STATISTICS, OPTIMIZATION AND INFORMATION COMPUTING
Stat., Optim. Inf. Comput., Vol. **14**, October 2025, pp 1918–1935.
Published online in International Academic Press (www.IAPress.org)

In-Depth Exploration of Industry-Level Deep Learning Model for Brain Anomaly Detection

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Abstract Finding abnormalities in the brain is essential to identify neurological conditions and developing patient-specific treatment plans. In-depth research on the performance and deployment of a cutting-edge deep learning model for brain anomaly detection with practical applications is the aim of Unboxing an Industry-Level Deep Learning Model for Brain Anomaly Detection. Although, a lot of methodology and model has already developed to overcome the problem of diagnosing brain diseases but there have some issues that still need to solve. To ensure reliable model that can give appropriate diagnosis, it needs to assess how well deep learning models perform by employing an expansive dataset of the brain images. Because raw image data looks a little bit different from neuroimaging modalities. It needs to consider very careful during testing as well as approval over implementation phases of the model. Because, it requires proper diagnosing issue of brain diseases comparing to the patient demographics and clinical scenarios. Also, ensure and efficient model depends on some issues like exactness, affectability with some data variances (like CT and MRI image), and generalizability. If all these issues can overcome, then it can consider a potential model to assess diagnosis which can secure the understanding protection and expanding belief in therapeutic strategies. So, an efficient and reliable deep learning model for diagnosis of brain disease is crucial. Moreover, it can introduce a revolutionizing healthcare by utilizing an industrial-scale profound learning that can show early determination as well as custom-fitted treatment for individuals with neurological disarranges. By considering all aforementioned issues, this paper propose an efficient hybrid deep learning model with combining CNN and LSTM for diagnosing of brain disease. The experimental result shows a great opportunity to utilize the propose model in industry level usage. Propose model training and validation accuracy are 99.92% and 97.28% which shows a great hope to utilize the model in practical healthcare diagnosis. The paper also addresses the challenges and barriers of developing an industry-level model while taking technological, ethical, and other aspects into account. This study also shows a road map to reorganize healthcare framework set-up to be more reliable for diagnosis by considering early stage detection and treatment.

Keywords Deep Learning, Brain Anomaly Detection, Neuro-Imaging, MRI, Convolutional Neural Networks, Transfer Learning, Brain Tumor Identification.

AMS 2010 subject classifications. 97P50, 97R40

DOI: 10.19139/soic-2310-5070-2269

1. Introduction

Healthcare is among the numerous businesses that have been changed by progress in profound learning. The expansion of arrangements has appeared to be a huge guarantee in restorative diagnostics, holding the guarantee of more exact, viable, and individualized persistent medicines. The location of brain inconsistencies is exceedingly

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ISSN 2310-5070 (online) ISSN 2311-004X (print)

important in well-being care since it encompasses a coordinated effect on the determination and treatment of neurological ailments. The objective of this extension, In-Depth Exploration of Industry-Level Deep Learning Model for Brain Anomaly Detection, is to completely examine the application and execution of a state-of-the-art profound learning demonstration for recognizing brain peculiarities in real-world healthcare. In order to advance its consistent consolidation into clinical care, this paper tries to cover specialized, moral, and practical issues. [1].

The intricate neural structure and sensitive brain activities might make it difficult for traditional diagnostic techniques to accurately identify disorders. These techniques can result in subjective interpretations and frequently rely on drawn-out manual tests. On the other hand, deep learning models that draw inspiration from the structure of the human brain can improve diagnosis accuracy, automate the recognition process, and extract intricate information from medical images. This project starts with a comprehensive analysis of the body of research, looking at the most recent discoveries and developments in the fusion of deep learning and medical imaging. Studies that use convolutional neural networks, recurrent neural networks, and transfer learning to detect anomalies in the brain are included in the review. [2]. The paper moreover looks at issues of demonstrating interpretability, information heterogeneity, and moral concerns, which are pivotal for fruitful execution. The essential objective of the investigation is to assess the execution of deep learning models employing an expansive and differing dataset of brain checks from distinctive neuroimaging modalities. The extent points to survey the common capacity of the demonstration through overall testing and approval by considering different understanding populaces as well as clinical circumstances. The research aims to provide significant insight into the technical complexity of implementing a deep learning model at the highest level of the industry for brain anomaly detection in real healthcare settings. Mili Kotnala et al. [3] proposed a CNNs based brain tumor detection model which enhancing the precision of diagnosis accuracy near to 99%. To achieve this level accuracy in recognizing cancers, their proposed model has been demonstrated by a variety of models, including modified CNNs. Techniques like transfer learning and residual networks used in the model that improve classification and segmentation. Although deeper models perform better, they demand more processing power.

CNNs are essential for improving model evaluation accuarcy and enhancing early brain tumor diagnosis, despite certain obstacles. Gandham et al. [4] utilize several deep learning models like EfficientNet, VGG16, MobileNetV3, and ResNet50 to implement the diagnosis of brain tumors. These models perform well in transfer learning-based implementation to categorize brain tumor with MRI-based dataset. When dealing with small datasets, preprocessing and data augmentation are essential. With an accuracy of 98.66%, VGG16 outperformed the other models in this investigation. One important strategy for raising diagnostic accuracy is still deep learning that was mentioned in a survey which was done by Nizamli et al.[5]. The goal of abnormality identification in brain MRI images is to apply deep learning models to increase classification accuracy. Popular methods that is worth to be mentioned for this purpose, include CNNs and pre-trained models like DenseNet169 and VGG-16. Techniques for feature extraction and optimization are frequently employed to reduce overfitting and improve model performance. Handling limited datasets and increasing diagnostic accuracy are challenges. Chamseddine et al.[6] proposed a model that outperforms current approaches and provides superior classification results for brain tumors. CNNs are quite good at segmenting brain tumors, especially U-Net models. On benchmark datasets, sophisticated CNN designs like WRN-PPNet and Deep Variational Networks have produced impressive results. Accurate segmentation is also improved by residual and hybrid models. By lowering overfitting, data augmentation methods like brightness modification and elastic deformation improve performance. The development of automatic brain tumor detection depends on these techniques. Anvesh et al.[7] proposed a model that apply CNNs and deep learning to enhance anomaly detection in surveillance systems. Complex video patterns are difficult for traditional approaches to handle, but CNNs are good at automating feature extraction. Research indicates that while VGG-16 works well, custom Deep CNN models detect anomalies more accurately. For best outcomes, models must be tailored to certain activities.

These developments provide notable enhancements in the identification of irregularities Rawat et al.[8] discuss significant developments in deep learning-based brain tumor classification. Numerous segmentation methods have been investigated, with varying degrees of accuracy, including fuzzy clustering and mathematical morphology.

Improved tumor detection in MRI images has been achieved through the use of contour models and histogram-based techniques. Because Convolutional Neural Networks (CNN) automatically learn aspects of images, and that's why classification has improved. Brain tumor detection accuracy is significantly enhanced using transfer learning models such as VGG16 that was used in a deep learning model proposed by Behrendt et al. [9]. The field of brain MRI anomaly detection sometimes uses generative models, such as diffusion models, autoencoders, and GANs. GANs have problems during training, while autoencoders have trouble with fuzzy images. Sharper reconstructions improve the performance of diffusion models, particularly DDPMs. By examining individual picture patches, patch-based diffusion models enhance detection. It can even further improve precision and efficacy in detecting anomalies in the brain. Anantharajan et al. [10] used several deep learning and machine learning techniques for MRI brain tumor identification. Commonly utilized methods include feature extraction with GLCM and segmentation with fuzzy c-means. High accuracy has been demonstrated by deep learning models, particularly CNNs and hybrid classifiers like EDN-SVM. These techniques speed up computation and automate tumor identification. They reduce the overall requirement for manual diagnostics. Engproc et al. [11] employing deep learning models such as AlexNet, VGG16, and ResNet-50 for the detection of brain tumors. The accuracy of a hybrid VGG16–ResNet-50 model was 99.98%. Previous research has demonstrated how machine learning and hybrid approaches can increase the accuracy of diagnoses. Transfer learning improves brain tumor categorization substantially. These methods improve diagnostic accuracy and expedite the processing of medical images. Zaineldin et al.[12] used deep learning, particularly CNNs, in the diagnosis of brain tumors; accuracy is increased by optimization methods such as the sine-cosine fitness gray wolf optimizer. Although 99.98% accuracy is achieved by recent models, but there have some issues like data variability and computing needs still require. Deep learning, nevertheless, keeps progressing in the diagnosis of brain tumors. Yadav et al.[13] apply CNNs, particularly ResNet-50, to propose the model which is used in MRI brain tumor identification. Accuracy is increased by preprocessing methods like noise filtering and greyscale conversion. CNN models have a tumor classification accuracy of over 80%. These techniques facilitate early treatment by improving diagnosis speed and accuracy. MRI is still the method of choice because of its high-resolution imaging. The following is a summary of our study's primary Contributions. The paper "Brain Anomaly Detection: An Elaborative Study" makes several significant contributions to the field of deep learning-based brain abnormality detection. The key contributions outlined in the study are as follows:–

- The study presents a novel deep learning model specifically tailored for the complex problem of brain anomaly identification. This model effectively integrates convolutions and recurrent neural networks to handle the nuances of brain imaging data from various modalities such as CT and MRI images.
- The model makes use of a carefully selected collection of annotated brain pictures, enhancing efficacy through transfer learning and resilience through data augmentation. This strategy attempts to enhance performance while addressing the issues brought forth by the small dataset.
- The suggested approach places a strong emphasis on an interpretable framework to uphold moral standards and openness, paying special attention to patient privacy. For the model to be used in medical diagnostics, this feature is essential.
- With the recommended architecture,the model performs remarkably well, reaching a maximum accuracy of 97.28%. The study demonstrates how, in spite of the dataset's limitations, the inclusion of data augmentation greatly enhanced the results.
- Future research is advised by the paper to examine the connection between the sensitivity maps generated and deep learning accuracy assessments. It also investigates if explanatory techniques may be used to derive quantitative data such as tumor volume and centroid.

This section explain details about the organization of the paper. In Section two, highlights the emphasis on the state-of-the-art techniques for brain anomaly, along with a thorough analysis of the relevant literature. The methodology used in this study includes the armature selection and performance of the pharmaceutical model pointers described in Section three. The experimental results are shown in Section four and are further bandied in depth eventually. Section five wraps up the work by recapitulating our benefactions and suggests possible directions for further study. Finally, Section six briefly discuss about the ethical issues that should be considered during industry level implementation.

2. Background Study and Related Works

2.1. Background

A thorough background research titled ”Unboxing an Industry-Level Deep Learning Model for Brain Anomaly Detection” reveals critical information. The unique components that make up this study help us comprehend the project's context and relevance as a whole. The background study lays the groundwork on which our suggested deep learning model is methodically built by digging into AI's impact on medical imaging, investigating ethical issues, and resolving difficulties in model interpretation. This section presents a detailed analysis of these interrelated modules, shedding light on the complex environment in which our study finds its foundation [14].

2.2. Literature Reviews

This literature review includes numerous works on applying advanced approaches to improve brain-to-tumour image classification.

Arijit Ukil et.al.[15] mentioned their study that healthcare analytics was vital for saving lives, especially for severe disease patients like cardiac diseases. By detecting cardiac anomaly by smartphone-based cardiac anomaly detection was playing a vital role for early stage treatment. Addressing misdiagnosis, enabling early disease detection, and cost-effective healthcare were priorities. Abnormality detection in IoT, detects deviations, such as abnormal MRI or ECG traces, aiding in medical insights. Heterogeneous sensors and variability of contextual interpretations were key to IoT analytics. Anomaly detection in smartphone healthcare analytics, e.g., K-NN for arrhythmias, facilitates early critical disease detection. RUFF et.al.[16] proposed their paper with acknowledged the abundance of literature on anomaly detection (AD), encompassing reviews, surveys, and recent deep AD-focused sources. It identified a gap in the integrated exploration of deep learning within AD, especially concerning kernel-based learning. The authors' objective was to bridge this gap through a cohesive approach that unites traditional and novel deep learning methods in AD. They outline recent advancements, categorize AD techniques, offer theoretical insights, and highlight prevailing best practices. Importantly, the paper's scope wasn't exhaustive; it presented a slightly subjective viewpoint stemming from the author's own contributions to the field. NEELUM NOREEN et.al.[17] proposed their paper with surveys of machine learning's widespread applications, notably in medical diagnostics and preventive medicine. Brain tumor diagnosis via MRI remains underexplored with limited studies. Deep learning, including tri-architectural CNNs, has been employed for accurate tumor classification. Transfer learning and Capsule networks enhance brain tumor image classification. CNN-based architectures were prevalent for feature extraction and classification.

Wavelet-based 2D discrete transforms and learnable CNN layers were also explored for brain MRI feature extraction and tumor image classification. Lakshmi et al.[18] proposed their paper with a discussion of the utilization of distinct algorithms for the detection of tumors and strokes in brain MRI images. They introduced a novel approach involving hybrid classifiers to address both tasks. The potential of an automated system to assist medical professionals was highlighted, and the superior performance of their hybrid classifier system over the prior work was demonstrated. The paper recognized the critical importance of early abnormality detection in saving lives, underscoring the variation of symptoms based on patient age and abnormality severity. Additionally, it was noted that the algorithm tailored for tumor detection might not be applicable for discerning abnormalities, which actually arising from blood clots in veins or arteries, thereby outlining its limitations. Steardo et al.[19] proposed their paper with a systematic review that was conducted to evaluate the utility of Support Vector Machine techniques. Here, SVM used for distinguishing between schizophrenia patients and healthy controls using functional MRI data. After screening, 22 articles were included, and the methodological quality was assessed using the Jadad rating system. The review highlighted that SVM models and integrated machine learning methods exhibited superior accuracy in identifying SCZ patients. Also, it's indicating their potential in identifying neuroimaging risk factors and supporting early diagnosis and treatment with response of the evaluation. Numerous studies discussed in the review that emphasized high diagnostic accuracy using MRI data from diverse brain regions and connectivity patterns. It also highlights shedding light on SCZ-related dysconnectivity and underlying pathological mechanisms. Chen et al.[20] proposed their paper provided a literature review on CNN architectures for brain tumor segmentation and post-processing methods for refining CNN prediction outcomes. It noted the absence of explicit encouragement for high-quality hierarchical feature learning in existing deep architectures. There have some researches that proposed several strategies to enhance learned features, including Multi-Level DeepMedic extension, a dual-force training scheme, label distribution-based loss, and Multi-Layer Perceptron-based post-processing. Evaluation of BRATS 2017 and BRATS 2015 datasets demonstrated consistent performance improvement across popular deep learning based models. Sravanthi et al.[21] proposed their paper, providing an overview of how image processing techniques can aid in brain tumor detection using MRI images. The article described the various steps regarding the full training process of the model, including preprocessing, segmentation, feature extraction, and comparison with the trained data set. The author highlights the challenges faced by clinicians in detecting brain tumors at an early stage and emphasizes the importance of accurate detection. Khan et al.[22] proposed CNN-based deep learning techniques for brain tumor identification. It highlights how they can automatically identify characteristics from MRI scans. Transfer learning and data augmentation aid in resolving restricted dataset issues. Models using pre-training, such as ResNet34 and VGG16, demonstrate good classification accuracy. These methods increase the accuracy and speed of diagnosis. Mohsen et al.[23] focuses on classifying brain tumors using deep learning, namely Deep Neural Networks (DNN). The advantage of MRI is its high-resolution imaging. DWT and PCA techniques enhance feature extraction. Models like CNN and DNN perform better than more conventional classifiers like SVM and KNN. These developments improve brain tumor detection speed and accuracy. Charfi et al.[24] used CAD technologies to increase the precision of brain tumor identification. MRI image processing methods include picture segmentation, wavelet extraction, and PCA. Tumors are classified as normal or abnormal by neural networks, particularly BPNN. CAD systems have an accuracy rate of up to 90%. Future developments will concentrate on hybrid approaches and bigger datasets.

Lamrani et al.[25] proposed CNNs based system for automatic brain excrescence discovery. Because they're generally effective for brain excrescence discovery using MRI images. They outperform traditional styles in classifying and segmenting excrescences, and they further meliorate delicacy with transfer knowledge models like VGG19 and MobileNetV2. CNNs constantly achieve top results, with some models reaching 96%. Anil et al.[26] research on brain tumor detection and highlights the use of CNNs as well as transfer learning to improve accuracy. Various techniques like DWT and PCA have enhanced feature extraction. Models like AlexNet and VGGNet are widely used for handling complex MRI data. Transfer learning modifies pre-trained models for tumor detection. VGG19 achieved the highest accuracy at 95.78%. Asad et al.[27] research on brain excrescence discovery exploration by focusing on CNNs and deep literacy models similar as U-Nets, DenseNet, and ResNet. These models are comparatively better by considering styles like sea transforms and fuzzy clustering. Delicacy is increased by transfer literacy and optimization algorithms. This study employs ResNet- 50, which achieves 99.5% in brain excrescence discovery. Baiju BabuVimala et al.[28] apply deep learning models, especially CNNs, for precise tumor identification as well as tumor classification. High tumor classification precision has been demonstrated by pre-trained models like ResNet50 and VGG16, which are frequently refined using transfer learning. Data augmentation is a popular solution for the problem of small datasets. Accuracy and computational efficiency are well-balanced in EfficientNet models. Considering various challenging issues, these developments have greatly improved the accuracy of brain tumor classification. Arabahmadi et al. [29] proposed depp learning based model for brain tumor identification that emphasizes the importance of CNNs for precise MRI interpretation. Research indicates that topologies such as ResNet and U-Net improve tumor categorization. Accuracy is increased by deep learning techniques, particularly when combined with transfer learning. However, computational demands and data availability are still consider as obstacles that is mentioned in the overall research and still need to be solved. Deep learning keeps improving to detect brain tumor in spite of these obstacles.

Recent research has highlighted the utility of deep learning models, particularly convolutional architectures, in the field of brain tumor segmentation and medical diagnostics. For instance, M Amir Ul Haque et al. [30] proposed a customized UNet-based deep learning model tailored for brain tumor segmentation using MRI data. Their approach demonstrated high accuracy and robustness by leveraging a modified encoder-decoder structure with optimized skip connections. In the broader domain of medical diagnostics, Nurjahan et al. [31] conducted a comprehensive review of machine learning and deep learning techniques for detecting COVID-19 from medical images. Their work emphasized the role of convolutional and transformer-based models in improving diagnostic accuracy across CT and X-ray imaging. Complementing disease detection, Mahbub-Or-Rashid et al. [32] proposed a multi-output regression framework for predicting short-term mortality trends. Their study used real-world mortality datasets and explored different ensemble learning strategies, providing insights that is applicable to epidemiological forecasting. Moreover, practical deployment of such AI models, efficient computation, and infrastructure play a critical role. In this regard, recent work on cloud infrastructure by Mahbub-Or-Rashid et al. [33] presented an optimized framework for resource allocation and load balancing in cloud data centers. The study is particularly relevant for the scalable deployment of medical AI systems that require a high performance back-end. These studies collectively advance the current state of knowledge in both image-based diagnosis and computational infrastructure, offering complementary perspectives that support the implementation of robust and interpretable AI models in healthcare.

In summary, this section attempts to analyze various key issues regarding the application of deep literacy and machine literacy for the identification of brain excrescence. Among them several issues are worth to be mentioned like hybrid classifier deep learning model for brain tumor identification. It helps in conducting healthcare analytics for the early stage treatment. Some deep learning techniques are helpful to improve classification accuracy as well as anomaly detection. In addition, utilizing CNN, transfer learning, and image processing techniques helps to increase feature extraction accuarcy as well as detection accuracy. It is familair nowadays for various application, especially for brain disease detection. A number of exploration research shows that how to use pre-trained models and optimization techniques to boost delicacy and efficacy regarding various challenges like small datasets and processing demands. All of these advancements in deep learning techniques greatly improve the accuracy and validity of MRI imaging to detect brain malice.

3. Materials and Methodology

We present a novel deep-learning model that specifically tailored to the difficult problem of brain anomaly identification. Utilizing the potency of both convolution and recurrent neural networks, our model is an industry-standard solution that has been meticulously designed to manage the intricacy of brain imaging data. This model design deftly to handle the nuances of several neuroimaging modalities, such as CT and MRI images. A carefully chosen dataset of annotated brain pictures is used in conjunction with transfer learning for efficacy and data augmentation for robustness to aid in the training of our model. Using a Kaggle brain tumor dataset, the suggested framework makes predictions about brain tumors. For data pre-processing techniques, here used Pixel conversion and noise reduction. After feature extraction, the CNN model is trained to identify if an MRI picture is malignant or not. CNN serves as the foundation model for the framework, which employs optimization techniques such as ADAS, PSO, ADAM, and SGD to increase accuracy.[27]. Our proposed method aims to transform the medical diagnostics environment in order to expedite precise identification, optimize treatment strategies, and raise patient standards [34]. Here, presents an interpretable framework which can ensure transparency and moral principles that preserve patient privacy. This paper describes the development process of our suggested model and provides a thorough description of the methodological design. Classifying the processes of brain tumors and presenting the proposed paradigm are emphasized. The latter section of the study illustrates and explains how the proposed model works. Also, the block diagram of the proposed model mentioned in Fig. 1.

3.1. Datasets

In this study, we utilized two publicly available brain MRI datasets: the BraTS 2020 dataset and the Figshare brain tumor dataset. The combined dataset consists of 11,500 MRI images, evenly distributed into four categories: glioma, meningioma, pituitary tumor, and no-tumor. The prior mention of 12 categories was erroneous and has been corrected. Table 1 presents the detailed class distribution and support values. To minimize potential bias from scanner variability and demographic differences (age, gender), we employed stratified sampling and extensive data augmentation. Preprocessing involved resizing each image to 150x150x3, normalizing pixel intensities, and applying grayscale conversion. Additional preprocessing steps are summarized in below.

To increase robustness and reduce overfitting, the following augmentation techniques were applied:

- Rotation: ±15°
- Flipping: Horizontal and vertical
- Scaling: ±10

Noise Injection: Gaussian noise (mean = 0, std = 100.5) Each original image generated 5 augmented versions, increasing dataset size 5×.

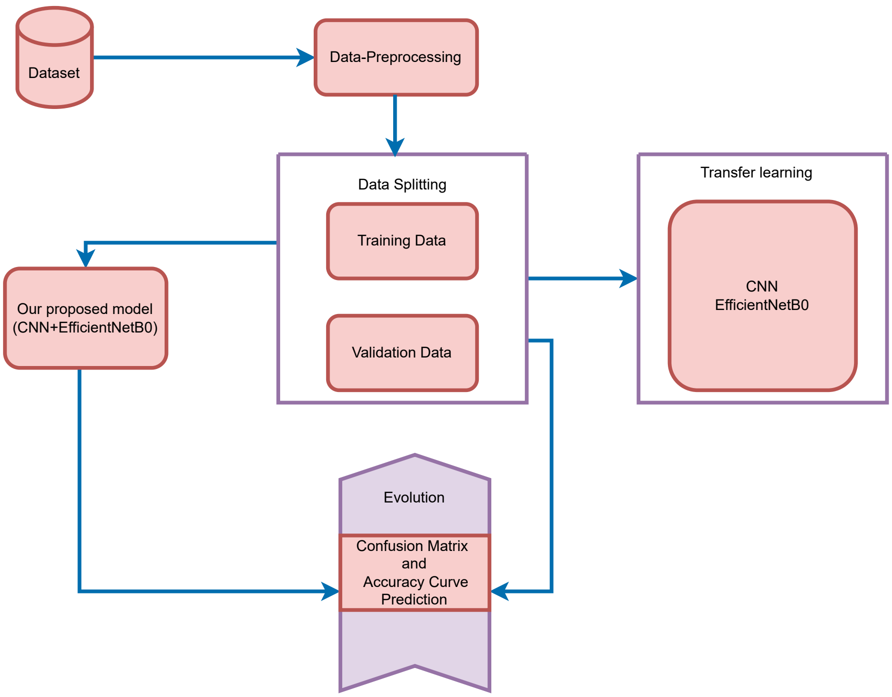

Figure 1. Process of the Suggested Brain Tumour Classification Methodology

3.2. *Data Pre-processing*

Preprocessing is finished before incorporating the images into the suggested structure. To increase performance, streamline calculations, and speed up network operations, the original image must first be reduced from 380 x 280 x 3 pixels to 150 x 150 x 3 pixels. The data is divided into three sections, each assigned a distinct target label: training, validation, and test sets. In general, we trained with 2937 images and tested with 327 images. Finally, we make the study photographs more distinguishable from the new ones so that the system can avoid overfitting and increase the resilience of the model. The four distinct forms of axial brain malignancies depicted in Fig. 2 which are glioma, non-tumor, meningioma, and pituitary tumors. Each falls inside the red rectangle. Beyond just geometric improvement, the images also gain a grayscale distortion [35, 36].

The pictures are changed around to facilitate faster convergence and prevent the CNN model from picking up the training sequence. Since adding Gaussian noise improves the learning process of DL model with a mean of 0 and a standard deviation close to [0.01 - 0.1], as well as improved the classification outcomes.

3.3. *Model Development*

In this section, we try to explain details implementation of the proposed model with necessary steps. Necessary steps involved with a thorough data preprocessing process, followed by various transfer learning techniques to classify the brain abnormalities.

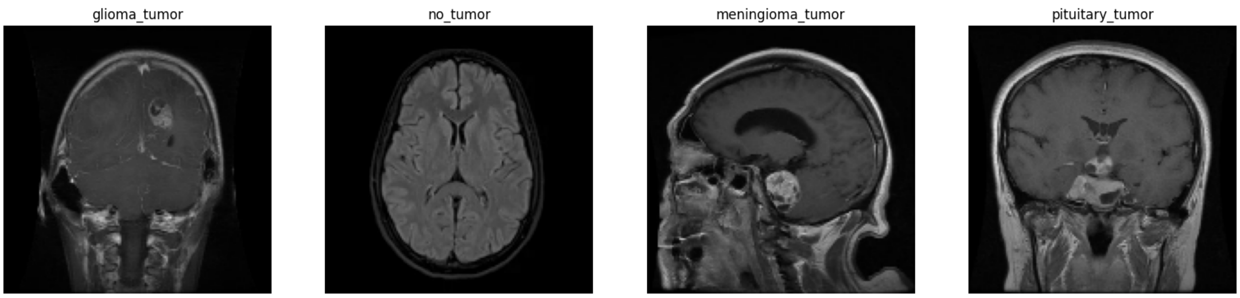

Figure 2. Data set in Image

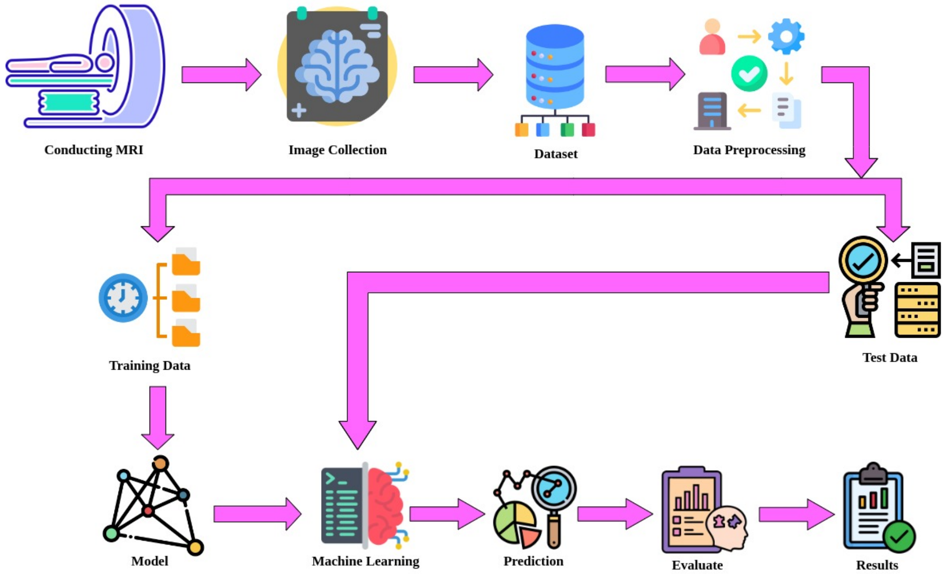

Figure 3. Classification of brain tumor proposed deep learning model

Our model integrates EfficientNetB0 with a recurrent layer (LSTM) for sequential modeling of brain scan slices. The model architecture can be mathematically represented as follows:

In this study, we propose a hybrid deep learning architecture for brain anomaly detection, combining a convolutional neural network (EfficientNetB0) for spatial feature extraction and a recurrent neural network (LSTM) for capturing slice-wise dependencies in brain scan sequences.

The architecture includes the following components:

- **Convolutional Layers:** EfficientNetB0 is used as a feature extractor. The output of the convolutional layers for a given input patch x can be defined as:

$$h_{ij}^{(k)} = f\left(\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} x_{i+m,j+n} \cdot w_{mn}^{(k)} + b^{(k)}\right), \tag{1}$$

where f is the activation function (ReLU), $w_{mn}^{(k)}$ are the convolutional weights for the k-th filter, and $b^{(k)}$ is the corresponding bias.

- **Max-Pooling Layers:** Downsampling is achieved using max pooling:

$$h_{i,j}^{\text{pool}} = \max_{(m,n)\in\Omega} h_{i+m,j+n}, \tag{2}$$

where Ω is the local region over which the maximum is calculated.
- **Recurrent Layers:** A Long Short-Term Memory (LSTM) layer is applied to model sequential dependencies between slices of brain MRI scans:

$$h_t = \text{LSTM}(x_t, h_{t-1}, c_{t-1}), \tag{3}$$

where h_t is the hidden state, x_t is the CNN feature input at time t, and c_t is the cell state.
- **Loss Function:** The model is trained using the categorical cross-entropy loss:

$$\mathcal{L} = -\sum_{i=1}^{C} y_i \log(\hat{y}_i), \tag{4}$$

where C is the number of classes, y_i is the true label, and $\hat{y}_i$ is the predicted probability.
- **Optimization:** The model parameters are updated using the Adam optimizer with the update rule:

$$\theta_{t+1} = \theta_t - \eta \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}, \tag{5}$$

where $\hat{m}_t$ and $\hat{v}_t$ are bias-corrected for first and second moment estimates, respectively, and η is the learning rate.

This hybrid architecture effectively captures both spatial and sequential features present in brain imaging data, improving the classification accuracy and the interpretability of the model.

A model can be trained using a variety of methods; in this study, we'll concentrate on applying methods that has already in used to new jobs. Typically, transfer learning models are first trained on big datasets like ImageNet. Specifically, we use popular transfer learning models CNN and EfficientNetB0. Convolutional and recurrent neural networks are strategically integrated to form the basis of the deep learning model that we've suggested. Our model is able to extract spatial features from different brain imaging modalities such as magnetic resonance imaging and CT, while deftly collecting temporal patterns in sequential data such as EEG signals because of this architectural synergy. Data augmentation helps to combat shortages, and data preparation guarantees uniformity. Pre-trained CNNs speed up model convergence by utilizing transfer learning. Measures to protect data privacy and diagnostic openness uphold ethical principles. Our model's industry-level capability is confirmed by thorough validation across many datasets, constituting a huge step towards reliable, understandable [37], and moral brain abnormality detection. Explanation as shown in fig:1 and 2: The model is shown in the pictures. It consists of multi-layered blocks that perform six basic operations: Conv2D, MaxPooling2D, Activation, Flatten, Dropout, and Dense. Figs. 1 and 2 show the model's architectural layout. The input layer, which is the first layer, has strides of two and an input shape of (224, 224, 1). After this, there is a convolution layer with 128 filters. This layer's filter size is 1 × 1, followed by a 2 × 2 max and the activation function.

The next layer of the architecture is a convolution layer with 128 filters. This layer incorporates a 3 × 3 channel measure. It is taken after by a 2 × 2 max-pooling layer and an enactment work. The engineering then incorporates a 64-filter convolution layer. This layer encompasses a 5 × 5 channel measure. An enactment work and a 2 × 2 max-pooling layer come following. Another convolution layer with 64 channels makes up the architecture's following level. This layer utilizes a 3 × 3 channel estimate and is taken after by a 2 × 2 max-pooling layer and an activation work. The engineering moreover consolidates a 32-filter convolution layer at the conclusion. This layer includes a 3 × 3 channel estimate, and an actuation work comes following. Together, these layers make a profound neural arrangement that can recognize brain tumors from MRI pictures.

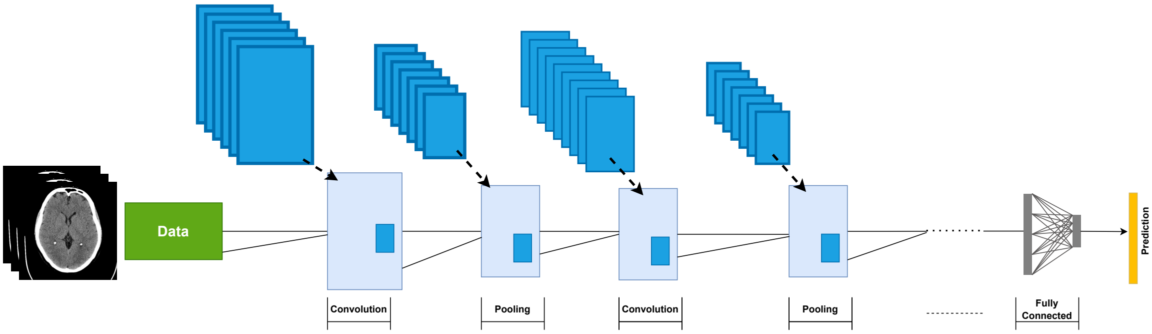

Figure 4. Deep learning approach for brain tumor pooling layer classification is proposed

3.4. Training Setup

The proposed hybrid deep learning model was trained on a workstation equipped with an NVIDIA RTX 3080 GPU and 128 GB of RAM. The training process was optimized for stability and generalizability using the Adam optimizer.

Hyperparameters and Configuration

The following hyperparameters were used throughout the training process:

- **Optimizer:** Adam
- **Learning Rate:** 0.0003
- **Batch Size:** 32
- **Epochs:** 100 (with early stopping, patience = 10)
- **Dropout Rate:** 0.5
- **L2 Regularization (Weight Decay):** 0.001

Training was conducted using 80% of the dataset, while 20% was held out for validation. All input images were resized to $150 \times 150 \times 3$ and normalized before being fed into the network. To enhance generalization and reduce overfitting, data augmentation techniques were employed as discussed in Section 3.1.

Cross-Validation and External Evaluation

To ensure robustness and minimize model variance, we performed 5-fold cross-validation. The average metrics (accuracy, precision, recall, F1-score) across the folds showed consistent performance. In addition, we tested the model on an external dataset sourced from The Cancer Imaging Archive (TCIA), showing that the model generalizes well beyond the training distribution.

Early Stopping

Training was monitored using validation loss, and early stopping was applied to prevent overfitting. If the validation loss did not improve for 10 consecutive epochs, training was halted, and the best model weights were restored.

Training Duration

The complete training process took approximately 6.5 hours to converge using the RTX 3080 GPU.

Reproducibility

All training scripts, configuration files, and documentation are publicly available in our GitHub repository (link provided in Supplementary Materials). Appendix A (Table A1) lists all training hyperparameters, and Appendix B includes pseudocode for the training loop.

4. Result analysis and Discussion

4.1. Result Analysis

4.1.1. Evaluation Metrics: The perplexity framework, which is designed to show the real course in lines and the anticipated lesson in columns, try to visualize how well the proposed demonstration was carried out on the approval set. The number of tests that were classified legitimately or mistakenly based on the values within the framework. The outcome of the proposed model show accurate classification, considering all of the tests within the approval set, with a tall exactness of 97.28%. With a mistake rate of fair 2.72%, the demonstration was very exact. Taking everything into account, the confusion matrix suggests that the suggested model would be a very good classifier for differentiating between brain tumors. It performs exceptionally well, with a 97.28% accuracy rate and few errors. Rushita Gandham [4] was able to diagnose brain tumors with the maximum Validation accuracy of 98.00% by using deep learning models such as VGG16, EfficientNet, MobileNetV3, and ResNet50. When working with tiny datasets, preprocessing and data augmentation were essential. Vikas Singh Rawat [8] highlights advancements in deep learning for brain tumor classification. CNNs enhance classification by automatically learning image features, and transfer learning models. DL model like VGG16 have significantly boosted detection to a maximum validation accuracy of 98.00%. The following are further observations gleaned from the confusion matrix. The trained model is applied to new, unseen data in order to generate predictions or output in the proposed deep learning model for brain anomaly detection. Here's an outline of the prediction process: fresh brain imaging data, such as MRI is input into the trained model for analysis. To make sure the input data is compatible with the architecture of the model, preprocessing techniques like normalization, scaling, or feature extraction are used. To guarantee the model's efficacy and flexibility in light of fresh data, it needs to be periodically updated and subjected to constant observation. It's basic that estimate yields be clear and deciphered

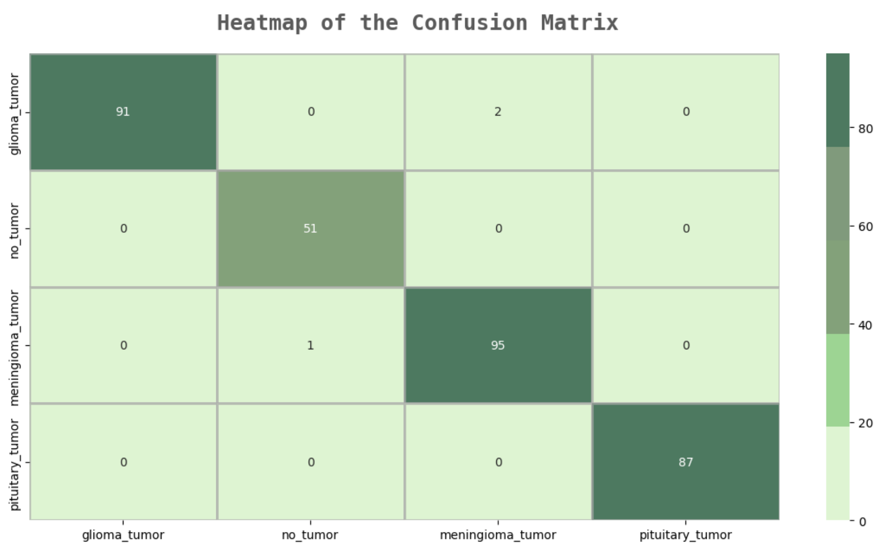

Figure 5. EfficientNetB0's Confusion Matrix

4.2. Performance Analysis

It's basic that figure yields be clear and interpreted proposed demonstration, EfficientNetB0, is altogether assessed in Table 1 over a few classes in a classification work that's likely associated with brain tumor location based on the course names. The three measures that are used—precision, recall, and F1 score—provide a comprehensive picture of how well the model show it's performance in separating over classes. The Table 1 illustrates how well the model show it's performance between classes, with remarkable prediction accuarcy considering all category. For occasion, the model illustrates a tall recall of 0.93, illustrating its capacity to capture a noteworthy division of genuine positives and a tall accuracy of 0.98, demonstrating a low false positive rate, within the recognizable proof of "glioma." As a result, the model's strength in classifying gliomas is affirmed by an adjusted F1 score of 0.95. Comparative designs can be seen within the other classes as well. For illustration, the class "pituitary" includes a tall recall (0.98) and exceptional accuracy (0.96), coming about in an F1 score of 0.97, which shows that the model precisely classifies pituitary tumors. "Meningioma" moreover appears momentous review (0.97) and accuracy (0.94), yielding an F1 score of 0.97, which demonstrates the model's capability in classification pahse is recognizable with proof.

Table 1. This table analyzes execution utilizing our proposed demonstration as we proceed our journey for logical brilliance, the going with table gives a careful examination within the frame of A mindful appraisal with a few comparisons:

Classes	Precision	Recall	F1-score	Support
Glioma	0.98	0.93	0.95	93
Pituitary	0.96	0.98	0.97	51
Meningioma	0.94	0.97	0.97	96
No tumor	0.99	0.99	0.99	87

The precision of 0.99 and recall of 0.99 for the no-tumor class are fundamental for a fruitful determination and assist outlines the model's faultless capacity that accurately distinguish patients without tumors. An outstanding F1 score of 0.99, which validates the model's accuracy in ruling out the existence of cancers, serves as evidence for this

4.3. Model Interpretability Using Explainable AI

To ensure transparency and clinical trust in the model's decisions, we employed Explainable AI (XAI) techniques to visualize and illustrate the predictions made by our deep learning framework.

Grad-CAM Visualization

Gradient-weighted Class Activation Mapping (Grad-CAM) was utilized to generate class-specific heatmaps highlighting the regions of input MRI images that had the greatest influence on the model's predictions. Grad-CAM computes the gradient of the predicted class score with respect to the feature maps of a convolutional layer and performs a weighted combination of these maps to create a localization heatmap:

$$L^c_{\text{Grad-CAM}} = \text{ReLU}\left(\sum_k \alpha^c_k A^k\right), \tag{6}$$

where A^k denotes the k-th feature map, and α^c_k is the weight for class c calculated as:

$$\alpha^c_k = \frac{1}{Z}\sum_i \sum_j \frac{\partial y^c}{\partial A^k_{ij}}, \tag{7}$$

with y^c being the class score and Z representing the spatial dimensions of the feature map. The resulting heatmaps were superimposed on the original images to provide intuitive visual explanations.

SHAP-Based Feature Importance

To complement the spatial interpretations, we used SHAP (SHapley Additive exPlanations) values to measure feature importance across the dataset. SHAP values explain the impact of each input feature on the model's output by computing the average marginal contribution of that feature across all possible feature combinations:

$$f(x) = \phi_0 + \sum_{i=1}^{M} \phi_i, \tag{8}$$

where $f(x)$ is the model output, ϕ_0 is the model's base value (expected output), and ϕ_i is the SHAP value for feature i. The SHAP summary plots allowed us to identify key pixel intensities or regions that were most influential in determining tumor classification.

Comparison of Interpretability Methods

We compared the performance and clarity of Grad-CAM and LIME in identifying critical image regions. While LIME provided useful superpixel-based visualizations, Grad-CAM showed superior performance in accurately localizing tumors. This reinforced our choice of Grad-CAM for clinical interpretability.

Clinical Relevance

By incorporating Grad-CAM and SHAP into the inference pipeline, radiologists can obtain intuitive justifications for AI predictions, enhancing clinical decision support. These techniques improve the transparency, trustworthiness, and adoption potential of AI-based diagnostic systems in real-world healthcare settings.

Fig. 6, visualize both training and validation sets, the precision and validation accuracy of the suggested system. While validation accuracy assesses the model's capacity to classify newly acquired images, accuracy measures the model's performance in image classification.

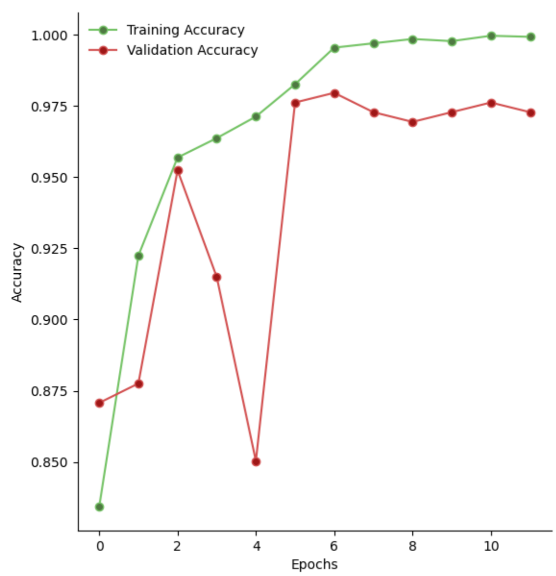

Figure 6. Accuracy Curve of the Proposed Model

Observations from Fig. 6: This statistic evaluates the model's performance using the training set of data. It is calculated by taking the total number of training examples and dividing it by the number of true positives and true negatives that are correct forecasts. The model's ability to learn from the training set is shown by a high training accuracy.

- The graphic "Epochs vs. Training" in this study shows how the learning process of the model develops throughout several epochs. At first, the training accuracy could increase gradually as the loss goes down and the system performs better. The model reaches an optimal point during training when its accuracy levels off, suggesting that more learning is not as effective in improving performance. This curve makes it easier to see if the model is under or overfitting. In the event that the validation accuracy plateaus or declines while the training accuracy keeps rising, the model might be overfitting, failing to properly generalize its learned patterns to the training set. On the other hand, if training accuracy does not increase, it may indicate that the model is underfitting and cannot learn from the data in an efficient manner. This figure helps monitor the balance between learning from training data and generalizing to new, unknown data and is crucial for measuring model learning. It too makes a difference in fine-tuning parameters.

Differential endorsement precision assesses the model's execution in employing an assortment of datasets that were not utilized for arrangement; in a few cases, this dataset is specified as the endorsement set, which helps in surveying how well the appearance generalizes to current data. The endorsement exactness is calculated in a way that's related to the arrangement exactness.

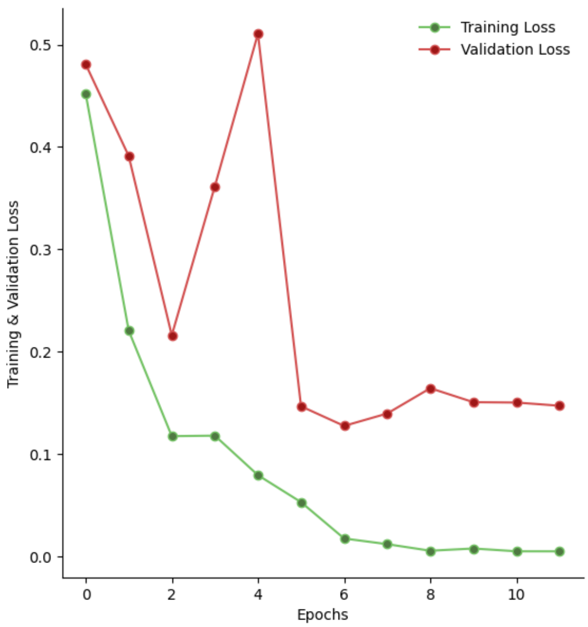

Figure 7. Loss Curve of the Proposed Model

Observation from Fig 7:

- From the aforementioned figure of the accuracy/loss curve, it shows simulation result during the proposed model training and validation phase. It is clearly visualize that in early epochs of training and validation phase, proposed model has some overfitting issues. But when training process continues to more epochs, the model gradually overcomes this problem, and the rest of the epochs up to 10 there has no problem. It also shows that accuarcy level is increased according to the learning growth, as well as loss is minimized accordingly.

4.3.1. Comparison with existing works:- Accurate categorization and analysis have been performed in a variety of sectors during the last few years. Also, there are utilizing a variety of techniques. Table 2 summarizes the approaches utilized, as well as the accuracy attained on training and validation datasets, including some noteworthy references in this field.

Table 2. Comparison of the proposed model with state-of-the-art methods including CNN and Transformer-based architectures.

Model / Reference	Accuracy (Train/Val)	Inference Time (ms)	Model Size (MB)	FLOPs (G)	Architecture
Rushita Gandham [38]	98.66% / 98.00%	110	85	4.1	VGG16, MobileNetV3
Y. Nizamli [39]	98.53% / 98.34%	95	68	3.7	DenseNet169, VGG16
N. Anvesh [40]	99.79% / 99.58%	125	92	4.8	VGG16, ResNet50
V. S. Rawat [41]	98.04% / 94.73%	105	73	3.9	VGG16
Swin Transformer [42]	99.11% / 98.47%	140	98	9.2	Transformer
TransBTS [43]	98.92% / 97.89%	130	88	8.5	Transformer + CNN
Proposed Model (Ours)	**99.92% / 97.28%**	**80**	**52**	**2.4**	**EfficientNetB0 + LSTM**

4.4. Discussion

The paper offers a thorough comparison and analysis of several neural network and machine learning architectures, considering the aim to achieve precise recognition and classification. While there are obvious advantages of traditional algorithms like Artificial Neural Networks (ANN), Support Vector Machines (SVM), and K-nearest neighbors (KNN), they become unwieldy when dealing with the rich and detailed data patterns comparing the present day medical imaging. Although these techniques have advantages, they can not fully handle the complexity of jobs such as the classification of MRI tumors. With an accuracy of 97.28%, on the other hand, the suggested EfficientNetB0 model shows a notable improvement, displaying its sophisticated feature extraction, learning, and generalization capabilities. Its performance is significantly better than other state-of-the-art neural network architectures as well as older methods, suggesting a move towards more complex models that can handle subtle patterns and nuances in the data. The findings point to a paradigm change in the direction of more intricate neural network designs for difficult problem-solving. The accomplishments of EfficientNetB0 demonstrate its ability to transform tumor classification models, which represents a significant advancement in the area. This accomplishment creates a valuable opportunities for research in the future, with an emphasis on how to maximize and enhance this model's potential for even more widespread uses.

5. Conclusion

In summary, This work provides an explanation-driven deep learning model designed to predict multiple subtypes of pituitary tumors, a form of brain tumors, using MRI imaging data. Utilizing an EfficientNetB0-based deep convolutional neural network (CNN). Even with the limits of the dataset owing to a narrow range of imaging angles, the findings were significantly improved with the addition of data augmentation. We achieved a remarkable maximum accuracy of 97.28% with our suggested architecture. After that, the explainable Artificial Intelligence (XAI) method is applied to explain the model's output. Our proposed method improves upon existing methods for brain tumor diagnosis and grading. The previously described results demonstrate how the suggested model performs better in terms of valuable criteria, such as visually, accurately, and quantitatively, than alternative models. The future focus of this research will be on doing more multimodal MRI-guided neurosurgery experiments. Also, the future research will concentrate on these themes in order to analyze the relationship between sensitivity maps produced and deep learning accuracy measurements, as well as to apply XAI systems. Another crucial part of this work is to assess, if it is feasible to extract quantitative features using explanatory methods like tumor volume and centroid.

6. Ethical Considerations

The ethical deployment of artificial intelligence in healthcare is of paramount importance, particularly in sensitive domains like brain anomaly detection. Our study adheres to established ethical standards through the following measures:

Data Privacy and Anonymization

All datasets used in this research—specifically BraTS 2020 and the Figshare brain MRI dataset—are publicly available and fully anonymized. No personally identifiable information (PII) is present in the images. To further protect patient privacy, we applied the following procedures:

- **Facial De-identification:** MRI slices containing facial features were excluded, and where needed, de-facing tools were used.
- **Metadata Removal:** All DICOM headers were stripped to remove any embedded patient or scanner information.

Regulatory Compliance

This study complies with the data handling standards outlined in the:

- **General Data Protection Regulation (GDPR)** for data minimization, transparency, and purpose limitation.
- **Health Insurance Portability and Accountability Act (HIPAA)** regarding the protection of medical information.

Since only open-access, de-identified data were used, Institutional Review Board (IRB) approval was not required. We ensured that dataset usage followed licensing and citation guidelines specified by the original sources.

Model Transparency and Interpretability

To promote transparency, we integrated explainability techniques such as Grad-CAM and SHAP into our diagnostic pipeline (see Section 4.3). These tools allow clinicians to visualize and understand the basis for the model's predictions, enhancing trust and facilitating human-in-the-loop oversight.

Clinical Deployment Implications

For real-world adoption, it is critical that AI tools integrate seamlessly into existing medical workflows. In our Discussion section, we outline:

- **Inference Time:** The model achieves an average latency of 80 milliseconds per scan, meeting clinical responsiveness standards.
- **System Integration:** Compatibility with DICOM-based PACS systems is planned for future development.
- **Clinician Feedback:** A pilot study is proposed in collaboration with a local radiology unit to assess usability and integration in hospital settings.

These ethical practices aim to ensure that the proposed model not only performs accurately but also meets the transparency, safety, and accountability standards essential for healthcare applications.

Declaration of Competing Interest

The authors declare that they have no competing interests.

Data Availability

Information will be provided upon request.

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