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# Deep Neural Network for Chromotogram Image Segmentation

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# Index

- Chromotography for Soil Analysis
- Traditional Segmentation Approach
- IRIS Segmentation
- Adapting the VGG Face Recognition Model for Iris Recognition
- Adapting Chromotogram For DNN based segementation

# Unfit Soil Types

- Saline and alkaline soils are too low in nutrients and too high in salt for productive agriculture.
- Marsh soils are  unfit, mainly because of their high acidity.

# Major Types of Crops Grown In India

- Cereals and pulses
- Oil-seed crops
- Fibre crops
- Commercial crops
- Plantation crops
- Fruit crops
- Medicinal and aromatic crops and spices.

# Crop Selection Criteria

- Land quality
- Moisture availability
- Oxygen availability
- Nutrient availability
- Rooting conditions
- Soil.toxicity or soil problems
- Erosion hazard

# Sustainability

- Sustainable land use depends on soil resilience.
- It is a balance between soil restorative and soil degradation processes.
- Ecologically every factor of environment exerts directly or indirectly a specific effect on growth and development of the plant

# Problem

- To determine a soil-site characteristics based on soil samples obtained from the site
- Testing the soil to obtain their chemical composition.
- Suggesting suitable crops based on the soil characteristics
- Suggesting ways to regenerate the soil for sustained production.

# Challenges

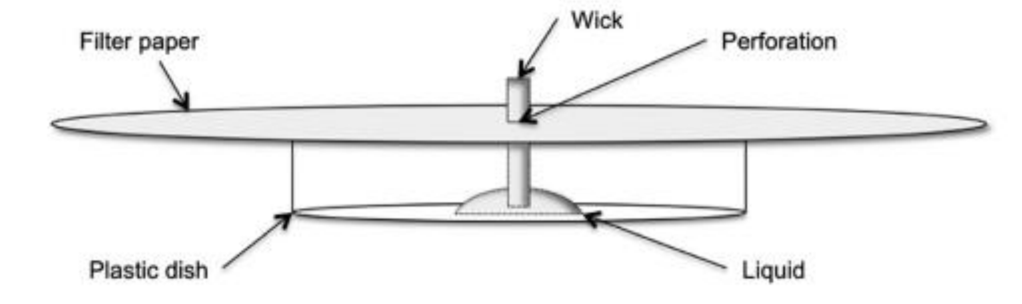
- Soil testing is very costly ranging from 40 to 50 dollars in India.
- Soil conditions change during or after the crop harvest requiring frequent tests.
- Soil testing laboratories are sparse and remote to many agricultural sites delaying the process.


# Chromotograms

- Image extracted from soil based on a process called PCC.
- Chromotograms act like the finger prints of soils
- The rings, color and texture depend on the chemical composition of the soil
- Soil with similar characteristics give rise to similar chromotograms

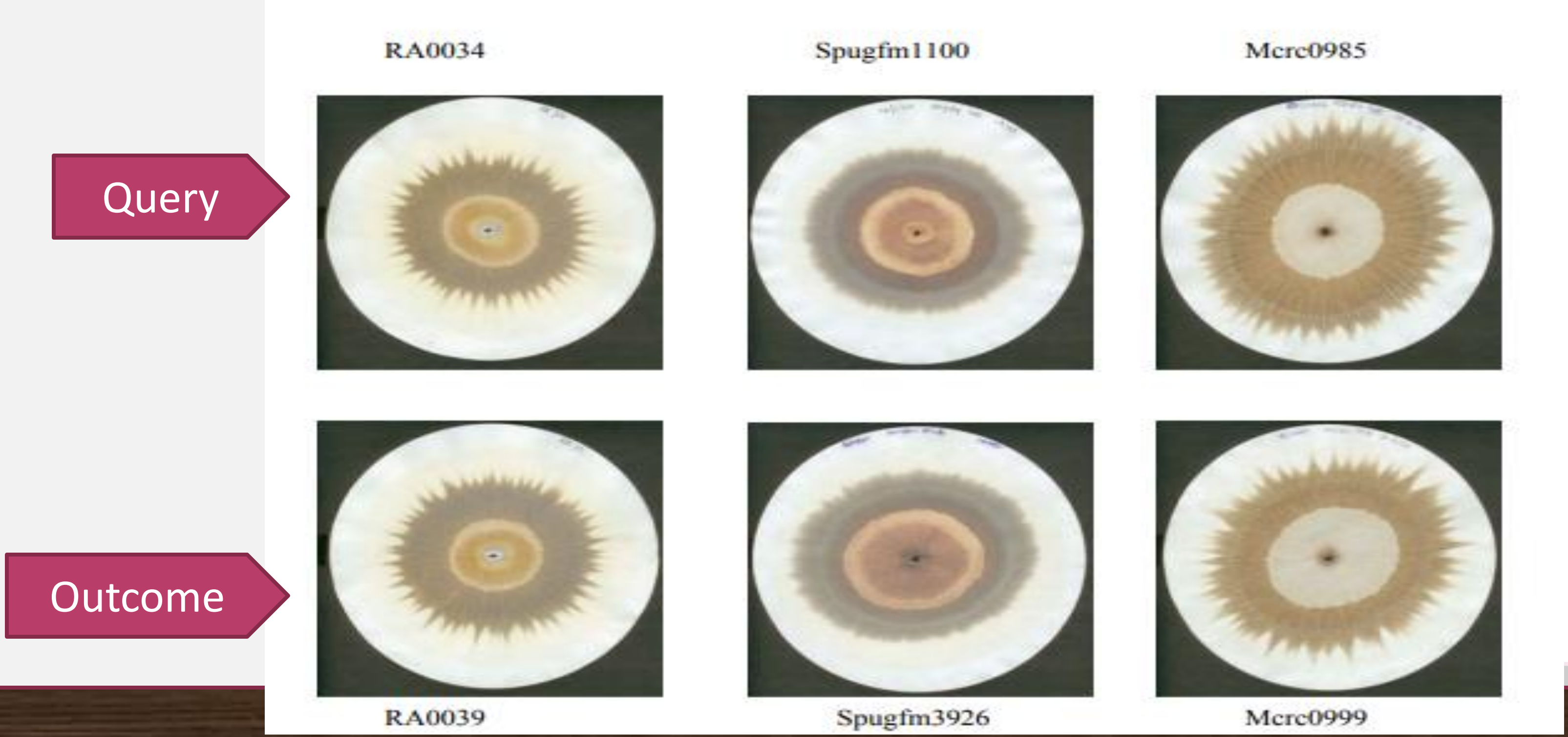
# Pfeiffer's circular chromatography (PCC)

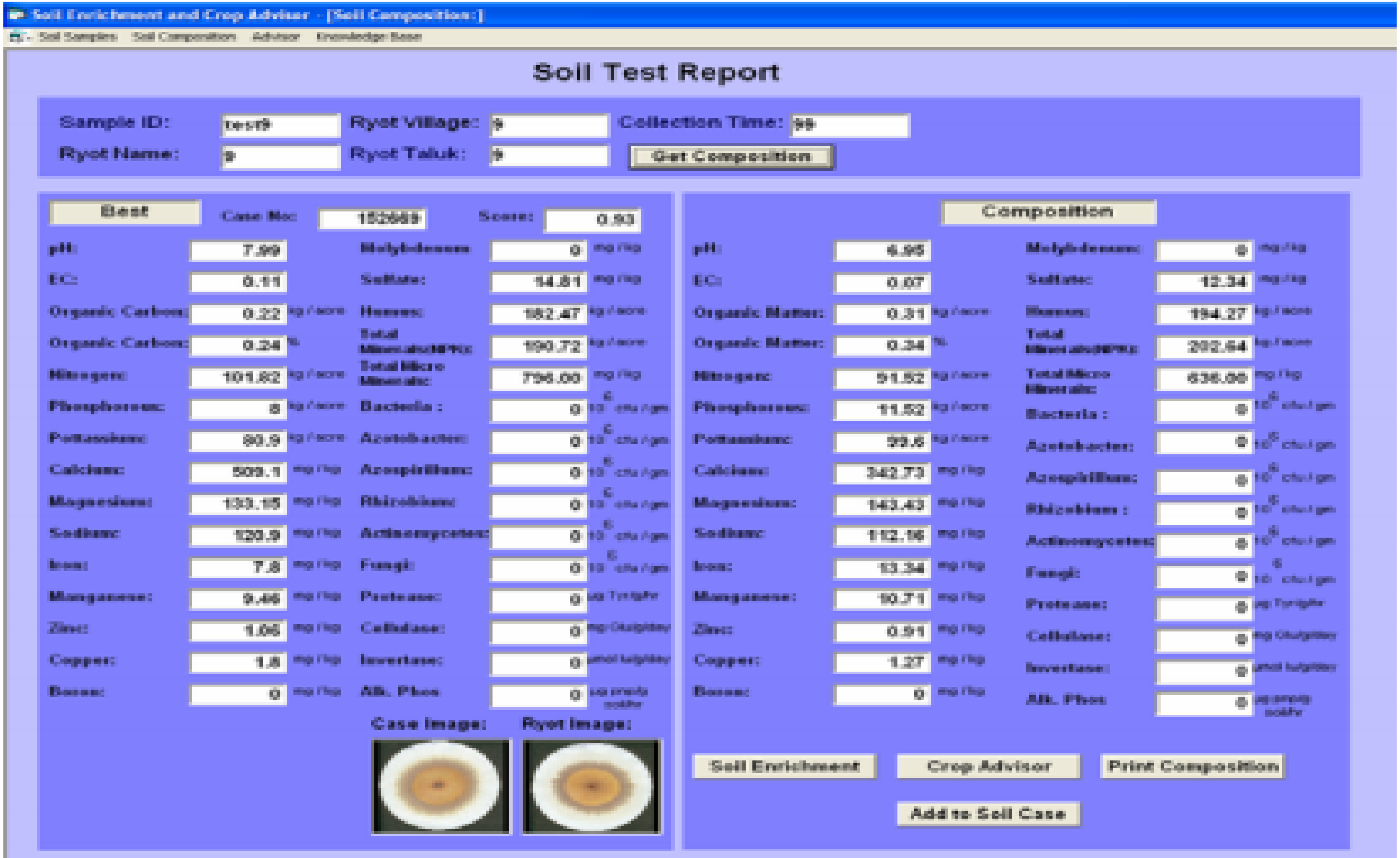
- Paper chromatography principles and applied to test the quality of soils.
- Filter papers are pretreated with a photosensitive substance, and imbibed with a NaOH aqueous extract of the soil sample.
- The output of PCC are colored patterns formed on circular filter paper,



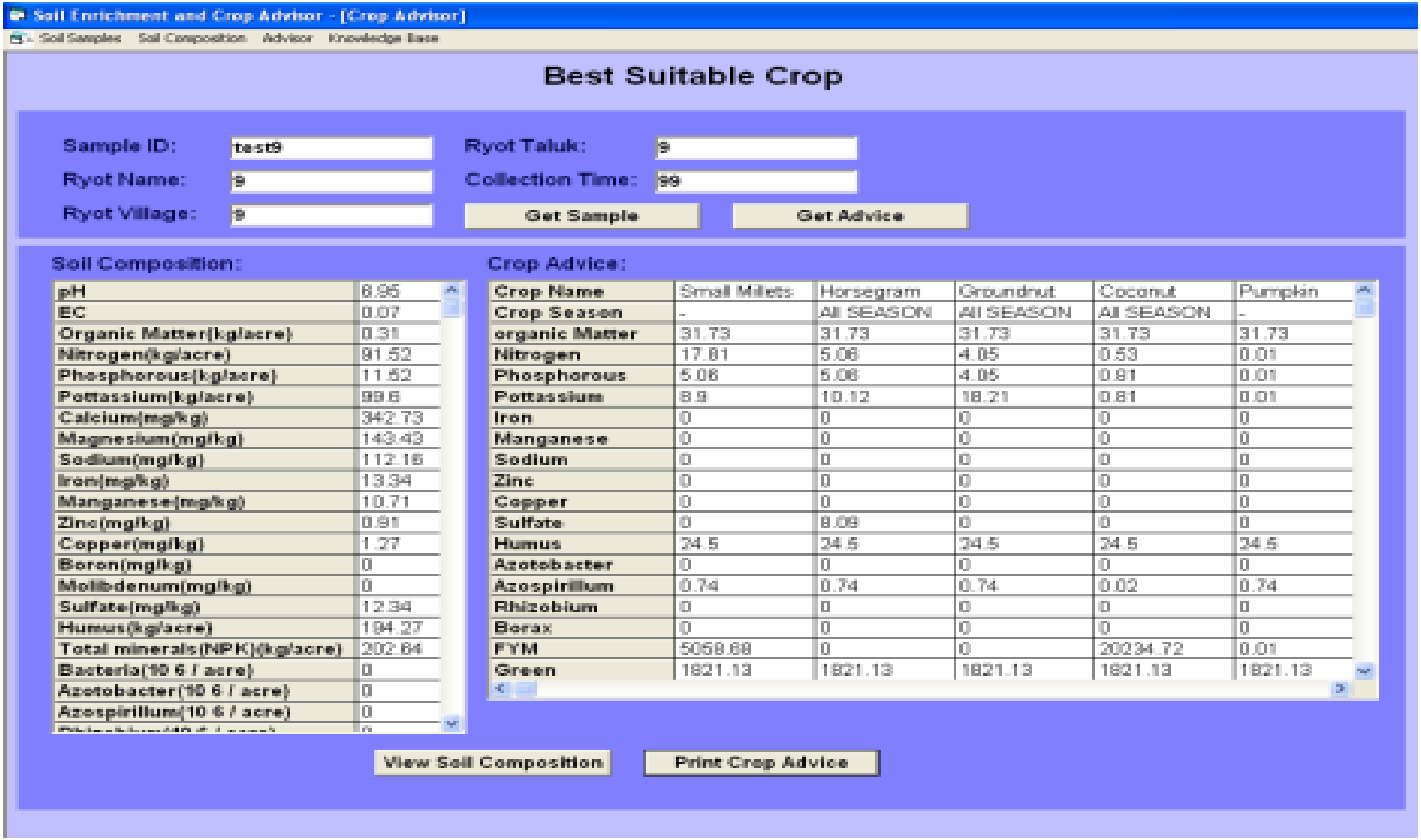
# Case Retrieval in Phase II

(Deepak Khemani et.al 2008)





Soil Enrichment and Crop Advisor - [Soil Composition:]
Soil Samples
Soil Composition
Advisor
Knowledge Base
Soil Test Report
Sample ID:
Ryot Village:
Collection Time:
Ryot Name:
Ryot Taluk:
Get Composition
Best
Case No:
Score:
Composition
pH:
EC:
Molybdenum:
Sulfate:
Humus:
Nitrogen:
Phosphorous:
Pottassium:
Calcium:
Magnesium:
Sodium:
Iron:
Manganese:
Zinc:
Copper:
Boron:
Bacteria :
Azotobacter:
Azospirillum:
Actinomycetes:
Fungi:
Protease:
Cellulase:
Invertase:
Alk. Phos
Case Image:
Ryot Image:
Soil Enrichment
Crop Advisor
Print Composition
Add to Soil Case



Soil Enrichment and Crop Advisor - [Crop Advisor]

Soil Samples  Soil Composition  Advisor  Knowledge Base

# Best Suitable Crop

Sample ID: test9  Ryot Taluk: 9

Ryot Name: 9  Collection Time: 99

Ryot Village: 9

Get Sample  Get Advice

**Soil Composition:**

| | |
|---|---|
| pH | 8.86 |
| EC | 0.07 |
| Organic Matter(kg/acre) | 0.31 |
| Nitrogen(kg/acre) | 91.52 |
| Phosphorous(kg/acre) | 11.52 |
| Pottassium(kg/acre) | 99.6 |
| Calcium(mg/kg) | 342.73 |
| Magnesium(mg/kg) | 143.43 |
| Sodium(mg/kg) | 112.16 |
| Iron(mg/kg) | 13.34 |
| Manganese(mg/kg) | 10.71 |
| Zinc(mg/kg) | 0.91 |
| Copper(mg/kg) | 1.27 |
| Boron(mg/kg) | 0 |
| Molibdenum(mg/kg) | 0 |
| Sulfate(mg/kg) | 12.34 |
| Humus(kg/acre) | 194.27 |
| Total minerals(NPK)(kg/acre) | 202.64 |
| Bacteria(10 6 / acre) | 0 |
| Azotobacter(10 6 / acre) | 0 |
| Azospirillum(10 6 / acre) | 0 |

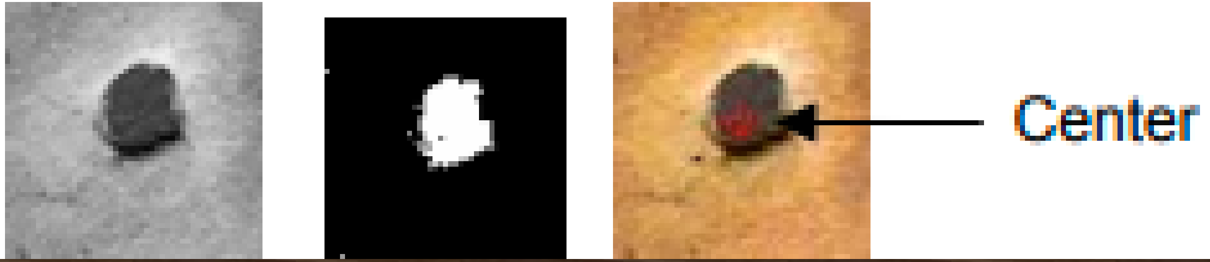
**Crop Advice:**

| Crop Name | Small Millets | Horsegram | Groundnut | Coconut | Pumpkin |
|---|---|---|---|---|---|
| Crop Season | - | All SEASON | All SEASON | All SEASON | - |
| organic Matter | 31.73 | 31.73 | 31.73 | 31.73 | 31.73 |
| Nitrogen | 17.81 | 5.06 | 4.05 | 0.53 | 0.01 |
| Phosphorous | 5.06 | 5.06 | 4.05 | 0.81 | 0.01 |
| Pottassium | 8.9 | 10.12 | 18.21 | 0.81 | 0.01 |
| Iron | 0 | 0 | 0 | 0 | 0 |
| Manganese | 0 | 0 | 0 | 0 | 0 |
| Sodium | 0 | 0 | 0 | 0 | 0 |
| Zinc | 0 | 0 | 0 | 0 | 0 |
| Copper | 0 | 0 | 0 | 0 | 0 |
| Sulfate | 0 | 8.09 | 0 | 0 | 0 |
| Humus | 24.5 | 24.5 | 24.5 | 24.5 | 24.5 |
| Azotobacter | 0 | 0 | 0 | 0 | 0 |
| Azospirillum | 0.74 | 0.74 | 0.74 | 0.02 | 0.74 |
| Rhizobium | 0 | 0 | 0 | 0 | 0 |
| Borax | 0 | 0 | 0 | 0 | 0 |
| FYM | 5058.68 | 0 | 0 | 20234.72 | 0.01 |
| Green | 1821.13 | 1821.13 | 1821.13 | 1821.13 | 1821.13 |

View Soil Composition  Print Crop Advice

# Center Detection

- We crop a portion of the image with a fixed window size so that it covers the hole of a chromatogram.
- The intensity of the hole is lower than the surrounding regions of chromatogram image map.
- A fixed threshold of about 90 can isolate the hole from the other part.

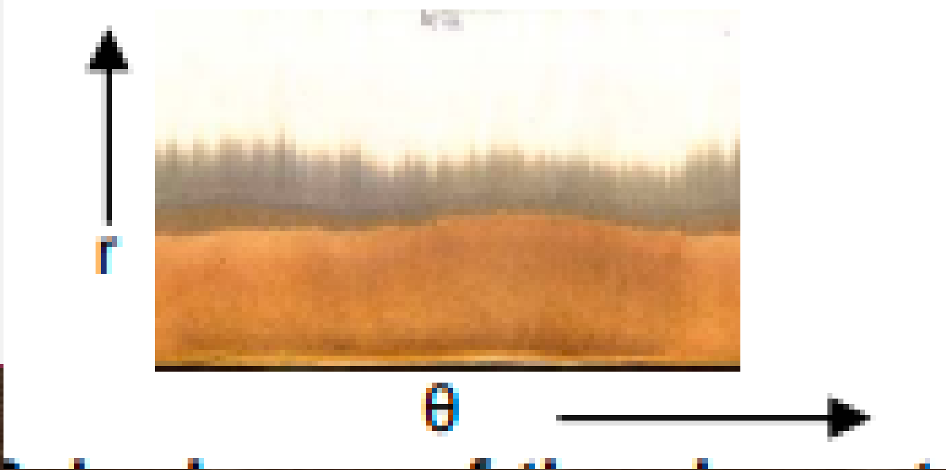


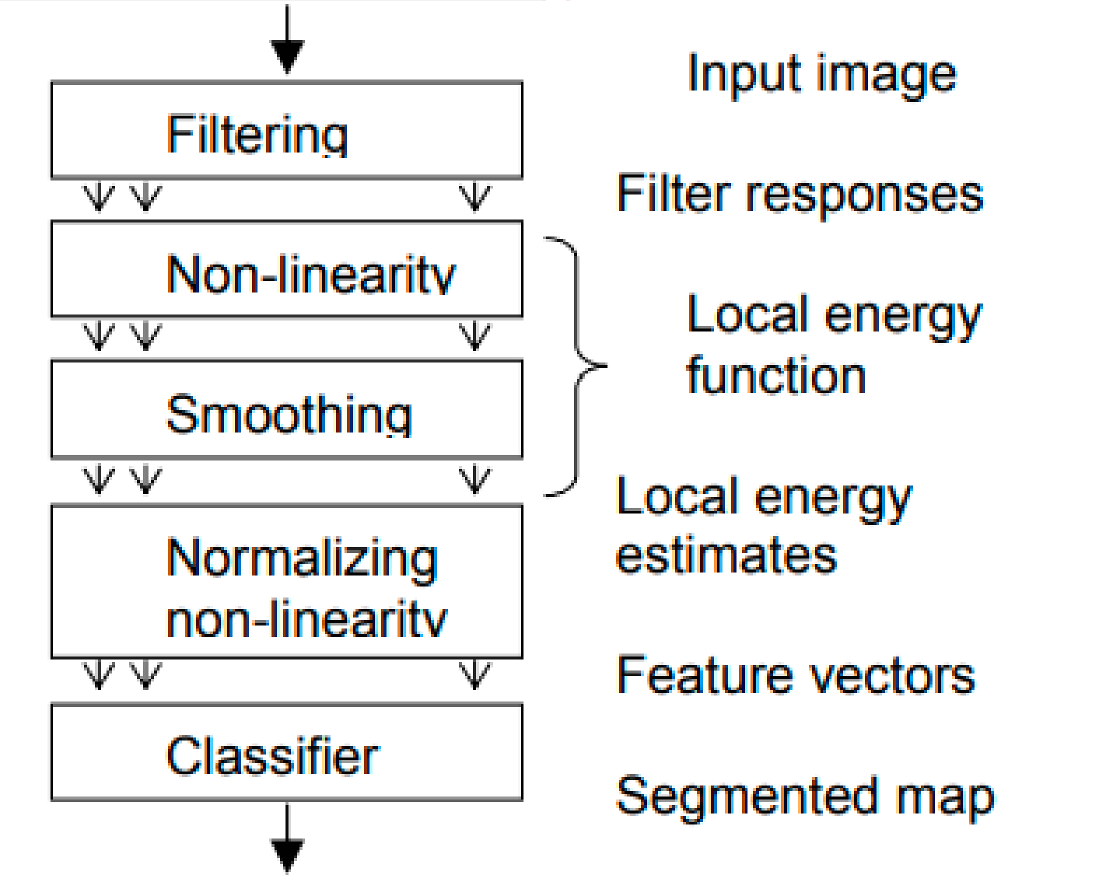
# Transformation to Polar Coordinates
## (Variganti Saritha2007)

- Once the center of the chromatogram is found, the original image is transformed to polar co-ordinate using this center as

$$I(x(r, \theta), y(r, \theta)) \rightarrow I(r, \theta)$$

$$\text{where} \quad x(r, \theta) = r * \cos\theta + x_c$$
$$y(r, \theta) = r * \sin\theta + y_c$$




Filtering
Non-linearity
Smoothing
Normalizing non-linearity
Classifier
Input image
Filter responses
Local energy function
Local energy estimates
Feature vectors
Segmented map

# Texture Classification

- steps of the overall methodology for texture classification
  - The image is filtered using dyadic discrete wavelet transforms
  - The filter coefficients (responses) are post-processed using a set of non-linear functions, which compute the local energy estimates of the filtered coefficients.

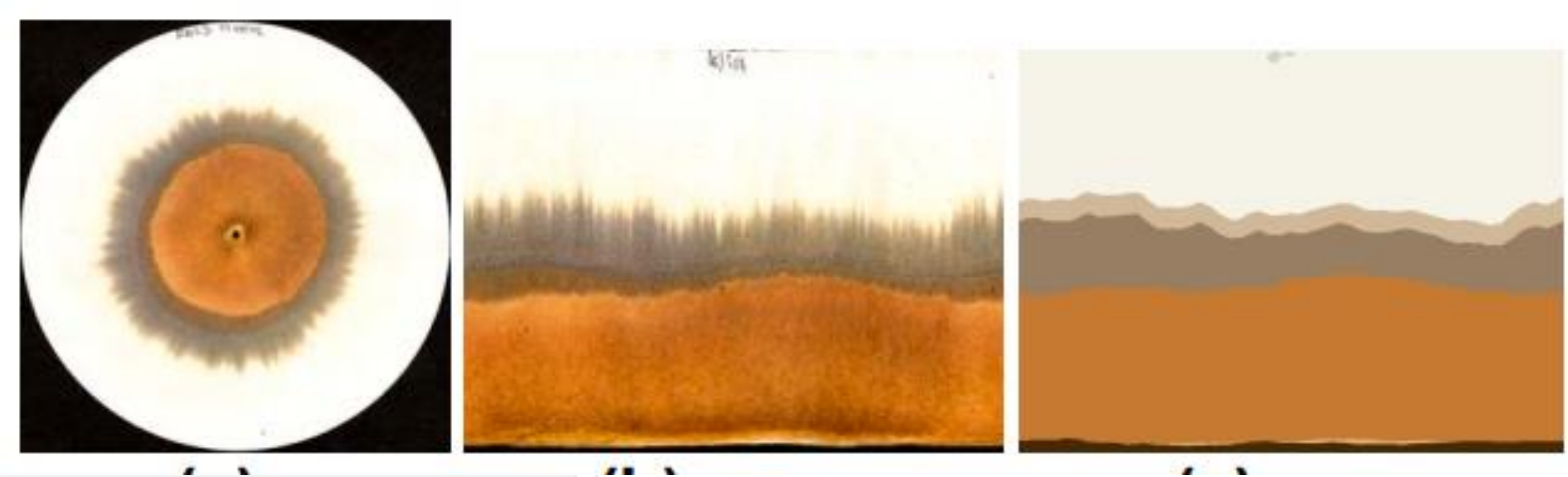
# DWT Features For Classification

- The DWT analyses a signal based on its content in different frequency ranges.
- Therefore it is very useful in analyzing repetitive patterns such as texture.
- The 2-D transform uses a family of wavelet functions and its associated scaling function to decompose the original image into different channels, namely the low-low, low-high, high-low and high-high (A,V,H,D respectively) channels.
- The decomposition process can be recursively applied to the low frequency channel (LL) to generate decomposition at the next level.

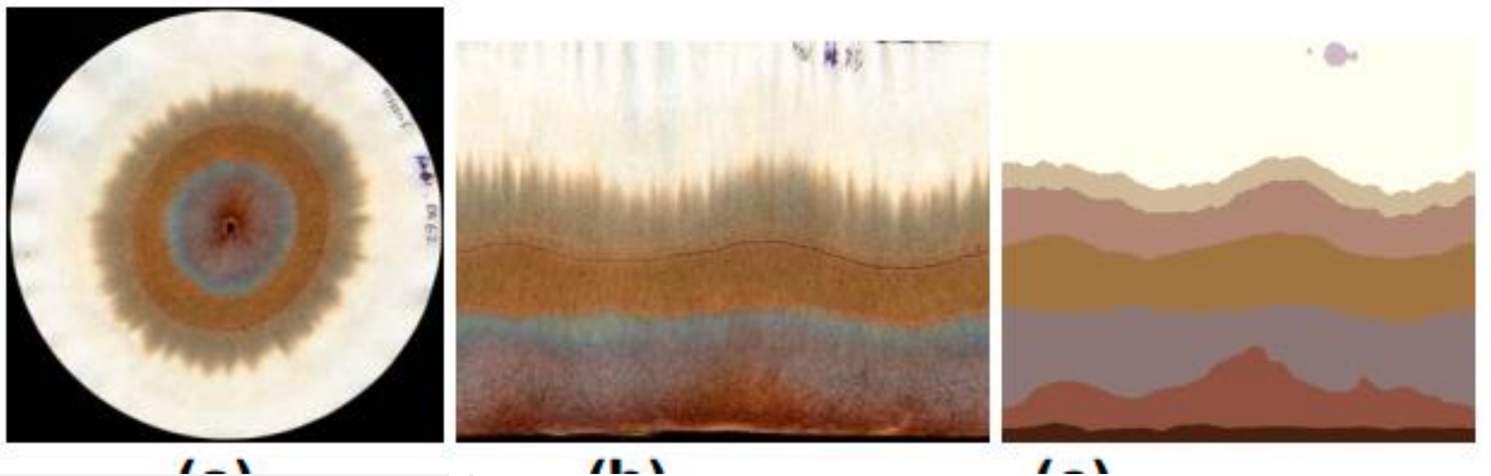
# Gaussian Filter For Feature Extraction

- The features are computed as the local energy of the filter responses.
- A local energy function is computed consisting of a non-linearity, by rectifying the filter response and smoothing.
- Rectification is understood as the operation of transforming negative amplitudes to the corresponding positive amplitudes.
- Commonly applied smoothing filters in the local energy function are rectangular and Gaussian. Gaussian filter is the better choice and will consequently be used in our experiments.

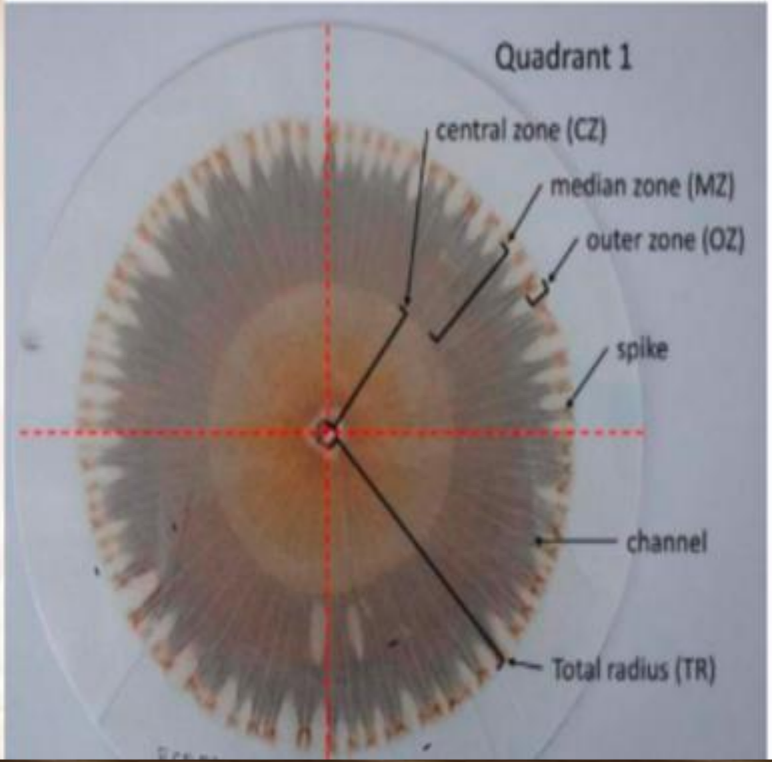
# Segmentation Results



# Segmentation Results

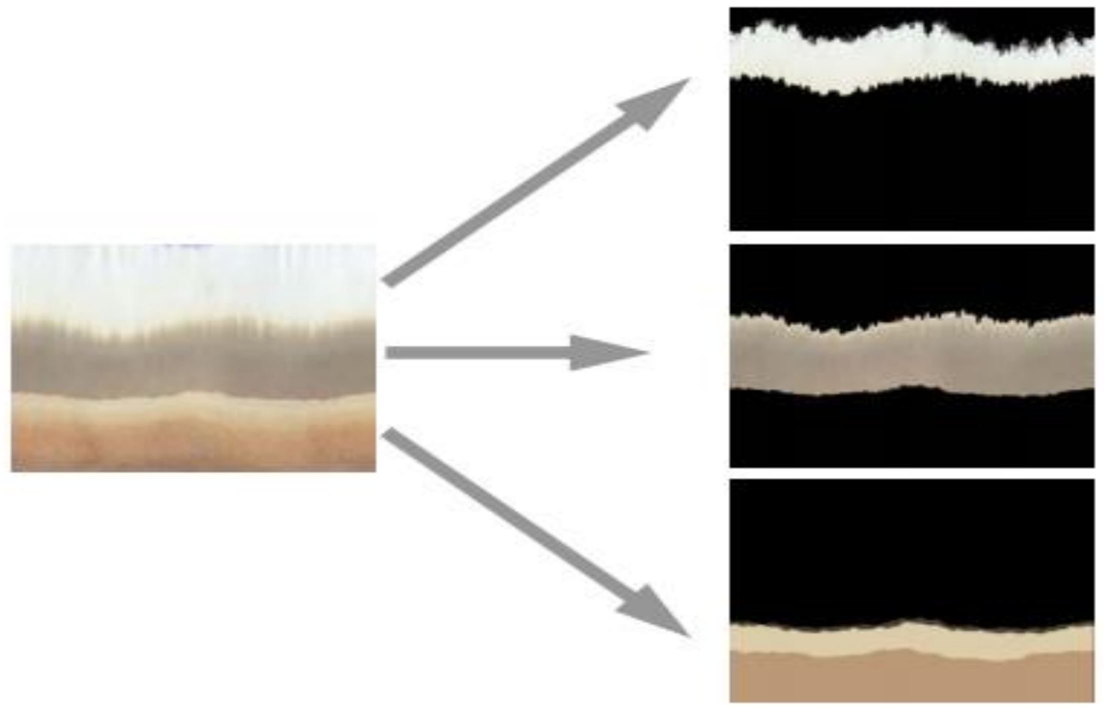


# Associating the Chromotogram Pattern With Soil Nutrients

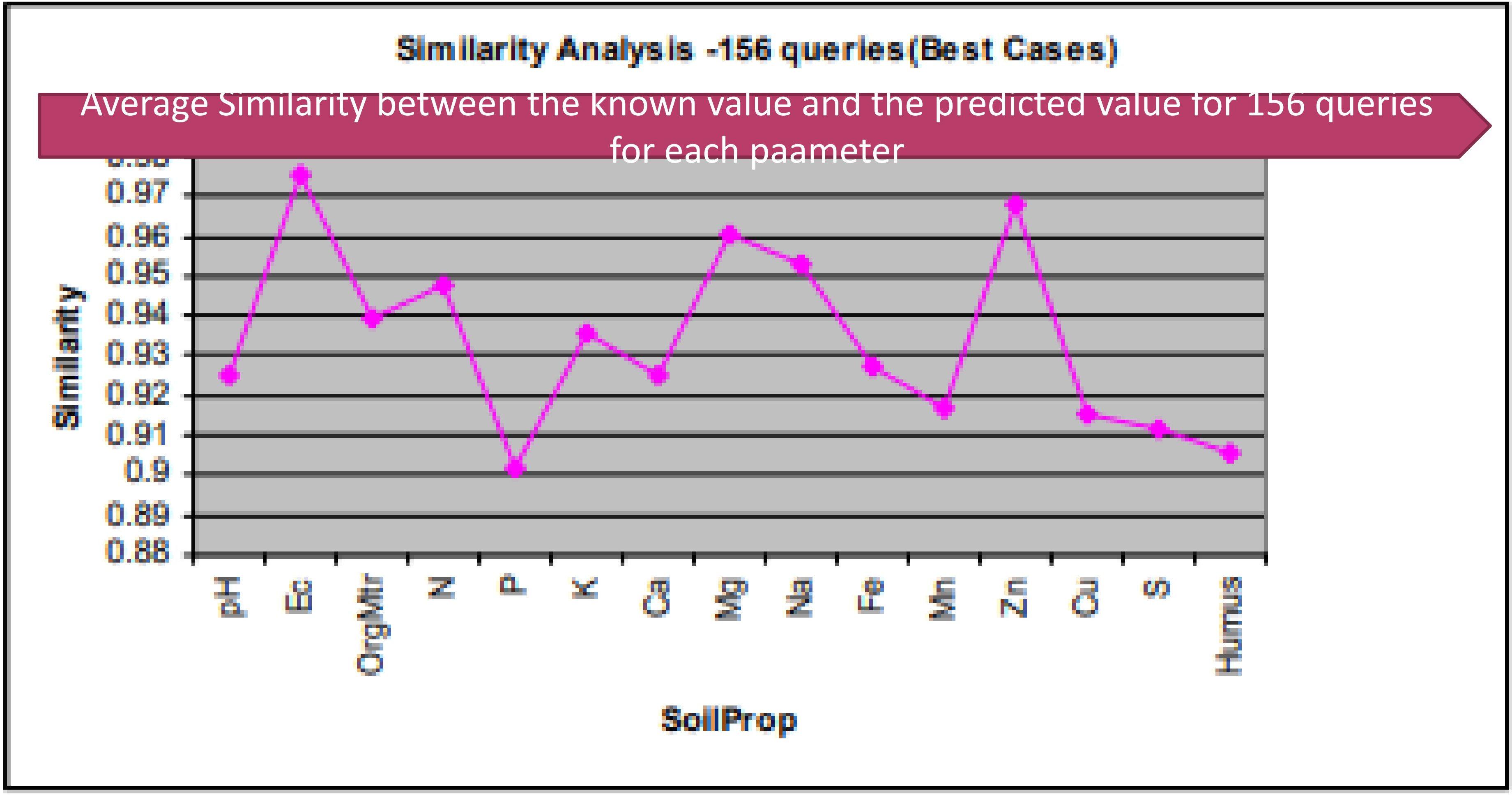



| Feature | Parameters measured | What it represents |
|---|---|---|
| Central | Central Zone radius (mm) | Patterns in the central zone inform about the presence of minerals. These are the heaviest contents of the digest to move into the filter paper and are thus move the least distance from the centre of the filter paper. |
| Median | Median Zone radius (mm) | Structure indicates the presence of proteins, organic carbon and organic matter (minerals and humus). |
| Outer | Outer Zone radius (mm) | "Clouds" at the ends of spikes indicate available nutrients. Bacterial enzyme activity displayed in this zone. |
| Total | Total radius (mm) | |
| Combinations | Median + Outer Zone radius (mm) | |
| | Central Zone radius: Median + Outer Zone radius | |
| Channels | Channels (1=absent, 5=fully developed) | Greater number of channels suggests increased organic matter and nutrients. Channels extending across zones indicate integration of soil components. |
| # channels | Number of channels in quadrant | |
| Spikes | Spikes (1=absent, 5=fully developed) | Greater number of spikes suggests increased organic matter and nutrients. Well-developed spikes are thought to represent healthy soil. |
| # spikes | Number of spikes in quadrant | |
| Colour | Colour intensity (1=blurred, | Warm colours (gold, red, yellow, orange, cream) and/or |

# Image Feature Extraction – Phase I

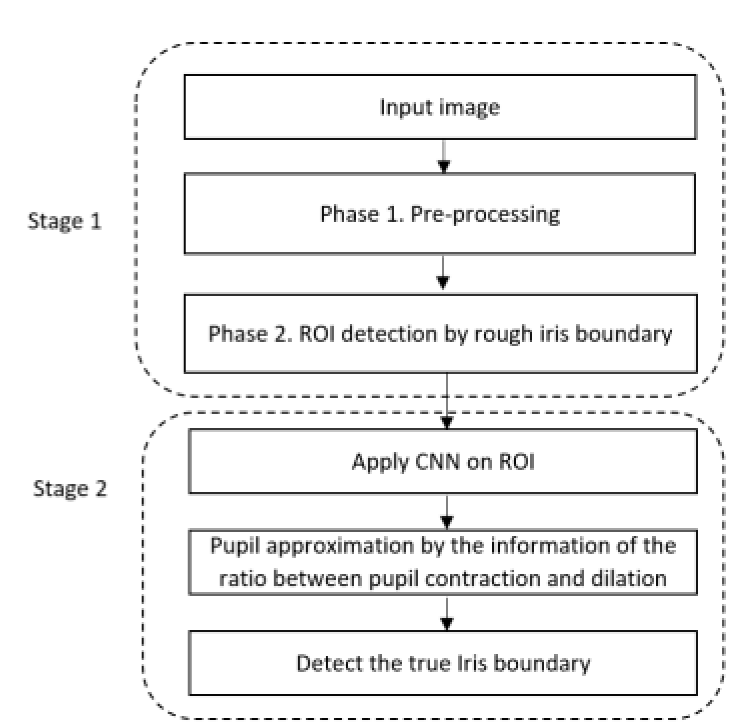


Average Similarity between the known value and the predicted value for 156 queries for each paameter

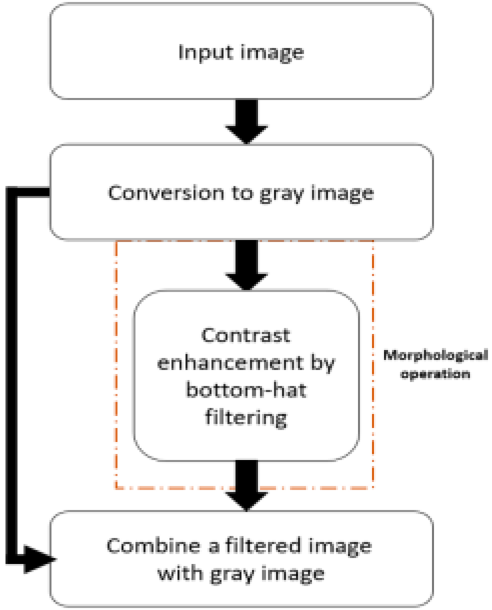


# Iris Segmentation Methods

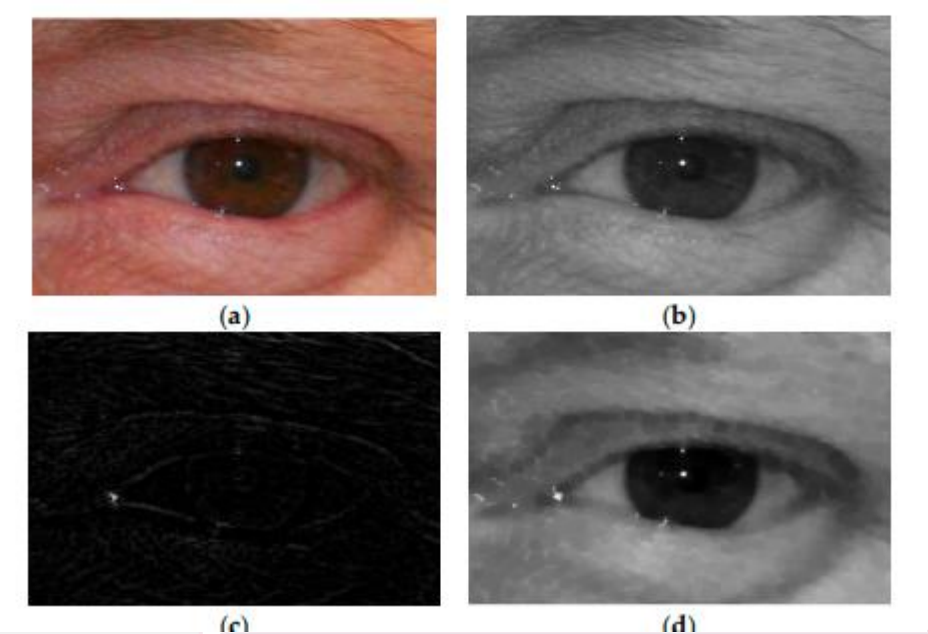
- Boundary-based methods
  - e Hough transform (HT) and Daugman's integro-differential operator
- Pixel Based Methods
  - specific color texture and illumination information gradient to discriminate between an iris pixel
- Active contours and circle fitting-based methods
  - A mask is created according to the size of the iris, and then an iterative process determines the true iris boundary with the help of the localized region-based formulation
- learning-based methods
  - Deep Learning Using CNN

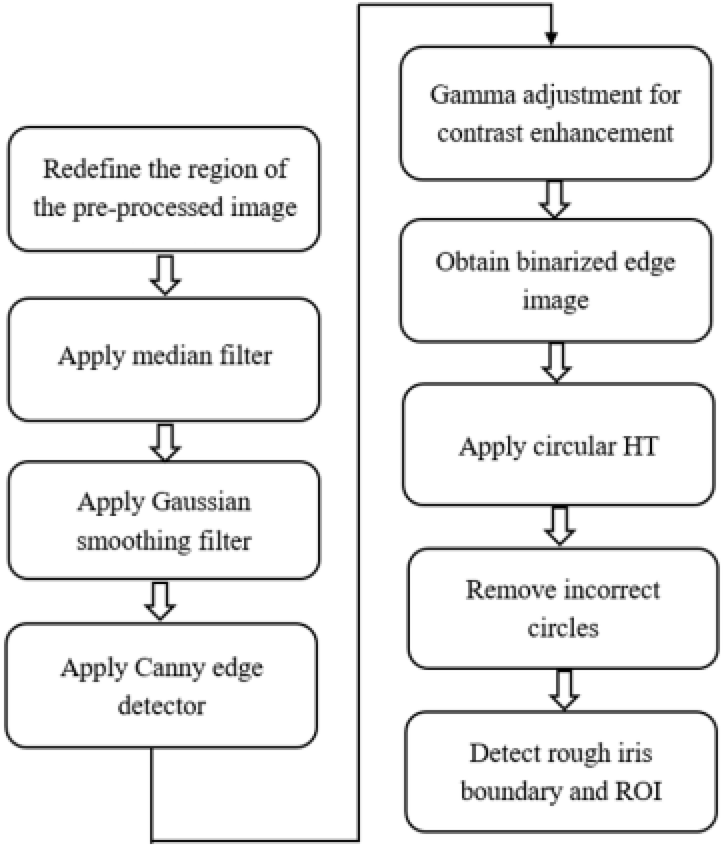

Input image
Stage 1
Phase 1. Pre-processing
Phase 2. ROI detection by rough iris boundary
Stage 2
Apply CNN on ROI
Pupil approximation by the information of the ratio between pupil contraction and dilation
Detect the true Iris boundary

# Pre Processing Stage

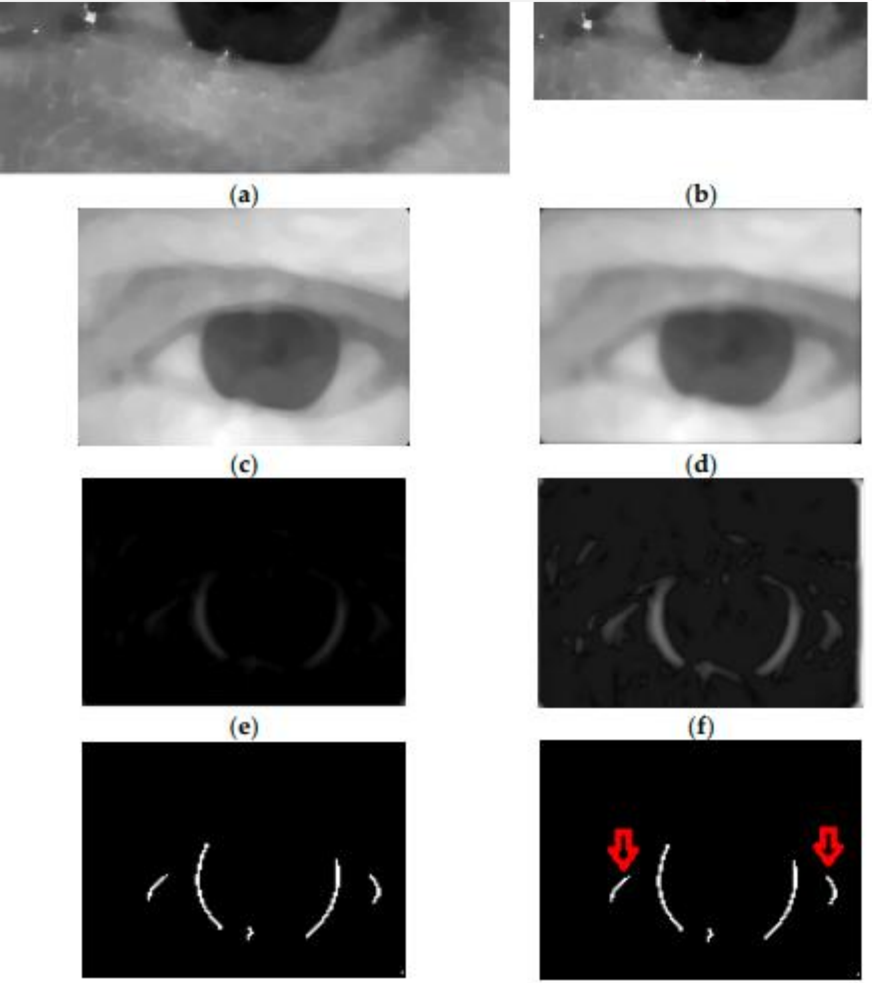


# Image Pre-Processing



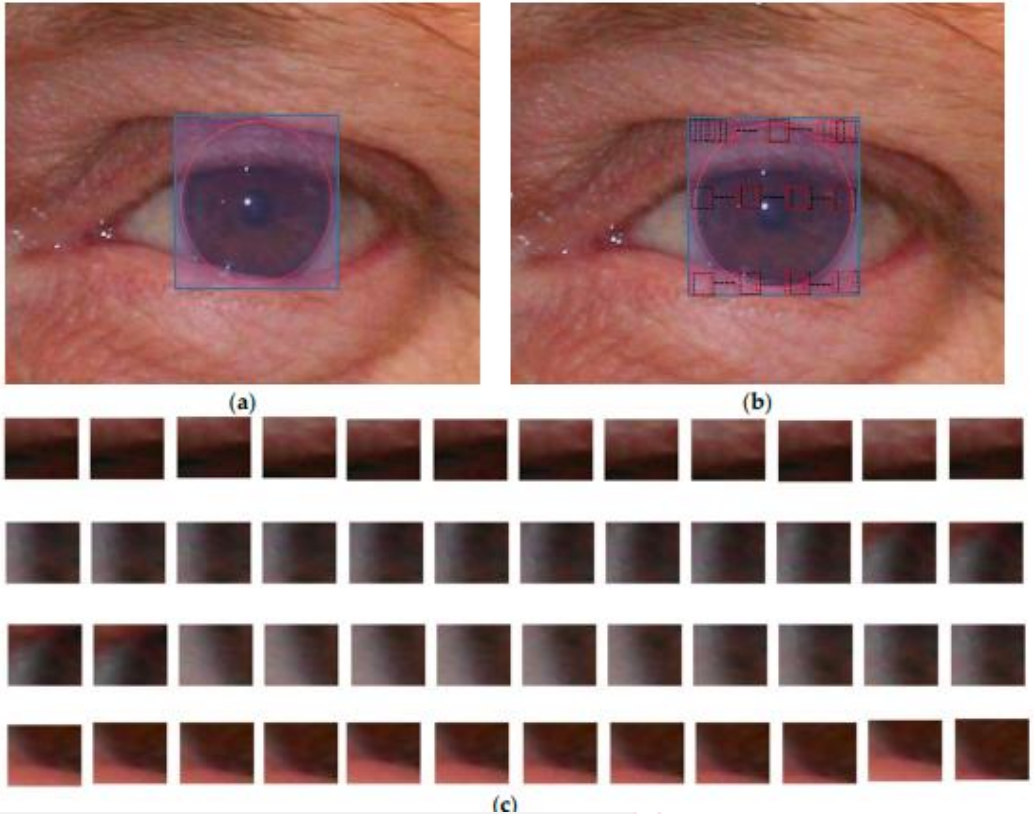



# Region of Interest




# ROI Results

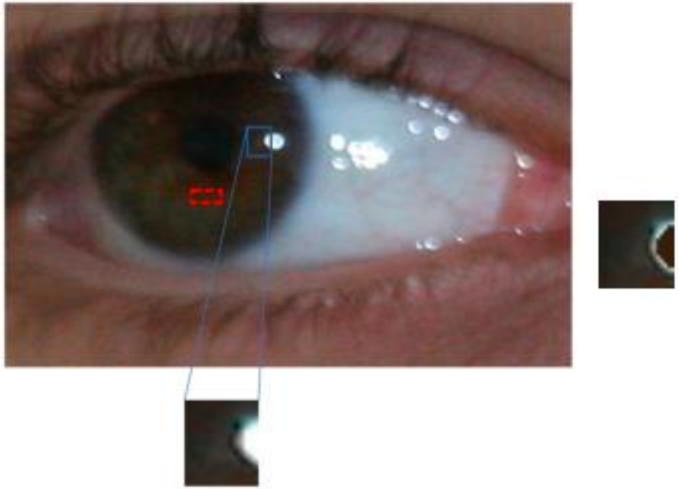
- To detect the iris region accurately, the square mask of 21 × 21 pixels is extracted from the ROI and is used as input to CNN.
- The mask is extracted within the ROI to reduce the number of objects to be classified.
- Specifically, in many cases, iris color can be similar to the eyebrows and eyelids.
- Furthermore, in non-ideal cases, the skin can have similar color to iris. Therefore, by extracting the mask only within the ROI, we can reduce the iris segmentation error by CNN.




# Mask Identified

- This mask is scanned in both horizontal and vertical directions as shown
- Based on the output of CNN, the center position of the mask is determined as an iris or non-iris pixel.
- The mask from the iris region has the characteristics where most pixels of the mask are from the iris texture, whereas that from the non-iris region has the characteristics where most pixels are from the skin, eyelid, eyelash, or sclera.

# Replacing Specular Reflection

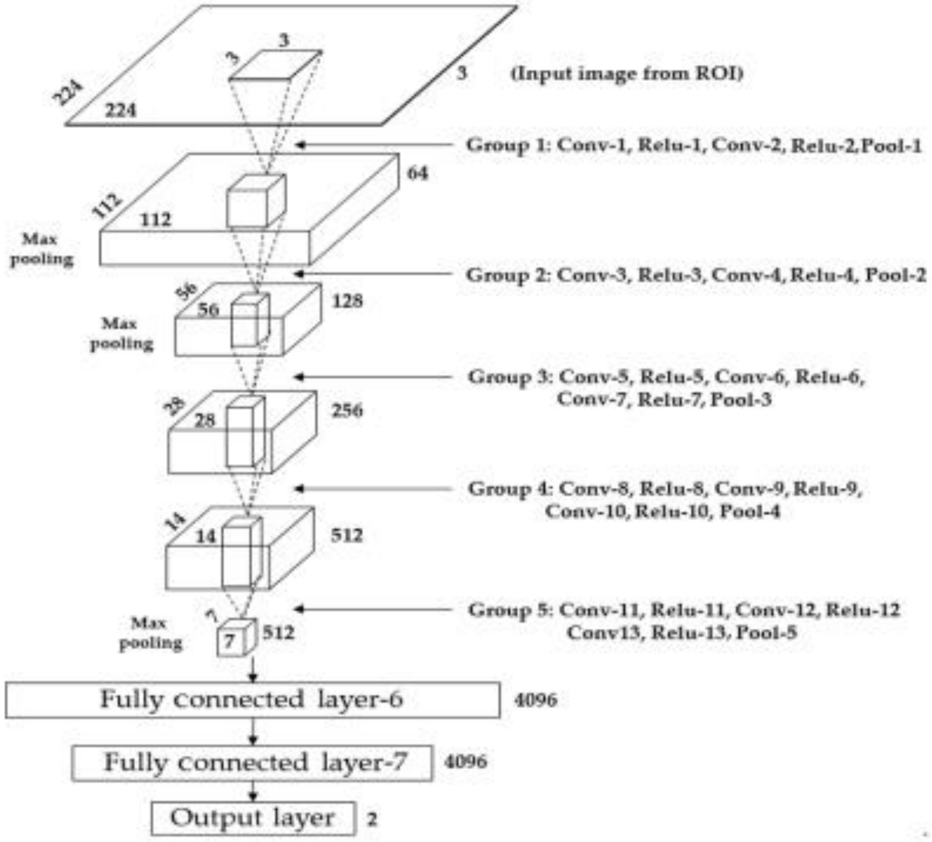


(a) (b)

# Finetuning VGG

- VGG is a CNN model pre-trained with about 2.6 million face images of 2,622 different people.
- To obtain an accurate boundary and its difference from other objects, the ROI is selected with slightly increased rough iris boundary detected by HT

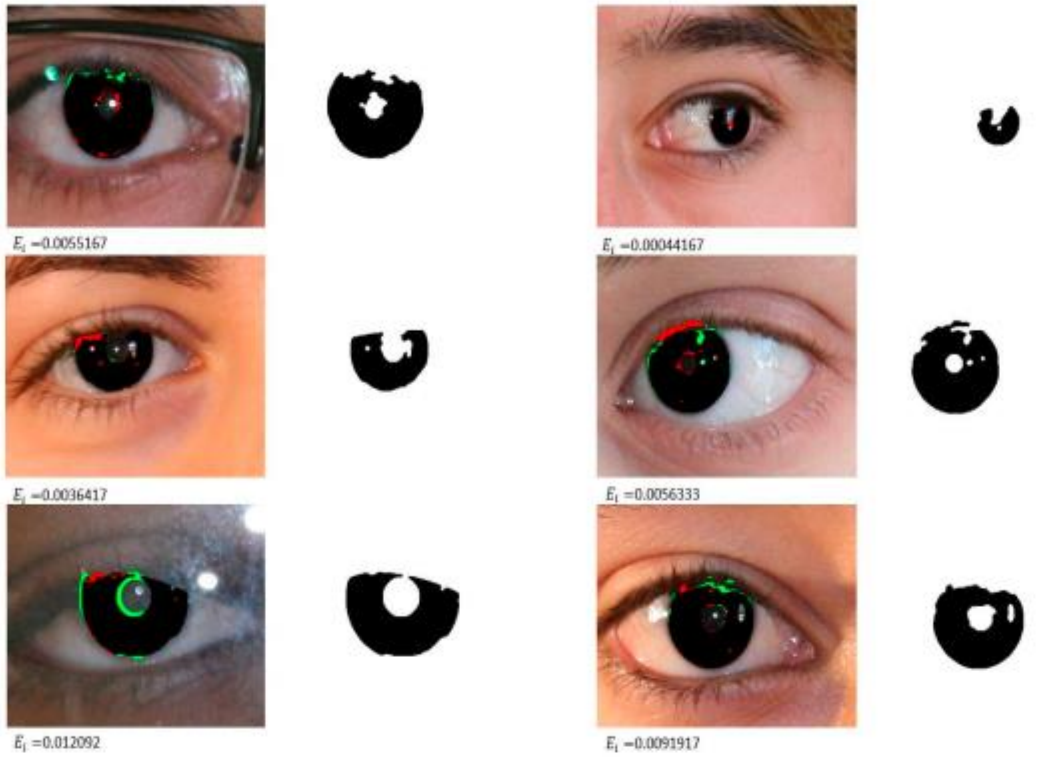
# VGG Model

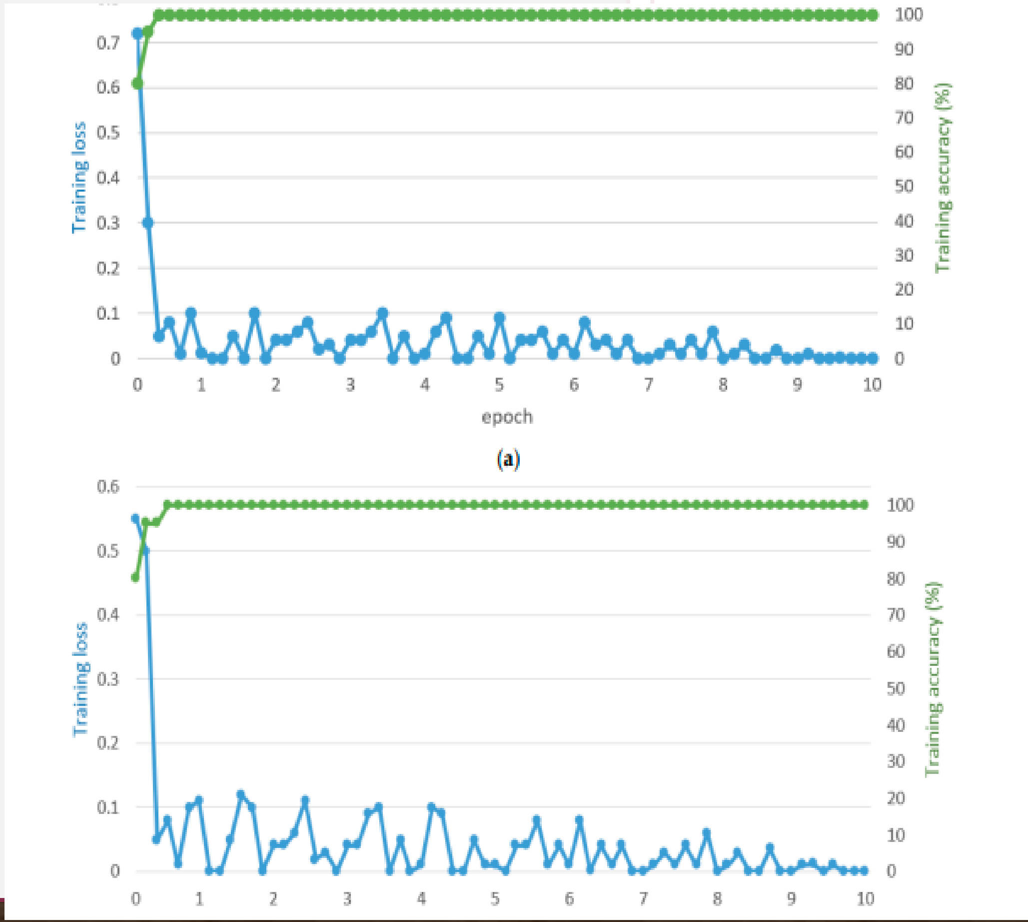

224
224
3
3
3
(Input image from ROI)
Group 1: Conv-1, Relu-1, Conv-2, Relu-2,Pool-1
112
112
64
Max pooling
Group 2: Conv-3, Relu-3, Conv-4, Relu-4, Pool-2
56
56
128
Max pooling
Group 3: Conv-5, Relu-5, Conv-6, Relu-6, Conv-7, Relu-7, Pool-3
28
28
256
Group 4: Conv-8, Relu-8, Conv-9, Relu-9, Conv-10, Relu-10, Pool-4
14
14
512
Group 5: Conv-11, Relu-11, Conv-12, Relu-12 Conv13, Relu-13, Pool-5
Max pooling
7
7
512
Fully connected layer-6
4096
Fully connected layer-7
4096
Output layer
2

# VGG Face Model

- The VGG-face model consists of 13 convolutional layers and 5 pooling layers in combination with 3 fully connected layers.
- The filter size, rectified linear unit (Relu), padding, pooling are chose
- A total of 64 $3 \times 3$ size filters are adopted in the 1st convolutional layer.
- Therefore, the size of the feature map is $224 \times 224 \times 64$ in the 1st convolutional layer

# Results


$E_1$ =0.0055167
$E_1$ =0.00044167
$E_1$ =0.0036417
$E_1$ =0.0056333
$E_1$ =0.012092
$E_1$ =0.0091917



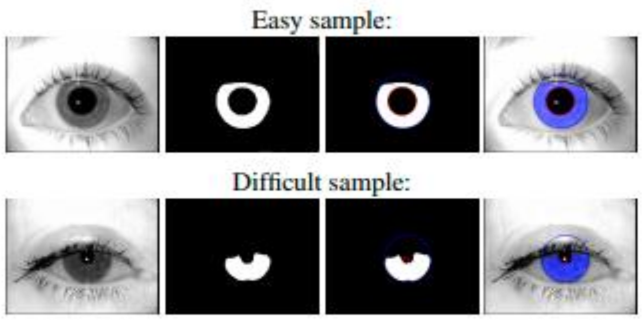

# Results

- For the fine-tuning of VGG-face, the optimum fine-tuning model was experimentally found based on the optimal parameters of initial learning rate of 0.00005
- the momentum value of 0.9, and the size of the mini-batch of 20

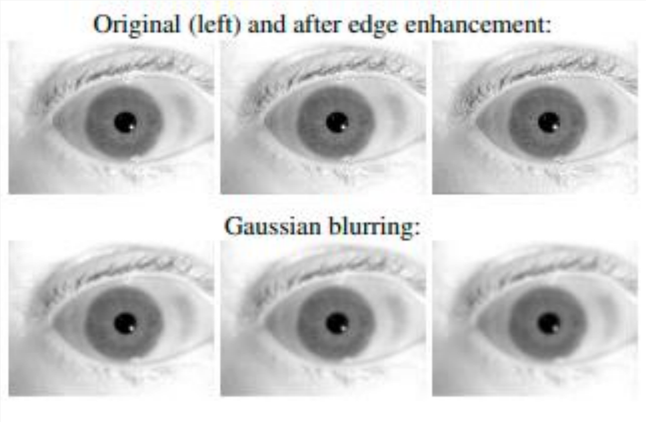
# OSIRIS iris recognition algorithm

(Mateusz et.al 2020)

- OSIRIS, is a open source project created in the framework of the BioSecure project, following the traditional Daugman's approach to iris recognition,
- Iris image normalization onto a polar-coordinate rectangle
- Encoding with Gabor-based filtering for three different complex Gabor kernels.
- The comparison results are given in the form of a fractional Hamming distance between the two binary iris codes.
- Iris and pupil circle parameters are required by the OSIRIS method.
- Circular Hough transform is used to approximate the inner and outer iris boundary in the binary mask



# Data Augmentation
## (Daniel Karrigen 2019)




- Data Augmentation helps to increase the data set for the training stage
- Each image in the training dataset may be augmented n-fold
- The augmentations were performed using the Pillow library for Python
- Gaussian blur may be added for different radius
- Different edge enhancements may be done

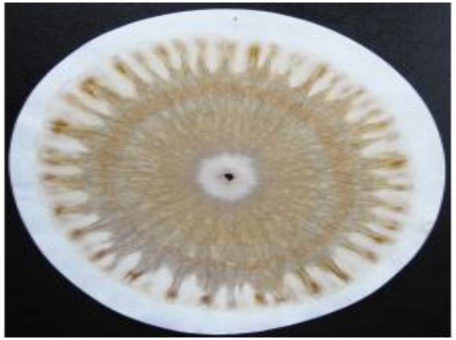
# Work Under Progress

- TO apply the proposed CNN architecture for pre processed Chromotogram Image
- We have collected 2000 chromotogram images
- Masks for these images are being created for the training data set

# Proposed Additional Functionalities to Software

- Compost Diagnosis and  Decision Support

Anaerobic and stagnated compost of very poor quality



Excellent humified compost

# References


- http://dm.dgu.edu/link.html
- https://cs231n.github.io/neural-networks-1/
- Mateusz Trokielewicz, Adam Czajka, Piotr Maciejewicz. Post-mortem iris recognition with deep-learning-based image segmentation, Image and Vision Computing, Volume 94, 2020, 103866, ISSN 0262-8856, https://doi.org/10.1016/j.imavis.2019.103866.
- Iris Recognition with Image Segmentation Employing Retrained Off-the-Shelf Deep Neural Networks , Daniel Kerrigan , Mateusz Trokielewicz, Adam Czajka, Kevin W. Bowyer, Iris Recognition with Image Segmentation Employing Retrained Off-the-Shelf Deep Neural Networks (2019)
- **Muhammad Arsalan, ,Hyung Hong,Rizwan Ali Naqvi, ,Min Beom Lee, ,Min Cheol Kim,Dong Seop Kim,Chan Sik Kim** and Kane Ryoung Park, **Deep Learning-Based Iris Segmentation for Iris Recognition in Visible Light Environment, Symmetry 9(11) 2017**
- Variganti Saritha, Mary Joseph Minu, Sukhendu Das, Deepak Khemani Chromatogram Image Pre-Processing and Feature Extraction for Automatic Soil Analysis, Conference: 2007 International Conference on Computing: Theory and Applications (ICCTA 2007), 5-7 March 2007, Kolkata, India
- Deepak Khemani, Minu Mary Joseph, Variganti Saritha, Case Based Interpretation of Soil Chromatograms, August 2008 Conference: Proceedings of the 9th European conference on Advances in Case-Based Reasoning