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Comparative Study of Deep Learning Architectures for Brain Tumor Classification

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Abstract: Brain tumor classification is an important medical imaging problem because early and correct diagnosis greatly enhances patient survival. In this paper, we investigate automatic brain tumor classification from MRI with deep learning models. We try different pre-trained CNN models, i.e., VGG19, ResNet101, EfficientNetB0, MobileNetV2, InceptionV3, and DenseNet121, on a Kaggle dataset of 13,196 MRI scans into four categories: pituitary, glioma, meningioma, and no tumor. EfficientNetB0 performed best among the other models with a highest accuracy rate of 98.63%. Data augmentation and transfer learning techniques were employed to train the model such that it stabilizes the performance. This paper describes an efficient, automated, and accurate method for detection of brain tumors, establishing the capability of deep learning in clinical diagnostics. The research proves the capability of AI medical imaging software to allow physicians to diagnose patients quicker and treat them better.

Keywords: EfficientNet, CNN, VGG16, Keras, Accuracy, ResNet

I. INTRODUCTION

One of the deadliest and life-taking diseases, brain tumors need to be diagnosed early and accurately so that they can be treated. Traditional diagnosis is time-consuming and not that accurate, e.g., visual inspection of MRI scans. Deep learning methods, especially Convolutional Neural Networks (CNNs), have proved useful for automatic brain tumor classification to combat these issues. These models have the ability to perform very accurate medical image analysis, and that allows radiologists to detect patients more effectively and accurately. For the brain cancer classification into four categories—glioma, meningioma, no tumor, and pituitary—multiple pretrained deep models are utilized and experimented for the same such as VGG19, ResNet101, EfficientNetB0, MobileNetV2, InceptionV3, and DenseNet121.

13,196 MRI scans form the data set, which was downloaded from the Kaggle webpage and separated 80:10:10 into train, validation, and test sets.

With 98.63% precision, our discovery reiterates that EfficientNetB0 outperforms every other model. The model can indeed prove to be an effective tool in the identification of tumors in an early stage and diagnosis of medical images because it is able to accurately classify MRI data. This research reiterates the extent to which deep learning can be utilized in order to achieve maximum healthcare through optimized and automated diagnosis that finally results in better patient outcomes.

II. LITERATURE REVIEW

Deep learning allows for automatic and very precise disease classification, e.g., brain tumor, it has transformed medical imaging. Deep learning-based methods of brain tumor classification from MRI scans have been explored in a huge majority of researches. Ismael and Abdel-Qader [1] proved the might of CNN architectures in clinical diagnostics by applying deep networks for brain cancer classification. Cheng et al. [2] used tumor region augmentation methods for better classification. Havaei et al. [3] laid the basis for pixel-wise classifications by applying a deep neural network-based segmentation method for brain tumors.

Hussain et al. [4] employed transfer learning techniques in order to attain high accuracy while deploying their deep learning model in the classification of brain tumors. Afshar et al. [5] employed capsule networks for tumor classification from MRI scans with satisfactory performance in image spatial relationship. Sultan et al. [6] also proved the performance of CNNs in radiology by the successful classification of breast cancer employing CNNs.

Tandel To improve classification accuracy, advanced fusion-based deep learning architectures—like those developed by Khan et al. [7]—are a combination of more than one architecture. To improve CNN-based cancer classification, Deepak and Ameer [8] compared transfer learning methods. Kadry et al. [9] proved the efficacy of automatic detection of brain abnormality with deep learning.

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Additionally, Tandel et al. [11] applied artificial intelligence paradigms to the classification of multiclass tumors on MRI and Özlem and Güngen [10] to brain tumor classification from MRI using deep transfer learning. Recent studies, such as that of Esav and Jibukumar [12], emphasize low-complexity architecture for real-time detection.

III. METHODOLOGY

A. About Dataset

Kaggle, the largest machine learning platform, provides this study's dataset in the form of MRI brain scan images. It possesses four main categories, and every category is a unique kind of brain condition: pituitary, meningioma, glioma, and no tumor. It has 13,196 images divided into three sets: testing (10%), validation (10%), and training (80%). Specifically, 1,323 images for validation, 10,555 images for training, and 1,318 images for testing.

In accurately classifying brain cancers, deep learning models utilize such MRI scans as a useful input. Properly balanced classification of the dataset ensures proper model testing. The work suggests the development of an efficient brain tumor detection system from this dataset that will assist in early diagnosis and improved medical imaging devices. The dataset is appropriately apt for training deep learning models on automatic brain tumor classification because it is labeled and of high quality.

B. Necessary Modules

1) Tensorflow:

TensorFlow is the basic deep learning library used within this work to accomplish realization and training of our brain tumor classifiers. For creation of deep learning networks, training, and testing, different base TensorFlow modules are called. Pre-trained EfficientNetB0, VGG19, ResNet101, MobileNetV2, InceptionV3, and DenseNet121 models are made available in the tensorflow.keras.applications module. The models are pre-tuned to classify properly. Sequence models can be found in the tensorflow.keras.models module and feature extraction layers can be built on top of classification layers. In a manner such that the model can learn optimally, modules like GlobalMaxPooling2D, Dense, and activation can be employed with the tensorflow.keras.layers module. Sparse Categorica lCrossentropy, multi-class classification problem's required loss, is also provided by tensorflow.keras.losses. It is backed by tensorflow.keras.optimizers package, i.e., Adam optimizer. Through combining these TensorFlow libraries, the brain tumor diagnosis system is efficient, precise, and automatic, enhancing medical diagnosis.

2) Keras:

We train and develop a number of pre-trained convolutional neural networks (CNNs) to classify brain tumors with Keras, a high-level TensorFlow deep learning API. Tensorflow.keras.applications, an important module provided by Keras that eases the creation of deep models, enables adding pre-trained models like VGG19, ResNet101, EfficientNetB0, MobileNetV2, InceptionV3, and DenseNet121 with minimal effort. The four classes on which these models split after fine-tuning and initialization with weights of ImageNet are glioma, meningioma, no tumor, and pituitary tumors.

Also, tensorflow.keras.layers contains basic layers such as Dense layers, carrying out fully connected computations for classification, and GlobalMaxPooling2D, shrinking spatial dimensions without losing valuable features. Multi-class classification is handled by Sparse Categorical Crossentropy, and tensorflow.keras.losses is used for helping define the loss function. And finally, model training is guaranteed through tensorflow.keras.optimizers such as Adam. All these Keras modules enhance model accuracy and provide automatic tumour detection for early diagnosis.

3) Convolutional Neural Network (CNN):

In this paper, here, Convolutional Neural Networks (CNNs) are used for brain tumor diagnosis based on MRI scans. CNNs are especially well-suited for medical image tasks because they are essentially hand-tuned to mess around with visual data. These convolutional layers of these networks are used to provide correct detection of tumors by extracting useful information in terms of edges, texture, and pattern.

To categorize MRI scans into four classes—glioma, meningioma, no tumor, and pituitary—we utilize some pre-trained CNN models in our work, such as VGG19, ResNet101, EfficientNetB0, MobileNetV2, InceptionV3, and DenseNet121. By detecting advanced patterns in brain scans, such models enhance diagnosis. CNNs can learn through hierarchical features by passing images through repeated passes through many layers, e.g., convolutional, pooling, and fully connected layers. EfficientNetB0, the best model, with an astounding accuracy rate of 98.63% established that CNNs are best applied to medical image analysis and tumor detection in its first phase. The approach significantly enhances automated development and diagnosis in medicine.

C. Keras Layers used

1) Conv2D

Our brain tumor classification model is highly dependent on Keras's Conv2D layer for spatial feature extraction of MRI scans. A convolution layer called Conv2D applies a sequence of learnable filters to the input images in such a manner that the pattern of similar shapes, edges, and textures can be revealed to the model. Because of the MRI scanning features, it is extremely helpful in differentiating glioma from meningioma, pituitary tumor, and no tumor. Our work enhances feature extraction by stacking Conv2D layers in multiple stages in deep learning architectures such as ResNet101, VGG19, and EfficientNetB0. For effectively processing image data, each Conv2D layer uses kernel filters and an activation function (ReLU). The model learns abstract representations required for proper tumor classification with convolutional processes. This increases the precision of early diagnosis and automated healthcare services by improving the capability to detect small differences in medical images.

2) Flatten

The Keras Flatten layer is important to our brain tumor classification task since it maps the output of the convolutional and pooling layers into one one-dimensional vector. The Flatten layer feeds these structured representations into a form consumable by fully connected layers, which can classify, since convolutional layers produce multi-dimensional feature maps. GlobalMaxPooling2D, whose function is basically reducing the spatial dimensions without losing significant features, replaces the Flatten layer in our deep learning model of EfficientNetB0 directly. The replacement enables the model to pump the extracted features into dense layers, which further classify the features into four categories of tumors: pituitary, meningioma, glioma, and no tumor. The Flatten operation improves the model efficiency by providing a more gradual transition from feature extraction to classification. The Flatten operation is instrumental in achieving the highest computing efficiency and enhancing the accuracy of brain tumor detection based on deep learning.

3) MaxPooling

One of the key convolutional neural network (CNN) layers, maxpooling diminishes the spatial dimensions of feature maps and retains significant information. MaxPooling greatly enhances computational efficiency along with reducing overfitting in our brain tumor classification study. This layer picks the maximum value within a given window (e.g., 2×2) of a feature map by conducting a pooling operation, commonly max pooling. We can downsample MRI images efficiently by incorporating MaxPooling layers into our models like EfficientNetB0, ResNet101, and VGG19, in a manner that retains only the important features. This maintains the significant tumor-related patterns with fewer trainable parameters. Moreover, Convolutional Neural Networks with MaxPooling improve the overall generalization ability of the model across different MRI images and produce more consistent classification performance. MaxPooling achieves our best model, EfficientNetB0 with 98.63% accuracy, which is quite effective in the early brain tumor detection.

4) AveragePooling

Keras' AveragePooling layer plays a vital role in our brain tumor classification study as it decreases feature map spatial size directly without losing useful information. Pooling layers, by down sampling features fed in, reduce computation and overfitting. AveragePooling reduces feature maps' sharpness and keeps useful patterns in MRI scans by averaging the pixel value in a frame. AveragePooling gives a more generalized view by taking into account all pixel values, whereas other CNN models use MaxPooling by taking into account only the maximum value within a region. That makes it easier for the model to take into account more generalized trends instead of high-value features. Pooling layers boost extracted tumor features to improve pre-trained models such as EfficientNetB0, ResNet101, and InceptionV3 and boost their classification accuracy. Our approach achieves improved feature extraction and effective learning through the implementation of Average Pooling for improving the accuracy of brain tumor detection.

5) Dense

Keras dense layer is a critical component of the final couple of steps in the deep learning model of our brain tumor classification study. The dense layer enables the model to observe subtle relationships between data retrieved as it is a fully connected layer wherein every neuron is provided with input from every other neuron from the preceding layer. We use two Dense layers in our EfficientNetB0 model: a terminal Dense layer of four neurons with softmax activation for MRI image classification into glioma, meningioma, no tumor, and pituitary classes and a Dense layer of 256 neurons with ReLU activation for deep pattern learning.

The softmax function enables accurate classification by returning class probabilities, which are used by the model. The dense layers provide strength and accuracy to the model by strengthening features learned by the convolutional layers. EfficientNetB0 achieved a highest accuracy of 98.63% for brain tumor classification with this setup.

6) Activation

Ever since the discovery of non-linearity, activation functions are a basic building block of deep models because they make it possible for neural networks to learn complex patterns. We utilize Softmax and ReLU (Rectified Linear Unit) activation functions in our EfficientNetB0 model for the purpose of maximizing performance for our brain tumor classification task. By removing negative values, smoothing gradient flow, and reducing calculation time, the ReLU activation function is used in the hidden layers to speed up training. It facilitates learning complex MRI scan data, including tumor texture and shape, by the model. Model predictions are transformed into probability distributions for each one of the four classes—glioma, meningioma, no tumor, and pituitary—via the Softmax activation function in the output layer. This makes the model assign the correct kind of tumor the highest probability.

7) Dropout

Our dropout-based brain tumor model addresses the overfitting issue, a primary regularization technique responsible for generalization. Deep learning overfitting is a state where a model will perform badly on novel data because the model has learned noise instead of important patterns on training data. Dropout will prevent the network from learning unique and specific characteristics by disabling randomly during training some of the neurons.

Dropout layers are implemented in our model based on EfficientNetB0 to enhance performance in our study, dividing MRI images into four classes (glioma, meningioma, no tumor, and pituitary). We become independent of specific neurons using dropout in dense layers to enhance test and validation dataset accuracy. Using this method allowed us to achieve our 98.63% accuracy in our model, thereby establishing its effectiveness for early brain tumor detection and medical image classification through deep learning.

IV. MODELS USED

A. VGG19

One of the most well-known deep models used for image classification problems, VGG16 possesses a very efficient but simple architecture. It has 16 layers that include max-pooling layers, fully connected layers, and several convolutional layers with tiny 3x3 filters. Because of its architecture, the model can extract hierarchical features and therefore is very suitable for applications related to medical imaging. VGG16 was used in our brain tumor classification research with MRI scans to classify the glioma, meningioma, no tumor, and pituitary classes. It was alright, but it wasn't quite as good as some of the other models, such as EfficientNetB0, which was 91.15% accurate. However, VGG16 is a strong model because it can effectively extract features and help in the early detection of tumors and their classification.

B. ResNet101

In order to classify brain tumors from MRI scans, we use a deep convolutional neural network in the form of the ResNet101 (Residual Network-101). With 101 layers and residual connections, it avoids the vanishing gradient problem for effective training of deep architecture. Medical imaging is suitable for the model because the residual connections enable it to learn the high-level features without losing anything. Glioma, meningioma, no tumor, and pituitary were employed to train ResNet101 in our research. Its accuracy was 91.38% and demonstrated how it is capable of extracting deep features that are extremely critical in the classification of tumors. EfficientNetB0 was the most effective model that can be employed in tumor early detection and diagnosis, but ResNet101 was adequate.

C. EfficientNetB0

EfficientNetB0 is our highest accuracy brain tumor classification model at 98.63% accuracy. This robust yet resource-constrained CNN draws on compound scaling to reduce depth, width, and resolution inside the network to deliver maximum efficiency and accuracy. We employed EfficientNetB0 in this study for the classification of brain tumors using MRI with pre-trained weights for ImageNet. By having high-level feature extraction for MRI images, the model supports accurate classification to meningioma, pituitary, glioma, and no tumor.

It promises to detect brain tumors early since it is able to outperform VGG19, ResNet101, MobileNetV2, InceptionV3, and DenseNet121. This bears witness to its raw capability for performance in medical imaging and computer-aided diagnosis.

D. MobileNetV2

Lightweight accurate deep model which is designed for computational economy is known as MobileNetV2. For MRI brain image classification to the four categories: pituitary, meningioma, glioma, and no tumor, in the present work it was utilized. MobileNetV2 reduces computation cost without compromising performance using inverted residual blocks and depthwise separable convolutions. For medical imaging tasks where inference speed is a concern, this method is optimal. MobileNetV2 worked well in differentiating different types of brain tumors in our study at a rate of 93.04%. Because it is resource-efficient, it can be applied in resource-constrained environments and real-time diagnosis. EfficientNetB0 worked best for our brain tumor classification task even though it performed well.

E. InceptionV3

The Since its operation in image classification, InceptionV3, a deep learning model, is a leading candidate to diagnose brain tumors through MRI scans. It employs a very sophisticated architecture that incorporates factorized convolutions, asymmetric kernels, and auxiliary classifiers with the goal of increasing accuracy and efficiency in processing. Our research utilized InceptionV3 to classify brain MRI scans into four groups: no tumor, glioma, meningioma, and pituitary. With effective extraction of fine information from MRI data, the software enables precise tumor diagnosis. Having been trained on our database, InceptionV3 proved its expertise in medical images with a 92.89% accuracy.

F. DenseNet121

We used MRI data to determine brain tumors using pretrained deep models like DenseNet121. Because each layer in this CNN takes inputs from all the previous layers, this model is notoriously renowned for having a dense connection strategy. It is very effective for medical image classification because it maximizes gradient flow, minimizes redundant computation, and promotes feature propagation. The training set that was utilized to train DenseNet121 in our study was classified into four categories: pituitary, glioma, meningioma, and no tumor. With a result of 91.08% accuracy, it proved to be capable of detecting complex patterns using MRI images. Regardless of that, EfficientNetB0 was superior to DenseNet121's best accuracy. DenseNet121 is no useless model for the detection of brain tumors, however.

V. IMPLEMENTATION

To classify the brain tumors, we used EfficientNetB0 with the highest accuracy of 98.63%. We used its pretrained ImageNet weights to carry out transfer learning and trained the model on TensorFlow and Keras. The input MRI scans were resized to the model's dimension requirement, and data augmentation procedures were carried out to promote generalization.

For the four-category classification of the image into glioma, meningioma, no tumor, and pituitary, the architecture takes the EfficientNetB0 as a base model, Global Max Pooling, a single dense (fully connected) layer containing 256 neurons, and the output layer comprising softmax activation. Training was on 30 epochs with the Adam optimizer and the loss function of Sparse Categorical Crossentropy. The model was found to have high accuracy on the training, validation, and test sets. This application gives a robust and efficient approach for medical image classification with significant improvement in early brain tumor detection.

VI. RESULTS OBTAINED

Our experiment proves the ability of deep learning in brain tumor classification from MRI scans. Different pretrained models were experimented with in our experiment to check the performance of the models. As can be seen from Table 1: Accuracy Comparison in Percentage, EfficientNetB0 was found to have 98.63% accuracy among the model options under experimentation, i.e., VGG19, ResNet101, EfficientNetB0, MobileNetV2, InceptionV3, and DenseNet121.

Algorithm	Accuracy
VGG19	91.15%
ResNet101	91.38%
EfficientNetB3	98.63%
MobileNetV2	93.04%
IncecptonV3	92.89%
DenseNet121	91.08%

Table 1 Accuracy Comparison in percentage

The precision of each model is graphically depicted in Figure 1: Accuracy Comparison Chart for closer observation of the performance of each model.

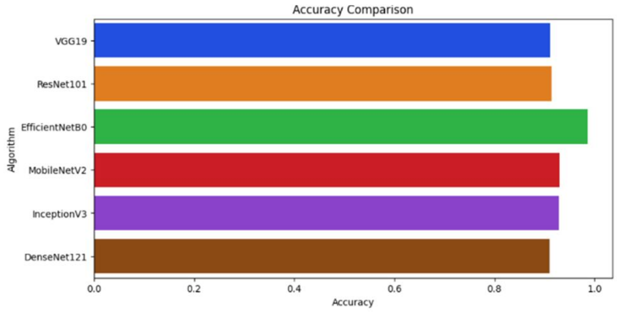

Figure 1 Accuracy Comparison Chart

The Classification Report provides proper analysis with precision, recall, and F1-score of each class assured in Figure 2: Classification Report.

	precision	recall	f1-score	support
0	0.9747	0.9904	0.9825	311
1	0.9749	0.9780	0.9765	318
2	1.0000	0.9941	0.9971	341
3	0.9943	0.9830	0.9886	353
accuracy			0.9864	1323
macro avg	0.9860	0.9864	0.9861	1323
weighted avg	0.9865	0.9864	0.9864	1323

Figure 2 Classification Report

The ability of the model to classify tumor types very well with a very low misclass rate can be observed from Confusion Matrix (Figure 3).

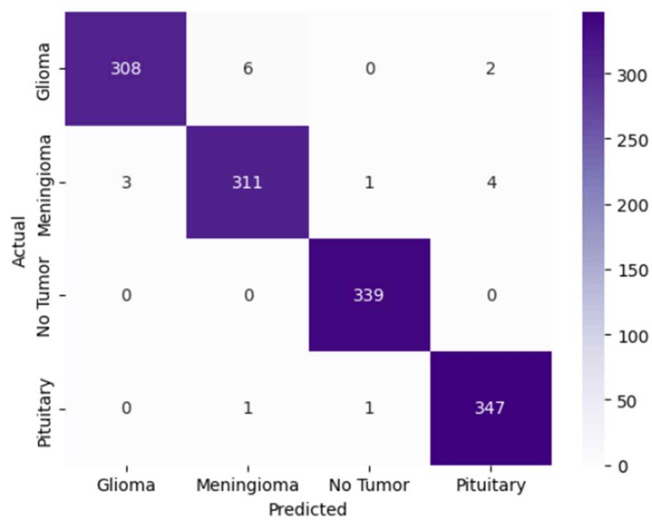

Figure 3 Confusion Matrix

Apart from that, repeated convergence is indicated by Model Accuracy Graph (Figure 5) and Model Loss Graph (Figure 4) displaying training as well as validation performance up to iteration 30.

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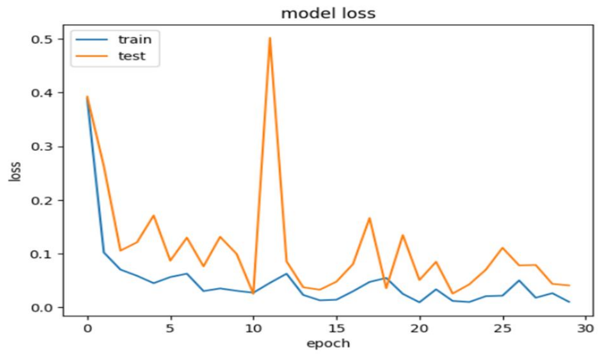

Figure 4 Model loss graph

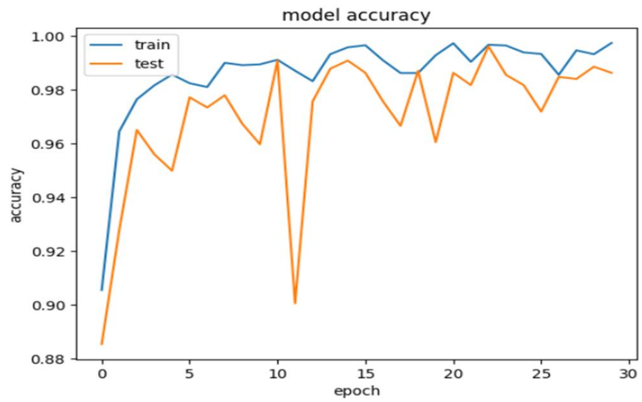

Figure 5 Model accuracy graph

The result of the final class prediction is presented on the Result Page (Figure 6), supporting the model.
Based on these results, EfficientNetB0 is the most suitable model to use for the early diagnosis of brain tumors. It is a very accurate, machine-based system with the capability of making physicians efficient at diagnosing brain tumors quickly and accurately.

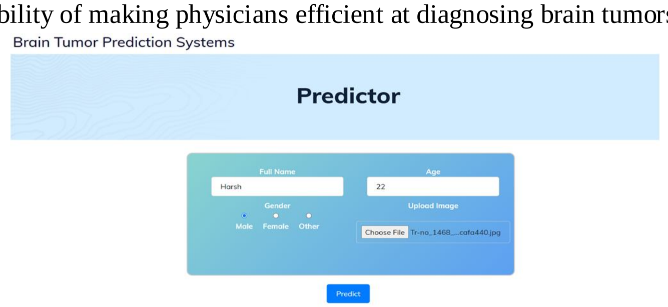

Figure 6 Web app predict page

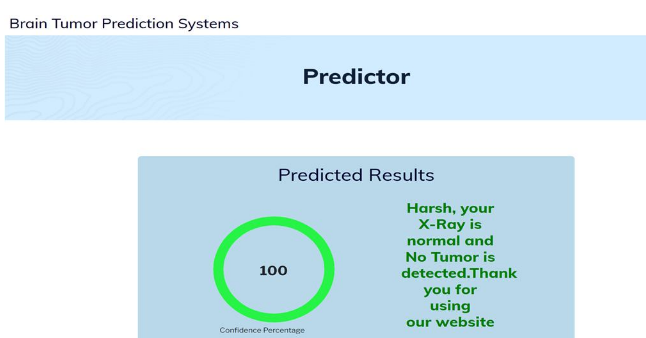

Figure 7 Result page

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VII. CONCLUSION

Based on the MRI scans, this study proves the power of deep learning models in brain tumor classification. We compared different pretrained convolutional neural networks (CNNs) to see which of them would perform the best. We tested VGG19, ResNet101, EfficientNetB0, MobileNetV2, InceptionV3, and DenseNet121. The highest among these in brain tumor detection was EfficientNetB0, which surpassed all the rest by an impressive 98.63% accuracy rate.

By applying transfer learning, data augmentation, and advanced optimization methods, we were able to train a robust model that is capable of distinguishing between four kinds of tumors: pituitary, meningioma, glioma, and no tumor. Accuracy plots, confusion matrix, and classification report all validate the consistency of the model in medical imaging.

Our research demonstrates the power of deep learning to be applied for early detection of tumors in an attempt to enable radiologists to diagnose more quickly and more precisely. Upcoming studies will emphasize improving the model's performance and integrating it into clinical practice.

REFERENCES

[1] Ismael, S. & Abdel-Qader, I. (2020). Brain tumor classification via deep learning networks. In 2020 International Conference on Electrical, Communication, and Computer Engineering (ICECCE) (pp. 1-6). IEEE.

[2] Cheng, J., Huang, W., Cao, S., Yang, R., Zhou, Y., Chen, Z., ... & Duan, H. (2015). Enhanced performance of brain tumor classification via tumor region augmentation and partition. PloS one, 10(10), e0140381.

[3] Havaei, M., Davy, A., Warde-Farley, D., Biard, A., Courville, A., Bengio, Y., ... & Larochelle, H. (2017). Brain tumor segmentation with deep neural networks. Medical image analysis, 35, 18-31.

[4] Hussain, S., Ahmad, W., Hassan, M. A., & Khan, M. A. (2021). Deep learning-based brain tumor classification using MRI images. Computational intelligence and neuroscience, 2021.

[5] Afshar, P., Mohammadi, A., & Plataniotis, K. N. (2019). Brain tumor type classification via capsule networks. In 2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019) (pp. 294-297). IEEE.

[6] Sultan, H. H., Chen, L., & Liu, Y. J. (2019). Convolutional neural network for breast cancer classification using ultrasound images. Biomedical Signal Processing and Control, 44, 139-147.

[7] Khan, M. A., Akram, T., Sharif, M., & Javed, M. Y. (2021). Intelligent fusion-assisted deep learning model for brain tumor classification using MRI. Computational intelligence and neuroscience, 2021.

[8] S. Deepak and P. Ameer, “Brain tumor classification using deep CNN features via transfer learning,” in *Proc. - 2nd Int. Conf. Intell. Comput. Instrum. Control Tech. ICICICT 2019*, 2019, pp. 1249–1255.

[9] S. Kadry, Y. Nam, H. T. Rauf, V. Rajinikanth, and I. A. Lawal, “Automated Detection of Brain Abnormality using Deep-Learning-Scheme: A Study,” in *Proc. 2021 Seventh Int. Conf. Bio Signals, Images, Instrum. (ICBSII)*, 2021, pp. 1–6.

[10] P. Özlem and C. Güngen, “Classification of brain tumors from MR images using deep transfer learning,” in *Proc. - 2019 8th Int. Conf. Comput. Intell. Commun. Networks, CICN 2019*, 2019, pp. 148–153.

[11] G. S. Tandel, A. Balestrieri, T. Jujaray, N. N. Khanna, L. Saba, and J. S. Suri, “Multiclass magnetic resonance imaging brain tumor classification using artificial intelligence paradigm,” *Comput. Methods Programs Biomed.*, vol. 177, pp. 208–217, Oct. 2019.

[12] N. esav and M. Jibukumar, “Efficient and low complex architecture for detection and classification of Brain Tumor using RCNN with Two Channel CNN,” in *Proc. 2021 Int. Conf. Commun. Electron. Syst. ICCES 2021*, 2021, pp. 1165–1169.

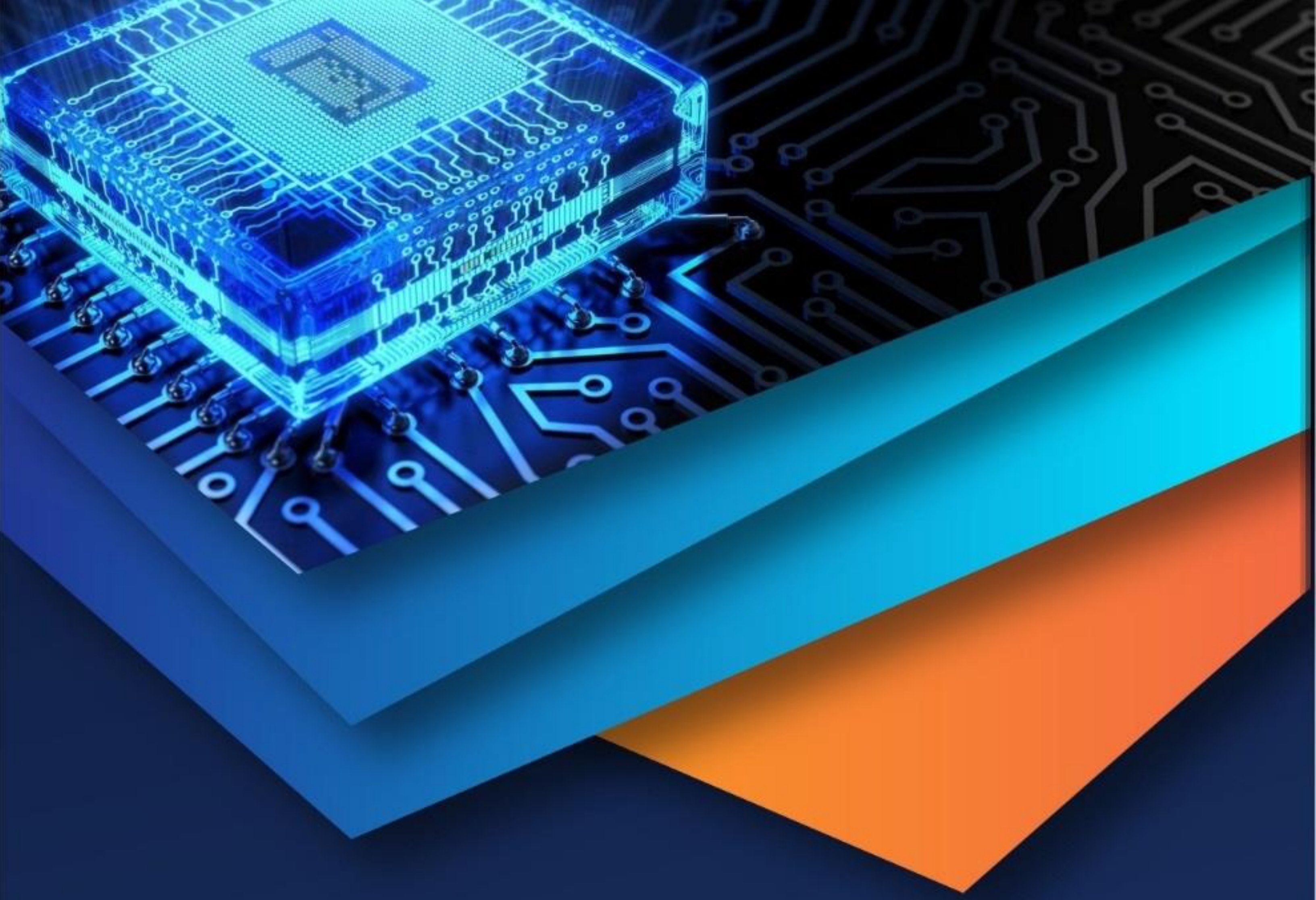
[13] M. Pareek, C. K. Jha, and S. Mukherjee, “Brain Tumor Classification from MRI Images and Calculation of Tumor Area,” in *Advances in Intelligent Systems and Computing*, vol. 1157, Springer, Singapore, 2020, pp. 249–258.

[14] A. Chaddad, P. O. Zinn, and R. R. Colen, “Radiomics texture feature extraction for characterizing gbm phenotypes using glcm,” in *Proc. IEEE 12th Int. Symp. Biomed. Imaging (ISBI)*, 2015, pp. 1018–1021.

[15] A. Chaddad, P. O. Zinn, and R. R. Colen, “Brain tumor identification using Gaussian Mixture Model features and Decision Trees classifier,” in *Proc. 48th Annu. Conf. Inf. Sci. Syst. (CISS)*, 2014, pp. 1–4.

[16] Q. Tian and S. Tian, “Radiomics Strategy for Glioma Grading Using Texture Features From Multiparametric MRI,” in *Proc. Int. Soc. Magn. Reson. Med. (ISMRM)*, 2018.

[17] M. Roboflow, “Brain Tumor Classification (QKEoA),” Roboflow Universe,[Online].Available: https://universe.roboflow.com/opendataacademia/brain-tumor-classification-qkeoa.



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