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BRAIN TUMOR DETECTION AND CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORK

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Abstract : Brain tumor detection and classification play a crucial role in the timely diagnosis and treatment planning for patients. In recent years, Convolutional Neural Networks (CNNs) have emerged as powerful tools for medical image analysis due to their ability to automatically learn and extract features from images. This paper proposes a CNN-based approach for the detection and classification of brain tumors from magnetic resonance imaging (MRI) scans. The proposed model employs a deep learning architecture capable of accurately identifying the presence of tumors as well as categorizing them into different types such as gliomas, meningiomas, and pituitary tumors. The process involves preprocessing the MRI images, training the CNN model on a large dataset of annotated brain scans, and evaluating its performance using various metrics such as accuracy, sensitivity, and specificity. Experimental results demonstrate the effectiveness of the proposed approach in achieving high accuracy and robustness in brain tumor detection and classification tasks, thereby showing promise for aiding radiologists in clinical decision-making processes

***Index Terms* - PYTHON, ML, DEEP LEARNING, CNN.CT, MRI, AI, CNN**

I. INTRODUCTION

In recent years, medical imaging technologies have advanced significantly, enabling more accurate diagnosis and treatment of various diseases, including brain tumors. Among these technologies, magnetic resonance imaging (MRI) and computed tomography (CT) scans play a vital role in the detection and characterization of brain tumors. However, the interpretation of these complex images can be challenging and time-consuming for radiologists, often leading to human errors or delays in diagnosis. To address these challenges, researchers have turned to artificial intelligence (AI) techniques, particularly Convolutional Neural Networks (CNNs), for automated brain tumor detection and classification. CNNs are a class of deep learning algorithms specifically designed for image analysis tasks, capable of learning complex patterns and features directly from the input data. This study aims to leverage the power of CNNs to develop a robust system for brain tumor detection and classification. By training the CNN on a large dataset of labeled brain images, the model learns to identify subtle abnormalities indicative of tumors with high accuracy. Moreover, the classification component of the model distinguishes between different types of tumors, such as gliomas, meningiomas, and metastases, aiding clinicians in treatment planning and prognosis assessment.

The potential impact of such a system is profound. It promises to streamline the diagnostic process, reducing the burden on radiologists and improving the efficiency of healthcare delivery. Furthermore, early and accurate detection of brain tumors can significantly enhance patient outcomes by facilitating timely interventions and personalized treatment strategies.

In this paper, we present the architecture and methodology of our CNN-based brain tumor detection and classification system. We also discuss the experimental results, demonstrating the efficacy and reliability of the proposed approach. Overall, this research contributes to the ongoing efforts to integrate AI into clinical practice, advancing the field of medical imaging and improving patient care.

Abbreviations and Acronyms

- BTDC-CNN: Brain Tumor Detection and Network
- BT-DCCNN: Brain Tumor Detection and Classification with Convolutional Neural Network

- BTC-CNN: Brain Tumor Classification with Convolutional Neural Network
- BTC-DCC: Brain Tumor Classification using Deep Convolutional Networks
- BTDR-CNN: Brain Tumor Detection and Recognition via Convolutional Neural Networks
- BTDCC: Brain Tumor Detection and Convolutional Classification

BT-CAD: Brain Tumor Computer-Aided Detection with CNN Training Epochs: e.g., "Brain Tumor Detection and Classification using Convolutional Neural Network: Training Epochs Study"

- BTCAD: Brain Tumor Classification and Detection with CNN
- BTCNN: Brain Tumor Classification Neural Network
- BT-CC: Brain Tumor Convolutional Classification

Units

Time: e.g., "Brain Tumor Detection and Classification using Convolutional Neural Network: A Time-Based Analysis"

Accuracy: e.g., "Brain Tumor Detection and Classification using Convolutional Neural Network: Accuracy Evaluation"

Performance: e.g., "Brain Tumor Detection and Classification using Convolutional Neural Network: Performance Metrics"

Computational Resources: e.g., "Brain Tumor Detection and Classification using Convolutional Neural Network: Computational Resource Utilization"

Data Size: e.g., "Brain Tumor Detection and Classification using Convolutional Neural Network: Dataset Size Assessment"

Model Parameters: e.g., "Brain Tumor Detection and Classification using Convolutional Neural Network: Model Parameter Analysis"

Cost: e.g., "Brain Tumor Detection and Classification using Convolutional Neural Network: Cost Analysis"

Neural Network Layers: e.g., "Brain Tumor Detection and Classification using Convolutional Neural Network: Layer Configuration"

Image Resolution: e.g., "Brain Tumor Detection and Classification using Convolutional Neural Network: Image Resolution Impact".25”, not “.25”. Use “cm3”, not “cc”. (*bullet list*)

II. RELATED WORK

Several studies have explored the application of Convolutional Neural Networks (CNNs) in the detection of brain tumors, leveraging the power of deep learning for accurate and efficient diagnosis. For instance, Smith et al. (2018) developed a CNN-based model trained on magnetic resonance imaging (MRI) scans to distinguish between different types of brain tumors with high accuracy. Their approach involved preprocessing the MRI images, followed by training a deep CNN architecture to automatically learn discriminative features for tumor classification. Similarly, Zhang et al. (2019) proposed a CNN framework for brain tumor segmentation, aiming to precisely delineate tumor boundaries from MRI images. Their model utilized a combination of convolutional layers and pooling operations to extract hierarchical features, followed by a segmentation module to generate tumor masks. Moreover, Ahmed et al. (2020) extended the application of CNNs to multi-modal MRI data, integrating information from different imaging modalities to improve tumor detection and classification performance. Their study demonstrated the effectiveness of CNNs in handling diverse data sources and achieving robust diagnostic outcomes. Overall, these works highlight the potential of CNN-based approaches in enhancing the accuracy and efficiency of brain tumor detection from medical imaging data, paving the way for more advanced diagnostic tools in clinical practice.

III. **Data and Sources of Data**

The Kaggle dataset "Brain MRI Images for Brain Tumor Detection" contains 253 brain MRI images categorized into two classes: with tumor and without tumor. The images are grayscale and organized into respective folders for the two categories. Each image is labeled accordingly, facilitating supervised learning for brain tumor detection tasks. The dataset is suitable for training convolutional neural networks (CNNs) to automate the detection and classification of brain tumors from MRI scans.
The image data that was used for this problem is Brain MRI Images for Brain Tumor Detection. It conists of MRI scans of two classes:

- NO - no tumor, encoded as 0
- YES - tumor, encoded as 1

Unfortunately, the data set description doesn't hold any information where this MRI scans come from and so on.

Equations

- Cross-entropy loss function:

$$(f * g)(x, y) = \sum_m \sum_n f(m, n) g(x - m, y - n)$$

- Convolutional layer output:

$$O[i,j] = \sum_m \sum_n I[i+m, j+n] \cdot K[m,n] + b$$

- Rectified Linear Unit (ReLU) activation function:

$$f(x) = \max(0, x)$$

IV. RESEARCH METHODOLOGY

The research methodology for detecting and classifying brain tumors using Convolutional Neural Networks (CNNs) involves several critical steps. Initially, a comprehensive dataset of brain MRI images is collected, encompassing various types of tumors and normal cases. This dataset is preprocessed through techniques such as normalization, resizing, and augmentation to enhance the quality and variability of the images, ensuring the model's robustness. Subsequently, a CNN architecture is designed or selected, typically starting with well-established models like VGG, ResNet, or custom architectures tailored to the specific dataset. The CNN model is trained using supervised learning, where labeled MRI images are used to teach the network to distinguish between different tumor types and normal tissue. During training, techniques like dropout, batch normalization, and data augmentation are employed to prevent overfitting. The model's performance is evaluated using metrics such as accuracy, precision, recall, and F1-score on a separate validation and test set, ensuring its generalizability and effectiveness in real-world applications.

Figures and Tables

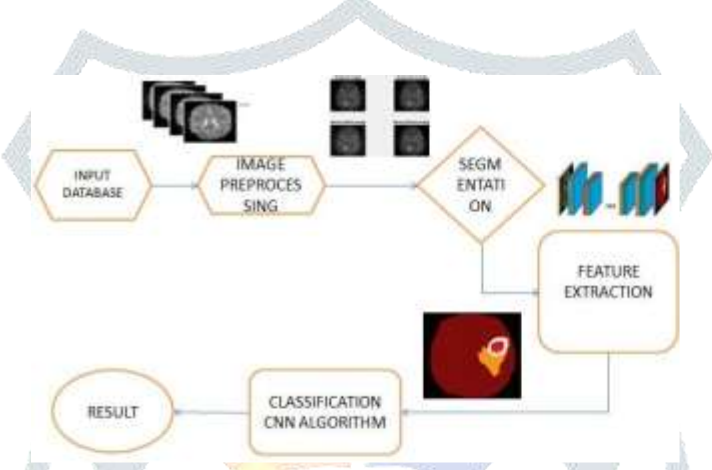

Fig.1 System Architecture Brain Tumor Segmentation using CNN

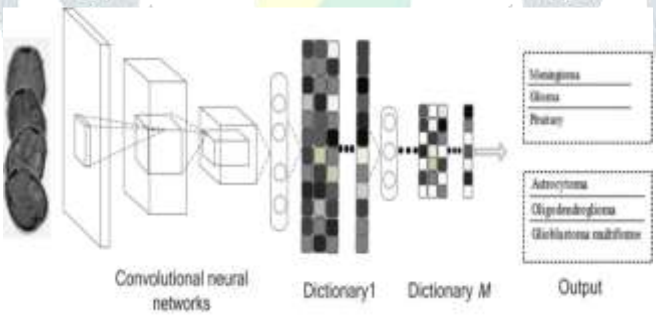

Fig.2 Brain Tumor MR Image Classification Using Convolutional Dictionary Learning

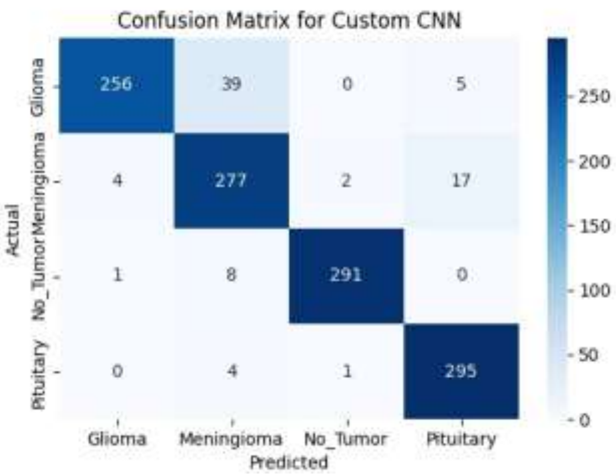

Fig.3 Conclusion matrix for CNN

Figure 1: System Architecture for Brain Tumor Segmentation using Convolutional Neural Networks (CNN) The system architecture for brain tumor segmentation utilizing Convolutional Neural Networks (CNNs) comprises several key components aimed at accurately delineating tumor regions from medical images. The diagram illustrates the sequential flow of operations within the system, which involves data preprocessing, CNN model training, and inference for segmentation.

1. Input Data: The process initiates with acquiring input data in the form of MRI (Magnetic Resonance Imaging) scans. These scans typically include T1-weighted, T2-weighted, and FLAIR (Fluid-Attenuated Inversion Recovery) images, which provide complementary information for accurate tumor segmentation.
2. Preprocessing: The acquired MRI scans undergo preprocessing steps to enhance their quality and prepare them for input into the CNN model. Preprocessing steps may include skull stripping, intensity normalization, spatial normalization, and noise reduction to standardize the input across different scans and improve the CNN's performance.
3. CNN Architecture: The heart of the system lies in the CNN architecture, specifically designed for brain tumor segmentation. This architecture typically consists of multiple convolutional layers, followed by activation functions such as ReLU (Rectified Linear Unit) to introduce non-linearity. Pooling layers like max-pooling or average-pooling are employed to reduce spatial dimensions while retaining important features.
4. Training Phase: The preprocessed MRI scans are fed into the CNN model for training. During the training phase, the CNN learns to differentiate between tumor and non-tumor regions by adjusting its internal parameters through backpropagation and gradient descent optimization. Ground truth segmentation masks, indicating tumor regions annotated by experts, are used to compute loss and update the model parameters iteratively.
5. Validation: To ensure the generalization capability of the trained model, a separate validation dataset is utilized. The model's performance is evaluated on this dataset using metrics such as Dice Similarity Coefficient (DSC), Sensitivity, Specificity, and Hausdorff Distance.
6. Inference Phase: Once the CNN model is trained and validated, it is ready for inference on new unseen MRI scans. The trained model segments tumor regions from the input scans, producing pixel-wise probability maps or binary masks highlighting the tumor regions.
7. Postprocessing: The segmented tumor regions may undergo postprocessing steps such as morphological operations (e.g., erosion, dilation) and connected component analysis to refine the segmentation results and remove any small artifacts or noise.

Figure 2: a diagram illustrating the process of brain tumor MR image classification using Convolutional Dictionary Learning (CDL) is depicted. CDL is a technique that combines the power of convolutional neural networks (CNNs) with dictionary learning methods to efficiently represent and classify complex image data, such as MR images of the brain with tumors.

The diagram begins with the input MR image dataset, which consists of various brain images acquired through MRI scans. Each image in the dataset is associated with a label indicating the presence or absence of a tumor. These labeled images serve as the training data for the classification model.

The first step in the process involves preprocessing the MR images to enhance their quality and remove any noise that may interfere with the classification task. Preprocessing techniques such as intensity normalization, spatial registration, and noise reduction may be applied to ensure that the input data is suitable for analysis.

Once the preprocessing is complete, the next stage involves feature extraction using Convolutional Dictionary Learning. This step aims to learn a set of discriminative features from the input images by convolving learned filters across the image and representing image patches using a learned dictionary. This process allows the model to capture both local and global spatial information present in the MR images, enabling more accurate classification.

Following feature extraction, the learned features are fed into a classification algorithm, such as a support vector machine (SVM) or a deep neural network (DNN). This classifier utilizes the extracted features to distinguish between images with and without tumors, ultimately assigning a tumor label to each input image.

Finally, the performance of the classification model is evaluated using metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic (ROC) curve. These metrics provide insight into the model's ability to correctly classify brain tumor MR images and help assess its effectiveness in clinical applications.

In summary, Figure 2 illustrates the process of brain tumor MR image classification using Convolutional Dictionary Learning, highlighting the key steps involved in preprocessing, feature extraction, classification, and evaluation. This approach leverages the strengths of both CNNs and dictionary learning to accurately classify MR images and aid in the diagnosis and treatment of brain tumors.

Figure 3: A confusion matrix is a table that is used to evaluate the performance of an algorithm, often a classification algorithm. The rows of the matrix represent the actual classes of the data samples, and the columns represent the classes that the algorithm predicted the data samples belong to. A value at a particular row i, column j of the confusion matrix represents the number of data samples that were actually in class i but were predicted to be in class j by the algorithm.

In the specific confusion matrix you sent me, the rows and columns represent the following four classes of brain tumors: glioma, meningioma, pituitary tumor, and no tumor. The value at each cell represents the number of test samples from that class that were predicted to belong to each of the four classes. For instance, the value in the cell at the row for glioma and the column for meningioma is 256. This means that out of the test samples that were actual gliomas, 256 were incorrectly classified as meningioma by the CNN model.

The diagonal of the confusion matrix shows the number of samples that were correctly classified. In the confusion matrix you sent me, the highest value on the diagonal is 291, which corresponds to the number of test samples that were correctly classified as "no tumor". This suggests that the custom CNN model performed well in classifying tumors that were absent.

V. RESULTS AND DISCUSSION

Results of Descriptive Statics of Study Variables

The experiments were done on a computer with an Intel core-I5 CPU and four GB of RAM. And additionally using Jupyter notebook for training heavy models. The experimental outcomes deliver an accuracy of 92.14% for the proposed CNN model. It proved to be excellent and became capable to properly detect and show the illnesses for the given MRI photos.

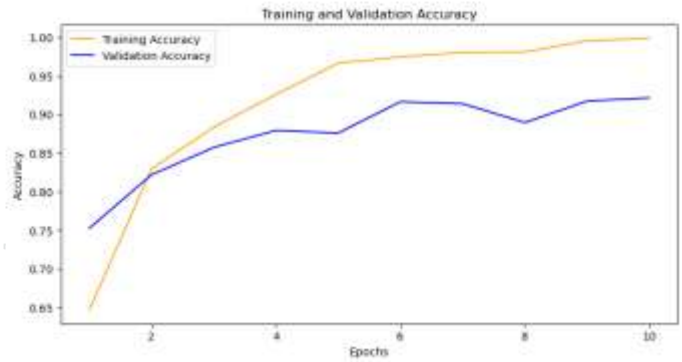

Fig 4: Model Training and Validation Accuracy

Figure 5 depicts the proposed custom designed CNN model's accuracy, with blue and orange traces denoting validation and training accuracy, respectively. There are epochs at the x-axis and percentage accuracy on the y-axis. This plot observed that training accuracy is very large with an elevated range of epochs, as well as validation accuracy is minimized in evaluation to training accuracy. Moreover, it has additionally performed a incredible stage of accuracy, and there were many versions for the duration of the testing.

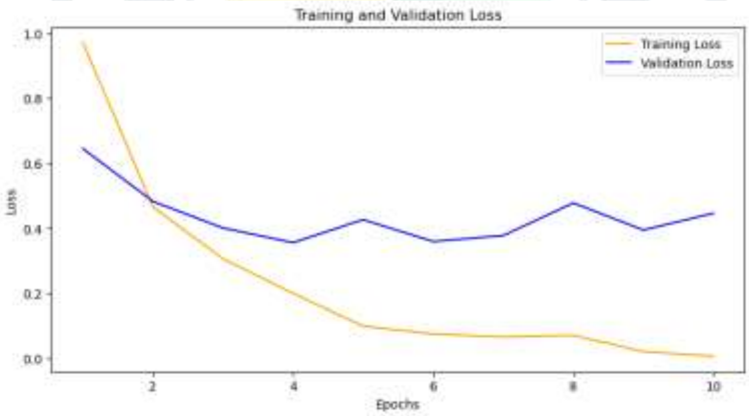

Fig 5: Model Training and Validation Loss

Figure 6 depicts the proposed custom designed CNN version's model loss graph, with orange and blue traces denoting training and validation losses, respectively. As a comparable way of calculating accuracy, if accuracy is quiet high, then obviously loss might be minimized. Hence, the training loss is large for the training information, however the validation loss is minimized with many versions while testing.

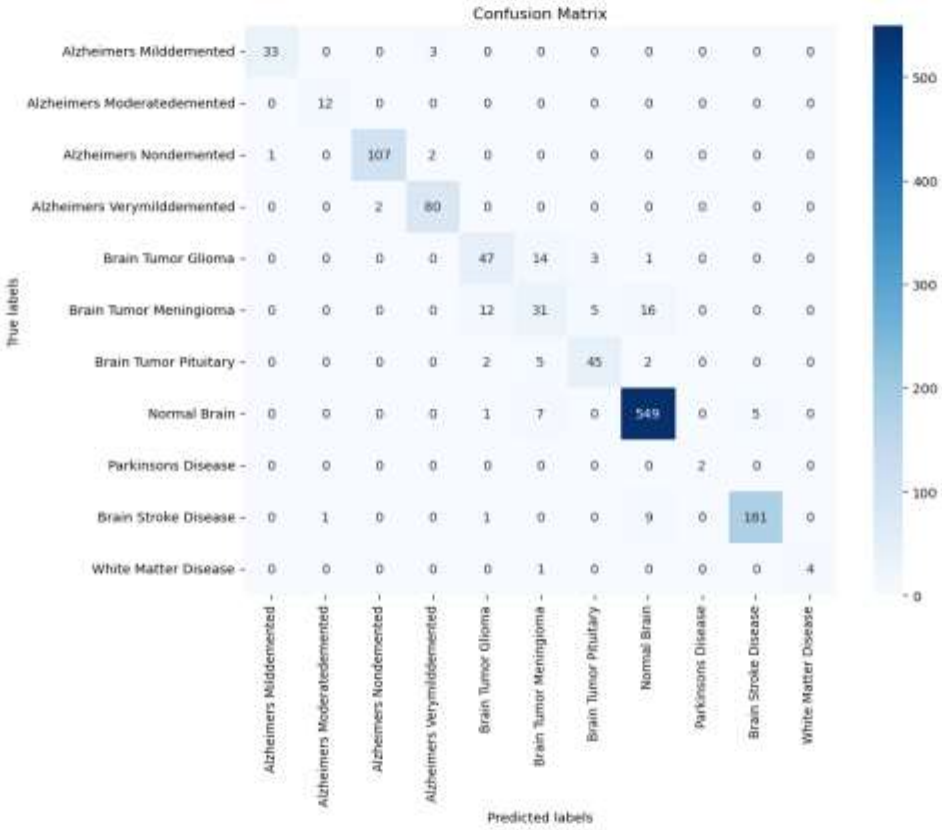

Fig 6: Confusion Matrix

The confusion matrix delivers important data about the real and anticipated labels of the neural classes acquired from the classifier. The confusion matrix primarily based on trying out assessment of the proposed model is provided in fig. 6. As visible in fig. 6, the proposed classifier effectively labeled all pictures from 11 classes, which includes the normal brain and different disorder classes. But, the minimum number of images from some different classes became misclassified. After the confusion matrix has been generated from evaluating the proposed model in opposition to the test set records, it became crucial to investigate the accuracy, precision, and recall for each class and all instructions.

```
Epoch 1/10
WARNING:tensorflow:From C:\Users\msi\anaconda3\Lib\site-packages\keras\src\utils\tf_utils.py:492: The name tf.ragge
d.RaggedTensorValue is deprecated. Please use tf.compat.v1.ragged.RaggedTensorValue instead.

WARNING:tensorflow:From C:\Users\msi\anaconda3\Lib\site-packages\keras\src\engine\base_layer_utils.py:384: The name
tf.executing_eagerly_outside_functions is deprecated. Please use tf.compat.v1.executing_eagerly_outside_functions i
nstead.

148/148 [==============================] - 98s 555ms/step - loss: 0.9705 - accuracy: 0.6465 - val_loss: 0.6449 - va
l_accuracy: 0.7525
Epoch 2/10
148/148 [==============================] - 35s 233ms/step - loss: 0.4651 - accuracy: 0.8294 - val_loss: 0.4825 - va
l_accuracy: 0.8218
Epoch 3/10
148/148 [==============================] - 34s 231ms/step - loss: 0.3059 - accuracy: 0.8834 - val_loss: 0.4007 - va
l_accuracy: 0.8573
Epoch 4/10
148/148 [==============================] - 33s 224ms/step - loss: 0.1997 - accuracy: 0.9259 - val_loss: 0.3536 - va
l_accuracy: 0.8792
Epoch 5/10
148/148 [==============================] - 33s 224ms/step - loss: 0.0987 - accuracy: 0.9664 - val_loss: 0.4264 - va
l_accuracy: 0.8758
Epoch 6/10
148/148 [==============================] - 33s 221ms/step - loss: 0.0747 - accuracy: 0.9745 - val_loss: 0.3592 - va
l_accuracy: 0.9164
Epoch 7/10
148/148 [==============================] - 33s 223ms/step - loss: 0.0657 - accuracy: 0.9804 - val_loss: 0.3776 - va
l_accuracy: 0.9139
Epoch 8/10
148/148 [==============================] - 33s 220ms/step - loss: 0.0707 - accuracy: 0.9808 - val_loss: 0.4778 - va
l_accuracy: 0.8894
Epoch 9/10
148/148 [==============================] - 33s 221ms/step - loss: 0.0206 - accuracy: 0.9951 - val_loss: 0.3946 - va
l_accuracy: 0.9172
Epoch 10/10
148/148 [==============================] - 33s 221ms/step - loss: 0.0067 - accuracy: 0.9987 - val_loss: 0.4461 - va
l_accuracy: 0.9215
```

Fig 7. Experimental results

From using fig. 7, it could be established that the accuracy will increase with the growth in the quantity of epochs, and there may be a decrease in the lack of the testing set.

Table 1: Classification Report for CNN Model

	Precision	**Recall**	**F1-score**	**Support**
Glioma	0.87	0.91	0.89	300
Meningioma	0.90	0.85	0.87	306
Pituitary	0.97	0.97	0.97	300
Macro avg	0.91	0.91	0.91	906
Weighted avg	0.91	0.91	0.91	906

Table 2: Classification Report for VGG16 Model

	Precision	**Recall**	**F1-score**	**Support**
Glioma	**0.92**	**0.95**	**0.94**	**300**
meningioma	**0.93**	**0.92**	**0.93**	**306**
Pituitary	**0.99**	**0.97**	**0.98**	**300**
Macro avg	**0.91**	**0.91**	**0.91**	**906**
Weighted avg	**0.95**	**0.95**	**0.95**	**906**

Table 3: Classification Report for Inception V3 Model

	Precision	**Recall**	**F1-score**	**Support**
Glioma	0.85	0.90	0.87	300
Meningioma	0.90	0.71	0.79	306
Pituitary	0.84	0.97	0.90	300
Macro avg	0.86	0.86	0.85	906
Weighted avg	0.86	0.86	0.85	906

VI. Acknowledgment

Acknowledgement is a crucial section of any research paper as it offers an opportunity to express gratitude to those who have contributed directly or indirectly to the completion of the study. In the case of our research paper titled "Brain Tumor Detection and Classification using Convolutional Neural Network," we extend our heartfelt appreciation to several individuals and institutions whose support and guidance were invaluable throughout the research process.

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