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IV3RN101: A Novel Deep Learning Model for Brain Tumor Classification with Comparative Performance Evaluation

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ABSTRACT

This study proposed IV3RN101, a novel deep learning model that ensembles InceptionV3 and ResNet101 to leverage their strengths for improved feature extraction and classification. InceptionV3 provides multi-scale feature learning using factorized convolutions, while ResNet101 ensures deep hierarchical feature representation through residual connections. By combining these architectures, IV3RN101 captures both fine-grained local details and global semantic features, enhancing accuracy in complex image classification tasks. The fusion can be achieved through feature concatenation, decision-level voting, or attention-based fusion to optimize performance. These hybrid approaches makes IV3RN101 well suited for tasks requiring robust medical imaging, such as multiclass classification of brain tumor prediction thereby enhancing predictive performance and adapt ability to dataset variations. The dataset used for training and evaluation is obtained from Kaggle, ensuring a solid foundation for model development. The efficiency of the proposed model is compared with various convolutional neural network (CNN) architectures, including VGG19, InceptionV3, ResNet101, MobileNetV3, and a custom-designed CNN model. Furthermore, a web-based application is built using Flask to provide real-time predictions by seamlessly integrating with the TensorFlow-based deep learning model. The experimental results demonstrate that the proposed IV3RN101 model outperforms existing CNN architectures in terms of accuracy, robustness, and adaptability for brain tumor classification. The integration of a Flask-based web application further enhances its practicality by enabling real-time medical diagnosis.

Keywords: Brain Tumor Classification, Ensemble Learning, TensorFlow, InceptionV3 and ResNet101 (IR)

1. INTRODUCTION

Accurate identification and categorization of brain tumors play a crucial role in medical imaging and diagnosis, historically reliant on manual interpretation by skilled radiologists. This manual approach, while valuable, has inherent limitations in terms of accuracy, consistency, and scalability. The effectiveness of classification techniques directly influences treatment strategies and significantly affects patient prognosis [1]. However, recent advancements in deep learning algorithms, notably within the TensorFlow framework, have revolutionized the field by introducing automated methods for brain tumor diagnosis. This work delves into the intricate landscape of brain tumor classification, leveraging the advancements in deep learning, particularly through frameworks like TensorFlow, to revolutionize medical image analysis with automated and precise solutions [2-3]. These automated techniques not only enhance accuracy but also improve scalability in tumor classification processes. Deep learning algorithms automatically extracting meaningful patterns from MRI scans. These algorithms excel at discerning subtle features and nuances within the images and reliable tumor classification outcomes [4]. The term multiclass brain tumor classification" encapsulates a multifaceted set of challenges and opportunities in healthcare. This process involves designing and implementing advanced deep learning frameworks that can accurately differentiate between multiple brain tumor types, such as glioma, meningioma, and pituitary tumors. The classification relies on MRI scans as the key imaging technique for diagnosis. These models harness the power of neural networks and advanced pattern recognition techniques to unravel complex features within medical images, enabling not just the identification but also the characterization of tumors granularity [5]. Central to the success of such endeavors is the availability of rich and well-curated datasets, and in this project, we utilize a comprehensive dataset sourced from Kaggle. Annotated datasets, such as the one sourced from Kaggle and utilized in this work [6], are indispensable for training and validating deep learning. This dataset, annotated with critical information, serves as the bedrock for training, validating, and fine-tuning the deep learning models. These datasets contain a diverse range of MRI images, capturing variations and complexities present in real-world tumor cases. Through meticulous data preprocessing, augmentation techniques, and rigorous model training regimes, our goal is to attain levels of accuracy and reliability that can significantly augment clinical decision-making processes [7]. This background provides the foundation for this study’s objectives, which aim to contribute to AI-driven health- care by developing accurate, efficient, and user-friendly solutions for multiclass brain tumor classification. By integrating advanced deep learning algorithms with annotated datasets, this research seeks to ultimately benefiting patients and healthcare providers by improving diagnostic capabilities and treatment outcomes.

Agarwal et al. (2021) evaluated ten modified deep learning models and assessed using macro-average metrics, and InceptionV3 emerged as the best performer in cross validation schemes, indicating its robustness and generalization capabilities across the dataset. This research provides a comprehensive comparison of well-known deep neural networks and highlights the challenges of working with unbalanced datasets in medical imaging [11]. Chan et al. (2020) highlights the transformative impact of deep neural networks on medical imaging, improving accuracy and efficiency in disease detection. The authors discuss various deep learning models applied to diagnostic radiology, emphasizing their role in enhancing clinical decision-making. They conclude that deep learning-driven CAD systems have the potential to revolutionize medical diagnostics by providing more reliable and automated assessments [12]. Amin et al. (2022) study examines various algorithms, including deep learning models, and their effectiveness in analyzing MRI scans. The authors highlight key challenges such as data scarcity, model interpretability, and computational complexity. They conclude that advanced machine learning approaches significantly enhance tumor classification accuracy, paving the way for improved medical diagnostics [13]. Abid and Munir (2025) conducted a systematic review and their study explores various deep learning architectures, including CNNs and hybrid models, used in medical imaging. The review highlights the advantages of automated tumor analysis in improving diagnostic accuracy and treatment planning. Challenges such as data scarcity, model generalization, and computational costs are discussed. The study emphasizes the need for robust and efficient deep learning models for clinical applications [14]. Appasami and Savarimuthu (2025) explored emphasizes privacy-preserving deep learning models that enable collaborative training without sharing raw patient data. The proposed approach enhances data security while maintaining high classification accuracy. The research discusses challenges like communication overhead and model convergence in federated settings [15]. Ba¸sarslan (2025) proposed a novel brain tumor classification model, MC&M-BL, which leverages convolutional networks for feature extraction and BiLSTM for sequential pattern learning, improving classification accuracy. The hybrid approach enhances tumor detection by capturing both spatial and temporal dependencies in MRI images. Experimental results demonstrate superior performance compared to traditional deep learning models. The research highlights the potential of combining CNN and BiL STMforrobust medical image classification [16]. Hosny et al. (2025) combines multiple deep learning architectures to enhance classification accuracy while ensuring model interpretability. Explainable AI techniques are integrated proposed approach demonstrates improved diagnostic reliability compared to single deep learning models. The research highlights the importance of interpretability in medical AI applications for clinical trust and adoption [17]. Karpakam and Kumareshan (2025) study compares the performance of DIR-GAN on MRI, X-ray, and FigShare datasets, demonstrating its effectiveness across different imaging modalities. The model improves tumor classification accuracy by generating high-quality synthetic data for training. Experimental results show superior performance over traditional deep learning models. The research highlights DIR-GAN's potential in overcoming data limitations and enhancing medical image analysis [18]. Dhakshnamurthy et al. (2024) the performance of pre-trained deep learning architectures in analyzing MRI scans for accurate diagnosis. The authors emphasize the efficiency of transfer learning in reducing computational complexity while maintaining high classification accuracy. They conclude that these models offer a promising approach for improving automated brain tumor detection in medical imaging [19]. Disci et al. (2025) utilized pre-trained deep CNN models for brain tumor classification, enhancing feature extraction and classification accuracy. Their approach leverages transfer learning to improve model efficiency and diagnostic precision. Experimental results show significant improvements in tumor detection performance. The study highlights the effectiveness of deep learning in medical image analysis. Their findings emphasize the role of pre-trained networks in advancing auto mated diagnosis [20]. Khan et al. (2025) enhances feature extraction and model efficiency by fine-tuning deep learning architectures. MRFO optimizes hyper parameters for better classification accuracy and convergence speed. The improved residual blocks strengthen feature learning, reducing computational complexity. Experimental results demonstrate superior performance compared to conventional deep learning models in brain tumor classification [21]. Liu et al. (2025) integrates convolutional and bidirectional fusion networks to enhance feature extraction and classification accuracy. Routing attention mechanisms improve information flow between layers, leading to better tumor differentiation. Experimental results show that ConvBiFuseNet outperforms traditional CNN-based models in terms of accuracy and efficiency. The study highlights the potential of parallel fusion architectures in medical image analysis [22]. Amin et al. (2025) proposed a dual-method approach for brain tumor segmentation using UNet for semantic segmentation and Mask R-CNN for instance segmentation. Their model enhances tumor detection by accurately segmenting tumor regions at both pixel and object levels. The combination of UNet and Mask R-CNN improves 4 boundary precision and classification performance. The study highlights the effectiveness of hybrid approaches in MRI-based brain tumor analysis [23]. Mansur et al. (2025) presented a deep learning-based approach for brain tumor image segmentation. The study explores various deep learning architectures to enhance segmentation accuracy in MRI scans. Their model effectively identifies tumor regions, improving diagnostic precision and treatment planning. The research compares multiple deep learning techniques, demonstrating the advantages of automated segmentation over traditional methods. Experimental results confirm the model's efficiency in accurately segment ing brain tumors [24]. Ticku et al. (2025) investigated Quantum Convolutional Neural Networks (QCNNs) for brain tumor detection in neuro-imaging. Their approach utilizes quantum computing to improve feature extraction and classification accuracy. The study demonstrates enhanced computational efficiency compared to classical CNNs. Experimental results highlight the potential of QCNNs in medical image analysis. The research emphasizes quantum deep learning as a promising advancement in tumor detection [25].

The models employed in this research encompass a spectrum of architectures which includes a custom-built CNN model (Convolutional Neural Network) designed specifically to excel in this domain, alongside renowned architectures such as VGG19, InceptionV3, ResNet101, and MobileNetV3. Additionally, the exploration of an IV3RN101, which amalgamates the strengths and diverse perspectives of these individual models, underscores our commitment to pushing the boundaries of classification performance [8-10]. However, the impact of these advanced technologies extends beyond the algorithms themselves. An integral part of this project is the seamless integration of the deep learning model into a frontend web application, ensuring accessibility and usability for medical professionals and stakeholders. This amalgamation of cutting-edge deep learning methodologies with user-friendly interfaces represents a significant stride towards democratizing AI-driven healthcare solutions. By pioneering robust, accurate, and user-centric solutions for multiclass brain tumor classification, this research endeavors to spearhead a paradigm shift in AI-driven healthcare applications. Ultimately, the outcomes of this project aim to significantly benefit patients, clinicians, and healthcare systems globally.

2. MATERIALS AND METHODS

Figure 1 shows the Multiclass Brain Tumor Classification employed a structured methodology, starting with the acquisition followed by data preprocessing involved techniques like image resizing, normalization, and augmentation to enhance diversity and quality.

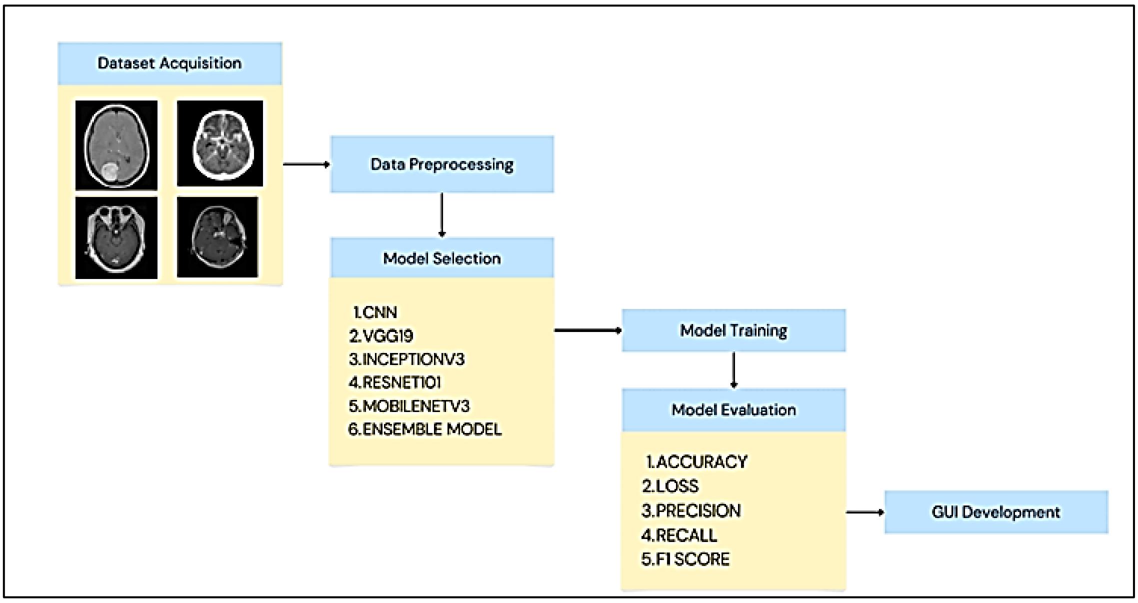

Figure 1: Flowchart of the Multiclass Brain Tumor Classification Methodology

Various deep learning models including proposed IV3RN101 along with a custom CNN model, VGG19, InceptionV3, ResNet101, and MobileNetV3 were trained on the preprocessed dataset. Model evaluation included testing on separate datasets and optimization techniques such as fine-tuning to improve accuracy and robustness. Additionally, a Flask-based GUI was developed for real-time tumor classification and result visualization for user experience enhancement.

Proposed IV3RN101 model: The IV3RN101 in deep learning models has gained significant attention for its ability to handle multiple architectures. In this section, we detail the steps involved in implementing an IV3RN101 ensemble model. We begin by importing essential libraries required for data handling, deep learning, and visualization. The Brain Tumor MRI Dataset from Kaggle is utilized, which comprises MRI images representing glioma, meningioma, pituitary tumors, and non-tumor cases [26]. To improve the quality and diversity of the dataset, various data preprocessing techniques such as image resizing, normalization, and augmentation are applied. Image Data Generator is used to augment data for training, validation, and testing sets. These steps ensure that the model receives well-structured input, enhancing its learning capability and generalization performance. The proposed model IV3RN101 architecture leverages an ensemble of InceptionV3 and ResNet101, chosen for their unique strengths in feature extraction and capturing intricate visual patterns. This fusion enhances the model's ability to extract both local and global features, ultimately improving classification accuracy for brain tumor detection which is shown in Algorithm 1. Combining the InceptionV3 and ResNet101 models into ensemble leverages the unique strengths of selected architecture, leading to enhanced performance in brain tumor classification is shown in Figure 2. The ResNet101 model is known for its deep hierarchical feature representation through residual connections, while the InceptionV3 model excels in capturing intricate visual features. This combination allows the ensemble model to handle complex data structures effectively, detect subtle anomalies in brain tissues, and achieve accurate tumor identification through comprehensive analysis across multiple layers. The ensemble model takes inputs through an input layer, which

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is then separately fed into the InceptionV3 and ResNet101 models. The outputs from these models are concatenated or merged using a suitable layer, such as a concatenate layer. In this case, the concatenated output is passed through batch normalization to stabilize and speed up the training process. Dense layers with dropout regularization are then applied to the normalized output, ensuring robust learning and preventing overfitting. The final dense layer with softmax activation is responsible for the final classification task, predicting the probability distribution across the classes (types of brain tumors). The ensemble architecture enhances its capability to handle diverse and complex features present in brain tumor images. By capitalizing on the complementary strengths of InceptionV3 and ResNet101, the ensemble model becomes a robust choice for brain tumor classification, providing a comprehensive and accurate analysis of brain tumor images.

Algorithm 1 IV3RN101 model

1: Initialize System Configuration

2: Load essential Libraries

3: Select Dataset: Brain Tumor MRI Dataset from Kaggle

4: **procedure** BUILD_IV3RN101 (input_size, num_classes)

5: Initialize Input Layer:

$$X \in \mathbb{R}^{224 \times 224 \times 3} \quad (1)$$

6: Base models are loaded without the top layers and set as non-trainable.

7: Feature Extraction

8:

$$F_{InceptionV3} = \text{InceptionV3}(X) \quad (2)$$

$$F_{ResNet101} = \text{ResNet101}(X) \quad (3)$$

9: Flatten Outputs

10:

$$F_{InceptionV3\_flat} = \text{Flatten}(F_{InceptionV3}) \quad (4)$$

$$F_{ResNet101\_flat} = \text{Flatten}(F_{ResNet101}) \quad (5)$$

11: Merge the Models

12:

$$F_{merged} = \text{Concatenate}([F_{InceptionV3\_flat}, F_{ResNet101\_flat}]) \quad (6)$$

13: Batch Normalization

14:

$$F_{normalized} = \text{BatchNormalization}(F_{merged}) \quad (7)$$

15: Dense Layers with ReLU Activation

16:

$$D_1 = \text{Dense}(units = 512, activation = \text{relu})(F_{normalized}) \quad (8)$$

17: Dropout Layer

18:

$$D\_1\_dropout = \text{Dropout}(rate = 0.5)(D_1) \quad (9)$$

19: Additional Dense Layer with ReLU Activation

20:

$$D\_2 = \text{Dense}\ (units = 256,\ activation = \text{relu})(D\_1\_dropout) \quad (10)$$

$$D\_2\_dropout = \text{Dropout}\ (rate = 0.5)(D\_2) \quad (11)$$

21: Final Dense Layer with Softmax Activation

22:

$$Y = \text{Dense}\ (units = 4,\ activation = \text{softmax})(D\_2\_dropout) \quad (12)$$

23: Adam optimizer and categorical cross-entropy loss function.

24: **return** Model with specified number of epochs

25: **end procedure**

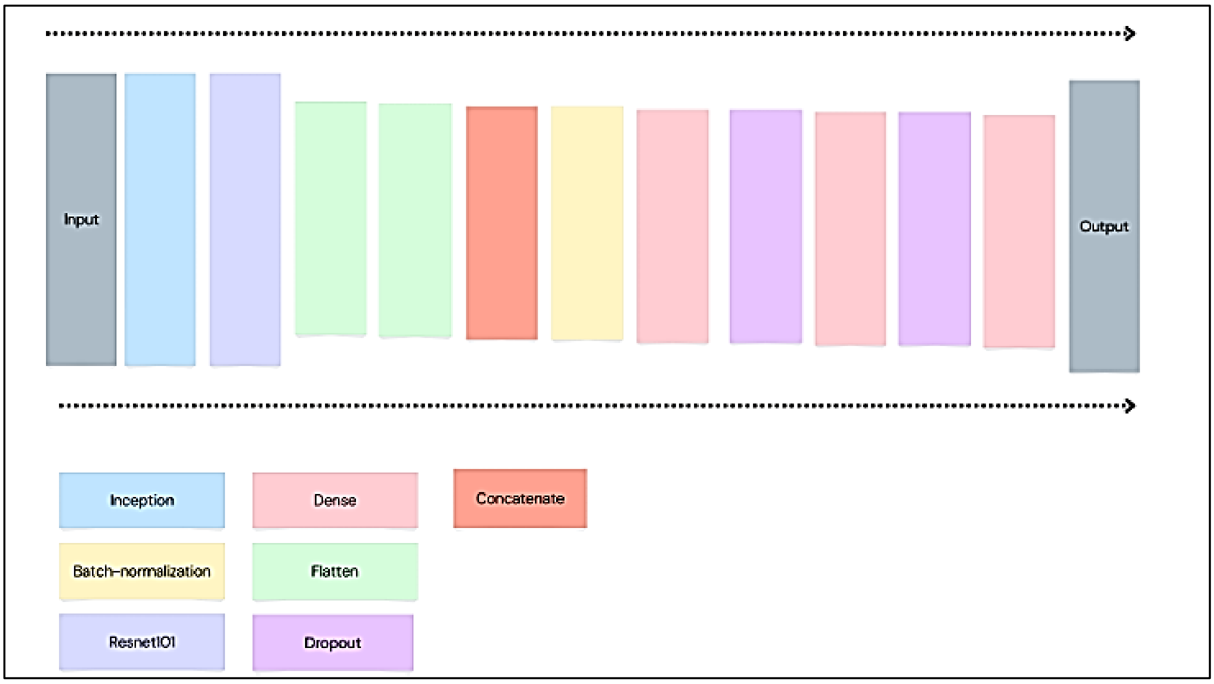


Figure 2: Proposed IV3RN101 model layers

2.1 Dataset Collection

Data collection for this work involved acquiring a comprehensive brain tumor dataset from Kaggle [26], a renowned platform for machine learning datasets which is represented in Figure3. It comprising a diverse array 4 classes and it dataset was meticulously organized into distinct directories for training and testing, with each directory containing subdirectories for various classes of brain images. This structured organization greatly facilitated data management and streamlined model training procedures.

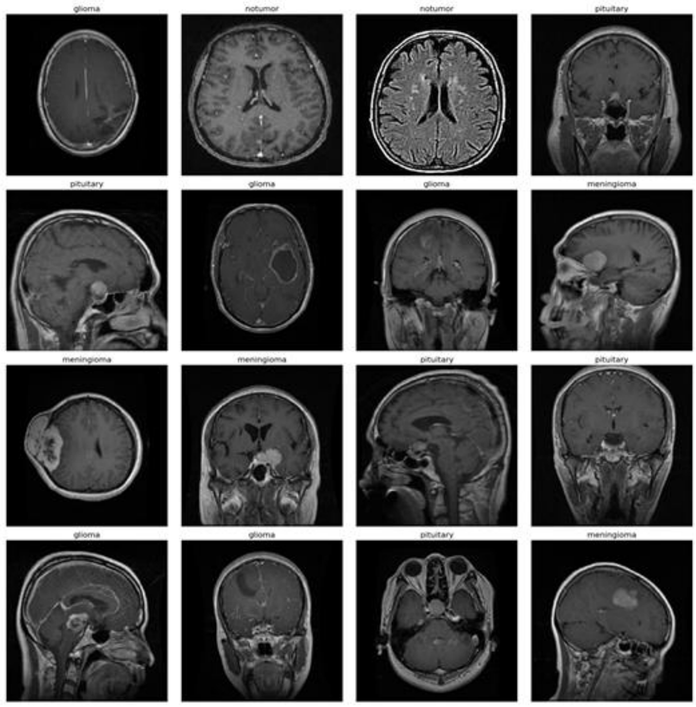


Figure 3: Multiclass Brain Tumor dataset (Sample Images)

2.2 Dataset preprocessing

Preprocessing of the dataset was a pivotal step aimed at optimizing model performance. Rigorous quality control measures encompassed checks for image resolution to ensure uniformity, normalization of pixel values to standardize image intensities across samples, and validation of class labels to ascertain accuracy and correctness in labeling. The distribution of the brain tumor dataset utilized in this project is succinctly summarized in Figure 4, providing valuable insights into the quantity of images available for each class in both the training and testing sets. The significance of data balancing cannot be overstated in machine learning tasks, particularly in classification scenarios involving multiple classes. Imbalanced datasets, the majority class and yielding subpar performance for minority classes. Such imbalance can distort the model's learning process and result in inaccurate predictions, especially for underrepresented classes. To tackle this challenge, maintaining a balanced class distribution within the dataset is imperative. In the domain of brain tumor classification, where different tumor type exhibit varying prevalence rates, achieving a balanced dataset is crucial for model effectiveness and fairness. This project placed special emphasis on data balancing techniques during the dataset preparation phase. The dataset was meticulously curated to ensure equitable representation of each brain tumor class: glioma, meningioma, no tumor, and pituitary. This balanced distribution was attained through careful image selection and annotation from the Brain Tumor MRI Dataset on Kaggle. The distribution of images across classes was validated and adjusted as necessary to prevent any class from dominating the dataset. Techniques such as stratified sampling during dataset splitting, as well as oversampling or undersampling methods, were employed to balance class distribution while preserving dataset integrity and representativeness. By establishing a balanced dataset, the models trained on this data set were able to learn from diverse samples of each class, leading to enhanced generalization and performance across all classes. This balanced distribution mitigated the risk of model bias toward dominant classes, resulting in more accurate and reliable predictions for all tumor types highlighted Fig. 5.

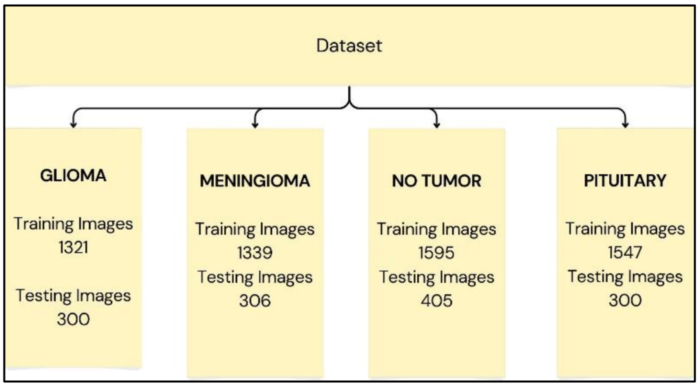


Figure 4: Representation of the dataset Distribution

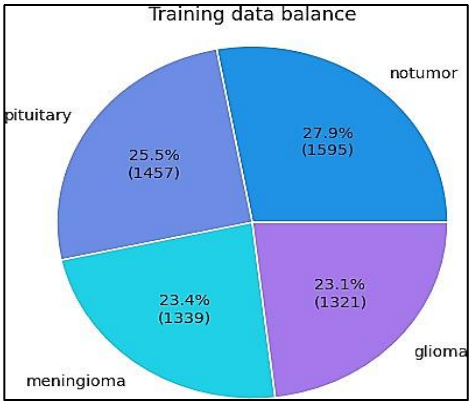


Figure 5: Representation of the balanced dataset

2.3 Dataset Splitting

Data splitting is crucial in machine learning, especially for tasks like brain tumor classification. In this project, using a 50-50 split ratio with random shuffling for reproducibility. This balanced splitting enhances model generalization to new data while ensuring fairness across tumor classes. Image data generators like Keras' Image Data Generator were used to optimize dataset preprocessing and model training. Batch processing with a batch size of 16 and 'flow from data frame' method integration streamlined augmentation and preprocessing, enhancing model robustness and classification accuracy. Image preprocessing standardized images to 224x224 pixels, crucial for CNN compatibility. Data generators facilitated real-time augmentation; diversifying training data and improving generalization. This systematic approach aligns with industry standards for deep learning in medical image analysis, promoting effective model development for brain tumor classification tasks.

2.4 Comparative model evaluation

The efficiency of the proposed model is compared with various convolutional neural network (CNN) architectures, including CNN, VGG19, InceptionV3, ResNet101, and MobileNetV3.

- **CNN(Convolutional Neural Network):** This hierarchical learning mimics how the human visual system processes information, starting from simple features like edges and textures and progressively combining them to recognize more complex structures and patterns [27] . In brain MRI scans, CNNs can detect subtle anomalies, such as irregularities in brain tissues or the boundaries of tumors, by analyzing pixel-level information across multiple layers.

- **VGG19:** It is a deep convolutional neural network known for its architecture with 19 layers. It is widely used in image recognition tasks due to its strong feature extraction capabilities [28]. Despite its depth, it is relatively straightforward to understand and implement, making it a popular choice in deep learning projects requiring high-level image analysis. Leveraging pre-trained weights from datasets like ImageNet, it can capture generic features for fine-tuning in brain tumor classification, while also adapting to specific features relevant to tumor identification. Its ability to learn hierarchical features and its straightforward architecture makes it a robust choice for image-related tasks, including brain tumor classification.

- **InceptionV3:** InceptionV3 is a deep learning architecture renowned for its efficient utilization of computational resources in processing visual data [29]. Designed to balance between model complexity and performance, InceptionV3 excels in capturing diverse feature representations while minimizing computational over head. This architecture incorporates a unique inception module that allows for multi-level feature extraction, enabling the network to learn both local and global features simultaneously. In brain tumor classification, InceptionV3's ability to capture intricate patterns and variations in brain MRI scans makes it a valuable choice. InceptionV3 can generalize well to new tasks while retaining the capacity to adapt to specific features relevant to brain tumor identification. The architecture's depth and breadth contribute to its capability to handle complex data structures, making it effective in detecting subtle anomalies and abnormalities in brain tissues, including tumor boundaries and irregularities, through comprehensive analysis across multiple layers.

- **ResNet101:** ResNet101 introduces skip connections as a result; it can effectively train deep models with hundreds of layers while maintaining strong performance and ease of optimization [30]. In the context of brain tumor classification, ResNet101's depth and resilience to vanishing gradients make it suitable for capturing complex patterns and variations in brain MRI scans. The residual connections allow for better gradient flow, facilitating the learning of intricate features relevant to tumor identification. Additionally, ResNet101's architecture benefits from pre trained weights on large datasets like ImageNet, providing a strong initialization for feature extraction and transfer learning tasks.

- **MobilenetV3:** It improves upon previous versions by enhancing accuracy and computational efficiency [31]. Using depth wise separable convolutions and inverted residuals with linear bottlenecks, MobileNetV3 optimizes parameter efficiency and computational cost while maintaining high accuracy. In the context of brain tumor classification, MobileNetV3's lightweight design and efficient processing make it ideal for real-time applications on mobile platforms. It captures essential features from MRI scans effectively while minimizing computational resources, making it practical for resource-constrained environments. Its ability to leverage transfer learning from pre-trained models like ImageNet further enhances its adaptability to specific tasks. The focus on efficiency and feature extraction makes it valuable for accurate tumor identification, particularly in scenarios with limited computational resources.

3. RESULTS

3.1 Result for setup 1

Table 1 illustrates the training, testing, and validation accuracy, along with the loss function, for various deep learning models, including CNN, VGG19, InceptionV3, ResNet101, and the proposed IV3RN101 model. Tables 2 to 5 provide a comparative analysis of performance metrics such as Precision, Recall, and F1-score across different brain tumor classes, including Glioma, Meningioma, Pituitary, and No Tumor. Additionally, Figure 6-7 presents the error matrices, accuracy-Loss plot for CNN, VGG19, InceptionV3, ResNet101, and the proposed IV3RN101 model, offering a visual representation of classification performance.

Table 1: **Accuracy & Loss function of different DL models**

		Accuracy			Loss	
Model	Training	Testing	Validation	Training	Testing	Validation
CNN	94.57	86.28	87.02	25.72	41.18	38.38
VGG19	91.61	84.14	84.88	26.57	49.09	46.95
InceptionV3	99.01	93.14	92.97	54.06	24.82	32.57
MobileNetV3	99.94	96.49	96.64	00.16	13.08	12.66
Resnet101	98.89	95.12	95.72	03.21	23.65	14.76
Proposed IV3RN101	99.96	96.79	96.94	00.17	09.88	09.38

Table 2: Glioma Classification Comparison

Model	**Precision**	**Recall**	**F1 score**
CNN	0.89	0.85	0.87
VGG19	0.79	0.81	0.80
InceptionV3	0.87	0.92	0.89
MobileNetV3	0.99	0.90	0.94
ResNet101	1.00	0.86	0.92
Proposed IV3RN101	0.97	0.95	0.96

Table 3: Meningioma Classification Comparison

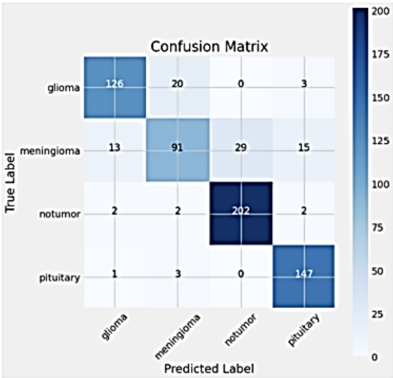
Model	Precision	Recall	F1 score
CNN	0.78	0.61	0.69
VGG19	0.73	0.61	0.67
InceptionV3	0.93	0.80	0.86
MobileNetV3	0.90	0.95	0.92
ResNet101	0.83	0.98	0.90
Proposed IV3RN101	0.94	0.92	0.93

Table 4: Pituitary Classification Comparison

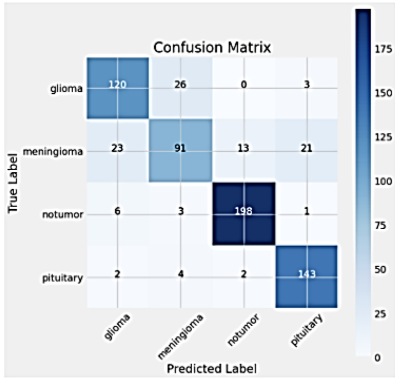
Model	Precision	Recall	F1 score
CNN	0.88	0.97	0.92
VGG19	0.85	0.95	0.90
InceptionV3	0.95	0.99	0.97
MobileNetV3	0.99	0.99	0.99
ResNet101	0.99	0.97	0.98
Proposed IV3RN101	0.97	0.99	0.98

Table 5: **No tumor Comparison**

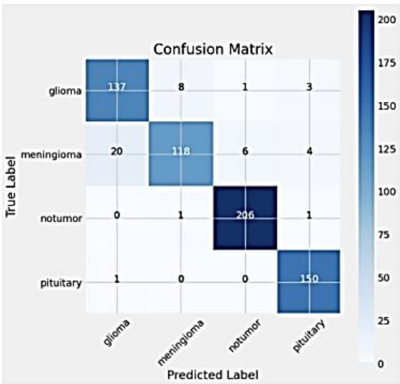
Model	Precision	Recall	F1 score
CNN	0.87	0.97	0.92
VGG19	0.93	0.95	0.94
InceptionV3	0.97	0.99	0.98
MobileNetV3	0.98	1.00	0.99
ResNet101	1.00	0.98	0.99
Proposed IV3RN101	0.98	1.00	0.99



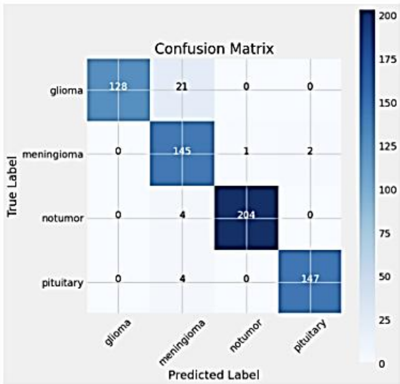
(a) Error matrix of CNN



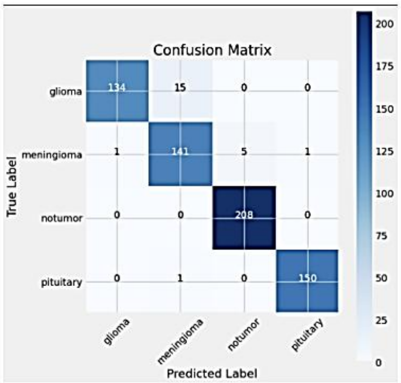
(b) Error matrix of VGG19



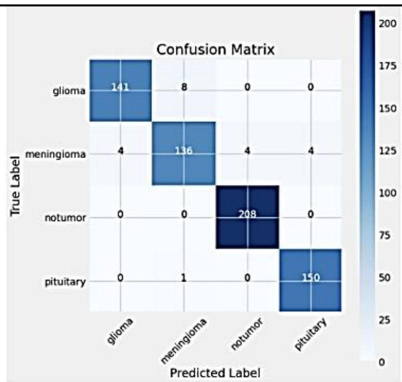
(c) Error matrix of InceptionV3



(d) Error matrix of ResNet101

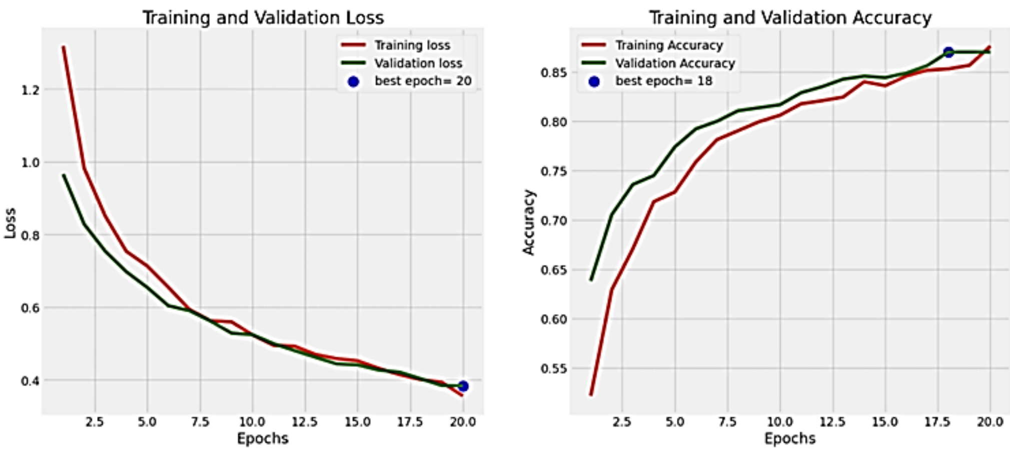


(e) Error matrix of MobileNetV3



(f) Error matrix of Proposed IV3RN101 model

Figure 6: Error matrices of different DL models



(a) Accuracy-loss plot of CNN

(b) Accuracy-loss plot of VGG19

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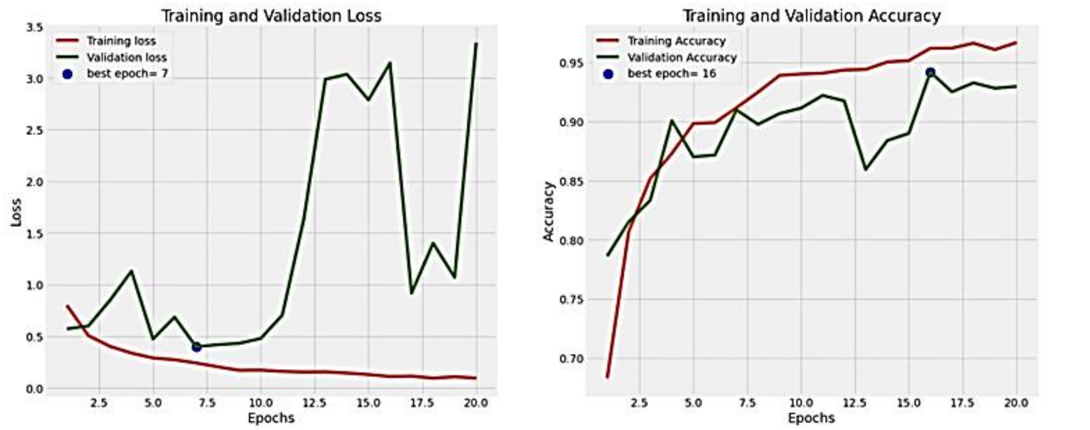
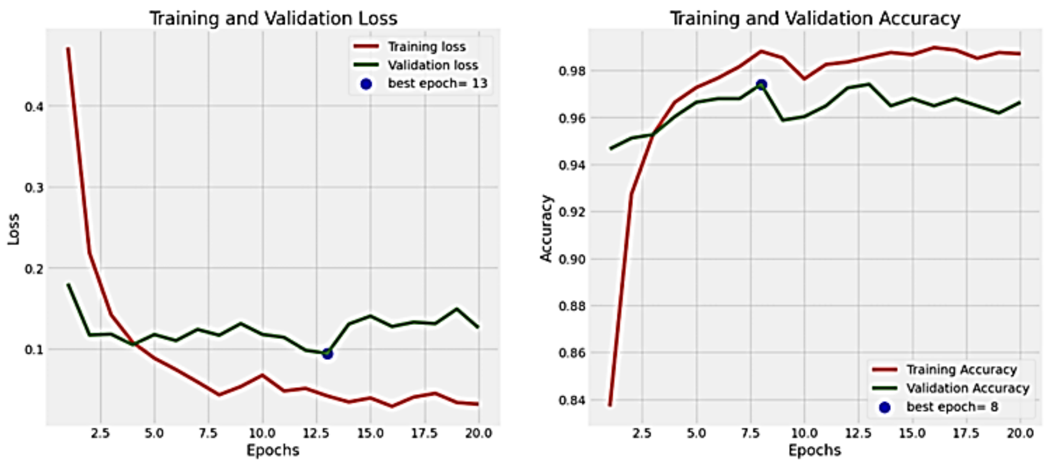


(c) Accuracy-loss plot of InceptionV3

(d) Accuracy-loss plot of ResNet101



(a) Accuracy-loss plot of MobileNetV3

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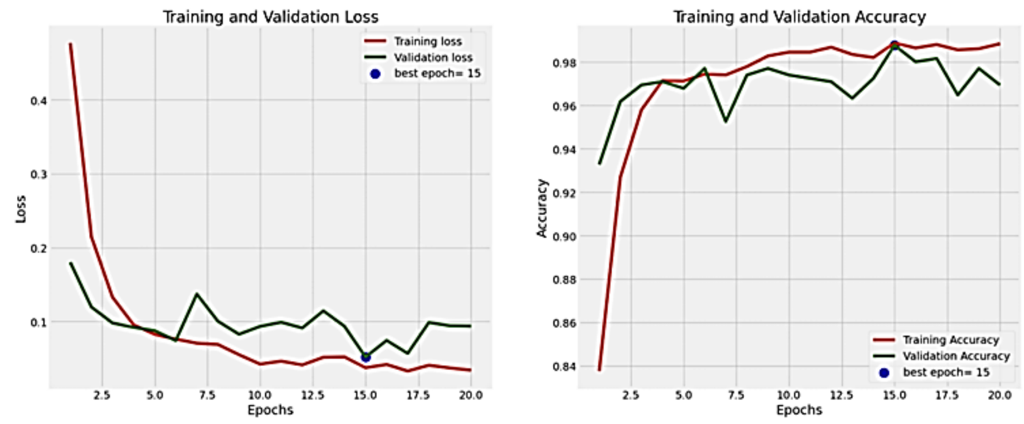

(b) Accuracy-loss plot of IV3RN101

Fig. 7: Evaluation Plots of different models

Based on the comprehensive analysis of the models and their performance metrics, it's evident that the ensemble learning model outshines the individual models in various aspects of brain tumor classification. Let's delve into a detailed result analysis to showcase why the ensemble model stands out as the best performer. Firstly, looking at the comparison Table 1, the ensemble model consistently achieves high accuracy and low loss rates across training, testing, and validation sets, indicating its robustness and generalization ability. Although some individual models like ResNet101 and MobileNetV3 exhibit impressive accuracies, they also show higher losses in the testing and validation phases compared to the ensemble model.

Now, focusing on the precision, recall, and F1 score comparison tables for each tumor type, we can observe that the ensemble model consistently achieves competitive or superior performance across all categories (Tables 2-5). Notably, in the crucial areas of glioma and meningioma classification, where accurate diagnosis is paramount for treatment decisions, the ensemble model demonstrates remarkable precision and recall rates, leading to higher F1 scores.

Moving on to the error matrices (Fig. 6), we can visually inspect the model's performance in classifying different tumor types. The ensemble model's error matrix shows a balanced distribution of misclassifications across categories, indicating its ability to avoid significant biases towards specific classes that can occur with individual models.

Analyzing the confusion matrices and their accompanying analyses for each model, we find that while some models excel in certain areas (e.g., CNN in glioma detection, VGG19 in meningioma classification), they often falter in other aspects (Fig 7). In contrast, the ensemble model maintains a consistently high performance level across all tumor types, showcasing its versatility and reliability in real-world applications. In conclusion, the ensemble learning model emerges as the top performer in brain tumor classification due to it's:

Balanced Performance: It achieves high accuracy, low loss rates, and competitive precision, recall, and F1 scores across all tumor types.

Versatility: Unlike individual models that may excel in specific areas but struggle in others, the ensemble model maintains a balanced and robust performance profile.

Clinical Relevance: The ensemble model's accuracy and reliability make it a valu- able tool for accurate brain tumor diagnostics, aiding healthcare professionals in making informed treatment decisions. Thus, based on the comprehensive analysis and comparison, it's evident that the ensemble learning model is the most suitable and effective choice for brain tumor classification tasks.

3.2 Result for setup 2

This section provides an overview of the feature extraction methodologies employed in various basic machine learning (ML) classification models, as described in the provided papers. Subsequently, we present a comparative analysis between ResNet101, the deep learning algorithm utilized in our work, and the ML classification models mentioned in some other works [32].

K-Nearest Neighbor (KNN) Algorithm:

The KNN algorithm does not involve explicit feature extraction. Instead, it relies on the similarity of feature vectors between data points to classify instances. Features are typically represented as vectors in a multi-dimensional space, and classification is based on the majority class among the k-nearest neighbors of a given data point.

Support Vector Machine (SVM):

SVM classifiers utilize feature vectors derived from the input data. Common fea- ture extraction techniques include methods such as wavelet transform and spatial filtering. These techniques enable the extraction of relevant features from MRI brain images, which are then used to train the SVM classifier.

Decision Tree Algorithm:

Decision tree models employ feature extraction methodologies that partition the input space based on feature attributes. Features such as tumor size, shape, and intensity may be utilized in the decision tree's node-splitting process to create a tree-like structure for classification.

Random Forest Algorithm:

The Random Forest algorithm, like Decision Trees, employs feature extraction techniques that partition the input space based on feature attributes. However, instead of constructing a single decision tree, Random Forest builds a forest of decision trees. Feature importance can be inferred from the average decrease in impurity across all trees in the forest, providing insights into which features are most discriminative for classification. Overall, Random Forest combines feature extraction through decision tree splitting with ensemble learning, making it robust and effective for a variety of classification tasks.

Comparison with Proposed IV3RN101 Model The comparative analysis between Proposed Ensemble (IR) and the aforementioned ML classification models is summarized in Table 6. Our results demonstrate that Proposed Ensemble (IR) achieved the highest accuracy of 96.79% among all models evaluated. The deep architecture of Proposed Ensemble (IR) allows it to capture complex patterns and relationships within the images, leading to superior classification performance.

Table 6: **Comparison of Proposed IV3RN101 with Basic ML Classification Models**

Model	Accuracy (%)
Proposed Ensemble IV3RN101	96.79
KNN	87.00
SVM	90.00
Decision Tree	91.1
Random Forest	83.00

In contrast, basic ML classification models such as K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Decision Tree, and Random Forest rely on explicit feature extraction methodologies. While these models have demonstrated rea- sonable accuracy ranging from 83% to 91.1%, they require handcrafted feature engineering or predefined feature extraction techniques. This manual process may be prone to bias and may not capture all relevant information present in the images. Overall, our findings suggest that deep learning algorithms like Proposed Ensemble (IR) offer a promising approach for accurate and efficient brain tumor classification tasks, especially when dealing with complex image data.

4. Conclusion

The thorough analysis conducted on various deep learning models for brain tumor classification reveals that the ensemble learning model significantly outperforms individual models in several key aspects. This conclusion is substantiated by a detailed examination of performance metrics, comparison tables, precision-recall-F1 score analysis, error matrices, and confusion matrices. The ensemble model consistently exhibits high accuracy rates and low loss rates across all phases of training, testing, and validation, showcasing its robustness and generalization capabilities. Although certain individual models demonstrate impressive accuracies, they often exhibit higher losses, especially during testing and validation phases, in contrast to the ensemble model. Furthermore, the precision, recall, and F1 score comparison tables illustrate that the ensemble model consistently achieves competitive or superior performance across all tumor types, particularly excelling in glioma and meningioma classification where accurate diagnosis is critical. The error matrices visually depict the ensemble model's balanced distribution of misclassifications, indicating its ability to avoid significant biases toward specific classes, a common issue with individual models. The ensemble learning model emerges as the top performer in brain tumor classification due to its balanced performance, versatility, and clinical relevance. Its ability to achieve high accuracy rates, low loss rates, and competitive precision, recall, and F1 scores across all tumor types makes it the most suitable and effective choice for real-world brain tumor classification tasks. This comprehensive analysis underscores the importance of ensemble learning approaches in improving diagnostic accuracy and lays a foundation for further advancements in medical image analysis using deep learning techniques.

Declarations

Author contribution Information

All authors are equally contributed.

Competing interests

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