Internship Task - 2

Install and imnport the Lib

In [1]:
```
# !pip install -q kaggle
# !pip install -U keras-efficientnet-v2 -q
```

In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import os
import tensorflow as tf
import tensorflow_hub as hub
import cv2
from sklearn.model_selection import train_test_split
# import keras_efficientnet_v2
from tensorflow.keras.applications import efficientnet
from tensorflow.keras.models import Sequential, load_model
from tensorflow.keras.layers import Dense, Activation, Conv2D, Flatten, Drop
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from keras import regularizers
from tensorflow.keras import metrics, optimizers, Sequential, activations, c
from sklearn.metrics import f1_score, classification_report, confusion_matri
import keras.backend as K
from tensorflow import keras
import warnings
warnings.filterwarnings('ignore')
```

Getting the data

In [3]:
```
# !rm -r ~/.kaggle
# !mkdir ~/.kaggle
# !mv ./kaggle.json ~/.kaggle/
# !chmod 600 ~/.kaggle/kaggle.json
```

In [4]:
```
# !kaggle datasets download lexset/synthetic-asl-alphabet
```

In [5]:
```
# !unzip -qq "synthetic-asl-alphabet.zip" -d "synthetic-asl-alphabet"
```

In [6]:
```
train_dir = '/kaggle/input/synthetic-asl-alphabet/Train_Alphabet'
test_dir = '/kaggle/input/synthetic-asl-alphabet/Test_Alphabet'
```

In [7]:
```
def load_df(dir_path):
    df = {
        'filename': [],
        'label': []
    }
```

```
    classes = os.listdir(dir_path)
    for c in classes:
        path = dir_path + '/' + c

        img_paths = os.listdir(path)

        for img_path in img_paths:
            df['filename'].append(c + '/' + img_path)
            df['label'].append(c)

    df = pd.DataFrame(df)
    return df

train_df = load_df(train_dir)
test_df = load_df(test_dir)
```

In [8]:
```
train_df.sample(5)
```

Out[8]:

	filename	label
8944	X/8e5d20e5-109c-4bd7-9e66-8f0d1b16080f.rgb_000...	X
6525	U/998bfaa6-0fd4-495a-b66c-0e522864baca.rgb_000...	U
4929	H/885c0cf6-84e0-4cfa-ad2e-523a4d7b4467.rgb_000...	H
8918	X/a94d77e6-1fdf-4fc0-bc7a-0a04e15db8d5.rgb_000...	X
10763	Q/0d99d487-da2f-4fc8-9521-a88dcd75283c.rgb_000...	Q

Split train-valid

In [9]:
```
X = train_df['filename']
y = train_df['label']

X_train, X_valid, y_train, y_valid = train_test_split(X, y, stratify=y, ranc
print(X_train.shape)
print(X_valid.shape)
```

```
(19440,)
(4860,)
```

In [10]:
```
train = pd.concat([X_train, y_train], axis=1)
valid = pd.concat([X_valid, y_valid], axis=1)
test = test_df
```

In [11]:
```
train['label'].value_counts()
```

```
Out[11]: E        720
K        720
O        720
M        720
X        720
P        720
N        720
B        720
W        720
S        720
Z        720
V        720
G        720
D        720
Y        720
J        720
L        720
U        720
A        720
C        720
R        720
H        720
Blank    720
I        720
T        720
F        720
Q        720
Name: label, dtype: int64
```

```
In [12]: valid['label'].value_counts()
```

Out[12]:
```
C        180
B        180
A        180
G        180
X        180
I        180
K        180
Y        180
P        180
H        180
T        180
O        180
U        180
E        180
J        180
L        180
Q        180
V        180
M        180
R        180
S        180
F        180
D        180
W        180
Blank    180
N        180
Z        180
Name: label, dtype: int64
```

In [13]:
```
test['label'].value_counts()
```

Out[13]:
```
N        100
S        100
D        100
W        100
L        100
P        100
C        100
Z        100
V        100
T        100
O        100
A        100
G        100
Blank    100
R        100
Y        100
Q        100
K        100
X        100
M        100
U        100
E        100
H        100
F        100
I        100
B        100
J        100
Name: label, dtype: int64
```

In [14]:
```
IMAGE_SIZE = (224, 224)

datagen = ImageDataGenerator(
    rescale=1./255,
#     rotation_range=40,
    zoom_range=0.2,
    width_shift_range=0.05,
    height_shift_range=0.05,
#     brightness_range=[0.5, 1.0],
)

train_generator = datagen.flow_from_dataframe(
    dataframe = train,
    directory = train_dir,
    x_col='filename',
    y_col='label',
    batch_size=32,
    # color_mode="rgb",
    seed=42,
    shuffle=True,
    class_mode='sparse',
    target_size=IMAGE_SIZE
)

valid_generator=datagen.flow_from_dataframe(
    dataframe=valid,
    directory=train_dir,
```

```
    x_col="filename",
    y_col="label",
    batch_size=32,
    # color_mode="rgb",
    seed=42,
    shuffle=True,
    class_mode="sparse",
    target_size=IMAGE_SIZE
)

test_datagen=ImageDataGenerator(rescale=1./255.)

test_generator=test_datagen.flow_from_dataframe(
    dataframe=test,
    directory=test_dir,
    x_col="filename",
    y_col=None,
    batch_size=1,
    # color_mode="rgb",
    seed=42,
    shuffle=False,
    class_mode=None,
    target_size=IMAGE_SIZE
)
```

```
Found 19440 validated image filenames belonging to 27 classes.
Found 4860 validated image filenames belonging to 27 classes.
Found 2700 validated image filenames.
```

EfficientNetV2B0

Training

In [15]:

```
tf.keras.backend.clear_session()
num_classes = 27

backbone = tf.keras.applications.EfficientNetB0(include_top=False)
backbone.trainable = False

inputs = Input(shape=IMAGE_SIZE + (3,), name='inputs')
x = backbone(inputs, training=False)
x = GlobalAveragePooling2D()(x)
x = Dropout(0.2)(x)
# x = Dense(100, activation='relu')(x)
outputs = Dense(27, activation='softmax')(x)

model_efficientnet = tf.keras.Model(inputs=inputs, outputs=outputs, name='ef
model_efficientnet.summary()
```

```
2023-01-06 08:32:48.777776: I tensorflow/stream_executor/cuda/cuda_gpu_execu
tor.cc:937] successful NUMA node read from SysFS had negative value (-1), bu
t there must be at least one NUMA node, so returning NUMA node zero
2023-01-06 08:32:48.889253: I tensorflow/stream_executor/cuda/cuda_gpu_execu
tor.cc:937] successful NUMA node read from SysFS had negative value (-1), bu
t there must be at least one NUMA node, so returning NUMA node zero
2023-01-06 08:32:48.890088: I tensorflow/stream_executor/cuda/cuda_gpu_execu
tor.cc:937] successful NUMA node read from SysFS had negative value (-1), bu
t there must be at least one NUMA node, so returning NUMA node zero
2023-01-06 08:32:48.891464: I tensorflow/core/platform/cpu_feature_guard.cc:
142] This TensorFlow binary is optimized with oneAPI Deep Neural Network Lib
rary (oneDNN) to use the following CPU instructions in performance-critical
operations:  AVX2 AVX512F FMA
To enable them in other operations, rebuild TensorFlow with the appropriate
compiler flags.
2023-01-06 08:32:48.891823: I tensorflow/stream_executor/cuda/cuda_gpu_execu
tor.cc:937] successful NUMA node read from SysFS had negative value (-1), bu
t there must be at least one NUMA node, so returning NUMA node zero
2023-01-06 08:32:48.892580: I tensorflow/stream_executor/cuda/cuda_gpu_execu
tor.cc:937] successful NUMA node read from SysFS had negative value (-1), bu
t there must be at least one NUMA node, so returning NUMA node zero
2023-01-06 08:32:48.893229: I tensorflow/stream_executor/cuda/cuda_gpu_execu
tor.cc:937] successful NUMA node read from SysFS had negative value (-1), bu
t there must be at least one NUMA node, so returning NUMA node zero
2023-01-06 08:32:51.147747: I tensorflow/stream_executor/cuda/cuda_gpu_execu
tor.cc:937] successful NUMA node read from SysFS had negative value (-1), bu
t there must be at least one NUMA node, so returning NUMA node zero
2023-01-06 08:32:51.148606: I tensorflow/stream_executor/cuda/cuda_gpu_execu
tor.cc:937] successful NUMA node read from SysFS had negative value (-1), bu
t there must be at least one NUMA node, so returning NUMA node zero
2023-01-06 08:32:51.149356: I tensorflow/stream_executor/cuda/cuda_gpu_execu
tor.cc:937] successful NUMA node read from SysFS had negative value (-1), bu
t there must be at least one NUMA node, so returning NUMA node zero
2023-01-06 08:32:51.149953: I tensorflow/core/common_runtime/gpu/gpu_device.
cc:1510] Created device /job:localhost/replica:0/task:0/device:GPU:0 with 15
401 MB memory:  -> device: 0, name: Tesla P100-PCIE-16GB, pci bus id: 0000:0
0:04.0, compute capability: 6.0
```

```
Downloading data from https://storage.googleapis.com/keras-applications/effi
cientnetb0_notop.h5
16711680/16705208 [==============================] - 0s 0us/step
16719872/16705208 [==============================] - 0s 0us/step
Model: "efficientnet_model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
inputs (InputLayer)          [(None, 224, 224, 3)]     0

_________________________________________________________________
efficientnetb0 (Functional)  (None, None, None, 1280)  4049571

_________________________________________________________________
global_average_pooling2d (Gl (None, 1280)              0

_________________________________________________________________
dropout (Dropout)            (None, 1280)              0

_________________________________________________________________
dense (Dense)                (None, 27)                34587
=================================================================
Total params: 4,084,158
Trainable params: 34,587
Non-trainable params: 4,049,571

_________________________________________________________________
```

In [16]:

```
tf.keras.backend.clear_session()
num_classes = 27
model_url = 'https://tfhub.dev/google/imagenet/efficientnet_v2_imagenet1k_b0

feature_extractor_layer = hub.KerasLayer(model_url,
                                         trainable=False, # freeze the under
                                         name='feature_extraction_layer',
                                         input_shape=IMAGE_SIZE + (3,))
# Create our own model
# inputs = Input(shape=IMAGE_SIZE + (3,), name='inputs')
# x = feature_extractor_layer(inputs, training=False)
# x = Dropout(0.2)(x)
# outputs = Dense(27, activation='softmax')(x)

# model_efficientnet = tf.keras.Model(inputs=inputs, outputs=outputs, name='

model_efficientnet = tf.keras.Sequential([
    feature_extractor_layer, # use the feature extraction layer as the base
    Dropout(0.2),
    Dense(num_classes, activation='softmax') # create our own output layer
])

model_efficientnet.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
feature_extraction_layer (Ke (None, 1280)              5919312

_________________________________________________________________
dropout (Dropout)            (None, 1280)              0

_________________________________________________________________
dense (Dense)                (None, 27)                34587
=================================================================
Total params: 5,953,899
Trainable params: 34,587
Non-trainable params: 5,919,312

_________________________________________________________________
```

In [17]:

```python
model_efficientnet.compile(optimizer=keras.optimizers.Adam(),
                           loss='sparse_categorical_crossentropy',
                           metrics=["accuracy"])
```

In [18]:

```python
cb = [
#     callbacks.EarlyStopping(monitor='val_loss', patience=5, restore_best_w
    callbacks.ModelCheckpoint('model_efficientnet.h5', save_best_only=True,
]

history_efficientnet = model_efficientnet.fit(
    train_generator,
    validation_data = valid_generator,
    epochs = 20,
    batch_size = 32,
    verbose = 1,
    callbacks = cb
)
```

```
2023-01-06 08:33:01.502070: I tensorflow/compiler/mlir/mlir_graph_optimizati
on_pass.cc:185] None of the MLIR Optimization Passes are enabled (registered
2)
Epoch 1/20
2023-01-06 08:33:09.749165: I tensorflow/stream_executor/cuda/cuda_dnn.cc:36
9] Loaded cuDNN version 8005
```

```
608/608 [==============================] - 714s 1s/step - loss: 1.7488 - acc
uracy: 0.5698 - val_loss: 1.0928 - val_accuracy: 0.7626
Epoch 2/20
608/608 [==============================] - 493s 811ms/step - loss: 0.9571 -
accuracy: 0.7684 - val_loss: 0.8192 - val_accuracy: 0.8109
Epoch 3/20
608/608 [==============================] - 491s 808ms/step - loss: 0.7490 -
accuracy: 0.8134 - val_loss: 0.6701 - val_accuracy: 0.8451
Epoch 4/20
608/608 [==============================] - 499s 821ms/step - loss: 0.6413 -
accuracy: 0.8355 - val_loss: 0.6055 - val_accuracy: 0.8486
Epoch 5/20
608/608 [==============================] - 487s 801ms/step - loss: 0.5730 -
accuracy: 0.8519 - val_loss: 0.5650 - val_accuracy: 0.8562
Epoch 6/20
608/608 [==============================] - 486s 799ms/step - loss: 0.5229 -
accuracy: 0.8580 - val_loss: 0.5226 - val_accuracy: 0.8599
Epoch 7/20
608/608 [==============================] - 481s 791ms/step - loss: 0.4897 -
accuracy: 0.8673 - val_loss: 0.4817 - val_accuracy: 0.8702
Epoch 8/20
608/608 [==============================] - 481s 791ms/step - loss: 0.4586 -
accuracy: 0.8751 - val_loss: 0.4687 - val_accuracy: 0.8778
Epoch 9/20
608/608 [==============================] - 477s 785ms/step - loss: 0.4399 -
accuracy: 0.8790 - val_loss: 0.4552 - val_accuracy: 0.8735
Epoch 10/20
608/608 [==============================] - 483s 795ms/step - loss: 0.4202 -
accuracy: 0.8825 - val_loss: 0.4390 - val_accuracy: 0.8819
Epoch 11/20
608/608 [==============================] - 479s 788ms/step - loss: 0.4080 -
accuracy: 0.8859 - val_loss: 0.4270 - val_accuracy: 0.8842
Epoch 12/20
608/608 [==============================] - 493s 810ms/step - loss: 0.3968 -
accuracy: 0.8836 - val_loss: 0.4192 - val_accuracy: 0.8815
Epoch 13/20
608/608 [==============================] - 486s 799ms/step - loss: 0.3824 -
accuracy: 0.8870 - val_loss: 0.3977 - val_accuracy: 0.8835
Epoch 14/20
608/608 [==============================] - 502s 826ms/step - loss: 0.3651 -
accuracy: 0.8942 - val_loss: 0.3997 - val_accuracy: 0.8866
Epoch 15/20
608/608 [==============================] - 485s 798ms/step - loss: 0.3547 -
accuracy: 0.8973 - val_loss: 0.3747 - val_accuracy: 0.8930
Epoch 16/20
608/608 [==============================] - 489s 804ms/step - loss: 0.3511 -
accuracy: 0.8989 - val_loss: 0.3943 - val_accuracy: 0.8877
Epoch 17/20
608/608 [==============================] - 488s 803ms/step - loss: 0.3439 -
accuracy: 0.8986 - val_loss: 0.3714 - val_accuracy: 0.8971
Epoch 18/20
608/608 [==============================] - 497s 818ms/step - loss: 0.3367 -
accuracy: 0.9012 - val_loss: 0.3806 - val_accuracy: 0.8934
Epoch 19/20
608/608 [==============================] - 499s 820ms/step - loss: 0.3271 -
accuracy: 0.9013 - val_loss: 0.3700 - val_accuracy: 0.8959
```

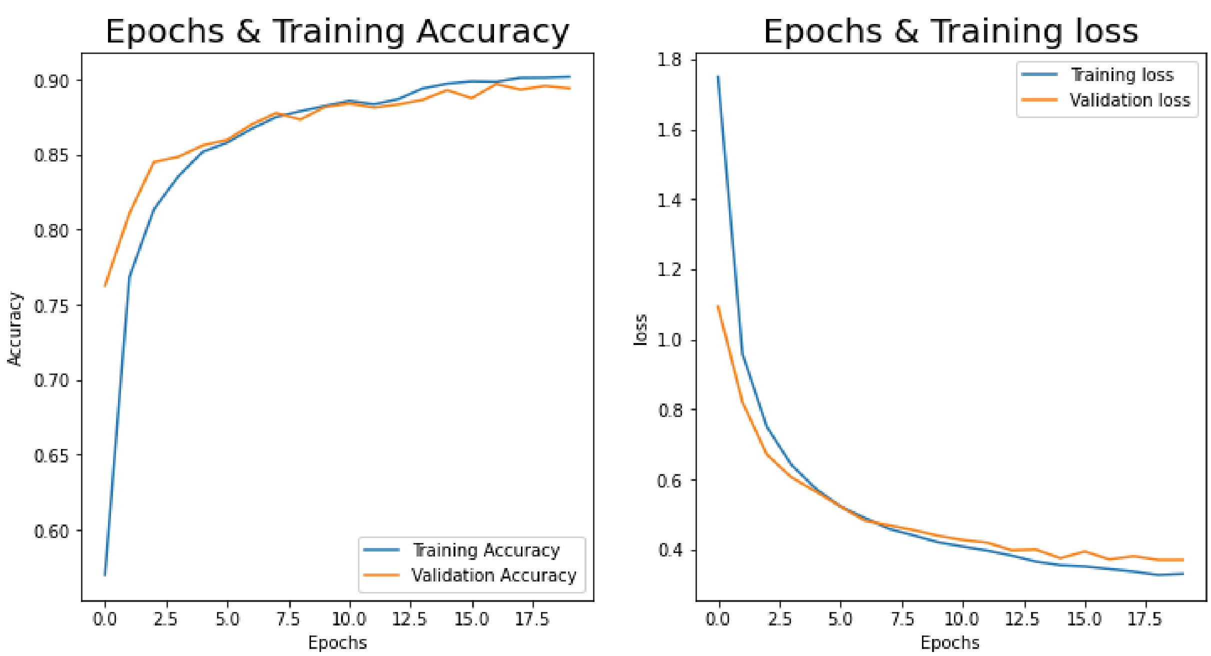
```
Epoch 20/20
608/608 [==============================] - 520s 856ms/step - loss: 0.3302 -
accuracy: 0.9019 - val_loss: 0.3700 - val_accuracy: 0.8942
```

In [19]:
```
fig, ax = plt.subplots(nrows = 1, ncols = 2, figsize = (12,6))

ax[0].plot(history_efficientnet.history['accuracy'], '-', label = 'Training
ax[0].plot(history_efficientnet.history['val_accuracy'], '-', label = 'Valic
ax[0].set_xlabel('Epochs')
ax[0].set_ylabel('Accuracy')
ax[0].set_title('Epochs & Training Accuracy', fontsize=20)
ax[0].legend(loc='best')

ax[1].plot(history_efficientnet.history['loss'], '-', label = 'Training loss
ax[1].plot(history_efficientnet.history['val_loss'], '-', label = 'Validatic
ax[1].set_xlabel('Epochs')
ax[1].set_ylabel('loss')
ax[1].set_title('Epochs & Training loss', fontsize=20)
ax[1].legend(loc='best')

plt.show()
```



In [20]:
```
model_loaded = model_efficientnet
```

In [21]:
```
test_generator.reset()
pred = model_loaded.predict(test_generator, verbose=1)
```

```
2700/2700 [==============================] - 65s 24ms/step
```

In [22]:
```
pred = np.argmax(pred,axis=1)
labels = (train_generator.class_indices)
labels = dict((v,k) for k,v in labels.items())
pred = [labels[k] for k in pred]

print(accuracy_score(test['label'], pred))
print(classification_report(test['label'], pred))
```

```
0.9222222222222223
              precision    recall  f1-score   support

           A       0.94      0.97      0.96       100
           B       0.99      0.92      0.95       100
       Blank       1.00      0.98      0.99       100
           C       0.99      0.98      0.98       100
           D       0.94      0.88      0.91       100
           E       0.91      0.94      0.93       100
           F       0.94      0.94      0.94       100
           G       0.91      0.96      0.93       100
           H       0.98      1.00      0.99       100
           I       0.91      0.89      0.90       100
           J       0.86      0.93      0.89       100
           K       0.94      0.88      0.91       100
           L       0.98      0.94      0.96       100
           M       0.80      0.90      0.85       100
           N       0.87      0.82      0.85       100
           O       0.97      0.99      0.98       100
           P       0.92      0.95      0.94       100
           Q       0.94      0.82      0.88       100
           R       0.96      0.94      0.95       100
           S       0.99      0.80      0.88       100
           T       0.85      0.97      0.91       100
           U       0.88      0.94      0.91       100
           V       0.81      0.90      0.85       100
           W       0.92      0.87      0.89       100
           X       0.84      0.92      0.88       100
           Y       0.97      0.96      0.96       100
           Z       0.97      0.91      0.94       100

    accuracy                           0.92      2700
   macro avg       0.93      0.92      0.92      2700
weighted avg       0.93      0.92      0.92      2700
```

Fine-tuning

In [23]:

```
feature_extractor_layer.trainable = True

model_efficientnet.compile(optimizer=keras.optimizers.Adam(learning_rate=1e-
                           loss='sparse_categorical_crossentropy',
                           metrics=["accuracy"])
```

In [24]:

```
cb = [
#     callbacks.EarlyStopping(monitor='val_loss', patience=5, restore_best_w
    callbacks.ModelCheckpoint('model_efficientnet_finetuned.h5', save_best_o
]

train_generator.reset()
valid_generator.reset()

history_efficientnet_2 = model_efficientnet.fit(
    train_generator,
```

```
    validation_data = valid_generator,
    epochs = 10,
    batch_size = 32,
    verbose = 1,
    callbacks = cb
)
```

```
Epoch 1/10
608/608 [==============================] - 518s 834ms/step - loss: 1.2017 -
accuracy: 0.6690 - val_loss: 0.2236 - val_accuracy: 0.9292
Epoch 2/10
608/608 [==============================] - 526s 866ms/step - loss: 0.3864 -
accuracy: 0.8756 - val_loss: 0.0874 - val_accuracy: 0.9753
Epoch 3/10
608/608 [==============================] - 554s 911ms/step - loss: 0.2046 -
accuracy: 0.9336 - val_loss: 0.0442 - val_accuracy: 0.9858
Epoch 4/10
608/608 [==============================] - 534s 879ms/step - loss: 0.1134 -
accuracy: 0.9632 - val_loss: 0.0265 - val_accuracy: 0.9922
Epoch 5/10
608/608 [==============================] - 527s 867ms/step - loss: 0.0789 -
accuracy: 0.9738 - val_loss: 0.0195 - val_accuracy: 0.9947
Epoch 6/10
608/608 [==============================] - 525s 864ms/step - loss: 0.0608 -
accuracy: 0.9801 - val_loss: 0.0158 - val_accuracy: 0.9953
Epoch 7/10
608/608 [==============================] - 526s 864ms/step - loss: 0.0431 -
accuracy: 0.9857 - val_loss: 0.0119 - val_accuracy: 0.9971
Epoch 8/10
608/608 [==============================] - 516s 848ms/step - loss: 0.0322 -
accuracy: 0.9898 - val_loss: 0.0069 - val_accuracy: 0.9984
Epoch 9/10
608/608 [==============================] - 524s 860ms/step - loss: 0.0283 -
accuracy: 0.9917 - val_loss: 0.0072 - val_accuracy: 0.9988
Epoch 10/10
608/608 [==============================] - 509s 836ms/step - loss: 0.0207 -
accuracy: 0.9935 - val_loss: 0.0067 - val_accuracy: 0.9984
```

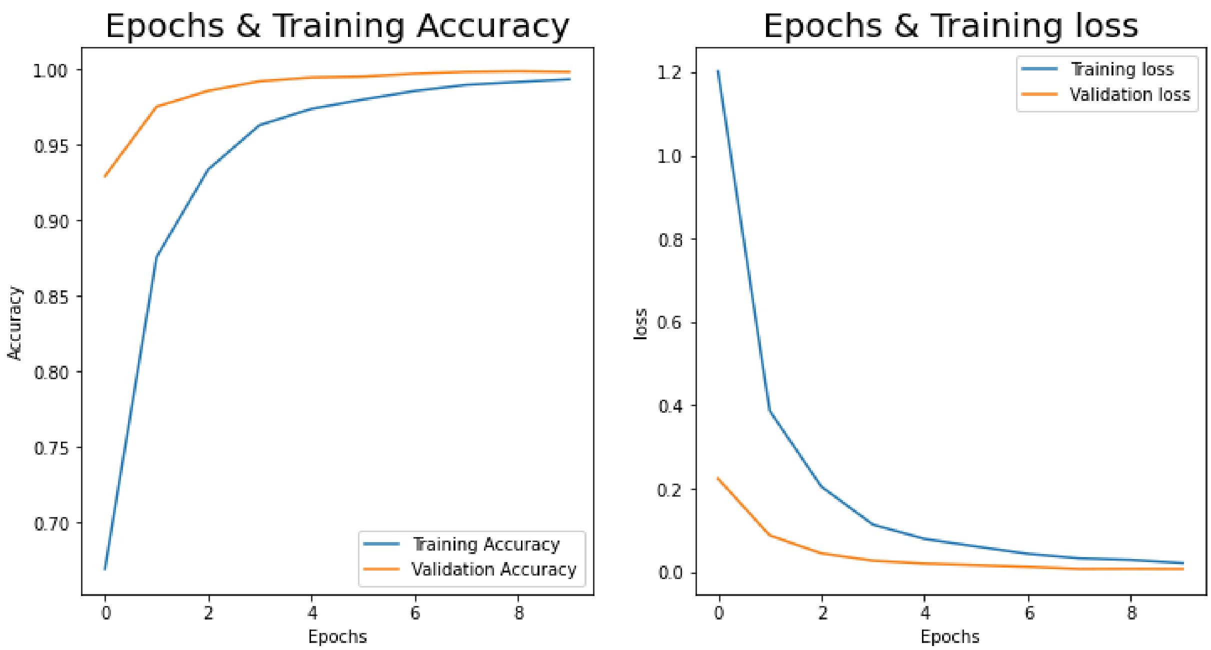
In [25]:

```
fig, ax = plt.subplots(nrows = 1, ncols = 2, figsize = (12,6))

ax[0].plot(history_efficientnet_2.history['accuracy'], '-', label = 'Trainir
ax[0].plot(history_efficientnet_2.history['val_accuracy'], '-', label = 'Val
ax[0].set_xlabel('Epochs')
ax[0].set_ylabel('Accuracy')
ax[0].set_title('Epochs & Training Accuracy', fontsize=20)
ax[0].legend(loc='best')

ax[1].plot(history_efficientnet_2.history['loss'], '-', label = 'Training lo
ax[1].plot(history_efficientnet_2.history['val_loss'], '-', label = 'Validat
ax[1].set_xlabel('Epochs')
ax[1].set_ylabel('loss')
ax[1].set_title('Epochs & Training loss', fontsize=20)
ax[1].legend(loc='best')

plt.show()
```



In [26]:
```
model_loaded = model_efficientnet
```

In [27]:
```
test_generator.reset()
pred = model_loaded.predict(test_generator, verbose=1)
```

```
2700/2700 [==============================] - 51s 19ms/step
```

In [28]:
```
pred = np.argmax(pred,axis=1)
labels = (train_generator.class_indices)
labels = dict((v,k) for k,v in labels.items())
pred = [labels[k] for k in pred]

print(accuracy_score(test['label'], pred))
print(classification_report(test['label'], pred))
```

```
0.9992592592592593
              precision    recall  f1-score   support

           A       1.00      1.00      1.00       100
           B       1.00      1.00      1.00       100
       Blank       1.00      1.00      1.00       100
           C       1.00      1.00      1.00       100
           D       1.00      1.00      1.00       100
           E       1.00      1.00      1.00       100
           F       1.00      1.00      1.00       100
           G       0.98      1.00      0.99       100
           H       1.00      1.00      1.00       100
           I       1.00      1.00      1.00       100
           J       1.00      0.99      0.99       100
           K       1.00      1.00      1.00       100
           L       1.00      1.00      1.00       100
           M       1.00      1.00      1.00       100
           N       1.00      1.00      1.00       100
           O       1.00      1.00      1.00       100
           P       1.00      1.00      1.00       100
           Q       1.00      0.99      0.99       100
           R       1.00      1.00      1.00       100
           S       1.00      1.00      1.00       100
           T       1.00      1.00      1.00       100
           U       1.00      1.00      1.00       100
           V       1.00      1.00      1.00       100
           W       1.00      1.00      1.00       100
           X       1.00      1.00      1.00       100
           Y       1.00      1.00      1.00       100
           Z       1.00      1.00      1.00       100

    accuracy                           1.00      2700
   macro avg       1.00      1.00      1.00      2700
weighted avg       1.00      1.00      1.00      2700
```