Level 1 investigation

Name: Soichiro Tanabe

Setup

In [1]:
```
import tensorflow as tf
import numpy as np
import csv
import os
import json
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers, optimizers, datasets, metrics, Seque
from tensorflow.keras.layers import *
from IPython.display import HTML, display
import matplotlib.pyplot as plt
%matplotlib inline
```

Data format and structure

The dataset contains just over 50,000 images, each showing a 60m × 60m region of a forest in Germany. Each image shows mainly one species of tree. There are three levels of label for each image: the English name (level 3), forest management class (level 2), and leaf type (level 1).

Treesat label levels

> Image detail from Ahlswede *et al.* (2023) figure 4.

The dataset has been split into 70% training, 10% validation, and 20% testing images.

The images are 304 × 304 pixels and encoded as four-channel PNG images. We are mis-using the PNG's alpha (transparency) channel to represent the near-IR light band in the original images.

The data resides in the `/datasets/treesat/` directory. All the images are in the `/datasets/treesat/images/` directory. There are three `.csv` files that specify which images are in which split of the dataset. There are three text files that list the different labels at each level.

In [2]:
```
!ls /datasets/treesat
```

```
images                  level_3_vocabulary.txt  validation_file_labels.csv
level_1_vocabulary.txt  test_file_labels.csv
level_2_vocabulary.txt  train_file_labels.csv
```

If we look at one of the `.csv` files, we can see the image name and labels at each level.

In [3]:
```
!head /datasets/treesat/train_file_labels.csv
```

Similarly, we can see the distinct labels at each level.

In [4]:
```
!cat /datasets/treesat/level_2_vocabulary.txt
```

```
larch
cleared
beech
oak
douglas fir
pine
fir
short-lived deciduous
long-lived deciduous
spruce
```

Defining constants

`label_level` is one of 1, 2, or 3, and is the level of labels used in this notebook.

In [5]:
```
data_dir = '/datasets/treesat'
label_level = 1
```

In [6]:
```
IMAGE_RESCALE = (100, 100)
input_shape = (IMAGE_RESCALE[0], IMAGE_RESCALE[1], 4)
batch_size = 64
label_key = f'level_{label_level}'
```

Loading data

First, we load the image names and labels into the `file_label` datasets.

In [7]:
```
train_file_labels = tf.data.experimental.make_csv_dataset(
    os.path.join(data_dir, 'train_file_labels.csv'), batch_size=batch_siz
train_file_labels = train_file_labels.unbatch()
```

In [8]:
```
validation_file_labels = tf.data.experimental.make_csv_dataset(
    os.path.join(data_dir, 'validation_file_labels.csv'), batch_size=batc
validation_file_labels = validation_file_labels.unbatch()
```

In [9]:
```
test_file_labels = tf.data.experimental.make_csv_dataset(
    os.path.join(data_dir, 'test_file_labels.csv'), batch_size=batch_size
test_file_labels = test_file_labels.unbatch()
```

We load the vocabulary for this level of labels and create a `StringLookup` encoder that will convert each label into a one-hot vector.

In [10]:
```
encoder_vocab_file = os.path.join(data_dir, f'level_{label_level}_vocabul
label_encoder = StringLookup(vocabulary=encoder_vocab_file, num_oov_indic

num_classes = len(label_encoder.get_vocabulary())

label_lookup = {i: n for i, n in enumerate(label_encoder.get_vocabulary()
label_lookup
```

Out[10]:
```
{0: 'cleared', 1: 'needleleaf', 2: 'broadleaf'}
```

With the labels defined, we know enough to pretty-print a confusion matrix.

In [11]:
```
def pretty_cm(cm):
    result_table  = '<h3>Confusion matrix</h3>\n'
    result_table += '<table border=1>\n'
    result_table += f'<tr><td> </td><td> </td><th colspan={len(
    result_table += '<tr><td> </td><td> </td>'

    for _, cn in sorted(label_lookup.items()):
        result_table += f'<td><strong>{cn}</strong></td>'
    result_table += '</tr>\n'

    result_table += '<tr>\n'
    result_table += f'<th rowspan={len(label_lookup) + 1}>Actual labels</

    for ai, an in sorted(label_lookup.items()):
        result_table += '<tr>\n'
        result_table += f'  <td><strong>{an}</strong></td>\n'
        for pi, pn in sorted(label_lookup.items()):
            result_table += f'  <td>{cm[ai, pi]}</td>\n'
        result_table += '</tr>\n'
    result_table += "</table>"
    # print(result_table)
    display(HTML(result_table))
```

We have a function that take a filename and text label and returns the image and one-hot encoded label.

In [12]:
```
# Adjusted load_image function to accept file_path and label separately
def load_image(file_path, label):
    # read the image from disk, decode it, resize it, and scale the pixel
    image = tf.io.read_file(file_path)
    image = tf.io.decode_png(image, channels=4)
    image = tf.image.resize(image, IMAGE_RESCALE)
    image /= 255.0

    # grab the label and encode it
    encoded_label = label_encoder(label)
```

```
    # return the image and the one-hot encoded label
    return image, encoded_label
```

Loading the images

Now we can load the images into datasets.

In [13]:
```
train_data = train_file_labels.map(lambda fl: (fl['file_name'], fl[label_
                                      num_parallel_calls=tf.data.AUTOTUNE
train_data = train_data.shuffle(200)
train_data = train_data.map(load_image,
                                      num_parallel_calls=tf.data.AUTOTUNE
train_data = train_data.batch(batch_size)
train_data = train_data.prefetch(tf.data.AUTOTUNE)
```

In [14]:
```
validation_data = validation_file_labels.map(lambda fl: (fl['file_name'],
                                      num_parallel_calls=tf.data.AUTOTUNE
validation_data = validation_data.map(load_image,
                                      num_parallel_calls=tf.data.AUTOTUNE
validation_data = validation_data.batch(batch_size)
validation_data = validation_data.prefetch(tf.data.AUTOTUNE)
```

In [15]:
```
test_data = test_file_labels.map(lambda fl: (fl['file_name'], fl[label_ke
                                      num_parallel_calls=tf.data.AUTOTUNE
test_data = test_data.map(load_image,
                                      num_parallel_calls=tf.data.AUTOTUNE
test_data = test_data.batch(batch_size)
test_data = test_data.prefetch(tf.data.AUTOTUNE)
```

Exploring the data

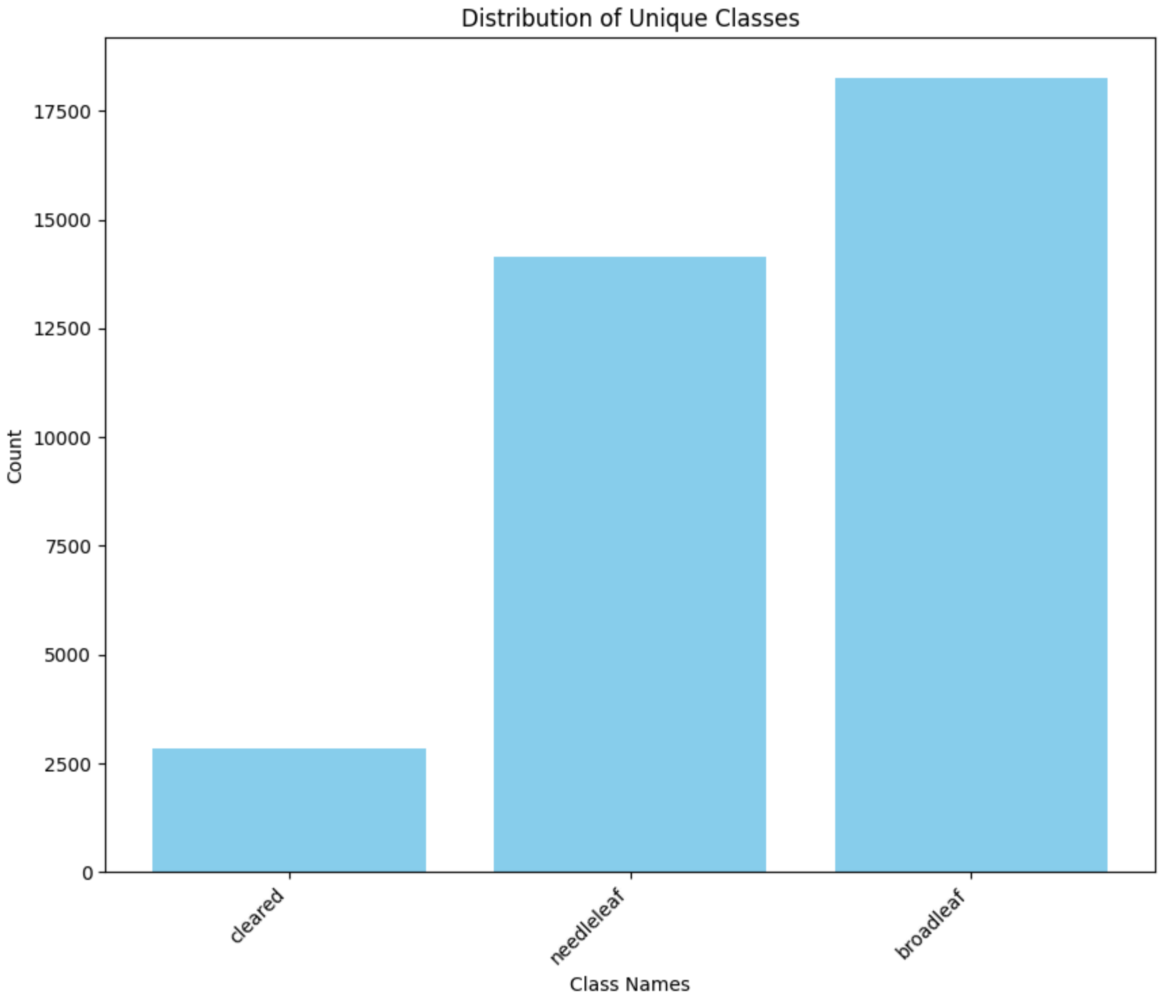
We can now explore some elements of the data, such as some sample images and the distribution of classes.

Distribution of classes

In [16]:
```
class_counts = train_file_labels.map(lambda fl: label_encoder(fl[label_ke
class_counts = class_counts.reduce(tf.zeros((num_classes,)),
                             lambda o, l: tf.math.add(o, l))
class_counts
```

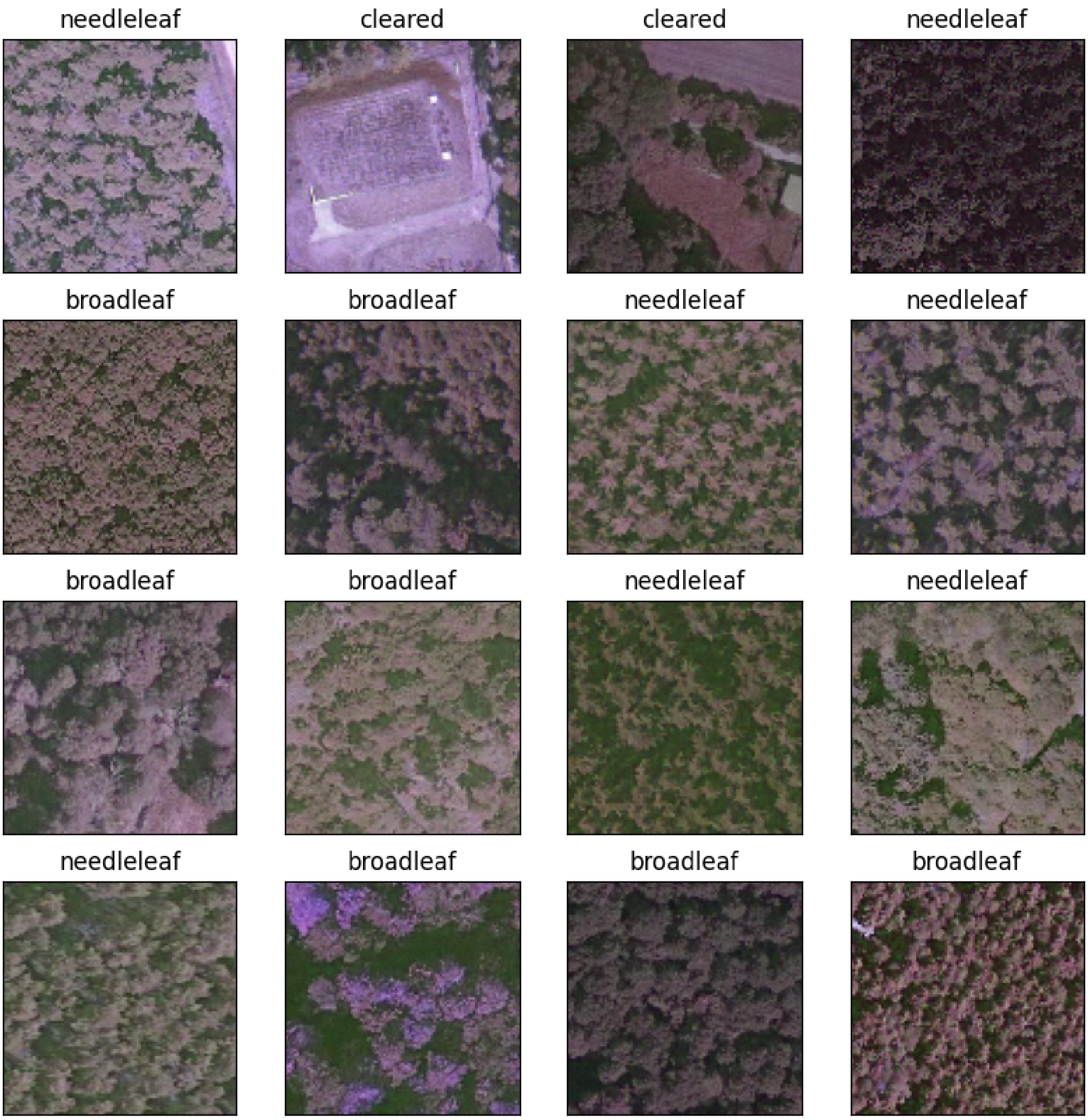
Out[16]:
```
<tf.Tensor: shape=(3,), dtype=float32, numpy=array([ 2844., 14150., 1827
2.], dtype=float32)>
```

