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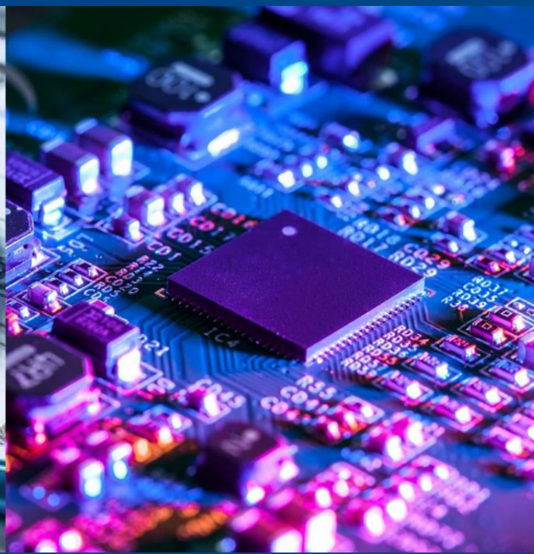

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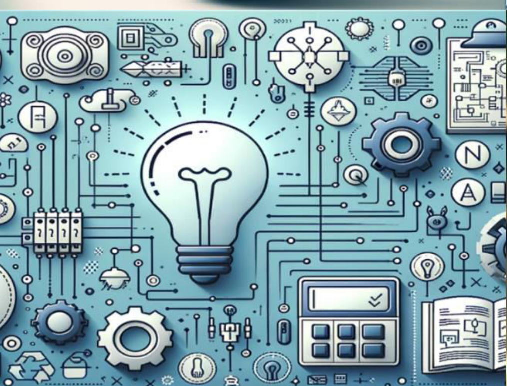

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Brain Tumor Classification Using Deep Learning Techniques

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ABSTRACT: Brain tumor classification using deep learning has gained significant attention due to its potential in assisting early diagnosis and treatment planning. This study explores the effectiveness of various convolutional neural networks (CNNs) in classifying brain tumors from MRI scans. The dataset utilized consists of brain tumor images obtained from Kaggle, encompassing different tumor types. Several deep learning architectures, including ResNet50, ResNet152, DenseNet201, Xception, NASNet, and an ensemble model combining Xception and NASNet, were implemented to evaluate classification performance. Each model was trained and fine-tuned using transfer learning techniques to enhance feature extraction and classification accuracy. The ensemble model, leveraging the complementary strengths of Xception and NASNet, outperformed individual models, achieving the highest accuracy. The superior performance of the ensemble approach demonstrates its capability to capture intricate patterns in MRI images, improving classification reliability. Comparative analysis of model performance highlights the advantages of deeper architectures in extracting hierarchical features. The findings suggest that deep learning-based ensemble models can significantly improve brain tumor detection, contributing to more accurate and automated diagnostic systems in medical imaging.

KEYWORDS: Brain Tumor, Classification, Convolutional Neural Network, Ensemble Model, Xception, NasNet, DenseNet201.

I. INTRODUCTION

Brain tumor classification is a crucial area in medical imaging, significantly impacting the early detection and treatment of life-threatening neurological disorders. Brain tumors are generally categorized as benign or malignant, with malignant tumors posing a severe risk due to their aggressive nature. Accurate and timely diagnosis is essential to improving patient survival rates, as early intervention can greatly enhance treatment efficacy.

Magnetic Resonance Imaging (MRI) is the standard imaging modality for detecting brain abnormalities, offering high-resolution images that provide detailed insights into tumor morphology and location [1]. However, manual examination of MRI scans by radiologists is time-consuming, prone to human errors, and highly dependent on expert interpretation, which may lead to inconsistencies in diagnosis. Consequently, there is an increasing demand for automated classification systems that can enhance accuracy, reduce workload, and support clinical decision-making [2].

Deep learning has emerged as a transformative technology in medical image analysis, offering robust solutions for brain tumor classification. Convolutional Neural Networks (CNNs) have demonstrated superior performance in extracting hierarchical features from MRI images, enabling precise tumor classification with minimal human intervention [3]. Unlike traditional machine learning models that rely on handcrafted features, CNN-based approaches learn complex representations directly from raw image data, improving classification accuracy. Recent advancements in deep learning have introduced transfer learning and ensemble models, further enhancing the performance of brain tumor detection systems. Transfer learning allows pre-trained models to be fine-tuned on medical datasets, leveraging knowledge from large-scale image classification tasks to improve diagnostic capabilities in medical imaging [4].

Several studies have explored various deep learning architectures for brain tumor classification. Researchers have employed optimization techniques such as metaheuristic algorithms to refine CNN performance, leading to improved classification accuracy and reduced computational complexity [5]. Additionally, hybrid models integrating deep learning with machine learning classifiers have been proposed to enhance robustness and generalization across different

MRI datasets [6]. Ensemble learning, which combines multiple deep learning models, has also proven effective in boosting classification performance by leveraging diverse feature representations from different architectures [7]. Furthermore, leveraging pre-trained convolutional networks such as RadImageNet has demonstrated promising results in increasing classification accuracy, showcasing the potential of transfer learning in brain tumor detection [8].

Automated brain tumor classification systems driven by deep learning can revolutionize medical diagnostics by providing reliable and efficient tools for radiologists. These AI-based approaches facilitate early and precise tumor identification, leading to better patient management and outcomes. As research progresses, integrating advanced deep learning techniques with clinical workflows can further enhance the accuracy and interpretability of brain tumor classification systems, paving the way for improved healthcare solutions.

II. LITERATURE SURVEY

Brain tumor classification has gained significant attention in recent years due to advancements in deep learning and machine learning techniques. Researchers have explored various approaches to improve classification accuracy, efficiency, and robustness by utilizing different deep learning architectures, transfer learning, and hybrid models.

Several studies have focused on integrating clustering techniques with machine learning classifiers to enhance brain tumor detection and categorization. Bhimavarapu et al. [9] proposed an improved unsupervised clustering approach combined with a machine learning classifier for brain tumor segmentation. Their method aimed to improve the accuracy of tumor detection by refining segmentation quality before classification. Agrawal et al. [10] conducted a comparative study on brain tumor classification using deep neural networks on an unbalanced dataset, highlighting the challenges of dataset imbalance and proposing techniques to mitigate its impact on classification performance.

Hybrid deep learning models have shown promising results in improving brain tumor classification. Gupta et al. [11] introduced a novel hybrid deep learning model that automates brain tumor classification and diagnosis. Their approach leveraged a combination of CNN-based feature extraction and machine learning classifiers to achieve high accuracy. Mohammadi and Jamshidi [12] proposed an enhancement in classification by integrating Tradaboost with multi-classifier deep learning approaches, demonstrating improved classification performance through adaptive learning techniques.

The effectiveness of transfer learning and feature fusion has been explored in various studies. Malakouti et al. [13] applied machine learning and transfer learning techniques for accurate brain tumor classification, emphasizing the role of pre-trained models in improving classification efficiency. Ullah et al. [14] introduced BrainNet, a novel framework combining residual blocks and stacked autoencoders for multimodal brain tumor classification. Their approach effectively fused features from multiple imaging modalities to enhance classification robustness.

Several studies have focused on optimizing deep learning models to achieve higher accuracy and efficiency. Priya and Vasudevan [15] developed a hybrid model combining AlexNet and GRU to improve brain tumor detection and classification. Their approach leveraged the advantages of convolutional and recurrent neural networks for enhanced feature extraction and classification. Sajol and Hasan [16] benchmarked CNN models against cutting-edge transformer-based models for brain tumor classification using transfer learning. Their study demonstrated the superior performance of transformer models in capturing complex patterns in MRI images.

The application of explainable AI techniques in brain tumor classification has also been explored. Padmapriya and Devi [17] proposed a computer-aided diagnostic system integrating explainable AI for brain tumor classification, aiming to enhance interpretability and transparency in model decision-making. Solanki et al. [18] conducted a systematic analysis of deep learning methods used for MRI-based brain tumor diagnosis, highlighting the strengths and limitations of various architectures.

Optimization techniques have played a crucial role in enhancing classification performance. Geetha et al. [19] introduced a hybrid Archimedes sine cosine optimization technique integrated with deep learning for multilevel brain tumor classification. Their approach optimized feature selection and classification processes, leading to improved accuracy. Dhakshnamurthy et al. [20] explored transfer learning models for brain tumor detection and classification, demonstrating the effectiveness of pre-trained architectures in medical image analysis.

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Overall, recent research has demonstrated significant advancements in brain tumor classification, with a strong focus on deep learning, hybrid models, transfer learning, and optimization techniques. These studies highlight the potential of AI-driven methods in improving diagnostic accuracy, reducing human intervention, and enhancing the efficiency of medical image analysis.

III. MATERIALS AND METHODS

The proposed system employs a deep learning-based approach for brain tumor classification using MRI scans, integrating advanced convolutional neural networks (CNNs) and ensemble learning. It utilizes state-of-the-art architectures such as ResNet50, ResNet152, DenseNet201, Xception, and NASNet, leveraging transfer learning to enhance feature extraction and classification accuracy [9][10]. The key innovation is an ensemble model combining Xception and NASNet, capitalizing on their complementary feature extraction capabilities to improve performance [11][12]. Preprocessing techniques, including image normalization and augmentation, are applied to enhance model generalization and reduce overfitting. The system employs categorical cross-entropy as the loss function and the Adam optimizer for efficient convergence. Performance evaluation is conducted using accuracy, precision, recall, and F1-score to ensure robust classification. By integrating multiple deep learning models and an ensemble strategy, the system enhances automated brain tumor detection, aiding in early diagnosis and improved patient care.

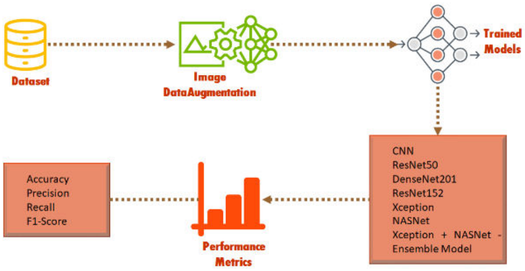

Fig.1 Proposed Architecture

This (Fig.1) diagram illustrates an image classification workflow. It starts with a Dataset, which undergoes Image Data Augmentation to increase data variability and improve model robustness. The augmented data is then fed into various deep learning models, including CNN, ResNet50, DenseNet201, ResNet152, Xception, NASNet, and an ensemble model of Xception and NASNet, resulting in Trained Models. The performance of these models is evaluated using Performance Metrics such as Accuracy, Precision, Recall, and F1-Score, represented by bar graphs. The process emphasizes the iterative nature of model development, where performance metrics guide the selection and refinement of models for optimal image classification.

i) Dataset Collection:

The dataset used for brain tumor classification is sourced from Kaggle's **Brain Tumor MRI Dataset** [MasoudNickparvar]. This dataset consists of MRI scan images categorized into tumor and non-tumor classes, enabling effective training and evaluation of deep learning models. It includes a diverse set of brain MRI images, ensuring variability in tumor shapes, sizes, and intensities, which enhances model generalization. The dataset undergoes preprocessing steps such as image resizing, normalization, and augmentation to improve classification performance. The curated dataset facilitates robust training of CNN architectures, contributing to accurate and reliable automated brain tumor detection in medical imaging applications.

ii) Image Data Augmentation:

Image data augmentation is a crucial preprocessing step to enhance the generalization capability of deep learning models for brain tumor classification. Several augmentation techniques are applied to the MRI dataset to improve model robustness and prevent overfitting. Re-scaling the image ensures pixel values are normalized, facilitating stable model convergence. Shear transformation distorts the image slightly to introduce variations, making the model more adaptable to different tumor shapes. Zooming the image helps in capturing tumor details at different scales, improving detection accuracy. Horizontal flip is used to create mirrored versions of images, aiding in model learning from diverse orientations. Reshaping the image ensures uniform dimensions across the dataset, maintaining consistency in input size for deep learning architectures. These augmentation techniques help in expanding the dataset artificially, improving the model's ability to recognize tumors under varied conditions, ultimately enhancing classification performance and diagnostic reliability in medical imaging.

iii) Algorithms:

CNN is a deep learning architecture designed for image recognition and classification. It consists of convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. It processes spatial hierarchies of features, making it effective for medical imaging tasks. It is widely used in detecting and classifying brain tumors by extracting patterns from MRI scans. The ability to learn spatial features enables accurate identification of tumor presence and type in medical diagnostics.

ResNet50 is a deep convolutional neural network with 50 layers, known for its residual connections that mitigate vanishing gradients. It enhances deep feature extraction while maintaining training efficiency. It is applied in brain tumor classification to improve accuracy by capturing complex patterns in MRI images. The skip connections enable deeper model training without performance degradation. It is widely adopted in medical imaging tasks requiring high precision in detecting subtle variations in tumor characteristics.

DenseNet201 is a deep learning model that introduces dense connections between layers, ensuring maximum feature reuse and reducing vanishing gradients. It enhances information flow, leading to improved classification performance. It is utilized in medical imaging to detect tumors by leveraging dense connections for better feature learning. The reduced number of parameters improves computational efficiency without compromising accuracy. Its ability to capture fine-grained details makes it highly effective in distinguishing tumor types from MRI images.

ResNet152 is a deeper variant of ResNet with 152 layers, designed to extract intricate patterns using residual learning. It minimizes training difficulties associated with deep networks, ensuring stable gradient flow. It is used in tumor classification to enhance feature extraction and improve prediction accuracy. The deep architecture allows learning from complex MRI patterns, distinguishing between different tumor types. Its efficient feature propagation mechanism helps in recognizing small or ambiguous tumors with higher precision in medical image analysis.

Xception is an advanced deep learning model based on depthwise separable convolutions, reducing computational complexity while maintaining high performance. It replaces standard convolutions with efficient factorized operations, improving learning efficiency. It is applied in MRI-based tumor detection to extract hierarchical features while maintaining computational feasibility. The model captures spatial dependencies effectively, ensuring robust classification. Its optimized architecture provides better generalization, making it ideal for identifying diverse tumor structures in medical imaging applications.

NASNet is a neural architecture search model designed to optimize convolutional structures automatically. It dynamically selects the best layer configurations for superior feature learning. It is used in brain tumor classification to enhance adaptability by learning the most efficient feature extraction patterns. The automated design selection improves model performance while maintaining computational efficiency. Its self-optimizing nature makes it particularly useful in medical imaging, where complex feature representation is necessary for accurate tumor detection.

Xception + NASNet ensemble model combines the strengths of both architectures to improve classification accuracy.Xception's depthwise separable convolutions efficiently capture local features, while NASNet's architecture search optimizes layer configurations for enhanced performance. This ensemble is applied in brain tumor classification to achieve superior feature extraction and robust decision-making. The complementary properties of both models enhance generalization and adaptability, ensuring precise tumor detection. The hybrid approach improves classification confidence by leveraging diverse feature representations from both models.

IV. RESULTS AND DISCUSSION

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

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$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} (1)$$

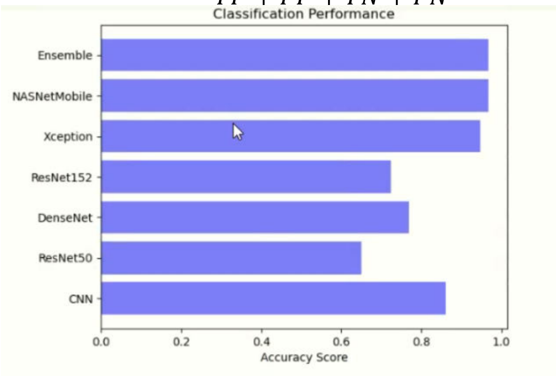

Fig.2 Accuracy Comparison Graph

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

$$Precision = \frac{True\ Positive}{True\ Positive\ + False\ Positive} (2)$$

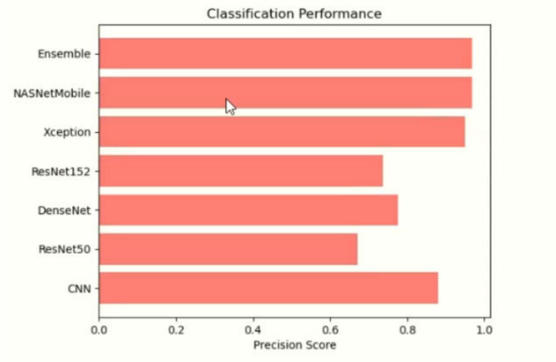

Fig.3 Precision Comparison Graph

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP\ +\ FN} (3$$

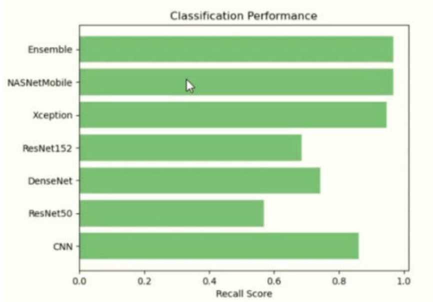

Fig.4 Recall Comparison Graph

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

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$$F1\ Score = 2 * \frac{Recall\ X\ Precision}{Recall + Precision} * 100(\ SEQ\ "equation"\ \backslash n\ \backslash *\ MERGEFORMAT\ 4)$$

Fig.5 Input Image

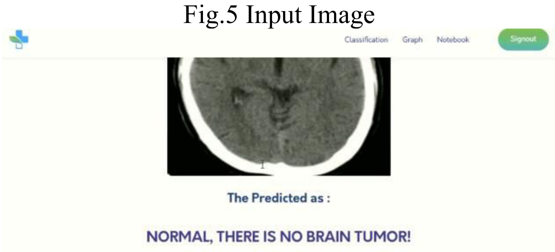

Fig.6 Predict Result, Normal, There is No Brain Tumor

Fig.7 Input Image

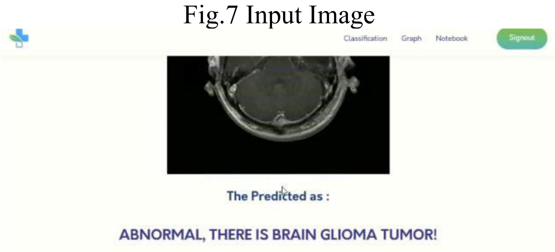

Fig.8 Final Outcome as Abnormal, There is Brain Glioma Tumor

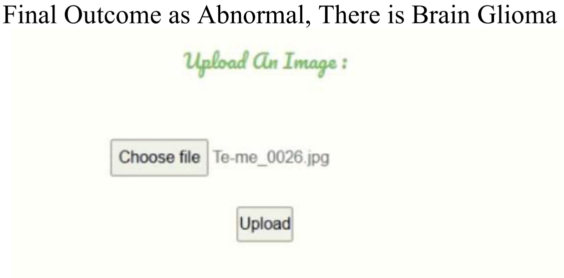

Fig.9 Another Input Image

Fig.10 Predict Result Abnormal, there is Brain Meningioma Tumor

Fig.11 Input Image

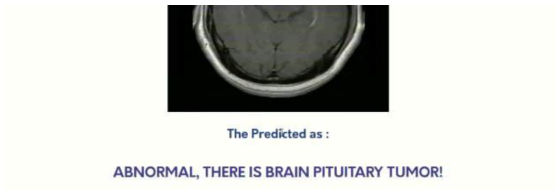

Fig.12 Final Outcome as Abnormal, There is Brain Pituitary Tumor.

V. CONCLUSION

The study demonstrates the effectiveness of deep learning in brain tumor classification using MRI scans, highlighting the superior performance of the Xception and NASNet ensemble model. By leveraging the strengths of both architectures, the ensemble approach achieved high classification accuracy, outperforming individual models. Xception's depthwise separable convolutions efficiently captured spatial hierarchies, while NASNet's automated architecture search optimized feature extraction, leading to enhanced tumor differentiation. Transfer learning further improved performance by utilizing pre-trained weights, enabling faster convergence and better generalization. Image preprocessing techniques, including normalization and augmentation, contributed to reducing overfitting and improving model robustness. The results validate the efficiency of advanced deep learning architectures in medical imaging, demonstrating their potential for automated and accurate tumor classification. The ensemble strategy proved to be highly effective in capturing intricate patterns in MRI scans, offering a reliable solution for assisting radiologists in early diagnosis. The findings emphasize the significance of deep learning-driven ensemble models in enhancing diagnostic accuracy and supporting clinical decision-making.

Future work will focus on improving model generalization by incorporating larger and more diverse MRI datasets, including multi-modal imaging data such as CT and PET scans. Advanced ensemble techniques, including weighted averaging and stacking, will be explored to further enhance classification accuracy. Integration of attention mechanisms and vision transformers will be investigated to improve feature extraction. Real-time deployment in clinical settings using edge AI and federated learning will be considered for privacy-preserving and efficient brain tumor diagnosis.

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