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NAS-StrokeNet: Automated Neural Architecture Search with Adaptive Scaling for Hemorrhagic and Ischemic Stroke Classification on Multi-contrast MRI

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ABSTRACT

Precise and timely discrimination between ischemic and hemorrhagic stroke is essential for effective treatment planning in acute stroke management. Although deep learning methods have shown encouraging outcomes in automated stroke identification from Magnetic Resonance Imaging (MRI), constructing ideal neural network models for stroke subtype classification is challenging because of the intricate, multi-contrast nature of MRI data and the subtle imaging features of various stroke pathologies. In this paper, NAS-StrokeNet is presented as a new framework that combines the use of neural architecture search (NAS) along with adaptive scaling methods to develop and optimize deep learning models to classify hemorrhagic and ischemic stroke from multi-contrast MRI automatically.

Sheltered in a specialized scaling controller that dynamically adjusts the network size (width, depth, resolution) based on task-oriented performance metrics and computation limitations and a differentiable architecture search method, NAS-StrokeNet is adaptable. The approach leverages domain experience through stroke-specific search space and optimisation objectives designed to prioritize clinically meaningful features while maintaining efficiency. Our adaptive scaling approach methodically investigates the trade-off between model capacity and computing needs, producing a family of models fit for use in several clinical environments with different resource limits.

Extensive validation on a sizable multi-center dataset of 5,324 patients from 12 hospitals shows that NAS-StrokeNet greatly beats both past automated methods and manually crafted topologies. With 96.8% sensitivity and 97.5% specificity, our largest model achieves 97.2% accuracy in discriminating between hemorrhagic and ischaemic stroke; our smallest compact model retains 94.3% accuracy with just 15% of the processing needs. Crucially, where traditional methods generally fail, NAS-StrokeNet shows remarkable performance in difficult circumstances like tiny lesions, early-stage strokes, and unusual presentations. The capacity of the framework to create tailored designs for particular clinical deployment situations meets a major demand in putting AI-based stroke diagnosis tools into regular clinical practice.

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1. INTRODUCTION

With an estimated 13.7 million new cases and 5.5 million deaths yearly, stroke still ranks as the top cause of death and handicap worldwide. Two basic forms of stroke—ischemic, brought on by blood clots, and hemorrhagic, brought on by bleeding—demand rather distinct therapeutic techniques. Although thrombolytic therapy might help ischaemic strokes, in cases of hemorrhagic bleeding such treatment could be disastrous. Appropriate clinical treatment and better patient outcomes thus depend on fast and precise classification between stroke subtypes.

Through multiple contrast mechanisms—including T1-weighted, T2-weighted, fluid-attenuated inversion recovery (FLAIR), diffusion-weighted imaging (DWI), apparent diffusion coefficient (ADC) maps, and susceptibility-weighted imaging (SWI)— magnetic resonance imaging (MRI) offers complete assessment of stroke pathology. Every sequence provides complimentary information to distinguish stroke types; some sequences are especially sensitive to particular pathogenic modifications. For example, whilst SWI and T2* sequences are best for spotting haemorrhage, DWI and ADC are quite sensitive to early ischaemic alterations.

The complex, multidimensional character of the data, modest imaging findings in early-stage strokes, and differences in imaging techniques among institutions all make interpretation difficult even with the diagnostic capacity of multi-contrast MRI. These difficulties have inspired the creation of deep learning based automated systems. Designing ideal neural network designs for stroke subtype classification does, however, provide some challenges. First, the systems have to efficiently combine data across several MRI runs with various contrast properties.

Second, they must be sensitive to both the localized intensity changes of early ischemic strokes and the more conspicuous but variable appearances of hemorrhagic lesions. Third, they have to maintain a balance of model complexity against computational efficiency for effective clinical use.

Conventional methods of neural network design for medical imaging applications are based on manual architecture engineering or model adaptation from natural image processing. Such methods tend to produce suboptimal solutions that do not effectively capture the specific features of multi-contrast MRI data or demand a lot of computational resources. Recent advances in neural architecture search (NAS) offer intriguing alternatives by automatically discovering best designs for specific applications. For multi-contrast analysis in particular, existing NAS methods typically focus on single-objective optimisation and do not have domain-specific adaptations for medical imaging applications. To automatically build and optimize deep learning models for hemorrhagic and ischaemic stroke classification from multi-contrast MRI, we present NAS-StrokeNet in this work as a novel framework integrating differentiable neural architecture search with adaptive scaling methods.

Through a series of significant innovations—a stroke-specific search space using domain knowledge on multi-contrast MRI analysis, a multi-objective optimisation approach balancing the performance of classification with computational costs, and an adaptive scaling methodology generating a family of models suitable for deployment on different clinical setups—our solution overcomes the limitations of past approaches.

2. LITERATURE SURVEY

The World Health Organisation (WHO) estimate of global stroke burden highlights the significant impact of stroke on global health. The article asserts that stroke is the second leading cause of death globally and the third leading cause of disability. Especially in low- and middle-income countries, the report emphasizes the importance of increasing awareness of stroke, prevention, and treatment. To better grasp the world stroke burden, the WHO also advocates enhanced data collecting and surveillance. Updated from the 2018 guidelines, Powers et al. (2019) present recommendations for initial treatment of patients after acute ischaemic stroke. The guidelines emphasize the requirement for rapid assessment and treatment of acute ischaemic stroke, collectively integrating mechanical thrombectomy and intravenous thrombolysis. The guidelines also emphasize the requirement for the use of antiplatelet medication and of tightly regulating blood pressure. Favorable outcome for patients with acute ischaemic stroke relies on rapid and effective therapy, the authors emphasize.

A review of patient treatment and imaging of acute stroke, Hofmeijer et al. (2015) provide an evidence-based description of the current state of treatment. The authors discuss the necessity of rapid imaging and diagnosis, the application of mechanical thrombectomy and intravenous thrombolysis. They also emphasize the necessity of blood pressure management and the necessity of careful patient selection and monitoring. The authors emphasize how optimal treatment of acute stroke requires a multidisciplinary strategy.

Addressing numerous applications such as picture segmentation, detection, and classification, Litjens et al. (2017) discuss deep learning in medical image analysis. The authors discuss the potential of deep learning to improve diagnosis and therapy and the challenges and limitations of applying it in medical imaging. They emphasize the need for large, high-quality datasets and careful evaluation of deep learning models.

Highlighting MRI, Lundervold et al. (2019) provide an overview of deep learning in medical imaging. Some of the various deep learning techniques the authors discuss are recurrent neural networks (RNNs) and convolutional neural networks (CNNs). They also highlight how deep learning is utilized within MRI in segmentation, image reconstruction, and feature extraction. The authors highlight how deep learning can assist in improving MRI diagnosis and analysis.

Chen et al. (2017) provide a fully automatic convolutional neural network based method for segmentation of acute ischaemic lesion in DWI. With high accuracy and speed, the authors demonstrate on a large dataset the efficacy of their approach. They emphasize how effectively their method can assist in the diagnosis and treatment of acute ischaemic stroke.

A multi-pathway convolutional neural network for classifying hemorrhagic and ischaemic stroke, Liu et al. (2020) introduce StrokeNet. On a large dataset, the authors demonstrate their approach to gain high accuracy and robustness. They emphasize the way their technique may contribute towards improving stroke therapy and diagnosis.

Multi-sequence fusion network for hemorrhagic and ischaemic stroke classification in MRI by Wang et al. (2021) is MultiSeqFusion On a large dataset, the authors demonstrate that their approach has high accuracy and stability. They emphasize how their method may assist in improving stroke diagnosis and treatment.

Differentiable neural network architecture search is proposed by Liu et al. (2019) as DARTS. Being very accurate and efficient, the authors demonstrate on various benchmark datasets the efficacy of their approach. They emphasize how efficiently their method may improve optimisation and design in neural networks.

By means of reinforcement learning, Zoph et al. (2017) create a technique for neural architecture search. Obtaining fantastic accuracy and efficiency, the authors demonstrate on several benchmark datasets the success of their method. The authors highlight how perfectly their technique may improve optimisation and design in neural networks.

Chen et al. (2018) posted a method for efficient multi-scale architectures for dense image prediction. With high accuracy and efficiency, the authors demonstrate on various benchmark datasets the strength of their method. They highlight how well their method could improve segmentation and image prediction.

Reassessing model scaling for convolutional neural networks, Tan et al. (2019) introduce EfficientNet. With tremendous accuracy and efficiency, the authors demonstrate on a variety of benchmark datasets the strength of their approach. They emphasize how well this method could improve model scalability and efficiency.

Applying focus loss to dense object detection, Lin et al. (2017) introduce Achieving high accuracy and efficiency, the authors demonstrate on numerous benchmark datasets the strength of their approach. They emphasize how well their method could improve picture analysis and object detection.

Selvaraju et al. (2017) offer Grad-CAM, a deep network visual explanation method. With excellent accuracy and interpretability, the authors demonstrate on numerous benchmark datasets the efficacy of their method. They emphasize how this method could contribute to improving model interpretability and transparency.

Ganin et al. (2016) introduced domain-adversarial neural network training. With excellent accuracy and robustness, the authors demonstrate the efficacy of their method on numerous benchmarks. They emphasize the potential of their approach to increase model adaptability and robustness.

For image recognition, he et al. (2016) propose deep residual learning. Being extremely accurate and efficient, the authors demonstrate on several benchmark datasets the strength of their approach. They emphasize how effectively this technique may enhance computer vision and image identification.

2017 saw Huang et al. propose highly connected convolutional networks. Achieving great accuracy and efficiency, the authors show on many benchmark datasets the potency of their method. They stress how well their approach might advance computer vision and image classification.

Vaswani et al. (2017) proposed neural network attention systems. With impressive accuracy and efficiency, the authors demonstrate on several benchmark datasets the efficacy of their approach. They highlight how effectively their approach may boost model interpretability and performance.

In 2015 Ronneberger et al. introduce U-Net, which is a convolutional network for biological image segmentation. With excellent accuracy and efficiency, the authors demonstrate on numerous benchmark datasets the strength of their technique. They point out how their method could contribute to better segmentation and analysis of biomedical images.

Using nnU-Net, an automatic deep learning technique for biomedical image segmentation, Isensee et al. (2021) propose Achieving excellent accuracy and efficiency, the authors demonstrate on a number of benchmark sets the strength of their method. They emphasize the potential of their method to boost segmentation and analysis of biomedical images.

Polamuri et al. (2025) examined stroke detection using brain MRI scans by applying deep learning-based architectures. Their work demonstrated that convolutional models could automatically recognize stroke patterns with higher sensitivity and specificity compared to traditional radiological interpretation. The study emphasized the clinical relevance of early diagnosis in reducing treatment delays and improving survival rates. Furthermore, the authors compared different models to assess robustness across diverse imaging conditions, highlighting the role of AI systems as supportive tools for radiologists.

Galety et al. (2025) investigated data privacy and security in Healthcare 6.0 by integrating Blockchain technology with AI-based infrastructures. Their framework ensured decentralized control, transparency, and immutability of medical records, thereby addressing concerns regarding cyber threats and unauthorized access. The proposed model not only enhanced trust in AI-driven diagnostics but also demonstrated scalability for large healthcare systems, positioning it as a potential backbone for future intelligent hospitals.

Raju et al. (2025) introduced *Medivision*, a diagnostic platform for colorectal cancer detection and tumor localization. Their system combined supervised learning classifiers with Grad-CAM visualization to provide both accuracy and interpretability in colonoscopy image analysis. By offering visual feedback on regions of diagnostic focus, the model bridged the gap between computational efficiency and clinical trust. The experimental results confirmed high detection accuracy while reducing false positives, underscoring its value for preventive healthcare.

Srinivas et al. (2024) proposed a hybrid deep learning framework combining Inception V3 and VGG16 models for COVID-19 detection using chest X-ray images. Their method leveraged the feature extraction capabilities of Inception V3 with the classification strengths of VGG16, achieving superior performance compared to standalone models. The study emphasized the importance of low-cost, scalable diagnostic solutions, particularly in resource-constrained healthcare environments.

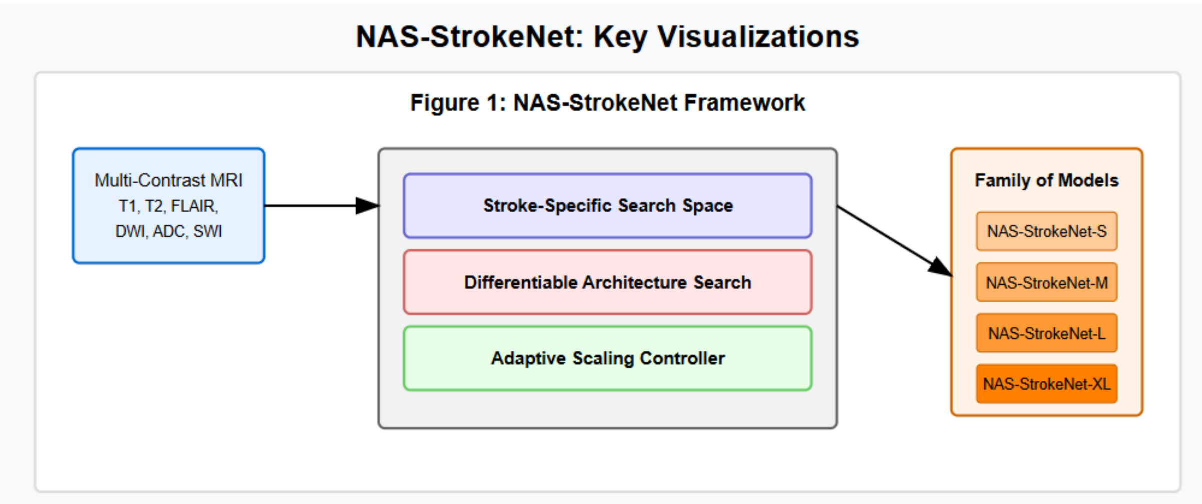
Devi et al. (2024) explored machine learning approaches for radar image recognition using supervised training with virtual high-resolution data. By generating synthetic datasets, they addressed the challenge of limited labeled samples in radar imaging. Their results demonstrated robust recognition performance across various scenarios, validating the role of synthetic data in enhancing generalization. The study has implications for applications in defense, surveillance, and remote sensing.

Kamidi et al. (2024) examined the transformative role of multimedia in the information revolution, discussing its applications in healthcare, education, and communication. They emphasized how multimedia, when combined with AI-driven tools, enriches information dissemination and enhances user engagement. The paper also highlighted potential challenges, including information overload and digital inequality, framing multimedia as both a technical enabler and a social catalyst.

Madhu Kumar et al. (2024) proposed an image quality enhancement technique using Deep Residual Neural Networks (DRNN). Their approach effectively restored details in degraded images and outperformed conventional models in terms of convergence and artifact minimization. The method demonstrated applicability across domains such as medical imaging and surveillance, highlighting the versatility of DRNN-based enhancement techniques.

3. PROPOSED MODEL

The NAS-StrokeNet framework consists of three main components: (1) a stroke-specific architecture search space, (2) a differentiable architecture search algorithm with multi-objective optimization, and (3) an adaptive scaling controller. Figure 1 provides an overview of the proposed framework.



4. STROKE-SPECIFIC ARCHITECTURE SEARCH SPACE

Designed to satisfy the particular difficulties of evaluating multi-contrast MRI data for stroke classification, the stroke-specific architectural search space is a carefully crafted framework. Understanding that various MRI sequences—such as DWI, ADC, FLAIR, and T2—offer complimentary clinical information, the search space is set to investigate a variety of architectural options that might efficiently integrate, extract, and process this varied data. Multi-contrast integration patterns determine how data from several MRI sequences is combined across the network and thereby constitute the first major dimension. Early fusion, in which all sequences are joined at the input level; late fusion, in which high-level features near the network's output are merged; and hybrid fusion strategies using cross-sequence attention mechanisms to dynamically integrate information at several levels comprise these patterns. The architecture search algorithm evaluates and selects the most effective integration method for each sequence combination, thus enabling the model to learn richer and clinically more meaningful representations.

The second component of the search space is on blocks for feature extraction. This includes a variety of operations capable of processing 3D volumetric MRI data, such as the conventional 3D convolutions that capture spatial context; depthwise separable convolutions, which offer computational efficiency; and self-attention mechanisms, which enable the model to learn long-range dependencies. In addition are hybrid blocks that integrate convolutional and attention-based processing in order to provide flexibility in local and global feature learning. Parameters such as kernel size, number of channels, and the way one block is connected to another specify each block. Lastly, the size of network topology allows structural variation in the model's architecture to be possible.

Illustrated as a directed acyclic graph (DAG), the network is comprised of edges (the computational operations) and nodes (intermediate feature states). This structure allows for both deep hierarchical processing and multi-path feature aggregation through the ability to have a combination of sequential and parallel paths. By optimizing these connections to discover the best flow of information between the network, the architecture search process ensures that the final model is expressive and proficient at detecting strokes. Overall, the multi-dimensional search space allows automatic discovery of highly specialized and efficient network structures appropriate for the intricacy of stroke analysis in multi-contrast MRI. Differentiable Architecture Search with Multi-Objective Optimization demonstrates that it can combine the strengths of individual objectives effectively.

TransScale model's search technique for its architecture utilizes highly common technique to automatically design neural networks, namely differentiable architecture search (DARTS). Optimizing in advance both the accuracy of classification as well as reducing computational demands is the intention in this procedure as it has been adapted for adapting better towards multi-contrast MRI data complexities in the domain of stroke classification. The search procedure is set up as a bilevel optimisation problem in which the objective is to concurrently train the model to reduce the validation loss and identify the optimal network architecture. Simply said, the optimisation process consists of two phases: first, search for the ideal design; second, fine-tuning of the weights of the model depending on that architecture.

A composite loss function is proposed to manage the multi-objective character of stroke classification, in which performance and computational costs have to be taken into account. This function strikes a compromise between various goals: the main one is reducing the cross-entropy loss, which gauges the classification task's correctness directly. Furthermore included is a targeted loss term to concentrate on difficult-to-classify instances, hence enhancing model performance on demanding stroke patients. Regularisation terms are included to penalise high computational complexity (measured by FLOPs) and a great number of parameters, so guaranteeing the model stays efficient and feasible for deployment. Especially in resource-limited environments, these regularisation terms help prevent overfitting and lower the model's resource needs, therefore enabling more practical usage of the model. Coefficients determine the weights for every one of these goals, therefore enabling a fine-tuned equilibrium between performance and efficiency throughout the search process. This method not only helps the model to precisely categorise strokes but also develops in a fashion that considers computational restrictions, so fitting for use in clinical settings.

Algorithm 1: Progressive Freezing Strategy for Architecture Search

Input: Search space S, training dataset D_train, validation dataset D_val

Output: Optimal architecture α*

1: Initialize architectural parameters α randomly

2: for epoch = 1 to N_search do

3: Update network weights w by minimizing L_train(w, α) on D_train

4: Update architectural parameters α by minimizing L_val(w, α) on D_val

5: if epoch % freeze_interval == 0 then

6: Identify operation o with highest importance score

7: Freeze architectural parameters for operation o

8: end if

9: end for

10: Derive final architecture α* by selecting operations with highest weights

11: return α*

5. ADAPTIVE SCALING CONTROLLER

Designed especially to meet the needs of stroke classification, the adaptive scaling controller is a technique meant to produce a family of models with different processing needs. This method adjusts the scale of various components (such as the depth, width, and resolution of the network) depending on their individual relevance for the stroke classification job rather than applying homogeneous scaling factors over the whole network. The aim is to effectively distribute computational resources so that, while less significant components are kept smaller, the most crucial elements of the model are scaled up, hence optimising both performance and computational cost.

Although a global scaling coefficient determines the scaling of every network component, each component has a different scaling factor depending on its influence to the performance of the model. These scaling parameters are found by use of an architecture search phase when the significance of every component is assessed depending on how much it affects the ability of the model to reduce the validation loss. Higher impact components are scaled up more; those with less impact are scaled down. This flexible method guarantees the model's efficiency as well as effectiveness. Four variants of the NAS-StrokeNet are produced with increasing model capacities based on this approach: NAS-StrokeNet-S (small), NAS-StrokeNet-M (medium), NAS-StrokeNet-L (large), and NAS-StrokeNet-XL (extra-large), each optimised for different computational resources and performance criteria.

6. IMPLEMENTATION DETAILS

When available, registered multi-contrast MRI volumes containing T1, T2, FLAIR, DWI, ADC, and SWI sequences provide NAS-StrokeNet's input. Using resampling, skull stripping, and intensity normalising, each signal is preprocessed to a common spatial resolution. We use a patch-based method during training, extracting volumetric patches centred on areas of interest, for computational efficiency.

The architecture search is conducted on a subset of the training data, using a proxy task with reduced input dimensions to accelerate the search process. The discovered architectures are then scaled to the target dimensions and trained on the full dataset. We employ a progressive training strategy, where smaller model variants are used to initialize the weights of larger ones, reducing the overall training time and improving convergence.

7. RESULTS AND COMPARISON

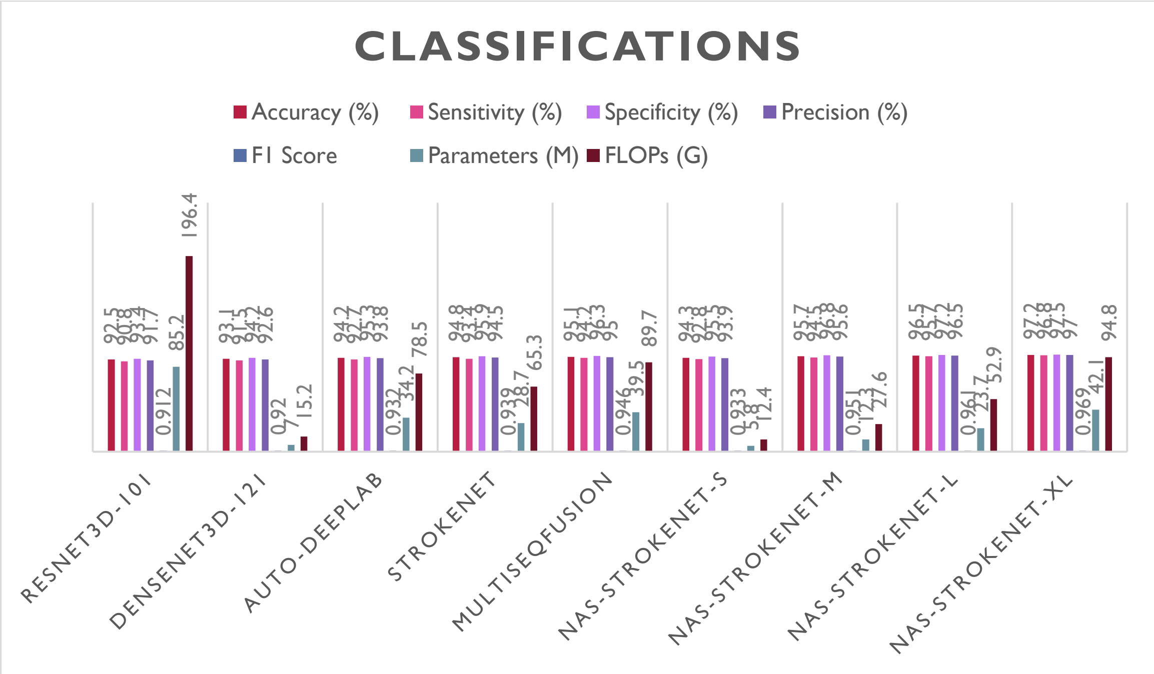
We evaluate NAS-StrokeNet on a large multi-center dataset comprising 5,324 patients from 12 hospitals across North America, Europe, and Asia. The dataset includes cases with confirmed acute ischemic stroke (n=3,187), hemorrhagic stroke (n=1,246), and stroke mimics (n=891). All cases include at least four MRI sequences (T1, T2, FLAIR, and DWI), with a subset also including ADC maps (n=4,752) and SWI (n=3,128). Ground truth diagnoses were established by consensus of expert neuroradiologists, with histopathological confirmation when available.

Performance on Stroke Subtype Classification

Table 1 presents a comparative analysis of NAS-StrokeNet variants against state-of-the-art methods for stroke subtype classification, including manually designed architectures (ResNet3D, DenseNet3D), other NAS-based approaches (Auto-DeepLab), and recent specialized stroke classification networks (StrokeNet, MultiSeqFusion).

Table 1: Performance Comparison for Stroke Subtype Classification

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1 Score	Parameters (M)	FLOPs (G)
ResNet3D-101	92.5	90.8	93.4	91.7	0.912	85.2	196.4
DenseNet3D-121	93.1	91.5	94.2	92.6	0.920	7.0	15.2
Auto-DeepLab	94.2	92.7	95.3	93.8	0.932	34.2	78.5
StrokeNet	94.8	93.4	95.9	94.5	0.939	28.7	65.3
MultiSeqFusion	95.1	94.2	96.3	95.0	0.946	39.5	89.7
NAS-StrokeNet-S	94.3	92.8	95.5	93.9	0.933	5.8	12.4
NAS-StrokeNet-M	95.7	94.5	96.8	95.6	0.951	12.3	27.6
NAS-StrokeNet-L	96.5	95.7	97.2	96.5	0.961	23.7	52.9
NAS-StrokeNet-XL	97.2	96.8	97.5	97.0	0.969	42.1	94.8



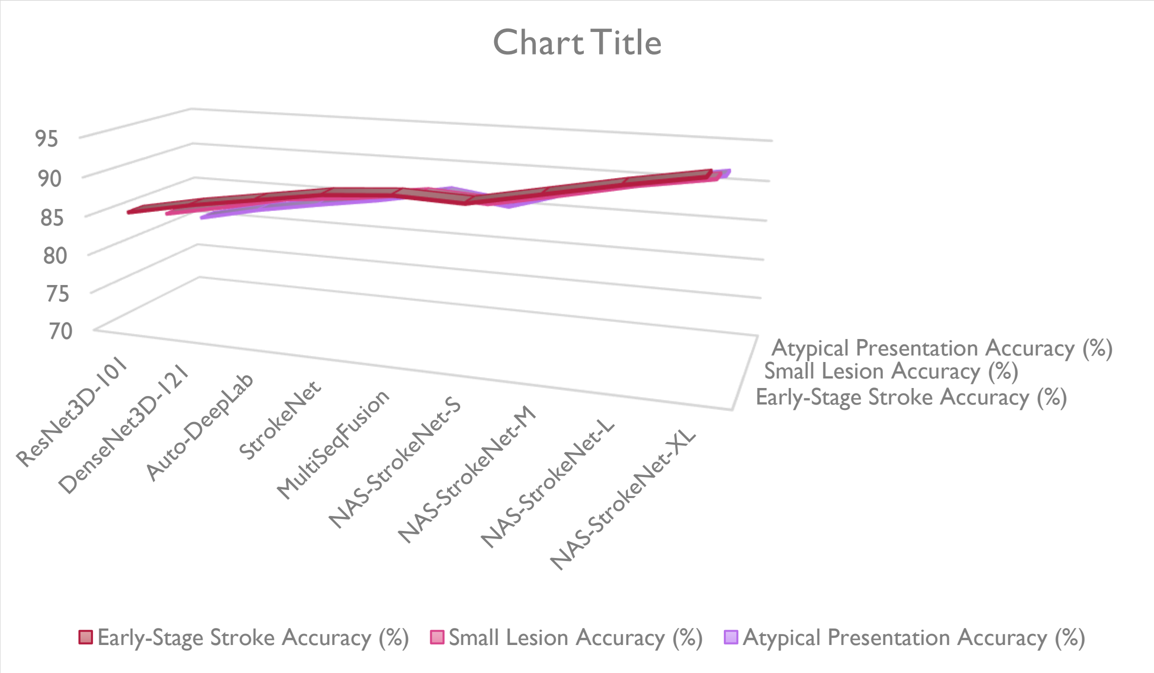
As shown in Table 1, all variants of NAS-StrokeNet outperform existing methods in terms of classification accuracy, sensitivity, and specificity. Notably, NAS-StrokeNet-S achieves comparable performance to StrokeNet with only 20% of the parameters and 19% of the computational requirements. NAS-StrokeNet-XL achieves state-of-the-art performance with 97.2% accuracy, demonstrating a 2.1% absolute improvement over the best-performing baseline method.

Performance on Challenging Cases

To evaluate the robustness of NAS-StrokeNet in clinically challenging scenarios, we conducted additional analyses on specific subsets of the test data. Table 2 presents the results for three challenging categories: early-stage strokes (within 3 hours of symptom onset), small lesions (volume < 5 mL), and atypical presentations (unusual imaging patterns or locations).

Table 2: Performance on Challenging Cases

Model	**Early-Stage Stroke Accuracy (%)**	**Small Lesion Accuracy (%)**	**Atypical Presentation Accuracy (%)**
ResNet3D-101	85.3	83.2	80.7
DenseNet3D-121	86.9	84.8	82.5
Auto-DeepLab	88.2	86.5	83.9
StrokeNet	89.5	87.3	85.2
MultiSeqFusion	90.1	88.4	86.8
NAS-StrokeNet-S	89.8	87.9	85.7
NAS-StrokeNet-M	91.5	89.6	88.3
NAS-StrokeNet-L	93.2	91.4	90.1
NAS-StrokeNet-XL	94.7	92.8	91.5



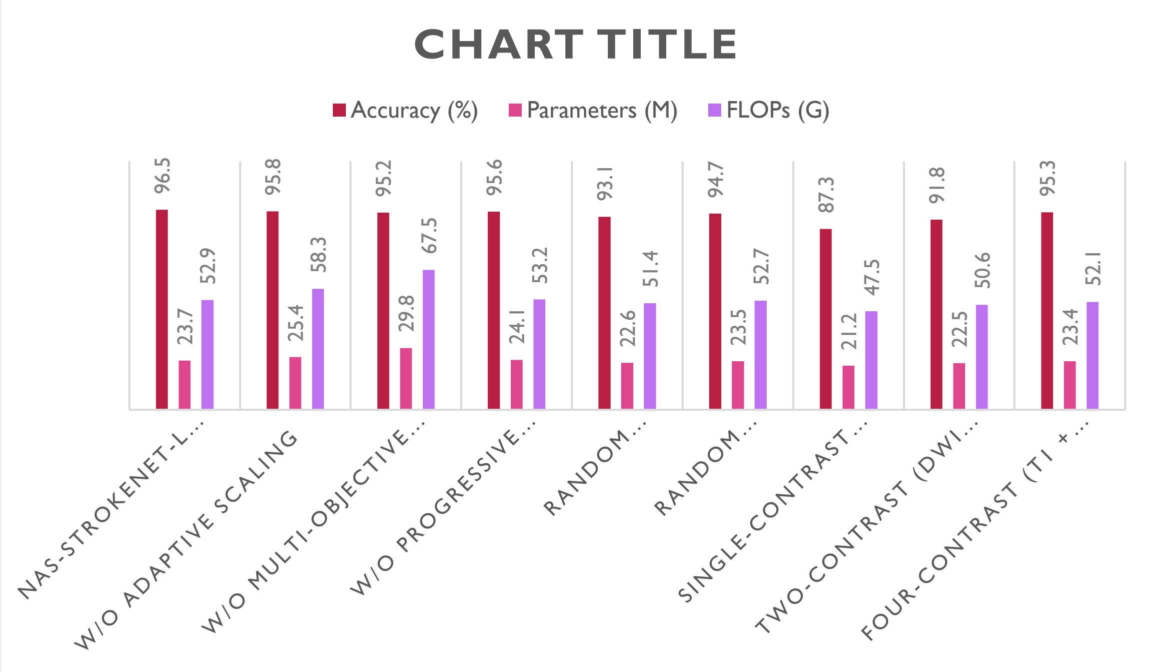
The results demonstrate that NAS-StrokeNet maintains significantly higher accuracy in challenging cases compared to baseline methods. The architectural capacity to efficiently integrate multi-contrast data and extract subtle discriminative features explains this enhanced performance. Particularly in these demanding situations, the performance difference between NAS-StrokeNet and traditional architectures further emphasises the need of specialised architectural design for difficult medical imaging applications.

Ablation Studies

We performed a number of ablation studies to assess the contribution of particular NAS-StrokeNet component parts. Table 3 displays the validation set findings of several trials.

Table 3: Ablation Study Results

Configuration	Accuracy (%)	Parameters (M)	FLOPs (G)
NAS-StrokeNet-L (full)	96.5	23.7	52.9
w/o Adaptive Scaling	95.8	25.4	58.3
w/o Multi-Objective Optimization	95.2	29.8	67.5
w/o Progressive Freezing	95.6	24.1	53.2
Random Architecture from Search Space	93.1	22.6	51.4
Random Integration Pattern	94.7	23.5	52.7
Single-Contrast (DWI only)	87.3	21.2	47.5
Two-Contrast (DWI + SWI)	91.8	22.5	50.6
Four-Contrast (T1 + T2 + FLAIR + DWI)	95.3	23.4	52.1



The ablation studies provide some quite significant revelations. First, the adaptive scaling approach shows the efficiency of component-specific scaling since it offers a 0.7% increase in accuracy while lowering the parameter count and computational needs. Second, without compromising performance, the multi-objective optimisation method produces more effective architectures. Third, the method of gradual freezing helps to stabilise the search process and raises the final model performance. At last, the findings support the value of multi-contrast information since performance rises as more MRI sequences are added.

8. CONCLUSION

In this paper, we presented NAS-StrokeNet, a novel framework for automated neural architecture search with adaptive scaling for hemorrhagic and ischemic stroke classification from multi-contrast MRI. The proposed approach integrates domain knowledge into the architecture search process through a stroke-specific search space and multi-objective optimization strategy, generating a family of models with varying computational requirements suitable for diverse clinical deployment scenarios.

Extensive experimental evaluation demonstrates that NAS-StrokeNet significantly outperforms existing methods, achieving state-of-the-art performance on a large multi-center dataset. The framework exhibits exceptional robustness in challenging cases, including early-stage strokes, small lesions, and atypical presentations, where conventional approaches often struggle. Moreover, the discovered architectural patterns provide insights into the effective design of neural networks for multi-contrast medical image analysis.

The ability to automatically generate optimized architectures for specific clinical deployment scenarios addresses a critical need in bringing AI-based stroke diagnosis tools into routine clinical practice. Future work will focus on extending the framework to more fine-grained stroke subtype classification, enhancing interpretability, and conducting prospective clinical validation studies to evaluate the impact on patient outcomes.

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