In [17]:
```
# Plot distribution using class names
plt.figure(figsize=(10, 8))
plt.bar(label_encoder.get_vocabulary(), class_counts.numpy(), color='skyb
plt.xlabel("Class Names")
plt.ylabel("Count")
plt.title("Distribution of Unique Classes")
plt.xticks(rotation=45, ha='right')  # Rotate x-axis labels for readabili
plt.show()  # Display the plotted distribution
```



Show some sample images

In [18]:
```
sample_images, sample_labels = train_data.as_numpy_iterator().next()

plt.figure(figsize=(10, 10))
for i in range(16):  # Adjust this number based on how many images you wa
    ax = plt.subplot(4, 4, i + 1)
    plt.imshow(sample_images[i, ..., :-1]) # drop the alpha channel, to m
#     plt.imshow(sample_images[i]) # image with alpha channel
    label_index = np.argmax(sample_labels[i])
    class_name = label_lookup[label_index]
    plt.xticks([])
    plt.yticks([])
    plt.grid(False)
    plt.title(class_name)
```



Create and train a base model

As the initial model, a simple CNN model was set up, with the following structure:

In [48]:
```
model_base_level_1 = Sequential([
    Conv2D(8, (5, 5), padding='same', activation='relu', input_shape=inpu
    Conv2D(8, (5, 5), padding='same', activation='relu'),
    MaxPooling2D(pool_size=(4, 4)),

    Flatten(),
    Dense(128, activation='relu'),
    Dense(num_classes, activation='softmax')
])

model_base_level_1.summary()
```

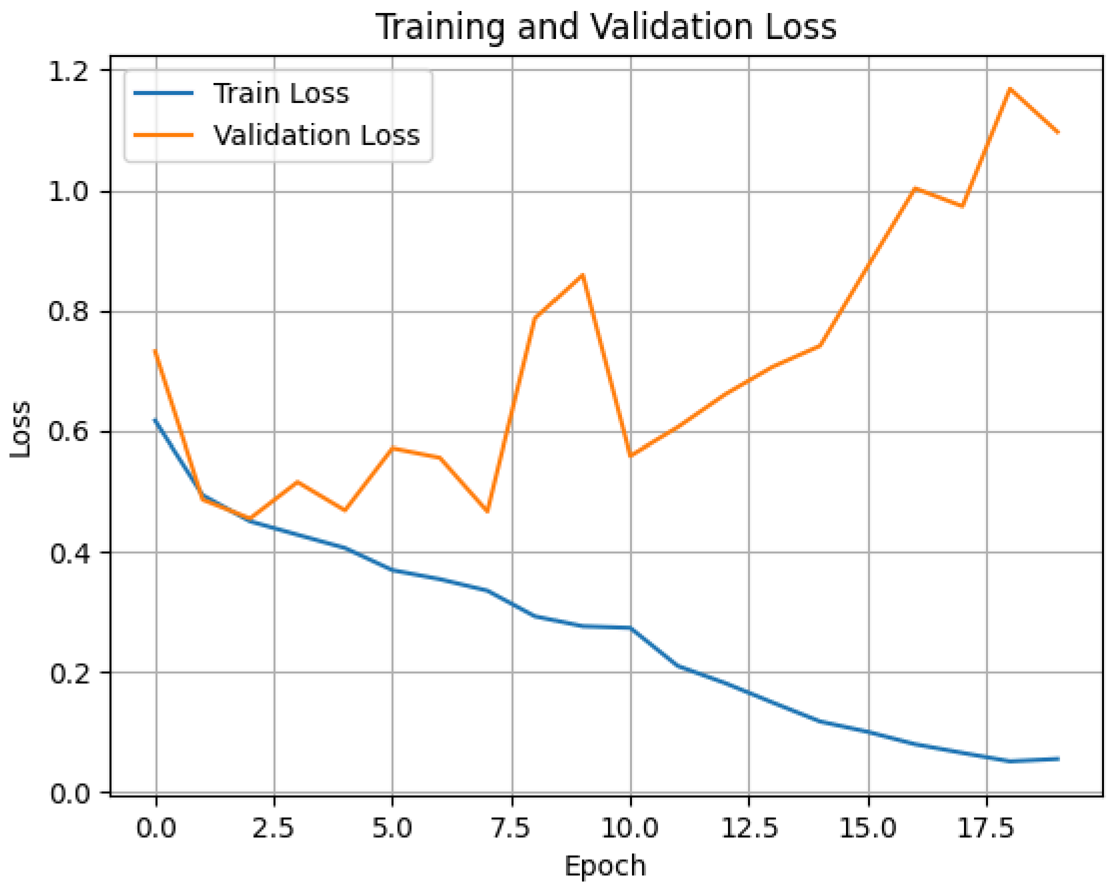
```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_8 (Conv2D)           (None, 100, 100, 8)       808

 conv2d_9 (Conv2D)           (None, 100, 100, 8)       1608

 max_pooling2d_4 (MaxPoolin  (None, 25, 25, 8)         0
 g2D)

 flatten_2 (Flatten)         (None, 5000)              0

 dense_4 (Dense)             (None, 128)               640128

 dense_5 (Dense)             (None, 3)                 387

=================================================================
Total params: 642931 (2.45 MB)
Trainable params: 642931 (2.45 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

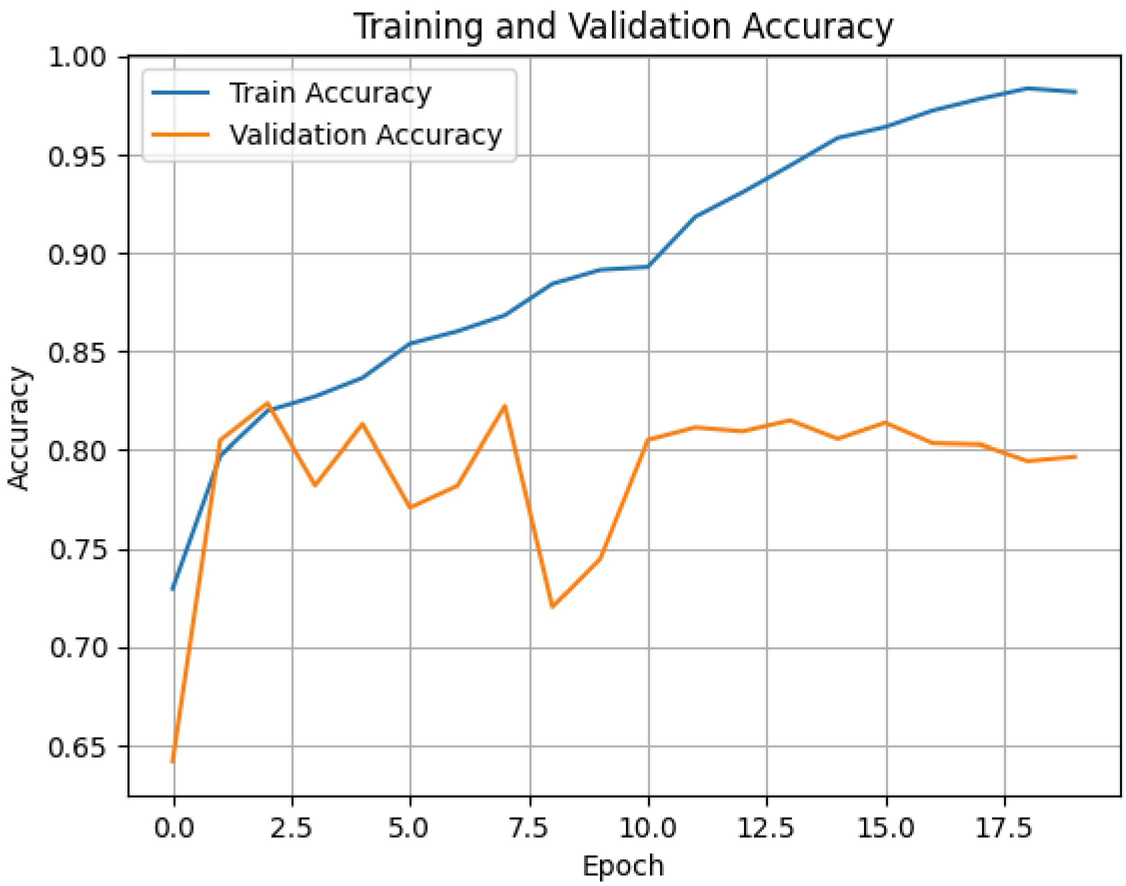
In [49]:
```
model_base_level_1.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

In [50]:
```
history_base_level_1 = model_base_level_1.fit(
    train_data,
    epochs=20,
    validation_data=validation_data,
    verbose=0
)
```

In [51]:
```
import matplotlib.pyplot as plt

# Assuming history contains the training history returned by model.fit
train_loss = history_base_level_1.history['loss']
val_loss = history_base_level_1.history['val_loss']
train_acc = history_base_level_1.history['accuracy']
val_acc = history_base_level_1.history['val_accuracy']

# Plot loss
plt.plot(train_loss, label='Train Loss')
plt.plot(val_loss, label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.grid(True)
plt.show()

# Plot accuracy
plt.plot(train_acc, label='Train Accuracy')
plt.plot(val_acc, label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
```

```
plt.grid(True)
plt.show()
```





Cache results for later

In [52]:
```python
model_base_level_1.save('model_base_level_1.keras')

with open('history_base_level_1.json', 'w') as f:
    json.dump(history_base_level_1.history, f)
```

In [53]:
```python
model_base_level_1 = tf.keras.models.load_model('model_base_level_1.keras

with open('history_base_level_1.json') as f:
    history_base_level_1 = json.load(f)
```

Evaluating the model

In [54]:
```python
model_base_level_1.evaluate(test_data, return_dict=True)
```

```
158/158 [==============================] - 18s 109ms/step - loss: 1.1165 - accuracy: 0.7887
```

Out[54]:
```
{'loss': 1.1165090799331665, 'accuracy': 0.788726806640625}
```

In [55]:
```python
test_predictions = model_base_level_1.predict(test_data)
```

```
158/158 [==============================] - 14s 90ms/step
```

In [56]:
```python
predict_labels = np.argmax(test_predictions, axis=1)
```

In [57]:
```python
test_labels = np.array(list(test_data.unbatch().map(lambda x, y: y).as_nu
test_labels = np.argmax(test_labels, axis=1)
```

In [58]:
```python
cm = tf.math.confusion_matrix(test_labels, predict_labels).numpy()
pretty_cm(cm)
```

Confusion matrix

		Predicted labels		
		cleared	**needleleaf**	**broadleaf**
	cleared	81	317	489
Actual labels	**needleleaf**	346	1414	2209
	broadleaf	474	1765	2982

Implementing more complicated model

Implementing a more intricate model involves adding additional layers to enable the neural network to capture more intricate patterns within the data, potentially enhancing its predictive capabilities (Saturn Cloud, 2023). Ramesh(2018) states that increasing the number of filters in each layer enhances the depth of the feature space, enabling the CNN to learn more levels of global abstract structures. Additionally, incorporating dropout is beneficial for mitigating overfitting, as demonstrated by the base model, as it encourages the network to learn more robust and generalized representations of the data (The Open University, 2023). Therefore, a more intricate model was structured with additional layers and dropout, as follows:

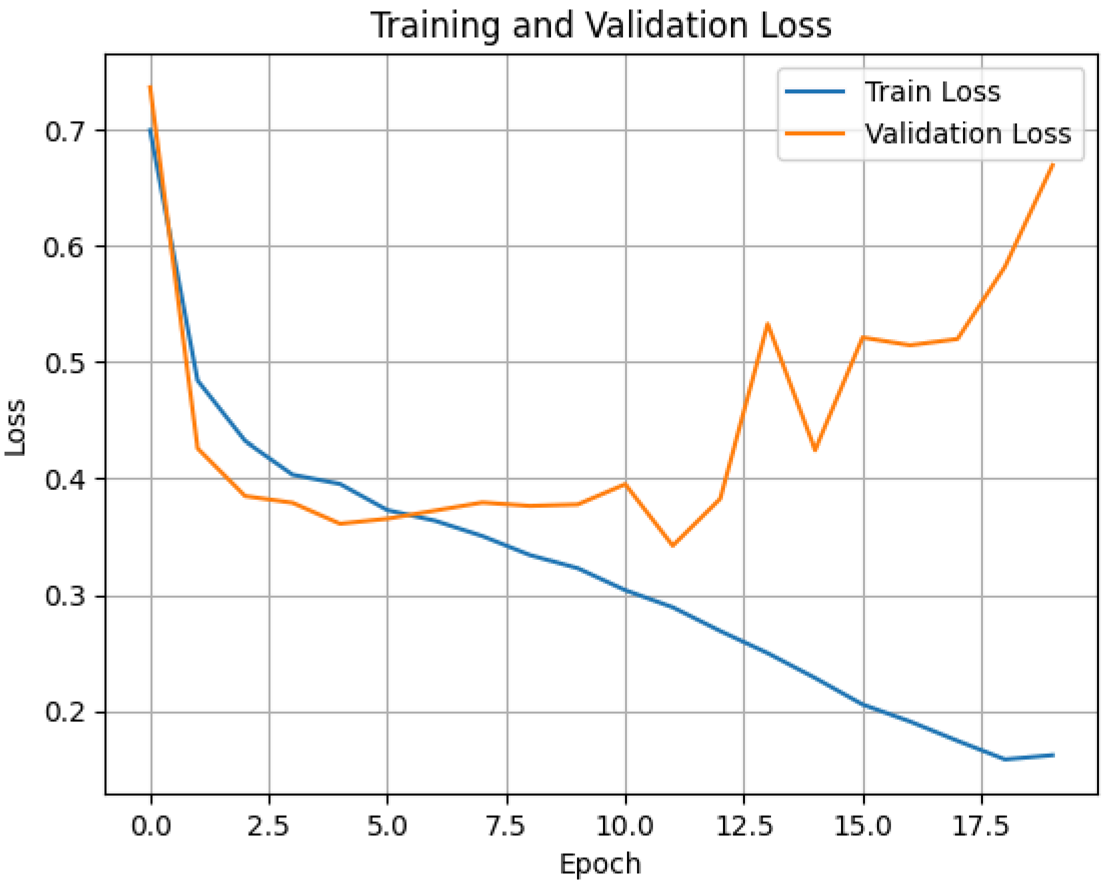
In [69]:
```
# Define the model architecture with additional convolutional layers
model_2_level_1 = Sequential([
    Conv2D(16, (5, 5), padding='same', activation='relu', input_shape=inp
    Conv2D(16, (5, 5), padding='same', activation='relu'),
    MaxPooling2D(pool_size=(4, 4)),

    Conv2D(32, (3, 3), padding='same', activation='relu'),
    Conv2D(32, (3, 3), padding='same', activation='relu'),
    MaxPooling2D(pool_size=(2, 2)),

    Conv2D(64, (3, 3), padding='same', activation='relu'),
    Conv2D(64, (3, 3), padding='same', activation='relu'),
    MaxPooling2D(pool_size=(2, 2)),
    Flatten(),
    Dense(128, activation='relu'),
    Dropout(rate=0.5),
    Dense(num_classes, activation='softmax')
])

# Print the summary of the improved model
model_2_level_1.summary()
```

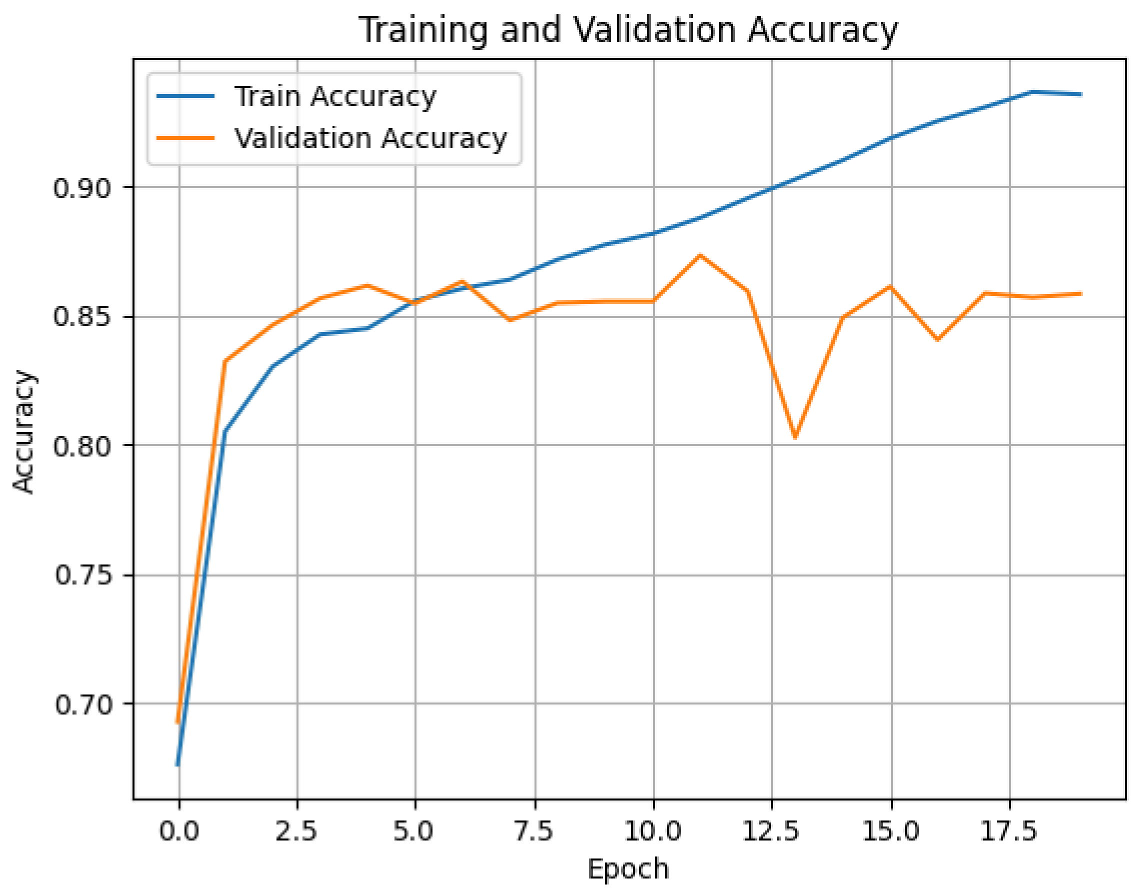
```
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d_12 (Conv2D)          (None, 100, 100, 16)      1616      
                                                                 
 conv2d_13 (Conv2D)          (None, 100, 100, 16)      6416      
                                                                 
 max_pooling2d_6 (MaxPoolin  (None, 25, 25, 16)        0         
 g2D)                                                            
                                                                 
 conv2d_14 (Conv2D)          (None, 25, 25, 32)        4640      
                                                                 
 conv2d_15 (Conv2D)          (None, 25, 25, 32)        9248      
                                                                 
 max_pooling2d_7 (MaxPoolin  (None, 12, 12, 32)        0         
 g2D)                                                            
                                                                 
 conv2d_16 (Conv2D)          (None, 12, 12, 64)        18496     
                                                                 
 conv2d_17 (Conv2D)          (None, 12, 12, 64)        36928     
                                                                 
 max_pooling2d_8 (MaxPoolin  (None, 6, 6, 64)          0         
 g2D)                                                            
                                                                 
 flatten_4 (Flatten)         (None, 2304)              0         
                                                                 
 dense_8 (Dense)             (None, 128)               295040    
                                                                 
 dropout_1 (Dropout)         (None, 128)               0         
                                                                 
 dense_9 (Dense)             (None, 3)                 387       
                                                                 
=================================================================
Total params: 372771 (1.42 MB)
Trainable params: 372771 (1.42 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [70]:
```
model_2_level_1.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
history_2_level_1 = model_2_level_1.fit(
    train_data,
    epochs=20,
    validation_data=validation_data,
    verbose=0
)
```

In [71]:
```
# Assuming history contains the training history returned by model.fit
train_loss_2 = history_2_level_1.history['loss']
val_loss_2 = history_2_level_1.history['val_loss']
train_acc_2 = history_2_level_1.history['accuracy']
val_acc_2 = history_2_level_1.history['val_accuracy']

# Plot loss
plt.plot(train_loss_2, label='Train Loss')
plt.plot(val_loss_2, label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epoch')
```

```
plt.ylabel('Loss')
plt.legend()
plt.grid(True)
plt.show()

# Plot accuracy
plt.plot(train_acc_2, label='Train Accuracy')
plt.plot(val_acc_2, label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)
plt.show()
```





Cache results for later

In [72]:
```
model_2_level_1.save('model_2_level_1.keras')

with open('history_2_level_1.json', 'w') as f:
    json.dump(history_2_level_1.history, f)

model_2_level_1 = tf.keras.models.load_model('model_2_level_1.keras')

with open('history_2_level_1.json') as f:
    history_2_level_1 = json.load(f)
```

Evaluating the model

In [73]:
```
model_2_level_1.evaluate(test_data, return_dict=True)
```

```
158/158 [==============================] - 17s 108ms/step - loss: 0.6259 -
accuracy: 0.8516
```

Out[73]:
```
{'loss': 0.6258849501609802, 'accuracy': 0.851642370223999}
```

In [74]:
```
test_predictions_2 = model_2_level_1.predict(test_data)
```

```
158/158 [==============================] - 14s 90ms/step
```

In [75]:
```
predict_labels_2 = np.argmax(test_predictions_2, axis=1)
```

In [76]:
```
test_labels_2 = np.array(list(test_data.unbatch().map(lambda x, y: y).as_
test_labels_2 = np.argmax(test_labels_2, axis=1)
```

In [77]:
```
cm_2 = tf.math.confusion_matrix(test_labels_2, predict_labels_2).numpy()
pretty_cm(cm_2)
```

Confusion matrix

		Predicted labels		
		cleared	**needleleaf**	**broadleaf**
	cleared	57	316	514
Actual labels	**needleleaf**	275	1488	2206
	broadleaf	396	1852	2973

In [ ]:

Add weighting

The figure:'Distribution of Unique classes' depicts imbalanced class data, which can profoundly affect classification algorithms, resulting in biased performance (The Open University, 2023). To address this issue, a technique involving weighting imbalanced data was applied to modify the training data. Subsequently, the previous two models, which incorporated increased filters and a more intricate architecture, utilised this modified training data for training.

Modify training dataset

In [78]:
```
class_counts = train_data.unbatch().reduce(tf.zeros((3,)),
                              lambda o, il: tf.math.add(o, il[1])).numpy()
class_counts
```

Out[78]:
```
array([ 2844., 14150., 18272.], dtype=float32)
```

In [79]:
```
all_train_size = sum(class_counts)
all_train_size
```

Out[79]:
```
35266.0
```

In [21]:
```
class_weights = tf.constant([all_train_size / (10 * cc) for cc in class_c
class_weights
```

Out[21]:
```
<tf.Tensor: shape=(3,), dtype=float64, numpy=array([1.24001406, 0.249229
68, 0.19300569])>
```

In [22]:
```
class_weights[0], class_weights[2]
```

Out[22]:
```
(<tf.Tensor: shape=(), dtype=float64, numpy=1.240014064697609>,
 <tf.Tensor: shape=(), dtype=float64, numpy=0.1930056917688266 2>)
```

In [23]:
```
def add_weight(image, one_hot_label):
    label = tf.argmax(one_hot_label)
    return image, one_hot_label, class_weights[label]
```

In [24]:
```
weighted_train_data = train_data.unbatch().map(add_weight)
weighted_train_data
```

Out[24]:
```
<_MapDataset element_spec=(TensorSpec(shape=(100, 100, 4), dtype=tf.floa
t32, name=None), TensorSpec(shape=(3,), dtype=tf.float32, name=None), Te
nsorSpec(shape=(), dtype=tf.float64, name=None))>
```

In [25]:
```
weighted_train_data = weighted_train_data.batch(batch_size)
weighted_train_data = weighted_train_data.shuffle(all_train_size)
weighted_train_data = weighted_train_data.prefetch(tf.data.AUTOTUNE)
```

the Model with Added weights

In [37]:
```
# Define the model architecture with additional convolutional layers
model_3_level_1 = Sequential = Sequential([
    Conv2D(16, (5, 5), padding='same', activation='relu', input_shape=inp
    Conv2D(16, (5, 5), padding='same', activation='relu'),
    MaxPooling2D(pool_size=(4, 4)),

    Conv2D(32, (3, 3), padding='same', activation='relu'),
    Conv2D(32, (3, 3), padding='same', activation='relu'),
    MaxPooling2D(pool_size=(2, 2)),

    Conv2D(64, (3, 3), padding='same', activation='relu'),
    Conv2D(64, (3, 3), padding='same', activation='relu'),
    MaxPooling2D(pool_size=(2, 2)),
    Flatten(),
    Dense(128, activation='relu'),
    Dropout(rate=0.5),
    Dense(num_classes, activation='softmax')
])

# Print the summary of the improved model
model_3_level_1 = Sequential.summary()
```

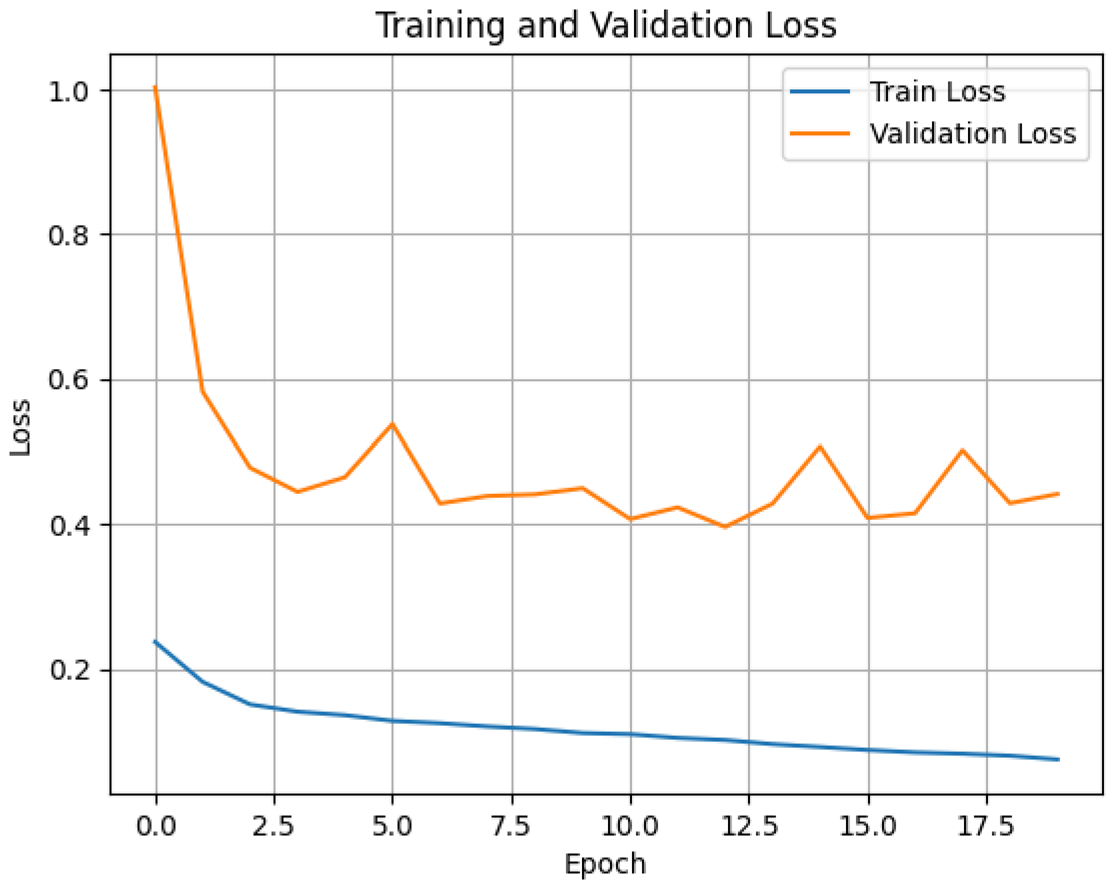
```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d_2 (Conv2D)           (None, 100, 100, 16)      1616      
                                                                 
 conv2d_3 (Conv2D)           (None, 100, 100, 16)      6416      
                                                                 
 max_pooling2d_1 (MaxPoolin  (None, 25, 25, 16)        0         
 g2D)                                                            
                                                                 
 conv2d_4 (Conv2D)           (None, 25, 25, 32)        4640      
                                                                 
 conv2d_5 (Conv2D)           (None, 25, 25, 32)        9248      
                                                                 
 max_pooling2d_2 (MaxPoolin  (None, 12, 12, 32)        0         
 g2D)                                                            
                                                                 
 conv2d_6 (Conv2D)           (None, 12, 12, 64)        18496     
                                                                 
 conv2d_7 (Conv2D)           (None, 12, 12, 64)        36928     
                                                                 
 max_pooling2d_3 (MaxPoolin  (None, 6, 6, 64)          0         
 g2D)                                                            
                                                                 
 flatten_1 (Flatten)         (None, 2304)              0         
                                                                 
 dense_2 (Dense)             (None, 128)               295040    
                                                                 
 dropout (Dropout)           (None, 128)               0         
                                                                 
 dense_3 (Dense)             (None, 3)                 387       
                                                                 
=================================================================
Total params: 372771 (1.42 MB)
Trainable params: 372771 (1.42 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

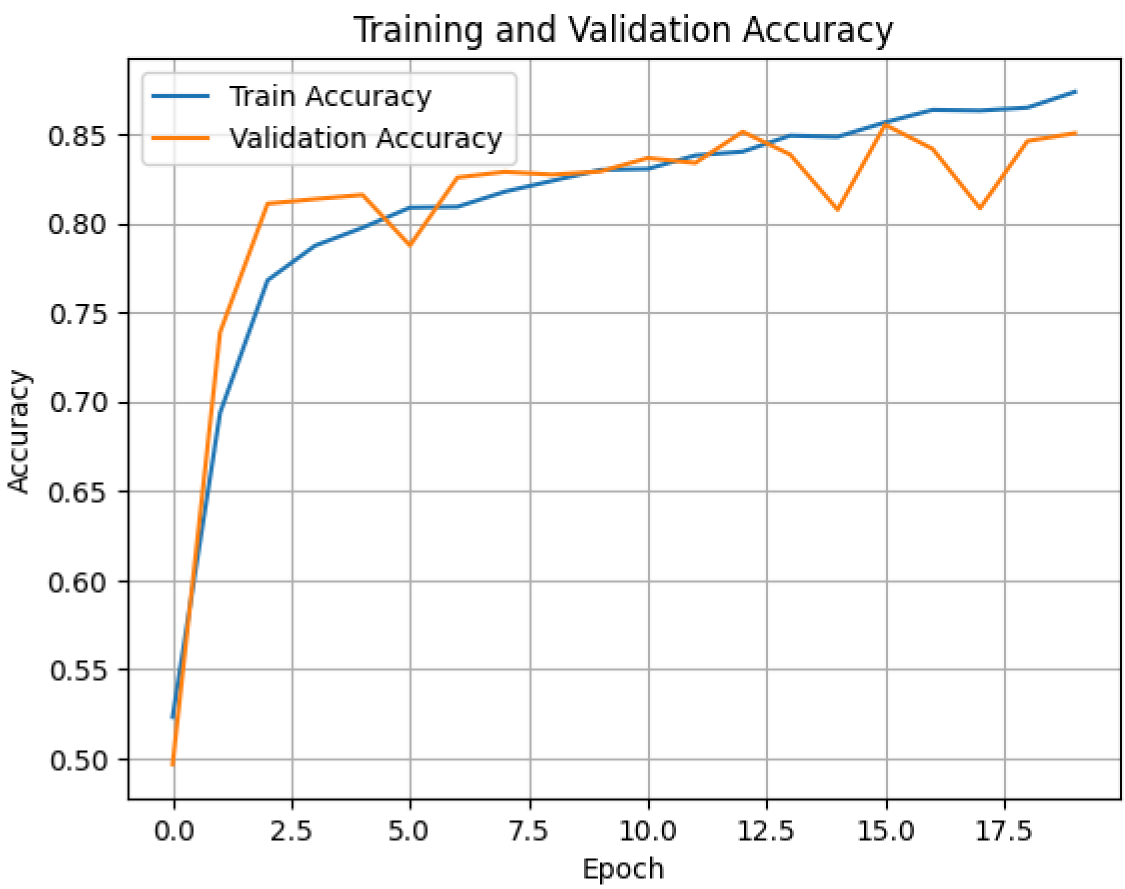
In [38]:
```
model_3_level_1.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

In [39]:
```
history_3_level_1 = model_3_level_1.fit(
    weighted_train_data,
    epochs=20,
    validation_data=validation_data,
    verbose=0
)
```

In [40]:
```
# Assuming history contains the training history returned by model.fit
train_loss_3 = history_3_level_1.history['loss']
val_loss_3 = history_3_level_1.history['val_loss']
train_acc_3 = history_3_level_1.history['accuracy']
val_acc_3 = history_3_level_1.history['val_accuracy']

# Plot loss
plt.plot(train_loss_3, label='Train Loss')
plt.plot(val_loss_3, label='Validation Loss')
```

```
plt.title('Training and Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.grid(True)
plt.show()

# Plot accuracy
plt.plot(train_acc_3, label='Train Accuracy')
plt.plot(val_acc_3, label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)
plt.show()
```





Cache results for later

In [41]:
```
model_3_level_1.save('model_3_level_1.keras')

with open('history_3_level_1.json', 'w') as f:
    json.dump(history_3_level_1.history, f)
```

In [42]:
```
model_3_level_1 = tf.keras.models.load_model('model_3_level_1.keras')

with open('history_3_level_1.json') as f:
    history_3_level_1 = json.load(f)
```

Evaluating the model

In [43]:
```
model_3_level_1.evaluate(test_data, return_dict=True)
```

```
158/158 [==============================] - 18s 109ms/step - loss: 0.4415 -
accuracy: 0.8476
```

Out[43]:
```
{'loss': 0.44151535630226135, 'accuracy': 0.8475736975669861}
```

In [44]:
```
test_predictions_3 = model_3_level_1.predict(test_data)
```

```
158/158 [==============================] - 14s 88ms/step
```

In [45]:
```
predict_labels_3 = np.argmax(test_predictions_3, axis=1)
```

In [46]:
```
test_labels_3 = np.array(list(test_data.unbatch().map(lambda x, y: y).as_
test_labels_3 = np.argmax(test_labels_3, axis=1)
```

In [47]:
```
cm_3 = tf.math.confusion_matrix(test_labels_3, predict_labels_3).numpy()
pretty_cm(cm_3)
```

Confusion matrix

		Predicted labels		
		cleared	**needleleaf**	**broadleaf**
Actual labels	**cleared**	92	330	465
	needleleaf	360	1515	2094
	broadleaf	511	1949	2761

Reference

Ramesh. S (2018) ' A guide to an efficient way to build neural network architectures-Part II: Hyper-parameter selection and tuning for Convolutional Neural Networks using Hyperas on Fashion-MNIST', Medium, 7 May 2018 [Online]. Available at https://towardsdatascience.com/a-guide-to-an-efficient-way-to-build-neural-network-architectures-part-ii-hyper-parameter-42efca01e5d7 (Accessed 11 May 2024).

Saturn Cloud (2023) How to Improve Accuracy in Neural Networks with Keras, 6 July 2023 [Online] Available at https://saturncloud.io/blog/how-to-improve-accuracy-in-neural-networks-with-keras/ (Accessed 11 May 2024).

The Open University (2023) 5 Training of CNNs, TM358 Weeks 8-11 Block 2: Image recognition with CNNs [Online]. Available at https://learn2.open.ac.uk/mod/oucontent/view.php?id=2152484&section=5.1 (Accessed 11 May 2024).

In [ ]: