```
# ---------------- Download and Extract Kaggle Dataset ---------------- #
!pip install kaggle
!mkdir -p ~/.kaggle
!echo '{"username":"harshgupta21bce6101","key":"7b4970149b4ff86915e405bd4386b8cb"}' > ~/.kaggle/kaggle.json
!chmod 600 ~/.kaggle/kaggle.json

!kaggle datasets download -d paultimothymooney/chest-xray-pneumonia
!unzip chest-xray-pneumonia.zip -d chest_xray
```

```
          inflating: chest_xray/chest_xray/val/PNEUMONIA/person1946_bacteria_4874.jpeg
          inflating: chest_xray/chest_xray/val/PNEUMONIA/person1946_bacteria_4875.jpeg
          inflating: chest_xray/chest_xray/val/PNEUMONIA/person1947_bacteria_4876.jpeg
          inflating: chest_xray/chest_xray/val/PNEUMONIA/person1949_bacteria_4880.jpeg
          inflating: chest_xray/chest_xray/val/PNEUMONIA/person1950_bacteria_4881.jpeg
          inflating: chest_xray/chest_xray/val/PNEUMONIA/person1951_bacteria_4882.jpeg
          inflating: chest_xray/chest_xray/val/PNEUMONIA/person1952_bacteria_4883.jpeg
          inflating: chest_xray/chest_xray/val/PNEUMONIA/person1954_bacteria_4886.jpeg
```

```
import os
import random
import numpy as np
import tensorflow as tf
import hashlib
import time
from keras_preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications import EfficientNetB1, ResNet50
from tensorflow.keras.layers import Input, GlobalAveragePooling2D, Dense, Dropout, BatchNormalization
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.losses import CategoricalCrossentropy
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
import shutil

# ---------------- Corrected Dataset Path ---------------- #
dataset_path = "./chest_xray/chest_xray"
num_clients = 2

# ---------------- Distribute Data Among Clients ---------------- #
for client_id in range(num_clients):
    client_dir = os.path.join(dataset_path, f'client_{client_id}')
    os.makedirs(client_dir, exist_ok=True)
    for class_name in ['NORMAL', 'PNEUMONIA']:
        class_dir = os.path.join(client_dir, class_name)
        os.makedirs(class_dir, exist_ok=True)

for class_name in ['NORMAL', 'PNEUMONIA']:
    class_path = os.path.join(dataset_path, 'train', class_name)
    for i, filename in enumerate(os.listdir(class_path)):
        client_id = i % num_clients
        source_path = os.path.join(class_path, filename)
        dest_path = os.path.join(dataset_path, f'client_{client_id}', class_name, filename)
        shutil.copy(source_path, dest_path)

# ---------------- Load Client Data ---------------- #
def load_client_data(client_id, dataset_path):
    client_dir = os.path.join(dataset_path, f'client_{client_id}')
    train_datagen = ImageDataGenerator(rescale=1./255, validation_split=0.2)

    train_dataset = train_datagen.flow_from_directory(
        client_dir, target_size=(240, 240), batch_size=16, class_mode='categorical', subset='training')
    val_dataset = train_datagen.flow_from_directory(
        client_dir, target_size=(240, 240), batch_size=16, class_mode='categorical', subset='validation')

    num_classes = len(train_dataset.class_indices)
    return train_dataset, val_dataset, num_classes
```

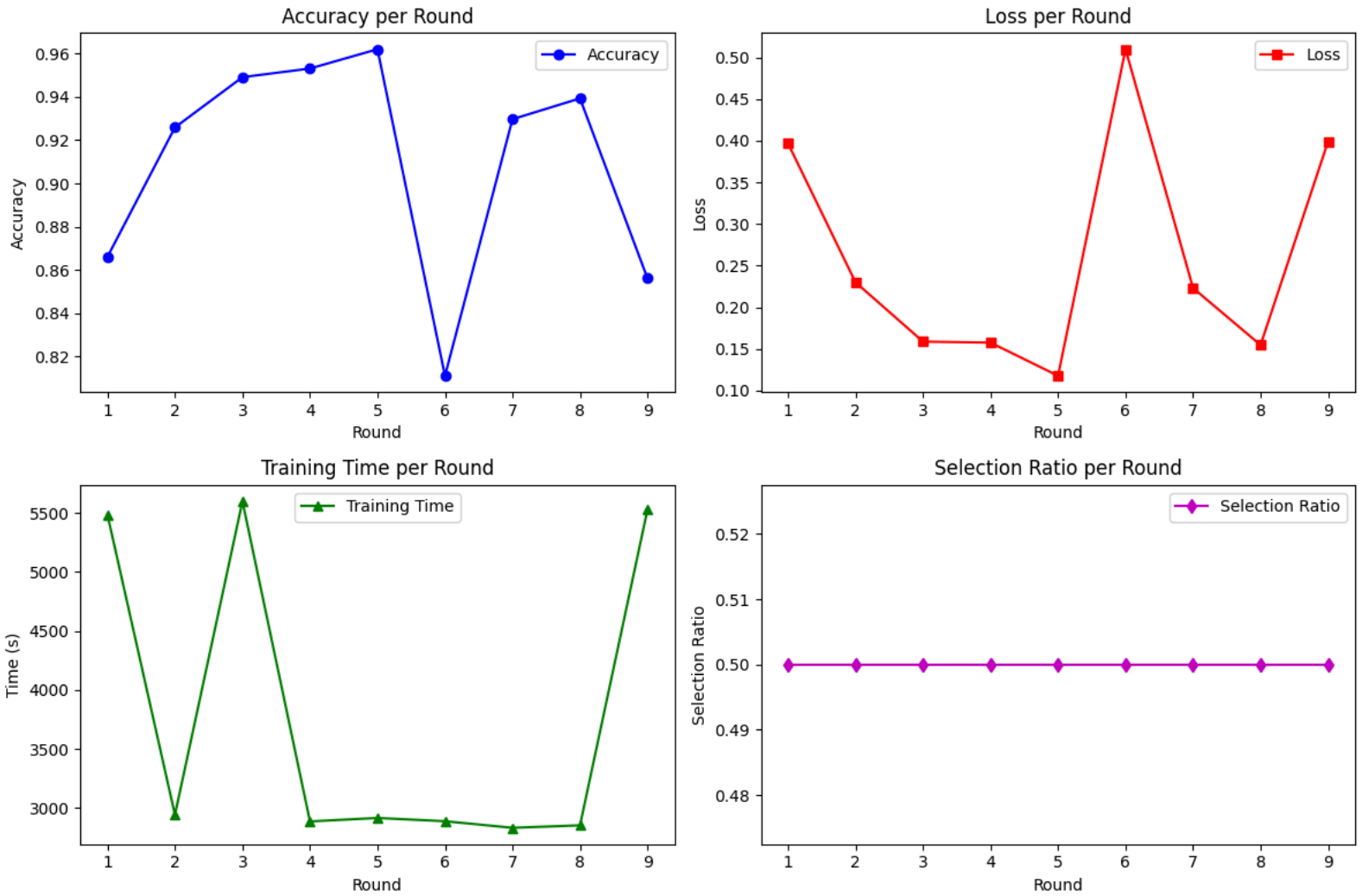
```
