TableNet - E2E Deep Learning Model for Table Detection & Data extraction

1. Description

TableNet is an end to end deep learning model which is capable of detecting the table from any image and then extract the tabular information from the table.

2. Business Problem

2.1 Overview

The uses of mobile phone and others digital devices are increasing day by day. With the advent of new technologies we are moving towards the digital era. And instead of handing over the physical documents we always prefer the scanned copy.

For e.g. To take an admission in any institution instead of entering all the required deatils manually what if we simply provide the scanned copy of the marksheets and certificates or while applying for a credit card/loan if the scanned copy of payslip is provided for a salaried person, In either of the cases system should able to extract the required information from the images and further process them as the required details are mainly provided in a tabular format. Not only that , even if we want to store the informations to maintain a dataset for the future purposes,that will also be helpful as data will be captured directly from the images so percentage of anamoly/outliers will be very less. So If we can develop this self sufficient system which is useful to extract the tabular informations from an image, the amount of manual intervention can significantly be reduced.

To solve this problem first we need the accurate detection of the tabular region within the image and then extracting the information from the rows and columns. The initial approahes were to use two different models to perform the entire tasks - one is for table detection and another on e is for data extraction.

TableNet, is a single deep learning model which is capable to perform the both tasks with high accuracy. The proposed model and extraction approach was evaluated on the publicly available ICDAR 2013 and Marmot Table datasets.

2.2. Problem Statement

1. First detect if there is any table present in the given image. It needn't be with borderline , it could be anything where rows columns like structure present
2. If table is present, extract the tabular information (in row - column format) and stored in a file

2.3. Dataset Source:

1. publicly available marmot dataset https://drive.google.com/drive/folders/1QZiv5RKe3xlOBdTzuTVuYRxixemVIODp (https://drive.google.com/drive/folders/1QZiv5RKe3xlOBdTzuTVuYRxixemVIODp)
2. ICDAR 2017 table dataset https://github.com/mawanda-jun/TableTrainNet/tree/master/dataset (https://github.com/mawanda-jun/TableTrainNet/tree/master/dataset)

2.4. Useful links

https://www.researchgate.net/publication/337242893_TableNet_Deep_Learning_Model_for_End-to-end_Table_Detection_and_Tabular_Data_Extraction_from_Scanned_Document_Images (https://www.researchgate.net/publication/337242893_TableNet_Deep_Learning_Model_for_End-to-end_Table_Detection_and_Tabular_Data_Extraction_from_Scanned_Document_Images)

2.5. Business Constraints

1. Accuracy has to be pretty high , otherwise we might end up with Information loss
2. Even though there is no strict low latency requirement , still it shouldn't be high
3. Model Interpretability is not required in this case

3. Data

3.1. Data Overview

We have total two kind of files- first, Scanned image is provided where table like structure can be found second, table annotations in terms of xml files ie table and column coordinates are mentioned for the corresponding image

4. ML/DL Problem

4.1. Type

We can consider it as classifiction problem , whether the model is capable of predicting the table accurately or not

4.2. Performance Metric

Precision, Recall and F1-Score should be considered to check the performance of the model

5. Exploratory Data Analysis

In [106]:
```
import numpy as np
import pandas as pd
import xml.etree.ElementTree as ET
from PIL import Image
```

We have total two datasets, one is Marmot Dataset and another one is ICDAR 2017 POD Competition dataset. We will check what exactly the dataset contain. The Marmot dataset is under marmot & ICDAR dataset is under tabledata directory

In general , we have the image in bmp format and corresponding annotation in xml format

In [116]:
```
!ls -l ../input/tabledata/Images/* | wc -l
```

```
1600
```

In [117]:
```
!ls -l ../input/tabledata/Annotations/* | wc -l
```

```
1600
```

In [118]:
```
!ls -l ../input/marmot/*.bmp | wc -l
```

```
509
```

In [119]:
```
!ls -l ../input/marmot/*.xml | wc -l
```

```
495
```

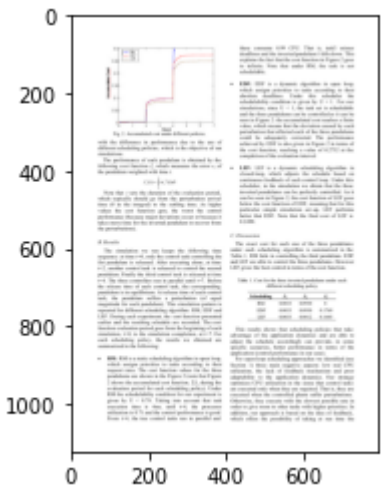
So the ICDAR Table dataset consists of 1600 files of each bmp and corresponding xml. However, in case of Marmot we found mismatches.

In case of Marmot , even though we have total 509 images however , there are only total corresponding annotations xml files present.

Now we will randomly load a file from each dataset , and check how does it look like

In [107]:
```
%pylab inline
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
img = mpimg.imread('../input/marmot/10.1.1.1.2006_3.bmp')
imgplot = plt.imshow(img)
plt.show()
```

```
Populating the interactive namespace from numpy and matplotlib

/opt/conda/lib/python3.7/site-packages/IPython/core/magics/pylab.py:160: User
Warning: pylab import has clobbered these variables: ['table']
`%matplotlib` prevents importing * from pylab and numpy
  "\n`%matplotlib` prevents importing * from pylab and numpy"
```



In [108]:
```
img = Image.open('../input/marmot/10.1.1.1.2006_3.bmp')
img.size
```

Out[108]: (793, 1123)

We have loaded 10.1.1.1.2006_3.bmp from the Marmot dataset and found the resolution is 793*1123. let's check for corresponding annotation (xml) file as well

In [109]:
```
import xml.dom.minidom
with open('../input/marmot/10.1.1.1.2006_3.xml') as xmldata:
    xml = xml.dom.minidom.parseString(xmldata.read())  # or xml.dom.minidom.pa
rseString(xml_string)
    xml_pretty_str = xml.toprettyxml()
print (xml_pretty_str)
```

```
<?xml version="1.0" ?>
<annotation verified="yes">

	<folder>MARMOT_ANNOTATION</folder>

	<filename>10.1.1.1.2006_3.bmp</filename>

	<path>/home/monika/Desktop/MARMOT_ANNOTATION/10.1.1.1.2006_3.bmp</pat
h>

	<source>

		<database>Unknown</database>

	</source>

	<size>

		<width>793</width>

		<height>1123</height>

		<depth>3</depth>

	</size>

	<segmented>0</segmented>

	<object>

		<name>column</name>

		<pose>Unspecified</pose>

		<truncated>0</truncated>

		<difficult>0</difficult>

		<bndbox>
```

```
                    <xmin>458</xmin>

                    <ymin>710</ymin>

                    <xmax>517</xmax>

                    <ymax>785</ymax>

            </bndbox>

    </object>

    <object>

            <name>column</name>

            <pose>Unspecified</pose>

            <truncated>0</truncated>

            <difficult>0</difficult>

            <bndbox>

                    <xmin>531</xmin>

                    <ymin>710</ymin>

                    <xmax>568</xmax>

                    <ymax>783</ymax>

            </bndbox>

    </object>

    <object>
```

```
                <name>column</name>

                <pose>Unspecified</pose>

                <truncated>0</truncated>

                <difficult>0</difficult>

                <bndbox>

                        <xmin>583</xmin>

                        <ymin>712</ymin>

                        <xmax>619</xmax>

                        <ymax>785</ymax>

                </bndbox>

        </object>

        <object>

                <name>column</name>

                <pose>Unspecified</pose>

                <truncated>0</truncated>

                <difficult>0</difficult>

                <bndbox>

                        <xmin>637</xmin>

                        <ymin>712</ymin>
```

```
                    <xmax>670</xmax>

                    <ymax>784</ymax>

                </bndbox>

            </object>

        </annotation>
```

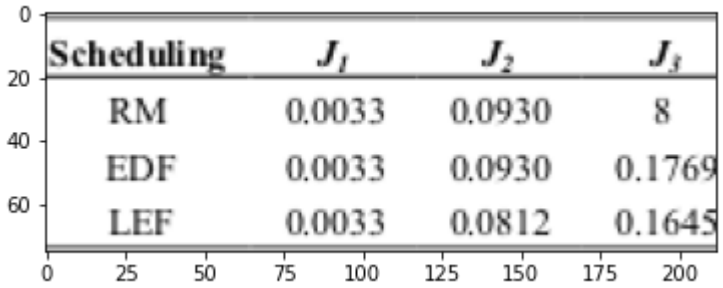
So there are various tags like width, height bndbox. As per the dataset description width*height denotes the resolution of the images and tells us about the column coordinates in xmin,ymin,xmax,ymax format.

In order to retrieve the information for the image , we should parse each xml files and extract the required informations.

Now we will check , manually if we can crop the exact table present in the image based on the bndbox

In [110]:
```
%pylab inline
img=Image.open('../input/marmot/10.1.1.1.2006_3.bmp')

#plt.show()
#the information are extracted manually from the xml file under <bndbox></bndb
ox>
xmin=min(458,531,583,637)
ymin=min(710,710,712,712)
xmax=max(517,568,619,670)
ymax=max(785,783,785,784)
crop_rectangle = (int(xmin),int(ymin),int(xmax),int(ymax))
cropped_im = img.crop(crop_rectangle)
imgplot = plt.imshow(cropped_im)
```

```
Populating the interactive namespace from numpy and matplotlib
```



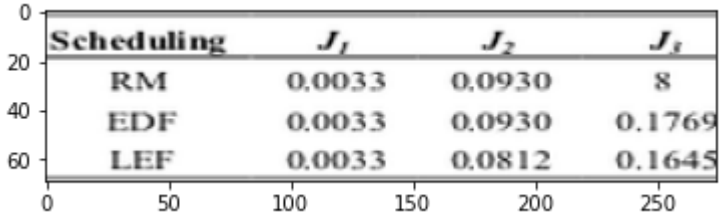
So we can conclude, the locations are correcly mentioned as we were able to extract only the table part from the image

The images could be different resolutions and as per the paper before feeding to the model we should resize them in 1024*1024 formt. In the next step We will check how the coordinates will be varied if we resize them

In [120]:
```
im = Image.open('../input/marmot/10.1.1.1.2006_3.bmp')
img=im.resize((1024,1024),Image.ANTIALIAS)
img.size
```

Out[120]: (1024, 1024)

In [121]:
```
targetsize=1024
x_=targetsize/(im.size[0])
y_=targetsize/(im.size[1])

xmin=min(458,531,583,637)
ymin=min(710,710,712,712)
xmax=max(517,568,619,670)
ymax=max(785,783,785,784)

xmin=np.round(xmin*x_)
xmax=np.round(xmax*x_)
ymin=np.round(ymin*y_)
ymax=np.round(ymax*y_)

crop_rectangle = (int(xmin),int(ymin),int(xmax),int(ymax))

cropped_im = img.crop(crop_rectangle)
imgplot = plt.imshow(cropped_im)
```

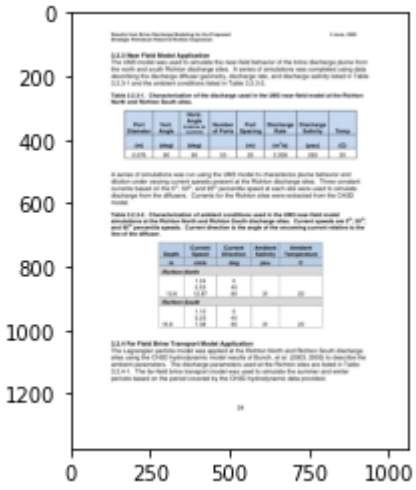


So after adjusting the coordinates - xmin,xmzx,ymin, ymax we can extract the table as shown above

Now we will check for the another dataset from ICDAR-2017

In [112]:
```
%pylab inline
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
img = mpimg.imread('../input/tabledata/Images/POD_0003.bmp')
imgplot = plt.imshow(img)
plt.show()
```

```
Populating the interactive namespace from numpy and matplotlib
```



In [115]:
```
img=Image.open('../input/tabledata/Images/POD_0003.bmp')
img.size
```

Out[115]:
```
(1061, 1373)
```

as we checked the image size is 1061*1373 ,let's check for the corresponding annotations file

In [111]:
```
import xml.dom.minidom
with open('../input/tabledata/Annotations/POD_0003.xml') as xmldata:
    xml = xml.dom.minidom.parseString(xmldata.read())  # or xml.dom.minidom.parseString(xml_string)
    xml_pretty_str = xml.toprettyxml()
print (xml_pretty_str)
```

```
<?xml version="1.0" ?>
<document filename="POD_0003.xml">

        <tableRegion>

                <Coords points="167,308 893,308 167,461 893,461"/>

        </tableRegion>

        <tableRegion>

                <Coords points="274,722 786,722 274,992 786,992"/>

        </tableRegion>

</document>
```

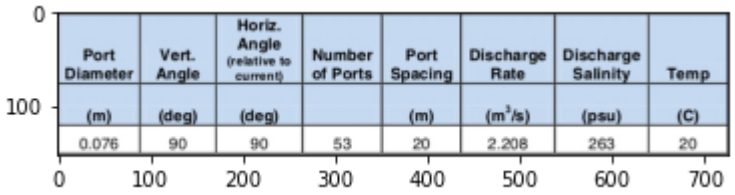
If we compare it is clear , here only the table coordinates are given under the tag . As per the dataset descriptions the points are in [[xmin, ymin], [xmax, ymin], [xmin, ymax], [xmax, ymax]] format.

However, no separate information is given w.r.t. the individual columns unlike Marmot dataset. Only the Table information is given.

let's check if we can crop the table from the image

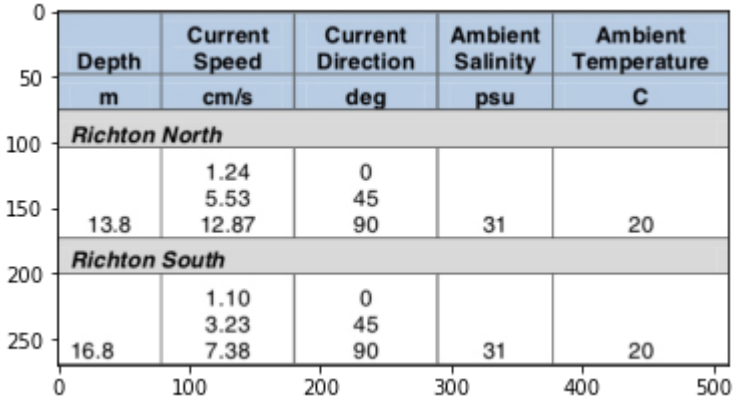
In [113]:
```
%pylab inline
img=Image.open('../input/tabledata/Images/POD_0003.bmp')
#img = mpimg.imread('../input/tabledata/Images/POD_0003.bmp')

plt.show()
xmin=167
ymin=308
xmax=893
ymax=461
crop_rectangle = (int(xmin),int(ymin),int(xmax),int(ymax))
cropped_im = img.crop(crop_rectangle)
imgplot = plt.imshow(cropped_im)
#cropped_im.show()
```

```
Populating the interactive namespace from numpy and matplotlib
```



In [114]:
```
%pylab inline
img=Image.open('../input/tabledata/Images/POD_0003.bmp')

plt.show()
xmin=274
ymin=722
xmax=786
ymax=992
crop_rectangle = (int(xmin),int(ymin),int(xmax),int(ymax))
cropped_im = img.crop(crop_rectangle)
imgplot = plt.imshow(cropped_im)
#cropped_im.show()
```

```
Populating the interactive namespace from numpy and matplotlib
```



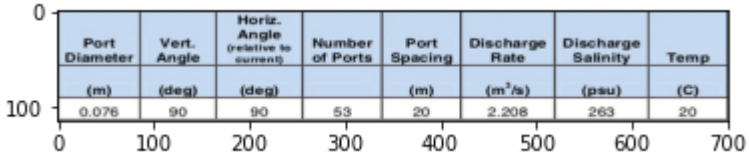
The tables are extracted as it is as per the information given

Now we will check after converting the image resolution in 1024*1024

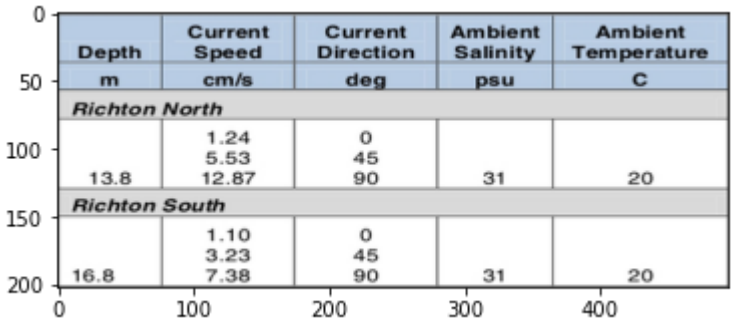
In [124]:
```
im = Image.open('../input/tabledata/Images/POD_0003.bmp')
img=im.resize((1024,1024),Image.ANTIALIAS)
img.size
```

Out[124]: (1024, 1024)

In [125]:
```
targetsize=1024
x_=targetsize/(im.size[0])
y_=targetsize/(im.size[1])

xmin=167
ymin=308
xmax=893
ymax=461

xmin=np.round(xmin*x_)
xmax=np.round(xmax*x_)
ymin=np.round(ymin*y_)
ymax=np.round(ymax*y_)

crop_rectangle = (int(xmin),int(ymin),int(xmax),int(ymax))

cropped_im = img.crop(crop_rectangle)
imgplot = plt.imshow(cropped_im)
```



In [126]:
```
targetsize=1024
x_=targetsize/(im.size[0])
y_=targetsize/(im.size[1])

xmin=274
ymin=722
xmax=786
ymax=992

xmin=np.round(xmin*x_)
xmax=np.round(xmax*x_)
ymin=np.round(ymin*y_)
ymax=np.round(ymax*y_)

crop_rectangle = (int(xmin),int(ymin),int(xmax),int(ymax))

cropped_im = img.crop(crop_rectangle)
imgplot = plt.imshow(cropped_im)
```



Depth	Current Speed	Current Direction	Ambient Salinity	Ambient Temperature
m	cm/s	deg	psu	C
Richton North				
13.8	1.24 5.53 12.87	0 45 90	31	20
Richton South				
16.8	1.10 3.23 7.38	0 45 90	31	20

So far we have analyzed one random entry from each dataset , as next step we will extract all the required information and converting the image resolution to 1024*1024 format

In [ ]:
```
!mkdir marmot_1024
```

In [ ]:
```
"""
the function will be useful for resizing the image in 1024*1024 format
"""
def resolution_1024(file):
    img=file.resize((1024,1024),Image.ANTIALIAS)
    return img
```

In [ ]:
```
#for Marmot data
import os
count=0
for dirname, _, filenames in os.walk('../input/marmot/'):
    for filename in filenames:
        if filename.endswith('.bmp'):
            count=count+1
            path='../input/marmot/'+filename
            img=Image.open(path)
            #print(type(img))
            img=resolution_1024(img)
            img.save('./marmot_1024/'+filename+'.jpeg')
```

In [ ]:
```
!mkdir table_1024
```

In [ ]:
```
#for ICDAR tabledata
import os
count=0
for dirname, _, filenames in os.walk('../input/tabledata/Images'):
    for filename in filenames:
        if filename.endswith('.bmp'):
            count=count+1
            path='../input/tabledata/Images/'+filename
            img=Image.open(path)
            #print(type(img))
            img=resolution_1024(img)
            img.save('./table_1024/'+filename+'.jpeg')
```

In [ ]:
```
!tar -cvf table_1024.tar ./table_1024
!tar -cvf marmot_1024.tar ./marmot_1024
```

In [ ]:
```
# here we are reading the each xml files and storing the useful informations i
n a dataframe such as filename, width,height,
#xmin,ymin,xmax,ymax

#ref: https://www.geeksforgeeks.org/xml-parsing-python/


"""
We are extracting the required information from Marmot dataset such as width,h
eight,xmin,ymin,xmax,ymax from the table annotation
(xml) files and corresponding adjusted value after resizing the image in 1024*
1024 format and then storing the value
in two different dataframes
"""

check=0
import os
df = pd.DataFrame()
df_1024=pd.DataFrame()
targetsize=1024
for dirname, _, filenames in os.walk('../input/marmot/'):
    for filename in filenames:
        if filename.endswith('.xml'):
            filename=os.path.join(dirname, filename)
            tree = ET.parse(filename)
            root = tree.getroot()
            name=root.find("./filename").text
            width=root.find("./size/width").text
            height=root.find("./size/height").text
            depth=root.find("./size/depth").text
            xmin=[]
            ymin=[]
            xmax=[]
            ymax=[]

            xmin_1024=[]
            ymin_1024=[]
            xmax_1024=[]
            ymax_1024=[]
            x_=float(targetsize/int(width))
            y_=targetsize/int(height)


            for bnd in root.findall("./object/bndbox/xmin"):
                xmin.append(bnd.text)

            for bnd in root.findall("./object/bndbox/ymin"):
                ymin.append(bnd.text)

            for bnd in root.findall("./object/bndbox/xmax"):
                xmax.append(bnd.text)

            for bnd in root.findall("./object/bndbox/ymax"):
                ymax.append(bnd.text)

            filename=[]
```

```
            table_width=[]
            table_height=[]
            table_depth=[]

            for i in range(0,len(xmax)):
                filename.append(name)
                table_width.append(width)
                table_height.append(height)
                table_depth.append(depth)

                scale=np.round(int(xmin[i])*x_)
                xmin_1024.append(int(scale))

                scale=np.round(int(xmax[i])*x_)
                xmax_1024.append(int(scale))

                scale=np.round(int(ymin[i])*y_)
                ymin_1024.append(int(scale))

                scale=np.round(int(ymax[i])*y_)
                ymax_1024.append(int(scale))

            Dict = dict({'filename': filename, 'table_width': table_width, 'ta
ble_height':table_height,
            'table_depth' : table_depth,'xmin':xmin,'ymin':ymin,'xmax':xmax,'y
max':ymax})

            Dict_1024 = dict({'filename': filename,'xmin':xmin_1024,'ymin':ymi
n_1024,'xmax':xmax_1024,'ymax':ymax_1024})

            if (check==0):
                #print("if executed")
                df=pd.DataFrame.from_dict(Dict)
                df_1024=pd.DataFrame.from_dict(Dict_1024)
                check=1

            elif(check!=0):
                #print("executed")
                df_new=pd.DataFrame.from_dict(Dict)
                df=df.append(df_new, ignore_index = True)

                df_new=pd.DataFrame.from_dict(Dict_1024)
                df_1024=df_1024.append(df_new, ignore_index = True)
```

In [ ]:
```
df.to_csv('marmot.csv')
df_1024.to_csv('marmot_1024.csv')
```

In [4]:
```
df.head(30)
```

Out[4]:

	Unnamed: 0	filename	table_width	table_height	table_depth	xmin	ymin	xmax
0	0	10.1.1.10.2226_5.bmp	816	1056	1	89	442	155
1	1	10.1.1.10.2226_5.bmp	816	1056	1	203	442	239
2	2	10.1.1.10.2226_5.bmp	816	1056	1	288	442	308
3	3	10.1.1.10.2226_5.bmp	816	1056	1	349	445	374
4	4	10.1.1.10.2226_5.bmp	816	1056	1	370	577	385
5	5	10.1.1.10.2226_5.bmp	816	1056	1	343	577	357
6	6	10.1.1.10.2226_5.bmp	816	1056	1	313	577	330
7	7	10.1.1.10.2226_5.bmp	816	1056	1	259	577	285
8	8	10.1.1.10.2226_5.bmp	816	1056	1	212	576	224
9	9	10.1.1.10.2226_5.bmp	816	1056	1	180	576	192
10	10	10.1.1.10.2226_5.bmp	816	1056	1	147	578	161
11	11	10.1.1.10.2226_5.bmp	816	1056	1	90	576	112
12	12	10.1.1.120.1518_6.bmp	816	1056	1	119	408	134
13	13	10.1.1.120.1518_6.bmp	816	1056	1	156	405	191
14	14	10.1.1.120.1518_6.bmp	816	1056	1	221	410	243
15	15	10.1.1.120.1518_6.bmp	816	1056	1	399	667	440
16	16	10.1.1.120.1518_6.bmp	816	1056	1	474	667	503
17	17	10.1.1.120.1518_6.bmp	816	1056	1	540	669	571
18	18	10.1.1.120.1518_6.bmp	816	1056	1	644	666	662
19	19	10.1.1.120.1527_4.bmp	793	1059	3	69	125	149
20	20	10.1.1.120.1527_4.bmp	793	1059	3	189	120	222
21	21	10.1.1.120.1527_4.bmp	793	1059	3	283	126	314
22	22	10.1.1.120.1527_4.bmp	793	1059	3	372	122	410
23	23	10.1.1.120.1527_4.bmp	793	1059	3	468	123	514
24	24	10.1.1.120.1527_4.bmp	793	1059	3	565	122	599
25	25	10.1.1.120.1527_4.bmp	793	1059	3	653	117	687
26	26	10.1.1.120.1527_4.bmp	793	1059	3	134	783	174
27	27	10.1.1.120.1527_4.bmp	793	1059	3	278	788	310
28	28	10.1.1.160.500_5.bmp	816	1056	1	75	341	247
29	29	10.1.1.160.500_5.bmp	816	1056	1	277	341	333

In [5]:
```
df_1024.head(30)
```

Out[5]:

	Unnamed: 0	filename	xmin	ymin	xmax	ymax
0	0	10.1.1.10.2226_5.bmp	112	429	195	491
1	1	10.1.1.10.2226_5.bmp	255	429	300	488
2	2	10.1.1.10.2226_5.bmp	361	429	387	491
3	3	10.1.1.10.2226_5.bmp	438	432	469	489
4	4	10.1.1.10.2226_5.bmp	464	560	483	609
5	5	10.1.1.10.2226_5.bmp	430	560	448	608
6	6	10.1.1.10.2226_5.bmp	393	560	414	610
7	7	10.1.1.10.2226_5.bmp	325	560	358	608
8	8	10.1.1.10.2226_5.bmp	266	559	281	612
9	9	10.1.1.10.2226_5.bmp	226	559	241	609
10	10	10.1.1.10.2226_5.bmp	184	560	202	610
11	11	10.1.1.10.2226_5.bmp	113	559	141	610
12	12	10.1.1.120.1518_6.bmp	149	396	168	497
13	13	10.1.1.120.1518_6.bmp	196	393	240	497
14	14	10.1.1.120.1518_6.bmp	277	398	305	501
15	15	10.1.1.120.1518_6.bmp	501	647	552	825
16	16	10.1.1.120.1518_6.bmp	595	647	631	822
17	17	10.1.1.120.1518_6.bmp	678	649	717	825
18	18	10.1.1.120.1518_6.bmp	808	646	831	825
19	19	10.1.1.120.1527_4.bmp	89	121	192	274
20	20	10.1.1.120.1527_4.bmp	244	116	287	282
21	21	10.1.1.120.1527_4.bmp	365	122	405	278
22	22	10.1.1.120.1527_4.bmp	480	118	529	276
23	23	10.1.1.120.1527_4.bmp	604	119	664	278
24	24	10.1.1.120.1527_4.bmp	730	118	773	279
25	25	10.1.1.120.1527_4.bmp	843	113	887	274
26	26	10.1.1.120.1527_4.bmp	173	757	225	929
27	27	10.1.1.120.1527_4.bmp	359	762	400	926
28	28	10.1.1.160.500_5.bmp	94	331	310	637
29	29	10.1.1.160.500_5.bmp	348	331	418	636

In [ ]:
```

```

In [ ]:
```
# here we are reading the each xml files and storing the useful informations i
n a dataframe such as filename, width,height,
#xmin,ymin,xmax,ymax

#ref: https://www.geeksforgeeks.org/xml-parsing-python/

"""
performing the same operations in ICDAR 2017 table dataset
"""

check=0
import os
df_table = pd.DataFrame()
df_table_1024=pd.DataFrame()
targetsize=1024
for dirname, _, filenames in os.walk('../input/tabledata/Annotations/'):
    for filename in filenames:
        if filename.endswith('.xml'):
            filesname=os.path.join(dirname, filename)
            tree = ET.parse(filesname)
            root = tree.getroot()

            fname="../input/tabledata/Images/" + filename[:-4]+".bmp"
            img=Image.open(fname)


            if(root.findall("tableRegion")):

                x_=float(targetsize/int(img.size[0]))
                y_=float(targetsize/int(img.size[1]))

                data=root.findall("tableRegion/Coords")
                for i in range(0,len(data)):
                    point=data[i].get("points")
                    table='Y'
                    points=point.split(" ")
                    tmp=points[3]
                    #print("point3:",point[3])
                    locn=tmp.split(",")
                    xmax=locn[0]
                    ymax=locn[1]

                    table_width=img.size[0]
                    table_height=img.size[1]

                    name=filename[:-4]+".bmp"


                    tmp=points[0]
                    #print()
                    locn=tmp.split(",")
                    #print(locn)
                    xmin=locn[0]
                    ymin=locn[1]

                    Dict = dict({'filename': name,'table_exists':table, 'table
```

```
_width': table_width, 'table_height':table_height,'xmin':xmin,'ymin':ymin,'xma
x':xmax,'ymax':ymax})
                    #print(Dict)

                    scale=np.round(int(xmin)*x_)
                    xmin_1024=int(scale)

                    scale=np.round(int(ymin)*y_)
                    ymin_1024=int(scale)

                    scale=np.round(int(xmax)*x_)
                    xmax_1024=int(scale)

                    scale=np.round(int(ymax)*y_)
                    ymax_1024=int(scale)

                    Dict_1024 = dict({'filename': name,'table_exists':table,
'table_width': table_width,'table_height':table_height,'xmin_1024':xmin_1024,
'ymin_1024':ymin_1024,'xmax_1024':xmax_1024,'ymax_1024':ymax_1024})

                    if (check==0):
                        df_table=pd.DataFrame([Dict])
                        df_table_1024=pd.DataFrame([Dict_1024])
                        check=1
                    elif(check!=0):
                        df_new=pd.DataFrame([Dict])
                        df_table=df_table.append(df_new, ignore_index = True)
                        df_new=pd.DataFrame([Dict_1024])
                        df_table_1024=df_table_1024.append(df_new, ignore_inde
x = True)
                ymax_1024.append(int(scale))

            else:
                name=filename[:-4]+".bmp"
                table='N'
                xmin=0
                xmax=0
                ymin=0
                ymax=0
                table_width=img.size[0]
                table_height=img.size[1]
                Dict = dict({'filename': name,'table_exists':table, 'table_wid
th': table_width, 'table_height':table_height,'xmin':xmin,'ymin':ymin,'xmax':x
max,'ymax':ymax})
                Dict_1024 = dict({'filename': name,'table_exists':table, 'tabl
e_width': table_width,'table_height':table_height,'xmin_1024':xmin,'ymin_1024'
:ymin,'xmax_1024':xmax,'ymax_1024':ymax})
                if (check==0):
                    df_table=pd.DataFrame([Dict])
                    df_table_1024=pd.DataFrame([Dict_1024])
                    check=1
                elif (check!=0):
                    df_new=pd.DataFrame([Dict])
                    df_table=df_table.append(df_new, ignore_index = True)

                    df_new=pd.DataFrame([Dict_1024])
                    df_table_1024=df_table_1024.append(df_new, ignore_index =
```

```
True)
                    #print(Dict)
```

In [ ]:
```
df_table.to_csv('df_table_data.csv')
df_table_1024.to_csv('df_table_data_1024.csv')
```

In [8]:
```
df_table.head(20)
```

Out[8]:

	Unnamed: 0	filename	table_exists	table_width	table_height	xmin	ymin	xmax	ymax
0	0	POD_1449.bmp	N	749	1123	0	0	0	0
1	1	POD_0017.bmp	Y	1031	1459	166	267	864	667
2	2	POD_0771.bmp	N	1061	1373	0	0	0	0
3	3	POD_0466.bmp	N	1031	1459	0	0	0	0
4	4	POD_0039.bmp	N	1061	1373	0	0	0	0
5	5	POD_0988.bmp	N	1032	1459	0	0	0	0
6	6	POD_0707.bmp	N	1031	1459	0	0	0	0
7	7	POD_0514.bmp	N	1061	1373	0	0	0	0
8	8	POD_0324.bmp	Y	1061	1373	194	184	865	984
9	9	POD_0724.bmp	Y	1061	1373	237	195	825	839
10	10	POD_0905.bmp	N	1031	1459	0	0	0	0
11	11	POD_1270.bmp	N	1032	1459	0	0	0	0
12	12	POD_0030.bmp	Y	1061	1373	153	758	904	953
13	13	POD_0145.bmp	N	1031	1459	0	0	0	0
14	14	POD_1239.bmp	Y	1031	1459	122	688	885	792
15	15	POD_1239.bmp	Y	1031	1459	123	847	883	1001
16	16	POD_0444.bmp	N	1032	1459	0	0	0	0
17	17	POD_0228.bmp	N	1061	1373	0	0	0	0
18	18	POD_0559.bmp	Y	1061	1373	399	515	489	590
19	19	POD_1572.bmp	Y	1061	1373	539	565	929	812

In [9]:
```
df_table_1024.head(20)
```

Out[9]:

	Unnamed: 0	filename	table_exists	table_width	table_height	xmin_1024	ymin_1024	xr
0	0	POD_1449.bmp	N	749	1123	0	0	
1	1	POD_0017.bmp	Y	1031	1459	165	187	
2	2	POD_0771.bmp	N	1061	1373	0	0	
3	3	POD_0466.bmp	N	1031	1459	0	0	
4	4	POD_0039.bmp	N	1061	1373	0	0	
5	5	POD_0988.bmp	N	1032	1459	0	0	
6	6	POD_0707.bmp	N	1031	1459	0	0	
7	7	POD_0514.bmp	N	1061	1373	0	0	
8	8	POD_0324.bmp	Y	1061	1373	187	137	
9	9	POD_0724.bmp	Y	1061	1373	229	145	
10	10	POD_0905.bmp	N	1031	1459	0	0	
11	11	POD_1270.bmp	N	1032	1459	0	0	
12	12	POD_0030.bmp	Y	1061	1373	148	565	
13	13	POD_0145.bmp	N	1031	1459	0	0	
14	14	POD_1239.bmp	Y	1031	1459	121	483	
15	15	POD_1239.bmp	Y	1031	1459	122	594	
16	16	POD_0444.bmp	N	1032	1459	0	0	
17	17	POD_0228.bmp	N	1061	1373	0	0	
18	18	POD_0559.bmp	Y	1061	1373	385	384	
19	19	POD_1572.bmp	Y	1061	1373	520	421	

In [ ]:

In [ ]:

In [ ]:

As next step we will generate the table and column masks

In [ ]:
```
!mkdir table_mask_table_data table_mask_table_data_1024
```

In [ ]:
```
"""
generating the table mask of original image for ICDAR Table dataset
"""

for i in df_table['filename'].unique():

    width=int(df_table[df_table['filename']==i]['table_width'].unique())
    height=int(df_table[df_table['filename']==i]['table_height'].unique())

    xmin=df_table[df_table['filename']==i]['xmin'].to_list()
    ymin=df_table[df_table['filename']==i]['ymin'].to_list()
    xmax=df_table[df_table['filename']==i]['xmax'].to_list()
    ymax=df_table[df_table['filename']==i]['ymax'].to_list()

    table_mask = np.zeros((height, width), dtype=np.int32)


    for j in range(0,len(xmin)):
        table_mask[int(ymin[j]):int(ymax[j]), int(xmin[j]):int(xmax[j])] = 255

    im_table = Image.fromarray(table_mask.astype(np.uint8),'L')

    im_table.save('./table_mask_table_data/' +i+"table" + ".jpeg")
```

In [ ]:
```
!tar -cvf table_mask_table_data.tar ./table_mask_table_data
```

In [ ]:
```

```

In [ ]:
```
"""
generate the table mask for the resize 1024*1024 image of ICDAR-tabledataset
"""

for i in df_table_1024['filename'].unique():

    width=1024
    height=1024

    xmin=df_table_1024[df_table_1024['filename']==i]['xmin_1024'].to_list()
    ymin=df_table_1024[df_table_1024['filename']==i]['ymin_1024'].to_list()
    xmax=df_table_1024[df_table_1024['filename']==i]['xmax_1024'].to_list()
    ymax=df_table_1024[df_table_1024['filename']==i]['ymax_1024'].to_list()

    table_mask = np.zeros((height, width), dtype=np.int32)

    for j in range(0,len(xmin)):
        table_mask[int(ymin[j]):int(ymax[j]), int(xmin[j]):int(xmax[j])] = 255

    im_table = Image.fromarray(table_mask.astype(np.uint8),'L')
    im_table.save('./table_mask_table_data_1024/' +i+"table" + ".jpeg")
```

In [ ]:
```
!tar -cvf table_mask_table_data_1024.tar ./table_mask_table_data_1024
```

In [ ]:
```

```

In [ ]:
```
"""
generate the table and column mask for the original Marmot dataset
"""

for i in df['filename'].unique():

    width=int(df[df['filename']==i]['table_width'].unique())
    height=int(df[df['filename']==i]['table_height'].unique())

    xmin=df[df['filename']==i]['xmin'].to_list()
    ymin=df[df['filename']==i]['ymin'].to_list()
    xmax=df[df['filename']==i]['xmax'].to_list()
    ymax=df[df['filename']==i]['ymax'].to_list()


    column_mask = np.zeros((height, width), dtype=np.int32)
    table_mask = np.zeros((height, width), dtype=np.int32)

    for ele in range(0,len(xmin)):
        xmin[ele]=int(xmin[ele])
        xmax[ele]=int(xmax[ele])
        ymin[ele]=int(ymin[ele])
        ymax[ele]=int(ymax[ele])

    table_xmin=int(min(xmin))
        #print(table_xmin)
    table_ymin=int(min(ymin))
        #print(table_ymin)
    table_xmax=int(max(xmax))
        #print(table_xmax)
    table_ymax=int(max(ymax))
        #print(table_ymax)

    table_mask[table_ymin:table_ymax, table_xmin:table_xmax] = 255

    for j in range(0,len(xmin)):
        column_mask[int(ymin[j]):int(ymax[j]), int(xmin[j]):int(xmax[j])] = 25
5

    im_col = Image.fromarray(column_mask.astype(np.uint8),'L')
    im_table = Image.fromarray(table_mask.astype(np.uint8),'L')
    im_col.save('./marmot_column/'+ i+"_col"+".jpeg")
    #!mv *.jpeg ./column_segment/
    im_table.save('./marmot_table/' +i+"_table" + ".jpeg")
```

In [ ]:
```
!tar -cvf marmot_table.tar ./marmot_table
!tar -cvf marmot_column.tar ./marmot_column
```

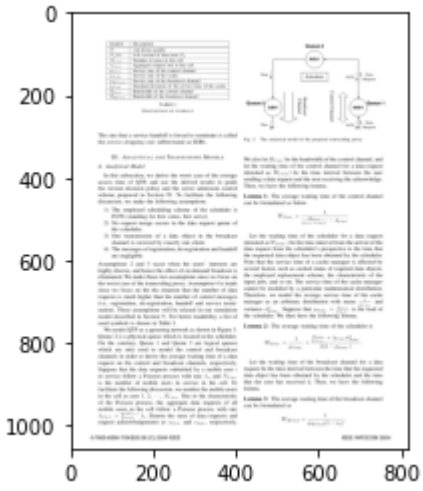
In [ ]:
```
"""
generate the table and column masks for resizing Marmot dataset in 1024*1024 r
esolution
"""

for i in df_1024['filename'].unique():

    width=1024
    height=1024

    xmin=df_1024[df_1024['filename']==i]['xmin'].to_list()
    ymin=df_1024[df_1024['filename']==i]['ymin'].to_list()
    xmax=df_1024[df_1024['filename']==i]['xmax'].to_list()
    ymax=df_1024[df_1024['filename']==i]['ymax'].to_list()


    column_mask = np.zeros((height, width), dtype=np.int32)
    table_mask = np.zeros((height, width), dtype=np.int32)

    for ele in range(0,len(xmin)):
        xmin[ele]=int(xmin[ele])
        xmax[ele]=int(xmax[ele])
        ymin[ele]=int(ymin[ele])
        ymax[ele]=int(ymax[ele])

    table_xmin=int(min(xmin))
        #print(table_xmin)
    table_ymin=int(min(ymin))
        #print(table_ymin)
    table_xmax=int(max(xmax))
        #print(table_xmax)
    table_ymax=int(max(ymax))
        #print(table_ymax)

    table_mask[table_ymin:table_ymax, table_xmin:table_xmax] = 255

    for j in range(0,len(xmin)):
        column_mask[int(ymin[j]):int(ymax[j]), int(xmin[j]):int(xmax[j])] = 25
5


    im_col = Image.fromarray(column_mask.astype(np.uint8),'L')
    im_table = Image.fromarray(table_mask.astype(np.uint8),'L')
    im_col.save('./marmot_column_1024/'+ i+"_col"+".jpeg")
    #!mv *.jpeg ./column_segment/
    im_table.save('./marmot_table_1024/' +i+"_table" + ".jpeg")
```

In [ ]:
```
!tar -cvf marmot_table_1024.tar ./marmot_table_1024
!tar -cvf marmot_column_1024.tar ./marmot_column_1024
```

Next we will randomly load one image from each category and check if our EDA was successful

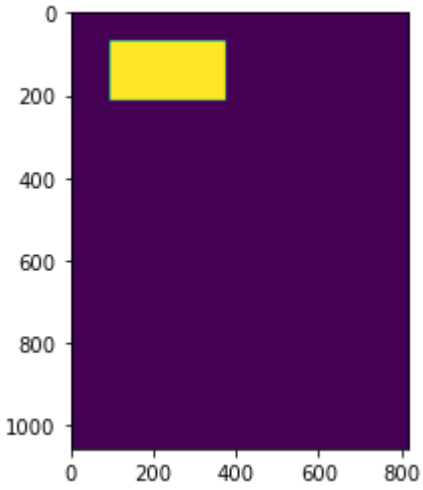
In [14]:
```
"""
marmot data in original format
"""
%pylab inline
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
img = mpimg.imread('CHK1/10.1.1.1.2018_4.bmp')
imgplot = plt.imshow(img)
plt.show()
```

```
Populating the interactive namespace from numpy and matplotlib
```



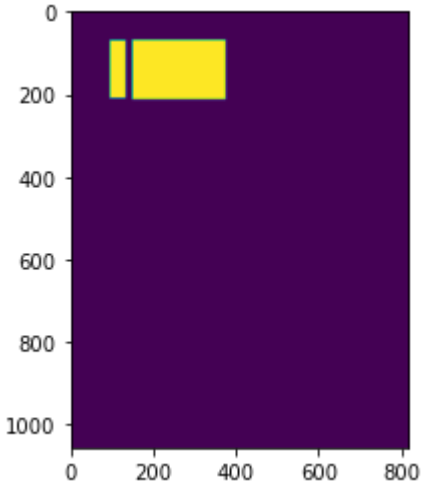
In [15]:
```
"""
corresponding table mask
"""

%pylab inline
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
img = mpimg.imread('CHK1/marmot_table/10.1.1.1.2018_4.bmp_table.jpeg')
imgplot = plt.imshow(img)
plt.show()
```

```
Populating the interactive namespace from numpy and matplotlib
```



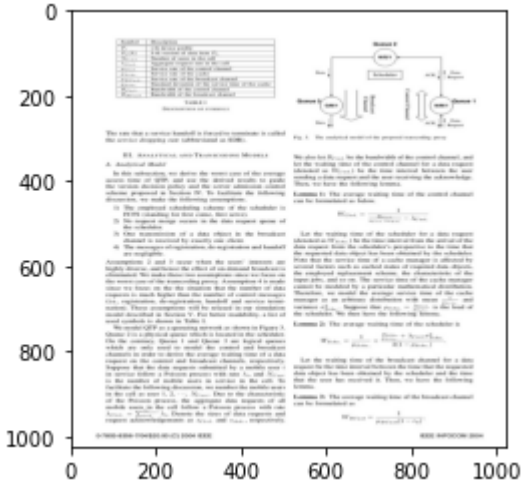
In [16]:
```
"""
corresponding column mask
"""

%pylab inline
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
img = mpimg.imread('CHK1/marmot_column/10.1.1.1.2018_4.bmp_col.jpeg')
imgplot = plt.imshow(img)
plt.show()
```

```
Populating the interactive namespace from numpy and matplotlib
```



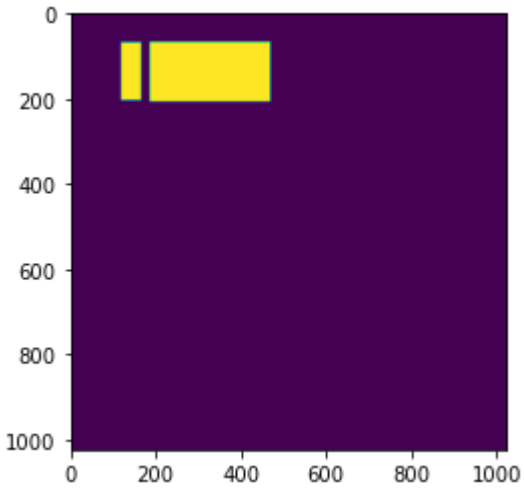
In [18]:
```
"""
corresponding marmot data in 1024*1024 format
"""

%pylab inline
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
img = mpimg.imread('CHK1/marmot_1024/10.1.1.1.2018_4.bmp.jpeg')
imgplot = plt.imshow(img)
plt.show()
```

```
Populating the interactive namespace from numpy and matplotlib
```



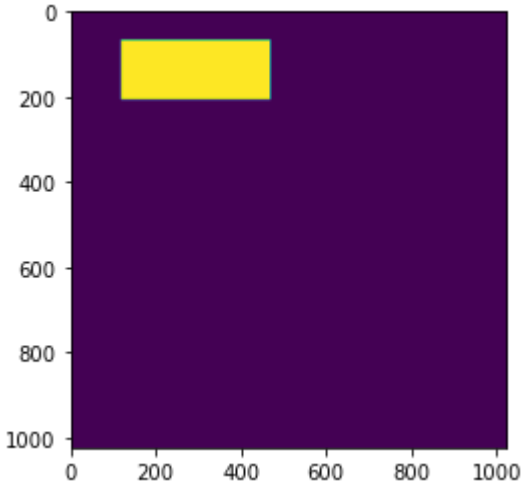
In [20]:
```
"""
column mask
"""

%pylab inline
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
img = mpimg.imread('CHK1/marmot_column_1024/10.1.1.1.2018_4.bmp_col.jpeg')
imgplot = plt.imshow(img)
plt.show()
```

```
Populating the interactive namespace from numpy and matplotlib
```



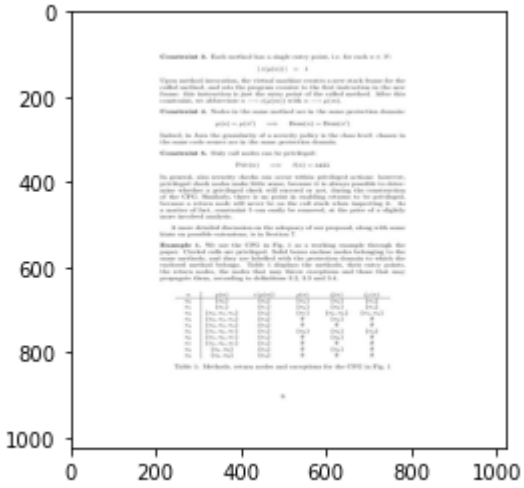
In [21]:
```
"""
table mask
"""

%pylab inline
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
img = mpimg.imread('CHK1/marmot_table_1024/10.1.1.1.2018_4.bmp_table.jpeg')
imgplot = plt.imshow(img)
plt.show()
```

```
Populating the interactive namespace from numpy and matplotlib
```



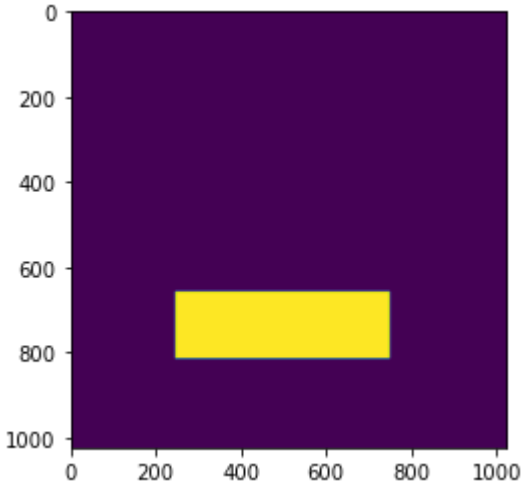
In [22]:
```
"""
ICDAR table data after resizing to 1024*1024
"""

%pylab inline
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
img = mpimg.imread('CHK1/table_1024/POD_0007.bmp.jpeg')
imgplot = plt.imshow(img)
plt.show()
```

```
Populating the interactive namespace from numpy and matplotlib
```



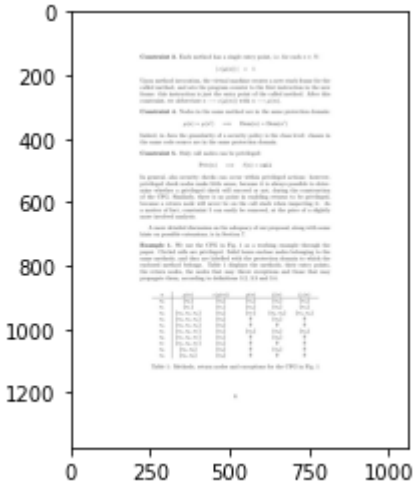
In [23]:
```
"""
corresponding table mask
"""

%pylab inline
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
img = mpimg.imread('CHK1/table_mask_table_data_1024/POD_0007.bmptable.jpeg')
imgplot = plt.imshow(img)
plt.show()
```

```
Populating the interactive namespace from numpy and matplotlib
```



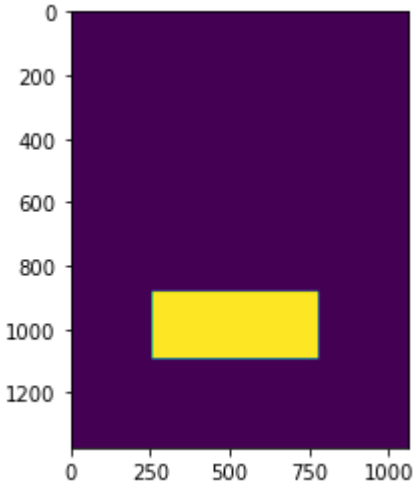
In [25]:
```
"""
ICDAR table data in original format
"""

%pylab inline
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
img = mpimg.imread('CHK1/POD_0007.bmp')
imgplot = plt.imshow(img)
plt.show()
```

```
Populating the interactive namespace from numpy and matplotlib
```



In [26]:
```
"""
table mask in original format
"""

%pylab inline
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
img = mpimg.imread('CHK1/table_mask_table_data/POD_0007.bmptable.jpeg')
imgplot = plt.imshow(img)
plt.show()
```

```
Populating the interactive namespace from numpy and matplotlib
```



6. Model Development

In [1]:
```
import tensorflow as tf
import matplotlib.pyplot as plt

from tensorflow.keras import Sequential
from tensorflow.keras.models import Model
from tensorflow.keras.layers import BatchNormalization
from tensorflow.keras.layers import Conv2D
from tensorflow.keras.layers import MaxPooling2D
from tensorflow.keras.layers import Activation
from tensorflow.keras.layers import Dropout
from tensorflow.keras.layers import Lambda
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Flatten
from tensorflow.keras.layers import Input, Concatenate, UpSampling2D
```

Ref: https://stackoverflow.com/questions/58185222/read-image-and-mask-for-segmentation-problem-in-tensorflow-2-0-using-tf-data (https://stackoverflow.com/questions/58185222/read-image-and-mask-for-segmentation-problem-in-tensorflow-2-0-using-tf-data)

before developing the Model architecture , we need to pre process the data. So for this we will load the Original Image and corresponding Table and column mask to create the final dataset which to be passed to the model as Input.

Since we have very limited amount of Image , so for now we will not split the data in Train-Test for validation . For now We will use the entire dataset as Train.

Ref: https://www.tensorflow.org/tutorials/images/segmentation (https://www.tensorflow.org/tutorials/images/segmentation)

In [2]:
```
file_path='../input/data/Image/*.jpg'
image_height=1024
image_width=1024
```

In [3]:
```
def normalize(input_image):
    input_image = tf.cast(input_image, tf.float32) / 255.0
    #input_mask -= 1
    return input_image
```

In [4]:
```
def decode_image(image):
    img=tf.io.decode_jpeg(image)
    img=tf.image.resize(img, [image_height, image_width])
    return img
```

In [5]:
```
def decode_mask(image):
    img=tf.io.decode_jpeg(image,channels=1)
    img=tf.image.resize(img, [image_height, image_width])
    return img
```

In [6]:
```
def process_path(file_path):

    file_path=tf.strings.regex_replace(file_path,".xml", ".jpg")
    table_mask_path = tf.strings.regex_replace(file_path,"Image", "table_mask"
)
    column_mask_path = tf.strings.regex_replace(file_path,"Image", "column_mas
k")

    table_mask_path=tf.strings.regex_replace(table_mask_path,'.jpg','.jpeg')
    column_mask_path=tf.strings.regex_replace(column_mask_path,'.jpg','.jpeg')

    img = tf.io.read_file(file_path)

    table_mask=tf.io.read_file(table_mask_path)
    column_mask=tf.io.read_file(column_mask_path)


    img = decode_image(img)
    table_mask=decode_mask(table_mask)
    column_mask=decode_mask(column_mask)


    img=normalize(img)
    table_mask=normalize(table_mask)
    column_mask=normalize(column_mask)

    return img, {'table_mask':table_mask,'column_mask':column_mask}
```

In [7]:
```
file_data = tf.data.Dataset.list_files("../input/data/Image/*.xml")

DATASET_SIZE = len(list(list_ds))
TRAIN_LENGTH = int(0.9 * DATASET_SIZE)
test_size = int(0.1 * DATASET_SIZE)
BATCH_SIZE = 3
BUFFER_SIZE = 1000
STEPS_PER_EPOCH = TRAIN_LENGTH // BATCH_SIZE
```

In [8]:
```
file_data = tf.data.Dataset.list_files("../input/data/Image/*.xml")
train=file_data.take(TRAIN_LENGTH)
test=file_data.skip(TRAIN_LENGTH)
```

In [9]:
```
train = train.map(process_path, num_parallel_calls=tf.data.experimental.AUTOTU
NE)
test = test.map(process_path)
```

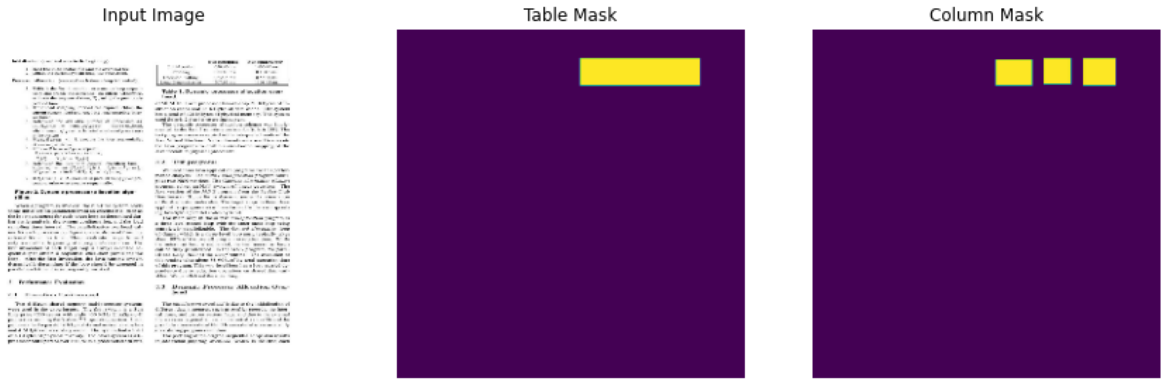
In [10]:
```
```

In [11]:
```
train_dataset = train.cache().shuffle(BUFFER_SIZE).batch(BATCH_SIZE).repeat()
train_dataset = train_dataset.prefetch(buffer_size=tf.data.experimental.AUTOTU
NE)
test_dataset = test.batch(BATCH_SIZE)
```

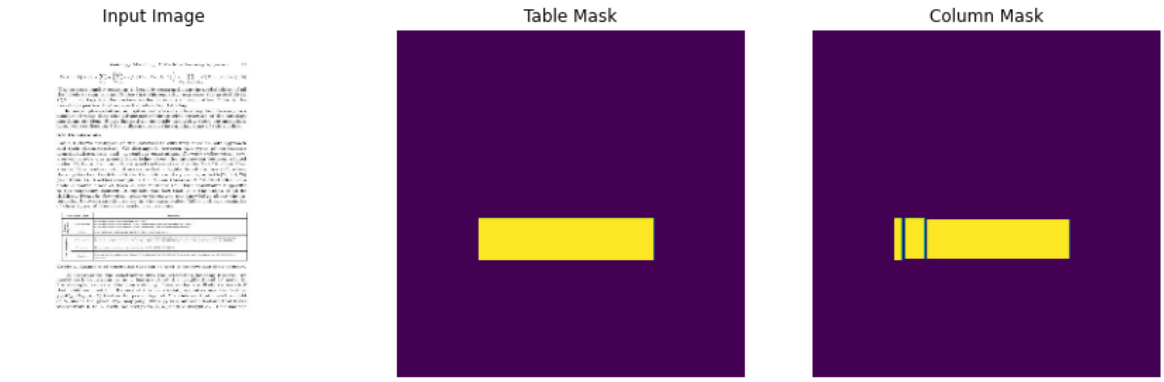
In [12]:
```
def display(display_list):

    plt.figure(figsize=(15, 15))

    title = ['Input Image', 'Table Mask', 'Column Mask']

    for i in range(len(display_list)):
    #print("i:",i)
        plt.subplot(1, len(display_list), i+1)
        plt.title(title[i])
        plt.imshow(tf.keras.preprocessing.image.array_to_img(display_list[i]))
        plt.axis('off')
    plt.show()
```

In [13]:
```
for image, mask  in train.take(2):
    print(image.shape)
    display([image, mask['table_mask'], mask['column_mask']])
```

```
(256, 256, 3)
```




```
(256, 256, 3)
```



Since we have prepared the Train-Test dataset , now as a next step we need to develop the Tablenet model architecture . Input data will be the Image and corresponding Table and column masks. Whereas o/p will be Table and Column masks generated by the model

Tensorflow documentation has been used extensively to create the mask of an image

https://www.tensorflow.org/tutorials/images/segmentation (https://www.tensorflow.org/tutorials/images/segmentation)

In [14]:
```
def table_decoder(inputs,pool3,pool4):

    x = Conv2D(512, (1, 1), activation = 'relu', name='conv7_table')(inputs)
    x = UpSampling2D(size=(2, 2))(x)

    concat1=Concatenate()([x,pool4])

    x = UpSampling2D(size=(2, 2))(concat1)

    concat2=Concatenate()([x,pool3])

    x = UpSampling2D(size=(2,2),name='table_op')(concat2)
    x = UpSampling2D(size=(2,2))(x)

    final_layer = tf.keras.layers.Conv2DTranspose(3, 3, strides=2,padding='sam
e', name='table_mask')

    x=final_layer(x)

    return x
```

In [17]:
```
def column_decoder(inputs,pool3,pool4):

    x = Conv2D(512, (1, 1), activation = 'relu', name='block7_conv1_column')(i
nputs)
    x = Dropout(0.8, name='block7_dropout_col')(x)

    x = Conv2D(512, (1, 1), activation = 'relu', name='block8_conv1_col')(x)
    x = UpSampling2D(size=(2, 2))(x)

    concat1=Concatenate()([x,pool4])
    x = UpSampling2D(size=(2, 2))(concat1)

    concat2=Concatenate()([x,pool3])
    x = UpSampling2D(size=(2,2),name='column_op')(concat2)

    x = UpSampling2D(size=(2,2))(x)

    final_layer = tf.keras.layers.Conv2DTranspose(3, 3, strides=2,padding='sam
e', name='column_mask')

    x = final_layer(x)

    return x
```

In [15]:
```
inputShape = (1024, 1024, 3)

#inputShape = (256, 256,3)
inputs = Input(shape=inputShape, name='input')

vgg_19=tf.keras.applications.VGG19(input_tensor=inputs,include_top=False, weig
hts='imagenet', pooling=None, classes=1000)
print(vgg_19.output_shape)

block3_pool=vgg_19.get_layer('block3_pool').output
print(block3_pool.get_shape)
block4_pool=vgg_19.get_layer('block4_pool').output
print(block4_pool.get_shape)

x = Conv2D(512, (1, 1), activation = 'relu', name='block6_conv1')(vgg_19.outpu
t)
print(x.get_shape)
x = Dropout(0.8, name='block6_dropout1')(x)
print(x.get_shape)

x = Conv2D(512, (1, 1), activation = 'relu', name='block6_conv2')(x)
print(x.get_shape)
x = Dropout(0.8, name = 'block6_dropout2')(x)
print(x.get_shape)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applica
tions/vgg19/vgg19_weights_tf_dim_ordering_tf_kernels_notop.h5
80142336/80134624 [==============================] - 1s 0us/step
(None, 8, 8, 512)
<bound method Tensor.get_shape of <tf.Tensor 'block3_pool/MaxPool:0' shape=(N
one, 32, 32, 256) dtype=float32>>
<bound method Tensor.get_shape of <tf.Tensor 'block4_pool/MaxPool:0' shape=(N
one, 16, 16, 512) dtype=float32>>
<bound method Tensor.get_shape of <tf.Tensor 'block6_conv1/Relu:0' shape=(Non
e, 8, 8, 512) dtype=float32>>
<bound method Tensor.get_shape of <tf.Tensor 'block6_dropout1/cond/Identity:
0' shape=(None, 8, 8, 512) dtype=float32>>
<bound method Tensor.get_shape of <tf.Tensor 'block6_conv2/Relu:0' shape=(Non
e, 8, 8, 512) dtype=float32>>
<bound method Tensor.get_shape of <tf.Tensor 'block6_dropout2/cond/Identity:
0' shape=(None, 8, 8, 512) dtype=float32>>
```

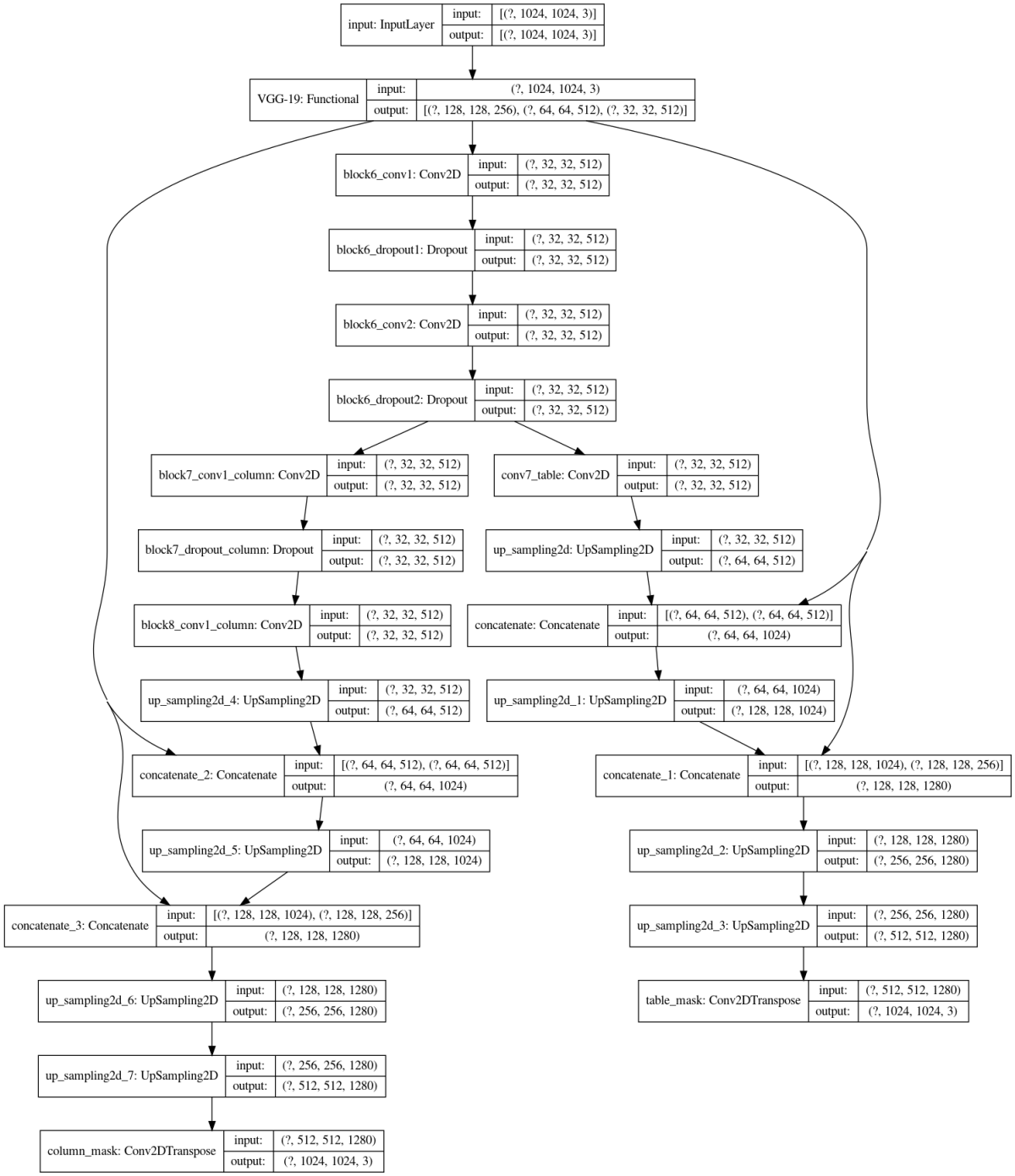
In [18]:
```
table_mask=table_decoder(x,block3_pool,block4_pool)
column_mask=column_decoder(x,block3_pool,block4_pool)
```

In [19]:
```
model = Model(inputs=inputs,outputs=[table_mask, column_mask],name="tablenet")
```

In [8]:
```
tf.keras.utils.plot_model(model,show_shapes=True,show_layer_names=True)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applica
tions/vgg19/vgg19_weights_tf_dim_ordering_tf_kernels_notop.h5
80142336/80134624 [==============================] - 1s 0us/step
```

Out[8]:



In [ ]:
```
```

In [21]:
```
losses = {
    "table_mask": tf.keras.losses.SparseCategoricalCrossentropy(from_logits=Tr
ue),
    "column_mask": tf.keras.losses.SparseCategoricalCrossentropy(from_logits=T
rue),
}

lossWeights = {"table_mask": 1.0, "column_mask": 1.0}

model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.0001, epsilon
=1e-08),
              loss=losses,
              metrics=['accuracy'],
              loss_weights=lossWeights)
```

In [22]:
```
def create_mask(pred_mask1, pred_mask2):
    pred_mask1 = tf.argmax(pred_mask1, axis=-1)
    pred_mask1 = pred_mask1[..., tf.newaxis]

    pred_mask2 = tf.argmax(pred_mask2, axis=-1)
    pred_mask2 = pred_mask2[..., tf.newaxis]
    return pred_mask1[0], pred_mask2[0]
```

In [23]:
```
def show_predictions(dataset=None, num=1):
    if dataset:

        for image, (mask1, mask2) in dataset.take(num):

            pred_mask1, pred_mask2 = model.predict(image, verbose=1)
            table_mask, column_mask = create_mask(pred_mask1, pred_mask2)
            display([image[0], table_mask, column_mask])
    else:
        pred_mask1, pred_mask2 = model.predict(sample_image, verbose=1)
        table_mask, column_mask = create_mask(pred_mask1, pred_mask2)

        display([sample_image[0], table_mask, column_mask])
```

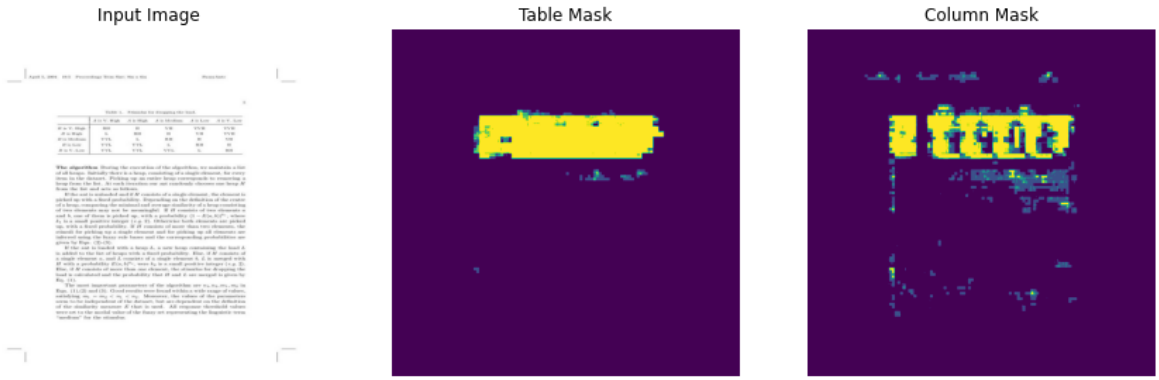
In [ ]:
```
!ls '../input/data19/pre_data/column_mask/10.1.1.1.2010_5.jpeg'
```

In [24]:
```
from IPython.display import clear_output

class DisplayCallback(tf.keras.callbacks.Callback):
    def on_epoch_end(self, epoch, logs=None):
        clear_output(wait=True)
        show_predictions()
        print ('\nSample Prediction after epoch {}\n'.format(epoch+1))
```

In [ ]:
```

```

In [13]:
```
EPOCHS = 100
VAL_SUBSPLITS = 5
VALIDATION_STEPS = test_size//BATCH_SIZE//VAL_SUBSPLITS


model_history = model.fit(train_dataset, epochs=EPOCHS,
                          steps_per_epoch=STEPS_PER_EPOCH,
                          validation_steps=VALIDATION_STEPS,
                          validation_data=test_dataset,
                          callbacks=[DisplayCallback(), model_checkpoint])
```

```
1/1 [==============================] - 0s 293ms/step
```




```
Sample Prediction after epoch 73


Epoch 00073: val_loss did not improve from 0.24500
444/444 [==============================] - 195s 438ms/step - loss: 0.2746 - t
able_mask_loss: 0.1348 - column_mask_loss: 0.1397 - table_mask_accuracy: 0.93
96 - column_mask_accuracy: 0.9202 - val_loss: 0.4148 - val_table_mask_loss:
0.1402 - val_column_mask_loss: 0.2746 - val_table_mask_accuracy: 0.9405 - val
_column_mask_accuracy: 0.8692
Epoch 74/100
117/444 [======>.......................] - ETA: 2:19 - loss: 0.2503 - table_m
ask_loss: 0.1258 - column_mask_loss: 0.1246 - table_mask_accuracy: 0.9429 - c
olumn_mask_accuracy: 0.9261
```

```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
<ipython-input-13-415bb7b2511b> in <module>
      8                           validation_steps=VALIDATION_STEPS,
      9                           validation_data=test_dataset,
---> 10                          callbacks=[DisplayCallback(), model_checkpo
int])

/opt/conda/lib/python3.7/site-packages/tensorflow/python/keras/engine/trainin
g.py in _method_wrapper(self, *args, **kwargs)
    106   def _method_wrapper(self, *args, **kwargs):
    107     if not self._in_multi_worker_mode():  # pylint: disable=protected
-access
--> 108       return method(self, *args, **kwargs)
    109
    110     # Running inside `run_distribute_coordinator` already.

/opt/conda/lib/python3.7/site-packages/tensorflow/python/keras/engine/trainin
g.py in fit(self, x, y, batch_size, epochs, verbose, callbacks, validation_sp
lit, validation_data, shuffle, class_weight, sample_weight, initial_epoch, st
eps_per_epoch, validation_steps, validation_batch_size, validation_freq, max_
queue_size, workers, use_multiprocessing)
   1101               logs = tmp_logs  # No error, now safe to assign to log
s.
   1102               end_step = step + data_handler.step_increment
-> 1103               callbacks.on_train_batch_end(end_step, logs)
   1104         epoch_logs = copy.copy(logs)
   1105

/opt/conda/lib/python3.7/site-packages/tensorflow/python/keras/callbacks.py i
n on_train_batch_end(self, batch, logs)
    438     """
    439     if self._should_call_train_batch_hooks:
--> 440       self._call_batch_hook(ModeKeys.TRAIN, 'end', batch, logs=logs)
    441
    442   def on_test_batch_begin(self, batch, logs=None):

/opt/conda/lib/python3.7/site-packages/tensorflow/python/keras/callbacks.py i
n _call_batch_hook(self, mode, hook, batch, logs)
    287       self._call_batch_begin_hook(mode, batch, logs)
    288     elif hook == 'end':
--> 289       self._call_batch_end_hook(mode, batch, logs)
    290     else:
    291       raise ValueError('Unrecognized hook: {}'.format(hook))

/opt/conda/lib/python3.7/site-packages/tensorflow/python/keras/callbacks.py i
n _call_batch_end_hook(self, mode, batch, logs)
    307       batch_time = time.time() - self._batch_start_time
    308
--> 309     self._call_batch_hook_helper(hook_name, batch, logs)
    310
    311     if self._check_timing:

/opt/conda/lib/python3.7/site-packages/tensorflow/python/keras/callbacks.py i
n _call_batch_hook_helper(self, hook_name, batch, logs)
    343       else:
    344         if numpy_logs is None:  # Only convert once.
```

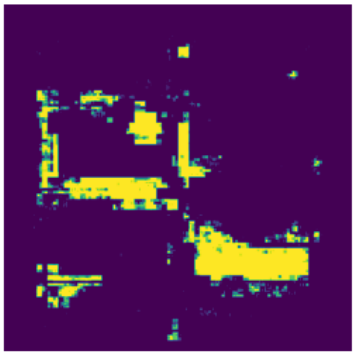
```
--> 345           numpy_logs = tf_utils.to_numpy_or_python_type(logs)
    346         hook(batch, numpy_logs)
    347

/opt/conda/lib/python3.7/site-packages/tensorflow/python/keras/utils/tf_util
s.py in to_numpy_or_python_type(tensors)
    535     return t  # Don't turn ragged or sparse tensors to NumPy.
    536
--> 537   return nest.map_structure(_to_single_numpy_or_python_type, tensors)
    538
    539

/opt/conda/lib/python3.7/site-packages/tensorflow/python/util/nest.py in map_
structure(func, *structure, **kwargs)
    633
    634   return pack_sequence_as(
--> 635       structure[0], [func(*x) for x in entries],
    636       expand_composites=expand_composites)
    637

/opt/conda/lib/python3.7/site-packages/tensorflow/python/util/nest.py in <lis
tcomp>(.0)
    633
    634   return pack_sequence_as(
--> 635       structure[0], [func(*x) for x in entries],
    636       expand_composites=expand_composites)
    637

/opt/conda/lib/python3.7/site-packages/tensorflow/python/keras/utils/tf_util
s.py in _to_single_numpy_or_python_type(t)
    531   def _to_single_numpy_or_python_type(t):
    532     if isinstance(t, ops.Tensor):
--> 533       x = t.numpy()
    534       return x.item() if np.ndim(x) == 0 else x
    535     return t  # Don't turn ragged or sparse tensors to NumPy.

/opt/conda/lib/python3.7/site-packages/tensorflow/python/framework/ops.py in
numpy(self)
   1061     """
   1062     # TODO(slebedev): Consider avoiding a copy for non-CPU or remote
 tensors.
-> 1063     maybe_arr = self._numpy()  # pylint: disable=protected-access
   1064     return maybe_arr.copy() if isinstance(maybe_arr, np.ndarray) else
maybe_arr
   1065

/opt/conda/lib/python3.7/site-packages/tensorflow/python/framework/ops.py in
_numpy(self)
   1027   def _numpy(self):
   1028     try:
-> 1029       return self._numpy_internal()
   1030     except core._NotOkStatusException as e:  # pylint: disable=protec
ted-access
   1031       six.raise_from(core._status_to_exception(e.code, e.message), No
ne)  # pylint: disable=protected-access

KeyboardInterrupt:
```

In [14]:
```
show_predictions(test_dataset, 10)
```

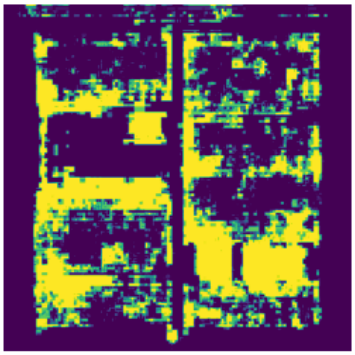
```
1/1 [==============================] - 0s 279ms/step
```

Input Image

Table Mask



Column Mask



```
1/1 [==============================] - 0s 271ms/step
```

Input Image

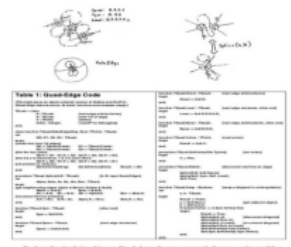
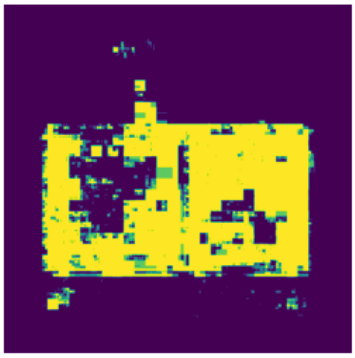
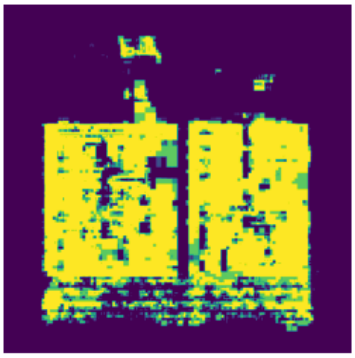


Table Mask



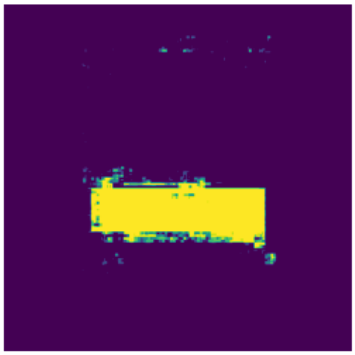
Column Mask



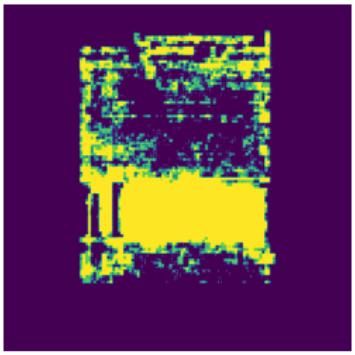
```
1/1 [==============================] - 0s 257ms/step
```

Input Image

Table Mask



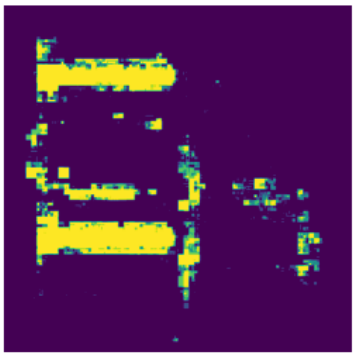
Column Mask



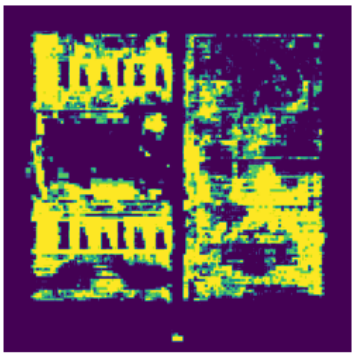
```
1/1 [==============================] - 0s 257ms/step
```

Input Image

Table Mask



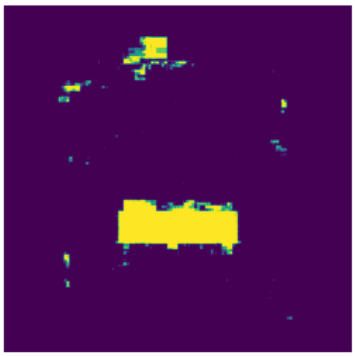
Column Mask



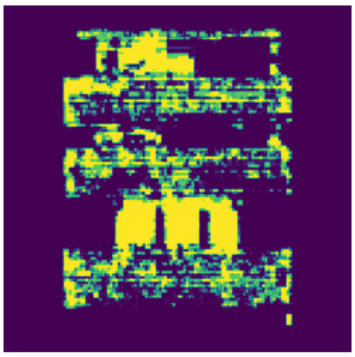
```
1/1 [==============================] - 0s 258ms/step
```

Input Image

Table Mask



Column Mask



```
1/1 [==============================] - 0s 256ms/step
```

Input Image

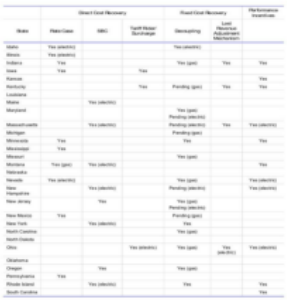
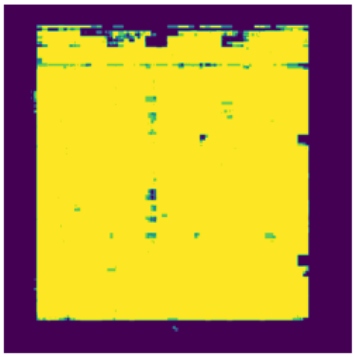
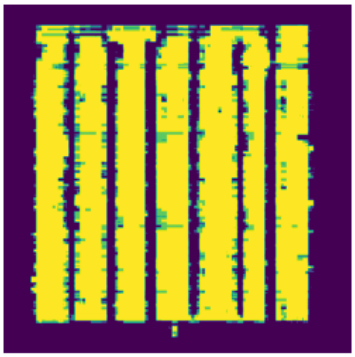


Table Mask



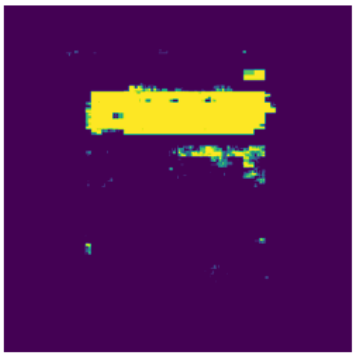
Column Mask



```
1/1 [==============================] - 0s 257ms/step
```

Input Image

Table Mask



Column Mask

```
1/1 [==============================] - 0s 258ms/step
```

Input Image

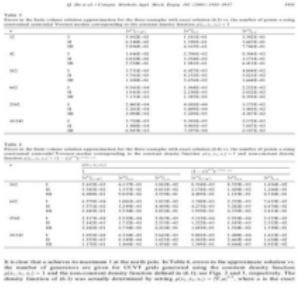
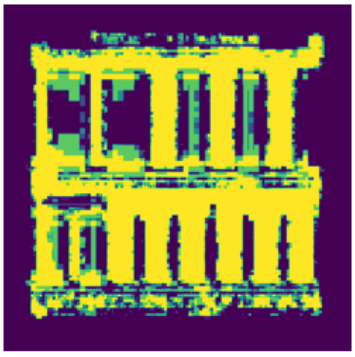
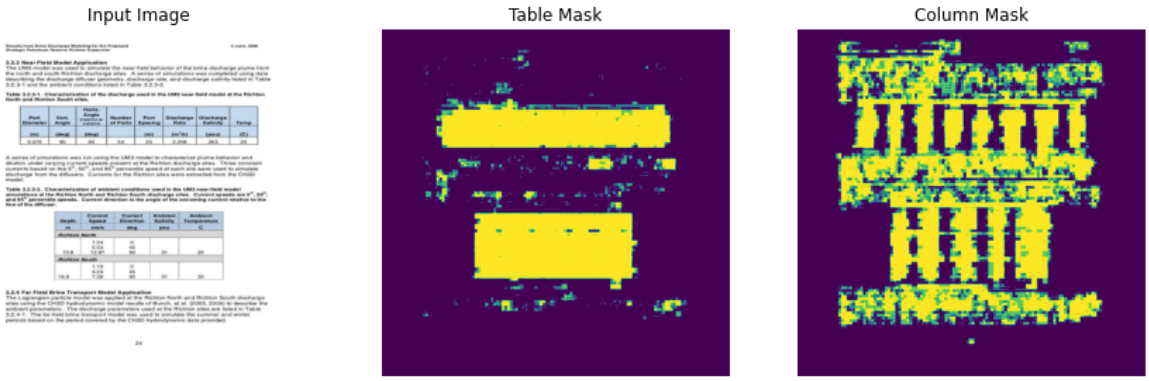


Table Mask

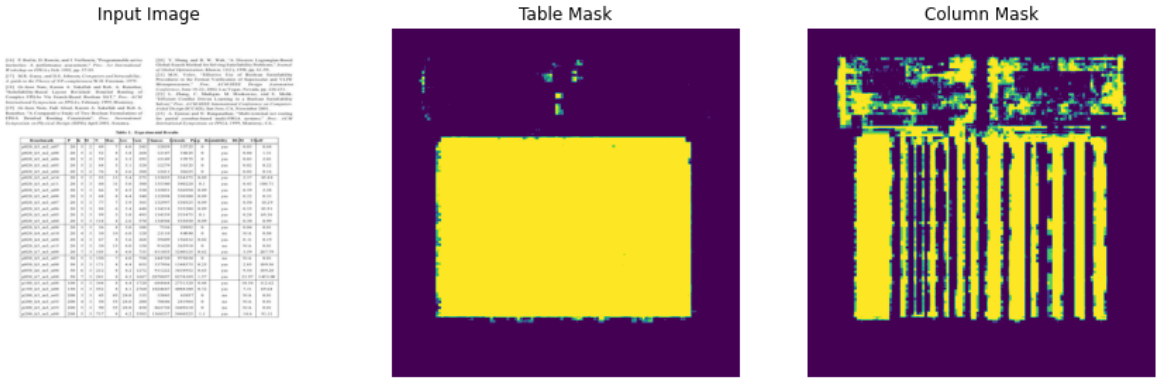
Column Mask



```
1/1 [==============================] - 0s 256ms/step
```




```
1/1 [==============================] - 0s 257ms/step
```



7. Model Prediction and Data Extraction

Since we were able to create the table and Column masks, as a next step we should be able to extract the informations based on the mask Image

For testing purpose we will randomly pick one data from the test dataset and see how well the model perform

In [21]:
```
"""
we are using the same show_prediction function which is defined earlier and mo
dified slightly. So instead of displaying the
image result we are going to save the Image and correspondings Table and Colum
n masks in a .bmp format

"""

def show_prediction(dataset=None, num=1):

    if dataset:

        print("if")

        for image, (mask1, mask2) in dataset.take(num):
            pred_mask1, pred_mask2 = model.predict(image, verbose=1)
            table_mask, column_mask = create_mask(pred_mask1, pred_mask2)

        im=tf.keras.preprocessing.image.array_to_img(image[0])
        im.save('image.bmp')

        im=tf.keras.preprocessing.image.array_to_img(table_mask)
        im.save('table_mask.bmp')

        im=tf.keras.preprocessing.image.array_to_img(column_mask)
        im.save('column_mask.bmp')
      #display([image[0], table_mask, column_mask])
    else:

        print("else")

        pred_mask1, pred_mask2 = model.predict(sample_image, verbose=1)
        table_mask, column_mask = create_mask(pred_mask1, pred_mask2)
        #im=tf.keras.preprocessing.image.array_to_img(display_list[i])

        im=tf.keras.preprocessing.image.array_to_img(image)
        image.save('image.png')

        im=tf.keras.preprocessing.image.array_to_img(table_mask)
        im.save('table_mask.png')

        im=tf.keras.preprocessing.image.array_to_img(column_mask)
        im.save('column_mask.png')

    #display([sample_image[0], table_mask, column_mask])
```

In [46]:
```
show_prediction(test_dataset,1)
```

```
if
1/1 [==============================] - 0s 271ms/step
```

let's display the randomly chosen image from the test dataset and generated table and column masks

Image

Table 2
Loss Distribution If Three Example Banks Failed
(Dollars in Millions)

	Bank A		Bank B		Bank C	
	Loss	% Total	Loss	% Total	Loss	% Total
Stockholders	$6	40%	$6	40%	$10	67%
Subordinated claimants	0	0%	0	0%	3	20%
Unsecured claimants	2	13%	2	13%	2	13%
FDIC/uninsured depositors	7	47%	7	47%	0	0%
Total Losses	15	100%	15	100%	15	100%

Thus the amount of bank capital, subordinated claims, and unsecured claims directly reduce the cost borne by the FDIC and the uninsured depositors on a dollar-for-dollar basis. The failure of Bank C, with strong capital plus some subordinated debt, costs the FDIC nothing, whereas the FDIC bears a large portion of the loss for the other two banks; however, Bank C has relatively high assessments. Banks A and B cost the same at failure, but Bank A pays much higher assessments.

Based on this static comparative analysis of FDIC losses at failure, the FDIC's risk of loss at failure is poorly aligned with the current pricing policy. This analysis provides support for either changing the assessment base to secured liabilities plus insured deposits or incorporating the lost assessment income associated with secured funding into the insurance price by other means.[12] Because secured liabilities are paid before the FDIC when a bank fails, they expose the FDIC to losses similar to those of insured deposits. When a bank replaces domestic deposits with secured lending, the FDIC's risk exposure changes very little, but the assessment income associated with the bank decreases.[13] Therefore, the insurance prices do not

[12] Note that the Call Reports do not record total secured borrowing, and only an estimate of insured deposits is recorded. Thus this possible change in the assessment base could involve issues related to regulatory burden and measurability.

[13] Typically the FDIC's loss exposure does not change in situations in which the bank reduces insured and uninsured deposits at the same rate. If uninsured deposits are replaced with secured lending, the FDIC's loss exposure increases slightly; if insured deposits are replaced with secured lending, the FDIC's loss exposure decreases slightly.

Table mask generated by the trained model

Column mask

In [49]:
```
#ref: https://stackoverflow.com/questions/65523727/python-image-masking-and-removing-background?noredirect=1&lq=1

"""
based on the generated masks this function will crop the image from the original one which is only covered by the
corresponding masks
"""

from PIL import Image

# load images
img_org  = Image.open('./image.bmp')
img_mask = Image.open('./table_mask.bmp')

# convert images
#img_org  = img_org.convert('RGB') # or 'RGBA'
img_mask = img_mask.convert('L')    # grayscale


# add alpha channel
img_org.putalpha(img_mask)

# save as png which keeps alpha channel
img_org.save('output.png')
```

let's check the output image

	Bank A		Bank B		Bank C	
	Loss	% Total	Loss	% Total	Loss	% Total
Stockholders	$6	40%	$6	40%	$10	67%
Subordinated claimants	0	0%	0	0%	3	20%
Unsecured claimants	2	13%	2	13%	2	13%
FDIC/uninsured depositors	7	47%	7	47%	0	0%
Total Losses	15	100%	15	100%	15	100%

Next we will extract the information using pytesseract

In [50]:
```
from PIL import Image
import pytesseract

def ocr_core(filename):
    """
    This function will handle the core OCR processing of images.
    """
    text = pytesseract.image_to_string(Image.open(filename))  # We'll use Pillow's Image class to open the image and pytesseract to detect the string in the image
    return text

print(ocr_core('./output.png'))
```

```
a;

¢ Vier
Bank A ™ Bank B Bank C
Loss %Total Loss %Total Loss % Totai
Stockholders 36 40%  S6 40% $10 67%
Subordinated claimants 0 0% 0 0% 3 20%
Unsecured claimants 2 13% 2 13% 2 13%
FD1IC/uninsured depositors Zz 47% 2 4% 9 0%
Total Losses 17 100% 15 100% if 100%
In
“
+s Suppo
ne
```

In [ ]:
```
#Unused as the procedure is not so useful and failed to return satisfactore re
sult
"""
To store the data in a csv file
"""

import csv

def split_list(l, n):
    splitted = []
    for i in range(0, len(l), n):
        splitted.append(l[i:i + n])
    return splitted

input_file = './myfile.txt'
output_file = './final.csv'
delimiter = ';'

# read input file
with open(input_file, 'r') as f:
    data = f.readlines()

# remove trailing whitespace and newlines
data = list(map(lambda x: x.strip(), data))
# remove empty elements
data = list(filter(None, data))
# split data to rows-sized lists
data = split_list(data, rows)
# shape data
data = list(map(list, zip(*data)))

# write to csv
with open(output_file, 'w', newline='\n') as f:
    wr = csv.writer(f, delimiter=delimiter)
    for i in range(len(data)):
        wr.writerow(data[i])
```

Let's Check few more examples by uploading images manually. We will check other cases

In [20]:
```
list_ds = tf.data.Dataset.list_files('./*.jpg')
```

In [20]:
```
def process(file_paths):
    img = normalize(decode_img(tf.io.read_file(file_paths)))
    return img
```

In [ ]:
```
DATASET_SIZE = len(list(list_ds))
test_size = DATASET_SIZE
test = list_ds.take(test_size)
BATCH_SIZE = 1
BUFFER_SIZE = 1000
test = test.map(process)
test_datasetss = test.batch(BATCH_SIZE)
```

In [ ]:
```
def show_prediction_sample_image(dataset=None, num=1):
    for image in dataset.take(num):
        pred_mask1, pred_mask2 = model.predict(image, verbose=1)
        table_mask, column_mask = create_mask(pred_mask1, pred_mask2)

        im=tf.keras.preprocessing.image.array_to_img(image[0])
        im.save('image.bmp')

        im=tf.keras.preprocessing.image.array_to_img(table_mask)
        im.save('table_mask.bmp')

        im=tf.keras.preprocessing.image.array_to_img(column_mask)
        im.save('column_mask.bmp')
```

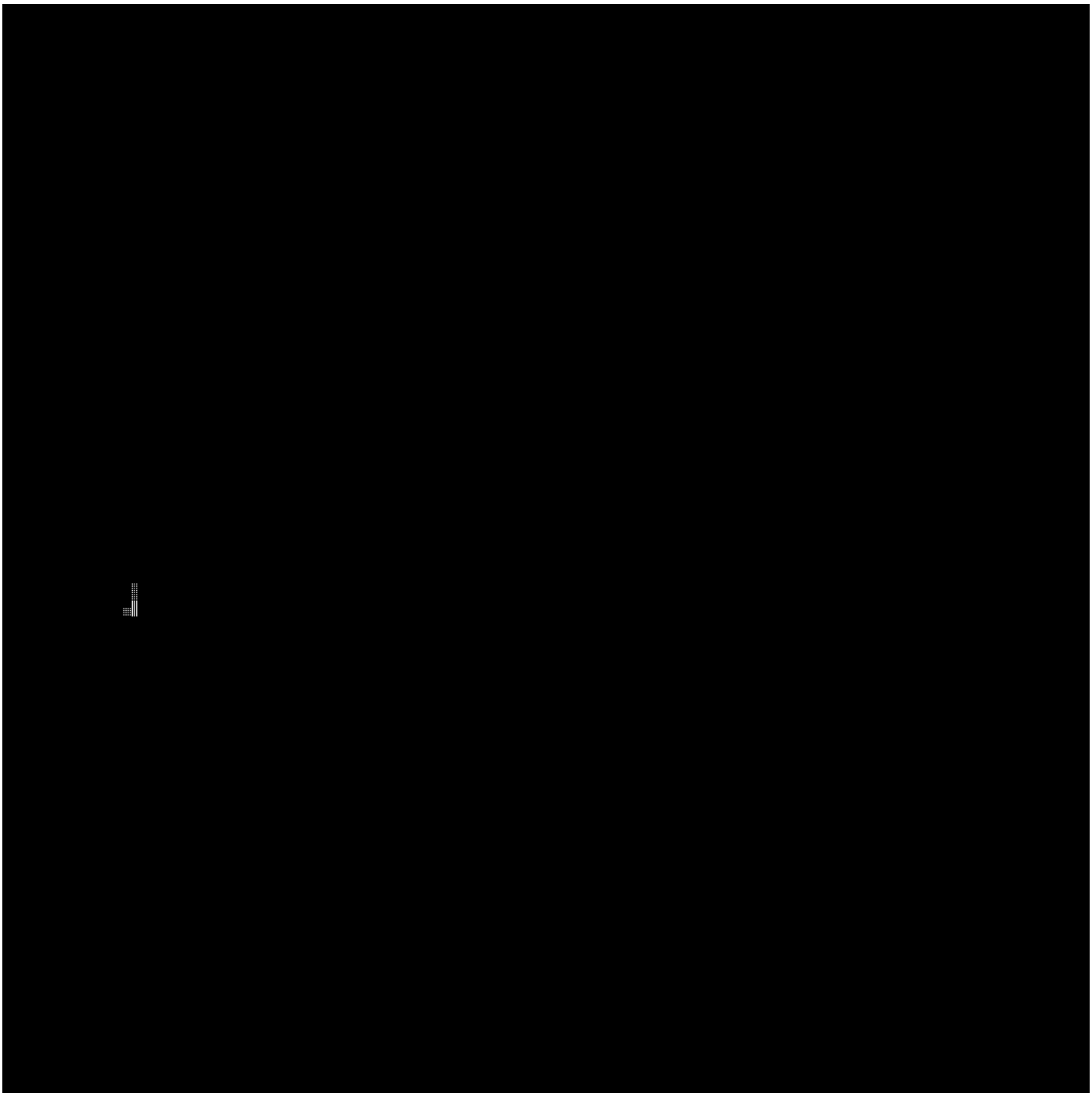
In [22]:
```
show_prediction_sample_image(test_dataset)
```

```
1/1 [==============================] - 0s 145ms/step
```

8.1 Example-1

The original image is , without any text

Now the generated table mask is



So the model can detect if there is no table present in the image (without any text)

8.2. Example-2

Now we will check another example where it doesn't contain any table but with text

$p \leq M$, which by the analysis in §7.6, happens with probability precisely

$$\prod_{p \leq M} p^{-e_p}(1 - 1/p) = \frac{U(M)}{n},$$

where

$$U(M) := \prod_{p \leq M} (1 - 1/p).$$

Now, the probability that this loop iteration produces n as output is equal to the probability that r takes the value n *and* $s \leq n$, which is

$$\frac{U(M)}{n} \cdot \frac{n}{M} = \frac{U(M)}{M}.$$

Thus, every n is equally likely, and summing over all $n = 1, \ldots, M$, we see that the probability that this loop iteration succeeds in producing *some* output is $U(M)$.

Now consider the expected running time of this loop iteration. From the analysis in §7.6, it is easy to see that this is $O(kW^*_M)$. That completes the analysis of a single loop iteration.

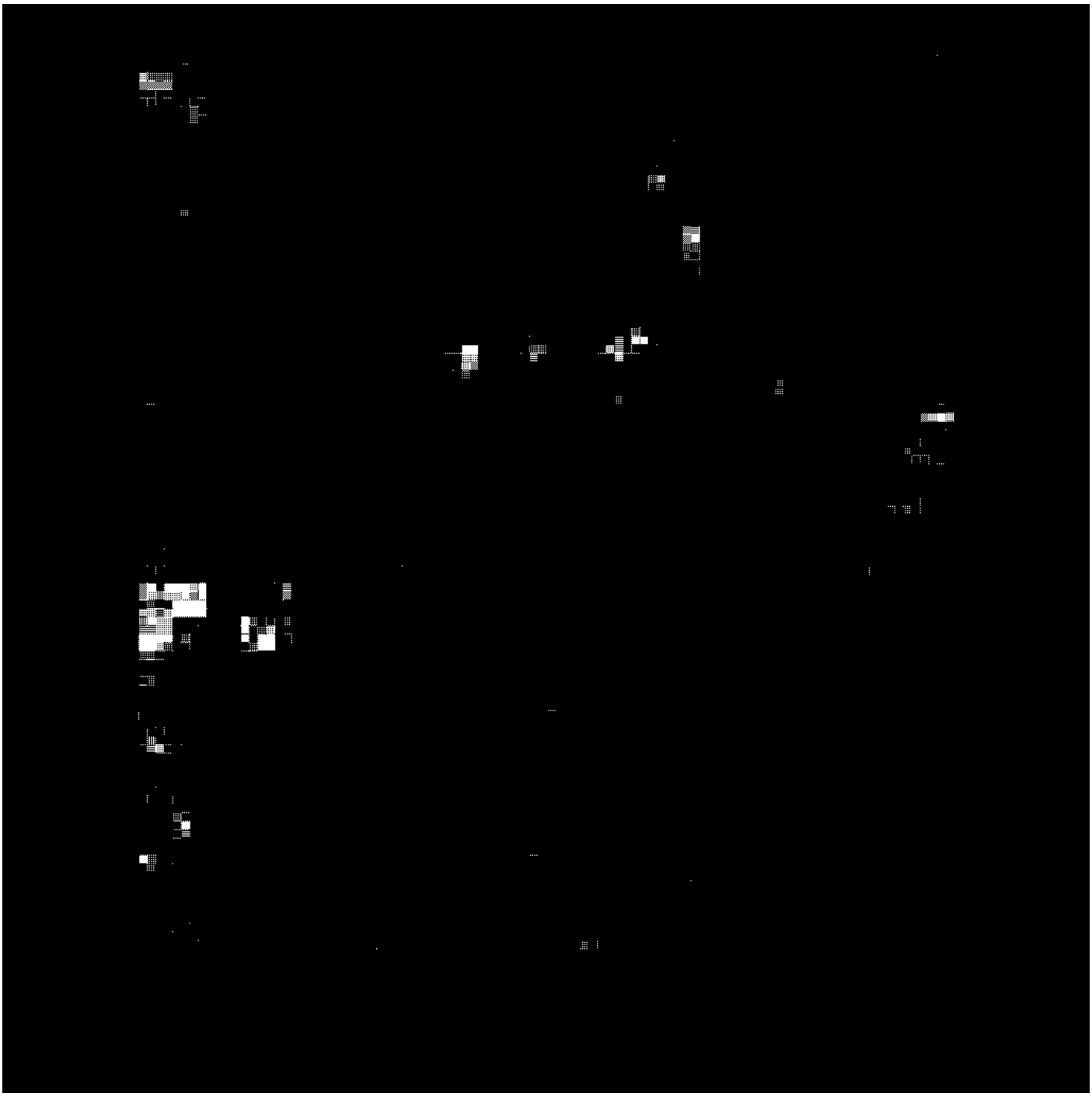
Finally, consider the behavior of Algorithm RFN as a whole. From our analysis of an individual loop iteration, it is clear that the output distribution of Algorithm RFN is as required, and if H denotes the number of loop iterations of the algorithm, then $\mathsf{E}[H] = U(M)^{-1}$, which by Mertens' theorem is $O(k)$. Since the expected running time of each individual loop iteration is $O(kW^*_M)$, it follows that the expected total running time is $O(k^2 W^*_M)$.

7.7.1 ♣ Using a probabilistic primality test

Analogous to the discussion in §7.5.1, we can analyze the behavior of Algorithm RFN under the assumption that *IsPrime* is a probabilistic algorithm which may erroneously indicate that a composite number is prime with probability bounded by ϵ. Here, we assume that W_n denotes the expected running time of the primality test on input n, and set $W^*_M := \max\{W_n : n = 2, \ldots, M\}$.

The situation here is a bit more complicated than in the case of Algorithm RP, since an erroneous output of the primality test in Algorithm RFN could lead either to the algorithm halting prematurely (with a wrong output), or to the algorithm being delayed (because an opportunity to halt may be missed).

The corresponding generated Table-mask is



so we can conclude , since there is no table present in the image so Table-mask has been generated accordingly

8.3. Example-3

Let's check another example where the table is present

3.2.3 Near Field Model Application

The UM3 model was used to simulate the near-field behavior of the brine discharge plume from the north and south Richton discharge sites. A series of simulations was completed using data describing the discharge diffuser geometry, discharge rate, and discharge salinity listed in Table 3.2.3-1 and the ambient conditions listed in Table 3.2.3-2.

Table 3.2.3-1. Characterization of the discharge used in the UM3 near-field model at the Richton North and Richton South sites.

Port Diameter	Vert. Angle	Horiz. Angle (relative to current)	Number of Ports	Port Spacing	Discharge Rate	Discharge Salinity	Temp
(m)	(deg)	(deg)		(m)	(m^3/s)	(psu)	(C)
0.076	90	90	53	20	2.208	263	20

A series of simulations was run using the UM3 model to characterize plume behavior and dilution under varying current speeds present at the Richton discharge sites. Three constant currents based on the 5^{th}, 50^{th}, and 95^{th} percentile speed at each site were used to simulate discharge from the diffusers. Currents for the Richton sites were extracted from the CH3D model.

Table 3.2.3-2. Characterization of ambient conditions used in the UM3 near-field model simulations at the Richton North and Richton South discharge sites. Current speeds are 5^{th}, 50^{th}, and 95^{th} percentile speeds. Current direction is the angle of the oncoming current relative to the line of the diffuser.

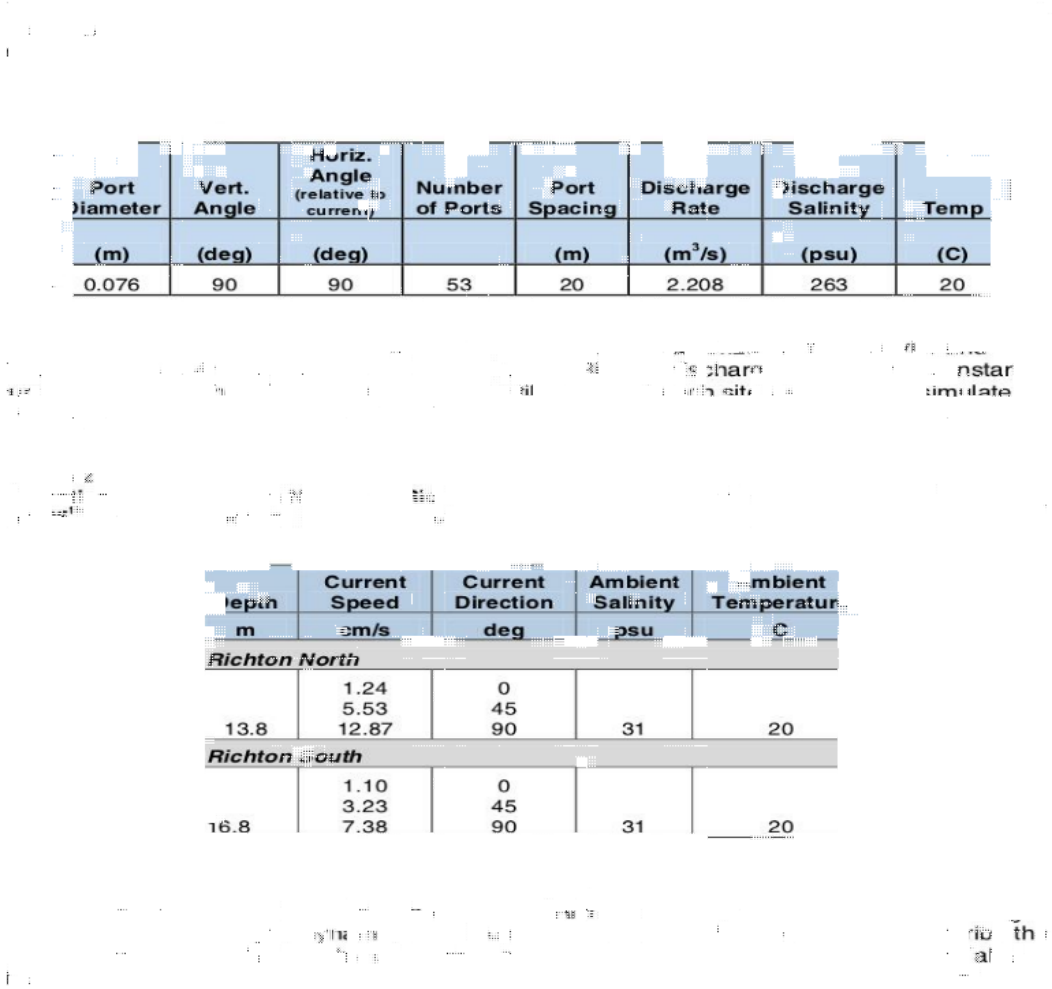
Depth	Current Speed	Current Direction	Ambient Salinity	Ambient Temperature
m	cm/s	deg	psu	C
Richton North				
13.8	1.24 5.53 12.87	0 45 90	31	20
Richton South				
16.8	1.10 3.23 7.38	0 45 90	31	20

3.2.4 Far Field Brine Transport Model Application

The Lagrangian particle model was applied at the Richton North and Richton South discharge sites using the CH3D hydrodynamic model results of Bunch, et al. (2003, 2005) to describe the ambient parameters. The discharge parameters used at the Richton sites are listed in Table 3.2.4-1. The far-field brine transport model was used to simulate the summer and winter periods based on the period covered by the CH3D hydrodynamic data provided.

In [ ]:

after applying the generated table_mask on the original image , we got



Port Diameter (m)	Vert. Angle (deg)	Horiz. Angle (relative to current) (deg)	Number of Ports	Port Spacing (m)	Discharge Rate (m^3/s)	Discharge Salinity (psu)	Temp (C)
0.076	90	90	53	20	2.208	263	20

Depth m	Current Speed cm/s	Current Direction deg	Ambient Salinity psu	Ambient Temperature C
Richton North				
13.8	1.24 5.53 12.87	0 45 90	31	20
Richton South				
16.8	1.10 3.23 7.38	0 45 90	31	20

So the model was able to detect the table region

8.4. Example-4

Next we will consider one final example where the entire image is table region , without any extra text.

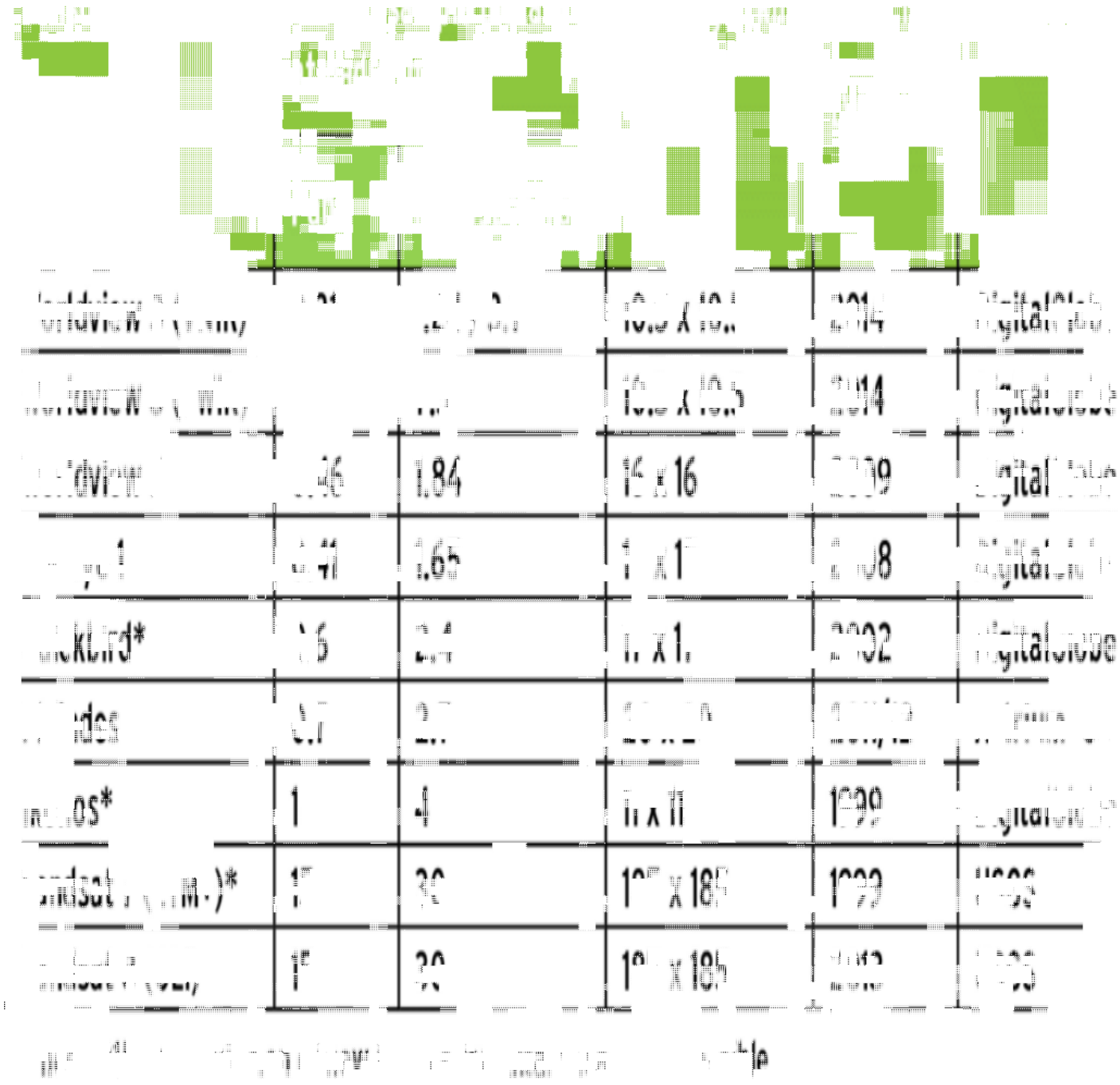
Sensor	Ground sample distance at nadir [m]		Coverage [km]	Launch [year]	Provider
	Pan	Multispectral			
Worldview 3 (VNIR)	0.31	1.24 / 3.7	10.5 x 10.5	2014	DigitalGlobe
Worldview 3 (SWIR)		7.5	10.5 x 10.5	2014	DigitalGlobe
Worldview 2	0.46	1.84	16 x 16	2009	DigitalGlobe
GeoEye 1	0.41	1.65	15 x 15	2008	DigitalGlobe
Quickbird*	0.6	2.4	17 x 17	2002	DigitalGlobe
Pléiades	0.7	2.7	20 x 20	2011/12	AstriumGeo
Ikonos*	1	4	11 x 11	1999	DigitalGlobe
Landsat 7 (ETM+)*	15	30	185 x 185	1999	USGS
Landsat 8 (OLI)	15	30	185 x 185	2013	USGS

* since 2015 an acquisition of new images for Antarctica is not possible

So in this image the model should detect the entire table

Unfortunately , our Model deliberately failed to detect the region properly

This is the final image after applying the generated Table-mask to the original image



In [ ]:

9. Precision & Recall

In [ ]:
```
"""
We are going to store the actual table and column mask in terms of tensor
"""
table=[]
column=[]
for i in test_dataset:
    table.append(i[1]['table_mask'])
    column.append(i[1]['column_mask'])
```

In [ ]:
```
"""
This will return the predicted Table and Column mask in terms of tensor
"""
def get_mask(dataset=None, num=1):
    tab=[]
    col=[]
    for image, (mask1, mask2) in dataset.take(num):
        pred_mask1, pred_mask2 = model.predict(image, verbose=1)
        table_mask, column_mask = create_mask(pred_mask1, pred_mask2)
        tab.append(table_mask)
        col.append(column_mask)

    return tab,col
```

In [28]:
```
tab_mask,col_mask=get_mask(test_dataset,len(test_dataset))
```

```
1/1 [==============================] - 0s 152ms/step
1/1 [==============================] - 0s 131ms/step
1/1 [==============================] - 0s 139ms/step
1/1 [==============================] - 0s 129ms/step
1/1 [==============================] - 0s 144ms/step
1/1 [==============================] - 0s 137ms/step
1/1 [==============================] - 0s 137ms/step
1/1 [==============================] - 0s 130ms/step
1/1 [==============================] - 0s 130ms/step
1/1 [==============================] - 0s 137ms/step
1/1 [==============================] - 0s 130ms/step
1/1 [==============================] - 0s 130ms/step
1/1 [==============================] - 0s 132ms/step
1/1 [==============================] - 0s 128ms/step
1/1 [==============================] - 0s 129ms/step
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1/1 [==============================] - 0s 130ms/step
1/1 [==============================] - 0s 130ms/step
1/1 [==============================] - 0s 137ms/step
1/1 [==============================] - 0s 130ms/step
1/1 [==============================] - 0s 130ms/step
1/1 [==============================] - 0s 131ms/step
1/1 [==============================] - 0s 130ms/step
1/1 [==============================] - 0s 130ms/step
1/1 [==============================] - 0s 130ms/step
1/1 [==============================] - 0s 130ms/step
1/1 [==============================] - 0s 132ms/step
1/1 [==============================] - 0s 136ms/step
1/1 [==============================] - 0s 130ms/step
1/1 [==============================] - 0s 130ms/step
1/1 [==============================] - 0s 129ms/step
1/1 [==============================] - 0s 129ms/step
```

In [ ]:
```
```

In [ ]:
```
"""
https://www.tensorflow.org/api_docs/python/tf/reshape

Need to reshape to match the shape of actual & predicted value
"""
mask_1=[]
mask_2=[]
for i in tab_mask:
    t2=tf.reshape(i, [1,1024, 1024])
    mask_1.append(t2)

for i in col_mask:
    t2=tf.reshape(i, [1,1024, 1024])
    mask_2.append(t2)
```

In [1]:
```
#https://www.tensorflow.org/api_docs/python/tf/keras/metrics/Recall
"""
Table mask Recall
"""

m = tf.keras.metrics.Recall()
m.update_state(table, mask_1)
m.result().numpy()
```

Out[1]: 0.42771236

In [2]:
```
"""
Column mask Recall
"""
m = tf.keras.metrics.Recall()
m.update_state(column, mask_2)
m.result().numpy()
```

Out[2]: 0.30130202

In [3]:
```
#https://www.tensorflow.org/api_docs/python/tf/keras/metrics/Precision
"""
Table mask Precision
"""
m = tf.keras.metrics.Precision()
m.update_state(table, mask_1)
m.result().numpy()
```

Out[3]: 0.44971604

In [4]:
```
"""
Column mask Precision
"""
m = tf.keras.metrics.Precision()
m.update_state(column, mask_2)
m.result().numpy()
```

Out[4]: 0.3701989

So For our model , Precision and Recall is significantly low

In [ ]:

10. Conclusion

1. A single Model is sufficient to detect the table regions and extract the informations from there also we can get the result in <1Sec , so it's quiet fast
2. For extracting the information , it's completely dependent on the Tesseract OCR (pytesseract). even though the model can detect the table in low resolution image , However Tesseract will not work for low resolution image . So result will hamper if the original image is not in High resolution (at least 1024*1024). hence further improvement is needed
3. It's vey difficult to store the result in terms of a csv file in case tesseract doesn't return the text in proper format. Tried few method but no luck so far . So need to work on that in future for better performance.Till now we can store the extracted data only in a normal text file.
4. As we checked in Example-4, Model failed to detect the tabular region properly in case The entire image contains Table i.e. outside the table there is no other extra text. So it should be taken up as future improvements.
5. Unfortunately Precison and Recall is still very low, one reason could be due to less number of images for training set (only 400 images are present) and comparatively less number of Epoch due to limited GPU and free session . In future we can train the model again if we can collect more images and with higher number of epochs

In [ ]: