esraaj_lab1

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MLPR Lab 1 By Ersaaj Sarkar Gupta U20240040

Report attached at the end

1 Introduction

[1]:
```
# ----- Install Libraries ----- #
!pip install opencv-python
!pip install numpy
!pip install matplotlib
```

```
Requirement already satisfied: opencv-python in
/home/esraaj/jupyterenv/lib/python3.13/site-packages (4.12.0.88)
Requirement already satisfied: numpy<2.3.0,>=2 in
/home/esraaj/jupyterenv/lib/python3.13/site-packages (from opencv-python)
(2.2.6)
Requirement already satisfied: numpy in
/home/esraaj/jupyterenv/lib/python3.13/site-packages (2.2.6)
Requirement already satisfied: matplotlib in
/home/esraaj/jupyterenv/lib/python3.13/site-packages (3.10.5)
Requirement already satisfied: contourpy>=1.0.1 in
/home/esraaj/jupyterenv/lib/python3.13/site-packages (from matplotlib) (1.3.3)
Requirement already satisfied: cycler>=0.10 in
/home/esraaj/jupyterenv/lib/python3.13/site-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/home/esraaj/jupyterenv/lib/python3.13/site-packages (from matplotlib) (4.59.1)
Requirement already satisfied: kiwisolver>=1.3.1 in
/home/esraaj/jupyterenv/lib/python3.13/site-packages (from matplotlib) (1.4.9)
Requirement already satisfied: numpy>=1.23 in
/home/esraaj/jupyterenv/lib/python3.13/site-packages (from matplotlib) (2.2.6)
Requirement already satisfied: packaging>=20.0 in
/home/esraaj/jupyterenv/lib/python3.13/site-packages (from matplotlib) (25.0)
Requirement already satisfied: pillow>=8 in
/home/esraaj/jupyterenv/lib/python3.13/site-packages (from matplotlib) (11.3.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/home/esraaj/jupyterenv/lib/python3.13/site-packages (from matplotlib) (3.2.3)
Requirement already satisfied: python-dateutil>=2.7 in
/home/esraaj/jupyterenv/lib/python3.13/site-packages (from matplotlib)
```

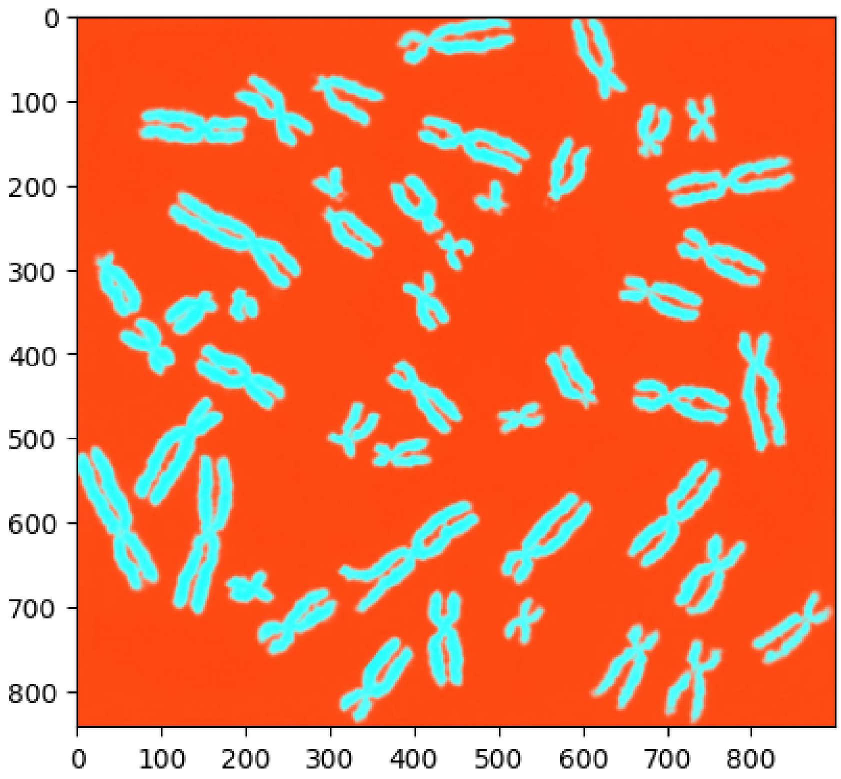
```
(2.9.0.post0)
Requirement already satisfied: six>=1.5 in
/home/esraaj/jupyterenv/lib/python3.13/site-packages (from python-
dateutil>=2.7->matplotlib) (1.17.0)
```

[2]:
```python
# ---- Imports ---- #

import cv2
import numpy as np
import matplotlib.pyplot as plt

from pathlib import Path
```

[ ]:
```python
# ---- Read Image ---- #

image_path : Path = Path("chromosomes.jpg")
image = cv2.imread(image_path) # <--- This is a stupid error, imread expects a␣
 ↪str for a path (non fatal error)

print(f"Image imported as {type(image)}")
# Display image
plt.imshow(image)
```

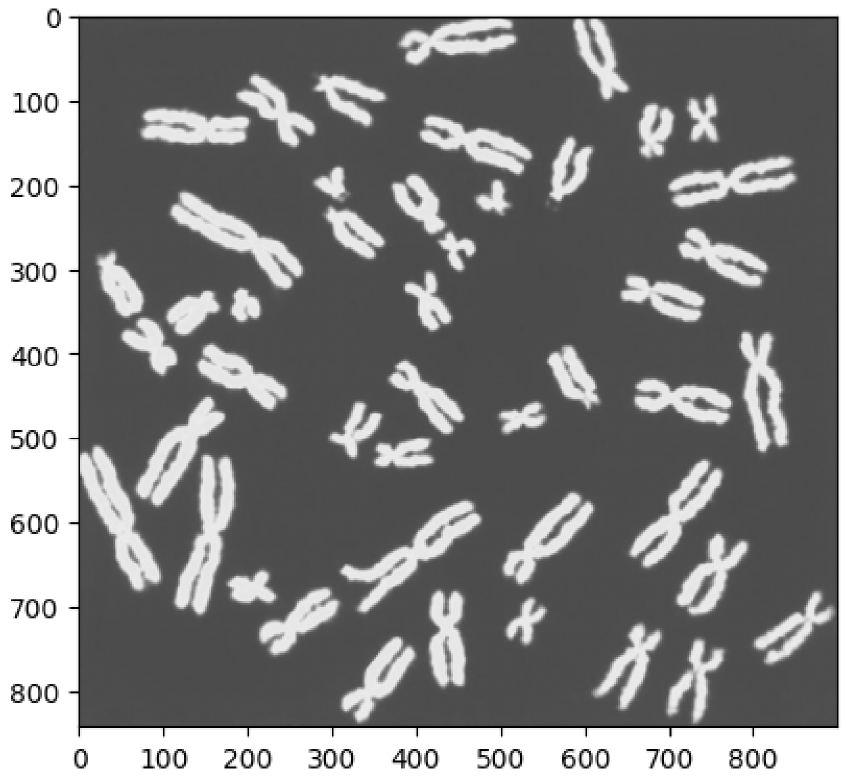
```
Image imported as <class 'numpy.ndarray'>
```

[ ]:
```
<matplotlib.image.AxesImage at 0x7cb8328eba10>
```



[4]:
```
# ---- Convert Image to Greyscale ---- #

grayscale_image : np.ndarray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)

# Display image
plt.imshow(grayscale_image, cmap='gray', vmin=0, vmax=255)
```

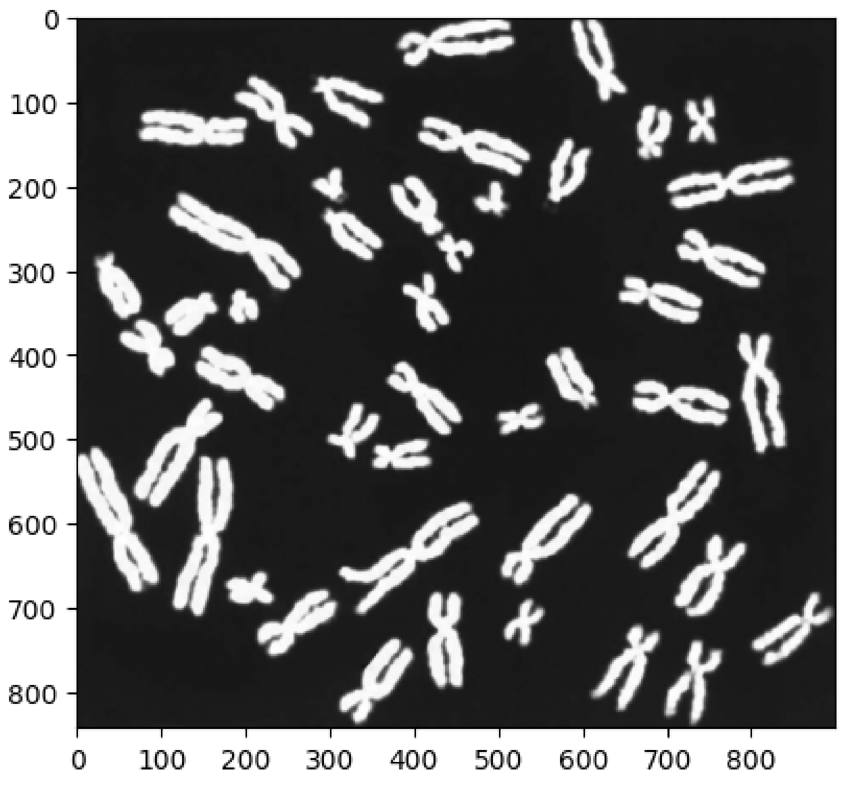
[4]:
```
<matplotlib.image.AxesImage at 0x7cb8327e5810>
```



```
[ ]: # ---- Morphological Opening for Background Removal ---- #

     # Define kernel
     kernel = cv2.getStructuringElement(
         cv2.MORPH_RECT, # Select shape
         (5,5), # Select k-size
         anchor=None
     )

     """
     Notes for Reference:
         Erosion:
             A pixel stays white only if the kernel fits fully in the white
             region.

             White blobs shrink, thin lines break and small white noise disappears.

         Dialtion:
             A pixel becomes white if any part of the kernel touches white.
```

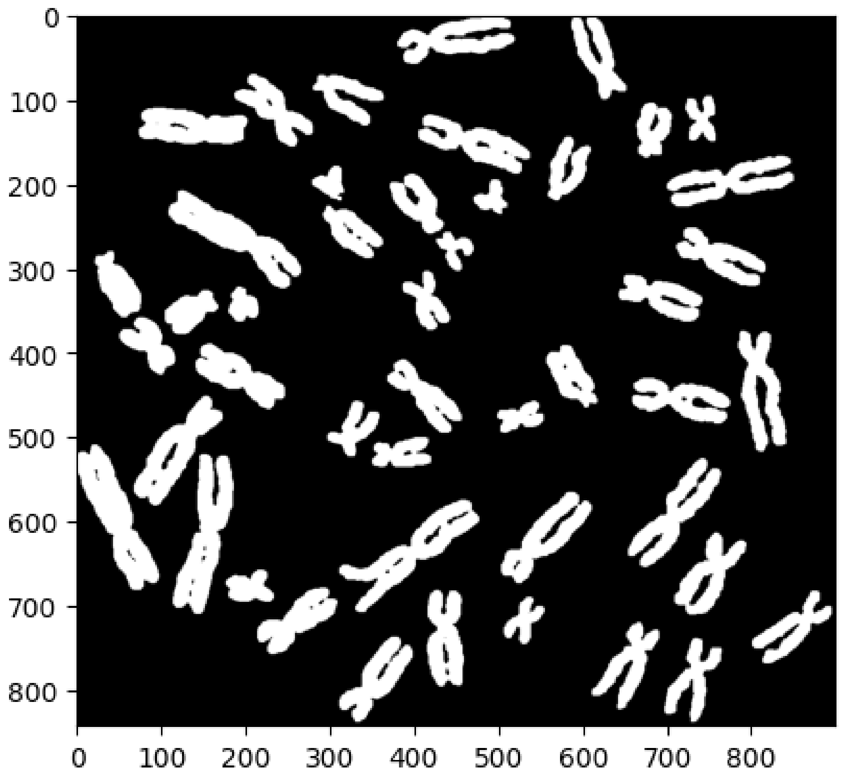
```
        White blobs grow, gaps between white regions may connect and holes get␣
↪smaller
        (since white expands into them).

    Opening: Erosion, followed by dialation
        Removes all small, white noise. Large shapes remain mostly intact and␣
↪boundaries
        are smooothened.

    Closing: Dialation, followed by erosion.
"""

# Morphological operation -- Opening
image_open = cv2.morphologyEx(grayscale_image, cv2.MORPH_OPEN, kernel)

# Display
plt.imshow(image_open, cmap="gray")
```

```
[ ]: <matplotlib.image.AxesImage at 0x7cb83286b110>
```



[ ]:
```
# ---- Image Thresholding ---- #

_, thresh_image = cv2.threshold(
    image_open,
    127, # Threshold
    255, # Maxval
    cv2.THRESH_BINARY, # Threshold type
)

# Display
plt.imshow(thresh_image, cmap='gray')
```

[ ]:
```
<matplotlib.image.AxesImage at 0x7cb83248bc50>
```



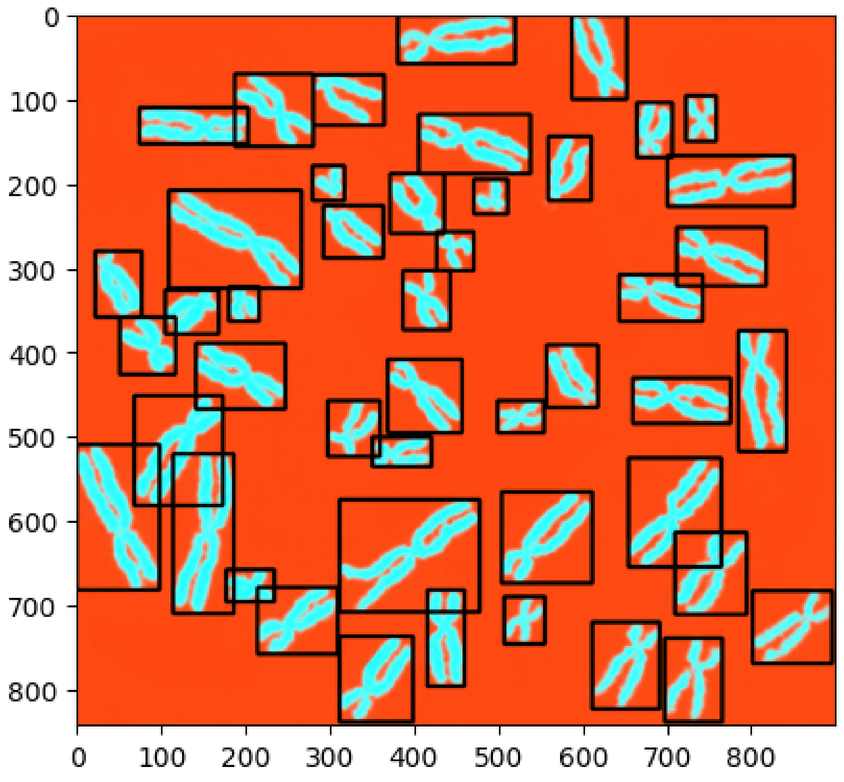
[ ]:
```
#  ---- Find Contours ---- #

contours, hierarchy = cv2.findContours(
    thresh_image,
    cv2.RETR_EXTERNAL, # Outermost contours, ignore holes (Contour Mode)
    cv2.CHAIN_APPROX_SIMPLE, # Stores corner pixels, uses less space (Contour␣
 ↪method)
)

print(f"Number of contours extracted: {len(contours)}")

if len(contours) < 5 :
    raise Exception("Too few contours!")

# Store features for each chromosome
features : list = list([])

# Loop through all the contours
for i,c in enumerate(contours):
    area = cv2.contourArea(c)
    perimeter = cv2.arcLength(c, True)
    circularity = (4 * np.pi * area) /  (perimeter**2)

    x,y,w,h = cv2.boundingRect(c) # Bounding box

    features.append(dict({
        'id': i,
        'x': x, 'y': y,
        'area': area,
        'perimeter': perimeter,
        'circularity': circularity,
        'width': w,
        'height': h,
        'aspect_ratio' : h / w # Shape
    }))


# ---- Place Features into a Dataframe ---- #

import pandas as pd

df : pd.DataFrame = pd.DataFrame(features)
print(df)

# Does anyone even read these comments?
```

```
Number of contours extracted: 46
    id    x    y    area   perimeter  circularity  width  height  aspect_ratio
0    0  696  739  2488.5  412.634556     0.183661     68      99      1.455882
1    1  311  737  3492.5  385.404108     0.295470     87     101      1.160920
2    2  610  720  2818.0  437.102592     0.185346     80     103      1.287500
3    3  506  690  1163.0  214.166520     0.318630     48      56      1.166667
4    4  800  683  2588.5  441.144223     0.167146     94      86      0.914894
5    5  415  682  3674.5  370.007140     0.337278     44     114      2.590909
6    6  214  679  3274.0  315.563488     0.413157     95      79      0.831579
```

```
7    7  177  658  1431.5  183.095453     0.536594    57       38        0.666667
8    8  708  614  3639.5  341.462984     0.392251    85       97        1.141176
9    9  311  575  5932.0  543.126977     0.252702   166      133        0.801205
10  10  503  566  4392.0  358.818322     0.428670   107      108        1.009346
11  11  653  526  4255.5  603.796025     0.146683   110      129        1.172727
12  12  114  521  6248.0  605.161468     0.214392    72      189        2.625000
13  13    0  510  6332.0  464.617312     0.368604    98      172        1.755102
14  14  350  501  1713.0  235.681239     0.387541    70       35        0.500000
15  15  498  458  1161.5  178.124891     0.460023    55       38        0.690909
16  16  297  458  1631.0  266.936072     0.287640    62       66        1.064516
17  17   68  452  4996.0  383.788885     0.426233   105      130        1.238095
18  18  658  431  3343.5  466.232535     0.193289   116       54        0.465517
19  19  368  409  2835.0  315.019332     0.358995    88       87        0.988636
20  20  556  392  2369.0  229.137083     0.567001    61       74        1.213115
21  21  141  390  3613.5  325.806129     0.427779   106       78        0.735849
22  22  783  375  3995.0  592.617312     0.142948    57      143        2.508772
23  23   51  359  2115.5  246.551296     0.437329    66       68        1.030303
24  24  105  327  1902.5  189.923879     0.662789    63       52        0.825397
25  25  180  323   967.0  133.053823     0.686407    36       41        1.138889
26  26  642  309  2945.5  292.693432     0.432059    99       55        0.555556
27  27  386  304  1718.5  271.036578     0.293970    56       70        1.250000
28  28   22  281  2331.5  222.894442     0.589721    55       78        1.418182
29  29  426  258   914.0  180.852812     0.351160    44       46        1.045455
30  30  710  253  3033.5  431.060963     0.205152   106       69        0.650943
31  31  292  227  2247.5  237.178714     0.502063    71       62        0.873239
32  32  109  209  5706.5  495.771639     0.291754   157      116        0.738854
33  33  470  196   830.5  143.982755     0.503418    40       41        1.025000
34  34  371  189  2387.5  227.379723     0.580296    64       71        1.109375
35  35  279  180   838.0  142.225395     0.520595    38       41        1.078947
36  36  699  168  4013.0  634.901582     0.125103   150       60        0.400000
37  37  558  145  1967.0  316.735062     0.246389    51       76        1.490196
38  38  405  119  3977.5  440.232535     0.257903   132       70        0.530303
39  39   74  111  4130.5  332.066015     0.470721   129       43        0.333333
40  40  663  105  1886.5  194.610172     0.625944    42       65        1.547619
41  41  721   97  1189.5  226.409160     0.291599    36       54        1.500000
42  42  280   72  2201.5  338.492421     0.241452    84       60        0.714286
43  43  187   71  2968.0  341.705624     0.319425    93       86        0.924731
44  44  586    2  2679.5  401.261972     0.209126    65       99        1.523077
45  45  380    2  3846.5  567.546244     0.150063   139       57        0.410072
```

[ ]:
```
# ----- Print Boxes ----- #

# Draw bounding boxes
out = image.copy() # Copy image

for c in contours:
    x, y, w, h = cv2.boundingRect(c)
    cv2.rectangle(
        out,
        (x,y), # Coordinates
        (x+w, y +h), # Bounds
        (0, 0, 0), # Box colour (BGR)
        3 # Box thickness
    )

# Display
plt.imshow(out)
```

```
[ ]: <matplotlib.image.AxesImage at 0x7cb7f7511f90>
```



```
[ ]: #  ----- Standardization ---- #

from sklearn.preprocessing import StandardScaler

feature_coloums : list = [
    'width', 'height', 'aspect_ratio', 'area', 'perimeter', 'circularity'
]

scaler = StandardScaler() # Define scaler
```

```
df_standard = df.copy()
df_standard[feature_coloums] = scaler.
 ↪fit_transform(df_standard[feature_coloums])

print(df_standard)
```

```
    id    x    y      area  perimeter  circularity     width    height  \
0    0  696  739 -0.299402   0.530183    -1.170675 -0.403718  0.538851
1    1  311  737  0.402025   0.329132    -0.421609  0.166314  0.596162
2    2  610  720 -0.069203   0.710838    -1.159382 -0.043698  0.653473
3    3  506  690 -1.225441  -0.935169    -0.266451 -1.003752 -0.693342
4    4  800  683 -0.229539   0.740678    -1.281314  0.376325  0.166327
5    5  415  682  0.529177   0.215451    -0.141518 -1.123758  0.968686
6    6  214  679  0.249374  -0.186523     0.366833  0.406327 -0.034262
7    7  177  658 -1.037858  -1.164576     1.193802 -0.733737 -1.209144
8    8  708  614  0.504725   0.004701     0.226776  0.106310  0.481540
9    9  311  575  2.106341   1.493649    -0.708135  2.536446  1.513143
10  10  503  566  1.030446   0.132841     0.470762  0.766347  0.796752
11  11  653  526  0.935083   1.941587    -1.418407  0.856352  1.398520
12  12  114  521  2.327110   1.951669    -0.964792 -0.283711  3.117860
13  13    0  510  2.385795   0.913987     0.068351  0.496332  2.630714
14  14  350  501 -0.841192  -0.776319     0.195217 -0.343715 -1.295111
15  15  498  458 -1.226489  -1.201275     0.680815 -0.793740 -1.209144
16  16  297  458 -0.898480  -0.545555    -0.474067 -0.583728 -0.406786
17  17   68  452  1.452421   0.317206     0.454439  0.706344  1.427176
18  18  658  431  0.297929   0.925913    -1.106174  1.036362 -0.750654
19  19  368  409 -0.057326  -0.190541     0.003976  0.196315  0.194983
20  20  556  392 -0.382889  -0.824637     1.397514 -0.613730 -0.177540
21  21  141  390  0.486560  -0.110899     0.464794  0.736345 -0.062918
22  22  783  375  0.753089   1.859051    -1.443430 -0.733737  1.799700
23  23   51  359 -0.559993  -0.696062     0.528774 -0.463722 -0.349474
24  24  105  327 -0.708801  -1.114160     2.039243 -0.553727 -0.807965
25  25  180  323 -1.362373  -1.534049     2.197470 -1.363772 -1.123177
26  26  642  309  0.019873  -0.355380     0.493467  0.526334 -0.721998
27  27  386  304 -0.837350  -0.515279    -0.431656 -0.763738 -0.292163
28  28   22  281 -0.409088  -0.870728     1.549725 -0.793740 -0.062918
29  29  426  258 -1.399400  -1.181134    -0.048512 -1.123758 -0.979899
30  30  710  253  0.081353   0.666230    -1.026692  0.736345 -0.320819
31  31  292  227 -0.467773  -0.765263     0.962459 -0.313713 -0.521408
32  32  109  209  1.948800   1.144010    -0.446507  2.266431  1.025997
33  33  470  196 -1.457736  -1.453357     0.971535 -1.243765 -1.123177
34  34  371  189 -0.369964  -0.837612     1.486583 -0.523725 -0.263507
35  35  279  180 -1.452497  -1.466333     1.086611 -1.303768 -1.123177
36  36  699  168  0.765664   2.171249    -1.562986  2.056419 -0.578720
37  37  558  145 -0.663740  -0.177873    -0.750425 -0.913747 -0.120229
38  38  405  119  0.740863   0.733947    -0.673292  1.516389 -0.292163
39  39   74  111  0.847754  -0.064680     0.752484  1.426384 -1.065866
40  40  663  105 -0.719980  -1.079559     1.792400 -1.183762 -0.435441
```

```
41  41  721   97 -1.206927  -0.844778    -0.447542 -1.363772 -0.750654
42  42  280   72 -0.499910  -0.017232    -0.783504  0.076309 -0.578720
43  43  187   71  0.035592   0.006492    -0.261120  0.346324  0.166327
44  44  586    2 -0.165963   0.446215    -1.000072 -0.493723  0.538851
45  45  380    2  0.649342   1.673944    -1.395764  1.726401 -0.664687

    aspect_ratio
0       0.709955
1       0.139011
2       0.384027
3       0.150136
4      -0.337208
5       2.906967
6      -0.498476
7      -0.817688
8       0.100796
9      -0.557269
10     -0.154382
11      0.161867
12      2.972955
13      1.289139
14     -1.140296
15     -0.770763
16     -0.047592
17      0.288396
18     -1.207042
19     -0.194468
20      0.240043
21     -0.683775
22      2.747979
23     -0.113816
24     -0.510442
25      0.096368
26     -1.032760
27      0.311440
28      0.636981
29     -0.084488
30     -0.848123
31     -0.417836
32     -0.677960
33     -0.124081
34      0.039239
35     -0.019658
36     -1.333861
37      0.776375
38     -1.081640
39     -1.462904
40      0.887525
```

```
41      0.795352
42     -0.725514
43     -0.318166
44      0.840020
45     -1.314365
```

[ ]:
```
# ---- Normalization ---- #

from sklearn.preprocessing import MinMaxScaler

feature_coloums : list = [
    'width', 'height', 'aspect_ratio', 'area', 'perimeter', 'circularity'
]

normalizer = MinMaxScaler() # Define scaler (normal)
df_normal = df.copy()

df_normal[feature_coloums] = normalizer.
 ↪fit_transform(df_normal[feature_coloums])
print(df_normal)
```

```
    id    x    y      area  perimeter  circularity     width    height  \
0    0  696  739  0.301372   0.557103     0.104325  0.246154  0.415584
1    1  311  737  0.483868   0.502842     0.303521  0.392308  0.428571
2    2  610  720  0.361265   0.605859     0.107328  0.338462  0.441558
3    3  506  690  0.060438   0.161628     0.344781  0.092308  0.136364
4    4  800  683  0.319549   0.613912     0.074904  0.446154  0.331169
5    5  415  682  0.516950   0.472162     0.378004  0.061538  0.512987
6    6  214  679  0.444152   0.363675     0.513188  0.453846  0.285714
7    7  177  658  0.109243   0.099715     0.733099  0.161538  0.019481
8    8  708  614  0.510588   0.415284     0.475943  0.376923  0.402597
9    9  311  575  0.927293   0.817127     0.227326  1.000000  0.636364
10  10  503  566  0.647369   0.449867     0.540825  0.546154  0.474026
11  11  653  526  0.622557   0.938018     0.038447  0.569231  0.610390
12  12  114  521  0.984731   0.940739     0.159075  0.276923  1.000000
13  13    0  510  1.000000   0.660685     0.433814  0.476923  0.889610
14  14  350  501  0.160411   0.204499     0.467550  0.261538  0.000000
15  15  498  458  0.060165   0.089810     0.596683  0.146154  0.019481
16  16  297  458  0.145506   0.266779     0.289571  0.200000  0.201299
17  17   68  452  0.757157   0.499624     0.536484  0.530769  0.616883
18  18  658  431  0.456785   0.663904     0.121478  0.615385  0.123377
19  19  368  409  0.364355   0.362591     0.416695  0.400000  0.337662
20  20  556  392  0.279651   0.191459     0.787271  0.192308  0.253247
21  21  141  390  0.505862   0.384085     0.539238  0.538462  0.279221
22  22  783  375  0.575207   0.915743     0.031793  0.161538  0.701299
23  23   51  359  0.233573   0.226159     0.556252  0.230769  0.214286
24  24  105  327  0.194856   0.113321     0.957923  0.207692  0.110390
25  25  180  323  0.024811   0.000000     1.000000  0.000000  0.038961
```

```
26  26  642  309  0.384441   0.318104      0.546863  0.484615  0.129870
27  27  386  304  0.161411   0.274949      0.300849  0.153846  0.227273
28  28   22  281  0.272835   0.179020      0.827748  0.146154  0.279221
29  29  426  258  0.015178   0.095246      0.402737  0.061538  0.071429
30  30  710  253  0.400436   0.593820      0.142614  0.538462  0.220779
31  31  292  227  0.257566   0.207483      0.671579  0.269231  0.175325
32  32  109  209  0.886304   0.722765      0.296900  0.930769  0.525974
33  33  470  196  0.000000   0.021777      0.673993  0.030769  0.038961
34  34  371  189  0.283014   0.187957      0.810957  0.215385  0.233766
35  35  279  180  0.001363   0.018276      0.704595  0.015385  0.038961
36  36  699  168  0.578479   1.000000      0.000000  0.876923  0.162338
37  37  558  145  0.206580   0.366010      0.216080  0.115385  0.266234
38  38  405  119  0.572026   0.612095      0.236592  0.738462  0.227273
39  39   74  111  0.599836   0.396559      0.615742  0.715385  0.051948
40  40  663  105  0.191948   0.122659      0.892282  0.046154  0.194805
41  41  721   97  0.065255   0.186023      0.296625  0.000000  0.123377
42  42  280   72  0.249205   0.409364      0.207284  0.369231  0.162338
43  43  187   71  0.388530   0.415767      0.346199  0.438462  0.331169
44  44  586    2  0.336090   0.534441      0.149693  0.223077  0.415584
45  45  380    2  0.548214   0.865785      0.044468  0.792308  0.142857

    aspect_ratio
0       0.489840
1       0.361129
2       0.416364
3       0.363636
4       0.253772
5       0.985124
6       0.217416
7       0.145455
8       0.352513
9       0.204162
10      0.294987
11      0.366281
12      1.000000
13      0.620408
14      0.072727
15      0.156033
16      0.319062
17      0.394805
18      0.057680
19      0.285950
20      0.383905
21      0.175643
22      0.949282
23      0.304132
24      0.214719
25      0.351515
```

```
26      0.096970
27      0.400000
28      0.473388
29      0.310744
30      0.138593
31      0.235595
32      0.176954
33      0.301818
34      0.338636
35      0.325359
36      0.029091
37      0.504813
38      0.085950
39      0.000000
40      0.529870
41      0.509091
42      0.166234
43      0.258065
44      0.519161
45      0.033486
```

2 Report

2.0.1 Question 1

Contour detection can be used to find objects in an image. It does this by tracing the boundaries. Here, this is done on a thresholded image to eliminate noise. Each detected body is returned as a contour.

2.0.2 Question 2

Standardization of data is useful for ML methods to ensure all data is weighted equally. Most ML algorithms are sensitive to feature scaling. Standardization ensures all continuous features exist within the same scale. Otherwise features with larger scales will dominate the ML model.

2.0.3 Question 3

There are multiple ways in which one may handle a missing value in a dataset.

- One may extrapolate the missing value using linear regression against a correlated feature.
- One may interpolate the missing value from the rest of the filled data.
- Mean imputation may be used to fill in missing values.
- The datapoint with the missing value may be dropped.
- If most of the datapoints in the coloumn (feature) are missing, the feature may be dropped in its entirety.

2.0.4 Question 4

Normalization allows features to be scaled to a bound range, usually between 0 and 1. This allows all features to live in the same range, equalising the contribution of each feature in scale sensitive ML algorithms. Normalization removes dimensionality from features.

2.0.5 Question 5

We may seperate overlapping chromosomes by applying morphological operatons (such as erosion) to break thin connections. One may also use rotated boxes instead of axis-aligned boxes. Merged contours may be split using shape cues.