IJNRD.ORG ISSN : 2456-4184

INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG

An International Open Access, Peer-reviewed, Refereed Journal

Automated Brain Tumor Classification using Fusion Model of VGG19 – EfficientNetB0

[1]Tejashwini P S,[2]Geetha N,[3]Dr. Thriveni J

[1]Assistant Professor, [2] M.tech Student ,[3]Professor
Department of Computer Science and Engineering
UVCE, Bangalore University, India

Abstract : The increasing mortality rate attributed to brain tumors, characterized by abnormal clusters of rapidly dividing cells in or around the brain, poses a growing concern. Early detection significantly improves survival prospects, underscoring the necessity of tools with automated assistance for prompt diagnosis. Magnetic resonance (MR) images play a crucial role in detecting brain tumors, with various deep learning algorithms like VGG19 and EfficientNetB0 being utilized. To capitalize on the strengths of these algorithms, a Fusion Model is employed, amalgamating their respective capabilities. This fusion model underwent testing on a challenging dataset comprising 7,023 MRI brain tumor images, yielding impressive results. It demonstrated 100% accuracy during training and 99% during testing, highlighting its efficacy in enhancing CNN performance for image classification on the Kaggle dataset Br35H.

***IndexTerms* - Fusion, Transfer learning, EfficientNetB0, VGG16.**

I. INTRODUCTION

The human brain is protected by the sturdy encasement of the skull, but even minor anomalies like tumors can have severe consequences. Tumors develop when certain areas of the brain experience inadequate oxygen flow, potentially leading to death or significant impairment. Medical assessments indicate a growing global population afflicted by brain tumors, emphasizing the critical importance of their detection and treatment. Magnetic resonance imaging (MRI) and computed tomography (CT) scans are commonly employed to identify brain tissue irregularities, with MRI scans generally preferred due to superior imaging capabilities. Automated procedures using medical image processing techniques are increasingly valued for brain tumor detection. However, the varied shapes, sizes, and locations of tumors present challenges for accurate detection and classification. Medical experts painstakingly analyze MRI images to identify potential tumor regions. Nevertheless, the indistinct tumor boundaries amid adjacent healthy tissue require extensive manual examination, which can lead to diagnostic inaccuracies. Enhancing brain tumor detection can be achieved through the integration of deep learning techniques, employing transfer learning approaches. This, however, demands the expertise of seasoned professionals to identify optimal feature extraction and segmentation algorithms[1]. Deep learning facilitates the analysis of large datasets, enabling rapid pattern recognition and model development, thereby bridging the gap between technology and medicine. Research efforts aim to improve treatment efficacy, reduce healthcare costs, and delay brain degeneration by enabling early tumor detection. Pre-processing steps, such as feature extraction and selection, are crucial before applying deep learning methods. Recent advancements have led to vast amounts of multimodal imaging data, advancing early tumor detection and classification efforts. Nonetheless, decision-making remains complex and time-consuming, necessitating consideration of various options.

The primary objective of this study is to develop a diagnostic system for early brain tumor detection using MRI images and innovative deep learning techniques. By training models on datasets like the Br35HData Kaggle MRI, their efficacy in tumor identification can be assessed using quantitative metrics such as recall, accuracy, precision, and F1-score[2]. The rapid evolution of machine learning, especially deep learning, has transformed medical imaging by enhancing the representational capacity of convolutional neural networks (CNNs)[3][4].

This paper advocates for an automated assisted method for brain tumor detection based on the fusion of deep learning features obtained from various techniques. Feature fusion improves model performance by combining lower- and higher-level features into cohesive vectors. The proposed methodology is evaluated using quantitative metrics on the Br35H dataset, demonstrating its effectiveness in multi-classification tasks. The system's primary contributions include automated feature extraction, deep feature fusion, and tumor type classification. Despite challenges like imperfect backgrounds and MRI artifacts, the proposed methodology enables successful tumor categorization. Subsequent sections of this paper explore relevant literature, materials and techniques used, model description, potential future work, and concluding remarks, with the model's performance showcased through graphs and a confusion matrix.

