Enhanced Brain Tumour Detection and Classification through Sophisticated Machine Learning Approaches

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Keywords: CNN, VGG16 Model, ResNet50 Model, EfficientNetB0 Model.

Abstract: If not treated, brain tumors pose a significant health risk. Detected and promptly treated. MRI examinations manual, but improved tumor detection Time-consuming and error-prone diagnosis prone. Deep learning will be used in this study. Methods, in particular Convolutional Neural Networks (CNNs), to boost precision and effectiveness in detecting brain tumors. The dataset of 7,023 MRI images is used in the research. From a variety of sources, such as Figshare, Br35H and SARTAJ. Preprocessing techniques like normalization, image resizing, and noise cancellation were used to improving the performance of a model. It was made a CNN model. Using TensorFlow and GPU training acceleration. Data-based additional techniques augmentation, adjusting the rate of learning, and making use of the Adam optimizer with a beta value made accuracy even better Callbacks such as Early Stopping and ReduceLR on Plateau were incorporated to prevent overfitting and ensure a stable training process. The machine learning model successfully divided brain tumors into four groups, achieving a remarkable accuracy of 99.54 percent. This demonstrates how effective deep learning in medical imaging and its potential as an accurate diagnostic instrument. The model makes use of important libraries like TensorFlow, Keras, Pandas and NumPy.

1 INTRODUCTION

Medical-diagnostics, which calls for precise prediction and treatment. Artificial intelligence (AI) is needed in medical imaging because traditional methods like MRI analysis take a long time and are prone to human error. Brain tumors are categorized into four categories using in this study: meningioma, pituitary tumor, no tumor, and glioma. Meningiomas, on the other hand, are benign but still require treatment, while gliomas are cancerous and necessitate immediate medical attention. The pituitary gland is affected by pituitary tumors, which can range in severity. Normal brain scans are represented by the No Tumor category, which serves as a comparison point. The CNN model's accuracy of 99.54 percent demonstrates its suitability to classify brain tumors. The dataset consisted of 7,023 MRI images from various sources. The Adam optimizer, Early Stopping, ReduceLR on Plateau, and GPU acceleration were utilized to improve performance. The study shows that deep learning has the potential to address real-world medical challenges and pave the way for future AI-driven healthcare.

2 LITERATURE REVIEW

Manually MRI scans which are time consuming and error - prone, are the foundation of conventional diagnostics. Mavrakis et al. (2005) and other early studies looked at clinical diagnosis without al. Kang et al. and subsequent methods Tumor features and ML classifiers face significant difficulties when dealing with brain tumors classification. Despite its potential, this was computationally prohibitive and challenging to make use of big data. Mahobiya and Minz (2017) also attempted the MRI algorithm AdaBoost. Classification, which although looked promising had difficulties with complex feature extraction to current deep learning.

An XG was described by Mudgal et al. (2017). optimization required extensive tuning for high-

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dimensional data.

Hemanth et al. (2018) proposed a novel but imperfectly optimized modified CNN architecture for large datasets.

Sudharani et al. (2015) used the k-NN algorithm, which is good for simple classification but bad for large preprocessing and high-dimensional data. Togacar et al. (2020) improved accuracy by optimizing CNN models with hyper columns and feature selection. However, the increased complexity raised computational costs and made scaling challenging.

ResNet-101 was used with squeeze-and-excitation networks by Ghosal et al. (2019), which improved classification performance but required a lot of resources

Szegedy et al. (2015) introduced the Inception architecture, which enhanced feature extraction in medical imaging; however, extensive modifications were required for its application to the classification of brain tumors.

The increasing use of ML and DL in the diagnosis of brain tumors was highlighted in systematic reviews by Khan et al. (2021) and Nadeem et al. (2020). Although these studies offered insights, they lacked specifics regarding how they could be put into practice

3 PROPOSED APPROACH

The proposed project eliminates data by employing a CNN framework that is optimized for processing. Artifacts solve problems related to the classification of brain tumors and improve the overall quality of the images, enhancement and transfer learning. The study aims to improve brain tumor diagnosis and classification by combining cutting-edge methods with real-world solutions, offering a superior alternative to existing methods.

3.1 Data Collection & Preprocessing

3.1.1 Data Collection

Brain tumors in four categories:

- Glioma: It is a tumor developing in the spinal cord or brain glial cells and is benign and malignant with varying growth rate and severity.
- Meningioma: A benign tumor found in the brain meninges, which cover the brain and spinal cord to protect it cord
- No tumor: Normal brain scans that reveal no tumors
- Pituitary: Tumors of the pituitary gland, either benign or cancerous.

3.1.2 Preprocessing

When dealing with MRI images that are prone to variations in resolution, intensity, and noise, it is an essential phase in preparing the raw data for machine learning. To address these issues, a methodical preprocessing pipeline was used.

Image Standardization.

Resizing: The resolution of each MRI image was resized to 128x128 pixels consistently. This is to keep important features for classification while making the images compatible with the CNN architecture.

Gray -Scale conversation: The pictures were changed to grayscale in order to emphasize the structural details and simplify computational processes by removing color variations that aren't needed.

Noise Reduction: To get rid of the noise, cutting – edges methods like gaussian method filtering were used.

The model can now detect more subtle characteristics of tumors thanks to this improvement.

Image Normalization: The images' pixel intensities were normalized to the 0-to-1 range. This step ensures uniformity across the dataset, allowing the model to learn more quickly during training and reducing biases caused by variations in image brightness.

Data Augmentation: To prevent overfitting and introduce diversity into the dataset, the data augmentation strategies are rotations, flipping, zooming, brightness adjustments, sharing and cropping.

Margin Trimming: Uninformative areas, such as black margins, were removed to concentrate on the brain region, raising the signal-to-noise ratio and data quality in general.

Class Balancing: Targeted data augmentation compensated for class imbalances to ensure that all classes were properly represented during training to avoid model bias.

Label Encoding: Each image received a numerical label for its class:

- Glioma: 0
- Meningioma: 1
- No Tumor: 2
- Pituitary: 3

The encoding readied the images for the CNN's classification layer. Because it enables machine learning algorithms to process categorical labels and make precise predictions, label encoding is essential for diagnosing brain tumors Label encoding refers to the process of changing categorical labels to numerical labels, which are consumed by machine learning algorithms.

Label encoding is utilized for numerically catego rizing different types of brain tumors in the case of brain tumors However, "glioma," "meningioma," and "pituitary adenoma" are normally stated while talking about brain tumors. Label encoding aids in changing such categorical labels to numerical representations that machine learning algorithms can handle.

Data Splitting: To work with successful preparation and impartial assessment, the dataset was partitioned into three subsets**:**

- Training Set: Accustomed to prepare the model and get familiar with the elements of every classification (figure 1).
- Validation Set: Accustomed to tune the model and assess its presentation during preparing.
- **Test Set**: Utilized for definite assessment to survey the model's speculation capacity (figure 2).
- **Training Set (70%):** The biggest piece, used to prepare the model with expanded information for speculation.

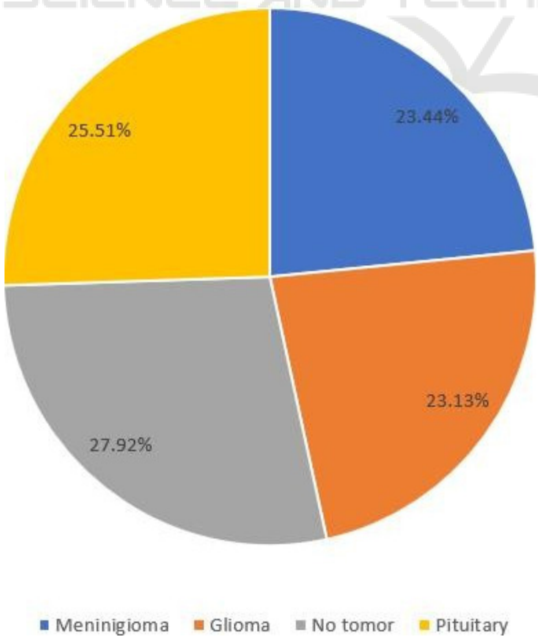

Figure 1: Training Data.

- **Validation Set (15%)**: Used for hyperparameter tuning and to monitor the performance during training.

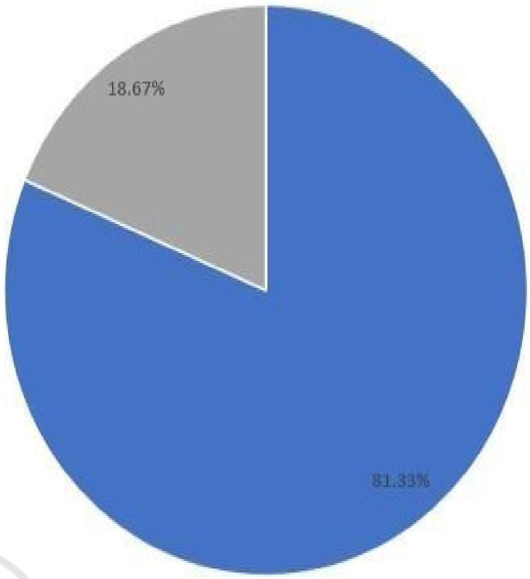

Figure 2: Train Test Split.

3.2 Feature Extraction and Transfer Learning

To further develop order exactness, move learning was coordinated into the model. Pretrained designs, like Google Net, were used for include extraction, giving areas of strength for an in light of information acquired from huge scope picture datasets. By utilizing these deeply grounded models, the growing experience was altogether sped up, permitting the CNN to rapidly adjust to X-ray cerebrum filters while keeping up with high exactness.

3.2.1 Dataset

The dataset comprises of X-ray cerebrum pictures arranged as cancer or non-growth. To address class irregularity, information expansion was applied to the minority class. Pictures were resized to 256×256 pixels, changed over completely to grayscale, and class marks were encoded in double arrangement for brain network reconciliation. The data were parted into 70% preparation and 30% test sets with separation to keep up with class appropriation. This preprocessing guaranteed a decent, improved dataset for productive model preparation and assessment. Table 1 shows the Class Distribution Before and After Preprocessing. Figure 3 illustrates the several forms of brain tumor images.

3.2.2 Class Distribution Before and After Preprocessing

Table 1: Class Distribution Before and After Preprocessing.

Label	Before Preprocessing	After Preprocessing
Tumor	850	1000
No-Tumor	750	1000

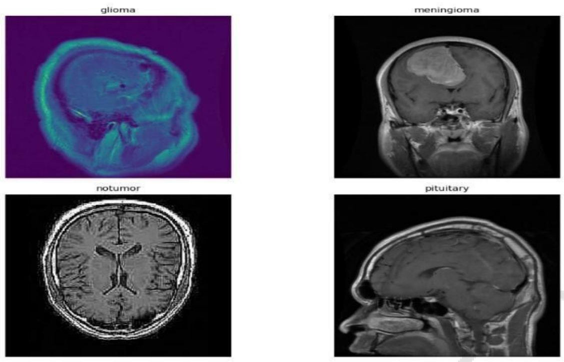

Figure 3: Several Forms of Brain Tumor Images.

4 METHODOLOGY

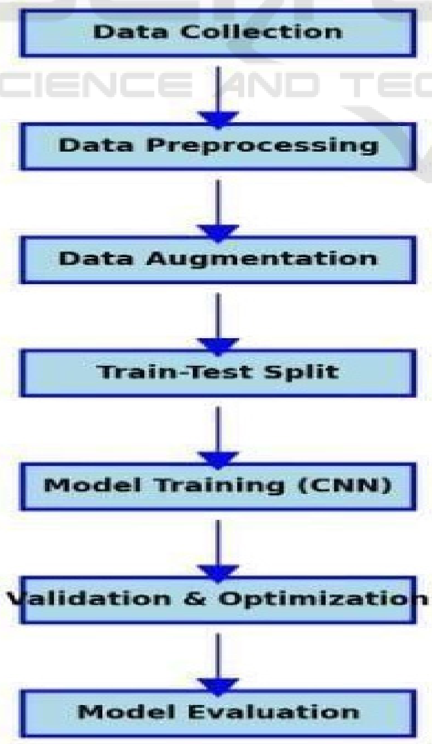

Figure 4: VGG19 Architecture.

4.1 Model

4.1.1 Convolutional Neural Networks (CNN)

Convolutional Brain Organizations are critical for mind cancer identification, robotizing highlight extraction from X-ray and CT filters. Not at all like conventional strategies, CNNs gain designs from crude pictures, permitting exact separation among sound and growth impacted tissues. They are hearty, precise, and proficient, even with uproarious information, and perform well with move realizing when marked information is scant. CNNs diminish human blunder, give steady judgments, and empower constant expectations for quicker treatment arranging. They can likewise arrange growth types, supporting customized treatment procedures. Figure 5 shows the CNN Architecture.

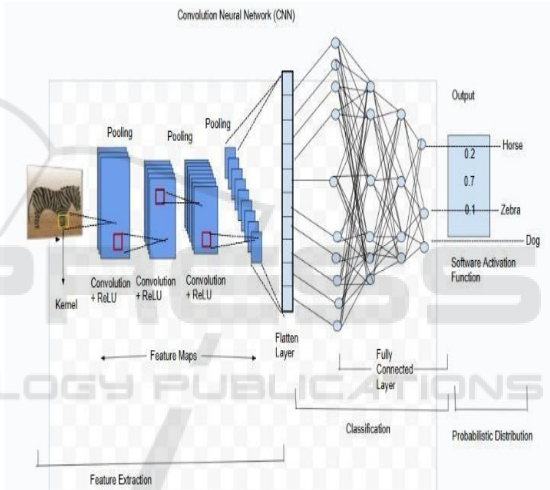

Figure 5: CNN Architecture.

4.1.2 VGG19 Model

VGG19 is a profound CNN with 19 layers, including 16 convolutional layers, intended to examine picture grouping execution (figure 4). It utilizes 3×3 convolution channels to catch fine subtleties, making it powerful for picture acknowledgment errands. By using pre-prepared loads from datasets like ImageNet and eliminating all associated layers, VGG19 serves as an element extractor in brain growth characterization, reducing preparation time and further developing execution. VGG19 is able to successfully separate complex examples for clinical imaging, despite its computationally demanding nature. Additionally, it can include multimodal data for improved indicative precision, enhancing growth discovery and patient outcomes.

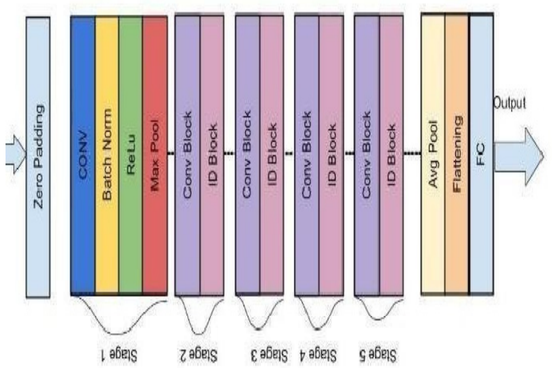

Figure 6: ResNet50 Architecture.

4.1.3 EfficientNet B0 Model

Using a compound scaling approach to change, EfficientNet B0 is a lightweight CNN that adjusts accuracy and computational proficiency. Assignments like characterization of cerebellar cancer that require very little preparation data. With its solid execution and low asset use, its proficient plan makes it ideal for ongoing clinical applications. EfficientNet B0 is a good choice for resource-constrained situations because it prioritizes speed and effectiveness without sacrificing accuracy, making it less complicated than more advanced models like ResNet50 (figure 6 and 7).

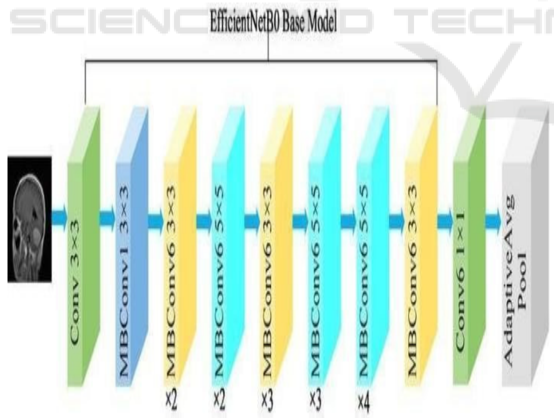

Figure 7: EfficientNetb0 Architecture.

4.2 Performance Metrics

When determining a model's viability in the mind cancer grouping, it is important to evaluate its presentation. Estimating the accuracy, dependability, and proficiency of the model's expectations is made easier by the various measurements.

4.2.1 Accuracy

Precision is one of the central measurements used to assess a grouping model. It addresses the level of accurately ordered cases out of the all-out expectations made. A higher exactness shows that the model performs well across both cancer and non-growth cases.

$$Accuracy = (TP + TN)/TP + FP + FN + TN) \quad (1)$$

Where:

- TP (True Positive) – Correctly predicted tumor cases
- TN (True Negative) – Correctly predicted non-tumor cases
- FP (False Positive) – Non-tumor cases incorrectly classified as tumors
- FN (False Negative) – Tumor cases incorrectly classified as non-tumor Classification Report.

4.2.2 Precision

Precision measures how many of the predicted tumor cases were actually tumors. A greater precision score demonstrates that the model generates fewer false-positive errors.

$$Precision = TP/(TP + FP) \quad (2)$$

4.2.3 Recall (Sensitivity)

Recall, commonly known as sensitivity, evaluates how many actual tumor cases the model correctly identifies. A greater recall score ensures that the model does not miss positive cases.

$$Recall = TP/(TP + FN) \quad (3)$$

4.2.4 F1-Score

The F1-score is a measure of a model's accuracy, balancing precision and recall. It is the harmonic mean of precision and recall, providing a single score to evaluate performance.

$$F1score = (2 \times Precision \times Recall)/(Precision + Recall) \quad (4)$$

4.3 Loss Function

A loss function quantifies how the model's predictions are differ from the actual values. It helps in optimizing the model by minimizing errors during training. The loss function used for this classification task is the Mean Squared Error (MSE):

$$Loss = (1/n) * \Sigma(y_i - \bar{y})^2 \quad (5)$$

Where:

- y_i indicates actual values
- $\bar{y}$ indicates predicted values
- n is the number of samples

5 RESULTS

5.1 CNN Accuracy and Loss

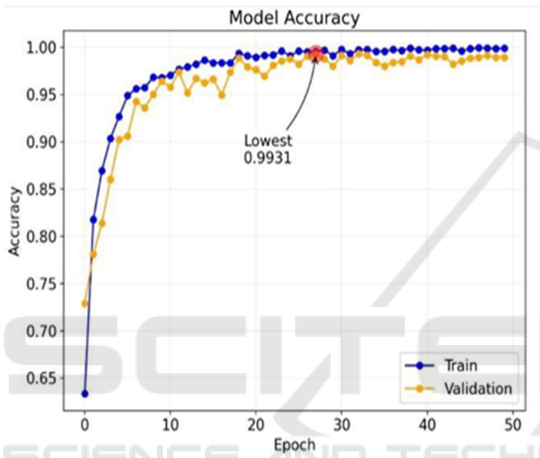

Figure 8: Progression of Training and Testing Accuracy of CNN.

Progression of training and testing accuracy of CNN and Progression of training and testing Loss of CNN are shown in figures 8 & 9 respectively.

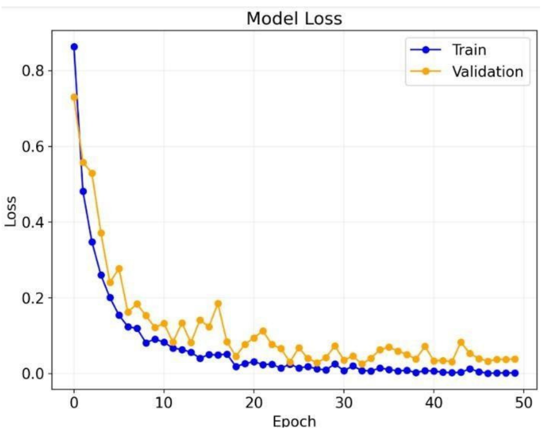

Figure 9: Progression of Training and Testing Loss of CNN.

5.2 Resnet 50 Model Accuracy

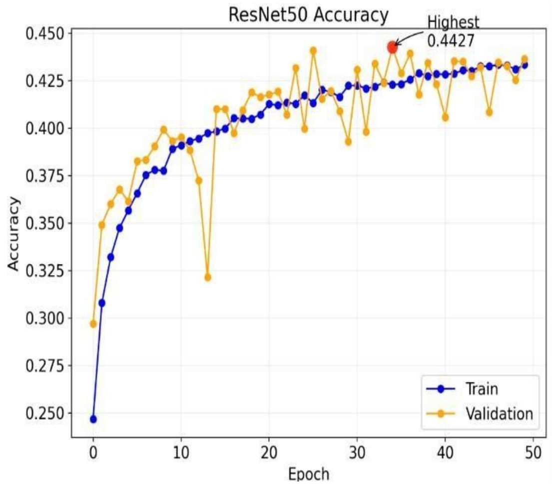

Figure 10: Progression of Training and Testing Accuracy of ResNet50.

Figure 10 depicts the Progression of training and testing accuracy of Resnet50.

5.3 VGG16 Model Accuracy

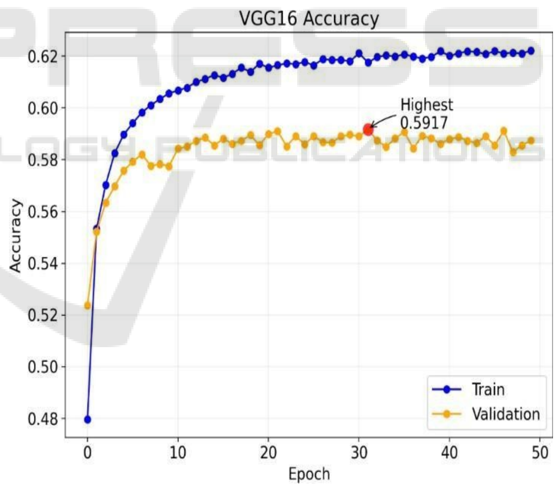

Figure 11: Progression of Training and Testing Accuracy of VGG16 Model.

Figure 11 depicts the Progression of training and testing Accuracy of VGG16 Model.

5.4 EfficientNet B0 Model Loss and Accuracy

Figure 12 shows the Progression of training and testing Accuracy of EfficientNet B0Model.

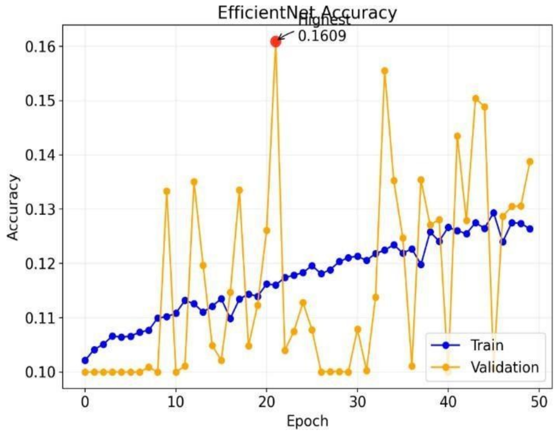

Figure 12: Progression of Training and Testing Accuracy of EfficientNet B0Model.

6 CONCLUSIONS

This task consolidates computerized picture handling procedures like division and expansion with profound learning models (CNNs, VGG16, ResNet50, EfficientNetB0) to accomplish high precision in mind cancer discovery and grouping. The model guides early conclusion by examining X-ray sweeps to distinguish cancer designs, offering solid outcomes in regions with restricted admittance to radiologists. VGG16 played out the best, exhibiting its capacity to remove complex highlights for exact order. Generally speaking, this undertaking gives a versatile, effective answer for cerebrum cancer identification, propelling clinical diagnostics and further developing medical care openness.

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