Model Optimization and Tuning Phase Template

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Team ID	739902
Project Title	Alzheimer Disease Prediction
Maximum Marks	10 Marks

Model Optimization and Tuning Phase

The Model Optimization and Tuning Phase involves refining neural network models for peak performance. It includes optimized model code, fine-tuning hyperparameters, comparing performance metrics, and justifying the final model selection for enhanced predictive accuracy and efficiency.

Hyperparameter Tuning Documentation (8 Marks):

Model	Tuned Hyperparameters
Xception model	To optimize the performance of the Xception model, hyperparameters such as learning rate, batch size, and the number of epochs must be tuned carefully. The learning rate determines how quickly the model adjusts weights during training, while the batch size affects the stability of gradient estimates.The number of epochs specifies how many times the entire dataset will pass through the network during training. A higher number of epochs may lead to overfitting if the model starts to memorize the training data rather than generalizing well to unseen data. Hence, it's important to tune it to find an optimal value that results in good generalization. It ensures the model converges efficiently and avoids overfitting or underfitting.

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[ ]: ###Configure the Learning Process

[29]: custom_inception_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

[ ]: ###Train the model

[31]: history = custom_inception_model.fit(train_data, train_labels, validation_data=(val_data, val_labels), epochs=30)

Epoch 1/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 201s 1s/step - accuracy: 0.3037 - loss: 1.7156 - val_accuracy: 0.5682 - val_loss: 1.1073
Epoch 2/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 203s 2s/step - accuracy: 0.4725 - loss: 1.2089 - val_accuracy: 0.6435 - val_loss: 0.8306
Epoch 3/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 218s 2s/step - accuracy: 0.5581 - loss: 0.9786 - val_accuracy: 0.6520 - val_loss: 0.7255
Epoch 4/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 224s 2s/step - accuracy: 0.6274 - loss: 0.8366 - val_accuracy: 0.6787 - val_loss: 0.6818
Epoch 5/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 195s 1s/step - accuracy: 0.6401 - loss: 0.7899 - val_accuracy: 0.6835 - val_loss: 0.6505
Epoch 6/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 218s 2s/step - accuracy: 0.6715 - loss: 0.7307 - val_accuracy: 0.6921 - val_loss: 0.6275
Epoch 7/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 224s 2s/step - accuracy: 0.6784 - loss: 0.7119 - val_accuracy: 0.7083 - val_loss: 0.6237
Epoch 8/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 187s 1s/step - accuracy: 0.6856 - loss: 0.6975 - val_accuracy: 0.7150 - val_loss: 0.5954
Epoch 9/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 220s 2s/step - accuracy: 0.6981 - loss: 0.6644 - val_accuracy: 0.7245 - val_loss: 0.5875
Epoch 10/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 177s 1s/step - accuracy: 0.7145 - loss: 0.6496 - val_accuracy: 0.7264 - val_loss: 0.5770
Epoch 11/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 283s 2s/step - accuracy: 0.7255 - loss: 0.6235 - val_accuracy: 0.7512 - val_loss: 0.5515
Epoch 12/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 218s 2s/step - accuracy: 0.7395 - loss: 0.6131 - val_accuracy: 0.7388 - val_loss: 0.5598
Epoch 13/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 242s 2s/step - accuracy: 0.7480 - loss: 0.5948 - val_accuracy: 0.7579 - val_loss: 0.5637
Epoch 14/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 320s 2s/step - accuracy: 0.7571 - loss: 0.5644 - val_accuracy: 0.7474 - val_loss: 0.5377
Epoch 15/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 319s 2s/step - accuracy: 0.7847 - loss: 0.5487 - val_accuracy: 0.7588 - val_loss: 0.5322
Epoch 16/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 216s 2s/step - accuracy: 0.7637 - loss: 0.5567 - val_accuracy: 0.7722 - val_loss: 0.5249

Epoch 17/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 205s 2s/step - accuracy: 0.7970 - loss: 0.5059 - val_accuracy: 0.7760 - val_loss: 0.5181
Epoch 18/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 215s 2s/step - accuracy: 0.8021 - loss: 0.4882 - val_accuracy: 0.7817 - val_loss: 0.5271
Epoch 19/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 199s 2s/step - accuracy: 0.8069 - loss: 0.4862 - val_accuracy: 0.7874 - val_loss: 0.5103
Epoch 20/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 196s 1s/step - accuracy: 0.8205 - loss: 0.4619 - val_accuracy: 0.7941 - val_loss: 0.5028
Epoch 21/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 210s 2s/step - accuracy: 0.8034 - loss: 0.4848 - val_accuracy: 0.7960 - val_loss: 0.5196
Epoch 22/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 211s 2s/step - accuracy: 0.8226 - loss: 0.4550 - val_accuracy: 0.7969 - val_loss: 0.4727
Epoch 23/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 276s 2s/step - accuracy: 0.8372 - loss: 0.4069 - val_accuracy: 0.8084 - val_loss: 0.4595
Epoch 24/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 302s 2s/step - accuracy: 0.8449 - loss: 0.3985 - val_accuracy: 0.8093 - val_loss: 0.4812
Epoch 25/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 226s 2s/step - accuracy: 0.8501 - loss: 0.4005 - val_accuracy: 0.7941 - val_loss: 0.4838
Epoch 26/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 253s 2s/step - accuracy: 0.8621 - loss: 0.3795 - val_accuracy: 0.8112 - val_loss: 0.4992
Epoch 27/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 231s 2s/step - accuracy: 0.8557 - loss: 0.3902 - val_accuracy: 0.8074 - val_loss: 0.4792
Epoch 28/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 224s 2s/step - accuracy: 0.8739 - loss: 0.3416 - val_accuracy: 0.8141 - val_loss: 0.4822
Epoch 29/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 238s 2s/step - accuracy: 0.8709 - loss: 0.3506 - val_accuracy: 0.8132 - val_loss: 0.4807
Epoch 30/30
132/132 ━━━━━━━━━━━━━━━━━━━━ 227s 2s/step - accuracy: 0.8684 - loss: 0.3752 - val_accuracy: 0.8208 - val_loss: 0.4703
```

Final Model Selection Justification (2 Marks):

Final Model	Reasoning
Xception model	The Xception model is often chosen for Alzheimer's disease prediction due to its superior feature extraction capabilities, particularly in

	handling complex patterns in medical imaging. Its architecture, based on depthwise separable convolutions, enables efficient learning of spatial and channel-wise features, which is crucial for identifying subtle changes in brain scans. Xception is computationally efficient, reducing the risk of overfitting while delivering high accuracy. It has shown strong results in Alzheimer's studies, outperforming other models like ResNet and VGG in tasks requiring detailed pattern recognition. Its compatibility with transfer learning and scalability further solidify its role as an ideal choice for predicting Alzheimer's disease.