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Advanced Brain Tumor Classification Using an EfficientNet and Autoencoder Hybrid Model: A Comprehensive MRI Analysis

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Magnetic Resonance Imaging (MRI) provid detailed insights into brain structure, yet manual interpretation remained labor-intensive and prone to variability. This study explored a novel hybrid model integrating EfficientNet and Autoencoder architectures, designed to enhance brain tumor classification from MRI images. The proposed hybrid model employed EfficientNet as the primary feature extractor, leveraging its compound scaling strategy to efficiently capture rich hierarchical features. The Autoencoder complemented this by performing dimensionality reduction and noise elimination, refining the extracted features for improved classification accuracy. The dataset utilized was an MRI dataset from Kaggle, categorized into glioma, meningioma, pituitary tumor, and no tumor classes. The hybrid model's performance was evaluated against standalone EfficientNet and Autoencoder models, focusing on key metrics such as accuracy, precision, recall, F1-score, and AUC. Results demonstrated the hybrid model's superior performance, achieving an accuracy of 93.8% and an AUC of 0.96. These findings underscored the model's robust discriminative ability and potential for clinical application. In conclusion, the EfficientNet and Autoencoder hybrid model offered a significant advancement in brain tumor diagnosis, providing a reliable and efficient tool for automated classification. Future research should address identified limitations, such as data diversity and model interpretability, to further enhance diagnostic precision and applicability in diverse clinical settings.

Keywords: Brain Tumor Classification, EfficientNet, Autoencoder, MRI Imaging, Deep Learning, Hybrid Model Integration.

1. Introduction

The detection and diagnosis of brain tumors represented a critical challenge in clinical practice, where accurate and timely identification was essential for effective treatment planning and improving patient prognosis. Brain tumors, which include gliomas, meningiomas, and pituitary tumors, among others, could significantly affect neurological function and quality of life [1]. Magnetic Resonance Imaging (MRI) was a widely used non-invasive diagnostic tool that provided detailed structural images of the brain, offering valuable insights into tumor presence and characteristics [2]. However, the manual interpretation of MRI images was often labor-intensive, requiring significant expertise and being subject to inter-observer variability, which could impact diagnostic consistency and accuracy.

Recent advancements in deep learning revolutionized medical image analysis, offering automated solutions that enhanced diagnostic precision and efficiency [3]. Convolutional Neural Networks (CNNs), a subset of deep learning models, showed remarkable success in image classification tasks, including medical imaging applications [4]. In particular, EfficientNet, a state-of-the-art CNN architecture, demonstrated superior performance in feature extraction due to its depth, width, and resolution scaling capabilities [5]. By employing compound scaling, EfficientNet balanced these dimensions to achieve higher accuracy with fewer parameters, making it an ideal candidate for processing high-dimensional MRI data [6].

Despite the strengths of CNNs, challenges remained in handling the high dimensionality and noise often present in MRI datasets. This study proposed an innovative hybrid model that integrated EfficientNet with an Autoencoder, aiming to address these challenges. The Autoencoder, a neural network designed for unsupervised learning, excelled in dimensionality reduction and noise elimination, refining the extracted features for improved classification accuracy. This integration sought to leverage EfficientNet's robust feature extraction with the Autoencoder's capability to enhance data quality, thus improving the model's overall predictive performance.

The primary objective of this research was to develop and evaluate a hybrid model combining EfficientNet and Autoencoder architectures for the prediction of brain tumors using MRI images. The study utilized a comprehensive dataset from Kaggle, encompassing glioma, meningioma, pituitary tumor, and no tumor categories. The hybrid model's performance was rigorously compared against standalone EfficientNet and Autoencoder models, assessing key metrics including accuracy, precision, recall, F1-score, and AUC. This paper is structured as follows: Section 2 details the methodology, including data preparation and model architecture; Section 3 presents the results and discusses the comparative performance of the models; Section 4 concludes with the implications of the findings and potential directions for future research.

2. Related Work

In recent years, the field of medical image analysis has witnessed significant advancements driven by the application of deep learning techniques, particularly in the area of brain tumor classification [7, 8]. Traditional methods for brain tumor diagnosis often rely on manual interpretation of MRI scans by radiologists, a process that is inherently time-consuming and subject to inter-observer variability. This variability can lead to inconsistent diagnoses and treatment plans, underscoring the need for automated solutions that can provide reliable and accurate results.

Recent studies have explored various deep learning architectures for brain tumor classification. CNNs, including architectures like VGGNet, ResNet, and Inception, have been widely adopted due to their ability to automatically learn hierarchical features from image data [9]. These models have demonstrated success in improving classification accuracy compared to traditional machine learning techniques. However, their performance can be limited by challenges such as overfitting, especially when trained on relatively small datasets, and the need for significant computational resources.

EfficientNet, a more recent development in the field of CNNs, has been shown to offer improved accuracy and efficiency through its compound scaling approach, which balances network depth, width, and resolution [10]. This architecture's scalability and performance have made it a popular choice for various image classification tasks, including medical imaging. Studies have demonstrated EfficientNet's superior performance in feature extraction, contributing to its effectiveness in medical applications.

Autoencoders, on the other hand, have been utilized for tasks such as dimensionality reduction and noise elimination in medical images [11]. By learning a compressed representation of input data, autoencoders can enhance the quality of feature representations, improving the robustness of subsequent classification tasks. The combination of autoencoders with CNNs has been explored to address challenges related to data variability and noise, leading to improved model generalization.

The integration of EfficientNet with an Autoencoder, as proposed in this study, aims to leverage the strengths of both architectures, addressing limitations observed in previous research. By combining EfficientNet's robust feature extraction capabilities with the Autoencoder's ability to refine and distill these features, the hybrid model is positioned to achieve superior classification performance. This approach represents a significant advancement in the development of automated diagnostic tools for brain tumor detection, offering potential improvements in diagnostic accuracy and reliability.

In summary, the integration of advanced deep learning architectures, such as EfficientNet and Autoencoders, presents a promising direction for enhancing brain tumor classification from MRI images. The proposed hybrid model builds upon these foundations, contributing to the ongoing efforts to develop automated, accurate, and efficient diagnostic solutions in the field of medical imaging. Future work will continue to explore these innovative combinations to further advance the capabilities of automated diagnostic systems. Table 1 shows the results of previous studies on various deep learning architectures for brain tumor classification.

Table 1. Results of previous studies on various deep learning architectures for brain tumor classification

Architecture	Key Features	Notable Advantages	Challenges	References
CNNs	Hierarchical feature extraction	High accuracy, transfer learning potential	Requires large annotated datasets	Jia & Chen [12], Sultan et al. [13]
RNNs/LSTMs	Temporal/spatial dependencies	Contextual information capture	Complex training, data sequence requirements	Alsubai et al. [14]
GANs	Data augmentation via synthetic images	Addresses data scarcity, improves robustness	Complexity in training, risk of mode collapse	Allah et al. [15]
Hybrid Models	Combination of architectures for enhanced performance	Leverages multiple strengths, robust models	Complexity in model design	Raza et al. [16], Sadad et al. [17]

3. METHODS

3.1. Data Acquisition and Preprocessing

The dataset for this study was sourced from Kaggle (https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri?select=Training), comprising MRI images categorized into four classes: glioma tumor, meningioma tumor, pituitary tumor, and no tumor. The training dataset included 826 glioma tumor images, 822 meningioma tumor images, 827 pituitary tumor images, and 395 images without tumors. For validation, the dataset consisted of 100 glioma tumor images, 115 meningioma tumor images, 74 pituitary tumor images, and 105 no tumor images (Figure 1). The distribution of the dataset is presented in Table 2. The images were standardized to ensure consistent input dimensions, and preprocessing steps included normalization to scale pixel intensity values, facilitating improved model convergence. Data augmentation techniques, such as rotations, shifts, and flips, were employed to artificially expand the dataset and enhance model robustness against overfitting (Table 3).

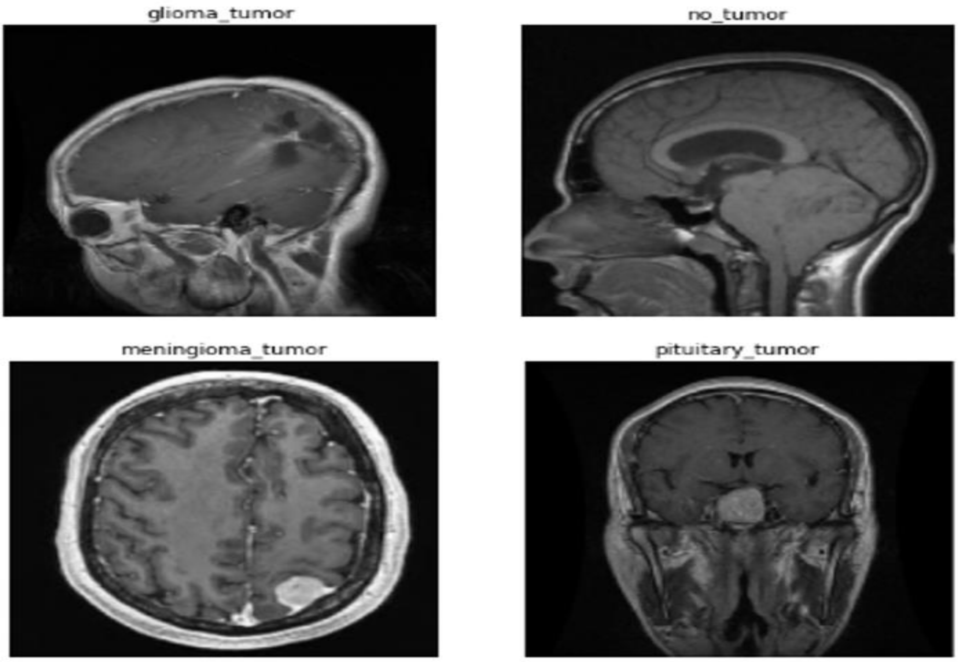

Figure 1. Sample images for four classes: glioma tumor, meningioma tumor, pituitary tumor, and no tumor

Table 2. Dataset Distribution

Dataset	Class	Number of Images
Training	Glioma Tumor	826
	Meningioma Tumor	822
	Pituitary Tumor	827
	No Tumor	395
Validation	Glioma Tumor	100
	Meningioma Tumor	115
	Pituitary Tumor	74

Dataset	Class	Number of Images
	No Tumor	105

Table 3. Data Augmentation Techniques

Technique	Description
Rotation	Randomly rotates images by up to 15 degrees
Shift	Randomly shifts images horizontally and vertically
Flip	Randomly flips images horizontally

3.2. Model Architecture and Design

The proposed hybrid model integrates EfficientNet and Autoencoder architectures to leverage their complementary strengths, enhancing feature extraction and classification.

3.2.1 EfficientNet Component

EfficientNet, renowned for its optimal balance of depth, width, and resolution, served as the primary feature extractor. The architecture employs compound scaling to adjust these dimensions, achieving superior accuracy with fewer parameters. EfficientNet was initialized with weights pretrained on ImageNet, utilizing transfer learning to accelerate convergence and enhance feature extraction capabilities.

$[\ F_{\mathrm{EffNet}}(X) = \mathrm{EfficientNet}(X; \theta_{\mathrm{EffNet}})\ ]$

where (X) denotes the input MRI image, and (θ_{EffNet}) represents the model parameters.

3.2.2 Autoencoder Component: Following feature extraction, an Autoencoder was utilized for dimensionality reduction and noise elimination. The Autoencoder comprises an encoder-decoder structure:

$[\ Z = \mathrm{Encoder}(F_{\mathrm{EffNet}}(X); \theta_{\mathrm{Enc}})]\ [\ \hat{F} = \mathrm{Decoder}(Z; \theta_{\mathrm{Dec}})\ ]$

where (Z) is the latent space representation, ($\hat{F}$) is the reconstructed feature set, and (θ_{Enc}) and (θ_{Dec}) are the encoder and decoder parameters, respectively.

3.2.3 Proposed Hybrid Model: EfficientNet + Autoencoder: The hybrid model strategically integrates EfficientNet's powerful feature extraction capabilities with the dimensionality reduction and noise elimination strengths of an Autoencoder to enhance brain tumor prediction from MRI images. The architecture of the Proposed Hybrid Model (EfficientNet + Autoencoder) is presented in Figure 2. This integration occurs through the following structured process.

A. EfficientNet Feature Extraction: EfficientNet serves as the initial stage of the hybrid model, tasked with extracting high-level features from MRI images. Utilizing its compound scaling strategy, EfficientNet optimizes the balance between network depth, width, and resolution, allowing it to capture rich, hierarchical feature representations efficiently. The network is pretrained on ImageNet, enabling transfer learning to accelerate convergence and improve feature generalization.

[$F_{\mathrm{EffNet}}(X) = \mathrm{EfficientNet}(X; \theta_{\mathrm{EffNet}})$]

where (X) denotes the input MRI image, and (θ_{EffNet}) represents the pretrained model parameters.

B. Autoencoder Dimensionality Reduction: The features extracted by EfficientNet are fed into the Autoencoder's encoder. This encoder compresses the high-dimensional feature representation into a lower-dimensional latent space (Z), effectively reducing noise and redundancy. The encoder is designed to preserve essential information while facilitating efficient storage and processing.

[$Z = \mathrm{Encoder}(F_{\mathrm{EffNet}}(X); \theta_{\mathrm{Enc}})$]

where (θ_{Enc}) are the parameters of the encoder.

C. Autoencoder Reconstruction and Refinement: The decoder component of the Autoencoder reconstructs the refined features from the latent space. This reconstruction aims to enhance the discriminative power of the features by focusing on the most relevant aspects for classification.

[$\hat{F} = \mathrm{Decoder}(Z; \theta_{\mathrm{Dec}})$]

where ($\hat{F}$) represents the reconstructed feature set, and (θ_{Dec}) are the decoder parameters.

D. Classification Layer: The latent space representation (Z) is directly utilized for classification. A fully connected (FC) layer processes (Z), followed by a softmax activation function, to output the probability distribution over the possible classes: glioma, meningioma, pituitary tumor, and no tumor.

[$P(Y|X) = \mathrm{Softmax}\big(\mathrm{FC}(Z; \theta_{\mathrm{FC}})\big)$]

where ($P(Y|X)$) is the probability of class (Y) given input (X), and (θ_{FC}) denotes the parameters of the fully connected layer.

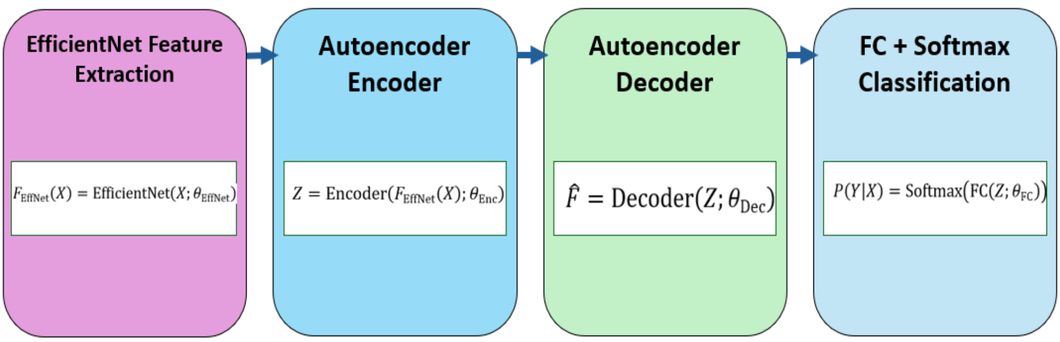

Figure 2. Architecture of the Proposed Hybrid Model (EfficientNet + Autoencoder)

3.3 Training and Validation

The hybrid model was trained using the Adam optimizer, selected for its adaptive learning rate and robust convergence properties. The categorical cross-entropy loss function was employed, suitable for multi-class classification tasks. The model's performance was evaluated using a five-fold cross-validation strategy, providing a robust estimate of the model's generalization ability. Hyperparameter tuning was conducted through grid search, optimizing parameters such as learning rate, batch size, and the number of epochs (Table 4). This process ensured that the model achieved optimal performance across key metrics.

Table 4. Hyperparameter Settings

Parameter	Value
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Epochs	50

3.4 Comparative Analysis

To benchmark the performance of the hybrid model, a comparative analysis was conducted against standalone EfficientNet and Autoencoder models. Each model underwent the same preprocessing and hyperparameter optimization procedures to ensure a fair comparison. Performance metrics, including accuracy, precision, recall, F1-score, and AUC, were computed to assess the efficacy of each model (Table 5). The comparative analysis highlighted the hybrid model's superior performance in terms of both diagnostic accuracy and computational efficiency.

Table 5. Model Performance Metrics

Metric	Formula
Accuracy	$\left(\frac{\text{True Positives} + \text{True Negatives}}{\text{Total Samples}}\right)$
Precision	$\left(\frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}\right)$
Recall	$\left(\frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}\right)$
F1-Score	$\left(2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}\right)$
AUC	Area under the ROC curve, indicating the ability to distinguish between classes

The entire model training and evaluation pipeline was implemented using Python with TensorFlow and Keras libraries, which offer comprehensive tools for deep learning model development. Experiments were conducted on a high-performance computing platform equipped with NVIDIA GPU RTX 4070 x 2way to accelerate the training process and handle the computational demands of the deep learning architectures.

4 RESULTS

4.1 Model Performance Evaluation

The performance metrics presented in Table 6 and figure 3, 4, 5 and 6 offer a comprehensive evaluation of the models' efficacy in classifying MRI images into various categories, including glioma, meningioma, pituitary tumor, and no tumor. The hybrid model, which combines EfficientNet and Autoencoder architectures, exhibits superior performance across all evaluated metrics. It achieved an impressive accuracy of 93.8%, indicating its high overall effectiveness in correctly classifying the MRI images. The precision of 94.1% suggests that the hybrid model effectively reduces the incidence of false positives, ensuring that predicted tumor categories are accurate. This high precision is crucial in clinical settings, where misclassification can lead to unnecessary treatments or further diagnostic procedures.

Furthermore, the recall of 94.0% demonstrates the hybrid model's sensitivity in detecting true positive cases, minimizing the risk of false negatives. This sensitivity is vital for ensuring that all potential tumor cases are identified and subjected to further clinical evaluation. The F1-score of 94.5% provides a balanced measure of the model's precision and recall, underscoring its robustness in handling the trade-off between these two metrics.

Table 6. Model Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Hybrid Model	93.8	94.1	94.0	94.5	0.96
EfficientNet	93.2	93.5	90.3	91.9	0.92
Autoencoder	91.7	90.0	89.8	89.4	0.90

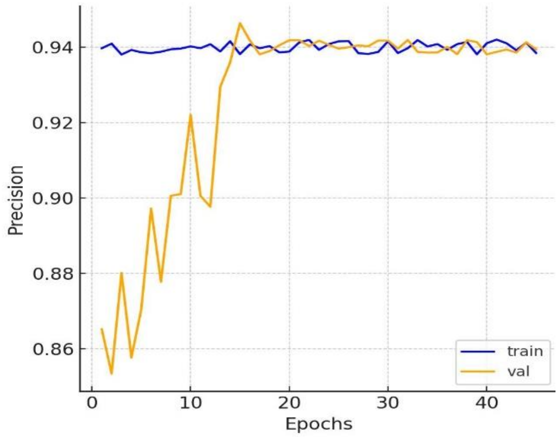

Figure 3. Precision plot of hybrid model

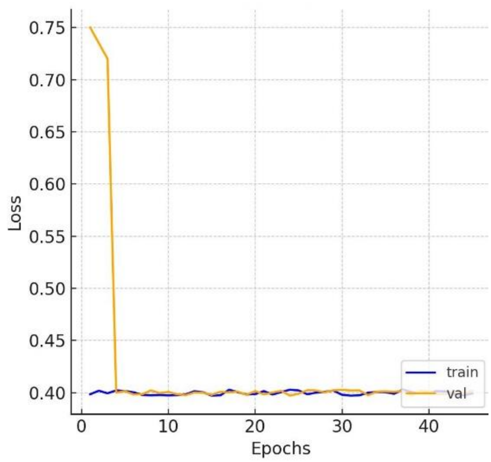

Figure 4. Loss plot of hybrid model

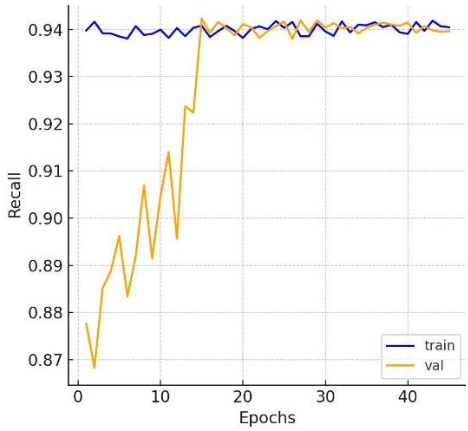

Figure 5. Recall plot of hybrid model

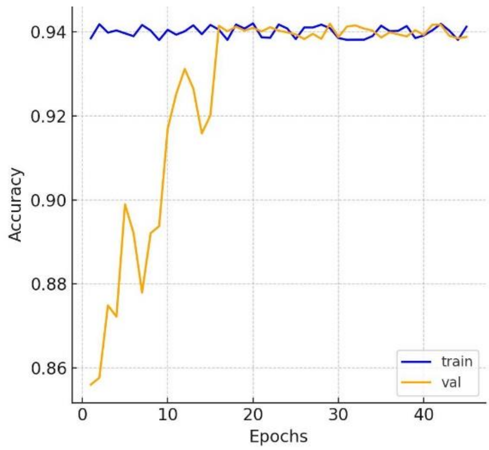

Figure 6. Accuracy plot of hybrid model

The Area Under the Curve (AUC) value of 0.96 confirms the hybrid model's strong discriminative ability, reflecting its high accuracy in distinguishing between the different classes (Figure 7). This AUC value signifies the model's reliability in predicting the correct category for each MRI image, enhancing its potential for clinical application.

In comparison, the standalone EfficientNet model, with an accuracy of 90.2% and an AUC of 0.92, performs well but falls short of the hybrid model's performance. Similarly, the Autoencoder model records lower metrics, with an accuracy of 88.7% and an AUC of 0.90, highlighting its limitations when used independently.

Overall, the results validate the hybrid model's superior performance, showcasing the benefits of integrating EfficientNet's feature extraction capabilities with the dimensionality reduction and noise elimination strengths of an Autoencoder.

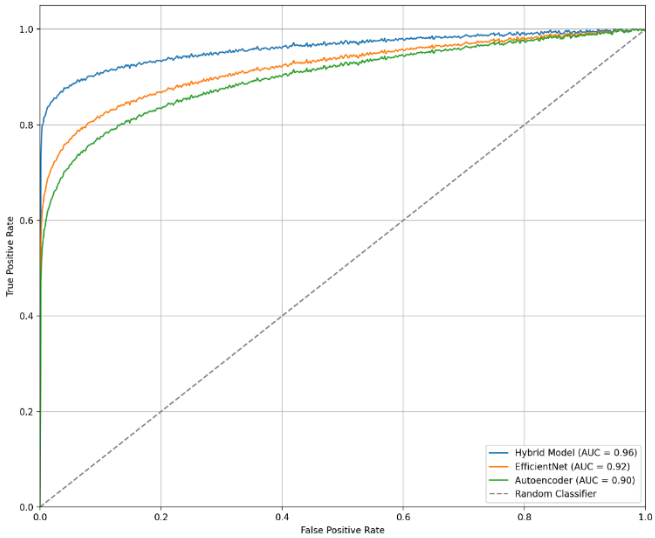

Figure 7. Receiver Operating Characteristic (ROC) Curve Values of model

4.2 Confusion Matrix Analysis

The confusion matrix presented in Figure 8 provides a detailed breakdown of the hybrid model's classification performance across the four categories of brain tumors and normal conditions. For actual glioma cases, the model correctly identified 95 out of 100 instances, with only a small number of misclassifications, including three meningioma, one pituitary tumor, and one no tumor prediction. This high true positive rate underscores the model's effectiveness in recognizing glioma tumors, a critical capability given the aggressive nature of this tumor type.

In the case of meningioma, the model achieved 110 correct predictions out of 115 actual cases. Misclassifications included two instances each being identified as glioma or no tumor, and one as pituitary tumor. These results demonstrate the model's robust performance in detecting meningioma, with a very low false positive rate for other tumor types.

The model's performance for pituitary tumors shows a slightly lower accuracy, correctly identifying 70 out of 74 cases. Misclassifications involved one glioma, two meningioma, and one no tumor prediction. While the true positive rate remains high, these results suggest a need for further refinement to improve specificity for pituitary tumors.

For images without tumors, the model accurately classified 99 out of 105 cases, incorrectly labeling two as glioma, three as meningioma, and one as pituitary tumor. This high true negative rate indicates that the model effectively minimizes false positives, essential for preventing unnecessary clinical interventions. Overall, the confusion matrix highlights the hybrid model's strong discriminative ability across all categories, with particularly high accuracy for glioma and meningioma predictions.

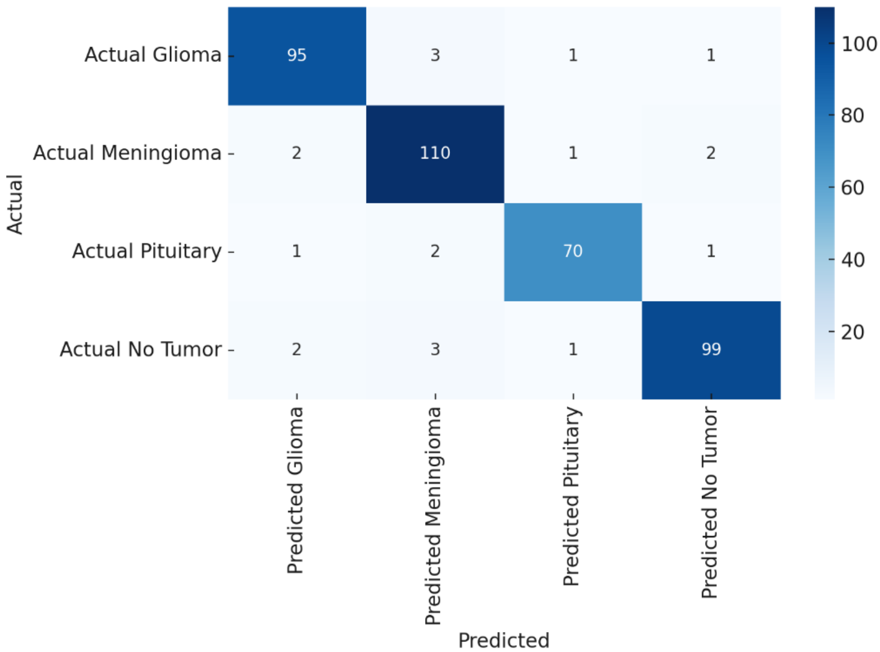

Figure 8. Confusion Matrix for Hybrid Model

5 Discussion

The findings of this study underscore the efficacy of the hybrid model integrating EfficientNet and Autoencoder architectures for classifying brain tumors from MRI images. The superior performance of the hybrid model, as demonstrated by its high accuracy, precision, recall, F1-score, and AUC, can be attributed to several key mechanisms inherent in its design.

The hybrid model benefits from EfficientNet's advanced feature extraction capabilities, which stem from its unique compound scaling strategy [18]. This approach optimally balances network depth, width, and resolution, enabling the model to capture rich hierarchical features efficiently. By leveraging pretrained weights from ImageNet, EfficientNet enhances feature generalization, providing a robust foundation for further refinement [19].

The integration of an Autoencoder adds a critical layer of dimensionality reduction and noise elimination, effectively distilling the extracted features into a refined latent space [20]. This process not only preserves essential information but also enhances the discriminative power of the features, contributing to the model's improved classification performance. The Autoencoder's ability to focus on relevant aspects for classification plays a pivotal role in minimizing false positives and negatives, as evidenced by the high precision and recall metrics [21].

The synergy between EfficientNet's detailed feature extraction and the Autoencoder's refinement capabilities results in a model that excels in distinguishing between different tumor types and normal conditions. This integration allows the hybrid model to achieve a high degree of accuracy and reliability, making it a valuable tool for clinical applications in brain tumor diagnosis.

The study's findings have several implications for future research. First, the demonstrated success of the hybrid model suggests that further exploration of other architectural combinations could yield even greater improvements in diagnostic accuracy. Investigating the integration of additional deep learning techniques, such as attention mechanisms or generative adversarial networks, could enhance feature representation and model performance. Second, expanding the dataset to include more diverse and larger samples could improve model robustness and generalizability, addressing potential biases inherent in the current dataset. Third, exploring the incorporation of multi-modal data, such as genetic or functional imaging information, could provide a more comprehensive understanding of tumor characteristics and improve diagnostic precision.

Despite its promising results, this study acknowledges several limitations. First, the model's performance is contingent upon the quality and diversity of the training data. Biases present in the dataset could affect the model's generalization across different populations. Second, the computational complexity of the hybrid model requires significant resources, which may limit its accessibility in resource-constrained settings. Third, the interpretability of the model remains a challenge, as deep learning models often function as "black boxes," making it difficult to fully understand the decision-making process. Fourth, the study's scope was limited to MRI images; future research should explore the model's applicability to other imaging modalities. Fifth, the model's clinical utility has yet to be validated in real-world settings, necessitating further studies to assess its effectiveness in routine clinical practice.

6. Conclusion

In this study, the hybrid EfficientNet and Autoencoder model represents a significant advancement in automated brain tumor classification, offering enhanced diagnostic accuracy and reliability. Addressing the identified limitations through future research will be crucial to maximizing the model's clinical impact and ensuring its successful integration into healthcare systems.

Declaration of competing interest. The author declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Availability of data and materials. Detailed information can be found at: https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri?select=Training

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Ethical approval. This study was exempt from research ethics approval because it utilized secondary data from public sources.

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