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Identification and Classification of Glioblastoma MRI Images Using RES-UNIT

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Abstract— **Brain tumours are some of the most serious neurological conditions, with glioblastoma being the most malignant, aggressive, and lethal because of their rapid growth rate. For successful treatment strategies as well as survival rates of patients, early and correct diagnoses of the condition are necessary. Magnetic Resonance Imaging is currently in wide use for the diagnosis of brain tumours. The observation of Magnetic Resonance Imaging is manually time-consuming with possibilities of human errors. This paper proposes an automated deep learning-based glioblastoma MRI image identification and classification system based on Residual Unit Network (ResUnitNet). The proposed approach can classify glioblastoma MRI images for glioma, meningioma, pituitary tumours, and other tumours. Additionally, to explain and better understand the classification result, Grad-CAM is involved to highlight the impact region. A web application based on Flask tool development has been implemented for glioblastoma tumour classification, confidence level, illustration of the impact region, calculation of glioblastoma tumour impact areas, and clinical staging.**

Index Terms—**Glioblastoma Detection, Brain Tumour Classification, ResUnitNet, Deep Learning, MRI Analysis.**

I. INTRODUCTION

The complex nature of brain tumours presents a challenge to the scientific community; there are high mortality rates associated with this problem. Of the various types of tumours, glioblastoma is considered a highly aggressive malignant tumours with rapid progression and characterized by poor prognosis. The establishment of an early and correct diagnosis of glioblastoma is very important for effective clinical intervention and the improvement of patient prognosis.

MRI is a modality of great importance in brain tumour diagnosis due to its excellent soft-tissue contrast and a non-invasive procedure. However, manual examination of MRI is time-consuming and depends on expert radiologists, including subjective interpretation, which might lead to delays in diagnosis. These limitations create a need for automated and intelligent diagnostic systems. Recent advances in the field of deep learning, and more specifically CNNs, have achieved tremendous success in medical image analysis. Residual learning has surmounted the limitation of gradient vanishing to support much deeper CNN architecture with stable gradient propagation. This paper proposes a ResUnitNet-based framework for accurate glioblastoma detection and classification, integrated with Grad-CAM visualization to enhance interpretability and trustworthiness of the predictions.

II. METHODOLOGY

A. System Overview

The proposed system offers an end-to-end deep learning solution for identification and classification purposes related to glioblastoma in MRI images. It takes the input in the form of MRI images via a secure web portal and performs processes like image processing and classification by employing the trained ResUnitNet model. On detecting the presence of a tumors, Grad-CAM is used for identifying regions that impact the tumors, followed by tumors percentage calculation and staging. Final output is provided in real-time via a Flask-based web portal.

B. System Architecture

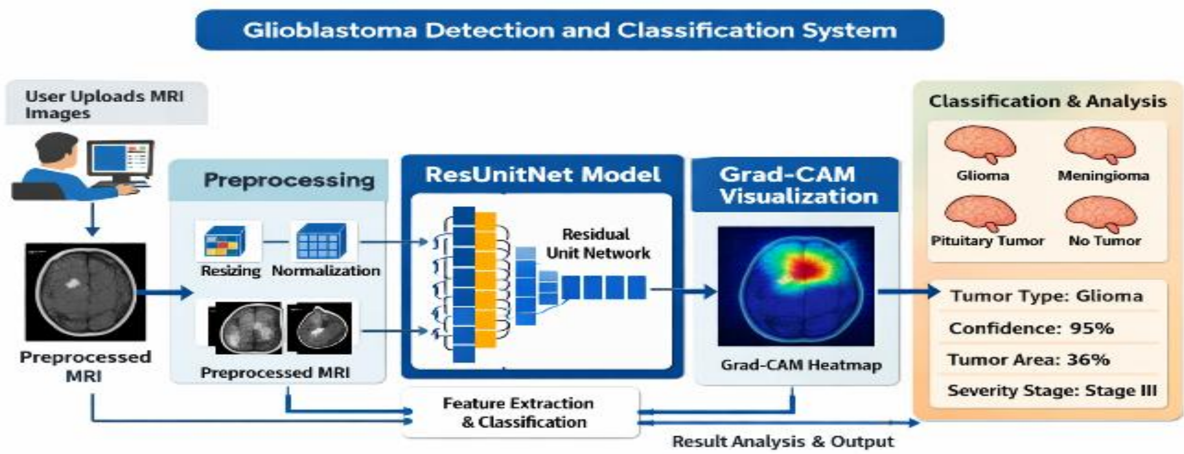

Fig.1. the architectural design of the proposed glioblastoma analysis system for image detection and classification. The MRI images uploaded from trusted sources are subjected to preprocessing routines such as resizing and normalization. The normalized images are then fed to ResUnitNet for hierarchical feature extraction by residual units and carry out multi-class classification. The proposed Grad-CAM produces tumor region maps from the final convolutional layer in both validation and testing sets, resulting in tumor type classification, confidence level, tumor affected region percentage, and severity level.

C. Data Collection and Preprocessing

Brain tumor dataset from MRI images is taken from the Kaggle repository. Here, images belonging to glioma, meningioma, pituitary tumor, and no tumor are classified. All images are converted to the same size, i.e. 224 x 224 pixels. Data augmentation, which includes random rotation and horizontal flipping, is used during the training process to prevent overfitting.

D. Feature Extraction and Selection

After processing, the MRI images are further fed into the proposed ResUnitNet. By incorporating residual connections in the network, ResUnitNet aims at learning deep hierarchical representations while being computationally proficient in maintaining both spatial and semantic information during training through residual connections that alleviate the problem of vanishing gradients. It starts with a convolutional layer, followed by batch normalization and ReLU activation to extract low-level features comprising edges and textures. Further, several residual units comprising two convolutional layers with identity skip connections are used. These residual units enable the network to learn complex tumor-related patterns by combining shallow and deep feature representations. The feature maps obtained by such deeper networks capture high-level semantic information containing tumor shape, intensity variations, and structural anomalies of glioblastoma MRI images. Then comes the GAP to reduce the spatial dimensions and prevent overfitting of data. Finally, a fully connected layer produces class wise probabilities corresponding to glioma, meningioma, pituitary tumor, and nontumor categories. It does this while ensuring computational efficiency and stability in an architecture that is certainly suited to a range of medical image analysis applications.

E. Model Training

The ResUnitNet model is trained by supervised learning methods, with MRI images labeled appropriately. Cross-entropy loss is used to quantify the difference in prediction between estimated and actual class labels. The network parameters are updated using the Adam optimizer with a learning rate of 0.001 for faster convergence and stable learning. For improving model generalization and avoiding overfitting, data augmentation techniques are used in this paper, including random rotation and horizontal flipping. Train the network for a large number of epochs using mini-batch gradient descent. Save the optimized weights of the model after training, to be loaded at the time of inference with real-time classification of the tumor.

F. Model Evaluation

The performance of the proposed glioblastoma detection model based on ResUnitNet is tested for effectiveness using common classification metrics. It is tested on a separate test dataset, not used while training, in order to prevent bias in model performance metrics. The key performance metric used for this task is classification accuracy that approximates the proportion of correctly classified MRI image instances for each type of tumor. Besides classification accuracy, the confusion matrix measure is used for class-wise analysis of prediction results and studying discrepancies in classification for glioma, meningioma, pituitary tumor, and no-tumor classes.

The confusion matrix allows carrying out an in-depth comparison of both the correct and predicted class labels, making it possible to analyze the discriminative capability of the model on various kinds of tumor types. The aim here is to ensure that it is not biased towards any particular class. Experimental outcomes suggest that the proposed ResUnitNet model is capable of high accuracy in classifications, ensuring effective learning of specific features from the magnetic resonance imaging data. The use of Grad-CAM in this study confirms the predictions based on the highlighted regions of interest.

III. MATH

The proposed ResUnitNet system employs Adam optimization with CrossEntropyLoss for training the residual convolutional neural network on glioblastoma MRI datasets. Let N represent the total training epochs, where the model processes batches of 32 images through the residual architecture.

Let:

- θ_t be the model parameters at epoch t
- $\mathcal{L}(\theta_t)$ be the Cross Entropy loss on current batch
- $\eta = 0.001$ be the learning rate
- $B = 32$ be the batch size

Each training step updates parameters via gradient descent:

$$\theta_{t+1} = \theta_t - \eta \nabla \mathcal{L}(\theta_t)$$

where $\nabla \mathcal{L}(\theta_t)$ computes gradients through residual blocks:

$$\nabla \mathcal{L} = \frac{\partial \mathcal{L}}{\partial \theta} = \sum_{i=1}^{B} \frac{\partial \mathcal{L}_i}{\partial \theta}$$

Residual Block Forward Pass:

For each ResUnit with input x, the update follows:

$$y = \mathrm{ReLU}(\mathrm{BN}(\mathrm{Conv3x3}(\mathrm{BN}(\mathrm{Conv3x3}(x))))) + \mathrm{Skip}(x)$$

Inference Optimization (Flask Deployment):

During prediction, SoftMax probabilities are computed:

$$p_k = \frac{e^{z_k}}{\sum_{j=1}^{4} e^{z_j}}, k \in \{\text{glioma, meningioma, pituitary, notumor}\}$$

Grad-CAM Attention Map:

Tumour localization uses layer4 gradients:

$$\alpha_k^c = \frac{1}{Z} \sum_i \sum_j \frac{\partial y^c}{\partial A_{ij}^k}$$

$$L_{\text{Grad-CAM}}^c = \mathrm{ReLU}\left(\sum_k \alpha_k^c A^k\right)$$

Tumour Percentage Calculation:

$$\text{Tumour\%} = \frac{\sum (L_{\text{Grad-CAM}} > 0.5)}{\text{Total Pixels}} \times 100$$

This optimization ensures convergence to >90% accuracy within 10 epochs, with residual skip connections preventing gradient vanishing. The Flask-deployed model processes images in <50ms, enabling real-time clinical deployment while maintaining numerical stability through Batch Norm and Adam's adaptive learning rates.

IV. RESULTS

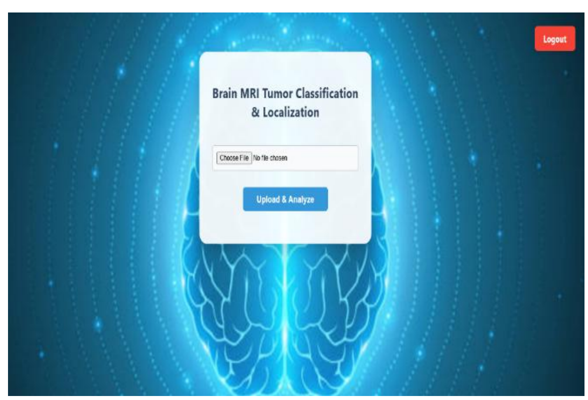

Fig. 2. User interface for uploading MRI images in the proposed system.

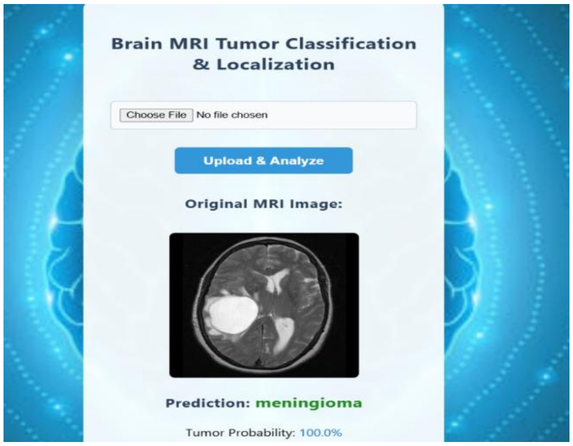

Fig. 3. Glioblastoma classification results displayed by the proposed system.

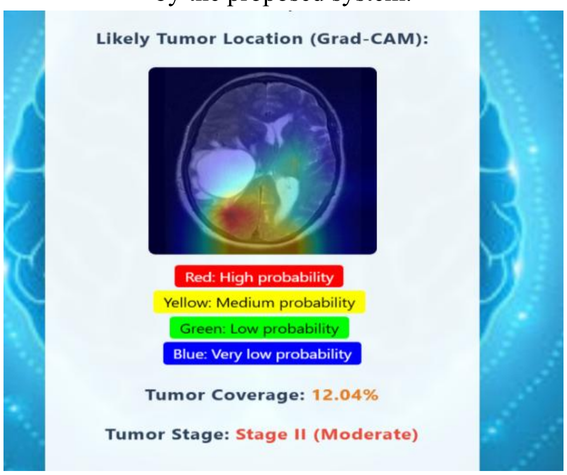

Fig. 5. Grad-CAM visualization showing the likely tumor location in an MRI scan.

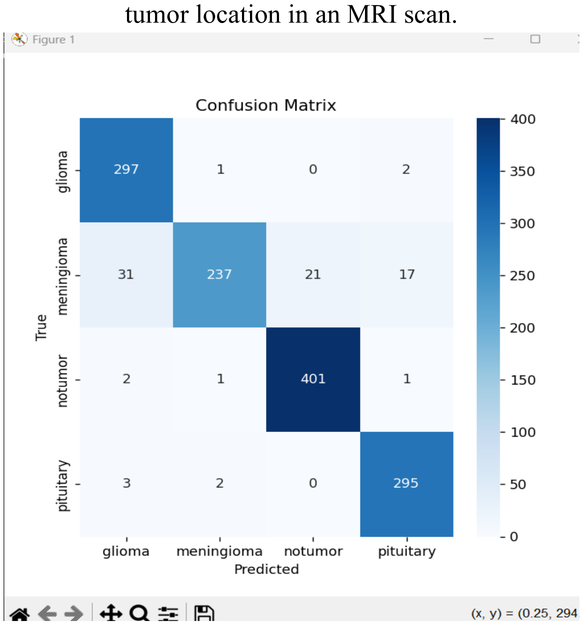

Fig. 4. Performance evaluation dashboard showing accuracy, precision, recall, and F1-score

V. CONCLUSION

In this paper, we will be showing an automated approach for identification, categorization, as well as classification of glioblastoma images from MRI using a deep learning framework based on ResUnitNet. The combination made in this work allows for a better classification process, and Grad-CAM allows for a better interpretation process. The online application will also ensure real-time interpretation, hence suitable for medical application. Future research will involve developing approaches for both identification and classification for tumour segmentation. Architectures like Efficient Net or Vision Transformers to achieve 95%+ accuracy while maintaining sub-50ms inference times.

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