COMPARATIVE ANALYSIS OF DEEP LEARNING TECHNIQUES FOR BRAIN TUMOR DETECTION

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Abstract—The project classifies brain tumors from MRI images using advanced deep learning. It employs CNNs with attention mechanisms and GANs for data augmentation. The dataset includes glioma, meningioma, pituitary tumors, and no tumors. DenseNet and custom Attention CNN improve detection accuracy. This assists medical professionals in early diagnosis and treatment planning.

Keywords—Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), DenseNet, Attention CNN

I. INTRODUCTION

Detecting and diagnosing brain tumors through MRI scans is critical for patient care and treatment planning. Traditional methods rely heavily on radiologists, which can be time-consuming and prone to human error. Deep learning offers a promising alternative, with CNNs, GANs, DenseNet, and Attention Mechanisms enhancing detection accuracy. This project uses a comprehensive MRI dataset categorized into glioma, meningioma, pituitary tumors, and no tumors. Models, including DenseNet for its feature extraction capabilities and Attention CNN to highlight relevant image parts, are trained on this data. GANs are used to generate synthetic images, addressing data scarcity and class imbalance. The goal is to develop a highly accurate and reliable model that assists medical professionals in diagnosing brain tumors, improving patient outcomes, and streamlining healthcare services. By integrating these advanced techniques, the project aims to enhance the accuracy, efficiency, and interpretability of brain tumor detection.

A. Objectves:

- Enhance Detection Accuracy Develop a model to significantly improve tumor detection accuracy.
- Increase Diagnostic Efficiency Streamline the diagnostic process to reduce time and resource consumption.
- Improve Model Interpretability Implement tools like Grad-CAM to make model decisions transparent.
- Address Data Limitations Use GANs for dataset augmentation to overcome data scarcity.
- Validate Model Generalizability Ensure robust performance across diverse data sets with rigorous validation techniques.
- Facilitate Clinical Integration Design the system for easy adoption in existing medical workflows.
- Contribute to Medical Research Provide actionable insights to advance medical imaging and oncology.

II. LITERATURE SURVEY

Anurag Goswami, Manish D.[3], aims to replace the missing parts of the facial photos using Recurrent Generative Adversarial Network. Feature Representation Net also regarded as the semantic feature extractor. Three feature extractors with multiple scales are in use. The use of dilated convolution has increased the receptive field. Feature Transformation Net regarded as mapping function over the feature domain. The input is the feature extracted from FTN and output will be transferred features. This is able to be rebuilt face images. Here ConvLSTM has been adopted. The image reconstruction net predicts the facial picture at each scale by using the characteristics produced by the FTN. Despite the fact that there are many of options for upsampling or downsampling, they adopt the simple bilinear interpolation for all the experiments in their work. To fully exploit the correction of adjacent level features of their model, they design a novel short link structure to fuse the multi-scale features. Discriminator network has global and local discriminator. Zhang, Mingming et al.[5], aims to construct an improved Generative Adversarial Networks based on the context encoder and proposes a self-localization occlusion method for restoring faces in images algorithm. The generator in this paper adopts the convolution network with the structure of Variational Autoencoder. The encoder uses 12 convolutional layers , 1 fully connected layer. The decoder uses 12 deconvolutional layer and one fully connected layer. Leaky ReLu is used as activation function in the first 25 layers and Tanh is used as activation in the last layer. The discriminator in this paper is based on VGG19 with 13 convolutional layer and 5 pooling layers. CelebA was the dataset used, and the training Adam optimizer had a learning rate of 0.002. Jiang, Yi, Jiajie Xu et al.[8], presents an approach for face image inpainting using skip connection layers between the encoder and the decoder. Inpainting is part of a large set of image generation problems. To solve this problem, an auto-encoder as the generator of model. The auto-encoder contains two networks: an encoder and a decoder. Different from the typical AutoEncoder architecture, they add skip-connection between the corresponding layers of the encoder and decoder sections to prevent the network layer from deteriorating due to the deepening of the network layers. Skip-connection can make sure that the decoding stage can utilize the output of the low-level coding stage of the corresponding resolution to supplement the decoder with part of the structural feature information lost during the encoder downsampling phase, and enhance the structure prediction capability of the generator. The encoder uses a multi-layer convolution layer architecture. Similarly, the architecture of the decoder is symmetric to the encoder with transposed convolution layers. Between the encoder and the decoder, we employ four layers of dilated convolution instead of fully connected layers. Wang, Chen et al.[11], aims to create a two stage generation network for face image restoration that integrates contextual attention and multiscale joint attention. The first stage of the generator consists of three parallel decoder-encoder branches which are used to extract feature information of different scales from input image X with mask. Then these units are upsampled to the original resolution through deconvolution operation, and three groups of features are merged into the feature map. The second stage contextual attention module consists of two parallel encoders. The upper part is the contextual propagation layer and the lower part is the attention propagation layer. The features are being extracted and the merged into the shared decoder. Restore the original input image through upsampling and finally output the fine reconstructed result. In the training, the WGAN-GP discriminator is used to compare the ground truth T and the output Y to obtain the adversarial loss. There are total four losses used here: spatial attenuation, reconstruction loss, adversarial loss and MRF-like loss. Shah, Riya, Anjali Gautam et al.

III. PROBLEM DEFINITION

Existing System and Drawbacks: The existing system for brain tumor classification primarily relies on traditional Convolutional Neural Networks (CNNs) like DenseNet, which use standard layers such as convolutional, pooling, and fully connected layers to extract features and classify images. While these models are effective in general image recognition tasks, they exhibit limitations in medical image analysis due to their uniform processing of all image regions. This uniformity can lead to suboptimal performance in identifying subtle and localized features crucial for accurate tumor detection. Additionally, standard CNNs may require extensive labeled datasets and computational resources, limiting their applicability in real-world medical scenarios where annotated data can be scarce and computational efficiency is critical. These drawbacks underscore the need for enhanced models that can dynamically focus on important image regions to improve diagnostic accuracy and efficiency.

Problem Statement: To compare advanced deep learning techniques for enhancing the detection and diagnosis of brain tumors in MRI scans, focusing on accuracy, efficiency, and interpretability to improve clinical outcomes and streamline neuro-oncological diagnostics.

IV. SYSTEM DESIGN

System Architecture:

Detecting brain tumors in MRI scans is challenging and traditionally relies on radiologists, which can be time-consuming and prone to errors. Deep learning, especially CNNs, offers automation and improved accuracy but struggles with capturing complex patterns in MRI images. Advanced models like Densenet 121 are being developed to enhance detection, aiming to improve patient outcomes by providing more precise and efficient diagnostics.As shown in Figure 1.

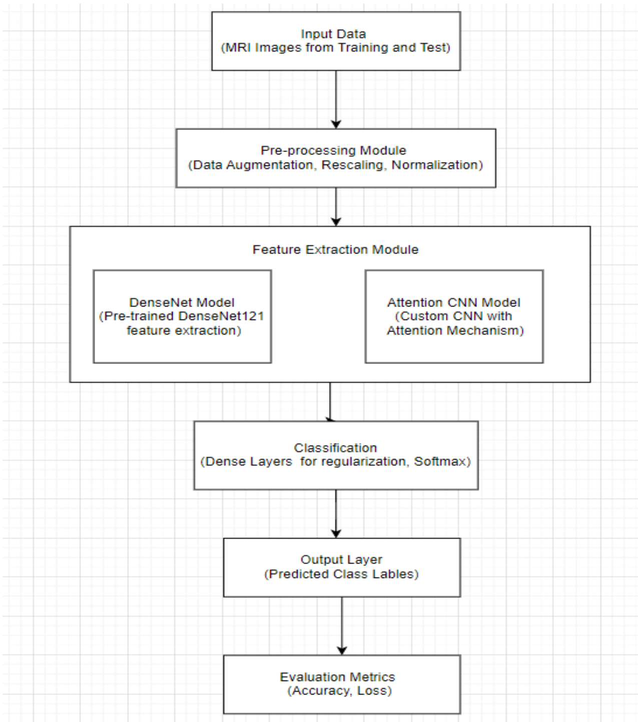

Figure 1: Architecture diagram

Proposed Modules:

- Data Pre Processing Module
- Feature Extraction
- Classification/Segmentation Module
- Evaluation module

Algorithms Used:

Convolutional Neural Networks (CNNs) are the backbone of the image classification tasks in this project. They are particularly effective for processing and analyzing visual data due to their ability to automatically and adaptively learn spatial hierarchies of features from input images. CNNs consist of several layers, including convolutional layers, pooling layers, and fully connected layers. In this project, CNNs are used to classify MRI images of brain tumors into four categories glioma tumor, meningioma tumor, no tumor, and pituitary tumor.

Attention Mechanism in CNN The attention mechanism is a powerful enhancement to traditional CNN architectures, enabling the model to focus on the most relevant parts of the input image when making predictions. In this project, the attention mechanism is integrated into a custom CNN model to improve the classification of brain tumor types. This mechanism works by assigning different weights to different regions of the feature map, effectively allowing the network to prioritize certain areas over others. For example, in an MRI scan, the attention mechanism can help the model concentrate on areas with tumor-like structures while ignoring irrelevant background information. This selective focus improves the model's ability to detect and classify tumors accurately.

Generative Adversarial Networks (GANs) Generative Adversarial Networks (GANs) are a critical component of this project, used primarily for generating synthetic MRI images to augment the training dataset. GANs consist of two neural networks the generator and the discriminator, which compete in a game-theoretic framework. The generator creates fake images, attempting to mimic real MRI scans, while the discriminator evaluates the authenticity of these images, distinguishing between real and fake ones.

DenseNet (Dense Convolutional Network) DenseNet, or Dense Convolutional Network, is a type of CNN that connects each layer to every other layer in a feed-forward fashion. For each layer, the feature maps of all preceding layers are used as inputs, and its own feature maps are passed on to all subsequent layers. This dense connectivity pattern improves the flow of information and gradients throughout the network, making it easier to train very deep networks. In this project, DenseNet121, a popular variant of DenseNet, was employed to leverage its strengths in handling complex image classification tasks. By reusing features across layers, DenseNet reduces the number of parameters, mitigates the vanishing gradient problem, and enhances feature propagation.

Dataset Used:

The dataset used in the project are taken from [Brain Tumor MRI Dataset (kaggle.com)](). It consists of four different categories as shown below. The total number of images used are 2000 images with each category containing approximately 500 images. The different categories of the dataset are mentioned below.

Categories: Glioma Tumor, Meningioma Tumor, Pituitary Tumor, No Tumor

Data Structure: The dataset is divided into two main directories: Training and Testing. Each directory contains subdirectories for each of the four categories, with the images stored within these subdirectories.

V. RESULTS

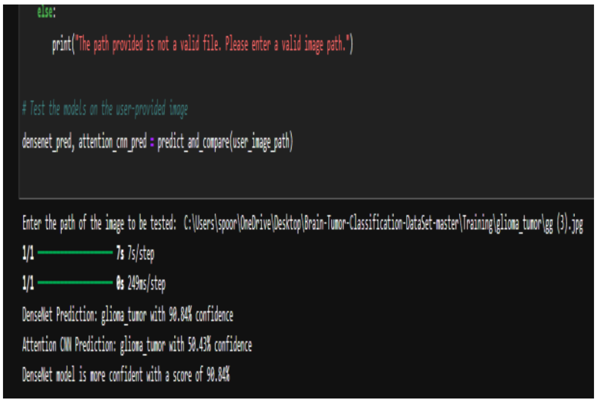

Figure 2: Results Comparison

As shown in the Figure 2, the user inputs the path of an MRI image to test the models. The DenseNet model predicts the image as a glioma tumor with 98.40% confidence, while the Attention CNN predicts the same with 94.58% confidence. DenseNet's prediction is deemed more confident with a higher score of 99.94%.

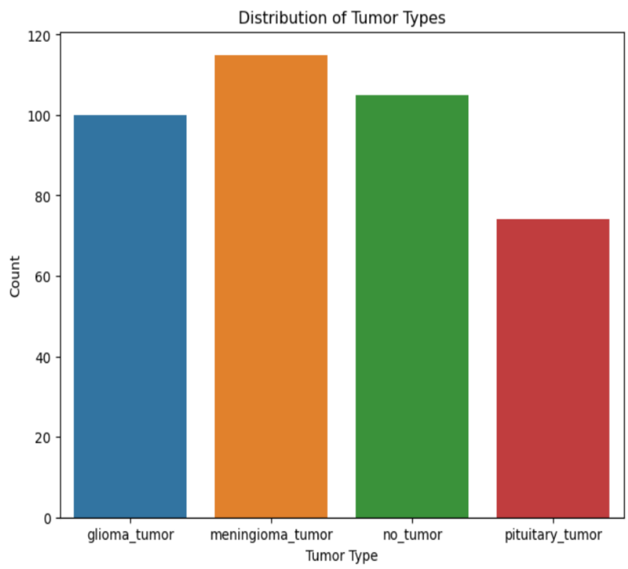

Figure 3: Visualize the distribution of tumor types in the training dataset

As shown in the Figure 3, the distribution of tumor types in the dataset is presented. Meningioma tumors are the most prevalent, followed by images with no tumor and glioma tumors. Pituitary tumors have the least representation in the dataset.

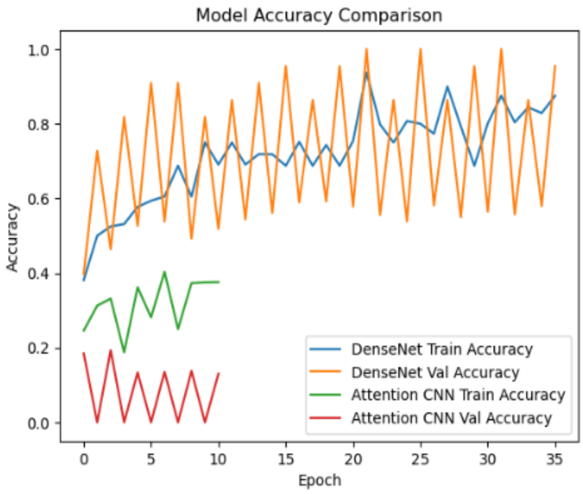

Figure 4: Model Accuracy Comparison

As shown in the Figure 4, the graph compares the training and validation accuracies of two models: DenseNet and Attention CNN, over 35 epochs. DenseNet exhibits a relatively stable training accuracy with fluctuating validation accuracy, while Attention CNN shows high variability in both training and validation accuracies. DenseNet's performance appears more consistent and potentially more reliable for this dataset compared to Attention CNN.

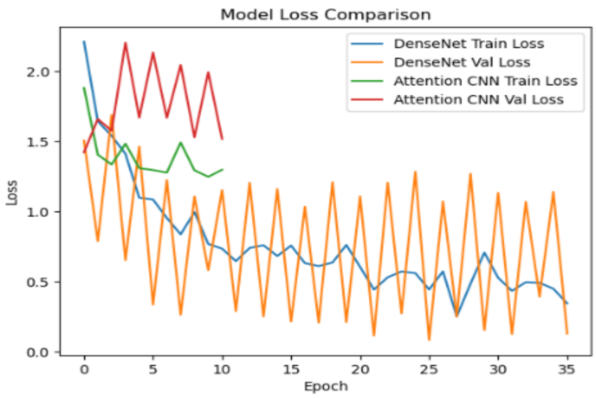

Figure 5 : Model Loss Comparison

As shown in the Figure 5, the graph compares the training and validation losses of DenseNet and Attention CNN over 35 epochs. DenseNet exhibits a consistent decrease in both training and validation losses, suggesting effective learning. In contrast, Attention CNN shows high variability in losses, indicating unstable learning behavior. DenseNet demonstrates more reliable performance with lower and more stable loss values compared to Attention CNN.

VI. CONCLUSION AND FUTURE

WORK Conclusion

In this proposed method, we developed and compared the performance of DenseNet and Attention CNN models for brain tumor classification using MRI images. Both models were trained on a labeled dataset with data augmentation techniques to improve generalization. While the DenseNet model demonstrated better performance and higher confidence in its predictions, the overall confidence levels were below the desired threshold of 90%. The integration of GANs for synthetic image generation and various techniques like hyperparameter tuning and learning rate adjustments showed potential for enhancing model accuracy.

Future Work

● Advanced Data Augmentation Experimenting with more sophisticated data augmentation tech.

● Hyperparameter Optimization Implementing automated hyperparameter tuning methods.

● Attention Mechanism Enhancements Investigating more advanced attention mechanisms.

● GAN Improvements Enhancing the quality and diversity of GAN-generated synthetic images.

● Larger and Diverse Datasets Acquiring more comprehensive datasets to train models, capturing a wider

VI. REFERENCE

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