Evaluating Performance on Test Set

Warning: This notebook will take a long time to run due to the complexity of the models and the size of the training set. Each model can take 20+ minutes to predict the test set, depending on computational resources.

Load and Preprocess

To prevent longer runtime, only test set will be preprocessed.

```
from transformers import AutoImageProcessor
from tensorflow.keras.datasets import cifar10
import joblib
import os

# Load data
(X_train, y_train), (X_test, y_test) = cifar10.load_data()

# Preprocess
processor = AutoImageProcessor.from_pretrained('google/vit-base-
patch16-224')
X_test_preprocessed = processor(images=X_test, return_tensors='tf')
['pixel_values']
```

```
/apps/tensorflow/2.18/lib/python3.11/site-packages/tqdm/auto.py:21:
TqdmWarning: IProgress not found. Please update jupyter and
ipywidgets. See
https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
2025-04-20 17:52:13.418589: E
external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:467] Unable to
register cuFFT factory: Attempting to register factory for plugin
cuFFT when one has already been registered
WARNING: All log messages before absl::InitializeLog() is called are
written to STDERR
E0000 00:00:1745185933.585332 2802827 cuda_dnn.cc:8579] Unable to
register cuDNN factory: Attempting to register factory for plugin
cuDNN when one has already been registered
E0000 00:00:1745185933.640424 2802827 cuda_blas.cc:1407] Unable to
register cuBLAS factory: Attempting to register factory for plugin
cuBLAS when one has already been registered
W0000 00:00:1745185934.001022 2802827 computation_placer.cc:177]
computation placer already registered. Please check linkage and avoid
linking the same target more than once.
W0000 00:00:1745185934.001047 2802827 computation_placer.cc:177]
computation placer already registered. Please check linkage and avoid
linking the same target more than once.
```

```
W0000 00:00:1745185934.001049 2802827 computation_placer.cc:177]
computation placer already registered. Please check linkage and avoid
linking the same target more than once.
W0000 00:00:1745185934.001050 2802827 computation_placer.cc:177]
computation placer already registered. Please check linkage and avoid
linking the same target more than once.
2025-04-20 17:52:14.041351: I
tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow
binary is optimized to use available CPU instructions in performance-
critical operations.
To enable the following instructions: AVX2 FMA, in other operations,
rebuild TensorFlow with the appropriate compiler flags.
2025-04-20 17:52:50.507276: E
external/local_xla/xla/stream_executor/cuda/cuda_platform.cc:51]
failed call to cuInit: INTERNAL: CUDA error: Failed call to cuInit:
UNKNOWN ERROR (303)
2025-04-20 17:52:50.508757: W
external/local_xla/xla/tsl/framework/cpu_allocator_impl.cc:83]
Allocation of 6021120000 exceeds 10% of free system memory.
```

Evaluate

Each model configuration or hyperparameter tweak was considered a "trial". The following will include performance evaluations of these trials on the full test set (10,000 samples) from CIFAR-10. Note that the original model was trained on half the samples in the training set (random sampling) and the others were trained on around 2/50 or 4/50 of the training set for exploration purposes. A personal function will be loaded from a .py file for evaluations and it requires *"..._vit_model"* folder and *"..._transfer_model.keras"* to be in the working directory.

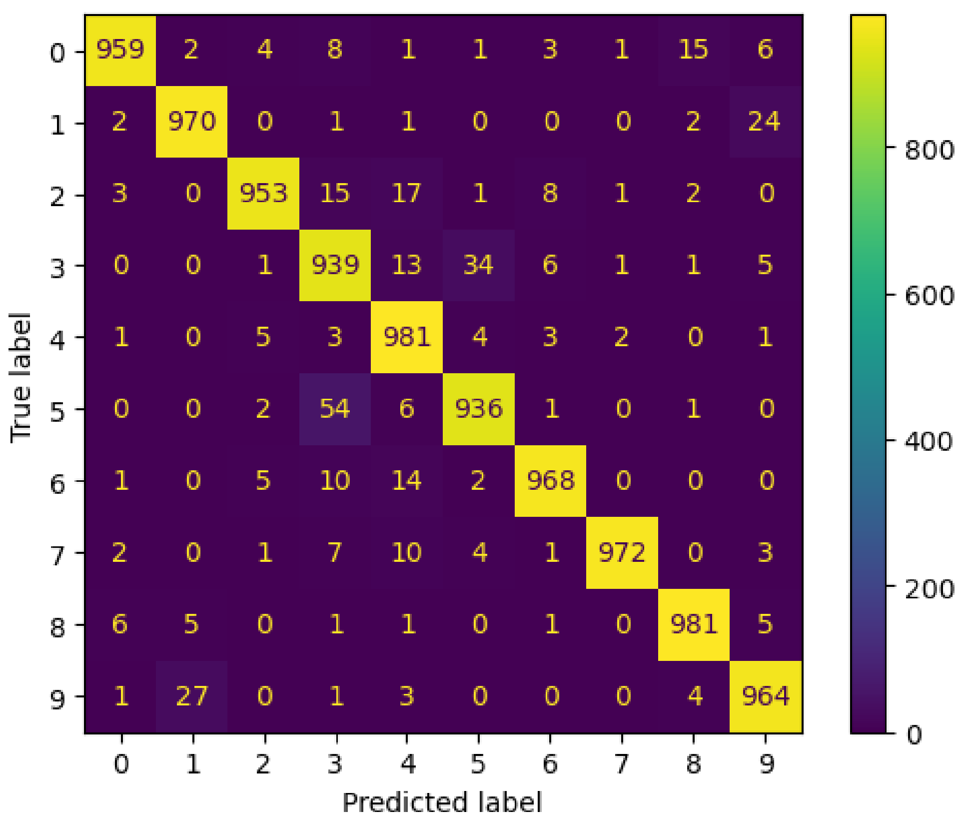
Baseline Model

This was the original model that was simply the transformer with a Dense classifier layer.

```python
from general_training import evaluate_trial

trial_name = 'baseline'
evaluate_trial(trial_name, X_test_preprocessed, y_test)
```

```
All model checkpoint layers were used when initializing TFViTModel.

All the layers of TFViTModel were initialized from the model
checkpoint at baseline_vit_model.
If your task is similar to the task the model of the checkpoint was
trained on, you can already use TFViTModel for predictions without
further training.

313/313 ━━━━━━━━━━━━━━━━━━━━ 1353s 4s/step
Time to Predict: 1352.907952785492 secs
```

```
Classification Report
              precision    recall  f1-score   support

           0       0.98      0.96      0.97      1000
           1       0.97      0.97      0.97      1000
           2       0.98      0.95      0.97      1000
           3       0.90      0.94      0.92      1000
           4       0.94      0.98      0.96      1000
           5       0.95      0.94      0.94      1000
           6       0.98      0.97      0.97      1000
           7       0.99      0.97      0.98      1000
           8       0.98      0.98      0.98      1000
           9       0.96      0.96      0.96      1000

    accuracy                           0.96     10000
   macro avg       0.96      0.96      0.96     10000
weighted avg       0.96      0.96      0.96     10000


Confusion Matrix
```

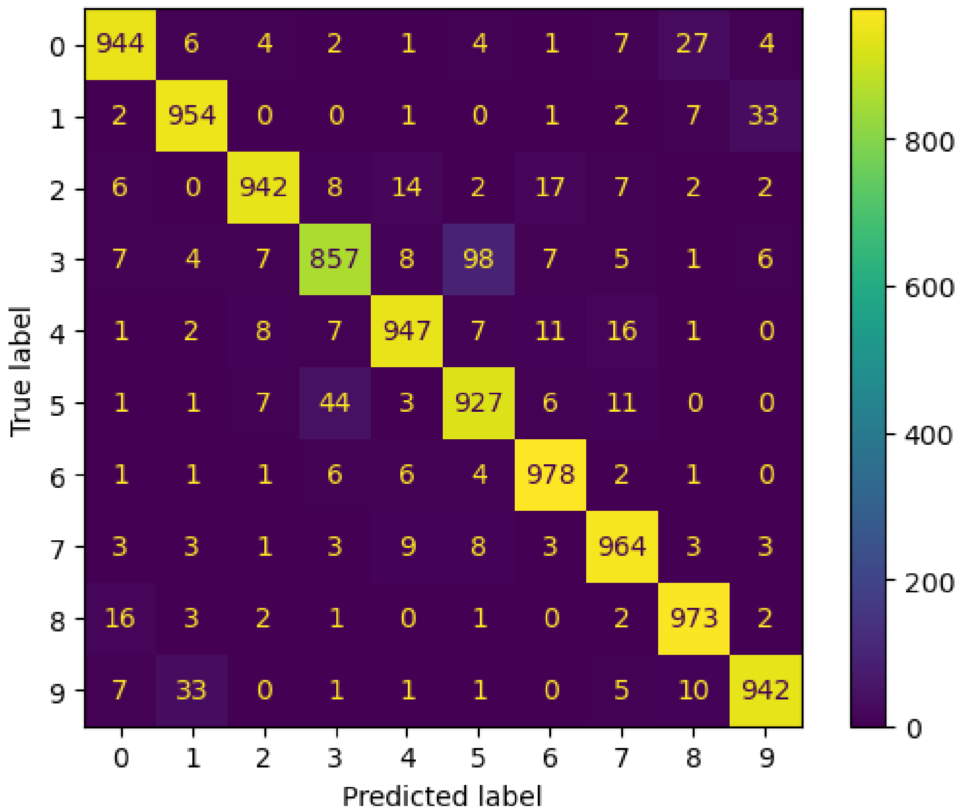


Augmented Data Model

This was the baseline model but with randomly augmented images (horizontal flip, +/- 72 degree rotation, and +/- 0.1 zoom).

```python
from general_training import evaluate_trial

trial_name = 'augment'
evaluate_trial(trial_name, X_test_preprocessed, y_test)
```

```
All model checkpoint layers were used when initializing TFViTModel.

All the layers of TFViTModel were initialized from the model
checkpoint at augment_vit_model.
If your task is similar to the task the model of the checkpoint was
trained on, you can already use TFViTModel for predictions without
further training.

313/313 ━━━━━━━━━━━━━━━━━━━━ 1352s 4s/step
Time to Predict: 1352.0381152629852 secs

Classification Report
              precision    recall  f1-score   support

           0       0.96      0.94      0.95      1000
           1       0.95      0.95      0.95      1000
           2       0.97      0.94      0.96      1000
           3       0.92      0.86      0.89      1000
           4       0.96      0.95      0.95      1000
           5       0.88      0.93      0.90      1000
           6       0.96      0.98      0.97      1000
           7       0.94      0.96      0.95      1000
           8       0.95      0.97      0.96      1000
           9       0.95      0.94      0.95      1000

    accuracy                           0.94     10000
   macro avg       0.94      0.94      0.94     10000
weighted avg       0.94      0.94      0.94     10000


Confusion Matrix
```



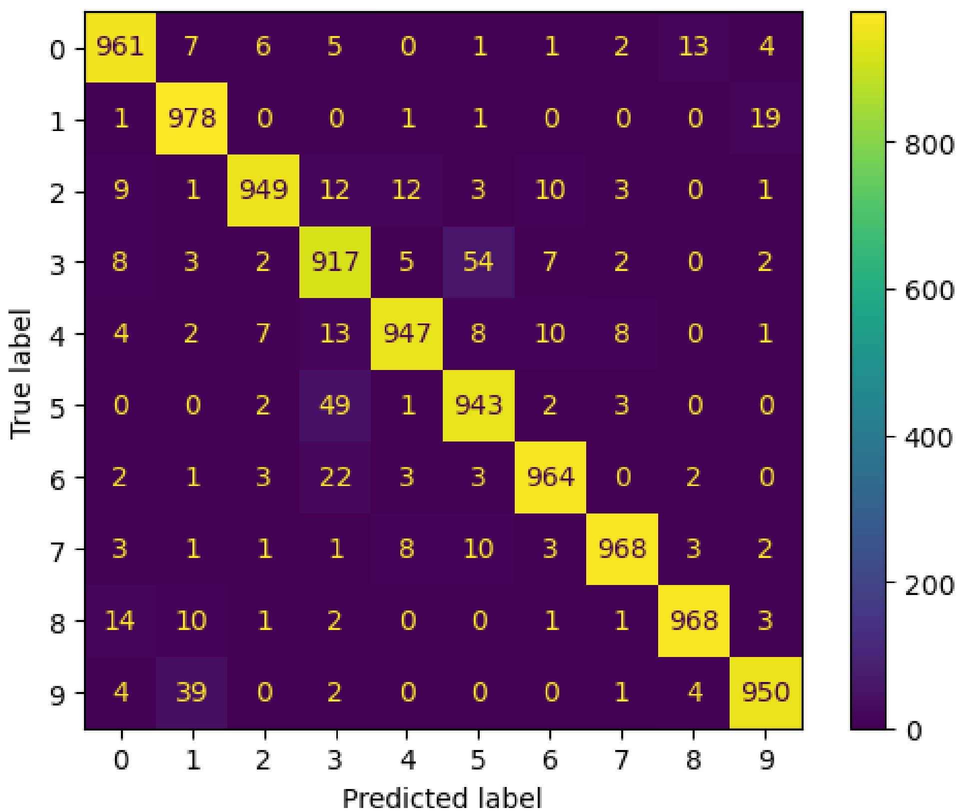
Regularized Model

This was the baseline model but with an extra Dense layer before the output. It used ReLU with 64 neurons, kernel regularizer of 0.001 and kernel initializer of "he_normal". It was proceeded by a dropout of 0.3 and then the classifier/output layer.

```python
from general_training import evaluate_trial

trial_name = 'regularize'
evaluate_trial(trial_name, X_test_preprocessed, y_test)
```

```
All model checkpoint layers were used when initializing TFViTModel.

All the layers of TFViTModel were initialized from the model
checkpoint at regularize_vit_model.
If your task is similar to the task the model of the checkpoint was
trained on, you can already use TFViTModel for predictions without
further training.

313/313 ━━━━━━━━━━━━━━━━━━━━ 1341s 4s/step
Time to Predict: 1341.0378098487854 secs

Classification Report
              precision    recall  f1-score   support
```

```
           0       0.96      0.96      0.96      1000
           1       0.94      0.98      0.96      1000
           2       0.98      0.95      0.96      1000
           3       0.90      0.92      0.91      1000
           4       0.97      0.95      0.96      1000
           5       0.92      0.94      0.93      1000
           6       0.97      0.96      0.96      1000
           7       0.98      0.97      0.97      1000
           8       0.98      0.97      0.97      1000
           9       0.97      0.95      0.96      1000

    accuracy                           0.95     10000
   macro avg       0.95      0.95      0.95     10000
weighted avg       0.95      0.95      0.95     10000


Confusion Matrix
```



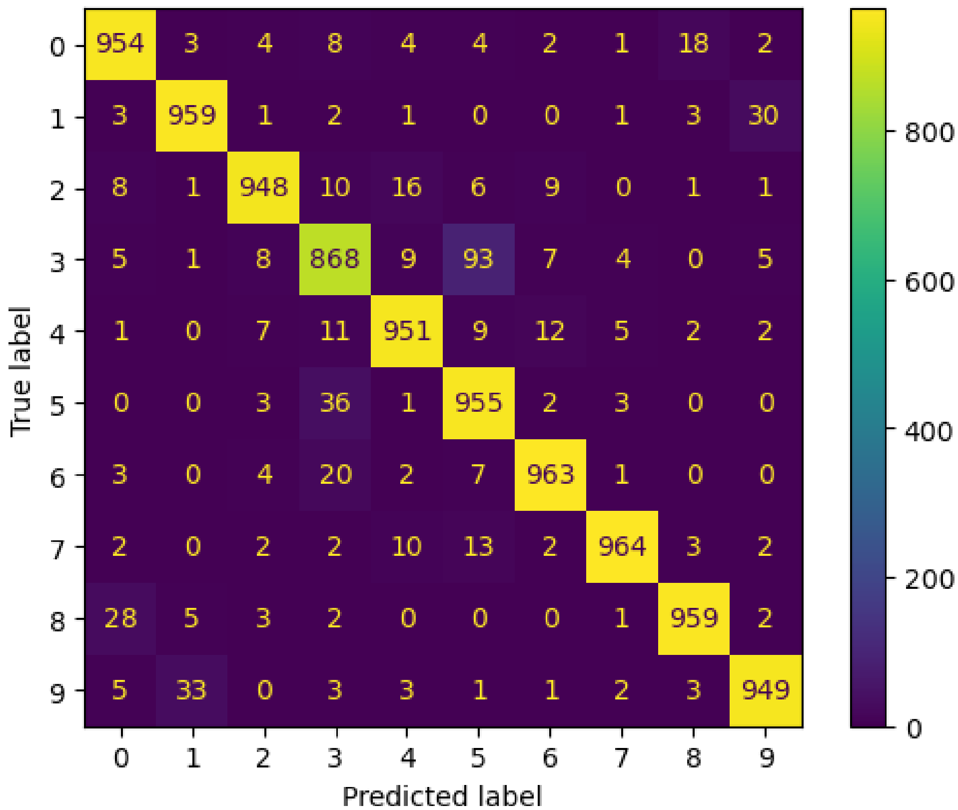
Regularized with Augmented Data Model

This combined the previous augmented and regularized model into one.

```
from general_training import evaluate_trial
```

```python
trial_name = 'regularize_and_augment'
evaluate_trial(trial_name, X_test_preprocessed, y_test)
```

```
All model checkpoint layers were used when initializing TFViTModel.

All the layers of TFViTModel were initialized from the model
checkpoint at regularize_and_augment_vit_model.
If your task is similar to the task the model of the checkpoint was
trained on, you can already use TFViTModel for predictions without
further training.

313/313 ━━━━━━━━━━━━━━━━━━━━ 1342s 4s/step
Time to Predict: 1341.9095242023468 secs

Classification Report
              precision    recall  f1-score   support

           0       0.95      0.95      0.95      1000
           1       0.96      0.96      0.96      1000
           2       0.97      0.95      0.96      1000
           3       0.90      0.87      0.88      1000
           4       0.95      0.95      0.95      1000
           5       0.88      0.95      0.91      1000
           6       0.96      0.96      0.96      1000
           7       0.98      0.96      0.97      1000
           8       0.97      0.96      0.96      1000
           9       0.96      0.95      0.95      1000

    accuracy                           0.95     10000
   macro avg       0.95      0.95      0.95     10000
weighted avg       0.95      0.95      0.95     10000


Confusion Matrix
```



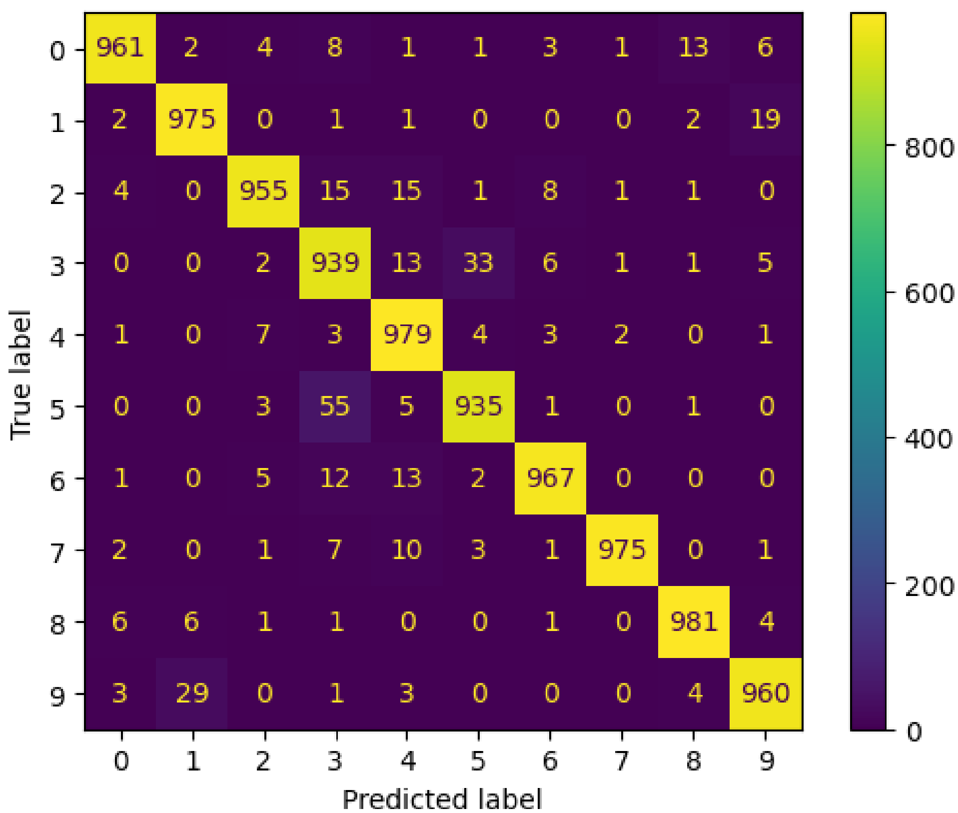
Baseline Model: Continued Training with Learning Rate Scheduler

This was the baseline model but with continued training using a learning rate schedular that exponentially decreased the learning rate by a factor of 0.5 after every epoch. It also started with a lower initial learning rate (1e-4 compared to 1e-3 for original training). This was done to see if the baseline model could be fine-tuned with a lower learning rate that would allow a better optimum to be reached. Note that random state 42 was used for the K-folds in all models, except this one where random state 0 was used so that the continued training would have a greater chance at seeing different samples

```
from general_training import evaluate_trial

trial_name = 'baseline_lr'
evaluate_trial(trial_name, X_test_preprocessed, y_test)
```

```
All model checkpoint layers were used when initializing TFViTModel.

All the layers of TFViTModel were initialized from the model checkpoint at baseline_lr_vit_model.
If your task is similar to the task the model of the checkpoint was trained on, you can already use TFViTModel for predictions without further training.

313/313 ━━━━━━━━━━━━━━━━━━━━ 1338s 4s/step
Time to Predict: 1338.5749015808105 secs
```

```
Classification Report
              precision    recall  f1-score   support

           0       0.98      0.96      0.97      1000
           1       0.96      0.97      0.97      1000
           2       0.98      0.95      0.97      1000
           3       0.90      0.94      0.92      1000
           4       0.94      0.98      0.96      1000
           5       0.96      0.94      0.94      1000
           6       0.98      0.97      0.97      1000
           7       0.99      0.97      0.98      1000
           8       0.98      0.98      0.98      1000
           9       0.96      0.96      0.96      1000

    accuracy                           0.96     10000
   macro avg       0.96      0.96      0.96     10000
weighted avg       0.96      0.96      0.96     10000


Confusion Matrix
```



Show Correct and Incorrect Predictions

From the confusion matrices, we can see that all the models are making similar mistakes. We will visualize correct and incorrect predictions made from the baseline model since it was the best one and seems to be representative of the errors for the other models.

```
from general_training import predict_trial
import numpy as np

# Make prediction on test set
trial_name = 'baseline'
y_pred = np.argmax(predict_trial(trial_name, X_test_preprocessed),
axis=-1)
```

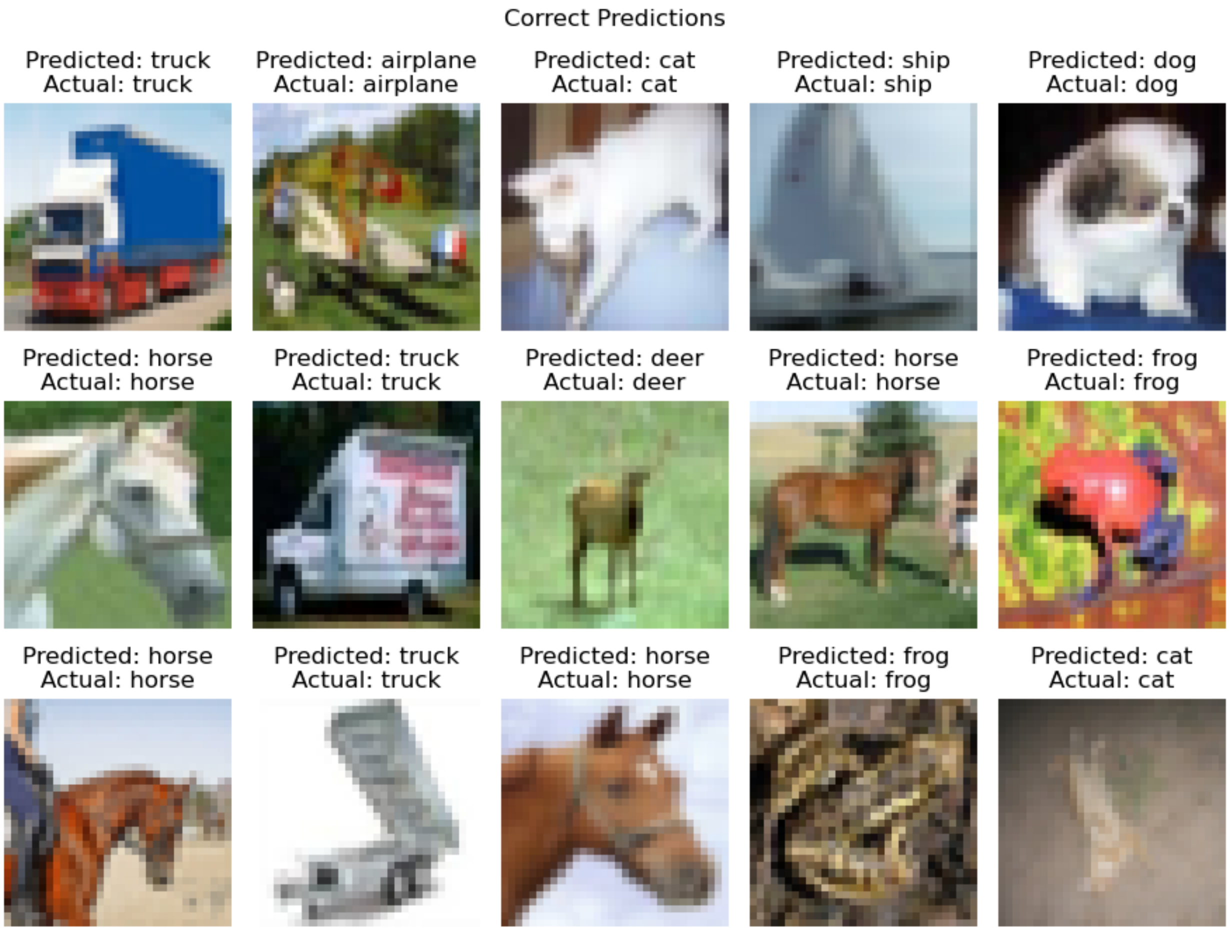
```
WARNING:tensorflow:From C:\Users\ethan\AppData\Roaming\Python\
Python311\site-packages\tf_keras\src\backend.py:873: The name
tf.get_default_graph is deprecated. Please use
tf.compat.v1.get_default_graph instead.


All model checkpoint layers were used when initializing TFViTModel.

All the layers of TFViTModel were initialized from the model
checkpoint at ../baseline_vit_model.
If your task is similar to the task the model of the checkpoint was
trained on, you can already use TFViTModel for predictions without
further training.

WARNING:tensorflow:From c:\Users\ethan\anaconda3\envs\ML_env\Lib\site-
packages\keras\src\backend\tensorflow\core.py:216: The name
tf.placeholder is deprecated. Please use tf.compat.v1.placeholder
instead.

313/313 ━━━━━━━━━━━━━━━━━━━━ 1152s 4s/step
```

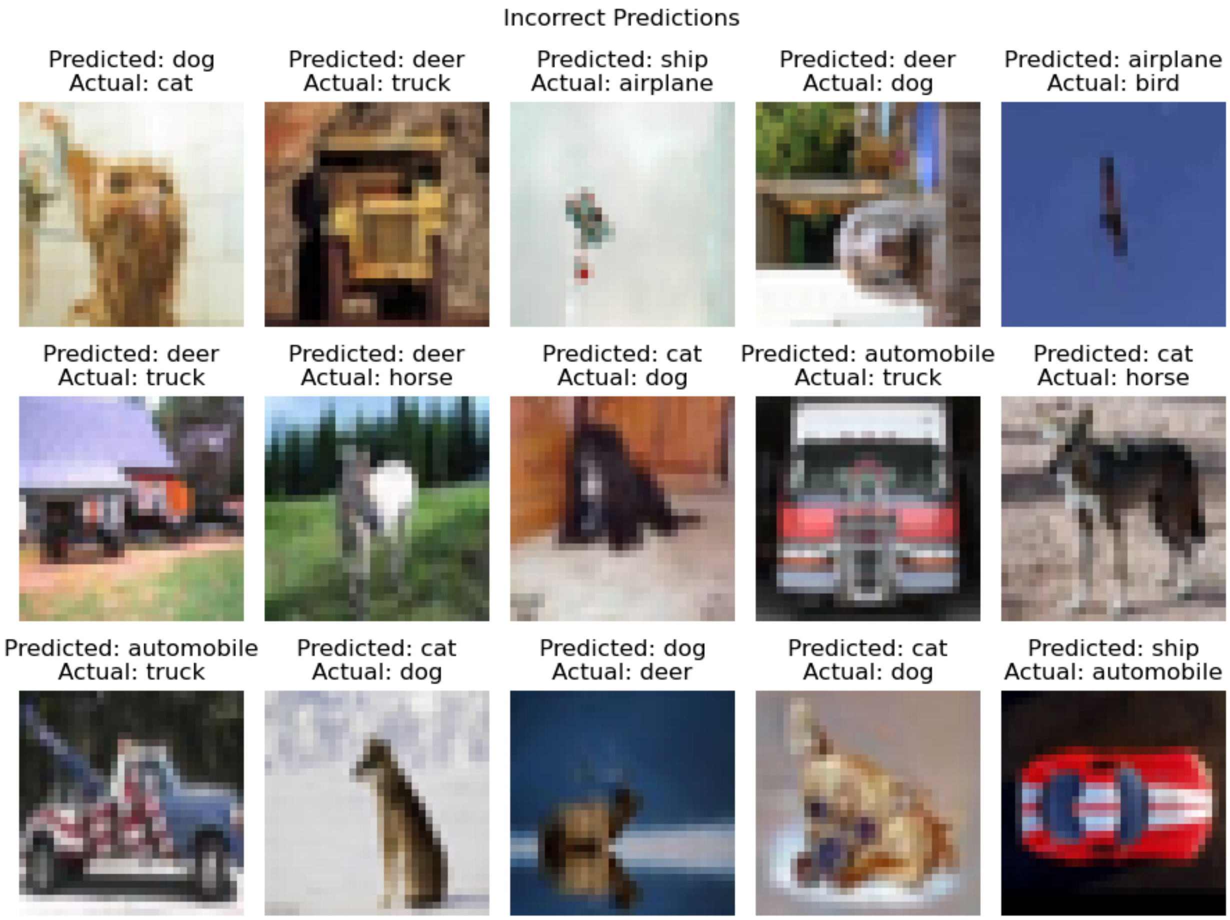
We can generate random samples, regardless of the class.

```
import matplotlib.pyplot as plt
import random

# Set seed
random.seed(42)

# Get correct and incorrect predictions
X_test_correct = X_test[(y_test.flatten() == y_pred.flatten())]
y_test_correct = y_test[(y_test.flatten() ==
y_pred.flatten())].flatten()
y_pred_correct = y_pred[(y_test.flatten() ==
y_pred.flatten())].flatten()
X_test_wrong = X_test[(y_test.flatten() != y_pred.flatten())]
```

```
y_test_wrong = y_test[(y_test.flatten() !=
y_pred.flatten())].flatten()
y_pred_wrong = y_pred[(y_test.flatten() !=
y_pred.flatten())].flatten()

# Grab samples
num_samples = 15
sample_indices = random.sample(range(len(X_test_correct)),
num_samples)
X_test_correct = X_test_correct[sample_indices]
y_test_correct = y_test_correct[sample_indices]
y_pred_correct = y_pred_correct[sample_indices]
sample_indices = random.sample(range(len(X_test_wrong)), num_samples)
X_test_wrong = X_test_wrong[sample_indices]
y_test_wrong = y_test_wrong[sample_indices]
y_pred_wrong = y_pred_wrong[sample_indices]

# List class names in order
class_names = [
    "airplane", "automobile", "bird", "cat", "deer",
    "dog", "frog", "horse", "ship", "truck"]

# Plot correct predictions
fig = plt.figure(figsize=(9, 7))

for i in range(len(y_test_correct)):

    ax = fig.add_subplot(3, 5, i+1)
    ax.imshow(X_test_correct[i])
    predicted_class = class_names[y_pred_correct[i]]
    true_class = class_names[y_test_correct[i]]
    ax.set_title(f'Predicted: {predicted_class}\nActual:
{true_class}')
    ax.axis('off')

plt.suptitle('Correct Predictions')

plt.tight_layout()
plt.show()

# Plot wrong predictions
fig = plt.figure(figsize=(9, 7))

for i in range(len(y_test_wrong)):

    ax = fig.add_subplot(3, 5, i+1)
    ax.imshow(X_test_wrong[i])
    predicted_class = class_names[y_pred_wrong[i]]
    true_class = class_names[y_test_wrong[i]]
    ax.set_title(f'Predicted: {predicted_class}\nActual:
```

```
{true_class}')
    ax.axis('off')

plt.suptitle('Incorrect Predictions')

plt.tight_layout()
plt.show()
```





Now we can show samples per class to have a better understanding of the confusion for each class.

```
num_classes = 10

# List class names in order
class_names = [
    "airplane", "automobile", "bird", "cat", "deer",
    "dog", "frog", "horse", "ship", "truck"]

for cl in range(num_classes):

    print('------------------------')
    print(class_names[cl])
    print('------------------------')

    # Get correct and incorrect predictions
    X_test_correct = X_test[(y_test.flatten() == y_pred.flatten()) &
(y_test.flatten() == cl)]
    y_test_correct = y_test[(y_test.flatten() == y_pred.flatten()) &
(y_test.flatten() == cl)].flatten()
    y_pred_correct = y_pred[(y_test.flatten() == y_pred.flatten()) &
```

```
(y_test.flatten() == cl)].flatten()
    X_test_wrong = X_test[(y_test.flatten() != y_pred.flatten()) &
(y_test.flatten() == cl)]
    y_test_wrong = y_test[(y_test.flatten() != y_pred.flatten()) &
(y_test.flatten() == cl)].flatten()
    y_pred_wrong = y_pred[(y_test.flatten() != y_pred.flatten()) &
(y_test.flatten() == cl)].flatten()

    # Grab samples
    num_samples = 15
    sample_indices = random.sample(range(len(X_test_correct)),
num_samples)
    X_test_correct = X_test_correct[sample_indices]
    y_test_correct = y_test_correct[sample_indices]
    y_pred_correct = y_pred_correct[sample_indices]
    sample_indices = random.sample(range(len(X_test_wrong)),
num_samples)
    X_test_wrong = X_test_wrong[sample_indices]
    y_test_wrong = y_test_wrong[sample_indices]
    y_pred_wrong = y_pred_wrong[sample_indices]

    # Plot correct predictions
    fig = plt.figure(figsize=(12, 8))

    for i in range(len(y_test_correct)):

        ax = fig.add_subplot(3, 5, i+1)
        ax.imshow(X_test_correct[i])
        predicted_class = class_names[y_pred_correct[i]]
        true_class = class_names[y_test_correct[i]]
        ax.set_title(f'Predicted: {predicted_class}\nActual:
{true_class}')
        ax.axis('off')

    class_name = class_names[cl]
    plt.suptitle(f'Correct Predictions for "{class_name}" Class',
y=1.01)
    plt.show()

    # Plot wrong predictions
    fig = plt.figure(figsize=(12, 8))

    for i in range(len(y_test_wrong)):

        ax = fig.add_subplot(3, 5, i+1)
        ax.imshow(X_test_wrong[i])
        predicted_class = class_names[y_pred_wrong[i]]
        true_class = class_names[y_test_wrong[i]]
        ax.set_title(f'Predicted: {predicted_class}\nActual:
{true_class}')
```

```
        ax.axis('off')

    class_name = class_names[cl]
    plt.suptitle(f'Incorrect Predictions for "{class_name}" Class',
y=1.01)
    plt.show()

-----------------------
airplane
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```

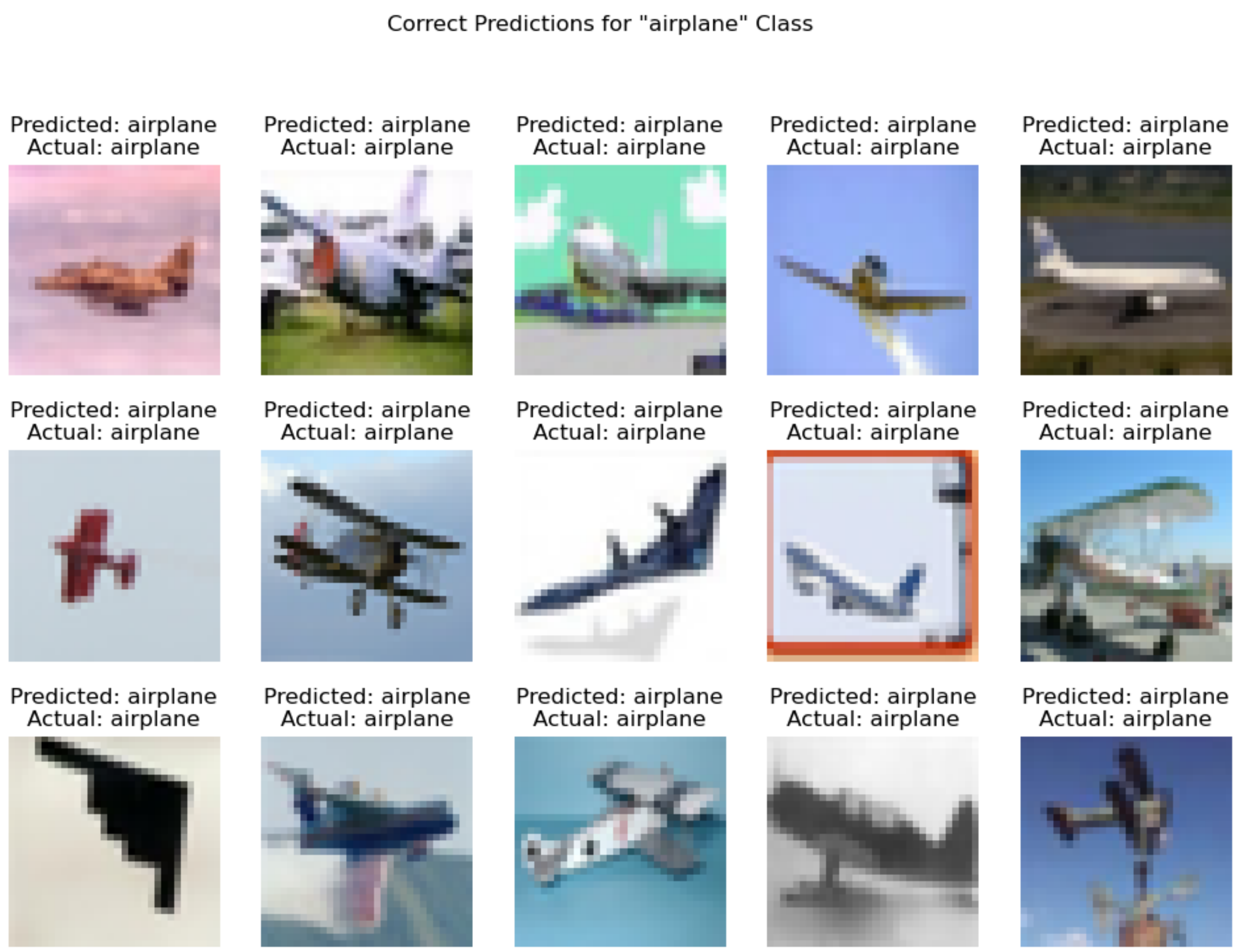

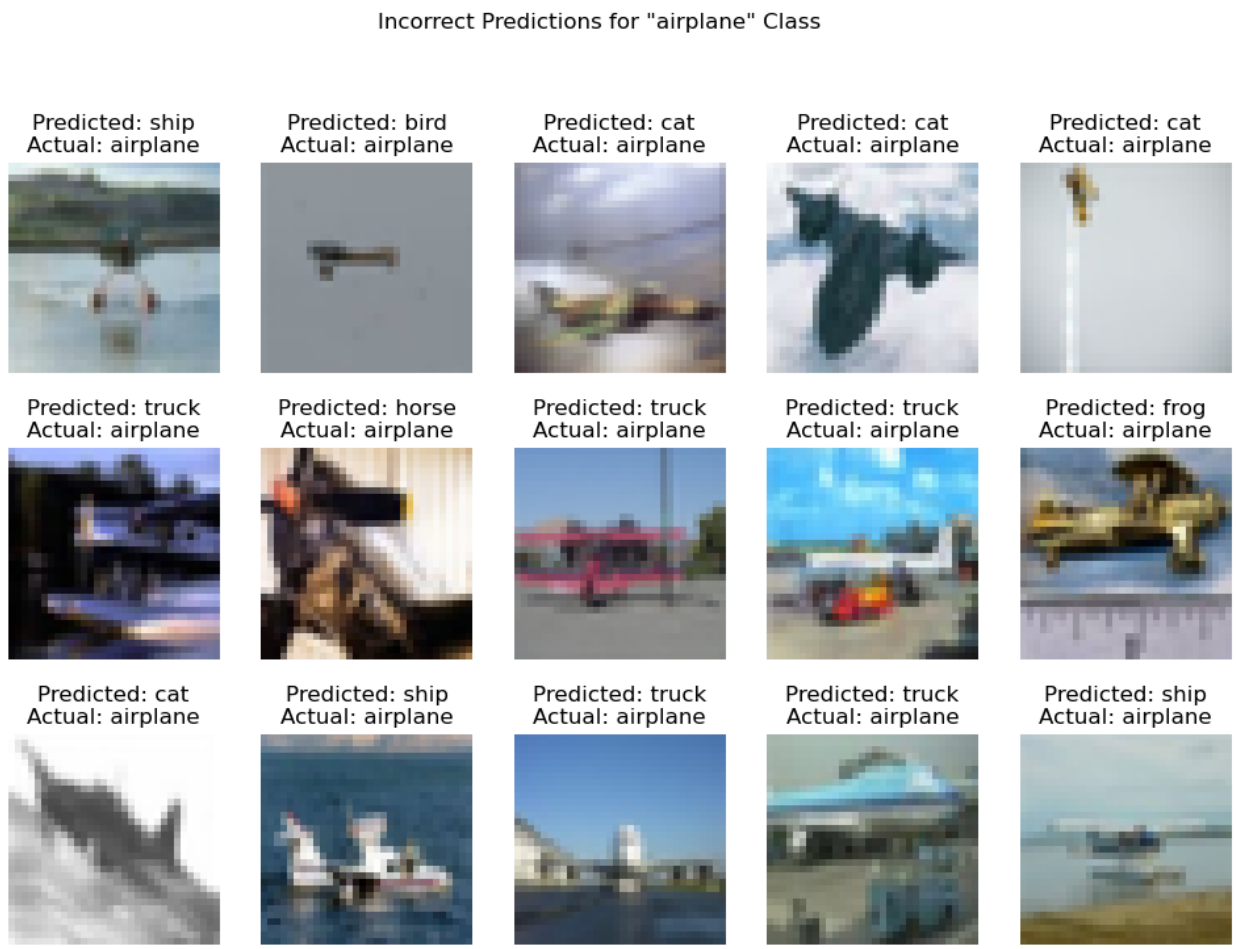
Incorrect Predictions for "airplane" Class
Predicted: ship
Actual: airplane
Predicted: bird
Actual: airplane
Predicted: cat
Actual: airplane
Predicted: cat
Actual: airplane
Predicted: cat
Actual: airplane
Predicted: truck
Actual: airplane
Predicted: horse
Actual: airplane
Predicted: truck
Actual: airplane
Predicted: truck
Actual: airplane
Predicted: frog
Actual: airplane
Predicted: cat
Actual: airplane
Predicted: ship
Actual: airplane
Predicted: truck
Actual: airplane
Predicted: truck
Actual: airplane
Predicted: ship
Actual: airplane