II. RELATED WORKS

This section provides an overview of the historical perspectives explored by researchers over the past few decades to address brain tumor detection, alongside subsequent advancements in the field. The increasing adoption of deep learning is driven by its promising applications in diagnosing diseases associated with tumors. Recent releases of various deep learning algorithms as tools for tumor detection have assisted physicians in making informed decisions about treatment options. Several CNN models, including GoogLeNet[7], VGG[6], and AlexNet[5], are currently utilized in medical image classification applications. Anichur Rahman et al.[8] present two deep learning models for binary and multiclass brain tumor diagnosis, utilizing datasets consisting of 3064 and 152 MRI images. They employ a 23-layer CNN and utilize VGG16 for transfer learning to mitigate overfitting in the smaller dataset. These models outperform all previously published state-of-the-art models, achieving remarkable classification accuracies of 97.8% and 100%. In another study, Muhammad Rizwan et al. [9] describe a CAD method employing deep learning, specifically a GCNN with a Gaussian filter, for accurate and efficient brain tumor identification. Achieving an impressive accuracy of 99.31%, the system combines predictions from five finely-tuned pre-trained models (GoogleNet, AlexNet, ShuffleNet, SqueezeNet, and NASNet-Mobile) through a hybrid approach[10] employing majority voting. By employing image preprocessing, extensive data augmentation, and feature extraction from various CNNs (AlexNet, GoogLeNet, and ResNet18), the system enhances tumor classification using SVM and KNN, achieving a remarkable 99.7% accuracy on a substantial dataset[11]. Utilizing a concatenate layer to blend the outputs of the Xception and NASNetMobile[12] architectures, a dropout layer to address overfitting in the CNN, and transfer learning to merge the two architectures, the model achieves exceptional performance. Preprocessing also includes optimization for "Best windowing of images."

Togacar et al.[13] introduced BrainMRNet, which utilizes the hypercolumn technique and attention modules. Prior to reaching attention modules, images undergo initial preprocessing. These modules identify significant areas and route the image to convolutional layers. Within BrainMRNet, the hypercolumn approach maintains features from each layer through an array structure in the final layer, resulting in an achieved system accuracy of 96.05%. The effectiveness of this approach is validated through tests conducted on three brain MRI datasets. For small datasets with two classes, DenseNet-169[14] is emphasized, while an ensemble of DenseNet-169, Inception V3, and ResNeXt-50 is recommended for larger datasets with two classes. Furthermore, for extensive datasets comprising four classes, the combination of ShuffleNetV2, MnasNet, and DenseNet-169 is identified. Findings consistently demonstrate that Support Vector Machine (SVM) with an RBF kernel outperforms other machine learning classifiers in MRI-based brain tumor classification.

Maqsood et al.[15] introduced a method for brain tumor detection utilizing edge detection and the U-NET model. They incorporate fuzzy logic for edge identification alongside a tumor segmentation framework that enhances image contrast. Within the U-NET architecture, features are extracted from subband images, focusing on detecting meningiomas in brain imaging. Khawaldeh et al.[19] presented a CNN model for brain tumor and glioma detection, enhancing a pre-trained architecture and achieving an overall accuracy of 91%. Despite significant efforts, further research is warranted to establish a dependable and effective method for categorizing brain MR images. One notable limitation of the research[16-19] is its focus solely on binary categorization of brain cancers, overlooking multiclass classification and indicating a need for further investigation to identify specific tumor subtypes.

Employing ensemble classifiers for classification, Noreen et al.[20] utilized VGG16, VGG19, and AlexNet for deep feature extraction, achieving a maximum system accuracy of 94.3%. Swati et al.[21] achieved a 94.8% accuracy rate in categorizing MRI images of brain tumors using refined versions of AlexNet and VGG. Saxena et al.[22] employed ResNet, Inception-V3, and VGG-16, with ResNet achieving the highest accuracy of 95%. However, these methods exhibited subpar performance overall, warranting extensive testing prior to real-time deployment. Afshar et al.[37] achieved a 90.89% accuracy rate in classifying and identifying brain tumors using Capsule networks. It's important to note that CapsNets are particularly sensitive to image backgrounds and perform better when trained with segmented images, which adds complexity to the architecture.

III. MATERIAL AND METHODOLOGY

This section presents a comprehensive approach for classifying tumors in brain MRI images, utilizing the capabilities of deep learning through convolutional neural networks (CNNs) and transfer learning techniques. The analysis thoroughly examines the model's architecture, providing detailed insights into its design and training procedures. Initially, two separate networks, VGG16 and VGG19, are investigated independently to understand their individual strengths and performance characteristics in tumor classification. After this individual exploration, a fusion model is introduced, integrating the strengths of both VGG16 and VGG19. This fusion model undergoes meticulous training and evaluation, offering a thorough assessment of its effectiveness in improving tumor classification accuracy. In summary, this section presents a comprehensive exploration of various deep learning methodologies, concluding with the development and evaluation of a fusion model aimed at enhancing tumor classification in brain MRI images.

3.1 Convolutional Neural Network

The remarkable performance of Convolutional Neural Networks (CNNs) has generated considerable interest among researchers, motivating them to tackle previously daunting challenges. In recent years, a plethora of CNN architectures has emerged, addressing a wide range of issues across various domains, notably in medical image analysis. CNNs typically comprise two primary components:

1) A feature extraction module, consisting of multiple layers stacked together, utilizing convolutional layers to learn complex features from input images, and pooling layers to reduce spatial dimensions while retaining crucial information.
2) A classification module, incorporating fully connected (FC) layers to interpret the learned features and make predictions, facilitating accurate image classification.

This modular framework enables CNNs to effectively capture intricate patterns within images and make informed classifications, thereby revolutionizing the landscape of image recognition tasks, particularly in domains such as medical imaging.

3.2 Transfer Learning

Transfer learning (TL) emerges as a crucial application of learned image classification methods downstream. TL has attracted significant attention in the field of artificial intelligence due to its effectiveness in addressing challenges such as shifting learning objectives or the scarcity of training data. Notably, TL has witnessed remarkable advancements over the past decade [33]. Rather than starting from scratch with extensive datasets, TL leverages knowledge acquired from completing source tasks across various domains to aid target tasks [34]. Utilizing one of the pre-trained architectures provides additional benefits. For example, it facilitates learning by utilizing pre-trained weights, eliminating the need to train extensive models from scratch, a process that typically takes weeks with large datasets. Furthermore, using pre-trained architectures reduces the computational resources required for model training, making the process more efficient and accessible [35].

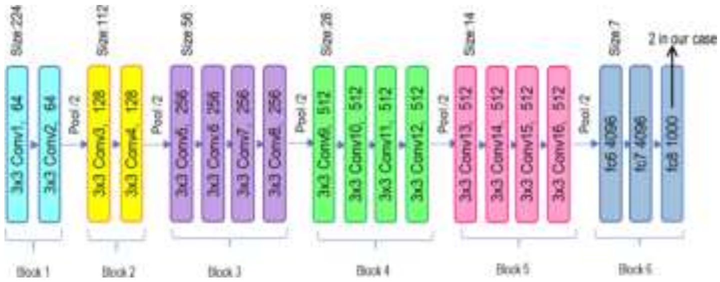

Fig 1: VGG19 architecture

3.3 VGG19

The VGG19 architecture, also developed by the Visual Geometry Group (VGG) at the University of Oxford, is a convolutional neural network (CNN) renowned for its depth and effectiveness. It comprises 19 weight layers, including 16 convolutional layers and 3 fully connected layers as shown in Fig 1.

1. Input Layer: Similar to VGG16, this layer accepts input images typically sized at 224x224 pixels with three color channels (RGB).
2. Convolutional Layers (Conv): The network begins with a series of convolutional layers, each followed by a Rectified Linear Unit (ReLU) activation function. These layers have small 3x3 receptive fields and are designed to learn low-level features such as edges and textures.
3. Max Pooling Layers (MaxPool): After every pair of convolutional layers, a max-pooling layer is inserted to reduce spatial dimensions while retaining important features. Max pooling is typically performed over a 2x2 window with a stride of 2.
4. Fully Connected Layers (FC): Following the convolutional layers, three fully connected layers are implemented. The first two FC layers consist of 4096 neurons each, while the third FC layer (output layer) comprises 1000 neurons corresponding to the 1000 classes in the ImageNet dataset, similar to VGG16.
5. Softmax Activation: The final layer applies a softmax activation function to produce class probabilities for classification.

Like VGG16, VGG19 is characterized by its deep layer stack and relatively small convolutional kernels, allowing it to capture intricate patterns and features within images effectively. Despite its increased depth compared to VGG16, VGG19 maintains a similar architecture and has demonstrated strong performance across various computer vision tasks.

3.4 EfficientNetB0

EfficientNetB0 utilizes compound scaling, a sophisticated approach that uniformly adjusts network width, depth, and image resolution to achieve an optimal balance between computational efficiency and accuracy. This characteristic makes EfficientNetB0, a convolutional neural network architecture, well-suited for applications on mobile devices with limited computational resources. Serving as the foundational model for the broader EfficientNet family, EfficientNetB0 achieves this balance through its use of mobile inverted bottleneck convolutional (MBConv) blocks and scaling factors such as depth (d), width (w), and resolution (r), systematically adapting the network architecture as depicted in Fig 2. This adaptability makes EfficientNetB0 versatile across various tasks, making it an ideal solution for a wide range of computer vision applications. Furthermore, EfficientNetB0's

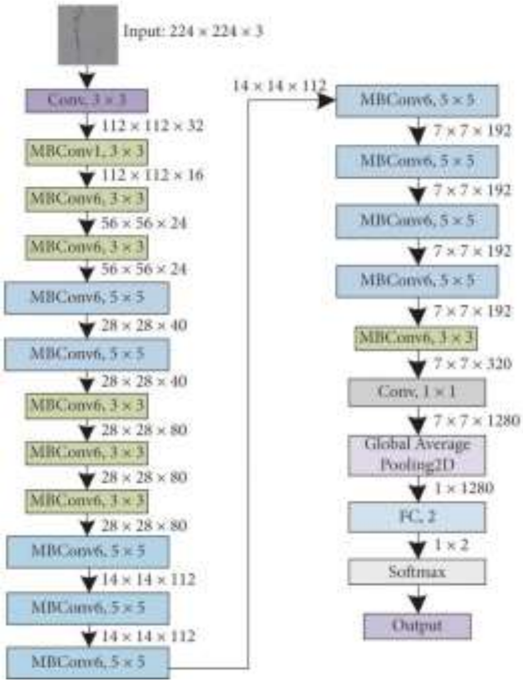

Fig 2: Architecture of EfficientNetB0

flexibility is augmented by its fine-tuning capabilities, robust generalization performance across diverse datasets, and availability of pre-trained models. These attributes enable EfficientNetB0 to maintain competitive accuracy in image classification tasks while remaining computationally efficient.

IV. PROPOSED METHODS

This study introduces a methodology for identifying and classifying brain tumors from MRI scans using deep convolutional neural network (CNN) feature fusion techniques. The workflow diagram depicted in Fig 3 outlines the steps involved in this approach. Prior to input into the CNN models for feature extraction, the MRI images undergo preprocessing steps including splitting for training and testing, normalization, and enhancement. To merge the extracted deep feature components into a unified representation for classification, the Softmax Activation layer of the fusion model is employed. This proposed method exhibits reliability and success in accurately categorizing various types of brain tumors, including meningioma, glioma, and pituitary tumors.

4.1 Datasets

MRI images are chosen as the primary input data for tumor detection due to their superior quality and suitability for medical diagnostics. The dataset used for classification is constructed from MRI images. Both the Classification-1 and Classification-2 models are trained using an open-access dataset available on Kaggle. Specifically, the Br35H dataset from Kaggle is employed for Classification-2, which includes four class labels: glioma, meningioma, pituitary, and normal. In total, there are 7,023 images in the Br35H dataset, with 5,712 images used for training and the remaining 1,023 for testing in Classification-2.
This dataset facilitates accurate categorization of various types of brain tumors in Classification-2. Table 1 presents the distribution of classes within the Classification-2 dataset.

4.2 Dataset Splitting

In machine learning, particularly in the development of Convolutional Neural Network (CNN) models, dataset splitting is a pivotal step. It involves partitioning the data into three distinct subsets: the training set, validation set, and test set. Each subset serves a specific role in ensuring the effectiveness and generalization capability of the model while guarding against overfitting.
The training set forms the core of the model, allowing it to learn intricate patterns, crucial features, and underlying relationships within the data. Through iterative optimization methods like gradient descent, the model adjusts its parameters to minimize the difference between its predictions and the observed outcomes in the training data. The validation set acts as a checkpoint during training. It evaluates the model's performance on unseen data, helping to monitor its ability to generalize while keeping hyperparameters in check. Periodically assessing the model's performance on the validation set aids in mitigating overfitting, where the model becomes overly specialized to the training data. The test set remains untouched until the final evaluation stage. It offers an unbiased measure of the model's ability to generalize to previously unseen data, providing insights into its real-world applicability and reliability. Furthermore, random shuffling of the dataset before splitting reduces bias and ensures that each subset is representative of the overall dataset. Although a common split ratio allocates 70% for training, 10% for validation, and

20% for testing, adjustments can be made based on specific requirements and dataset size. In summary, proper dataset splitting is essential for developing robust and reliable machine learning models.

Table 1: Dataset Distribution

Class Label	Tumor Class	Images
0	Glioma	1321
1	Meningioma	1339
2	No Tumor	1595
3	Pituitory	1457

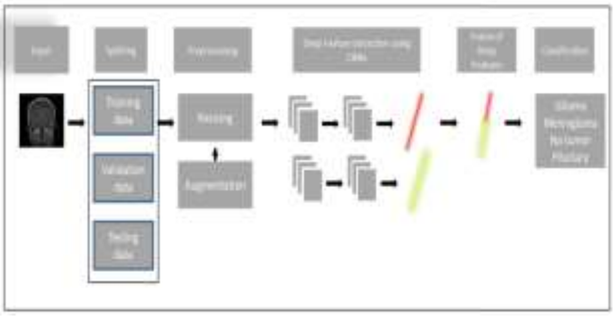

Fig 3: VGG19-ENetB0 Fusion Model

4.3 Data Preprocessing
During this stage, fundamental preprocessing tasks are executed on each subset separately. This may encompass a range of data-specific modifications, such as scaling images or normalization. Moreover, data augmentation techniques can be employed on image datasets to augment the size of the training set and enhance model generalization. These techniques may entail operations such as rotation, flipping, and zooming.

4.4 Deep Feature Extraction
Transfer learning is predominantly applied in interdisciplinary domains, particularly in fields like medical image diagnosis. This strategy eliminates the requirement for extensive datasets and considerably shortens the prolonged training times usually associated with constructing custom deep learning models. Our examination involved the utilization of diverse Convolutional Neural Network (CNN) architectures, including EfficientNetB0 and VGG19. These CNNs serve as proficient deep feature extractors, proficiently capturing significant attributes autonomously, without necessitating manual intervention.

4.5 Fusion Model
The quality of the input feature vector significantly influences the performance of a machine learning classifier, especially in accurately identifying tumors from Magnetic Resonance Images (MRIs). To achieve this, an algorithm capable of generating and recognizing characteristics from MRIs is crucial. In this particular phase, deep features extracted from transfer-learned Convolutional Neural Networks (CNNs) are combined.

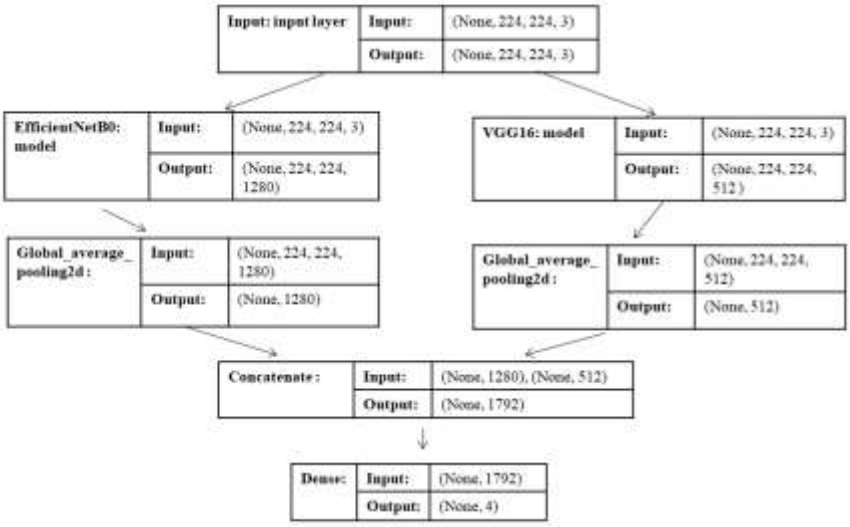

Fig 4: VGG19-ENetB0 Fusion Model

Feature fusion is a vital technique used to amalgamate multiple features from different models into a unified feature vector, reducing reliance on potentially inferior feature elements from any single model. The fusion model structure, illustrated in Figure 4, integrates features from EfficientNetB0 and VGG19, offering more comprehensive information about MR images than a single vector could provide, thereby enhancing classification outcomes. By employing CNN architectures with diverse designs and depths, heterogeneity is introduced, overcoming potential limitations such as redundant feature spaces from homogeneous architectures. This ensures the extraction of various higher-level and lower-level characteristics from MR images. The feature fusion process organizes each independent feature vector into four feature spaces, corresponding to the number of classes in the dataset, facilitating efficient tumor classification.

4.6 Classification

At this point, the dense layer within the fusion architecture processes the feature elements. By employing the softmax activation function, the labels of the features are compared to ascertain higher probabilities, subsequently assigning appropriate class labels like pituitary, glioma, meningioma, and normal. This procedure proves immensely valuable across diverse tasks, ranging from image categorization to brain tumor classification, as it assists the system in understanding intricate relationships and patterns within the data.

V. RESULTS DISCUSSIONS

To assess the effectiveness of each prediction model, a distinct test set comprising 20% of the images from each classification class was utilized. Various metrics, including accuracy, loss, precision, recall, and F1-score, were employed to evaluate the performance of each prediction model. Additionally, accuracy-graphs and loss-graphs were examined to visualize the performance trends of the models. Furthermore, the performance of the proposed model was evaluated using metrics such as the confusion matrix, F1-score, overall accuracy, specificity, sensitivity, and precision. Emphasizing the F1-score, particularly, it is favored over a simple mean as it accounts for extreme circumstances by being the harmonic mean of recall and precision values.

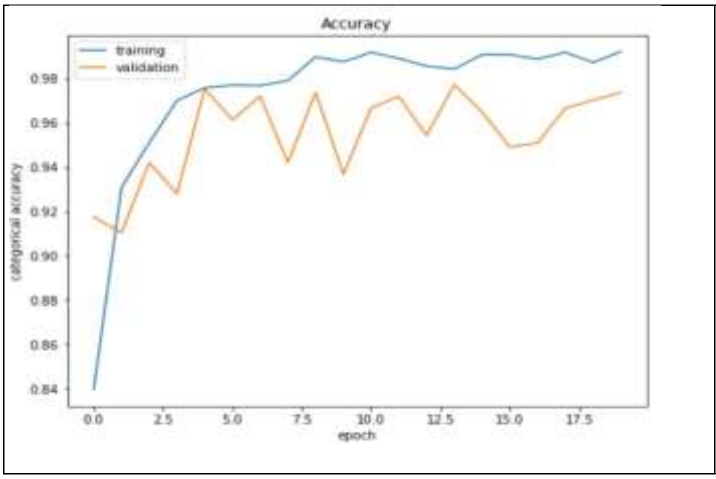

Fig 5: Accuracy Graph of Fusion model

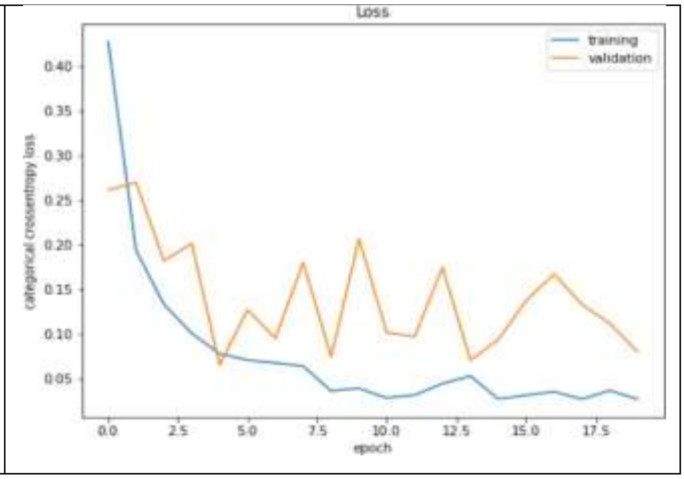

Fig 6: Loss Graph of Fusion model

This thorough evaluation approach offers insights into the performance of the models across multiple dimensions, ensuring a comprehensive assessment of their effectiveness in classification tasks.

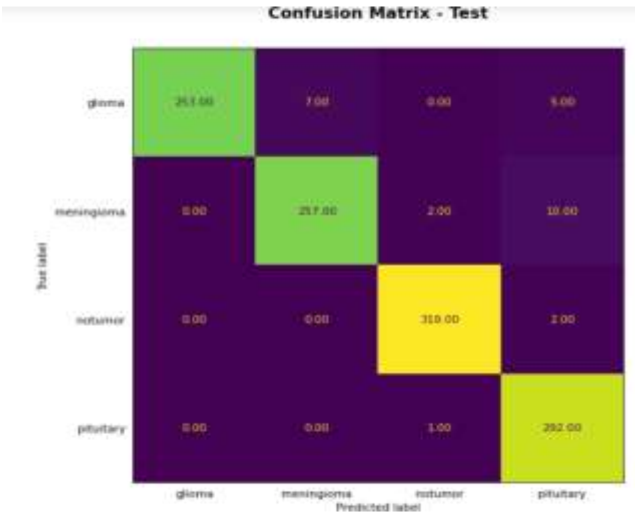

Fig 7: Confusion Matrix of Fusion model

Table 2: Classification Report CA:Class-Accuracy, P:Precision, R:Recall,F:F1-score, S:Support, E:EfficientNetB0,

Fusion-Model	Label	CA	P	R	F	S
VGG19 – E Net	0	0.99	1.00	0.97	0.98	265
	1	0.99	0.97	0.96	0.96	269
	2	1.00	0.99	1.00	0.99	320
	3	0.99	0.96	1.00	0.97	293

Table 3: Accuracy Report E:EfficientNetB0

Fusion-Model	Train	Val	Test
VGG16-E Net	1.00	0.98	0.99

Figures 5 and 6 showcase the accuracy and loss graphs of the model, respectively. These graphs distinctly illustrate that as the number of epochs increases, the accuracy enhances, and the loss function diminishes. The blue line in the graph denotes the training accuracy, while the orange line represents the validation accuracy. Additionally, Table 2 provides the Classification Report, offering a breakdown of the Fusion-model's performance for each individual class label, where 0 denotes no class label. This report encompasses precision, recall, F1-score, and support metrics for each unique class label.

VI. CONCLUSIONS

The increasing demand for efficient and unbiased assessment of extensive medical datasets has led to a rise in MRI-based medical image processing for brain tumor analysis. Early detection of brain tumors is crucial for reducing mortality rates and ensuring effective treatment. To address the labor-intensive and subjective nature of manual diagnosis, a transfer learning-based deep learning (DL) model was developed, combining various deep learning approaches for brain cancer classification from MRI images. The proposed fusion model, which integrates EfficientB0 and VGG19, achieved remarkable accuracy rates of 100% during training and 98% during testing. Future research directions include enhancing the study's robustness by broadening the scope of input images, exploring the incorporation of 2D and 3D data for brain tumor categorization, and potentially enabling tumor grading with larger datasets, possibly through collaborations with hospitals. The establishment of a Benchmark Dataset by relevant Medical Authorities would facilitate method assessment. Various deep learning approaches for brain cancer classification from MRI images were explored, with the proposed fusion model, integrating EfficientB0 and VGG19, achieving exceptional results in accurately classifying the type of brain tumor.

REFERENCES

[1] Mohan, P., Veerappampalayam Easwaramoorthy, S., Subramani, N., Subramanian, M., Meckanzi, S., Handcrafted deep-feature-based brain tumor detection and classification using mri images, 2022, Electronics 11.

[2] Debshree Bhattacharya, Manoj Kumar Nigam. Energy efficient fault detection and classification using hyperparameter-tuned machine learning classifiers with sensors, Measurement: Sensors. Volume 30, December,2023, 100908

[3] J.-S. Kang, J. Kang, J.-J. Kim, K.-W. Jeon, H.-J. Chung, and B.-H. Park. Neural Architecture Search Survey: A Computer Vision Perspective. Sensors, 23(3), 2023, 1713, 1- 17.

[4] H. Lee and J. Song, Introduction to convolutional neural network using Keras; an understanding from a statistician. Commun Stat Appl Methods, 26(6), 2019, 591–610.

[5] A. Krizhevsky, I. Sutskever, and G. E. Hinton, Imagenet classification with deep convolutional neural networks, Advances in Neural Information Processing Systems, vol. 25,2012, pp. 1097–1105.

[6] K. Simonyan and A. Zisserman, Very deep convolutional networks for large-scale image recognition,2014,

[7] C. Szegedy and W. Liu, Going deeper with convolutions, in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 1–9, 2015, Boston, MA, USA.

[8] Md. Saikat Islam Khan,[a] Anichur Rahman,[a,b,*] Tanoy Debnath,[a,c] Md. Razaul Karim,[a] Mostofa Kamal Nasir,[a] Shahab S. Band,[d,*] Amir Mosavi,[e,f,*] and Iman Dehzangi[g,h,] Accurate brain tumor detection using deep convolutional neural network, Computer Struct Biotechnol J.; 20: 2022." 4733–4745.

[9] Muhammed Rizwan, Aysha Shabbir, Maryam Shabbir , Thar Baker, Brain Tumor and Glioma Grade Classification Using Gaussian Convolutional Neural Network, VOLUME 10, Digital Object Identifier 10.1109/ACCESS.2022.3153108.

[10] Shaimaa E. Nassar , Ibrahim Yasser, Hanan M. Amer and Mohamed A. Mohamed1, A robust MRI-based brain tumor classifcation via a hybrid deep learning technique, in Proc. Int. The Journal of Supercomputing, Jul 2023.

[11] Hareem Kibriya, Rashid Amin , Asma Hassan Alshehri, Momina Masood, Sultan S. Alshamrani , and Abdullah Alshehri, A Novel and Effective Brain Tumor Classification Model Using Deep Feature Fusion and Famous Machine Learning Classifiers, Hindawi Computational Intelligence and Neuroscience Volume 2022, Article ID 7897669.

[12] Hiba Kahdum Dishar and Lamia AbedNoor Muhammed, Detection Brain Tumor Disease Using a Combination of Xception and NASNetMobile, in Int. J. Advance Soft Compu. Appl, Vol. 15, No. 2, July 2023.

[13] M. Toğaçar, B. Ergen and Z. Cömert. BrainMRNet: Brain Tumor Detection using Magnetic Resonance Images with a Novel Convolutional Neural Network Model. Medical Hypotheses, 2019, 134. 109531.

[14] J. Kang, Z. Ullah, and J. Gwak, MRI-based brain tumor classification using ensemble of deep features and machine learning classifiers, Sensors, vol. 21, no. 6, p. 2222, March 2021

[15] S. Maqsood, R. Damasevicius, and F. M. Shah, An efficient approach for the detection of brain tumor using fuzzy logic and U-NET CNN classification, in Computational Science and Its Applications - ICCSA 2021, pp. 105–118, Springer, New York, NY, USA, 2021.

[16] H. Mzoughi, I. Njeh, A. Wali et al., Deep multi-scale 3D convolutional neural network (CNN) for MRI gliomas brain tumor classification,"Journal of Digital Imaging, vol. 33, no. 4, pp. 903–915, 2020.

[17] S. Maqsood, R. Damasevicius, and F. M. Shah, An efficient approach for the detection of brain tumor using fuzzy logic and U-NET CNN classification, in Computational Science and Its Applications - ICCSA 2021, pp. 105–118, Springer, New York, NY, USA, 2021.

[18] M To˘gaçar, B Ergen, and Z C¨omert, BrainMRNet: brain tumor detection using magnetic resonance images with a novel convolutional neural network model, Medical Hypotheses, vol. 134, Article ID 109531, 2020.

[19] S. Khawaldeh, U. Pervaiz, A. Rafiq, and R. S. Alkhawaldeh, Noninvasive grading of glioma tumor using magnetic resonance imaging with convolutional neural networks, Applied Sciences, vol. 8, no. 1, p. 27, 2018.

[20] N. Noreen, S. Palaniappan, A. Qayyum, I. Ahmad, and M. O. Alassafi, Brain tumor classification based on finetuned models and the ensemble method, Computers, Materials & Continua, vol. 67, no. 3, pp. 3967–3982, 2021.

[21] Z. N. K. Swati, Q. Zhao, M. Kabir et al., Brain tumor classification for MR images using transfer learning and finetuning, Computerized Medical Imaging and Graphics, vol. 75, pp. 34–46, 2019.
[22] P. Saxena, A. Maheshwari, and S. Maheshwari, Predictive modeling of brain tumor: a Deep learning approach, in Innovations in Computational Intelligence and Computer Vision, pp. 275–285, Springer, New York, NY, USA, 2021.
[23] N. Ghassemi, A. Shoeibi, and M. Rouhani, Deep neural network with generative adversarial networks pre-training for brain tumor classification based on MR images, Biomedical Signal Processing and Control, vol. 57, Article ID 101678, 2020.
[24] H. Kibriya, R. Rafique, W. Ahmad, and S. Adnan, Tomato leaf disease detection using convolution neural network, in Proceedings of the IEEE International Bhurban Conference on Applied Sciences and Technologies (IBCAST), pp. 346–351, Islamabad, Pakistan, August, 2021.
[25] H. H. Sultan, N. M. Salem, and W. Al-Atabany, Multiclassification of brain tumor images using deep neural network, IEEE Access, vol. 7, Article ID 69215, 2019.
[26] M. A. Khan, I. Ashraf, M. Alhaisoni et al., Multimodal brain tumor classification using deep learning and robust feature selection: a machine learning application for radiologists, Diagnostics, vol. 10, no. 8, p. 565, 2020.
[27] Z. A. Sejuti and M. S. Islam, An efficient method to classify brain tumor using CNN and SVM, in Proceedings of the IEEE 2nd International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST), pp. 644–648, IEEE, Dhaka, Bangladesh, January, 2021.
[28] J. Cheng, W. Huang, S. Cao et al., Correction: enhanced performance of brain tumor classification via tumor region augmentation and partition, PloS One, vol. 10, no. 12, Article ID e0144479, 2015.
[29] P. Tejaswini, M. B. Bhat, and M. K. Prakash, Detection and classification of tumour in brain MRI, Int. J. Eng. Manufact.(IJEM), vol. 9, no. 1, pp. 11–20, 2019.
[30] K. Kaplan, Y. Kaya, M. Kuncan, and H. M. Ertunç, Brain tumor classification using modified local binary patterns (LBP) feature extraction methods, Medical Hypotheses , vol. 139, 2020.
[31] H. Habib, R. Amin, B. Ahmed, and A. Hannan, Hybrid algorithms for brain tumor segmentation, classification and feature extraction, Journal of Ambient Intelligence and Humanized Computing, vol. 119, pp. 1–22, 2021.
[32] M. N. Ullah, Y. Park, G. B. Kim et al., Simultaneous acquisition of ultrasound and gamma signals with a singlechannel readout, Sensors, vol. 21, no. 4, p. 1048, 2021
[33] S. Niu, Y. Liu, J. Wang, and H. Song, A decade survey of transfer learning, IEEE Transactions on Artificial Intelligence, 1(2), 2020, 151–166.
[34] F. Maria Carlucci, L. Porzi, B. Caputo, E. Ricci, and S. Rota Bulo, Autodial: Automatic domain alignment layers. in Proceedings of the IEEE international conference n computer vision, 2017, (pp. 5067–5075). IEEE.
[35] S. T. Krishna and H. K. Kalluri, "Deep learning and transfer learning approaches for image classification, International Journal of Recent Technology and Engineering (IJRTE), 2019, 7(5S4), 427–432.
[36] T. He, Z. Zhang, H. Zhang, Z. Zhang, J. Xie, and M. Li, Bag of tricks for image classification with convolutional neural networks. in Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2019, (pp. 558–567). IEEE.
[37] P. Afshar, K. N. Plataniotis, and A. Mohammadi, Capsule networks for brain tumor classification based on mri images and coarse tumor boundaries, in Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 1368–1372, Brighton, UK, May, 2019.