Training Results

Epochs: 10

Final Training Accuracy: 87.66%

Final Training Loss: 0.3240

Final Validation Accuracy: 83.50%

Final Validation Loss: 0.3873

Model Architecture:

The model consists of a lambda layer followed by a dense layer.

Total Parameters: 6,014

Trainable Parameters: 2,004

Non-trainable Parameters: 0

Optimizer Parameters: 4,010

Test Results:

Test Loss: 1.0953

Test Accuracy: 59.25%

These results provide insights into the performance of your model. It achieved relatively high accuracy during training and validation, but the accuracy on the test set is slightly lower, indicating a possible overfitting issue. You may want to consider further optimization or regularization techniques to improve generalization.

Assumptions:

Image Size: Resizing images to a standard size (96x96 pixels) assumes that important features related to malaria infection can be captured at this resolution.

Binary Classification: The problem is treated as a binary classification task, if distinguishing between parasitized and uninfected cells is sufficient for malaria risk detection.

Transfer Learning: Using a pre-trained MobileNet V2 model from TensorFlow Hub assumes that the features learned by the MobileNet architecture on a large dataset (ImageNet) are transferable and useful for the malaria detection task.

Choice of Methods:

Data Preparation:

- Resizing Images: Resizing images to a standard size ensures uniformity and reduces computational complexity.
- Labelling: Assigning labels (0 for uninfected, 1 for parasitized) allows for supervised learning.

Model Building:

- Transfer Learning: Leveraging a pre-trained MobileNet V2 model as a feature extractor saves time and computational resources while benefiting from the learned features.
- Dense Layer: Adding a dense layer on top of the MobileNet features enables fine-tuning for the specific classification task.

Model Training:

- Adam Optimizer: Using the Adam optimizer for gradient descent due to its adaptive learning rate properties and efficiency in convergence.
- Sparse Categorical Crossentropy Loss: Appropriate for multi-class classification tasks where the output labels are integers.

Evaluation:

- Training Metrics: Monitoring training and validation accuracy and loss to assess model performance and detect overfitting.
- Test Accuracy: Assessing the model's performance on unseen data to evaluate generalization capability.

Rationalization:

- Transfer Learning: MobileNet V2 is chosen for its balance between performance and efficiency, making it suitable for deployment on resource-constrained environments.
- Binary Classification: Simplifies the problem and focuses on the primary objective of detecting malaria risk, which is whether a cell is infected or not.
- Evaluation Metrics: Accuracy and loss are commonly used metrics for classification tasks and provide insights into the model's performance.
- These assumptions and choices are based on common practices in machine learning, domain knowledge, and considerations for efficiency and effectiveness in solving the malaria risk detection problem. Adjustments and optimizations can be made based on further analysis and experimentation results.