```python
# 1. Import necessary libraries, such as TensorFlow, PyTorch, or
Keras.

# 2. Download and load the CIFAR-10 dataset.

# 3. Normalize pixel values to the [0, 1] range and consider data
augmentation techniques.

# 4. Define CNN architecture, ensuring at least two different hidden
layer sizes.

# 5. Implement L2 regularization to prevent overfitting.

# 6. Specify loss function, optimizer, and metrics.

# 7. Train the model using the training data.

# 8. Evaluate the model on both training and testing datasets to
obtain classification error.

# 9. Repeat the process for different hidden layer sizes and
regularization configurations.

# 10. Create a table with classification errors for each
configuration.

#CODE

import numpy as np
import matplotlib.pyplot as plt
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
from keras.datasets import cifar10
from keras.utils import to_categorical
from keras.preprocessing.image import ImageDataGenerator
from keras.regularizers import l2
from sklearn.model_selection import train_test_split
import pandas as pd

# Step 1: Import Libraries and Load Dataset
(x_train, y_train), (x_test, y_test) = cifar10.load_data()

# Step 2: Data Preprocessing
x_train = x_train.astype('float32') / 255.0
x_test = x_test.astype('float32') / 255.0

datagen = ImageDataGenerator(
    rotation_range=15,
    width_shift_range=0.1,
    height_shift_range=0.1,
    horizontal_flip=True
```

```
)

datagen.fit(x_train)

# Step 3 and 4: Define CNN Architecture and Add Regularization
hidden_layer_sizes = [128, 64]
regularization_strengths = [0.01, 0.001]

results = []

for size in hidden_layer_sizes:
    for strength in regularization_strengths:
        # Define CNN architecture with different hidden layer sizes
and regularization
        model = Sequential()
        model.add(Conv2D(32, (3, 3), activation='relu',
kernel_regularizer=l2(strength), input_shape=(32, 32, 3)))
        model.add(MaxPooling2D((2, 2)))
        model.add(Conv2D(64, (3, 3), activation='relu',
kernel_regularizer=l2(strength)))
        model.add(MaxPooling2D((2, 2)))
        model.add(Flatten())
        model.add(Dense(size, activation='relu',
kernel_regularizer=l2(strength)))
        model.add(Dense(10, activation='softmax'))

        # Step 5: Compile Model
        model.compile(optimizer='adam',
loss='categorical_crossentropy', metrics=['accuracy'])

        # Step 6: Train the Model
        history = model.fit(datagen.flow(x_train,
to_categorical(y_train), batch_size=64),
                            epochs=10, validation_data=(x_test,
to_categorical(y_test)))

        # Step 7: Evaluate Model
        train_loss, train_accuracy = model.evaluate(x_train,
to_categorical(y_train))
        test_loss, test_accuracy = model.evaluate(x_test,
to_categorical(y_test))

        # Step 8: Store Results
        results.append({
            'Hidden Layer Size': size,
            'Regularization Strength': strength,
            'Train Classification Error': 1 - train_accuracy,
            'Test Classification Error': 1 - test_accuracy
        })
```

```
Epoch 1/10
782/782 [==============================] - 109s 138ms/step - loss:
2.0341 - accuracy: 0.3453 - val_loss: 1.7540 - val_accuracy: 0.4284
Epoch 2/10
782/782 [==============================] - 106s 135ms/step - loss:
1.7884 - accuracy: 0.4151 - val_loss: 1.6855 - val_accuracy: 0.4485
Epoch 3/10
782/782 [==============================] - 93s 119ms/step - loss:
1.7300 - accuracy: 0.4337 - val_loss: 1.6037 - val_accuracy: 0.4877
Epoch 4/10
782/782 [==============================] - 90s 115ms/step - loss:
1.6877 - accuracy: 0.4546 - val_loss: 1.5929 - val_accuracy: 0.4910
Epoch 5/10
782/782 [==============================] - 88s 113ms/step - loss:
1.6568 - accuracy: 0.4667 - val_loss: 1.5675 - val_accuracy: 0.5042
Epoch 6/10
782/782 [==============================] - 89s 114ms/step - loss:
1.6353 - accuracy: 0.4757 - val_loss: 1.5501 - val_accuracy: 0.5056
Epoch 7/10
782/782 [==============================] - 90s 115ms/step - loss:
1.6120 - accuracy: 0.4866 - val_loss: 1.5471 - val_accuracy: 0.5223
Epoch 8/10
782/782 [==============================] - 89s 114ms/step - loss:
1.5965 - accuracy: 0.4955 - val_loss: 1.4945 - val_accuracy: 0.5342
Epoch 9/10
782/782 [==============================] - 89s 113ms/step - loss:
1.5800 - accuracy: 0.5047 - val_loss: 1.4898 - val_accuracy: 0.5341
Epoch 10/10
782/782 [==============================] - 87s 111ms/step - loss:
1.5700 - accuracy: 0.5067 - val_loss: 1.4644 - val_accuracy: 0.5573
1563/1563 [==============================] - 21s 14ms/step - loss:
1.4696 - accuracy: 0.5543
313/313 [==============================] - 4s 12ms/step - loss: 1.4644
- accuracy: 0.5573
Epoch 1/10
782/782 [==============================] - 91s 115ms/step - loss:
1.7388 - accuracy: 0.4046 - val_loss: 1.4948 - val_accuracy: 0.4954
Epoch 2/10
782/782 [==============================] - 90s 115ms/step - loss:
1.5150 - accuracy: 0.4979 - val_loss: 1.3986 - val_accuracy: 0.5413
Epoch 3/10
782/782 [==============================] - 90s 115ms/step - loss:
1.4189 - accuracy: 0.5407 - val_loss: 1.2803 - val_accuracy: 0.5972
Epoch 4/10
782/782 [==============================] - 90s 115ms/step - loss:
1.3639 - accuracy: 0.5643 - val_loss: 1.3511 - val_accuracy: 0.5804
Epoch 5/10
782/782 [==============================] - 88s 112ms/step - loss:
1.3278 - accuracy: 0.5808 - val_loss: 1.2327 - val_accuracy: 0.6181
Epoch 6/10
```

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782/782 [==============================] - 89s 113ms/step - loss:
1.2943 - accuracy: 0.5978 - val_loss: 1.3105 - val_accuracy: 0.6044
Epoch 7/10
782/782 [==============================] - 88s 112ms/step - loss:
1.2728 - accuracy: 0.6051 - val_loss: 1.1853 - val_accuracy: 0.6359
Epoch 8/10
782/782 [==============================] - 87s 111ms/step - loss:
1.2461 - accuracy: 0.6151 - val_loss: 1.2145 - val_accuracy: 0.6333
Epoch 9/10
782/782 [==============================] - 87s 112ms/step - loss:
1.2311 - accuracy: 0.6219 - val_loss: 1.1866 - val_accuracy: 0.6400
Epoch 10/10
782/782 [==============================] - 88s 113ms/step - loss:
1.2101 - accuracy: 0.6309 - val_loss: 1.1742 - val_accuracy: 0.6530
1563/1563 [==============================] - 19s 12ms/step - loss:
1.1449 - accuracy: 0.6632
313/313 [==============================] - 5s 15ms/step - loss: 1.1742
- accuracy: 0.6530
Epoch 1/10
782/782 [==============================] - 85s 108ms/step - loss:
2.0456 - accuracy: 0.3240 - val_loss: 1.8263 - val_accuracy: 0.4018
Epoch 2/10
782/782 [==============================] - 86s 110ms/step - loss:
1.8044 - accuracy: 0.4066 - val_loss: 1.6898 - val_accuracy: 0.4537
Epoch 3/10
782/782 [==============================] - 86s 109ms/step - loss:
1.7377 - accuracy: 0.4292 - val_loss: 1.6354 - val_accuracy: 0.4674
Epoch 4/10
782/782 [==============================] - 84s 107ms/step - loss:
1.7038 - accuracy: 0.4470 - val_loss: 1.6610 - val_accuracy: 0.4570
Epoch 5/10
782/782 [==============================] - 84s 107ms/step - loss:
1.6674 - accuracy: 0.4590 - val_loss: 1.6039 - val_accuracy: 0.4845
Epoch 6/10
782/782 [==============================] - 85s 109ms/step - loss:
1.6466 - accuracy: 0.4651 - val_loss: 1.5627 - val_accuracy: 0.4966
Epoch 7/10
782/782 [==============================] - 85s 108ms/step - loss:
1.6313 - accuracy: 0.4710 - val_loss: 1.5358 - val_accuracy: 0.5121
Epoch 8/10
782/782 [==============================] - 83s 107ms/step - loss:
1.6218 - accuracy: 0.4745 - val_loss: 1.5400 - val_accuracy: 0.5081
Epoch 9/10
782/782 [==============================] - 85s 109ms/step - loss:
1.6046 - accuracy: 0.4814 - val_loss: 1.5514 - val_accuracy: 0.5029
Epoch 10/10
782/782 [==============================] - 84s 107ms/step - loss:
1.5942 - accuracy: 0.4841 - val_loss: 1.4941 - val_accuracy: 0.5220
1563/1563 [==============================] - 19s 12ms/step - loss:
1.4944 - accuracy: 0.5226
```

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313/313 [==============================] - 5s 15ms/step - loss: 1.4941
- accuracy: 0.5220
Epoch 1/10
782/782 [==============================] - 89s 111ms/step - loss:
1.7433 - accuracy: 0.3925 - val_loss: 1.4915 - val_accuracy: 0.4927
Epoch 2/10
782/782 [==============================] - 86s 110ms/step - loss:
1.5126 - accuracy: 0.4944 - val_loss: 1.4216 - val_accuracy: 0.5266
Epoch 3/10
782/782 [==============================] - 86s 110ms/step - loss:
1.4230 - accuracy: 0.5377 - val_loss: 1.2791 - val_accuracy: 0.5900
Epoch 4/10
782/782 [==============================] - 85s 109ms/step - loss:
1.3681 - accuracy: 0.5579 - val_loss: 1.2658 - val_accuracy: 0.5903
Epoch 5/10
782/782 [==============================] - 87s 111ms/step - loss:
1.3246 - accuracy: 0.5784 - val_loss: 1.2053 - val_accuracy: 0.6282
Epoch 6/10
782/782 [==============================] - 84s 108ms/step - loss:
1.2957 - accuracy: 0.5899 - val_loss: 1.1580 - val_accuracy: 0.6434
Epoch 7/10
782/782 [==============================] - 87s 111ms/step - loss:
1.2767 - accuracy: 0.5997 - val_loss: 1.1949 - val_accuracy: 0.6377
Epoch 8/10
782/782 [==============================] - 85s 108ms/step - loss:
1.2528 - accuracy: 0.6100 - val_loss: 1.1823 - val_accuracy: 0.6359
Epoch 9/10
782/782 [==============================] - 87s 111ms/step - loss:
1.2346 - accuracy: 0.6169 - val_loss: 1.1289 - val_accuracy: 0.6602
Epoch 10/10
782/782 [==============================] - 85s 108ms/step - loss:
1.2258 - accuracy: 0.6188 - val_loss: 1.1238 - val_accuracy: 0.6554
1563/1563 [==============================] - 21s 13ms/step - loss:
1.1011 - accuracy: 0.6639
313/313 [==============================] - 4s 14ms/step - loss: 1.1238
- accuracy: 0.6554
```
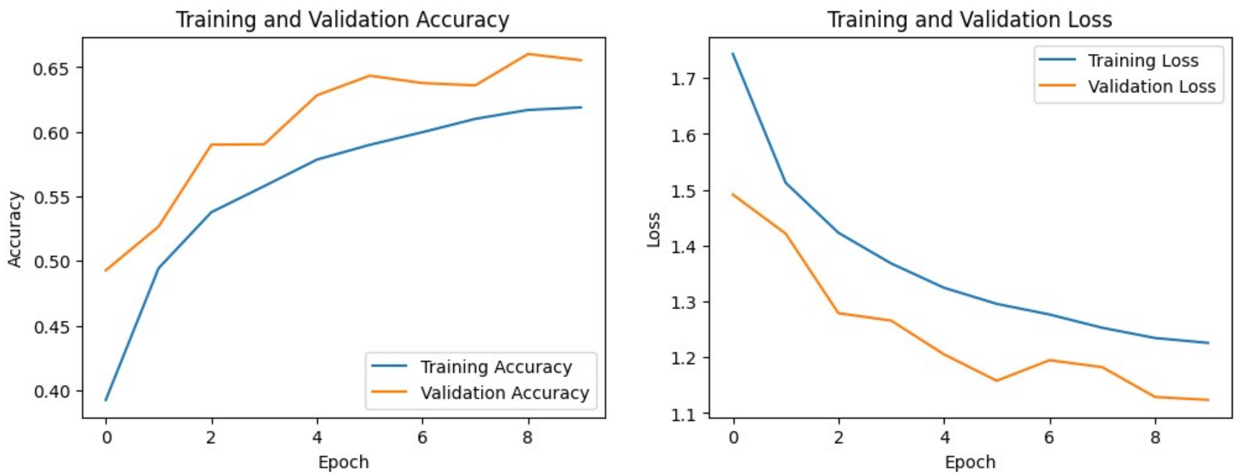

```
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Training and Validation Accuracy')
plt.legend()


plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
```

```
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Training and Validation Loss')
plt.legend()

plt.show()


# Step 9: Create a Table with Classification Errors
results_df = pd.DataFrame(results)

# Print the results table
print(results_df)
```




```
   Hidden Layer Size  Regularization Strength  Train Classification
Error  \
0                128                    0.010
0.44570
1                128                    0.001
0.33684
2                 64                    0.010
0.47740
3                 64                    0.001
0.33606

   Test Classification Error
0                     0.4427
1                     0.3470
2                     0.4780
3                     0.3446


# Solution 2:
```

```
# Understand the Baseline:

# Carefully read and understand the baseline code provided.
# Identify the architecture, hyperparameters, and training process
used in the baseline model.

# Try Different Architectures:

# Modify the baseline architecture by experimenting with different
types of RNN architectures, such as LSTM or GRU layers.
# Adjust the number of layers, hidden units, and dropout rates to find
a better configuration.

# Train Multiple Models:

# Train multiple language models with different configurations.
# Experiment with varying learning rates, batch sizes, and training
epochs.

# Ensemble Models:

# Implement model ensembling by training multiple models and combining
their predictions.
# You can use techniques like averaging or weighted averaging to
ensemble the outputs of multiple models.

# Implement Regularization Techniques:

# Apply regularization techniques, such as dropout or L2
regularization, to prevent overfitting.
# Optimize Hyperparameters:

# Conduct a hyperparameter search to find optimal values for learning
rate, batch size, and other relevant parameters.


# Monitor Training Progress:

# Implement callbacks to monitor training progress and prevent
overfitting.
# Visualize training curves, including training and validation loss,
to identify potential issues.

# Evaluate Model Performance:

# Evaluate the performance of each modified model on a separate
validation set.
# Compare the results against the baseline and identify models that
show improvement.
```

```python
# CODE

import numpy as np
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt

# Load your dataset
with open('human_chat.txt', 'r', encoding='utf-8') as file:
    data = file.readlines()

# Assuming data is a list of conversations
# Preprocess the text data
tokenizer = Tokenizer()
tokenizer.fit_on_texts(data)
total_words = len(tokenizer.word_index) + 1

# Convert text data to sequences
input_sequences = tokenizer.texts_to_sequences(data)

# Create input sequences and corresponding target sequences
sequences = []
for seq in input_sequences:
    for i in range(1, len(seq)):
        n_gram_sequence = seq[:i+1]
        sequences.append(n_gram_sequence)

# Pad sequences for equal length
max_sequence_length = max([len(seq) for seq in sequences])
sequences = pad_sequences(sequences, maxlen=max_sequence_length,
padding='pre')

X, y = sequences[:, :-1], sequences[:, -1]

# Split the dataset into training and validation sets
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2,
random_state=42)

# Basic LSTM Model
def build_lstm_model(vocab_size, embedding_dim, lstm_units):
    model = Sequential()
    model.add(Embedding(input_dim=vocab_size,
output_dim=embedding_dim, input_length=X.shape[1]))
    model.add(LSTM(units=lstm_units))
    model.add(Dense(units=vocab_size, activation='softmax'))
    model.compile(optimizer=Adam(),
```

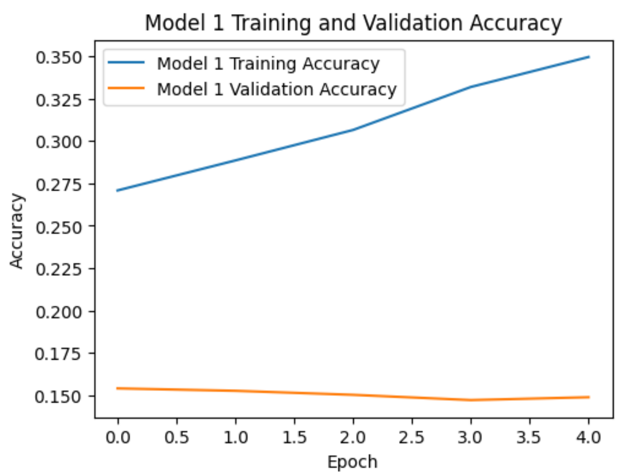
```
loss='sparse_categorical_crossentropy', metrics=['accuracy'])
    return model

# Ensemble of LSTM Models
def ensemble_models(num_models, vocab_size, embedding_dim,
lstm_units):
    models = []
    for _ in range(num_models):
        model = build_lstm_model(vocab_size, embedding_dim,
lstm_units)
        models.append(model)
    return models

# Train and Evaluate Models
def train_and_evaluate(models, X_train, y_train, X_val, y_val, epochs,
batch_size):
    for i, model in enumerate(models):
        print(f"Training Model {i + 1}...")
        model.fit(X_train, y_train, epochs=epochs,
batch_size=batch_size, validation_data=(X_val, y_val))

embedding_dim = 50
lstm_units = 100
num_models = 3

models = ensemble_models(num_models, total_words, embedding_dim,
lstm_units)

# Train and Evaluate Ensemble
train_and_evaluate(models, X_train, y_train, X_val, y_val, epochs=5,
batch_size=32)

Training Model 1...
Epoch 1/5
527/527 [==============================] - 90s 165ms/step - loss:
6.2281 - accuracy: 0.0534 - val_loss: 5.9531 - val_accuracy: 0.0793
Epoch 2/5
527/527 [==============================] - 76s 144ms/step - loss:
5.6745 - accuracy: 0.0882 - val_loss: 5.8931 - val_accuracy: 0.0921
Epoch 3/5
527/527 [==============================] - 76s 143ms/step - loss:
5.4801 - accuracy: 0.1031 - val_loss: 5.8479 - val_accuracy: 0.1011
Epoch 4/5
527/527 [==============================] - 79s 150ms/step - loss:
5.3015 - accuracy: 0.1147 - val_loss: 5.7942 - val_accuracy: 0.1154
Epoch 5/5
527/527 [==============================] - 75s 142ms/step - loss:
5.1126 - accuracy: 0.1316 - val_loss: 5.7421 - val_accuracy: 0.1242
Training Model 2...
Epoch 1/5
```

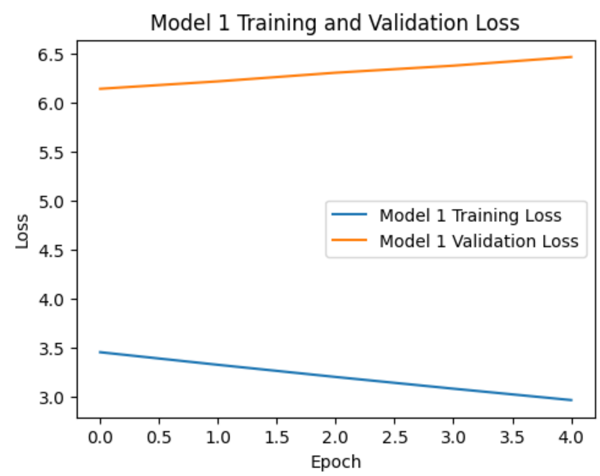
```
527/527 [==============================] - 78s 142ms/step - loss:
6.2387 - accuracy: 0.0509 - val_loss: 5.9593 - val_accuracy: 0.0748
Epoch 2/5
527/527 [==============================] - 75s 142ms/step - loss:
5.6796 - accuracy: 0.0892 - val_loss: 5.9034 - val_accuracy: 0.0909
Epoch 3/5
527/527 [==============================] - 73s 139ms/step - loss:
5.4861 - accuracy: 0.1061 - val_loss: 5.8344 - val_accuracy: 0.1052
Epoch 4/5
527/527 [==============================] - 73s 139ms/step - loss:
5.2865 - accuracy: 0.1196 - val_loss: 5.7764 - val_accuracy: 0.1185
Epoch 5/5
527/527 [==============================] - 75s 142ms/step - loss:
5.0957 - accuracy: 0.1333 - val_loss: 5.7312 - val_accuracy: 0.1273
Training Model 3...
Epoch 1/5
527/527 [==============================] - 78s 141ms/step - loss:
6.2043 - accuracy: 0.0568 - val_loss: 5.9161 - val_accuracy: 0.0700
Epoch 2/5
527/527 [==============================] - 74s 140ms/step - loss:
5.6553 - accuracy: 0.0895 - val_loss: 5.9064 - val_accuracy: 0.0916
Epoch 3/5
527/527 [==============================] - 74s 140ms/step - loss:
5.4930 - accuracy: 0.1004 - val_loss: 5.8791 - val_accuracy: 0.0969
Epoch 4/5
527/527 [==============================] - 75s 142ms/step - loss:
5.3347 - accuracy: 0.1099 - val_loss: 5.8478 - val_accuracy: 0.1078
Epoch 5/5
527/527 [==============================] - 76s 144ms/step - loss:
5.1678 - accuracy: 0.1231 - val_loss: 5.7824 - val_accuracy: 0.1192

# Modify the train_and_evaluate function
# Modify the train_and_evaluate function
def train_and_evaluate(models, X_train, y_train, X_val, y_val, epochs,
batch_size):
    histories = []  # To store the training history of each model

    for i, model in enumerate(models):
        print(f"Training Model {i + 1}...")
        history = model.fit(X_train, y_train, epochs=epochs,
batch_size=batch_size, validation_data=(X_val, y_val))
        histories.append(history)

    return histories


training_histories = train_and_evaluate(models, X_train, y_train,
X_val, y_val, epochs=5, batch_size=32)
for i, history in enumerate(training_histories):
    plt.figure(figsize=(12, 4))
```

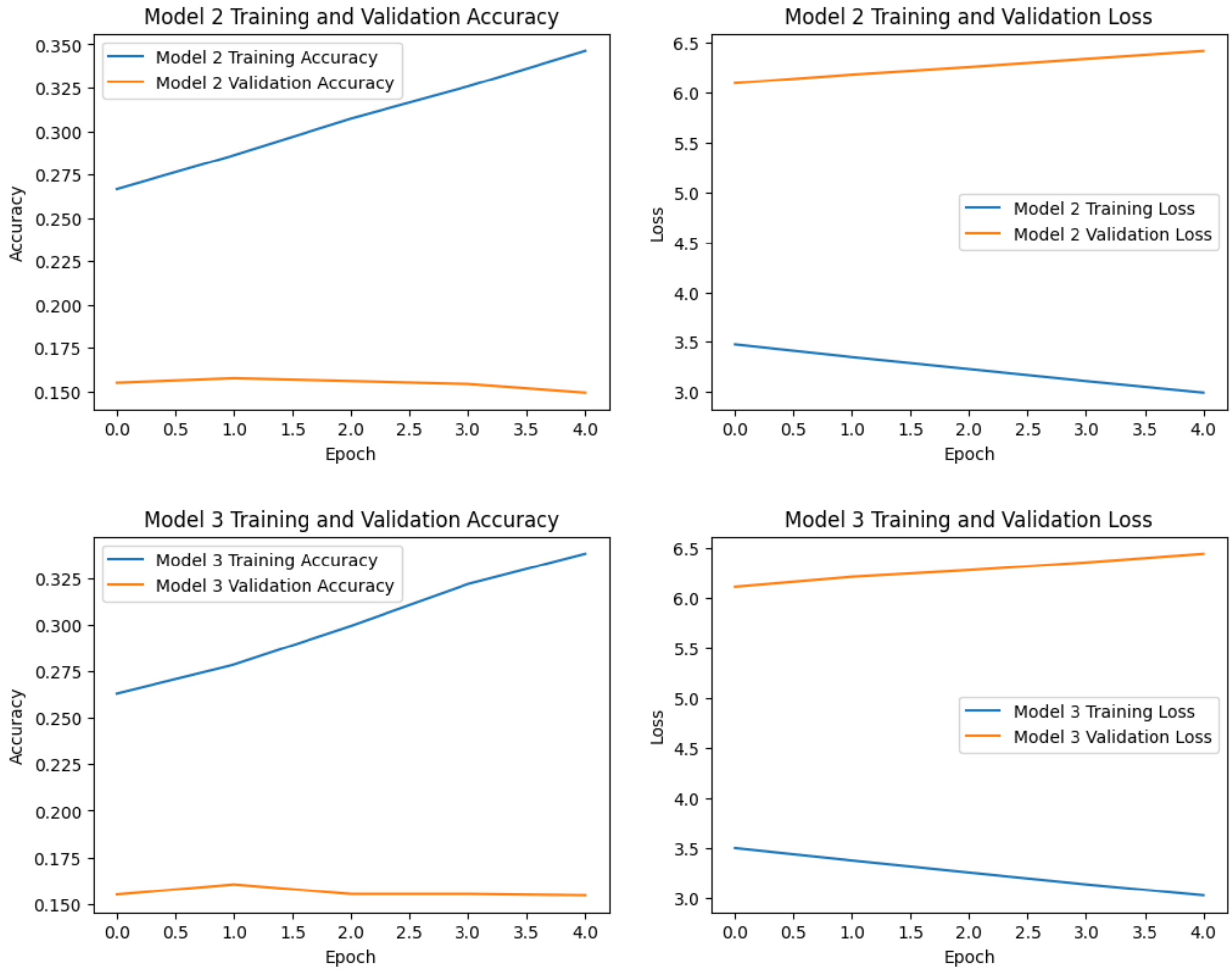
```
    # Plot Training & Validation Accuracy
    plt.subplot(1, 2, 1)
    plt.plot(history.history['accuracy'], label=f'Model {i + 1}
Training Accuracy')
    plt.plot(history.history['val_accuracy'], label=f'Model {i + 1}
Validation Accuracy')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.title(f'Model {i + 1} Training and Validation Accuracy')
    plt.legend()

    # Plot Training & Validation Loss
    plt.subplot(1, 2, 2)
    plt.plot(history.history['loss'], label=f'Model {i + 1} Training
Loss')
    plt.plot(history.history['val_loss'], label=f'Model {i + 1}
Validation Loss')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.title(f'Model {i + 1} Training and Validation Loss')
    plt.legend()

    plt.show()
```

```
Training Model 1...
Epoch 1/5
527/527 [==============================] - 74s 141ms/step - loss:
3.4532 - accuracy: 0.2709 - val_loss: 6.1391 - val_accuracy: 0.1541
Epoch 2/5
527/527 [==============================] - 75s 142ms/step - loss:
3.3249 - accuracy: 0.2886 - val_loss: 6.2148 - val_accuracy: 0.1527
Epoch 3/5
527/527 [==============================] - 74s 140ms/step - loss:
3.2008 - accuracy: 0.3065 - val_loss: 6.3031 - val_accuracy: 0.1503
Epoch 4/5
527/527 [==============================] - 74s 140ms/step - loss:
3.0813 - accuracy: 0.3319 - val_loss: 6.3749 - val_accuracy: 0.1472
Epoch 5/5
527/527 [==============================] - 73s 139ms/step - loss:
2.9653 - accuracy: 0.3496 - val_loss: 6.4631 - val_accuracy: 0.1489
Training Model 2...
Epoch 1/5
527/527 [==============================] - 75s 142ms/step - loss:
3.4750 - accuracy: 0.2666 - val_loss: 6.0968 - val_accuracy: 0.1550
Epoch 2/5
527/527 [==============================] - 73s 138ms/step - loss:
3.3483 - accuracy: 0.2861 - val_loss: 6.1832 - val_accuracy: 0.1576
Epoch 3/5
527/527 [==============================] - 74s 140ms/step - loss:
```

```
3.2287 - accuracy: 0.3073 - val_loss: 6.2591 - val_accuracy: 0.1560
Epoch 4/5
527/527 [==============================] - 78s 149ms/step - loss:
3.1089 - accuracy: 0.3258 - val_loss: 6.3409 - val_accuracy: 0.1543
Epoch 5/5
527/527 [==============================] - 73s 140ms/step - loss:
2.9939 - accuracy: 0.3463 - val_loss: 6.4205 - val_accuracy: 0.1493
Training Model 3...
Epoch 1/5
527/527 [==============================] - 74s 140ms/step - loss:
3.5000 - accuracy: 0.2631 - val_loss: 6.1140 - val_accuracy: 0.1550
Epoch 2/5
527/527 [==============================] - 74s 140ms/step - loss:
3.3759 - accuracy: 0.2786 - val_loss: 6.2145 - val_accuracy: 0.1605
Epoch 3/5
527/527 [==============================] - 72s 137ms/step - loss:
3.2558 - accuracy: 0.2995 - val_loss: 6.2818 - val_accuracy: 0.1553
Epoch 4/5
527/527 [==============================] - 71s 134ms/step - loss:
3.1369 - accuracy: 0.3220 - val_loss: 6.3587 - val_accuracy: 0.1553
Epoch 5/5
527/527 [==============================] - 72s 136ms/step - loss:
3.0265 - accuracy: 0.3383 - val_loss: 6.4457 - val_accuracy: 0.1546
```






Model 2 Training and Validation Accuracy
Model 2 Training Accuracy
Model 2 Validation Accuracy
Accuracy
Epoch
Model 2 Training and Validation Loss
Model 2 Training Loss
Model 2 Validation Loss
Loss
Epoch
Model 3 Training and Validation Accuracy
Model 3 Training Accuracy
Model 3 Validation Accuracy
Accuracy
Epoch
Model 3 Training and Validation Loss
Model 3 Training Loss
Model 3 Validation Loss
Loss
Epoch