SUDOKU SOLVING USING DIGIT CLASSIFICATION, IMAGE PROCESSING AND MATHEMATICS

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Theory

Sudoku

A number placement puzzle has 9×9 grids with 0–9 occurring once horizontally, vertically and in each box.
Sudoku was a Japanese invented game for fun and later on it became popular for its brain testing puzzles.
This is a newspaper cutting from 1895 of a French newspaper.

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PROGRAMME

Libraries

OpenCV:

OpenCV is a library of programming functions mainly aimed at real-time computer vision plus its open-source, fun to work with and my personal favorite. I have used version 4.1.0 for this project.

Keras:

Easy to use and widely supported, Keras makes deeplearning about as simple as deeplearning can be.

Scikit-Learn:

It is a free software machine learning library for the Python programming language.

Digit Recognition

Data Augmentation:

Data augmentation is a technique to artificially create new training data from existing training data. This is done by applying domain-specific techniques to examples from the training data that create new and different training examples.

Image Processing

Grey scaling the images

It takes average of the 3 RGB values of every pixel.

Gaussian Blur:

An image blurring technique in which the image is convolved with a Gaussian kernel. I'll be using it to smoothen the input image by reducing noise.

Thresholding:

In grayscaled images, each pixel has a value between 0–255, to convert such an image to a binary image we apply thresholding. To do this, we choose a threshold value between 0–255 and check each pixel's value in the grayscale image. If the value is less than the threshold, it is given a value of 0 else 1.

Contour detection:

Contours can be explained simply as a curve joining all the continuous points (along the boundary), having the same color or intensity.

Cropping and wrapping the contour

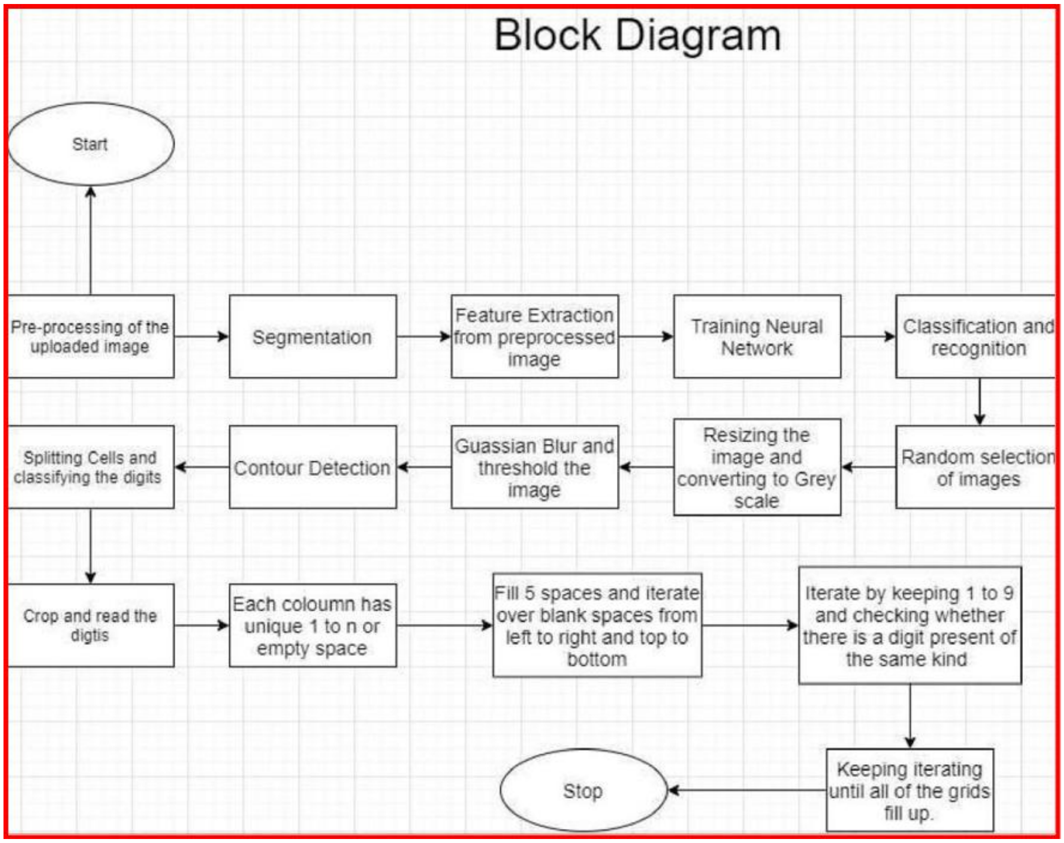
We can extract the actual image through the wrapping and contour and also read the digits to extract the puzzle.

Suduko Solving

Back tracking:

Backtracking is an algorithmic technique for solving problems recursively by trying to build a solution incrementally, one piece at a time, removing those solutions that fail to satisfy the constraints of the problem at any point.

And hence, we print the final result.



Block Diagram
Start
Pre-processing of the uploaded image
Segmentation
Feature Extraction from preprocessed image
Training Neural Network
Classification and recognition
Random selection of images
Resizing the image and converting to Grey scale
Guassian Blur and threshold the image
Contour Detection
Splitting Cells and classifying the digits
Crop and read the digtis
Each coloumn has unique 1 to n or empty space
Fill 5 spaces and iterate over blank spaces from left to right and top to bottom
Iterate by keeping 1 to 9 and checking whether there is a digit present of the same kind
Keeping iterating until all of the grids fill up.
Stop

Sudoku Solving using Digit classification, image processing and mathematics

Part 1: Digit Classification Model

Importing Libraries

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import os, random
import cv2
from glob import glob
import sklearn
from sklearn.model_selection import train_test_split
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from keras.preprocessing.image import ImageDataGenerator, load_img
from keras.utils.np_utils import to_categorical
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Activation, Dropout, Dense, Flatten, BatchNormalizat
ion, Conv2D, MaxPooling2D
from tensorflow.keras.optimizers import RMSprop
from tensorflow.keras import backend as K
from tensorflow.keras.preprocessing import image
from sklearn.metrics import accuracy_score, classification_report
from pathlib import Path
from PIL import Image
```

Loading the data

In [2]:

```
data = os.listdir(r"../input/digits/Digits" )
data_X = []
data_y =  []
data_classes = len(data)
for i in range (0,data_classes):
    data_list = os.listdir(r"../input/digits/Digits" +"/"+str(i))
    for j in data_list:
        pic = cv2.imread(r"../input/digits/Digits" +"/"+str(i)+"/"+j)
        pic = cv2.resize(pic,(32,32))
        data_X.append(pic)
        data_y.append(i)
```

```
if len(data_X) == len(data_y) :
    print("Total Dataponits = ",len(data_X))

# Labels and images
data_X = np.array(data_X)
data_y = np.array(data_y)
```

```
Total Dataponits =  10160
```

Data Spliting

In [3]:

```
train_X, test_X, train_y, test_y = train_test_split(data_X,data_y,test_size=0.05)
train_X, valid_X, train_y, valid_y = train_test_split(train_X,train_y,test_size=0.2)
print("Training Set Shape = ",train_X.shape)
print("Validation Set Shape = ",valid_X.shape)
print("Test Set Shape = ",test_X.shape)
```

```
Training Set Shape =  (7721, 32, 32, 3)
Validation Set Shape =  (1931, 32, 32, 3)
Test Set Shape =  (508, 32, 32, 3)
```

Preprocessing the images

In [4]:

```
def Prep(img):
    img = cv2.cvtColor(img,cv2.COLOR_BGR2GRAY) #making image grayscale
    img = cv2.equalizeHist(img) #Histogram equalization to enhance contrast
    img = img/255 #normalizing
    return img

train_X = np.array(list(map(Prep, train_X)))
test_X = np.array(list(map(Prep, test_X)))
valid_X= np.array(list(map(Prep, valid_X)))

#Reshaping the images
train_X = train_X.reshape(train_X.shape[0], train_X.shape[1], train_X.shape[2],1)
test_X = test_X.reshape(test_X.shape[0], test_X.shape[1], test_X.shape[2],1)
valid_X = valid_X.reshape(valid_X.shape[0], valid_X.shape[1], valid_X.shape[2],1)

#Augmentation
datagen = ImageDataGenerator(width_shift_range=0.1, height_shift_range=0.1, zoom_range=0.
2, shear_range=0.1, rotation_range=10)
datagen.fit(train_X)
```

In [5]:

```
train_y = to_categorical(train_y, data_classes)
test_y = to_categorical(test_y, data_classes)
valid_y = to_categorical(valid_y, data_classes)
```

Building the model

In [6]:

```
model = Sequential()

model.add((Conv2D(60,(5,5),input_shape=(32, 32, 1) ,padding = 'Same' ,activation='relu')
))
model.add((Conv2D(60, (5,5),padding="same",activation='relu')))
model.add(MaxPooling2D(pool_size=(2,2)))
#model.add(Dropout(0.25))
```

```
model.add((Conv2D(30,  (3,3),padding="same", activation='relu')))
model.add((Conv2D(30,  (3,3), padding="same", activation='relu')))
model.add(MaxPooling2D(pool_size=(2,2), strides=(2,2)))
model.add(Dropout(0.5))

model.add(Flatten())
model.add(Dense(500,activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(10, activation='softmax'))

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d (Conv2D)              (None, 32, 32, 60)        1560      
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 32, 32, 60)        90060     
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 16, 16, 60)        0         
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 16, 16, 30)        16230     
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 16, 16, 30)        8130      
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 8, 8, 30)          0         
_________________________________________________________________
dropout (Dropout)            (None, 8, 8, 30)          0         
_________________________________________________________________
flatten (Flatten)            (None, 1920)              0         
_________________________________________________________________
dense (Dense)                (None, 500)               960500    
_________________________________________________________________
dropout_1 (Dropout)          (None, 500)               0         
_________________________________________________________________
dense_1 (Dense)              (None, 10)                5010      
=================================================================
Total params: 1,081,490
Trainable params: 1,081,490
Non-trainable params: 0
_________________________________________________________________
```

Model Compilation and Model training

In [7]:

```
optimizer = RMSprop(lr=0.001, rho=0.9, epsilon = 1e-08, decay=0.0)
model.compile(optimizer=optimizer,loss='categorical_crossentropy',metrics=['accuracy'])

#Fit the model

history = model.fit(datagen.flow(train_X, train_y, batch_size=32),
                              epochs = 30, validation_data = (valid_X, valid_y),
                              verbose = 2, steps_per_epoch= 200)
```

```
Epoch 1/30
200/200 - 72s - loss: 1.0519 - accuracy: 0.6371 - val_loss: 0.1685 - val_accuracy: 0.9467
Epoch 2/30
200/200 - 70s - loss: 0.3084 - accuracy: 0.9043 - val_loss: 0.0778 - val_accuracy: 0.9751
Epoch 3/30
200/200 - 70s - loss: 0.2047 - accuracy: 0.9338 - val_loss: 0.0367 - val_accuracy: 0.9881
Epoch 4/30
200/200 - 70s - loss: 0.1714 - accuracy: 0.9470 - val_loss: 0.0363 - val_accuracy: 0.9896
Epoch 5/30
200/200 - 70s - loss: 0.1385 - accuracy: 0.9581 - val_loss: 0.0272 - val_accuracy: 0.9922
Epoch 6/30
200/200 - 70s - loss: 0.1256 - accuracy: 0.9627 - val_loss: 0.0450 - val_accuracy: 0.9896
Epoch 7/30
```

```
200/200 - 71s - loss: 0.1127 - accuracy: 0.9668 - val_loss: 0.0256 - val_accuracy: 0.9907
Epoch 8/30
200/200 - 72s - loss: 0.1162 - accuracy: 0.9650 - val_loss: 0.0545 - val_accuracy: 0.9850
Epoch 9/30
200/200 - 70s - loss: 0.0982 - accuracy: 0.9718 - val_loss: 0.0291 - val_accuracy: 0.9907
Epoch 10/30
200/200 - 70s - loss: 0.0886 - accuracy: 0.9731 - val_loss: 0.0329 - val_accuracy: 0.9943
Epoch 11/30
200/200 - 69s - loss: 0.0960 - accuracy: 0.9735 - val_loss: 0.0240 - val_accuracy: 0.9959
Epoch 12/30
200/200 - 70s - loss: 0.0906 - accuracy: 0.9737 - val_loss: 0.0168 - val_accuracy: 0.9953
Epoch 13/30
200/200 - 72s - loss: 0.0735 - accuracy: 0.9780 - val_loss: 0.0229 - val_accuracy: 0.9933
Epoch 14/30
200/200 - 70s - loss: 0.0920 - accuracy: 0.9721 - val_loss: 0.0266 - val_accuracy: 0.9927
Epoch 15/30
200/200 - 70s - loss: 0.0927 - accuracy: 0.9750 - val_loss: 0.0157 - val_accuracy: 0.9959
Epoch 16/30
200/200 - 70s - loss: 0.0894 - accuracy: 0.9741 - val_loss: 0.0228 - val_accuracy: 0.9948
Epoch 17/30
200/200 - 70s - loss: 0.0783 - accuracy: 0.9775 - val_loss: 0.0375 - val_accuracy: 0.9922
Epoch 18/30
200/200 - 70s - loss: 0.0799 - accuracy: 0.9788 - val_loss: 0.0235 - val_accuracy: 0.9938
Epoch 19/30
200/200 - 71s - loss: 0.0856 - accuracy: 0.9754 - val_loss: 0.0345 - val_accuracy: 0.9902
Epoch 20/30
200/200 - 71s - loss: 0.0793 - accuracy: 0.9765 - val_loss: 0.0194 - val_accuracy: 0.9948
Epoch 21/30
200/200 - 70s - loss: 0.0836 - accuracy: 0.9798 - val_loss: 0.0288 - val_accuracy: 0.9927
Epoch 22/30
200/200 - 70s - loss: 0.0730 - accuracy: 0.9798 - val_loss: 0.0162 - val_accuracy: 0.9953
Epoch 23/30
200/200 - 71s - loss: 0.0804 - accuracy: 0.9789 - val_loss: 0.0646 - val_accuracy: 0.9860
Epoch 24/30
200/200 - 70s - loss: 0.0767 - accuracy: 0.9791 - val_loss: 0.0540 - val_accuracy: 0.9876
Epoch 25/30
200/200 - 70s - loss: 0.0866 - accuracy: 0.9771 - val_loss: 0.0124 - val_accuracy: 0.9959
Epoch 26/30
200/200 - 70s - loss: 0.0819 - accuracy: 0.9788 - val_loss: 0.0297 - val_accuracy: 0.9938
Epoch 27/30
200/200 - 70s - loss: 0.0826 - accuracy: 0.9780 - val_loss: 0.0208 - val_accuracy: 0.9969
Epoch 28/30
200/200 - 70s - loss: 0.0730 - accuracy: 0.9812 - val_loss: 0.0191 - val_accuracy: 0.9959
Epoch 29/30
200/200 - 70s - loss: 0.0910 - accuracy: 0.9751 - val_loss: 0.0327 - val_accuracy: 0.9917
Epoch 30/30
200/200 - 70s - loss: 0.0697 - accuracy: 0.9818 - val_loss: 0.0216 - val_accuracy: 0.9933
```

Evaluating the model

In [8]:

```
score = model.evaluate(test_X, test_y, verbose=0)
print('Test Score = ',score[0])
print('Test Accuracy =', score[1])
```

```
Test Score =  0.0032084500417113304
Test Accuracy = 0.998031497001648
```

Part 2: Reading the Sudoku

Random Selection of an Image

In [79]:

```
folder=r"../input/sudoku-box-detection/aug"
```

```
a=random.choice(os.listdir(folder))
print(a)
sudoku_a = cv2.imread(folder+'/'+a)
plt.figure()
plt.imshow(sudoku_a)
plt.show()
```

```
_197_2443114.jpeg
```

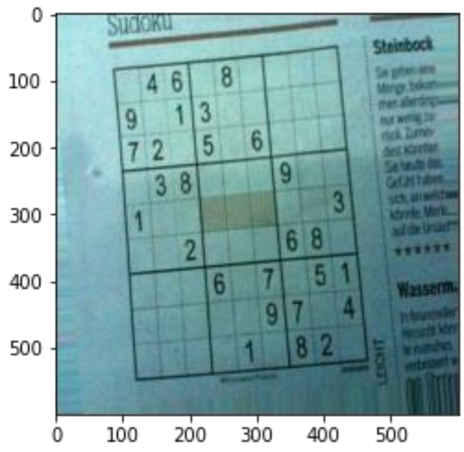
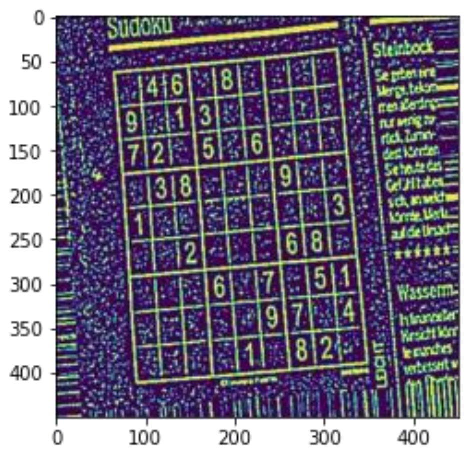


Image preprocessing

In [80]:

```
sudoku_a = cv2.resize(sudoku_a, (450,450))

# function to greyscale, blur and change the receptive threshold of image
def preprocess(image):
    gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
    blur = cv2.GaussianBlur(gray, (3,3),6)
    #blur = cv2.bilateralFilter(gray,9,75,75)
    threshold_img = cv2.adaptiveThreshold(blur,255,1,1,11,2)
    return threshold_img

threshold = preprocess(sudoku_a)


plt.figure()
plt.imshow(threshold)
plt.show()
```

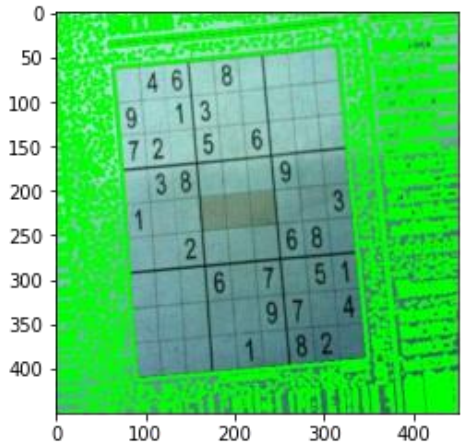


Contour Detection

In [81]:

```
# Finding the outline of the sudoku puzzle in the image
```

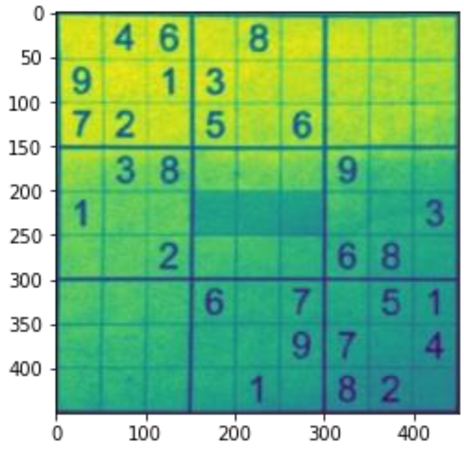
```
contour_1 = sudoku_a.copy()
contour_2 = sudoku_a.copy()
contour, hierarchy = cv2.findContours(threshold,cv2.RETR_EXTERNAL,cv2.CHAIN_APPROX_SIMPLE
)
cv2.drawContours(contour_1, contour,-1,(0,255,0),3)


plt.figure()
plt.imshow(contour_1)
plt.show()
```



In [82]:

```
def main_outline(contour):
    biggest = np.array([])
    max_area = 0
    for i in contour:
        area = cv2.contourArea(i)
        if area >50:
            peri = cv2.arcLength(i, True)
            approx = cv2.approxPolyDP(i , 0.02* peri, True)
            if area > max_area and len(approx) ==4:
                biggest = approx
                max_area = area
    return biggest ,max_area

def reframe(points):
    points = points.reshape((4, 2))
    points_new = np.zeros((4,1,2),dtype = np.int32)
    add = points.sum(1)
    points_new[0] = points[np.argmin(add)]
    points_new[3] = points[np.argmax(add)]
    diff = np.diff(points, axis =1)
    points_new[1] = points[np.argmin(diff)]
    points_new[2] = points[np.argmax(diff)]
    return points_new

def splitcells(img):
    rows = np.vsplit(img,9)
    boxes = []
    for r in rows:
        cols = np.hsplit(r,9)
        for box in cols:
            boxes.append(box)
    return boxes


black_img = np.zeros((450,450,3), np.uint8)
biggest, maxArea = main_outline(contour)
if biggest.size != 0:
    biggest = reframe(biggest)
    cv2.drawContours(contour_2,biggest,-1, (0,255,0),10)
    pts1 = np.float32(biggest)
    pts2 = np.float32([[0,0],[450,0],[0,450],[450,450]])
    matrix = cv2.getPerspectiveTransform(pts1,pts2)
    imagewrap = cv2.warpPerspective(sudoku_a,matrix,(450,450))
```

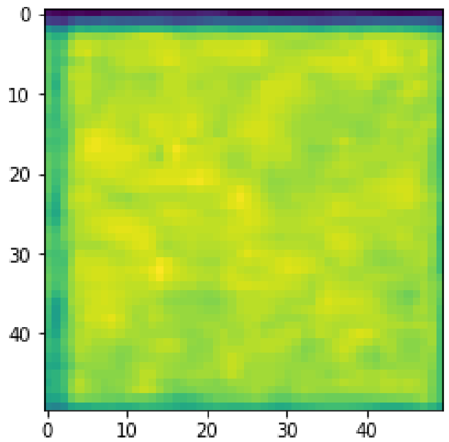
```
    imagewrap =cv2.cvtColor(imagewrap, cv2.COLOR_BGR2GRAY)

plt.figure()
plt.imshow(imagewrap)
plt.show()
```



Splitting cells and classifying the digits

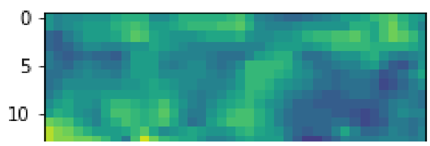
In [83]:

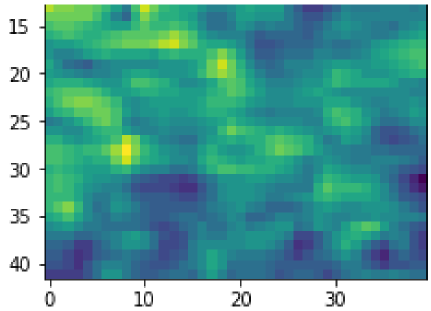
```
sudoku_cell = splitcells(imagewrap)

plt.figure()
plt.imshow(sudoku_cell[58])
plt.show()
```



In [84]:

```
def CropCell(cells):
    Cells_croped = []
    for image in cells:

        img = np.array(image)
        img = img[4:46, 6:46]
        img = Image.fromarray(img)
        Cells_croped.append(img)

    return Cells_croped

sudoku_cell_croped= CropCell(sudoku_cell)
plt.figure()
plt.imshow(sudoku_cell_croped[58])
plt.show()
```





In [85]:

```
def read_cells(cell,model):

    result = []
    for image in cell:
        # preprocess the image as it was in the model
        img = np.asarray(image)
        img = img[4:img.shape[0] - 4, 4:img.shape[1] -4]
        img = cv2.resize(img, (32, 32))
        img = img / 255
        img = img.reshape(1, 32, 32, 1)
        # getting predictions and setting the values if probabilities are above 65%

        predictions = model.predict(img)
        classIndex = model.predict_classes(img)
        probabilityValue = np.amax(predictions)

        if probabilityValue > 0.65:
            result.append(classIndex[0])
        else:
            result.append(0)
    return result

grid = read_cells(sudoku_cell_croped, model)
grid = np.asarray(grid)
```

Part 3: Solving the Sudoku

In [86]:

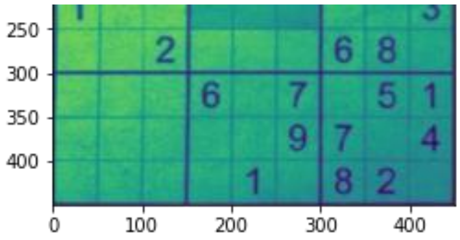
```
grid = np.reshape(grid,(9,9))
grid
```

Out[86]:

```
array([[0, 0, 6, 0, 0, 0, 0, 0, 0],
       [9, 0, 0, 0, 0, 0, 0, 0, 0],
       [7, 2, 0, 5, 0, 6, 0, 0, 0],
       [0, 3, 8, 0, 0, 0, 9, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 3],
       [0, 0, 2, 0, 0, 0, 6, 8, 0],
       [0, 0, 0, 6, 0, 7, 0, 0, 0],
       [0, 0, 0, 0, 0, 9, 7, 0, 4],
       [0, 0, 0, 0, 0, 0, 8, 2, 0]])
```

In [87]:

```
plt.figure()
plt.imshow(imagewrap)
plt.show()
```



In [88]:

```
#This function finds the next box to solve

def next_box(quiz):
    for  row in  range(9):
        for col in range(9):
            if quiz[row][col] == 0:
                return (row, col)
    return False

#Function to fill in the possible values by evaluating rows collumns and smaller cells

def possible (quiz,row, col, n):
    #global quiz
    for i in range (0,9):
        if quiz[row][i] == n and row != i:
            return False
    for i in range (0,9):
        if quiz[i][col] == n and col != i:
            return False

    row0 = (row)//3
    col0 = (col)//3
    for i in range(row0*3, row0*3 + 3):
        for j in range(col0*3, col0*3 + 3):
            if quiz[i][j]==n and (i,j) != (row, col):
                return False
    return True

#Recursion function to loop over untill a valid answer is found.

def solve(quiz):
    val = next_box(quiz)
    if val is False:
        return True
    else:
        row, col = val
        for n in range(1,10): #n is the possible solution
            if possible(quiz,row, col, n):
                quiz[row][col]=n
                if solve(quiz):
                    return True
                else:
                    quiz[row][col]=0
        return

def Solved(quiz):
    for row in range(9):
        if row % 3 == 0 and row != 0:
            print("....................................")

        for col in range(9):
            if col % 3 == 0 and col != 0:
                print("|", end=" ")

            if col == 8:
                print(quiz[row][col])
            else:
                print(str(quiz[row][col]) + " ", end="")
```

In [89]:

```
solve(grid)
```

Out[89]:

```
True
```

In [90]:

```
if solve(grid):
    Solved(grid)
else:
    print("Solution don't exist. Model misread digits.")
```

```
1 4 6 | 1 2 3 | 5 7 9
9 8 5 | 4 7 8 | 1 6 2
7 2 3 | 5 9 6 | 4 3 8
. . . . . . . . . . . . . . . . . . . .
1 3 8 | 2 6 5 | 9 4 7
6 5 7 | 9 8 4 | 2 1 3
4 9 2 | 7 3 1 | 6 8 5
. . . . . . . . . . . . . . . . . . . .
2 8 4 | 6 5 7 | 3 9 1
3 6 1 | 2 8 9 | 7 5 4
5 7 9 | 3 4 1 | 8 2 6
```