In [1]:
```
import pandas as pd
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
import os
import random
import cv2
import imageio
import sklearn

from sklearn.model_selection import train_test_split
from PIL import Image
from os import listdir
from tqdm import tqdm_notebook
from skimage.color import rgb2gray
from collections import Counter
from sklearn.metrics import roc_auc_score,accuracy_score
from tensorflow.keras import backend as K
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Dropout, Flatten, Dense
from tensorflow.keras.models import Sequential
from tensorflow.keras.preprocessing.image import ImageDataGenerator


random_seed = 33
```

Load Images and Resize them

In [2]:
```
# cell labels are 1 if infected, 0 if uninfected.
cell_labels = []

# cells image
cell_images = []

def read_images(file_path, label):
    images_addresses=os.listdir(file_path)
    images_addresses.remove('Thumbs.db')
    cells_image_array = np.zeros((len(images_addresses),125,125,3),dtype=np.int16)

    for ind,img_address in tqdm_notebook(enumerate(images_addresses),total=len(imag
es_addresses)):
        path = file_path +'/'+ img_address
        image = Image.open(path)
        image = image.resize((125,125))
        image_array = np.asarray(image)
        image_array = image_array.astype(np.int32)
        cells_image_array[ind]=image_array
        cell_images.append(image_array)
        cell_labels.append(label)
    return cells_image_array
```

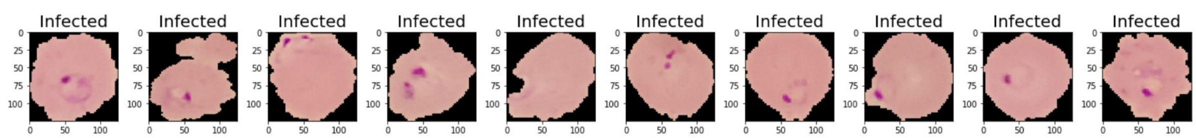
In [3]:
```
infected_cells = read_images("D:/Neural/Project/cell_images/cell_images/Parasitized", 1)
uninfected_cells = read_images("D:/Neural/Project/cell_images/cell_images/Uninfected",0)
```

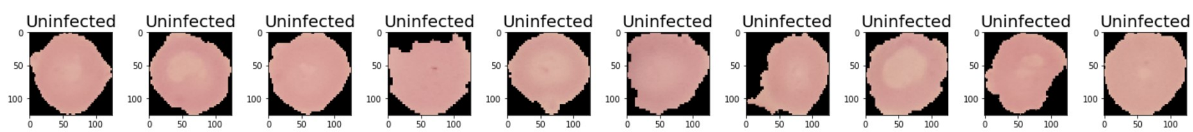
```
D:\Anaconda\envs\TensorFlow-GPU\lib\site-packages\ipykernel_launcher.py:12: Tqdm
DeprecationWarning: This function will be removed in tqdm==5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
  if sys.path[0] == '':
```

Sample Images of Infected and Uninfected Cells

In [4]:
```
def SampleCells(images_arr,title):

    fig, axes = plt.subplots(1, 10, figsize=(20,20))

    for img, ax in zip( images_arr, axes):
        ax.imshow(img)
        ax.set_title(title,fontsize=20)
    plt.tight_layout()
    plt.show()
```

In [5]:
```
SampleCells(infected_cells,'Infected')
SampleCells(uninfected_cells,'Uninfected')
```

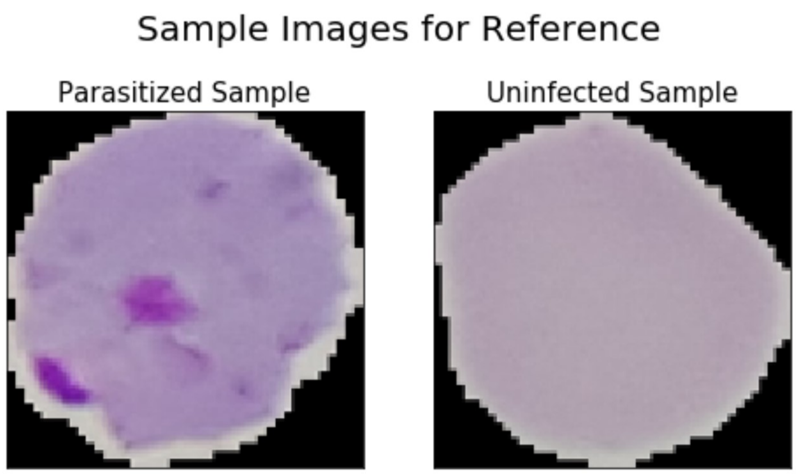




Data Exploration

select one sample from each category - Infected and Uninfected Cells

In [6]:
```
np.random.seed(random_seed)
rand=np.random.randint(infected_cells.shape[0])
parasitized_sample=infected_cells[rand]
np.random.seed(random_seed)
rand=np.random.randint(uninfected_cells.shape[0])
uninfected_sample=uninfected_cells[rand]

fig=plt.figure(figsize=(8,5))
plt.title("Sample Images for Reference",fontsize=20)
plt.axis('off')
ax1=fig.add_subplot(121)
ax1.imshow(parasitized_sample)
ax1.get_xaxis().set_visible(False)
ax1.get_yaxis().set_visible(False)
ax1.set_title("Parasitized Sample",fontsize=15)
ax2=fig.add_subplot(122)
ax2.imshow(uninfected_sample)
ax2.get_xaxis().set_visible(False)
ax2.get_yaxis().set_visible(False)
ax2.set_title("Uninfected Sample",fontsize=15)
plt.show()
```

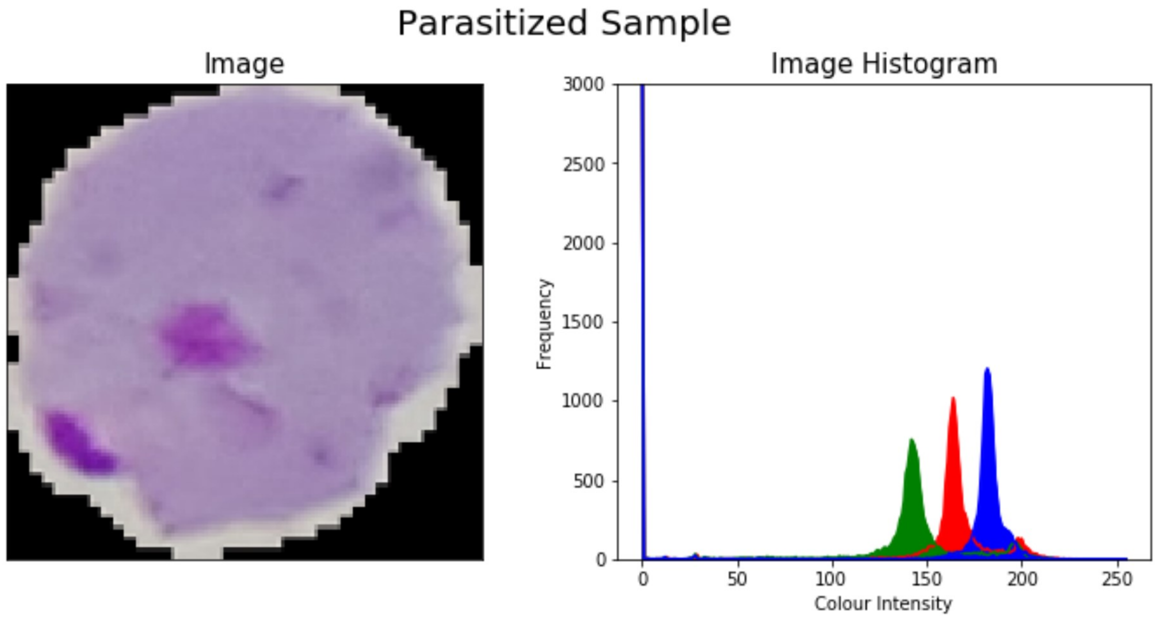


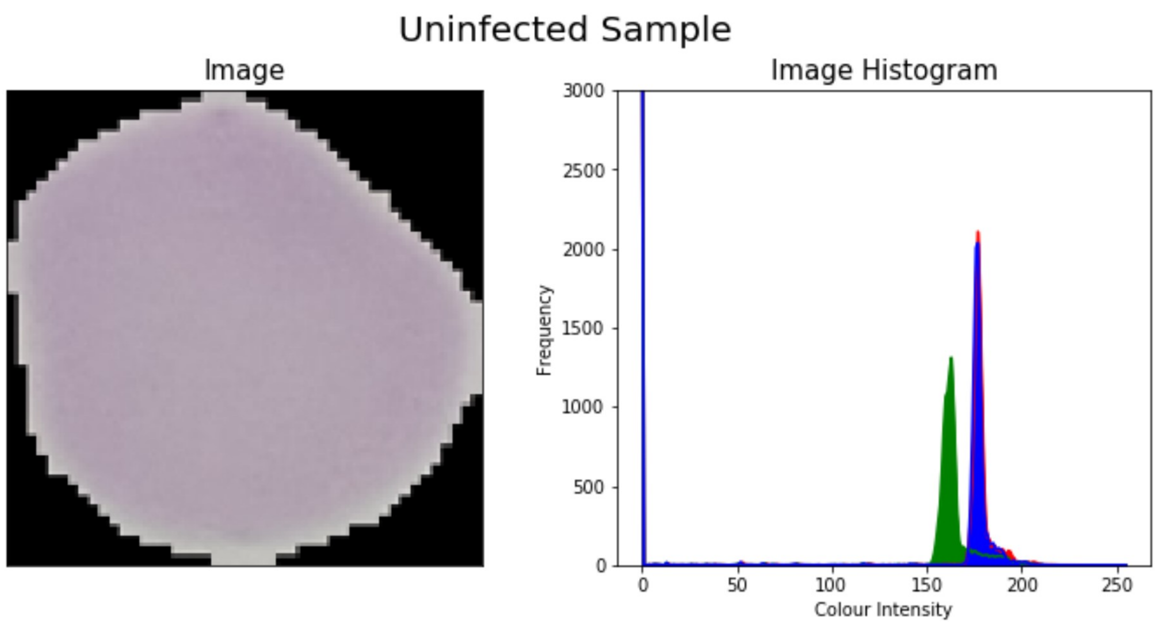
Analyse Blood Cell Color

To do so we plot the image histogram which shows Red-Green-Blue (RGB) color distribution for an image

In [7]:
```
def get_RGB_hist(sample_data,title,to_return=False):
    sample=Image.fromarray(sample_data.astype(np.uint8),'RGB')
    hist=sample.histogram()
    hist_r=hist[:256]
    hist_g=hist[256:512]
    hist_b=hist[512:]
    if(to_return==True):
        return hist_r,hist_g,hist_b
    x=np.arange(256)

    fig=plt.figure(figsize=(12,5))
    plt.title(title+'\n',fontsize=20)
    plt.axis('off')
    ax1=fig.add_subplot(121)
    ax1.imshow(sample)
    ax1.set_title("Image",fontsize=15)
    ax1.get_xaxis().set_visible(False)
    ax1.get_yaxis().set_visible(False)
    ax2=fig.add_subplot(122)
    ax2.plot(hist_r,color='red')
    ax2.fill_between(x,hist_r,color='red')
    ax2.plot(hist_g,color='green')
    ax2.fill_between(x,hist_g,color='green')
    ax2.plot(hist_b,color='blue')
    ax2.fill_between(x,hist_b,color='blue')
    ax2.set_ylim(0,3000)
    ax2.set_title("Image Histogram",fontsize=15)
    ax2.set_ylabel("Frequency")
    ax2.set_xlabel("Colour Intensity")
    plt.show()
```

In [8]:
```
get_RGB_hist(parasitized_sample,"Parasitized Sample")
get_RGB_hist(uninfected_sample,"Uninfected Sample")
```





Training, Testing and Validation Data Preparation

In [9]:
```
def reordering_list(old_list,order):
    new_list = []
    for i in order:
        new_list.append(old_list[i])
    return new_list
```

In [10]:
```
np.random.seed(seed=42)
indices = np.arange(len(cell_labels))
np.random.shuffle(indices)
indices = indices.tolist()
cell_labels = reordering_list(cell_labels,indices)
cell_images = reordering_list(cell_images,indices)

#change to arrays
image_array = np.array(cell_images)
label_array = np.array(cell_labels)
```

In [11]:
```
X_train, X_test, y_train, y_test = train_test_split(image_array, label_array, test_
size=0.3, random_state=100)
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.1,
random_state=100)
```

In [12]:
```
print(X_train.shape, X_val.shape, X_test.shape)
print('Train:', Counter(y_train), '\nVal:', Counter(y_val), '\nTest:', Counter(y_te
st))
```

```
(17361, 125, 125, 3) (1929, 125, 125, 3) (8268, 125, 125, 3)
Train: Counter({1: 8703, 0: 8658})
Val: Counter({1: 978, 0: 951})
Test: Counter({0: 4170, 1: 4098})
```

CNN Basic Model

Label Encoding (One Hot Encoding)

In [13]:
```
y_train=tf.keras.utils.to_categorical(y_train,2)
y_test=tf.keras.utils.to_categorical(y_test,2)
y_val=tf.keras.utils.to_categorical(y_val,2)
```

Model Hyperparameter Values

In [14]:
```
EPOCHS = 20
BATCH_SIZE = 64
```

CNN Basic Model Architecture

In [15]:
```
model_cnn = Sequential()
model_cnn.add(Conv2D(filters=16,kernel_size=2,padding="same",activation="relu",inpu
t_shape=(125,125,3)))
model_cnn.add(MaxPooling2D(pool_size=2))
model_cnn.add(Conv2D(filters=32,kernel_size=2,padding="same",activation="relu"))
model_cnn.add(MaxPooling2D(pool_size=2))
model_cnn.add(Conv2D(filters=64,kernel_size=2,padding="same",activation="relu"))
model_cnn.add(MaxPooling2D(pool_size=2))
model_cnn.add(Dropout(0.2))
model_cnn.add(Flatten())
model_cnn.add(Dense(500,activation="relu"))
model_cnn.add(Dropout(0.2))
model_cnn.add(Dense(2,activation="softmax"))#2 represent output layer neurons
```

In [16]:
```
model_cnn.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accu
racy'])
model_cnn.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d (Conv2D)              (None, 125, 125, 16)      208       
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 62, 62, 16)        0         
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 62, 62, 32)        2080      
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 31, 31, 32)        0         
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 31, 31, 64)        8256      
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 15, 15, 64)        0         
_________________________________________________________________
dropout (Dropout)            (None, 15, 15, 64)        0         
_________________________________________________________________
flatten (Flatten)            (None, 14400)             0         
_________________________________________________________________
dense (Dense)                (None, 500)               7200500   
_________________________________________________________________
dropout_1 (Dropout)          (None, 500)               0         
_________________________________________________________________
dense_1 (Dense)              (None, 2)                 1002      
=================================================================
Total params: 7,212,046
Trainable params: 7,212,046
Non-trainable params: 0
_________________________________________________________________
```

Train the Model

In [17]:

```
history_bsic_cnn = model_cnn.fit(X_train,y_train, batch_size=256,
                                 epochs = 20, validation_data = (X_val,y_val))
```

```
Train on 17361 samples, validate on 1929 samples
Epoch 1/20
17361/17361 [==============================] - 15s 880us/sample - loss: 29.7327
- accuracy: 0.5608 - val_loss: 0.6507 - val_accuracy: 0.6195
Epoch 2/20
17361/17361 [==============================] - 8s 462us/sample - loss: 0.6248 -
accuracy: 0.6527 - val_loss: 0.6003 - val_accuracy: 0.6739
Epoch 3/20
17361/17361 [==============================] - 8s 459us/sample - loss: 0.5855 -
accuracy: 0.6920 - val_loss: 0.5764 - val_accuracy: 0.7045
Epoch 4/20
17361/17361 [==============================] - 8s 474us/sample - loss: 0.5405 -
accuracy: 0.7278 - val_loss: 0.5322 - val_accuracy: 0.7429
Epoch 5/20
17361/17361 [==============================] - 8s 463us/sample - loss: 0.4464 -
accuracy: 0.7932 - val_loss: 0.4322 - val_accuracy: 0.7880
Epoch 6/20
17361/17361 [==============================] - 8s 465us/sample - loss: 0.3334 -
accuracy: 0.8642 - val_loss: 0.3577 - val_accuracy: 0.8455
Epoch 7/20
17361/17361 [==============================] - 8s 470us/sample - loss: 0.2599 -
accuracy: 0.8986 - val_loss: 0.2944 - val_accuracy: 0.8828
Epoch 8/20
17361/17361 [==============================] - 8s 474us/sample - loss: 0.2038 -
accuracy: 0.9199 - val_loss: 0.2447 - val_accuracy: 0.9005
Epoch 9/20
17361/17361 [==============================] - 8s 471us/sample - loss: 0.1629 -
accuracy: 0.9355 - val_loss: 0.2473 - val_accuracy: 0.9129
Epoch 10/20
17361/17361 [==============================] - 15s 886us/sample - loss: 0.1462 -
accuracy: 0.9434 - val_loss: 0.2511 - val_accuracy: 0.9145
Epoch 11/20
17361/17361 [==============================] - 8s 466us/sample - loss: 0.1270 -
accuracy: 0.9497 - val_loss: 0.2357 - val_accuracy: 0.9222
Epoch 12/20
17361/17361 [==============================] - 8s 467us/sample - loss: 0.1133 -
accuracy: 0.9545 - val_loss: 0.2278 - val_accuracy: 0.9155
Epoch 13/20
17361/17361 [==============================] - 8s 473us/sample - loss: 0.1006 -
accuracy: 0.9593 - val_loss: 0.2255 - val_accuracy: 0.9279
Epoch 14/20
17361/17361 [==============================] - 8s 477us/sample - loss: 0.0919 -
accuracy: 0.9611 - val_loss: 0.2183 - val_accuracy: 0.9222
Epoch 15/20
17361/17361 [==============================] - 8s 471us/sample - loss: 0.0795 -
accuracy: 0.9670 - val_loss: 0.2562 - val_accuracy: 0.9248
Epoch 16/20
17361/17361 [==============================] - 8s 473us/sample - loss: 0.0730 -
accuracy: 0.9700 - val_loss: 0.2524 - val_accuracy: 0.9342
Epoch 17/20
17361/17361 [==============================] - 8s 475us/sample - loss: 0.0686 -
accuracy: 0.9696 - val_loss: 0.2358 - val_accuracy: 0.9336
Epoch 18/20
17361/17361 [==============================] - 8s 476us/sample - loss: 0.0585 -
accuracy: 0.9756 - val_loss: 0.2510 - val_accuracy: 0.9362
Epoch 19/20
17361/17361 [==============================] - 9s 493us/sample - loss: 0.0520 -
accuracy: 0.9791 - val_loss: 0.2940 - val_accuracy: 0.9098
Epoch 20/20
17361/17361 [==============================] - 8s 474us/sample - loss: 0.0775 -
accuracy: 0.9711 - val_loss: 0.2712 - val_accuracy: 0.9311
```

Transfer Learning using VGG-19 convolutional neural network

Image Augmentation

In [18]:
```
train_image_data_generator = tf.keras.preprocessing.image.ImageDataGenerator(rescal
e=1./255,
                                                                  zoom_range=0.05,
                                                                  rotation_range=25,
                                                                  width_shift_range=
0.05,
                                                                  height_shift_range=
0.05,
                                                                  shear_range=0.05, h
orizontal_flip=True,
                                                                  fill_mode='nearest
')
val_data_gen = tf.keras.preprocessing.image.ImageDataGenerator(rescale=1./255)


train_generator = train_image_data_generator.flow(X_train, y_train, batch_size=BATC
H_SIZE, shuffle=True)
val_generator = val_data_gen.flow(X_val, y_val, batch_size=BATCH_SIZE, shuffle=Fals
e)
```

Fine-tuned Pre-trained VGG-19 CNN Model

Build Model Architecture

In [19]:
```
vgg_cnn = tf.keras.applications.vgg19.VGG19(include_top=False, weights='imagenet',
                                        input_shape=(125,125,3))
# Freeze the layers
vgg_cnn.trainable = True

set_trainable = False
for layer in vgg_cnn.layers:
    if layer.name in ['block5_conv1', 'block4_conv1']:
        set_trainable = True
    if set_trainable:
        layer.trainable = True
    else:
        layer.trainable = False
```

In [20]:
```
base_vgg_cnn = vgg_cnn
base_vgg_out = base_vgg_cnn.output
vgg_pool_out = tf.keras.layers.Flatten()(base_vgg_out)
hidden1 = tf.keras.layers.Dense(512, activation='relu')(vgg_pool_out)
drop1 = tf.keras.layers.Dropout(rate=0.3)(hidden1)

out = tf.keras.layers.Dense(2, activation='softmax')(drop1)

model_vgg_cnn = tf.keras.Model(inputs=base_vgg_cnn.input, outputs=out)
```

In [21]:
```
model_vgg_cnn.compile(loss='categorical_crossentropy', optimizer=tf.keras.optimizer
s.RMSprop(lr=1e-5), metrics=['accuracy'])
model_vgg_cnn.summary()
```

```
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
input_1 (InputLayer)         [(None, 125, 125, 3)]     0         
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 125, 125, 64)      1792      
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 125, 125, 64)      36928     
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 62, 62, 64)        0         
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 62, 62, 128)       73856     
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 62, 62, 128)       147584    
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 31, 31, 128)       0         
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 31, 31, 256)       295168    
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 31, 31, 256)       590080    
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 31, 31, 256)       590080    
_________________________________________________________________
block3_conv4 (Conv2D)        (None, 31, 31, 256)       590080    
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 15, 15, 256)       0         
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 15, 15, 512)       1180160   
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 15, 15, 512)       2359808   
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 15, 15, 512)       2359808   
_________________________________________________________________
block4_conv4 (Conv2D)        (None, 15, 15, 512)       2359808   
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 7, 7, 512)         0         
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 7, 7, 512)         2359808   
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 7, 7, 512)         2359808   
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 7, 7, 512)         2359808   
_________________________________________________________________
block5_conv4 (Conv2D)        (None, 7, 7, 512)         2359808   
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 3, 3, 512)         0         
_________________________________________________________________
flatten_1 (Flatten)          (None, 4608)              0         
_________________________________________________________________
dense_2 (Dense)              (None, 512)               2359808   
_________________________________________________________________
dropout_2 (Dropout)          (None, 512)               0         
_________________________________________________________________
dense_3 (Dense)              (None, 2)                 1026      
=================================================================
Total params: 22,385,218
Trainable params: 20,059,650
Non-trainable params: 2,325,568
_________________________________________________________________
```

Train the Model

In [22]:
```
train_steps_per_epoch = train_generator.n // train_generator.batch_size
val_steps_per_epoch = val_generator.n // val_generator.batch_size

history_vgg_cnn = model_vgg_cnn.fit(train_generator, steps_per_epoch=train_steps_pe
r_epoch, epochs=20,
                              validation_data=val_generator, validation_steps=val_s
teps_per_epoch,
                              verbose=1)
```

```
WARNING:tensorflow:sample_weight modes were coerced from
  ...
    to
  ['...']
WARNING:tensorflow:sample_weight modes were coerced from
  ...
    to
  ['...']
Train for 271 steps, validate for 30 steps
Epoch 1/20
271/271 [==============================] - 110s 406ms/step - loss: 0.2084 - accu
racy: 0.9205 - val_loss: 0.1241 - val_accuracy: 0.9573
Epoch 2/20
271/271 [==============================] - 150s 555ms/step - loss: 0.1375 - accu
racy: 0.9535 - val_loss: 0.1139 - val_accuracy: 0.9589
Epoch 3/20
271/271 [==============================] - 188s 695ms/step - loss: 0.1234 - accu
racy: 0.9580 - val_loss: 0.1059 - val_accuracy: 0.9620
Epoch 4/20
271/271 [==============================] - 213s 785ms/step - loss: 0.1173 - accu
racy: 0.9605 - val_loss: 0.0999 - val_accuracy: 0.9630
Epoch 5/20
271/271 [==============================] - 212s 783ms/step - loss: 0.1116 - accu
racy: 0.9617 - val_loss: 0.1068 - val_accuracy: 0.9609
Epoch 6/20
271/271 [==============================] - 216s 796ms/step - loss: 0.1082 - accu
racy: 0.9638 - val_loss: 0.0939 - val_accuracy: 0.9651
Epoch 7/20
271/271 [==============================] - 214s 791ms/step - loss: 0.1030 - accu
racy: 0.9640 - val_loss: 0.0932 - val_accuracy: 0.9661
Epoch 8/20
271/271 [==============================] - 1277s 5s/step - loss: 0.1026 - accura
cy: 0.9658 - val_loss: 0.0899 - val_accuracy: 0.9656
Epoch 9/20
271/271 [==============================] - 223s 824ms/step - loss: 0.0993 - accu
racy: 0.9653 - val_loss: 0.0845 - val_accuracy: 0.9661
Epoch 10/20
271/271 [==============================] - 212s 784ms/step - loss: 0.0960 - accu
racy: 0.9664 - val_loss: 0.1028 - val_accuracy: 0.9625
Epoch 11/20
271/271 [==============================] - 212s 781ms/step - loss: 0.0960 - accu
racy: 0.9678 - val_loss: 0.0916 - val_accuracy: 0.9672
Epoch 12/20
271/271 [==============================] - 215s 792ms/step - loss: 0.0934 - accu
racy: 0.9677 - val_loss: 0.0904 - val_accuracy: 0.9656
Epoch 13/20
271/271 [==============================] - 212s 781ms/step - loss: 0.0904 - accu
racy: 0.9695 - val_loss: 0.0958 - val_accuracy: 0.9661
Epoch 14/20
271/271 [==============================] - 211s 780ms/step - loss: 0.0890 - accu
racy: 0.9688 - val_loss: 0.1058 - val_accuracy: 0.9609
Epoch 15/20
271/271 [==============================] - 212s 780ms/step - loss: 0.0890 - accu
racy: 0.9702 - val_loss: 0.1022 - val_accuracy: 0.9646
Epoch 16/20
271/271 [==============================] - 215s 793ms/step - loss: 0.0903 - accu
racy: 0.9692 - val_loss: 0.1052 - val_accuracy: 0.9599
Epoch 17/20
271/271 [==============================] - 216s 798ms/step - loss: 0.0841 - accu
racy: 0.9697 - val_loss: 0.0779 - val_accuracy: 0.9703
Epoch 18/20
271/271 [==============================] - 212s 781ms/step - loss: 0.0851 - accu
racy: 0.9706 - val_loss: 0.0968 - val_accuracy: 0.9641
Epoch 19/20
```

Model Evaluation for Basic CNN and VGG-19 CNN

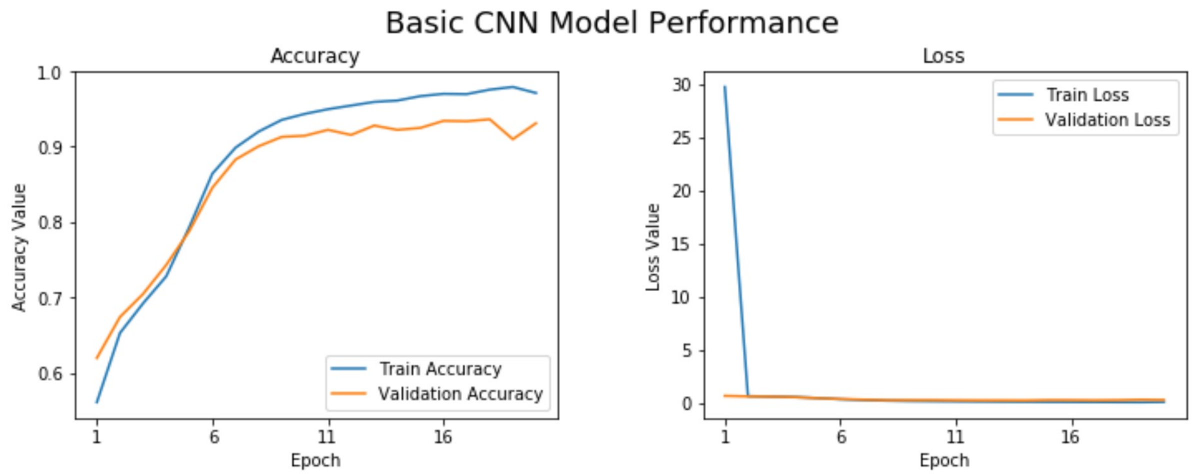
Retrieve Training and Validation Dataset Accuracy and Loss

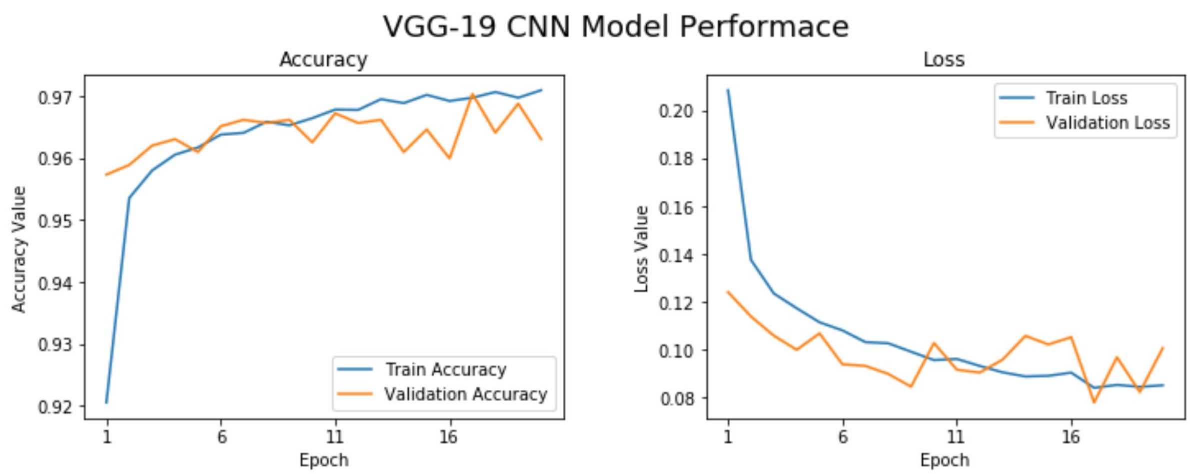
In [23]:
```
#accuracy
#for Basic CNN
train_accuracy_cnn = history_bsic_cnn.history['accuracy']
validation_accuracy_cnn = history_bsic_cnn.history['val_accuracy']

#for VGG-19 cnn
train_accuracy_vgg = history_vgg_cnn.history['accuracy']
validation_accuracy_vgg = history_vgg_cnn.history['val_accuracy']

#loss
#for Basic CNN
train_loss_cnn = history_bsic_cnn.history['loss']
validation_loss_cnn = history_bsic_cnn.history['val_loss']

#for VGG-19 CNN
train_loss_vgg = history_vgg_cnn.history['loss']
validation_loss_vgg = history_vgg_cnn.history['val_loss']
```

Plot Accuracy and Loss Graph for Basic CNN and VGG-19 CNN Models

In [24]:
```
def plot_accuracy_loss_graph(train_accuracy, validation_accuracy, train_loss, valid
ation_loss, title):
    f, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 4))
    t = f.suptitle(title, fontsize=18)
    f.subplots_adjust(top=0.85, wspace=0.3)

    epoch_range = len(train_accuracy)+1
    epoch_list = list(range(1,epoch_range))

    ax1.plot(epoch_list, train_accuracy, label='Train Accuracy')
    ax1.plot(epoch_list, validation_accuracy, label='Validation Accuracy')
    ax1.set_xticks(np.arange(1, epoch_range, 5))
    ax1.set_ylabel('Accuracy Value')
    ax1.set_xlabel('Epoch')
    ax1.set_title('Accuracy')
    l1 = ax1.legend(loc="best")

    ax2.plot(epoch_list, train_loss, label='Train Loss')
    ax2.plot(epoch_list, validation_loss, label='Validation Loss')
    ax2.set_xticks(np.arange(1, epoch_range, 5))
    ax2.set_ylabel('Loss Value')
    ax2.set_xlabel('Epoch')
    ax2.set_title('Loss')
    l2 = ax2.legend(loc="best")
```

In [25]:
```
plot_accuracy_loss_graph(train_accuracy_cnn, validation_accuracy_cnn, train_loss_cn
n, validation_loss_cnn, "Basic CNN Model Performance")
plot_accuracy_loss_graph(train_accuracy_vgg, validation_accuracy_vgg, train_loss_vg
g, validation_loss_vgg, "VGG-19 CNN Model Performace")
```





Test Data Accuracy for Basic CNN and VGG-19 CNN Model

In [26]:
```
accuracy_cnn = model_cnn.evaluate(X_test, y_test, verbose=1)
print('\n', 'Basic CNN Model Test_Accuracy:-', accuracy_cnn[1])

test_scaled = X_test / 255.
accuracy_vgg = model_vgg_cnn.evaluate(test_scaled, y_test, verbose=1)
print('\n\n\n', 'VGG19 CNN Model Test_Accuracy:-', accuracy_vgg[1])
```

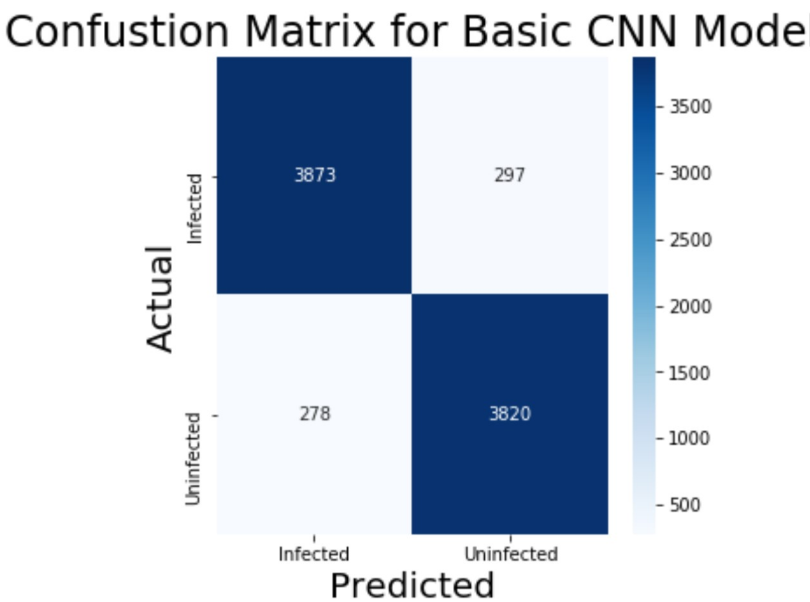
```
8268/8268 [==============================] - 8s 1ms/sample - loss: 0.2646 - accu
racy: 0.9305

 Basic CNN Model Test_Accuracy:- 0.9304548
8268/8268 [==============================] - 31s 4ms/sample - loss: 0.1482 - acc
uracy: 0.9624



 VGG19 CNN Model Test_Accuracy:- 0.9623851
```

Confusion Matrix for Basic CNN and VGG-19 CNN Model

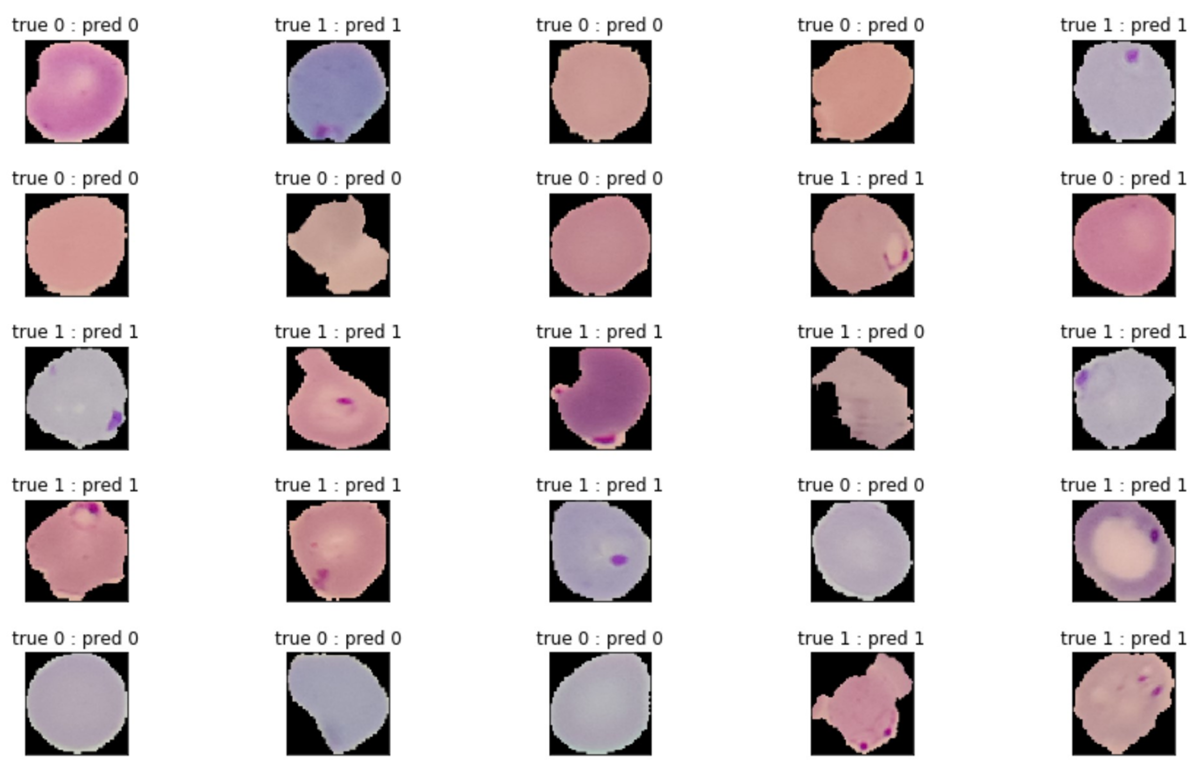
In [31]:
```
from sklearn.metrics import confusion_matrix, classification_report , accuracy_scor
e
import seaborn as sns
def evaluation_matrix(X_test, y_test,model,title):
    pred = model.predict(X_test)
    pred = np.argmax(pred,axis = 1)
    y_true = np.argmax(y_test,axis = 1)

    fig = plt.figure(figsize=(5,5))
    ax =  fig.gca()
    sns.heatmap(confusion_matrix(y_true , pred),ax=ax,cmap='Blues',annot=True,fmt='
g',
                xticklabels = ['Infected','Uninfected'],
                yticklabels=['Infected','Uninfected'])
    ax.set_ylabel('Actual',fontsize=20)
    ax.set_xlabel('Predicted',fontsize=20)
    plt.title(title,fontsize=24)
    plt.show()

    print('\n\n\n{} \n{}'.format(classification_report(y_true , pred) ,
                               accuracy_score(y_true , pred)))

    plt.figure(1 , figsize = (15 , 9))
    n = 0
    for i in range(25):
        n += 1
        r = np.random.randint( 0  , X_test.shape[0] , 1)
        plt.subplot(5 , 5 , n)
        plt.subplots_adjust(hspace = 0.5 , wspace = 0.5)
        plt.imshow(X_test[r[0]])
        plt.title('true {} : pred {}'.format(y_true[r[0]] , pred[r[0]]) )
        plt.xticks([]) , plt.yticks([])

    plt.show()
```

Basic CNN Model

In [32]:
```
evaluation_matrix(X_test, y_test, model_cnn, 'Confustion Matrix for Basic CNN Model
')
```

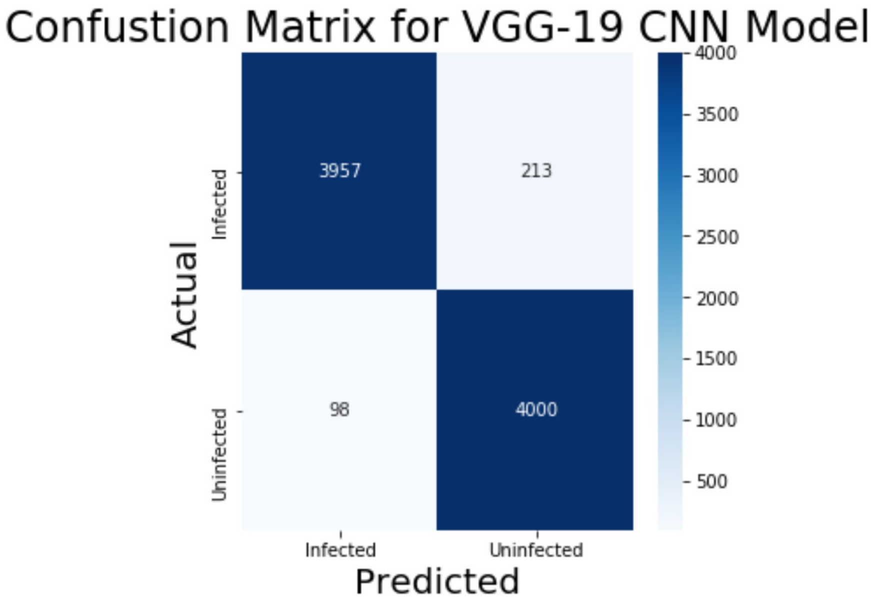



```
              precision    recall  f1-score   support

           0       0.93      0.93      0.93      4170
           1       0.93      0.93      0.93      4098

    accuracy                           0.93      8268
   macro avg       0.93      0.93      0.93      8268
weighted avg       0.93      0.93      0.93      8268

0.9304547653604257
```



VGG-19 CNN Model

In [33]:
```
evaluation_matrix(test_scaled, y_test, model_vgg_cnn, 'Confustion Matrix for VGG-19 CNN Model')
```




```
              precision    recall  f1-score   support

           0       0.98      0.95      0.96      4170
           1       0.95      0.98      0.96      4098

    accuracy                           0.96      8268
   macro avg       0.96      0.96      0.96      8268
weighted avg       0.96      0.96      0.96      8268

0.962385099177552
```