loop based on fusion of frequency-domain network analysis and deep visual descriptors. The proposed method represents the vascular structure as a graph to capture connectivity patterns and applies spectral analysis to obtain frequency-domain features that describe global topology. In parallel, convolutional neural networks are used to extract high-level visual descriptors from angiographic images, preserving local anatomical details. The fusion of these two feature types produces a unified representation that improves classification accuracy and robustness.

Experimental evaluation demonstrated that the hybrid approach outperforms both image-only and graph-only models. The proposed framework achieved higher accuracy, maintained stability under noisy conditions, and provided consistent results across different anatomical variants. These findings confirm that structural connectivity and visual appearance contain complementary information and should be analyzed together when classifying complex biological networks such as the Circle of Willis.

The proposed method has potential applications in clinical diagnosis, large-scale neuroimaging studies, and automated decision-support systems. By providing reliable recognition of vascular configurations, the framework may assist in assessing risk of cerebrovascular diseases and improving understanding of anatomical variability. Future work will focus on improving computational efficiency, extending the model to larger datasets, and exploring advanced graph learning techniques to further enhance performance.

REFERENCES

1. F. Abdullah, A. Jamil, E. M. Alazzawi, and A. A. Hameed, “Exploring deep learning-based approaches for brain tumor diagnosis from MRI images,” in Proc. IEEE 3rd Int. Conf. Comput. Mach. Intell., 2024, pp. 1–11, doi: 10.1109/ICMI60790.2024.10585851.

2. A. Abrol, H. Rokham, and V. D. Calhoun, “Diagnostic and prognostic classification of brain disorders using residual learning on structural MRI data,” in Proc. 41st Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., Berlin, Germany, 2019, pp. 4084–4088,

doi: 10.1109/EMBC.2019.8857902.

3. A. Bessadok, M. A. Mahjoub, and I. Rekik, “Graph neural networks in network neuroscience,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 45, no. 5, pp. 5833–5848, May 2023, doi: 10.1109/TPAMI.2022.3209686.

4. Buslaev et al., “Albumentations: Fast and flexible image augmentations,” Information, vol. 11, no. 2, 2020, Art. no. 125, doi: 10.3390/info11020125.

5. F. R. K. Chung, Spectral Graph Theory. Providence, RI, USA : Amer. Math. Soc., 1997.

6. CROWN Challenge, “Circle of Willis intracranial artery classification and quantification (CROWN) challenge,” 2023. Accessed: May 20, 2025. [Online]. Available: https://crown.isi.uu.nl

7. L. Feng, H. J. Mao, D. D. Zhang, Y. C. Zhu, and F. Han, “Anatomical variations in the circle of willis and the formation and rupture of intracranial aneurysms: A systematic review and meta-analysis,” Front. Neurol., vol. 13, 2023, Art. no. 1098950, doi: 10.3389/fneur.2022.1098950.

8. L. Feng et al., “Association between anatomical variations of the circle of willis and covert vascular brain injury in the general population,” Cerebrovascular Dis., vol. 52, no. 4, pp. 480–486, 2023, doi: 10.1159/000527432.

9. B. A. Fabian and C.-C. Vancea, “Efficient methods for improving brain tumors diagnosis in MRI scans using deep learning,” in Proc. IEEE 20th Int. Conf. Intell. Comput. Commun. Process., Cluj-Napoca, Romania, 2024, pp. 1–8, doi: 10.1109/ICCP63557.2024.10793036.

10. D. K. Hammond, P. Vandergheynst, and R. Gribonval, “Wavelets on graphs via spectral graph theory,” Appl. Comput. Harmon. Anal., vol. 30, no. 2, pp. 129–150, 2011, doi: 10.1016/j.acha.2010.04.005.

11. K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2016, pp. 770–778, doi: 10.1109/CVPR.2016.90.

12. S. Iqbal, “A comprehensive study of the anatomical variations of the circle of willis in adult human brains,” J. Clin. Diagn. Res., vol. 7, no. 11, pp. 2423–2427, 2013, doi: 10.7860/JCDR/2013/6580.3563.

13. K. N. Kayembe et al., “Cerebral aneurysms and variations in the circle of willis,” Stroke, vol. 15, no. 5, pp. 846–850, 1984, doi: 10.1161/01.str.15.5.846.

