In [2]:
```python
import tensorflow as tf
import matplotlib.pyplot as plt
import numpy as np
import os
import random
```

```
2024-12-18 14:04:38.736531: E external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:
477] Unable to register cuFFT factory: Attempting to register factory for plugin cuFFT
when one has already been registered
WARNING: All log messages before absl::InitializeLog() is called are written to STDERR
E0000 00:00:1734510878.748773   69571 cuda_dnn.cc:8310] Unable to register cuDNN facto
ry: Attempting to register factory for plugin cuDNN when one has already been register
ed
E0000 00:00:1734510878.752322   69571 cuda_blas.cc:1418] Unable to register cuBLAS fac
tory: Attempting to register factory for plugin cuBLAS when one has already been regis
tered
2024-12-18 14:04:38.765870: I tensorflow/core/platform/cpu_feature_guard.cc:210] This
TensorFlow binary is optimized to use available CPU instructions in performance-critic
al operations.
To enable the following instructions: AVX2 FMA, in other operations, rebuild TensorFlo
w with the appropriate compiler flags.
```

In [3]:
```python
train_dir = 'data/train'  # path to your training directory
test_dir = 'data/test'    # path to your test directory
```

In [4]:
```python
# Check classes
classes = sorted(os.listdir(train_dir))
print("Classes:", classes)
```

```
Classes: ['actinic keratosis', 'basal cell carcinoma', 'dermatofibroma', 'melanoma',
'nevus', 'pigmented benign keratosis', 'seborrheic keratosis', 'squamous cell carcinom
a', 'vascular lesion']
```

In [5]:
```python
# Check data distribution in training set
class_counts = {}
for cls in classes:
    class_path = os.path.join(train_dir, cls)
    if os.path.isdir(class_path):
        class_counts[cls] = len(os.listdir(class_path))
print("Class distribution in training data:", class_counts)
```

```
Class distribution in training data: {'actinic keratosis': 114, 'basal cell carcinom
a': 376, 'dermatofibroma': 95, 'melanoma': 438, 'nevus': 357, 'pigmented benign kerato
sis': 462, 'seborrheic keratosis': 77, 'squamous cell carcinoma': 181, 'vascular lesio
n': 139}
```

In [6]:
```python
#-------------------------------------------------------------------
# DATASET CREATION
# Create train & validation dataset with image size 180x180 and batch size 32
#-------------------------------------------------------------------
img_size = (180, 180)
batch_size = 32

train_ds = tf.keras.preprocessing.image_dataset_from_directory(
    train_dir,
    validation_split=0.2,
    subset="training",
    seed=42,
    image_size=img_size,
    batch_size=batch_size
)

val_ds = tf.keras.preprocessing.image_dataset_from_directory(
    train_dir,
```

```
    validation_split=0.2,
    subset="validation",
    seed=42,
    image_size=img_size,
    batch_size=batch_size
)
```

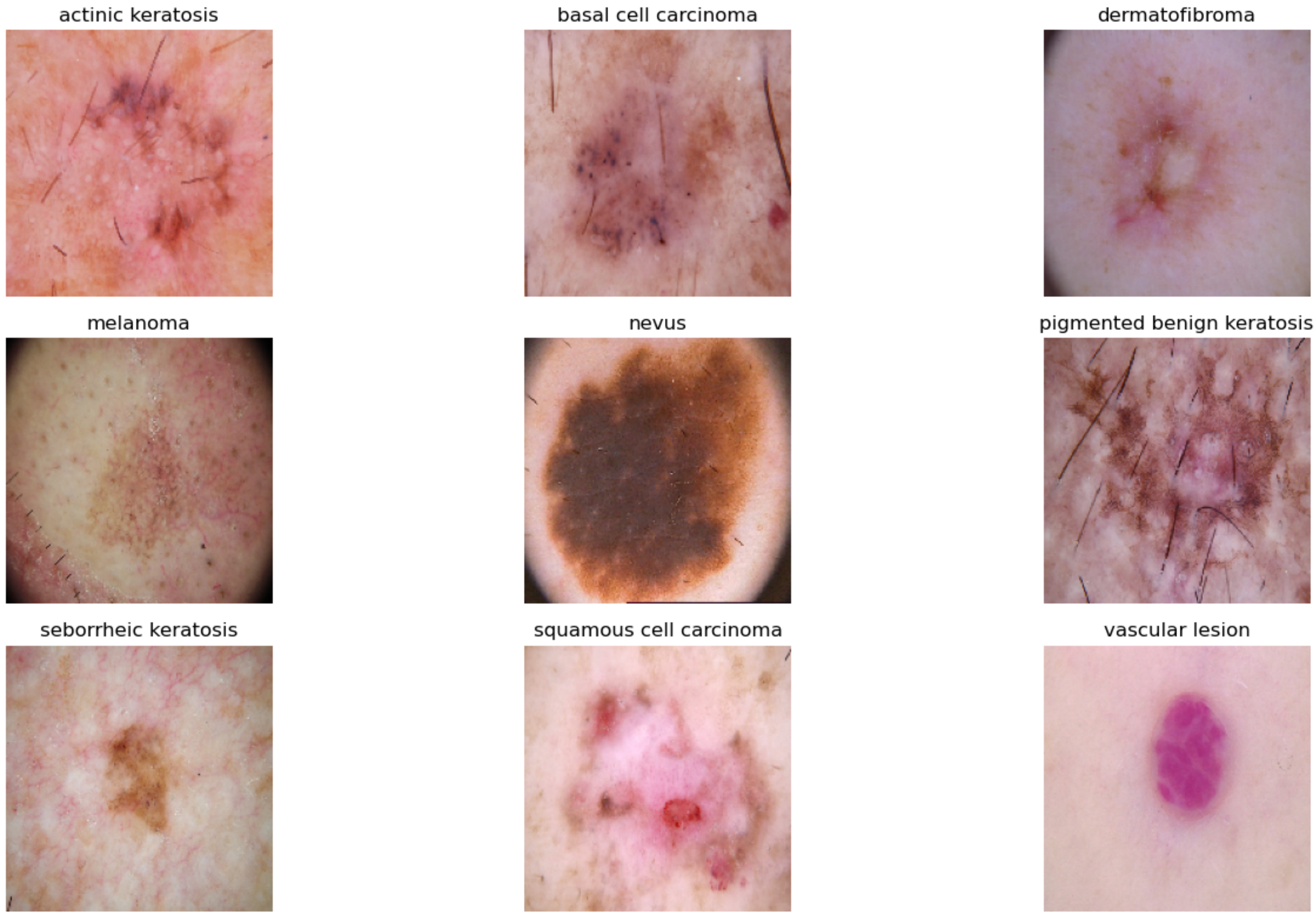
```
Found 2239 files belonging to 9 classes.
Using 1792 files for training.
I0000 00:00:1734510880.343890   69571 gpu_device.cc:2022] Created device /job:localhost/replica:0/task:0/device:GPU:0 with 2273 MB memory:  -> device: 0, name: NVIDIA GeForce RTX 3050 Ti Laptop GPU, pci bus id: 0000:01:00.0, compute capability: 8.6
Found 2239 files belonging to 9 classes.
Using 447 files for validation.
```

In [7]:

```
# Prefetch for performance
train_ds = train_ds.cache().shuffle(1000).prefetch(buffer_size=tf.data.experimental.A
val_ds = val_ds.cache().prefetch(buffer_size=tf.data.experimental.AUTOTUNE)
```

In [8]:

```
#--------------------------------------------------------------------
# DATASET VISUALIZATION
# Visualize one sample image from each class
#--------------------------------------------------------------------
plt.figure(figsize=(15, 8))
for i, cls in enumerate(classes):
    cls_path = os.path.join(train_dir, cls)
    img_files = os.listdir(cls_path)
    # Filter to ensure we only pick image files
    img_files = [f for f in img_files if f.lower().endswith(('.png', '.jpg', '.jpeg'))
    if len(img_files) > 0:
        sample_img = random.choice(img_files)
        img_path = os.path.join(cls_path, sample_img)
        img = tf.keras.utils.load_img(img_path, target_size=img_size)
        plt.subplot(3, 3, i+1)
        plt.imshow(img)
        plt.title(cls)
        plt.axis('off')
plt.tight_layout()
plt.show()
```



In [9]:

```
#-------------------------------------------------------------------
# INITIAL MODEL BUILDING & TRAINING (NO AUGMENTATION)
#-------------------------------------------------------------------
num_classes = len(classes)

model = tf.keras.Sequential([
    tf.keras.layers.Rescaling(1./255, input_shape=(180,180,3)),
    tf.keras.layers.Conv2D(32, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(),
    tf.keras.layers.Conv2D(64, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(),
    tf.keras.layers.Conv2D(128, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(),
    tf.keras.layers.Conv2D(256, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dropout(0.3),
    tf.keras.layers.Dense(num_classes, activation='softmax')
])

model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

model.summary()

epochs = 20
history = model.fit(train_ds, validation_data=val_ds, epochs=epochs)
```

```
/home/alpesh/anaconda3/lib/python3.11/site-packages/keras/src/layers/preprocessing/tf_
data_layer.py:19: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a
layer. When using Sequential models, prefer using an `Input(shape)` object as the firs
t layer in the model instead.
  super().__init__(**kwargs)
```

Model: "sequential"

Layer (type)	Output Shape	Param #
rescaling (Rescaling)	(None, 180, 180, 3)	0
conv2d (Conv2D)	(None, 178, 178, 32)	896
max_pooling2d (MaxPooling2D)	(None, 89, 89, 32)	0
conv2d_1 (Conv2D)	(None, 87, 87, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 43, 43, 64)	0
conv2d_2 (Conv2D)	(None, 41, 41, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 20, 20, 128)	0
conv2d_3 (Conv2D)	(None, 18, 18, 256)	295,168
max_pooling2d_3 (MaxPooling2D)	(None, 9, 9, 256)	0
flatten (Flatten)	(None, 20736)	0
dense (Dense)	(None, 128)	2,654,336
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 9)	1,161

Total params: 3,043,913 (11.61 MB)

Trainable params: 3,043,913 (11.61 MB)

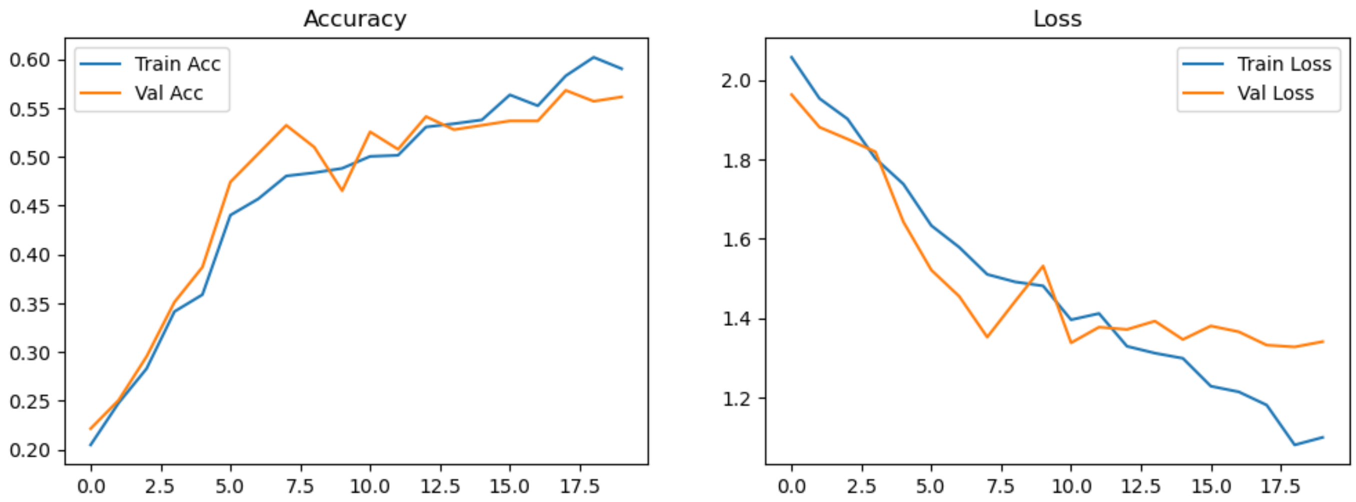
Non-trainable params: 0 (0.00 B)

```
Epoch 1/20
WARNING: All log messages before absl::InitializeLog() is called are written to STDERR
I0000 00:00:1734510884.621065   69688 service.cc:148] XLA service 0x7a9bac002210 initi
alized for platform CUDA (this does not guarantee that XLA will be used). Devices:
I0000 00:00:1734510884.621087   69688 service.cc:156]   StreamExecutor device (0): NVI
DIA GeForce RTX 3050 Ti Laptop GPU, Compute Capability 8.6
2024-12-18 14:04:44.645286: I tensorflow/compiler/mlir/tensorflow/utils/dump_mlir_uti
l.cc:268] disabling MLIR crash reproducer, set env var `MLIR_CRASH_REPRODUCER_DIRECTOR
Y` to enable.
I0000 00:00:1734510884.771742   69688 cuda_dnn.cc:529] Loaded cuDNN version 90300
 5/56 ━━━━━━━━━━━━━━━━━━━━ 1s 36ms/step - accuracy: 0.1834 - loss: 2.1705
I0000 00:00:1734510889.253024   69688 device_compiler.h:188] Compiled cluster using XL
A!  This line is logged at most once for the lifetime of the process.
```

```
56/56 ━━━━━━━━━━━━━━━━━━━━ 12s 85ms/step - accuracy: 0.1927 - loss: 2.0910 - val_accur
acy: 0.2215 - val_loss: 1.9637
Epoch 2/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 38ms/step - accuracy: 0.2467 - loss: 1.9694 - val_accura
cy: 0.2506 - val_loss: 1.8815
Epoch 3/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 38ms/step - accuracy: 0.2789 - loss: 1.8929 - val_accura
cy: 0.2953 - val_loss: 1.8517
Epoch 4/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 38ms/step - accuracy: 0.3350 - loss: 1.8170 - val_accura
cy: 0.3512 - val_loss: 1.8195
Epoch 5/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 38ms/step - accuracy: 0.3352 - loss: 1.7969 - val_accura
cy: 0.3870 - val_loss: 1.6428
Epoch 6/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 38ms/step - accuracy: 0.4475 - loss: 1.6537 - val_accura
cy: 0.4743 - val_loss: 1.5213
Epoch 7/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 38ms/step - accuracy: 0.4554 - loss: 1.5838 - val_accura
cy: 0.5034 - val_loss: 1.4550
Epoch 8/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 38ms/step - accuracy: 0.4582 - loss: 1.5573 - val_accura
cy: 0.5324 - val_loss: 1.3522
Epoch 9/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 37ms/step - accuracy: 0.4893 - loss: 1.4709 - val_accura
cy: 0.5101 - val_loss: 1.4428
Epoch 10/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 37ms/step - accuracy: 0.4803 - loss: 1.5149 - val_accura
cy: 0.4653 - val_loss: 1.5316
Epoch 11/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 38ms/step - accuracy: 0.5014 - loss: 1.4125 - val_accura
cy: 0.5257 - val_loss: 1.3380
Epoch 12/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 37ms/step - accuracy: 0.4976 - loss: 1.4008 - val_accura
cy: 0.5078 - val_loss: 1.3774
Epoch 13/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 37ms/step - accuracy: 0.5239 - loss: 1.3440 - val_accura
cy: 0.5414 - val_loss: 1.3716
Epoch 14/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 38ms/step - accuracy: 0.5134 - loss: 1.3431 - val_accura
cy: 0.5280 - val_loss: 1.3927
Epoch 15/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 37ms/step - accuracy: 0.5192 - loss: 1.3273 - val_accura
cy: 0.5324 - val_loss: 1.3464
Epoch 16/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 37ms/step - accuracy: 0.5594 - loss: 1.2344 - val_accura
cy: 0.5369 - val_loss: 1.3804
Epoch 17/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 37ms/step - accuracy: 0.5459 - loss: 1.2298 - val_accura
cy: 0.5369 - val_loss: 1.3658
Epoch 18/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 37ms/step - accuracy: 0.5858 - loss: 1.1373 - val_accura
cy: 0.5682 - val_loss: 1.3321
Epoch 19/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 38ms/step - accuracy: 0.6062 - loss: 1.0564 - val_accura
cy: 0.5570 - val_loss: 1.3276
Epoch 20/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 38ms/step - accuracy: 0.5827 - loss: 1.1146 - val_accura
cy: 0.5615 - val_loss: 1.3409
```

In [10]:
```
# Plot training results
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
loss = history.history['loss']
val_loss = history.history['val_loss']
```

```python
plt.figure(figsize=(12, 4))
plt.subplot(1,2,1)
plt.plot(acc, label='Train Acc')
plt.plot(val_acc, label='Val Acc')
plt.legend()
plt.title('Accuracy')

plt.subplot(1,2,2)
plt.plot(loss, label='Train Loss')
plt.plot(val_loss, label='Val Loss')
plt.legend()
plt.title('Loss')
plt.show()
```



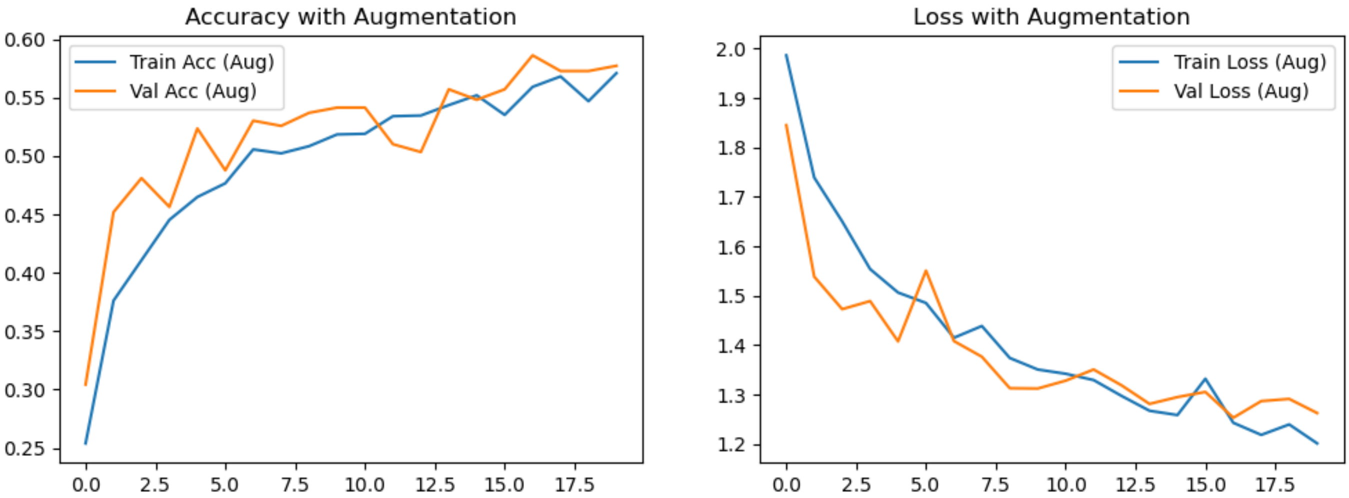
In [11]:
```python
# After analysis, we apply data augmentation.

#-------------------------------------------------------------------
# DATA AUGMENTATION
#-------------------------------------------------------------------
data_augmentation = tf.keras.Sequential([
    tf.keras.layers.RandomFlip('horizontal'),
    tf.keras.layers.RandomRotation(0.1),
    tf.keras.layers.RandomZoom(0.1),
])

augmented_train_ds = train_ds.map(
    lambda x, y: (data_augmentation(x, training=True), y),
    num_parallel_calls=tf.data.experimental.AUTOTUNE
)
```

In [12]:
```python
#-------------------------------------------------------------------
# MODEL RE-TRAINING WITH AUGMENTATION
#-------------------------------------------------------------------
model_aug = tf.keras.Sequential([
    tf.keras.layers.Rescaling(1./255, input_shape=(180,180,3)),
    tf.keras.layers.Conv2D(32, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(),
    tf.keras.layers.Conv2D(64, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(),
    tf.keras.layers.Conv2D(128, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(),
    tf.keras.layers.Conv2D(256, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dropout(0.3),
    tf.keras.layers.Dense(num_classes, activation='softmax')
])
```

```python
model_aug.compile(optimizer='adam',
                  loss='sparse_categorical_crossentropy',
                  metrics=['accuracy'])

history_aug = model_aug.fit(augmented_train_ds, validation_data=val_ds, epochs=20)
```

```
Epoch 1/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 5s 50ms/step - accuracy: 0.2155 - loss: 2.0616 - val_accura
cy: 0.3043 - val_loss: 1.8451
Epoch 2/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 40ms/step - accuracy: 0.3302 - loss: 1.8110 - val_accura
cy: 0.4519 - val_loss: 1.5385
Epoch 3/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 40ms/step - accuracy: 0.3986 - loss: 1.6382 - val_accura
cy: 0.4810 - val_loss: 1.4727
Epoch 4/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 40ms/step - accuracy: 0.4358 - loss: 1.5732 - val_accura
cy: 0.4564 - val_loss: 1.4890
Epoch 5/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 40ms/step - accuracy: 0.4568 - loss: 1.4968 - val_accura
cy: 0.5235 - val_loss: 1.4075
Epoch 6/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 40ms/step - accuracy: 0.4911 - loss: 1.4751 - val_accura
cy: 0.4877 - val_loss: 1.5506
Epoch 7/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 40ms/step - accuracy: 0.4896 - loss: 1.4582 - val_accura
cy: 0.5302 - val_loss: 1.4081
Epoch 8/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 40ms/step - accuracy: 0.4949 - loss: 1.4122 - val_accura
cy: 0.5257 - val_loss: 1.3764
Epoch 9/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 40ms/step - accuracy: 0.5079 - loss: 1.3900 - val_accura
cy: 0.5369 - val_loss: 1.3126
Epoch 10/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 40ms/step - accuracy: 0.5156 - loss: 1.3539 - val_accura
cy: 0.5414 - val_loss: 1.3120
Epoch 11/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 40ms/step - accuracy: 0.5111 - loss: 1.3389 - val_accura
cy: 0.5414 - val_loss: 1.3279
Epoch 12/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 40ms/step - accuracy: 0.5504 - loss: 1.2964 - val_accura
cy: 0.5101 - val_loss: 1.3505
Epoch 13/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 40ms/step - accuracy: 0.5547 - loss: 1.2801 - val_accura
cy: 0.5034 - val_loss: 1.3185
Epoch 14/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 40ms/step - accuracy: 0.5439 - loss: 1.2710 - val_accura
cy: 0.5570 - val_loss: 1.2809
Epoch 15/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 40ms/step - accuracy: 0.5672 - loss: 1.2226 - val_accura
cy: 0.5481 - val_loss: 1.2947
Epoch 16/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 40ms/step - accuracy: 0.5506 - loss: 1.2878 - val_accura
cy: 0.5570 - val_loss: 1.3051
Epoch 17/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 40ms/step - accuracy: 0.5688 - loss: 1.2432 - val_accura
cy: 0.5861 - val_loss: 1.2529
Epoch 18/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 40ms/step - accuracy: 0.5709 - loss: 1.2074 - val_accura
cy: 0.5727 - val_loss: 1.2866
Epoch 19/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 40ms/step - accuracy: 0.5589 - loss: 1.1849 - val_accura
cy: 0.5727 - val_loss: 1.2910
Epoch 20/20
56/56 ━━━━━━━━━━━━━━━━━━━━ 2s 40ms/step - accuracy: 0.5766 - loss: 1.2088 - val_accura
cy: 0.5772 - val_loss: 1.2624
```

In [13]:
```python
# Plot training results for augmented model
acc_aug = history_aug.history['accuracy']
val_acc_aug = history_aug.history['val_accuracy']
loss_aug = history_aug.history['loss']
val_loss_aug = history_aug.history['val_loss']

plt.figure(figsize=(12,4))
plt.subplot(1,2,1)
plt.plot(acc_aug, label='Train Acc (Aug)')
plt.plot(val_acc_aug, label='Val Acc (Aug)')
plt.legend()
plt.title('Accuracy with Augmentation')

plt.subplot(1,2,2)
plt.plot(loss_aug, label='Train Loss (Aug)')
plt.plot(val_loss_aug, label='Val Loss (Aug)')
plt.legend()
plt.title('Loss with Augmentation')
plt.show()
```



In [14]:
```python
#-----------------------------------------------------------------------
# CLASS DISTRIBUTION ANALYSIS
#-----------------------------------------------------------------------
print("Class counts:", class_counts)
least_class = min(class_counts, key=class_counts.get)
most_class = max(class_counts, key=class_counts.get)
print("Least Class:", least_class, "Count:", class_counts[least_class])
print("Most Class:", most_class, "Count:", class_counts[most_class])

#-----------------------------------------------------------------------
# HANDLING CLASS IMBALANCES WITH AUGMENTOR
# This step requires the Augmentor library and might need to be run outside
# the notebook environment. After augmentation, the dataset directory will
# contain more images for minority classes.
```

```
Class counts: {'actinic keratosis': 114, 'basal cell carcinoma': 376, 'dermatofibrom
a': 95, 'melanoma': 438, 'nevus': 357, 'pigmented benign keratosis': 462, 'seborrheic
keratosis': 77, 'squamous cell carcinoma': 181, 'vascular lesion': 139}
Least Class: seborrheic keratosis Count: 77
Most Class: pigmented benign keratosis Count: 462
```

In [15]:
```python
import Augmentor
```

In [16]:
```python
# Determine target count (max class count)
target_count = max(class_counts.values())
print("Target count for balancing:", target_count)

for cls in classes:
    class_path = os.path.join(train_dir, cls)
```

```
    current_count = len([f for f in os.listdir(class_path) if f.lower().endswith(('.p
    samples_to_generate = target_count - current_count
    if samples_to_generate > 0:
        p = Augmentor.Pipeline(source_directory=class_path, output_directory=class_pa
        p.flip_left_right(probability=0.5)
        p.rotate(probability=0.5, max_left_rotation=10, max_right_rotation=10)
        p.zoom(probability=0.3, min_factor=1.1, max_factor=1.5)
        p.sample(samples_to_generate)
```

```
Target count for balancing: 462
Initialised with 114 image(s) found.
Output directory set to data/train/actinic keratosis/data/train/actinic keratosis.
Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x7A9CD7EC8790>: 100%|█████
█████| 348/348 [00:01<00:00, 322.79 Samples/s]
Initialised with 376 image(s) found.
Output directory set to data/train/basal cell carcinoma/data/train/basal cell carcinom
a.
Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x7A9CE0DA16D0>: 100%|█████
█████| 86/86 [00:00<00:00, 316.65 Samples/s]
Initialised with 95 image(s) found.
Output directory set to data/train/dermatofibroma/data/train/dermatofibroma.
Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x7A9CD7E99650>: 100%|█████
█████| 367/367 [00:01<00:00, 317.56 Samples/s]
Initialised with 438 image(s) found.
Output directory set to data/train/melanoma/data/train/melanoma.
Processing <PIL.Image.Image image mode=RGB size=1024x768 at 0x7A9CD7ECA910>: 100%|████
██████| 24/24 [00:00<00:00, 29.10 Samples/s]
Initialised with 357 image(s) found.
Output directory set to data/train/nevus/data/train/nevus.
Processing <PIL.Image.Image image mode=RGB size=767x576 at 0x7A9CD7EA0510>: 100%|█████
█████| 105/105 [00:01<00:00, 64.27 Samples/s]
Initialised with 77 image(s) found.
Output directory set to data/train/seborrheic keratosis/data/train/seborrheic keratosi
s.
Processing <PIL.Image.Image image mode=RGB size=1024x768 at 0x7A9CE0DA16D0>: 100%|████
██████| 385/385 [00:02<00:00, 141.31 Samples/s]
Initialised with 181 image(s) found.
Output directory set to data/train/squamous cell carcinoma/data/train/squamous cell ca
rcinoma.
Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x7A9CD7F60850>: 100%|█████
█████| 281/281 [00:00<00:00, 320.00 Samples/s]
Initialised with 139 image(s) found.
Output directory set to data/train/vascular lesion/data/train/vascular lesion.
Processing <PIL.Image.Image image mode=RGB size=600x450 at 0x7A9CD7E771D0>: 100%|█████
█████| 323/323 [00:01<00:00, 312.78 Samples/s]
```

In [17]:

```
# After running the Augmentor pipeline, reload the datasets with balanced data
train_ds_balanced = tf.keras.preprocessing.image_dataset_from_directory(
    train_dir,
    validation_split=0.2,
    subset="training",
    seed=42,
    image_size=img_size,
    batch_size=batch_size
)

val_ds_balanced = tf.keras.preprocessing.image_dataset_from_directory(
    train_dir,
    validation_split=0.2,
    subset="validation",
    seed=42,
    image_size=img_size,
    batch_size=batch_size
)
```

```
train_ds_balanced = train_ds_balanced.cache().shuffle(1000).prefetch(tf.data.experime
val_ds_balanced = val_ds_balanced.cache().prefetch(tf.data.experimental.AUTOTUNE)
```

```
Found 4158 files belonging to 9 classes.
Using 3327 files for training.
Found 4158 files belonging to 9 classes.
Using 831 files for validation.
```

In [18]:

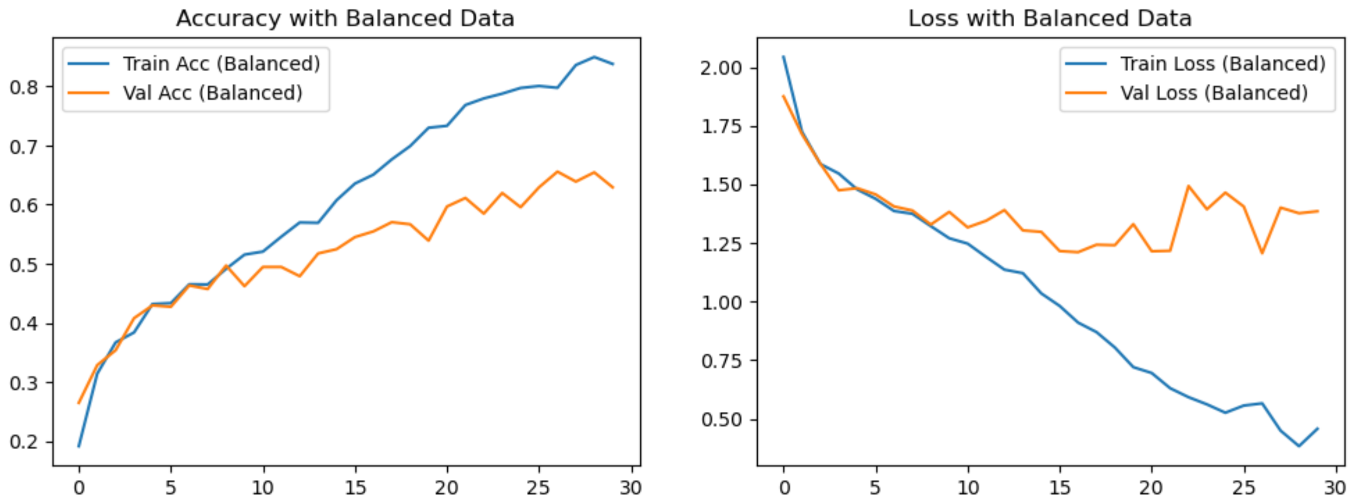
```
#--------------------------------------------------------------------
# MODEL BUILDING & TRAINING AFTER HANDLING CLASS IMBALANCES
#--------------------------------------------------------------------
model_balanced = tf.keras.Sequential([
    tf.keras.layers.Rescaling(1./255, input_shape=(180,180,3)),
    tf.keras.layers.Conv2D(32, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(),
    tf.keras.layers.Conv2D(64, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(),
    tf.keras.layers.Conv2D(128, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(),
    tf.keras.layers.Conv2D(256, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(256, activation='relu'),
    tf.keras.layers.Dropout(0.4),
    tf.keras.layers.Dense(num_classes, activation='softmax')
])

model_balanced.compile(optimizer='adam',
                       loss='sparse_categorical_crossentropy',
                       metrics=['accuracy'])

history_balanced = model_balanced.fit(train_ds_balanced, validation_data=val_ds_balan
```

```
Epoch 1/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 15s 96ms/step - accuracy: 0.1405 - loss: 2.1561 - val_acc
uracy: 0.2647 - val_loss: 1.8752
Epoch 2/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.2981 - loss: 1.7405 - val_accu
racy: 0.3285 - val_loss: 1.7141
Epoch 3/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.3761 - loss: 1.5868 - val_accu
racy: 0.3538 - val_loss: 1.5880
Epoch 4/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.3792 - loss: 1.5447 - val_accu
racy: 0.4079 - val_loss: 1.4746
Epoch 5/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.4313 - loss: 1.4596 - val_accu
racy: 0.4296 - val_loss: 1.4835
Epoch 6/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.4041 - loss: 1.4944 - val_accu
racy: 0.4272 - val_loss: 1.4571
Epoch 7/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.4631 - loss: 1.4031 - val_accu
racy: 0.4633 - val_loss: 1.4056
Epoch 8/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.4574 - loss: 1.3897 - val_accu
racy: 0.4573 - val_loss: 1.3883
Epoch 9/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.4789 - loss: 1.3478 - val_accu
racy: 0.4970 - val_loss: 1.3285
Epoch 10/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.5185 - loss: 1.2785 - val_accu
racy: 0.4621 - val_loss: 1.3825
Epoch 11/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.5060 - loss: 1.2672 - val_accu
racy: 0.4946 - val_loss: 1.3163
Epoch 12/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.5446 - loss: 1.2012 - val_accu
racy: 0.4946 - val_loss: 1.3444
Epoch 13/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.5533 - loss: 1.1421 - val_accu
racy: 0.4789 - val_loss: 1.3901
Epoch 14/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.5628 - loss: 1.1297 - val_accu
racy: 0.5174 - val_loss: 1.3035
Epoch 15/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.6082 - loss: 1.0458 - val_accu
racy: 0.5247 - val_loss: 1.2972
Epoch 16/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.6364 - loss: 0.9943 - val_accu
racy: 0.5451 - val_loss: 1.2153
Epoch 17/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.6380 - loss: 0.9255 - val_accu
racy: 0.5548 - val_loss: 1.2106
Epoch 18/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.6849 - loss: 0.8379 - val_accu
racy: 0.5704 - val_loss: 1.2424
Epoch 19/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.7030 - loss: 0.7839 - val_accu
racy: 0.5668 - val_loss: 1.2403
Epoch 20/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.7365 - loss: 0.6967 - val_accu
racy: 0.5391 - val_loss: 1.3303
Epoch 21/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.7241 - loss: 0.7228 - val_accu
racy: 0.5969 - val_loss: 1.2145
Epoch 22/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.7806 - loss: 0.6040 - val_accu
racy: 0.6113 - val_loss: 1.2166
```

```
Epoch 23/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.7919 - loss: 0.5806 - val_accu
racy: 0.5848 - val_loss: 1.4930
Epoch 24/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.7971 - loss: 0.5390 - val_accu
racy: 0.6197 - val_loss: 1.3936
Epoch 25/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.7767 - loss: 0.5981 - val_accu
racy: 0.5957 - val_loss: 1.4646
Epoch 26/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.7902 - loss: 0.5719 - val_accu
racy: 0.6294 - val_loss: 1.4052
Epoch 27/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.7836 - loss: 0.6001 - val_accu
racy: 0.6558 - val_loss: 1.2059
Epoch 28/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.8451 - loss: 0.4243 - val_accu
racy: 0.6390 - val_loss: 1.4006
Epoch 29/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.8584 - loss: 0.3643 - val_accu
racy: 0.6546 - val_loss: 1.3767
Epoch 30/30
104/104 ━━━━━━━━━━━━━━━━━━━━ 4s 38ms/step - accuracy: 0.8476 - loss: 0.4130 - val_accu
racy: 0.6294 - val_loss: 1.3850
```

In [19]:

```
# Plot training results for balanced dataset model
acc_bal = history_balanced.history['accuracy']
val_acc_bal = history_balanced.history['val_accuracy']
loss_bal = history_balanced.history['loss']
val_loss_bal = history_balanced.history['val_loss']

plt.figure(figsize=(12,4))
plt.subplot(1,2,1)
plt.plot(acc_bal, label='Train Acc (Balanced)')
plt.plot(val_acc_bal, label='Val Acc (Balanced)')
plt.legend()
plt.title('Accuracy with Balanced Data')

plt.subplot(1,2,2)
plt.plot(loss_bal, label='Train Loss (Balanced)')
plt.plot(val_loss_bal, label='Val Loss (Balanced)')
plt.legend()
plt.title('Loss with Balanced Data')
plt.show()
```



In [ ]: