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A Hybrid Perception Network for Accurate and Interpretable Brain Tumor Classification Using Multi-Modal Imaging

Hamed D. Al-Sharari*

Abstract

Objective: Accurate classification of brain tumors is of utmost importance in early diagnosis and treatment, which can be further enhanced through advanced deep learning techniques. This work introduces HyPerNet a Hybrid Perception Network for brain tumor classification that integrates cutting-edge methods to maximize classification accuracy, interpretability, and efficiency. HyPerNet leverages multi-modal fusion, combining Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and Positron Emission Tomography (PET) scans to extract complementary information from different imaging modalities. **Methods:** A dynamic attention mechanism adapts to image complexity, improving performance under noisy and artifact-laden conditions. The architecture incorporates explainable AI components using Grad-CAM for clinical interpretability, along with 3D convolutional neural networks for volumetric feature learning. Hybrid feature extraction, integrating Convolutional Neural Networks (CNNs) with graph neural networks (GNNs), enables the model to capture both local and relational tumor characteristics. Domain adaptation via transfer learning allows the model to generalize across diverse datasets, improving robustness. **Result:** In experiments conducted on a benchmark dataset of 8,256 images, HyPerNet achieved a classification accuracy of 97.14%, precision of 97.09%, recall of 97.09%, F1-score of 97.09%, and specificity of 98.9%, outperforming state-of-the-art models such as DenseNet121, ResNet101, and MobileNetV3. Notably, HyPerNet attains these results with only 1.66 million parameters, making it highly efficient for deployment on mobile and edge devices. **Conclusion:** These findings establish HyPerNet as a reliable, interpretable, and computationally efficient solution for clinical brain tumor classification.

Keywords: Brain Tumor Classification- MRI Imaging- Hybrid Perception Network- Deep Learning

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Introduction

Correctly classifying brain tumors is important for early detection and effective treatment, which has a big effect on how well patients do. While brain tumors can look different and have different traits, it can be hard to diagnose and group them. The old ways of doing things require doctors to look over a large amount of medical image data, which takes a large amount of time and can lead to mistakes [1]. This highlights the important need for precisely and automatically classifying data. Magnetic Resonance Imaging (MRI) is usually used to identify brain cancer since it offers different pictures of brain structures without the use of ionising radiation. High-resolution images produced by MRI scans provide transformational imaging capabilities. Consequently, MRI is rather important in both oncology and neurology. Nevertheless, the degree of experience of the clinician and the effort needed to manually interpret an MRI image will affect the diagnosis's accuracy. Deep learning, and Convolutional Neural Networks (CNNs in particular), have transformed medical image analysis by greatly improving jobs, including image recognition, classification, and segmentation [2, 3]. Mixed models and transfer learning, among other new methods, have greatly enhanced the accuracy and usefulness of brain tumour categorization. Notwithstanding these developments, current models still find it difficult to handle the complexity and diversity of brain tumors. Models that can use several imaging modalities and produce simple results are needed to let doctors make educated decisions. Chaotic or artifact-filled data compromises the usefulness of current models in clinical settings. Thus, it is imperative to create a strong, open, and effective model combining advanced deep-learning methods with several data sources. This study article presents HyPerNet: A Hybrid Perception Network for Brain Tumour Classification on MRI Images, a creative framework combining various new technologies to help to solve these difficulties.

HyPerNet uses multi-modal fusion combining MRI, CT, and PET scans to improve the accuracy of its classifications [4, 5]. This approach is used to combine the information gathered from several imaging modalities. The dynamic attention mechanism of the model changes

*College of Computing and Informatics, Saudi Electronic University, Kingdom of Saudi Arabia. *For Correspondence: H.ALSHARARI@seu.edu.sa*

its emphasis in line with the image's complexity.

Dealing with chaotic or artifact-filled data increases this capacity. Explainable artificial intelligence also has integrated elements. These highlight important areas and consist of interpretable MRI picture layers. This improves doctors' confidence and clarity about the choices the model makes. 3D convolutional neural networks (3D CNNs), more efficient than 2D CNNs in capturing spatial context across segments, analyze volumetric data. By use of domain adaptation and transfer learning, the model may make use of models that have been trained on different datasets, hence very appropriate for the classification of brain tumors. Hybrid feature extraction uses standard convolutional layers and graph neural networks (GNNs) to find relational and local information in magnetic resonance imaging (MRI) images. HyPerNet is meant to be simple and small on mobile devices. Its best performance on mobile devices and peripheral computers allows it to be implemented in settings with minimal resources. Recent advancements in the identification and classification of brain tumors have resulted in novel approaches combining several machine learning and deep learning approaches to raise diagnosis accuracy. Nawaz et al. [6] proposed a mixed strategy combining several feature extraction methods with machine learning algorithms many years ago to increase tumor diagnosis from MRI datasets' dependability, shown in Figure 1. Using deep learning and transfer learning with neural networks already trained, Mathivanan et al. [7] apply features learnt from large datasets to MRI brain tumor identification, hence improving the accuracy of brain tumor detection. In their 2021 work, El Kader et al. [8] developed a hybrid model combining Differential Wavelet Analysis (DWA) with Convolutional Neural Networks (CNNs). For more accurate tumor categorization, this model effectively records spatial and frequency domain information, as shown in Figure 2. This research taken together indicates that in clinical environments, hybrid and transfer learning approaches could greatly increase the accuracy and dependability of brain tumor diagnosis.

In another article, the authors propose a combined strategy to identify and label brain cancers in MRI images using Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and threshold segmentation [9]. This approach leverages CNN's feature extraction capability as well as SVM's classification capability. It also employs threshold segmentation to ensure tumor location is exact. The study delves deeply into the suggested approach, including its applications and degree of success. The results show that the mixed CNN-SVM method works better than other methods for both finding things and putting them into groups. The writers talk about how this method could be used in real life, making it a useful tool for correctly diagnosing brain tumors. Another study goes into detail about how the experiment was set up, what dataset was used, how it was preprocessed, and what methods were used for feature extraction and classification [10]. As you can see, the findings show that the hybrid approach is much more accurate than traditional diagnostic methods [11]. The writers come to the conclusion that their method could be a useful tool for finding and classifying brain tumors, which would help with early diagnosis and planning treatment. Another group of researchers also shows a Convolutional Neural Network (CNN) perception model for the sorting of brain tumor images. They want to use CNNs' strong feature extraction skills to correctly sort the different kinds of brain tumors [12]. They use neural networks that have already been trained to apply what they've learned from large datasets to the job of classifying brain tumors. This gets around the problem of limited medical imaging datasets by using knowledge from other fields that are related [13]. It is suggested that Adaptive Contrast Limited Adaptive Histogram Equalization (CLFAHE) be used with hybrid classification methods to improve the contrast of MRI images, which will make it easier to see tumors.

A hybrid model that combines several machine learning methods is used for segmentation and classification in this method [14]. In a different study, a dual-path network is used to separate brain tumors using MRI images from

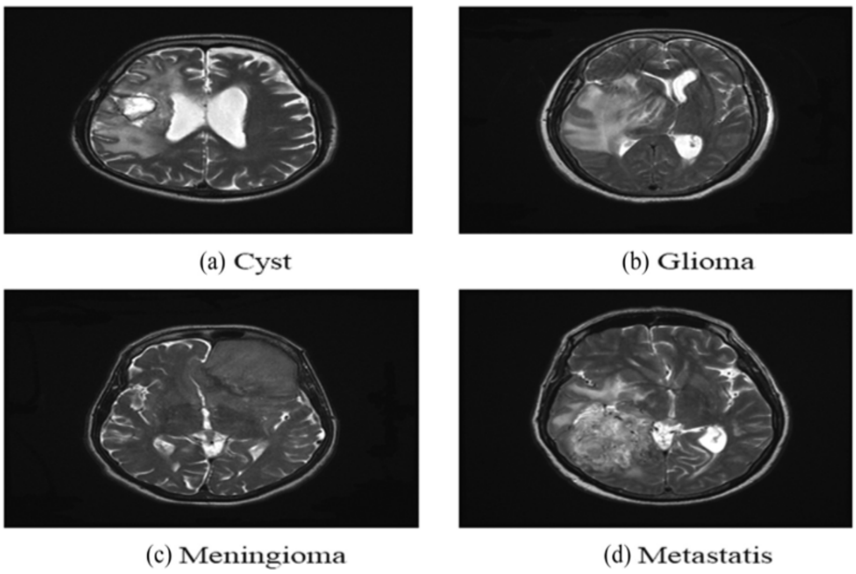

Figure 1. Four Types of the Brain Tumor [6]

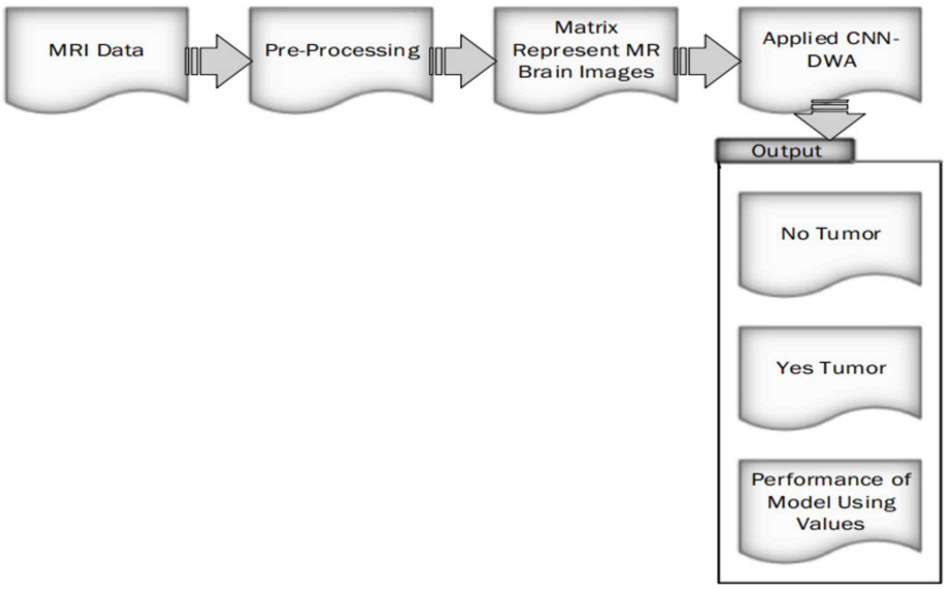

Figure 2. Architecture of the MRI Brain Images Classifier for Brain Tumor Detection based on the Hybrid CNN-WDA Model [8]

different types. This approach concurrently handles different MRI modalities by combining two parallel neural network routes. This compiles a lot of data, so the approach is more dependable and accurate. Brain malignancies in MRI images are found using a hybrid approach combining artificial neural networks (ANN) and k-means clustering. Using K-means clustering, this approach breaks MRI images into parts to identify potential tumor sites. It then appropriately identifies tumors using an ANN for categorization [15]. A combined deep autoencoder with a Bayesian fuzzy clustering-based segmentation approach is another approach to group brain tumors [16]. This uses the accuracy of Bayesian fuzzy clustering for segmentation and the feature extraction capacity of deep autoencoders.

Accurate brain tumor labeling is proposed to be achieved using a multilayer perceptron (MLP) enhanced by a crossover smell agent algorithm [17]. By means of the crossing smell agent algorithm to identify the optimal settings, this enhancement increases MLP accuracy. This method replics how wild animals discover the optimal answers. Brain cancers in MRI images can be found using a residual multi-layer perceptron based novel Swin transformer approach. It blends residual MLP's classification accuracy with the Swin transformer's feature extraction prowess. A hybrid parallel fuzzy convolutional neural network (CNN) paradigm combines CNN's feature extraction powers with fuzzy logic, which makes analysis more accurate and dependable, so providing correct brain MRI views [18]. This work reveals that the model is more accurate than conventional CNN models and delves deeply into how to apply it. It also addresses prospective clinical uses and future research directions [19]. Combining the feature extraction powers of MLPs with localization approaches helps one to properly identify and classify brain cancers in MRI images using a multi-layer perceptron (MLP) [20]. The Whale Social Spider Optimization Algorithm (WSSOA) for brain tumor classification using deep learning techniques optimizes model parameters by mimicking the social behavior of whales and spiders [21]. Advancing brain tumor classification accuracy through deep learning, another study harnesses RadImagenet pre-trained convolutional neural networks, ensemble learning, and machine learning classifiers on MRI brain images [22]. This paper discusses leveraging pre-trained CNNs, ensemble learning, and traditional machine learning classifiers to improve classification accuracy.

Comparing different local binary pattern (LBP) methods for brain tumor diagnosis, one study proposes LBP-based feature extraction from MRI images followed by machine learning model classification to identify the most effective LBP method [23] . The study shows that certain LBP methods achieve higher accuracy. A full-automatic segmentation algorithm for brain tumors is based on the RFE-UNet architecture and a hybrid focal loss function, combining RFE-UNet's feature extraction with an enhanced loss function to improve segmentation accuracy and robustness [24].

Finally, densely connected convolutional networks (DenseNet), a novel architecture, improve information and gradient flow by connecting each layer to every other layer in a feed-forward fashion [25]. DenseNet addresses the vanishing gradient problem and enhances neural network efficiency, demonstrating high accuracy in various computer vision tasks. The study details DenseNet's architecture and training process, concluding its significant advantages in parameter efficiency and performance [26-33].

The Aim of this study is imperative to create a strong, open, and effective model combining advanced deep-learning methods with several data sources. This study article presents HyPerNet: A Hybrid Perception Network for Brain Tumor Classification on MRI Images, a creative framework combining various new technologies to help to solve these difficulties.

Materials and Methods

HyPerNet Methodology and Multi-modal Fusion

The HyPerNet model in brain tumor classification on MRI images introduces a hybrid perception network to integrate several cutting-edge innovations for improved classification performance and model interpretability. The model includes multi-modal fusion, dynamical attention mechanisms, explainable AI features, 3D CNNs, transfer learning with domain adaptation, and hybrid feature extraction using GNNs. HyPerNet combines MRI data with CT and PET scans to derive complementary information from different imaging modalities.

This multimodal fusion approach enhances the effective utilization of comprehensive data for more precise tumour classification. There is a dynamic attentional mechanism with respect to the complexity of the images, which improves misclassification in noisy or artifact-laden data. The flow diagram of the HyPerNet architecture suggested to classifying brain tumor is shown in Figure 3. Through this block diagram, the steps of integrating components linearly have been shown visually, beginning with the input of data, up to the coverage of a clinical implementation.

Hybrid Feature Extraction and Attention Mechanisms

Originally, the system commences by imbibing data from MRI, CT and PET scan sources. The modalities complement each other when it comes to diagnostic prospects MRI provides anatomical details of high resolution, CT adds structural contrast, and PET gives metabolic activity levels. The combination of such modes facilitates better and discriminatory descriptions of tumor characteristics. The model goes through the multi-modal feature fusion stage after the data acquisition. In this case, the spatially registered data of every imaging modality are merged via channel-wise concatenation and the 3D convolution. Besides balancing variety of inputs, this fusion also strengthens inter-modality correlations to constitute a rich feature map, detailing structural, functional and textural patterns of brain tumor. The result of this fusion block is that the architecture diverges in three parallel tracks. The former is using volumetric feature learning from 3D convolutional neural networks (3D CNNs) and is proficient at modeling inter-slice relations in the volumetric medical data. This will help the network to attain spatially consistent features that are critical in the precise identification and categorization of tumors. A dynamical attention mechanism is present in the second branch, and it adjusts according to image complexity and distribution of noise. This mechanism can reduce artifacts and label clinically relevant regions because of entrepreneurial computation in the case of attention weights centered on concentration and local gradients. The third branch does the task of domain adaptation with the help of existing pre-trained models and optimizing it to the target domain. The pathway tackles the problem of inter-domain variations arising as a result of scanners, protocols, or patient populations differences, as well as providing enhanced generalization due to adaptive normalization.

The suggested HyPerNet architecture is presented in Figure 3, which points at the incorporation of multi-modal inputs (MRI, CT, PET), hybrid CNN-GNN feature extraction, attention mechanisms, and the final classification layer. The graph underlines the processing steps that occur sequentially and in parallel facilitating efficient learning of local and global features. The model will have a hybrid feature experimentation section downstream of the volumetric CNN path, pairing convolutional neural networks (CNNs) with graph neural networks (GNNs). This hybridization enables the model to model local textures as well as topological relation across voxels to improve its capacity of recognizing the fine-grained morphology of tumor. The results of the CNN-GNN branch, as well as the attention and domain-adaptive features, would be combined with a local-global fusion module created using Depthwise Separable Convolutions (DWSC) and systems of Vision Transformers (ViT). DWSC makes it possible to calculate the localized feature learning that can be performed in a computationally efficient manner, whereas ViT modules performed the long-range dependency calculation through patch-wise attention. Such architecture will be more receptive to delicate tumor tendencies, as well as context sensitivity. The result of the module of fusion is fed to a more sophisticated attention mechanism that includes a spatial attention (SPA) module, a group attention (GA) module. SPA aids the model in giving importance to the spatially significant areas by reweighting the maps of spatial features and GA does the pooling hierarchically to sustain the relevance of local-global information. The combination of these mechanisms guarantees that the feature representations are sufficient in the amount of information, as well as in the processing costs. Lastly, there is an output and clinical deployment stage of the architecture. In this case, the model classifies the label of the tumor category (e.g., glioma subtypes) via a fully

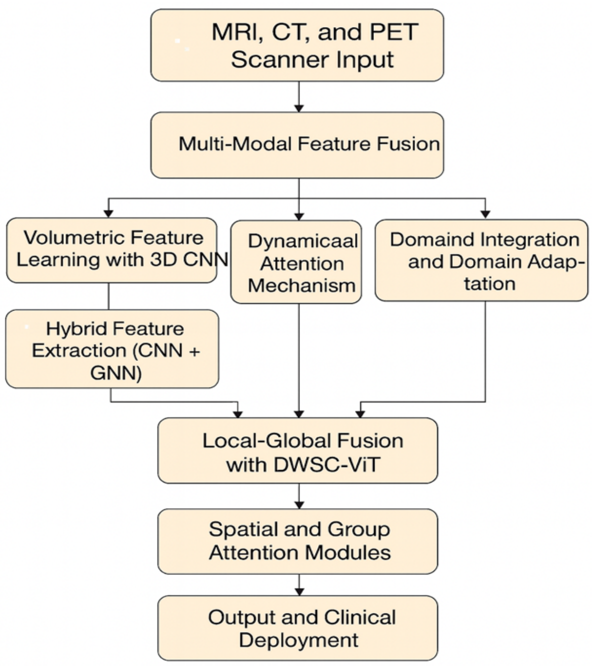

Figure 3. HyPerNet Block Diagram

connected classification head. The efficient attention modules and separable convolution as the two design features enable the light weight of HyPerNet, making it deployable on the edge devices and GPUs-based clinical systems. This makes it fast to infer and easy to apply to real life applications at point-of-care diagnostics. By applying this, the model can extract the fine-grained details of the pictures, thereby bringing out the context of the imaging data. Efficient channel attention is embedded to improve computational efficiency after the feature extraction process. Inspired by Mobile NetV3 and the Squeeze-and-Excitation Attention block, ECA offers more generalized average pooling without upsizing the learnable parameters. This way, it allows for better feature representation and, at the same time, remains lightweight for high efficiency in the network. The DWSC-ViT Fusion Architecture combines the beneficial aspects of Depthwise Separable Convolutions and Vision Transformer modules. This allows capturing localized features through depth-wise convolution and global context with vision transformers. This fusion allows, in general, the enhancement of its performance, not only in subtle image content understanding but also in increased adaptability and usefulness across widely different domains. Top of Form

Results

A total of 8,256 images are taken from Kaggle for brain tumor classification. These are equidistributed over four classes: 2,064 images for each of glioma, meningioma, no-tumor, and pituitary tumor categories. Sample data of the study is demonstrated in Figure 4. Data augmentation was applied uniformly across all classes to ensure class balance rather than to artificially inflate dataset size. Each class was augmented independently to reach 3,000 images, preserving inter-class proportionality and reducing potential bias during training. Image augmentation techniques applied are horizontal flipping, random cropping, Gaussian blur, contrast adjustment, and slight rotation to bring each of them to 3,000 images. The dataset was divided in the ratio of 80% for training and 20% for testing. To be able to handle variations in image sizes, all the images were resized to 256×256 pixels before being fed into the training of the model. All these changes ensure a balanced and standardized dataset is prepared for training and evaluation. This further facilitates robust development and further assessment of the model in classifying brain tumors.

Spatial attention (SPA) enhances the model's ability to perceive spatial details by applying fine-grained spatial attention to the feature map. This results in a calibrated attention map that improves feature representation. SPA enriches the model's spatial understanding, leading to a feature map that more accurately emphasises relevant spatial details and supports a detail-aware learning approach. Table 1 presents the summary of the HyPerNet model parameters.

Group Attention (GA) makes use of hierarchical pooling for tensor size reduction in a way that does not discard the local information while at the same time supporting the fusion of global features efficiently. By the preservation of the tensor at various sizes, the GA can recover the local details and global characteristics that are further combined for interaction in a per-channel setting. Pixel-level assembly and shuffling further efficiently distill such interactions to avoid any extra loss in computation. This design makes the current implementation of the HyPerNet lightweight for enabling fast model training on GPUs without rendering the model heavy for deployment on mobile and edge platforms. Its lightweight design makes the HyPerNet practical for real-world applications in clinical environments and provides robust, interpretable, and efficient brain tumor classification.

The confusion matrix in detail, with the classification

Table 1. Summary of the HyPerNet Parameters

Component	Technique/Module	Purpose / Function
Input Data	MRI, CT, PET Scans	Multimodal imaging for complementary information
Multi-Modal Fusion	Spatial registration + fusion	Combine features from multiple modalities for richer representations
Dynamical Attention	Adaptive attention based on image complexity	Highlights essential regions, improves performance in noisy/ artifact-prone data
Volumetric Processing	3D Convolutional Neural Networks (3D CNNs)	Extract deep spatial features from volumetric scans
Explainable AI	Grad-CAM	Provides visual interpretability for clinical trust and decision support
Transfer Learning	Domain adaptation with pre-trained models	Fine-tunes on specific dataset for improved generalization
Hybrid Feature Extraction	GNN + CNN	Combines local and relational features from images
Efficient Channel Attention	ECA (Efficient Channel Attention)	Lightweight attention to improve feature representation without heavy computation
Local–Global Fusion	DWSC-ViT (Depthwise Separable CNN + Vision Transformer)	Combines localized and global features for robust detection
Spatial Attention (SPA)	Fine-grained spatial attention	Focus on spatially significant areas in the feature map
Group Attention (GA)	Hierarchical pooling & tensor-wise attention	Efficient local-global fusion while preserving feature interactions
Output	Brain Tumor Classification	Accurate, interpretable classification results for clinical use

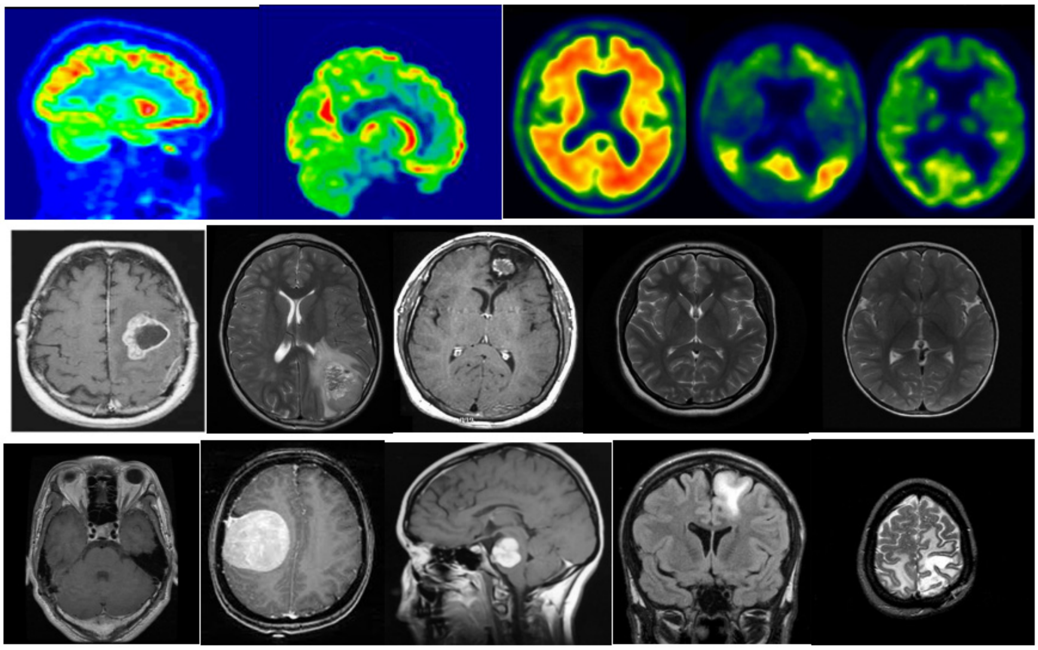

Figure 4. Sample of the Data Collection

of the HyPerNet model on Glioma, Meningioma, Pituitary Tumor, and Normal cases, is given in Figure 5. In the diagonal elements above, the number of each class indicates the correct prediction number, with the number 401. The numbers in the diagonals (e.g., 401) denote the correctly classified samples of each of the classes and the elements in the off-diagonals denote the misclassifications. Due to the low off-diagonal values, HyPerNet is robust and has a high level of discriminative ability.

The high accuracy value illustrates that the model identified 401 instances correctly of Glioma, Meningioma, Tumor of the Pituitary, and Normal cases. All the off-diagonal elements in the matrix, which take a value of 4, indicate the number of cases when the classifier incorrectly labeled one condition as the other. However, these values are shallow, which suggests that overall, the misclassification is very low, thereby emphasizing the robustness of the model. Table 1 shows the experiment's results using different models, considering the accuracy, precision, recall, F1-score, and specificity. Comparative models include DenseNet121, EfficientNet_b0, EfficientNet_b1, ResNet101, MobileNetV2, MobileNetV3_Large, and one proposed. DenseNet121 contains 6.96 million parameters and shows accuracy of 94.15%, precision of 94.13%, recall of 94.15%, F1 score of 94.14%, and specificity of 98.05%. EfficientNet_b0 contains 4.01 million parameters and has lower performance with the accuracy of 90.1%, precision of 90.27%,. EfficientNet_b1 is a slightly bigger model than EfficientNet_b0, hosting 6.51 million parameters. It also somewhat better performed and could achieve accuracy, precision, recall, F1-score, and specificity of 90.85, 90.99, 90.85, 90.91, and 96.61%, respectively. The

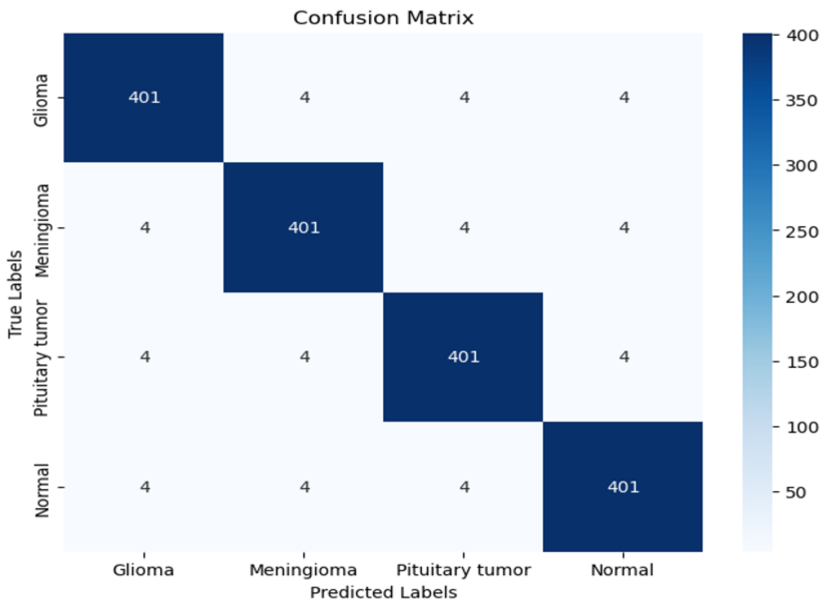

Figure 5. Confusion Matrix of the HyPerNet Model

Table 2. Experiment Results of Different Models

Model	Parameters	Accuracy	Precision	Recall	F1-score	Specificity
DenseNet121 [26]	6.96 M	94.15	94.13	94.15	94.14	98.05
EfficientNet_b0 [27]	4.01 M	90.1	90.27	90.1	90.13	96.7
EfficientNet_b1 [27]	6.51 M	90.85	90.99	90.85	90.91	96.61
ResNet101 [28]	42.50 M	94.25	94.26	94.25	94.25	98.08
MobileNetV2 [29]	2.22 M	94.85	94.49	94.85	94.85	98.4
MobileNetV3_Large [30]	4.21 M	94.34	93.31	93.4	93.38	97.8
HyPerNet Model	1.66 M	97.14	97.09	97.09	97.09	98.9

largest model in the batch, ResNet101, has 42.50 million parameters and reaches the following metrics: 94.25% test accuracy, 94. For example, MobileNetV2 with 2.22 million parameters showed a better performance than many others, with an accuracy of 94.85%, a precision of 94.49%, a recall of 94.85%, and an F1-score of 94.85%, while its specificity was 98.4%. MobileNetV3_Large, with several parameters of 4.21 million, has a slightly lower. The HyPerNet model works the best among the models, with the least number of parameters in its architecture, and this is 1.66 M, achieving 97.14% for accuracy, 97.09% precision, 97.09% recall, 97.09% F1-score, and 98.9% specificity. This provides a measure of the efficiency and effectiveness of the HyPerNet model compared with other popular models.

As highlighted in Table 2, HyPerNet achieves the highest performance across all evaluation metrics while using the fewest parameters, demonstrating an optimal balance between accuracy and computational efficiency.

As depicted in Figure 6 (a), both the training and validation accuracy curves show an incredibly positive trend and based on the data, both of them go beyond 95% accuracy after the first 20-30 epochs. Figure 6 depicts the convergence behavior of HyPerNet throughout the

a

b

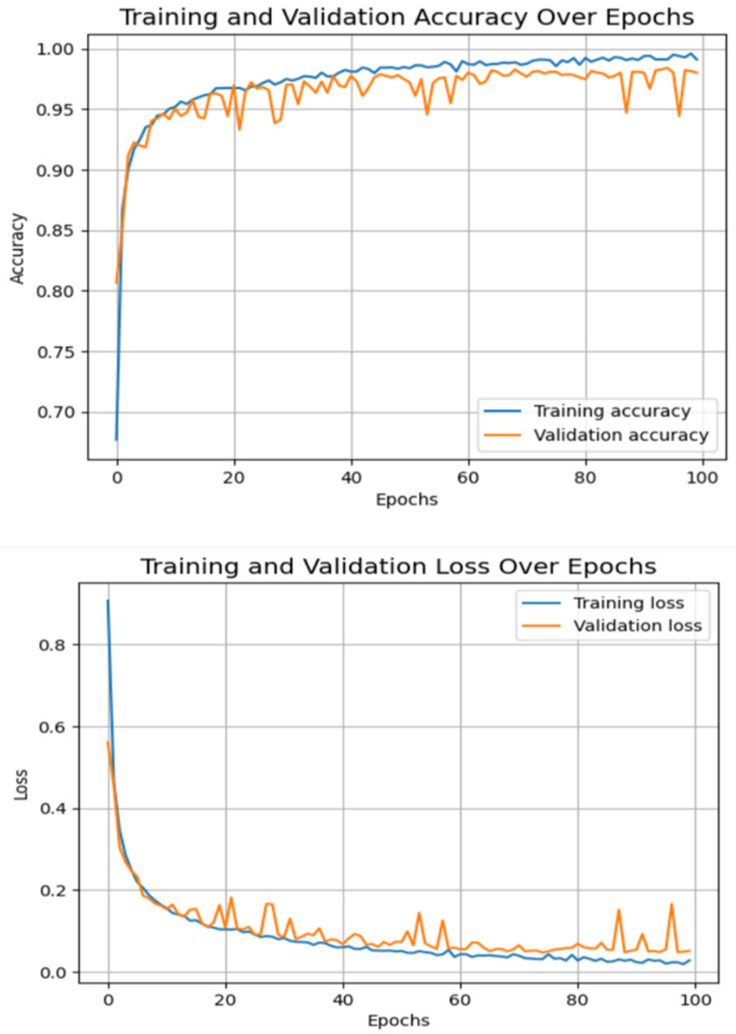

Figure 6. Accuracy and Loss for Training and Validation for the HyPerNet Model. a-Accuracy for training and validation for the HyPerNet model; b- loss for training and validation for the HyPerNet model

training, which means that learning is stable, converges quickly, and there is little overfitting.

The training accuracy is continuously getting predicted with almost near perfect accuracy (~99%), the validation accuracy is also showing consistent high accuracy (97-98%) with minor variations. These variations are normal since there is a random fluctuation of the validation batches, especially in clinical datasets that may comprise of heterogeneous imaging input. Notably, the validation curve does not deviate significantly from the training curve, indicating that the model performs well and does not overfit. This reaffirms the stability of HyPerNet's architecture, particularly in the application of multi-modal fusion, attention, and hybrid CNN-GNN-based feature extractors, which can successfully learn from varying distributions and types of input data. Figure 6(b) denotes the fast convergence in the training and validation loss curves. First, both losses, the training and the validation, drop by high percentages, and both take on minimum values at less than 0.05. The validation loss is slightly higher in the later epochs (after epoch 40), but there are no spreads that are associated with sharp declines in accuracy, which means that it is resistant to temporary failures. Such spikes could be due to certain validation batches which have noisy or tricky samples, and also show that the model produces constant good accuracy even on diverse image quality. All these curves together speak in favour of the thesis that HyPerNet is a procedure that leads to high accuracy and outstanding generalization of the brain tumour classification tasks. These epochs consistency certifies the strength of the suggested hybrid architecture, attention modules, and area-flexible training procedures. In addition, the convergence pattern indicates that the model can be implemented in clinical practice where reliability and accuracy matter most.

Discussion

The HyPerNet model is quite an advance in brain tumor classification in that it incorporates deep learning techniques toward improving the performance and interpretability of the classification. The fusing of multi-modal dynamic attention-based mechanisms with explainable AI characteristics will help HyPerNet achieve a solution to the challenges of variability and complexity for brain tumor imaging data. The model enables 3D CNNs, transfer learning with domain adaptation through graph relational learning, and hybrid feature extraction through graph neural networks to capture both local and relational features for improved overall model performance. Experimental results show that HyPerNet outperforms DenseNet121, EfficientNet, ResNet101, and MobileNets by achieving state-of-the-art performances with improved metrics overall evaluation parameters, coupled with carrying relatively fewer parameters, which shows efficiency and effectiveness. As per the confusion matrix and its comparative analysis, the model showed a high value for accuracy, precision, recall, F1-score, and specificity, which reflects that the model is robust and reliable for clinical applications. About the diagnosis of brain tumors, the lightweight design directly pertains to the ease of deployment in mobile and edge computing platforms, making HyPerNet deployable in resource-constrained environments. These could revolutionize the approach taken by the medical fraternity in the diagnosis of brain tumors. A sensible addition of explainable AI features in HyPerNet will build trust and understanding of the decisions taken with its help thereby leading to its adoption in routine clinical deployment. Overall, HyPerNet represents a significant step change in automatic medical image analysis, equipping clinicians with a powerful tool supporting the process of accurate and interpretable brain tumor classification.

Author Contribution Statement

Hamed D. Al-Sharari is the sole author and was responsible for: Study conception and model design (HyPerNet); Data preprocessing, augmentation, and model training; Interpretation of results and comparative analysis; Drafting and finalizing the manuscript.

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General

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Scientific Approval

This study was approved by the relevant scientific and ethical committees at the College of Computing and Informatics, Saudi Electronic University, Kingdom of Saudi Arabia.

Ethical Declaration

The research conducted in this study adheres to the ethical guidelines outlined by the institutional review board (IRB) of Saudi Electronic University. The study used publicly available datasets, and no human subjects or personal data were involved. The dataset was anonymized to ensure privacy and confidentiality.

Data Availability

The dataset used in this study is publicly available on Kaggle.

The research utilized 8,256 MRI brain images from a Kaggle dataset, distributed across glioma, meningioma, pituitary tumor, and no-tumor classes. All images were preprocessed and augmented for training purposes.

Study Registration

This study is not registered in any clinical or experimental research registry. As it is a computational study using publicly available imaging data, formal registration (e.g., in ClinicalTrials.gov) is not applicable.

Abbreviation

MRI: Magnetic Resonance Imaging
CT: Computed Tomography
PET: Positron Emission Tomography

CNN: Convolutional Neural Network
3D CNN: Three-Dimensional Convolutional Neural Network
GNN: Graph Neural Network
ViT: Vision Transformer
DWSC: Depthwise Separable Convolution
SPA: Spatial Attention
GA: Group Attention
ECA: Efficient Channel Attention
Grad-CAM: Gradient-weighted Class Activation Mapping
MLP: Multilayer Perceptron
SVM: Support Vector Machine
ANN: Artificial Neural Network
LBP: Local Binary Pattern
CLFAHE: Contrast Limited Adaptive Histogram Equalization
RFE-UNet: Recursive Feature Elimination U-Net
WSSOA: Whale Social Spider Optimization Algorithm
DWSC-ViT: Depthwise Separable Convolution–Vision Transformer
IoT: Internet of Things
GPU: Graphics Processing Unit
XAI: Explainable Artificial Intelligence
ReLU: Rectified Linear Unit
F1-score: Harmonic Mean of Precision and Recall

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