The ResNet 50 architecture to classify brain tumors

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***Abstract*: Diagnosing brain tumors relies heavily on Magnetic Resonance Imaging (MRI) images, and tissue analysis methods are commonly used for tumor identification. However, challenges arise from factors such as the quality of MRI devices and low image resolution, which can degrade the accuracy of tumor detection. In this work, a solution is proposed using an Artificial Intelligence (AI)-based classification approach, specifically employing Convolutional Neural Networks (CNNs), to classify brain tumors using open-access datasets. The study introduces a novel framework that combines a Discrete Cosine Transformbased image fusion technique with a CNN to enhance image resolution and serve as a classifier. The framework achieves a high accuracy rate of 98% with the integration of super- resolution and the ResNet50 architecture. The performance of the proposed CNN models is compared to other state-of-the-art models, including Alex Net, ResNet-50, VGG-16, and Google Net. The results demonstrate satisfactory classification outcomes using large, publicly available clinical datasets. This approach shows promise in overcoming the limitations of low-resolution MRI images for accurate brain tumor classification, potentially improving diagnostic accuracy in clinical settings.**

***Keywords*: Convolution Neural Network, Brain tumor, Image recognition, Brain tumors' diagnoses, Magnetic resonance imaging, Deep learning, Neural networks, Image classification, Medical imaging**

I. INTRODUCTION

Brain tumors are abnormal growths that result from the uncontrolled proliferation of cells in the brain, often bypassing the brain's regulatory mechanisms. These tumors, when located within the skull, can exert pressure on the brain and have detrimental effects on overall health. Early detection and accurate classification of brain tumors are crucial in medical imaging to determine the most appropriate treatment methods and improve patient outcomes.

Brain tumors can be classified in various ways, with one common classification being the differentiation between benign and malignant tumors. Benign brain tumors typically develop within the skull but outside the brain tissue. Meningiomas are a significant subgroup within this category. Although benign, some brain tumors can pose life-threatening conditions, and there is a rare possibility of their transformation into malignant tumors. Due to their limited invasion of the surrounding brain tissue, benign tumors often have a high chance of successful removal through surgical intervention.

Pituitary tumors, which originate in the pituitary gland responsible for hormone regulation and bodily functions, are another type of benign brain tumor. Pituitary tumors rarely spread to other parts of the body. Although most pituitary tumors are benign, there is a small risk of recurrence or transformation into malignant tumors.

The presence of an abnormal and uncontrolled synapse characterizes brain tumors that form within the skull. Such tumors can cause pressure on the brain and have detrimental effects on an individual's health. According to data from the National Brain Tumor Foundation (NBTF), the mortality rate associated with brain tumors has recently increased by nearly 200% in many countries. Early detection and classification of brain tumors play a vital role in biomedical imaging research, enabling the development of treatment methods that increase the likelihood of patient survival.

Magnetic Resonance Imaging (MRI) is the most widely used imaging technique for detailed visualization of brain tumors. However, factors such as the quality of the MRI device and low image resolution can negatively impact the quality of the MRI images. Additionally, detecting tumors in low-resolution images presents a significant challenge for accurate diagnosis and classification.

In our future research, we took this into account and tried to deeply understand this issue. In contrast to the majority of other researchers, we utilized a large dataset of 7023 MRI scans, which is considerably more than what is typically used in many studies. Initially, our system took a long time to process because of the low

GPU resources, but we improved the system and lowered the training time. Though other research works had some limitations, we worked to enhance our method, shorten the training period, and increase the performance.

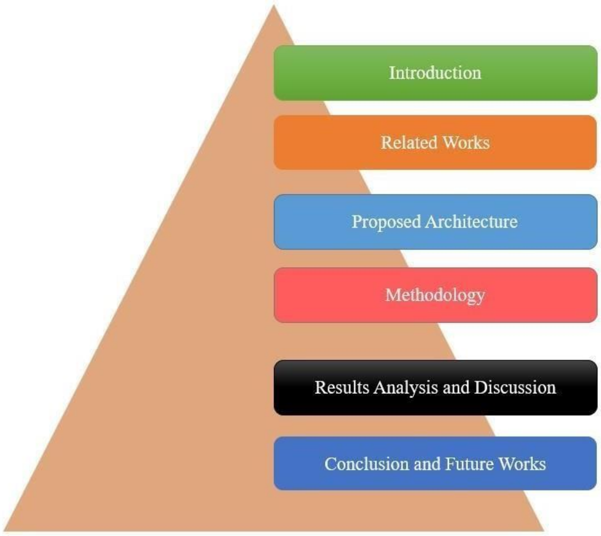


Fig.1: Outline of this paper

II. Related Work

In the field of brain tumor detection, various deep learning techniques have been employed for automatic segmentation and detection. This section discusses some current techniques in brain tumor detection.

Yanming Sun et al. [1] proposed a reliable and computationally efficient approach using Convolutional Neural Networks (CNN) for brain tumor segmentation. Their method showed promising results.

Zexun Zhou et al. [2] addressed the limitations of traditional deep convolutional neural networks for autonomous brain tumor segmentation. They highlighted the loss of spatial information due to recurrent pooling/striding and the lack of multi-scale lesion processing capabilities.

John Schmeelk [3] utilized a two-dimensional wavelet transform (2D-WT) for working with 2D brain images. The author compared this transform with the Fourier transform (FT) method and discussed their respective advantages and limitations.

Parra et al. [3] implemented an artificial neural network (ANN) algorithm for MRI brain image segmentation. They used multi-spectral features from MR images, including T1-weighted, T2-weighted, and proton density (P.D.), to segment different brain tissues. The proposed ANN algorithm employed a learning vector quantization (LVQ) network.

El-Sayed et al. [4] presented a hybrid framework for decision assistance systems in medical imaging. They used a discrete wavelet transform (DWT) for feature extraction from MRI scans and applied principal component analysis (PCA) to reduce the dimensionality of the image characteristics. Two classifiers, the FP-ANN and k-NN classifiers, were used to categorize normal and abnormal MR images.

These techniques demonstrate the ongoing efforts to develop accurate and efficient methods for brain tumor detection and classification using deep learning and other computational approaches.

III. Proposed Methodology

The proposed work in this paper introduces a new deep learning-based classification technique called ResNet 50 for brain tumor classification. The main objective is to decrease the death rate associated with brain tumors and improve human lifespan. The proposed methodology consists of four stages: preprocessing, segmentation, feature extraction, and classification.

A) Environment Setup:

For our environment setup, we utilized the Google Colab Pro+ platform, which is a fully cloud-based solution. Google Colab Pro+ offers various resources for efficient machine learning model training, including access to NVIDIA Tesla K80, T4, and P100 GPUs, as well as a high-RAM runtime with 52 GB of memory. This customized platform allows for faster and more effective training of machine learning models. B) Dataset Collection:

To construct our dataset for brain tumor detection, we collected publicly accessible data from abell.com [1]. Magnetic resonance imaging (MRI) images were specifically chosen for our research, as MRI is considered the most effective technique for detecting brain tumors.

Our dataset consists of four different types of brain tumor data:

1. Meningioma: This category includes 1339 photos of MRI images depicting patients with meningioma tumors.
2. No tumor: We included 2096 MRI images that do not exhibit any brain tumors in this category.
3. Pituitary tumor: This category comprises 1457 MRI images representing patients with pituitary tumors.
4. Glioma tumor: We incorporated 1321 MRI images showing patients with glioma tumors.

In total, our dataset consists of 7023 MRI images, encompassing the four types of brain tumor data mentioned above.

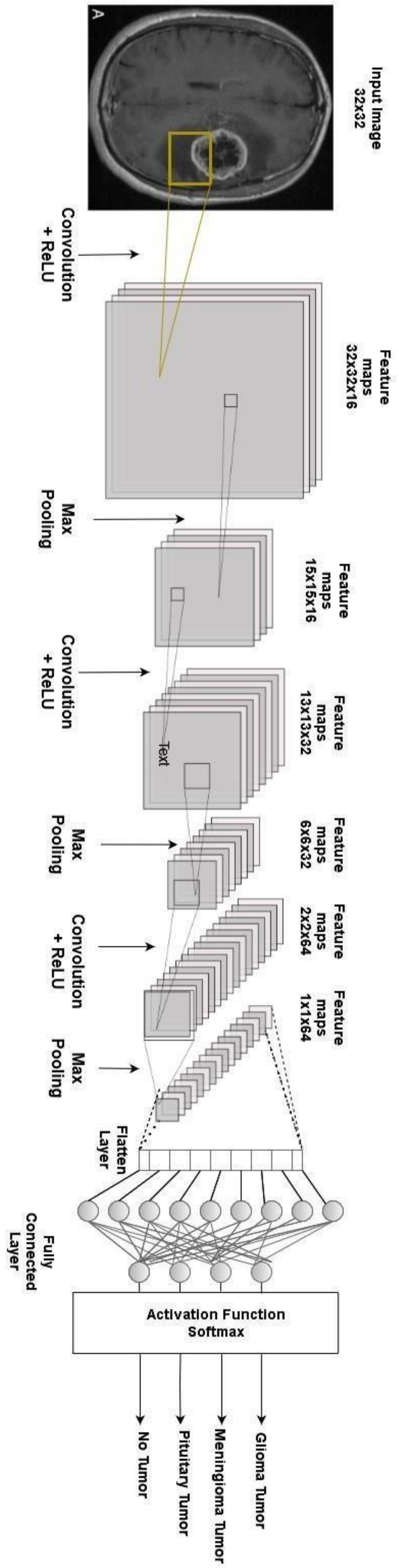


Fig.2:Proposed CNN model

The Brain Tumor MRI Dataset is a curated collection of MRI (Magnetic Resonance Imaging) images specifically designed for research and development purposes in the field of brain tumor detection and classification. This dataset plays a significant role in training and evaluating machine learning and deep learning models for brain tumor analysis.

The dataset typically consists of a variety of MRI scans, including different sequences such as T1-weighted, T2-weighted, FLAIR (Fluid-Attenuated Inversion Recovery), and contrast-enhanced images. These sequences provide different types of information about the brain tissue and help in identifying and analyzing tumors.

The dataset may include images from patients with various types of brain tumors, such as gliomas, meningiomas, pituitary tumors, or metastatic tumors. It may also contain images from different grades or stages of tumors, ranging from low-grade to high-grade tumors.

The number of images and the size of the dataset can vary depending on the specific dataset source. Some datasets may consist of a few hundred images, while others can contain thousands of images. The images are typically abelled or annotated to indicate the presence and location of tumors.

Researchers and developers use the Brain Tumor MRI Dataset to train and test their algorithms and models for tasks such as tumor segmentation, classification, and detection. These tasks aim to accurately identify the presence, type, location, and characteristics of brain tumors in MRI scans.

It’s worth noting that there are several publicly available brain tumor MRI datasets, such as BRATS (Multimodal Brain Tumor Segmentation Challenge), TCGA-LGG, TCGA-GBM (The Cancer Genome Atlas), and other datasets curated by research institutions and organizations.

Access to the Brain Tumor MRI Dataset can typically be obtained by requesting access from the dataset creators or through publicly available repositories or platforms that host medical imaging datasets. Researchers should ensure compliance with data usage agreements and ethical considerations when working with medical imaging datasets.

C) Pre-processing:

In the preprocessing stage, an adaptive filtering algorithm is applied to reduce noise and unwanted distortions in the images. This step aims to enhance the quality of the images before further processing

D) Segmentation:

The segmentation stage is crucial for separating the images into meaningful regions. Manual segmentation of a large number of medical images is impractical, so automated segmentation techniques are employed. The K-means clustering algorithm is used for image segmentation, dividing the image into non-overlapping regions. This technique helps identify relevant regions of interest within the image.

After segmentation, the feature extraction stage is performed using a gray-level co-occurrence matrix (GLCM). The GLCM captures the spatial relationships between pixels and extracts texture features that are relevant for tumor classification.

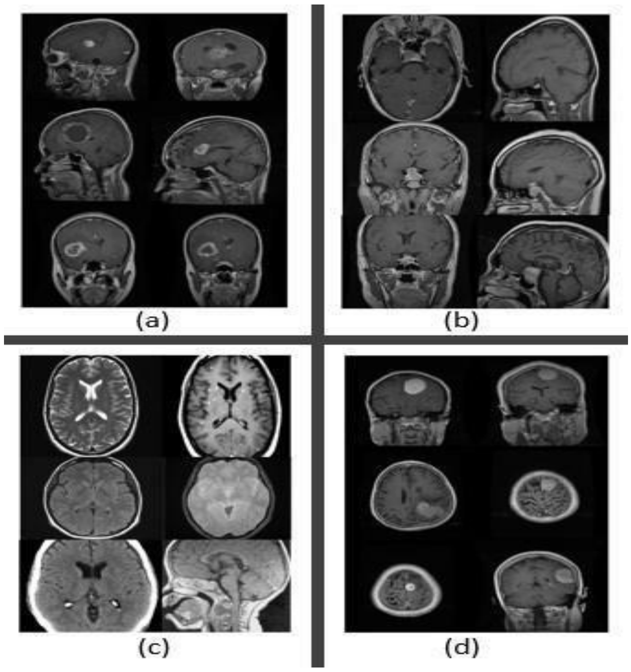
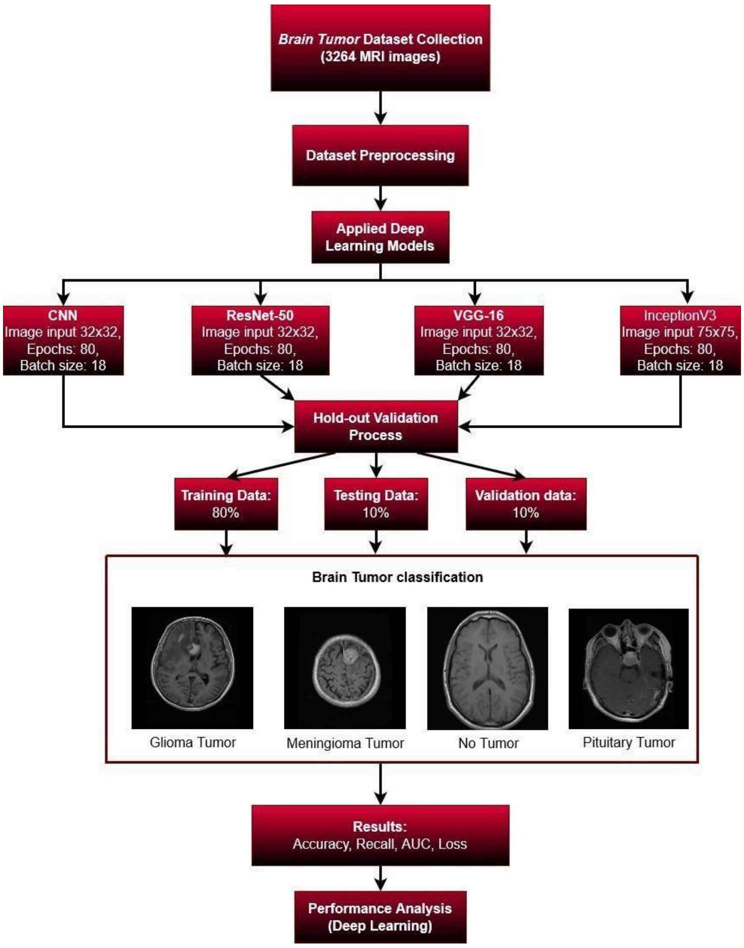


Fig.3: MR images of brain tumors:(a) Glioma tumor.(b) Pituitary tumor.(c) No tumor.(d) Meningioma tumor

Finally, the classification stage utilizes the ResNet 50 architecture to classify the brain tumors. ResNet 50 is a deep neural network architecture known for its ability to handle complex image classification tasks. It is used to accurately classify the brain tumor images into different categories.

Overall, the proposed methodology aims to achieve high accuracy rates with low complexity compared to previous developments. By combining preprocessing, segmentation, feature extraction, and classification using ResNet 50, the proposed approach seeks to improve the accuracy and efficiency of brain tumor classification.



Brain Tumor Type	Count
Glioma Tumor	1321
Meningioma Tumor	1339
No Tumor	2906
Pituitary Tumor	1457
Total	7023

E) Transfer Learning Models:

Transfer learning is a widely used technique in machine learning, particularly in the context of neural networks. It involves utilizing pre-trained models and adapting them for new tasks. In the field of image categorization and detection, several popular transfer learning models are employed, such as VGG16, ResNet-50, and Inception V3. This approach offers significant advantages in terms of cost and time efficiency. Rather than starting from scratch, which requires substantial computational resources and extensive image databases, transfer learning leverages the knowledge gained from pre-trained models to expedite the learning process and accomplish the task at hand.

1) ResNet-50:

ResNet-50 is a variant of the ResNet (Residual Network) architecture that consists of 50 deep layers. It has been trained on a large dataset, typically using at least one million examples from the ImageNet database. The ResNet-50 architecture includes a series of convolutional units with average pooling. Unlike traditional neural networks, where the output of each layer is directly connected to the input of the next layer, ResNet introduces residual connections. These connections allow the output of a layer to skip ahead and be connected to layers further ahead in the network. This mechanism proves beneficial when dealing with deeper networks and a large number of parameters, as it helps mitigate issues like vanishing gradients. By skipping unnecessary layers, ResNet achieves better accuracy and performance. Skip-connections, also known as residual connections, can be established between multiple layers in the network

2) *CNN:*

The most commonly used deep learning model for brain tumor classification is the Convolutional Neural Network (CNN). CNNs have proven to be effective in image recognition tasks, including tumor detection.In CNN-based brain tumor detection, the goal is to classify brain tumor images as either “Tumor” or “No Tumor.” However, training CNNs from scratch requires a large amount of abelled data, which may be limited in the case of brain tumor datasets.

To overcome the data limitations, CNN-based brain tumor detection approaches often utilize pre-trained CNN models. These pre-trained models, such as Inceptionv3, AlexNet, GoogLeNet, VGG-16, and ResNet50, have been trained on large-scale datasets like ImageNet for general image recognition tasks. The lower layers of these networks capture general image features that are useful for tumor classification.

In the classification process, the softmax layers of the pre-trained CNN models are used to identify tumor images. The pre-trained models are fine-tuned by training them multiple times using Stochastic Gradient Descent with Momentum (SGDM) to optimize their performance on the specific brain tumor classification task.While the features extracted from the pre-trained networks are valuable for tumor classification, fine-tuning the parameters of the network allows for training a more precise classifier specifically tailored to the brain tumor detection task.

Overall, CNN-based approaches, utilizing pre-trained models and fine-tuning, provide an effective and efficient solution for brain tumor classification, even with limited available datasets.

F) Performance Metrics:

To evaluate the machine learning models and analyze their performances, we considered some metrics such as the accuracy, recall, and area under the curve (AUC).

G) Accuracy:

Accuracy is a commonly used metric to evaluate the performance of a machine learning model. It quantifies the proportion of correct predictions compared to the total number of samples in the dataset. The accuracy can be calculated using Equation (1).

Fig.5: Residual Block

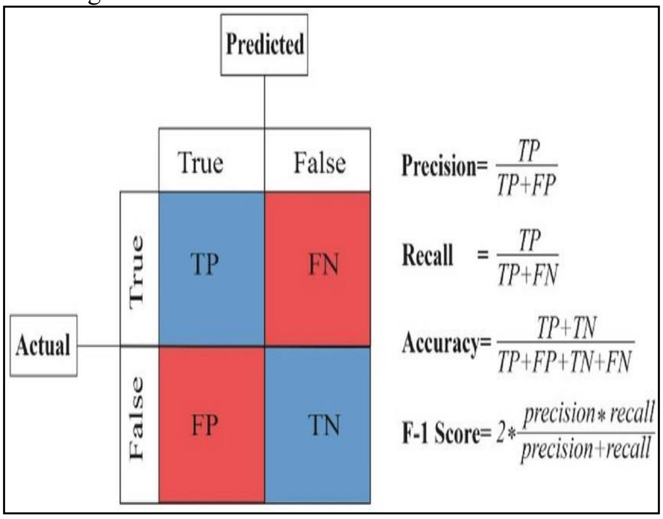


Fig.6: Performance Matrix

Accuracy = ((TN + TP) / (TP + TN + FP + FN)) × 100% ... (1)

Where:
TP = True positive
TN = True negative
FN = False negative
FP = False positive

Recall, also known as sensitivity or true positive rate, is another important metric for evaluating machine learning models. It measures the ability of the model to correctly identify positive samples. The recall can be calculated using Equation (2).

Recall = TP / (TP + FN) ... (2)

Note: The figures mentioned (Fig.5 and Fig.6) are not provided in the text and may contain visual representations or performance evaluation results relevant to the topic.

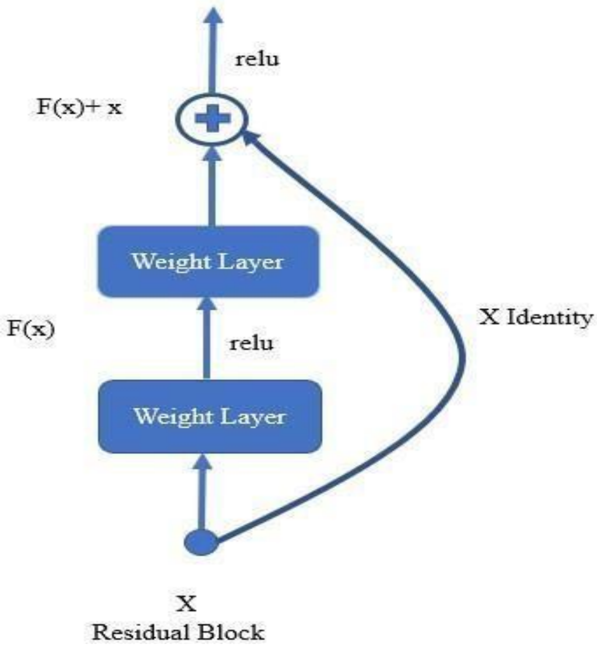


Fig.5: Residual Block

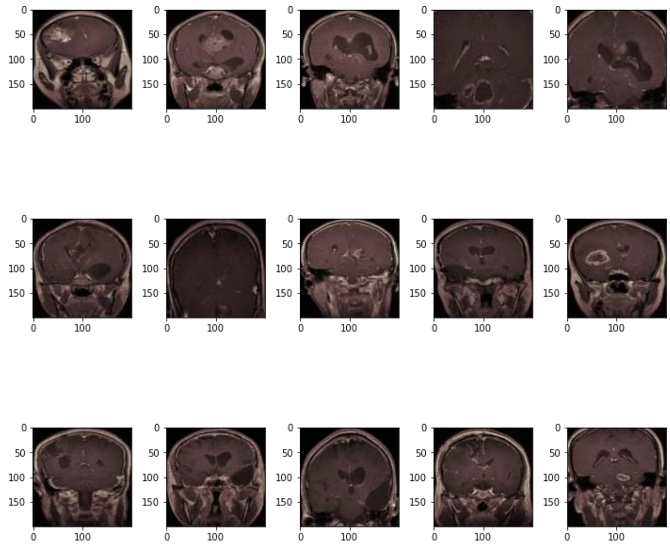


Fig.8:After Pre-processing

IV. RESULTS

Among the investigated combinations, the CNN model ResNet-50 achieved the highest accuracy and AUC values. Specifically, when ResNet-50 was used, it obtained an accuracy of 98% after 15 iterations. This indicates that the ResNet-50 model performed exceptionally well in classifying brain tumor images as "Tumor" or "No Tumor."

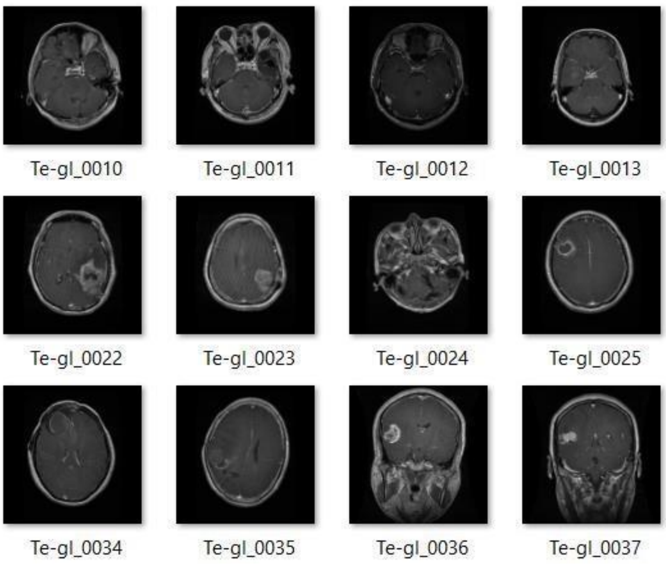


Fig.7: Before Pre-Processing

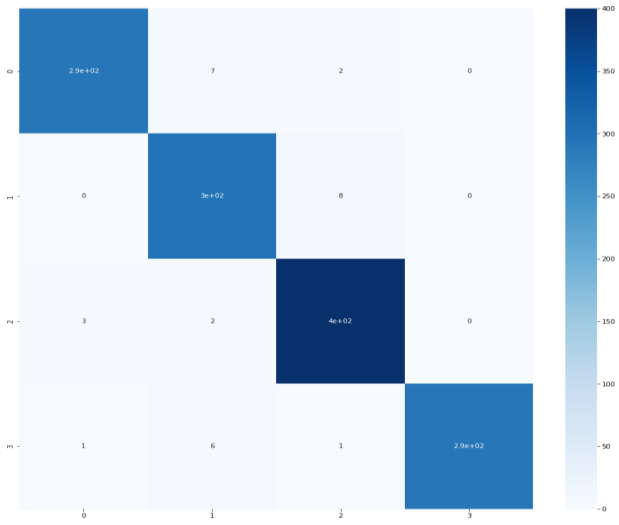


Fig.9: Confusion Matrix

The evaluation of the framework's performance included additional metrics such as sensitivity, precision, and the AUC of the ROC curve. These metrics provide insights into the system's ability to correctly classify tumors, the closeness of the measured values, and the overall performance of the framework.

The high accuracy and AUC values obtained from the ResNet-50 model demonstrate its effectiveness in brain tumor classification, indicating its potential for accurate and reliable locality constraint to preserve the manifold structure of the tumor detection. codes, enhancing the performance of the classification.

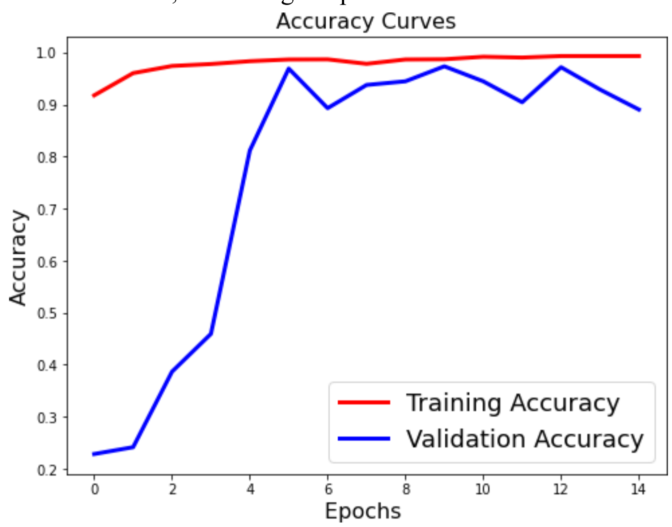


Fig.10:Accuracy Curve

Unlike traditional dictionary learning methods that rely on manual feature extraction, CDLLC automatically extracts relevant CNN features within the deep learning architecture. We apply our proposed method to classify different types of brain tumors, including meningiomas, gliomas, and pituitary tumors, using the Cheng dataset. The experimental results demonstrate high performance in terms of accuracy, recall, precision, F1-score, and balance loss.

However, one limitation of CDLLC is the increased complexity in parameter selection as the number of layers in the network grows. In our future work, we aim to address this challenge by designing a more streamlined approach for parameter selection, particularly focusing on network architectures based on CDLLC, such as ResNet-50.

Acknowledgment

We thank Dr. Visalakshi Annepu, the teaching assistant at the School of Computer Engineering, for their valuable comments.

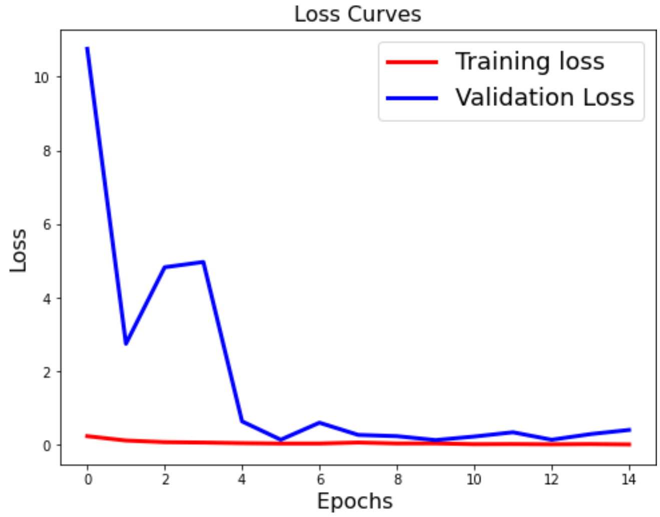


Fig.11:Loss Curve of model

V. CONCLUSION

In this research study, we propose a method called CDLLC (Convolutional Dictionary Learning with Locality Constraint) for the classification of brain tumor MR images. Our approach utilizes a CNN (Convolutional Neural Network) structure to obtain sparse representations in the nonlinear space, allowing the resulting coding vectors of different classes to capture discriminative features. Additionally, CDLLC incorporates a

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