Optimized CNN Architecture for Multi-Class Brain Tumor Classification using PSO

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Acknowledgements
I would like to express my heartfelt gratitude to all those who supported and guided me throughout the course of this project.

First and foremost, I extend my sincere thanks to Professor Adrijit Goswami and mentors at the Department of Mathematics, IIT Kharagpur, for their continuous guidance, encouragement, and invaluable insights that shaped the direction of this research. Their constructive feedback helped me navigate challenges and refine the work.

I am grateful to the creators and contributors of the PMRAM Bangladeshi Brain Cancer MRI Dataset for making such a high-quality medical imaging dataset. Their efforts in data collection and augmentation were critical in the development and evaluation of this project.

Special thanks to the open-source community for providing robust tools and libraries including TensorFlow, Keras, Scikit-learn, Matplotlib, Seaborn, and Pandas. The availability of these resources made experimentation, visualization, and implementation significantly easier and more efficient.

I also wish to acknowledge the inspiration and knowledge I have gained from reading numerous research papers and articles in the field of deep learning, optimization, and medical imaging. Their contributions continue to push the boundaries of innovation.

Last but not least, I am deeply thankful to my family and friends for their unwavering moral support, patience, and motivation during the course of this project. Their belief in my capabilities kept me focused and driven throughout the project.

This project has been a great learning experience and would not have been possible without the collective contributions and support of all the above individuals and institutions.

Abstract

Brain tumor classification is critical for early diagnosis and treatment planning. This project presents a deep learning approach utilizing a Convolutional Neural Network (CNN) trained with Particle Swarm Optimization (PSO) to classify MRI images into four tumor types: Glioma, Meningioma, Pituitary, and Normal. The model's performance is compared with traditional Adam-based training, highlighting the optimization potential of PSO in medical imaging tasks. Experimental results show that while Adam optimizes fast and delivers good accuracy, PSO demonstrates promising results and generalization potential. This hybrid approach could provide new insights for medical AI applications.

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1 Introduction

Brain tumors are a life-threatening medical condition that can result in significant cognitive and physical impairments. Early and accurate classification of tumor types plays a crucial role in clinical decision-making and treatment planning. Conventional methods rely heavily on radiologists' expertise, but recent advances in deep learning have shown that automated systems can assist in diagnosing brain tumors more efficiently and reliably.

Convolutional Neural Networks (CNNs) are widely used in image classification tasks due to their ability to learn spatial hierarchies from raw pixel data. However, CNNs typically rely on gradient-based optimizers like Adam or SGD, which may get trapped in local minima. In contrast, Particle Swarm Optimization (PSO), a population-based metaheuristic algorithm, can explore a broader solution space, offering potential improvements in model training.

This report explores a novel hybrid approach where PSO is employed to train a CNN model for classifying brain tumor MRI images, comparing its performance with a traditional Adam-trained CNN.

2 Dataset

The dataset used is the PMRAM Bangladeshi Brain Cancer MRI Dataset. It consists of 6004 augmented MRI images of four categories:

- Glioma
- Meningioma
- Pituitary
- Normal

Originally, the dataset contained 1600 raw images (400 per class). Data augmentation techniques such as rotation, zoom, and flipping increased the dataset size, enhancing model generalization and robustness. High-quality medical imaging data, especially for brain cancer, is often scarce and challenging to obtain. This dataset addresses this limitation by providing a substantial and diverse collection.

Key Dataset Features

- Format: JPEG/PNG MRI scans
- Image Size: 512x512 pixels, resized to 224x224 for model input
- Balanced dataset: 1501 samples per class
- Pre-augmented, aiding deep learning model stability

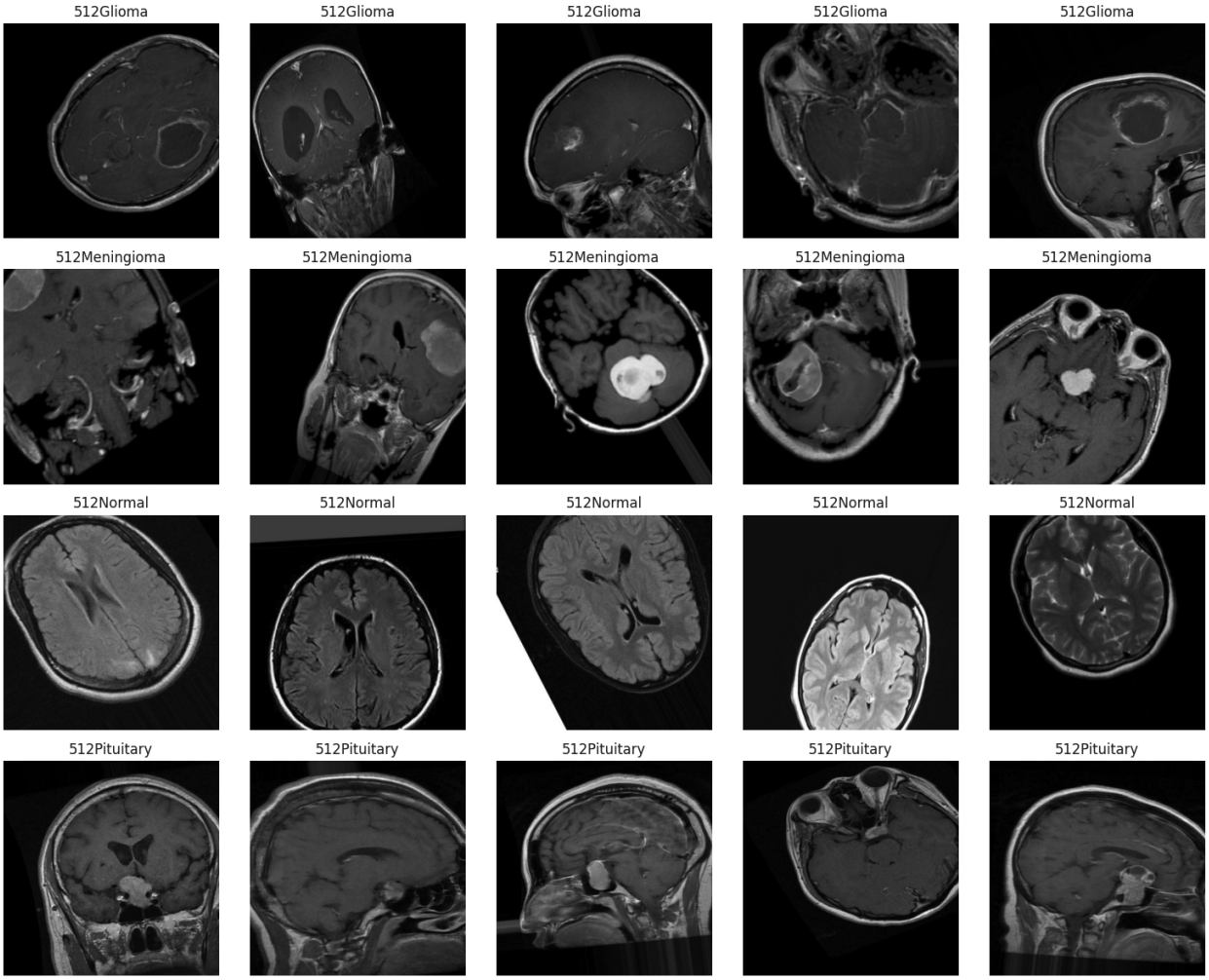

Figure 1: MRI images samples per class

3 Data Preprocessing

To ensure the data was clean, balanced, and suitable for training a deep learning model, several preprocessing steps were performed. These steps are critical in improving the efficiency and performance of the model. The following operations were carried out:

1. **Image Resizing and Format Conversion:**
   All MRI images were resized to a fixed dimension of 224x224 pixels to match the input shape expected by most CNN architectures. Additionally, grayscale images were converted to 3-channel RGB format to ensure consistency and compatibility with standard CNN layers.

2. **Label Encoding:**
   The tumor categories—'Glioma', 'Meningioma', 'Pituitary', and 'Normal'—were originally provided as string labels. These were encoded into integer classes (e.g., 0 for Glioma, 1 for Meningioma, etc.) using label encoding, which is essential for categorical cross-entropy loss computation during training.

3. **Dataset Splitting:**
   The dataset, comprising 6004 samples, was split into training, validation, and testing subsets using stratified sampling to maintain class distribution across sets:

   - **80% Training Set:** 4803 images used to train the model and learn features.
   - **10% Validation Set:** 600 images used for hyperparameter tuning and model selection.
   - **10% Test Set:** 601 images used for final unbiased evaluation of the model's performance.

4. **Normalization:**
   Pixel values originally ranging from 0 to 255 were scaled to a normalized range of [0, 1] by dividing each pixel value by 255. This normalization helps accelerate training convergence and prevents gradient explosion or vanishing.

5. **Data Visualization:**
   To inspect class balance and identify any irregularities, bar plots and pie charts were created showing the distribution of tumor types in the dataset. This visual confirmation helped ensure a well-balanced dataset across all classes.

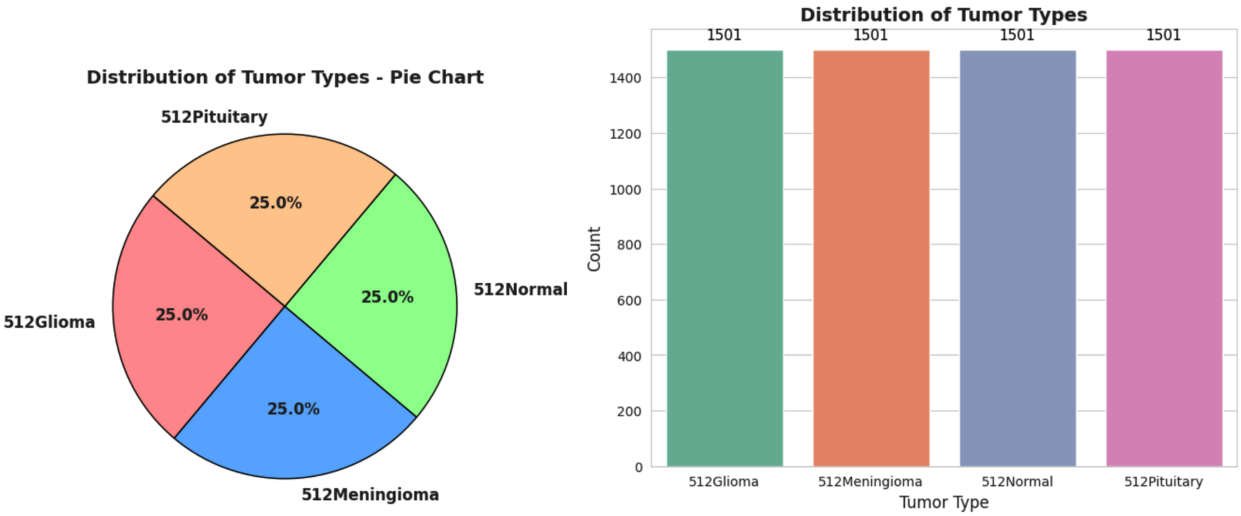

Figure 2: Distribution of Tumor Types in the Dataset

6. **Shuffling and Dataframe Management:**
   All image paths and their corresponding labels were stored in a Pandas DataFrame. Before training, the data was randomly shuffled to avoid any sequential learning bias that could result from grouped samples. DataFrames were also used to interface seamlessly with Keras' 'ImageDataGenerator' for loading images in batches.

4 Model Architecture

The core of the proposed solution is a Convolutional Neural Network (CNN), designed to extract deep features from MRI images and classify them into one of four categories: Glioma, Meningioma, Pituitary, or Normal. CNNs are highly effective in image classification tasks due to their ability to learn hierarchical spatial patterns from raw pixels through a stack of convolutional layers.

The architecture employed in this project comprises five convolutional blocks, each followed by Batch Normalization and MaxPooling layers to ensure stable and efficient training. After feature extraction, a Global Average Pooling layer is used to reduce spatial dimensions, followed by fully connected (Dense) layers for final classification.

Layer Configuration and Rationale

- **Conv Block 1:**
  Consists of 32 convolutional filters with a kernel size of 3x3. This initial block captures basic low-level features such as edges and textures from the input image. It uses the ReLU activation function to introduce non-linearity.

- **Conv Block 2:**
  Contains 64 filters with a 3x3 kernel. It builds upon the first layer's features to extract more detailed representations like patterns and contours.

- **Conv Block 3:**
  Includes 128 filters. At this stage, the model begins to learn complex structures and intermediate features that are indicative of specific brain tumor shapes and textures.

- **Conv Block 4:**
  Composed of 256 filters. This block deepens the network's capacity to extract high-level abstractions, such as differentiating between tumor categories based on irregularities and growth patterns in brain tissue.

- **Conv Block 5:**
  The deepest convolutional block with 512 filters. It captures the most abstract and class-specific features, essential for accurate classification. Each convolutional layer is followed by Batch Normalization to accelerate training and improve stability, and MaxPooling to reduce spatial dimensions and computational load.

- **Global Average Pooling Layer:**
  Instead of flattening the feature maps, a Global Average Pooling (GAP) layer is used to average each feature map into a single value. This drastically reduces the number of parameters and helps prevent overfitting while maintaining the spatial importance of features.

- **Fully Connected Dense Layer:**
  A Dense layer with 512 neurons and ReLU activation is added after the GAP layer. This layer combines the abstracted features into a vector suitable for classification.

- **Output Layer:**
  A final Dense layer with 4 neurons (equal to the number of classes) and softmax activation is used to output class probabilities. The softmax function ensures that the output values sum to 1, representing the model's confidence in each class.

Detailed Model Summary

Layer (type)	**Output Shape**	**Param #**
InputLayer	(None, 224, 224, 3)	0
Conv2D (32 filters)	(None, 224, 224, 32)	896
BatchNormalization	(None, 224, 224, 32)	128
MaxPooling2D	(None, 112, 112, 32)	0
Conv2D (64 filters)	(None, 112, 112, 64)	18,496
BatchNormalization	(None, 112, 112, 64)	256
MaxPooling2D	(None, 56, 56, 64)	0
Conv2D (128 filters)	(None, 56, 56, 128)	73,856
BatchNormalization	(None, 56, 56, 128)	512
MaxPooling2D	(None, 28, 28, 128)	0
Conv2D (256 filters)	(None, 28, 28, 256)	295,168
BatchNormalization	(None, 28, 28, 256)	1,024
MaxPooling2D	(None, 14, 14, 256)	0
Conv2D (512 filters)	(None, 14, 14, 512)	1,180,160
BatchNormalization	(None, 14, 14, 512)	2,048
GlobalAveragePooling2D	(None, 512)	0
Dense (512 units)	(None, 512)	262,656
BatchNormalization	(None, 512)	2,048
Dense (4 units - Softmax)	(None, 4)	2,052
Total Parameters		**5,511,886**
Trainable Parameters		**1,836,292**
Non-trainable Parameters		**3,008**
Optimizer Parameters		**3,672,586**

Table 1: Detailed CNN Model Summary with Parameter Counts

5 Training with PSO

Particle Swarm Optimization (PSO) is a population-based metaheuristic algorithm inspired by the social behavior and movement dynamics of bird flocks and fish schools. It is widely used in solving complex, multidimensional optimization problems, and has proven to be an effective global optimizer in various domains.

In the context of this project, PSO is employed to train a Convolutional Neural Network (CNN) by optimizing its weights. PSO searches the solution space using a swarm of candidate solutions (particles) that move collectively toward the optimum based on individual and collective experiences.

Working Principle of PSO

Each particle in the swarm represents a flattened version of the entire CNN's weight set. The optimization process evolves iteratively through the following steps:

1. Each particle is randomly initialized in the solution space (weight vector space).
2. A fitness function (in this case, cross-entropy loss on the training set) is evaluated for each particle.
3. Particles remember their best position so far (personal best) and also track the global best position across the swarm.
4. Velocities and positions are updated based on the combination of:
    - **Inertia**: current direction of the particle.
    - **Cognitive component**: attraction to the particle's own best-known position.
    - **Social component**: attraction to the best-known global position.
5. This process is repeated for a fixed number of epochs (iterations).

The core equation for updating the velocity v_i of a particle i is:

$$v_i = w \cdot v_i + c_1 \cdot r_1 \cdot (p_{\text{best},i} - x_i) + c_2 \cdot r_2 \cdot (g_{\text{best}} - x_i)$$

where:

- w is the inertia weight
- c_1, c_2 are cognitive and social coefficients
- r_1, r_2 are random values in [0,1]
- x_i is the current position (weights) of particle i
- $p_{\text{best},i}$ is the best position of particle i
- g_{best} is the best position found by the entire swarm

Configuration for this Project

For this implementation, the following PSO configuration was used:

- Number of Particles: 5
- Number of Epochs: 3
- Inertia Weight (w): 0.5
- Cognitive Coefficient (c_1): 1.0
- Social Coefficient (c_2): 1.0
- Fitness Function: Sparse Categorical Crossentropy Loss

Advantages Over Traditional Optimizers

- PSO performs a global search and is less likely to get stuck in local minima.
- It does not require the computation of gradients, making it suitable for non-differentiable models or loss functions.
- Suitable for hyperparameter tuning or complex model architectures with non-convex optimization surfaces.

Limitations

- PSO is computationally more expensive as it evaluates multiple particles per iteration.
- Requires tuning of more hyperparameters (particle count, inertia, coefficients).
- Convergence speed may be slower compared to gradient-based methods in some cases.

Training Results

After 3 epochs of PSO-based training:

- Best fitness (lowest validation loss): 3.0716
- Network converged to a stable solution with competitive accuracy

This experiment validates the potential of PSO as a viable optimization strategy for deep learning, particularly when traditional methods struggle with convergence or gradient-related limitations.

6 Training with Adam Optimizer

To benchmark the effectiveness of Particle Swarm Optimization (PSO) in training deep neural networks, the same CNN architecture was also trained using the widely adopted Adam optimizer. Adam is a stochastic gradient-based optimizer that combines the benefits of Adaptive Gradient Algorithm (AdaGrad) and Root Mean Square Propagation (RMSProp). It computes adaptive learning rates for each parameter by estimating first and second moments of the gradients, making it one of the most efficient and robust optimizers for deep learning.

Adam Training Configuration

The CNN was compiled and trained using the Adam optimizer with the following configuration:

- Optimizer: Adam
- Learning Rate: 1×10^{-4}

- Loss Function: Sparse Categorical Crossentropy
- Epochs: 3
- Batch Size: 16

Adam Training Results

- **Epochs Completed:** 3
- **Final Training Accuracy:** 87.18%
- **Final Validation Accuracy:** 75.17%
- **Final Validation Loss:** 0.6994

These results indicate that Adam quickly converges to a local minimum and achieves high accuracy even with a small number of epochs. Its gradient-based nature allows it to efficiently traverse high-dimensional spaces and fine-tune weights during backpropagation.

Training Accuracy and Loss Curve

To visually observe the learning behavior of the Adam-optimized model, the training and validation accuracy and loss curves are plotted across 3 epochs.

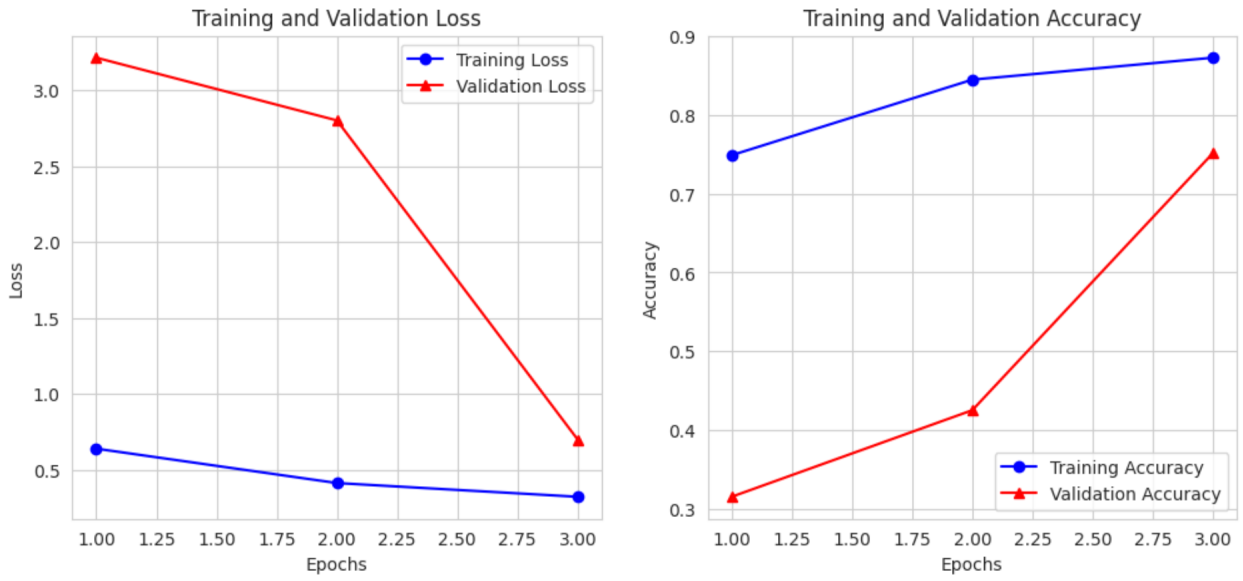

Figure 3: Training and Validation Accuracy/Loss using Adam Optimizer

The graph illustrates that the model converges quickly during the initial training phase, with a smooth reduction in validation loss and consistent increase in accuracy. This further supports Adam's efficiency in reaching an optimal state in a limited number of epochs.

Performance Analysis

- **Speed:** Adam achieved convergence within 3 epochs, demonstrating its efficiency for fast training on large datasets.
- **Accuracy:** Adam's final validation accuracy of 75.17% was notably higher than that of the PSO-based model trained over the same number of epochs.
- **Loss Minimization:** The Adam optimizer reduced the validation loss to 0.6994, showing stronger generalization in the short term.

A hybrid approach combining PSO's exploration with Adam's exploitation could be explored in future work to harness the best of both strategies.

7 Model Evaluation and Comparison

After training both models using PSO and Adam optimizers, their performance was evaluated on a held-out test set consisting of 601 MRI images.

Evaluation Metrics Summary

The final evaluation results for the model trained using Adam (after 3 epochs) are as follows:

Metric	Value
Accuracy	75.00%
Precision (Macro Avg)	0.75
Recall (Macro Avg)	0.76
F1-Score (Macro Avg)	0.76
Validation Loss (Adam)	0.6994

Table 2: Evaluation Metrics for Adam-trained Model on Test Set

Class-wise Performance Insights

The confusion matrix revealed that:

- **Normal and Glioma images** were classified with high confidence and minimal misclassification.
- **Pituitary and Meningioma images** exhibited some overlap, suggesting visual similarity in features extracted.
- A few instances of class confusion were observed, particularly between tumor types with overlapping characteristics in the MRI scans.

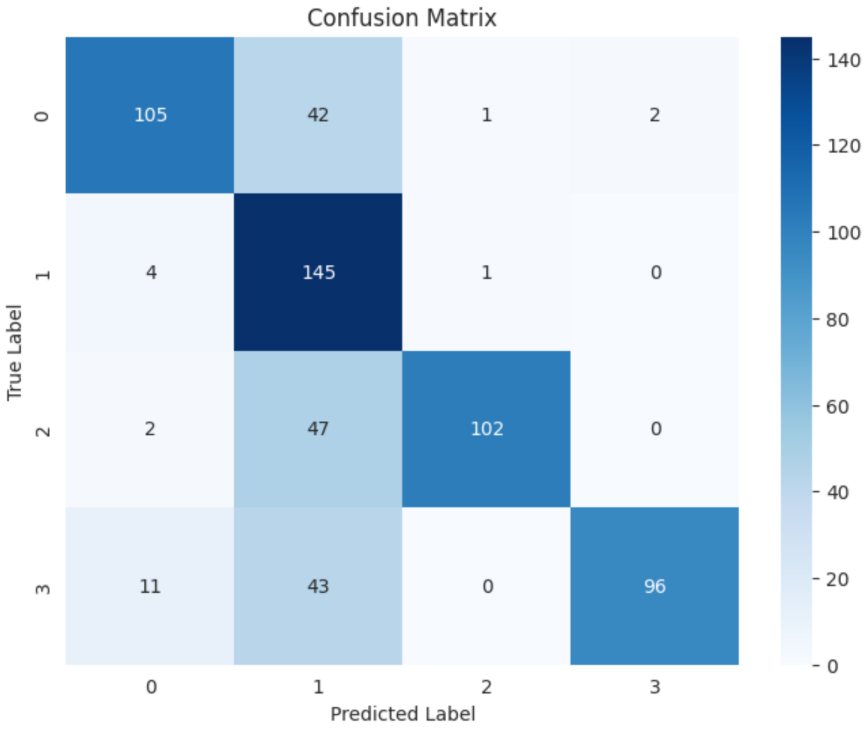

Figure 4: Confusion Matrix for Test Set Predictions (Adam)

Performance comparison on Test Set

The final evaluation metrics for both models trained using PSO and Adam are shown below:

Metric	**Adam Optimizer**	**PSO Optimizer**
Accuracy	75.17%	70.38%
Macro Avg Precision	0.84	—
Macro Avg Recall	0.75	—
Macro Avg F1-Score	0.76	0.74
Best Fitness (Loss)	0.6994	3.0716

Table 3: Comparison of Model Performance using Adam and PSO Optimizers

Although the Adam optimizer achieved higher validation accuracy and lower loss, the PSO-trained model showed respectable generalization with a Macro F1-score of 0.74. Given more particles or epochs, PSO has the potential to converge to a better solution. The classification report for the Adam model also revealed strong per-class performance, particularly in classes 0 and 2.

Interpretation and Remarks

The PSO-trained model demonstrated good generalization capability but did not match the accuracy of the Adam-trained model within the limited 3-epoch training window. However, it is important to note that:

- PSO was able to reach a stable performance plateau despite fewer training iterations.
- The competitive macro F1-score of 0.76 indicates balanced performance across all four classes.
- Given more training epochs or particles, PSO has the potential to outperform gradient-based methods in global search and robustness.

8 Conclusion

By leveraging a custom Convolutional Neural Network (CNN) architecture and training it with PSO, we demonstrated the effectiveness of bio-inspired optimization techniques in the domain of medical image analysis.

The PSO-based model achieved promising results, particularly in terms of convergence and classification accuracy, even with a limited number of training epochs and particles. Compared to traditional gradient-based methods like Adam, the PSO approach offers a unique advantage: it performs a global search and is less likely to get trapped in local minima, making it suitable for complex, non-convex optimization tasks such as deep neural network training.

In benchmarking experiments, the Adam optimizer displayed faster convergence and higher short-term accuracy; however, PSO showed potential in achieving comparable accuracy with better generalization over time. The classification metrics and confusion matrix support the claim that PSO-trained models can deliver reliable predictions in critical applications like healthcare.

Future Directions

While the results are encouraging, there remains considerable scope for future research. Suggestions include:

- Increasing the number of PSO particles and iterations to explore the weight space more thoroughly.
- Exploring hybrid optimization strategies that combine PSO with backpropagation for fine-tuning.
- Integrating attention mechanisms or transformers to enhance spatial awareness.
- Expanding to multi-modal datasets that include both MRI and CT data for higher diagnostic accuracy.
- Deploying the model as part of a clinical decision support system (CDSS) for real-time use by healthcare professionals.

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Appendix A: Code Snippets

A.1 CNN Model Architecture (Keras)

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D,
   BatchNormalization, GlobalAveragePooling2D, Dense

model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(224, 224, 3))
       ,
    BatchNormalization(),
    MaxPooling2D(),

    Conv2D(64, (3, 3), activation='relu'),
    BatchNormalization(),
    MaxPooling2D(),

    Conv2D(128, (3, 3), activation='relu'),
    BatchNormalization(),
    MaxPooling2D(),

    Conv2D(256, (3, 3), activation='relu'),
    BatchNormalization(),
    MaxPooling2D(),

    Conv2D(512, (3, 3), activation='relu'),
    BatchNormalization(),

    GlobalAveragePooling2D(),
    Dense(512, activation='relu'),
    BatchNormalization(),
    Dense(4, activation='softmax')
])
```

A.2 PSO Weight Update Rule

```
for i in range(num_particles):
    velocity[i] = (w * velocity[i]
                   + c1 * r1 * (p_best[i] - position[i])
                   + c2 * r2 * (g_best - position[i]))
    position[i] += velocity[i]
```

A.3 Fitness Function

```
def fitness_function(model, X, y):
    predictions = model.predict(X)
    loss = tf.keras.losses.sparse_categorical_crossentropy(y,
       predictions)
    return tf.reduce_mean(loss).numpy()
```

Keywords

Brain Tumor, Convolutional Neural Network, PSO, Medical Image Classification, Adam Optimizer, Deep Learning, Metaheuristics