# ---------------- Random Client Selection Strategy ---------------- #
def select_clients(num_clients, fraction=0.5):
    num_selected = max(1, int(num_clients * fraction))
    return random.sample(range(num_clients), num_selected)

# ---------------- Model Aggregation ---------------- #
def aggregate_client_updates(global_model, client_models):
    if not client_models:
        return global_model  # No updates if no clients trained

    global_weights = global_model.get_weights()
    client_weights_list = [model.get_weights() for model in client_models]

    if not client_weights_list:  # Ensure clients have valid weights
        return global_model

    averaged_weights = []
    for i in range(len(global_weights)):
        layer_weights = [client_weights[i] for client_weights in client_weights_list if client_weights[i].shape == global_weights[i].shape]
        if layer_weights:  # Only aggregate valid weights
            averaged_layer_weights = np.mean(layer_weights, axis=0)
            averaged_weights.append(averaged_layer_weights)
        else:
            averaged_weights.append(global_weights[i])  # Use previous weights if mismatch occurs

    global_model.set_weights(averaged_weights)
    return global_model

# ---------------- Define Model Creation Function ---------------- #
def create_model(num_classes, model_type='EfficientNet'):
    image_input = Input(shape=(240, 240, 3))
    base_model = EfficientNetB1(weights='imagenet', include_top=False, input_tensor=image_input) if model_type == 'EfficientNet' else ResNet50(weights='imagenet', include_top=False, input_tensor=image_

    x = base_model.output
    x = GlobalAveragePooling2D()(x)
    x = Dense(512, activation='relu')(x)
    x = BatchNormalization()(x)
    x = Dropout(0.5)(x)
    x = Dense(256, activation='relu')(x)
    x = BatchNormalization()(x)
    x = Dropout(0.3)(x)
    output = Dense(num_classes, activation='softmax')(x)

    model = Model(inputs=image_input, outputs=output)
    model.compile(loss=CategoricalCrossentropy(), optimizer=Adam(learning_rate=0.0005), metrics=['accuracy'])
    return model

# ---------------- Hybrid HFL-PFL Federated Learning ---------------- #
def federated_learning(dataset_path, num_clients=2, global_rounds=9):
    global_models = {"EfficientNet": [], "ResNet": []}
    client_personalized_models = {}
    performance_metrics = []

    # Initialize global models using random client
    random_client = random.choice(range(num_clients))
    train_dataset, val_dataset, num_classes = load_client_data(random_client, dataset_path)
```

```
        train_dataset, val_dataset, num_classes = load_client_data(random_client, dataset_path)
        for model_type in global_models:
            global_model = create_model(num_classes, model_type)
            global_models[model_type].append(global_model)

        for round_num in range(global_rounds):
            selected_clients = select_clients(num_clients)
            round_start_time = time.time()
            client_models = {}

            for client_id in selected_clients:
                model_type = 'EfficientNet' if client_id % 2 == 0 else 'ResNet'
                train_dataset, val_dataset, num_classes = load_client_data(client_id, dataset_path)
