Model Optimization and Tuning Phase Template

Date	11 November 2024
Team ID	SWTID1727274979
Project Title	Deep Learning Techniques for breast cancer risk 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
Model 1 : (CNN)	**1) Batch Size :** 32 Batch size plays a crucial role in the training process of a CNN model, influencing its convergence speed, stability, and generalization performance. **Here's a breakdown of its impact on breast cancer risk prediction :** **a) Gradient Estimation :** • Determines the number of samples processed before updating model weights. • Larger batch sizes can accelerate training but may require more memory. **b) Generalization Performance :** Smaller Batch Sizes : Can improve generalization by exposing the model to more diverse training data. Can lead to better performance on unseen data. **c) Computational Efficiency:** Larger Batch Sizes :

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- Can leverage hardware acceleration (GPUs) more efficiently.
- Faster training due to parallel processing.

Smaller Batch Sizes :

- Can be more memory-efficient, especially on smaller hardware.

```
data_dir = '12932'
batch_size = 32
img_size = (128, 128)
```

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2) Epochs : 20

In the context of training a CNN for breast cancer risk prediction, the number of epochs represents the number of complete passes through the entire training dataset . Each epoch involves the model learning from the training data and adjusting its parameters to minimize the loss function.

- Number of complete passes through the training dataset .
- More epochs can potentially lead to better performance .

```
Epoch 1/20
/usr/local/lib/python3.10/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:122: UserWarning: Your `PyDat
  self._warn_if_super_not_called()
19/19 ━━━━━━━━━━━━━━━━━━━━ 12s 240ms/step - accuracy: 0.5123 - loss: 0.9328 - val_accuracy: 0.5890 - val_loss: 0.6076
Epoch 2/20
19/19 ━━━━━━━━━━━━━━━━━━━━ 1s 26ms/step - accuracy: 0.6427 - loss: 0.5853 - val_accuracy: 0.8356 - val_loss: 0.4441
Epoch 3/20
19/19 ━━━━━━━━━━━━━━━━━━━━ 1s 27ms/step - accuracy: 0.7605 - loss: 0.5271 - val_accuracy: 0.8082 - val_loss: 0.4205
Epoch 4/20
19/19 ━━━━━━━━━━━━━━━━━━━━ 1s 41ms/step - accuracy: 0.7547 - loss: 0.5116 - val_accuracy: 0.8219 - val_loss: 0.4304
Epoch 5/20
19/19 ━━━━━━━━━━━━━━━━━━━━ 1s 35ms/step - accuracy: 0.8249 - loss: 0.4348 - val_accuracy: 0.8219 - val_loss: 0.4447
Epoch 6/20
19/19 ━━━━━━━━━━━━━━━━━━━━ 1s 35ms/step - accuracy: 0.8288 - loss: 0.4264 - val_accuracy: 0.8288 - val_loss: 0.4352
```

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3) Optimizer : Adam **(Adaptive Moment Estimation optimizer)**

An optimizer is a crucial component in training a CNN for breast cancer risk prediction. It's responsible for updating the model's weights and biases during the training process to minimize the loss function.

- Popular choice for its combination of momentum and adaptive learning rates .

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	`` #Compilimg The Model model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy']) ```

Final Model Selection Justification (2 Marks) :

Selected Model : - Convolutional Neural Networks (CNN) approach of Deep Learning

Final Model	Reasoning
Convolutional Neural Networks (CNNs)	**CNN models** have emerged as a popular choice for breast cancer risk prediction due to their ability to automatically learn complex patterns from large image datasets. Here's a breakdown of why CNNs are well-suited for this task : **1) Handling High-Dimensional Data :** **Efficient Processing :** CNNs are designed to handle large image datasets with high dimensionality. They can efficiently process and analyze the vast amount of information contained in medical images . **2) Potential for Early Detection :** **Identifying Subtle Patterns :** CNNs can learn to identify subtle patterns in medical images that may be difficult for human radiologists to detect. This could lead to earlier detection of breast cancer, which is crucial for improving patient outcomes .

	Assisting Clinical Decision-Making : CNN-based models can provide valuable insights to clinicians, helping them make more informed decisions about patient care . **3) State-of-the-Art Performance :** **High Accuracy :** CNNs have consistently demonstrated state-of-the-art performance in various image classification tasks, including medical image analysis. They often outperform traditional machine learning models in terms of accuracy and sensitivity . **Continuous Improvement :** The field of deep learning is rapidly evolving, with new architectures and techniques being developed regularly. This means that CNN models for breast cancer risk prediction can benefit from ongoing research and improvements .

Conclusion :

- CNNs offer a powerful and flexible approach to breast cancer risk prediction. Their ability to automatically learn features, handle high-dimensional data , and achieve high accuracy makes them a compelling choice for this challenging task .

- As the technology continues to evolve, CNN-based systems have the potential to revolutionize breast cancer screening and early detection, ultimately improving patient outcomes .