In [ ]:

```
##Install relevant packages required
# pip install matplotlib
# pip install opencv-python
# pip install tensorflow_hub
# pip install pandas
# pip install sklearn
# pip install tqdm
# pip install ipywidgets --user
# pip install Pandoc
# pip install nbconvert
```

I will be using transfer learning and take pre-trained model from google's Tensorflow Hub and re-train the last layer on our training dataset because using pre-trained model saves lot of time and computational budget for new classification problem at hand

In [114]:

```
cd C:\Users\User\OneDrive\Desktop\video_dsta\ml-dev
```

```
C:\Users\User\OneDrive\Desktop\video_dsta\ml-dev
```

Import relevant packages

In [15]:

```
import numpy as np
import cv2
import matplotlib.pylab as plt
import PIL.Image as Image
import os
import pandas as pd
import glob
import csv
import tensorflow as tf
import tensorflow_hub as hub
```

In [2]:

```
from tqdm.notebook import tqdm
from sklearn.model_selection import train_test_split
from tensorflow.keras.preprocessing.image import load_img, img_to_array

from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.models import Sequential
```

Setting the path to load training dataset and label

In [20]:

```
train_img_path = r'C:\Users\User\OneDrive\Desktop\video_dsta\ml-dev\training_data\\'
train_label = r'C:\Users\User\OneDrive\Desktop\video_dsta\ml-dev\labels.csv'
```

In [21]:

```
image_list = glob.glob(os.path.join(train_img_path, "*"))
len(image_list)
```

Out[21]:

```
900
```

In [58]:

```
x_train = []
y_train = []
```

Read images from disk into numpy array

In [59]:

```
with open(train_label, "rt") as dataset:
    reader = csv.reader(dataset)
    next(reader, None)

    for line in tqdm(reader, total=900):
        x_train.append(
                np.asarray(
                    # Load image Without Grayscale Flag and change image to our target size of 224 by 224
                    load_img(
                        train_img_path + line[0] , target_size=(224,224,3), color_mode="rgb"
                    )
                )
            #)
        )
        y_train.append(int(line[1]))
```

In [60]:

```
X = x_train
y = y_train
```

Performing train test split

In [84]:

```
x_train, x_val, y_train, y_val = train_test_split(X, y, test_size= 0.7, random_state=1337)
```

Preprocessing of images by performing Data Scaling to Improve Deep Learning Model Stability and Performance

In [85]:

```
x_train_scaled = [x / 255 for x in x_train]
x_val_scaled = [x / 255 for x in x_val]
```

In [86]:

```
x_train_scaled = np.array(x_train_scaled)
x_val_scaled = np.array(x_val_scaled)
y_train = np.array(y_train)
y_val = np.array(y_val)
```

I WILL BE USING PRE-TRAINED MODEL(MOBILENET_V2) IMPORTED FROM TENSORFLOW HUB. I WILL FREEZE AND USE THE TRAINED WEIGHTS OF THE MOBILENET_V2 MODEL AND ONLY

RETRAIN THE LAST LAYER USING OUR OWN TRAINING IMAGES.

In [30]:

```
feature_extractor_model = "https://tfhub.dev/google/tf2-preview/mobilenet_v2/feature_vector/4"
pretrained_model_without_top_layer = hub.KerasLayer(
feature_extractor_model, input_shape= (224,224,3), trainable = False)   #trainable = false
```

In [104]:

```
#model will do prediction for 5 classes
num_of_ship_class = 5
model = tf.keras.Sequential([pretrained_model_without_top_layer,
                             tf.keras.layers.Dense(num_of_ship_class)])
model.summary()
```

```
Model: "sequential_10"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
keras_layer_1 (KerasLayer)   (None, 1280)              2257984
_________________________________________________________________
dense_9 (Dense)              (None, 5)                 6405
=================================================================
Total params: 2,264,389
Trainable params: 6,405
Non-trainable params: 2,257,984
_________________________________________________________________
```

In [71]:

```
#Sparse Categorical Crossentropy
#If you have two or more classes and  the labels are integers, the SparseCategoricalCrossentropy should be use
```

In [105]:

```
model.compile(
    optimizer = "adam",
    loss = tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
    metrics=["acc"])

history = model.fit(x_train_scaled, y_train, epochs=12 ,validation_data = (x_val_scaled, y_val))
```

```
Epoch 1/12
9/9 [==============================] - 9s 1
s/step - loss: 1.3671 - acc: 0.4593 - val_l
oss: 1.1563 - val_acc: 0.6238
Epoch 2/12
9/9 [==============================] - 8s 9
70ms/step - loss: 0.9074 - acc: 0.7259 - va
l_loss: 0.8825 - val_acc: 0.7270
Epoch 3/12
9/9 [==============================] - 8s 9
78ms/step - loss: 0.6662 - acc: 0.8259 - va
l_loss: 0.7441 - val_acc: 0.7746
Epoch 4/12
9/9 [==============================] - 8s 1
s/step - loss: 0.5231 - acc: 0.8630 - val_l
oss: 0.6479 - val_acc: 0.7984
Epoch 5/12
9/9 [==============================] - 8s 9
74ms/step - loss: 0.4331 - acc: 0.8852 - va
l_loss: 0.5921 - val_acc: 0.8222
Epoch 6/12
9/9 [==============================] - 8s 1
s/step - loss: 0.3706 - acc: 0.9185 - val_l
oss: 0.5576 - val_acc: 0.8270
Epoch 7/12
9/9 [==============================] - 9s 1
s/step - loss: 0.3277 - acc: 0.9370 - val_l
oss: 0.5291 - val_acc: 0.8286
Epoch 8/12
9/9 [==============================] - 9s 1
s/step - loss: 0.2970 - acc: 0.9444 - val_l
oss: 0.5081 - val_acc: 0.8397
Epoch 9/12
9/9 [==============================] - 8s 9
```

```
84ms/step - loss: 0.2667 - acc: 0.9519 - va
l_loss: 0.4920 - val_acc: 0.8492
Epoch 10/12
9/9 [==============================] - 8s 9
85ms/step - loss: 0.2411 - acc: 0.9593 - va
l_loss: 0.4801 - val_acc: 0.8460
Epoch 11/12
9/9 [==============================] - 8s 1
s/step - loss: 0.2197 - acc: 0.9667 - val_l
oss: 0.4674 - val_acc: 0.8476
Epoch 12/12
9/9 [==============================] - 8s 9
87ms/step - loss: 0.2026 - acc: 0.9741 - va
l_loss: 0.4634 - val_acc: 0.8460
```

In [99]:

```
history_dict = history.history
print(history_dict.keys())
```

```
dict_keys(['loss', 'acc', 'val_loss', 'val_
acc'])
```

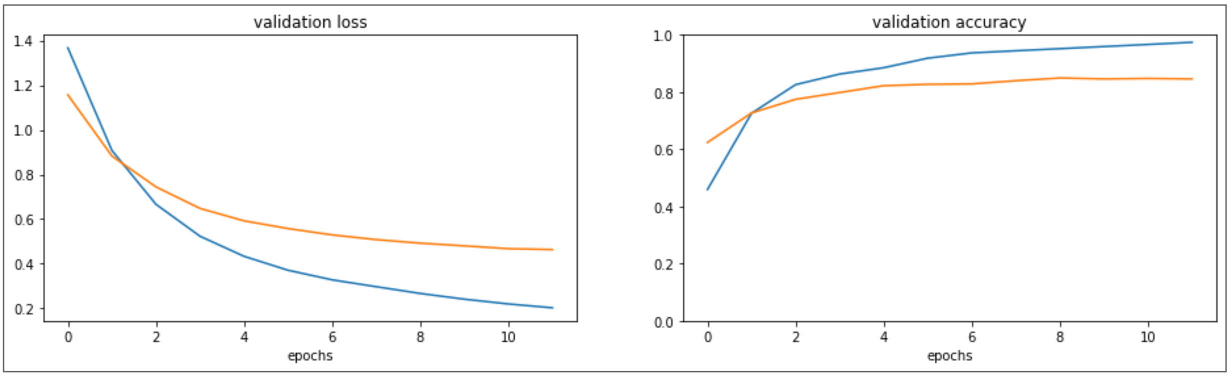
Train Learning Curve: Learning curve calculated from the training dataset that gives an idea of how well the model is learning.
Validation Learning Curve: Learning curve calculated from a hold-out validation dataset that gives an idea of how well the model is generalizing.

In [106]:

```
fig = plt.figure(figsize=(16,4))
ax = fig.add_subplot(121)
ax.plot(history.history["loss"])
ax.plot(history.history["val_loss"])
ax.set_title("validation loss")
ax.set_xlabel("epochs")

ax2 = fig.add_subplot(122)
ax2.plot(history.history["acc"])
ax2.plot(history.history["val_acc"])
ax2.set_title("validation accuracy")
ax2.set_xlabel("epochs")
ax2.set_ylim(0, 1)

plt.show()
```



The learning curve charts show a good fit because the training loss decreases to a point of stability and the validation loss decreases to a point of stability and has a small gap with the training loss. We can further improve our model with more datasets and fine tuning.

After 12 epoch, the model managed to achieve training and validation loss that decreases to a point of stability with a minimal gap between the two final loss values. The loss of model on the training dataset is lower than the validation dataset (generalization gap).

In [107]:

```
model.evaluate(x_val_scaled,y_val)
```

```
20/20 [==============================] - 6s 278ms/step - loss: 0.4634 - acc: 0.8460
```

Out[107]:

```
[0.46337440609931946, 0.8460317254066467]
```

Making a prediction

In [96]:

```
x, y = x_val_scaled,y_val
image = x[0, :, :, :]
true_index = np.argmax(y[0])
plt.imshow(image)
plt.axis('off')
plt.show()

# Expand the validation image to (1, 224, 224, 3) before predicting the label
prediction_scores = model.predict(np.expand_dims(image, axis=0))
predicted_index = np.argmax(prediction_scores)
print("True label: " + str(true_index))
print("Predicted label: " + str(predicted_index))
```

```
True label: 0
Predicted label: 0
```

In [129]:

```
image = r"C:\Users\User\OneDrive\Desktop\video_dsta\ml-dev\training_data\718949.jpg"
image_pil = Image.open(image)
image_pil
```

Out[129]:

In [ ]:

```
model.predict()
```

In [140]:

```
image = r"C:\Users\User\OneDrive\Desktop\video_dsta\ml-dev\training_data\718949.jpg"
image = load_img(image, target_size=(224, 224))
image = img_to_array(image)
image = np.expand_dims(image, axis=0)
prediction_scores = model.predict(image)
predicted_index = np.argmax(prediction_scores)
predicted_index
```

Out[140]:

```
4
```

Creating model path and saving model

In [120]:

```
model.save('my_model.h5')
```

In [121]:

```
# saved_model_path = r'C:\Users\User\OneDrive\Desktop\video_dsta\ml-dev\trained_model'
# tf.saved_model.save(model, saved_model_path)
```

In [126]:

```
# Recreate the exact same model, including its weights and the optimizer
loaded_model = tf.keras.models.load_model(('my_model.h5') ,
       custom_objects={'KerasLayer':hub.KerasLayer})
```

In [127]:

```
# Show the model architecture
loaded_model.summary()
```

```
Model: "sequential_10"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
keras_layer_1 (KerasLayer)   (None, 1280)              2257984
_________________________________________________________________
dense_9 (Dense)              (None, 5)                 6405
=================================================================
Total params: 2,264,389
Trainable params: 6,405
Non-trainable params: 2,257,984
_________________________________________________________________
```

In [ ]:

```
def predict(model, x_input, y_input):
    x_val = np.array(x_input)
    y_val = np.array(y_input)
    x, y = x_val/255, y_val
    image = x[0, :, :, :]
    true_index = np.argmax(y[0])

    # Expand the validation image to (1, 224, 224, 3) before predicting the label
    prediction_scores = model.predict(np.expand_dims(image, axis=0))
    predicted_index = np.argmax(prediction_scores)
    print("True label: " + str(true_index))
    print("Predicted label: " + str(predicted_index))
    return (predicted_index)


prediction = predict(model, x_input, y_input)
print(prediction)
```