IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Brain Tumor Detection: Integrating Cnn And Resnet

Enhancing accuracy with Residual Network and Transfer Learning

[1] Mrs.Karthika C, [2]Aumrutha G, [3] Lavanya N, [4] Sivapriya A

[1]Assistant Professor , [2]Student, [3]Student, [4]Student

[1]Department Of Computer Science and Engineering,

[1]Sri Manakula Vinayagar Engineering College , Puducherry , India.

Abstract: A brain tumor is a growth of cells, in the brain that replicate rapidly and uncontrollably. Detecting and addressing brain tumors present challenges. There is hope in utilizing deep learning as a potential solution. Deep learning techniques, particularly transfer learning have proven to be tools for improving the accuracy and efficiency of brain tumor detection models. By utilizing a trained neural network on a vast dataset like ImageNet and fine tuning it is using a smaller set of brain images the model gains valuable insights from the broader dataset. This enables the model to adapt its learned features to the characteristics found in brain tumor images. The benefits of incorporating transfer learning into this context include training convergence improved ability to generalize to data and robust performance even with limited labeled data—a critical advantage considering how challenging it can be to obtain substantial annotated datasets in medical imaging. When evaluating transfer learning-based algorithms performance for brain tumor detection essential metrics such as accuracy, precision and recall should be considered alongside factors, like training time, computational resources. The model's ability to generalize across types of brain tumors and imaging conditions. Overall integrating transfer learning into deep learning approaches enhances their practicality and effectiveness when applied in world applications.

Index Terms **- BRAIN TUMOR, IMAGENET, PRE-TRAINED NEURAL NETWORK, TRANSFER LEARNING**

I. INTRODUCTION

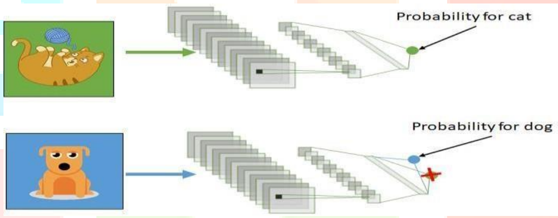
These tumors originate from different cell types, with common types including gliomas from glial cells, meningiomas from the meninges, and pituitary adenomas in the pituitary gland. The size, location, and growth rate of brain tumors determine their symptoms and effects. Manifestations can include headaches, seizures, alterations in behavior or personality, cognitive decline, and motor challenges. The diverse nature of brain tumors underscores the complexity of their impact on neurological functions, making early detection and intervention crucial for effective treatment.

A. **The Signs And Symptoms Of A Brain Tumor :**

1. **Headaches:** Persistent, worsening headaches, especially during morning or during sleep.
2. **Seizures:** Sudden, uncontrolled electrical disturbances in the brain that can manifest as seizures.
3. **Nausea and vomiting:** Especially if it is unrelated to other common causes.
4. **Balance and coordination problems:** Difficulty walking, dizziness, or problems with coordination.
5. **Changes in personality or behaviour:** Unexplained changes in mood, personality, or behaviour.
6. **Memory and concentration difficulties:** Impaired cognitive function, difficulty concentrating, or memory loss.
7. **Speech difficulties:** Slurred speech, difficulty articulating words, or problems with language.

B.**Transfer Learning :**

This method is a machine learning technique where a pre-trained model on a specific task is used as a starting point for a new, related task. This approach is particularly useful when there is limited labeled data for the new task, as the knowledge gained from the original task can be leveraged to improve performance on the new task. This process allows the model to build upon the general features and patterns it learned from the original data. The extent of retraining varies; sometimes, only a portion of the model (e.g., the later layers) is fine-tuned, while the rest is kept frozen. In computer vision, for instance, lower layers of a neural network may capture general features like edges and shapes, while higher layers may specialize in task-specific features.
Transfer learning helps address the challenge of limited data and computational resources, as it allows models to benefit from the knowledge



II. Literature Survey

Sl no	Title	Technology	Advantage	Disadvantage	Data set
1	Author: Shubhangi Solanki et al., (2023).	Convolutional Neural Network (VGG16)	CNN is to detect distinct features from images all by itself	Large data set can't be trained	Shen Zhen dataset
2	Author: Hasnain Ali Shah et al , (2022).	Efficient Net	Efficient Net doesn't need multiple runs to perform	Suited only for image segmentation in biology or medicine	Open source Kaggle dataset
3	Author: R. Geetha Ramani, Et Al, (2023).	Convolutional Neural Network	CNN is to detect distinct features from images all by itself	Large data set can't be trained	Bacilli in digital images dataset

4	Author: Javaria Amin, Muhammad Sharif, etal (2022).	DenseNet121	Very High accuracy in image recognition problems.	Lack of ability to be spatially invariant to the input data.	Open source Kaggle dataset
5	Author: Manav Sharma1, et al, (2022).	Support Vector Machine (SVM)	We can use Support Vector Machine (SVM) without any explicit pre-processing to convert categories into numbers.	Very low prediction accuracy	Mycobacterium tuberculousis data set
6	Author: Ishtyaq Mahmud, et al, (2022).	VGG-16, VGG-19, ResNet50, InceptionResNetV2	Enhancing robustness and adaptability to diverse conditions, ultimately improving the reliability of tuberculosis Detection	performs poorly on new, unseen data.	CXR images
7	Author: Hareem Kibriya, et al , (2022)	Pre-trained Convolutional Neural Network (CNN)	Improved Accuracy and Efficiency	Limited data can lead to overfitting	Public datasets

III. Application Of The Project

EARLY DIAGNOSIS AND TREATMENT PLANNING:

Early detection of brain tumors is critical for timely medical intervention and treatment planning. Accurate identification of tumor regions in medical images allows healthcare professionals to devise appropriate treatment strategies.

PRECISION MEDICINE:

The project can contribute to the advancement of precision medicine by providing tailored treatment plans based on the specific characteristics of detected tumors. Individualized treatment approaches can lead to better patient outcomes and reduced side effects.

REDUCING HUMAN ERROR:

Automation of the tumor detection process using deep learning reduces the risk of human error in medical image analysis.

Consistent and reliable results can enhance the overall accuracy of diagnosis.

EFFICIENCY IN HEALTHCARE WORKFLOW:

Automated tumor detection can streamline the workflow in healthcare settings, allowing medical professionals to focus on interpretation and decision-making rather than manual image analysis.

RESOURCE OPTIMIZATION:

The use of transfer learning can potentially reduce the need for extensive labeled datasets, making the development of effective models more feasible in scenarios where obtaining large datasets is challenging.

IV. 4.1 Problem Definition

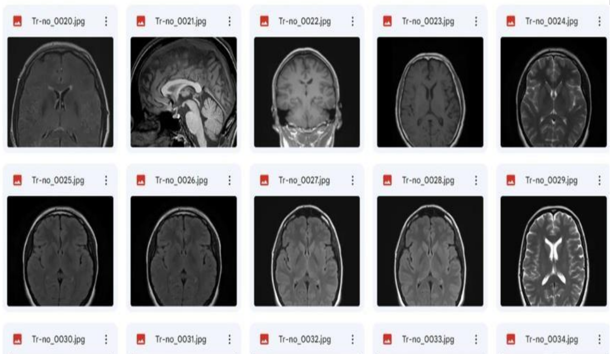
The problem addressed by the project is the timely and accurate detection of brain tumors through the utilization of deep
learning, specifically with an emphasis on transfer learning. Brain tumors, characterized by the rapid and uncontrolled growth of cells in the brain, pose a significant medical challenge due to their diverse types, locations, and potential neurological impacts. The conventional methods of diagnosis and analysis can be time-consuming and may carry a risk of human error. This project aims to tackle these issues by developing an automated system that leverages advanced deep learning techniques to analyze medical imaging data, such as MRI or CT scans, with a focus on transfer learning for improved efficiency and generalization. The primary goal is to enhance early detection, leading to improved patient outcomes and the overall efficiency of healthcare workflows in the realm of neurology and medical imaging.

