Analyzing and evaluating a convolutional neural network model for image classification

Name: Divya Muraleedharan

Student ID: 22030331

Introduction

This report provides a thorough examination and critical evaluation of the image classification model created for the Animals dataset. The model's primary goal is to accurately categorise photographs into three classes: 'cat,' 'dog,' and 'wild.' The evaluation uses the convolutional neural network (CNN) architecture to determine the model's strengths, limitations, and overall efficacy.

Model Architecture

The model architecture includes Convolutional and Dense layers for excellent feature extraction and classification. Global Average Pooling aids in feature consolidation, resulting in a compact yet powerful model. The model excels in sophisticated pattern recognition, with 359,555 parameters, ensuring accurate multiclass categorization for the 'cat,' 'dog,' and 'wild' categories.

Data Preprocessing

The provided dataset, separated into training and validation sets, contains images labelled as 'cat,' 'dog,' or 'wild.' The parse_image method retrieves labels, whereas img_process converts images to tf.float32 format, resizes them to (64, 64), and applies normalisation. Dataset loading includes best practices such as caching, shuffling, batching, and prefetching to improve efficiency.

Model Training

The model is trained using the Adam optimizer, with a learning rate of 5e-5 and a sparse categorical crossentropy loss function. The training is performed for 100 epochs, and ModelCheckpoint and LearningRateScheduler callbacks are implemented.

Results and Evaluation

The model was trained for 100 epochs, and the performance indicators were constantly evaluated. The loss curve depicts the model's convergence throughout the training process. The first plot depicts the training and validation loss across 100 epochs (Fig 1), while the second plot (Fig 2) shows the training and validation accuracy throughout the training procedure.

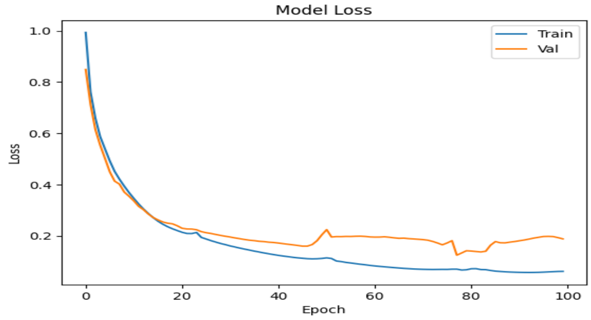


Figure 1

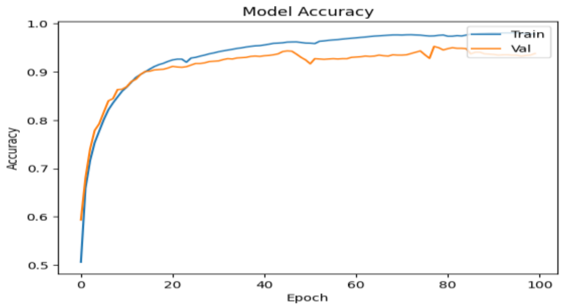


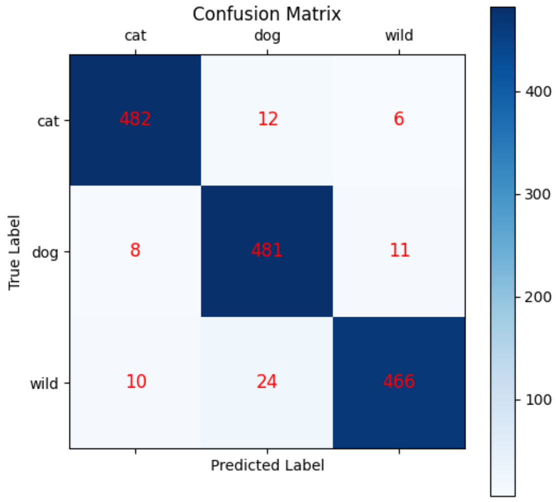
Figure 2

The loss graph indicates a consistent drop in training and validation loss over the epochs, indicating that the model is effectively learning from the training data without overfitting. The increasing trend in accuracy for both the training and validation sets demonstrates that the model is learning to generalise effectively to previously unseen data. The validation accuracy stabilises, indicating that the model has reached an acceptable level of performance.

Confusion Matrix Insights

The confusion matrix is an effective tool for determining the model's strengths and flaws. It demonstrates the model's strong performance throughout the 'cat,' 'dog,' and 'wild' classifications, with many right predictions in the diagonal parts. However, it exposes several misclassifications, including 12 occurrences of 'cat' misclassified as 'dog,' 8 instances of 'dog' misclassified as 'cat,' and 24 cases of 'wild' misclassified as 'dog.' These errors, though relatively few, highlight the significance of improving the model to reduce specific misclassification patterns. The confusion matrix reflects strong overall performance of the model, correctly categorising most examples for each class.

In summary, the model performs well on both the training and validation sets, with high accuracy and a balanced confusion matrix.



Example

True Positive: The confusion matrix reveals that the model correctly detected 481 instances of the second class. This is critical because reliable identification of 'dog' images is required. For example, accurately identifying these instances ensures that relevant images, such as those with dogs, are recognised. This result greatly helps to model's overall performance in differentiating the second class.

False Negative: On the other hand, the model struggled to recognise 24 instances of the third class and misclassified them as the second class ('dog'). These are shown in the matrix as false negatives. This misclassification is critical, demonstrating the model's difficulties recognising 'wild' class occurrences. Addressing these false negatives is critical for improving accuracy, particularly when exact identification of 'wild' photos is required for the application.

Conclusion

In summary, the image classification model works well identifying 'cat' and 'dog' photos, but confronts difficulty with 'wild' images. Future work could include expanding the dataset, fine-tuning the model architecture, or investigating advanced approaches like transfer learning to improve performance in the difficult 'wild' class.