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AI-Enabled Brain Tumor Detection Using MobileNetV2: A Lightweight Deep Learning Approach in Healthcare

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ABSTRACT :

This paper deep learning, especially using the Mobilenetv2 model, examines an AI-manual method to diagnose brain tumors. By taking advantage of MRI imaging data, the model classifies three major tumor types: glioma, meningooma and pituitary. The proposed system addresses the current boundaries in manual diagnosis by offering an automatic, light and efficient solution. The model receives 83% accuracy and is designed for real-time application in the clinical environment including mobile and low-resources settings.

Introduction

Brain tumors significantly affect the central nervous system and face challenges in diagnosis due to their diverse shapes, sizes and locations. MRI is widely used for brain imaging but manual interpretation can be inconsistent and time -consuming. The AI provides an effective option to automate diagnosis with better accuracy, especially through deepest learning models such as the Convisional Neural Network (CNN). Mobilentv2 is a light CNN architecture that is suitable for efficiency and is well suited for deployment in devices with limited computational capacity. The study uses Mobilenetv2 to detect three primary brain tumor types from MRI scans.

Literature

Traditional methods rely too much on radiologist expertise and manual MRI interpretation, often supported by classical ML models such as SVM and KNN. These approaches, while struggling with fundamental, generalization and accuracy. Deep CNNs such as VGG16 and Resanet have improved clinical performance but have demanded high computational resources. Mobilenetv2, while maintaining high accuracy, introduces separate residual blocks separately from depth

Methodology

The methodology followed in this study incorporates several well structured stages to ensure accurate, strong and deployable brain tumor classification using Mobilentv2 architecture. These stages include data acquisition, preprosying, model architecture configuration, training and evaluation.

3.1 Dataset Collection

The dataset used in this research was obtained from publicly available medical imaging repository, including brain tumor segmentation (Brats) dataset. This dataset is widely recognized in the medical imaging community for its diversity and broad labeling. It contains T1-weighted MRI images of four classes: glioma, meningooma, pituitary tumors and normal brain tissues. By incorporating several tumor types, the dataset allows the model to learn class-specific features that are essential for multi-class classification functions.

3.2 Data Preproseing

To ensure uniformity and enhance learning efficiency, each MRI scan undergoes a series of pre -proprousing stages:

- Regeneration: Images are shaped for 224x224 pixels, which corresponds to the expected input dimensions of Mobilentv2. This not only standardize the input shape, but also reduces computational complexity.
- Generalization: Pixel intensity values are scales between 0 and 1, stabilizing the training process by ensuring a uniform feature range.
- Growth: data growth techniques such as horizontal and vertical flipping, random rotation, zooming and translation are applied to artificially expand the dataset. This reduces the risk of overfiting and improves the normality of the model in unseen data.

- Label encoding: Each square label is converted using a-hot encoding. This format is necessary for multi-class classification, as it allows the model to compute category.

3.3 Model architecture

- The basic Mobilenetv2 is the original Mobilenetv2 architecture of the detection system, which has been chosen for balance between accuracy and efficiency. Major architectural components include:
- Deeply viouted conversion: These break the standard resolution in depth and points conversion, dramatically reduces the number of parameters and computational costs.
- Inverted residual blocks: These blocks help maintain performance with low layers using shortcut connections and bring it back to a low-dimensional output before expanding alcohol within each block.
- Linear hurdles: These avoid non-lectural changes in the production of residual blocks, preserve useful information and aid shield flow.
- Last layers: A global average pooling layer reduces spatial dimensions, followed by fully connected (dense) with Relu activation. The output layer uses softmax activation to generate a probability distribution on four sections.

3.4 Training Strategy

- The training phase includes a two-step process that increases the performance during preventing overfiting:
- Transfer Learning: Initially, the base Mobilenetv2 model is loaded with imagenet pre-informed weight and is frozen to maintain the features learned. A custom classification head is trained at its top.
- Fine-tuning: Once the classification heads are the head conversions, the selected layers of the Mobilentv2 base are unfriendly and fine with the head. This allows the model to adjust its earlier characteristics to the specific characteristics of brain MRI images.
- Optimizer and Loss: Adam Optimizer is used for its adaptive learning capabilities, which has a learning rate of 0.001. The graded cross-anropy is used as a disadvantage function because the function is multi-class.
- Classification Regularization: Dropout is applied in the dense layers to mitigate overfitting. Early stopping and model checkpoint callbacks are used to preserve the best-performing model and halt training if the validation loss ceases to improve.

3.5 Evaluation Matrix

To validate the effectiveness of the model, many performance matrix is calculated:

- Accuracy: overall purity of classification.
- Accurate, recall, and F1-score: provide deep insight into the balance of models between false positivity and false negatives, especially useful in medical diagnosis where both are important.
- Confusion Matrix: Displays the right versus wrong predictions per square, providing insight into specific strengths and weaknesses.
- ROC-AUC score: All probability measures the ability of the model to differentiate between classes, indicating strength in decision making.
- This broad functioning ensures that the brain tumor detection system is not only accurate, but also practical for deployment in various clinical scenarios.

Results and Discussion

The proposed Mobilenetv2-based brain tumor detection system was evaluated extensively using various classification matrix. The model gained overall classification accuracy of about 83% in four categories: glioma, meningiaa, pituitary tumor and non-tumor brain MRI. This result is particularly important given the mild nature of the model, which is adapted to deployment in the resource-based environment..

One of the main attractions of the results is a strong performance of the model in detection of glioma tumors. In several testing examples, the confidence level for glioma classification reached 98.71%, which suggests models' ability to identify major imaging facilities associated with this tumor type. Detection of meningooma and pituitary tumors also gives high confidence scores, although slightly less than glioma. This performance inequality can be attributed to the variation in tumor morphology and image representation within the dataset.

Confusion Matrix further depicted the strong classification capacity of the model. This showed minimal confusion between various tumor classes, showing that the model effectively learned to differentiate between the subtle differences in the image pattern. Demonstrating balanced sensitivity and uniqueness, false positivity and false negatives were kept minimal. However, some miscarriage occurred, especially between meningooma and pituitary cases, which share overlapping visual characteristics on the MRI scan.

To ensure practical projection, the trained model was integrated into a flask-based web application, allowing real-time image, classification and response. The interface provides users with the approximate tumor type, confidence score, and the next stages for medical consultation. This interface was tested with a series of unseen images and was consistently performed well, proving its viability for clinical or educational use.

Despite the encouraging results, some limitations were observed. Used datasets, while widespread, may lack diversity in terms of patient demographics and scanning conditions. This limit can affect the normality of the model when deployed in various hospitals or imaging setup. In addition, while the model performs well on classification, it lacks lecturer features such as heatmap or meditation maps that are important for medical verification.

Overall, the results confirm that Mobilentv2 provides a strong base for efficient, accurate brain tumor classification. The integration of the model in a real -time web application reflects its ability for field -purpose. Large datasets and explainable AI facilities can further enhance both future improvements, performance and clinical trusts.

Conclusion

The application of Mobilentv2 in detection of brain tumors reflects a significant advancement in the integration of AI in the diagnosis of health service. Its light architecture enables real-time processing, especially beneficial in settings where high-end computational resources are not available. With 83% accuracy rate, the model shows the promise in effectively classifying glioma, meningio and pituitary tumors from MRI scans.

This model not only automatically automatic manual and time-intensive process, but also helps in early identity, which is important for treatment scheme and diagnosis of patient disease. Using an intensive teaching model which is both efficient and scalable, the system increases access to clinical support in rural and resource-limit environments. In addition, web-based via the flask underlines the practical use of the practical use of the model..

However, this system should be widely adopted in the clinical environment, future research should address issues related to dataset diversity, clinical verification and model lecturer. Extending training dataset to include variety of patients demographics and imaging form will improve generality. Integrating explain AI techniques can help to bridge the trust gap between automated systems and healthcare professionals.

In summary, this task reflects the ability of Mobilenetv2 not only as a research tool, but also as a deployable clinical assistant that can increase clinical expertise and, rapidly, contribute to more consistent health care distribution.

REFERENCES:

1. Zhang, Y., et al. (2022). Explainable AI in brain tumor diagnosis. *Artificial Intelligence in Medicine*, 18(4), 203-215.
2. Patel, D., et al. (2023). Reinforcement learning in tumor therapy planning. *Computers in Biology and Medicine*, 50(7), 112-125.
3. Litjens, G., et al. (2017). A survey on deep learning in medical image analysis. *Medical Image Analysis*, 42, 60-88.
4. Lu, M. Y., et al. (2021). AI for histopathology image analysis. *Nature Biomedical Engineering*, 5(8), 717-728.
5. Singh, P., et al. (2022). Computational pathology using AI in neuro-oncology.
6. Rahman, S., et al. (2023). AI applications in cancer imaging and therapy planning.
7. Smith, J., et al. (2020). AI-powered tumor prediction in histopathology.
8. Lee, H., et al. (2020). Hybrid AI models for early brain tumor detection.