rtdatacentric57

September 28, 2021

[1]:
```
# rtdatacentric52 rerun of rtdatacentric46
# changed number of images augmented
```

[2]:
```
import numpy as np
import os
import PIL
import PIL.Image
import tensorflow as tf
import tensorflow_datasets as tfds
from keras.preprocessing.image import ImageDataGenerator
```

[3]:
```
import cv2
import numpy as np
from skimage import io
from skimage.transform import rotate, AffineTransform, warp
import matplotlib.pyplot as plt
import random
from skimage import img_as_ubyte
import os
from skimage.util import random_noise

from PIL import Image
import pathlib
import shutil
```

[4]:
```
print(tf.__version__)
```

```
2.4.1
```

[5]:
```
batch_size = 8
img_height = 32
img_width = 32
tf.random.set_seed(123)
data_set = 'rtdatacentric57'

train_dir = os.path.join(data_set,'train')
val_dir = os.path.join(data_set,'val')
all_dir = os.path.join(data_set,'all')
```

```
test_dir = os.path.join(data_set,'test')
aug_dir = os.path.join(data_set,'aug')
add_dir = os.path.join(data_set,'add')
data_dir = pathlib.Path(os.path.join(all_dir))
```

[6]:
```
class_names = np.array(sorted([item.name for item in data_dir.glob('*') if item.
 ↪name != "LICENSE.txt"]))
print(class_names)

image_count = len(list(data_dir.glob('*/*.png')))
print(f"all: { image_count} ")

train_data_dir = pathlib.Path(os.path.join(train_dir))
train_image_count = len(list(train_data_dir.glob('*/*.png')))
print(f"train: { train_image_count} ")

val_data_dir = pathlib.Path(os.path.join(val_dir))
val_image_count = len(list(val_data_dir.glob('*/*.png')))
print(f"val: { val_image_count} ")

test_data_dir = pathlib.Path(os.path.join(test_dir))
test_image_count = len(list(test_data_dir.glob('*/*.png')))
print(f"test: { test_image_count} ")
```

```
['i' 'ii' 'iii' 'iv' 'ix' 'v' 'vi' 'vii' 'viii' 'x']
all: 1809
train: 8169
val: 466
test: 52
```

[7]:
```
def clear_dir(target_dir):
    # clear all images in train and val directories
    for rn in class_names:
        dir = os.path.join(target_dir, rn)
        for f in os.listdir(dir):
            path = os.path.join(dir, f)
            try:
                shutil.rmtree(path)
            except OSError:
                os.remove(path)
```

[8]:
```
clear_dir(train_data_dir)

clear_dir(val_data_dir)
```

[9]:
```
val_percent =.25
```

[10]:
```
list_ds = tf.data.Dataset.list_files(str(data_dir/'*/*.png'), shuffle=True)
list_ds = list_ds.shuffle(image_count, reshuffle_each_iteration=True)
```

[11]:
```
val_size = int(image_count * val_percent)
if val_percent > 0.0:
    train_ds = list_ds.skip(val_size)
    val_ds = list_ds.take(val_size)
else:
    val_image_count = len(list(val_data_dir.glob('*/*.png')))
    print(val_image_count)
    val_ds = tf.data.Dataset.list_files(str(val_data_dir/'*/*.png'),␣
 ↪shuffle=True)
    val_ds = val_ds.shuffle(val_image_count, reshuffle_each_iteration=True)
    train_ds = list_ds.skip(val_size)
```

[12]:
```
print(tf.data.experimental.cardinality(train_ds).numpy())
print(tf.data.experimental.cardinality(val_ds).numpy())
```

```
1357
452
```

[13]:
```
for rom_num in class_names:
    images_path = os.path.join(train_dir, rom_num)
    print(f"{rom_num} : {len(os.listdir(images_path))}")
```

```
i : 0
ii : 0
iii : 0
iv : 0
ix : 0
v : 0
vi : 0
vii : 0
viii : 0
x : 0
```

[14]:
```
def get_label(file_path):
    # convert the path to a list of path components
    parts = tf.strings.split(file_path, os.path.sep)
    # The second to last is the class-directory
    one_hot = parts[-2] == class_names
    # Integer encode the label
    return tf.argmax(one_hot)

def decode_img(img):
```

```
    # convert the compressed string to a 3D uint8 tensor
    img = tf.image.decode_jpeg(img, channels=3)
    # resize the image to the desired size
    return tf.image.resize(img, [img_height, img_width])

def process_path(file_path):
    label = get_label(file_path)
    # load the raw data from the file as a string
    img = tf.io.read_file(file_path)
    img = decode_img(img)
    return img, label, file_path
```

[15]:
```
AUTOTUNE = tf.data.AUTOTUNE
# Set `num_parallel_calls` so multiple images are loaded/processed in parallel.
train_ds = train_ds.map(process_path, num_parallel_calls=AUTOTUNE)
val_ds = val_ds.map(process_path, num_parallel_calls=AUTOTUNE)
```

[16]:
```
train_ds = train_ds.cache().prefetch(buffer_size=AUTOTUNE)
val_ds = val_ds.cache().prefetch(buffer_size=AUTOTUNE)
```

[17]:
```
trainimg = {}
valimg = {}
```

[18]:
```
# put training images into a directory
for image, label, file_path in train_ds:
    basename = os.path.basename(file_path.numpy())
    cur_class_name = os.path.join(class_names[label.numpy()])
    class_name_path = os.path.join(cur_class_name)
    newfile_dir = os.path.join(train_dir,class_name_path)
    newfile_path = os.path.join(newfile_dir, basename.decode('utf-8'))

    trainimg[basename.decode('utf-8')] = cur_class_name
```

[19]:
```
if val_percent > 0.0:
    # put validation images into a directory
    for image, label, file_path in val_ds:
        basename = os.path.basename(file_path.numpy())
        cur_class_name = os.path.join(class_names[label.numpy()])
        class_name_path = os.path.join(cur_class_name)
        newfile_dir = os.path.join(val_dir,class_name_path)
        newfile_path = os.path.join(newfile_dir, basename.decode('utf-8'))

        valimg[basename.decode('utf-8')] = cur_class_name
```

[20]:
```
# put images into their respective dirs
dirall = data_dir
for itname in trainimg:
```

```python
    src = os.path.join(dirall, trainimg[itname], itname)
    dest = os.path.join(train_dir, trainimg[itname],itname)
    shutil.copy(src, dest)
print("Images copied into train")

if val_percent > 0.0:
    for iname in valimg:
        src = os.path.join(dirall, valimg[iname], iname)
        dest = os.path.join(val_dir,valimg[iname],iname)
        shutil.copy(src, dest)
    print("Images copied into val")
```

```
Images copied into train
Images copied into val
```

[21]:
```python
for rom_num in class_names:
    images_path = os.path.join(train_dir, rom_num)
    print(f"{rom_num} : {len(os.listdir(images_path))}")
```

```
i : 162
ii : 143
iii : 106
iv : 192
ix : 147
v : 143
vi : 113
vii : 114
viii : 114
x : 123
```

[22]:
```python
# Data augmentation settings
# datagen = ImageDataGenerator(
#     rotation_range=10,
#     width_shift_range=0.1,
#     height_shift_range=0.1,
#     shear_range=0.15,
#     zoom_range=0.1,
#     channel_shift_range = 10,
#     horizontal_flip=False
#)

datagen = ImageDataGenerator(rotation_range=10,
                             width_shift_range=0.1,
                             height_shift_range=0.1,
                             shear_range=5,
                             zoom_range=0.1,
                             cval=0.0,)
```

```
# numeral_multiplier =[2, 4, 4, 3, 3, 3, 3, 3, 4, 2]
numeral_multiplier =[4, 4, 4, 4, 4, 4, 4, 4, 4, 4]
```

[23]:
```
# Data augmentation create images
save_here = aug_dir
class_names = np.array(sorted([item.name for item in data_dir.glob('*') if item.
↪name != "LICENSE.txt"]))
class_numeral = ['i', 'ii', 'iii', 'iv', 'v', 'vi', 'vii', 'viii', 'ix', 'x']
numeral_number_images = []
numeral_count = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0]

for numeral in class_names:
    array_index = class_numeral.index(numeral)
    # path to original images
    images_path=os.path.join(train_dir,numeral)
    print(f"images_path = { images_path }")
    num_range = numeral_multiplier[class_numeral.index(numeral)]
    print(f"multiplier = { num_range }")
    # path to store aumented images
    augmented_path=os.path.join(aug_dir,numeral)
    # path to store aumented images
    images=[]
    # to store paths of images from folder
    for image in os.listdir(images_path):
        image_path = os.path.join(images_path, image)
        image = np.expand_dims(cv2.imread(image_path), 0)
        datagen.fit(image)
        for x, val in zip(datagen.flow(image,                    #image we chose
            save_to_dir=os.path.join(train_dir,numeral),     #this is where we␣
↪figure out where to save
            save_prefix='aug',        # it will save the images as 'aug_0912'␣
↪some number for every new augmented image
            save_format='png'),range(num_range)) :     # here we define a range␣
↪because we want 10 augmented images otherwise it will keep looping forever I␣
↪think
                pass
```

```
images_path = rtdatacentric57/train/i
multiplier = 4
images_path = rtdatacentric57/train/ii
multiplier = 4
images_path = rtdatacentric57/train/iii
multiplier = 4
images_path = rtdatacentric57/train/iv
multiplier = 4
images_path = rtdatacentric57/train/ix
```

```
multiplier = 4
images_path = rtdatacentric57/train/v
multiplier = 4
images_path = rtdatacentric57/train/vi
multiplier = 4
images_path = rtdatacentric57/train/vii
multiplier = 4
images_path = rtdatacentric57/train/viii
multiplier = 4
images_path = rtdatacentric57/train/x
multiplier = 4
```

[24]:

```
for rom_num in class_names:
    images_path = os.path.join(train_dir, rom_num)
    print(f"{rom_num} : {len(os.listdir(images_path))}")
```

```
i : 939
ii : 829
iii : 624
iv : 1104
ix : 854
v : 831
vi : 661
vii : 665
viii : 666
x : 724
```

[25]:

```
#Lets define functions for each operation
def anticlockwise_rotation(image):
    angle= random.randint(0,20)
    return rotate(image, angle)

def clockwise_rotation(image):
    angle= random.randint(0,20)
    return rotate(image, -angle)

def h_flip(image):
    return np.fliplr(image)

def v_flip(image):
    return np.flipud(image)

def add_noise(image):
    return random_noise(image)

def blur_image(image):
    return cv2.GaussianBlur(image, (9,9),0)
```

```
    #I would not recommend warp_shifting, because it distorts image, but can␣
↪be␣used in many use case like
    #classifying blur and non-blur images

def warp_shift(image):
    # chose x,y values according to your convinience
    transform = AffineTransform(translation=(0,40))
    warp_image = warp(image, transform, mode="wrap")
    return warp_image
```

[26]:
```
for rom_num in class_names:
    images_path = os.path.join(train_dir, rom_num)
    print(f"{rom_num} : {len(os.listdir(images_path))}")
for rom_num in class_names:
    images_path = os.path.join(val_dir, rom_num)
    print(f"{rom_num} : {len(os.listdir(images_path))}")
```

```
i : 939
ii : 829
iii : 624
iv : 1104
ix : 854
v : 831
vi : 661
vii : 665
viii : 666
x : 724
i : 65
ii : 41
iii : 31
iv : 62
ix : 48
v : 48
vi : 35
vii : 48
viii : 35
x : 39
```

[27]:
```
class_numeral = ['i', 'ii', 'iii', 'iv', 'v', 'vi', 'vii', 'viii', 'ix', 'x']
```

[28]:
```
for rom_num in class_names:
    images_path = os.path.join(train_dir, rom_num)
    print(f"{rom_num} : {len(os.listdir(images_path))}")
```

```
i : 939
```

```
ii : 829
iii : 624
iv : 1104
ix : 854
v : 831
vi : 661
vii : 665
viii : 666
x : 724
```

[29]:

```python
# check total number of images
train_data_dir = pathlib.Path(os.path.join(train_dir))
train_image_count = len(list(train_data_dir.glob('*/*.*g')))
print(train_image_count)

val_data_dir = pathlib.Path(os.path.join(val_dir))
val_image_count = len(list(val_data_dir.glob('*/*.*g')))
print(val_image_count)
```

```
7897
452
```

[31]:

```python
# end of image augmentation
```

[32]:

```python
# new training dataset with augmented images
new_train_ds = tf.keras.preprocessing.image_dataset_from_directory(
    train_dir,
    labels='inferred',
    label_mode='categorical',
    class_names=["i", "ii", "iii", "iv", "v", "vi", "vii", "viii", "ix", "x"],
    batch_size=8,
    image_size=(32,32),
    shuffle=True,
    seed=123,
    validation_split=None
)
```

```
Found 7897 files belonging to 10 classes.
```

[33]:

```python
# new val dataset with augmented images
new_val_ds = tf.keras.preprocessing.image_dataset_from_directory(
    val_dir,
    labels='inferred',
    label_mode='categorical',
    class_names=["i", "ii", "iii", "iv", "v", "vi", "vii", "viii", "ix", "x"],
    batch_size=8,
    image_size=(32,32),
    shuffle=True,
```

```
    seed=123,
    validation_split=None
)
```

Found 452 files belonging to 10 classes.

[34]:
```
new_test_ds = tf.keras.preprocessing.image_dataset_from_directory(
    test_dir,
    labels="inferred",
    label_mode="categorical",
    class_names=["i", "ii", "iii", "iv", "v", "vi", "vii", "viii", "ix", "x"],
    shuffle=False,
    batch_size=8,
    image_size=(32,32),
    seed=123,
    validation_split=None
)
```

Found 52 files belonging to 10 classes.

[35]:
```
from tensorflow.keras import layers

normalization_layer = tf.keras.layers.experimental.preprocessing.Rescaling(1./
 ↪255)
```

[36]:
```
for image_batch, labels_batch in new_train_ds:
    print(image_batch.shape)
    print(labels_batch.shape)
    break
```

```
(8, 32, 32, 3)
(8, 10)
```

[37]:
```
normalized_ds = new_train_ds.map(lambda x, y: (normalization_layer(x), y))
image_batch, labels_batch = next(iter(normalized_ds))
first_image = image_batch[0]
# Notice the pixels values are now in `[0,1]`.
print(np.min(first_image), np.max(first_image))
```

0.0 1.0

[38]:
```
AUTOTUNE = tf.data.AUTOTUNE

train_ds = new_train_ds.cache().prefetch(buffer_size=AUTOTUNE)
val_ds = new_val_ds.cache().prefetch(buffer_size=AUTOTUNE)
```

[39]:

```
base_model = tf.keras.applications.ResNet50(
    input_shape=(32, 32, 3),
    include_top=False,
    weights=None,
)
base_model = tf.keras.Model(
    base_model.inputs, outputs=[base_model.get_layer("conv2_block3_out").output]
)

inputs = tf.keras.Input(shape=(32, 32, 3))
x = tf.keras.applications.resnet.preprocess_input(inputs)
x = base_model(x)
x = tf.keras.layers.GlobalAveragePooling2D()(x)
x = tf.keras.layers.Dense(10)(x)
model = tf.keras.Model(inputs, x)

model.compile(
    optimizer=tf.keras.optimizers.Adam(lr=0.0001),
    loss=tf.keras.losses.CategoricalCrossentropy(from_logits=True),
    metrics=["accuracy"],
)
model.summary()
```

```
Model: "model_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_2 (InputLayer)         [(None, 32, 32, 3)]       0
_________________________________________________________________
tf.__operators__.getitem (Sl (None, 32, 32, 3)         0
_________________________________________________________________
tf.nn.bias_add (TFOpLambda)  (None, 32, 32, 3)         0
_________________________________________________________________
model (Functional)           (None, 8, 8, 256)         229760
_________________________________________________________________
global_average_pooling2d (Gl (None, 256)               0
_________________________________________________________________
dense (Dense)                (None, 10)                2570
=================================================================
Total params: 232,330
Trainable params: 229,386
Non-trainable params: 2,944
_________________________________________________________________
```

[40]:

```
loss_0, acc_0 = model.evaluate(new_val_ds)
print(f"loss {loss_0}, acc {acc_0}")
```

```
57/57 [==============================] - 12s 88ms/step - loss: 48.8832 -
```

```
accuracy: 0.0682
loss 49.848636627197266, acc 0.07743363082408905
```

[41]:
```
checkpoint = tf.keras.callbacks.ModelCheckpoint(
    "best_model",
    monitor="val_accuracy",
    mode="max",
    save_best_only=True,
    save_weights_only=True,
)
```

[42]:
```
model03 = model.fit(
  new_train_ds,
  validation_data=new_val_ds,
  epochs=100,
  callbacks=[checkpoint],
)
```

```
Epoch 1/100
988/988 [==============================] - 40s 33ms/step - loss: 1.4570 -
accuracy: 0.5180 - val_loss: 0.9658 - val_accuracy: 0.6814
Epoch 2/100
988/988 [==============================] - 22s 22ms/step - loss: 0.7321 -
accuracy: 0.7676 - val_loss: 0.6122 - val_accuracy: 0.7765
Epoch 3/100
988/988 [==============================] - 21s 21ms/step - loss: 0.5175 -
accuracy: 0.8342 - val_loss: 0.5164 - val_accuracy: 0.8164
Epoch 4/100
988/988 [==============================] - 22s 22ms/step - loss: 0.3951 -
accuracy: 0.8746 - val_loss: 0.2721 - val_accuracy: 0.9137
Epoch 5/100
988/988 [==============================] - 22s 22ms/step - loss: 0.2960 -
accuracy: 0.9111 - val_loss: 0.3931 - val_accuracy: 0.8584
Epoch 6/100
988/988 [==============================] - 22s 22ms/step - loss: 0.2584 -
accuracy: 0.9187 - val_loss: 0.2653 - val_accuracy: 0.9137
Epoch 7/100
988/988 [==============================] - 22s 23ms/step - loss: 0.2087 -
accuracy: 0.9378 - val_loss: 0.2907 - val_accuracy: 0.9004
Epoch 8/100
988/988 [==============================] - 22s 22ms/step - loss: 0.1818 -
accuracy: 0.9457 - val_loss: 0.2109 - val_accuracy: 0.9358
Epoch 9/100
988/988 [==============================] - 22s 22ms/step - loss: 0.1442 -
accuracy: 0.9585 - val_loss: 0.2924 - val_accuracy: 0.9115
Epoch 10/100
988/988 [==============================] - 22s 23ms/step - loss: 0.1216 -
accuracy: 0.9651 - val_loss: 0.1525 - val_accuracy: 0.9735
```

```
Epoch 11/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0985 -
accuracy: 0.9738 - val_loss: 0.3422 - val_accuracy: 0.8960
Epoch 12/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0927 -
accuracy: 0.9739 - val_loss: 0.2428 - val_accuracy: 0.9270
Epoch 13/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0832 -
accuracy: 0.9764 - val_loss: 0.2656 - val_accuracy: 0.9226
Epoch 14/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0763 -
accuracy: 0.9781 - val_loss: 0.1180 - val_accuracy: 0.9757
Epoch 15/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0739 -
accuracy: 0.9785 - val_loss: 0.0930 - val_accuracy: 0.9757
Epoch 16/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0603 -
accuracy: 0.9818 - val_loss: 0.2060 - val_accuracy: 0.9381
Epoch 17/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0563 -
accuracy: 0.9837 - val_loss: 0.0986 - val_accuracy: 0.9735
Epoch 18/100
988/988 [==============================] - 22s 23ms/step - loss: 0.0527 -
accuracy: 0.9868 - val_loss: 0.2070 - val_accuracy: 0.9469
Epoch 19/100
988/988 [==============================] - 22s 23ms/step - loss: 0.0477 -
accuracy: 0.9859 - val_loss: 0.2178 - val_accuracy: 0.9270
Epoch 20/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0472 -
accuracy: 0.9868 - val_loss: 0.1143 - val_accuracy: 0.9735
Epoch 21/100
988/988 [==============================] - 22s 23ms/step - loss: 0.0404 -
accuracy: 0.9884 - val_loss: 0.1053 - val_accuracy: 0.9779
Epoch 22/100
988/988 [==============================] - 22s 23ms/step - loss: 0.0425 -
accuracy: 0.9878 - val_loss: 0.1743 - val_accuracy: 0.9447
Epoch 23/100
988/988 [==============================] - 22s 23ms/step - loss: 0.0356 -
accuracy: 0.9914 - val_loss: 0.1049 - val_accuracy: 0.9757
Epoch 24/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0369 -
accuracy: 0.9901 - val_loss: 0.0903 - val_accuracy: 0.9757
Epoch 25/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0375 -
accuracy: 0.9880 - val_loss: 0.1171 - val_accuracy: 0.9668
Epoch 26/100
988/988 [==============================] - 22s 23ms/step - loss: 0.0261 -
accuracy: 0.9935 - val_loss: 0.2382 - val_accuracy: 0.9270
```

```
Epoch 27/100
988/988 [==============================] - 22s 23ms/step - loss: 0.0414 -
accuracy: 0.9873 - val_loss: 0.0873 - val_accuracy: 0.9779
Epoch 28/100
988/988 [==============================] - 21s 21ms/step - loss: 0.0332 -
accuracy: 0.9909 - val_loss: 0.1126 - val_accuracy: 0.9690
Epoch 29/100
988/988 [==============================] - 21s 22ms/step - loss: 0.0304 -
accuracy: 0.9913 - val_loss: 0.1001 - val_accuracy: 0.9801
Epoch 30/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0247 -
accuracy: 0.9938 - val_loss: 0.0915 - val_accuracy: 0.9690
Epoch 31/100
988/988 [==============================] - 21s 22ms/step - loss: 0.0265 -
accuracy: 0.9927 - val_loss: 0.0590 - val_accuracy: 0.9735
Epoch 32/100
988/988 [==============================] - 22s 23ms/step - loss: 0.0255 -
accuracy: 0.9939 - val_loss: 0.1225 - val_accuracy: 0.9712
Epoch 33/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0267 -
accuracy: 0.9916 - val_loss: 0.0844 - val_accuracy: 0.9757
Epoch 34/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0225 -
accuracy: 0.9939 - val_loss: 1.1302 - val_accuracy: 0.8208
Epoch 35/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0289 -
accuracy: 0.9904 - val_loss: 0.0803 - val_accuracy: 0.9801
Epoch 36/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0173 -
accuracy: 0.9952 - val_loss: 0.0785 - val_accuracy: 0.9779
Epoch 37/100
988/988 [==============================] - 22s 23ms/step - loss: 0.0202 -
accuracy: 0.9947 - val_loss: 0.0723 - val_accuracy: 0.9823
Epoch 38/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0215 -
accuracy: 0.9944 - val_loss: 0.0658 - val_accuracy: 0.9823
Epoch 39/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0221 -
accuracy: 0.9935 - val_loss: 0.0566 - val_accuracy: 0.9823
Epoch 40/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0170 -
accuracy: 0.9949 - val_loss: 0.1108 - val_accuracy: 0.9602
Epoch 41/100
988/988 [==============================] - 22s 23ms/step - loss: 0.0205 -
accuracy: 0.9944 - val_loss: 0.0460 - val_accuracy: 0.9823
Epoch 42/100
988/988 [==============================] - 22s 23ms/step - loss: 0.0218 -
accuracy: 0.9930 - val_loss: 0.1065 - val_accuracy: 0.9757
```

```
Epoch 43/100
988/988 [==============================] - 22s 23ms/step - loss: 0.0127 -
accuracy: 0.9971 - val_loss: 0.0830 - val_accuracy: 0.9757
Epoch 44/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0194 -
accuracy: 0.9946 - val_loss: 0.0695 - val_accuracy: 0.9801
Epoch 45/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0196 -
accuracy: 0.9939 - val_loss: 0.0932 - val_accuracy: 0.9801
Epoch 46/100
988/988 [==============================] - 21s 21ms/step - loss: 0.0154 -
accuracy: 0.9954 - val_loss: 0.1920 - val_accuracy: 0.9403
Epoch 47/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0153 -
accuracy: 0.9951 - val_loss: 0.0852 - val_accuracy: 0.9757
Epoch 48/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0174 -
accuracy: 0.9946 - val_loss: 0.1607 - val_accuracy: 0.9602
Epoch 49/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0135 -
accuracy: 0.9973 - val_loss: 0.0887 - val_accuracy: 0.9757
Epoch 50/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0149 -
accuracy: 0.9961 - val_loss: 0.0611 - val_accuracy: 0.9779
Epoch 51/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0152 -
accuracy: 0.9967 - val_loss: 0.0804 - val_accuracy: 0.9779
Epoch 52/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0162 -
accuracy: 0.9956 - val_loss: 0.0799 - val_accuracy: 0.9757
Epoch 53/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0140 -
accuracy: 0.9962 - val_loss: 0.0942 - val_accuracy: 0.9801
Epoch 54/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0074 -
accuracy: 0.9984 - val_loss: 0.1360 - val_accuracy: 0.9535
Epoch 55/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0142 -
accuracy: 0.9959 - val_loss: 0.0672 - val_accuracy: 0.9779
Epoch 56/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0086 -
accuracy: 0.9984 - val_loss: 0.0735 - val_accuracy: 0.9801
Epoch 57/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0198 -
accuracy: 0.9957 - val_loss: 0.0964 - val_accuracy: 0.9712
Epoch 58/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0089 -
accuracy: 0.9972 - val_loss: 0.0640 - val_accuracy: 0.9757
```

```
Epoch 59/100
988/988 [==============================] - 21s 22ms/step - loss: 0.0174 -
accuracy: 0.9947 - val_loss: 0.1128 - val_accuracy: 0.9735
Epoch 60/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0167 -
accuracy: 0.9948 - val_loss: 0.0879 - val_accuracy: 0.9757
Epoch 61/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0070 -
accuracy: 0.9981 - val_loss: 0.0563 - val_accuracy: 0.9867
Epoch 62/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0146 -
accuracy: 0.9959 - val_loss: 0.0695 - val_accuracy: 0.9801
Epoch 63/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0133 -
accuracy: 0.9961 - val_loss: 0.0982 - val_accuracy: 0.9757
Epoch 64/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0126 -
accuracy: 0.9968 - val_loss: 0.0804 - val_accuracy: 0.9801
Epoch 65/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0128 -
accuracy: 0.9965 - val_loss: 0.0716 - val_accuracy: 0.9823
Epoch 66/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0097 -
accuracy: 0.9976 - val_loss: 0.0829 - val_accuracy: 0.9779
Epoch 67/100
988/988 [==============================] - 21s 21ms/step - loss: 0.0135 -
accuracy: 0.9963 - val_loss: 0.0674 - val_accuracy: 0.9779
Epoch 68/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0100 -
accuracy: 0.9973 - val_loss: 0.0835 - val_accuracy: 0.9801
Epoch 69/100
988/988 [==============================] - 21s 21ms/step - loss: 0.0132 -
accuracy: 0.9959 - val_loss: 0.1438 - val_accuracy: 0.9602
Epoch 70/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0082 -
accuracy: 0.9978 - val_loss: 0.0627 - val_accuracy: 0.9845
Epoch 71/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0157 -
accuracy: 0.9963 - val_loss: 0.0687 - val_accuracy: 0.9801
Epoch 72/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0060 -
accuracy: 0.9984 - val_loss: 0.0705 - val_accuracy: 0.9845
Epoch 73/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0159 -
accuracy: 0.9954 - val_loss: 0.0611 - val_accuracy: 0.9823
Epoch 74/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0127 -
accuracy: 0.9970 - val_loss: 0.0672 - val_accuracy: 0.9867
```

```
Epoch 75/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0050 -
accuracy: 0.9989 - val_loss: 0.0582 - val_accuracy: 0.9867
Epoch 76/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0071 -
accuracy: 0.9981 - val_loss: 0.0681 - val_accuracy: 0.9889
Epoch 77/100
988/988 [==============================] - 21s 21ms/step - loss: 0.0110 -
accuracy: 0.9968 - val_loss: 0.0661 - val_accuracy: 0.9845
Epoch 78/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0144 -
accuracy: 0.9953 - val_loss: 0.0666 - val_accuracy: 0.9845
Epoch 79/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0089 -
accuracy: 0.9973 - val_loss: 0.0710 - val_accuracy: 0.9801
Epoch 80/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0058 -
accuracy: 0.9984 - val_loss: 0.0648 - val_accuracy: 0.9867
Epoch 81/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0049 -
accuracy: 0.9991 - val_loss: 0.0603 - val_accuracy: 0.9779
Epoch 82/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0098 -
accuracy: 0.9973 - val_loss: 0.0794 - val_accuracy: 0.9801
Epoch 83/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0105 -
accuracy: 0.9968 - val_loss: 0.0690 - val_accuracy: 0.9823
Epoch 84/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0100 -
accuracy: 0.9971 - val_loss: 0.1066 - val_accuracy: 0.9779
Epoch 85/100
988/988 [==============================] - 21s 21ms/step - loss: 0.0105 -
accuracy: 0.9972 - val_loss: 0.4672 - val_accuracy: 0.9115
Epoch 86/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0066 -
accuracy: 0.9980 - val_loss: 0.0581 - val_accuracy: 0.9845
Epoch 87/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0082 -
accuracy: 0.9977 - val_loss: 0.0708 - val_accuracy: 0.9867
Epoch 88/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0046 -
accuracy: 0.9990 - val_loss: 0.0660 - val_accuracy: 0.9823
Epoch 89/100
988/988 [==============================] - 21s 21ms/step - loss: 0.0065 -
accuracy: 0.9981 - val_loss: 0.1130 - val_accuracy: 0.9735
Epoch 90/100
988/988 [==============================] - 21s 22ms/step - loss: 0.0124 -
accuracy: 0.9957 - val_loss: 0.0961 - val_accuracy: 0.9757
```

```
Epoch 91/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0064 -
accuracy: 0.9981 - val_loss: 0.1312 - val_accuracy: 0.9624
Epoch 92/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0019 -
accuracy: 0.9999 - val_loss: 0.0624 - val_accuracy: 0.9867
Epoch 93/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0132 -
accuracy: 0.9959 - val_loss: 0.1152 - val_accuracy: 0.9757
Epoch 94/100
988/988 [==============================] - 21s 22ms/step - loss: 0.0074 -
accuracy: 0.9978 - val_loss: 0.1255 - val_accuracy: 0.9779
Epoch 95/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0077 -
accuracy: 0.9980 - val_loss: 0.0577 - val_accuracy: 0.9889
Epoch 96/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0062 -
accuracy: 0.9980 - val_loss: 0.0907 - val_accuracy: 0.9757
Epoch 97/100
988/988 [==============================] - 21s 21ms/step - loss: 0.0070 -
accuracy: 0.9980 - val_loss: 0.1127 - val_accuracy: 0.9690
Epoch 98/100
988/988 [==============================] - 21s 21ms/step - loss: 0.0108 -
accuracy: 0.9970 - val_loss: 0.0691 - val_accuracy: 0.9845
Epoch 99/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0064 -
accuracy: 0.9985 - val_loss: 0.0570 - val_accuracy: 0.9845
Epoch 100/100
988/988 [==============================] - 22s 22ms/step - loss: 0.0065 -
accuracy: 0.9980 - val_loss: 0.1001 - val_accuracy: 0.9801
```

[43]:
```
model.load_weights("best_model")
loss, acc = model.evaluate(new_val_ds)
print(f"final loss {loss}, final acc {acc}")
```

```
57/57 [==============================] - 1s 11ms/step - loss: 0.0681 - accuracy:
0.9889
final loss 0.06814993172883987, final acc 0.98893803358078
```

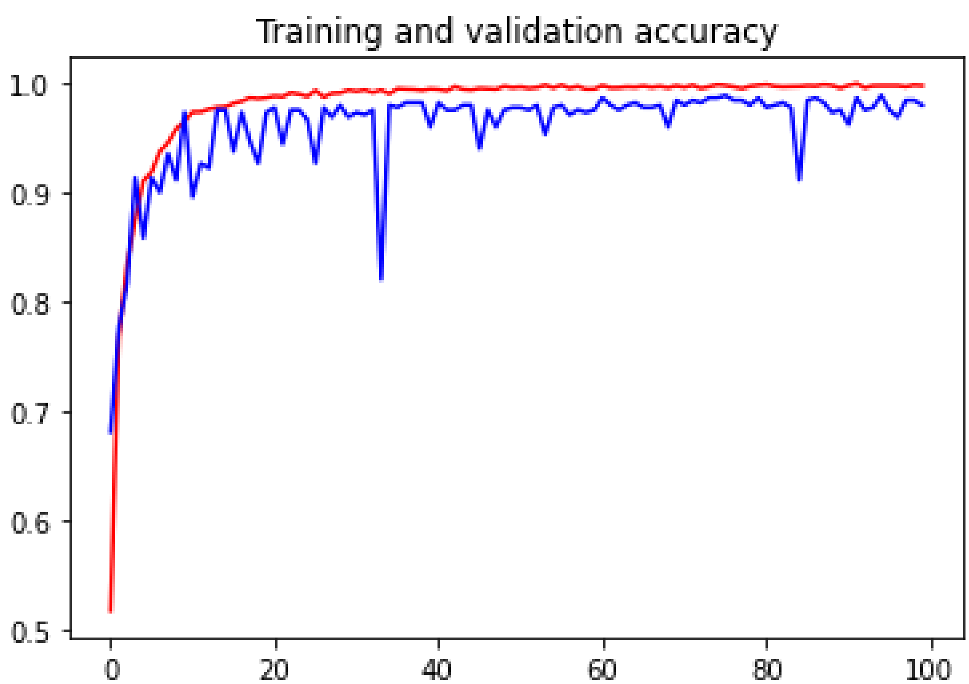
[44]:
```
test_loss, test_acc = model.evaluate(new_test_ds)
print(f"test loss {test_loss}, test acc {test_acc}")
```

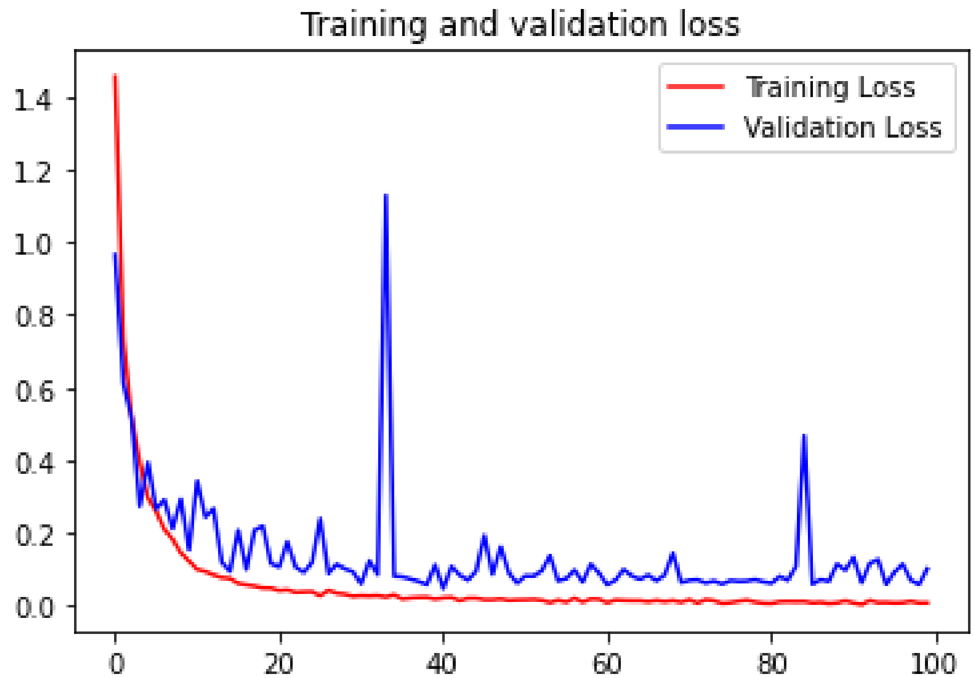
```
7/7 [==============================] - 0s 11ms/step - loss: 1.0142 - accuracy:
0.8269
test loss 1.014161467552185, test acc 0.8269230723381042
```

[45]:
```
import matplotlib.pyplot as plt
```

[46]:

```
acc = model03.history['accuracy']
val_acc = model03.history['val_accuracy']
loss = model03.history['loss']
val_loss = model03.history['val_loss']


epochs = range(len(acc))

plt.plot(epochs, acc, 'r', label='Training accuracy')
plt.plot(epochs, val_acc, 'b', label='Validation accuracy')
plt.title('Training and validation accuracy')

plt.figure()

plt.plot(epochs, loss, 'r', label='Training Loss')
plt.plot(epochs, val_loss, 'b', label='Validation Loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```





[47]:
```
probability_model = tf.keras.Sequential([model,
                                         tf.keras.layers.Softmax()])
predictions = probability_model.predict(new_val_ds)
predictions = np.array(predictions)
```

[48]:
```
test_predictions = probability_model.predict(new_test_ds)
test_predictions = np.array(test_predictions)
```

[49]:
```
def plot_image(i, predictions_array, true_label, img):
  true_label, img = true_label[i], img[i]
  plt.grid(False)
  plt.xticks([])
  plt.yticks([])

  plt.imshow(img, cmap=plt.cm.binary)

  print(f"true_label = { true_label}")

  predicted_label = np.argmax(predictions_array)
  print(f"predicted_label = { predicted_label }")
  if predicted_label == true_label:
    color = 'blue'
  else:
    color = 'red'
```

```
  filepath = images[i+beginatimg]
  filepath_arr = filepath.split("/")
  curimage = filepath_arr[3]

  # plt.xlabel("{} {:2.0f}% ({})".format(class_names[predicted_label],
  #                              100*np.max(predictions_array),
  #                              true_label),
  #                              color=color)
  plt.xlabel("{} {}".format(class_names[predicted_label],
                          curimage), color=color)

def plot_value_array(i, predictions_array, true_label):
  true_label = true_label[i]
  plt.grid(False)
  plt.xticks(range(10))
  plt.yticks([])
  thisplot = plt.bar(range(10), predictions_array, color="#777777")
  plt.ylim([0, 1])
  predicted_label = np.argmax(predictions_array)

  thisplot[predicted_label].set_color('red')
  thisplot[true_label].set_color('blue')
```

[50]:
```
class_val = {"i" : 0, "ii" : 1, "iii" : 2, "iv" : 3, "v" : 4, "vi" : 5,
             "vii" : 6, "viii" : 7, "ix" : 8, "x" : 9 }
```

[51]:
```
# to store paths of images from folder
validation_images = []
true_labels = []
pred_labels = []
predictions = []
predictions2 = []
scores = []
count = 0;
probability_mode = tf.keras.Sequential([model, tf.keras.layers.Softmax()])

for numeral in class_names:
    # path to original images
    images_path=os.path.join(val_dir,numeral)
    print(images_path)
    for im in os.listdir(images_path):
        validation_images.append(os.path.join(images_path,im))


        true_labels.append(class_val[numeral])
        cur_image_path = os.path.join(images_path,im)
```

```
        img = tf.keras.preprocessing.image.load_img(
            cur_image_path, target_size=(img_height, img_width)
        )
        img_array = tf.keras.preprocessing.image.img_to_array(img)
        img_array = tf.expand_dims(img_array, 0) # Create a batch

        prediction2 = probability_model.predict(img_array)
        predictions2.append(prediction2)
        prediction = model.predict(img_array)
        # predictions.append(prediction)
        score = tf.nn.softmax(prediction)
        predictions.append(score)
        pred_labels.append(np.argmax(prediction))
print(f"# of validation images: { len(validation_images) }")
print(f"# of true_label: { len(true_labels) }")
print(f"# of pred_label: { len(pred_labels) }")
print(f"# of prediction: { len(predictions) }")
```

```
rtdatacentric57/val/i
rtdatacentric57/val/ii
rtdatacentric57/val/iii
rtdatacentric57/val/iv
rtdatacentric57/val/ix
rtdatacentric57/val/v
rtdatacentric57/val/vi
rtdatacentric57/val/vii
rtdatacentric57/val/viii
rtdatacentric57/val/x
# of validation images: 452
# of true_label: 452
# of pred_label: 452
# of prediction: 452
```

[52]:

```
# to store paths of images from folder
test_images = []
test_true_labels = []
test_pred_labels = []
test_predictions = []
test_predictions2 = []
test_scores = []
count = 0;
probability_mode = tf.keras.Sequential([model, tf.keras.layers.Softmax()])

for numeral in class_names:
    # path to original images
    images_path=os.path.join(test_dir,numeral)
    print(images_path)
```

```
    for im in os.listdir(images_path):
        test_images.append(os.path.join(images_path,im))


        test_true_labels.append(class_val[numeral])
        cur_image_path = os.path.join(images_path,im)
        img = tf.keras.preprocessing.image.load_img(
            cur_image_path, target_size=(img_height, img_width)
        )
        img_array = tf.keras.preprocessing.image.img_to_array(img)
        img_array = tf.expand_dims(img_array, 0) # Create a batch

        test_prediction2 = probability_model.predict(img_array)
        test_predictions2.append(test_prediction2)
        test_prediction = model.predict(img_array)
        # predictions.append(prediction)
        test_score = tf.nn.softmax(test_prediction)
        test_predictions.append(test_score)
        test_pred_labels.append(np.argmax(test_prediction))
print(f"# of test images: { len(test_images) }")
print(f"# of true_label: { len(test_true_labels) }")
print(f"# of pred_label: { len(test_pred_labels) }")
print(f"# of prediction: { len(test_predictions) }")
```

```
rtdatacentric57/test/i
rtdatacentric57/test/ii
rtdatacentric57/test/iii
rtdatacentric57/test/iv
rtdatacentric57/test/ix
rtdatacentric57/test/v
rtdatacentric57/test/vi
rtdatacentric57/test/vii
rtdatacentric57/test/viii
rtdatacentric57/test/x
# of test images: 52
# of true_label: 52
# of pred_label: 52
# of prediction: 52
```

[53]:
```
predictions2 = np.array(predictions2)
print(np.argmax(predictions2[200]))
print(true_labels[200])
```

```
8
8
```

[54]:
```
test_predictions2 = np.array(test_predictions2)
print(np.argmax(test_predictions2[10]))
print(test_true_labels[10])
```

```
2
2
```

[55]:
```
def plot_image(i, predictions_array, true_labels, images, beginatimg):
  # print(f"i = {i} beginatimg = {beginatimg}")
  true_label = true_labels[i] + beginatimg;
  img = tf.keras.preprocessing.image.load_img(
      images[i+beginatimg], target_size=(img_height, img_width)
  )

  img_array = tf.keras.preprocessing.image.img_to_array(img)
  img_array = img_array / 255.0

  plt.grid(False)
  plt.xticks([])
  plt.yticks([])

  plt.imshow(img_array, cmap=plt.cm.binary)
  predicted_label = np.argmax(predictions_array)

  if predicted_label == true_label:
    color = 'blue'
  else:
    color = 'red'

  filepath = images[i+beginatimg]
  filepath_arr = filepath.split("/")
  curimage = filepath_arr[3]

  # plt.xlabel("{} {:2.0f}% ({})".format(class_names[predicted_label],
  #                               100*np.max(predictions_array),
  #                               true_label),
  #                               color=color)
  plt.xlabel("{}".format(curimage), color=color)

def plot_value_array(i, predictions_array, true_labels, beginatimg):
  true_label = true_labels[i+beginatimg]
  plt.grid(False)
  plt.xticks(range(10))
  plt.yticks([])

  predictions_array = np.array(predictions_array)
  predictions1d = predictions_array[0]
```

```
  thisplot = plt.bar(range(10), predictions1d, color="#777777")
  plt.ylim([0, 1])
  predicted_label = np.argmax(predictions1d)
  thisplot[predicted_label].set_color('red')
  thisplot[true_label].set_color('blue')
```

[56]:
```
numeral_number_images
```

[56]: []

[57]:
```
summary_results = []
test_summary_results = []
```

[58]:
```
import math
```

[59]:
```
# Plot the first X test images, their predicted labels, and the true labels.
# Color correct predictions in blue and incorrect predictions in red.
def show_classifications(rn, startrange ):
  count_arr = np.bincount(true_labels)
  endrange = startrange[rn] + count_arr[rn]
  # print(f"startrange : {startrange[rn]} endrange : {endrange}")
  # print(f"Number of {class_names[rn]}: {count_arr[rn]}")
  num_rows = math.ceil(count_arr[rn] / 3 )
  num_cols = 3
  num_images = num_rows*num_cols
  num_errors = 0
  plt.figure(figsize=(2*2*num_cols, 2*num_rows))
  for i in range(num_images):
    plt.subplot(num_rows, 2*num_cols, 2*i+1)
    try:
      plot_image(i, predictions2[i+startrange[rn]], true_labels,␣
↪validation_images, startrange[rn])
      plt.subplot(num_rows, 2*num_cols, 2*i+2)
      # print(f" true_labels={true_labels[i]} pred={np.
↪argmax(predictions2[i])}")
      if (true_labels[i+startrange[rn]] != np.
↪argmax(predictions2[i+startrange[rn]])):
        num_errors += 1
      plot_value_array(i, predictions2[i+startrange[rn]],  true_labels,␣
↪startrange[rn])
    except:
      print(f"i = {i}")
  plt.tight_layout()
  plt.show()
  print(f"roman numeral: { class_names[rn]}")
```

```
    print(f"number of images: {count_arr[rn]}")
    print(f"start range: { startrange[rn] }")
    print(f"end range: { startrange[rn] + count_arr[rn]}")

    print(f"number of errors: {num_errors}")
    accuracy = 1 - (num_errors / count_arr[rn])
    print(f"accuracy: { accuracy }")

    summary_results.append({'Roman Numeral': class_names[rn], 'Number of Images':␣
↪count_arr[rn],
                            'Number of Errors': num_errors, 'Accuracy': accuracy})
```

[60]:

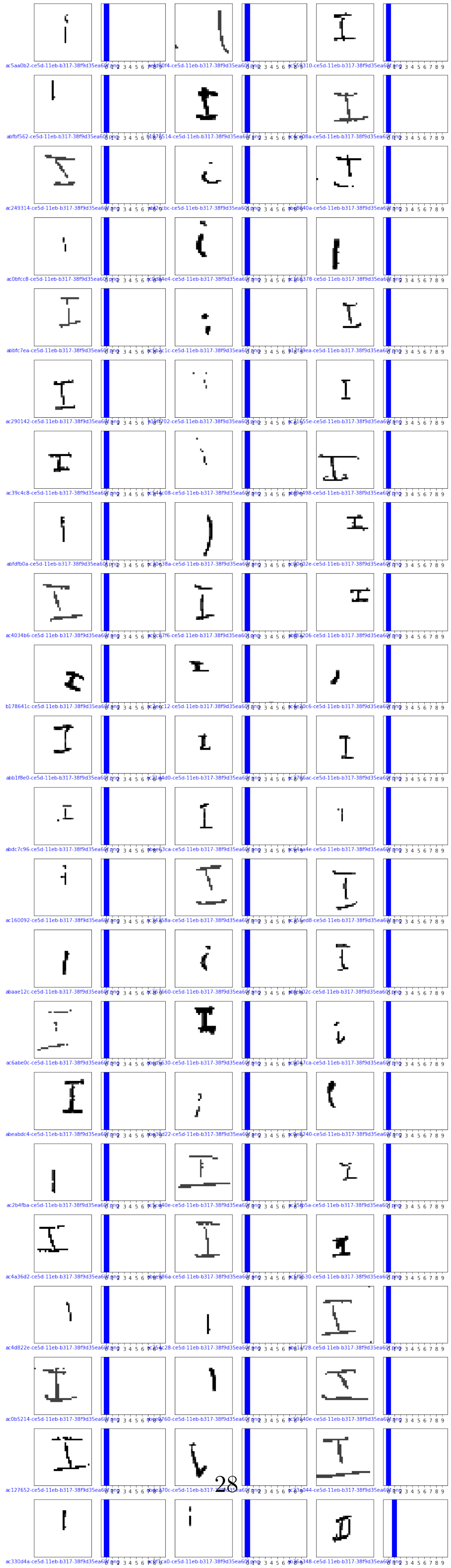
```
# Plot the first X test images, their predicted labels, and the true labels.
# Color correct predictions in blue and incorrect predictions in red.
def test_show_classifications(rn, startrange ):
  test_count_arr = np.bincount(test_true_labels)
  endrange = startrange[rn] + test_count_arr[rn]
  # print(f"startrange : {startrange[rn]} endrange : {endrange}")
  # print(f"Number of {class_names[rn]}: {count_arr[rn]}")
  num_rows = math.ceil(test_count_arr[rn] / 3 )
  num_cols = 3
  num_images = num_rows*num_cols
  num_errors = 0
  plt.figure(figsize=(2*2*num_cols, 2*num_rows))
  for i in range(num_images):
        plt.subplot(num_rows, 2*num_cols, 2*i+1)
        try:
            plot_image(i, test_predictions2[i+startrange[rn]],␣
↪test_true_labels, test_images, startrange[rn])
            plt.subplot(num_rows, 2*num_cols, 2*i+2)
            # print(f" true_labels={true_labels[i]} pred={np.
↪argmax(predictions2[i])}")
            if (test_true_labels[i+startrange[rn]] != np.
↪argmax(test_predictions2[i+startrange[rn]])):
                num_errors += 1
            plot_value_array(i, test_predictions2[i+startrange[rn]], ␣
↪test_true_labels, startrange[rn])
        except:
            print(f"i = {i}")
  plt.tight_layout()
  plt.show()
  print(f"roman numeral: { class_names[rn]}")

  print(f"number of images: {test_count_arr[rn]}")
  print(f"start range: { startrange[rn] }")
  print(f"end range: { startrange[rn] + test_count_arr[rn]}")
```

```
    print(f"number of errors: {num_errors}")
    accuracy = 1 - (num_errors / test_count_arr[rn])
    print(f"accuracy: { accuracy }")

    test_summary_results.append({'Roman Numeral': class_names[rn], 'Number of␣
↪Images': test_count_arr[rn],
                                 'Number of Errors': num_errors, 'Accuracy': accuracy})
```

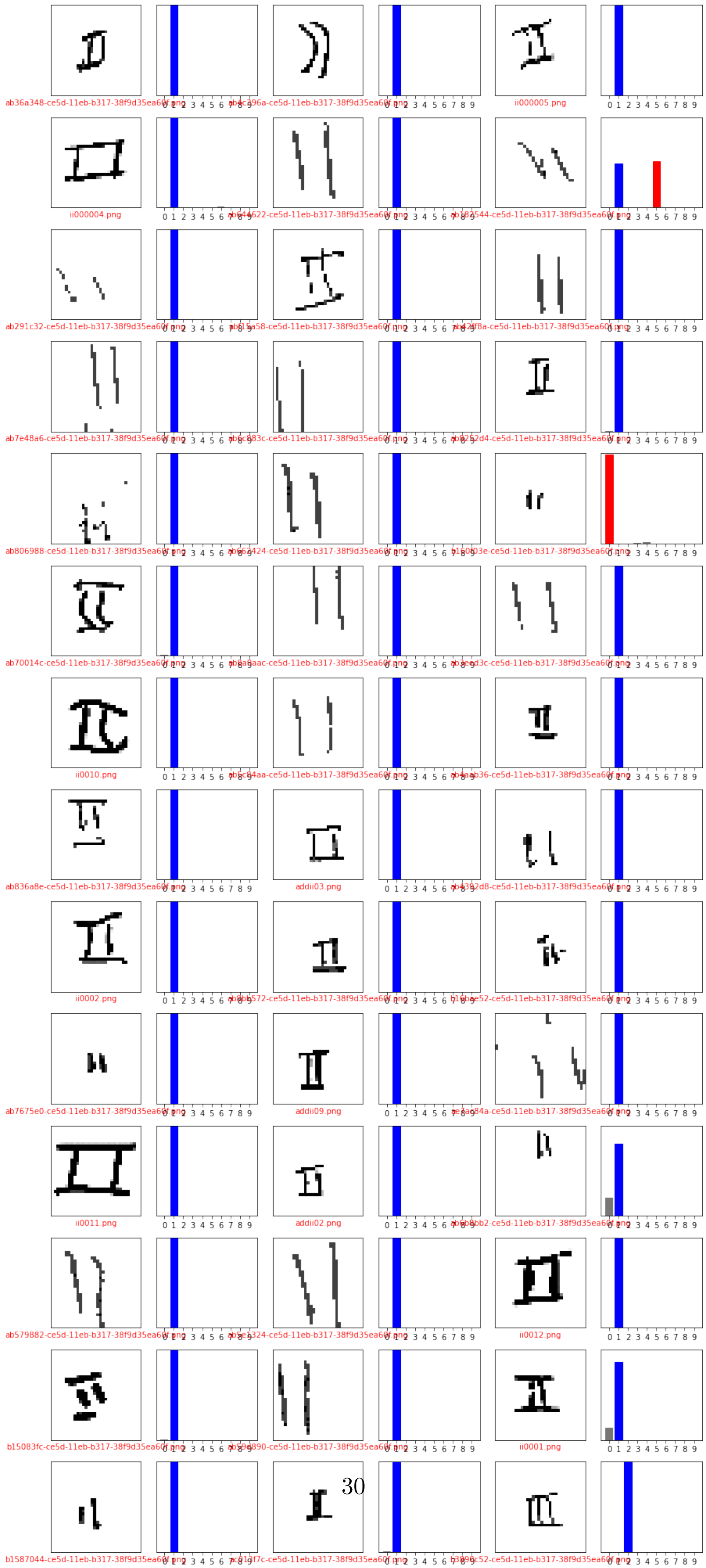
[61]:
```
count_arr = np.bincount(true_labels)
rnindex = 0
beginrange = []
for rnum in range(10):
    beginrange.append(rnindex)
    rnindex = rnindex + count_arr[rnum]
```

[62]:
```
test_count_arr = np.bincount(test_true_labels)
test_rnindex = 0
test_beginrange = []
for rnum in range(10):
    test_beginrange.append(test_rnindex)
    test_rnindex = test_rnindex + test_count_arr[rnum]
```

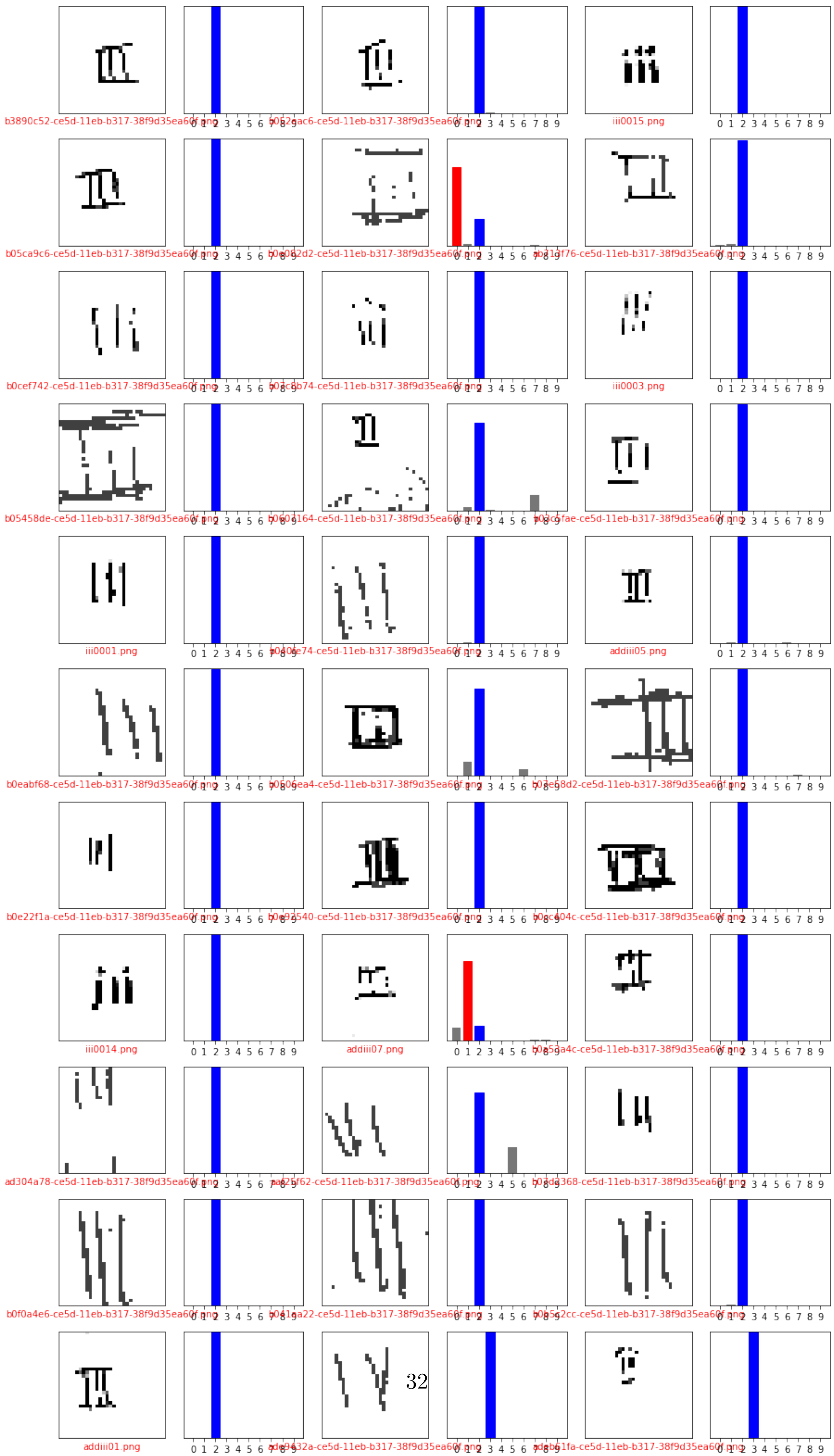
[63]:
```
for rnum in range(10):
  show_classifications(rnum, beginrange)
```



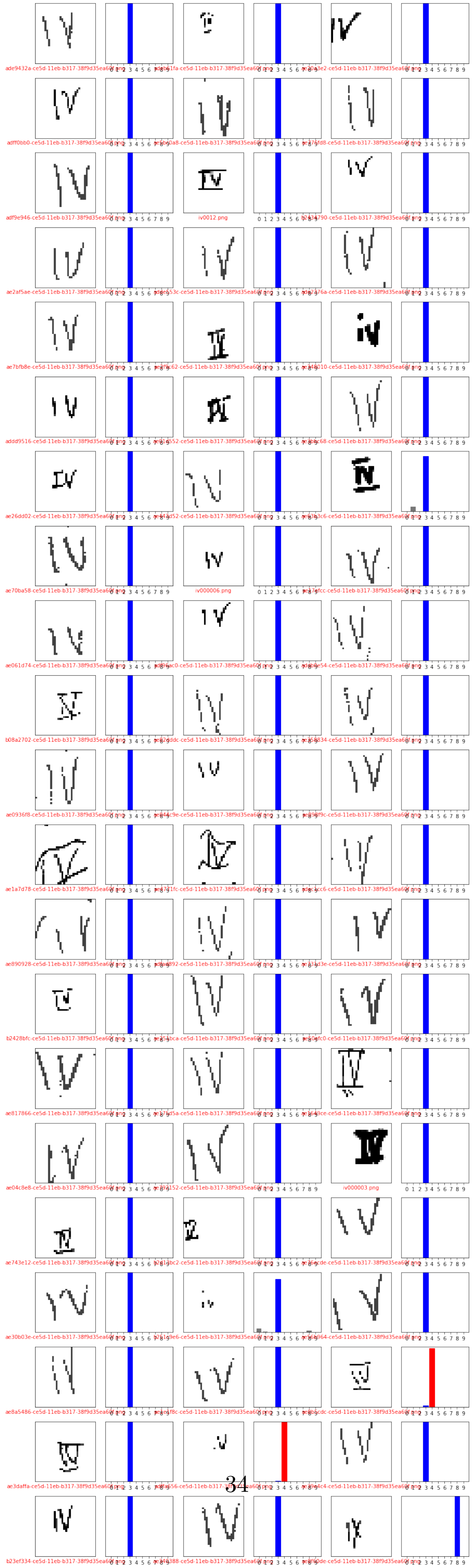
```
roman numeral: i
number of images: 65
start range: 0
end range: 65
number of errors: 0
accuracy: 1.0
```


ii000005.png
ii000004.png
ii0010.png
addii03.png
ii0002.png
addii09.png
ii0011.png
addii02.png
ii0012.png
ii0001.png

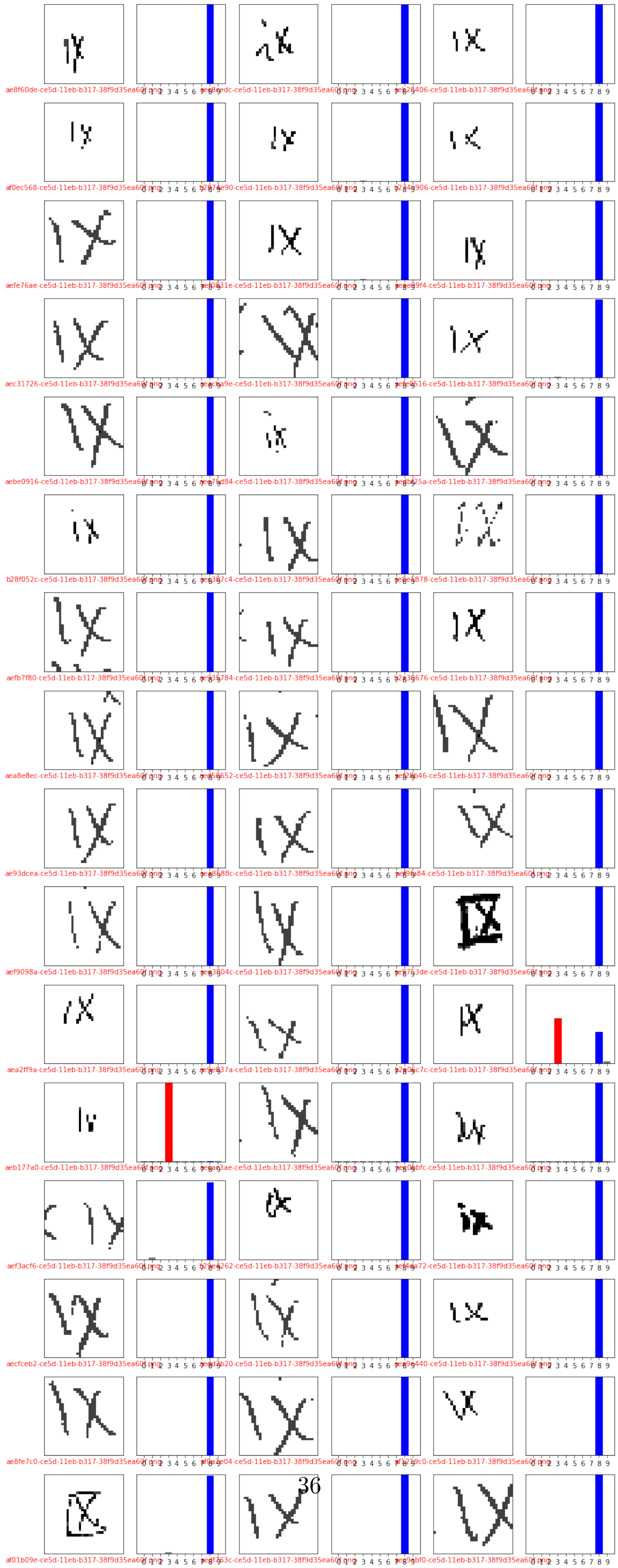
```
roman numeral: ii
number of images: 41
start range: 65
end range: 106
number of errors: 2
accuracy: 0.9512195121951219
```


b3890c52-ce5d-11eb-b317-38f9d35ea60f.png
iii0015.png
b05ca9c6-ce5d-11eb-b317-38f9d35ea60f.png
b0cef742-ce5d-11eb-b317-38f9d35ea60f.png
iii0003.png
b05458de-ce5d-11eb-b317-38f9d35ea60f.png
iii0001.png
addiii05.png
b0eabf68-ce5d-11eb-b317-38f9d35ea60f.png
b0e22f1a-ce5d-11eb-b317-38f9d35ea60f.png
iii0014.png
addiii07.png
ad304a78-ce5d-11eb-b317-38f9d35ea60f.png
b0f0a4e6-ce5d-11eb-b317-38f9d35ea60f.png
addiii01.png
0 1 2 3 4 5 6 7 8 9

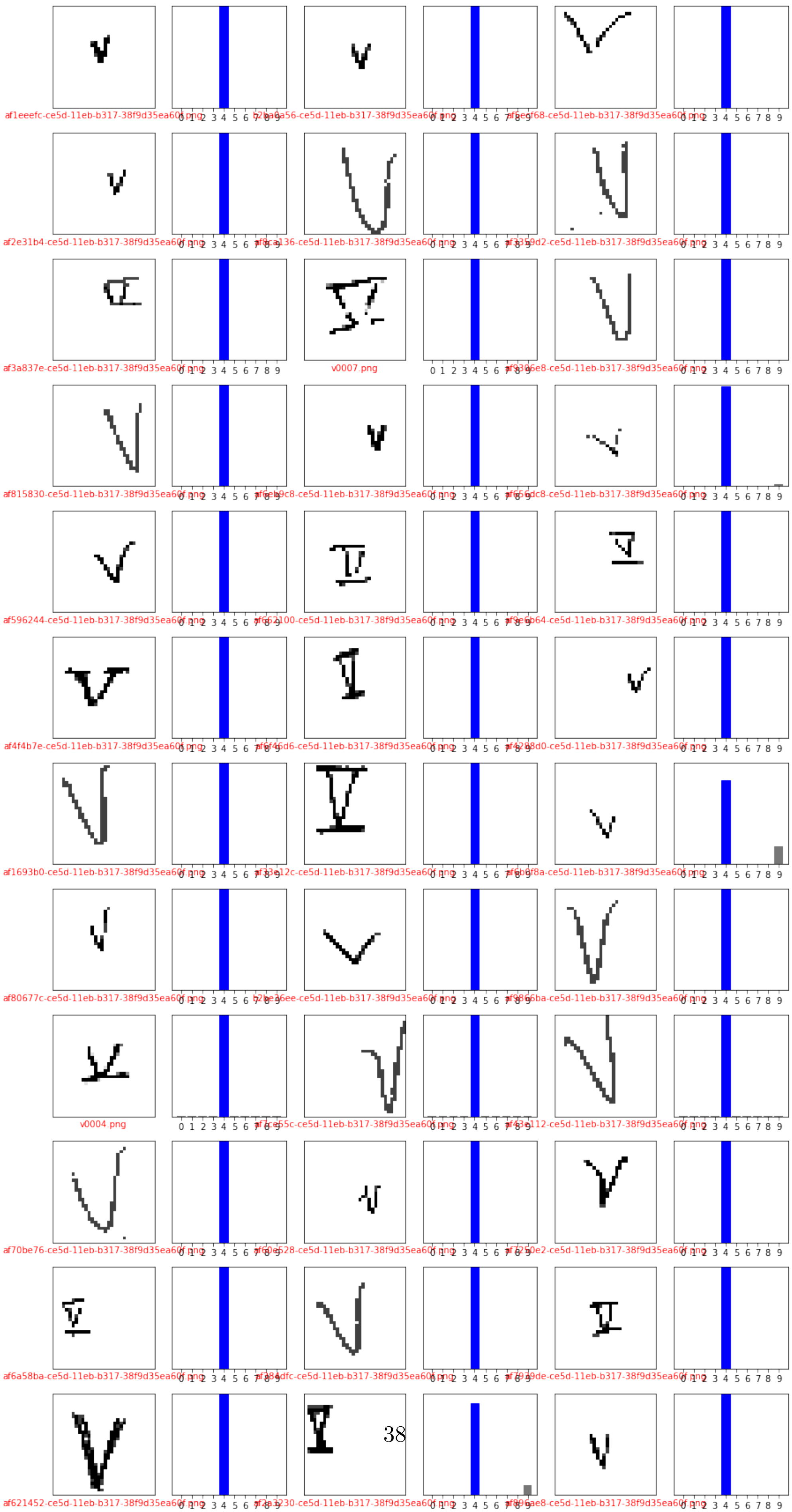
```
roman numeral: iii
number of images: 31
start range: 106
end range: 137
number of errors: 2
accuracy: 0.935483870967742
```



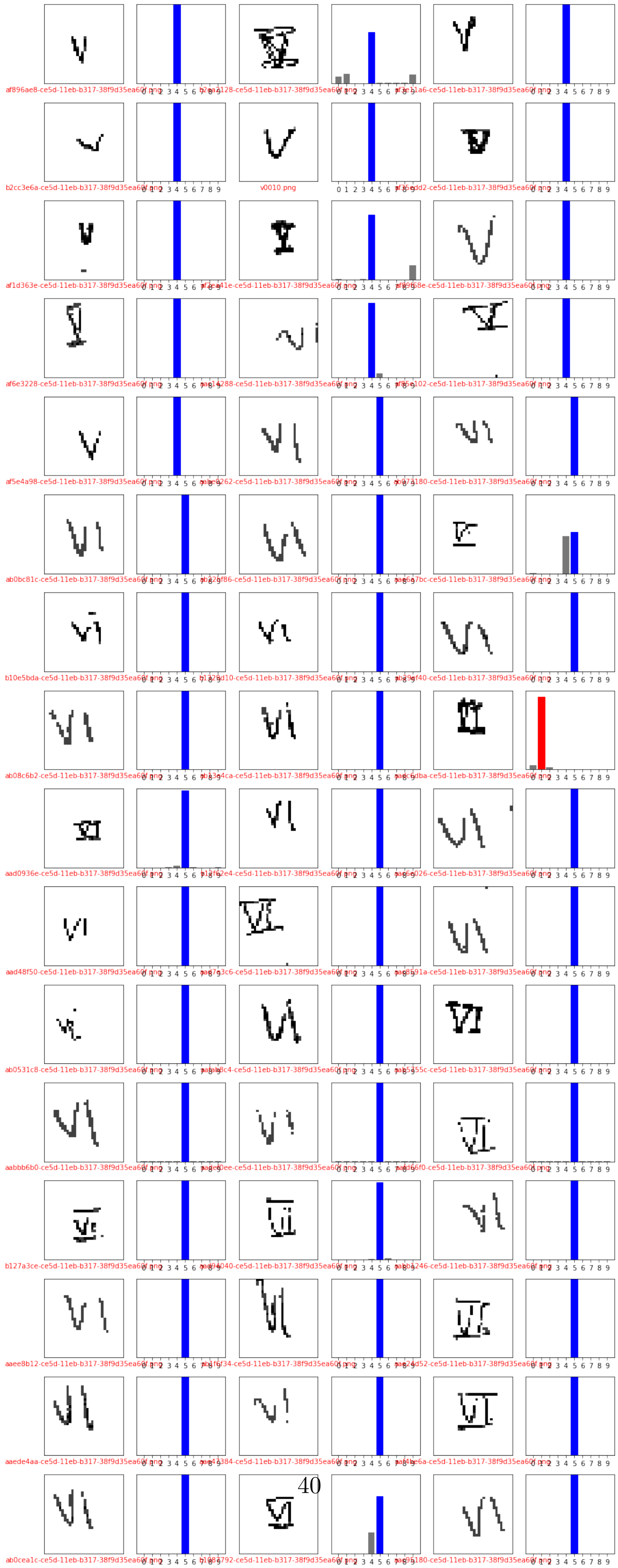
```
roman numeral: iv
number of images: 62
start range: 137
end range: 199
number of errors: 2
accuracy: 0.967741935483871
```



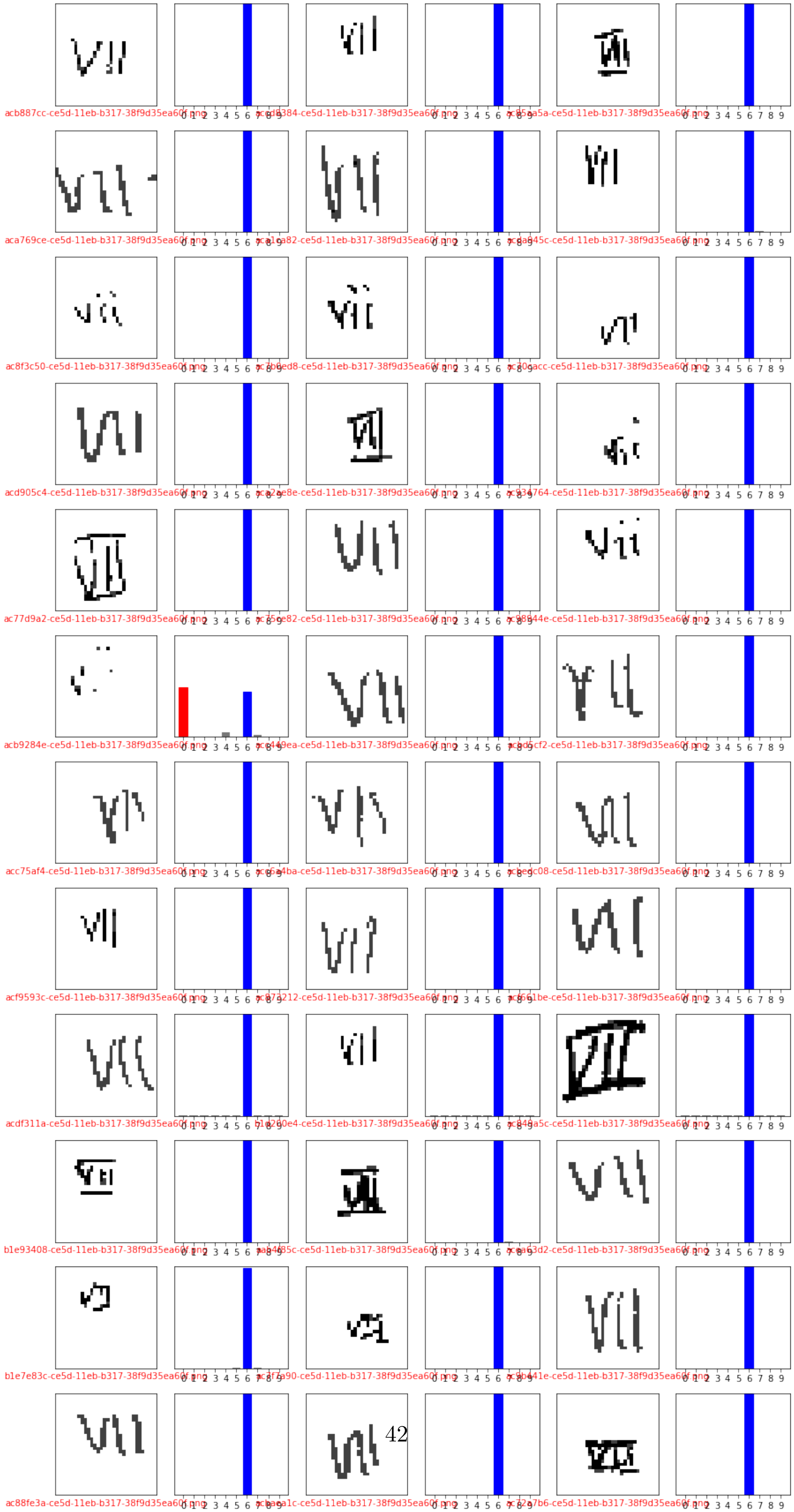
```
roman numeral: ix
number of images: 48
start range: 199
end range: 247
number of errors: 2
accuracy: 0.9583333333333334
```


v0007.png
v0004.png

```
roman numeral: v
number of images: 35
start range: 247
end range: 282
number of errors: 0
accuracy: 1.0
```

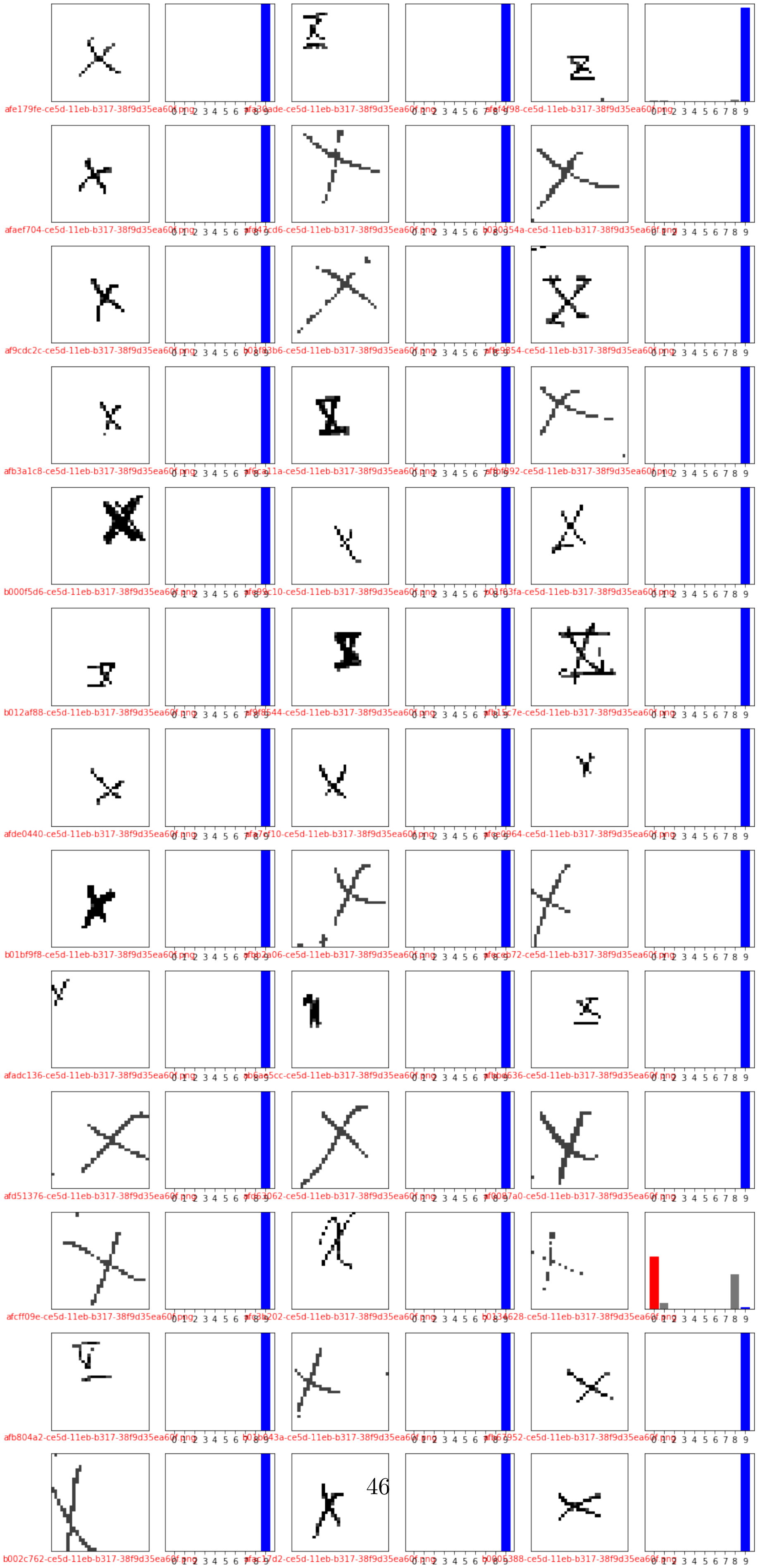


```
roman numeral: vi
number of images: 48
start range: 282
end range: 330
number of errors: 1
accuracy: 0.9791666666666666
```


acb887cc-ce5d-11eb-b317-38f9d35ea60f
aca769ce-ce5d-11eb-b317-38f9d35ea60f
ac8f3c50-ce5d-11eb-b317-38f9d35ea60f
acd905c4-ce5d-11eb-b317-38f9d35ea60f
ac77d9a2-ce5d-11eb-b317-38f9d35ea60f
acb9284e-ce5d-11eb-b317-38f9d35ea60f
acc75af4-ce5d-11eb-b317-38f9d35ea60f
acf9593c-ce5d-11eb-b317-38f9d35ea60f
acdf311a-ce5d-11eb-b317-38f9d35ea60f
b1e93408-ce5d-11eb-b317-38f9d35ea60f
b1e7e83c-ce5d-11eb-b317-38f9d35ea60f
ac88fe3a-ce5d-11eb-b317-38f9d35ea60f
0 1 2 3 4 5 6 7 8 9

```
roman numeral: vii
number of images: 35
start range: 330
end range: 365
number of errors: 1
accuracy: 0.9714285714285714
```

```
roman numeral: viii
number of images: 48
start range: 365
end range: 413
number of errors: 1
accuracy: 0.9791666666666666
```



```
roman numeral: x
number of images: 39
start range: 413
end range: 452
number of errors: 1
accuracy: 0.9743589743589743
```

[64]:

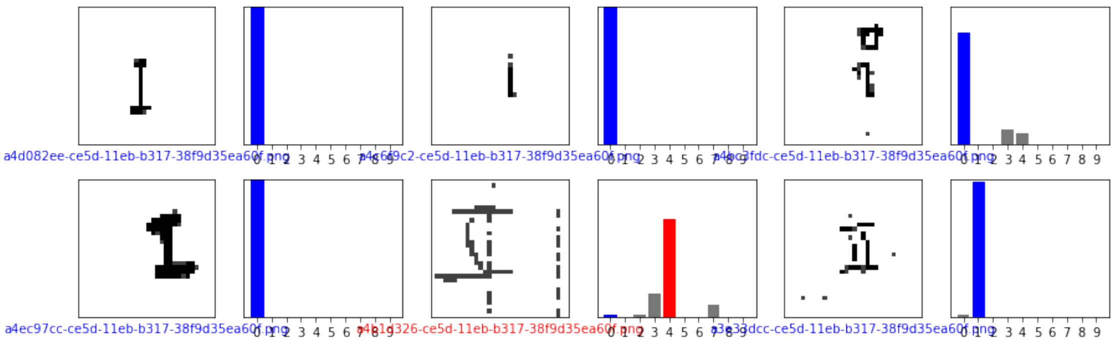
```
summary_results
```

[64]:

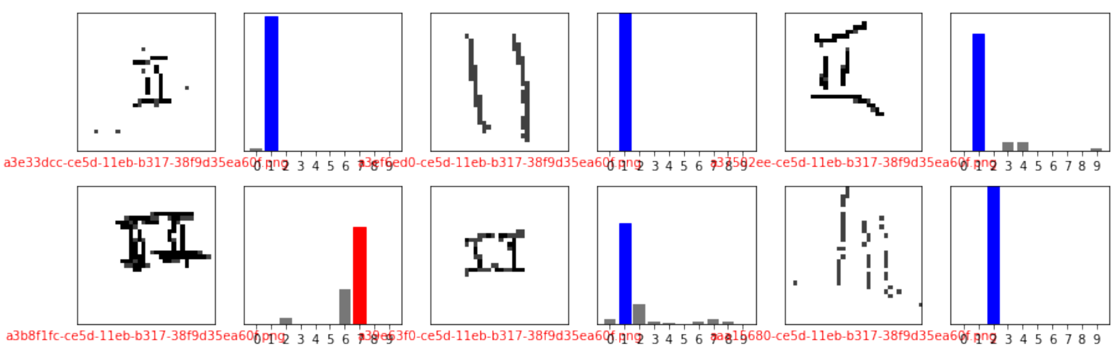
```
[{'Roman Numeral': 'i',
  'Number of Images': 65,
  'Number of Errors': 0,
  'Accuracy': 1.0},
 {'Roman Numeral': 'ii',
  'Number of Images': 41,
  'Number of Errors': 2,
  'Accuracy': 0.9512195121951219},
 {'Roman Numeral': 'iii',
  'Number of Images': 31,
  'Number of Errors': 2,
  'Accuracy': 0.935483870967742},
 {'Roman Numeral': 'iv',
  'Number of Images': 62,
  'Number of Errors': 2,
  'Accuracy': 0.967741935483871},
 {'Roman Numeral': 'ix',
  'Number of Images': 48,
  'Number of Errors': 2,
  'Accuracy': 0.9583333333333334},
 {'Roman Numeral': 'v',
  'Number of Images': 35,
  'Number of Errors': 0,
  'Accuracy': 1.0},
 {'Roman Numeral': 'vi',
  'Number of Images': 48,
  'Number of Errors': 1,
  'Accuracy': 0.9791666666666666},
 {'Roman Numeral': 'vii',
  'Number of Images': 35,
  'Number of Errors': 1,
  'Accuracy': 0.9714285714285714},
 {'Roman Numeral': 'viii',
  'Number of Images': 48,
  'Number of Errors': 1,
  'Accuracy': 0.9791666666666666},
```

```
{'Roman Numeral': 'x',
 'Number of Images': 39,
 'Number of Errors': 1,
 'Accuracy': 0.9743589743589743}]
```

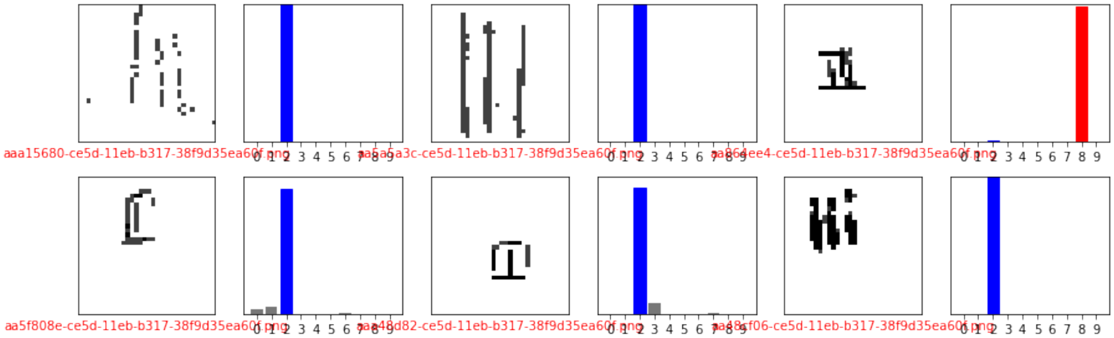
[65]:
```python
for rnum in range(10):
    test_show_classifications(rnum, test_beginrange)
```



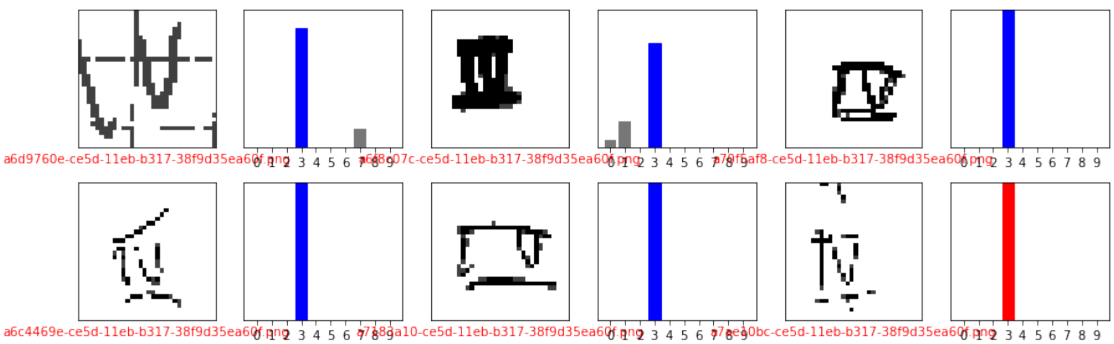

```
roman numeral: i
number of images: 5
start range: 0
end range: 5
number of errors: 1
accuracy: 0.8
```



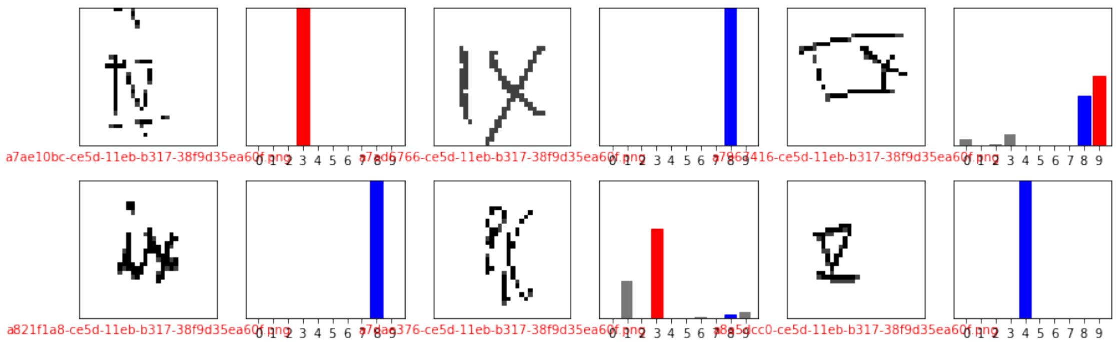

```
roman numeral: ii
number of images: 5
start range: 5
end range: 10
number of errors: 1
accuracy: 0.8
```



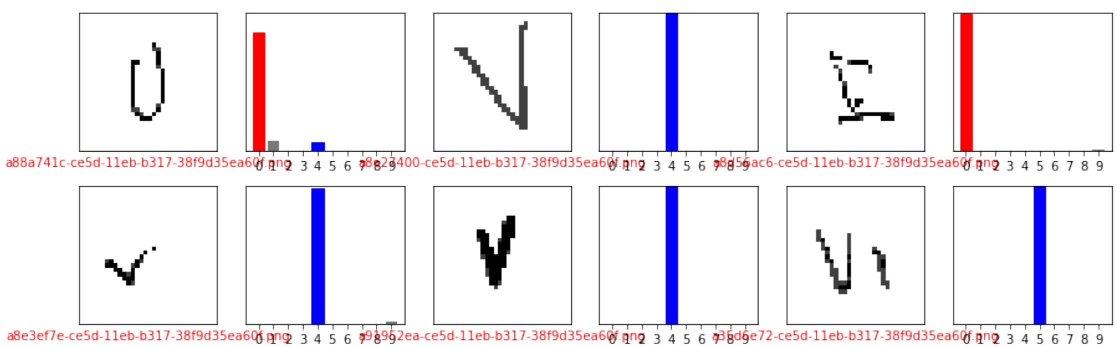
```
roman numeral: iii
number of images: 6
start range: 10
end range: 16
number of errors: 1
accuracy: 0.8333333333333334
```



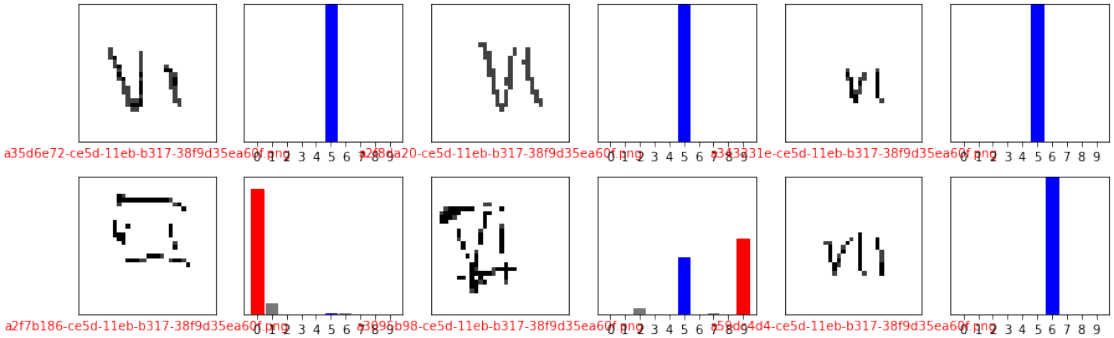
```
roman numeral: iv
number of images: 5
start range: 16
end range: 21
number of errors: 1
accuracy: 0.8
```



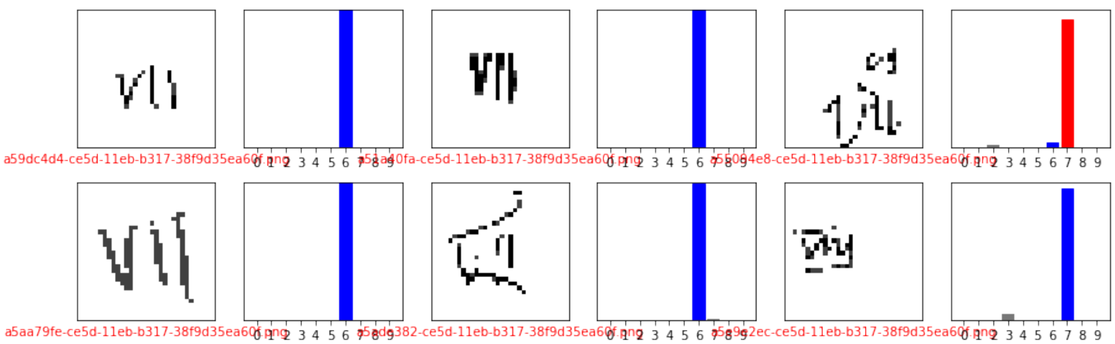
```
roman numeral: ix
number of images: 6
start range: 21
end range: 27
number of errors: 3
accuracy: 0.5
```



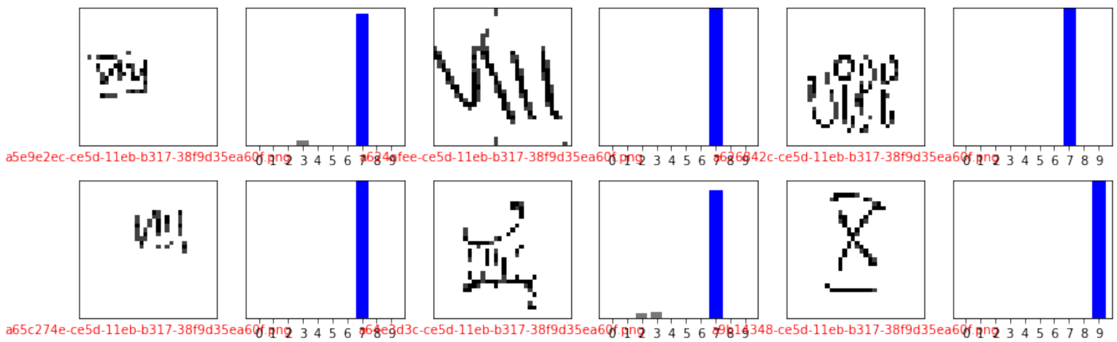
```
roman numeral: v
number of images: 5
start range: 27
end range: 32
number of errors: 2
accuracy: 0.6
```



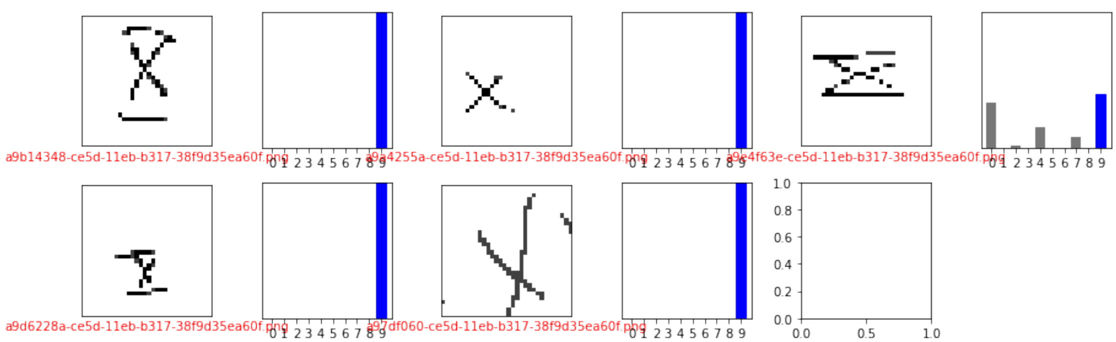
```
roman numeral: vi
number of images: 5
start range: 32
end range: 37
number of errors: 2
accuracy: 0.6
```



```
roman numeral: vii
number of images: 5
start range: 37
end range: 42
number of errors: 1
accuracy: 0.8
```



```
roman numeral: viii
number of images: 5
start range: 42
end range: 47
number of errors: 0
accuracy: 1.0
i = 5
```



```
roman numeral: x
number of images: 5
start range: 47
end range: 52
number of errors: 0
accuracy: 1.0
```

[66]:
```
test_summary_results
```

[66]:
```
[{'Roman Numeral': 'i',
  'Number of Images': 5,
  'Number of Errors': 1,
  'Accuracy': 0.8},
 {'Roman Numeral': 'ii',
```

```
 'Number of Images': 5,
 'Number of Errors': 1,
 'Accuracy': 0.8},
{'Roman Numeral': 'iii',
 'Number of Images': 6,
 'Number of Errors': 1,
 'Accuracy': 0.8333333333333334},
{'Roman Numeral': 'iv',
 'Number of Images': 5,
 'Number of Errors': 1,
 'Accuracy': 0.8},
{'Roman Numeral': 'ix',
 'Number of Images': 6,
 'Number of Errors': 3,
 'Accuracy': 0.5},
{'Roman Numeral': 'v',
 'Number of Images': 5,
 'Number of Errors': 2,
 'Accuracy': 0.6},
{'Roman Numeral': 'vi',
 'Number of Images': 5,
 'Number of Errors': 2,
 'Accuracy': 0.6},
{'Roman Numeral': 'vii',
 'Number of Images': 5,
 'Number of Errors': 1,
 'Accuracy': 0.8},
{'Roman Numeral': 'viii',
 'Number of Images': 5,
 'Number of Errors': 0,
 'Accuracy': 1.0},
{'Roman Numeral': 'x',
 'Number of Images': 5,
 'Number of Errors': 0,
 'Accuracy': 1.0}]
```

[ ]:

[ ]: