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In [2]: import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.datasets import cifar10
from tensorflow.keras import layers, models
from tensorflow.keras.optimizers import SGD
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
import seaborn as sns
import time
```

```
In [3]: # Load CIFAR-10 dataset
(X_train, y_train), (X_test, y_test) = cifar10.load_data()

# Normalize the images
X_train = X_train.astype('float32') / 255.0
X_test = X_test.astype('float32') / 255.0

# Ensure labels are integers (no one-hot encoding)
y_train = y_train.astype('int')
y_test = y_test.astype('int')

X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.2,
print (X_train.shape )
print (X_test.shape )

(40000, 32, 32, 3)
(10000, 32, 32, 3)
```

```
In [4]: # Create model function
def create_model(optimizer):
    model = models.Sequential()
    model.add(layers.Flatten(input_shape=(32, 32, 3)))
    model.add(layers.Dense(128, activation='relu'))
    model.add(layers.Dense(10, activation='softmax'))
    model.compile(optimizer=optimizer, loss='sparse_categorical_crossentropy', metr
    return model

# SGD with Warm Restarts optimizer
optimizer = SGD(learning_rate=tf.keras.optimizers.schedules.ExponentialDecay(
    initial_learning_rate =0.001,
    decay_steps =1000,
    decay_rate =0.96,
    staircase =False
))
```

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In [5]: from tensorflow.keras.callbacks import EarlyStopping

# Train and evaluate model
start_time = time.time()
model = create_model(optimizer)
early_stop = EarlyStopping(monitor='val_accuracy', patience=5, restore_best_weights
```

```
history = model.fit(X_train, y_train, epochs=50, batch_size=64, validation_data=(X_
end_time = time.time()

# Record training time
training_time = end_time - start_time
print(f"Training time: {training_time:.2f} seconds")
```

Epoch 1/50
625/625 [=====] - 5s 8ms/step - loss: 2.1772 - accuracy: 0.2069 - val_loss: 2.0739 - val_accuracy: 0.2672
Epoch 2/50
625/625 [=====] - 5s 8ms/step - loss: 2.0218 - accuracy: 0.2835 - val_loss: 1.9865 - val_accuracy: 0.2977
Epoch 3/50
625/625 [=====] - 4s 7ms/step - loss: 1.9571 - accuracy: 0.3135 - val_loss: 1.9369 - val_accuracy: 0.3236
Epoch 4/50
625/625 [=====] - 4s 6ms/step - loss: 1.9173 - accuracy: 0.3325 - val_loss: 1.9036 - val_accuracy: 0.3327
Epoch 5/50
625/625 [=====] - 6s 10ms/step - loss: 1.8899 - accuracy: 0.3434 - val_loss: 1.8819 - val_accuracy: 0.3411
Epoch 6/50
625/625 [=====] - 4s 6ms/step - loss: 1.8686 - accuracy: 0.3505 - val_loss: 1.8620 - val_accuracy: 0.3487
Epoch 7/50
625/625 [=====] - 4s 7ms/step - loss: 1.8517 - accuracy: 0.3570 - val_loss: 1.8462 - val_accuracy: 0.3552
Epoch 8/50
625/625 [=====] - 4s 6ms/step - loss: 1.8374 - accuracy: 0.3631 - val_loss: 1.8341 - val_accuracy: 0.3609
Epoch 9/50
625/625 [=====] - 4s 7ms/step - loss: 1.8251 - accuracy: 0.3676 - val_loss: 1.8239 - val_accuracy: 0.3624
Epoch 10/50
625/625 [=====] - 5s 7ms/step - loss: 1.8148 - accuracy: 0.3715 - val_loss: 1.8135 - val_accuracy: 0.3693
Epoch 11/50
625/625 [=====] - 4s 7ms/step - loss: 1.8050 - accuracy: 0.3753 - val_loss: 1.8037 - val_accuracy: 0.3720
Epoch 12/50
625/625 [=====] - 4s 6ms/step - loss: 1.7964 - accuracy: 0.3785 - val_loss: 1.7959 - val_accuracy: 0.3727
Epoch 13/50
625/625 [=====] - 4s 6ms/step - loss: 1.7884 - accuracy: 0.3818 - val_loss: 1.7893 - val_accuracy: 0.3756
Epoch 14/50
625/625 [=====] - 4s 7ms/step - loss: 1.7819 - accuracy: 0.3832 - val_loss: 1.7826 - val_accuracy: 0.3808
Epoch 15/50
625/625 [=====] - 4s 7ms/step - loss: 1.7749 - accuracy: 0.3865 - val_loss: 1.7785 - val_accuracy: 0.3803
Epoch 16/50
625/625 [=====] - 5s 7ms/step - loss: 1.7687 - accuracy: 0.3893 - val_loss: 1.7732 - val_accuracy: 0.3815
Epoch 17/50
625/625 [=====] - 5s 8ms/step - loss: 1.7632 - accuracy: 0.3892 - val_loss: 1.7657 - val_accuracy: 0.3832
Epoch 18/50
625/625 [=====] - 5s 8ms/step - loss: 1.7579 - accuracy: 0.3912 - val_loss: 1.7622 - val_accuracy: 0.3858
Epoch 19/50
625/625 [=====] - 5s 8ms/step - loss: 1.7529 - accuracy: 0.

3939 - val_loss: 1.7578 - val_accuracy: 0.3872
Epoch 20/50
625/625 [=====] - 4s 7ms/step - loss: 1.7479 - accuracy: 0.
3965 - val_loss: 1.7545 - val_accuracy: 0.3839
Epoch 21/50
625/625 [=====] - 4s 6ms/step - loss: 1.7435 - accuracy: 0.
3979 - val_loss: 1.7487 - val_accuracy: 0.3889
Epoch 22/50
625/625 [=====] - 4s 6ms/step - loss: 1.7394 - accuracy: 0.
3991 - val_loss: 1.7453 - val_accuracy: 0.3921
Epoch 23/50
625/625 [=====] - 4s 7ms/step - loss: 1.7353 - accuracy: 0.
4004 - val_loss: 1.7423 - val_accuracy: 0.3930
Epoch 24/50
625/625 [=====] - 4s 6ms/step - loss: 1.7315 - accuracy: 0.
4009 - val_loss: 1.7375 - val_accuracy: 0.3966
Epoch 25/50
625/625 [=====] - 4s 7ms/step - loss: 1.7277 - accuracy: 0.
4028 - val_loss: 1.7340 - val_accuracy: 0.3946
Epoch 26/50
625/625 [=====] - 3s 5ms/step - loss: 1.7244 - accuracy: 0.
4040 - val_loss: 1.7312 - val_accuracy: 0.3977
Epoch 27/50
625/625 [=====] - 4s 7ms/step - loss: 1.7210 - accuracy: 0.
4065 - val_loss: 1.7302 - val_accuracy: 0.3961
Epoch 28/50
625/625 [=====] - 4s 6ms/step - loss: 1.7176 - accuracy: 0.
4082 - val_loss: 1.7252 - val_accuracy: 0.4000
Epoch 29/50
625/625 [=====] - 3s 5ms/step - loss: 1.7146 - accuracy: 0.
4082 - val_loss: 1.7235 - val_accuracy: 0.3991
Epoch 30/50
625/625 [=====] - 4s 6ms/step - loss: 1.7114 - accuracy: 0.
4101 - val_loss: 1.7201 - val_accuracy: 0.4022
Epoch 31/50
625/625 [=====] - 3s 5ms/step - loss: 1.7087 - accuracy: 0.
4110 - val_loss: 1.7177 - val_accuracy: 0.4032
Epoch 32/50
625/625 [=====] - 4s 6ms/step - loss: 1.7059 - accuracy: 0.
4119 - val_loss: 1.7156 - val_accuracy: 0.4026
Epoch 33/50
625/625 [=====] - 4s 6ms/step - loss: 1.7033 - accuracy: 0.
4119 - val_loss: 1.7134 - val_accuracy: 0.4027
Epoch 34/50
625/625 [=====] - 3s 5ms/step - loss: 1.7005 - accuracy: 0.
4131 - val_loss: 1.7109 - val_accuracy: 0.4053
Epoch 35/50
625/625 [=====] - 3s 6ms/step - loss: 1.6983 - accuracy: 0.
4142 - val_loss: 1.7087 - val_accuracy: 0.4059
Epoch 36/50
625/625 [=====] - 4s 6ms/step - loss: 1.6960 - accuracy: 0.
4161 - val_loss: 1.7066 - val_accuracy: 0.4063
Epoch 37/50
625/625 [=====] - 6s 9ms/step - loss: 1.6936 - accuracy: 0.
4166 - val_loss: 1.7048 - val_accuracy: 0.4068
Epoch 38/50

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625/625 [=====] - 4s 7ms/step - loss: 1.6918 - accuracy: 0.4168 - val_loss: 1.7032 - val_accuracy: 0.4057
Epoch 39/50
625/625 [=====] - 10s 15ms/step - loss: 1.6894 - accuracy: 0.4179 - val_loss: 1.7022 - val_accuracy: 0.4069
Epoch 40/50
625/625 [=====] - 5s 8ms/step - loss: 1.6875 - accuracy: 0.4186 - val_loss: 1.6990 - val_accuracy: 0.4087
Epoch 41/50
625/625 [=====] - 4s 7ms/step - loss: 1.6858 - accuracy: 0.4203 - val_loss: 1.6974 - val_accuracy: 0.4073
Epoch 42/50
625/625 [=====] - 5s 7ms/step - loss: 1.6839 - accuracy: 0.4196 - val_loss: 1.6972 - val_accuracy: 0.4098
Epoch 43/50
625/625 [=====] - 4s 6ms/step - loss: 1.6820 - accuracy: 0.4207 - val_loss: 1.6945 - val_accuracy: 0.4118
Epoch 44/50
625/625 [=====] - 5s 7ms/step - loss: 1.6803 - accuracy: 0.4229 - val_loss: 1.6932 - val_accuracy: 0.4092
Epoch 45/50
625/625 [=====] - 4s 7ms/step - loss: 1.6785 - accuracy: 0.4228 - val_loss: 1.6921 - val_accuracy: 0.4080
Epoch 46/50
625/625 [=====] - 4s 7ms/step - loss: 1.6768 - accuracy: 0.4225 - val_loss: 1.6907 - val_accuracy: 0.4102
Epoch 47/50
625/625 [=====] - 4s 6ms/step - loss: 1.6751 - accuracy: 0.4238 - val_loss: 1.6907 - val_accuracy: 0.4117
Epoch 48/50
625/625 [=====] - 4s 6ms/step - loss: 1.6738 - accuracy: 0.4242 - val_loss: 1.6877 - val_accuracy: 0.4108
Training time: 208.52 seconds

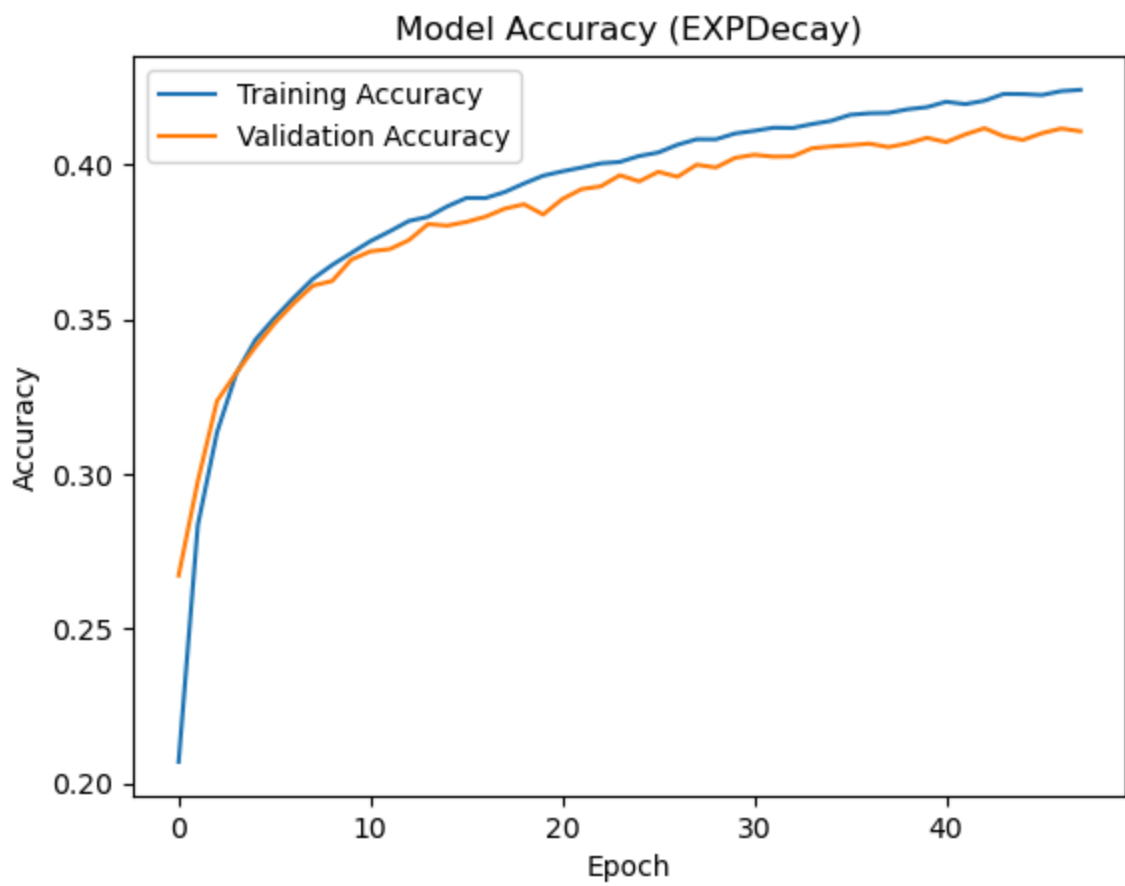
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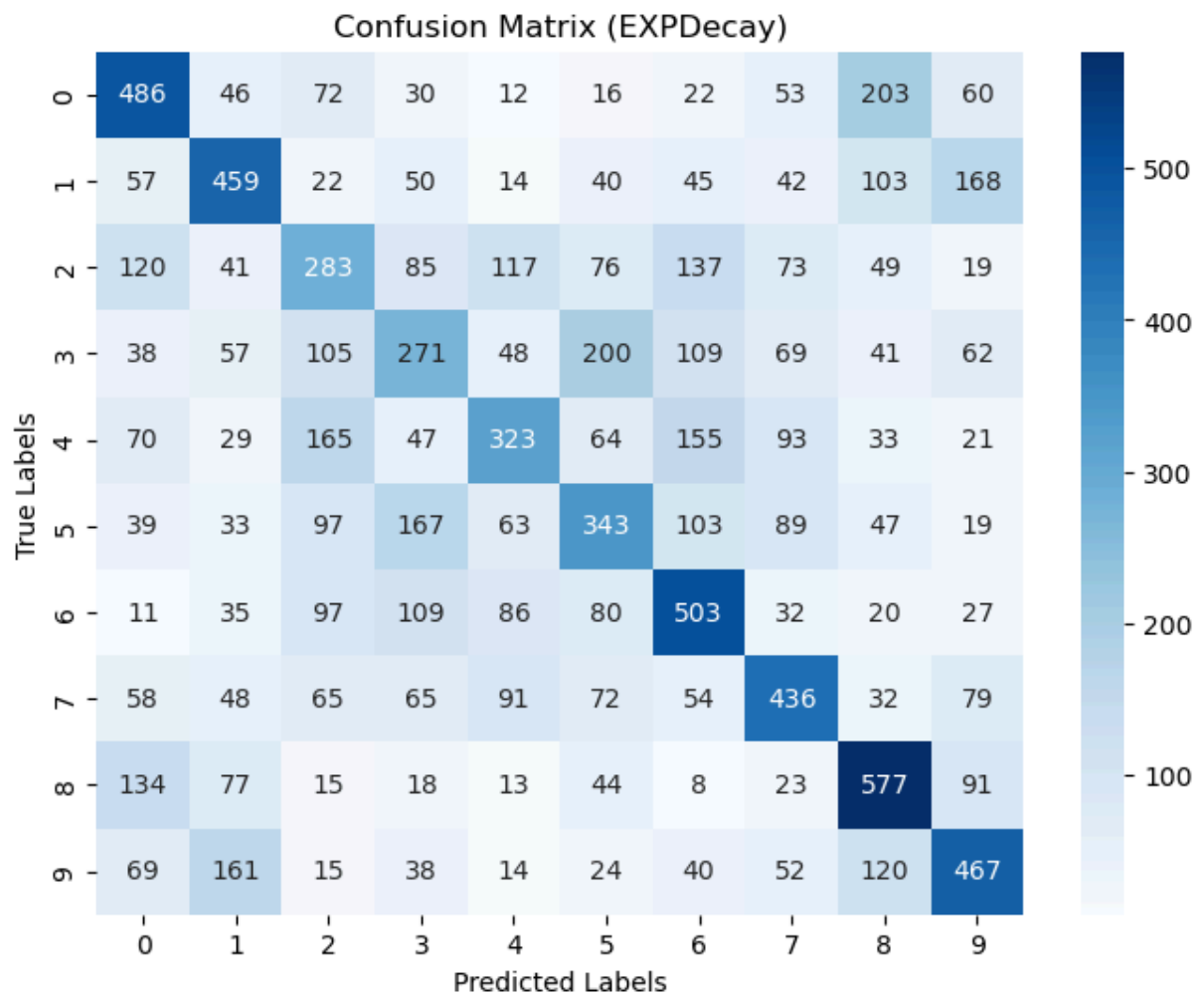
In [6]: # Plot training and validation accuracy
accuracy = history.history['accuracy']
val_accuracy = history.history['val_accuracy']
plt.plot(accuracy, label='Training Accuracy')
plt.plot(val_accuracy, label='Validation Accuracy')
plt.title('Model Accuracy (EXPDecay)')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

# Confusion Matrix
y_pred = np.argmax(model.predict(X_test), axis=1)
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=np.arange(10), yticklabels=np.arange(10))
plt.title('Confusion Matrix (EXPDecay)')
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()

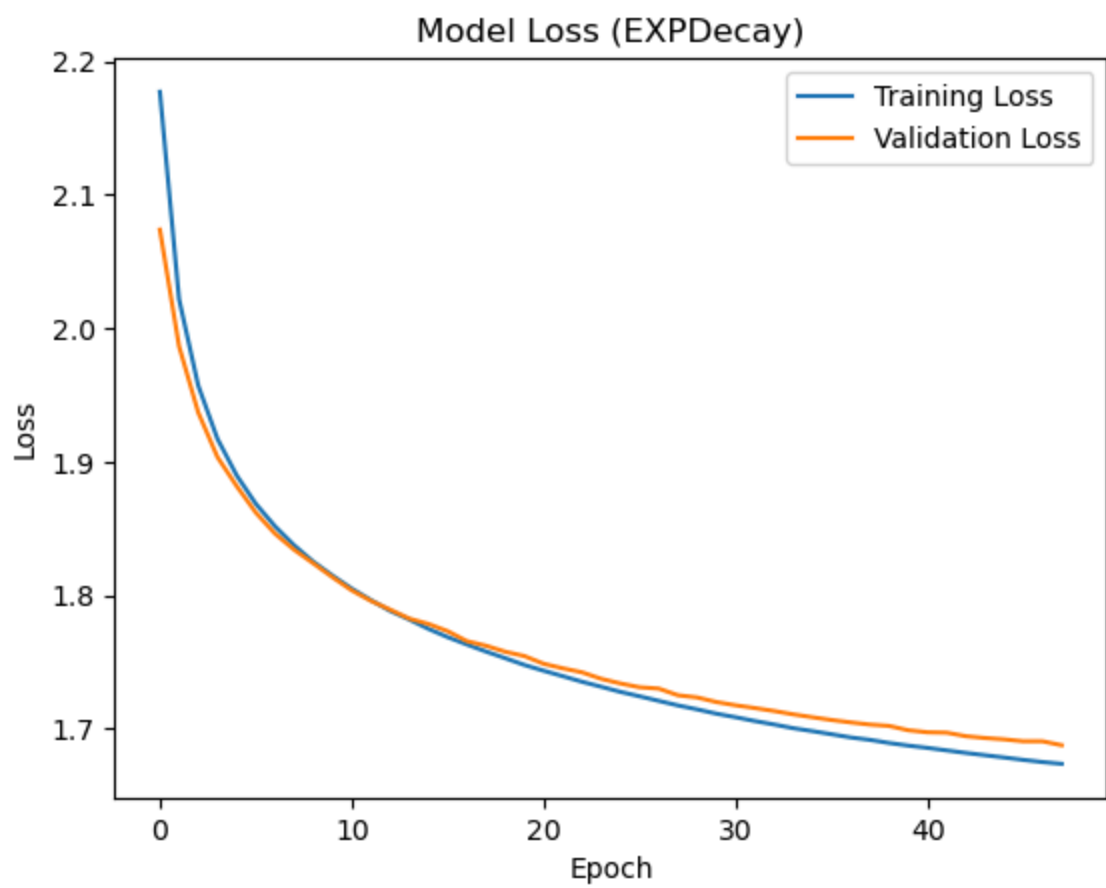
```



313/313 [=====] - 5s 15ms/step



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In [7]: # Plot training and validation accuracy
accuracy = history.history['loss']
val_accuracy = history.history['val_loss']
plt.plot(accuracy, label='Training Loss')
plt.plot(val_accuracy, label='Validation Loss')
plt.title('Model Loss (EXPDecay)')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



In []: