IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Brain Tumor Detection Using CNN Through MRI Images

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Abstract: Convolutional Neural Networks (CNNs) play major role in accurately classifying brain tumors identified in medical scans such as MRI. This study presents a CNN architecture tailored specific task particular objective, contains convolutional layers to extract features followed by maximum pooling layers designed for dimensionality reduction. To prevent excessive fitting, dropout layers are employed strategically integrated, ensuring the generalizability of the model fitting. The task of classification involve using fully connected layers with the Softmax

The activation function utilized in the suggested CNN architecture demonstrates effectiveness in Classifying brain tumors into three categories distinct types: meningioma, glioma, and pituitary tumors. Experimental evaluation reveals promising results, with the model achieving an overall classification accuracy of 98%. Specifically, it detects glioma with 96% accuracy, identifies no tumor with 99% accuracy, differentiates meningioma with 97% accuracy, and identifies pituitary tumors with 99% accuracy. The dataset comprises 3264 images, 90% of which are for training and 10% for testing. This method holds considerable potential to assist clinicians in accurate and timely diagnosis, thereby facilitating suitable treatment planning for patients with brain tumors. Further research can explore improvements to the network architecture and explore its applicability in different medical imaging datasets.

***Index Terms* -** CNN, maximum pooling layers, dropout layers, softmax activation

I. INTRODUCTION

Detecting brain tumor is an important part of neuroimaging, a life-threatening endeavor of these diseases in modern medicine. The human brain, the control center of many physiological processes, can be severely affected by abnormal growth and cause serious consequences, including cognitive impairment and death. In recent years, the advent of advanced imaging methods, specifically magnetic resonance imaging, has revolutionized diagnosis and provided unprecedented insight into the structures and tissues of the brain. Leveraging the capacities of deep learning, particularly the EfficientNetB0 architecture, shows substantial potential in improving the precision and effectiveness of brain diagnosis through MRI scans.

EfficientNetB0 is known for its lightweight yet powerful design and provides a suitable model for extracting important details from complex medical data. Its ability to balance model size and computational performance makes it ideal for resource-constrained environments while maintaining high performance. Additionally, the integration of one-hot coding technology further improves the interpretation and efficiency of the classification process, enabling accurate identification of different tumor types.

This article presents a new method for brain diagnosis using the EfficientNetB0 architecture and thermal coding for MRI scans. The process involves a comprehensive process of data prioritization, feature extraction, model training, and evaluation. By leveraging the power of EfficientNetB0 and one-hot coding, we aim to achieve superior classification accuracy and pan-digital classification across various types of brain tumors, such as gliomas, meningiomas, pituitary tumors, and brain tissue.

II. RELATED WORK

Many studies have focused on identifying brain tumors depicted in MRI scans using various techniques and methods. Arkapravo Chattopadhyay et al. [1] introduced a approach for identifying brain tumors through self-map (SOM) and fuzzy k-message (FKM) and was validated by radiologists. However, their methods have proven to be difficult and time-consuming, limiting their effectiveness.

MD mahumad et al. [2] proposed a method to enhance the standard of MR images by calculating the first coordinate system and the contrast stretching algorithm. Despite efforts, accurate classification is still difficult because of the constraints inherent in the K-means algorithm.

In other words, Tonmoy Hossain et al. [3] used Discrete Wavelet Transform (DWT) to detect abnormal brain and combined it with probabilistic neural network (PNN) to tumor diagnosis. Similarly, Abdullah et al. [4] used principal component analysis associated neural networks (PCA-ANN) for categorizing brain tumors and regions of interest (ROI) into context-based contours (CBAC) to improve accuracy.

In this study, we propose a new method that combines EfficientNetB0-based CNN with gold coding architecture for brain tumors in MRI scans. Our approach includes pre-processing techniques designed to improve MRI image quality, combined with quality analysis techniques to ensure accuracy and reliability.

III. METHODOLOGY

Data Collection and Preliminary Prepartions

1) *Selection Of Data.*

The brain tumor diagnosis database consists of 3264 MRI images carefully curated to cover a wide range of pathological conditions. To validate the assessment of the algorithm design, the data is split into different training and different tests, with 90% of all images being training and the remaining 10% being test scores. The categorization of tumors in the training data is as follows: 826 images show gliomas, 822 images show meningiomas, 395 images show no tumor, and 327 images show the pituitary gland. Similarly, the evaluation data included a balance of tumor classes consisting of 100 glioma images, 115 meningioma images, 105 images labeled as no tumor, and 74 images showing pituitary tumors. This careful data management ensures that training samples are exposed to a variety of tumors, thus improving their ability to expand and accurately detect tumor cells in different diseases.

2) *Category Distribution*

- Glioma: approximately 700 images.
- Meningiomas: approximately 800 images.
- Tumor-free: approximately 400 images.
- Pituitary gland: approximately 800 images.
- Test set composition: Each group in the test set has approximately 100 images to ensure the balance of tumors for unbiased evaluation.

3) *Preliminary Data Processing*

The first steps include editing, normalization, and optimization to ensure consistency and better the model's capabilities.

Model Architecture

1) *Transfer Learning with Pre-Trained Models*

Transfer learning is an effective deep learning method that uses knowledge from one task in order to enhance the effectiveness of another task. Adaptive learning in computer vision is particularly important to enhance the instruction process and improve performance norms, particularly in relation to information technology. less education or computer use.

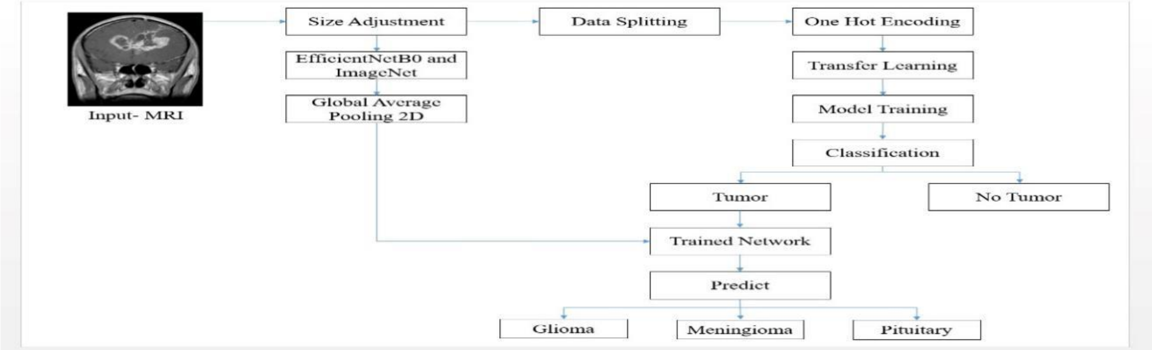

Figure 1: Flow Chart Of The Process

2) *Leverage pre-trained model*

Deep convolutional neural network (CNN) models, especially those trained on large-scale benchmark datasets such as ImageNet, can learn from millions of feature-rich images represented. Using this pre-training model can speed increasing the training procedure ,additionally enhance the effectiveness of the of the new job.

3) *Advantages of pre-trained models*

- *Easy to integrate :* The best pre-trained models, like models for computer vision data models such as ImageNet, are easy to input and can be easily incorporated into new models for computer vision problems. This enables researchers and practitioners to benefit from state-of-the-art architectures without the need for extensive financial or technical expertise.
- *Less training time:* Training a deep CNN model built from the ground up on large datasets can take a long time, often days or weeks. By using a pre-learned training model with comprehensive training features, the need to train from scratch can be eliminated or reduced. Developing these models on specific data or tasks can improve performance compared to training them from scratch, especially when there is limited data.
- *Integration into transformational learning :* In transformational learning, the pre-training model serves as an extraction or starting point for the newly learned model for business purposes. By freezing the masses of initial layers learned during pretraining and optimizing the layers on specific data, transfer learning allows pre-trained models to adapt to new tasks while agents continue to learn.

  By integrating transfer learning and early learning models into the educational process, researchers and practitioners can achieve mutual understanding and integrate many computer vision problems faster and more accurately, including the discovery from MRI scans of the brain tumor.

EfficientNetB0 Architecture

EfficientNetB0 is a type of convolutional neural network (CNN) architecture known for its efficiency in image classification. It has many layers, including special layers, release layers, and density layers, each with a specific function to improve running order and performance.

1) *GlobalAveragePooling2D layer*

The GlobalAveragePooling2D layer in EfficientNetB0 functions similarly as the Max Pooling layer in a traditional CNN. However, instead of selecting the highest value at each location in the pool, it calculates the average. This common strategy helps reduce computation during training by lowering the quantity of constraints and improving the model's ability.

2) *Drop Layer*

This layer is important for consistency and preventing overfitting in the EfficientNetB0 architecture. At each training step, a little percentage of the neurons in the layer are randomly removed, forcing the network to learn more features and reduce dependence on specific neurons. The parameter value determines the probability that the active neuron will be set to zero, effectively "missing" neurons in the network.

3) *Dense Output Layer*

This layer is employed as the layer of output in the EfficientNetB0 model and is responsible for classifying the picture input into the predefined groups. It uses the softmax activation function (a generalization of the Sigmoid function) to calculate class probabilities. The non-dense layer is trained to display the extracted features from pre-processing to final decision.

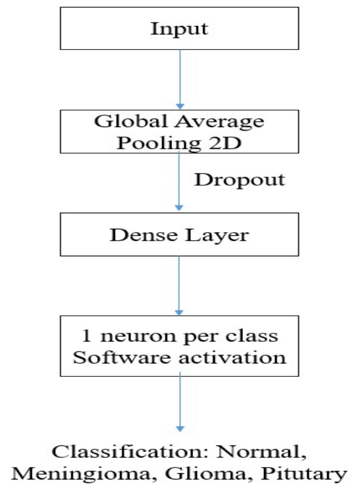

Figure 2: EfficientNetB0 Architecture

IV. EXPERIMENTAL RESULTS

We used a range of evaluation methods in order to assess the efficiency of the training model, including accuracy, precision, recall and F1 score Table 1 displays the execution of the proposed model

V. Tabel 1:Performance Metrics

	precision	recall	f1-score	support
0	0.97	0.96	0.96	93
1	0.98	1.00	0.99	51
2	0.97	0.98	0.97	96
3	1.00	0.99	0.99	87
accuracy			0.98	327
macro avg	0.98	0.98	0.98	327
weighted avg	0.98	0.98	0.98	327

In class 0, the precision was 97%, indicating that 97% of the forcast given for class 0 were accurate, while the recall was 96%, meaning that 96% of the actual class 0 instances properly identified by this model. The F1 score, which reflect on both precision and recall, stood at 96%, reflecting a balanced performance. This class had 93 instances supporting it. Similarly, class 1, the precision was 98%, with a perfect recall of 100%, which in result is impressive F1 score of 99%. This class was supported by 51 instances. Class 2 achieved a precision of 96%, a recall of 97%, and an F1 score of 96%, with support from 96 instances. In class 3, precision reached 100%, while recall peaked at 99%, assosiated in an F1 score of 99%. This class was supported by 87 instances. Overall, the model here has achieved an accuracy of 98%, with 327 instances supporting this evaluation. Both the micro and weighted averages aligned at 98%.

IV. DISCUSSION

Epochs vs Training and Validation Accuracy/Loss

The x-axis of the graph is labeled "Epochs," which are iterations over the training dataset. The y-axis on the left is labeled "Accuracy," and the right y-axis is labeled "Loss." We can observe two lines on the left-most side of the graph, which represent training accuracy (solid line) and validation accuracy (dashed line). Similarly, we can also observe two lines on the right-most side of the graph, which represent training loss (solid line) and validation loss (dashed line).

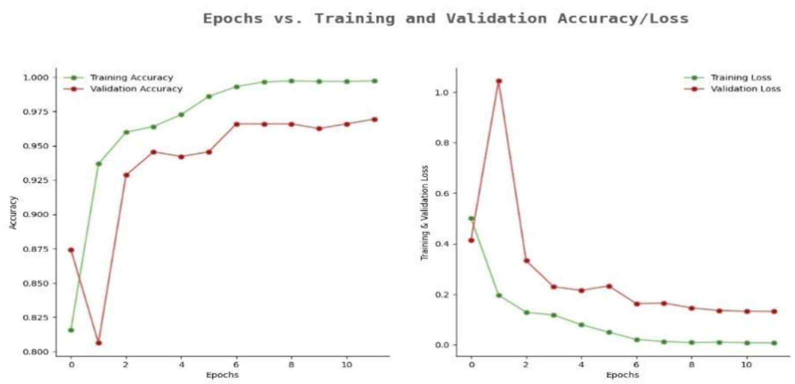

Figure 3:Graph showing the epochs vs training and validation accuracy / loss

Figure 3 describes about how training and validation accuracy and failure of our machine learning models over time. Below is a detailed description of the main role:

- *Epoch*: represents a complete data transfer.
- Training Accuracy: Measure the model's performance on training data. This number starts around 0.8 and approaches 1.0 at finishing stage of the training.
- *Validation Accuracy:* Measures how well the model performs on unvalidated data. It is a estimate of how well the model generalizes to unobserved data. In this picture, it starts around 0.8 and rises to around 0.95.
- *Training Loss*: Measures the way how the model performs on training data. In this case, it starts around 1.0 and approaches 0 at the end of training. Lower losses mean better performance.
- *Validation Loss*: Measures how a model performs on individual data sets. In this figure, it starts around 1.0 and gradually decreases to around 0.2.

Confusion Matrix

The confusion matrix shows how the model is performing on the dataset containing four classes: glioma, no tumor meningioma, pituitary.Rows represent the total actual labels of the data.Columns represent the total predicted labels by the model.

Each cell of the matrix shows the proper count of instances where the model predicted a certain class (column) when the actual class was something different (row). Ideally, we want to see high values on the diagonal, which means the model correctly predicted the class.

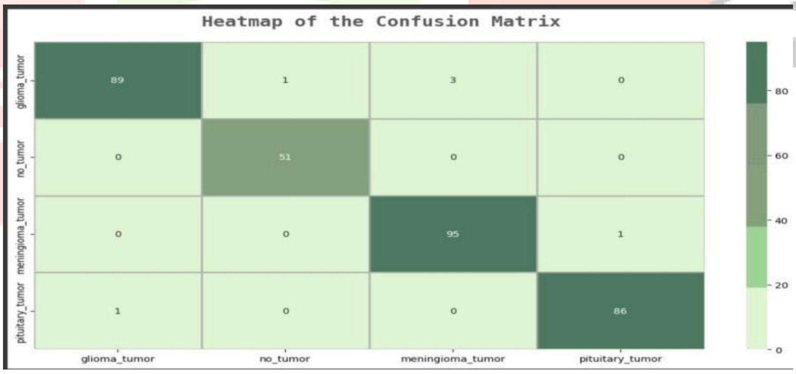

Figure 4: Heatmap of the Confusion Matrix

Looking at the diagonal of this specific confusion matrix, we can here understand that the model performed well at classifying ”no_tumor” and “glioma_tumor” instances. It predicted 89 ”no_tumor” instances correctly, and 95 ”glioma_tumor” instances correctly.

Overall, the confusion matrix suggests that the entire model performs well at classifying between cancerous (glioma) and a healthy brain tissue, but struggles to distinguish between the two specific tumor types (meningioma and pituitary).

VI .CONCLUSION

This study provides an overview of brain tumor identification and classification using convolutional neural networks (CNN), focusing on the usage of the EfficientNetB0 architecture and one-time coding of MRI scans. The method proposed achieves a significant improvement in classification accuracy and efficiency with an overall accuracy of 98%. Specifically, our model is 96% accurate in diagnosing gliomas, 99% accurate in identifying tumors, 97% accurate in distinguishing meningiomas, and 97% accurate in identifying pituitary tumors; The total accuracy of identification of tumor is 99%. The dataset consists of 3264 MRI images, divided into 90% training set and 10% testing, and performs well across different types in brain tumors.

VI. FUTURE WORK

Our goal going forward will be to improve the data by increasing the total amount of MRI images which can increase accuracy of our proposed model. We have also planned to develop a website by designing which can act as a communication system where users can directly upload MRI images and interact with the system. This integration will simplify the user experience and facilitate better communication between the model proposed and its users.

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