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Attention-Based CNN for MRI Brain Tumor Classification with Enhanced Sensitivity and Interpretability

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ABSTRACT

Brain tumor is one of the most serious and life-threatening neurological condition, and getting its diagnosis as early as possible is important for effective treatment. Magnetic Resonance Imaging (MRI) is the preferred modality because it has a high spatial resolution and better contrast for soft tissue. However, interpreting MRI images manually a long time and can lead to differences between observers. This research study presents an Attention-Based Convolutional Neural Network (CNN) model for the automated classification of brain tumors. The model selectively highlights spatial and channel-wise features, thereby improving tumor localization and classification. We compared our model to traditional machine learning models like Logistic Regression, Support Vector Machines (SVM), Random Forest, Gradient Boosting, XGBoost, and K-Nearest Neighbors (KNN), as well as deep learning architectures like Basic CNN, VGG16, and ResNet50. Experimental results show that the proposed Attention-Based CNN achieved an accuracy of 0.9900, precision of 0.9862, recall of 0.9930, F1-score of 0.9896, and an AUC-ROC of 0.9928, outperforming all other models. These findings demonstrate its potential as a reliable decision-support system for radiologists, offering high diagnostic accuracy, interpretability through attention maps, and robustness across varied MRI data.

Keywords: Brain Tumor, MRI, Machine Learning, Deep Learning, Hybrid Model, Convolutional Neural Network, Classification, Medical Imaging

1. INTRODUCTION

Accurate and timely detection of brain tumors from MRI scans is critical for improving patient outcomes and has become a key focus of medical imaging research.

1.1 Brain Tumor

Medical science aims to understand the physiological mechanisms of the human body and diagnose diseases using advanced imaging techniques. Each imaging modality provides unique advantages and limitations in visualizing internal anatomical structures. Among numerous health conditions, brain tumors are recognized as one of the most critical and life-threatening diseases. A brain tumor refers to the abnormal proliferation of cells within brain tissue and can be classified as either benign or malignant, depending on its growth rate, histopathological characteristics, and clinical behavior (Kharrat et al., 2009). Malignant tumors are particularly dangerous due to their rapid growth, invasiveness, and potential to metastasize, while benign tumors grow slowly and are generally non-cancerous. However, the location of a tumor in critical brain regions can make even benign tumors life-threatening.

Brain tumors are further categorized as primary or secondary (metastatic). Primary tumors originate within the brain, whereas secondary tumors result from the spread of cancer from other organs, such as the lungs, breasts, kidneys, or skin. Despite advances in medical research, the exact etiology of most brain tumors remains unclear, though genetic and environmental factors are considered significant contributors. Common clinical symptoms include persistent headaches, seizures, cognitive disorientation, behavioral changes, and motor deficits. Early detection and accurate diagnosis are crucial to improving patient outcomes and guiding effective treatment strategies(*Brain Tumor - Symptoms and Causes - Mayo Clinic*, n.d.).

Magnetic Resonance Imaging (MRI) has emerged as the gold standard for brain tumor detection due to its non-invasive nature, high spatial resolution, and excellent soft-tissue contrast. Different MRI sequences, including T1-

weighted, T2-weighted, and FLAIR, provide complementary information regarding tumor size, location, and tissue heterogeneity. However, accurate interpretation of MRI images requires significant expertise and is prone to inter-observer variability (Vankdothu & Hameed, 2022). Manual assessment can also be time-consuming, and subtle distinctions between tumor types may be overlooked. These challenges have motivated the development of automated classification systems using machine learning (ML) and deep learning (DL) techniques.

1.2 Types of Brain Tumors

Brain tumors are broadly classified into primary and secondary types, depending on their origin and progression.

1.2.1 Primary Brain Tumors

Primary brain tumors arise from the brain itself or its immediate structures, such as the meninges, cranial nerves, pituitary gland, and pineal gland. These tumors result from genetic mutations in normal brain cells, leading to uncontrolled cell proliferation. Common primary brain tumors include gliomas, astrocytomas, oligodendrogliomas, and meningiomas, with gliomas being among the most aggressive. MRI plays a crucial role in evaluating these tumors, helping determine their extent, infiltration into surrounding tissue, and response to treatment (Cocosco et al., 2003).

1.2.2 Secondary Brain Tumors

Secondary or metastatic brain tumors occur when cancer spreads from other regions of the body. These tumors are inherently malignant and are the most frequent brain tumors in adults. Primary cancers that commonly metastasize to the brain include lung carcinoma, breast carcinoma, renal cell carcinoma, and melanoma. MRI assists in distinguishing metastatic lesions from primary tumors and provides vital information for surgical planning and radiotherapy (Brain Tumor - Symptoms and Causes - Mayo Clinic, n.d.).

1.3 Motivation and Objectives

Accurate classification of brain tumors using MRI is essential for timely treatment planning and improving patient survival. Traditional manual evaluation of MRI scans is subjective, influenced by the radiologist's experience, and limited by fatigue. To overcome these limitations, automated classification frameworks using ML and DL have been proposed. Classical ML methods, such as Support Vector Machines (SVM) and Random Forest, rely on handcrafted features, whereas DL approaches, especially Convolutional Neural Networks (CNNs), can automatically learn complex features from raw images.

Hybrid models that combine DL for feature extraction with ML classifiers for decision-making have shown promise, leveraging the strengths of both approaches. Despite recent advances, comprehensive comparisons of ML, DL, and hybrid models on the same MRI dataset, with clinically relevant evaluation metrics, remain limited.

The primary objectives of this research are:

1. To develop a hybrid ML/DL framework for classifying brain tumors as benign or malignant.
2. To compare the performance of classical ML, DL, and hybrid models using MRI images.

By addressing these objectives, this study contributes to the development of robust, automated brain tumor classification systems, offering potential benefits for early detection, reducing diagnostic errors, and supporting radiologists in clinical practice.

2. LITERATURE REVIEW

Schmidt et al. addressed the challenge of automating the detection and segmentation of brain tumors in magnetic resonance imaging (MRI), a task that was traditionally performed by medical experts. They evaluated the effectiveness of four different types of alignment-based (AB) features that incorporated spatial anatomical information for supervised pixel classification. The authors demonstrated that combining textural and AB features significantly enhanced segmentation performance, achieving results that closely matched expert annotations, particularly in scenarios where existing methods struggled.(Schmidt et al., 2005)

Kharrat et al. proposed a hybrid approach for the automatic classification of brain tissues in magnetic resonance images (MRI) that combines genetic algorithms (GA) with support vector machines (SVM). The methodology involves deriving a wavelet-based texture feature set, which is essential for distinguishing between normal and tumor regions (Ahmed Kharrat et al., 2010).

Pan et al. explored brain tumor grading using multiphase MRI images, comparing the performance of Convolutional Neural Networks (CNNs) with traditional Neural Networks. Their approach directly utilized the MRI images without the need for extensive feature engineering, leveraging the deep learning capabilities of CNNs. The study reported an 18% improvement in grading performance based on sensitivity and specificity when using CNNs compared to baseline Neural Networks. Additionally, the authors visualized the learned kernels at different layers, showcasing the self-learned features of the CNNs (Pan et al., 2015).

Sachdeva et al. conducted a study on multiclass brain tumor classification using a dataset of 428 post-contrast T1-weighted MR images, focusing on various tumor types including astrocytoma, glioblastoma, and meningioma. They extracted 856 segmented regions of interest (SROIs) and 218 intensity and texture features, employing Principal Component Analysis (PCA) for dimensionality reduction and classifying the data with an Artificial Neural Network (ANN). The PCA-ANN approach achieved classification accuracies ranging from 85.23% to 91%, demonstrating its potential as a computer-aided diagnostic tool to assist radiologists in the localization and interpretation of brain tumors (Sachdeva et al., 2013).

Cheng, Huang, and Feng developed a method to enhance the classification of three brain tumor types (meningioma, glioma, and pituitary tumor) using T1-weighted contrast-enhanced MRI images. They introduced an augmented tumor region, obtained through image dilation, as the region of interest (ROI), recognizing the importance of surrounding tissues. By partitioning this region into fine ring-form subregions and applying three feature extraction methods, they achieved significant accuracy improvements: 82.31%, 84.75%, and 88.19% for intensity histogram, GLCM, and BoW models, respectively. Further partitioning increased accuracies to 87.54%, 89.72%, and 91.28%, demonstrating the method's effectiveness for brain tumor classification (Cheng et al., 2015).

Pugalenthi et al. developed a machine learning technique for classifying brain tumors as low or high grade, achieving over 94% accuracy using an SVM-RBF classifier on the BRATS2015 database. The method involved pre-processing with SGO-assisted Fuzzy-Tsallis thresholding and post-processing with Level-Set Segmentation for effective tumor region extraction (Pugalenthi et al., 2019).

Kang et al. proposed a brain tumor classification method that combines an ensemble of deep features extracted from pre-trained convolutional neural networks with various machine learning classifiers. The study demonstrated that using an ensemble approach significantly improved classification performance, with the support vector machine (SVM) using a radial basis function (RBF) kernel achieving the best results, particularly on larger datasets. The method was validated on three publicly available MRI datasets (Kang et al., 2021).

Appalaraju et al. developed a meningioma detection and segmentation approach utilizing MRI images, focusing on accurately categorizing the presence of meningioma. Their method employs Edge-based Contourlet Transformation for registration, region expanding segmentation, and combines texture features using Otsu's thresholding, k-means, and local binary patterns. The system achieved improved classification accuracy through a backpropagation neural network, effectively distinguishing between normal and tumor-affected tissues (Appalaraju et al., 2022).

Vidyarthi et al. developed a machine learning methodology for multiclass classification of high-grade malignant brain tumors, utilizing a comprehensive feature set extracted from six domains. Their approach incorporated a new feature selection algorithm, Cumulative Variance Method (CVM), and achieved mean classification accuracies of 88.43% (KNN), 92.5% (multi-class SVM), and 93.86% (Neural Network), with the Neural Network outperforming existing algorithms by approximately 4%. The results indicate the effectiveness of the proposed method in accurately distinguishing between different classes of malignant brain tumors (Vidyarthi et al., 2022).

Srinivas et al. conducted a comparative performance analysis of transfer learning-based CNN models (VGG-16, ResNet-50, and Inception-v3) for brain tumor classification using MRI images. Their results indicated that the VGG-

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16 pretrained model achieved the highest accuracy in identifying tumor cells from a dataset of 233 images. The study highlights the effectiveness of deep learning in enhancing the prediction rates for brain tumor detection (Srinivas et al., 2022).

Wahlang et al. utilized various deep learning architectures, including LeNet, CNN, and DNN, to classify brain MRI images into normal or abnormal, incorporating gender and age as significant factors. The study achieved an overall accuracy of 88% with the LeNet-inspired model and 80% with the CNN-DNN approach, outperforming traditional methods like SVM (82%) and AlexNet (64%). The findings highlight the importance of age and gender in enhancing classification accuracy in brain tumor analysis (Wahlang et al., 2022).

Saeedi et al. developed a 2D Convolutional Neural Network (CNN) and a convolutional auto-encoder for brain tumor classification, achieving training accuracies of 96.47% and 95.63%, respectively, on a dataset of 3,264 MRI images. The 2D CNN demonstrated exemplary performance with an average recall of 95% and an area under the ROC curve of 0.99. The study concluded that the 2D CNN outperformed several machine learning methods, including K-Nearest Neighbors, and is suitable for clinical use in brain tumor detection (Saeedi et al., 2023).

Mallampati B. et al. developed a hybrid machine learning model for brain tumor detection using features extracted from MRI via 3D-UNet and 2D-UNet segmentation. The model combines K-nearest neighbor (KNN) and gradient boosting classifier (GBC) through soft voting, achieving an accuracy of 71% with 3D-UNet features, surpassing existing state-of-the-art models. In contrast, the model achieved 64% accuracy with 2D-UNet segmentation features (Mallampati et al., 2023).

Amin J. et al. developed an automated brain tumor detection method using a fused feature vector that combines Gabor wavelet features, HOG, LBP, and SFTA, achieving effective segmentation and classification of complete, enhancing, and non-enhancing tumor regions with a Random Forest classifier. The proposed approach demonstrated promising detection efficiency, highlighting its effectiveness in addressing the challenges of tumor variability and complexity (Amin et al., 2024).

Mohanty B. C. and Subudhi P. K. proposed a feature-enhanced deep learning model for MRI-based brain tumor classification, utilizing a soft attention mechanism to improve accuracy. Their model aggregates features from all convolutional layers, ensuring that critical information is preserved and emphasized for classification. Comparative analysis with existing state-of-the-art models demonstrated the superiority of their approach in enhancing classification performance in medical diagnostics (Mohanty et al., 2024).

Khan S. U. R., Zhao M., and Chen X. introduced Hybrid-NET, a model that combines DenseNet169 with advanced machine learning classifiers (RF, SVM, XGBoost) to improve brain tumor diagnosis from MRI scans. The approach addresses challenges posed by limited medical image archives, achieving an overall classification accuracy of 94.10%. By leveraging deep learning features and optimizing hyperparameters, the model demonstrates enhanced performance in distinguishing between glioma, meningioma, and pituitary tumors (Khan et al., 2024).

Almufareh M. F., Imran M., and Asim M. explored automated brain tumor segmentation and classification in MRI using YOLOv5 and YOLOv7 in IEEE Access (2024). Their study focused on three tumor types: meningiomas, gliomas, and pituitary tumors, utilizing advanced mask alignment for accurate segmentation. YOLOv5 achieved a recall of 0.905 and a mean Average Precision (mAP) of 0.947 at an IoU threshold of 0.5, while YOLOv7 showed a box detection accuracy of 0.936 and an mAP of 0.94. The performance of these models was compared with established methods like RCNN and Mask RCNN, demonstrating significant advancements in brain tumor detection (Almufareh et al., 2024).

3. MATERIALS AND METHODS

This section outlines the methodological framework adopted for brain tumor classification, including dataset preparation, preprocessing, model development, and evaluation procedures.

3.1 Dataset Description

A reliable and representative dataset is fundamental for developing accurate machine learning and deep learning models, especially in medical imaging. This study uses the publicly available Brain Tumor Classification (MRI) dataset from Kaggle, which contains labeled MRI scans categorized into two classes: tumor-positive ("Yes") and tumor-negative ("No"). The dataset includes 3,000 images evenly distributed across both classes, ensuring balance for unbiased model evaluation. Images are stored in JPEG format and were annotated by medical imaging professionals, making them suitable for supervised learning. The MRI scans exhibit natural variations in brightness, contrast, anatomical orientation, and imaging modalities, including T1-weighted, T2-weighted, and FLAIR sequences. These variations present realistic challenges for model training, promoting better generalization. Additionally, the dataset is fully anonymized and ethically approved for academic research, though clinical deployment would require additional validation and regulatory compliance.

3.2 Data Preprocessing

Data preprocessing is a critical step to ensure the input data is standardized, noise-reduced, and suitable for both classical and deep learning models. The MRI images were programmatically loaded using OpenCV, with each image assigned a binary label (1 for tumor presence, 0 for tumor absence). All images were resized to 128 × 128 pixels to provide uniform input dimensions for convolutional neural networks and to reduce computational complexity. Pixel intensities were normalized to a [0,1] range, improving model convergence during training by stabilizing gradient updates. The dataset was split into training (80%) and testing (20%) sets using stratified sampling to preserve class distribution. For deep learning models, binary labels were converted into one-hot encoded vectors, aligning with the requirements of categorical cross-entropy loss.

3.3 Feature Extraction

Classical machine learning models require structured feature representations, as they cannot directly process raw image tensors. In this study, ResNet50, a pre-trained deep convolutional neural network, was used as a fixed feature extractor. The fully connected classification layers were removed to retain only the convolutional base, which captures hierarchical features from low-level textures to high-level semantic patterns. A Global Average Pooling (GAP) layer reduced the output feature maps into compact, high-level vectors for each MRI image. To further optimize computational efficiency and reduce redundancy, Principal Component Analysis (PCA) was applied to reduce the feature dimensions from 2,048 to 300 while retaining the majority of the variance. These extracted features were then used as input to classical machine learning classifiers, including Support Vector Machines, Random Forest, Gradient Boosting, and XGBoost, ensuring effective learning and accurate tumor classification.

3.4 Model Development and Implementation

This study employed both classical machine learning and deep learning models to perform binary classification of brain tumors using MRI images. The models were implemented using Python, TensorFlow, and scikit-learn, leveraging the preprocessed dataset and feature representations extracted from the ResNet50 convolutional base. The machine learning pipeline was designed to evaluate multiple architectures in parallel, enabling a comprehensive performance comparison.

3.4.1 Classical Machine Learning Models

For traditional machine learning, extracted features from ResNet50 were first reduced in dimensionality using Principal Component Analysis (PCA), from 2,048 to 100 components, reducing redundancy and computational cost while preserving key discriminative information. Six classical algorithms were implemented: Logistic Regression, Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Gradient Boosting, and XGBoost. Each model was trained on the PCA-transformed feature vectors and evaluated using the independent test set. Probabilistic outputs were obtained for models supporting predict_proba, enabling calculation of AUC-ROC curves. Hyperparameters were set to standard values, with logistic regression using a maximum iteration of 500 and KNN using five neighbors. Random Forest and Gradient Boosting models were trained with default parameters, while XGBoost was configured with use_label_encoder=False and eval_metric='logloss' to ensure compatibility with the dataset.

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3.4.2 Deep Learning Models

Several deep learning architectures were implemented to directly process raw MRI images. These included a Basic Convolutional Neural Network (CNN), VGG16 and ResNet50 transfer learning models, and the proposed Attention-based CNN with Convolutional Block Attention Module (CBAM). The basic CNN consisted of sequential convolutional and pooling layers, followed by fully connected dense layers and dropout for regularization. Transfer learning models employed pre-trained weights from ImageNet, with the top layers replaced by global average pooling and fully connected layers to adapt the network for binary tumor classification.

3.4.3 Proposed Attention-Based Convolutional Neural Network Model

The proposed model integrates the Convolutional Block Attention Module (CBAM) into a CNN architecture to improve tumor region localization and classification performance. The CBAM applies channel and spatial attention sequentially, enhancing feature maps by emphasizing tumor-relevant regions while suppressing irrelevant areas. The architecture begins with convolutional and pooling layers, followed by three CBAM blocks to refine features at multiple levels. Flattened outputs are then passed through fully connected dense layers with dropout to reduce overfitting, culminating in a softmax output layer for binary classification. The model was trained using the Adam optimizer and categorical cross-entropy loss with label smoothing, with early stopping and learning rate reduction callbacks applied to prevent overfitting. This proposed model is a novel contribution of the study, combining attention mechanisms with CNNs to specifically target discriminative tumor features in MRI images.

3.4.4 Training, Evaluation, and Metrics

All models were trained on an 80/20 stratified train-test split of the dataset. Deep learning models used one-hot encoded labels, while classical models used PCA-transformed feature vectors with scalar labels. Performance was evaluated using multiple metrics, including accuracy, precision, recall, F1-score, and AUC-ROC, to ensure a robust assessment of predictive performance. Confusion matrices, ROC curves, and performance bar charts were generated to visualize model performance across all metrics. The results demonstrated the effectiveness of attention mechanisms and transfer learning in enhancing classification accuracy, while classical models provided a baseline for comparison.

3.4.5 Hybrid Approach and Feature Integration

The pipeline leveraged a hybrid approach by combining deep feature extraction with classical machine learning classifiers. ResNet50 was used as a fixed feature extractor to produce high-level feature representations, which were then reduced via PCA and fed into traditional classifiers. This approach allowed the models to benefit from pre-trained deep learning representations while avoiding the computational expense of end-to-end deep model training for every algorithm. The hybrid methodology highlighted the complementarity of deep feature extraction and classical machine learning in achieving high-performance brain tumor classification.

4. RESULTS

This section presents the experimental findings and performance evaluation of the proposed and benchmark models.

4.1 Comparative Performance of All Models

A comparative analysis was conducted on ten machine learning and deep learning models using five key metrics: Accuracy, Precision, Recall, F1-Score, and AUC-ROC. Table 5.1 summarizes the performance of all models.

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Attention-Based CNN	0.9900	0.9862	0.9930	0.9896	0.9928
Basic CNN	0.9883	0.9861	0.9895	0.9878	0.9944
VGG16	0.9783	0.9757	0.9791	0.9774	0.9964
XGBoost	0.9317	0.9184	0.9408	0.9294	0.9768

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Random Forest	0.9217	0.8896	0.9547	0.9210	0.9754
KNN	0.8883	0.8986	0.8641	0.8810	0.9464
Gradient Boosting	0.8617	0.8469	0.8676	0.8571	0.9414
SVM	0.8350	0.8176	0.8432	0.8302	0.8992
Logistic Regression	0.7883	0.7667	0.8014	0.7836	0.8593
ResNet50 (Full)	0.7783	0.7711	0.7631	0.7671	0.8393

Table 1: Comparative Performance of All Models

The experimental evaluation demonstrated a clear performance advantage of deep learning models over traditional machine learning approaches for brain tumor classification from MRI images. Among all models, the proposed Attention-Based CNN achieved the highest overall performance, with an accuracy of 0.9900, precision of 0.9862, recall of 0.9930, F1-Score of 0.9896, and an AUC-ROC of 0.9928. The high recall was particularly significant, as it indicated the model's capability to minimize missed tumor detections, which is critical in clinical settings (Table 5.1).

4.2 Confusion Matrix

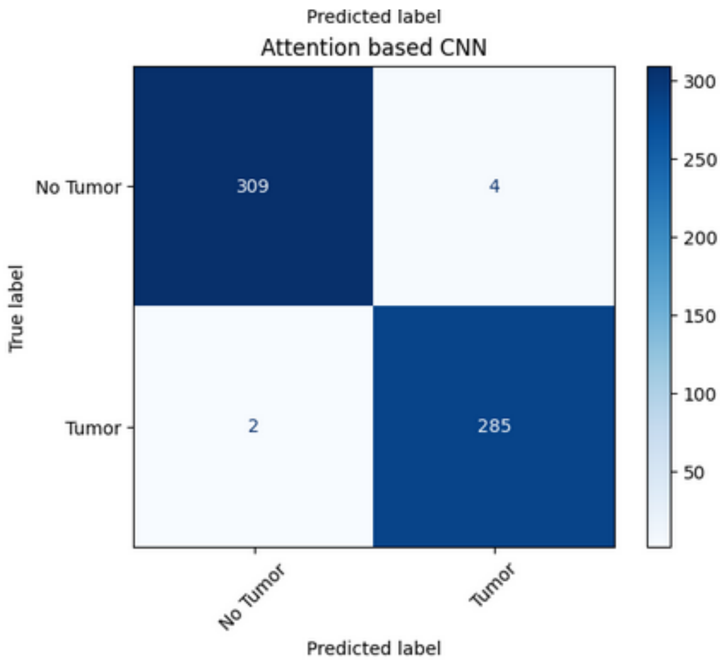

Figure 1: Confusion matrix of the proposed Attention-Based CNN

Confusion matrix analysis revealed that the Attention-Based CNN misclassified only five cases, comprising 2 false negatives and 4 false positives. True positive detection was 285 cases, and true negatives were 309 cases, confirming both high sensitivity and specificity. This performance exceeded that of ensemble methods such as XGBoost and Random Forest, which, despite demonstrating reasonable recall, produced higher numbers of false positives and false negatives due to their reliance on pre-extracted features (Figure 1).

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4.3 Visual Performance Comparisons

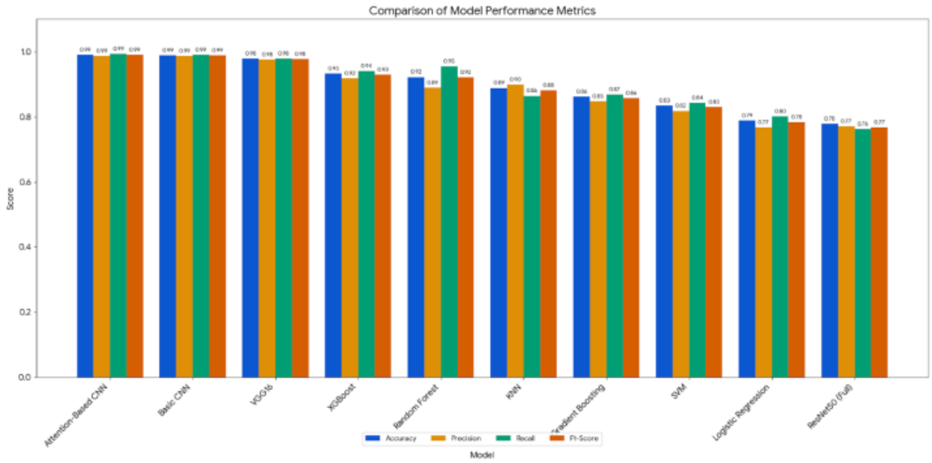

Figure 2: Bar chart illustrating performance matrices across all models

Visual comparison through bar chart illustrated performance trends across all models, with deep learning models—particularly the proposed Attention-Based CNN, Basic CNN, and VGG16—dominating across all metrics (Figure 2). Traditional machine learning models such as Logistic Regression, SVM, and Gradient Boosting showed comparatively lower performance in terms of accuracy, precision, recall, and F1-Score.

4.4 ROC Curve

ROC curve analysis further confirmed the superior discriminative power of the Attention-Based CNN demonstrating its ability to effectively distinguish tumor and non-tumor cases (Figure 3).

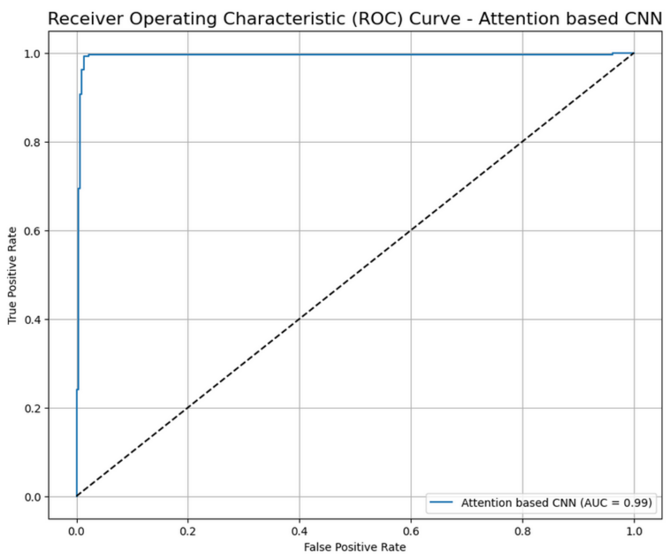

Figure 3: ROC curve for Proposed Attention-Based CNN

5. DISCUSSION

From a clinical perspective, the integration of the Convolutional Block Attention Module (CBAM) enabled the network to selectively focus on relevant tumor regions while suppressing irrelevant background features. This attention mechanism enhanced both spatial and channel-wise feature representation, improving the model's interpretability and robustness to variability in MRI scans. The Attention-Based CNN not only achieved superior quantitative performance but also provided attention maps that could guide clinicians in understanding the model's decision-making process.

The proposed Attention-Based CNN outperformed all other evaluated models in accuracy, sensitivity, and specificity. It achieved an optimal balance between clinical reliability and computational efficiency, highlighting the effectiveness of attention mechanisms in MRI-based brain tumor classification and making it the most suitable candidate for practical deployment in medical diagnostics.

6. CONCLUSION AND FUTURE WORK

This study evaluated deep learning and traditional machine learning models for brain tumor classification from MRI images, demonstrating the superior performance of the proposed Attention-Based CNN with a Convolutional Block Attention Module (CBAM). The model achieved an accuracy of 0.9900, precision of 0.9862, recall of 0.9930, F1-Score of 0.9896, and an AUC-ROC of 0.9928, highlighting its ability to selectively focus on tumor regions and enhance both spatial and channel-wise feature representations. This attention mechanism contributed to high sensitivity and specificity, minimizing false negatives—an essential factor in clinical settings. Comparative analysis showed that attention-equipped deep learning models outperformed traditional machine learning approaches, which relied on pre-extracted features and could not capture complex spatial patterns. Additionally, the Attention-Based CNN generated interpretable attention maps, providing valuable visual insights for clinicians and supporting trust in AI-assisted diagnostic decision-making.

Future work may focus on several directions to further enhance model performance and clinical applicability. First, expanding the dataset to include multi-institutional MRI scans could improve model generalizability and robustness to variations in imaging protocols. Second, integrating multi-modal imaging data, such as combining MRI with CT or PET scans, may provide richer feature representations and improve classification accuracy. Third, optimizing the attention mechanism or exploring hybrid attention architectures could further refine the model's focus on subtle tumor features. Finally, deploying the model in real-time clinical settings with feedback loops from radiologists can facilitate adaptive learning and continuous improvement, ensuring the model remains clinically relevant.

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