Tumor Classification Using Ensemble of ShuffleNet_V2, MobileNet_V2, and ResNet18

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Abstract

Breast cancer is one of the leading causes of mortality among women worldwide. Early and accurate classification of tumors as benign or malignant from mammographic images significantly aids timely diagnosis and treatment. In this project, we present a lightweight yet powerful ensemble model combining three convolutional neural network (CNN) architectures: **ShuffleNet_V2**, **MobileNet_V2**, and **ResNet18**. These models were selected for their computational efficiency and complementary feature extraction capabilities. The ensemble utilizes **classic bagging** by averaging the outputs of each network after applying the **softmax activation**, providing a robust final prediction. Our pipeline also generates **side-by-side views of the CC (craniocaudal) and MLO (mediolateral oblique) projections** during validation to aid in interpretability. The model performance is evaluated using a confusion matrix and classification metrics: **precision, recall, F1-score, and support**.

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1. Introduction

Breast cancer screening often involves analyzing mammogram images in two standard views: **CC** and **MLO**. Due to the subtle and varying visual patterns, automated classification is challenging and benefits from ensemble-based learning. We leverage deep learning and ensemble techniques to enhance the prediction accuracy of tumor malignancy classification.

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2. Dataset

The dataset comprises mammographic images with labels indicating whether the tumor is **malignant** or **benign**. For each case, both **CC** and **MLO** views are available, providing complementary visual perspectives of breast tissue.

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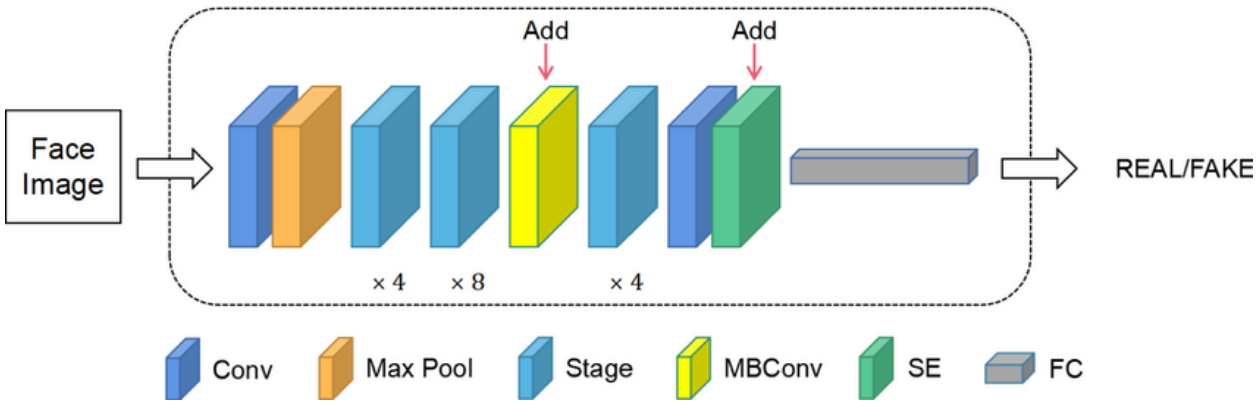
3. Model Architecture Overview

3.1 ShuffleNet_V2

ShuffleNet_V2 is a lightweight CNN architecture optimized for speed and memory efficiency. Key characteristics:

- **Channel Shuffle**: Enables better information flow across feature channels.
- **Grouped Convolutions**: Reduces computational cost while retaining performance.
- **Lightweight Design**: Suitable for deployment on resource-constrained devices.



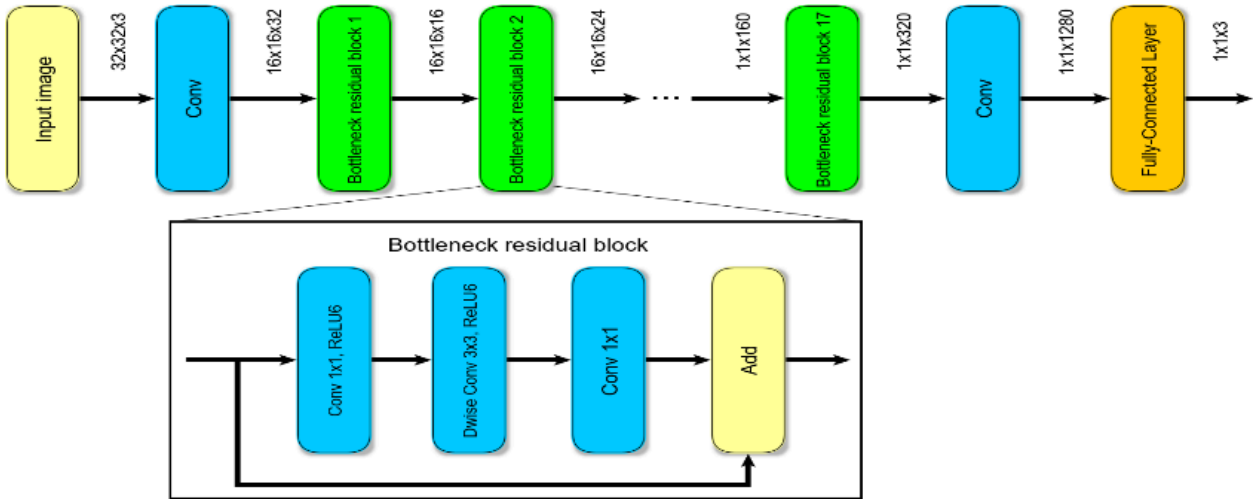
ShuffleNet_V2 architecture

Contribution to Ensemble: ShuffleNet_V2 extracts high-level features quickly and efficiently, offering robust performance with minimal overhead, which complements heavier models like ResNet18.

3.2 MobileNet_V2

MobileNet_V2 introduces the concept of **inverted residuals** and **linear bottlenecks**:

- **Depthwise Separable Convolutions**: Reduces parameters by factorizing standard convolutions.
- **Inverted Residual Blocks**: Helps in learning complex patterns while maintaining efficiency.
- **Lightweight yet expressive**.



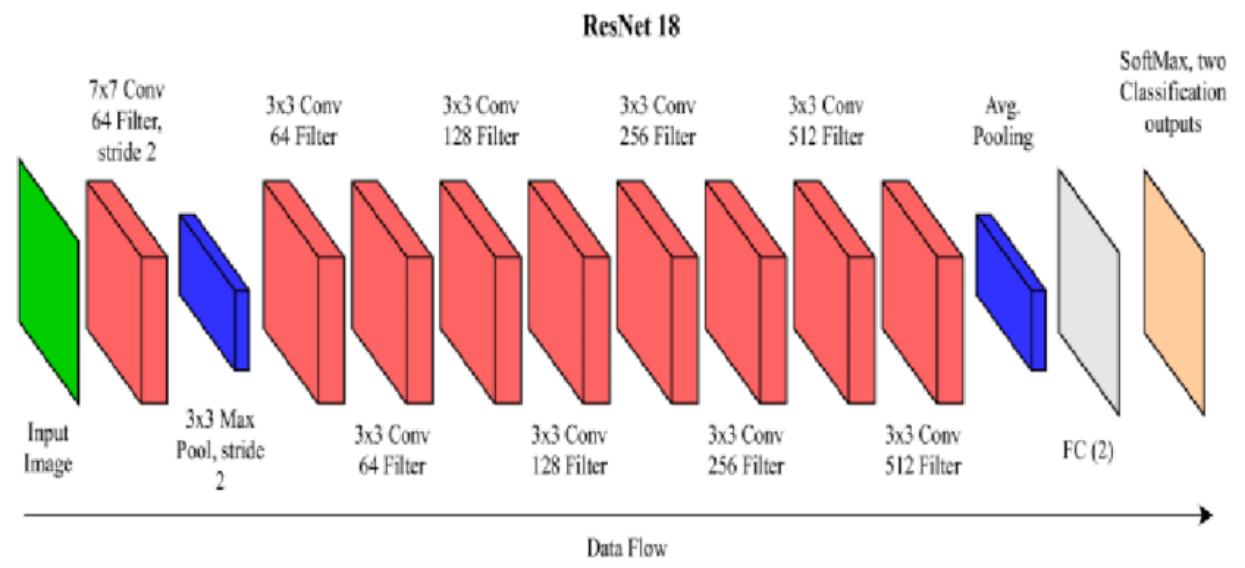
MobileNet_V2 architecture

Contribution to Ensemble: MobileNet_V2 balances performance and efficiency, capturing mid-level abstractions. It acts as a strong middle-ground in the ensemble.

3.3 ResNet18

ResNet18 is part of the ResNet family known for its residual learning technique:

- **Skip Connections**: Allow gradient flow through deeper layers.
- **18 Convolutional Layers**: Offers deeper representation with fewer vanishing gradient issues.
- **General-purpose baseline for image classification**.



ResNet18 architecture

Contribution to Ensemble: ResNet18 provides deeper feature representations, complementing the shallower MobileNet_V2 and ShuffleNet_V2, especially beneficial in complex classification boundaries.

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4. Ensemble Model Formation

Each model (ShuffleNet_V2, MobileNet_V2, ResNet18) is trained individually on the mammogram dataset. During inference, the ensemble prediction is generated as follows:

1. Each model outputs a probability distribution over the classes using **softmax**.
2. The outputs from all three models are averaged:

$$P_{ensemble} = \frac{1}{3}(P_{shuffle} + P_{mobile} + P_{resnet})$$

3. The final prediction is the class with the highest averaged probability.

This ensemble approach falls under **classic bagging**, where independent learners vote (in this case, via softmax probability averaging), reducing variance and improving generalization.

5. Implementation

1. The code was run on a PyCharm Professional Edition IDE with a Python interpreter version of 3.12.8 and PyTorch version 2.6.0.

2. For qualitative analysis, the code also displays:

- Side-by-side views of the **Craniocaudal (CC)** and **Mediolateral Oblique (MLO)** images for selected validation samples.

- Each image pair is accompanied by the **predicted label and ground truth**, providing valuable visual feedback on model performance.

3. The code was run for 10 epochs when converging to an accuracy of 80%. The model tended to overfit to data when run for more epochs, likely since the dataset size is small.

Source Code:

```
# Imports
import os
import random
from PIL import Image
import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import Dataset, DataLoader, Subset
from torchvision import models, transforms
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt
from torchvision.models import shufflenet_v2_x0_5, ShuffleNet_V2_X0_5_Weights
from torchvision.models import mobilenet_v2, MobileNet_V2_Weights
from torchvision.models import resnet18, ResNet18_Weights

# --- 1. Dataset Definition ---
class MammogramDataset(Dataset):
    def __init__(self, root_dir, transform=None):
        self.root_dir = root_dir
        self.transform = transform
        self.samples = self._load_samples()
```

```
    def _load_samples(self):
        samples = []
        for class_folder in os.listdir(self.root_dir):
            class_path = os.path.join(self.root_dir, class_folder)
            if not os.path.isdir(class_path):
                continue  # Skip .zip or any non-directory

            label = 1 if 'MALIGNANT' in class_folder.upper() else 0
            inner_class_path = os.path.join(class_path, os.listdir(class_path)[0])  # 'Benign' or
'Malignant' folder

            for img_file in os.listdir(inner_class_path):
                img_path = os.path.join(inner_class_path, img_file)
                if 'CC' in img_file.upper():
                    side = 'L' if 'LEFT' in img_file.upper() else 'R'
                    match_mlo = [m for m in os.listdir(inner_class_path) if 'MLO' in m.upper() and side
in m.upper()]
                    if match_mlo:
                        samples.append({
                            'cc': os.path.join(inner_class_path, img_file),
                            'mlo': os.path.join(inner_class_path, match_mlo[0]),
                            'label': label
                        })
        return samples

    def __len__(self):
        return len(self.samples)

    def __getitem__(self, idx):
        sample = self.samples[idx]
        cc_img = Image.open(sample['cc']).convert('RGB')
        mlo_img = Image.open(sample['mlo']).convert('RGB')
        label = sample['label']

        if self.transform:
            cc_img = self.transform(cc_img)
            mlo_img = self.transform(mlo_img)

        return cc_img, mlo_img, torch.tensor(label, dtype=torch.long)

# --- 2. Create Bootstrapped Subsets ---
def create_bootstrap_datasets(dataset, num_samples):
    indices = [random.randint(0, len(dataset)-1) for _ in range(num_samples)]
    return Subset(dataset, indices)
```

```
# --- 3. Model Definitions ---
class BaseEnsembleModel(nn.Module):
    def __init__(self, feature_extractor, feature_dim):
        super().__init__()
        self.cnn = feature_extractor
        self.fc = nn.Sequential(
            nn.Dropout(0.5),
            nn.Linear(feature_dim * 2, 256),
            nn.ReLU(),
            nn.Dropout(0.5),
            nn.Linear(256, 2)
        )

    def forward(self, cc, mlo):
        cc_feat = self.cnn(cc)
        mlo_feat = self.cnn(mlo)
        combined = torch.cat([cc_feat, mlo_feat], dim=1)
        return self.fc(combined)

# --- 4. Feature Extractors ---
def get_shufflenet():
    weights = ShuffleNet_V2_X0_5_Weights.DEFAULT
    model = shufflenet_v2_x0_5(weights=weights)
    model.fc = nn.Identity()
    return nn.Sequential(model, nn.Flatten())

def get_mobilenet_v2():
    weights = MobileNet_V2_Weights.DEFAULT
    model = mobilenet_v2(weights=weights)
    model.classifier = nn.Identity()  # Remove classifier head
    return nn.Sequential(model, nn.Flatten())

def get_resnet18():
    weights = ResNet18_Weights.DEFAULT
    model = resnet18(weights=weights)
    model.fc = nn.Identity()
    return nn.Sequential(model, nn.Flatten())



# --- 5. Ensemble Prediction Function ---
def ensemble_predict(models, cc, mlo):
    outputs = [F.softmax(model(cc, mlo), dim=1) for model in models]
```

