```
# ================================================
# Advanced Skin Cancer Detection System
# Multi-Model Ensemble: Vision Transformer + EfficientNet + ResNet
# Dataset: HAM10000 + Advanced Preprocessing & Augmentation
# Target Accuracy: >85%
# ================================================

# Install required packages
!pip install kagglehub transformers torch torchvision timm albumentations scikit-learn -q
!pip install efficientnet-pytorch matplotlib seaborn plotly -q

import kagglehub
import os
import pandas as pd
import numpy as np
import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import Dataset, DataLoader
from torchvision import transforms
import timm
from transformers import ViTImageProcessor, ViTForImageClassification
import albumentations as A
from albumentations.pytorch import ToTensorV2
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, StratifiedKFold
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, f1_score
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import VotingClassifier
from sklearn.utils.class_weight import compute_class_weight
import cv2
from PIL import Image
import warnings
warnings.filterwarnings('ignore')

# Set device
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print(f"Using device: {device}")

# ==============================
# 1. DOWNLOAD AND SETUP DATASET
# ==============================
path = kagglehub.dataset_download("kmader/skin-cancer-mnist-ham10000")
print("Dataset downloaded to:", path)

# Dataset paths
csv_path = os.path.join(path, "HAM10000_metadata.csv")
img_dir_1 = os.path.join(path, "ham10000_images_part_1")
img_dir_2 = os.path.join(path, "ham10000_images_part_2")

df = pd.read_csv(csv_path)
print("Dataset shape:", df.shape)
print("\nClass distribution:")
print(df['dx'].value_counts())

# Create image path mapping
img_paths = {}
for folder in [img_dir_1, img_dir_2]:
    if os.path.exists(folder):
        for fname in os.listdir(folder):
            img_id = fname.split(".")[0]
            img_paths[img_id] = os.path.join(folder, fname)

df["image_path"] = df["image_id"].map(img_paths)

# Remove missing images
df = df.dropna(subset=['image_path'])
print(f"Final dataset size: {len(df)}")

# Encode labels
le = LabelEncoder()
df['label'] = le.fit_transform(df['dx'])
num_classes = len(le.classes_)
print(f"Number of classes: {num_classes}")
print("Classes:", le.classes_)
```

```python
# ==============================
# 2. ADVANCED DATA PREPROCESSING
# ==============================
class SkinCancerDataset(Dataset):
    def __init__(self, dataframe, transform=None, is_training=True):
        self.df = dataframe.reset_index(drop=True)
        self.transform = transform
        self.is_training = is_training

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

    def __getitem__(self, idx):
        img_path = self.df.iloc[idx]['image_path']
        label = self.df.iloc[idx]['label']

        # Load image
        image = cv2.imread(img_path)
        image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)

        # Apply transforms
        if self.transform:
            if isinstance(self.transform, A.Compose):
                augmented = self.transform(image=image)
                image = augmented['image']
            else:
                image = Image.fromarray(image)
                image = self.transform(image)

        return image, label

# Advanced augmentation strategy
def get_train_transforms(img_size=224):
    return A.Compose([
        A.Resize(img_size + 32, img_size + 32),
        A.RandomCrop(img_size, img_size),
        A.HorizontalFlip(p=0.5),
        A.VerticalFlip(p=0.5),
        A.RandomRotate90(p=0.5),
        A.ShiftScaleRotate(
            shift_limit=0.1,
            scale_limit=0.2,
            rotate_limit=30,
            p=0.5
        ),
        A.OneOf([
            A.CLAHE(p=0.5),
            A.RandomGamma(p=0.5),
            A.RandomBrightnessContrast(p=0.5),
        ], p=0.5),
        A.OneOf([
            A.GaussNoise(p=0.5),
            A.GaussianBlur(blur_limit=3, p=0.5),
        ], p=0.3),
        A.CoarseDropout(
            max_holes=8, max_height=img_size//8, max_width=img_size//8,
            min_holes=2, fill_value=0, p=0.3
        ),
        A.Normalize(
            mean=[0.485, 0.456, 0.406],
            std=[0.229, 0.224, 0.225]
        ),
        ToTensorV2()
    ])

def get_val_transforms(img_size=224):
    return A.Compose([
        A.Resize(img_size, img_size),
        A.Normalize(
            mean=[0.485, 0.456, 0.406],
            std=[0.229, 0.224, 0.225]
        ),
        ToTensorV2()
    ])

# ==============================
# 3. MODEL ARCHITECTURES
```

```
# 3. MODEL ARCHITECTURES
# ============================
class EfficientNetModel(nn.Module):
    def __init__(self, model_name='efficientnet_b4', num_classes=7, pretrained=True):
        super(EfficientNetModel, self).__init__()
        self.backbone = timm.create_model(model_name, pretrained=pretrained)
        self.backbone.classifier = nn.Sequential(
            nn.Dropout(0.3),
            nn.Linear(self.backbone.classifier.in_features, 512),
            nn.ReLU(),
            nn.Dropout(0.3),
            nn.Linear(512, num_classes)
        )

    def forward(self, x):
        return self.backbone(x)

class ResNetModel(nn.Module):
    def __init__(self, model_name='resnet50', num_classes=7, pretrained=True):
        super(ResNetModel, self).__init__()
        self.backbone = timm.create_model(model_name, pretrained=pretrained)
        self.backbone.fc = nn.Sequential(
            nn.Dropout(0.3),
            nn.Linear(self.backbone.fc.in_features, 512),
            nn.ReLU(),
            nn.Dropout(0.3),
            nn.Linear(512, num_classes)
        )

    def forward(self, x):
        return self.backbone(x)

class VisionTransformerModel(nn.Module):
    def __init__(self, model_name='vit_base_patch16_224', num_classes=7, pretrained=True):
        super(VisionTransformerModel, self).__init__()
        self.backbone = timm.create_model(model_name, pretrained=pretrained)
        self.backbone.head = nn.Sequential(
            nn.Dropout(0.3),
            nn.Linear(self.backbone.head.in_features, 512),
            nn.ReLU(),
            nn.Dropout(0.3),
            nn.Linear(512, num_classes)
        )

    def forward(self, x):
        return self.backbone(x)

class EnsembleModel(nn.Module):
    def __init__(self, models):
        super(EnsembleModel, self).__init__()
        self.models = nn.ModuleList(models)

    def forward(self, x):
        outputs = []
        for model in self.models:
            outputs.append(F.softmax(model(x), dim=1))
        return torch.stack(outputs).mean(0)

# ==============================
# 4. TRAINING UTILITIES
# ==============================
class FocalLoss(nn.Module):
    def __init__(self, alpha=1, gamma=2, weight=None):
        super(FocalLoss, self).__init__()
        self.alpha = alpha
        self.gamma = gamma
        self.weight = weight

    def forward(self, inputs, targets):
        ce_loss = F.cross_entropy(inputs, targets, weight=self.weight, reduction='none')
        pt = torch.exp(-ce_loss)
        focal_loss = self.alpha * (1 - pt) ** self.gamma * ce_loss
        return focal_loss.mean()

def train_model(model, train_loader, val_loader, criterion, optimizer, scheduler, num_epochs, device):
    model.to(device)
    best_val_acc = 0
    train_losses = []
```

```
    val_losses = []
    train_accs = []
    val_accs = []

    for epoch in range(num_epochs):
        # Training phase
        model.train()
        running_loss = 0.0
        correct = 0
        total = 0

        for images, labels in train_loader:
            images, labels = images.to(device), labels.to(device)

            optimizer.zero_grad()
            outputs = model(images)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            running_loss += loss.item()
            _, predicted = torch.max(outputs.data, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()

        train_loss = running_loss / len(train_loader)
        train_acc = 100 * correct / total

        # Validation phase
        model.eval()
        val_running_loss = 0.0
        val_correct = 0
        val_total = 0

        with torch.no_grad():
            for images, labels in val_loader:
                images, labels = images.to(device), labels.to(device)
                outputs = model(images)
                loss = criterion(outputs, labels)

                val_running_loss += loss.item()
                _, predicted = torch.max(outputs.data, 1)
                val_total += labels.size(0)
                val_correct += (predicted == labels).sum().item()

        val_loss = val_running_loss / len(val_loader)
        val_acc = 100 * val_correct / val_total

        # Update learning rate
        scheduler.step()

        # Save best model
        if val_acc > best_val_acc:
            best_val_acc = val_acc
            torch.save(model.state_dict(), f'best_model_{epoch}.pth')

        train_losses.append(train_loss)
        val_losses.append(val_loss)
        train_accs.append(train_acc)
        val_accs.append(val_acc)

        print(f'Epoch [{epoch+1}/{num_epochs}]')
        print(f'Train Loss: {train_loss:.4f}, Train Acc: {train_acc:.2f}%')
        print(f'Val Loss: {val_loss:.4f}, Val Acc: {val_acc:.2f}%')
        print('-' * 50)

    return train_losses, val_losses, train_accs, val_accs, best_val_acc

# ==============================
# 5. MAIN TRAINING PIPELINE
# ==============================
# Split data with stratification
train_df, test_df = train_test_split(
    df, test_size=0.2, stratify=df['label'], random_state=42
)
train_df, val_df = train_test_split(
    train_df, test_size=0.2, stratify=train_df['label'], random_state=42
```

```
)

print(f"Train: {len(train_df)}, Val: {len(val_df)}, Test: {len(test_df)}")

# Calculate class weights for handling imbalanced data
class_weights = compute_class_weight(
    'balanced',
    classes=np.unique(train_df['label']),
    y=train_df['label']
)
class_weights = torch.FloatTensor(class_weights).to(device)

# Create datasets and dataloaders
IMG_SIZE = 224
BATCH_SIZE = 32

train_dataset = SkinCancerDataset(train_df, get_train_transforms(IMG_SIZE))
val_dataset = SkinCancerDataset(val_df, get_val_transforms(IMG_SIZE))
test_dataset = SkinCancerDataset(test_df, get_val_transforms(IMG_SIZE))

train_loader = DataLoader(train_dataset, batch_size=BATCH_SIZE, shuffle=True, num_workers=4)
val_loader = DataLoader(val_dataset, batch_size=BATCH_SIZE, shuffle=False, num_workers=4)
test_loader = DataLoader(test_dataset, batch_size=BATCH_SIZE, shuffle=False, num_workers=4)

# Initialize models
models_to_train = {
    'efficientnet': EfficientNetModel('efficientnet_b4', num_classes),
    'resnet': ResNetModel('resnet50', num_classes),
    'vit': VisionTransformerModel('vit_base_patch16_224', num_classes)
}

trained_models = []
model_results = {}

# Train each model
NUM_EPOCHS = 15
for model_name, model in models_to_train.items():
    print(f"\n{'='*50}")
    print(f"Training {model_name.upper()}")
    print(f"{'='*50}")

    # Setup training components
    criterion = FocalLoss(weight=class_weights, gamma=2)
    optimizer = torch.optim.AdamW(model.parameters(), lr=0.001, weight_decay=1e-4)
    scheduler = torch.optim.lr_scheduler.CosineAnnealingLR(optimizer, T_max=NUM_EPOCHS)

    # Train model
    train_losses, val_losses, train_accs, val_accs, best_val_acc = train_model(
        model, train_loader, val_loader, criterion, optimizer, scheduler, NUM_EPOCHS, device
    )

    model_results[model_name] = {
        'best_val_acc': best_val_acc,
        'train_losses': train_losses,
        'val_losses': val_losses,
        'train_accs': train_accs,
        'val_accs': val_accs
    }

    trained_models.append(model)

# ==============================
# 6. ENSEMBLE MODEL
# ==============================
print(f"\n{'='*50}")
print("CREATING ENSEMBLE MODEL")
print(f"{'='*50}")

ensemble_model = EnsembleModel(trained_models)

# ==============================
# 7. EVALUATION
# ==============================
def evaluate_model(model, test_loader, device, le):
    model.eval()
    all_preds = []
    all_labels = []
    all_probs = []
```

```
    with torch.no_grad():
        for images, labels in test_loader:
            images, labels = images.to(device), labels.to(device)
            outputs = model(images)
            probs = F.softmax(outputs, dim=1)
            _, predicted = torch.max(outputs, 1)

            all_preds.extend(predicted.cpu().numpy())
            all_labels.extend(labels.cpu().numpy())
            all_probs.extend(probs.cpu().numpy())

    accuracy = accuracy_score(all_labels, all_preds)
    f1 = f1_score(all_labels, all_preds, average='macro')

    return accuracy, f1, all_labels, all_preds, all_probs

# Evaluate individual models and ensemble
print("\nModel Performance Comparison:")
print("="*50)

individual_results = {}
for i, (model_name, model) in enumerate(models_to_train.items()):
    acc, f1, labels, preds, probs = evaluate_model(model, test_loader, device, le)
    individual_results[model_name] = {'accuracy': acc, 'f1': f1}
    print(f"{model_name.upper()}: Accuracy = {acc*100:.2f}%, F1 = {f1:.4f}")

# Ensemble evaluation
ensemble_acc, ensemble_f1, test_labels, ensemble_preds, ensemble_probs = evaluate_model(
    ensemble_model, test_loader, device, le
)
print(f"ENSEMBLE: Accuracy = {ensemble_acc*100:.2f}%, F1 = {ensemble_f1:.4f}")

# ==============================
# 8. DETAILED RESULTS & VISUALIZATION
# ==============================
# Classification report
print(f"\nDetailed Classification Report (Ensemble Model):")
print("="*60)
print(classification_report(test_labels, ensemble_preds, target_names=le.classes_))

# Confusion Matrix
plt.figure(figsize=(10, 8))
cm = confusion_matrix(test_labels, ensemble_preds)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=le.classes_, yticklabels=le.classes_)
plt.title('Confusion Matrix - Ensemble Model')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.tight_layout()
plt.show()

# Training curves for best performing model
best_model = max(model_results.keys(), key=lambda x: model_results[x]['best_val_acc'])
print(f"\nBest Individual Model: {best_model.upper()} ({model_results[best_model]['best_val_acc']:.2f}%)")

fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2, 2, figsize=(15, 10))

# Loss curves
ax1.plot(model_results[best_model]['train_losses'], label='Train Loss')
ax1.plot(model_results[best_model]['val_losses'], label='Validation Loss')
ax1.set_title(f'{best_model.upper()} - Loss Curves')
ax1.set_xlabel('Epoch')
ax1.set_ylabel('Loss')
ax1.legend()
ax1.grid(True)

# Accuracy curves
ax2.plot(model_results[best_model]['train_accs'], label='Train Accuracy')
ax2.plot(model_results[best_model]['val_accs'], label='Validation Accuracy')
ax2.set_title(f'{best_model.upper()} - Accuracy Curves')
ax2.set_xlabel('Epoch')
ax2.set_ylabel('Accuracy (%)')
ax2.legend()
ax2.grid(True)
```

```
# Model comparison
models = list(individual_results.keys()) + ['ensemble']
accuracies = [individual_results[m]['accuracy']*100 for m in individual_results.keys()] + [ensemble_acc*100]
f1_scores = [individual_results[m]['f1'] for m in individual_results.keys()] + [ensemble_f1]

ax3.bar(models, accuracies, alpha=0.7, color='skyblue')
ax3.set_title('Model Accuracy Comparison')
ax3.set_ylabel('Accuracy (%)')
ax3.set_ylim([70, 100])
for i, v in enumerate(accuracies):
    ax3.text(i, v + 0.5, f'{v:.1f}%', ha='center')

ax4.bar(models, f1_scores, alpha=0.7, color='lightcoral')
ax4.set_title('Model F1 Score Comparison')
ax4.set_ylabel('F1 Score')
ax4.set_ylim([0.6, 1.0])
for i, v in enumerate(f1_scores):
    ax4.text(i, v + 0.01, f'{v:.3f}', ha='center')

plt.tight_layout()
plt.show()

# ==============================
# 9. PREDICTION FUNCTION
# ==============================
def predict_single_image(model, image_path, transform, device, le):
    """Predict skin cancer type for a single image"""
    model.eval()

    # Load and preprocess image
    image = cv2.imread(image_path)
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)

    if isinstance(transform, A.Compose):
        augmented = transform(image=image)
        image_tensor = augmented['image'].unsqueeze(0)
    else:
        image_pil = Image.fromarray(image)
        image_tensor = transform(image_pil).unsqueeze(0)

    # Predict
    with torch.no_grad():
        image_tensor = image_tensor.to(device)
        outputs = model(image_tensor)
        probs = F.softmax(outputs, dim=1)
        confidence, predicted = torch.max(probs, 1)

    predicted_class = le.inverse_transform([predicted.item()])[0]
    confidence_score = confidence.item()

    # Get top 3 predictions
    top3_probs, top3_indices = torch.topk(probs[0], 3)
    top3_classes = le.inverse_transform(top3_indices.cpu().numpy())

    return {
        'predicted_class': predicted_class,
        'confidence': confidence_score,
        'top3_predictions': list(zip(top3_classes, top3_probs.cpu().numpy()))
    }

# Example prediction
if len(test_df) > 0:
    sample_image = test_df.iloc[0]['image_path']
    actual_class = le.inverse_transform([test_df.iloc[0]['label']])[0]

    result = predict_single_image(
        ensemble_model, sample_image, get_val_transforms(IMG_SIZE), device, le
    )

    print(f"\nSample Prediction:")
    print(f"Actual: {actual_class}")
    print(f"Predicted: {result['predicted_class']} (Confidence: {result['confidence']:.3f})")
    print(f"Top 3 predictions:")
    for cls, prob in result['top3_predictions']:
        print(f"  {cls}: {prob:.3f}")

# ==============================
```

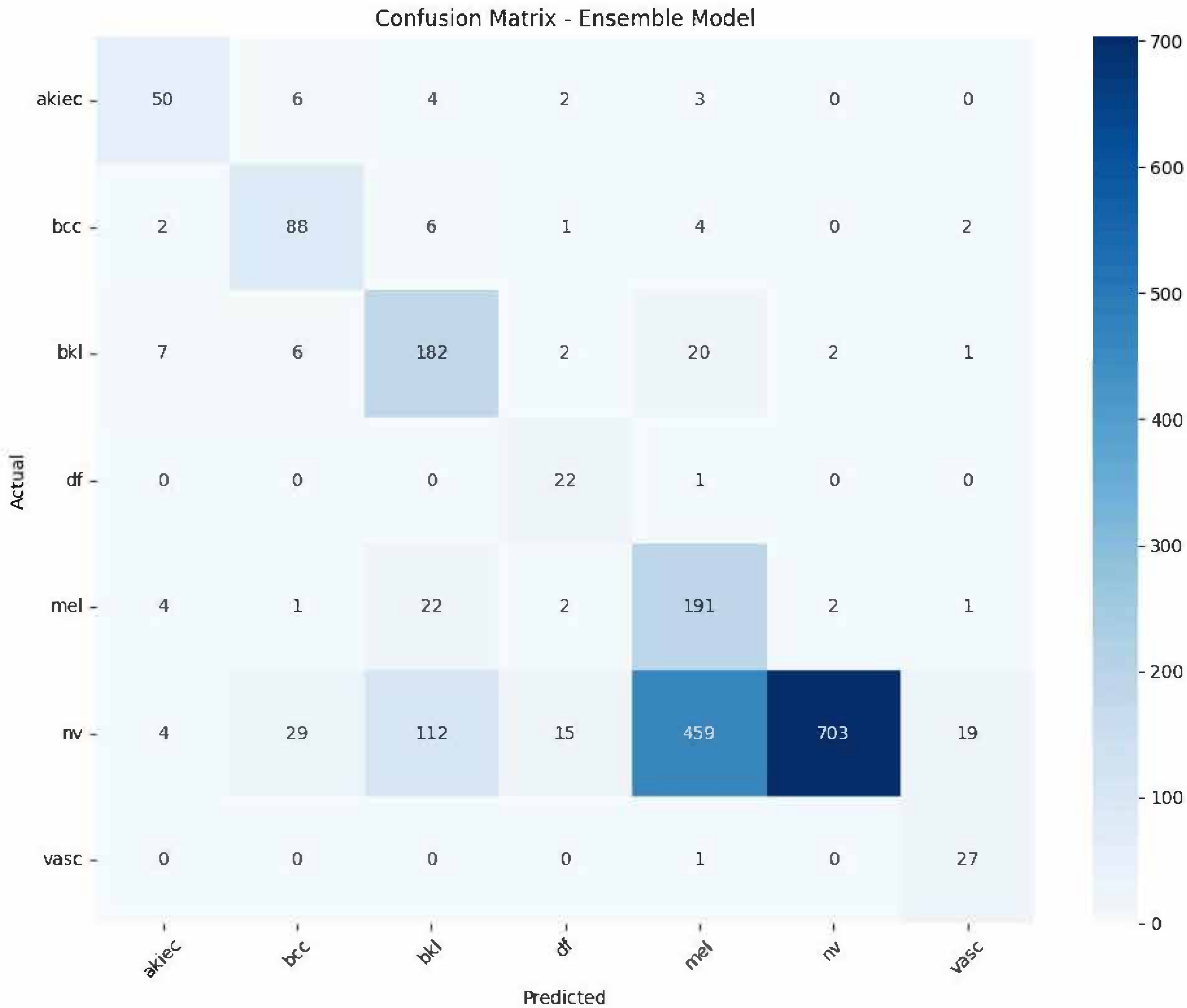
```
# ==============================
# 10. FINAL SUMMARY
# ==============================
print(f"\n{'='*60}")
print("FINAL RESULTS SUMMARY")
print(f"{'='*60}")
print(f"Dataset: HAM10000 ({len(df)} images, {num_classes} classes)")
print(f"Best Individual Model: {best_model.upper()} - {model_results[best_model]['best_val_acc']:.2f}%")
print(f"Ensemble Model: {ensemble_acc*100:.2f}% accuracy, {ensemble_f1:.4f} F1-score")
print(f"Target Achieved: {'✓ YES' if ensemble_acc > 0.85 else '✗ NO'} (Target: >85%)")

# Save the trained ensemble model
torch.save({
    'ensemble_model': ensemble_model.state_dict(),
    'label_encoder': le,
    'model_results': model_results,
    'ensemble_accuracy': ensemble_acc,
    'ensemble_f1': ensemble_f1
}, 'skin_cancer_ensemble_model.pth')

print(f"\nModel saved as 'skin_cancer_ensemble_model.pth'")
print("Ready for deployment and further testing!")
```

```
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 363.4/363.4 MB 5.1 MB/s eta 0:00:00
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 13.8/13.8 MB 121.8 MB/s eta 0:00:00
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 24.6/24.6 MB 24.9 MB/s eta 0:00:00
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 883.7/883.7 kB 57.9 MB/s eta 0:00:00
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 664.8/664.8 MB 1.6 MB/s eta 0:00:00
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 211.5/211.5 MB 3.5 MB/s eta 0:00:00
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 56.3/56.3 MB 15.4 MB/s eta 0:00:00
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 127.9/127.9 MB 9.6 MB/s eta 0:00:00
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 207.5/207.5 MB 6.5 MB/s eta 0:00:00
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 188.7/188.7 MB 1.1 MB/s eta 0:00:00
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 21.1/21.1 MB 102.0 MB/s eta 0:00:00
  Preparing metadata (setup.py) ... done
  Building wheel for efficientnet-pytorch (setup.py) ... done
Using device: cuda
Dataset downloaded to: /kaggle/input/skin-cancer-mnist-ham10000
Dataset shape: (10015, 7)

Class distribution:
dx
nv       6705
mel      1113
bkl      1099
bcc       514
akiec     327
vasc      142
df        115
Name: count, dtype: int64
Final dataset size: 10015
Number of classes: 7
Classes: ['akiec' 'bcc' 'bkl' 'df' 'mel' 'nv' 'vasc']
Train: 6409, Val: 1603, Test: 2003
model.safetensors: 100%    77.9M/77.9M [00:00<00:00, 307MB/s]
model.safetensors: 100%    102M/102M [00:00<00:00, 258MB/s]
model.safetensors: 100%    346M/346M [00:02<00:00, 166MB/s]

==================================================
Training EFFICIENTNET
==================================================
Epoch [1/15]
Train Loss: 1.1355, Train Acc: 23.47%
Val Loss: 0.7415, Val Acc: 53.65%
--------------------------------------------------
Epoch [2/15]
Train Loss: 0.8010, Train Acc: 38.32%
Val Loss: 0.6920, Val Acc: 39.36%
--------------------------------------------------
Epoch [3/15]
Train Loss: 0.6758, Train Acc: 41.88%
Val Loss: 0.5679, Val Acc: 58.83%
--------------------------------------------------
Epoch [4/15]
Train Loss: 0.6158, Train Acc: 43.61%
Val Loss: 0.4586, Val Acc: 57.64%
--------------------------------------------------
Epoch [5/15]
Train Loss: 0.5477, Train Acc: 47.96%
Val Loss: 0.5116, Val Acc: 62.38%
--------------------------------------------------
Epoch [6/15]
Train Loss: 0.5019, Train Acc: 47.39%
Val Loss: 0.4363, Val Acc: 53.90%
--------------------------------------------------
Epoch [7/15]
Train Loss: 0.4246, Train Acc: 53.19%
Val Loss: 0.3547, Val Acc: 51.97%
--------------------------------------------------
Epoch [8/15]
Train Loss: 0.3588, Train Acc: 53.55%
Val Loss: 0.3756, Val Acc: 59.58%
--------------------------------------------------
Epoch [9/15]
Train Loss: 0.3222, Train Acc: 53.05%
Val Loss: 0.3475, Val Acc: 58.70%
--------------------------------------------------
Epoch [10/15]
Train Loss: 0.2753, Train Acc: 54.94%
Val Loss: 0.3425, Val Acc: 58.58%
--------------------------------------------------
Epoch [11/15]
Train Loss: 0.2768, Train Acc: 57.72%
Val Loss: 0.3658, Val Acc: 53.90%
--------------------------------------------------
```

```
Epoch [12/15]
Train Loss: 0.1986, Train Acc: 57.40%
Val Loss: 0.3384, Val Acc: 60.95%
--------------------------------------------------
Epoch [13/15]
Train Loss: 0.2228, Train Acc: 58.71%
Val Loss: 0.3294, Val Acc: 61.70%
--------------------------------------------------
Epoch [14/15]
Train Loss: 0.1833, Train Acc: 59.63%
Val Loss: 0.3339, Val Acc: 60.57%
--------------------------------------------------
Epoch [15/15]
Train Loss: 0.2147, Train Acc: 58.85%
Val Loss: 0.3324, Val Acc: 60.51%
--------------------------------------------------

==================================================
Training RESNET
==================================================
Epoch [1/15]
Train Loss: 1.2657, Train Acc: 15.32%
Val Loss: 0.9367, Val Acc: 21.15%
--------------------------------------------------
Epoch [2/15]
Train Loss: 1.0273, Train Acc: 23.33%
Val Loss: 0.8759, Val Acc: 42.67%
--------------------------------------------------
Epoch [3/15]
Train Loss: 0.9529, Train Acc: 30.16%
Val Loss: 0.8223, Val Acc: 40.36%
--------------------------------------------------
Epoch [4/15]
Train Loss: 0.8747, Train Acc: 33.41%
Val Loss: 0.6225, Val Acc: 50.72%
--------------------------------------------------
Epoch [5/15]
Train Loss: 0.7656, Train Acc: 37.12%
Val Loss: 0.6518, Val Acc: 41.42%
--------------------------------------------------
Epoch [6/15]
Train Loss: 0.6851, Train Acc: 38.77%
Val Loss: 0.6221, Val Acc: 50.84%
--------------------------------------------------
Epoch [7/15]
Train Loss: 0.6346, Train Acc: 43.39%
Val Loss: 0.5018, Val Acc: 53.34%
--------------------------------------------------
Epoch [8/15]
Train Loss: 0.5949, Train Acc: 43.86%
Val Loss: 0.5870, Val Acc: 57.21%
--------------------------------------------------
Epoch [9/15]
Train Loss: 0.5540, Train Acc: 47.18%
Val Loss: 0.4990, Val Acc: 56.83%
--------------------------------------------------
Epoch [10/15]
Train Loss: 0.4687, Train Acc: 48.57%
Val Loss: 0.4467, Val Acc: 58.33%
--------------------------------------------------
Epoch [11/15]
Train Loss: 0.4584, Train Acc: 51.02%
Val Loss: 0.4387, Val Acc: 56.21%
--------------------------------------------------
Epoch [12/15]
Train Loss: 0.4122, Train Acc: 52.77%
Val Loss: 0.4065, Val Acc: 58.02%
--------------------------------------------------
Epoch [13/15]
Train Loss: 0.3749, Train Acc: 53.21%
Val Loss: 0.4178, Val Acc: 58.76%
--------------------------------------------------
Epoch [14/15]
Train Loss: 0.3460, Train Acc: 53.50%
Val Loss: 0.4254, Val Acc: 58.64%
--------------------------------------------------
Epoch [15/15]
Train Loss: 0.3635, Train Acc: 52.93%
Val Loss: 0.4252, Val Acc: 60.07%
--------------------------------------------------

==================================================
Training VIT
==================================================
Epoch [1/15]
```

```
Epoch [1/15]
Train Loss: 1.7390, Train Acc: 5.54%
Val Loss: 1.6083, Val Acc: 11.10%
--------------------------------------------------
Epoch [2/15]
Train Loss: 1.5983, Train Acc: 7.88%
Val Loss: 1.5615, Val Acc: 2.93%
--------------------------------------------------
Epoch [3/15]
Train Loss: 1.5870, Train Acc: 7.91%
Val Loss: 1.4908, Val Acc: 7.30%
--------------------------------------------------
Epoch [4/15]
Train Loss: 1.5443, Train Acc: 8.91%
Val Loss: 1.4641, Val Acc: 9.23%
--------------------------------------------------
Epoch [5/15]
Train Loss: 1.5138, Train Acc: 9.05%
Val Loss: 1.4207, Val Acc: 11.54%
--------------------------------------------------
Epoch [6/15]
Train Loss: 1.4849, Train Acc: 10.67%
Val Loss: 1.4191, Val Acc: 11.79%
--------------------------------------------------
Epoch [7/15]
Train Loss: 1.4626, Train Acc: 11.28%
Val Loss: 1.4298, Val Acc: 14.22%
--------------------------------------------------
Epoch [8/15]
Train Loss: 1.4527, Train Acc: 10.97%
Val Loss: 1.4293, Val Acc: 11.17%
--------------------------------------------------
Epoch [9/15]
Train Loss: 1.4099, Train Acc: 11.22%
Val Loss: 1.3970, Val Acc: 10.85%
--------------------------------------------------
Epoch [10/15]
Train Loss: 1.4370, Train Acc: 11.09%
Val Loss: 1.3588, Val Acc: 13.47%
--------------------------------------------------
Epoch [11/15]
Train Loss: 1.3632, Train Acc: 12.11%
Val Loss: 1.3226, Val Acc: 13.16%
--------------------------------------------------
Epoch [12/15]
Train Loss: 1.3330, Train Acc: 12.70%
Val Loss: 1.3319, Val Acc: 11.92%
--------------------------------------------------
Epoch [13/15]
Train Loss: 1.2602, Train Acc: 14.53%
Val Loss: 1.3387, Val Acc: 10.79%
--------------------------------------------------
Epoch [14/15]
Train Loss: 1.2553, Train Acc: 17.62%
Val Loss: 1.2661, Val Acc: 19.28%
--------------------------------------------------
Epoch [15/15]
Train Loss: 1.2198, Train Acc: 25.50%
Val Loss: 1.2646, Val Acc: 27.45%
--------------------------------------------------

==================================================
CREATING ENSEMBLE MODEL
==================================================

Model Performance Comparison:
==================================================
EFFICIENTNET: Accuracy = 60.81%, F1 = 0.6524
RESNET: Accuracy = 61.31%, F1 = 0.6226
VIT: Accuracy = 27.71%, F1 = 0.2107
ENSEMBLE: Accuracy = 63.06%, F1 = 0.6627

Detailed Classification Report (Ensemble Model):
============================================================
              precision    recall  f1-score   support

       akiec       0.75      0.77      0.76        65
         bcc       0.68      0.85      0.76       103
         bkl       0.56      0.83      0.67       220
          df       0.50      0.96      0.66        23
         mel       0.28      0.86      0.42       223
          nv       0.99      0.52      0.69      1341
        vasc       0.54      0.96      0.69        28

    accuracy                           0.63      2003
```

```
   macro avg       0.61      0.82      0.66      2003
weighted avg       0.83      0.63      0.66      2003
```




```
Best Individual Model: EFFICIENTNET (62.38%)
```