```
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automobile
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```
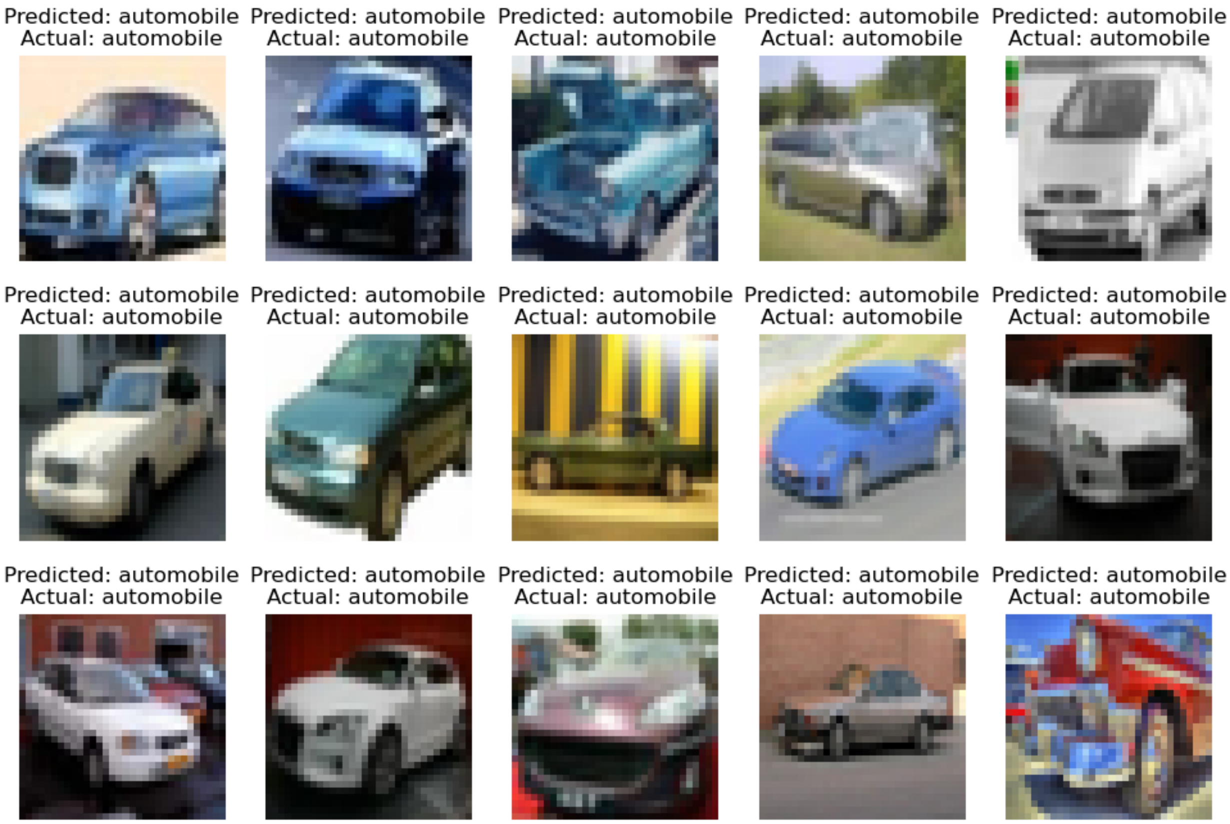
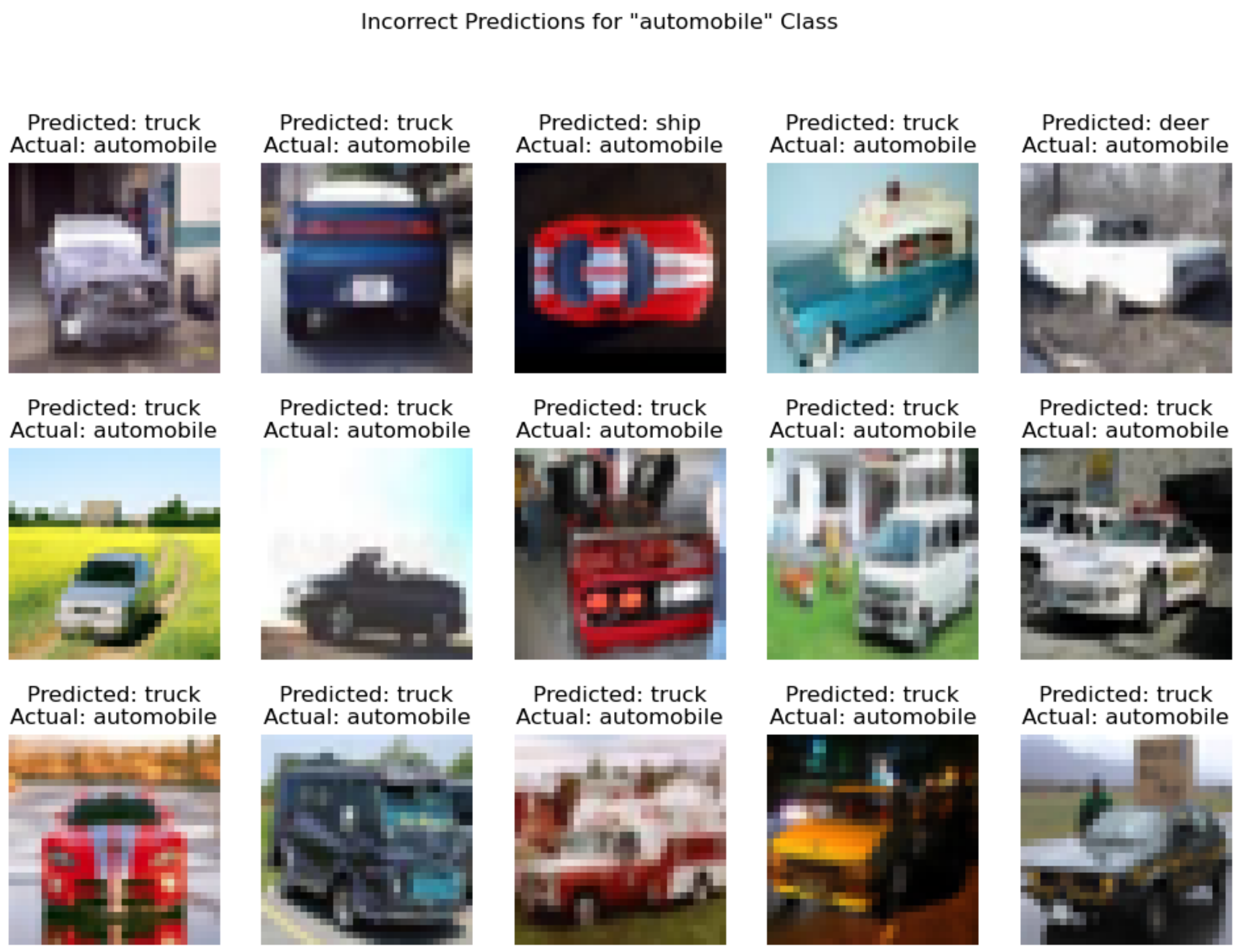

Correct Predictions for "automobile" Class




Incorrect Predictions for "automobile" Class
Predicted: truck
Actual: automobile
Predicted: truck
Actual: automobile
Predicted: ship
Actual: automobile
Predicted: truck
Actual: automobile
Predicted: deer
Actual: automobile
Predicted: truck
Actual: automobile
Predicted: truck
Actual: automobile
Predicted: truck
Actual: automobile
Predicted: truck
Actual: automobile
Predicted: truck
Actual: automobile
Predicted: truck
Actual: automobile
Predicted: truck
Actual: automobile
Predicted: truck
Actual: automobile
Predicted: truck
Actual: automobile
Predicted: truck
Actual: automobile

```
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bird
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```
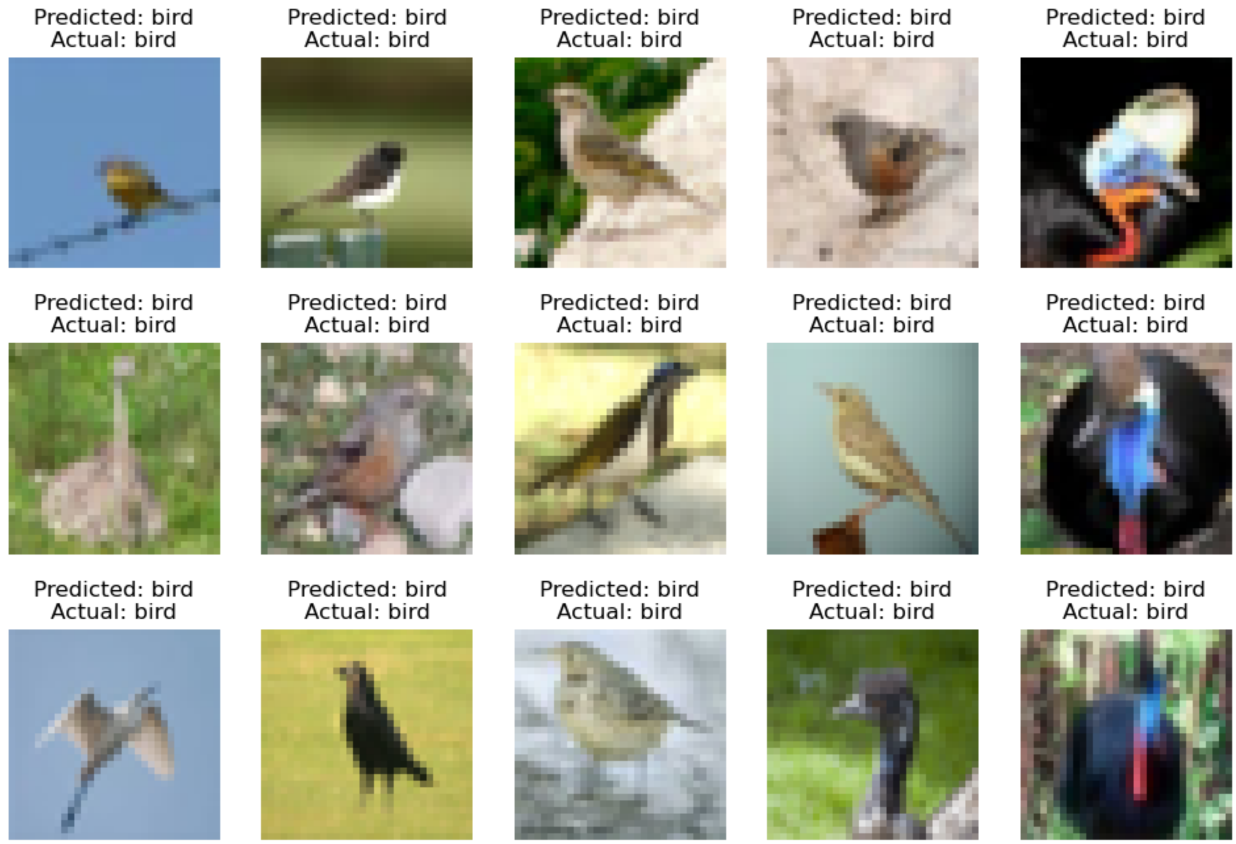
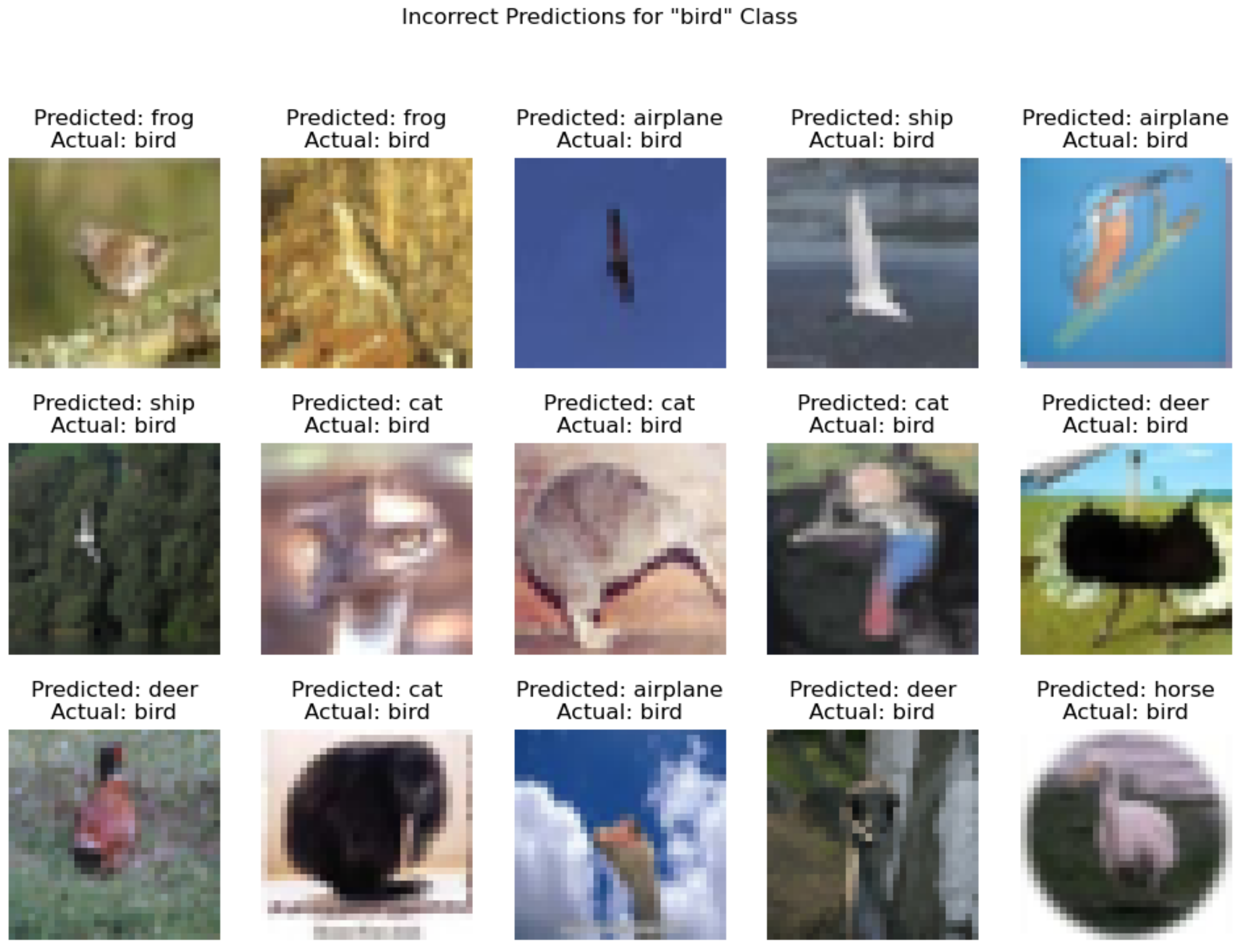

Correct Predictions for "bird" Class




Incorrect Predictions for "bird" Class
Predicted: frog
Actual: bird
Predicted: frog
Actual: bird
Predicted: airplane
Actual: bird
Predicted: ship
Actual: bird
Predicted: airplane
Actual: bird
Predicted: ship
Actual: bird
Predicted: cat
Actual: bird
Predicted: cat
Actual: bird
Predicted: cat
Actual: bird
Predicted: deer
Actual: bird
Predicted: deer
Actual: bird
Predicted: cat
Actual: bird
Predicted: airplane
Actual: bird
Predicted: deer
Actual: bird
Predicted: horse
Actual: bird

```
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cat
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```
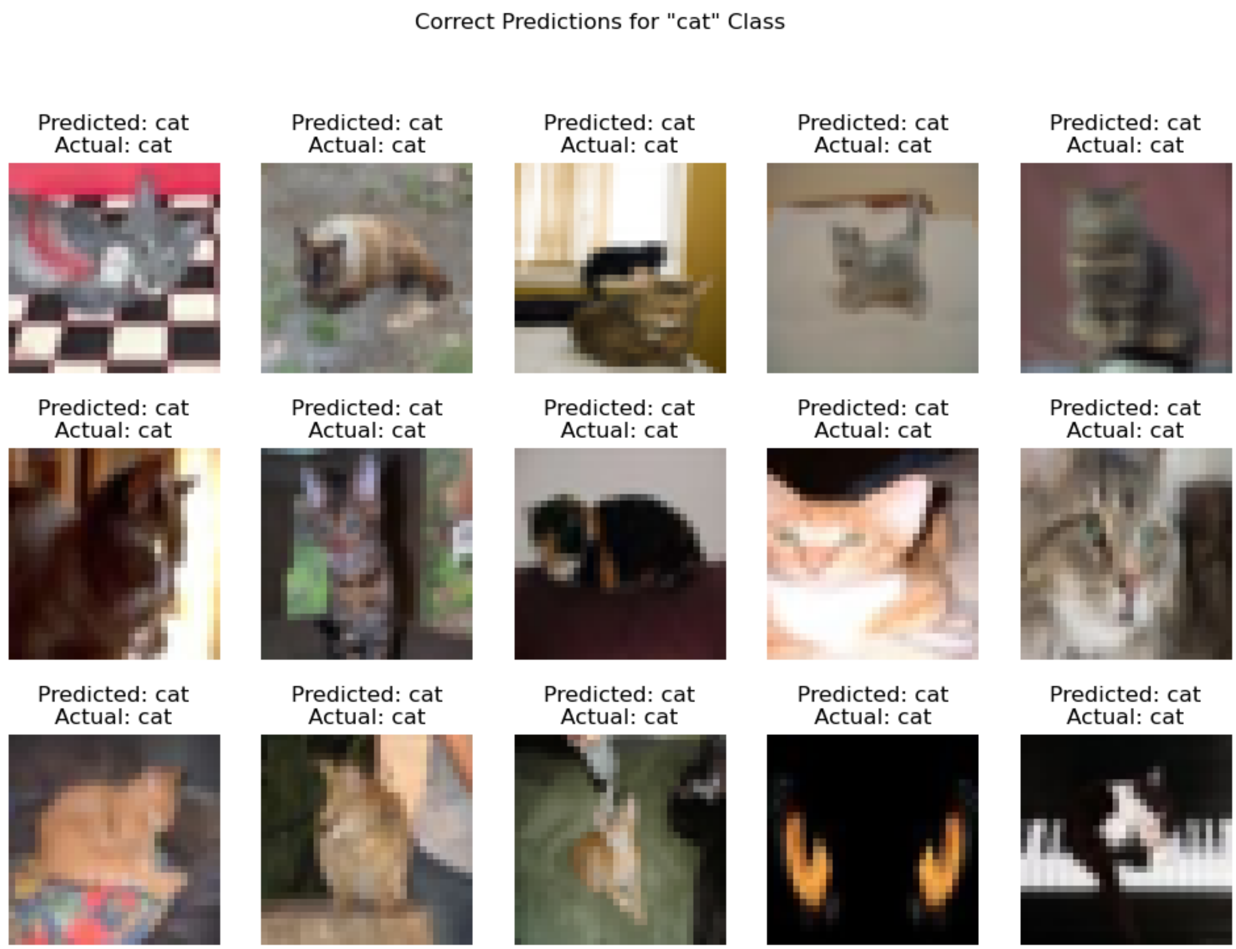
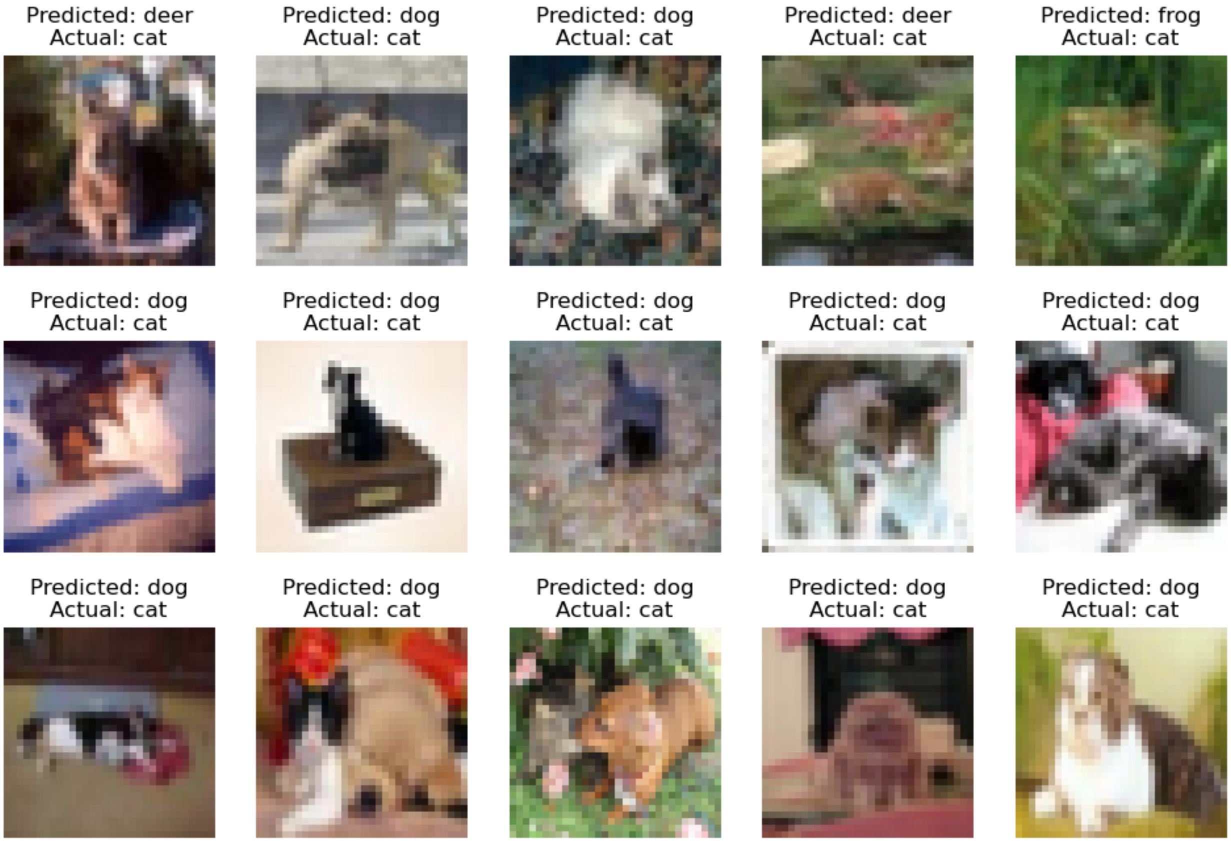


Correct Predictions for "cat" Class
Predicted: cat
Actual: cat
Predicted: cat
Actual: cat
Predicted: cat
Actual: cat
Predicted: cat
Actual: cat
Predicted: cat
Actual: cat
Predicted: cat
Actual: cat
Predicted: cat
Actual: cat
Predicted: cat
Actual: cat
Predicted: cat
Actual: cat
Predicted: cat
Actual: cat
Predicted: cat
Actual: cat
Predicted: cat
Actual: cat
Predicted: cat
Actual: cat
Predicted: cat
Actual: cat
Predicted: cat
Actual: cat

Incorrect Predictions for "cat" Class

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deer
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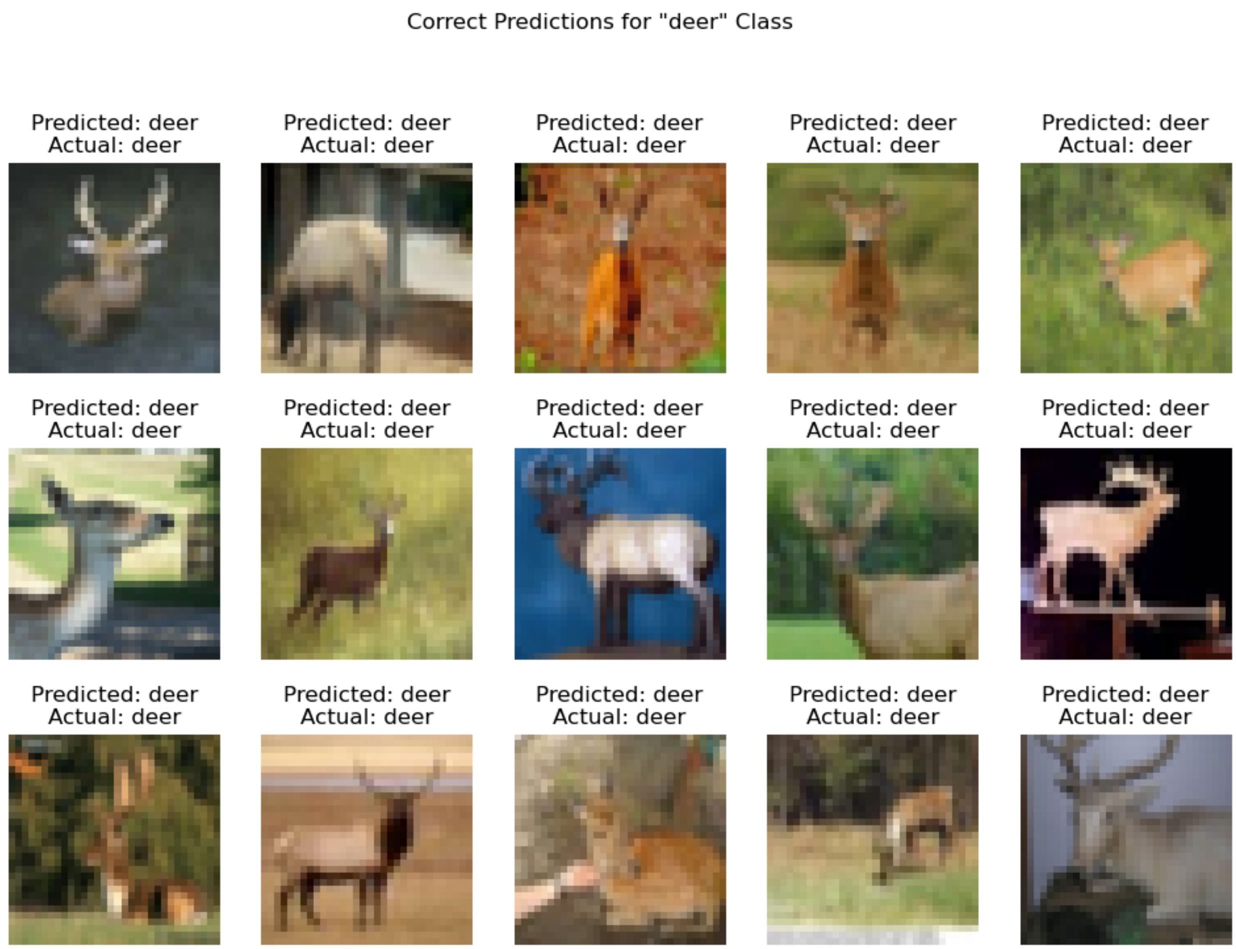
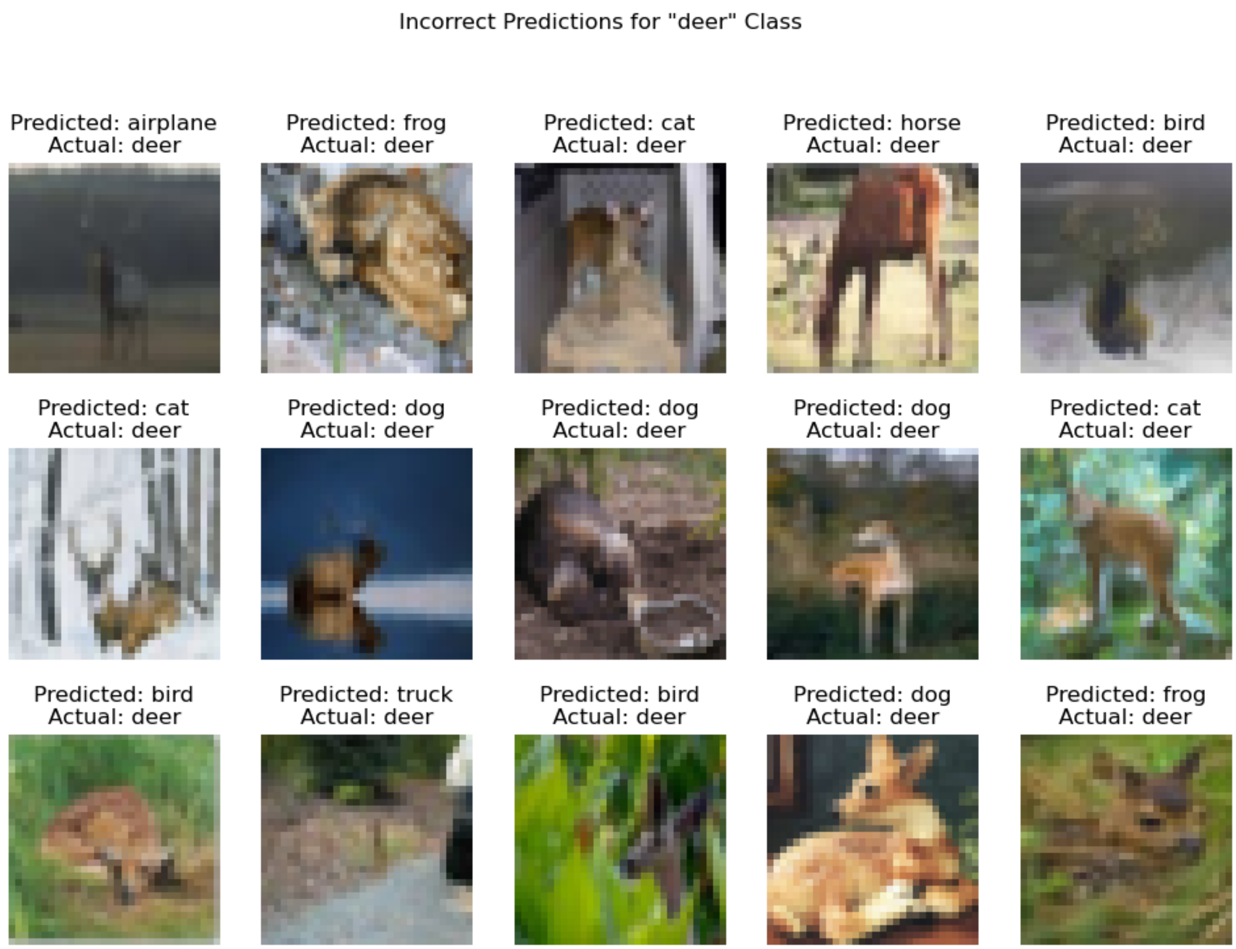

Correct Predictions for "deer" Class
Predicted: deer
Actual: deer
Predicted: deer
Actual: deer
Predicted: deer
Actual: deer
Predicted: deer
Actual: deer
Predicted: deer
Actual: deer
Predicted: deer
Actual: deer
Predicted: deer
Actual: deer
Predicted: deer
Actual: deer
Predicted: deer
Actual: deer
Predicted: deer
Actual: deer
Predicted: deer
Actual: deer
Predicted: deer
Actual: deer
Predicted: deer
Actual: deer
Predicted: deer
Actual: deer
Predicted: deer
Actual: deer


Incorrect Predictions for "deer" Class
Predicted: airplane
Actual: deer
Predicted: frog
Actual: deer
Predicted: cat
Actual: deer
Predicted: horse
Actual: deer
Predicted: bird
Actual: deer
Predicted: cat
Actual: deer
Predicted: dog
Actual: deer
Predicted: dog
Actual: deer
Predicted: dog
Actual: deer
Predicted: cat
Actual: deer
Predicted: bird
Actual: deer
Predicted: truck
Actual: deer
Predicted: bird
Actual: deer
Predicted: dog
Actual: deer
Predicted: frog
Actual: deer

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dog
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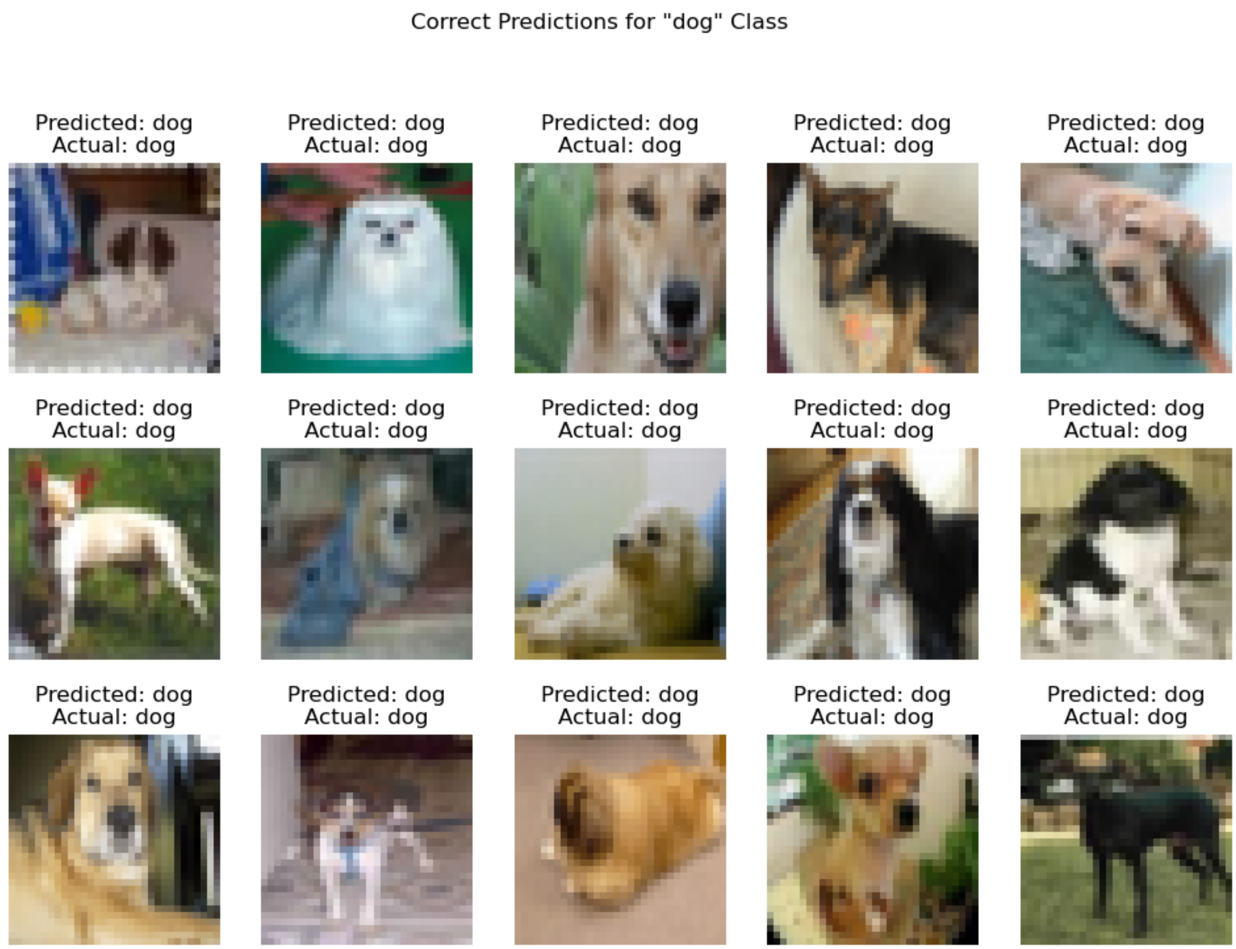
Correct Predictions for "dog" Class
Predicted: dog
Actual: dog
Predicted: dog
Actual: dog
Predicted: dog
Actual: dog
Predicted: dog
Actual: dog
Predicted: dog
Actual: dog
Predicted: dog
Actual: dog
Predicted: dog
Actual: dog
Predicted: dog
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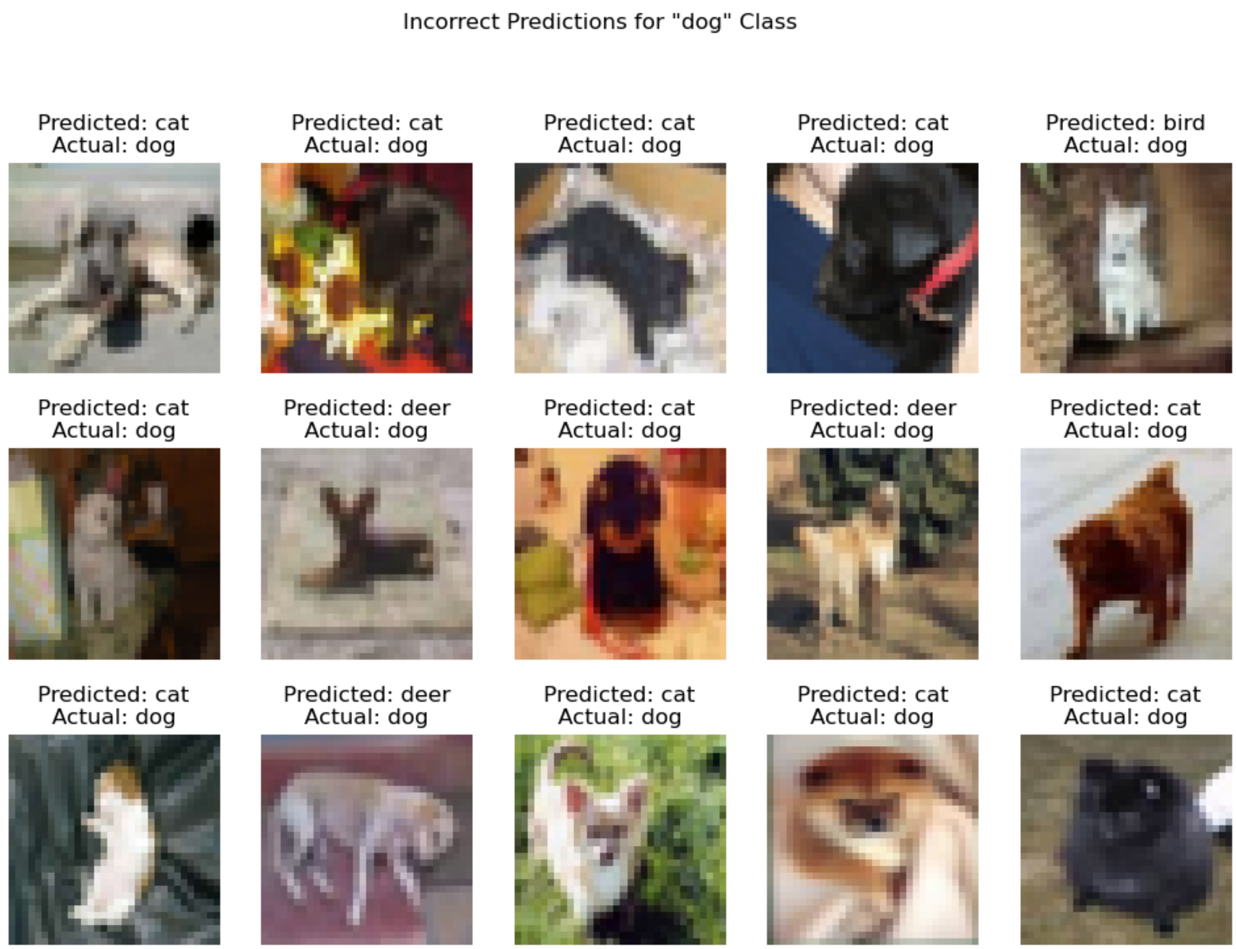
Predicted: dog
Actual: dog
Predicted: dog
Actual: dog
Predicted: dog
Actual: dog
Predicted: dog
Actual: dog
Predicted: dog
Actual: dog
Predicted: dog
Actual: dog


Incorrect Predictions for "dog" Class
Predicted: cat
Actual: dog
Predicted: cat
Actual: dog
Predicted: cat
Actual: dog
Predicted: cat
Actual: dog
Predicted: bird
Actual: dog
Predicted: cat
Actual: dog
Predicted: deer
Actual: dog
Predicted: cat
Actual: dog
Predicted: deer
Actual: dog
Predicted: cat
Actual: dog
Predicted: cat
Actual: dog
Predicted: deer
Actual: dog
Predicted: cat
Actual: dog
Predicted: cat
Actual: dog
Predicted: cat
Actual: dog

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frog
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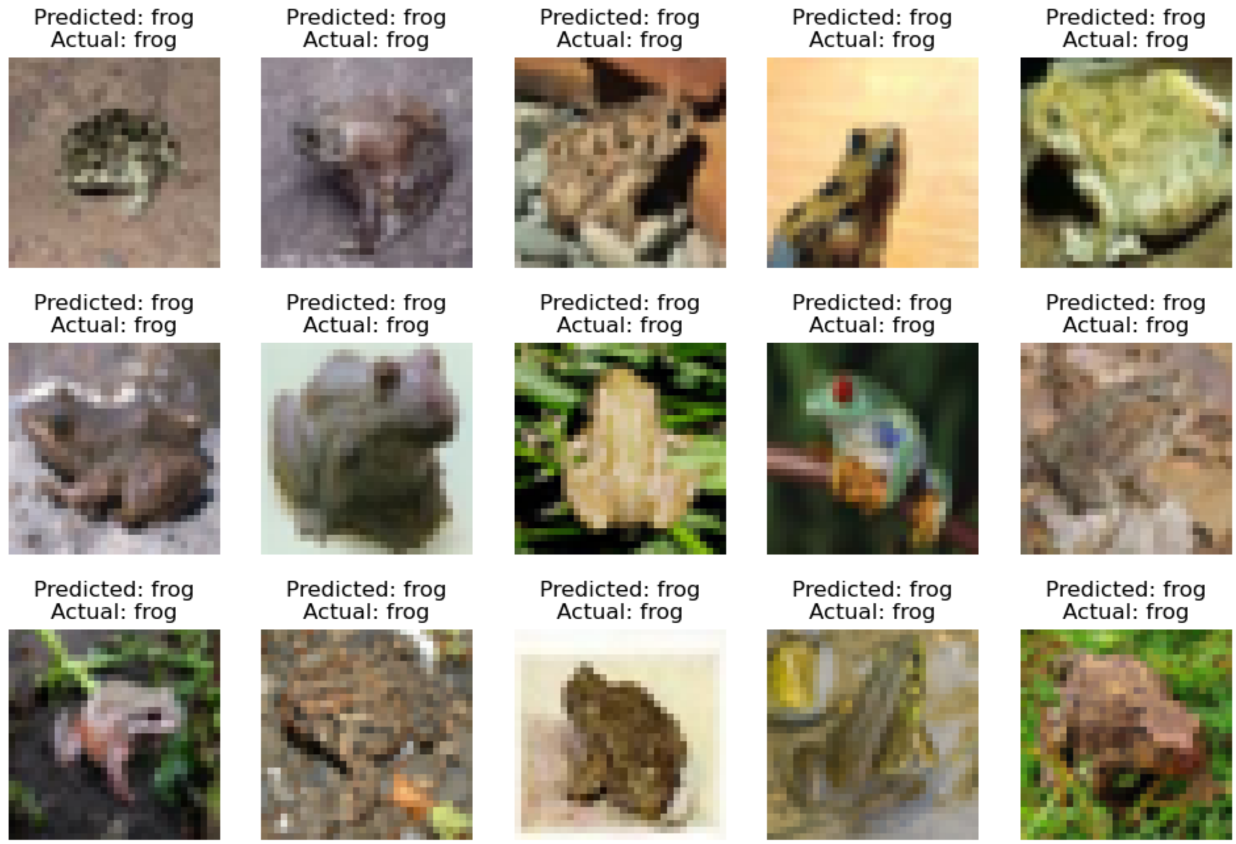
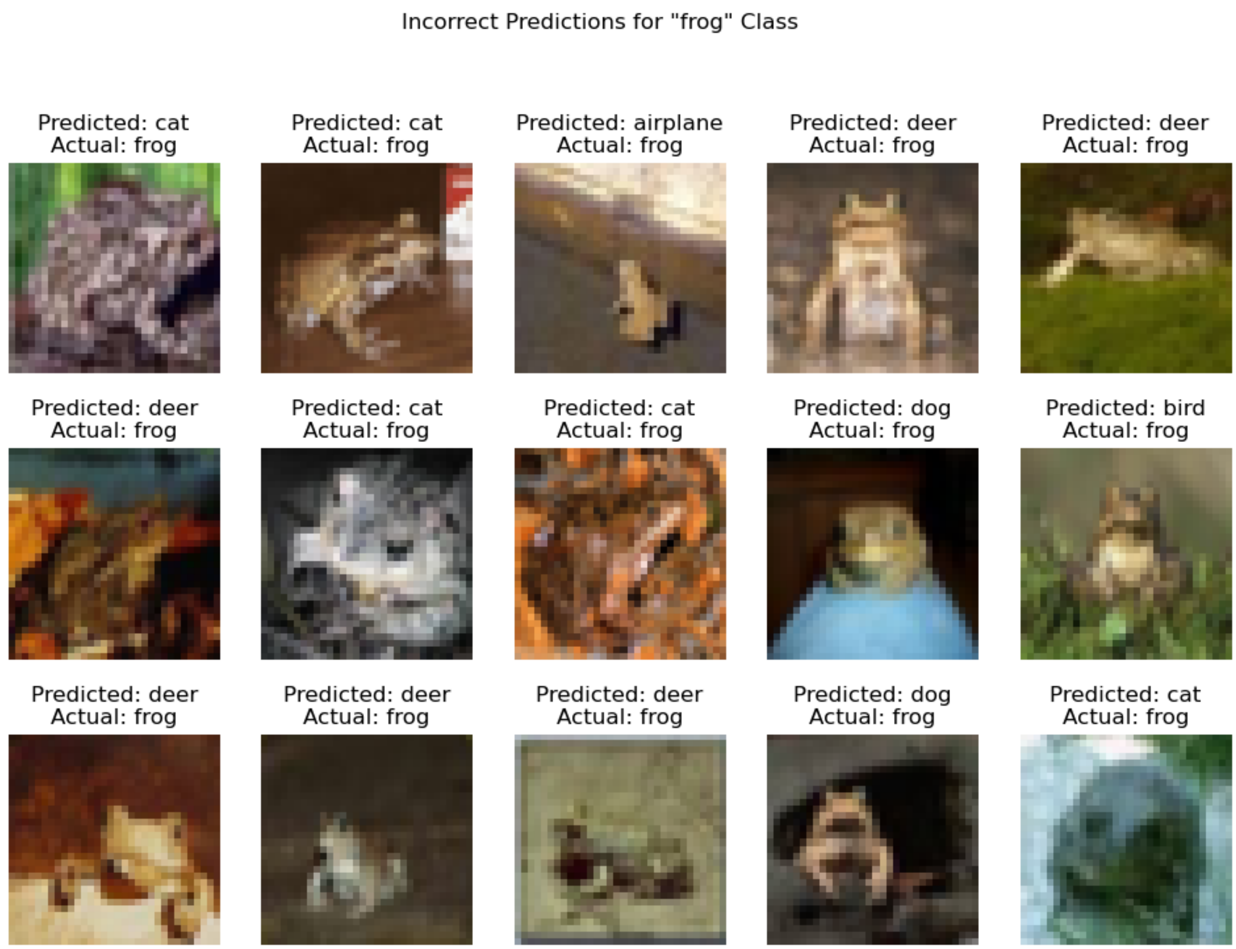
Correct Predictions for "frog" Class




Incorrect Predictions for "frog" Class
Predicted: cat
Actual: frog
Predicted: cat
Actual: frog
Predicted: airplane
Actual: frog
Predicted: deer
Actual: frog
Predicted: deer
Actual: frog
Predicted: deer
Actual: frog
Predicted: cat
Actual: frog
Predicted: cat
Actual: frog
Predicted: dog
Actual: frog
Predicted: bird
Actual: frog
Predicted: deer
Actual: frog
Predicted: deer
Actual: frog
Predicted: deer
Actual: frog
Predicted: dog
Actual: frog
Predicted: cat
Actual: frog

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horse
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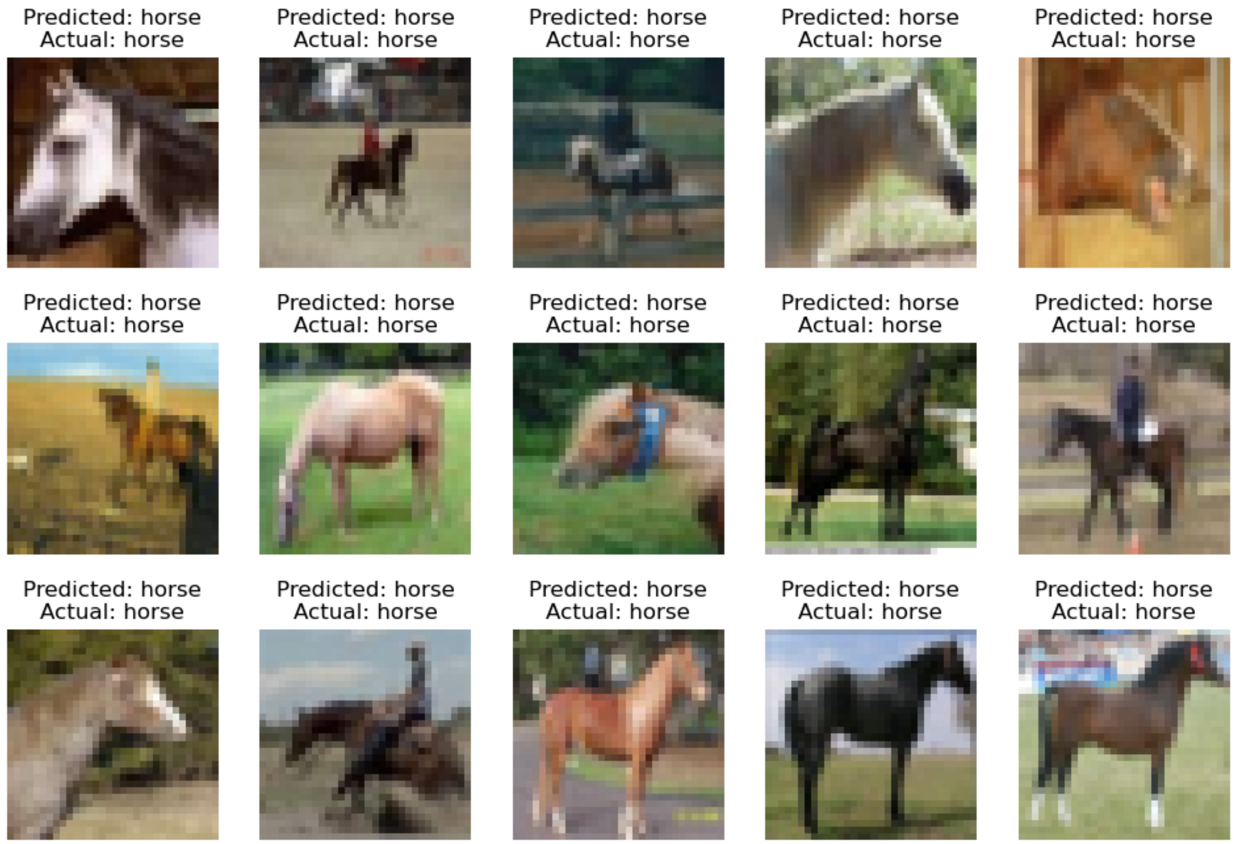
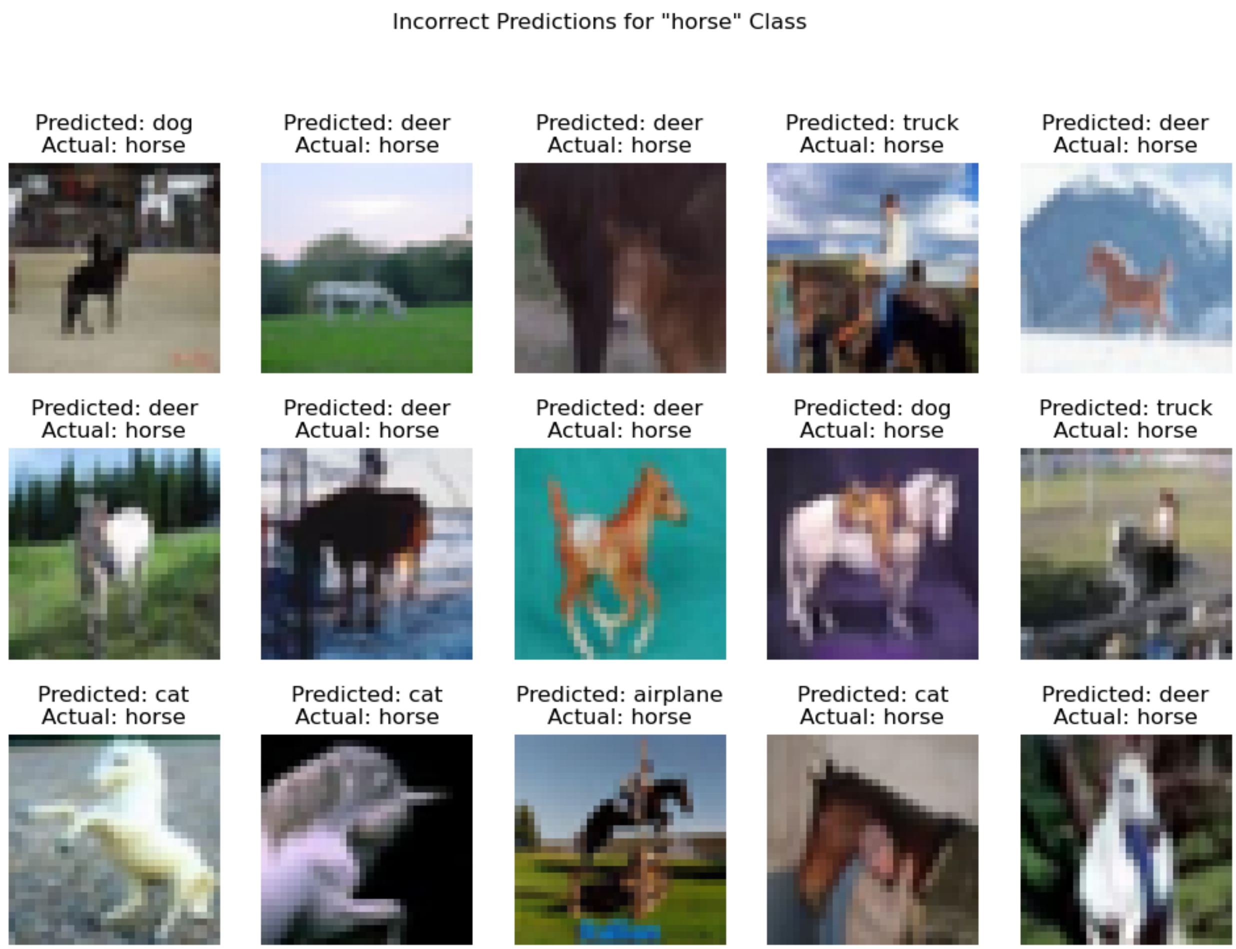
Correct Predictions for "horse" Class




Incorrect Predictions for "horse" Class
Predicted: dog
Actual: horse
Predicted: deer
Actual: horse
Predicted: deer
Actual: horse
Predicted: truck
Actual: horse
Predicted: deer
Actual: horse
Predicted: deer
Actual: horse
Predicted: deer
Actual: horse
Predicted: deer
Actual: horse
Predicted: dog
Actual: horse
Predicted: truck
Actual: horse
Predicted: cat
Actual: horse
Predicted: cat
Actual: horse
Predicted: airplane
Actual: horse
Predicted: cat
Actual: horse
Predicted: deer
Actual: horse

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ship
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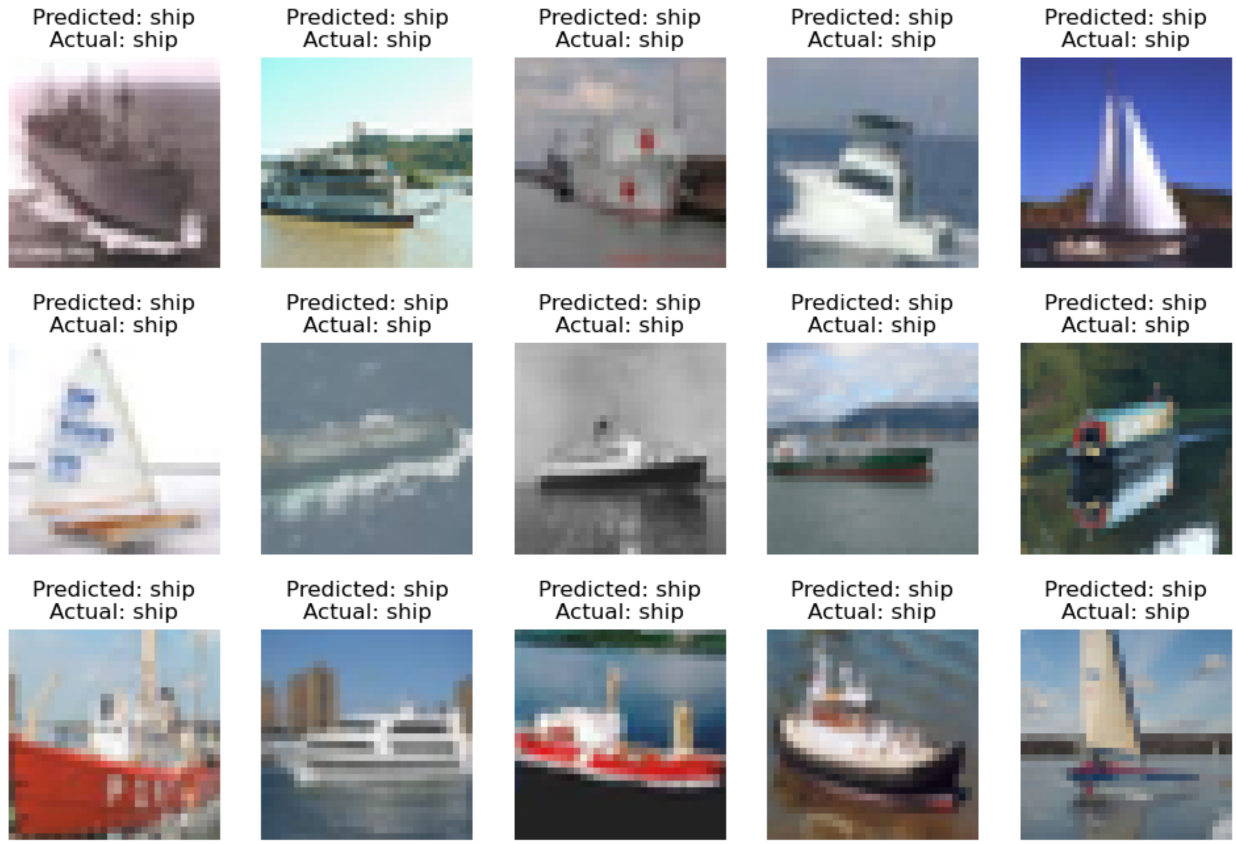
Correct Predictions for "ship" Class




Incorrect Predictions for "ship" Class
Predicted: cat
Actual: ship
Predicted: truck
Actual: ship
Predicted: automobile
Actual: ship
Predicted: automobile
Actual: ship
Predicted: deer
Actual: ship
Predicted: airplane
Actual: ship
Predicted: airplane
Actual: ship
Predicted: truck
Actual: ship
Predicted: automobile
Actual: ship
Predicted: truck
Actual: ship
Predicted: airplane
Actual: ship
Predicted: airplane
Actual: ship
Predicted: truck
Actual: ship
Predicted: frog
Actual: ship
Predicted: airplane
Actual: ship

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truck
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Correct Predictions for "truck" Class


Incorrect Predictions for "truck" Class
Predicted: automobile
Actual: truck
Predicted: automobile
Actual: truck
Predicted: automobile
Actual: truck
Predicted: automobile
Actual: truck
Predicted: deer
Actual: truck
Predicted: automobile
Actual: truck
Predicted: automobile
Actual: truck
Predicted: automobile
Actual: truck
Predicted: automobile
Actual: truck
Predicted: automobile
Actual: truck
Predicted: cat
Actual: truck
Predicted: automobile
Actual: truck
Predicted: automobile
Actual: truck
Predicted: deer
Actual: truck
Predicted: ship
Actual: truck