Ensemble-Based Brain Tumour Detection Using ResNet18 and Feature Optimization Techniques

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Abstract

Brain tumour has a serious health issues that has to be identified accurately and promptly in order to be effectively treated. Because they need a lot of labelled data and might miss intricate patterns in medical images traditional techniques and basic deep learning models have trouble correctly identifying and categorizing various kinds of brain tumours. This study offers sophisticated ensemble DL frameworks that enhance brain tumour classification by combining several intelligent systems. The Deep Multiple Fusion Network (DMFN) an intelligent fusion system that integrates the predictions from several neural networks to classify four types of brain tumours—glioma meningioma pituitary and normal cases—with an accuracy of 98.36% is one method that uses a framework that includes data generation techniques to create more training examples feature extraction models. Another complementary method achieves 99.1% accuracy 98.8% precision 98.9% recall and 99.0% F1-measure by processing MRI images using a hybrid model that combines CNN with LSTM networks. Ultimately such ensemble based solutions enhance patient survival rates and clinical outcomes as they provide physicians and radiologists with powerful and reliable tools to assist them diagnose brain tumours faster and more accurately.

Keywords- Education, Computer Graphics, Visual Depiction, Virtual Reality, Animation, Visual Effects

1. Introduction

Brain tumours are a serious health danger for the practice of modern medicine. According to a report conducted by the WHO in 2020, around 10 million deaths were reported on brain cancer making it the second-leading cause of death in the world. The condition may go into life-threatening stages as a misdiagnosed brain tumour may make the patients subjected to medical treatments that are ineffectual, which implies that their survival chances are reduced by a big margin. The biggest issue as regards to the detection of brain tumours is the fact that the tumours may differ in terms of location, type, size, and shape. To compound the situation, there are various forms of tumours, and the specifics of the diagnosis and detection process may be extremely complicated as the specialists should distinguish between pituitary, glioma, lymphomas and medulloblastoma.

There are the challenges of standard diagnostic methods. The potential for early diagnosis and identification of a tumour are high because of the accuracy of an MRI, however, the determination of tumour type is tedious, and it is high risk, of producing a determined diagnosis. This type of work requires a radiologist that is highly skilled. The many types of tumours mislead radiologist and creates situations where sound diagnosis cannot be made. It is for these reasons that artificial intelligence (AI) is needed in computer-aided diagnostic (CAD) systems. Using AI in this manner is an effort to alleviate the workload of the healthcare professional.

A potent remedy for these problems is ensemble DLmodels. Ensemble models use several neural networks cooperating to improve the diagnostic accuracy and robustness instead of depending on a single classification method. Ensemble architectures like the Deep Multiple Fusion Network (DMFN) perform better in differentiating between closely related tumour classes by decomposing the difficult to multi-class brain tumour classification problem into several binary classification tasks and using fusion mechanisms to combine predictions. To get cutting-edge brain tumour classification accuracy this paper presents an advanced ensemble-based framework that combines GANsfor data augmentation multiple ResNet18 models for feature extraction and sophisticated fusion mechanisms. This ultimately supports radiologists in providing timely and accurate diagnoses that are crucial for patient survival.

2. Related Work

Identifying and classifying brain tumours :

The main problems in contemporary medical diagnostics is brain tumours which have a substantial impact on patient survival and important of life. Effective treatment planning and better patient outcomes depend on the timely and accurate detection of brain tumours. The field of medical image analysis has undergone a revolution in earlier year due to the integration of artificial intelligence and DL and ML techniques which provide previously unheard-of accuracy and efficiency in the classification of brain tumours from MRI scans. Conventional techniques for diagnosing brain tumours mainly depend on invasive biopsy procedures and radiologists manual interpretation. But these methods take a lot of time are prone to human error and frequently postpone important treatment choices. Some of the restrictions address by the implement of deep learning-based computer-aided diagnostic (CAD) systems which offer automated precise non-invasive diagnostic tools that can act as a trustworthy second opinion for medical professionals. This review of the literature compares the approaches datasets and performance results of several studies used for DL technology for brain tumour classification. The most prevalent tumour types—gliomas meningiomas and pituitary tumours—as well as the binary distinction between malignant and benign cases are the main topics of this review.

A. Deep Learning Architecture-Based Brain Tumour Classification

CNN are now the most uses the DL technique for medical image analysis because they can automated extract hierarchical features from an unprocessed image data.CNN can use MRI scans to directly learn discriminative features capturing both high-level features (tumour morphology tissue patterns) and low-level features (edges textures) in contrast to conventional ML techniques that necessitate manual feature engineering (Neamah et al. in 2024). Several researches have demonstrated how successful CNN-based methods are. To address information loss during deep feature extraction Patil and Kirange (2023) proposed an EDCNN that combines VGG16 with a shallow CNN (SCNN). Their model was able to classify multi-class tumours (gliomas meningiomas and pituitary tumours) with an accuracy of 97. 77%. The value of combining shallow and deep features was demonstrated by the ensemble approaches superior performance over individual models. As a result Gayathri et al. (2023) assessed the VGG-16 architecture for brain tumour detection following hyper parameter optimization 94% accuracy was attained. Due to its strong ability to extract features the VGG-16 model—which is renowned for its simplicity and depth—has been extensively used in medical imaging applications. Mahmud as well. (2023) created a unique CNN architecture intended for effective identification of brain tumours with magnetic resonance imaging. Their model outperformed well-known models achieving 93. 3 percent accuracy and a 98. 43 percent of AUC. For particular clinical applications this study demonstrated the significance of architecture optimization.

B. Method Of Transfer Learning

TL is a powerful technology for categorizing brain tumours, particularly when working with a small medical imaging datasets. Researchers can optimize these networks for particular medical imaging tasks by utilizing pre-trained models on sizable datasets like ImageNet greatly cutting training time and boosting performance. The Monirul et al. (2025) achieved an astounding accuracy of 99. 60 percent by using transfer learning with MobileNet InceptionV3 and DenseNet121 architectures on the Kaggle Brain Tumour MRI Dataset. This excellent performance shows how well pre-trained models work for medical image classification tasks when they are properly adjusted. Manowarul and associates. (2024) achieved 99. 69 percent precision in the brain tumour classification using EfficientNetB3 on a publicly accessible contrast-enhanced MRI dataset. Medical imaging applications have demonstrated exceptional performance with EfficientNet models which are renowned for their effective scaling of network depth width and resolution. Majib and associates. (2022) suggested a stacked classifier network (VGG-SCNet) that combines a stacked classification method with the advantages of the VGG architecture. Their model demonstrated the potential of ensemble approaches in transfer learning frameworks achieving 99. 20 percent accuracy on a combination of Kaggle dataset and pathology institute data.

C. Hybrid Models: Integrating ML with DL technique

Numerous studies have examined hybrid techniques that integrated a deep learning for a future extraction with a conventional machine learning classifiers for a final classification .This method makes use of CNNs automatic feature learning capabilities while taking advantage of the efficiency and interpretability of traditional machine learning algorithms. Shanjida & Co. (2024) presented a lightweight CNN-SVM model that achieved 96. 70 percent accuracy using k-fold cross-validation on the Figshare Brain Tumour Dataset. For managing the complexity of brain tumour classification CNN feature extraction using SVM classification worked well together. Hossain and associates. (2023) used the BRATS dataset to compare several methods including Fuzzy C-Means with SVM KNN and CNN with an accuracy of 97. 87 percent. The relative advantages of various algorithmic techniques for tumour detection were illustrated by their comparative analysis. Khan & Co. (2023) achieved 94% accuracy by using SVM with PCAand DWT on the Cancer Imaging Archive dataset. This study demonstrated the benefits of using sophisticated feature extraction methods in conjunction with reliable classification algorithms.

Author (Year)	Dataset	Tumour Type	Model	Accuracy
Patil & Kirange (2023) [10]	MRI Scans	Multi-class (Glioma, Meningioma, Pituitary)	Ensemble Deep CNN (SCNN + VGG16)	97.77%
Woźniak et al. (2023) [11]	CT Brain Scans	Not specified	CLM (support neural network with CNN)	~96.00%
Mahmud et al. (2023) [13]	MR Images	Brain tumour	Proposed CNN Architecture	93.30%
Asad et al. (2023) [14]	Not specified	Brain tumour	Deep CNN and SGD Optimization	Not specified (Outperformed baseline)
Kanchanamala et al. (2023) [15]	Not specified	Brain tumour	ExpDHO-based ShCNN and Deep CNN	> 90.00%
Gayathri et al. (2023) [18]	Not specified	Brain tumour	VGG-16	94.00%
Haq et al. (2023) [19]	MRI Data	Brain tumour	CNN-based techniques	High accuracy (specific value not mentioned)
Hossain et al. [2]	BRATS Dataset	Brain tumour	Fuzzy C-Means + SVM, KNN, CNN	97.87%
Islam et al. [4]	Br35H, SARTAJ, Radiya, etc.	Brain tumour	2D CNN, CNN-LSTM + Ensemble	98.82%
Monirul et al. [5]	Kaggle Brain Tumour MRI Dataset	Brain tumour	Transfer Learning (MobileNet, InceptionV3, DenseNet121)	99.60%
Shawon et al. [3]	Br35H, Brain Tumour Detection	Brain tumour	Cost-sensitive learning with InceptionV3, CNN	99.33%
Majeed et al. [6]	Private Collection (44 Classes)	Brain tumour	Lightweight MobileNetV3	91.00%
Rahman et al. [7]	MRI Brain Tumour Dataset (44 Classes)	Brain tumour	EfficientNetB5	94.75%
Khan et al. [8]	Cancer Imaging Archive	Brain tumour	SVM with DWT + PCA	94.00%
Shanjida et al. [9]	Figshare	Brain tumour	Lightweight	96.70%

Table 1: summarizing the key information from the various studies cited within the text

3. Materials and Methods

The Deep Multiple Fusion Network (DMFN) an ensemble the proposed methodology for classifying a brain tumour is based on DL architecture .The classification system will include glioma, meningioma, pituitary tumour, and no tumour as the four categories for classification of brain MRI images. Features extraction, data augmentation and data pre-processing , feature selection and ensemble classification from the process.

- Data Collection: The BRATS2021 1 dataset that is normally used for analysing brain tumors is the source from which the brain MRI images uses some case are obtained, Glioma, meningioma, pituitary tumour, and no tumour are the four categories in which the more than 3000 images in the dataset will be classified.
- Data Preprocessing: Preprocessing is performed on the obtained MRI images to boost their uniformity and overall quality. This includes scaling images to a standard size of 224 × 225 pixels normalization to balance the value of pixels to make them the same and skull stripping so as to remove the unwanted non brain areas. Standardizing data allows for an input-output relationship, allowing for performance quality to be consistent with what was learned through training.
- Augmentation of Data: Augmented data created through Generative Adversarial Networks GANs is generally viewed as an advanced way to augment data sets when limited data is available for training, but GANs also be used to create realistic synthetic MRI scans that will allow for additional training data, thereby decreasing over fitting and improving the ability of models to generalize to new medical imaging data.
- The Features Extraction Model: The pre-processed MRI image data was passed through Resnet18 to extract the respective features. We decided to adopt this approach because residual learning is particularly useful for mitigating the vanishing gradient problem and facilitating the learning of complex associations. Features that were extracted should give insight into heterogeneous nature of tumors while being able to differentiate between tumors.
- Hybrid Feature Selection: The hybrid feature selection strategy we used was a combination of PCA (Principal Component Analysis) and PSO (Particles Swarm Optimization). PSO and PCA help to determine the best set of features, whereas PCA offers dimensionality reduction by removing redundancy without sacrificing informative features. By performing this, we can

improve the efficiency of classifiers and computing.

- Ensemble Model Construction (DMFN): The approach is based on the Deep Multiple Fusion Network (DMFN) ensemble model which includes multiple ResNet18 classifiers. Based on the binary cross-entropy loss function, two dissimilar types of model training will be expected to be performed for tumor representation extraction in terms of differentiating tumors. Training to classify two different categories of tumours (instead of having multiple classes) ensures that the model learns the decision boundary for each Resnet18 model; the Resnet18's will use only binary classifications in order to accurately optimize the binary classification problem.
- Additionally, a further method in which ResNet18's are trained is by using the technique dropout which is a form of regularization used to help the ResNet18 model perform better when evaluated on images that are unseen. During the training process, dropout is achieved by randomly turning on and off the neurons, it consequently aids in achieving a dropout improvement when the models is assessed using untrained images.
- Weighted Fusion: After that, a separate model's output combination is trained using a weighted fusion mechanism. The model weights are analogous to the best performing model on the validation set regarding output probability scores for those models. Each class's final score is the weighted average of these probabilities, where the more reliable models exert greater control on the outcome.
- Final classification: This phase takes description from combined output of fusion layers and performed final decision of class label. In other words, the class with maximum likelihood is selected. The MRI image is classified to the four groups by the system; glioma meningioma, pituitary tumor, or no tumor.
- Performance Evaluation: In the final phase, the performance of the models is evaluated using basic metrics including F1 score, accuracy, precision and recall. These metrics convey the advantages inherent to ensemble methods over single model approaches while serving as a deeper dive into the model's ability at correctly classifying brain tumor types.

A. Ensemble Model Architecture for Brain Tumour Classification

The Deep Multiple Fusion Network (DMFN) approach which combines several DL Techniques to increase classification accuracy and robustness is used to design the ensemble model architecture for brain tumour classification. Glioma meningioma pituitary tumour and no tumour are the four categories into which this system divides MRI brain images. The architecture employs three ResNet18 models as base classifiers rather than just one since ResNet18 is efficient at extracting deep features from medical images. Better deep network training is made possible by ResNet18s residual learning mechanism which also aids in overcoming the vanishing gradient issue. The system uses a pairwise binary classification strategy in which each model is trained to differentiate between two distinct tumour classes in order to simplify the multi-class classification problem. This enhances overall discriminative performance by enabling the models to concentrate on learning precise decision boundaries between similar classes.

A weighted fusion mechanism is used to combine the outputs from these separate models each of which produces probability scores for its specific classification task. The final prediction is made by adding up the weighted probabilities and choosing the class with the highest score after these outputs are given weights according to their validation performance. Binary cross-entropy loss is used to train each ResNet18 model independently and dropout is used as a regularization strategy to avoid overfitting. The ensemble model functions within a full pipeline that includes feature extraction using ResNet18 feature selection using a hybrid PCA-PSO technique to reduce dimensionality and improve efficiency and data augmentation using GANsto address the scarcity of medical imaging data. By achieving high accuracy robustness and decreased misclassification—especially when it comes to differentiating closely related tumour types—this integrated approach improves the systems overall performance.

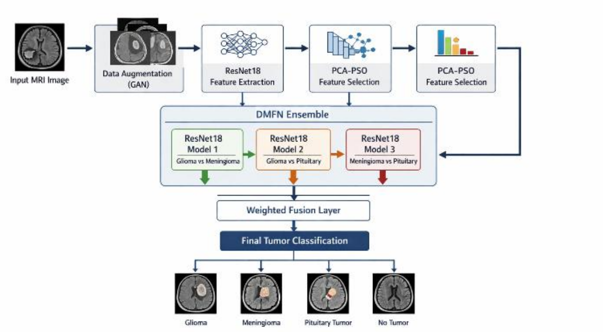

Figure 1: ensemble model architecture for brain tumour classification

In order to increase dataset diversity the suggested ensemble model architecture fig1. Shows that brain tumour classification starts with input MRI images which are then improved using data augmentation techniques based on Generative Adversarial Networks (GANs). After the images have been enhanced the ResNet18 model is use extract deep and significant features from the images. In order to minimize dimensionality and choose the most pertinent features these features are further refined using a hybrid PCA-PSO feature selection technique. After that the chosen features are fed into the Deep Multiple Fusion Network (DMFN) which is made up of three ResNet18 models that has trained using a pairwise binary classification strategy. Each model can distinguish between two types of tumours. A weighted fusion layer that determines the significance of each models prediction is used to combine the outputs from these models. The MRI image is finally classified into one of four classes by the system: glioma meningioma pituitary tumour or no tumour.

4. Results and Discussion

Using common classification metrics like accuracy precision recall and F1-score the suggested ensemble model's performance based on the Deep Multiple Fusion Network (DMFN) was assessed. On the BRATS2021 dataset the model demonstrated a high accuracy 98. 36 percent indicating its efficacy in identifying various types of brain tumours. The model generates very few false positive predictions as evidenced by the precision of 98. 8%. While the F1-score of 99.0% indicates a balanced performance between precision and recall the recall value of 98.9% indicates that the model successfully identifies the majority of the real tumour cases. A comparison with current models such as single Res-Net-based classifiers and conventional CNN was conducted to further validate the efficacy of the suggested approach. According to the findings the suggested ensemble approach performs better than these models across all evaluation metrics. The weighted fusion strategy which lowers individual model bias and improves overall prediction accuracy and the utilize several models are primarily responsible for the performance improvement. Additionally tabular and graphical analysis are used to present the results. While graphs like accuracy and loss curves demonstrate stable training and improved convergence performance comparison tables unequivocally demonstrate the suggested models superiority over current methods. All things considered the suggested ensemble model yields solid and trustworthy classification outcomes which qualifies it for practical medical uses.

Model	Accuracy	Precision	Recall	F1-Score
CNN	94.2%	94.5%	93.8%	94.1%
ResNet18 (Single)	96.5%	96.8%	96.2%	96.5%
Proposed DMFN Ensemble	**98.36%**	**98.8%**	**98.9%**	**99.0%**

Table 2: Performance Comparison of Proposed DMFN Ensemble Model with Existing Models

5. Conclusion

In order to accurately classify brain tumours using MRI images this paper proposed an efficient ensemble model architecture based on the Deep Multiple Fusion Network (DMFN). To enhance classification performance the system combines multiple ResNet18 models with a weighted fusion mechanism and a pairwise binary classification strategy. Additionally the ensemble framework exhibits increased robustness and decreased misclassification especially for tumour classes that are closely related. As a result the suggested approach offers a dependable and efficient way to classify brain tumours automatically and it has great potential for practical medical uses.

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