                local_model = create_model(num_classes, model_type)
                local_model.fit(train_dataset, epochs=3, validation_data=val_dataset, verbose=1)
                client_models[client_id] = local_model
                client_personalized_models[client_id] = local_model

            for model_type in global_models:
                client_models_of_type = [client_models[client_id] for client_id in client_models if client_id % 2 == (0 if model_type == 'EfficientNet' else 1)]
                if client_models_of_type:  # Only aggregate if there are models
                    global_models[model_type].append(
                        aggregate_client_updates(global_models[model_type][-1], client_models_of_type)
                    )

            round_time = time.time() - round_start_time
            performance_metrics.append({
                'round': round_num + 1,
                'selected_clients': selected_clients,
                'training_time': round_time,
            })

        return global_models, client_personalized_models, performance_metrics

    # ---------------- Run Federated Learning ---------------- #
    if __name__ == "__main__":
        global_models, client_personalized_models, performance_metrics = federated_learning(dataset_path)
        print("Federated Learning Completed")
        print("Performance Metrics:", performance_metrics)
```

```
Epoch 1/3
131/131 ━━━━━━━━━━━━━━━━━━━━ 1014s 7s/step - accuracy: 0.8312 - loss: 0.4868 - val_accuracy: 0.7428 - val_loss: 0.5891
Epoch 2/3
131/131 ━━━━━━━━━━━━━━━━━━━━ 918s 7s/step - accuracy: 0.9219 - loss: 0.2593 - val_accuracy: 0.7428 - val_loss: 0.5843
Epoch 3/3
131/131 ━━━━━━━━━━━━━━━━━━━━ 938s 7s/step - accuracy: 0.9628 - loss: 0.1113 - val_accuracy: 0.7409 - val_loss: 0.9880
Found 2088 images belonging to 2 classes.
Found 521 images belonging to 2 classes.
Epoch 1/3
131/131 ━━━━━━━━━━━━━━━━━━━━ 1018s 7s/step - accuracy: 0.8294 - loss: 0.4425 - val_accuracy: 0.7428 - val_loss: 0.6136
Epoch 2/3
131/131 ━━━━━━━━━━━━━━━━━━━━ 920s 7s/step - accuracy: 0.9240 - loss: 0.1989 - val_accuracy: 0.7428 - val_loss: 0.8054
Epoch 3/3
131/131 ━━━━━━━━━━━━━━━━━━━━ 947s 7s/step - accuracy: 0.9466 - loss: 0.1827 - val_accuracy: 0.7428 - val_loss: 1.2631
Found 2088 images belonging to 2 classes.
Found 521 images belonging to 2 classes.
Epoch 1/3
131/131 ━━━━━━━━━━━━━━━━━━━━ 997s 7s/step - accuracy: 0.8112 - loss: 0.5347 - val_accuracy: 0.7428 - val_loss: 0.5821
Epoch 2/3
131/131 ━━━━━━━━━━━━━━━━━━━━ 900s 7s/step - accuracy: 0.9388 - loss: 0.2354 - val_accuracy: 0.7428 - val_loss: 0.5302
Epoch 3/3
131/131 ━━━━━━━━━━━━━━━━━━━━ 932s 7s/step - accuracy: 0.9406 - loss: 0.1657 - val_accuracy: 0.7428 - val_loss: 1.1575
Found 2088 images belonging to 2 classes.
Found 521 images belonging to 2 classes.
Epoch 1/3
131/131 ━━━━━━━━━━━━━━━━━━━━ 1000s 7s/step - accuracy: 0.8091 - loss: 0.5018 - val_accuracy: 0.7428 - val_loss: 0.6753
Epoch 2/3
131/131 ━━━━━━━━━━━━━━━━━━━━ 943s 7s/step - accuracy: 0.9285 - loss: 0.2246 - val_accuracy: 0.7428 - val_loss: 0.6094
Epoch 3/3
131/131 ━━━━━━━━━━━━━━━━━━━━ 907s 7s/step - accuracy: 0.9466 - loss: 0.1631 - val_accuracy: 0.7428 - val_loss: 0.9743
Found 2086 images belonging to 2 classes.
Found 521 images belonging to 2 classes.
Epoch 1/3
131/131 ━━━━━━━━━━━━━━━━━━━━ 1856s 14s/step - accuracy: 0.8661 - loss: 0.3967 - val_accuracy: 0.7428 - val_loss: 8.3018
Epoch 2/3
131/131 ━━━━━━━━━━━━━━━━━━━━ 1810s 14s/step - accuracy: 0.9259 - loss: 0.2301 - val_accuracy: 0.7428 - val_loss: 6.3499
Epoch 3/3
131/131 ━━━━━━━━━━━━━━━━━━━━ 1860s 14s/step - accuracy: 0.9491 - loss: 0.1589 - val_accuracy: 0.7428 - val_loss: 1.0923
Federated Learning Completed
Performance Metrics: [{'round': 1, 'selected_clients': [1], 'training_time': 5484.932447195053}, {'round': 2, 'selected_clients': [0], 'training_time': 2942.6449196338654}, {'round': 3, 'select
```

```
import os
import numpy as np
import matplotlib.pyplot as plt

# ---------------- Performance Metrics Plotting ---------------- #
def plot_performance_metrics(performance_metrics, accuracies, losses, num_clients=2):
    rounds = [entry['round'] for entry in performance_metrics]
    training_times = [entry['training_time'] for entry in performance_metrics]
    selection_ratios = [len(entry['selected_clients']) / num_clients for entry in performance_metrics]

    fig, axs = plt.subplots(2, 2, figsize=(12, 8))

    axs[0, 0].plot(rounds, accuracies, marker='o', label='Accuracy', color='b')
    axs[0, 0].set_title("Accuracy per Round")
    axs[0, 0].set_xlabel("Round")
    axs[0, 0].set_ylabel("Accuracy")
    axs[0, 0].legend()

    axs[0, 1].plot(rounds, losses, marker='s', label='Loss', color='r')
```

```
        axs[0, 1].set_title("Loss per Round")
        axs[0, 1].set_xlabel("Round")
        axs[0, 1].set_ylabel("Loss")
        axs[0, 1].legend()

        axs[1, 0].plot(rounds, training_times, marker='^', label='Training Time', color='g')
        axs[1, 0].set_title("Training Time per Round")
        axs[1, 0].set_xlabel("Round")
        axs[1, 0].set_ylabel("Time (s)")
        axs[1, 0].legend()

        axs[1, 1].plot(rounds, selection_ratios, marker='d', label='Selection Ratio', color='m')
        axs[1, 1].set_title("Selection Ratio per Round")
        axs[1, 1].set_xlabel("Round")
        axs[1, 1].set_ylabel("Selection Ratio")
        axs[1, 1].legend()

        plt.tight_layout()
        plt.show()

    # Example Performance Metrics (Replace with actual data)
    performance_metrics = [
        {'round': 1, 'selected_clients': [1], 'training_time': 5484.93},
        {'round': 2, 'selected_clients': [0], 'training_time': 2942.64},
        {'round': 3, 'selected_clients': [1], 'training_time': 5598.28},
        {'round': 4, 'selected_clients': [0], 'training_time': 2886.30},
        {'round': 5, 'selected_clients': [0], 'training_time': 2915.78},
        {'round': 6, 'selected_clients': [0], 'training_time': 2888.08},
        {'round': 7, 'selected_clients': [0], 'training_time': 2832.29},
        {'round': 8, 'selected_clients': [0], 'training_time': 2853.13},
        {'round': 9, 'selected_clients': [1], 'training_time': 5528.26},
    ]

    accuracies = [0.8661, 0.9259, 0.9491, 0.9531, 0.9620, 0.8112, 0.9297, 0.9393, 0.8562]
    losses = [0.3967, 0.2301, 0.1589, 0.1577, 0.1179, 0.5097, 0.2232, 0.1548, 0.3990]

    plot_performance_metrics(performance_metrics, accuracies, losses)
```




```
!pip install keras-preprocessing
```

```
Collecting keras-preprocessing
  Downloading Keras_Preprocessing-1.1.2-py2.py3-none-any.whl.metadata (1.9 kB)
Requirement already satisfied: numpy>=1.9.1 in /usr/local/lib/python3.11/dist-packages (from keras-preprocessing) (2.0.2)
Requirement already satisfied: six>=1.9.0 in /usr/local/lib/python3.11/dist-packages (from keras-preprocessing) (1.17.0)
Downloading Keras_Preprocessing-1.1.2-py2.py3-none-any.whl (42 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 42.6/42.6 kB 3.0 MB/s eta 0:00:00
Installing collected packages: keras-preprocessing
Successfully installed keras-preprocessing-1.1.2
```

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