

# German Traffic Sign Classification

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import cv2
import tensorflow as tf
from PIL import Image
import os
import plotly
import plotly.graph_objs as go
import time
import itertools
import seaborn as sns
import warnings
import tqdm
import math
from mpl_toolkits.mplot3d import Axes3D
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from keras.utils import to_categorical
from keras.models import Sequential, load_model
from keras.layers import Conv2D, MaxPool2D, Dense, Flatten, Dropout

warnings.simplefilter(action='ignore', category=FutureWarning)
%matplotlib inline
plotly.offline.init_notebook_mode(True)
```

Using TensorFlow backend.

## Exploratory Data Analysis & Data Wrangling

Here we will be creating the functions for plotting of graph by per column distribution, Correlation Matrix and Scatter Plot

In [2]:

```
# Distribution graphs (histogram/bar graph) of column data
def plotPerColumnDistribution(df, nGraphShown, nGraphPerRow):
    nunique = df.nunique()
    df = df[[col for col in df if nunique[col] > 1 and nunique[col] < 50]] # For displaying
    nRow, nCol = df.shape
    columnNames = list(df)
    nGraphRow = (nCol + nGraphPerRow - 1) / nGraphPerRow
    plt.figure(num = None, figsize = (6 * nGraphPerRow, 8 * nGraphRow), dpi = 80, facecolor = 'w', edgecolor = 'k')
    for i in range(min(nCol, nGraphShown)):
        plt.subplot(nGraphRow, nGraphPerRow, i + 1)
        columnDf = df.iloc[:, i]
        if (not np.issubdtype(type(columnDf.iloc[0]), np.number)):
            valueCounts = columnDf.value_counts()
            valueCounts.plot.bar()
        else:
            columnDf.hist()
        plt.ylabel('counts')
        plt.xticks(rotation = 90)
        plt.title(f'{columnNames[i]} (column {i})')
    plt.tight_layout(pad = 1.0, w_pad = 1.0, h_pad = 1.0)
    plt.show()
```

In [3]:

```
# Correlation matrix
def plotCorrelationMatrix(df, graphWidth):
    filename = df.dataframeName
    df = df.dropna('columns') # drop columns with NaN
    df = df[[col for col in df if df[col].nunique() > 1]] # keep columns where there are more than 1 unique values
    if df.shape[1] < 2:
        print(f'No correlation plots shown: The number of non-NaN or constant columns ({df.shape[1]}) is less than 2')
        return
    corr = df.corr()
    plt.figure(num=None, figsize=(graphWidth, graphWidth), dpi=80, facecolor='w', edgecolor='k')
    corrMat = plt.matshow(corr, fignum = 1)
    plt.xticks(range(len(corr.columns)), corr.columns, rotation=90)
    plt.yticks(range(len(corr.columns)), corr.columns)
    plt.gca().xaxis.tick_bottom()
    plt.colorbar(corrMat)
    plt.title(f'Correlation Matrix for {filename}', fontsize=15)
    plt.show()
```

In [4]:

```
# Scatter and density plots
def plotScatterMatrix(df, plotSize, textSize):
    df = df.select_dtypes(include=[np.number]) # keep only numerical columns
    # Remove rows and columns that would lead to df being singular
    df = df.dropna('columns')
    df = df[[col for col in df if df[col].nunique() > 1]] # keep columns where there are more than 1 unique values
    columnNames = list(df)
    if len(columnNames) > 10: # reduce the number of columns for matrix inversion of kernel
        columnNames = columnNames[:10]
    df = df[columnNames]
    ax = pd.plotting.scatter_matrix(df, alpha=0.75, figsize=[plotSize, plotSize], diagonal=True)
    corrs = df.corr().values
    for i, j in zip(*plt.np.triu_indices_from(ax, k = 1)):
        ax[i, j].annotate('Corr. coef = %.3f' % corrs[i, j], (0.8, 0.2), xycoords='axes fraction')
    plt.suptitle('Scatter and Density Plot')
    plt.show()
```

Now you're ready to read in the data and use the plotting functions to visualize the data.

## Let's check 1st file: Meta.csv

In [5]:

```
nRowsRead = 1000 # specify 'None' if want to read whole file
df1 = pd.read_csv('Meta.csv', delimiter=',', nrows = nRowsRead)
df1.dataframeName = 'Meta.csv'
nRow, nCol = df1.shape
print(f'There are {nRow} rows and {nCol} columns')
```

There are 43 rows and 5 columns

Let's take a quick look at what the data looks like:

In [6]:

```
df1.head(5)
```

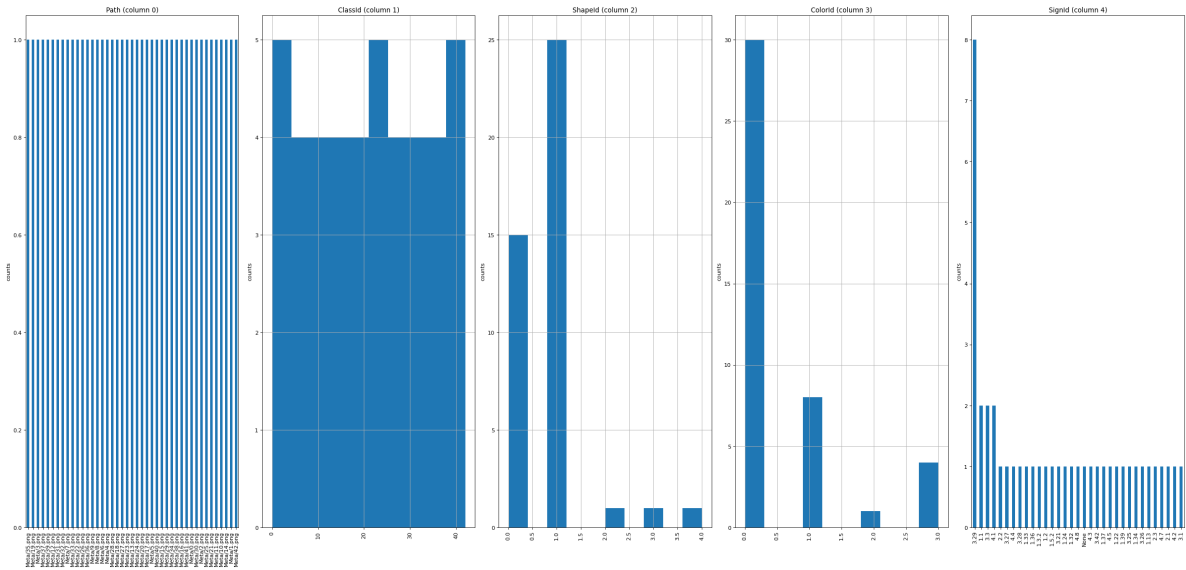
Out[6]:

	Path	ClassId	ShapeId	ColorId	SignId
0	Meta/27.png	27	0	0	1.32
1	Meta/0.png	0	1	0	3.29
2	Meta/1.png	1	1	0	3.29
3	Meta/10.png	10	1	0	3.27
4	Meta/11.png	11	0	0	1.22

Distribution graphs (histogram/bar graph) of sampled columns:

In [7]:

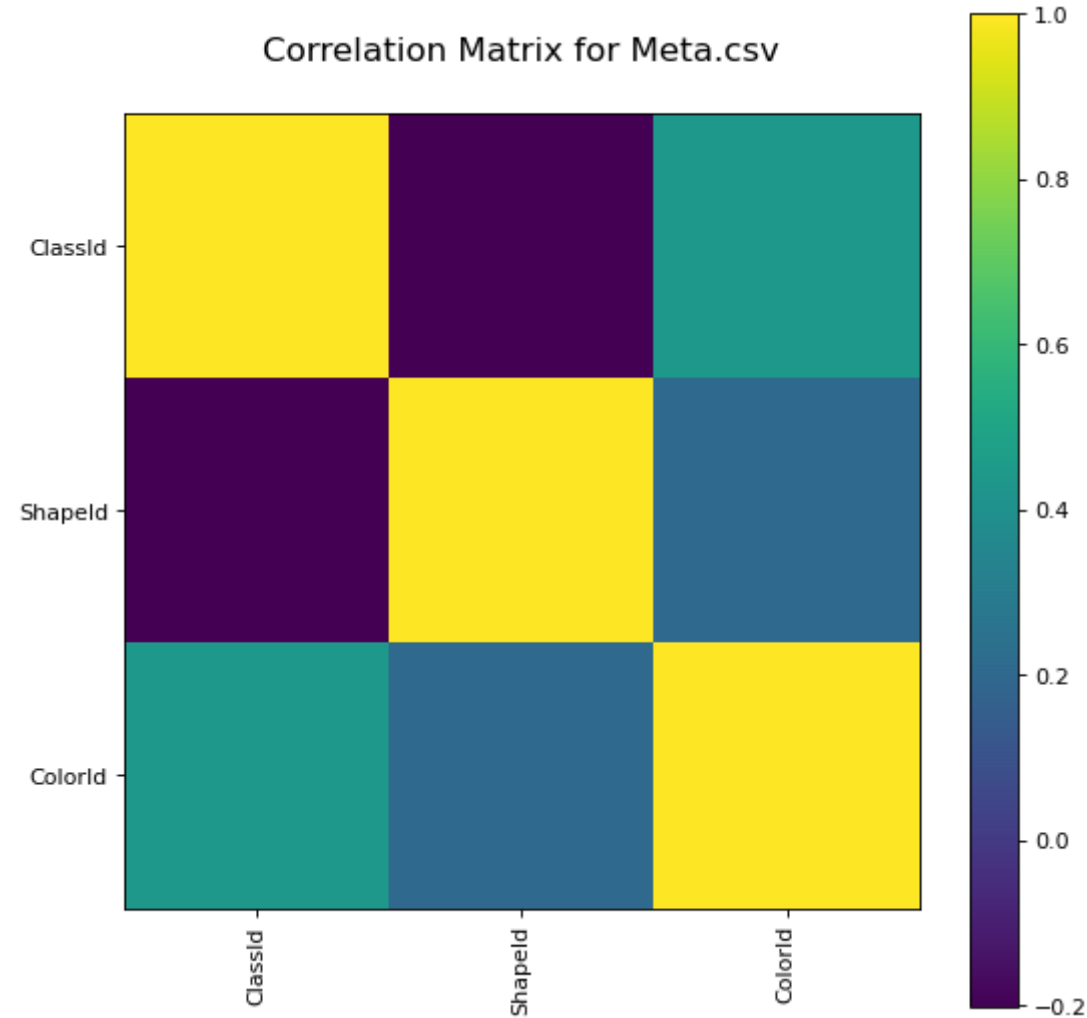
```
plotPerColumnDistribution(df1, 10, 5)
```



Correlation matrix:

In [8]:

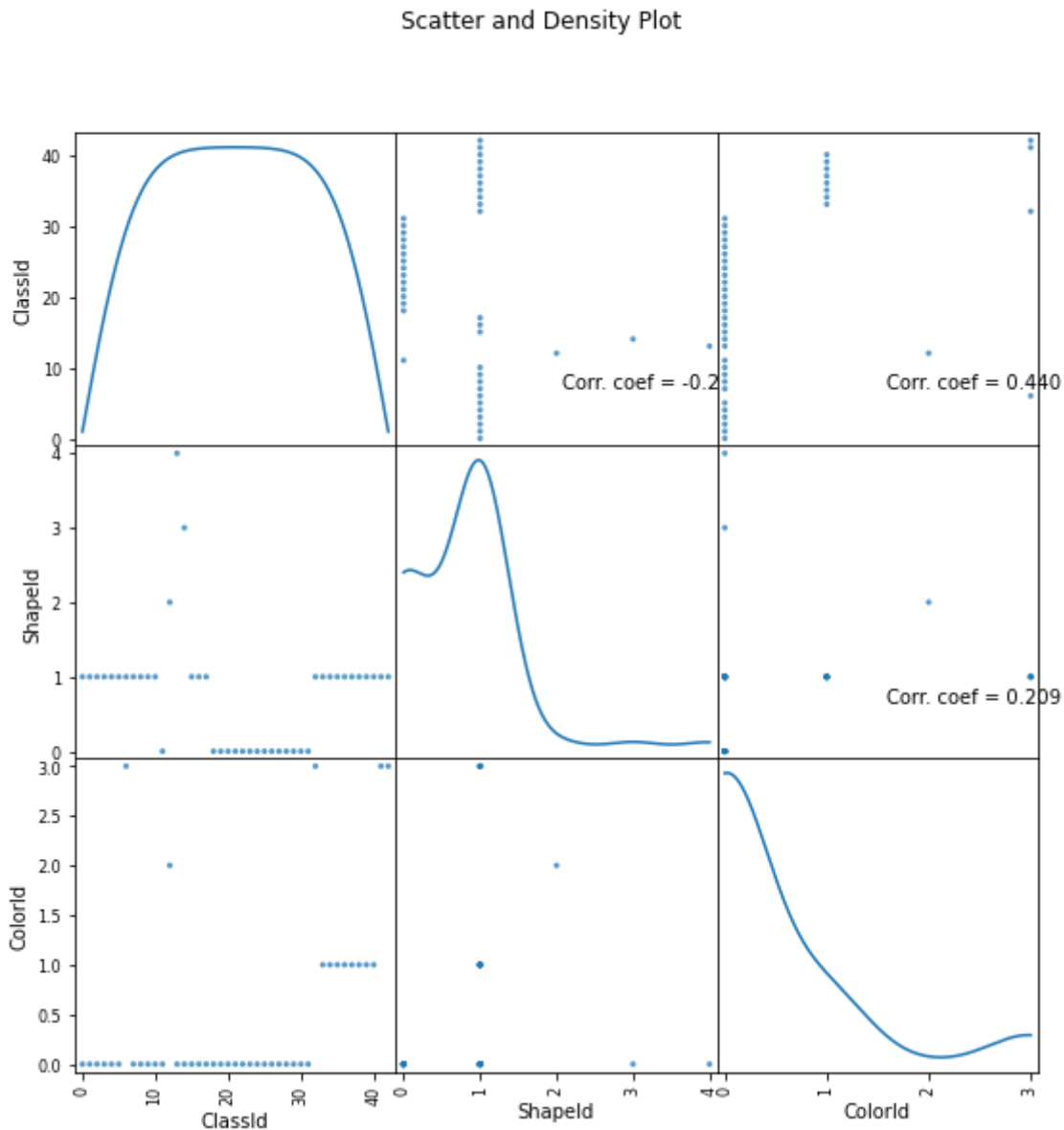
```
plotCorrelationMatrix(df1, 8)
```



Scatter and density plots:

In [9]:

```
plotScatterMatrix(df1, 9, 10)
```



**Let's check 2nd file: Test.csv**

In [10]:

```
nRowsRead = 1000 # specify 'None' if want to read whole file
# Test.csv has 12630 rows in reality, but we are only loading/previewing the first 1000 row
df2 = pd.read_csv('Test.csv', delimiter=',', nrows = nRowsRead)
df2.dataframeName = 'Test.csv'
nRow, nCol = df2.shape
print(f'There are {nRow} rows and {nCol} columns')
```

There are 1000 rows and 8 columns

Let's take a quick look at what the data looks like:

In [11]:

```
df2.head(5)
```

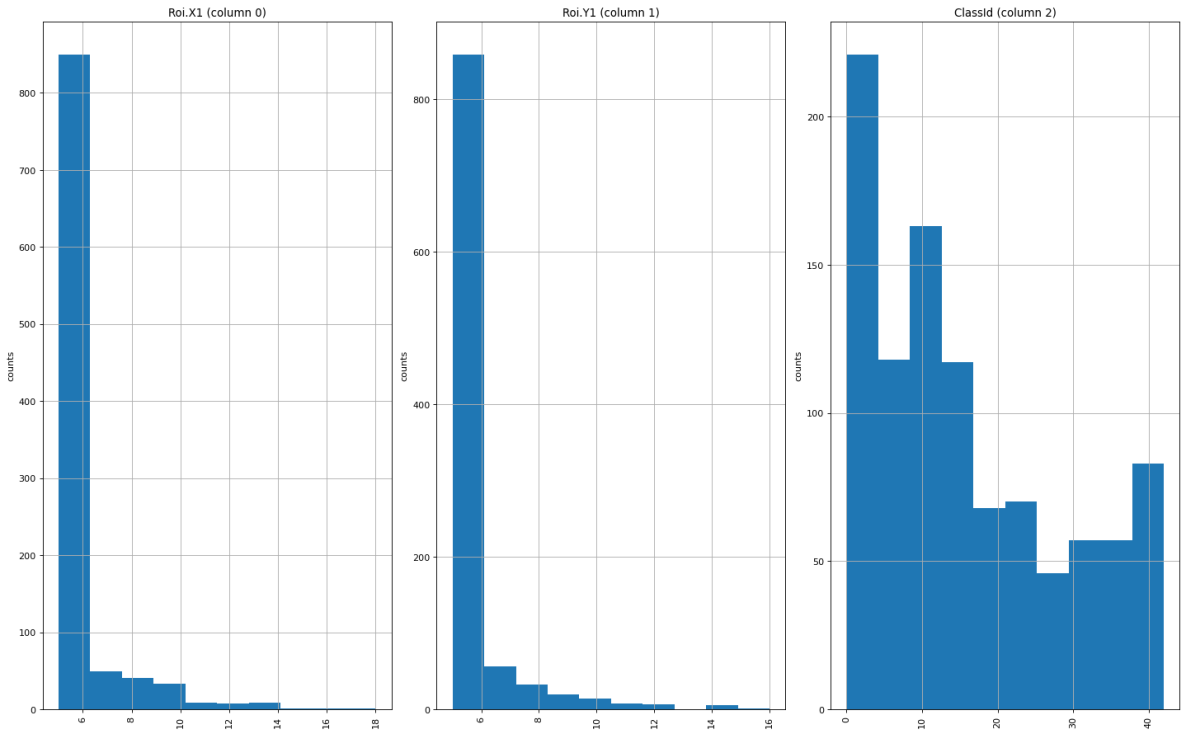
Out[11]:

	Width	Height	Roi.X1	Roi.Y1	Roi.X2	Roi.Y2	ClassId	Path
0	53	54	6	5	48	49	16	Test/00000.png
1	42	45	5	5	36	40	1	Test/00001.png
2	48	52	6	6	43	47	38	Test/00002.png
3	27	29	5	5	22	24	33	Test/00003.png
4	60	57	5	5	55	52	11	Test/00004.png

Distribution graphs (histogram/bar graph) of sampled columns:

In [12]:

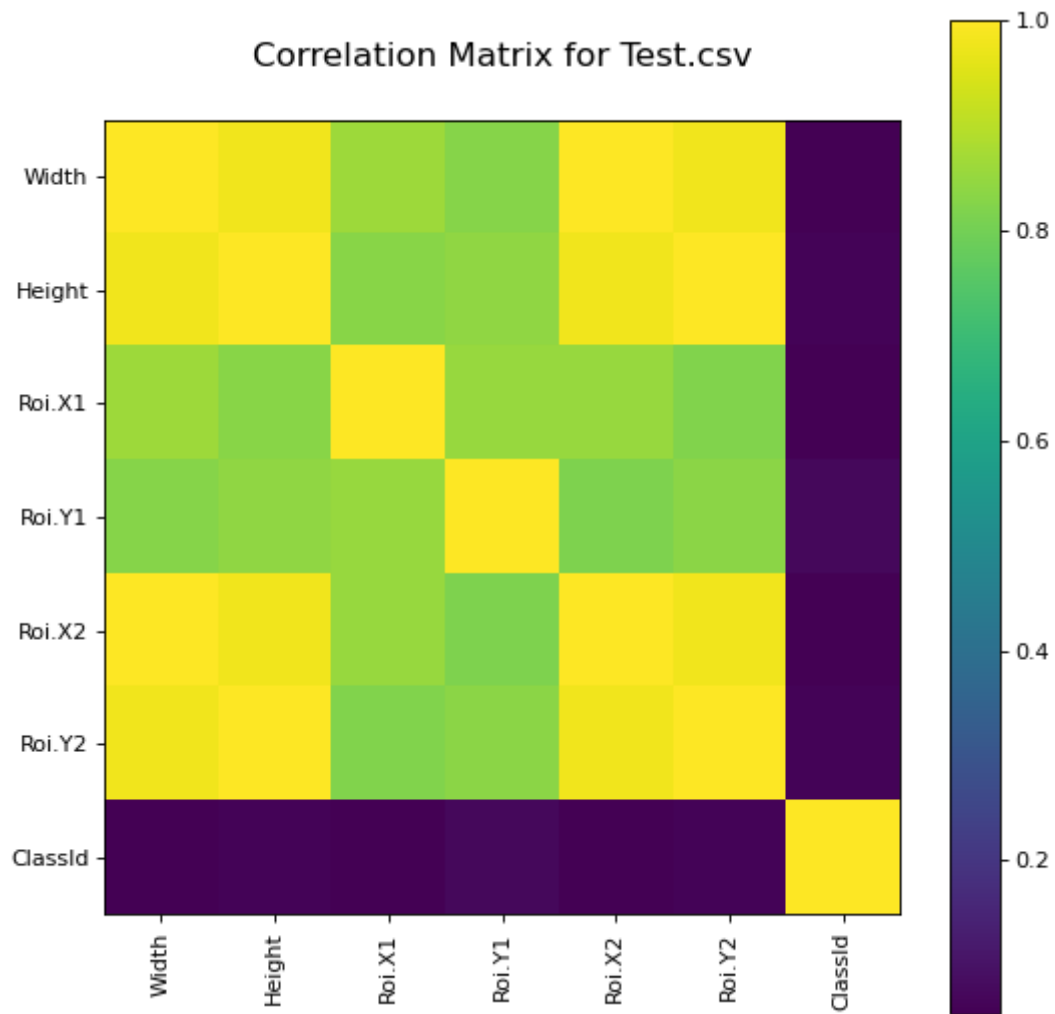
```
plotPerColumnDistribution(df2, 10, 5)
```



Correlation matrix:

In [13]:

```
plotCorrelationMatrix(df2, 8)
```

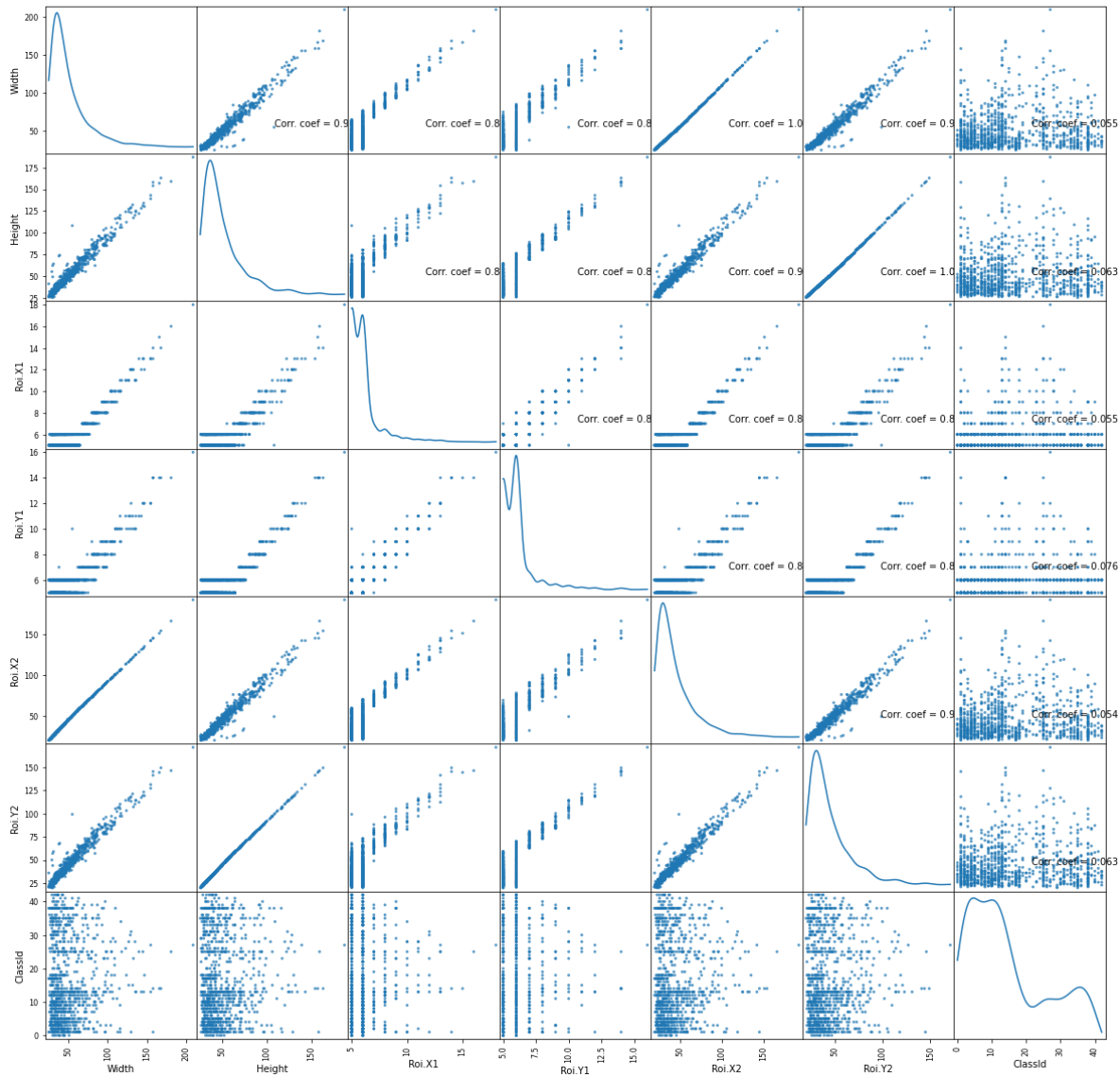


Scatter and density plots:

In [14]:

```
plotScatterMatrix(df2, 20, 10)
```

Scatter and Density Plot



**Let's check 3rd file: Train.csv**



In [15]:

```
nRowsRead = 1000 # specify 'None' if want to read whole file
# Train.csv has 39209 rows in reality, but we are only loading/previewing the first 1000 rows
df3 = pd.read_csv('Train.csv', delimiter=',', nrows = nRowsRead)
df3.dataframeName = 'Train.csv'
nRow, nCol = df3.shape
print(f'There are {nRow} rows and {nCol} columns')
```

There are 1000 rows and 8 columns

Let's take a quick look at what the data looks like:

In [16]:

```
df3.head(5)
```

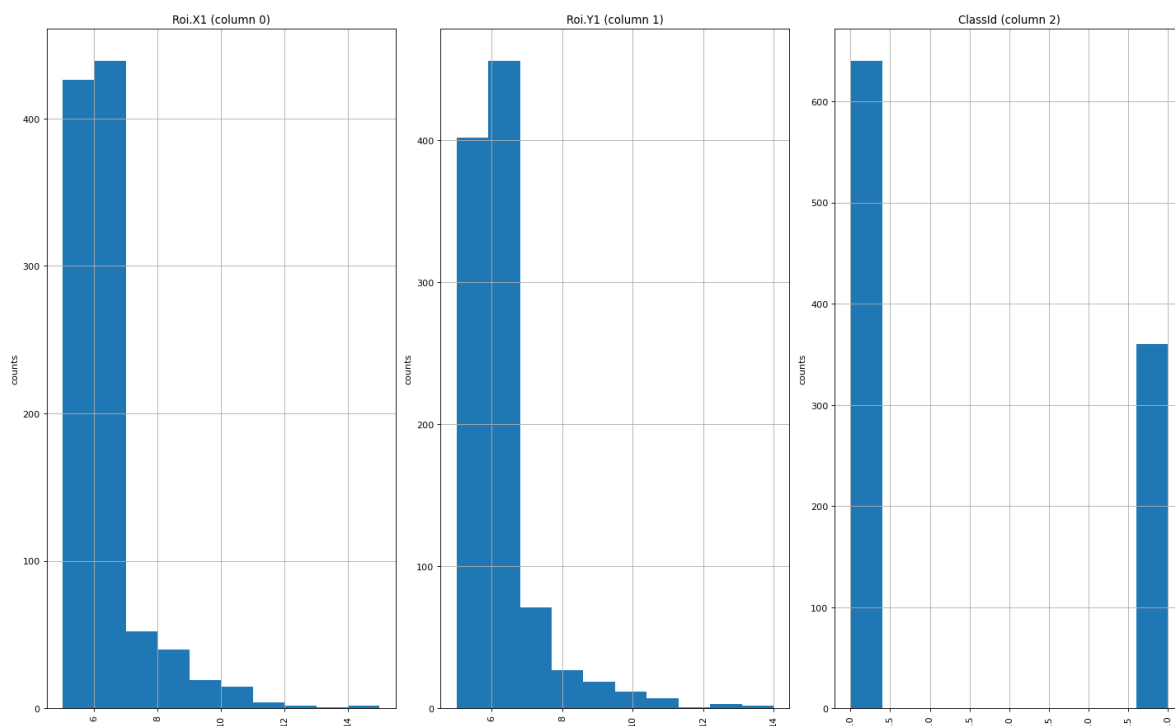
Out[16]:

	Width	Height	Roi.X1	Roi.Y1	Roi.X2	Roi.Y2	ClassId	Path
0	27	26	5	5	22	20	20	Train/20/00020_00000_00000.png
1	28	27	5	6	23	22	20	Train/20/00020_00000_00001.png
2	29	26	6	5	24	21	20	Train/20/00020_00000_00002.png
3	28	27	5	6	23	22	20	Train/20/00020_00000_00003.png
4	28	26	5	5	23	21	20	Train/20/00020_00000_00004.png

Distribution graphs (histogram/bar graph) of sampled columns:

In [17]:

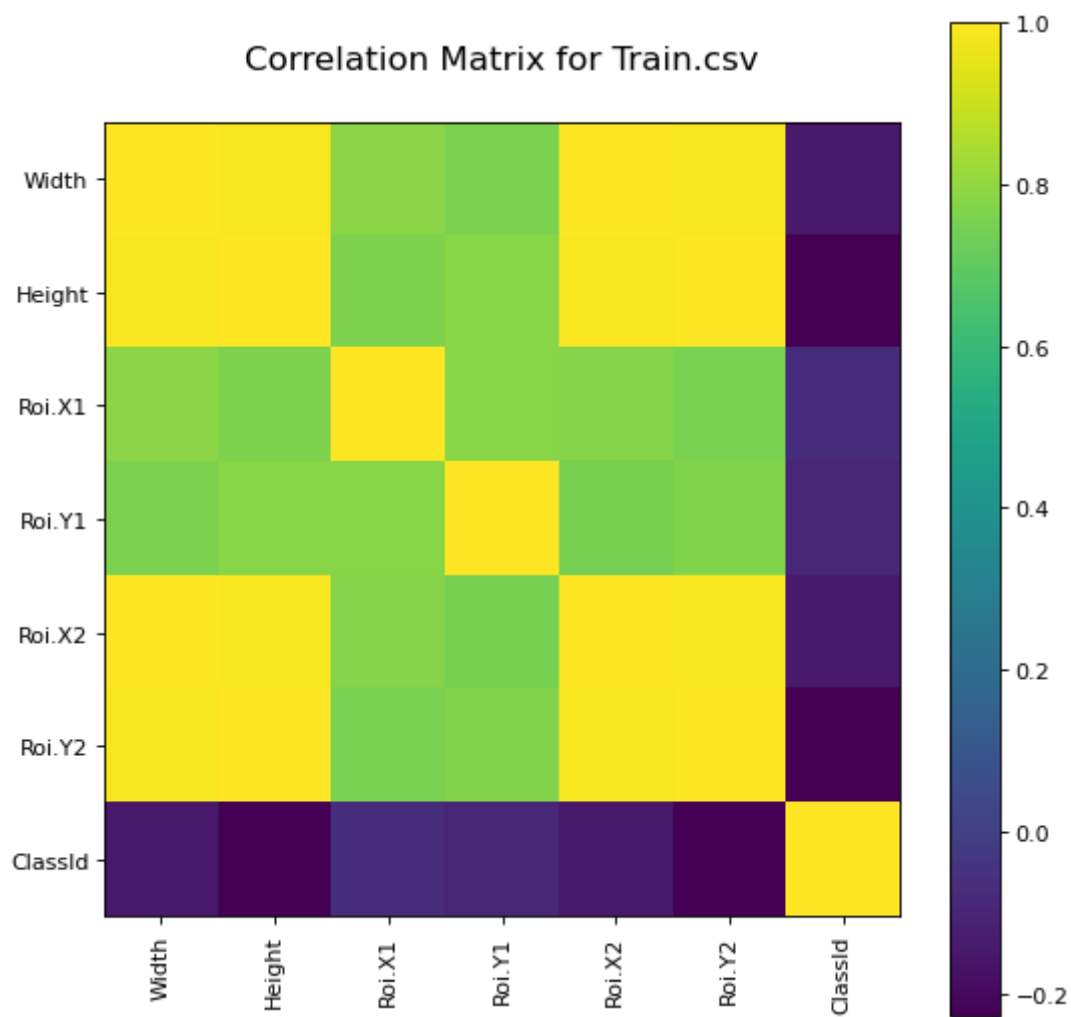
```
plotPerColumnDistribution(df3, 10, 5)
```



Correlation matrix:

In [18]:

```
plotCorrelationMatrix(df3, 8)
```

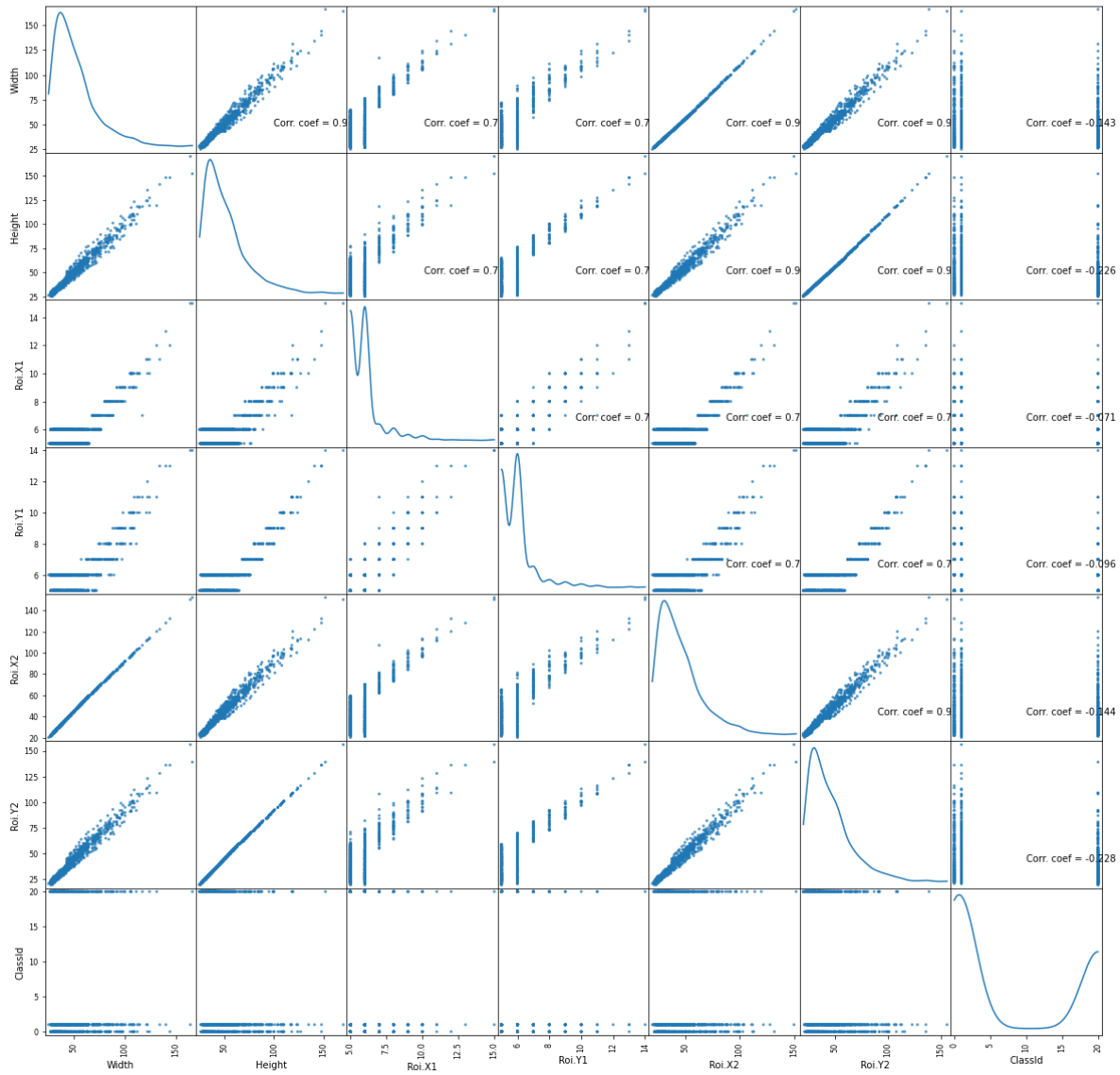


Scatter and density plots:

In [19]:

```
plotScatterMatrix(df3, 20, 10)
```

Scatter and Density Plot



In [20]:

```

data = []
labels = []
classes = 43
cur_path = os.getcwd()

#Retrieving the images and their labels
for i in range(classes):
    path = os.path.join(cur_path, 'train', str(i))
    images = os.listdir(path)

    for a in images:
        try:
            image = Image.open(path + '\\' + a)
            image = image.resize((30,30))
            image = np.array(image)
            #sim = Image.fromarray(image)
            data.append(image)
            labels.append(i)
        except:
            print("Error loading image")

#Converting lists into numpy arrays
data = np.array(data)
labels = np.array(labels)
print(data.shape, labels.shape)

#Splitting training and testing dataset
X_train, X_test, y_train, y_test = train_test_split(data, labels, test_size=0.2, random_state=42)

print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)

#Converting the labels into one hot encoding
y_train = to_categorical(y_train, 43)
y_test = to_categorical(y_test, 43)

```

```

(39209, 30, 30, 3) (39209,)
(31367, 30, 30, 3) (7842, 30, 30, 3) (31367,) (7842,)

```

## Creating The Model

In [24]:

```

#Building the model
model = Sequential()
model.add(Conv2D(filters=32, kernel_size=(5,5), activation='relu', input_shape=X_train.shape[1:]))
model.add(Conv2D(filters=32, kernel_size=(5,5), activation='relu'))
model.add(MaxPool2D(pool_size=(2, 2)))
model.add(Dropout(rate=0.25))
model.add(Conv2D(filters=64, kernel_size=(3, 3), activation='relu'))
model.add(Conv2D(filters=64, kernel_size=(3, 3), activation='relu'))
model.add(MaxPool2D(pool_size=(2, 2)))
model.add(Dropout(rate=0.25))
model.add(Flatten())
model.add(Dense(256, activation='relu'))
model.add(Dropout(rate=0.5))
model.add(Dense(43, activation='softmax'))

#Compilation of the model
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

epochs = 15
history = model.fit(X_train, y_train, batch_size=32, epochs=epochs, validation_data=(X_test, y_test))
model.save("my_model.h5")

#plotting graphs for accuracy
plt.figure(0)
plt.plot(history.history['accuracy'], label='training accuracy')
plt.plot(history.history['val_accuracy'], label='val accuracy')
plt.title('Accuracy')
plt.xlabel('epochs')
plt.ylabel('accuracy')
plt.legend()
plt.show()

plt.figure(1)
plt.plot(history.history['loss'], label='training loss')
plt.plot(history.history['val_loss'], label='val loss')
plt.title('Loss')
plt.xlabel('epochs')
plt.ylabel('loss')
plt.legend()
plt.show()

#testing accuracy on test dataset
from sklearn.metrics import accuracy_score

y_test = pd.read_csv('Test.csv')

labels = y_test["ClassId"].values
imgs = y_test["Path"].values

data=[]

for img in imgs:
    image = Image.open(img)
    image = image.resize((30,30))
    data.append(np.array(image))

X_test=np.array(data)

pred = model.predict_classes(X_test)

```

```
#Accuracy with the test data
from sklearn.metrics import accuracy_score
print(accuracy_score(labels, pred))
```

Train on 31367 samples, validate on 7842 samples

Epoch 1/15

31367/31367 [=====] - 193s 6ms/step - loss: 2.0391  
- accuracy: 0.4941 - val\_loss: 0.4327 - val\_accuracy: 0.8938

Epoch 2/15

31367/31367 [=====] - 166s 5ms/step - loss: 0.5824  
- accuracy: 0.8343 - val\_loss: 0.1541 - val\_accuracy: 0.9609

Epoch 3/15

31367/31367 [=====] - 161s 5ms/step - loss: 0.3630  
- accuracy: 0.8984 - val\_loss: 0.0857 - val\_accuracy: 0.9797

Epoch 4/15

31367/31367 [=====] - 157s 5ms/step - loss: 0.2997  
- accuracy: 0.9165 - val\_loss: 0.0887 - val\_accuracy: 0.9767

Epoch 5/15

31367/31367 [=====] - 158s 5ms/step - loss: 0.2658  
- accuracy: 0.9281 - val\_loss: 0.0602 - val\_accuracy: 0.9837

Epoch 6/15

31367/31367 [=====] - 167s 5ms/step - loss: 0.2547  
- accuracy: 0.9331 - val\_loss: 0.0929 - val\_accuracy: 0.9764

Epoch 7/15

31367/31367 [=====] - 189s 6ms/step - loss: 0.2216  
- accuracy: 0.9403 - val\_loss: 0.1025 - val\_accuracy: 0.9744

Epoch 8/15

31367/31367 [=====] - 172s 5ms/step - loss: 0.2341  
- accuracy: 0.9386 - val\_loss: 0.0585 - val\_accuracy: 0.9864

Epoch 9/15

31367/31367 [=====] - 165s 5ms/step - loss: 0.2317  
- accuracy: 0.9423 - val\_loss: 0.0685 - val\_accuracy: 0.9855

Epoch 10/15

31367/31367 [=====] - 180s 6ms/step - loss: 0.2102  
- accuracy: 0.9474 - val\_loss: 0.0541 - val\_accuracy: 0.9864

Epoch 11/15

31367/31367 [=====] - 207s 7ms/step - loss: 0.2316  
- accuracy: 0.9408 - val\_loss: 0.0588 - val\_accuracy: 0.9843

Epoch 12/15

31367/31367 [=====] - 199s 6ms/step - loss: 0.2240  
- accuracy: 0.9445 - val\_loss: 0.0574 - val\_accuracy: 0.9864

Epoch 13/15

31367/31367 [=====] - 182s 6ms/step - loss: 0.2028  
- accuracy: 0.9507 - val\_loss: 0.0588 - val\_accuracy: 0.9853

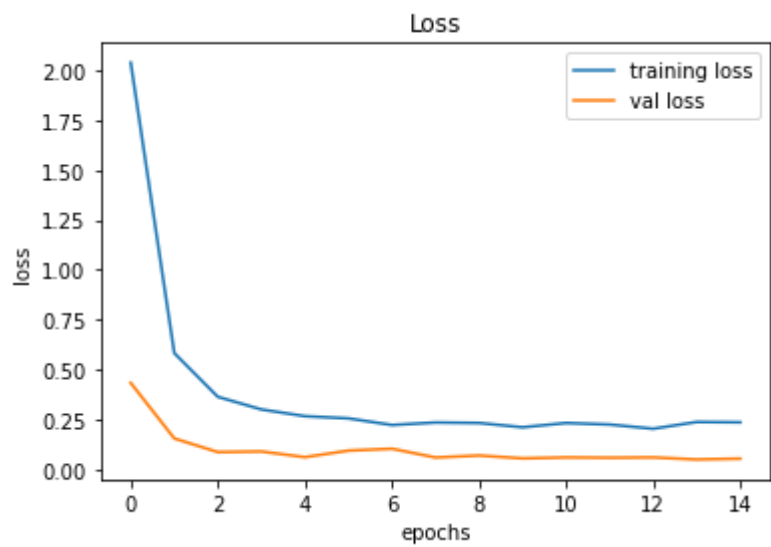
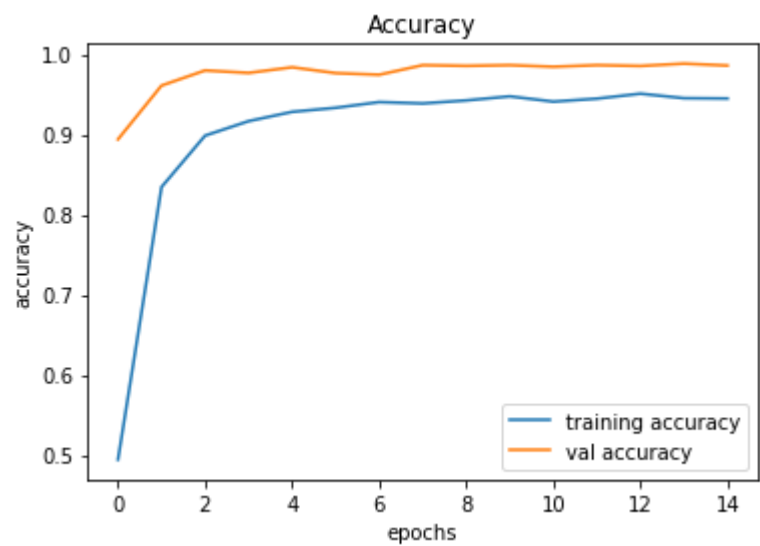
Epoch 14/15

31367/31367 [=====] - 194s 6ms/step - loss: 0.2368  
- accuracy: 0.9451 - val\_loss: 0.0486 - val\_accuracy: 0.9883

Epoch 15/15

31367/31367 [=====] - 182s 6ms/step - loss: 0.2350  
- accuracy: 0.9447 - val\_loss: 0.0526 - val\_accuracy: 0.9858





0.9537608867775138