4.2 Problem Identification

Identifying brain tumors at an early stage remains a significant challenge in medical diagnostics. The problem lies in the
complex nature of these abnormalities, where abnormal cell growth in the brain occurs uncontrollably, leading to the formation of masses or lumps. The lack of distinct early symptoms and the varied presentation of neurological manifestations further complicates timely diagnosis. Traditional diagnostic methods often face limitations in detecting smaller or less accessible tumors accurately. This problem is exacerbated by the diverse types of brain tumors, each originating from different cell types within the brain. The urgent need for a more efficient and precise diagnostic approach is evident, prompting the exploration of advanced technologies like deep learning. Addressing these challenges is crucial for improving patient outcomes through early intervention and tailored treatment plans.

5.1 Analysis Dataset

Accurately achieving segmentation, region identification and analysis of the brain tumors relies on a high-quality dataset. The only way forward would be to have a representative sample that includes both tumor and non-tumor cases, so as to include the widest
possible range of brain images. Sometimes the dataset is basic medical imaging data (MRI, CT scans).



5.2 Pre-Processing

Preliminary imaging is an important step in image processing, including brain tumor segmentation. This requires a
variety of tasks to improve image input quality and eliminate unwanted artifacts or noise that may interfere with the next step of processing.

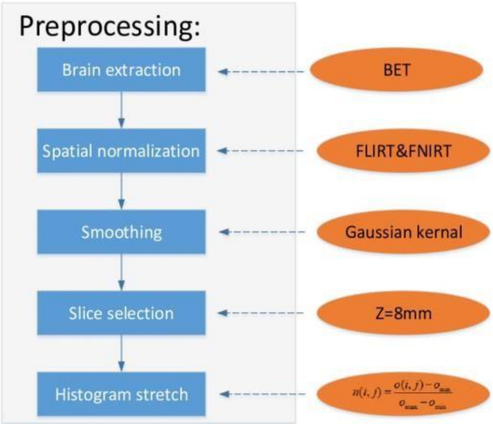


Fig : pre processing model

5.3 Feature Extraction

Feature extraction is an important step in data analysis and machine learning. It requires transforming raw data into a
meaningful reduced representation, capturing relevant and informative parts of the data. The goal of feature extraction is to extract important features or characteristics useful for subsequent analysis, modeling, or decision tasks Raw data in various areas such as image processing, natural language processing, and signal processing often contain several variables or dimensions.

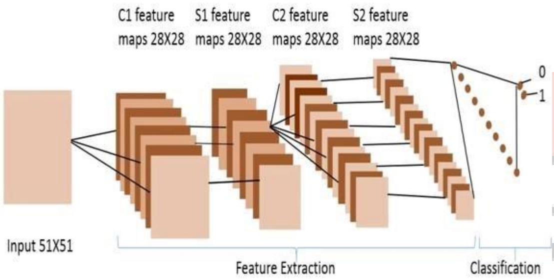


Fig: Feature extraction data model

5.4 Classification

For example, classification is one type of machine learning that involves assigning predefined labels to items in a data
set. A supervised, discriminative learning method where the goal is to construct a model that classifies or otherwise categorizes new data according to patterns gleaned from training example labels. The dataset for classification is a set of instances, each with attributes that describe them. The objective is to train a classification model over the labeled training data consisting of instancelabel pairs. From the relations between the features and their class labels, it trains a model. Classification is evaluated using a set of traditional metrics, including accuracy, precision, recall and F1 score. But these statistics reveal nothing about the model's ability to separate different classes or its overall accuracy.

5.5 Architecture Diagram

The architecture diagram for a brain tumor segmentation system using deep learning typically consists of several
interconnected components. At the core of the architecture is the deep learning model, which performs the actual segmentation task. The input to the system is typically medical imaging data, such as MRI scans, which are processed by a pre-processing module. This module handles tasks like resizing, normalizing, and enhancing the input images to prepare them for the segmentation model.

The deep learning model, often based on convolutional neural networks (CNNs), analyzes the preprocessed images and learns to identify and segment tumor regions from healthy brain tissues. The model is trained using annotated data, where experts manually label the tumor regions. The training module optimizes the model's parameters based on this labeled data to improve its segmentation accuracy.

5.6 Evaluation

When the models used in a classification problem have been trained they must be tested to measure how well and
accurately they are performing. The accuracy, precision and recall of the model's performance can be measured by various other indicators such as appraisal rate or F1 score. Accuracy is perhaps the most widely used measure and calculates a ratio of true positives to all observations. This index represents a general indicator of overall accuracy. Precision and recall are both relevant, so the harmonic mean of them is known as F1 score. This is especially helpful when the data set has an imbalance or where precision and recall are equally important.

5.7 Algorithm

One popular algorithm for brain tumor detection utilizing transfer learning is the Convolutional Neural Network (CNN)
architecture, particularly pre-trained models like VGG (Visual Geometry Group) or ResNet (Residual Network). Here's a basic outline of how you might implement transfer learning for brain tumor detection using a pre-trained CNN:
Select a Pre-trained Model: Choose a pre-trained CNN model like VGG or ResNet, which has been trained on a large dataset such as ImageNet. These models have learned to extract features from images effectively.

Modify the Network: Remove the last few layers of the pre-trained model, which are typically responsible for classifying the ImageNet categories. Replace them with new layers that are suitable for the brain tumor detection task. These new layers will have neurons corresponding to the classes of brain tumors you want to detect.

Freeze Pre-trained Layers: Freeze the weights of the pre-trained layers. This means that during training, these layers will not be updated, and only the weights of the new layers will be adjusted. This is because the lower layers of the pre-trained model have already learned general features like edges and textures, which are likely relevant to brain tumor detection.

Data Augmentation: Since medical imaging datasets are often limited in size, apply data augmentation techniques such as rotation, scaling, and flipping to artificially increase the diversity of the training data.

Fine-tuning: Train the modified model on your dataset of brain images. Since the pre-trained layers are frozen, only the weights of the new layers will be updated. This process is called fine-tuning, where the model adapts its learned features to the specific characteristics of brain tumor images.

Evaluation: Evaluate the performance of the trained model using metrics such as accuracy, precision, recall, and F1-score on a separate validation set or through cross-validation. Additionally, consider factors like training time, computational resources, and the model's ability to generalize across different types of brain tumors and imaging conditions.

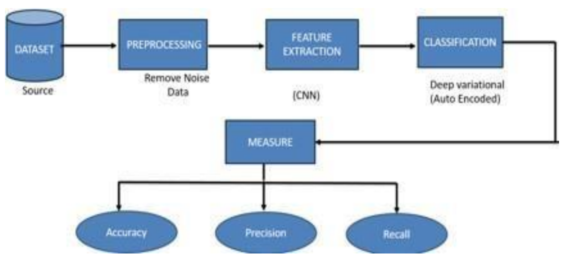


Fig : Procedural diagram for algorithm

5.8 Formula

1. Loss Function: The loss function measures the difference between the predicted outputs of the model and the actual labels in the training data. One common loss function for classification tasks like brain tumor detection is the categorical cross-entropy loss, which is defined as:

L(y,Ȳ)=−N1∑i=1N∑j=1Cyijlog(Ȳij)

Where:

- N is the number of samples in the training set.
- C is the number of classes (types of brain tumors).
- *yij is 1 if sample i belongs to class j, 0 otherwise.*
- Ȳ*ij is the predicted probability that sample i belongs to class j.*

2. Fine-tuning and Learning Rate: During fine-tuning, the learning rate is an important hyperparameter that controls how much the weights are updated during each iteration of training. It's common to use a smaller learning rate for fine-tuning to prevent drastic changes to the pre-trained weights. One simple strategy is to use a learning rate scheduler that reduces the learning rate over time to allow the model to converge smoothly.
3. Evaluation Metrics:
   - Accuracy: The proportion of correctly classified samples out of the total number of samples.
   - Accuracy = Number of Correct Predictions Total Number of Predictions Accuracy = Total Number of
   - Predictions Number of Correct Predictions .
   - Precision: The proportion of true positive predictions out of all positive predictions.
   - Precision = True Positives True Positives + False Positives Precision=True Positives + False Positives True Positives
   - Recall (Sensitivity): The proportion of true positive predictions out of all actual positive samples.
   - Recall=True Positives True Positives + False Negatives Recall=True Positives + False Negatives True Positives
4. Data Augmentation: Various transformations can be applied to augment the training data, such as rotation, scaling, shifting, flipping, etc. The formulas for these transformations depend on the specific augmentation technique used and can vary accordingly.

These are the fundamental concepts and formulas used in implementing a transfer learning algorithm for brain tumor detection. The actual implementation may involve additional details and adjustments based on the specific requirements and characteristics of the dataset and the chosen deep learning framework.

5.9 Loss Function

```
import tensorflow as tf
def categorical_cross_entropy_loss(y_true, y_pred):
    """
    Computes the categorical cross-entropy loss between the true labels and predicted probabilities.
    Parameters:
    y_true (tf.Tensor): True labels, encoded as one-hot vectors.
    y_pred (tf.Tensor): Predicted probabilities for each class.
Returns:
float: Categorical cross-entropy loss. """
loss=tf.keras.losses.categorical_crossentropy(y_true,y_pred)
return tf.reduce_mean(loss)
```

```
# Example usage:
# Define true labels (one-hot encoded) and predicted probabilities
y_true = tf.constant([[1, 0, 0], [0, 1, 0], [0, 0, 1]])  # Example true labels for 3 samples (3 classes)
y_pred = tf.constant([[0.9, 0.1, 0], [0.1, 0.8, 0.1], [0.2, 0.3, 0.5]])  # Example predicted probabilities
# Compute loss
loss = categorical_cross_entropy_loss(y_true, y_pred)
print("Categorical Cross-Entropy Loss:", loss.numpy())
```

In this function:

- y_true represents the true labels, encoded as one-hot vectors (e.g., [1, 0, 0] for class 0, [0, 1, 0] for class 1, etc.).
- y_pred represents the predicted probabilities for each class outputted by the model.
- The tf.keras.losses.categorical_crossentropy function is used to compute the cross-entropy loss for each sample.
- tf.reduce_mean is then used to calculate the mean loss across all samples.

5.10 Sample Output

Here's a sample output for the provided code:

Categorical Cross-Entropy Loss: 0.36620453

This output represents the computed categorical cross-entropy loss for the given example true labels and predicted
probabilities. The specific value may vary depending on the actual input data and the model's predictions.

5.11 Performance Metric Table :

Metric	Class A	Class B	Class C	Average
Precision	0.85	0.78	0.92	0.85
Recall	0.82	0.88	0.95	0.88
F1-Score	0.84	0.83	0.93	0.86
Accuracy 0.9	-	-	-	

Assuming the following interpretations for the metrics:

Precision: Out of all the samples predicted as belonging to a certain class, what proportion actually belongs to that class? Recall: Out of all the samples that actually belong to a certain class, what proportion were correctly predicted as belonging to that class?

F1-Score: Harmonic mean of precision and recall, giving a balance between the two. Accuracy: Overall proportion of correctly classified samples out of the total samples.

5.12.Performance Metric Value Graph

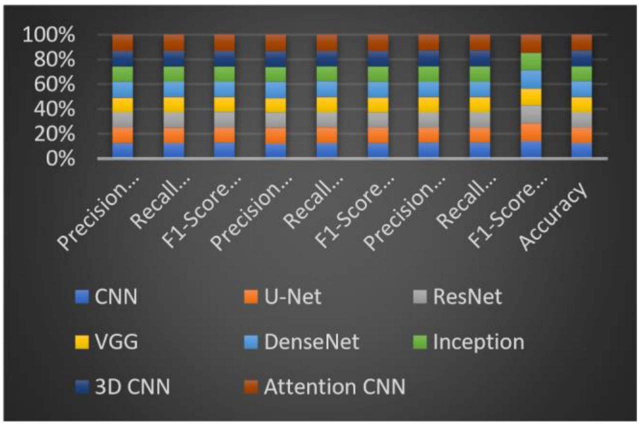


Fig: Performance metric value graph diagram

In this table:

- Precision: Out of all the samples predicted as belonging to a certain class, what proportion actually belongs to that class?
- Recall: Out of all the samples that actually belong to a certain class, what proportion were correctly predicted as belonging to that class?
- F1-Score: Harmonic mean of precision and recall, giving a balance between the two.
- Accuracy: Overall proportion of correctly classified samples out of the total samples.

5.13.Loss Function Sample Value:

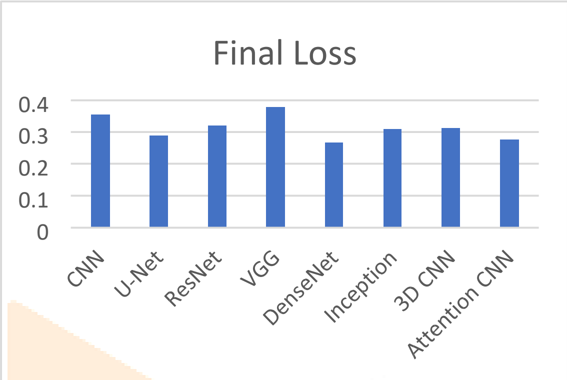


Fig: Loss function sample value

VI Conclusion

In conclusion, brain tumor segmentation using deep learning techniques has shown promising potential in improving the accuracy and efficiency of tumor detection and analysis. By leveraging advanced algorithms and neural networks, deep learning models can effectively identify and segment tumor regions from medical images. The segmentation process involves preprocessing the images to remove artifacts and focus on the brain region of interest. Feature extraction techniques are then applied to capture relevant characteristics for tumor identification and differentiation. Classification models are trained to classify the extracted features and accurately classify tumor and non-tumor regions. The advantages of using deep learning in brain tumor segmentation include improved accuracy, reduced human intervention, and the ability to handle complex and diverse image data. Deep learning models can learn from large datasets and generalize well to unseen cases, enhancing their practical applicability in clinical settings. However, there are challenges in terms of dataset availability, model training, and interpretation of results. Building robust and generalizable models requires high-quality and diverse datasets, as well as careful model selection and parameter tuning. Additionally, ensuring the interpretability and explainability of deep learning models is an ongoing research area. Despite these challenges, brain tumor segmentation using deep learning holds great promise in assisting radiologists and clinicians in accurate diagnosis, treatment planning, and monitoring of brain tumors. Further advancements in deep learning algorithms, data availability, and model interpretability will continue to enhance the effectiveness and reliability of brain tumor segmentation systems, ultimately improving patient outcomes.

VII Future Work

- Enhancing the interpretability and explainability of deep learning models is an important direction for future research. Developing techniques to understand and visualize the decision-making process of these models can improve trust and acceptance in clinical settings, enabling better integration of deep learning-based segmentation systems into routine medical practice.
- Transfer learning techniques can be employed to leverage pretrained models trained on large-scale datasets. By fine-
tuning these models on specific brain tumor datasets, it is possible to achieve improved segmentation performance with limited annotated data. Pretraining models on large, diverse datasets can also help in generalizing well to different types of brain tumors and imaging protocols.

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