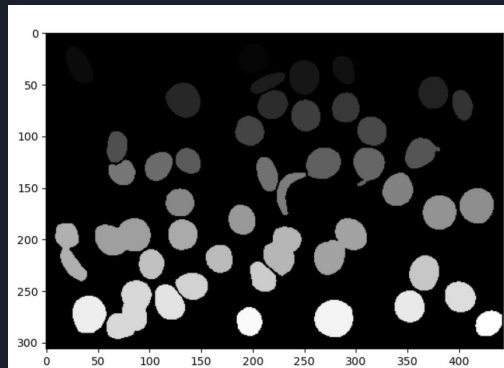


A decorative graphic on the left side of the slide consisting of two overlapping parallelograms. The front one is blue and the back one is a light green color. They are positioned diagonally, with the blue one partially covering the green one.

Sickle Cell Classification

By: Ori Weiss

Image Preparation



```
def image_prep(path):  
    mask_size = 400  
    img = cv2.imread(path, cv2.IMREAD_GRAYSCALE)  
    edges = canny(img/255.)  
    fill_coins = ndi.binary_fill_holes(edges)  
    label_objects, nb_labels = ndi.label(fill_coins)  
    sizes = np.bincount(label_objects.ravel())  
    mask_sizes = sizes > mask_size  
    mask_sizes[0] = 0  
    img_cleaned = mask_sizes[label_objects]  
    labeled_img, num_features = ndi.label(img_cleaned)  
    return labeled_img, num_features
```

- Python libraries used; OpenCV, numpy, skimage, scipy-ndimage, matplotlib
- Image Prep Steps
 - Read in image,
 - convert to 8 bit black and white,
 - Detect Edges
 - Fill in holes
 - Use mask to filter out undesirable cells
 - Label each cell
- Resulting image should become a 2D (black and white) array with pixel values corresponding to the cell's individual ID

Extract Individual Cell Features

```
def findperimeter(mat, num_features):
    perimeter = [0] * (num_features+1)

    # Traversing the matrix and finding ones to
    # calculate their contribution.
    for i in range(len(mat)):
        for j in range(0, len(mat[i])):
            if (mat[i][j] != 0):
                perimeter[mat[i][j]] += (4 - numofneighbour(mat, i, j, mat[i][j]))

    return perimeter

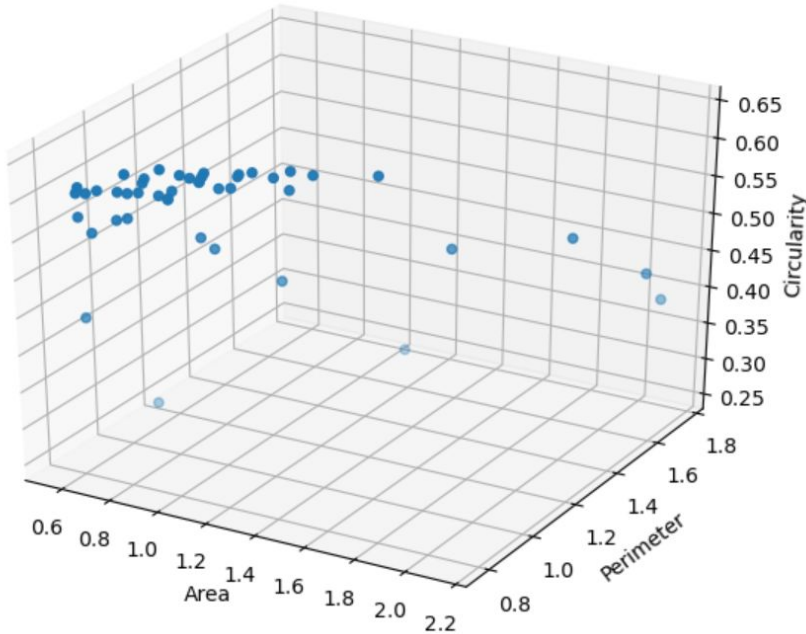
def extract_area_perim(img, num_features):
    area = [0] * (num_features+1)
    for i in range(len(img)):
        for j in range(len(img[i])):
            value = img[i][j]
            if (value != 0):
                area[value] += 1
    return area, findperimeter(img, num_features)

def extract_circularity(area, perimeter):
    circularity = [0] * (len(area))
    for i in range(len(area)):
        circularity[i] = 4 * (math.pi * area[i]) / (math.pow(perimeter[i], 2))
    return circularity

def convert_to_relative(cellAreas, cellPerims):
    averageCellSize = np.mean(cellAreas)
    averagePerimSize = np.mean(cellPerims)
    relativeArea = [0] * len(cellAreas)
    relativePerim = [0] * len(cellPerims)
    for i in range(len(cellAreas)):
        relativeArea[i] = cellAreas[i] / averageCellSize
        relativePerim[i] = cellPerims[i] / averagePerimSize
    return relativeArea, relativePerim
```

- Extract the area and perimeter of each cell by:
 - Counting all border pixels of each cell
 - Counting all pixels of the same number
- Extract each cell's sphericity or circularity by using the formula:
 - $(4 * \pi * \text{AREA}) / (\text{PERIMETER}^2)$
- Retrieve the relative perimeter and area of each cell by using the formulas:
 - RelativeArea =
 - $\text{Area}[i] / \text{AverageArea}$
 - RelativePerimeter =
 - $\text{Perimeter}[i] / \text{AveragePerimeter}$

Graphing

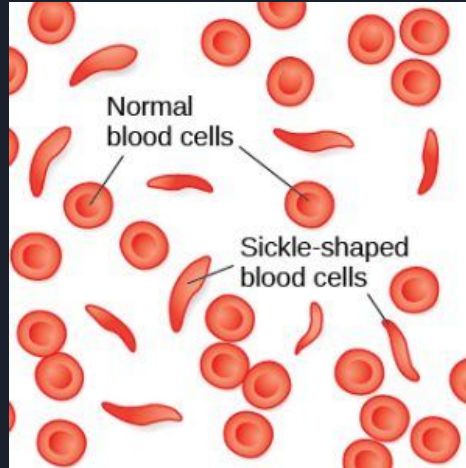


- We can now Graph our features onto a 3D array
- This shows us how each cell's features compare to each other on a scatter plot
- We can use this information to later classify our cells

Creating Training Data

```
def getSickleData():
    return [
        [0.5775517617144933, 1.1320754716981132, 0.25695125098805405],
        [0.5598438067562659, 0.8647798742138365, 0.42684118367781987],
        [0.7349189934505344, 0.9518477043673013, 0.4635207984396843],
        [0.7624956911409859, 1.097424412094065, 0.3617869090868712],
        [0.7493967597380213, 1.097424412094065, 0.3555717632707315],
        [0.7838676318510859, 0.9742441209406495, 0.47192374780441204],
        [0.649464946464947, 1.226705796038151, 0.25019609083298217],
        [0.6621530563131719, 0.9361702127659575, 0.43799255485541405],
        [0.6029237922610134, 0.9192918510804479, 0.38168882707165713],
        [0.5357396169910946, 1.1168966414996095, 0.22976381774183338],
        [0.8200803845850737, 0.996615464722284, 0.4417280990323854],
        [0.7186539522420995, 0.8935173131996876, 0.4815791993021336],
    ]

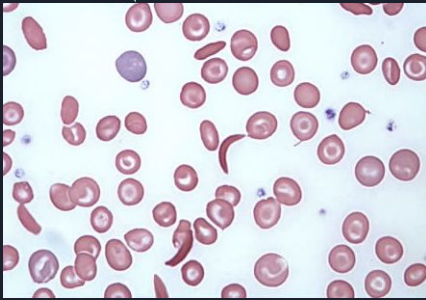
def getHealthyData():
    return [
        [1.0177914720206738, 0.9837898267188373, 0.6231258155880581],
        [0.8673756750488685, 0.9167132476243711, 0.6115920261078285],
        [1.5326508299373818, 1.285634432643935, 0.5494520837620561],
        [1.01514097339562, 0.9837898267188373, 0.6215030921099642],
        [0.8832786667991915, 0.9167132476243711, 0.6228053252878041],
        [0.7931617135473611, 0.8831749580771381, 0.6025454905218607],
        [0.8143657025477917, 0.8831749580771381, 0.6186536406444249],
        [1.4954538491866282, 1.330352152040246, 0.5007114341608758],
        [0.7467779876089189, 0.8831749580771381, 0.5673089121287769],
        [0.9382765132690587, 0.9390721073225266, 0.6304556685775435],
        [0.9064705297684126, 0.9390721073225266, 0.6090842899816946],
        [0.75274160951529, 0.8719955282280604, 0.5865958669424729],
        [0.6984063877016864, 0.8160983789826719, 0.6213621048758945],
        [0.7348507437961767, 0.8272778088317495, 0.6362356195820088],
        [1.1847728853990656, 1.073225265511458, 0.6095016997198948],
        [1.0992943047410793, 1.0396869759642258, 0.602601712603245],
        [1.1841102607428022, 1.0844046953605366, 0.5966655406488427],
        [0.6891296425139979, 0.8719955282280604, 0.5370243852290244],
        [0.754066858827817, 0.9055338177752934, 0.54490666361507673],
    ]
```



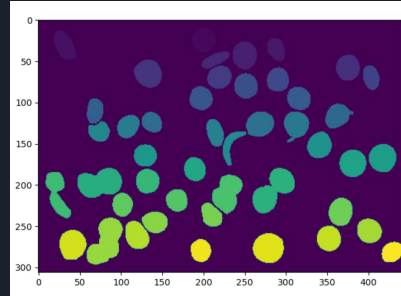
- Done by person
- Look at an image and separate out the area, perimeter, and circularity of sickle cells and healthy cells into two different groups or arrays
- Mark those groups for future use

Classification using KNN

Original Image

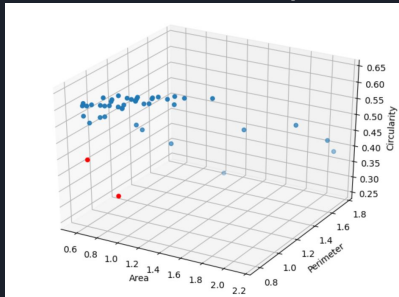


Prepped Image

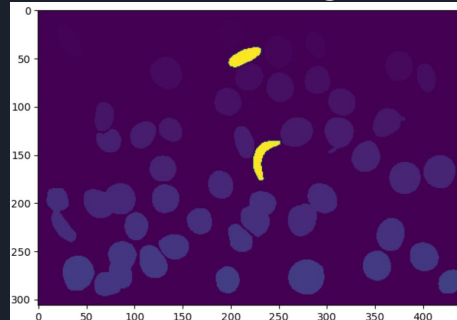


- Using our preloaded training data, we can classify new data using K-Nearest-Neighbor Algorithm
- My algorithm is set to use $k = 3$
- We can then see which cells are classified as sickle, highlight them on the image and graph

Classified Graph



Classified Image



```
Total Cells: 45
Sickle Cells: 2
Healthy Cells: 43
Percent Sickle: 4.444444444444445 %
Percent Healthy: 95.55555555555556 %
```



Discussion & Conclusion

- The program was able to successfully classify the majority of sickle cells in any given image
- However, if a sickle cell was overlapping a healthy cell, the algorithm was not able to classify these cells as different, it classified them as one giant healthy cell.
- These Cells are seen as outliers in the graph, with a giant area
- They can be removed in later versions of this program by removing any cell that is over two standard deviations away.
- I made the methods for this, they are in FeatureExtraction.py and are titled `removeOutliers()` and `removeFromImg()`. However utilizing these methods would have required me to redo the training data step which would have been time consuming.