Report on CNN Model Training and Performance

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1. Description of the Chosen CNN Architecture

The chosen architecture is a convolutional neural network (CNN) that is designed to classify images from the CIFAR-10 dataset, which contains 60,000 32x32 color images across 10 different classes. The CNN architecture follows a deep network structure with multiple convolutional layers, batch normalization, max-pooling, and dropout layers to prevent overfitting. The model ends with a fully connected layer that produces output for 10 classes using softmax activation. The detailed layers are as follows:

- **Conv2D layers**: Multiple convolutional layers with increasing filters (32, 64, and 128) to capture features in the image.
- **MaxPooling2D layers**: Used after each pair of convolutional layers to reduce spatial dimensions.
- **BatchNormalization layers**: Applied after each convolutional layer to improve training stability.
- **Dropout layer**: Used to prevent overfitting by randomly deactivating neurons.
- **Dense layer**: The final fully connected layer with 10 neurons, corresponding to the 10 classes of the CIFAR-10 dataset.

Additionally, the second model employs **Transfer Learning** with the **InceptionResNetV2** architecture, pre-trained on ImageNet, to leverage already learned feature representations. Custom dense layers are added to adapt the model for the CIFAR-10 classification.

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2. Explanation of Preprocessing Steps

The preprocessing of the CIFAR-10 dataset is as follows:

1. **Data Resizing**: The images are resized from their original dimensions (32x32) to 80x80 pixels to allow the model to capture more detailed features.
2. **Normalization**: The pixel values are normalized to the range [0, 1] by dividing by 255. This helps to stabilize training and improve convergence.
3. **Label Encoding**: The target labels are one-hot encoded using `to_categorical()` to convert the categorical labels into binary format suitable for classification.
4. **Data Augmentation**: To artificially increase the dataset size and improve model robustness, augmentation techniques such as random rotations, width/height shifts, and horizontal flipping are applied.

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3. Details of the Training Process

- **Model 1 (CNN)**:
  - **Optimizer**: Adam optimizer is used with a learning rate of 0.001.
  - **Loss function**: Categorical cross-entropy loss function.
  - **Batch Size**: 800 (400*2).
  - **Epochs**: 50 epochs with early stopping based on validation loss.
  - **Callbacks**: Early stopping is used to avoid overfitting by stopping training once the validation loss stops improving for 5 consecutive epochs.
- **Model 2 (Transfer Learning with InceptionResNetV2)**:
  - **Optimizer**: Adam optimizer with a learning rate of 0.0001.
  - **Loss function**: Categorical cross-entropy.
  - **Batch Size**: 800 (400*2).
  - **Epochs**: 50 epochs with early stopping and learning rate reduction.
  - **Callbacks**:
    - **EarlyStopping**: Stops training if validation loss doesn't improve for 10 epochs.
    - **ReduceLROnPlateau**: Reduces the learning rate when the validation loss plateaus.
    - **ModelCheckpoint**: Saves the best model based on validation accuracy.

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4. Results and Analysis of Model Performance

- **Model 1 (CNN)** achieved a test accuracy of approximately 0.73
- **Model 2 (Transfer Learning)** achieved a test accuracy of 0.84, significantly better than the baseline CNN model. The use of InceptionResNetV2, pre-trained on ImageNet, allowed the model to leverage learned feature representations for more effective classification on the CIFAR-10 dataset.

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5. Best Model and Why

The best model is **Model 2 (Transfer Learning with InceptionResNetV2)**. This model achieved higher accuracy and generalization performance compared to the standard CNN. The reason for its success is the ability to leverage pre-trained weights from ImageNet, which are capable of extracting more complex features from the images, even though CIFAR-10 is a smaller dataset.

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6. Insights Gained from the Experimentation Process

1. **Transfer Learning Effectiveness**: The transfer learning model demonstrated significant improvement in performance, validating the hypothesis that leveraging pre-trained models can drastically improve accuracy, especially on smaller datasets like CIFAR-10.

2. **Augmentation Impact**: Data augmentation improved the model's robustness by helping it generalize better, especially on more challenging classes.

Conclusion

The experiment demonstrated the power of using transfer learning for image classification tasks. The CNN model served as a strong baseline but was outperformed by the transfer learning approach. The analysis and results underscore the importance of leveraging pre-trained models for better performance on image datasets.