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Comparative Analysis of Deep Learning and Machine Learning for Brain Tumor Detection and Classification

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Abstract:

Brain tumor detection is critical for early diagnosis and treatment. The study looks into advanced approaches for using MRI images, utilizing deep learning models with machine learning classifiers. VGG16, ResNet50, and a custom Xception model were used to extract and classify features from MRI images labeled with glioma, meningioma, no tumor, and pituitary tumors. Data augmentation and K-means clustering were used to improve model performance. The custom Xception model outperformed VGG16 and ResNet50, obtaining a test accuracy of 99.69%. This study demonstrates the potential of deep learning in medical imaging, which can greatly improve diagnostic accuracy for brain tumor identification. Detailed performance measurements and comparative analysis demonstrate the resilience of the offered techniques, emphasizing their practical applicability.

Keywords — **Brain Tumor Detection, MRI, Deep Learning, VGG16, ResNet50, Xception Model, Data Augmentation, K-means Clustering, Machine Learning, Medical Imaging.**

I. INTRODUCTION

Considering intricate nature and significant potential for negative health consequences, brain tumors pose a complex and formidable challenge in the field of medical diagnostics [1]. These tumors can be benign or malignant, with malignant tumors posing a particularly serious threat due to their aggressive growth and ability to metastasize to other parts of the brain or body [2]. Early and accurate detection of brain tumors is critical for effective treatment and improved patient outcomes. Brain tumors must be detected early and accurately to ensure effective therapy and better patient out-comes. Traditionally, brain tumor identification relied mainly on radiologists manually analyzing Magnetic Resonance Imaging (MRI) data, which is not only time-consuming but also prone to human error [3]. This has highlighted the importance of automated systems capable of detecting and classifying brain tumours with high accuracy and efficiency [4].

Magnetic resonance imaging (MRI) is the most widely used imaging technology for detecting and diagnosing brain cancers. MRI generates high-resolution pictures that enable precise viewing of brain structures and disorders. However, manually analyzing MRI images is time-consuming and demands a high level of competence. To address these issues, researchers have turned to machine learning (ML) and deep learning (DL) approaches, which provide promising solutions for automatic and accurate MRI im-age processing [6].

The pathophysiology of brain tumors varies greatly, with the most common kinds being gliomas, meningiomas, and pituitary tumors, as well as cases when no tumors exist [7]. Gliomas develop from glial cells and are frequently extremely can-cerous, making them especially hazardous and difficult to cure. Meningiomas develop from the meninges, the protective membranes that surround the brain and spinal cord. They are usually benign, but their size and location can lead to serious consequences. Pituitary tumors develop in the pituitary gland and can disrupt hormone levels, causing a variety of symptoms [8].

Machine learning, a subset of artificial intelligence, is the process of creating algorithms that can learn from and anticipate data [9]. Deep learning, a more advanced type of machine learning, uses artificial neural networks with numerous layers to model complicated patterns in data. Both machine learning and deep learning techniques have demonstrated tremendous potential in the field of medical imaging, particularly for the detection and classification of brain tumours [5].

Pre-trained models such as VGG16, ResNet50, and Xception are commonly used in medical image analysis. These models, which are originally trained on massive datasets like ImageNet, may be fine-tuned for specialized tasks like detecting brain tumors. For example, VGG16 and ResNet50 have shown great accuracy in recognizing and classifying brain cancers by exploiting their abilities to extract significant characteristics from MRI images [6,18]. Custom deep learning architectures built specifically for brain tumour detection have also been created. These models are specifically de-signed to capture the distinct properties of brain tumors, resulting in increased detection and classification performance [21]. Custom architectures usually contain layers for convolution, pooling, dropout, and fully linked networks, which collabo-rate to learn and recognize patterns in MRI images [20].

K-means clustering is another technique that has been successfully integrated with pre-trained models to improve brain tumour detection and classification. K-means clustering, an unsupervised learning technique, divides data into k separate clusters based on feature similarity [19]. When used with data derived from pre-trained models such as VGG16 or ResNet50, k-means clustering can assist group similar patterns and identify various tumor types more effectively. This strategy improves the classification system's robustness and tumor detection performance by combining the clustering capabilities of k-means with the feature extraction power of deep learning models [9].

A comparison examination of several models is required to determine the most effective technique for brain tumor detection and classification. This study assesses three basic approaches. The first method combines the VGG16 model with conventional classifiers such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Logistic Regression. This combination combines VGG16's feature extraction skills with classical classifiers' decision-making powers, resulting in higher performance measures [7]. The second technique combines the ResNet50 model, which is well-known for its residual learning framework, with SVM, KNN, and Logistic Regression classifiers. ResNet50 addresses the vanishing gradient problem and enables for the construction of very deep networks, giving it a strong candidate for brain tumor classification [5]. Both approaches are integrated with the segmented image using kmeans to improve the results. The third method employs a special Xception model that was built and trained specifically for brain tumor detection. This model comprises layers for convolution, pooling, dropout, and dense networks that are fine-tuned to capture the various properties of brain tumors, resulting in a complete and highly accurate classification system [8].

These models' performance is measured using a number of criteria, including accuracy, precision, recall, and F1-score. Accuracy measures the model's overall correctness, precision indicates the proportion of true positive predictions among all positive predictions, recall (or sensitivity) measures the model's ability to identify all relevant instances, and the F1-score strikes a balance be-tween precision and recall. These metrics provide a thorough assessment of the models' abilities to detect and classify brain tumours [6].

The integration of machine learning and deep learning techniques to brain tumour identification and classification has great promise for enhancing diagnostic accuracy and efficiency. Researchers and physicians can create robust, automated systems for the fast and accurate diagnosis of brain cancers by combining advanced models such as VGG16, ResNet50, and bespoke Xception with classic classifiers [4]. This, in turn, can lead to better treatment planning and patient outcomes, indicating a substantial improvement in medical imaging.

This research work seeks to contribute to ongoing efforts to improve diagnostic accuracy and patient care in neuro-oncology by offering detailed insights into the numerous models and methodolo-gies utilized for brain tumour detection and classification [9].

II. LITERATURE SURVEY

Tiwari et al. [10] emphasize the important necessity for precise categorization of brain tumours, given their high death rate in adults and children. Misclassification can have serious repercussions, needing exact multiclass categorization based on tumor texture, location, and form. They emphasize the usefulness of Magnetic Resonance Imaging (MRI) in detecting brain tumors. Their study, which takes use of advances in image classification technology, employs Convolutional Neural Net-works (CNN) to solve the brain tumor classification challenge. Their suggested approach success-fully classifies MRI brain pictures into four categories: no tumour, glioma, meningioma, and pituitary tumour, with an amazing 99% accuracy.

Namachivayam and Puviarasan [11] propose a new representation for MRI analysis that categorizes brain tumors into four types: no tumor, glioma, meningioma, and pituitary. This work ad-dresses the obstacle of manually analysing a large number of MRI scans, which is not only time-consuming but also subjective due to the complexity of the equipment and the difficulties distinguishing between different tumor kinds. To address this, the authors propose employing computer-based detection to ensure precise, rapid, and accurate identification. The proposed method makes use of Convolutional Neural Network (CNN) and Support Vector Machine (SVM) models. To identify brain MRI pictures, the SVM classifier uses Histogram of Oriented Gradients (HOG) features, whereas the CNN model, trained with three convolutional layers and a softmax classifier, categorizes them. According to the results, the CNN model obtains 97% accuracy, while the SVM model reaches 92%.

Sharma et al. [12] present a model that uses ma-chine learning methods to detect brain cancers with good accuracy in magnetic resonance imaging. Convolutional Neural Networks (CNN) were used in this study to extract and segment features. The data used was obtained from an internet domain. The results show that this technique is quite promising, with an accuracy of 97.79%.

Vinu et al. [13] use an integrated strategy based on recent machine learning models to achieve the critical objective of brain tumor segmentation in MRI data. Their approach entails a demanding preparation procedure that involves scaling, rotation, conversion, and augmentation to enhance the dataset for further evaluation. To capture detailed tumor features, feature extraction uses shape-based, intensity-based, and model-based techniques. The study uses a variety of machine learning models, including Convolutional Neural Networks (CNN), Support Vector Machines (SVM), Recurrent Neural Networks (RNN), K-Nearest Neighbors (KNN), and Random Forest (RF). On a dataset of 3290 images, CNN had the highest segmentation accuracy of 97.8%, followed by SVM at 94.3%, RNN at 91.3%, KNN at 87.6%, and RF at 85.4%. This ensemble approach emphasizes the importance of combining different machine learning paradigms to improve the robustness and accuracy of brain tumor segmentation, which holds significant promise for improving diagnostic accuracy and assisting doctors in identifying and planning malignancies.

Gajula and Rajesh [14] discuss the complexities of MRI brain diagnosis, emphasizing the limitations of previous models in predicting the shape and location of brain tumors. According to the WHO, brain-related disorders cause significant mortality, affecting around 10 billion individuals each year, highlighting the need for current detection applications. Their paper presents a logistic regression-based method for detecting brain ab-normalities automatically. Training and testing were carried out utilizing the ADNI-1 and ADNI-2 datasets, as well as real-time MRI samples. The suggested system outperformed previous models, with a classification accuracy of 97%, precision of 97.9%, and recall of 97%, indicating the efficacy of machine learning systems in this domain.

Anantharajan et al. [15] discuss the development of aberrant brain cells that can evolve into cancer, highlighting the necessity of early detection and treatment to improve patient quality of life and life expectancy. MRI scans are the most prevalent approach for detecting brain cancers, although the process is labor intensive due to the reliance on radiologists' skills. The work suggests a novel MRI brain tumor detection method based on Deep Learning (DL) and Machine Learning (ML). The method begins with MRI image capture and pre-processing with the Adaptive Contrast Enhancement Algorithm (ACEA) and median filtering. Fuzzy c-means are used for segmentation, while the Gray-level co-occurrence matrix (GLCM) is used to extract variables such as energy, mean, entropy, and contrast. The aberrant tissues are subsequently identified using the Ensemble Deep Neural Support Vector Machine (EDN-SVM) classifier. The study found great accuracy (97.93%), sensitivity (92%), and specificity (98%) in discriminating diseased and normal tissue from MRI scans, confirming the efficacy of the suggested method.

Kumar et al. [16] emphasize the importance of brain tumors as one of the most lethal diseases, emphasizing the need for rapid and precise diagnosis procedures. Their technique begins with optimizing MRI scans through pre- and post-processing to select the best images for re-search. To segment the MRI pictures, a threshold was imposed using the mean grey level technique. The second stage involved extracting statistical characteristics with Haralick's feature equations and the spatial gray-level dependency matrix (SGLD). This allowed for proper tumor location and the selection of the best features. The final phase used supervised learning and artificial intelligence approaches to develop an automated tool for determining whether or not the photos contained tumors. The network's performance was tested effectively, yielding a 97% success rate.

Selvy et al. [17] discuss the increasing occurrence of brain tumors, notably gliomas, which ac-count for a large fraction of brain cancers. They underline the necessity of accurate brain tumor detection methods. They use Magnetic Resonance Imaging (MRI) to detect and classify gliomas. The system uses a Probabilistic Neural Network (PNN) for picture preprocessing, feature extraction, and classification. Histogram Equalization (HE) is used at the pre-processing step to improve image contrast. Feature extraction uses the Gray Level Co-occurrence Matrix (GLCM) to capture visual attributes. The collected characteristics are subsequently supplied into the PNN for training and testing purposes. This method detects tumor spots in brain MRI data with an accuracy of roughly 90.9%.

Table 1 outlines the key contributions of recent studies addressing the challenges of brain tumor detection and classification, emphasizing advancements in accuracy and methodology.

TABLE I KEY CONTRIBUTIONS OF STUDIES

Study	Key Contribution
Tiwari et al. [10]	Developed a CNN-based system for multiclass tumor classification with high accuracy.
Namachivayam and Puviarasan [11]	Proposed CNN and SVM models to automate the classification of brain tumors into four types.
Sharma et al. [12]	Utilized CNN to extract features and segment brain tumors for improved diagnosis.
Vinu et al. [13]	Introduced an ensemble approach combining multiple ML models to improve segmentation accuracy.
Gajula and Rajesh [14]	Presented a logistic regression-based automatic tumor detection system.
Anantharajan et al. [15]	Proposed an EDN-SVM classifier for accurate detection of abnormal brain tissues.
Kumar et al. [16]	Automated tumor detection using statistical feature extraction and segmentation.
Selvy et al. [17]	Employed PNN with GLCM-based feature extraction for glioma detection in MRI images.

Table 2 outlines the key features and primary techniques utilized by the related studies for an overview.

TABLE II METHOD USED IN RELATED STUDIES

Study	Primary Techniques	Key Features/Algorithms
Tiwari et al. [10]	CNN-based classification	Multiclass tumor classification.
Namachivayam and Puviarasan [11]	CNN with softmax classifier and SVM with HOG features	Three convolutional layers (CNN), Histogram of Oriented Gradients (HOG) features for SVM.
Sharma et al. [12]	CNN for feature extraction and segmentation	Internet domain dataset for MRI analysis.
Vinu et al. [13]	Ensemble ML models: CNN, SVM, RNN, KNN, RF	Shape-based, intensity-based, and model-based feature extraction.
Gajula and	Logistic	Training on ADNI datasets

Rajesh [14]	regression-based automatic detection	with preprocessing.
Anantharajan et al. [15]	EDN-SVM classifier, Fuzzy c-means segmentation	Adaptive Contrast Enhancement Algorithm (ACEA), GLCM features.
Kumar et al. [16]	Statistical feature extraction, threshold segmentation	Haralick's equations, spatial gray-level dependency matrix (SGLD).
Selvy et al. [17]	PNN with GLCM-based feature extraction	Histogram Equalization (HE) preprocessing.

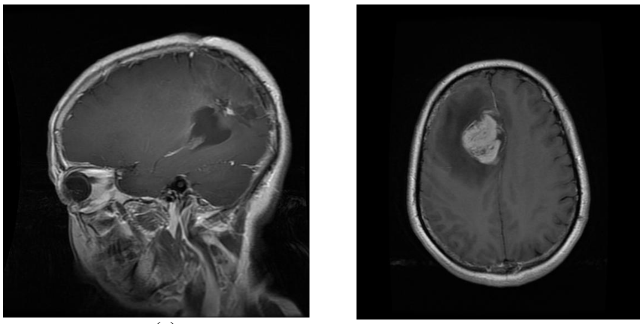
III. MATERIALS AND METHODS

A. Experimental Setup

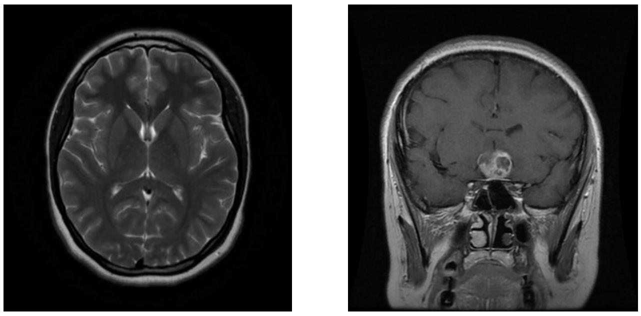
The proposed architectures were implemented using Google Colab with a Tesla T4 15 GB of VRAM GPU and 20 GB of RAM.

B. Dataset

The Kaggle brain tumor detection dataset was studied with 7023 MRI pictures, which were classified into four types of brain tumors: glioma, meningioma, no tumor, and pituitary tumor, as indicated. Table 3 gives a thorough summary of the dataset's structure, including the distribution and characteristics of each tumor type. This diversified dataset ensures that the models are properly trained and tested. Fig. 1 shows the image of each category in the dataset.



(a) (b)



(c) (d)

Fig. 1 Types of Tumor (a) Glioma (b) Meningioma (c) No tumor (d) Pituitary

TABLE III COMPREHENSIVE DATASET OVERVIEW

Tumor type	Number of images
Glioma	1621
Meningioma	1645
Pituitary	1757
No tumor	2000
Total	7023

C. Data Augmentation

Data augmentation approaches were used to diversify the training set and improve model generalization. These techniques included rotating images within a 10-degree range, altering brightness levels between 0.85 and 1.15, shifting images by 0.002 in width and height, performing a shear transformation up to 12.5 degrees, and enabling horizontal flipping. These augmentations improve the model's capacity to generalize from training data to new images. Table 4 outlines the data augmentation techniques utilized in preprocessing.

TABLE IV DATA AUGMENTATION TECHNIQUES

Augmentation Technique	Parameter Range
Rotation	±10°
Brightness Adjustment	0.85–1.15
Width Shift	±0.002
Height Shift	±0.002
Shear Transformation	Up to 12.5°
Horizontal Flipping	Enabled

D. K-means Clustering

K-means clustering was combined with transfer learning algorithms (VGG16 and ResNet50) to improve feature extraction and clustering of MRI image data. This preprocessing phase sought to improve model performance by categorizing related data points into clusters, allowing for more efficient learning and classification.

E. Proposed Methodology

Recent advances in deep learning, notably in medical picture categorization, provide exciting prospects to use several CNN frameworks. Transfer learning approaches speed up data training and minimize the number of samples necessary, allowing newly learned models to make better use of existing data. This study compares the efficacy of three baseline computer vision models: VGG16, ResNet50, and a proprietary Xception model.

*1) **VGG16:*** VGG16 (Visual Geometry Group 16) is a deep CNN architecture that excels at image categorization because to its simplicity and effectiveness. It consists of 16 layers, including convolutional and fully connected ones. In this study, VGG16 is used as a feature extractor, and its output is fed into machine learning classifiers such Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Logistic Regression for brain tumor classification.

*2) **ResNet50:*** ResNet50 (Residual Network 50) is a deeper CNN architecture that uses skip connections to solve the vanishing gradient problem in very deep networks. ResNet50 has demonstrated higher performance in a variety of image recognition tests due to its capacity to build deeper networks more efficiently. ResNet50, like VGG16, is used in this study using the same ML classifiers for a comparative assessment of classification performance.

*3) **Xception**:* In addition to pre-trained models, a bespoke Xception model was created just for this investigation. Xception is another deep CNN architecture distinguished by its depthwise separable convolutions, which may capture subtle patterns in data more efficiently than typical convolutional layers. Unlike VGG16 and ResNet50, the Xception model was trained from scratch on the brain tumor dataset, utilizing transfer learning methods such as initializing weights with pre-learned ImageNet weights for the initial layers. This strategy ensures that the model learns discriminative features unique to brain tumor classification while also taking use of transfer learning's generalization capabilities. Fig. 2 depicts the architecture of the Xception model, which contains layers for convolution, separable convolution, and batch normalization. Figure 3 displays the layers' input and output forms in flowchart format, demonstrating how data flows through the model.

F. Evaluation Metrics

The performance of each model was assessed using common measures such as accuracy, precision, recall, and F1-score. These measures reveal information on overall classification performance, accuracy in properly detecting cases of tumors, recall in capturing cases, and the harmonic mean of precision and F1-score, which balances the two metrics. In addition, a complete categorization report was created to provide a thorough review of the model's performance across all classes.

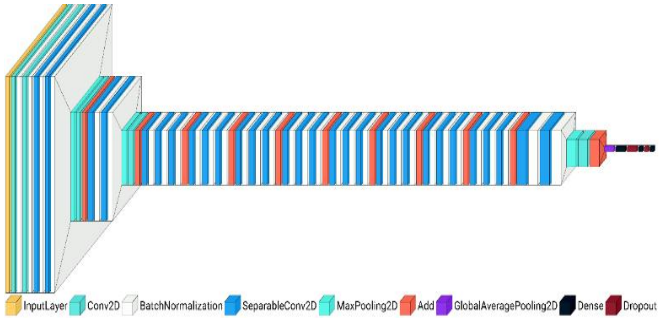


Fig. 2 Architecture of Xception Model

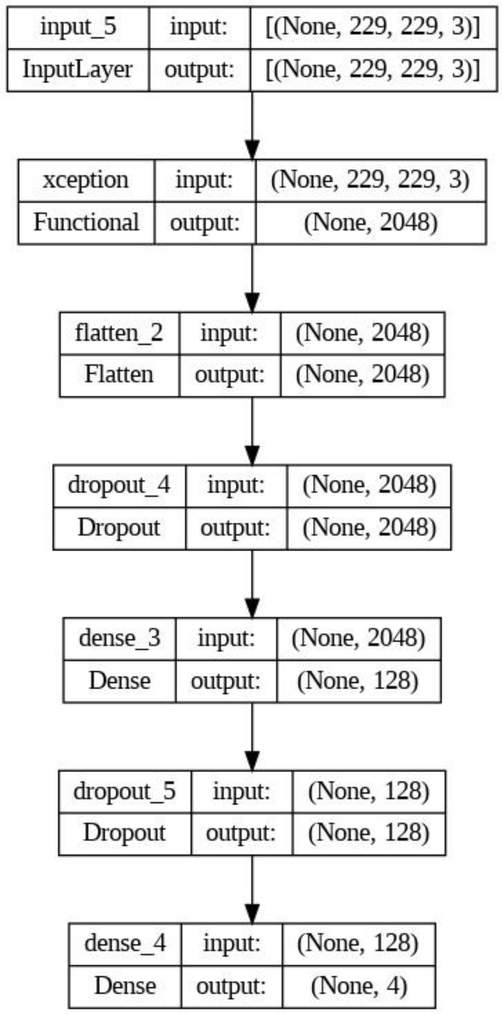


Fig. 3 Flowchart of Image Data Flow of Xception Model

IV. RESULTS AND COMPARATIVE ANALYSIS

Table 5 summarizes the performance metrics of the models and Fig. 3 depicts their comparative effectiveness. The classification results, which provide deep insights into the precision, recall, and F1 scores for each class, support the bespoke Xception model's resilience when compared to VGG16 and ResNet50.

TABLE V PERFORMANCE EVALUATION OF MODELS

Classifiers	Accuracy	Precision	Recall	F1 Score
VGG16+SVM	95.71%	95.71%	95.71%	95.71%
VGG16+Logistic Regression	95.28%	95.24%	95.28%	95.25%
VGG16+KNN	95.45%	95.43%	95.45%	95.42%
ResNet50+SVM	97.11%	97.16%	97.11%	97.12%
ResNet50+Logistic Regression	95.80%	95.79%	95.80%	95.79%
ResNet5+KNN	96.24%	96.22%	96.24%	96.21%
Custom Xception	99.69%	99.69%	99.62%	99.66%

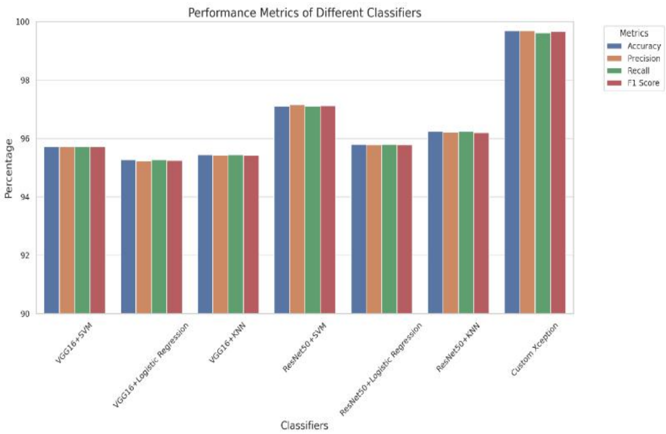


Fig. 3 Performance Metrics

The performance of the models examined in this work demonstrates advances in deep learning for brain tumour classification. The metrics produced from the VGG16, ResNet50, and bespoke Xception models show considerable differences in accuracy, precision, recall, and F1 scores among several classifiers, including SVM, Logistic Regression, and KNN.

The SVM classifier achieved 95.71% accuracy for the VGG16 model, including precision, recall, and F1 scores. The Logistic Regression classifier performed slightly worse, with an accuracy of 95.28% and comparable precision, recall, and F1 scores of 95.25%. The KNN classifier obtained 95.45% accuracy, with the metrics closely aligned. In comparison, the Res-Net50 model beat the VGG16 model, particularly with the SVM classifier, with an accuracy of 97.11% and slightly higher precision and F1 scores of 97.16% and 97.12%. The Logistic Regression classifier with ResNet50 achieved 95.80% accuracy, with precision, recall, and F1 scores of 95.79%. The KNN classifier using ResNet50 obtained 96.24% accuracy, showing steady performance gains over all metrics when compared to VGG16.

The custom Xception model outperformed the other models, attaining a test accuracy of 99.69%, precision of 99.69%, recall of 99.62%, and an F1 score of 99.66%. These findings demonstrate the Xception model's improved capacity to detect subtle patterns within MRI data, which is critical for correct tumor categorization.

Table 6 summarizes the performance metrics of various models proposed in recent studies for brain tumor classification. It provides a comparative perspective on the accuracy, precision, recall, and F1-score achieved by different method-ologies, demonstrating the effectiveness of deep learning and hybrid approaches in this domain.

TABLE VI COMPARATIVE ANALYSIS OF MODELS AND METRICS FROM RELATED STUDIES

Study	Model	Accuracy	Additional Metrics
Tiwari et al. [10]	CNN	99%	Not specified.
Namachivayam and Puviarasan [11]	CNN, SVM	CNN: 97%, SVM: 92%	Not specified.
Sharma et al. [12]	CNN	97.79%	Not specified.
Vinu et al. [13]	CNN, SVM, RNN, KNN, RF	CNN: 97.8%, SVM: 94.3%, RNN: 91.3%, KNN: 87.6%, RF: 85.4%	Comparison between ML models.
Gajula and Rajesh [14]	Logistic Regression	97%	Precision: 97.9%, Recall: 97%.
Anantharajan et al. [15]	EDN-SVM	Accuracy: 97.93%	Sensitivity: 92%, Specificity: 98%.
Kumar et al. [16]	Supervised ML models	97%	Not specified.
Selvy et al. [17]	PNN	90.9%	Not specified.

The classification report, as shown in Table 6, gives extensive data for each class in the proposed method, including precision, recall, F1-score, and support, confirming the model's high accuracy and effectiveness in categorizing brain tumor kinds.

TABLE VII CLASSIFICATION REPORT PROPOSED METHOD

Classes	Precision	Recall	F1-Score	Support
Glioma	1.00	1.00	1.00	300
Meningioma	0.99	0.99	0.99	306
Pituitary	1.00	1.00	1.00	405
No Tumor	0.99	1.00	1.00	400

The comparative study shows that, while VGG16 and ResNet50 perform well, the bespoke Xception model outperforms them thanks to its unique architecture and rigorous training approach. The addition of data augmentation and K-means clustering improves the model's capacity to generalize and correctly categorize brain tumor photos. This study demonstrates the potential of tailored deep learning models to advance medical imaging and improve diagnostic accuracy in clinical settings.

V. CONCLUSION

This study highlights the considerable advances that deep learning models, namely the proprietary Xception model, make in the field of brain tumor categorization. The proprietary Xception model obtained a test accuracy of 99.69% by combining transfer learning and innovative data augmentation techniques, outperforming known models such as VGG16 and ResNet50. The use of K-means clustering improves feature extraction, resulting in improved model performance. These findings highlight deep learning's potential for generating highly accurate diagnostic tools that can aid in the early and precise diagnosis of brain tumors, thereby improving patient outcomes.

The comparative analysis showed that while classic models like as VGG16 and ResNet50 perform well, unique architectures suited to specific datasets and workloads can outperform them. This study also underlines the value of employing a diversified and supplemented dataset to increase model generalization and resilience. The bespoke Xception model's promising results indicate that future research should continue to investigate tailored deep learning approaches and the integration of sophisticated machine learning techniques to improve diagnostic accuracy and reliability in medical imaging. These developments have substantial practical significance, providing new paths for early detection and therapy planning for patients with brain tumors.

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