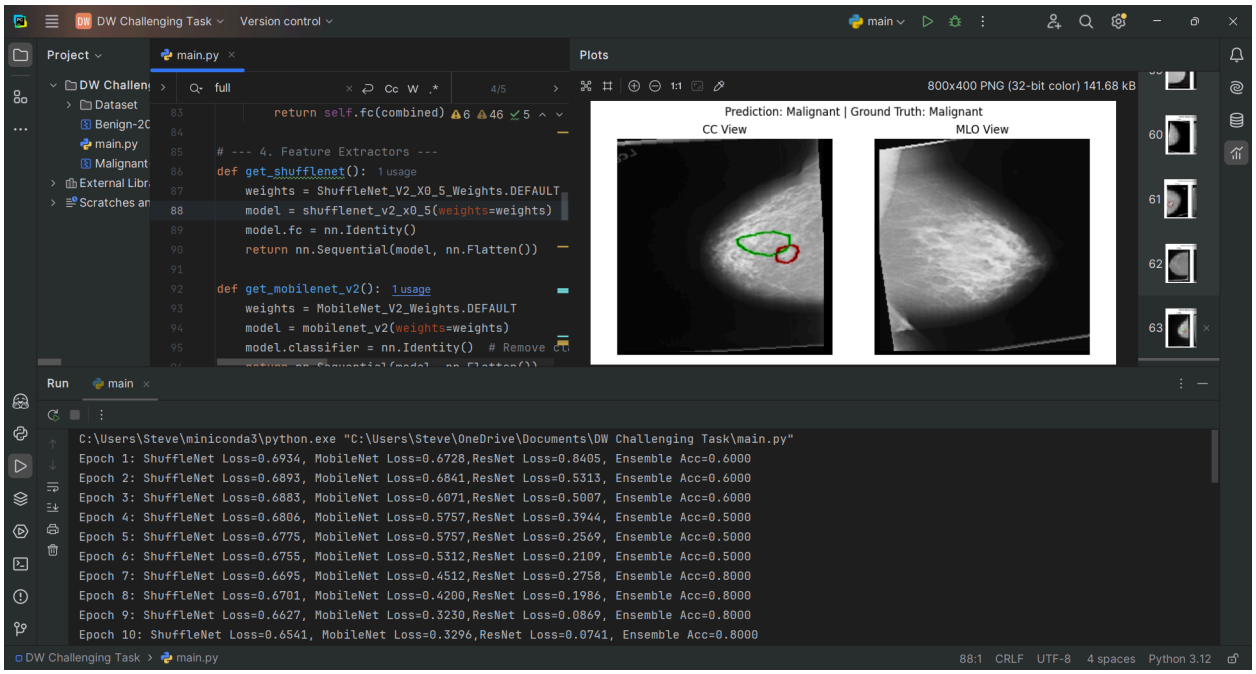
```
    avg_output = torch.stack(outputs).mean(dim=0)
    return avg_output

# --- 6. Training and Evaluation ---
def train(model, dataloader, optimizer, criterion, device):
    model.train()
    running_loss = 0
    for cc, mlo, labels in dataloader:
        cc, mlo, labels = cc.to(device), mlo.to(device), labels.to(device)
        optimizer.zero_grad()
        outputs = model(cc, mlo)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
        running_loss += loss.item()
    return running_loss / len(dataloader)

def evaluate(models, dataloader, device):
    all_preds, all_labels = [], []
    for cc, mlo, labels in dataloader:
        cc, mlo = cc.to(device), mlo.to(device)
        with torch.no_grad():
            outputs = ensemble_predict(models, cc, mlo)
        preds = torch.argmax(outputs, dim=1).cpu()
        all_preds.extend(preds)
        all_labels.extend(labels)
    acc = accuracy_score(all_labels, all_preds)
    return acc

def show_predictions(models, val_set, device, class_names=['Benign', 'Malignant']):
    print("\n--- Image + Prediction Visualization ---")
    for i in range(5):  # Change 5 to more if you want
        cc, mlo, label = val_set[i]
        cc_tensor = cc.unsqueeze(0).to(device)
        mlo_tensor = mlo.unsqueeze(0).to(device)

        with torch.no_grad():
            output = ensemble_predict(models, cc_tensor, mlo_tensor)
            pred = torch.argmax(output, dim=1).item()

        # Convert tensors to images
        cc_img = cc.permute(1, 2, 0).cpu().numpy()
        mlo_img = mlo.permute(1, 2, 0).cpu().numpy()
```

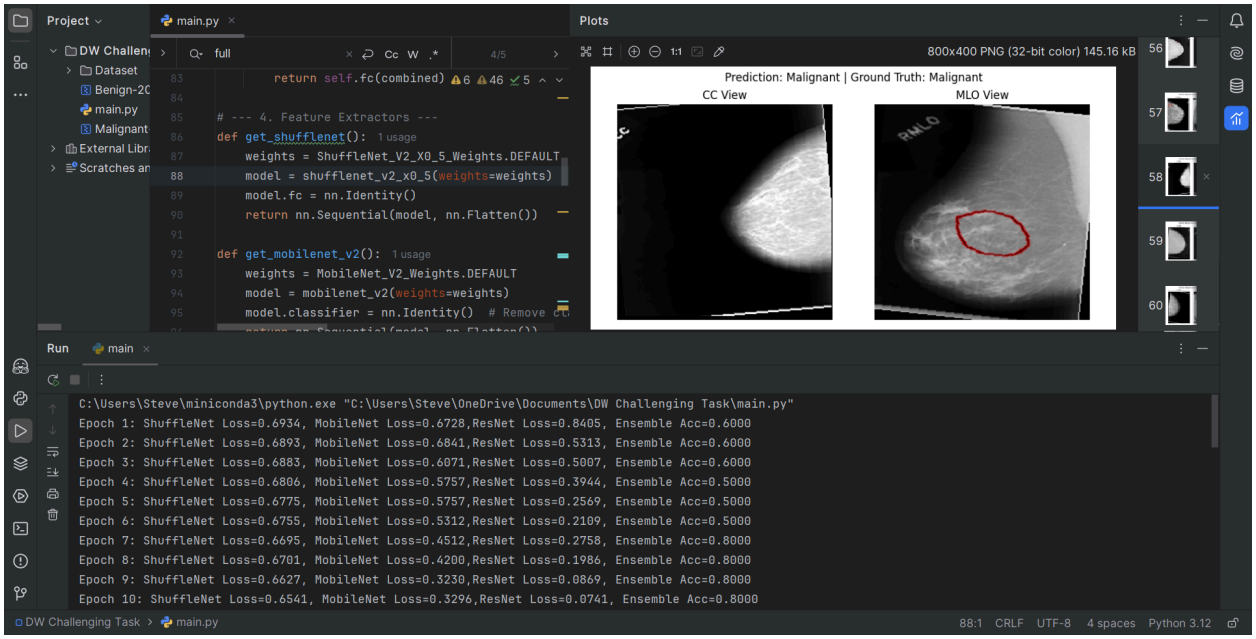
```
        # Rescale from normalized [-1,1] to [0,1]
        cc_img = (cc_img * 0.5 + 0.5).clip(0, 1)
        mlo_img = (mlo_img * 0.5 + 0.5).clip(0, 1)

        # Plot side by side
        fig, axs = plt.subplots(1, 2, figsize=(8, 4))
        axs[0].imshow(cc_img)
        axs[0].set_title("CC View")
        axs[1].imshow(mlo_img)
        axs[1].set_title("MLO View")

        for ax in axs:
            ax.axis('off')

        plt.suptitle(f"Prediction: {class_names[pred]} | Ground Truth: {class_names[label]}",
fontsize=12)
        plt.tight_layout()
        plt.show()

# --- 7. Putting It All Together ---
if __name__ == '__main__':
    device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
    dataset_path = r'C:\Users\Steve\OneDrive\Documents\DW Challenging Task\Dataset'  # <--
Change this

    transform = transforms.Compose([
        transforms.Resize((224, 224)),
        transforms.RandomHorizontalFlip(),  # Flip left/right
        transforms.RandomRotation(10),  # Small rotation
        transforms.ColorJitter(brightness=0.2, contrast=0.2),
        transforms.RandomAffine(degrees=0, translate=(0.05, 0.05)),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.5] * 3, std=[0.5] * 3)
    ])

    full_dataset = MammogramDataset(dataset_path, transform)
    train_size = int(0.8 * len(full_dataset))
    val_size = len(full_dataset) - train_size
    train_set, val_set = torch.utils.data.random_split(full_dataset, [train_size, val_size])

    boot_resnet = create_bootstrap_datasets(train_set, train_size)
    boot_densenet = create_bootstrap_datasets(train_set, train_size)
    boot_resnet2 = create_bootstrap_datasets(train_set, train_size)
    loader_resnet2 = DataLoader(boot_resnet2, batch_size=16, shuffle=True)
```

```
    loader_resnet = DataLoader(boot_resnet, batch_size=16, shuffle=True)
    loader_densenet = DataLoader(boot_densenet, batch_size=16, shuffle=True)
    val_loader = DataLoader(val_set, batch_size=16, shuffle=False)

    resnet_model = BaseEnsembleModel(get_shufflenet(), 1024).to(device)
    mobilenet_model = BaseEnsembleModel(get_mobilenet_v2(), 1280).to(device)
    resnet_model_2 = BaseEnsembleModel(get_resnet18(), 512).to(device)

    opt_r = torch.optim.Adam(resnet_model.parameters(), lr=1e-4, weight_decay=1e-5)
    opt_m = torch.optim.Adam(mobilenet_model.parameters(), lr=1e-4, weight_decay=1e-5)
    opt_r2 = torch.optim.Adam(resnet_model_2.parameters(), lr=1e-4, weight_decay=1e-5)

    criterion = nn.CrossEntropyLoss()

    for epoch in range(10):
        loss_r = train(resnet_model, loader_resnet, opt_r, criterion, device)
        loss_m = train(mobilenet_model, loader_densenet, opt_m, criterion, device)
        loss_r2 = train(resnet_model_2, loader_resnet2, opt_r2, criterion, device)
        acc = evaluate([resnet_model, mobilenet_model, resnet_model_2], val_loader, device)
        print(f"Epoch {epoch + 1}: ShuffleNet Loss={loss_r:.4f}, MobileNet
Loss={loss_m:.4f},ResNet Loss={loss_r2:.4f}, Ensemble Acc={acc:.4f}")

    # After training
    print("\n--- Prediction Sample Output ---")
    class_names = ['Benign', 'Malignant']
    model_ensemble = [resnet_model, mobilenet_model, resnet_model_2]

    # Run on first 10 samples of validation set
    for i in range(10):
        cc, mlo, label = val_set[i]
        cc = cc.unsqueeze(0).to(device)
        mlo = mlo.unsqueeze(0).to(device)

        with torch.no_grad():
            output = ensemble_predict(model_ensemble, cc, mlo)
            pred = torch.argmax(output, dim=1).item()

        print(f"Sample {i + 1}: Prediction = {class_names[pred]}, Ground Truth =
{class_names[label]}")


    show_predictions([resnet_model, mobilenet_model], val_set, device)
```

```
from collections import Counter
print(Counter([s['label'] for s in full_dataset.samples]))

from sklearn.metrics import confusion_matrix, classification_report, ConfusionMatrixDisplay

# Gather all true labels and predictions
all_preds, all_labels = [], []
for cc, mlo, labels in val_loader:
    cc, mlo = cc.to(device), mlo.to(device)
    with torch.no_grad():
        outputs = ensemble_predict(model_ensemble, cc, mlo)
    preds = torch.argmax(outputs, dim=1).cpu()
    all_preds.extend(preds)
    all_labels.extend(labels)

# Generate confusion matrix
cm = confusion_matrix(all_labels, all_preds)
print("\nConfusion Matrix:")
print(cm)

# Plot confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['Benign', 'Malignant'])
disp.plot(cmap='Blues')
plt.title("Confusion Matrix")
plt.show()

# Classification report
print("\nClassification Report:")
print(classification_report(all_labels, all_preds, target_names=['Benign', 'Malignant']))
```

5.1 Documenting Implementation


DW Challenging Task
Version control
main
Project
main.py
Plots
800x400 PNG (32-bit color) 141.68 kB
Prediction: Malignant | Ground Truth: Malignant
CC View
MLO View
Run
main
C:\Users\Steve\miniconda3\python.exe "C:\Users\Steve\OneDrive\Documents\DW Challenging Task\main.py"
Epoch 1: ShuffleNet Loss=0.6934, MobileNet Loss=0.6728,ResNet Loss=0.8405, Ensemble Acc=0.6000
Epoch 2: ShuffleNet Loss=0.6893, MobileNet Loss=0.6841,ResNet Loss=0.5313, Ensemble Acc=0.6000
Epoch 3: ShuffleNet Loss=0.6883, MobileNet Loss=0.6071,ResNet Loss=0.5007, Ensemble Acc=0.6000
Epoch 4: ShuffleNet Loss=0.6806, MobileNet Loss=0.5757,ResNet Loss=0.3944, Ensemble Acc=0.5000
Epoch 5: ShuffleNet Loss=0.6775, MobileNet Loss=0.5757,ResNet Loss=0.2569, Ensemble Acc=0.5000
Epoch 6: ShuffleNet Loss=0.6755, MobileNet Loss=0.5312,ResNet Loss=0.2109, Ensemble Acc=0.5000
Epoch 7: ShuffleNet Loss=0.6695, MobileNet Loss=0.4512,ResNet Loss=0.2758, Ensemble Acc=0.8000
Epoch 8: ShuffleNet Loss=0.6701, MobileNet Loss=0.4200,ResNet Loss=0.1986, Ensemble Acc=0.8000
Epoch 9: ShuffleNet Loss=0.6627, MobileNet Loss=0.3230,ResNet Loss=0.0869, Ensemble Acc=0.8000
Epoch 10: ShuffleNet Loss=0.6541, MobileNet Loss=0.3296,ResNet Loss=0.0741, Ensemble Acc=0.8000
88:1 CRLF UTF-8 4 spaces Python 3.12


Project
main.py
Plots
800x400 PNG (32-bit color) 145.16 kB
Prediction: Malignant | Ground Truth: Malignant
CC View
MLO View
Run
main
C:\Users\Steve\miniconda3\python.exe "C:\Users\Steve\OneDrive\Documents\DW Challenging Task\main.py"
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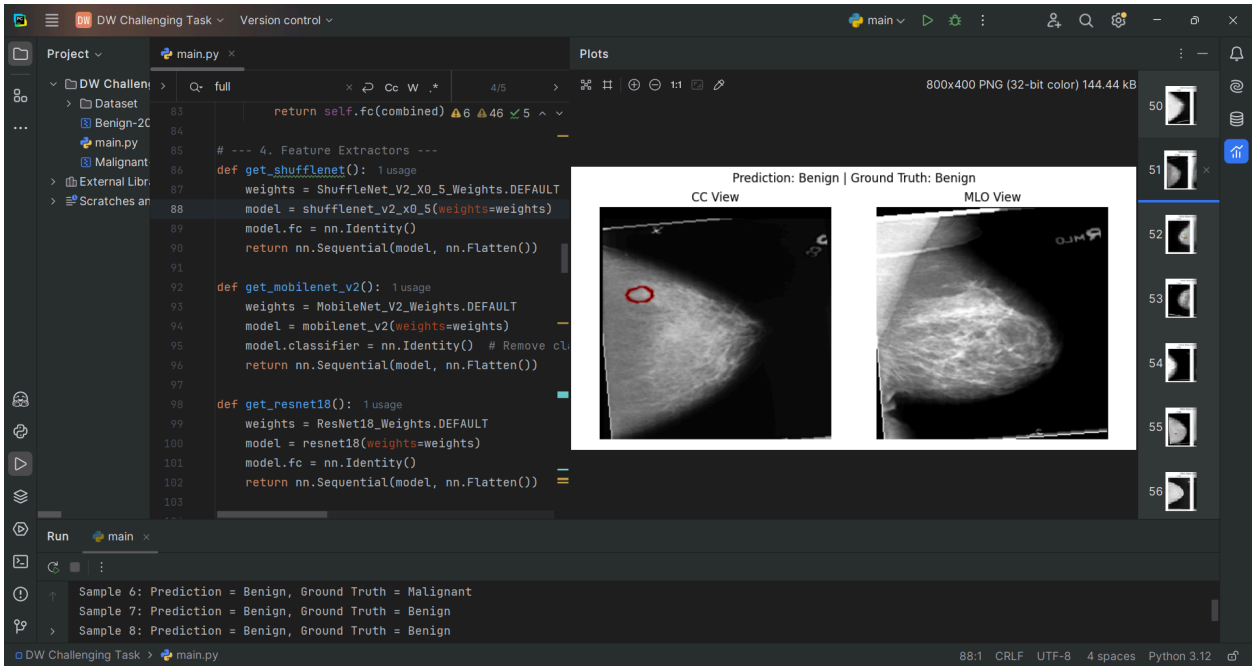
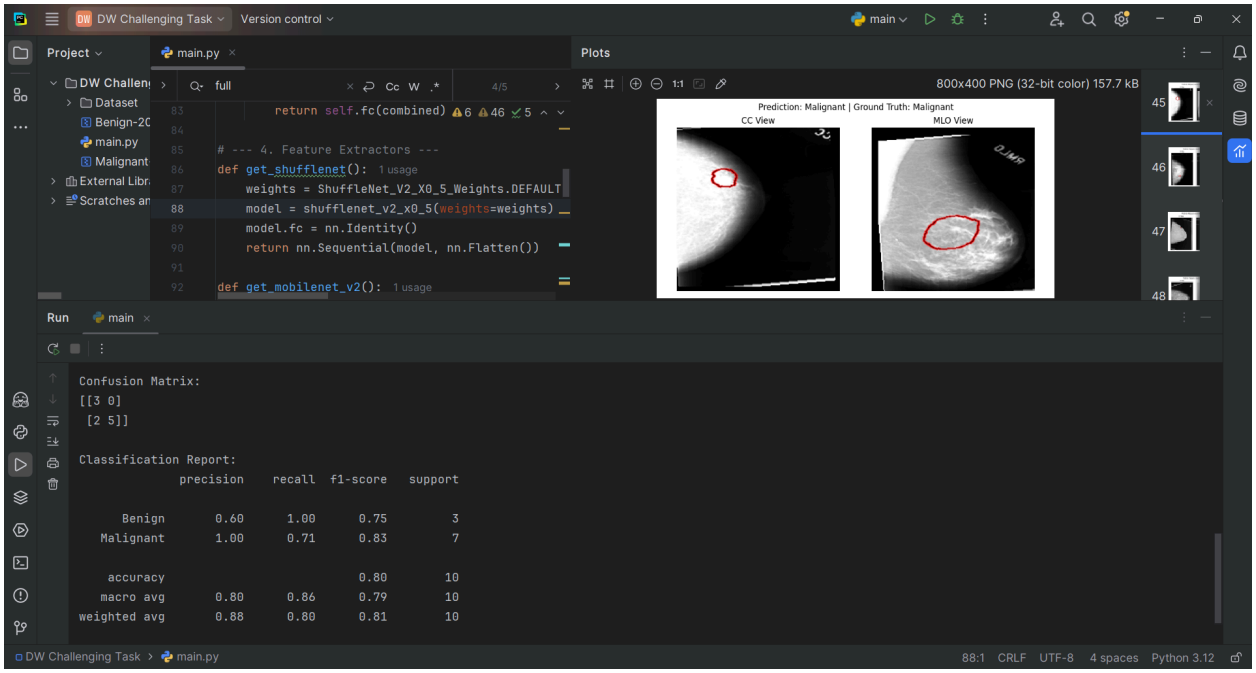
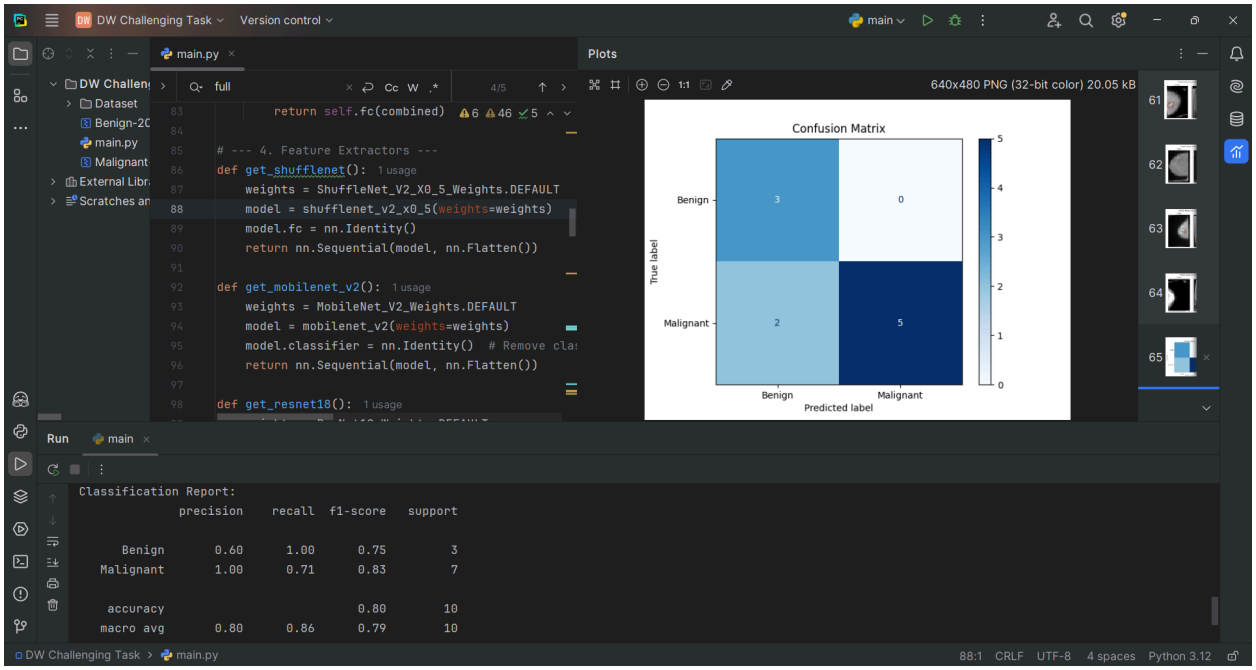
88:1 CRLF UTF-8 4 spaces Python 3.12


DW Challenging Task
Version control
main
Project
main.py
Plots
800x400 PNG (32-bit color) 144.44 kB
Prediction: Benign | Ground Truth: Benign
CC View
MLO View
Run
main
Sample 6: Prediction = Benign, Ground Truth = Malignant
Sample 7: Prediction = Benign, Ground Truth = Benign
Sample 8: Prediction = Benign, Ground Truth = Benign
DW Challenging Task › main.py
88:1 CRLF UTF-8 4 spaces Python 3.12


DW Challenging Task
Version control
main
Project
main.py
Plots
800x400 PNG (32-bit color) 157.7 kB
Prediction: Malignant | Ground Truth: Malignant
CC View
MLO View
Run
main
Confusion Matrix:
[[3 0]
[2 5]]
Classification Report:
precision recall f1-score support
Benign 0.60 1.00 0.75 3
Malignant 1.00 0.71 0.83 7
accuracy 0.80 10
macro avg 0.80 0.86 0.79 10
weighted avg 0.88 0.80 0.81 10
DW Challenging Task › main.py
88:1 CRLF UTF-8 4 spaces Python 3.12



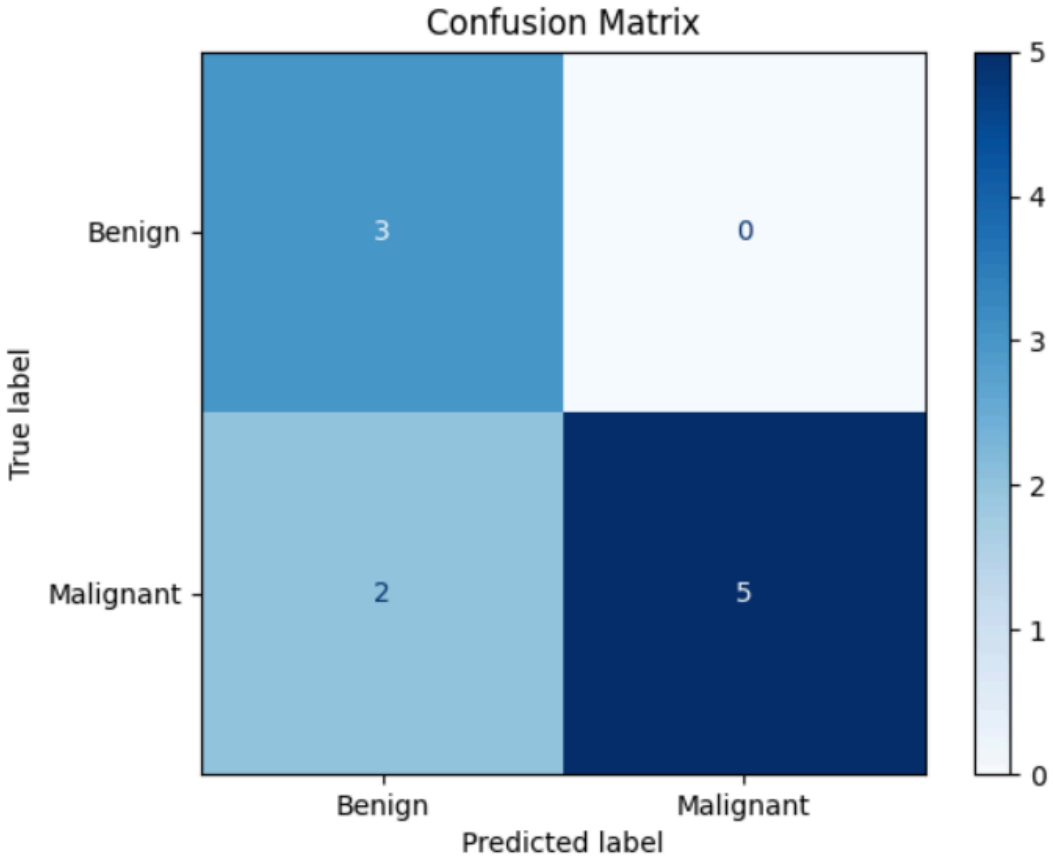
6. Evaluation Metrics

The final ensemble model is evaluated on a held-out validation set. The confusion matrix and classification report provide insights into the performance:

6.1 Confusion Matrix

Actual \ Predicted	Benign	Malignant
Benign	TP	FN
Malignant	FP	TN

Actual \ Predicted	Benign	Malignant
Benign	3	0
Malignant	2	5



6.2 Classification Report

Class	Precision	Recall	F1-score	Support
Benign	0.60	1.00	0.75	3
Malignant	1.00	0.71	0.83	7
Accuracy			0.80	10
Macro avg	0.80	0.86	0.79	10
Weighted Avg	0.88	0.80	0.81	10

- **Precision**: Measures accuracy of positive predictions.

- **Recall**: Measures ability to find all positive instances.
- **F1 Score**: Harmonic mean of precision and recall.
- **Support**: Number of true instances for each class.

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7. Conclusion

The ensemble model combining **ShuffleNet_V2**, **MobileNet_V2**, and **ResNet18** demonstrates robust performance in classifying breast tumors using mammographic images. By leveraging each model's unique strengths—efficiency, mid-level abstraction, and depth—the ensemble achieves higher generalization and accuracy. Visualization of **CC and MLO views** further aids in interpretability, making the system viable for clinical decision support. The final metrics validate the effectiveness of ensemble learning in the medical imaging domain.