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Attention-Guided Framework for Enhanced Brain Tumor Classification from MRI Images

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Abstract: Accurate classification of brain tumors[1] is a critical step in medical imaging, as it enables timely diagnosis and supports the design of effective therapeutic plans. This study explored a fusion of traditional machine learning methods and hybrid deep learning strategies to classify brain tumors from MRI scans. The Kaggle Brain Tumor Dataset was used consisting of 253 MRI images, including 155 tumor and 98 non-tumor samples. E The study concentrated on the preprocessing actions like resizing, normalization, and augmentation to optimize model performance. Several Machine learning models (Logistic Regression, Random Forest, SVM, KNN, Gradient Boosting, and XGBoost)[2] and proposed Attention-based CNN were trained and tested with the help of model accuracy. The findings exhibited that the Attention-Based CNN was able to outperform all other models in showing that it yielded the best accuracy of 94.2 percent, thus revealing its effectiveness in its ability to focus attention on tumor-specific features. This paper indicated the effectiveness of proposed Attention-based CNN method to produce a certain solution to classify brain tumors with a high percentage of certainty. The advancements of AI in Neuro-Oncology represent a noteworthy breakthrough with substantial clinical impact.

Keywords: *Brain Tumor, MRI Analysis, Machine Learning Techniques, CNN, SVM, KNN, Accuracy.*

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I. INTRODUCTION

Brain tumors[3] represent a significant challenge within the field of neurology due to their erratic progression, structural heterogeneity, and potential to become malignant. They may develop in different areas of the brain and often exhibit symptoms that overlap with other neurological disorders, complicating the diagnostic process. Accurate and early classification is crucial for selecting the most appropriate treatment approach whether surgical removal, radiotherapy, or chemotherapy.

Magnetic Resonance Imaging (MRI)[4] is still the gold standard in brainimaging, offering detailed visualization ofstructural and pathological anomalies suchas tumors, edema and tissue necrosis.Through various imaging modalities likeT1, T2 and FLAIR, with MRI multi-dimensional Anat evaluation can be obtained.But, these had to be manually analysed in these 196–200.scans is time-consuming, susceptible toobserver bias and may be unreliable inservices in settings with little medical knowledge orinfrastructure.

For addressing these challenges, the research community has increasingly turned to Machine Learning (ML) and Deep Learning (DL)[5] methods to automate the analysis of brain images. Such AI methods have shown great potential for capturing patterns from the vast amount of complex imaging data, and can support tumor detection, segmentation and classification. The ML stylized algorithm with traditional approaches is frequently based on preselected features such as shape, intensity, texture and generally work well for much of the domain-specific inputs. In contrast, a method like Deep Learning including Convolutional Neural Networks (CNNs) allows raw images to be directly learned from and automatically extract hierarchical features in an end-to-end manner.

The development of new annotated datasets, the availability of BRATS, increased computer processing power, and the introduction of platforms like TensorFlow and PyTorch has significantly improved the capabilities of modern technology. As a result, machine learning and deep learning not only improve the classification of brain tumors, but they also provide real-time diagnostic tools for radiologists. The incorporation of these technologies into clinical practice marks a fundamental change towards the use of precise and tailored diagnostic and therapeutic avenues in neuro-oncology [6].

II. LITERATURE REVIEW

Pan et al. studied the grading of brain tumors with multiphase MRI and evaluated the performance of Convolutional Neural Networks (CNNs) in comparison with traditional neural networks. Their technique worked with the MRI scans in their raw form, meaning that no manual feature extraction was performed. As highlighted in the results, CNNs provided 18% better sensitivity and specificity. They also provided visualizations of kernel activations which illustrated feature learning by the CNNs [7].

In the study by Sachdeva et al., they performed a multiclass classification on brain tumors utilizing 428 post-contrast T1 weighted MR images that contained astrocytoma, glioblastoma, and meningioma. They created 856 regions of interest and extracted 218 texture and intensity features. Their classification results using PCA for dimensionality reduction and ANNs were between 85.23 and 91% showcasing MRI's significant capability in assisting radiologists [8].

Cheng, Huang, and Feng enhanced brain tumor classification for meningioma, glioma, and pituitary tumors using T1-weighted contrast-enhanced MRI. They introduced an augmented region of interest (ROI) via dilation, emphasizing peripheral tissue features. Subdividing this ROI into ring-shaped subregions and applying multiple feature extraction methods resulted in accuracy gains—up to 91.28%—when using histogram, GLCM, and BoW techniques, with further improvement upon refined partitioning [9].

Pugalenthi et al. proposed an SVM-based technique using an RBF kernel for binary tumor grading (low vs. high), achieving over 94% accuracy on the BRATS2015 dataset. Their pipeline included SGO-based Fuzzy-Tsallis thresholding in preprocessing and Level-Set Segmentation to isolate tumor regions [10].

Vidyarthi et al. developed a comprehensive ML framework for classifying malignant brain tumors across multiple classes. They applied a new feature selection method—Cumulative Variance Method (CVM)—to a six-domain feature set. Achieved accuracies were 88.43% (KNN), 92.5% (multi-class SVM), and 93.86% (ANN), with the neural network outperforming baseline algorithms by roughly 4% [11].

Saeedi et al. designed both a 2D CNN and a convolutional autoencoder for brain tumor identification. On a dataset of 3,264 MRI images, the 2D CNN achieved 96.47% training accuracy, a recall of 95%, and an AUC of 0.99, outperforming ML models such as KNN and demonstrating its clinical applicability[12].

Mallampati et al. introduced a hybrid classification approach utilizing MRI features extracted from 3D-UNet and 2D-UNet segmentations. They combined KNN and Gradient Boosting Classifier (GBC) via soft voting. The model reached 71% accuracy using 3D-UNet features, surpassing contemporary techniques, while 2D-UNet features yielded 64% accuracy[13].

Khan, Zhao, and Chen presented Hybrid-NET, a diagnostic model that combines DenseNet169 with ML classifiers such as RF, SVM, and XGBoost. It addressed the challenge of limited medical imaging data and achieved a 94.10% accuracy rate, showing strong performance in distinguishing glioma, meningioma, and pituitary tumors [14].

Almufareh, Imran, and Asim investigated automated segmentation and classification of brain tumors using YOLOv5 and YOLOv7. Focusing on meningiomas, gliomas, and pituitary tumors, YOLOv5 achieved a recall of 0.905 and mAP of 0.947 (IoU=0.5), while YOLOv7 scored a detection accuracy of 0.936 and mAP of 0.94. Both models surpassed traditional approaches such as RCNN and Mask RCNN[15].

III. THE PROPOSED METHODOLOGY

- *Data collection and data pre-processing*

This proposed methodology of classifying brain tumors working on the Kaggle Brain Tumor Dataset comprising of MRI images belonging to the tumor, and non-tumor organizations data-set. It is a high-resolution brain MRI dataset, and every MRI image in the dataset is labeled as either having a tumor or not. The brain tumors MRI are classified into two: tumor or no tumor. The sample will have a variety of data on benign and malignant types of tumor, and the model can differentiate between different types of tumor. It also includes photos of the healthy (that are not tumors) brains. These pictures are rescaled to the same size of 224x224 pixels to be able to adapt to the deep learning architectures. The range of pixel intensity values is also converted to the range of [0, 1], which also facilitates the improvement of the convergence of the model and the faster training. Also, data augmentation strategies are used, including horizontal and vertical flipping, random rotation, zooming and changing brightness to increase, essentially, the size of the dataset with the end result of the model (being able) to generalize better on unseen data.

- *Model Selection*

Machine Learning (Ml) Models for Brain Tumor Classification.

- *Logistic Regression*

Logistic Regression stands out as one of the most important and an interpretable algorithm as it is primarily used for classification tasks, most often on binary classifications. Using the sigmoid function, it processes input features and produces probability values, hence allowing the prediction of categorical outcomes. Even though it excels with linearly separable data, it often falls short for more intricate patterns (especially in complex datasets, like medical images), which is why it is outperformed by other more sophisticated algorithms[16].

- *Support Vector Machine (SVM)*

Support Vector Machine (SVM) focuses on determining the best separating hyperplane for the given classes in a feature

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space with multiple dimensions. The ability of SVMs to perform non-linear classification problems receives a boost with the addition of kernel functions. Regardless of its applicability, the algorithm is often criticized for its inflexibility because of its reliance on strict parameter optimization and its need for a large amount of computational resources when operating on large or high dimensional data, such as MRI scans [17].

➢ *K-Nearest Neighbors (KNN)*

K-Nearest Neighbors (KNN) is a non-parametric instance based learning method that assigns a class to new samples by considering the ‘k’ nearest data points in the feature space and selecting the predominant class among them. The ease of implementation and the intuitive nature of KNN come with the lack of strong performance with high dimensional image data that require encoding the spatial relationships within the data [18].

➢ *Random Forest*

Described as a robust ensemble method, Random Forest combines the output of many decision trees to improve the overall classification accuracy. It minimizes the overfitting problems brought by a single decision tree, and works well with heterogeneous data. Yet, spatial dependence of image data is a challenge for classification, and because of this, Random Forest’s performance is limited as image data often lacks spatial dependence [19].

➢ *Gradient Boosting*

The sequential model that Gradient Boosting creates adds new learners that attempt to correct the mistakes made by prior models. Complex problems benefit greatly from this iterative process as the predictive accuracy tends to be higher. Gradient Boosting is known to be sensitive to hyper parameter settings, and without tuning, it can easily overfit intricate datasets [13].

➢ *XGBoost*

Known for its speed and scalability, XGBoost is widely adopted as a more efficient and advanced implementation of gradient boosting. Its performance is remarkable on the structured datasets, and in tasks such as the classification of brain tumors, it performs exceptionally well, due to regularization, tree pruning, and meticulous hyperparameter optimization[14].

➢ *Proposed Hybrid Deep Learning Model:*

- *Attention-Based CNN-*

A handcrafted deep learning network that integrates Convolutional Block Attention Module. This module balances the existing feature extraction by means of paying attention to the most pertinent spatial and channel characteristics of the images in the model.

- *Evaluation Metric Used: Accuracy*

Model Accuracy is used in an effort to have a comprehensive assessment of how well the model is performing. Accuracy is used to measure the percentage of correctly identified cases, tumor or non-tumor, with the total data.

➢ *Model Optimization*

The models were also optimized using the following techniques to achieve a further improvement:

- *Early Stopping*:

This prevents over fitting of the model on the training data. It keeps track of the validation loss and prevents ongoing training in case it gets worse in 5 consecutive periods to save time and computational power.

- *ReduceLROnPlateau*:

This is a dynamic process of adapting the learning rate in case the validation loss is reaching a plateau. A learning rate of 0.5 is a factor of decrease, which enables the optimizer to apply smaller updates of the weight, which may help the algorithm to escape the local minima or level off the loss graph.

- *Optimizer (Adam)*:

The Adam optimizer is selected due to its adaptive learning rate which brings together the benefits of the RMSProp and Momentum optimizers together.It is good when it comes to sparse gradients and noisy data.

➢ *Attention Mechanisms*

- *Channel Attention:*

✓ Introduces an emphasis on the channels that are the most important and it does this by utilizing a learned weight on each of the channels.
✓ Assists the network to concentrate on the pertinent sections of feature map in the task.

- *Spatial Attention:*

Concentrates on where in the spatial aspects (the height and the width) network ought to concentrate more.
This combination of the channel and spatial attention suggests that the model is resistant to important features of input.

➢ *Proposed Workflow*

The workflow proposed to accomplish brain tumor classification will be as follows:

- *Input Data*:

MRI images are loaded and preprocessed in order to have data in uniformity and compatibility with the models.

- *Data Visualization:*

Because the distribution of the tumor images in the whole dataset, the training subset and the test subset are of interest, Figure 1 contains three pie charts representing the three sets. The balance between the Yes (the presence of a tumor) and No (the absence of a tumor) classes in each dataset can be understood with the help of such visualizations.

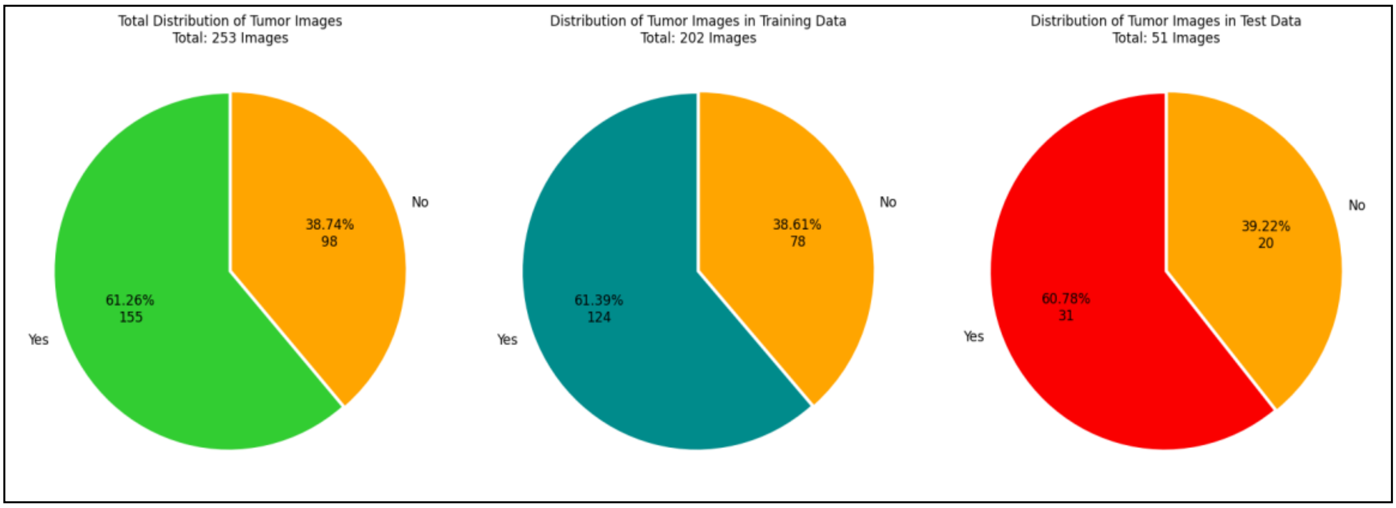

Fig 1: Distribution of Tumor Images

- *Feature Extraction*:

The relevant features are extracted based on convolutional neural network (CNN).

- *Classification*:

Deep learning CNN and Attention-Based CNN are used when making a final prediction.

- *Performance Comparison:*

Models are compared using selected metrics to know the best and stable model of the algorithm to classify brain tumors.

IV. RESULTS & DISCUSSION

- *Performance and Evaluation Metrics of Models*:

The comparison of all provided models on the basis of accuracy, is shown in the next table. Accuracy was calculated in each of the models once they were trained using the Kaggle Brain Tumor Dataset.

Table 1 Analysis of Accuracy for Machine Learning and Proposed Attention-Based CNN Models for classification of Brain Tumor

odel	**Accuracy**
Logistic Regression	86%
Random Forest	86%
XGBoost	84%
KNN	73%
SVM	88%
Gradient Boosting	80%
Proposed Attention-Based CNN	94.12%

The table 1 shows that the Attention-Based CNN has shown the best results in accuracy 94.12% which is pretty substantial over other models. The machine learning models had different performances where SVM had performance accuracy of 88%, Random Forest and LR had accuracy of 86%, XGBoost had accuracy of 84%, Gradient Boosting achieved accuracy of 80% and KNN had lowest accuracy of 73%. Such performance demonstrates the usefulness of Attention-Based CNN in using essential features in classifying brain tumors, and traditional and other deep learning models displayed less promising performance.

- *Bar Chart: Model Comparison Based on Accuracy*

To visually compare the performance of all models, the following bar chart illustrates the accuracy of each model.

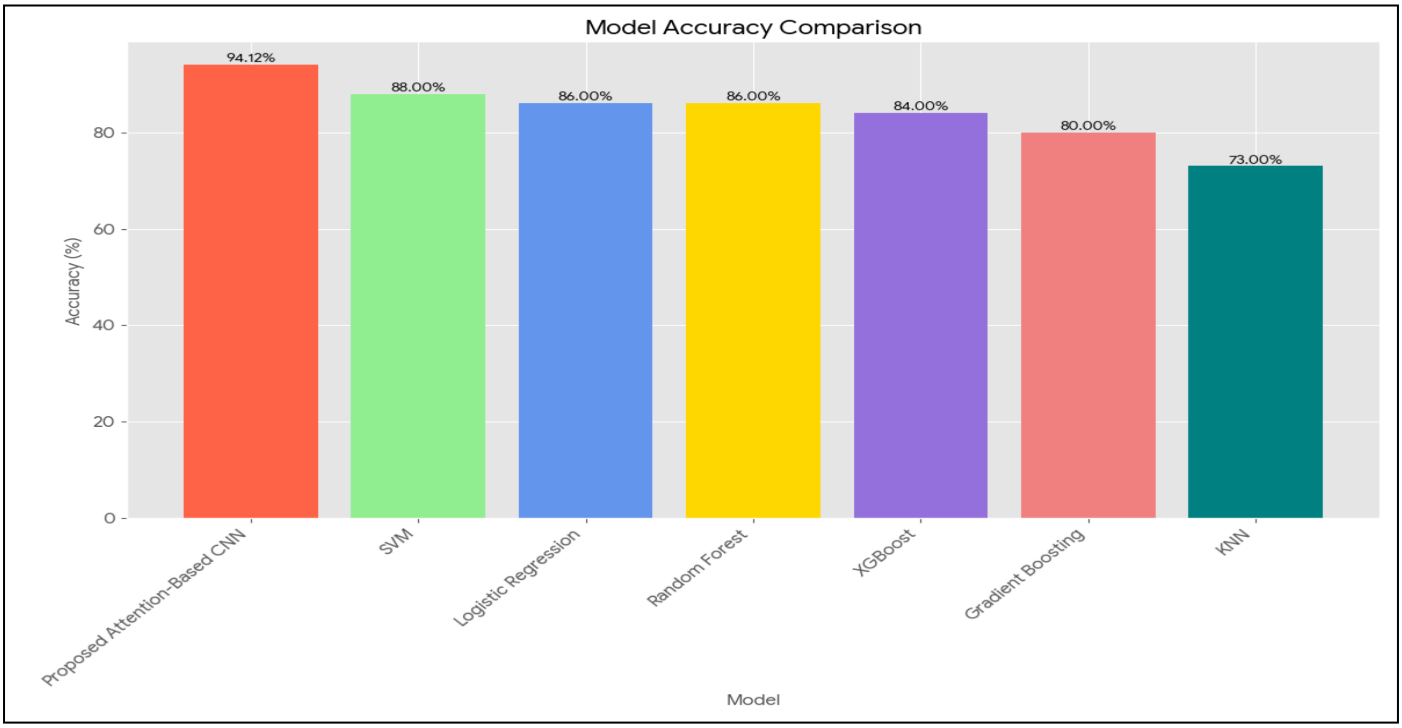

Fig 2: Bar Chart for Models Comparison Based on Accuracy for Brain Tumor Classification

This bar chart clearly displays the comparative performance of all models used in the study, highlighting how proposed hybrid deep learning models outperformed traditional machine learning models in terms of accuracy.

V. CONCLUSION

This paper compared various machine learning models and proposed hybrid deep learning model in brain tumor classification with MRI as inputs and the evaluation measures done were for accuracy. Out of the estimated models, Attention-Based CNN showed the best results on all measures with the accuracy being 94.12 percent. These findings show that this model would be very useful in clinical use as a diagnostic tool where the concern is more of reducing the amount of false negatives. The SVM received decent performance with a 88-accuracy which means that a fairly simple machine learning model can also cope with an adequate training and preprocessing. Nevertheless, it has its scope to be more precise and in generalizing. The other model such as KNN and Gradient Boosting did not perform as well as it was expected as the accuracy was only 73 percent and 80 percent respectively.

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