MRI Brain tumor detection

Leveraging Deep Learning for Precise Healthcare Diagnosis

Team 77
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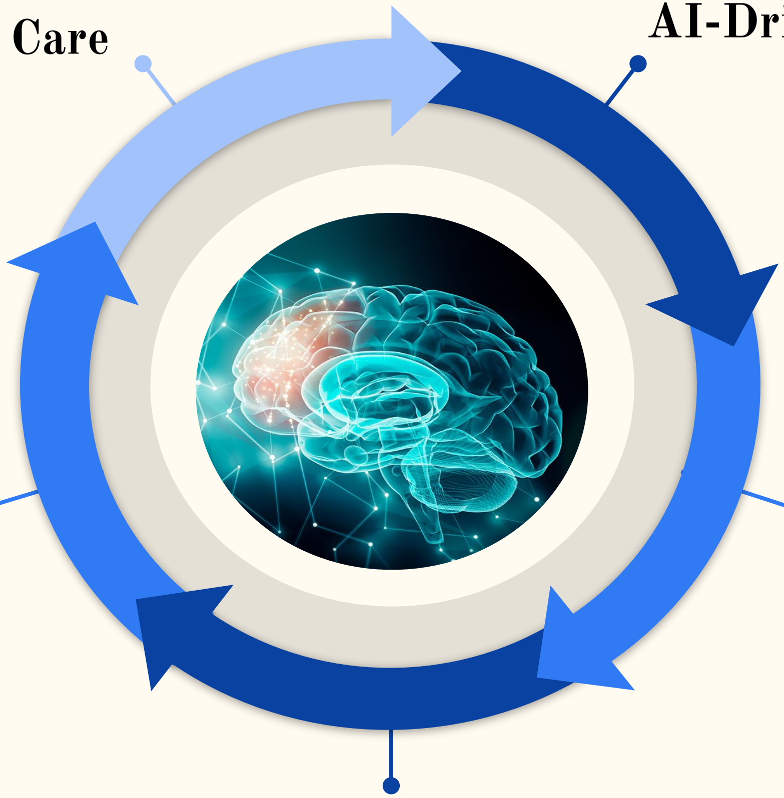
Motivation

Patient-Centric Care

AI-Driven Diagnosis



Reduced Manual Workload

Precision and Speed

Efficient Treatment Planning

Motivation

- **Healthcare Assistance:** Empower healthcare professionals with an AI-driven tool for accurate and rapid brain tumour diagnosis.
- **Treatment Planning:** Facilitate timely treatment planning, enhancing patient outcomes and quality of life.
- **Precision and Speed:** Achieve high precision in detecting and classifying brain tumours from MRI scans swiftly and efficiently.
- **Reduce Manual Workload:** Automate the process of tumour detection and classification, reducing the manual workload of healthcare professionals.
- **Patient-Centric Care:** Enhance patient care by enabling earlier detection and intervention, potentially saving lives and reducing long-term healthcare costs.

Project tasks

- **Data Preprocessing:** Standardize MRI images of varying sizes and formats to create a uniform dataset for model training.
- **Feature Extraction:** Identify and extract critical features from MRI scans that distinguish between different types and locations of brain tumours.
- **Model Selection and Interpretability:** Evaluate and choose appropriate neural network architectures capable of accurately classifying brain tumours from MRI data. Ensure the model's predictions are interpretable, providing clinicians with insights into the decision-making process.
- **Hyperparameter Tuning:** Optimize model parameters and architecture to achieve the best performance and generalization on the test dataset.
- **Model Training and Validation:** Train the selected model using the preprocessed data and validate its performance using a separate test dataset.
- **Evaluation Metrics:** Assess the model's accuracy, precision, recall, and F1-score to determine its reliability and effectiveness in clinical settings.

Project tasks

Standardize MRI images to uniform sizes and formats for consistent model training.

Data Preprocessing

Feature Extraction and Model Selection

Extract key features from MRI scans and select neural networks

Optimize model parameters for peak performance and validate using a test dataset.

Hyperparameter Tuning and Validation

Model Training

Train the model with preprocessed data to ensure robust and reliable outputs.

Use metrics like accuracy, precision, recall, and F1-score to assess model effectiveness in clinical applications.

Performance Evaluation

Dataset

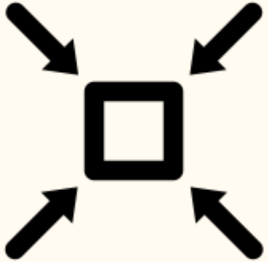
Source

Kaggle

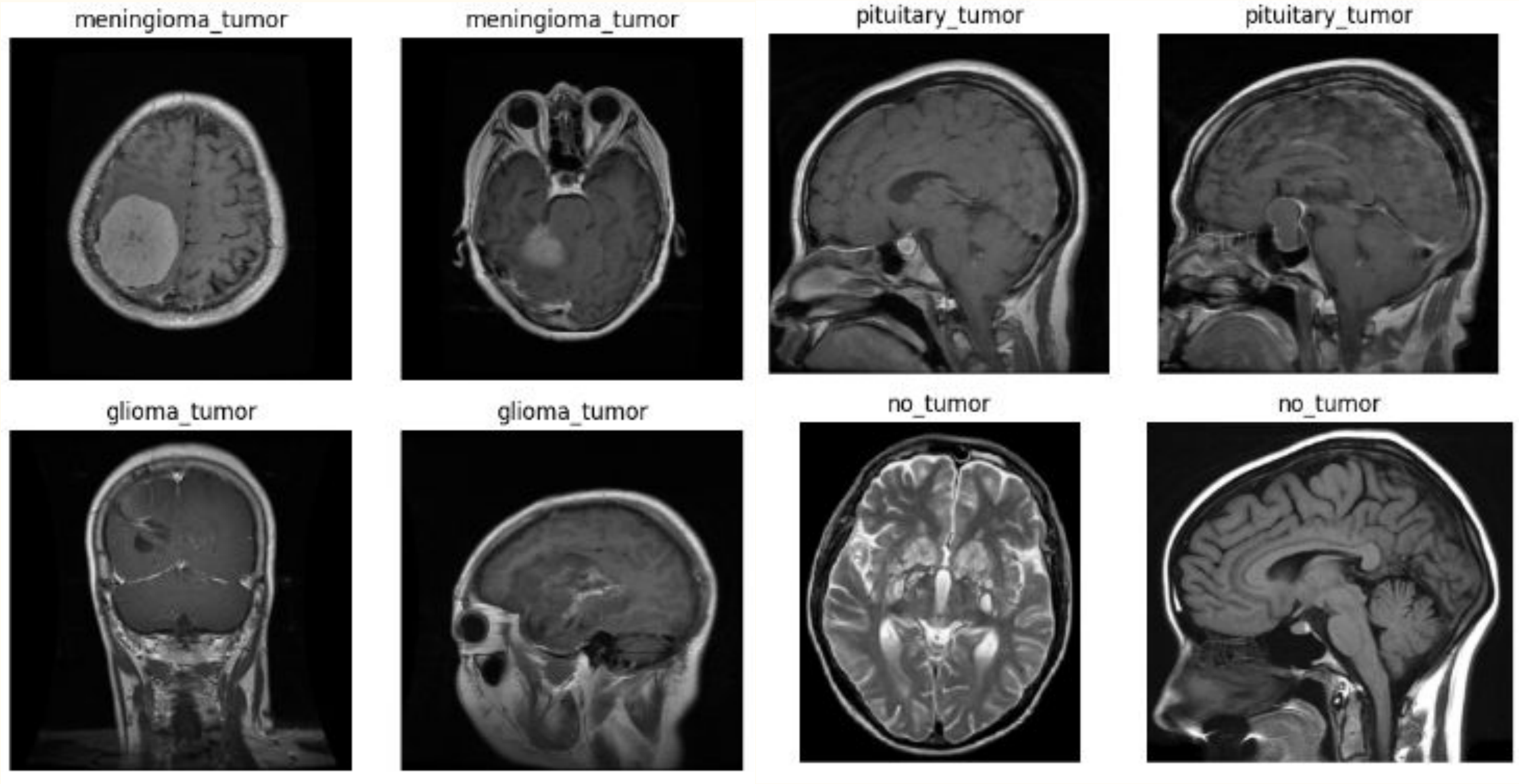
Format

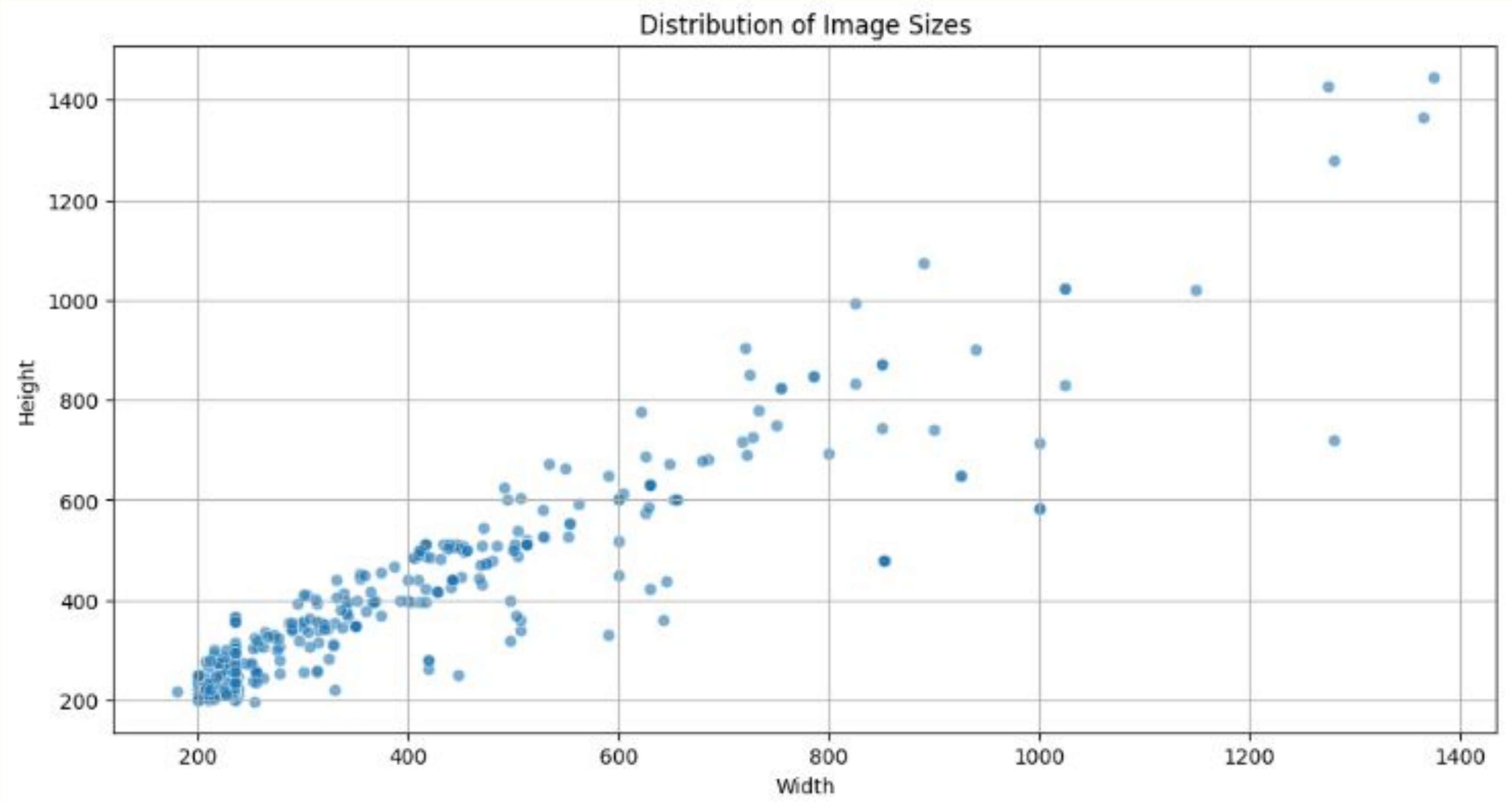
Images of brain
MRI scans

Size

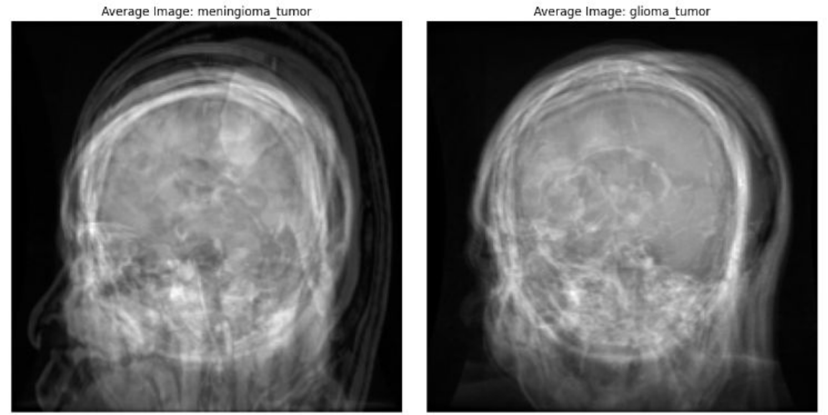


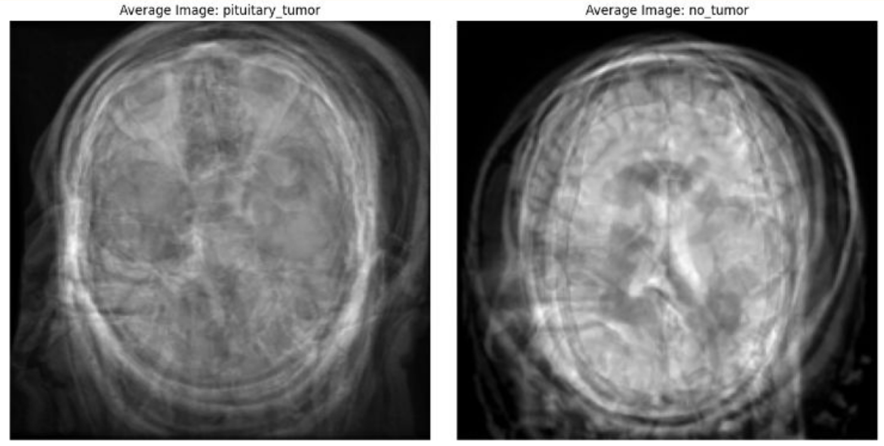
X_train.shape()
300 * 300


meningioma_tumor
meningioma_tumor
pituitary_tumor
pituitary_tumor
glioma_tumor
glioma_tumor
no_tumor
no_tumor


Distribution of Image Sizes
Height
Width
200
400
600
800
1000
1200
1400
200
400
600
800
1000
1200
1400

Average Image





Data Augmentation

Purpose of Data Augmentation: To artificially expand the size of a training dataset by creating modified versions of images in the dataset. This helps improve the model's ability to generalize from our data to new data, an essential aspect for robust machine learning models, especially in medical imaging.

Techniques:

Rotation: Images rotated by up to 10 degrees, aiding the model in learning from various orientations.

Width and Height Shifts: Shifts images horizontally and vertically by 5% of total width and height respectively, simulating slight variations in the positioning of brain tumors.

Horizontal Flip: Enabled, to add a mirrored version of the original images.

Data Augmentation

Enhancing dataset size with modified image versions to improve model generalization, crucial for robust machine learning in medical imaging.

Techniques

Rotation

Rotate images up to 10 degrees to help the model learn from different orientations.

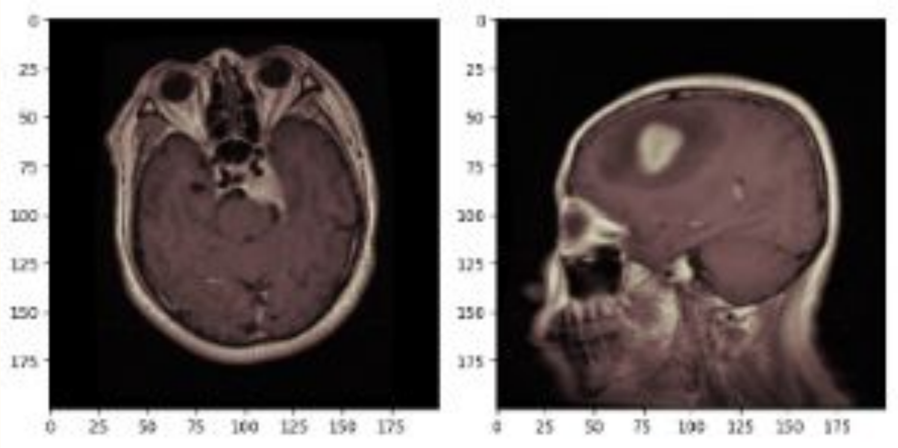
Width and Height Shifts

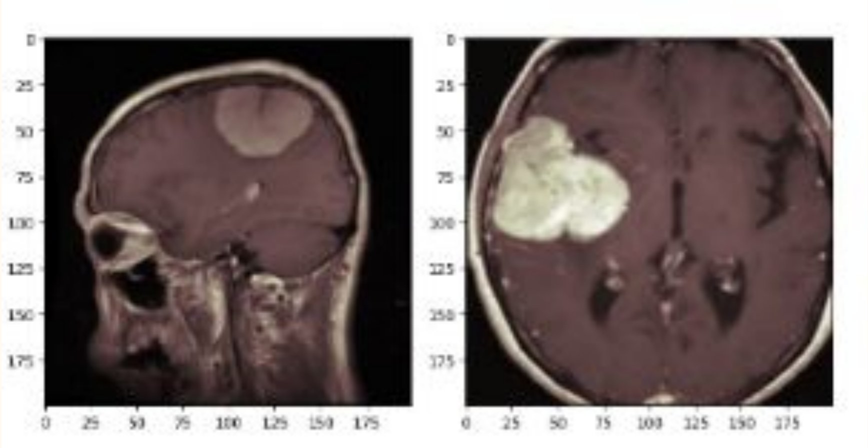
Shift images horizontally and vertically by 5% to mimic variations in tumor positioning.

Horizontal Flip

Include mirrored versions of original images for diversity.

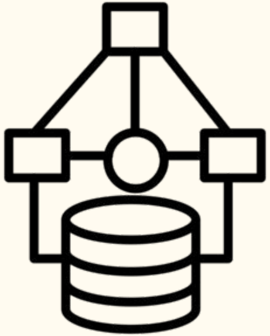
Processed image





Baseline model (ResNet50)

Base

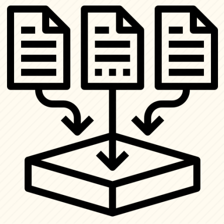


Uses a 50-layer Residual Neural Network.

Pre-trained Weights

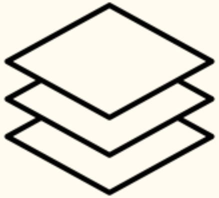
Implements weights from a pre-trained ResNet50 to enhance feature recognition.

Global Pooling 2D



Reduces spatial dimensions and integrates global context

Dense Layer



Fully connected layer with softmax activation for classification.

Optimizer

Uses Adam optimizer with a learning rate of 0.0001 for efficient training.

Implementation

```
def build_model():
    net = ResNet50(weights=None, include_top=False, input_shape=(image_size, image_size, 3))
    net.load_weights(weights_path)
    x = net.output
    x = GlobalAveragePooling2D()(x)
    x = Dropout(0.4)(x)
    predictions = Dense(len(labels), activation="softmax")(x)
    model = Model(inputs=net.input, outputs=predictions)
    model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.0001),
                  loss='categorical_crossentropy', metrics=['accuracy'])
    return model
```

Loss function: Categorical Cross Entropy

Objective

To measure the dissimilarity between the predicted probabilities and the actual class labels.

Benefits

Suitable for multi-class classification problems and provides efficient gradient computation.

Model Architecture (key components)

Convolutional Layers	• Multiple layers with different filter sizes and strides to extract features at different levels.
Batch Normalisation	• Applied after each convolutional layer to normalize the activations.
MaxPooling2D	• Used to downsample feature maps, retaining important features.
Flatten Layer	• Converts the 3D feature maps to 1D for the fully connected layers.
Dense Layer	• Fully connected layers with large number of neurons to learn complex patterns.

Baseline results

- **Test Accuracy:** Achieved an accuracy of 77% on the test dataset.

- **Loss:** Recorded a categorical cross entropy loss of 0.8

- **Training Time:** 8 mins showing efficient convergence.

Updated(New) model

Input Resizing

Images resized to 32x32 for uniformity.

Batch Normalization

Applied after each Conv2D layer to stabilize learning.

Flattening

Converts the 2D features maps to a 1D vector for the dense layers.

First Layer

Conv2D with 6 filters of size 5x5, followed by ReLU activation.

Pooling Layers

AveragePooling2D reduces dimensionality after each Conv2D layer.

Dense Layers

Three dense layers with 120 and 84 neurons, and a final output layer with 4 neurons

Implementation

```
model = Sequential([
    Resizing(32, 32, interpolation='bilinear', input_shape=(300, 300, 3)),
    Conv2D(6, kernel_size=(5, 5), activation='relu'),
    BatchNormalization(),
    AveragePooling2D(pool_size=(2, 2)),
    Conv2D(16, kernel_size=(5, 5), activation='relu'),
    BatchNormalization(),
    AveragePooling2D(pool_size=(2, 2)),
    Flatten(),
    Dense(120, activation='relu'),
    Dense(84, activation='relu'),
    Dense(4, activation='softmax')
])
```

Data Augmentation

Zoom

Adjusts the zoom by 10%, helping the model manage different sizes of tumors.

Fill Mode

Set to 'nearest' to fill in new pixels that can appear after a rotation or width/height shift.

Rotation

Rotate images up to 10 degrees to help the model learn from different orientations.

Width and Height Shifts

Shift images horizontally and vertically by 5% to mimic variations in tumor positioning.

Flips

No horizontal or vertical flips used, respecting the anatomical structure orientation in medical imaging.

Model training

Model trained over 20 epochs with a batch size of 64, showing steady decrease in loss and increase in accuracy.

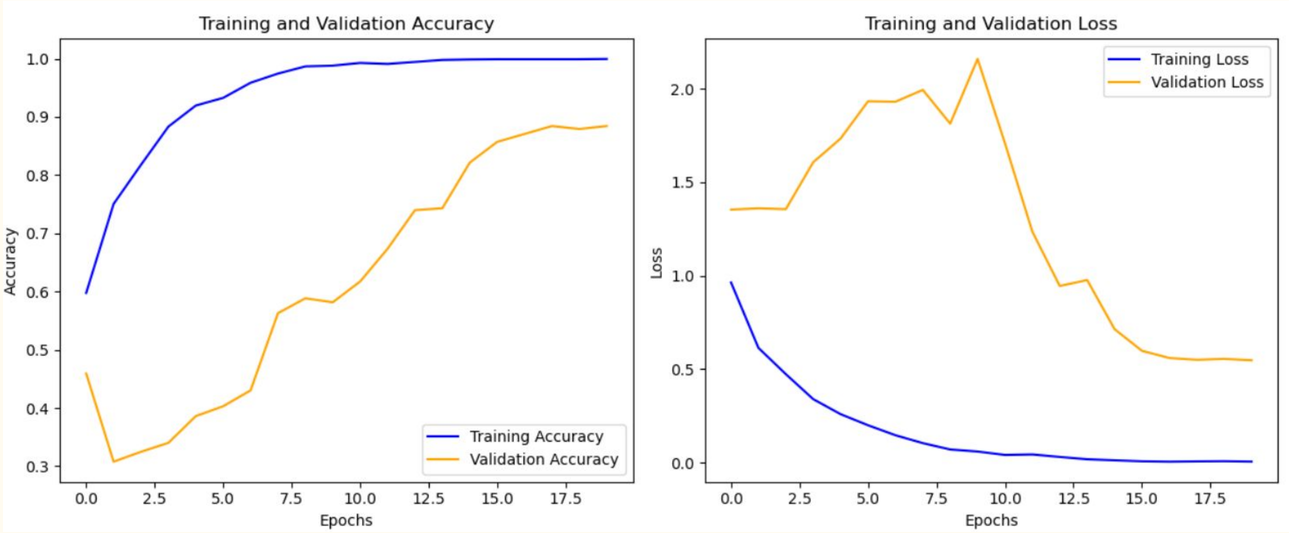
Kept aside a portion of data as a validation set to monitor and prevent overfitting.

Used Adam optimizer with categorical crossentropy as the loss function to fine-tune the model parameters.

```
Epoch 17/20
37/37 ━━━━━━━━━━━━━━━━━━━━ 1s 20ms/step - accuracy: 0.9976 - loss: 0.0074 - val_accuracy: 0.8707 - val_loss: 0.5601
Epoch 18/20
37/37 ━━━━━━━━━━━━━━━━━━━━ 1s 20ms/step - accuracy: 0.9995 - loss: 0.0068 - val_accuracy: 0.8844 - val_loss: 0.5506
Epoch 19/20
37/37 ━━━━━━━━━━━━━━━━━━━━ 1s 19ms/step - accuracy: 0.9989 - loss: 0.0086 - val_accuracy: 0.8793 - val_loss: 0.5556
Epoch 20/20
37/37 ━━━━━━━━━━━━━━━━━━━━ 1s 20ms/step - accuracy: 0.9996 - loss: 0.0057 - val_accuracy: 0.8844 - val_loss: 0.5481
```

Updated model results

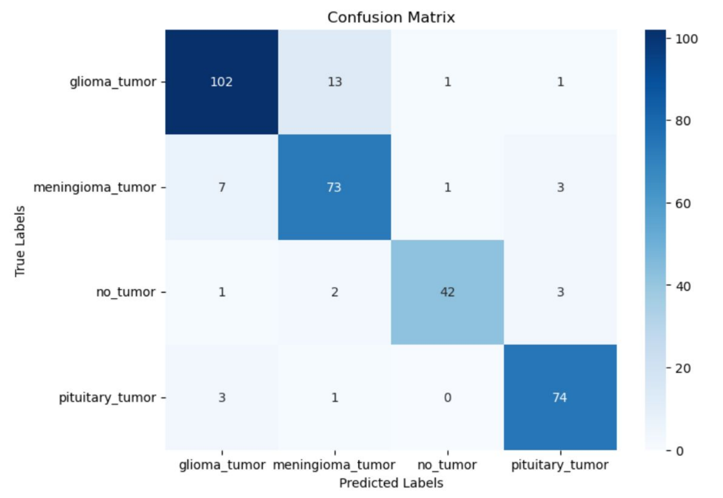
- **Training Accuracy:** Achieved a peak training accuracy of approximately 99%.
- **Validation Accuracy:** Consistently high across epochs, indicating good model generalization.
- **Loss Metrics:** Observed decreasing trend in training and validation loss, suggesting effective learning and convergence.



- **Test accuracy:**

```
11/11 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8844 - loss: 0.4601
Test Loss: 0.4206874668598175
Test Accuracy: 0.8899082541465759
11/11 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step
```

- **Confusion matrix:**

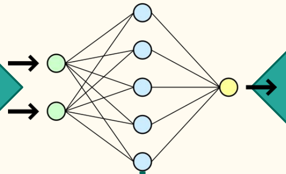


Classification report:

```
Classification Report:
                  precision    recall  f1-score   support

    glioma_tumor       0.90      0.87      0.89       117
meningioma_tumor       0.82      0.87      0.84        84
        no_tumor       0.95      0.88      0.91        48
 pituitary_tumor       0.91      0.95      0.93        78

        accuracy                           0.89       327
       macro avg       0.90      0.89      0.89       327
    weighted avg       0.89      0.89      0.89       327
```

Baseline Model		Improved Model
Utilizes ResNet50 with 50 layers and residual connections for deep network training.	**Model Architecture**	Employs a custom CNN with fewer layers, specifically optimized for brain tumor classification.
Limited to rotation, horizontal shifts, and flips.	**Data Augmentation**	Includes a broader range of augmentations such as rotation, shifts, and zoom to enhance training diversity.
Uses GlobalAveragePooling2D, which may lose some spatial information due to aggressive reduction of feature maps.	**Pooling Techniques**	Adopts AveragePooling2D, retaining more spatial information for better feature localization.
Despite its depth, shows lower accuracy, indicating potential overfitting or inefficiency for the specific task	**Performance and Suitability**	Achieves higher accuracy, demonstrating better suitability for the dataset characteristics.

Conclusion

Our project successfully demonstrated the capability of neural networks to aid in the precise classification of brain tumors from MRI scans. The improved model not only outperformed the baseline but also highlighted the importance of tailored design and data augmentation in achieving superior results for medical image classification tasks.

Significant Accuracy Boost: Successfully elevated the test accuracy from 77% to 89%, enhancing the reliability of brain tumour diagnosis.

Efficient Diagnosis: Implemented a robust neural network model that efficiently categorizes brain tumour locations from MRI data.

Future Potential: Through rigorous training and validation, our improved model demonstrated significant enhancement, achieving a test accuracy of 89%. This showcases that our model was trained effectively and indicates its potential for practical clinical applications.

Enhanced Patient Care: Contributed to more precise and timely brain tumour diagnosis, leading to improved treatment planning and patient outcomes.

Innovative Approach: Utilized advanced machine learning techniques to tackle complex medical imaging challenges, setting a precedent for future healthcare applications.

Conclusion

The improved model surpassed the baseline, emphasizing the importance of custom design and advanced data augmentation.

Significant Accuracy Boost
Increased test accuracy from 77% to 89% thereby enhanced the reliability and trust in brain tumor diagnosis.

Developed a robust neural network that accurately categorizes brain tumor locations and efficiently processed and classified from MRI data.

Achieved a consistent test accuracy of 89%, indicating strong potential for adoption in practical clinical settings.

More accurate and timely diagnosis, thereby contributing to better treatment strategies and patient outcomes.

Advanced machine learning methods for medical imaging that paved the way for future innovations in healthcare technology.

Thank You