In [ ]:
```
# from google.colab import drive
# drive.mount('/content/drive')
```

In [1]:
```
import os
from pathlib import Path
import numpy as np
import matplotlib.pyplot as plt
from tqdm import tqdm
from collections import Counter
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader
from sklearn.metrics import f1_score
import time, copy
from torch.optim.lr_scheduler import ReduceLROnPlateau
from torchvision.models import resnet50, ResNet50_Weights
from torchvision import transforms, datasets, models
from sklearn.metrics import classification_report, confusion_matrix, f1_score, accuracy_score
import pandas as pd
```

In [2]:
```
print("PyTorch CUDA version:", torch.version.cuda)
print("CUDA available:", torch.cuda.is_available())

if torch.cuda.is_available():
    print("GPU Name:", torch.cuda.get_device_name(0))
else:
    print("No GPU detected by PyTorch.")

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

```
PyTorch CUDA version: 12.1
CUDA available: True
GPU Name: NVIDIA GeForce MX350
Device used: cuda
```

In [3]:
```
base_dir = r"C:\Users\user\Desktop\DL"
train_dir = os.path.join(base_dir, "train")
val_dir   = os.path.join(base_dir, "val")
```

```
test_dir  = os.path.join(base_dir, "test")

# Data transforms
train_transforms = transforms.Compose([
    transforms.RandomResizedCrop(224),  # randomly crop and resize to 224x224
    transforms.RandomHorizontalFlip(),  # randomly flip images horizontally to improve generalization
    transforms.RandomRotation(20), # randomly rotate images by up to 20 degrees
    transforms.ColorJitter(brightness=0.1, contrast=0.1, saturation=0.1), # randomly change brightness, contrast, sat
    transforms.ToTensor(), # convert images to PyTorch tensors
    transforms.Normalize([0.485, 0.456, 0.406], # normalize with mean and std for pre-trained models to understand
                         [0.229, 0.224, 0.225])
])

# Validation and Test transforms for no randomness, cvonsistent evaluation
val_test_transforms = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                         [0.229, 0.224, 0.225])
])

# Datasets
# datasets.ImageFolder automatically labels images based on subfolder names.
train_dataset = datasets.ImageFolder(train_dir, transform=train_transforms)
val_dataset   = datasets.ImageFolder(val_dir, transform=val_test_transforms)
test_dataset  = datasets.ImageFolder(test_dir, transform=val_test_transforms)

class_names = train_dataset.classes

# DataLoaders
batch_size = 32
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True, num_workers=2, pin_memory=True) # shuf
val_loader   = DataLoader(val_dataset, batch_size=batch_size, shuffle=False, num_workers=2, pin_memory=True) # num_wo
test_loader  = DataLoader(test_dataset, batch_size=batch_size, shuffle=False, num_workers=2, pin_memory=True)

# Class info
num_classes = len(class_names)
print(f"Classes ({num_classes}):", class_names)
print("Train size:", len(train_dataset))
print("Val size:", len(val_dataset))
print("Test size:", len(test_dataset))
```

```
Classes (10): ['Actinic keratoses', 'Chickenpox', 'Cowpox', 'Dermatofibroma', 'HFMD', 'Healthy', 'Measles', 'Monkeypo
x', 'Squamous cell carcinoma', 'Vascular lesions']
Train size: 10648
Val size: 1327
Test size: 1337
```

In [4]:
```
if isinstance(train_dataset, torch.utils.data.Subset):
    # For Subset, use the original dataset and indices
    labels = [train_dataset.dataset.samples[i][1] for i in train_dataset.indices]
else:
    labels = [y for _, y in train_dataset.samples]

# Compute class counts
counts = Counter(labels)
counts_list = [counts[i] for i in range(len(class_names))]
print("Class counts:", counts_list)

# Compute class weights (inverse frequency), minority classes get more importance during training.
class_weights = torch.tensor([sum(counts_list)/c for c in counts_list], dtype=torch.float).to(device)
print("Class weights:", class_weights)

# Define weighted CrossEntropyLoss
criterion = nn.CrossEntropyLoss(weight=class_weights)
```

```
Class counts: [693, 900, 792, 191, 1932, 1368, 660, 3408, 502, 202]
Class weights: tensor([15.3651, 11.8311, 13.4444, 55.7487,  5.5114,  7.7836, 16.1333,  3.1244,
        21.2112, 52.7129], device='cuda:0')
```

In [5]:
```
# load pretrained ResNet-50
weights = ResNet50_Weights.DEFAULT
model = resnet50(weights=weights)

# freeze all layers initially
for param in model.parameters():
    param.requires_grad = False

# unfreeze only the last block (layer4) and the final fully connected layer
for name, param in model.named_parameters():
    if "layer4" in name or "fc" in name:
        param.requires_grad = True

# replace the final fully connected layer to match my number of classes
```

```
num_ftrs = model.fc.in_features
model.fc = nn.Linear(num_ftrs, num_classes)

# move model to device (GPU if available)
model = model.to(device)

# print trainable layers
trainable_layers = [name for name, param in model.named_parameters() if param.requires_grad]
print("Trainable layers:")
for layer in trainable_layers:
    print("  ", layer)

print(f"\nTotal trainable parameters: {sum(p.numel() for p in model.parameters() if p.requires_grad):,}")
```

```
Trainable layers:
   layer4.0.conv1.weight
   layer4.0.bn1.weight
   layer4.0.bn1.bias
   layer4.0.conv2.weight
   layer4.0.bn2.weight
   layer4.0.bn2.bias
   layer4.0.conv3.weight
   layer4.0.bn3.weight
   layer4.0.bn3.bias
   layer4.0.downsample.0.weight
   layer4.0.downsample.1.weight
   layer4.0.downsample.1.bias
   layer4.1.conv1.weight
   layer4.1.bn1.weight
   layer4.1.bn1.bias
   layer4.1.conv2.weight
   layer4.1.bn2.weight
   layer4.1.bn2.bias
   layer4.1.conv3.weight
   layer4.1.bn3.weight
   layer4.1.bn3.bias
   layer4.2.conv1.weight
   layer4.2.bn1.weight
   layer4.2.bn1.bias
   layer4.2.conv2.weight
   layer4.2.bn2.weight
   layer4.2.bn2.bias
   layer4.2.conv3.weight
   layer4.2.bn3.weight
   layer4.2.bn3.bias
   fc.weight
   fc.bias

Total trainable parameters: 14,985,226
```

In [6]:
```
# only update trainable parameters layer 4 and the fully connected layer
optimizer = optim.Adam(
    filter(lambda p: p.requires_grad, model.parameters()),
    lr=1e-4,        # Lower LR for fine-tuning pretrained layers
    weight_decay=1e-5
)
```

```
# reduce learning rate when validation F1 plateaus
scheduler = ReduceLROnPlateau(optimizer, mode='max', factor=0.5, patience=3, verbose=True)
```

```
c:\Users\user\CODING\Skin-Lession-Detection\.venv\Lib\site-packages\torch\optim\lr_scheduler.py:62: UserWarning: The
verbose parameter is deprecated. Please use get_last_lr() to access the learning rate.
  warnings.warn(
```

In [7]:
```
def train_model(model, criterion, optimizer, scheduler, num_epochs=20, model_name="ResNet50"):
    since = time.time()
    best_model_wts = copy.deepcopy(model.state_dict())
    best_f1 = 0.0

    history = {"train_loss":[], "val_loss":[], "train_acc":[], "val_acc":[], "val_f1":[]}

    for epoch in range(num_epochs):
        print(f"\nEpoch {epoch+1}/{num_epochs}")
        for phase in ["train","val"]:
            if phase == "train":
                model.train()
                loader = train_loader
            else:
                model.eval()
                loader = val_loader

            running_loss = 0.0
            running_corrects = 0
            y_true = []
            y_pred = []

            for inputs, labels in loader:
                inputs = inputs.to(device)
                labels = labels.to(device)

                optimizer.zero_grad()
                with torch.set_grad_enabled(phase == "train"):
                    outputs = model(inputs)
                    _, preds = torch.max(outputs, 1)
                    loss = criterion(outputs, labels)

                    if phase == "train":
                        loss.backward()
```

```
                optimizer.step()

            running_loss += loss.item() * inputs.size(0)
            running_corrects += torch.sum(preds == labels.data).item()
            y_true.extend(labels.cpu().numpy())
            y_pred.extend(preds.cpu().numpy())

        epoch_loss = running_loss / len(loader.dataset)
        epoch_acc = running_corrects / len(loader.dataset)
        epoch_f1 = f1_score(y_true, y_pred, average='macro')

        print(f"{phase} Loss: {epoch_loss:.4f} Acc: {epoch_acc:.4f} F1: {epoch_f1:.4f}")

        if phase == "train":
            history["train_loss"].append(epoch_loss)
            history["train_acc"].append(epoch_acc)
        else:
            history["val_loss"].append(epoch_loss)
            history["val_acc"].append(epoch_acc)
            history["val_f1"].append(epoch_f1)

            # Save best model
            if epoch_f1 > best_f1:
                best_f1 = epoch_f1
                best_model_wts = copy.deepcopy(model.state_dict())
                torch.save(model.state_dict(), f"{model_name}_best.pth")

    # Step scheduler using validation F1
    scheduler.step(best_f1)
    print("-"*40)

time_elapsed = time.time() - since
print(f"\nTraining complete in {time_elapsed//60:.0f}m {time_elapsed%60:.0f}s")
print(f"Best val F1: {best_f1:.4f}")

# Load best model weights
model.load_state_dict(best_model_wts)
return model, history
```

In [14]:

```
num_epochs = 30
model, history = train_model(
    model,
```

```
    criterion,
    optimizer,
    scheduler,
    num_epochs=num_epochs,
    model_name="ResNet50_Finetuned"
)
```

```
Epoch 1/30
train Loss: 0.3302 Acc: 0.8628 F1: 0.8524
val Loss: 0.2259 Acc: 0.9096 F1: 0.8852
----------------------------------------

Epoch 2/30
train Loss: 0.3021 Acc: 0.8726 F1: 0.8641
val Loss: 0.2012 Acc: 0.9307 F1: 0.9185
----------------------------------------

Epoch 3/30
train Loss: 0.3035 Acc: 0.8697 F1: 0.8645
val Loss: 0.1734 Acc: 0.9427 F1: 0.9218
----------------------------------------

Epoch 4/30
train Loss: 0.3040 Acc: 0.8744 F1: 0.8655
val Loss: 0.2060 Acc: 0.9352 F1: 0.9239
----------------------------------------

Epoch 5/30
train Loss: 0.2858 Acc: 0.8815 F1: 0.8733
val Loss: 0.1729 Acc: 0.9405 F1: 0.9233
----------------------------------------

Epoch 6/30
train Loss: 0.2784 Acc: 0.8878 F1: 0.8798
val Loss: 0.1701 Acc: 0.9488 F1: 0.9347
----------------------------------------

Epoch 7/30
train Loss: 0.2678 Acc: 0.8907 F1: 0.8828
val Loss: 0.1598 Acc: 0.9412 F1: 0.9256
----------------------------------------

Epoch 8/30
train Loss: 0.2737 Acc: 0.8882 F1: 0.8800
val Loss: 0.1658 Acc: 0.9480 F1: 0.9217
----------------------------------------

Epoch 9/30
train Loss: 0.2441 Acc: 0.8946 F1: 0.8915
```

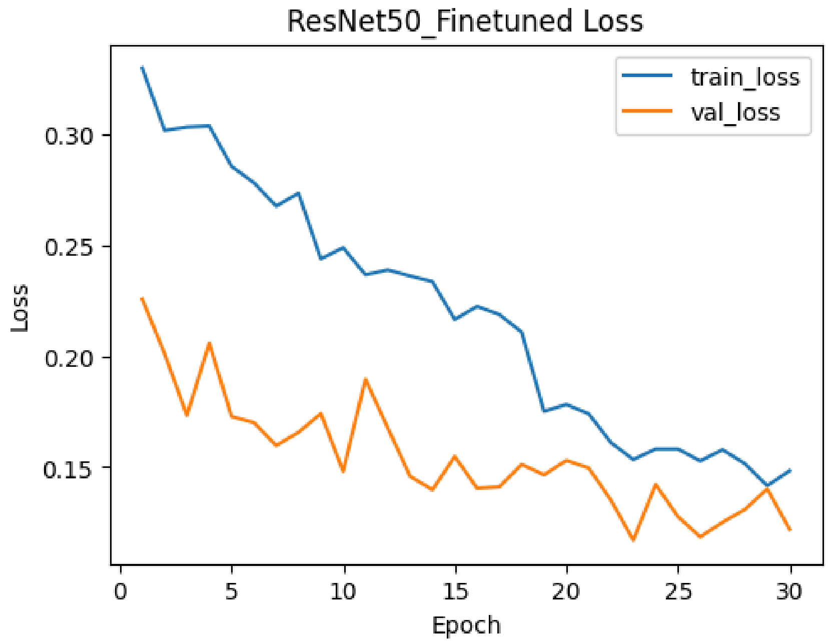
```
val Loss: 0.1742 Acc: 0.9427 F1: 0.9307
----------------------------------------

Epoch 10/30
train Loss: 0.2490 Acc: 0.9002 F1: 0.8920
val Loss: 0.1482 Acc: 0.9570 F1: 0.9396
----------------------------------------

Epoch 11/30
train Loss: 0.2369 Acc: 0.8993 F1: 0.8938
val Loss: 0.1897 Acc: 0.9382 F1: 0.9215
----------------------------------------

Epoch 12/30
train Loss: 0.2391 Acc: 0.9018 F1: 0.8971
val Loss: 0.1677 Acc: 0.9427 F1: 0.9237
----------------------------------------

Epoch 13/30
train Loss: 0.2363 Acc: 0.9051 F1: 0.8943
val Loss: 0.1459 Acc: 0.9533 F1: 0.9303
----------------------------------------

Epoch 14/30
train Loss: 0.2337 Acc: 0.9037 F1: 0.8985
val Loss: 0.1398 Acc: 0.9525 F1: 0.9406
----------------------------------------

Epoch 15/30
train Loss: 0.2167 Acc: 0.9072 F1: 0.9046
val Loss: 0.1548 Acc: 0.9510 F1: 0.9393
----------------------------------------

Epoch 16/30
train Loss: 0.2226 Acc: 0.9086 F1: 0.9018
val Loss: 0.1405 Acc: 0.9495 F1: 0.9395
----------------------------------------

Epoch 17/30
train Loss: 0.2189 Acc: 0.9148 F1: 0.9077
val Loss: 0.1411 Acc: 0.9457 F1: 0.9330
----------------------------------------
```

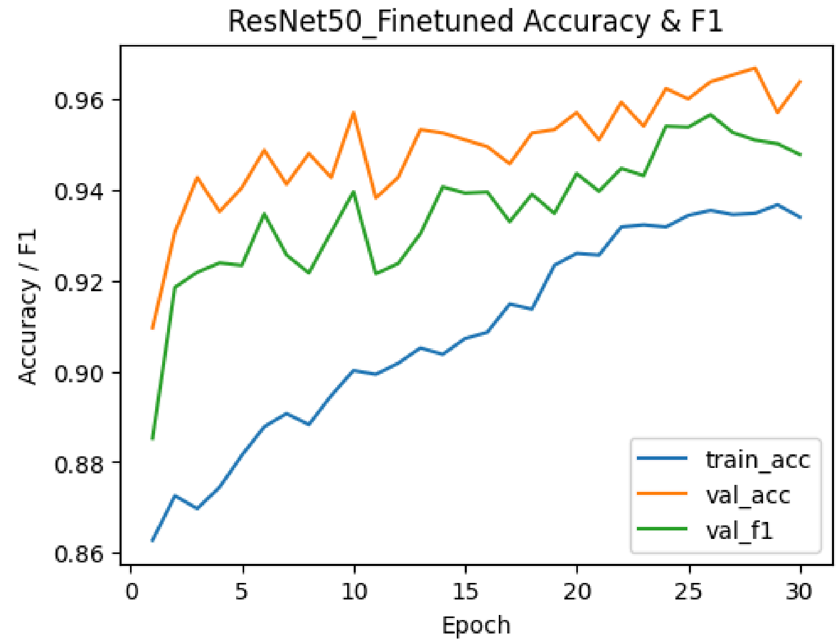
```
Epoch 18/30
train Loss: 0.2110 Acc: 0.9137 F1: 0.9093
val Loss: 0.1513 Acc: 0.9525 F1: 0.9390
----------------------------------------

Epoch 19/30
train Loss: 0.1752 Acc: 0.9234 F1: 0.9241
val Loss: 0.1466 Acc: 0.9533 F1: 0.9348
----------------------------------------

Epoch 20/30
train Loss: 0.1783 Acc: 0.9260 F1: 0.9259
val Loss: 0.1531 Acc: 0.9570 F1: 0.9436
----------------------------------------

Epoch 21/30
train Loss: 0.1741 Acc: 0.9256 F1: 0.9221
val Loss: 0.1497 Acc: 0.9510 F1: 0.9397
----------------------------------------

Epoch 22/30
train Loss: 0.1611 Acc: 0.9318 F1: 0.9290
val Loss: 0.1351 Acc: 0.9593 F1: 0.9447
----------------------------------------

Epoch 23/30
train Loss: 0.1535 Acc: 0.9323 F1: 0.9343
val Loss: 0.1171 Acc: 0.9540 F1: 0.9431
----------------------------------------

Epoch 24/30
train Loss: 0.1582 Acc: 0.9318 F1: 0.9315
val Loss: 0.1422 Acc: 0.9623 F1: 0.9540
----------------------------------------

Epoch 25/30
train Loss: 0.1582 Acc: 0.9344 F1: 0.9311
val Loss: 0.1277 Acc: 0.9601 F1: 0.9538
----------------------------------------

Epoch 26/30
```

```
train Loss: 0.1529 Acc: 0.9355 F1: 0.9333
val Loss: 0.1186 Acc: 0.9638 F1: 0.9566
----------------------------------------

Epoch 27/30
train Loss: 0.1579 Acc: 0.9345 F1: 0.9296
val Loss: 0.1251 Acc: 0.9653 F1: 0.9526
----------------------------------------

Epoch 28/30
train Loss: 0.1516 Acc: 0.9348 F1: 0.9340
val Loss: 0.1309 Acc: 0.9668 F1: 0.9510
----------------------------------------

Epoch 29/30
train Loss: 0.1416 Acc: 0.9367 F1: 0.9367
val Loss: 0.1402 Acc: 0.9570 F1: 0.9502
----------------------------------------

Epoch 30/30
train Loss: 0.1484 Acc: 0.9340 F1: 0.9352
val Loss: 0.1220 Acc: 0.9638 F1: 0.9478
----------------------------------------

Training complete in 509m 33s
Best val F1: 0.9566
```

In [15]:

```
epochs = range(1, len(history["train_loss"]) + 1)
model_name = "ResNet50_Finetuned"

plt.figure(figsize=(12,4))
plt.subplot(1,2,1)
plt.plot(epochs, history["train_loss"], label="train_loss")
plt.plot(epochs, history["val_loss"], label="val_loss")
plt.xlabel("Epoch"); plt.ylabel("Loss"); plt.legend(); plt.title(f"{model_name} Loss")

plt.subplot(1,2,2)
plt.plot(epochs, history["train_acc"], label="train_acc")
plt.plot(epochs, history["val_acc"], label="val_acc")
plt.plot(epochs, history["val_f1"], label="val_f1")  # add validation F1
plt.xlabel("Epoch"); plt.ylabel("Accuracy / F1"); plt.legend(); plt.title(f"{model_name} Accuracy & F1")
plt.show()
```





In [16]:

```
# Load best model checkpoint (if needed) and run final evaluation on validation set
def evaluate_model(model):
    model.eval()
    y_true = []
    y_pred = []
    with torch.no_grad():
        for inputs, labels in val_loader:
            inputs = inputs.to(device)
            labels = labels.to(device)
            outputs = model(inputs)
            _, preds = torch.max(outputs, 1)
            y_true.extend(labels.cpu().numpy().tolist())
            y_pred.extend(preds.cpu().numpy().tolist())
    print(classification_report(y_true, y_pred, target_names=class_names))
    cm = confusion_matrix(y_true, y_pred)
    print("Confusion matrix:\n", cm)
```

In [17]:

```
evaluate_model(model)
```

```
                         precision    recall  f1-score   support

      Actinic keratoses       0.87      0.95      0.91        86
            Chickenpox       0.94      0.96      0.95       112
                Cowpox       0.99      0.96      0.97        99
        Dermatofibroma       0.96      0.96      0.96        23
                  HFMD       0.96      0.99      0.98       241
               Healthy       0.98      0.98      0.98       171
               Measles       0.98      0.99      0.98        82
             Monkeypox       0.98      0.96      0.97       426
Squamous cell carcinoma       0.93      0.81      0.86        62
      Vascular lesions       1.00      1.00      1.00        25

              accuracy                           0.96      1327
             macro avg       0.96      0.96      0.96      1327
          weighted avg       0.96      0.96      0.96      1327

Confusion matrix:
 [[ 82   0   0   0   0   0   0   0   4   0]
 [  0 108   0   0   0   0   1   3   0   0]
 [  0   1  95   0   1   0   0   2   0   0]
 [  1   0   0  22   0   0   0   0   0   0]
 [  0   0   0   0 239   0   1   1   0   0]
 [  0   0   0   0   1 168   0   2   0   0]
 [  0   0   0   0   0   1  81   0   0   0]
 [  0   6   1   0   8   2   0 409   0   0]
 [ 11   0   0   1   0   0   0   0  50   0]
 [  0   0   0   0   0   0   0   0   0  25]]
```

In [18]:

```python
print("Test classes order:", test_dataset.classes)
print("Test size:", len(test_dataset))

# Load best model checkpoint
ckpt_path = "ResNet50_best.pth"
try:
    state = torch.load(ckpt_path, map_location=device)
    model.load_state_dict(state)
    print("Loaded checkpoint:", ckpt_path)
except Exception as e:
    print("Checkpoint load failed (using current model):", e)
```

```
model.to(device)
model.eval()  # set to evaluation mode
```

```
Test classes order: ['Actinic keratoses', 'Basal cell carcinoma', 'Benign keratosis-like lesions', 'Chickenpox', 'Cow
pox', 'Dermatofibroma', 'HFMD', 'Healthy', 'Measles', 'Melanoma', 'Monkeypox', 'Squamous cell carcinoma', 'Vascular l
esions']
Test size: 2386
Checkpoint load failed (using current model): [Errno 2] No such file or directory: 'ResNet50_best.pth'
```

```
C:\Users\user\AppData\Local\Temp\ipykernel_25344\951452986.py:7: FutureWarning: You are using `torch.load` with `weig
hts_only=False` (the current default value), which uses the default pickle module implicitly. It is possible to const
ruct malicious pickle data which will execute arbitrary code during unpickling (See https://github.com/pytorch/pytorc
h/blob/main/SECURITY.md#untrusted-models for more details). In a future release, the default value for `weights_only`
will be flipped to `True`. This limits the functions that could be executed during unpickling. Arbitrary objects will
no longer be allowed to be loaded via this mode unless they are explicitly allowlisted by the user via `torch.seriali
zation.add_safe_globals`. We recommend you start setting `weights_only=True` for any use case where you don't have fu
ll control of the loaded file. Please open an issue on GitHub for any issues related to this experimental feature.
  state = torch.load(ckpt_path, map_location=device)
```

Out[18]:
```
ResNet(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
  (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (relu): ReLU(inplace=True)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
  (layer1): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(64, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (downsample): Sequential(
        (0): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
    (2): Bottleneck(
      (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
  )
  (layer2): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
```

```
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (downsample): Sequential(
        (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
    (2): Bottleneck(
      (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
    (3): Bottleneck(
      (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
  )
  (layer3): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(512, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
```

```
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (downsample): Sequential(
        (0): Conv2d(512, 1024, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
    (2): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
    (3): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
    (4): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
```

```
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
    (5): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
  )
  (layer4): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(1024, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (downsample): Sequential(
        (0): Conv2d(1024, 2048, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
    (2): Bottleneck(
      (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
```

```
        (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
      )
    )
    (avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
    (fc): Linear(in_features=2048, out_features=10, bias=True)
  )
```

In [19]:

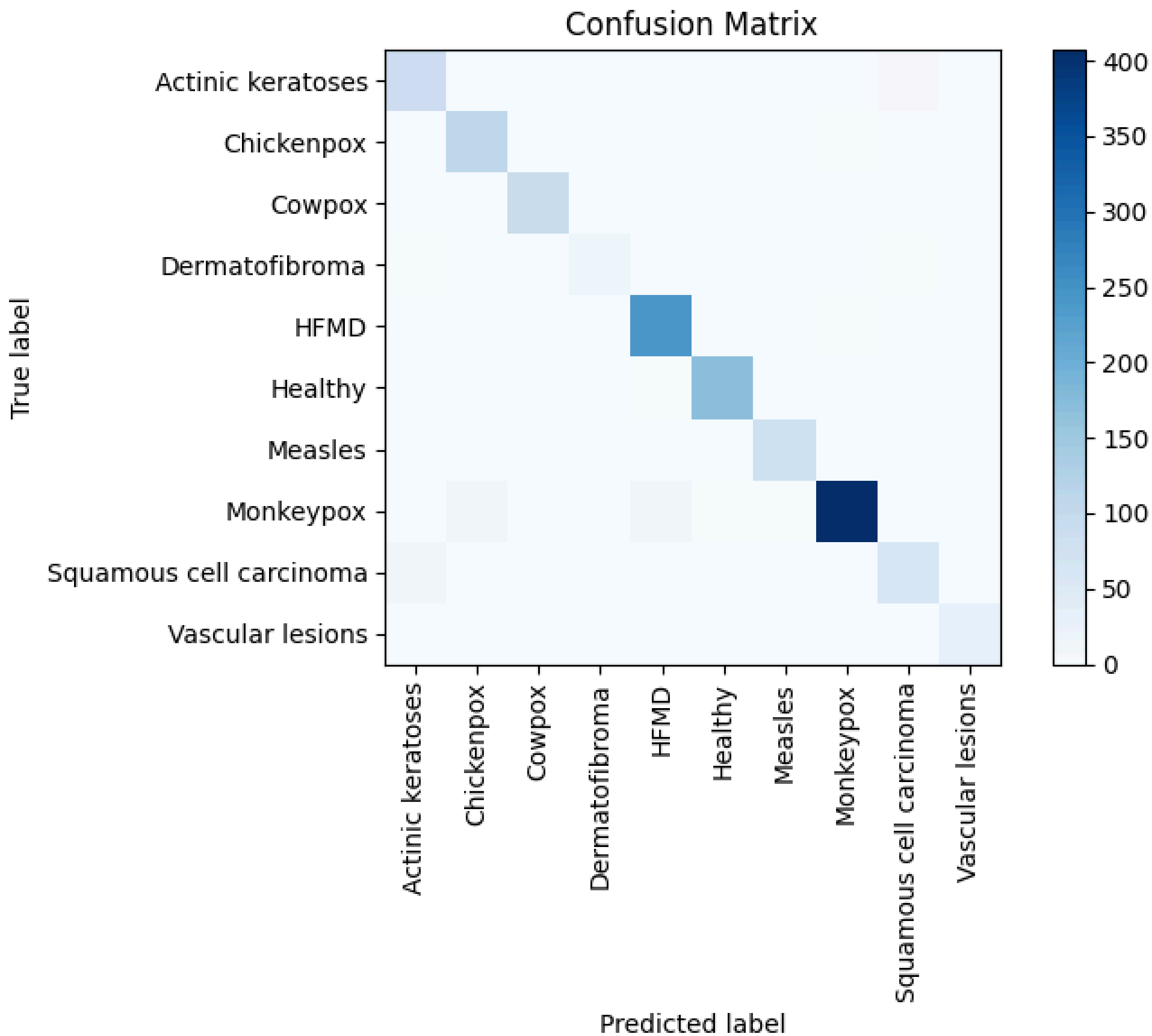
```
test_dir  = os.path.join(base_dir, "test")
test_dataset  = datasets.ImageFolder(test_dir, transform=val_test_transforms)

# DataLoaders
batch_size = 32
test_loader  = DataLoader(test_dataset, batch_size=batch_size, shuffle=False, num_workers=2, pin_memory=True)

y_true, y_pred, probs = [], [], []

# Iterate through test dataset
with torch.no_grad():
    for inputs, labels in test_loader:
        inputs, labels = inputs.to(device), labels.to(device)
        outputs = model(inputs)
        ps = torch.softmax(outputs, dim=1)  # probabilities
        _, preds = torch.max(outputs, 1)    # predicted class

        y_true.extend(labels.cpu().numpy())
        y_pred.extend(preds.cpu().numpy())
        probs.extend(ps.cpu().numpy())

# metrics
print("\nClassification Report:\n")
print(classification_report(y_true, y_pred, target_names=class_names))
```

```
Classification Report:

                          precision    recall  f1-score   support

       Actinic keratoses       0.89      0.94      0.92        88
              Chickenpox       0.94      0.97      0.96       113
                  Cowpox       0.97      0.98      0.97        99
          Dermatofibroma       1.00      0.76      0.86        25
                    HFMD       0.96      0.99      0.97       242
                 Healthy       0.98      0.98      0.98       171
                 Measles       0.96      0.98      0.97        83
              Monkeypox       0.99      0.96      0.97       426
Squamous cell carcinoma       0.89      0.88      0.88        64
        Vascular lesions       0.93      1.00      0.96        26

                accuracy                           0.96      1337
               macro avg       0.95      0.94      0.94      1337
            weighted avg       0.96      0.96      0.96      1337
```

In [20]:

```
cm = confusion_matrix(y_true, y_pred)
print("\nConfusion Matrix:\n", cm)

# plot confusion matrix
plt.figure(figsize=(8,6))
plt.imshow(cm, interpolation='nearest', cmap='Blues')
plt.title("Confusion Matrix")
plt.colorbar()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names, rotation=90)
plt.yticks(tick_marks, class_names)
plt.xlabel('Predicted label')
plt.ylabel('True label')
plt.tight_layout()
plt.show()
```

```
Confusion Matrix:
 [[ 83   0   0   0   0   0   0   0   4   1]
 [  0 110   1   0   0   0   0   2   0   0]
 [  0   1  97   0   0   0   0   1   0   0]
 [  3   0   0  19   0   0   0   0   3   0]
 [  0   0   1   0 239   0   0   2   0   0]
 [  0   0   0   0   3 167   0   1   0   0]
 [  0   1   0   0   1   0  81   0   0   0]
 [  0   5   1   0   7   3   3 407   0   0]
 [  7   0   0   0   0   0   0   0  56   1]
 [  0   0   0   0   0   0   0   0   0  26]]
```

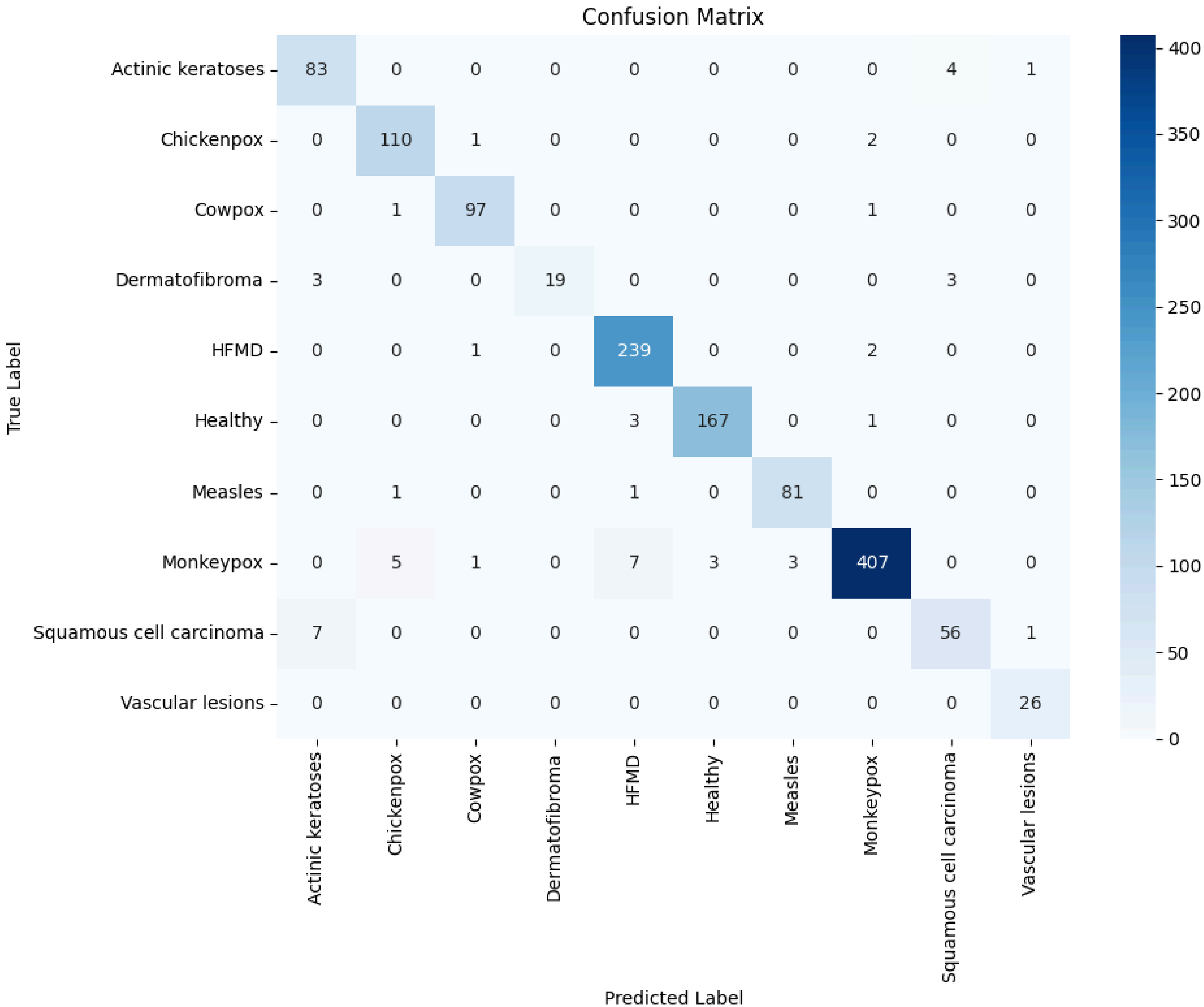


In [21]:
```
# save per-image predictions in to CSV
filenames = [os.path.basename(p[0]) for p in test_dataset.samples]
df = pd.DataFrame({
    "file": filenames,
    "true": [class_names[i] for i in y_true],
    "pred": [class_names[i] for i in y_pred],
```

```
    "prob_top": [round(float(np.max(p)),4) for p in probs]
})
df.to_csv("test_predictions.csv", index=False)
print("Saved test_predictions.csv")
```

```
Saved test_predictions.csv
```

In [22]:
```
import seaborn as sns

plt.figure(figsize=(10,8))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=class_names, yticklabels=class_names)
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.tight_layout()
plt.show()
```


Confusion Matrix
True Label
Predicted Label
Actinic keratoses
Chickenpox
Cowpox
Dermatofibroma
HFMD
Healthy
Measles
Monkeypox
Squamous cell carcinoma
Vascular lesions
83 0 0 0 0 0 0 0 4 1
0 110 1 0 0 0 0 2 0 0
0 1 97 0 0 0 0 1 0 0
3 0 0 19 0 0 0 0 3 0
0 0 1 0 239 0 0 2 0 0
0 0 0 0 3 167 0 1 0 0
0 1 0 0 1 0 81 0 0 0
0 5 1 0 7 3 3 407 0 0
7 0 0 0 0 0 0 0 56 1
0 0 0 0 0 0 0 0 0 26
400
350
300
250
200
150
100
50
0

In [23]:
```
pd.DataFrame(history).to_csv("training_history.csv", index=False)
```

In [6]:
```
# Load best model for inference
model = resnet50(weights=None)
num_ftrs = model.fc.in_features
model.fc = nn.Linear(num_ftrs, num_classes)
model.load_state_dict(torch.load("ResNet50_Finetuned_best.pth", map_location=device))
model.to(device)
model.eval()
```

```
C:\Users\user\AppData\Local\Temp\ipykernel_21580\1542041176.py:5: FutureWarning: You are using `torch.load` with `wei
ghts_only=False` (the current default value), which uses the default pickle module implicitly. It is possible to cons
truct malicious pickle data which will execute arbitrary code during unpickling (See https://github.com/pytorch/pytor
ch/blob/main/SECURITY.md#untrusted-models for more details). In a future release, the default value for `weights_only
` will be flipped to `True`. This limits the functions that could be executed during unpickling. Arbitrary objects wi
ll no longer be allowed to be loaded via this mode unless they are explicitly allowlisted by the user via `torch.seri
alization.add_safe_globals`. We recommend you start setting `weights_only=True` for any use case where you don't have
full control of the loaded file. Please open an issue on GitHub for any issues related to this experimental feature.
  model.load_state_dict(torch.load("ResNet50_Finetuned_best.pth", map_location=device))
```

Out[6]:
```
ResNet(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
  (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (relu): ReLU(inplace=True)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
  (layer1): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(64, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (downsample): Sequential(
        (0): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
    (2): Bottleneck(
      (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
  )
  (layer2): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
```

```
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (downsample): Sequential(
        (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
    (2): Bottleneck(
      (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
    (3): Bottleneck(
      (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
  )
  (layer3): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(512, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
```

```
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (downsample): Sequential(
        (0): Conv2d(512, 1024, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
    (2): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
    (3): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
    (4): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
```

```
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
    (5): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
  )
  (layer4): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(1024, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (downsample): Sequential(
        (0): Conv2d(1024, 2048, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
    (2): Bottleneck(
      (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
```

```
        (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
      )
    )
    (avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
    (fc): Linear(in_features=2048, out_features=10, bias=True)
  )
```

In [7]:

```python
from PIL import Image
import torch
from torchvision import transforms

image_path = r"C:\Users\user\Desktop\DL\test\Chickenpox\CHP_02_01_1.jpg"

val_test_transforms = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                         [0.229, 0.224, 0.225])
])

image = Image.open(image_path).convert("RGB")  # ensure 3 channels
input_tensor = val_test_transforms(image).unsqueeze(0)  # add batch dimension
input_tensor = input_tensor.to(device)

model.eval()
with torch.no_grad():
    outputs = model(input_tensor)
    probabilities = torch.softmax(outputs, dim=1)
    predicted_class_idx = torch.argmax(probabilities, dim=1).item()

predicted_label = class_names[predicted_class_idx]
confidence = probabilities[0][predicted_class_idx].item()

print(f"Predicted Class: {predicted_label}")
print(f"Confidence: {confidence:.4f}")
```

```
Predicted Class: Chickenpox
Confidence: 0.9999
```

In [8]:
```
plt.imshow(image)
plt.title(f"Predicted: {predicted_label} ({confidence*100:.2f}%)")
plt.axis("off")
plt.show()
```

Predicted: Chickenpox (99.99%)

In [ ]: