EX 5 COMPARATIVE ANALYSIS OF VGG, RESNET, AND GOOGLENET

DATE:

Problem Statement:

Implement and compare the performance of three popular CNN architectures: VGG, ResNet, and GoogLeNet for image classification. Use a labeled dataset to train each model and evaluate their convergence and accuracy.

Suggested Dataset: Dogs vs. Cats dataset

Objectives:

1. Understand the architectural differences between VGG, ResNet, and GoogLeNet.
2. Train all three models on the same dataset using transfer learning.
3. Analyze and compare performance using validation accuracy.
4. Apply the trained models to predict classes for custom images.

Scope:

This experiment demonstrates the power of transfer learning using pre-trained CNN models. Students explore how architectural changes affect accuracy and generalization. Comparing models under identical training settings aids in choosing the right model for real-world applications.

Tools and Libraries Used:

1. Python 3.x
2. PyTorch
3. torchvision
4. Matplotlib
5. PIL (Python Imaging Library)

Implementation Steps:

Step 1: Import Necessary Libraries

```
import torch
import torch.nn
as nn import
torch.optim as
optim
from torchvision import datasets, models,
transforms from torch.utils.data import DataLoader,
random_split, Subset import matplotlib.pyplot as plt
from PIL import Image import os
```

Step 2: Configure Device and Define Labels

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print("Using device:", device)

class_names = ['airplane', 'automobile', 'bird', 'cat',
'deer',             'dog', 'frog', 'horse', 'ship', 'truck']
```

Step 3: Preprocess Data and Load CIFAR-10

```
transform = transforms.Compose([
transforms.Resize((224, 224)),
transforms.ToTensor(),
   transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
])

dataset      =        datasets.CIFAR10(root='./data',    train=True,
      download=True, transform=transform)
test_dataset        =        datasets.CIFAR10(root='./data',    train=False,
      download=True, transform=transform)

dataset = Subset(dataset,
range(500)) train_size = int(0.8
* len(dataset)) val_size =
len(dataset) - train_size
train_dataset, val_dataset = random_split(dataset, [train_size, val_size])

train_loader = DataLoader(train_dataset, batch_size=64, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=64, shuffle=False)
```

Step 4: Define Training and Evaluation Function

```
def train_and_evaluate(model, name, num_epochs=5):
   model =
model.to(device)
criterion =
nn.CrossEntropyLoss()
   optimizer = optim.Adam(model.parameters(), lr=1e-4)

   train_accs, val_accs = [], []

   for epoch in range(num_epochs):
model.train()        correct, total = 0, 0        for
inputs, labels in train_loader:          inputs,
labels = inputs.to(device), labels.to(device)
```

```
optimizer.zero_grad()
outputs = model(inputs)
loss = criterion(outputs,
labels)
loss.backward()
optimizer.step()
          _, predicted = torch.max(outputs,
1)           correct += (predicted ==
labels).sum().item()           total +=
labels.size(0)
       train_accs.append(100 * correct / total)

       model.eval()        correct, total = 0, 0
with torch.no_grad():           for inputs, labels in
val_loader:                inputs, labels =
inputs.to(device), labels.to(device)
outputs = model(inputs)                _, predicted =
outputs.max(1)
              correct += (predicted ==
labels).sum().item()               total +=
labels.size(0)
       val_accs.append(100 * correct / total)

       print(f"{name} Epoch {epoch+1}/{num_epochs} - Train Acc: {train_accs[-
1]:.2f}%, Val Acc: {val_accs[-1]:.2f}%")

    return model, train_accs, val_accs
```

Step 5: Select Pretrained Models and Replace Final Layers

```
def get_model(name):     if name ==
"vgg":        model =
models.vgg16(pretrained=True)
model.classifier[6] = nn.Linear(4096,
10)     elif name == "resnet":        model =
models.resnet18(pretrained=True)
model.fc =
nn.Linear(model.fc.in_features, 10)
elif name == "googlenet":
       model = models.googlenet(pretrained=True,
aux_logits=True)        model.fc =
nn.Linear(model.fc.in_features, 10)     else:
       raise ValueError("Unknown
model")     return model
```

Step 6: Train All Models and Collect Results

```
results = {}
trained_models
= {}

for model_name in ["vgg", "resnet", "googlenet"]:
   print(f"\n◆ Training {model_name.upper()} on CIFAR-10...")
   model = get_model(model_name)
   trained_model, train_acc, val_acc = train_and_evaluate(model,
model_name.upper(), num_epochs=5)
   results[model_name] = (train_acc, val_acc)
trained_models[model_name] = trained_model
```

Step 7: Plot Accuracy Comparison

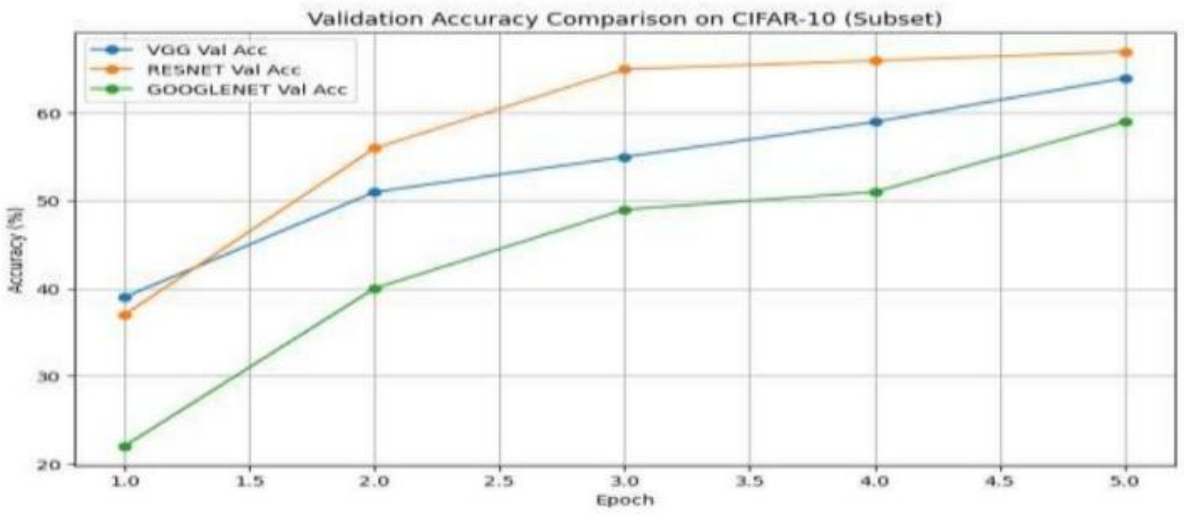
```
plt.figure(figsize=(10, 6)) for name,
(train_acc, val_acc) in results.items():
plt.plot(val_acc, label=f'{name.upper()} Val
Acc') plt.title('Validation Accuracy
Comparison on CIFAR-10') plt.xlabel('Epoch')
plt.ylabel('Accuracy (%)') plt.legend()
plt.grid(True)
plt.show()
```

Step 8: Predict on Custom Image

```
def predict_image(image_path, models_dict):
   image =
Image.open(image_path).convert('RGB')
image =
transform(image).unsqueeze(0).to(device)


   print(f"\n🖼 Prediction results for image:
{image_path}")    for model_name, model in
models_dict.items():        model.eval()        with
torch.no_grad():
         outputs =
model(image)           _,
predicted =
outputs.max(1)
         pred_class = class_names[predicted.item()]
         print(f"{model_name.upper():<10} => {pred_class}")

custom_image_path = "download.jpeg" if
os.path.exists(custom_image_path):
predict_image(custom_image_path,
trained_models) else:
    print(f"\n❗ Image not found: {custom_image_path}. Please add an image to
test.")
```



Conclusion:

This experiment successfully compares three state-of-the-art CNN architectures—VGG16, ResNet18, and GoogLeNet—on an image classification task. The experiment demonstrates how model depth, skip connections (ResNet), and inception modules (GoogLeNet) influence learning capability and accuracy. Such comparisons guide model selection for future deployment tasks.