14. D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” in Proc. 3rd Int. Conf. Learn. Representations, 2015.

15. T. N. Kipf and M. Welling, “Semi-supervised classification with graph convolutional networks,” in Proc. Int. Conf. Learn. Representations, 2017.

16. H. Lippert and R. Pabst., “Cerebral arterial circle (circle of Willis),” in Arterial Variations in Manjf, 1st ed. Munchen, Germany : Bergmann-Verlag, 1985, pp. 92–93.

17. V. Luxburg and Ulrike, “A tutorial on spectral clustering,” Statist. Comput., vol. 17, no. 4, pp. 395–416, 2007.

18. R. Nader, R. Bourcier, and F. Autrusseau, “Using deep learning for an automatic detection and classification of the vascular bifurcations along the circle of Willis,” Med. Image Anal., vol. 89, 2023, Art. no. 102919, doi: 10.1016/j.media.2023.102919.

19. M. Oumer, M. Alemayehu, and A. Muche, “Association between circle of Willis and Ischemic Stroke: A systematic review and meta-analysis,” BMC Neurosci., vol. 22, no. 1, 2021, Art. no. 3, doi: 10.1186/s12868-021-00609-4.

20. S. Parisot et al., “Disease prediction using graph convolutional networks: Application to autism spectrum disorder and alzheimer’s disease,” Med. Image Anal., vol. 48, pp. 117–130, 2018, doi: 10.1016/j.media.2018.06.001.

21. A. Shah and S. Aran, “A review of magnetic resonance (MR) safety: The essentials to patient safety,” Cureus, vol. 15, no. 10, 2023, Art. no. e47345, doi: 10.7759/cureus.47345.

22. K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” in Proc. 3rd Int. Conf. Learn. Representations, Comput. Biol. Learn. Soc., 2015, pp. 1–14.

23. S. A. Sivaprakasam, S. S. Pandi, S. Varsha, M. Vishnu, and J. Sharath, “Parkinson’s disease detection: VGG-ResNet hybrid approach,” in Proc. 10th Int. Conf. Commun. Signal Process., 2024, pp. 54–59, doi: 10.1109/ICCSP60870.2024.10543805.

24. T.-A. Song et al., “Graph convolutional neural networks for Alzheimer’s disease classification,” in Proc. IEEE 16th Int. Symp. Biomed. Imag., 2019, pp. 414–417, doi: 10.1109/ISBI.2019.8759531.

25. Y. Uchiyama et al., “Automated classification of cerebral arteries in MRA images and its application to maximum intensity projection,” in Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., 2006, pp. 4865–4868, doi: 10.1109/IEMBS.2006.260438.

26. I. N. Vos et al., “Anatomical markers associated with the presence of intracranial aneurysms in individuals screened for aneurysms,” Stroke, Vasc. Interventional Neurol., vol. 4, no. 4, 2024, Art. no. e001299, doi: 10.1161/SVIN.124.001299.

27. I. Vos et al., “Data of the circle of willis intracranial artery classification and quantification (CROWN) challenge,” DataverseNL, V2, 2023, doi: 10.34894/R05G1L.

28. I. N. Vos et al., “Evaluation of techniques for automated classification and artery quantification of the circle of willis on TOF-MRA images: The CROWN challenge,” Med. Image Anal., vol. 105, 2025, Art. no. 103650, doi: 10.1016/j.media.2025.103650.

29. Z. Vrselja, H. Brkic, S. Mrdenovic, R. Radic, and G. Curic, “Function of circle of willis,” J. Cereb. Blood Flow Metab., vol. 34, no. 4, pp. 578–584, 2014, doi: 10.1038/jcbfm.2014.7.

30. L. Zhang et al., “An improved MeshCNN with active learning for anatomical labeling of the circle of willis,” in Proc. Int. Conf. Virtual Reality Visual., 2020, pp. 154–158, doi: 10.1109/ICVRV51359.2020.00040.

31. X. Zhang et al., “Brain age prediction using interpretable multi-feature-based convolutional neural network in mild traumatic brain injury,” NeuroImage, vol. 297, 2024, Art. no. 120751, doi: 10.1016/j.neuroimage.2024.120751.