

Real vs Fake Images Detection with ELA(Error Level Analysis) and CNN

In [1]:

```
1 #import necessary libraries
2 import numpy as np
3 import matplotlib.pyplot as plt
4 %matplotlib inline
5 np.random.seed(2)
6 from sklearn.model_selection import train_test_split
7 from sklearn.metrics import confusion_matrix
8 from keras.utils.np_utils import to_categorical
9 from keras.models import Sequential
10 from keras.layers import Dense, Flatten, Conv2D, MaxPool2D, Dropout
11 from keras.optimizers import Adam
12 from keras.preprocessing.image import ImageDataGenerator
13 from keras.callbacks import EarlyStopping
14
```

In [2]:

```
1 from PIL import Image, ImageChops, ImageEnhance
2 import os
3 import itertools
```

In [3]:

```
1 def convert_to_elastic_image(path, quality):
2     temp_filename = 'temp_file_name.jpg'
3     ela_filename = 'temp_elastic.png'
4
5     image = Image.open(path).convert('RGB')
6     image.save(temp_filename, 'JPEG', quality = quality)
7     temp_image = Image.open(temp_filename)
8
9     elastic_image = ImageChops.difference(image, temp_image)
10
11     extrema = elastic_image.getextrema()
12     max_diff = max([ex[1] for ex in extrema])
13     if max_diff == 0:
14         max_diff = 1
15     scale = 255.0 / max_diff
16
17     elastic_image = ImageEnhance.Brightness(elastic_image).enhance(scale)
18
19     return elastic_image
```

Open a real image

```
In [5]: 1 real_image_path = 'CASIA2/Au/Au_ani_00001.jpg'  
2 Image.open(real_image_path)
```

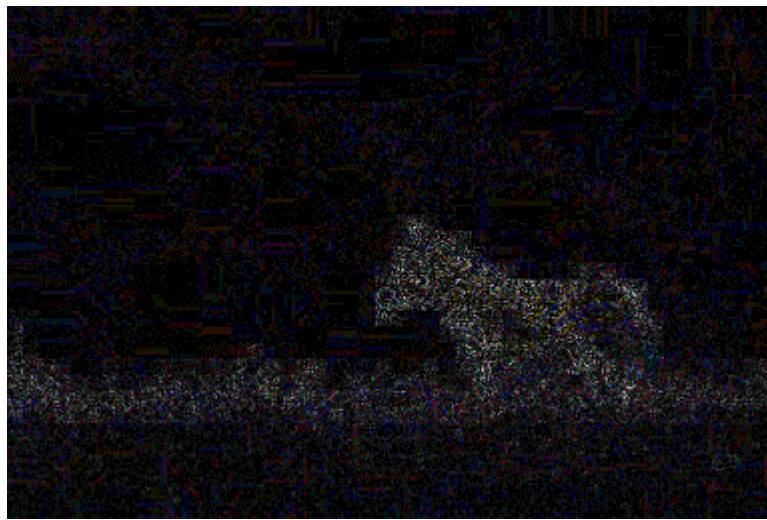
Out[5]:



After converting to ELA image

```
In [6]: 1 convert_to_elastic_image(real_image_path, 90)
```

Out[6]:



Open a fake image

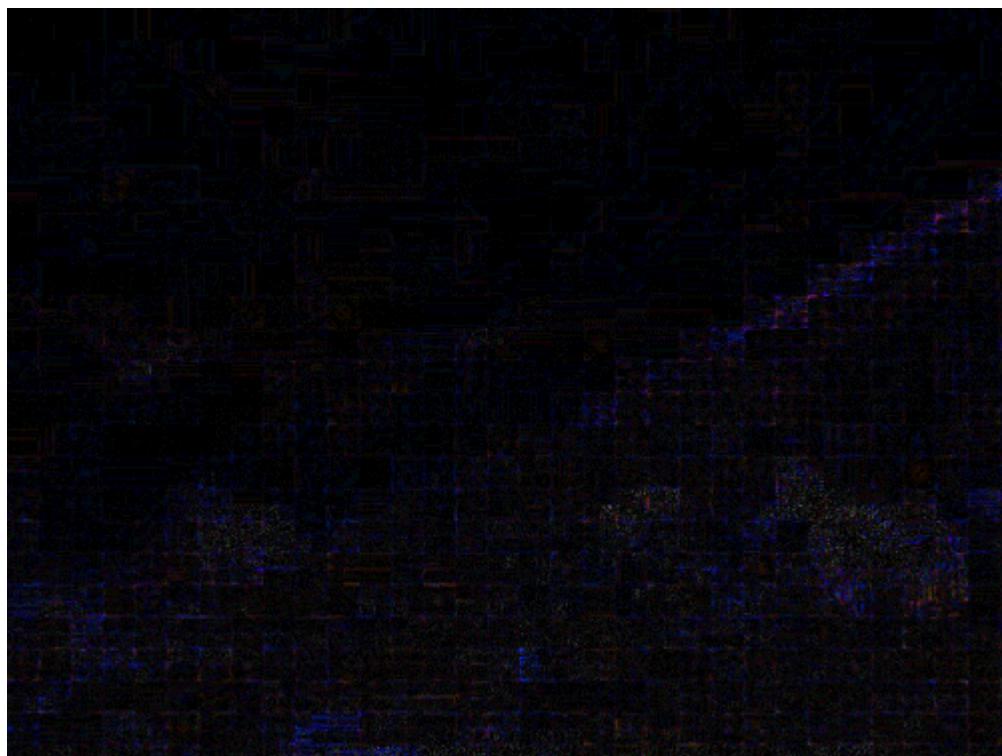
```
In [7]: 1 fake_image_path = 'CASIA2/Tp/Tp_D_NRN_S_N_ani10171_ani00001_12458.jpg'  
2 Image.open(fake_image_path)
```

Out[7]:



```
In [8]: 1 convert_to_elastic_image(fake_image_path, 90)
```

Out[8]:



Dataset Preparation

```
In [9]: 1 image_size = (128, 128)
```

```
In [10]: 1 def prepare_image(image_path):
2     return np.array(convert_to_elastic(image_path, 90)).resize(image_size)
```

```
In [11]: 1 X = [] # ELA converted images
2 Y = [] # 0 for fake, 1 for real
```

Au => Total Images 7354, Take 2100 random images from the list

Tp => Total Images 2064

```
In [12]: 1 import random
2 path = 'CASIA2/Au/'
3 for dirname, _, filenames in os.walk(path):
4     for filename in filenames:
5         if filename.endswith('jpg') or filename.endswith('png'):
6             full_path = os.path.join(dirname, filename)
7             X.append(prepare_image(full_path))
8             Y.append(1)
9             if len(Y) % 500 == 0:
10                 print(f'Processing {len(Y)} images')
11
12 random.shuffle(X)
13 X = X[:2100]
14 Y = Y[:2100]
15 print(len(X), len(Y))
```

```
Processing 500 images
Processing 1000 images
Processing 1500 images
Processing 2000 images
Processing 2500 images
Processing 3000 images
Processing 3500 images
Processing 4000 images
Processing 4500 images
Processing 5000 images
Processing 5500 images
Processing 6000 images
Processing 6500 images
Processing 7000 images
2100 2100
```

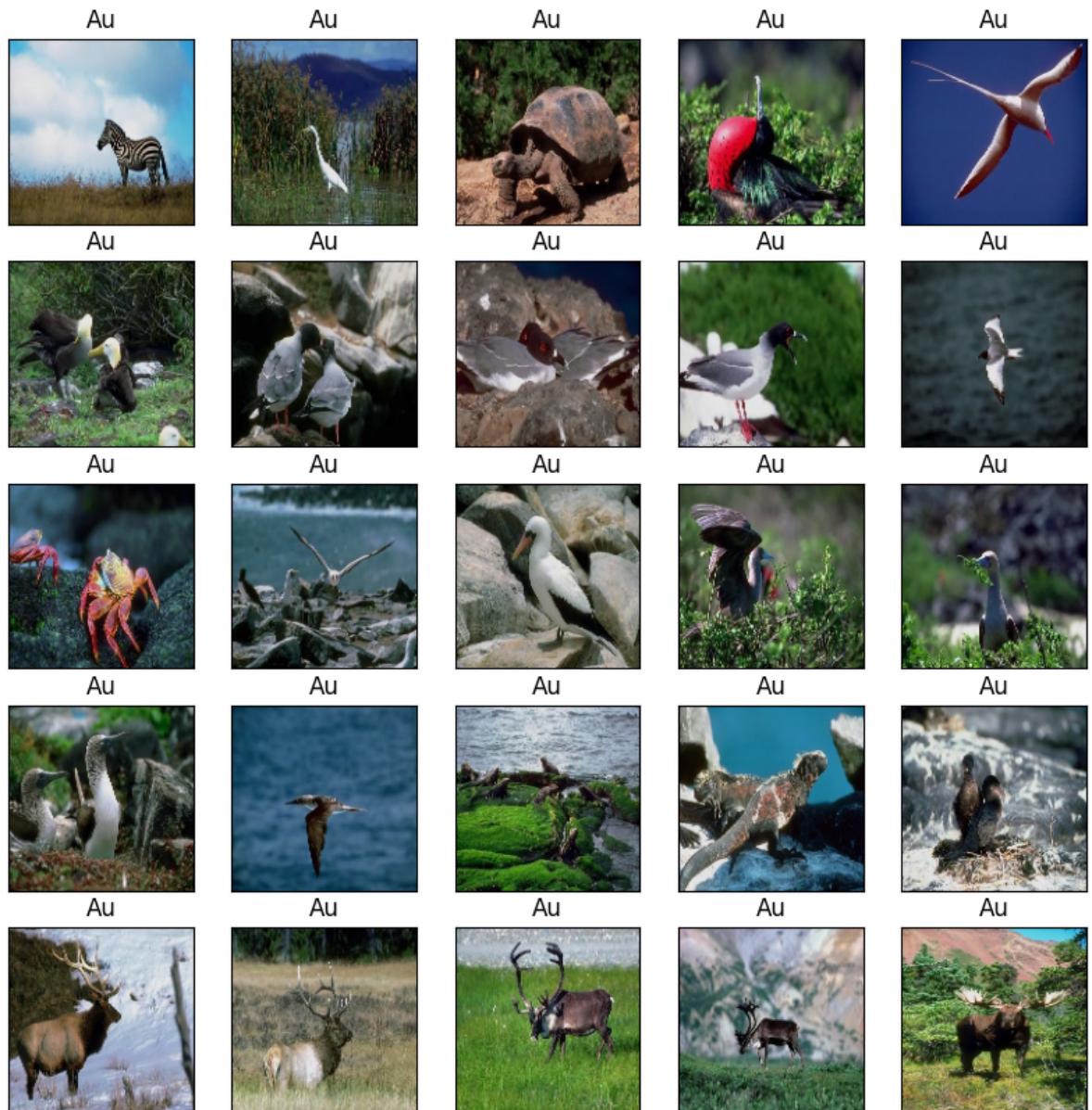
In [13]:

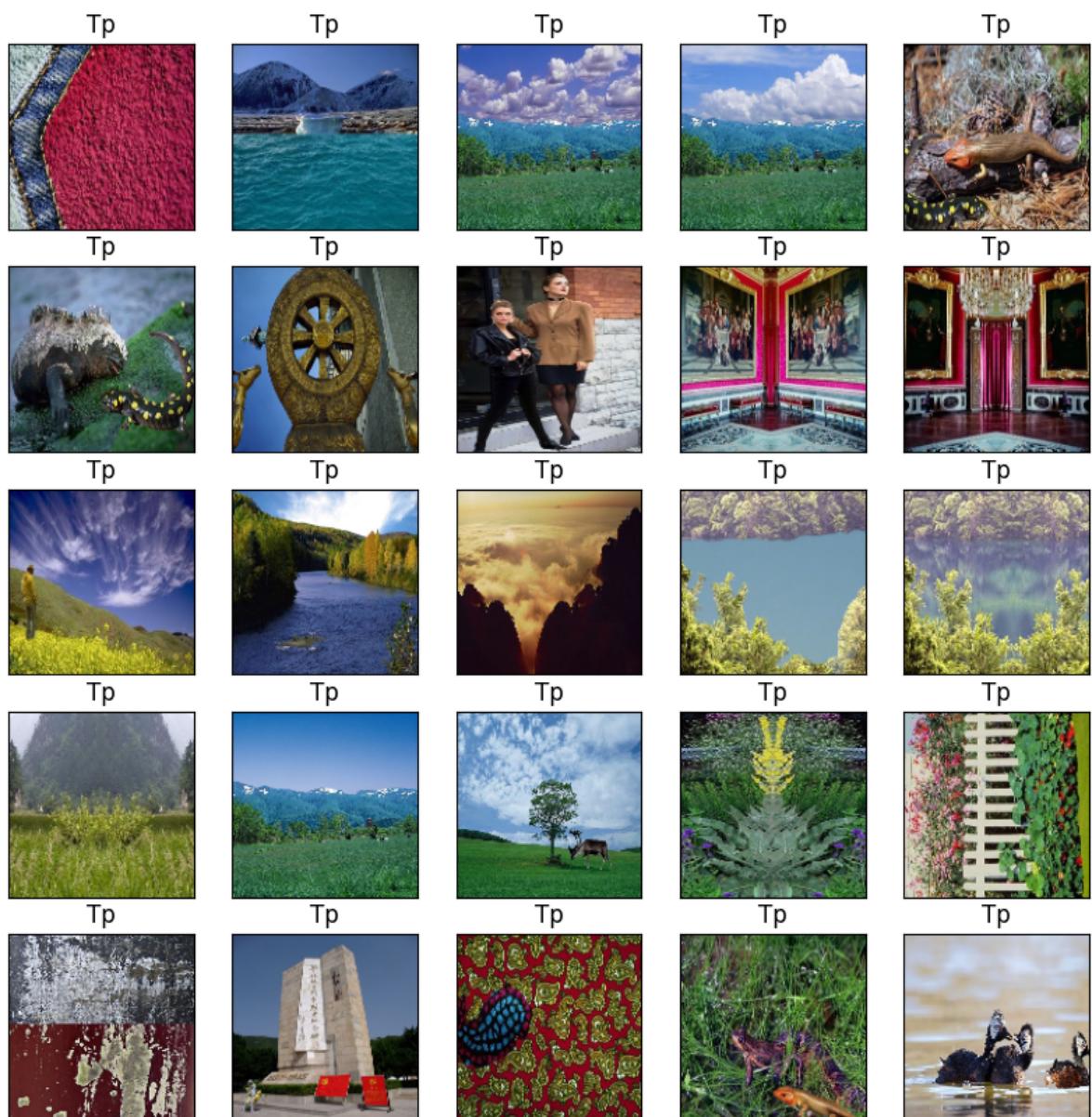
```
1 path = 'CASIA2/Tp/'  
2 for dirname, _, filenames in os.walk(path):  
3     for filename in filenames:  
4         if filename.endswith('jpg') or filename.endswith('png'):  
5             full_path = os.path.join(dirname, filename)  
6             X.append(prepare_image(full_path))  
7             Y.append(0)  
8             if len(Y) % 500 == 0:  
9                 print(f'Processing {len(Y)} images')  
10  
11 print(len(X), len(Y))
```

Processing 2500 images
Processing 3000 images
Processing 3500 images
Processing 4000 images
4164 4164

In [51]:

```
1 import os
2 import random
3 import matplotlib.pyplot as plt
4
5 # ... [Your existing code for importing and defining prepare_image]
6
7 def plot_images(image_list, title):
8     plt.figure(figsize=(10,10))
9     for i in range(25):
10         plt.subplot(5,5,i+1)
11         plt.xticks([])
12         plt.yticks([])
13         plt.imshow(image_list[i])
14         plt.title(title)
15     plt.show()
16
17 path = 'CASIA2/Au/'
18 au_images = []
19 for dirname, _, filenames in os.walk(path):
20     for filename in filenames:
21         if filename.endswith('jpg') or filename.endswith('png'):
22             full_path = os.path.join(dirname, filename)
23             au_images.append(prepare_image(full_path))
24             if len(au_images) == 25:
25                 break
26     if len(au_images) == 25:
27         break
28
29 path = 'CASIA2/Tp/'
30 tp_images = []
31 for dirname, _, filenames in os.walk(path):
32     for filename in filenames:
33         if filename.endswith('jpg') or filename.endswith('png'):
34             full_path = os.path.join(dirname, filename)
35             tp_images.append(prepare_image(full_path))
36             if len(tp_images) == 25:
37                 break
38     if len(tp_images) == 25:
39         break
40
41 # Plotting the images
42 plot_images(au_images, "Au")
43 plot_images(tp_images, "Tp")
```





One Hot Encoding to Categorical

```
In [14]: 1 X = np.array(X)
          2 Y = to_categorical(Y, 2)
          3 X = X.reshape(-1, 128, 128, 3)
```

Train Test split with 80:20 ratio

```
In [15]: 1 X_train, X_val, Y_train, Y_val = train_test_split(X, Y, test_size = 0.2, r
          2 X = X.reshape(-1,1,1,1)
          3 print(len(X_train), len(Y_train))
          4 print(len(X_val), len(Y_val))
```

3331 3331
833 833

Custom CNN Model

In [16]:

```
1 def build_model():
2     model = Sequential()
3     model.add(Conv2D(filters = 32, kernel_size = (5, 5), padding = 'valid'))
4     model.add(Conv2D(filters = 32, kernel_size = (5, 5), padding = 'valid'))
5     model.add(MaxPool2D(pool_size = (2, 2)))
6     model.add(Dropout(0.25))
7     model.add(Flatten())
8     model.add(Dense(256, activation = 'relu'))
9     model.add(Dropout(0.5))
10    model.add(Dense(2, activation = 'softmax'))
11    return model
```

In [17]:

```
1 model = build_model()
2 model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
<hr/>		
conv2d (Conv2D)	(None, 124, 124, 32)	2432
conv2d_1 (Conv2D)	(None, 120, 120, 32)	25632
max_pooling2d (MaxPooling2D)	(None, 60, 60, 32)	0
dropout (Dropout)	(None, 60, 60, 32)	0
flatten (Flatten)	(None, 115200)	0
dense (Dense)	(None, 256)	29491456
dropout_1 (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 2)	514
<hr/>		
Total params: 29,520,034		
Trainable params: 29,520,034		
Non-trainable params: 0		

In [18]:

```
1 epochs = 30
2 batch_size = 32
3
```

```
In [19]: 1 init_lr = 1e-4
          2 optimizer = Adam(lr = init_lr, decay = init_lr/epochs)
```

```
C:\Users\Nawaz\anaconda3\envs\media\lib\site-packages\keras\optimizers\optimizer_v2\adam.py:114: UserWarning: The `lr` argument is deprecated, use `learning_rate` instead.
          super().__init__(name, **kwargs)
```

```
In [20]: 1 model.compile(optimizer = optimizer, loss = 'binary_crossentropy', metrics
```

```
In [21]: 1 early_stopping = EarlyStopping(monitor = 'val_acc',
          2                               min_delta = 0,
          3                               patience = 2,
          4                               verbose = 0,
          5                               mode = 'auto')
```

```
In [22]: 1 hist = model.fit(X_train,
2                      Y_train,
3                      batch_size = batch_size,
4                      epochs = epochs,
5                      validation_data = (X_val, Y_val),
6                      callbacks = [early_stopping])
```

```
Epoch 1/30
105/105 [=====] - ETA: 0s - loss: 0.5010 - accuracy: 0.7544WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 8s 19ms/step - loss: 0.5010 - accuracy: 0.7544 - val_loss: 0.3261 - val_accuracy: 0.8896
Epoch 2/30
105/105 [=====] - ETA: 0s - loss: 0.3036 - accuracy: 0.8973WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.3036 - accuracy: 0.8973 - val_loss: 0.2523 - val_accuracy: 0.9160
Epoch 3/30
104/105 [=====>..] - ETA: 0s - loss: 0.2477 - accuracy: 0.9186WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.2485 - accuracy: 0.9183 - val_loss: 0.2277 - val_accuracy: 0.9196
Epoch 4/30
101/105 [=====>..] - ETA: 0s - loss: 0.2276 - accuracy: 0.9177WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.2330 - accuracy: 0.9168 - val_loss: 0.2180 - val_accuracy: 0.9232
Epoch 5/30
102/105 [=====>..] - ETA: 0s - loss: 0.2001 - accuracy: 0.9265WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.2005 - accuracy: 0.9264 - val_loss: 0.2219 - val_accuracy: 0.9160
Epoch 6/30
103/105 [=====>..] - ETA: 0s - loss: 0.1930 - accuracy: 0.9272WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.1921 - accuracy: 0.9273 - val_loss: 0.2445 - val_accuracy: 0.9064
Epoch 7/30
101/105 [=====>..] - ETA: 0s - loss: 0.1764 - accuracy: 0.9369WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.1751 - accuracy: 0.9373 - val_loss: 0.2024 - val_accuracy: 0.9244
Epoch 8/30
102/105 [=====>..] - ETA: 0s - loss: 0.1571 - accuracy: 0.9406WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.1570 - accuracy: 0.9409 - val_loss: 0.2412 - val_accuracy: 0.9064
Epoch 9/30
101/105 [=====>..] - ETA: 0s - loss: 0.1372 - accuracy: 0.9505WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.1379 - accuracy: 0.9508 - val_loss: 0.2319 - val_accuracy: 0.9076
Epoch 10/30
102/105 [=====>..] - ETA: 0s - loss: 0.1298 - accuracy: 0.9525WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which
```

```
is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.1299 - accuracy: 0.9529 - val_loss: 0.1881 - val_accuracy: 0.9304
Epoch 11/30
104/105 [=====>.] - ETA: 0s - loss: 0.1102 - accuracy: 0.9633WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.1101 - accuracy: 0.9634 - val_loss: 0.1766 - val_accuracy: 0.9388
Epoch 12/30
104/105 [=====>.] - ETA: 0s - loss: 0.1028 - accuracy: 0.9615WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.1028 - accuracy: 0.9616 - val_loss: 0.1765 - val_accuracy: 0.9376
Epoch 13/30
104/105 [=====>.] - ETA: 0s - loss: 0.0910 - accuracy: 0.9697WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.0910 - accuracy: 0.9697 - val_loss: 0.2175 - val_accuracy: 0.9280
Epoch 14/30
103/105 [=====>.] - ETA: 0s - loss: 0.0767 - accuracy: 0.9760WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.0764 - accuracy: 0.9763 - val_loss: 0.1710 - val_accuracy: 0.9388
Epoch 15/30
102/105 [=====>.] - ETA: 0s - loss: 0.0744 - accuracy: 0.9776WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.0757 - accuracy: 0.9769 - val_loss: 0.1932 - val_accuracy: 0.9328
Epoch 16/30
104/105 [=====>.] - ETA: 0s - loss: 0.0700 - accuracy: 0.9790WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.0699 - accuracy: 0.9790 - val_loss: 0.1750 - val_accuracy: 0.9376
Epoch 17/30
105/105 [=====] - ETA: 0s - loss: 0.0567 - accuracy: 0.9811WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.0567 - accuracy: 0.9811 - val_loss: 0.2171 - val_accuracy: 0.9352
Epoch 18/30
104/105 [=====>.] - ETA: 0s - loss: 0.0511 - accuracy: 0.9868WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.0511 - accuracy: 0.9868 - val_loss: 0.1886 - val_accuracy: 0.9436
Epoch 19/30
105/105 [=====] - ETA: 0s - loss: 0.0437 - accuracy: 0.9898WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.0437 - accuracy: 0.9898 - val_loss: 0.1894 - val_accuracy: 0.9484
```

Epoch 20/30

```
104/105 [=====>.] - ETA: 0s - loss: 0.0430 - accuracy: 0.9871
WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.0430 - accuracy: 0.9871 - val_loss: 0.1773 - val_accuracy: 0.9436
```

Epoch 21/30

```
102/105 [=====>.] - ETA: 0s - loss: 0.0439 - accuracy: 0.9859
WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.0437 - accuracy: 0.9859 - val_loss: 0.1860 - val_accuracy: 0.9412
```

Epoch 22/30

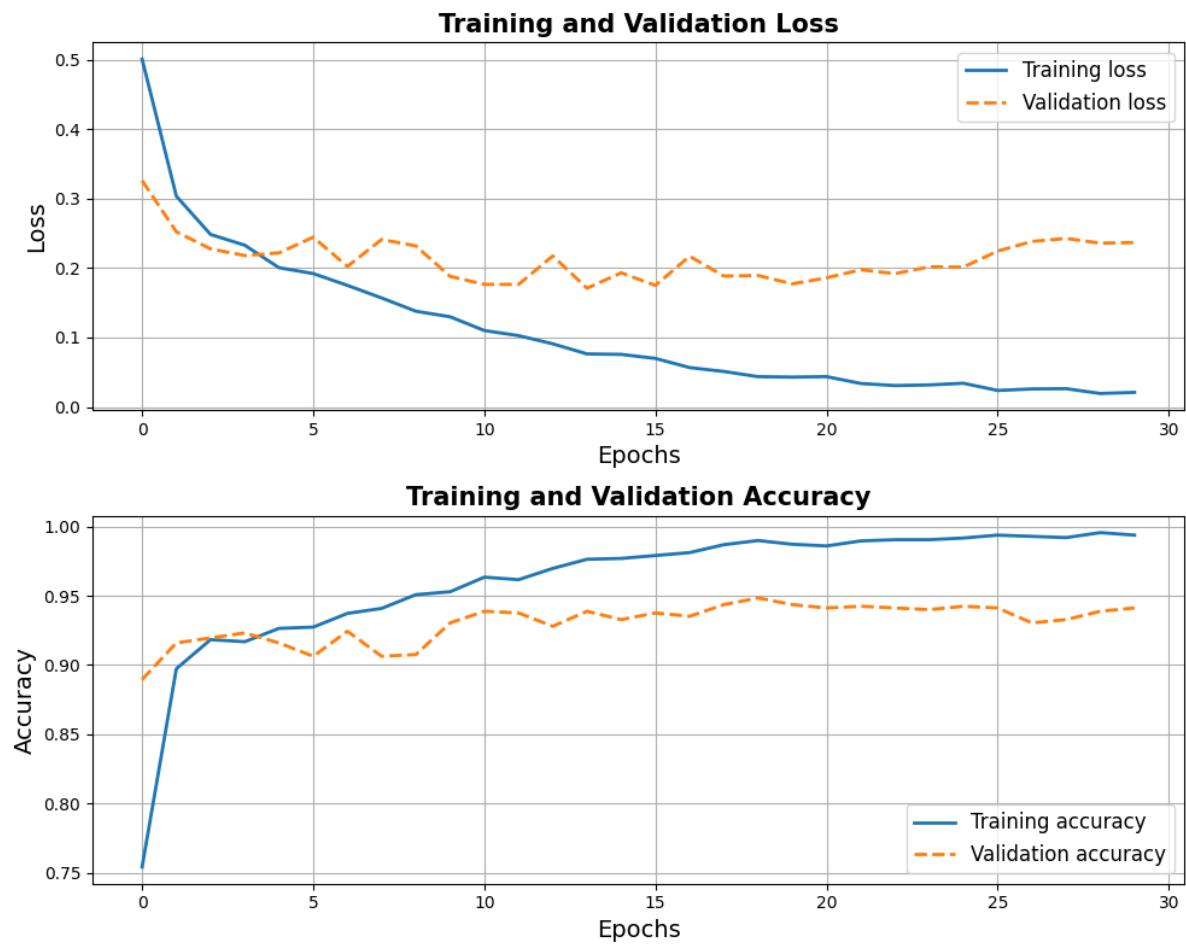
```
105/105 [=====] - ETA: 0s - loss: 0.0338 - accuracy: 0.9895
WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.0338 - accuracy: 0.9895 - val_loss: 0.1976 - val_accuracy: 0.9424
```

```
Epoch 23/30
103/105 [=====>.] - ETA: 0s - loss: 0.0307 - accuracy: 0.9903WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.0308 - accuracy: 0.9904 - val_loss: 0.1919 - val_accuracy: 0.9412
Epoch 24/30
104/105 [=====>.] - ETA: 0s - loss: 0.0315 - accuracy: 0.9907WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.0317 - accuracy: 0.9904 - val_loss: 0.2019 - val_accuracy: 0.9400
Epoch 25/30
102/105 [=====>..] - ETA: 0s - loss: 0.0336 - accuracy: 0.9920WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.0341 - accuracy: 0.9916 - val_loss: 0.2015 - val_accuracy: 0.9424
Epoch 26/30
101/105 [=====>..] - ETA: 0s - loss: 0.0237 - accuracy: 0.9938WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.0238 - accuracy: 0.9937 - val_loss: 0.2245 - val_accuracy: 0.9412
Epoch 27/30
104/105 [=====>.] - ETA: 0s - loss: 0.0259 - accuracy: 0.9928WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.0260 - accuracy: 0.9928 - val_loss: 0.2384 - val_accuracy: 0.9304
Epoch 28/30
102/105 [=====>.] - ETA: 0s - loss: 0.0263 - accuracy: 0.9917WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.0263 - accuracy: 0.9919 - val_loss: 0.2427 - val_accuracy: 0.9328
Epoch 29/30
102/105 [=====>.] - ETA: 0s - loss: 0.0196 - accuracy: 0.9954WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.0194 - accuracy: 0.9955 - val_loss: 0.2359 - val_accuracy: 0.9388
Epoch 30/30
102/105 [=====>.] - ETA: 0s - loss: 0.0212 - accuracy: 0.9936WARNING:tensorflow:Early stopping conditioned on metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy
105/105 [=====] - 2s 16ms/step - loss: 0.0210 - accuracy: 0.9937 - val_loss: 0.2368 - val_accuracy: 0.9412
```

In [23]: 1 model.save('model_casia_run_hamad.h5')

In [24]:

```
1 import matplotlib.pyplot as plt
2
3 # Set a consistent color palette
4 colors = {
5     'train': '#1f77b4', # blue
6     'val': '#ff7f0e'    # orange
7 }
8
9 fig, ax = plt.subplots(2, 1, figsize=(10, 8)) # Adjusted the figure size
10
11 # Training and validation loss
12 ax[0].plot(hist.history['loss'], color=colors['train'], label="Training loss")
13 ax[0].plot(hist.history['val_loss'], color=colors['val'], label="Validation loss")
14 ax[0].set_title('Training and Validation Loss', fontweight='bold', fontsize=16)
15 ax[0].set_xlabel('Epochs', fontsize=14)
16 ax[0].set_ylabel('Loss', fontsize=14)
17 ax[0].legend(loc='upper right', fontsize=12)
18 ax[0].grid(True)
19
20 # Training and validation accuracy
21 ax[1].plot(hist.history['accuracy'], color=colors['train'], label="Training accuracy")
22 ax[1].plot(hist.history['val_accuracy'], color=colors['val'], label="Validation accuracy")
23 ax[1].set_title('Training and Validation Accuracy', fontweight='bold', fontsize=16)
24 ax[1].set_xlabel('Epochs', fontsize=14)
25 ax[1].set_ylabel('Accuracy', fontsize=14)
26 ax[1].legend(loc='lower right', fontsize=12)
27 ax[1].grid(True)
28
29 plt.tight_layout() # Adjust the spacing between plots
30 plt.show()
31
```



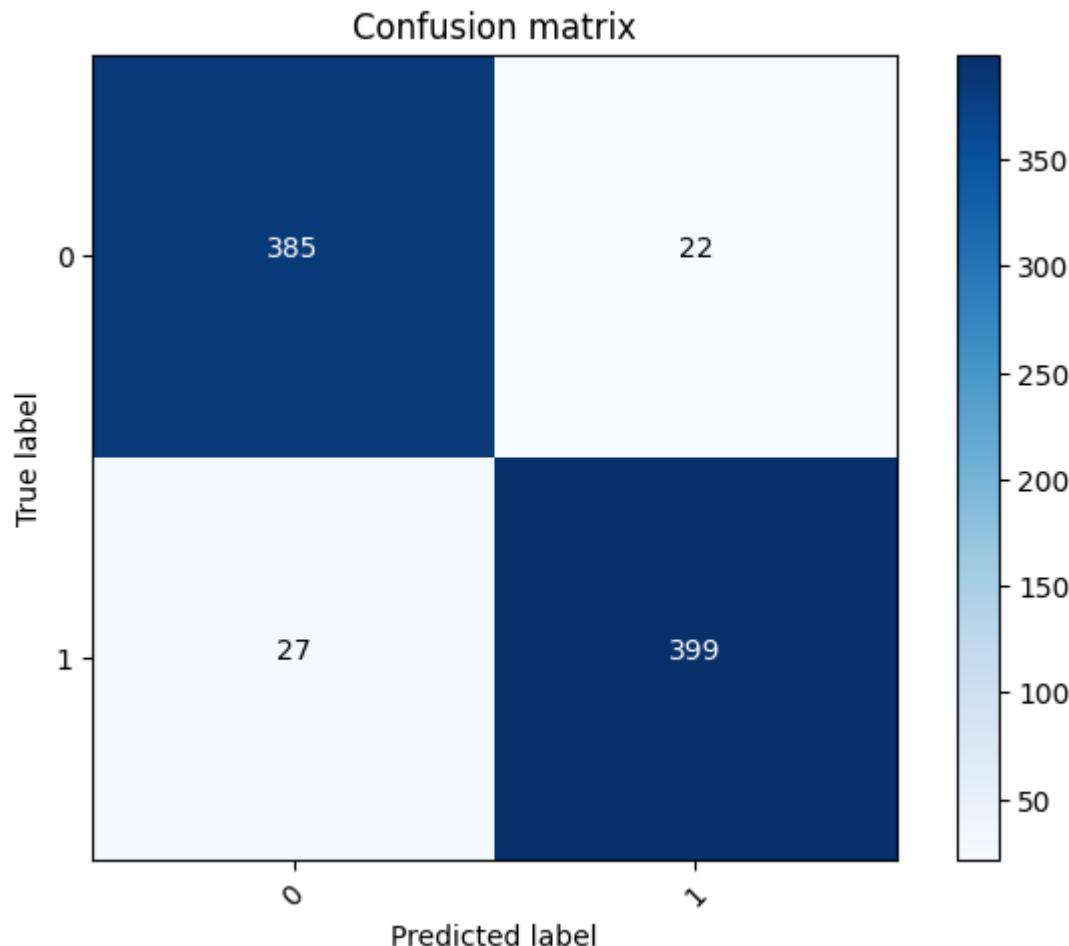
In [26]:

```
1 def plot_confusion_matrix(cm, classes,
2                           normalize=False,
3                           title='Confusion matrix',
4                           cmap=plt.cm.Blues):
5     """
6     This function prints and plots the confusion matrix.
7     Normalization can be applied by setting `normalize=True`.
8     """
9     plt.imshow(cm, interpolation='nearest', cmap=cmap)
10    plt.title(title)
11    plt.colorbar()
12    tick_marks = np.arange(len(classes))
13    plt.xticks(tick_marks, classes, rotation=45)
14    plt.yticks(tick_marks, classes)
15
16    if normalize:
17        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
18
19    thresh = cm.max() / 2.
20    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
21        plt.text(j, i, cm[i, j],
22                  horizontalalignment="center",
23                  color="white" if cm[i, j] > thresh else "black")
24
25    plt.tight_layout()
26    plt.ylabel('True label')
27    plt.xlabel('Predicted label')
28
29
30
```

In [27]:

```
1 # Predict the values from the validation dataset
2 Y_pred = model.predict(X_val)
3 # Convert predictions classes to one hot vectors
4 Y_pred_classes = np.argmax(Y_pred, axis = 1)
5 # Convert validation observations to one hot vectors
6 Y_true = np.argmax(Y_val, axis = 1)
7 # compute the confusion matrix
8 confusion_mtx = confusion_matrix(Y_true, Y_pred_classes)
9 # plot the confusion matrix
10 plot_confusion_matrix(confusion_mtx, classes = range(2))
```

27/27 [=====] - 1s 16ms/step



Testing Prediction

In [37]:

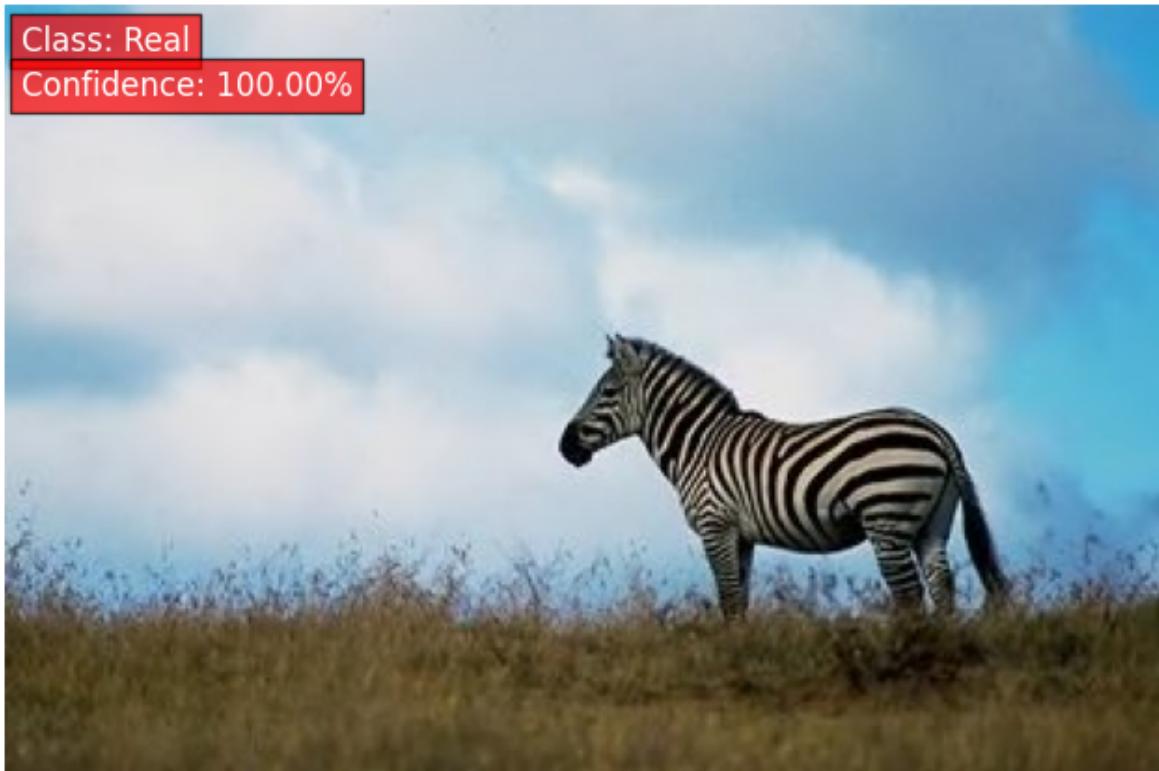
```
1 class_names = ['Forgery', 'Real']
```

In [38]:

```
1 import numpy as np
2 import matplotlib.pyplot as plt
3 import matplotlib.image as mpimg
4
5 # Assuming the prepare_image function loads and preprocesses the image
6 def prepare_image(image_path):
7     img = mpimg.imread(image_path)
8     # ... any other preprocessing steps you might have ...
9     return img
10
11 real_image_path = 'CASIA2/Au/Au_ani_00001.jpg'
12 image = prepare_image(real_image_path)
13 image_for_model = image.reshape(-1, 128, 128, 3) # reshaping for the model
14
15 y_pred = model.predict(image_for_model)
16 y_pred_class = np.argmax(y_pred, axis = 1)[0]
17 print('Image Shape',image.shape)
18
19 # Display the image using matplotlib
20 plt.figure(figsize=(8, 6)) # adjust the figure size
21 plt.imshow(image)
22 plt.axis('off') # turn off axis numbers and ticks
23
24 # Overlay the predicted class and confidence level on the image
25 confidence = np.amax(y_pred) * 100
26 plt.text(5, 15, f"Class: {class_names[y_pred_class]}", color='white', fontweight='bold')
27 plt.text(5, 30, f"Confidence: {confidence:.2f}%", color='white', fontsize=12)
28
29 plt.show()
30
```

1/1 [=====] - 0s 19ms/step

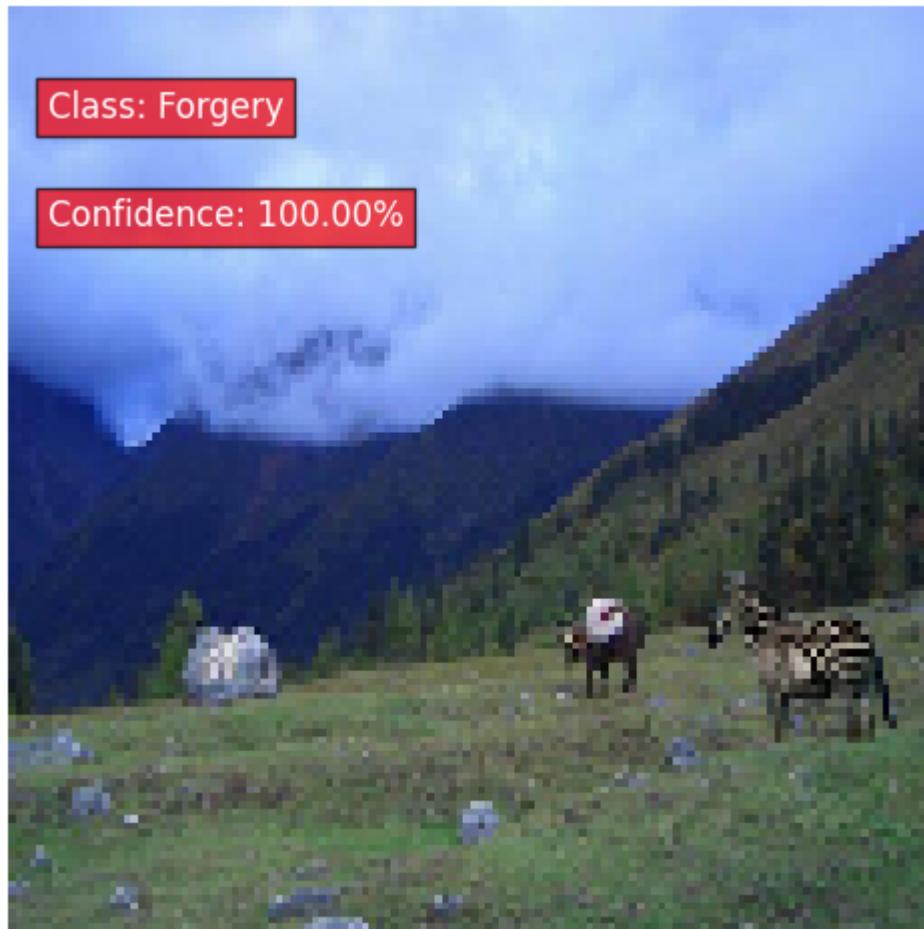
Image Shape (256, 384, 3)



In [43]:

```
1 import cv2
2 import numpy as np
3 import matplotlib.pyplot as plt
4
5 def prepare_image(image_path):
6     img = cv2.imread(image_path)
7     img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB) # Convert from BGR to RGB
8     img = cv2.resize(img, (128, 128)) # Resize the image
9     img = img / 255.0 # Normalize
10    return img
11
12 fake_image_path = 'CASIA2/Tp/Tp_D_NRN_S_N_ani10171_ani00001_12458.jpg'
13 image = prepare_image(fake_image_path)
14 image_for_model = image.reshape(-1, 128, 128, 3) # reshaping for the model
15
16 y_pred = model.predict(image_for_model)
17 y_pred_class = np.argmax(y_pred, axis=1)[0]
18 confidence = np.amax(y_pred) * 100
19
20 # If confidence is below 40%, Label it as "Forgery"
21 if confidence < 40:
22     label = "Forgery"
23     confidence = 100 - confidence # Flip the confidence to represent the
24 else:
25     label = class_names[y_pred_class]
26
27 # Display the image using matplotlib
28 plt.figure(figsize=(8, 6)) # adjust the figure size
29 plt.imshow(image)
30 plt.axis('off') # turn off axis numbers and ticks
31
32 # Overlay the predicted class and confidence level on the image
33 plt.text(5, 15, f"Class: {label}", color='white', fontsize=12, bbox=dict(f
34 plt.text(5, 30, f"Confidence: {confidence:.2f}%", color='white', fontsize=12,
35
36 plt.show()
37
```

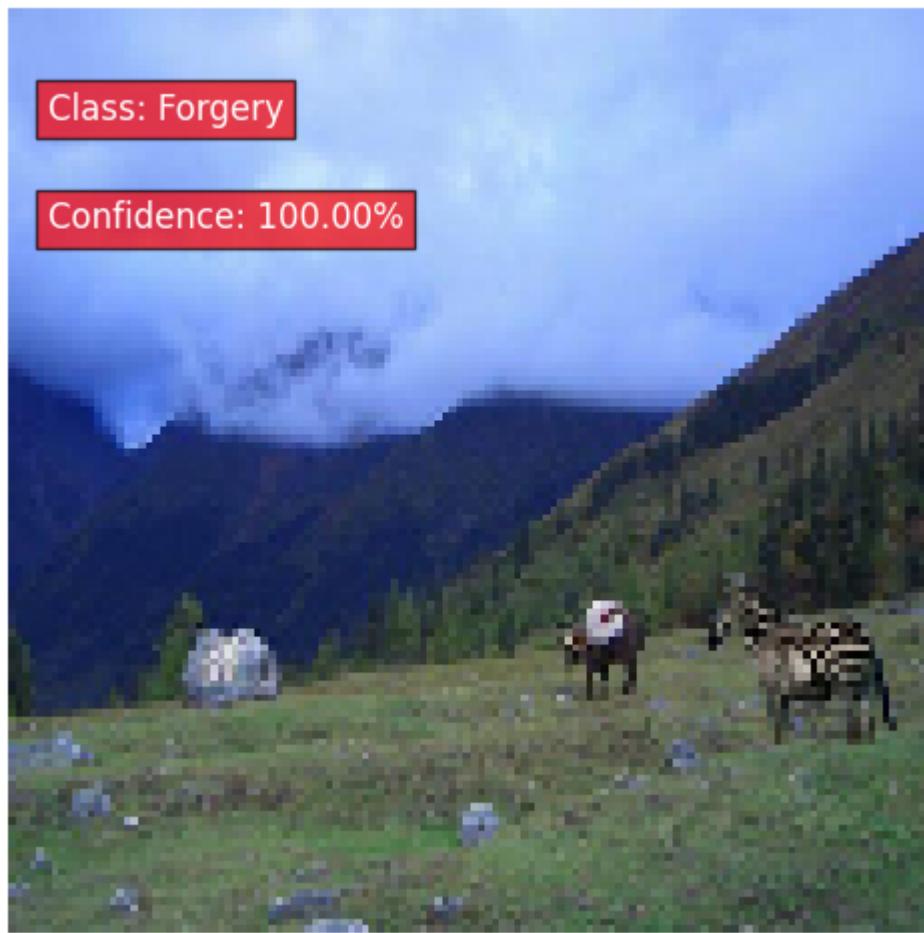
1/1 [=====] - 0s 16ms/step



In [57]:

```
1 import cv2
2 import numpy as np
3 import matplotlib.pyplot as plt
4
5 def prepare_image(image_path):
6     img = cv2.imread(image_path)
7     img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB) # Convert from BGR to RGB
8     img = cv2.resize(img, (128, 128)) # Resize the image
9     img = img / 255.0 # Normalize
10    return img
11
12 fake_image_path = 'CASIA2/Tp/Tp_D_NRN_S_N_ani10171_ani00001_12458.jpg'
13 image = prepare_image(fake_image_path)
14 image_for_model = image.reshape(-1, 128, 128, 3) # reshaping for the model
15
16 y_pred = model.predict(image_for_model)
17 y_pred_class = np.argmax(y_pred, axis=1)[0]
18
19 # Display the image using matplotlib
20 plt.figure(figsize=(8, 6)) # adjust the figure size
21 plt.imshow(image)
22 plt.axis('off') # turn off axis numbers and ticks
23
24 # Overlay the predicted class and confidence Level on the image
25 confidence = np.amax(y_pred) * 100
26 plt.text(5, 15, f"Class: {class_names[y_pred_class]}", color='white', fontweight='bold')
27 plt.text(5, 30, f"Confidence: {confidence:.2f}%", color='white', fontsize=12)
28
29 plt.show()
30
```

1/1 [=====] - 0s 20ms/step



In [58]:

```
1 # fake_image = os.listdir('CASIA2/Tp/')
2 # correct = 0
3 # total = 0
4 # for file_name in fake_image:
5 #     if file_name.endswith('jpg') or filename.endswith('png'):
6 #         fake_image_path = os.path.join('CASIA2/Tp/', file_name)
7 #         image = prepare_image(fake_image_path)
8 #         image = image.reshape(-1, 128, 128, 3)
9 #         y_pred = model.predict(image)
10 #        y_pred_class = np.argmax(y_pred, axis = 1)[0]
11 #        total += 1
12 #        if y_pred_class == 0:
13 #            correct += 1
14 #        print(f'Class: {class_names[y_pred_class]} Confidence: {np.a
```

In [55]:

```
1 # print(f'Total: {total}, Correct: {correct}, Acc: {correct / total * 100.0}
```

In [52]:

```
1 # real_image = os.listdir('CASIA2/Au/')
2 # correct_r = 0
3 # total_r = 0
4 # for file_name in real_image:
5 #     if file_name.endswith('jpg') or file_name.endswith('png'):
6 #         real_image_path = os.path.join('CASIA2/Au/', file_name)
7 #         image = prepare_image(real_image_path)
8 #         image = image.reshape(-1, 128, 128, 3)
9 #         y_pred = model.predict(image)
10 #        y_pred_class = np.argmax(y_pred, axis = 1)[0]
11 #        total_r += 1
12 #        if y_pred_class == 1:
13 #            correct_r += 1
14 #            print(f'Class: {class_names[y_pred_class]} Confidence: {np.a
```

In [54]:

```
1 # correct += correct_r
2 # total += total_r
3 # print(f'Total: {total_r}, Correct: {correct_r}, Acc: {correct_r / total_r * 100.}
4 # print(f'Total: {total}, Correct: {correct}, Acc: {correct / total * 100.}
```