Loading the libraries

In [85]:

```
import numpy as np

import matplotlib.pyplot as plot
import matplotlib.gridspec as gridspec
import matplotlib.image as mpimg

import string

import os

import cv2

from sklearn.utils import shuffle

import tensorflow as tf
import tensorflow.keras.layers as Layers
import tensorflow.keras.activations as Actications
import tensorflow.keras.models as Models
import tensorflow.keras.optimizers as Optimizer
import tensorflow.keras.metrics as Metrics
import tensorflow.keras.utils as Utils
from keras.utils.vis_utils import model_to_dot
```

- **Preparing the data generator**

In [16]:

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator
```

Normalizing the data before feeding to model

In [17]:

```
train_datagen = ImageDataGenerator(rescale = 1/255, validation_split = 0.2)
test_datagen = ImageDataGenerator(rescale = 1/255)
```

Loading data as 28 * 28 grayscale images

In [18]:

```
train_generator = train_datagen.flow_from_directory(
    './Train/',
    target_size = (28, 28),
    batch_size = 128,
    class_mode = "sparse",
    color_mode='grayscale',
    subset = 'training'
    )

validation_generator = train_datagen.flow_from_directory(
    './Train/',
    target_size = (28, 28),
    batch_size = 128,
    class_mode = "sparse",
    color_mode='grayscale',
    subset = 'validation'
    )

test_generator = test_datagen.flow_from_directory(
    './Test/',
    target_size = (28, 28),
    batch_size = 128,
    class_mode = "sparse",
    color_mode='grayscale'
    )
```

```
Found 21974 images belonging to 24 classes.
Found 5481 images belonging to 24 classes.
Found 7172 images belonging to 24 classes.
```

Class Labels

24 classes excluding J and Z

In [19]:

```
classes = [char for char in string.ascii_uppercase if char != "J" if char != "Z"]
print(classes, end = " ")
```

```
['A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I', 'K', 'L', 'M', 'N', 'O', 'P', 'Q', 'R', 'S', 'T', 'U',
'V', 'W', 'X', 'Y']
```

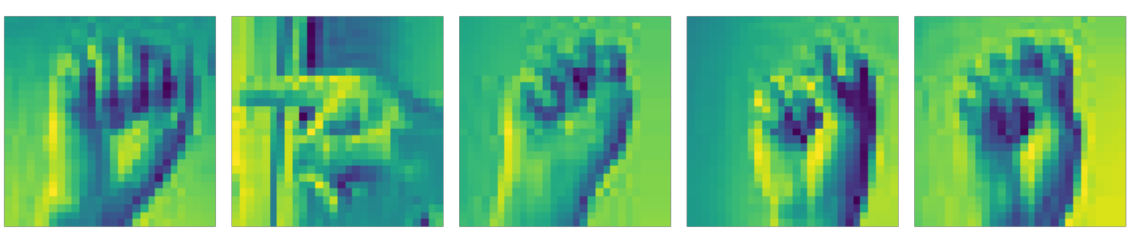
In [20]:

```
def plotImages(images_arr):
    fig, axes = plt.subplots(1, 5, figsize=(10,10))
    axes = axes.flatten()
    for img, ax in zip( images_arr, axes):
        ax.imshow(img[:,:,0])
        ax.axis('off')
    plt.tight_layout()
    plt.show()
```

Visualizing the dataset

In [21]:

```
sample_training_images, _ = next(train_generator)
plotImages(sample_training_images[:5])
```



Preparing the CNN model

Create optimizers

In [22]:

```
sgd = tf.keras.optimizers.SGD(learning_rate=0.001, momentum=0.9)
rmsprob = tf.keras.optimizers.RMSprop(learning_rate=0.001,rho=0.9,momentum=0.0,epsilon=1e-07,centered=Fal
adam = tf.keras.optimizers.Adam(
    learning_rate=0.001,
    beta_1=0.9,
    beta_2=0.999,
    epsilon=1e-07,
    amsgrad=False,
    name="Adam"
)
adamax = tf.keras.optimizers.Adamax(
    learning_rate=0.001, beta_1=0.9, beta_2=0.999, epsilon=1e-07, name="Adamax"
)
```

A small network of single convolution and 3 Dense layers

In [23]:

```
def learn(opt):
  model = Models.Sequential()

  model.add(Layers.Conv2D(64,kernel_size=(3,3),activation='relu',input_shape=(28,28,1)))
  model.add(Layers.MaxPool2D(2,2))
  model.add(Layers.Flatten())
  model.add(Layers.Dense(256,activation='relu'))
  model.add(Layers.Dense(256,activation='relu'))
  model.add(Layers.Dropout(rate=0.5))
  model.add(Layers.Dense(len(classes), activation = "softmax"))

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

```
  return model
```

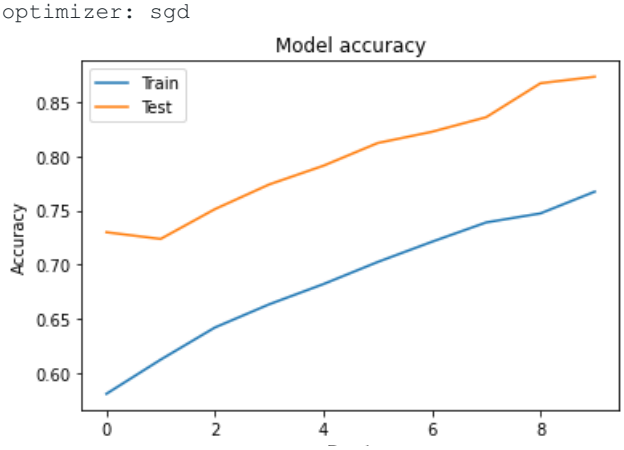
In [24]:

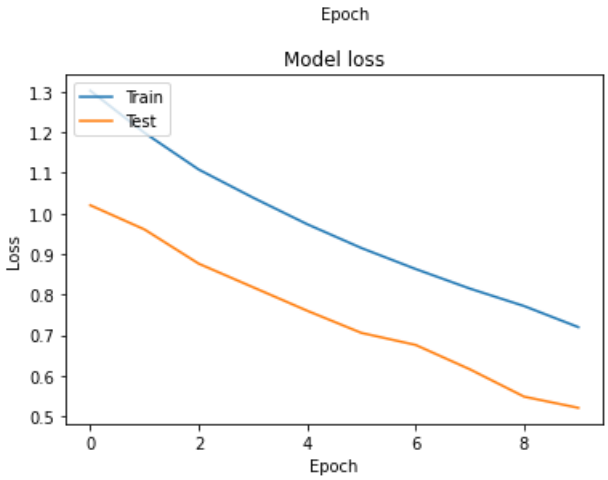
```
optimizer_list = {'sgd':sgd, 'rmsprob':rmsprob, 'adam':adam,'adamax':adamax}
models=[]
for opt in optimizer_list:
  models.append([opt, learn(optimizer_list[opt])])
```

In [28]:

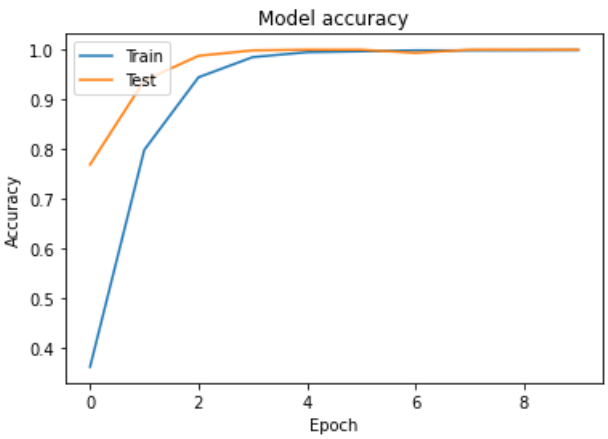
```
for model in models:
  trained = model[1].fit(train_generator,epochs=10,validation_data = validation_generator)
  print('optimizer:',model[0])
  plot.plot(trained.history['accuracy'])
  plot.plot(trained.history['val_accuracy'])
  plot.title('Model accuracy')
  plot.ylabel('Accuracy')
  plot.xlabel('Epoch')
  plot.legend(['Train', 'Test'], loc='upper left')
  plot.show()

  plot.plot(trained.history['loss'])
  plot.plot(trained.history['val_loss'])
  plot.title('Model loss')
  plot.ylabel('Loss')
  plot.xlabel('Epoch')
  plot.legend(['Train', 'Test'], loc='upper left')
  plot.show()
```

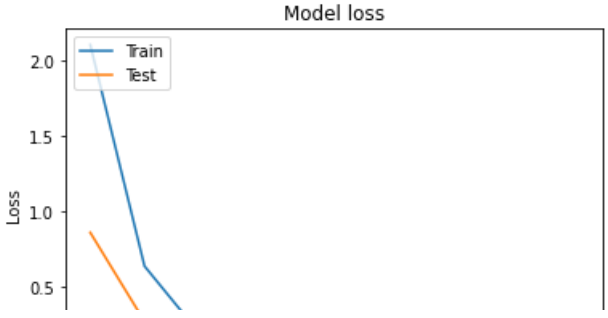
```
Epoch 1/10
172/172 [==============================] - 6s 33ms/step - loss: 1.3026 - accuracy: 0.5804 - val_loss: 1.
0204 - val_accuracy: 0.7298
Epoch 2/10
172/172 [==============================] - 6s 32ms/step - loss: 1.1989 - accuracy: 0.6120 - val_loss: 0.
9606 - val_accuracy: 0.7236
Epoch 3/10
172/172 [==============================] - 5s 32ms/step - loss: 1.1084 - accuracy: 0.6417 - val_loss: 0.
8763 - val_accuracy: 0.7511
Epoch 4/10
172/172 [==============================] - 5s 32ms/step - loss: 1.0392 - accuracy: 0.6631 - val_loss: 0.
8183 - val_accuracy: 0.7739
Epoch 5/10
172/172 [==============================] - 5s 31ms/step - loss: 0.9736 - accuracy: 0.6819 - val_loss: 0.
7603 - val_accuracy: 0.7913
Epoch 6/10
172/172 [==============================] - 6s 32ms/step - loss: 0.9148 - accuracy: 0.7023 - val_loss: 0.
7056 - val_accuracy: 0.8123
Epoch 7/10
172/172 [==============================] - 6s 32ms/step - loss: 0.8631 - accuracy: 0.7210 - val_loss: 0.
6760 - val_accuracy: 0.8227
Epoch 8/10
172/172 [==============================] - 6s 33ms/step - loss: 0.8149 - accuracy: 0.7389 - val_loss: 0.
6159 - val_accuracy: 0.8362
Epoch 9/10
172/172 [==============================] - 6s 32ms/step - loss: 0.7718 - accuracy: 0.7472 - val_loss: 0.
5485 - val_accuracy: 0.8675
Epoch 10/10
172/172 [==============================] - 6s 32ms/step - loss: 0.7198 - accuracy: 0.7673 - val_loss: 0.
5209 - val_accuracy: 0.8736
optimizer: sgd
```

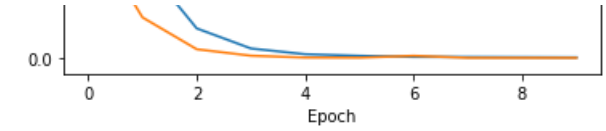




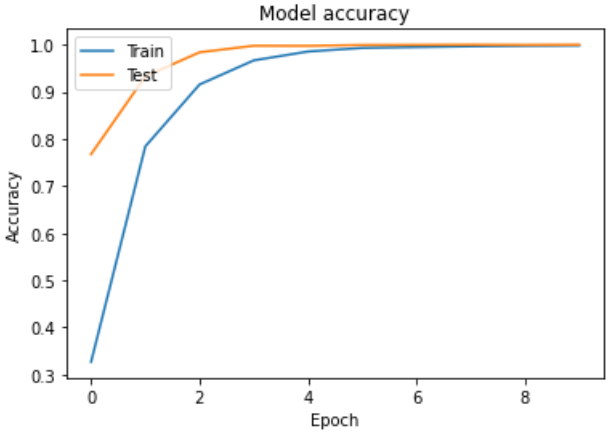

```
Epoch 1/10
172/172 [==============================] - 6s 33ms/step - loss: 2.1074 - accuracy: 0.3627 - val_loss: 0.
8594 - val_accuracy: 0.7692
Epoch 2/10
172/172 [==============================] - 6s 33ms/step - loss: 0.6363 - accuracy: 0.7987 - val_loss: 0.
2688 - val_accuracy: 0.9381
Epoch 3/10
172/172 [==============================] - 6s 33ms/step - loss: 0.1959 - accuracy: 0.9447 - val_loss: 0.
0573 - val_accuracy: 0.9878
Epoch 4/10
172/172 [==============================] - 6s 33ms/step - loss: 0.0623 - accuracy: 0.9852 - val_loss: 0.
0144 - val_accuracy: 0.9987
Epoch 5/10
172/172 [==============================] - 6s 33ms/step - loss: 0.0244 - accuracy: 0.9950 - val_loss: 0.
0021 - val_accuracy: 1.0000
Epoch 6/10
172/172 [==============================] - 6s 33ms/step - loss: 0.0137 - accuracy: 0.9968 - val_loss: 0.
0011 - val_accuracy: 1.0000
Epoch 7/10
172/172 [==============================] - 6s 33ms/step - loss: 0.0063 - accuracy: 0.9987 - val_loss: 0.
0137 - val_accuracy: 0.9936
Epoch 8/10
172/172 [==============================] - 6s 33ms/step - loss: 0.0057 - accuracy: 0.9985 - val_loss: 1.
2723e-04 - val_accuracy: 1.0000
Epoch 9/10
172/172 [==============================] - 6s 33ms/step - loss: 0.0046 - accuracy: 0.9987 - val_loss: 1.
3886e-04 - val_accuracy: 1.0000
Epoch 10/10
172/172 [==============================] - 6s 33ms/step - loss: 0.0034 - accuracy: 0.9991 - val_loss: 1.
1887e-04 - val_accuracy: 1.0000
optimizer: rmsprob
```

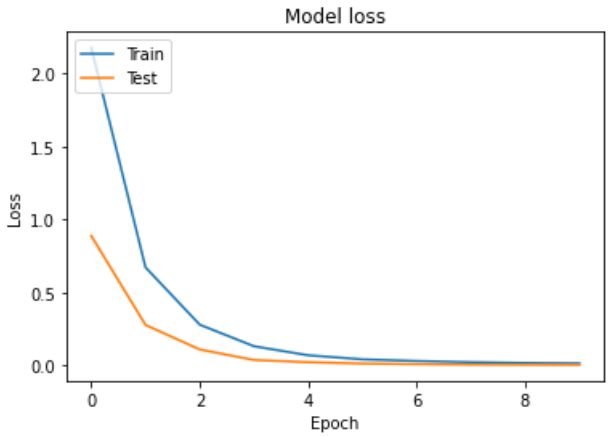






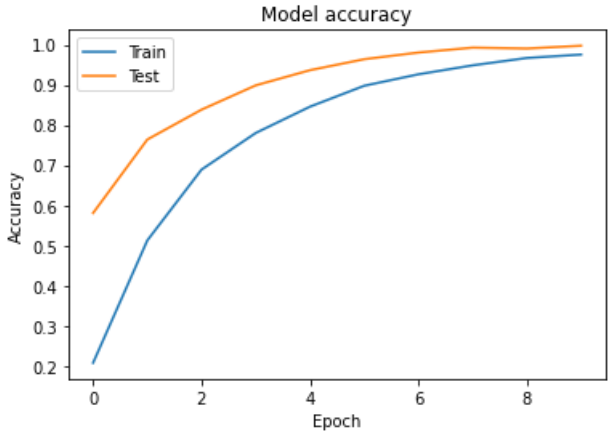

```
Epoch 1/10
172/172 [==============================] - 6s 33ms/step - loss: 2.1789 - accuracy: 0.3271 - val_loss: 0.
8871 - val_accuracy: 0.7677
Epoch 2/10
172/172 [==============================] - 6s 33ms/step - loss: 0.6709 - accuracy: 0.7842 - val_loss: 0.
2756 - val_accuracy: 0.9329
Epoch 3/10
172/172 [==============================] - 6s 33ms/step - loss: 0.2775 - accuracy: 0.9156 - val_loss: 0.
1074 - val_accuracy: 0.9839
Epoch 4/10
172/172 [==============================] - 6s 33ms/step - loss: 0.1295 - accuracy: 0.9668 - val_loss: 0.
0351 - val_accuracy: 0.9978
Epoch 5/10
172/172 [==============================] - 6s 33ms/step - loss: 0.0674 - accuracy: 0.9856 - val_loss: 0.
0199 - val_accuracy: 0.9976
Epoch 6/10
172/172 [==============================] - 6s 33ms/step - loss: 0.0397 - accuracy: 0.9932 - val_loss: 0.
0105 - val_accuracy: 0.9995
Epoch 7/10
172/172 [==============================] - 6s 33ms/step - loss: 0.0283 - accuracy: 0.9950 - val_loss: 0.
0064 - val_accuracy: 0.9996
Epoch 8/10
172/172 [==============================] - 6s 33ms/step - loss: 0.0198 - accuracy: 0.9967 - val_loss: 0.
0034 - val_accuracy: 1.0000
Epoch 9/10
172/172 [==============================] - 6s 32ms/step - loss: 0.0143 - accuracy: 0.9978 - val_loss: 0.
0023 - val_accuracy: 0.9996
Epoch 10/10
172/172 [==============================] - 6s 33ms/step - loss: 0.0119 - accuracy: 0.9984 - val_loss: 0.
0017 - val_accuracy: 1.0000
optimizer: adam
```

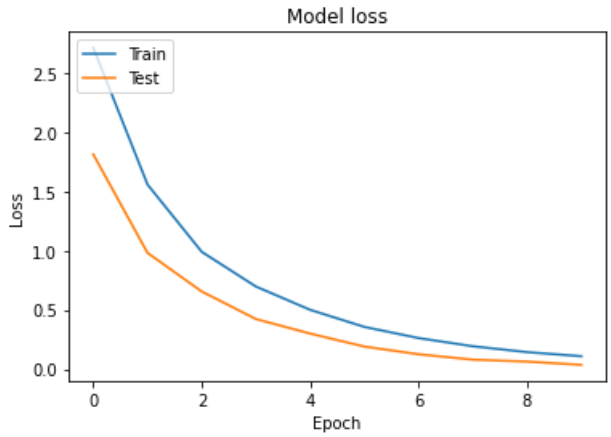





```
Epoch 1/10
172/172 [==============================] - 6s 34ms/step - loss: 2.7140 - accuracy: 0.2073 - val_loss: 1.
8133 - val_accuracy: 0.5806
Epoch 2/10
172/172 [==============================] - 6s 33ms/step - loss: 1.5586 - accuracy: 0.5123 - val_loss: 0.
9812 - val_accuracy: 0.7637
Epoch 3/10
172/172 [==============================] - 6s 33ms/step - loss: 0.9900 - accuracy: 0.6889 - val_loss: 0.
```

```
6549 - val_accuracy: 0.8382
Epoch 4/10
172/172 [==============================] - 6s 33ms/step - loss: 0.6966 - accuracy: 0.7801 - val_loss: 0.
4221 - val_accuracy: 0.8987
Epoch 5/10
172/172 [==============================] - 6s 33ms/step - loss: 0.5000 - accuracy: 0.8456 - val_loss: 0.
2993 - val_accuracy: 0.9365
Epoch 6/10
172/172 [==============================] - 6s 33ms/step - loss: 0.3556 - accuracy: 0.8977 - val_loss: 0.
1896 - val_accuracy: 0.9639
Epoch 7/10
172/172 [==============================] - 6s 33ms/step - loss: 0.2614 - accuracy: 0.9263 - val_loss: 0.
1246 - val_accuracy: 0.9805
Epoch 8/10
172/172 [==============================] - 6s 33ms/step - loss: 0.1923 - accuracy: 0.9486 - val_loss: 0.
0792 - val_accuracy: 0.9927
Epoch 9/10
172/172 [==============================] - 6s 34ms/step - loss: 0.1426 - accuracy: 0.9670 - val_loss: 0.
0629 - val_accuracy: 0.9905
Epoch 10/10
172/172 [==============================] - 6s 33ms/step - loss: 0.1082 - accuracy: 0.9754 - val_loss: 0.
0353 - val_accuracy: 0.9974
optimizer: adamax
```





Evaluating

Testing the model on unseen dataset of 7k images

In [30]:

```
for model in models:
  print(model[0])
  model[1].evaluate(test_generator, verbose=1)
  print('\n\n')
```

```
sgd
57/57 [==============================] - 2s 26ms/step - loss: 0.8697 - accuracy: 0.7313
```

```
rmsprob
57/57 [==============================] - 1s 24ms/step - loss: 0.9481 - accuracy: 0.8600
```

```
adam
57/57 [==============================] - 1s 24ms/step - loss: 0.7581 - accuracy: 0.8298
```

```
adamax
57/57 [==============================] - 1s 24ms/step - loss: 0.5677 - accuracy: 0.8399
```

Predicting

Randomly choose an alphabet from folder and display its prediction

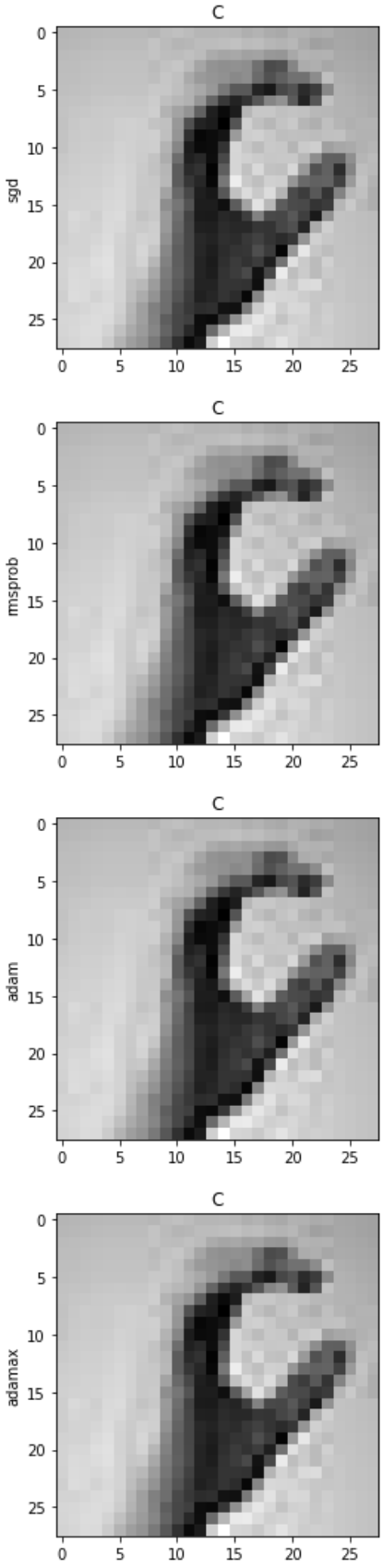
In [50]:

```
from random import randint
import cv2 as cv

def testModel(alphabet):
    dirname, _, filenames = list(os.walk(f'./Test/{alphabet.upper()}'))[0]
    img_path = os.path.join(dirname, filenames[randint(0, len(filenames))])
    print(img_path)
    img = cv.imread(img_path, 0).reshape(1, 28, 28, 1)
    for model in models:
      pred = model[1].predict(img)
      pred_label = classes[np.argmax(pred)]

      plt.figure()
      plt.title(pred_label)
      plt.ylabel(model[0])
      plt.imshow(img[0,:,:,0], cmap = "gray")
```

In [57]:

```
testModel("C")
```

```
./Test/C/2155_C.jpg
```



In [58]:

```
testModel("M")
```

./Test/M/6924_M.jpg