Computer Vision System for Automated Medicinal Plant Identification

Estadistica '21

Statistics Society of

University of Sri Jayewardenepura

September 19, 2021

P.G. Jayani Lakshika

B.Sc. (Honours) in Statistics

Temporary Instructor in the Department of Statistics, University of Sri Jayewardenepura

Associate Data Analyst at Vizuamatix Pvt. Ltd.

My SUPERVISOR

Dr. Thiyanga S. Talagala

Senior Lecturer in the Department of Statistics, Faculty of Applied Sciences at the University of Sri Jayewardenepura

PhD in Statistics, Monash University, Australia

https://thiyanga.netlify.app/

Department of Statistics
University of Sri Jayewardenepura, Sri Lanka

Department of Mathematics
University of Sri Jayewardenepura, Sri Lanka

Department of Computer Science
University of Sri Jayewardenepura, Sri Lanka


පිළිකාවට ඔසුවක්?


RAJAGIRIYA AND NAVINNA AYURVEDIC HOSPITALS TO ADMIT COVID PATIENTS

Ayurvedic treatment not for Covid, but for immunity

- Not specifically focused on Covid
- Discussion today on collaboration with Western hospitals


Authentic Ayurveda


'Dhammika *paniya*' : Expert warns against unethical research under the guise of scientific benefit

By Kumudini Hettiarachchi, Ruqyyaha Deane & Meleeza Rathnayake

As the controversy around the 'Dhammika paniya' concoction that took the country by storm recently does the rounds across the country, there were strong protests from experts about the events surrounding the issue.

The Commissioner of Ayurveda, Chatura Kumaratunga, told *the Sunday Times* that tests were being carried out on COVID-19 patients in a government (western) hospital on the 'Dhammika *paniya*', a syrup, some of the ingredients of which are a secret only known to the manufac-

Sumathipala has earned international recognition from WHO and UNESCO as an expert in research ethics .

He was adamant that permitting this type of untested medicines to be given to people is dangerous as it can pave the way for unethical testing/distribution of untested medicines and vaccines in Sri Lanka.

"Don't open the floodgates to untested medicines/vaccines," said Prof. Sumathipala.

Referring to the fact that the "issue lies in the process", he quotes the New England Journal of Medicine which states that though the need for health and mental health research in low and mid-


Deegayu launches new product brochure on 'truly authentic' Ayurveda products


SUREFIRE TREATMENT FOR DIABETES KILLER


Focus shifts to research on Ayurveda to fight diabetes

DNA Correspondent
correspondent@dnaindia.net

'Madhumeha through Ayurveda', a holistic approach to beat diabetes started by the Narendra Modi government in 2016, is going strong.

The Health Ministry has now roped in reputed institutes — the Indian Institute of Technology (IIT) Bombay and the All India Institute of Medical Sciences (AIIMS) — for research on Ayurvedic medicines to battle diabetes.

The emphasis on efficient research on the matter is an attempt to counter allegations which point towards the inefficiency of Ayurvedic medicines.

India has the highest number of diabetic patients in the world, with over 50 million suffering from the lifestyle disease. The number is expected to rise by 200 per cent in the next 10 years.

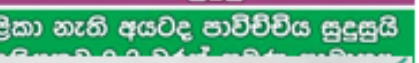
The AYUSH ministry has also integrated ayurveda, yoga, naturopathy, unani, siddha and homeopathy with the health ministry's schemes to keep a check on lifestyle conditions.

The herbal drug, BGR-34, developed by the Council of Scientific & Industrial Research (CSIR) laboratory, is slowly gaining attention. It has already acquired the top slot in the anti-diabetic ayurvedic product category in the IMS Health ranking.

"Developed by the well-established research institution, BGR-34 has been found extremely effective in controlling every type of the disease. In fact, it is even prescribed by allopathic practitioners, which is enough to explain its efficacy," says Sanchit Sharma from AIMIL Pharmaceuticals, the company which sells the drug.


කටුපිල තේ පිළිකා සෛල මරා දැමීමේ හැකියාවක් ඇත

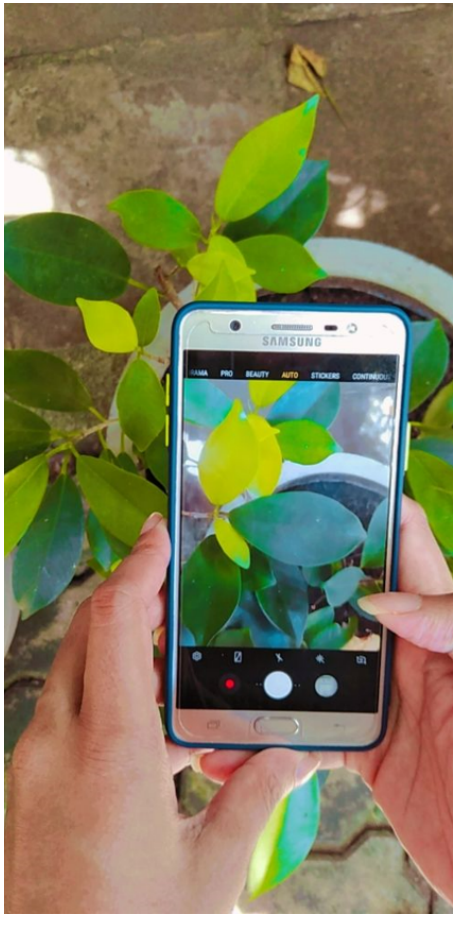

සියලුම පිළිකාවන් දියවැඩියාව සහ දියවැඩියා තුවාල වලට කටුපිල තේ පානය සුදුසුයි


පිළිකා නැති අයටද පාවිච්චිය සුදුසුයි


'පිනසය' සුව කරන හෙළ වෙදකම ගැන කියන

Main objective

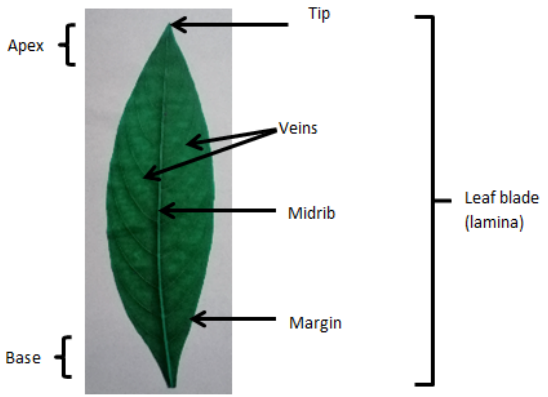
- To develop an automatic algorithm to classify medicinal plants by using statistical machine learning approach

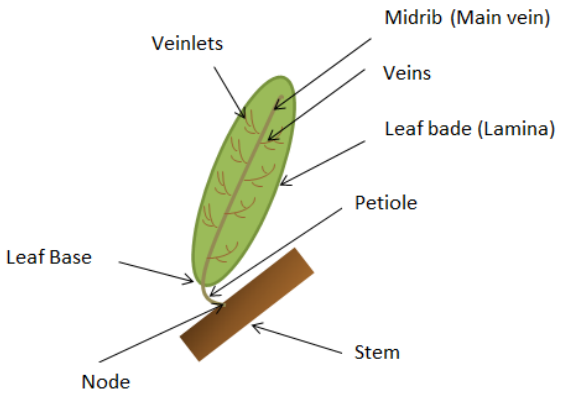


Limitations

Why medicinal plant leaves?

- Leaf images are considered as they contain large number of diverse set of features such as shape, veins, edge features, apices, etc.

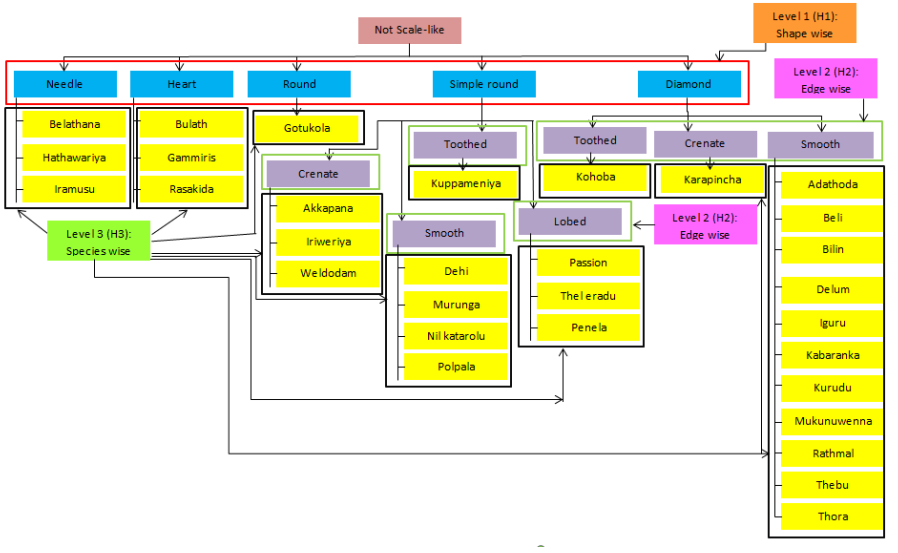




- We used non-diseased leaves with simple arrangement.
- We used the leaves without a petiole.

Significance of the study

- **To avoid misidentifying medicinal plants in Sri Lanka**
- The algorithm developed by us is based on the leaf images. Since leaves are **relatively easy to obtain without damaging the plants**, there is no harm for the plants because of the development of algorithm.
- Our algorithm works as a hierarchical classification system. Therefore even though we don't know the exact species name, we can follow the first 2 levels. As the result of that **misidentification rate and computation time will be decreased**.



Methodology

Workflow

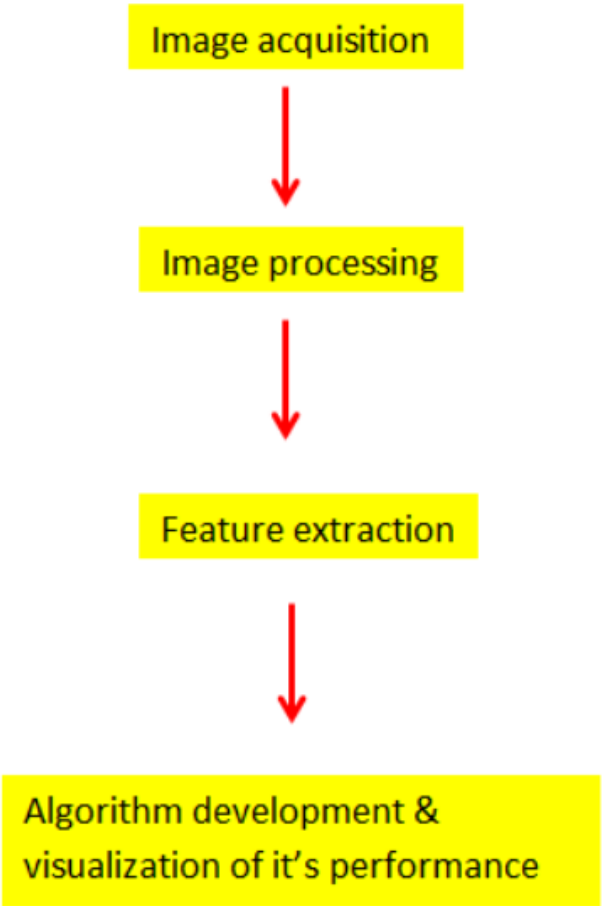
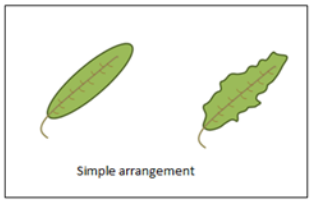
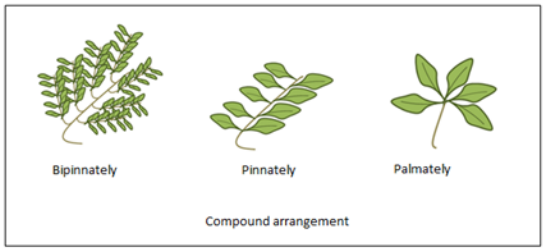


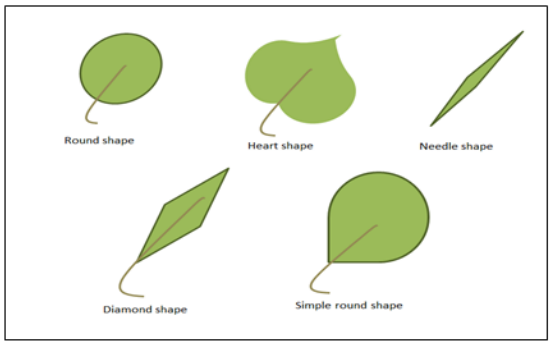
Image acquisition
Image processing
Feature extraction
Algorithm development &
visualization of it's performance

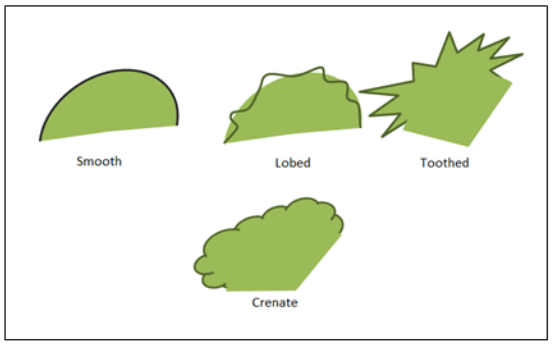
Image Acquisition

- A database of leaf images of medicinal plants in Sri Lanka is not yet available.
- Establish a repository of medicinal plant images.
- Preliminary study by using 471 medicinal plants and recorded their characteristics like leaf arrangement, shape, edge type etc.

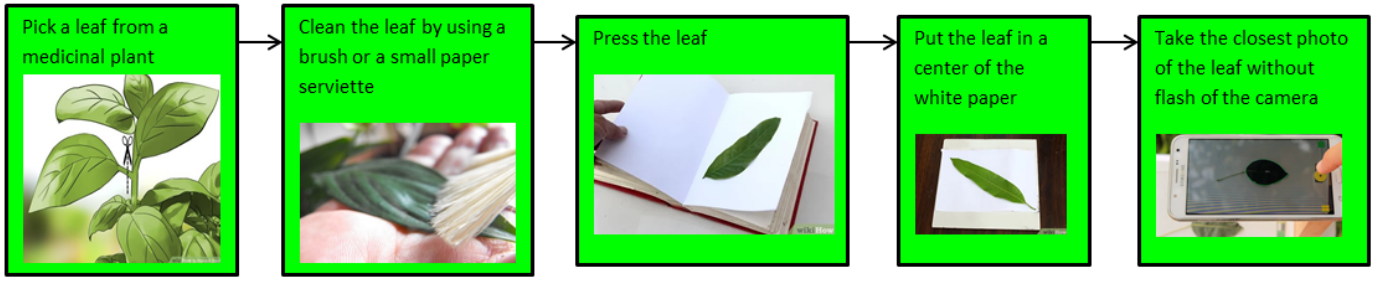




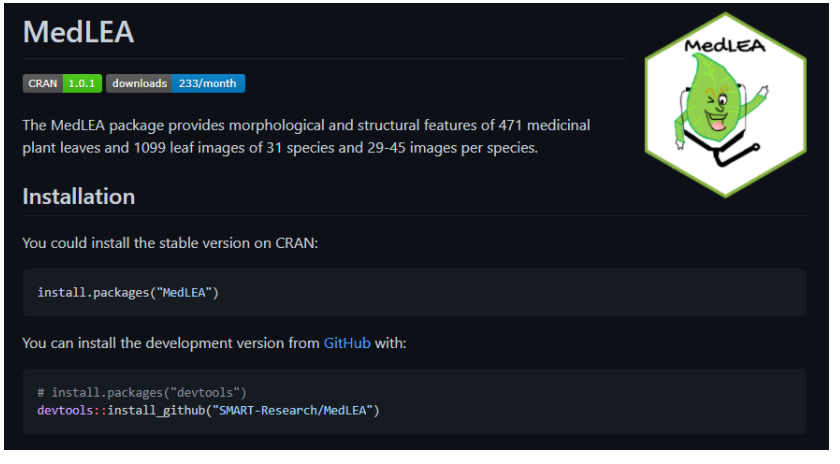




- Collected **1099** leaf images from **31 species**

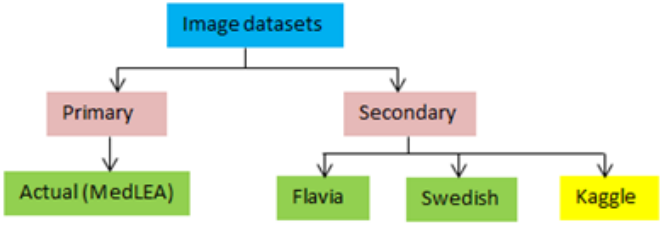


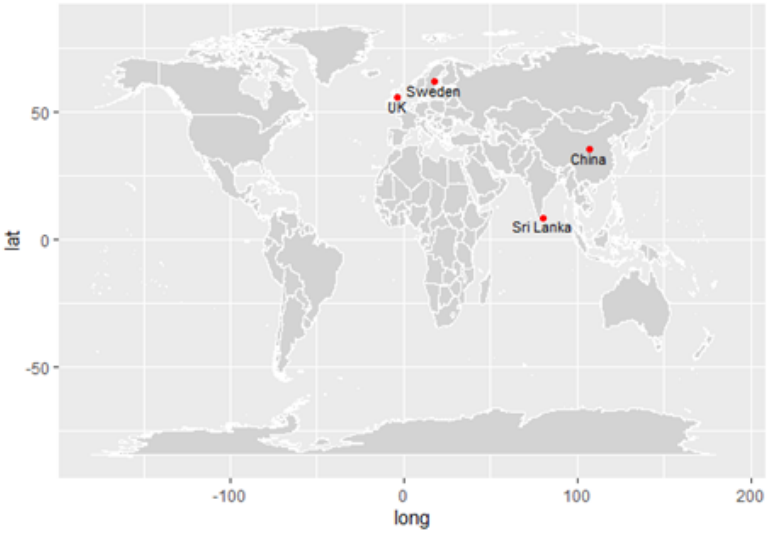
MedLEA: Medicinal LEAf



repository is made available to the public through an **open-source R software MedLEA**, available at url(https://CRAN.R-project.org/package=MedLEA) for research reproducibility

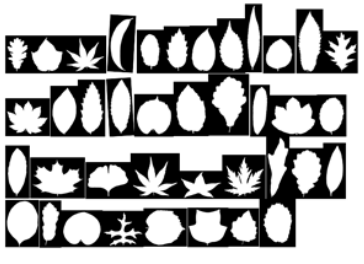
Total downloads: More than 1000





Sample of Flavia dataset

Sample of Swedish dataset



Sample of Kaggle dataset

Sample of MedLEA dataset

Methodology Diagram

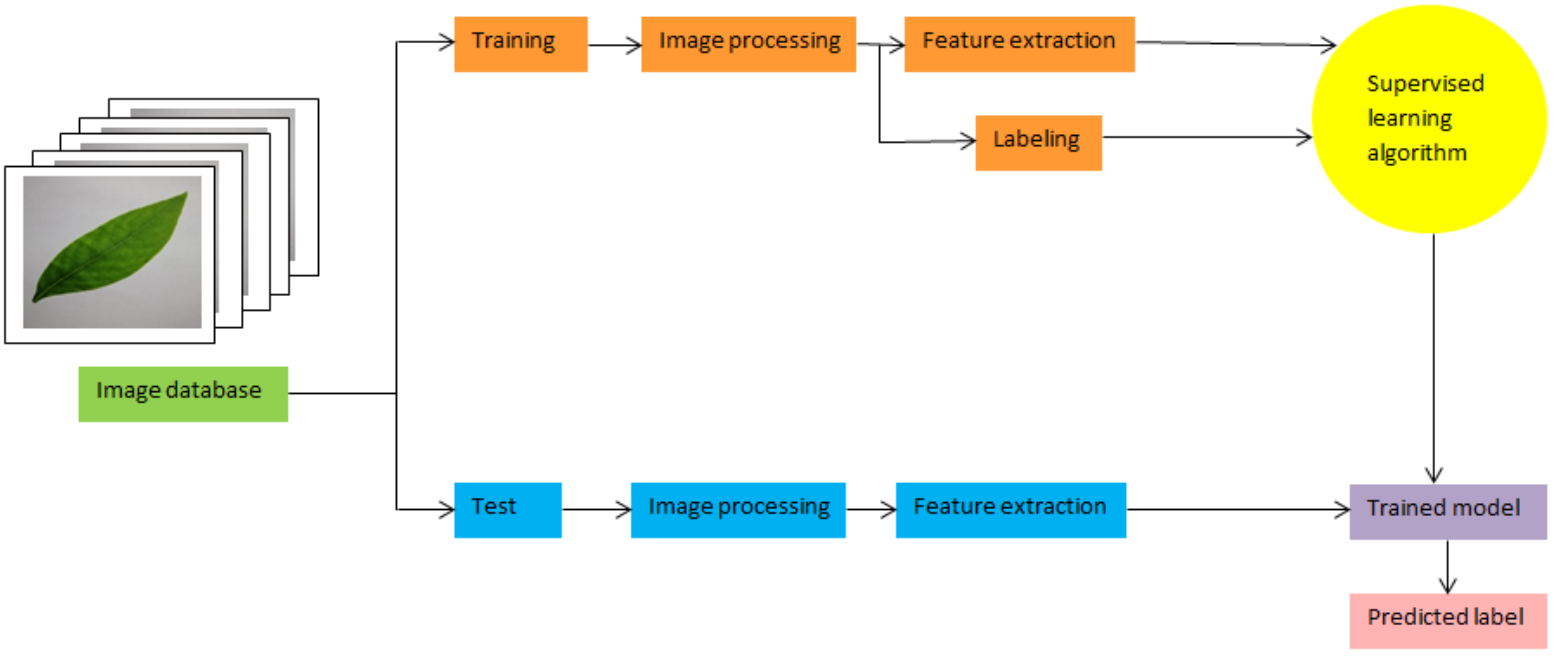
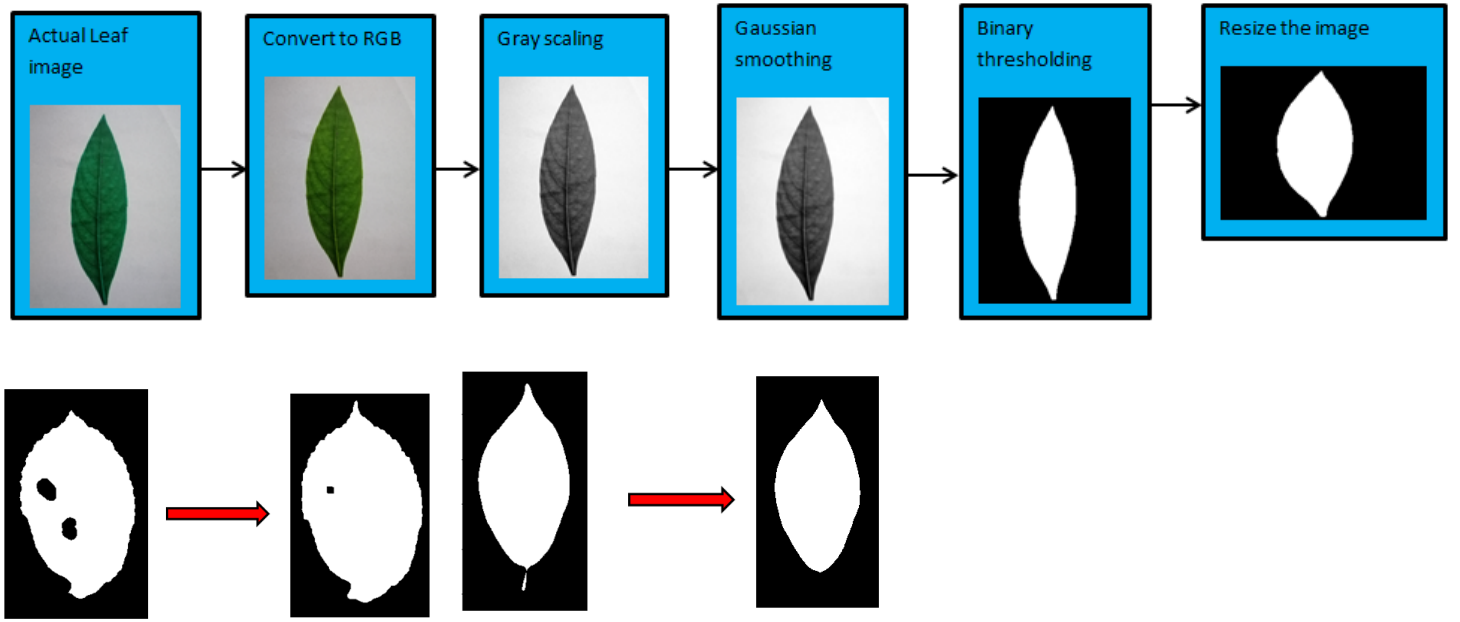
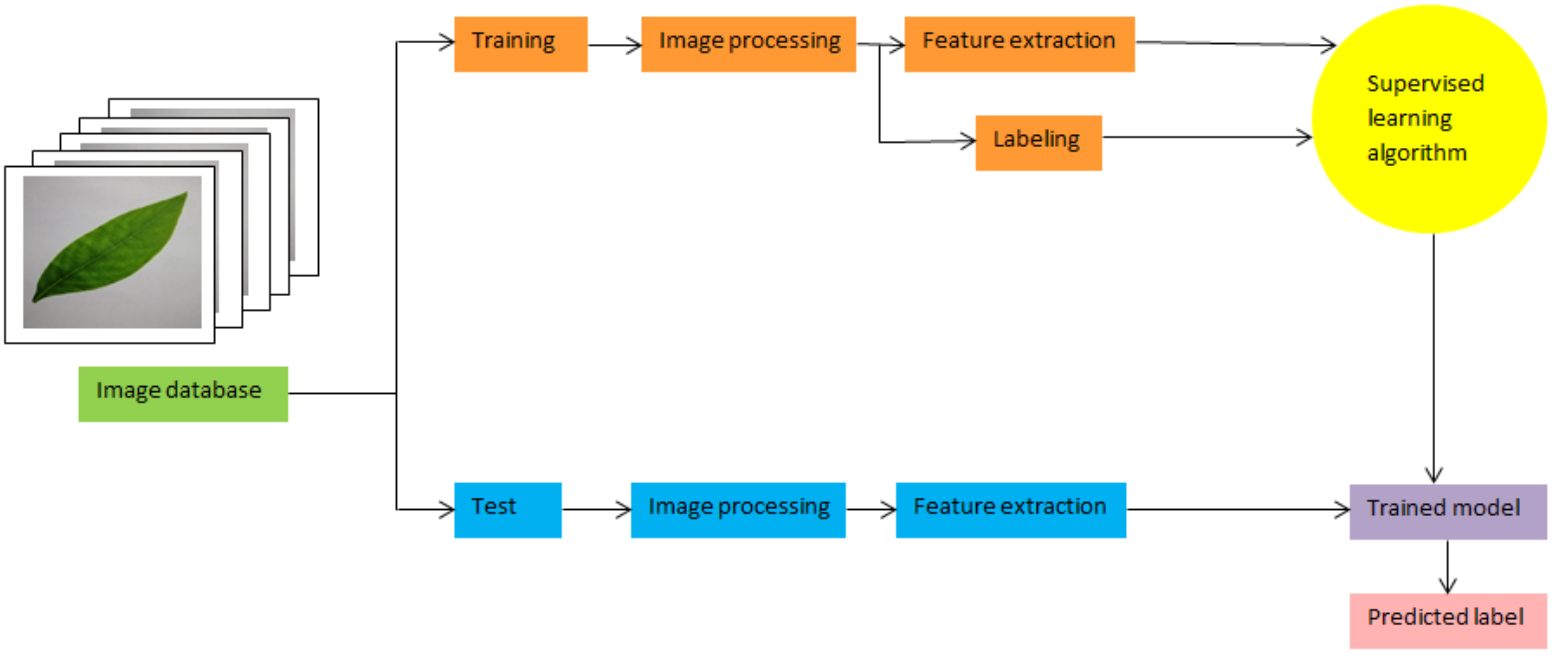


Image processing

- The image processing receives an image as input and generates a **modified image** as an output which is suitable for better **morphological analysis, feature extraction**.
- Image processing is an essential step to **reduce noise, background subtraction and content enhancement** in the identification process.



Methodology Diagram

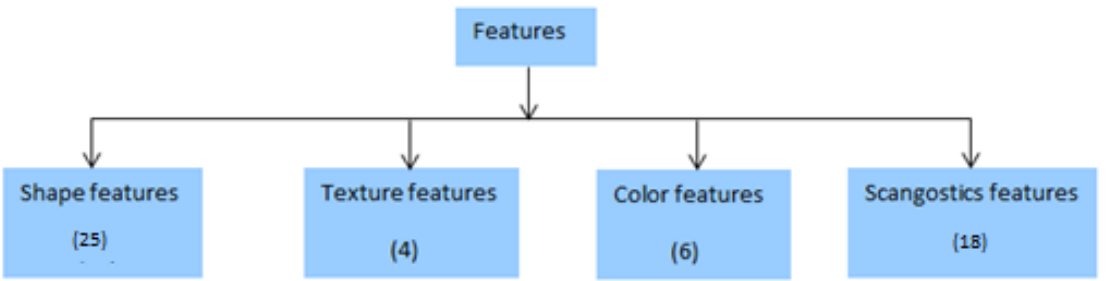


Why feature extraction is important?

- Recently, many researchers use deep learning methods like CNN (Convolution Neural Network) to classify plants - directly using plant images.
- Even though deep learning models have achieved great success, their interpretability, and transparency of the deep learning models are limited.

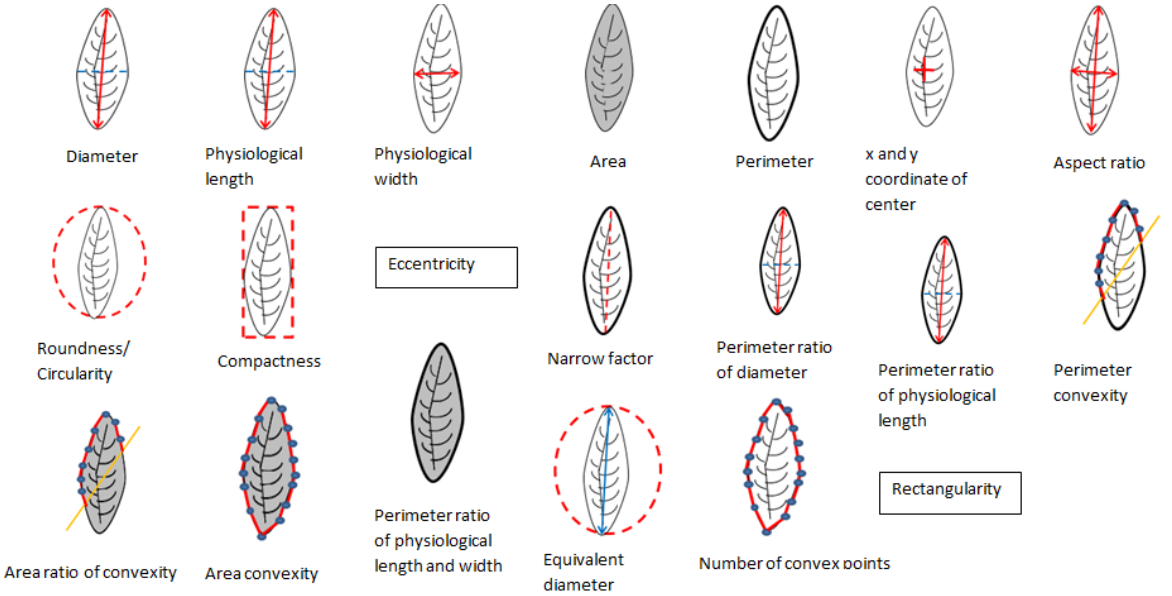
Features

- In identification of plant species by using leaf images, **features of the leaves play a main role**.
- In previous research, let the algorithm like **CNN** to extract features by itself and do the classification.
- Therefore it is so **hard to interpret and generalize** the features.
- We introduced **pre-calculate features** which can be **easy to interpret and generalize**. They are also **computational efficient**.

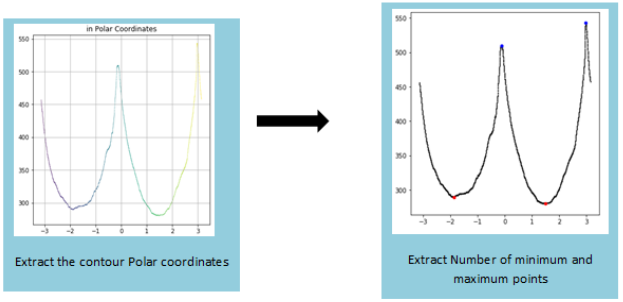


- We identified altogether **52 features**.

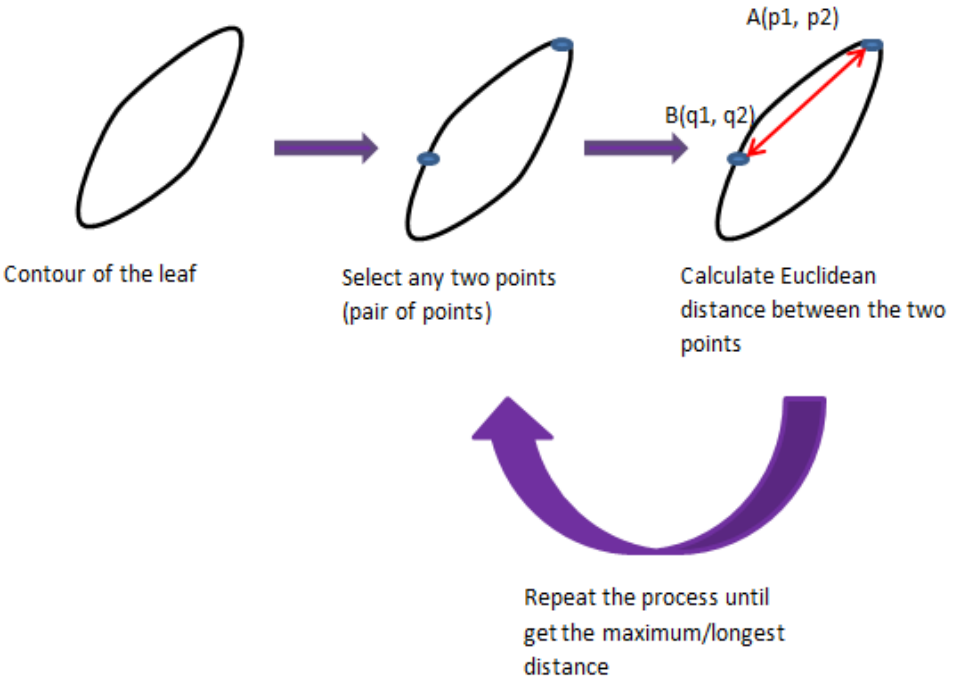
Shape features



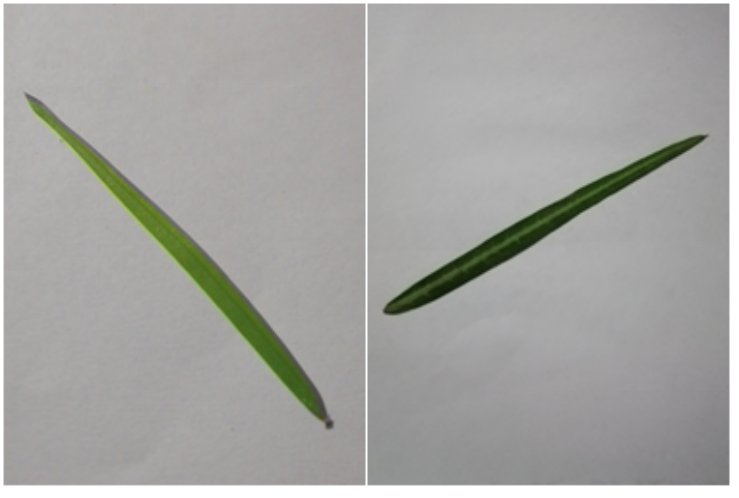
New shape features: Correlation of cartesian coordinate, number of convex points, number of minimum and maximum points



Diameter calculation



Color features



Hathawariya Iramusu

$$M = \frac{\text{Total insensity value of } r^{th}\text{channel of the image pixels}}{\text{Total intensity value of the image}},$$

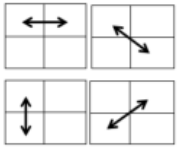
$$SD = \frac{\sqrt{\sum_{j=0}^{h}(r^{th}\text{channel intensity}_j - r^{th}\text{mean value})^2}}{\text{Total intensity value of the image}}.$$

Texture features

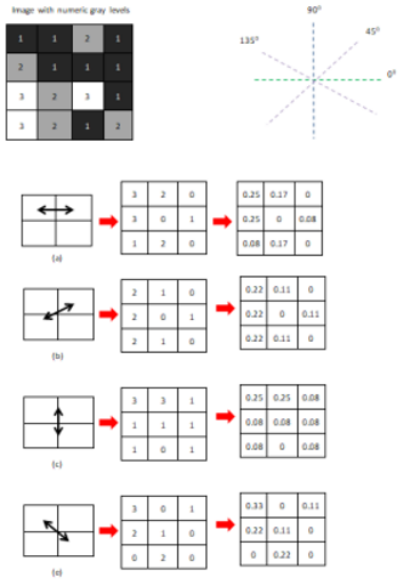
Feature name	Detailed description	Formula	Value range
Contrast	Measures the relation or difference between the highest and lowest gray levels of the GLCM	$\frac{\sum_{a=1}^{columns}\sum_{b=1}^{rows}(a-b)^2 h(a,b)}{\text{Number of gray levels}-1}$	$[0,\infty]$
Entropy	Measures the randomness which means that how uniform the image is	$-\sum_{a=1}^{columns}\sum_{b=1}^{rows} h(a,b)log_2(h(a,b))$	$[-\infty,0]$
Correlation	Measurement of dependence of gray levels of the GLCM. It measures that how a particular pixel is correlated to it's neighbor pixel over the whole image	$\frac{\sum_{a=1}^{columns}\sum_{b=1}^{rows}(ab)h(a,b)-\mu_x\mu_y}{\sigma_x\sigma_y}$	[-1,1]
Inverse difference moments	It's a measure of homogeneity. Inverse level of contrast that measures how close the values of GLCM to diagonal values in GLCM	$\sum_{a=1}^{columns}\sum_{b=1}^{rows}\frac{h(a,b)}{(a-b)^2}$	$[0,\infty]$

$$GLCM = \begin{bmatrix} h(1,1) & h(1,2) & \cdot & \cdot & \cdot & h(1,n) \\ h(2,1) & h(2,2) & \cdot & \cdot & \cdot & h(2,n) \\ \cdot & \cdot & \cdot & & & \cdot \\ \cdot & \cdot & & \cdot & & \cdot \\ \cdot & \cdot & & & \cdot & \cdot \\ h(n,1) & h(n,2) & \cdot & \cdot & \cdot & h(n,n) \end{bmatrix}$$

$$h(a,b) = \frac{\text{Number of times a pixel with value a is adjacent to a pixel with value b}}{\text{Total number of such comparisons made}}.$$



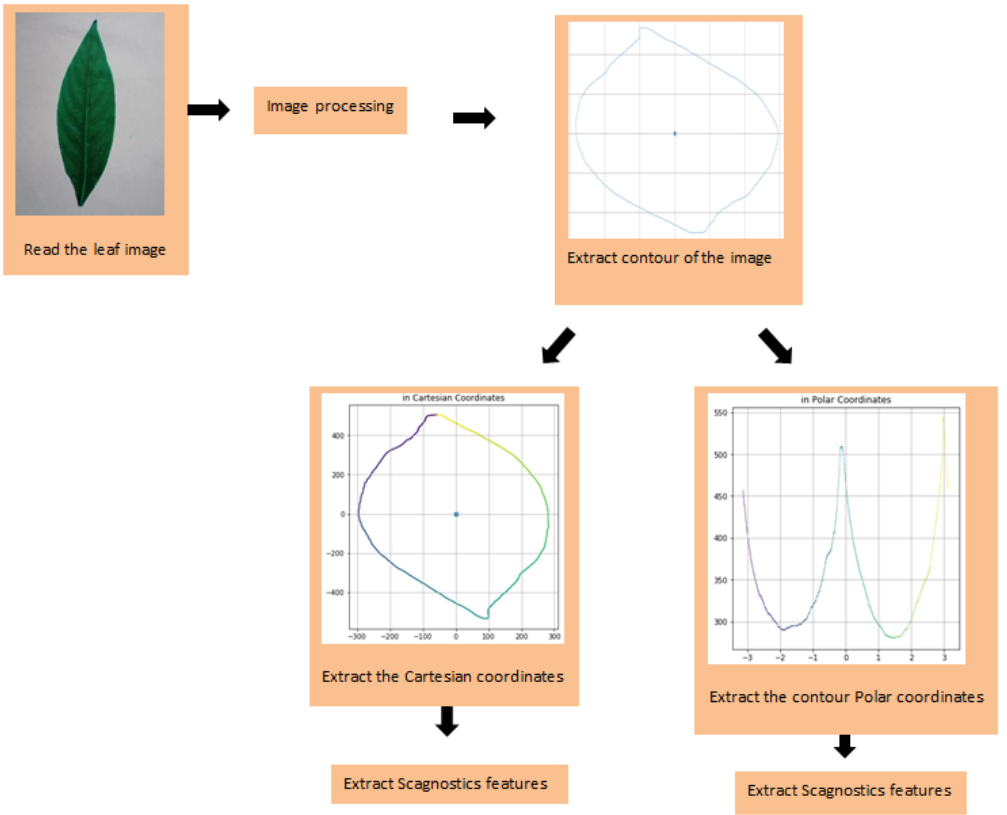
Four directions of adjacency as defined for calculation of the Haralick texture features

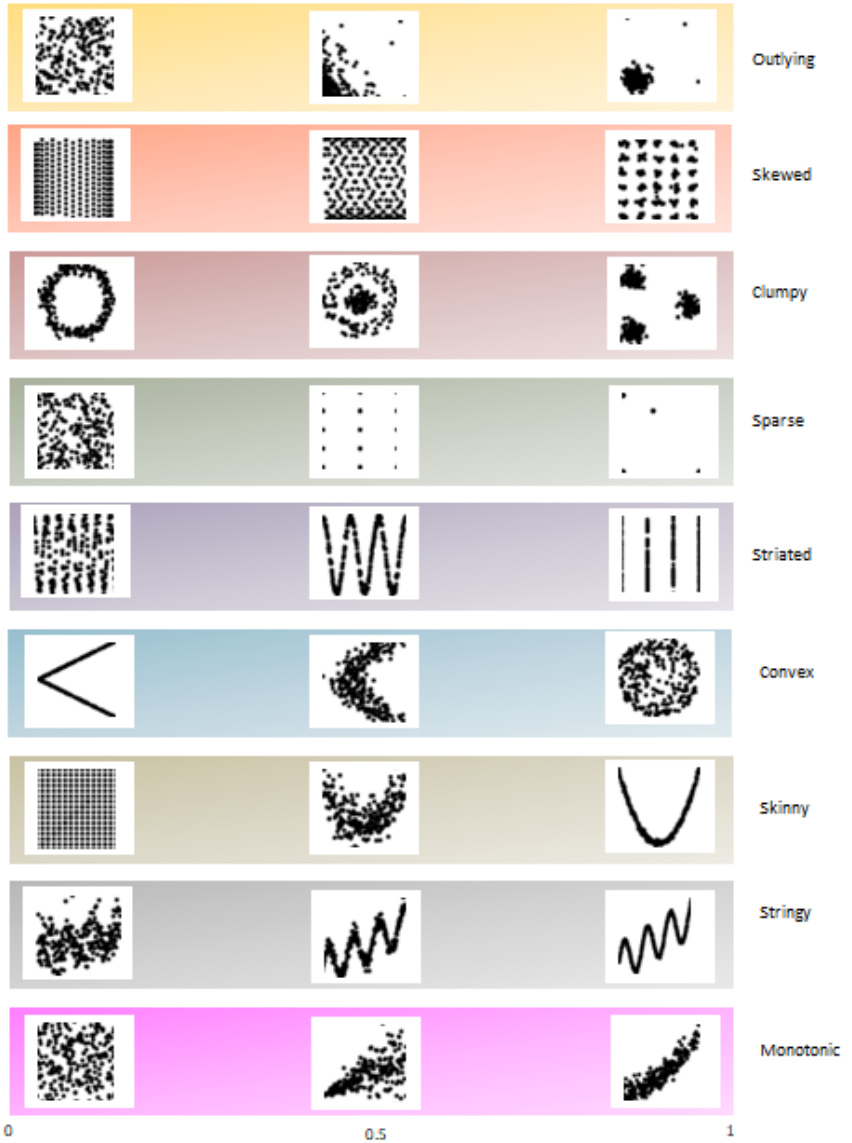


|7: Computing the Haralick texture features from a 4 × 4 example image step by step

Computing the Haralick texture features from a 4 × 4 example image with all direction

Scagnostic features

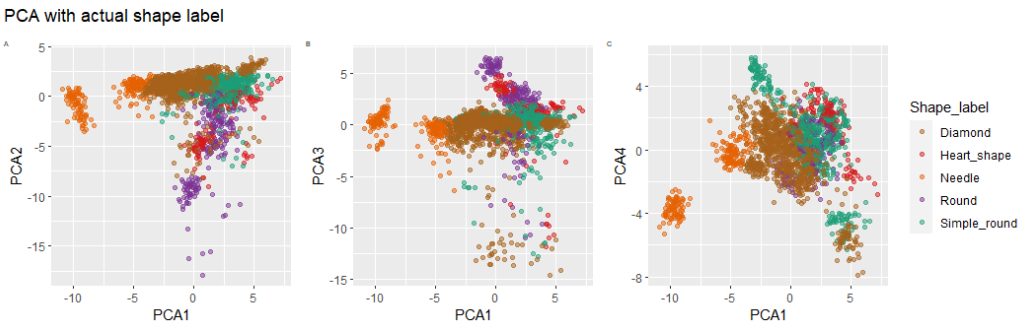



Outlying
Skewed
Clumpy
Sparse
Striated
Convex
Skinny
Stringy
Monotonic
0
0.5
1

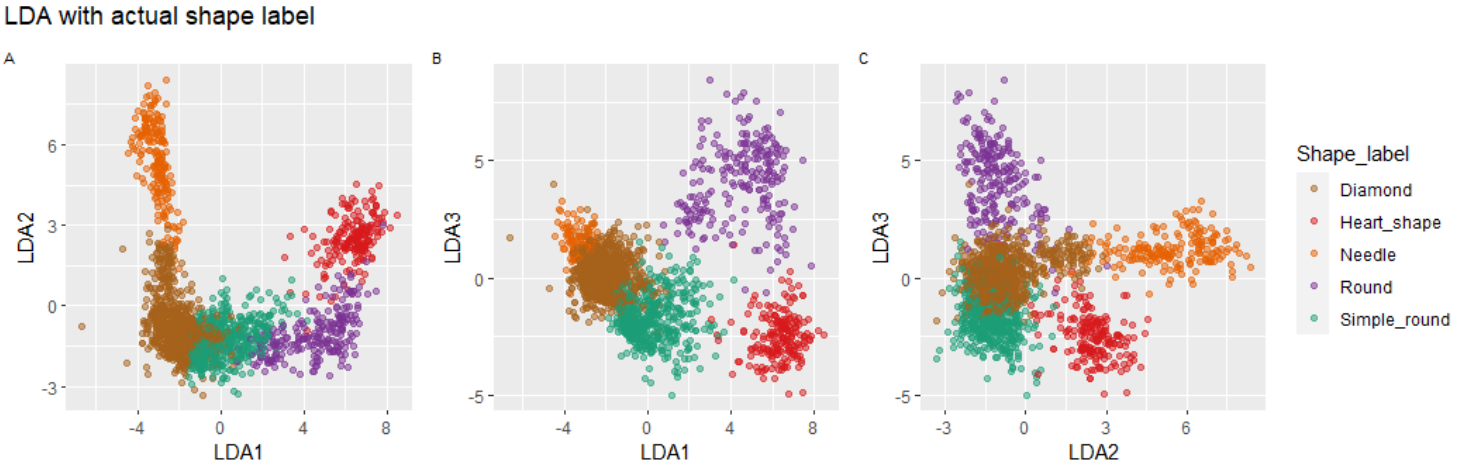
Visualization of Leaf Images in the Feature Space

Example: Flavia

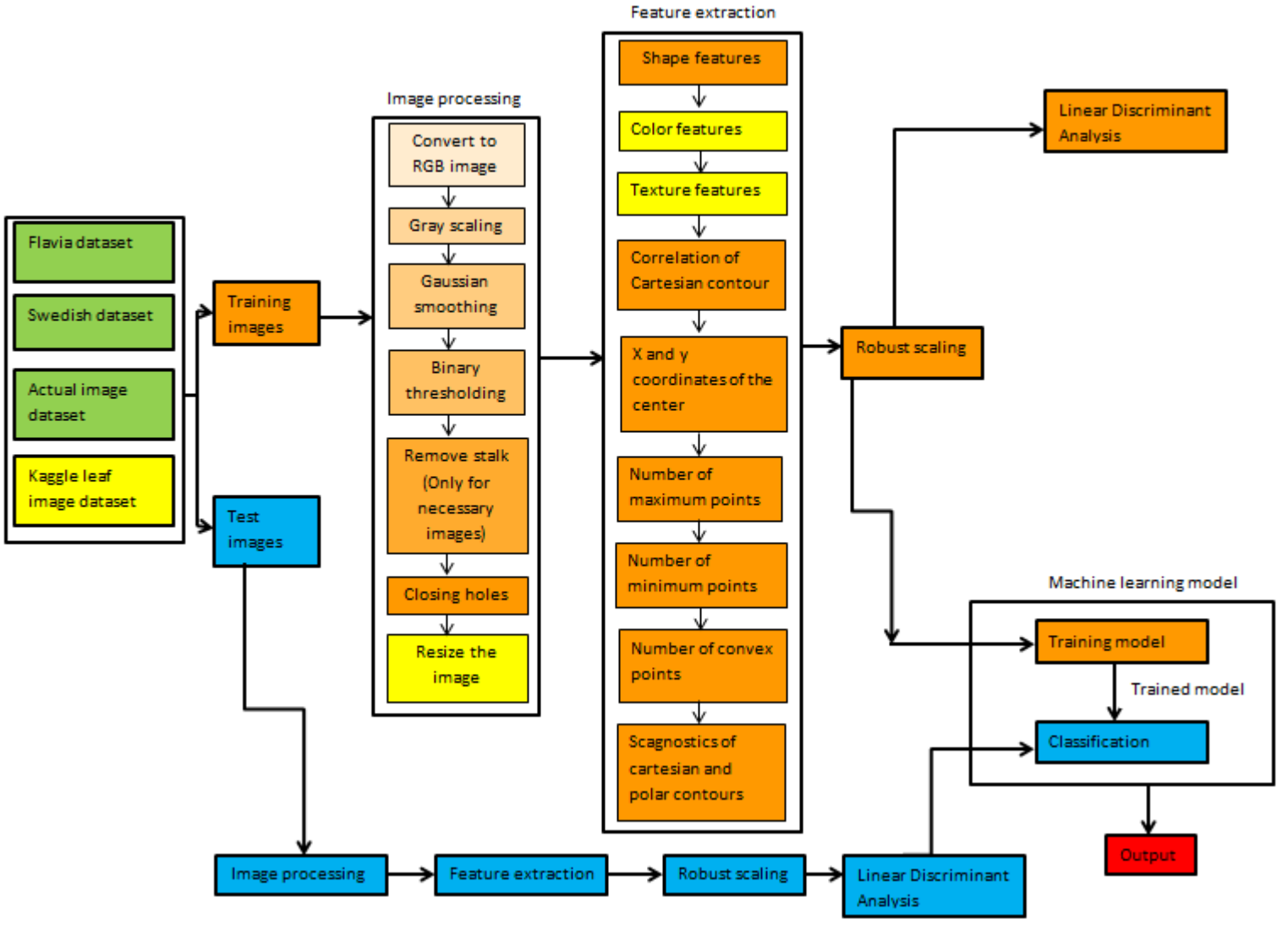
- LDA is a supervised dimensionality reduction technique, and PCA is unsupervised dimensionality reduction technique
- The first **three principal components (PCs)** accounting for approximately **83%** of the total variance in the original data



Let's see the 3D View

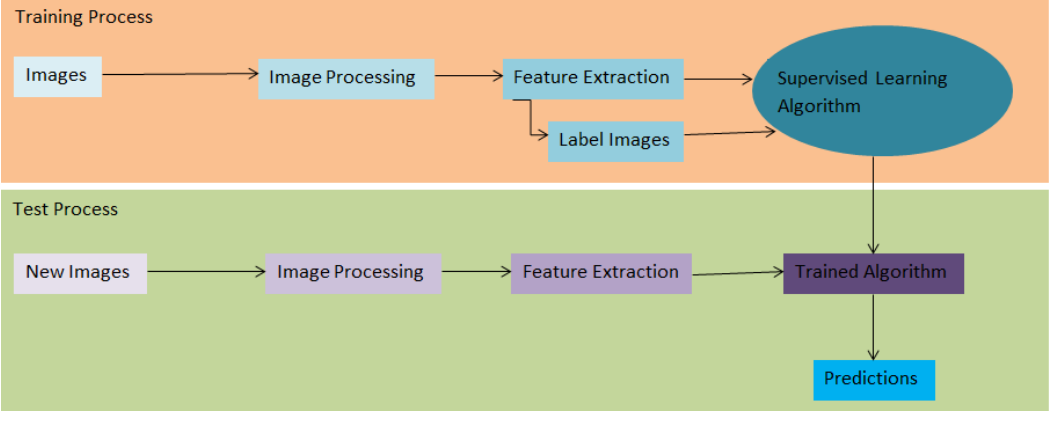


- Under both experimental settings class separation is more clearly on the LDA space than the PCA space. The reason could be LDA is a supervised learning algorithm while PCA space is an unsupervised learning algorithm.

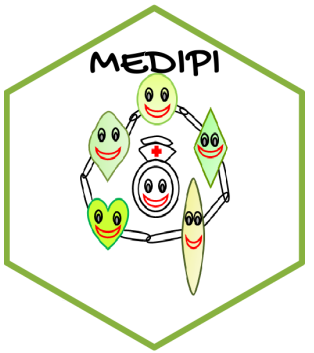

Flavia dataset
Swedish dataset
Actual image dataset
Kaggle leaf image dataset
Training images
Test images
Image processing
Convert to RGB image
Gray scaling
Gaussian smoothing
Binary thresholding
Remove stalk (Only for necessary images)
Closing holes
Resize the image
Feature extraction
Shape features
Color features
Texture features
Correlation of Cartesian contour
X and y coordinates of the center
Number of maximum points
Number of minimum points
Number of convex points
Scagnostics of cartesian and polar contours
Linear Discriminant Analysis
Robust scaling
Machine learning model
Training model
Trained model
Classification
Output
Image processing
Feature extraction
Robust scaling
Linear Discriminant Analysis

Algorithm Development

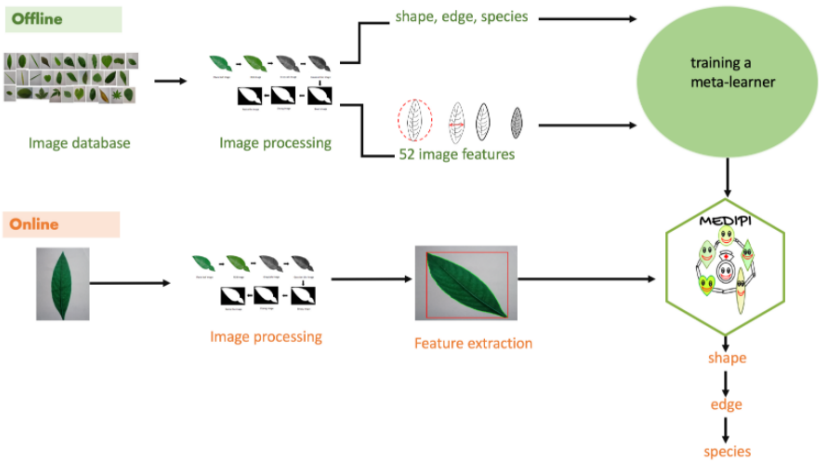
- Our medicinal plant classification algorithm contains **two process: Training process and Test process**.
- Our classification algorithm operates on the **features extracted from the image leaves**.
- The training process e of the algorithm contains four main steps: **i) Image processing, ii) Feature extraction, iii) Label images, and iv) Trained a algorithm**.
- In the test process, image processing and feature extraction steps are followed by the **new image before feed to the pre-trained model**.
- Mainly **Random Forest, Gradient Boosting and Extreme Gradient Boosting** classification algorithms are used in our research.



MEDIPI: MEDIcinal Plant Identification



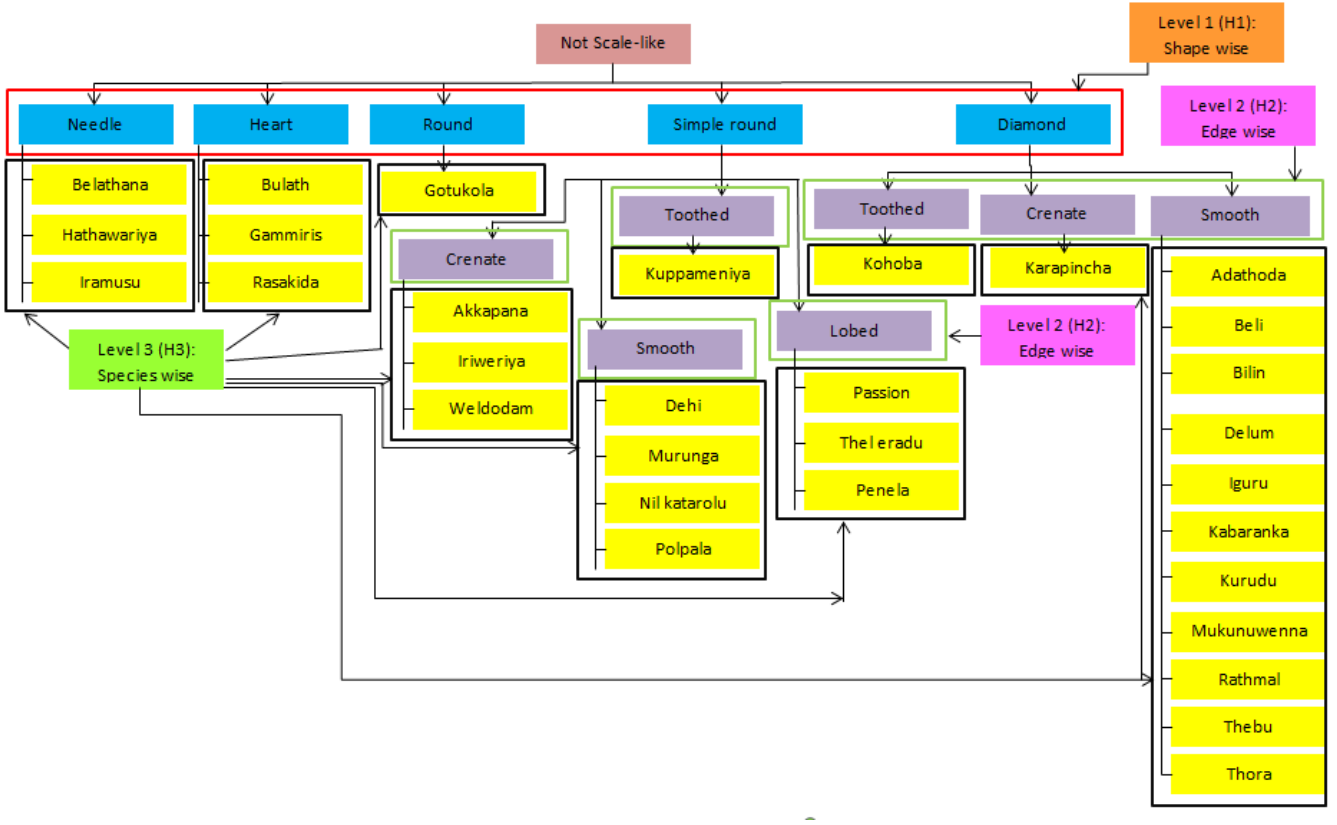
Our medicinal plant classification algorithm is defined as **MEDIPI**.



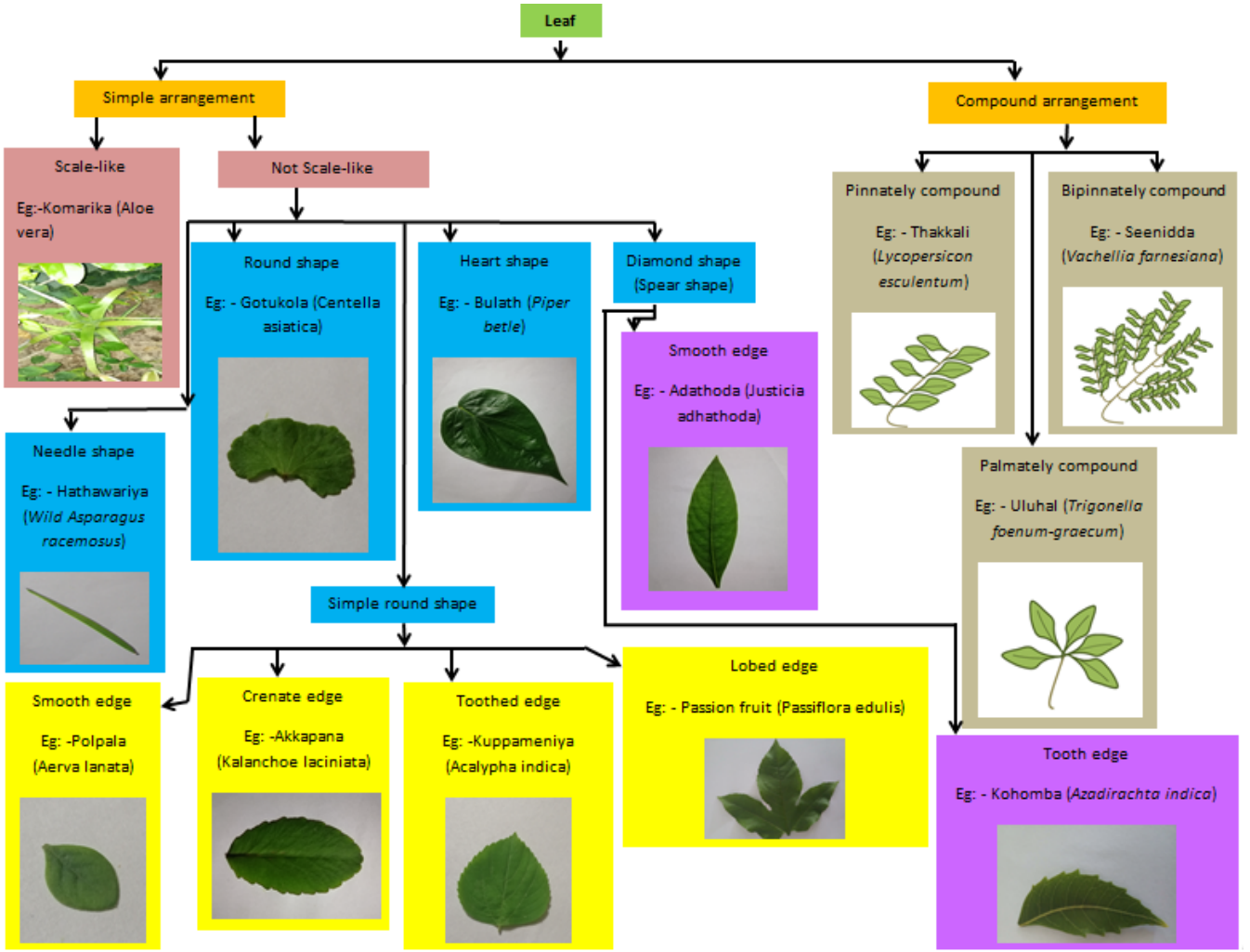
Discussion & Conclusions

Hierarchical Approach

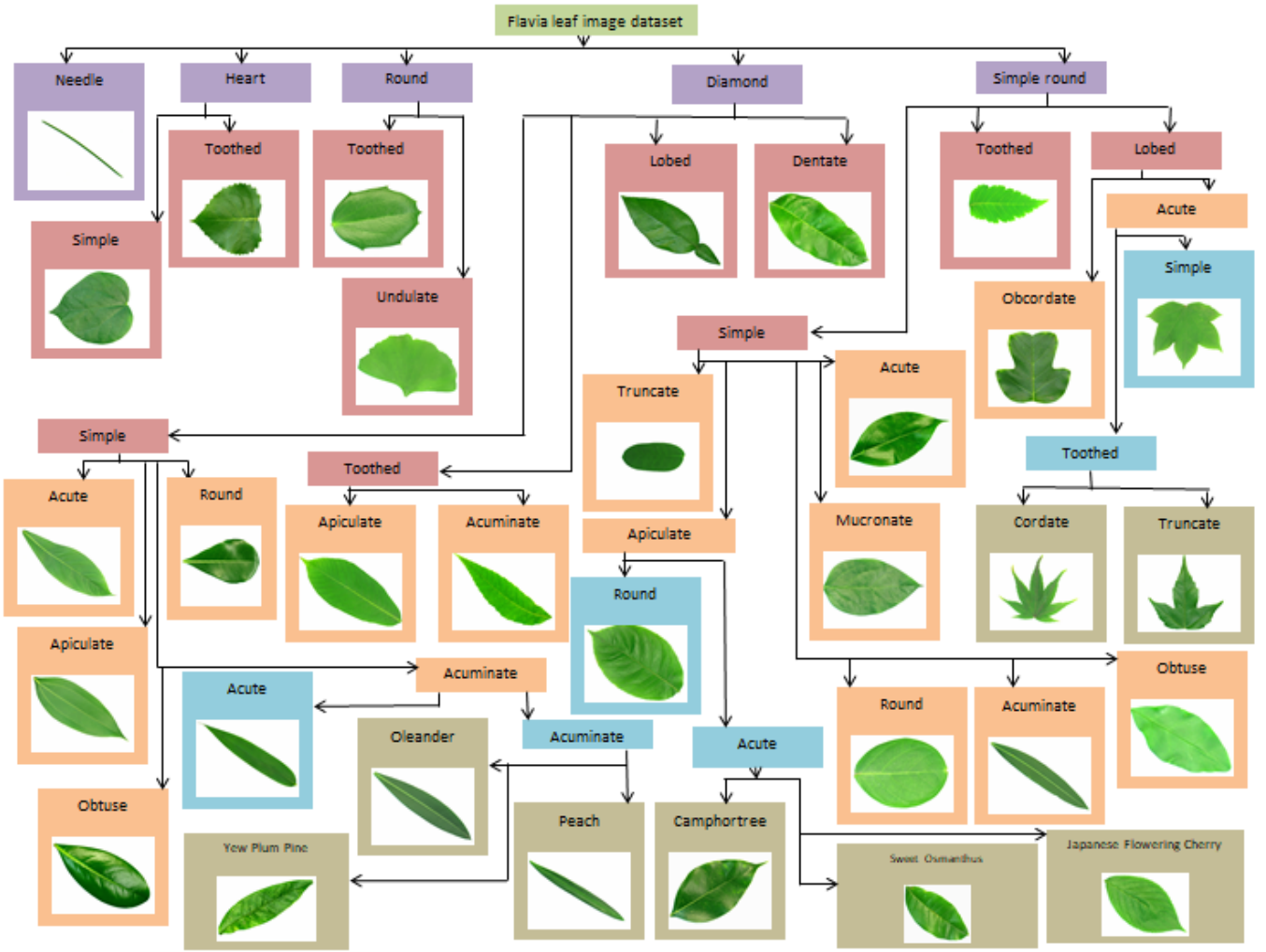
- Our algorithm works as a **hierarchical classification system**. The hierarchy contains **3 levels**. The first level classifies images according to the **shape**. The second level classifies according to the **edge types**. The bottom level classifies the **plant species**.



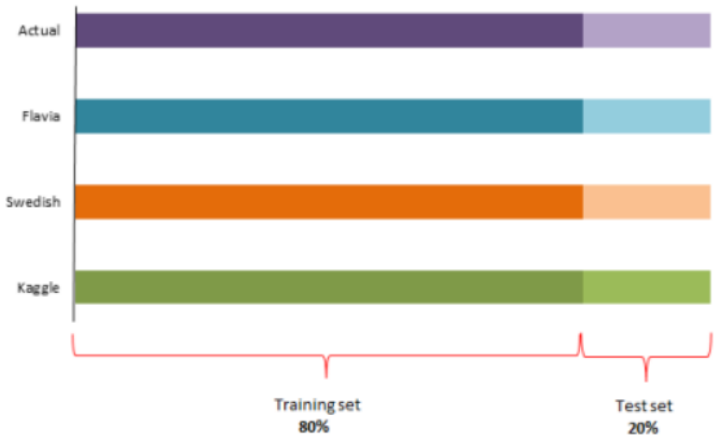
Hierarchy of Actual leaf image dataset

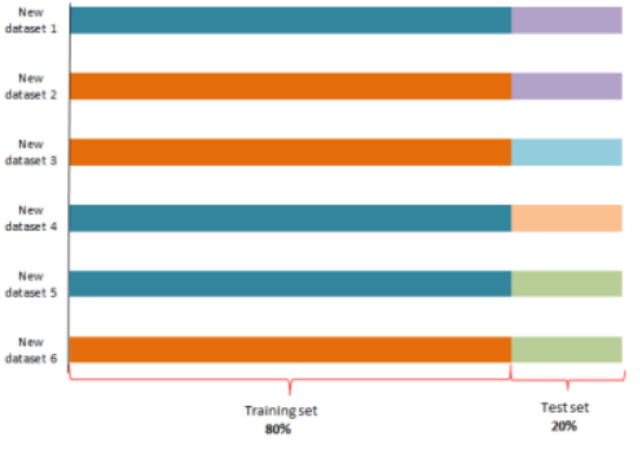


Hierarchy of Flavia leaf image dataset



Experiments





We have to use training/test from same dataset to get accurate results.

Compare results features of all categories and only with shape features

Training and test datasets from same dataset

Dataset	Diamond	Simple Round	Needle	Heart Shape	Round	Overall Classification Accuracy
Actual						
Random Forest	0.94	**1.00**	**1.00**	**1.00**	**1.00**	**0.97**
Extreme Gradient Boosting	0.94	0.95	**1.00**	0.96	**1.00**	0.95
Gradient Boosting	**0.96**	0.96	**1.00**	**1.00**	**1.00**	**0.97**
Flavia						
Random Forest	0.98	**0.97**	0.96	0.97	**1.00**	**0.98**
Extreme Gradient Boosting	**0.99**	0.95	0.93	0.98	**1.00**	0.97
Gradient Boosting	0.98	0.96	**1.00**	**1.00**	**1.00**	**0.98**
Swedish						
Random Forest	0.99	**1.00**	**1.00**	**0.95**	**1.00**	**0.98**
Extreme Gradient Boosting	**1.00**	**1.00**	**1.00**	0.88	0.92	0.97
Gradient Boosting	0.99	0.98	0.96	0.86	**1.00**	0.96
Kaggle						
Random Forest	**0.76**	**0.69**	-	0.82	**0.77**	**0.74**
Extreme Gradient Boosting	0.75	0.68	-	0.70	0.70	0.71
Gradient Boosting	0.74	0.68	-	**0.92**	0.66	0.71

Shape-wise and overall classification accuracy (Training and test sets are from the same dataset)

Training Set	Test Set	Diamond	Simple Round	Needle	Heart shape	Round	Overall Classification Accuracy
	Dataset						
Actual	**Actual**						
	Random Forest	0.89	0.86	**1.00**	**1.00**	0.86	0.90
	Extreme Gradient Boosting	0.92	**0.89**	0.97	0.97	**1.00**	**0.92**
	Gradient Boosting	**0.93**	0.83	**1.00**	0.92	0.71	0.90
Flavia	**Flavia**						
	Random Forest	0.93	**1.00**	0.91	0.97	**1.00**	**0.96**
	Extreme Gradient Boosting	**0.96**	0.96	**1.00**	0.96	0.98	**0.96**
	Gradient Boosting	0.94	0.98	0.95	**1.00**	**1.00**	**0.96**
Swedish	**Swedish**						
	Random Forest	0.96	**1.00**	**1.00**	0.85	0.94	0.95
	Extreme Gradient Boosting	**0.99**	**1.00**	**1.00**	0.82	**1.00**	**0.97**
	Gradient Boosting	0.95	0.98	**1.00**	**1.00**	0.92	0.96

Shape-wise and overall classification accuracy (Training and test sets are from the same datasets: Only with shape features)

Compare results features of all categories and only with shape features

Training and test datasets from different datasets

Training Set	Test Set	Diamond	Simple Round	Needle	Heart shape	Round	Overall Classification Accuracy
Flavia	**Actual**						
	Random Forest	**0.70**	0.28	0.23	**0.04**	0.10	0.41
	Extreme Gradient Boosting	0.65	0.28	**0.56**	0.03	**0.29**	**0.43**
	Gradient Boosting	0.63	**0.31**	0.45	0.03	0.26	0.42
Swedish	**Actual**						
	Random Forest	0.38	0.22	0.06	**0.12**	0.39	0.26
	Extreme Gradient Boosting	0.40	0.23	**0.18**	0.04	0.23	0.25
	Gradient Boosting	**0.50**	**0.33**	0.11	**0.12**	**0.55**	**0.36**
Swedish	**Flavia**						
	Random Forest	0.29	**0.43**	0.46	0.0	0.0	0.27
	Extreme Gradient Boosting	**0.42**	0.34	0.40	0.01	0.01	0.31
	Gradient Boosting	0.40	0.37	**0.53**	**0.12**	**0.27**	**0.37**
Flavia	**Swedish**						
	Random Forest	0.57	0.72	0.03	0.0	0.01	0.39
	Extreme Gradient Boosting	**0.58**	0.67	**0.13**	0.0	0.15	**0.41**
	Gradient Boosting	0.51	**0.79**	0.12	0.0	**0.18**	**0.41**
Flavia	**Kaggle**						
	Random Forest	**0.66**	0.39	0.0	0.0	0.17	**0.44**
	Extreme Gradient Boosting	0.56	**0.48**	0.0	0.0	0.21	0.43
	Gradient Boosting	0.51	0.47	0.0	0.0	**0.25**	0.42
Swedish	**Kaggle**						
	Random Forest	0.42	1dd2	0.0	0.07	0.05	0.24
	Extreme Gradient Boosting	0.35	0.12	0.0	0.10	**0.14**	0.23
	Gradient Boosting	**0.44**	**0.14**	-	**0.14**	0.13	**0.27**

Shape-wise and overall classification accuracy (Training and test sets are from the different datasets)

Training Set	Test Set	Diamond	Simple Round	Needle	Heart shape	Round	Overall Classification Accuracy
Flavia	**Actual**						
	Random Forest	0.57	0.29	0.81	0.04	0.13	0.42
	Extreme Gradient Boosting	**0.65**	**0.37**	0.85	0.03	0.48	**0.50**
	Gradient Boosting	0.55	0.36	**0.95**	**0.05**	**0.58**	0.49
Swedish	**Actual**						
	Random Forest	0.37	0.31	**0.09**	**0.10**	0.14	0.24
	Extreme Gradient Boosting	0.38	**0.35**	0.0	0.05	0.08	0.23
	Gradient Boosting	**0.53**	0.27	0.03	0.08	**0.39**	**0.31**
Swedish	**Flavia**						
	Random Forest	0.29	**0.45**	0.38	0.0	0.0	0.27
	Extreme Gradient Boosting	0.46	0.32	**0.41**	0.0	0.06	0.33
	Gradient Boosting	**0.52**	0.36	0.27	**0.13**	**0.20**	**0.38**
Flavia	**Swedish**						
	Random Forest	0.46	**0.88**	0.15	0.0	**0.01**	**0.39**
	Extreme Gradient Boosting	**0.47**	0.72	**0.16**	0.0	**0.01**	0.36
	Gradient Boosting	0.39	0.84	**0.16**	0.0	**0.01**	0.36

Shape-wise and overall classification accuracy (Training and test sets are from the different datasets: Only with Shape Features)

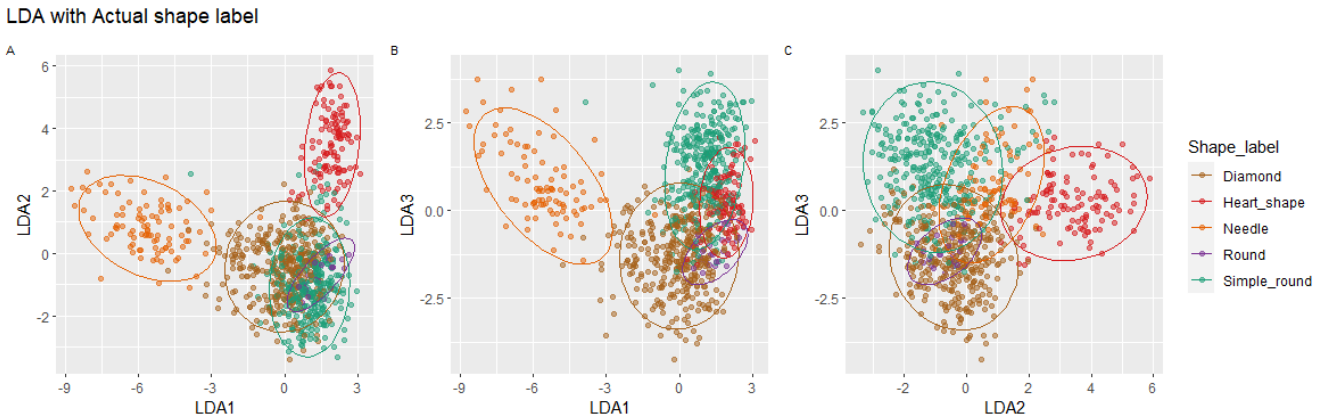
Compare algorithms

Case	Algorithm	Overall classification		Macro average		Weighted average		Average
		Accuracy	Rank	Accuracy	Rank	Accuracy	Rank	of ranks
Using hierarchical level	Random forest	**1.00**	1	**0.99**	1	**1.00**	1	**1**
	Extreme gradient boosting	0.99	2	0.99	1	0.99	2	1.67
	Gradient boosting	0.99	2	0.99	1	0.99	2	1.67
	Radom forest	0.99	2	0.99	1	0.99	2	1.67
Without using hierarchical level	Extreme gradient boosting	0.98	5	0.98	5	0.98	5	5
	Gradient boosting	0.98	5	0.98	5	0.98	5	5
	LDA	0.98	5	0.98	5	0.98	5	5
	KNN	0.84	9	0.81	9	0.84	9	9
	SVM	0.47	10	0.40	11	0.42	11	10.67
	PNN	0.47	10	0.44	10	0.45	10	10
	ANN	0.98	5	0.98	5	0.98	5	5

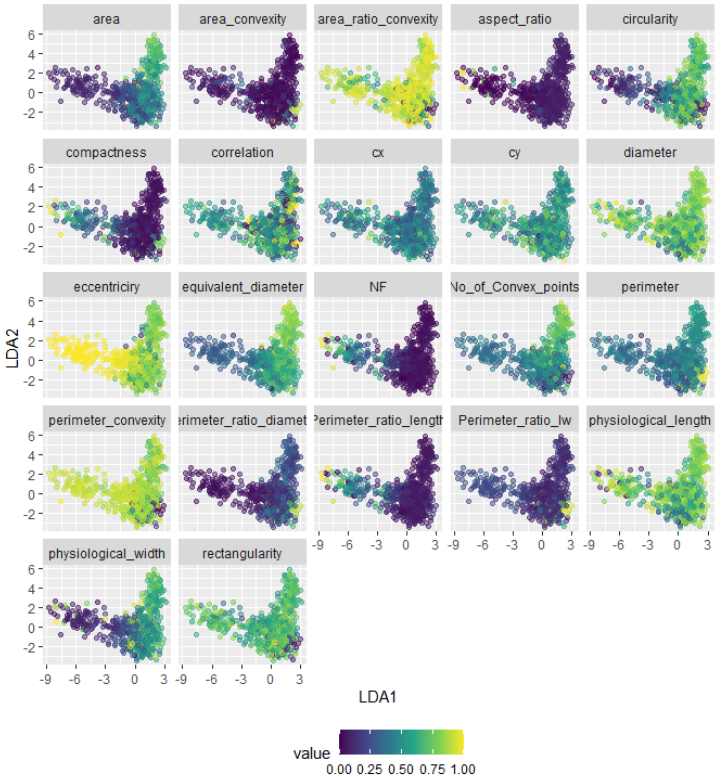
The model trained with **Random Forest** algorithm provides the highest accuracy.

Linear Discriminant Analysis

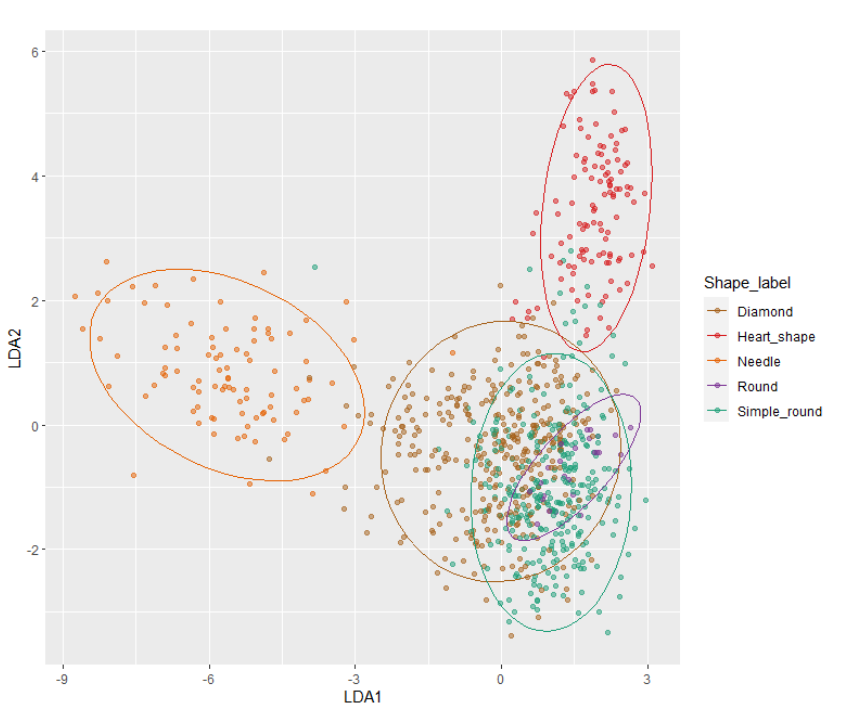
- High dimensional visualization approach
- To visualize what is **happening inside** the trained algorithm and provides **transparency** to our black-box model

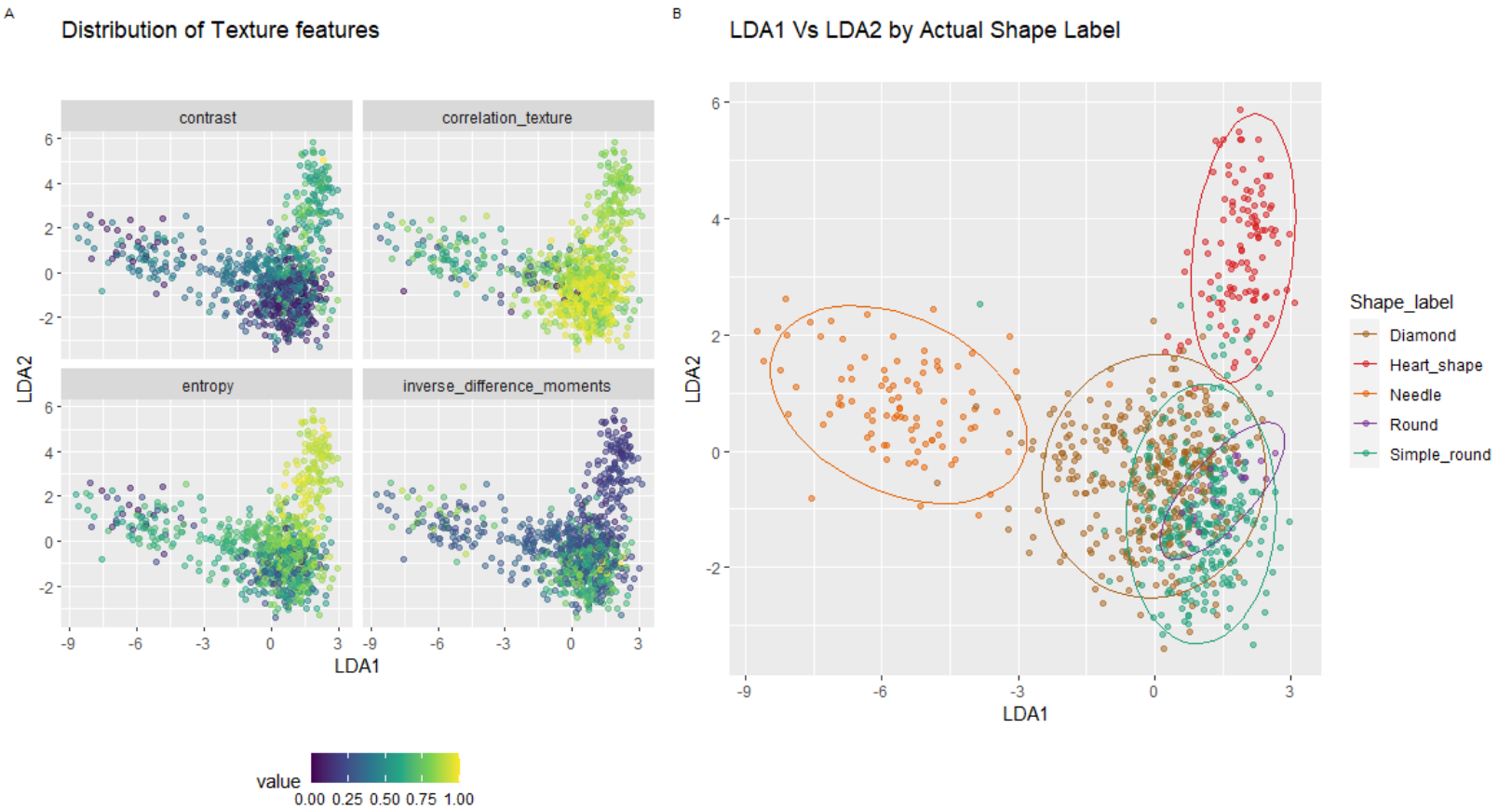


A

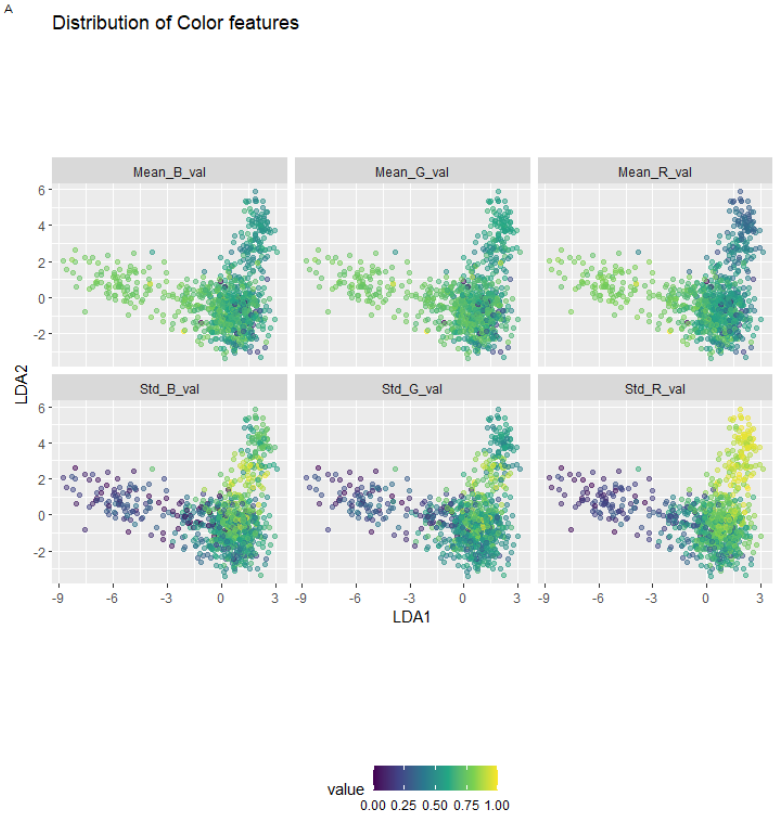

Distribution of Shape features
area
area_convexity
area_ratio_convexity
aspect_ratio
circularity
compactness
correlation
cx
cy
diameter
eccentricity
equivalent_diameter
NF
No_of_Convex_points
perimeter
perimeter_convexity
rimeter_ratio_diamet
erimeter_ratio_length
Perimeter_ratio_lw
physiological_length
physiological_width
rectangularity
LDA2
LDA1
value
0.00 0.25 0.50 0.75 1.00

B

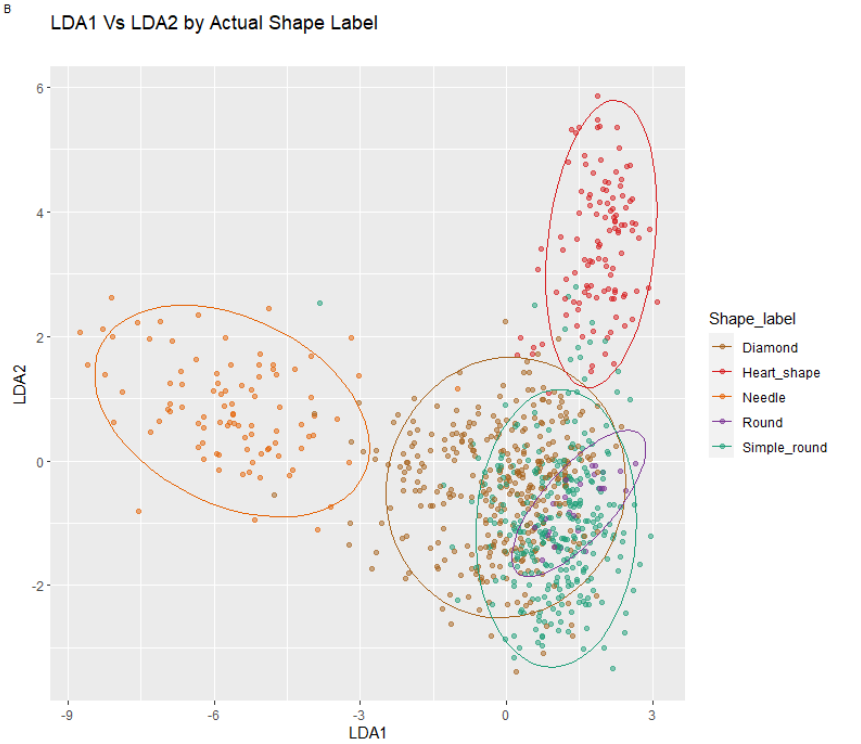

LDA1 Vs LDA2 by Actual Shape Label
LDA2
LDA1
Shape_label
Diamond
Heart_shape
Needle
Round
Simple_round


A
Distribution of Texture features
contrast
correlation_texture
entropy
inverse_difference_moments
LDA2
LDA1
value
0.00 0.25 0.50 0.75 1.00
B
LDA1 Vs LDA2 by Actual Shape Label
LDA2
LDA1
Shape_label
Diamond
Heart_shape
Needle
Round
Simple_round

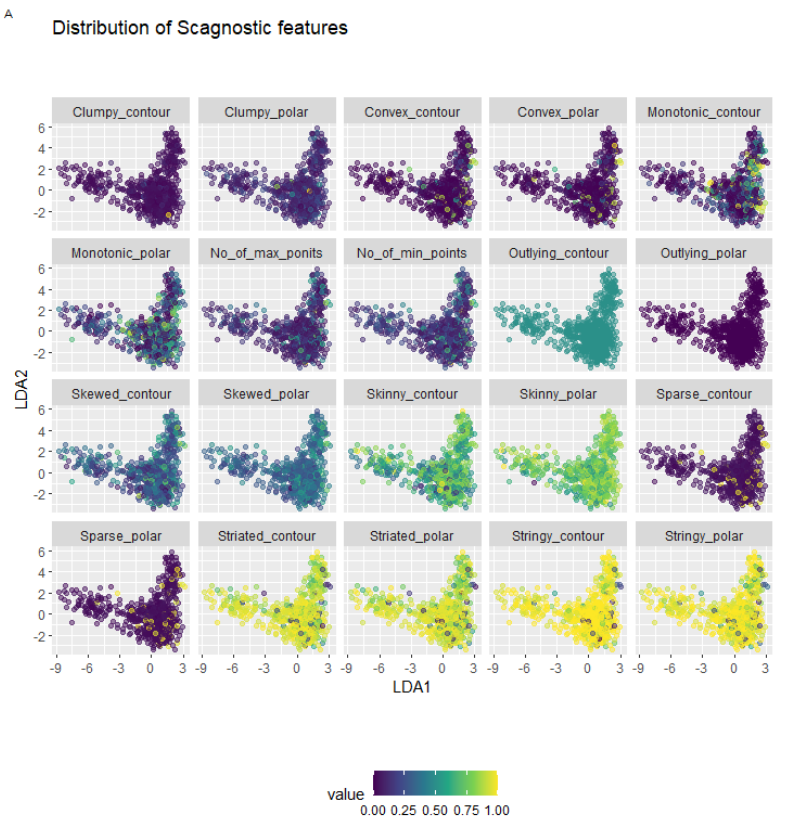
A


Distribution of Color features
Mean_B_val
Mean_G_val
Mean_R_val
Std_B_val
Std_G_val
Std_R_val
LDA2
LDA1
value
0.00 0.25 0.50 0.75 1.00

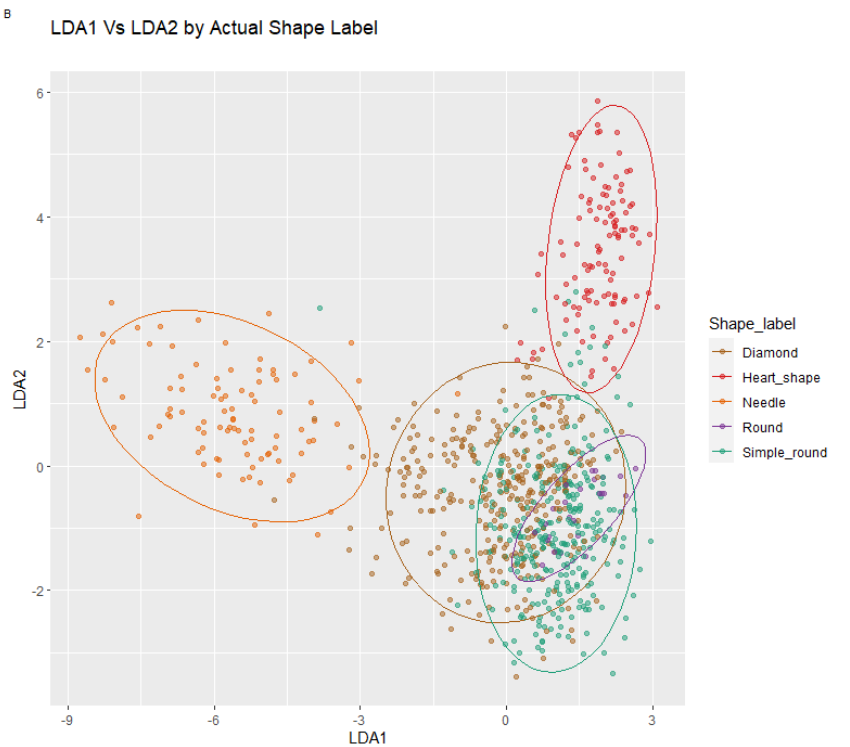
B

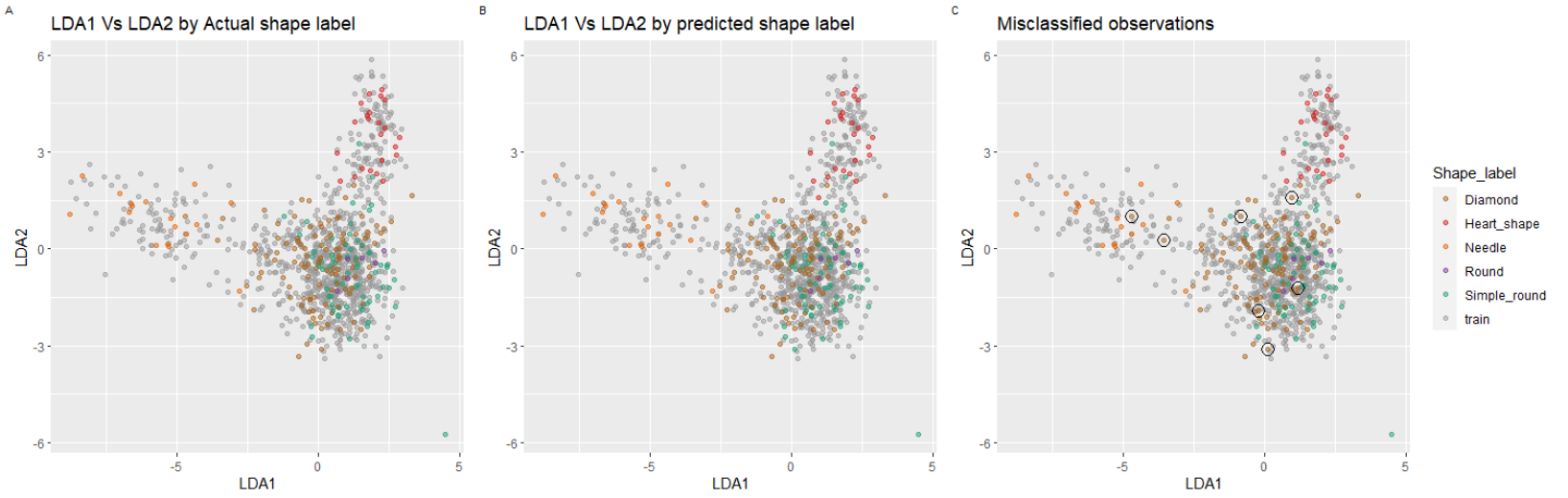

LDA1 Vs LDA2 by Actual Shape Label
LDA2
LDA1
Shape_label
Diamond
Heart_shape
Needle
Round
Simple_round

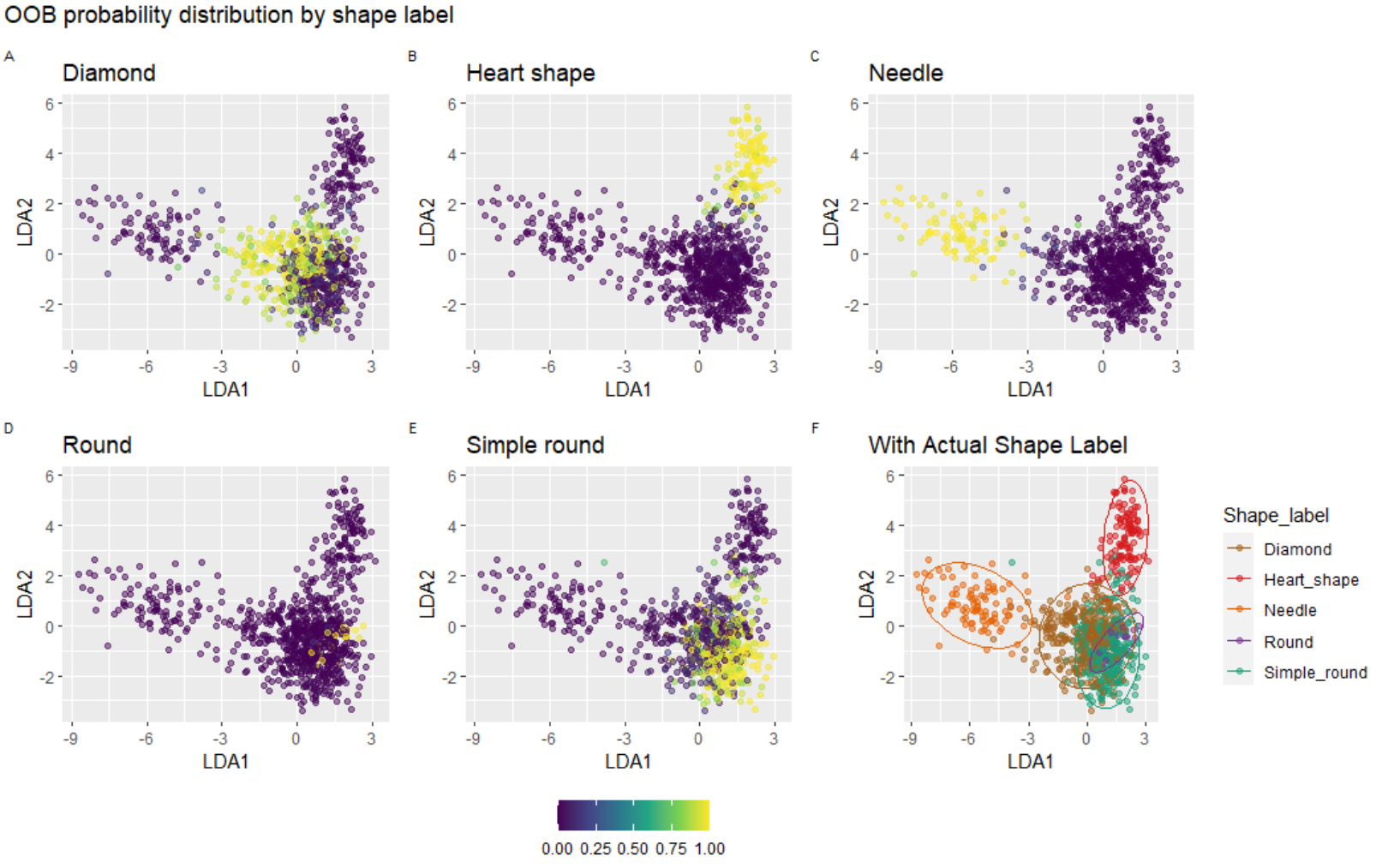
A


Distribution of Scagnostic features
Clumpy_contour
Clumpy_polar
Convex_contour
Convex_polar
Monotonic_contour
Monotonic_polar
No_of_max_ponits
No_of_min_points
Outlying_contour
Outlying_polar
Skewed_contour
Skewed_polar
Skinny_contour
Skinny_polar
Sparse_contour
Sparse_polar
Striated_contour
Striated_polar
Stringy_contour
Stringy_polar
LDA2
LDA1
value
0.00 0.25 0.50 0.75 1.00

B


LDA1 Vs LDA2 by Actual Shape Label
LDA2
LDA1
Shape_label
Diamond
Heart_shape
Needle
Round
Simple_round


A
LDA1 Vs LDA2 by Actual shape label
B
LDA1 Vs LDA2 by predicted shape label
C
Misclassified observations
LDA2
LDA1
6
3
0
-3
-6
-5
0
5
Shape_label
Diamond
Heart_shape
Needle
Round
Simple_round
train


OOB probability distribution by shape label
A
Diamond
B
Heart shape
C
Needle
D
Round
E
Simple round
F
With Actual Shape Label
LDA1
LDA2
Shape_label
Diamond
Heart_shape
Needle
Round
Simple_round
0.00 0.25 0.50 0.75 1.00

Conclusions

- The model trained with **random forest** algorithm provides the highest accuracy.
- Our algorithm works as a **hierarchical classification system**.
- We observe that **shape features** like (i) x value of Center (cx), (ii) y value of Center (cy), (iii) Entropy, (iv) Perimeter ratio of length and width, (v) Diameter, (vi) Area convexity, (vii) Perimeter convexity, (viii) Narrow Factor, (ix) Area ratio convexity, (x) Physiological length, (xi) Physiological width, (xii) Rectangularity, and (xiii) Eccentricity are more important when classify the leaf images in the **first level** of the hierarchy.
- **Scagnostic features** like (i) Monotonic contour, (ii) Convex polar, (iii) Convex contour, (iv) Striated polar, (v) Striated contour, (vii) Skinny contour, and (vii) Skinny contour are more important in identifying leaf species in the **bottom level** of the hierarchy.
- The **MEDIPI** algorithm yields accurate results to the state-of-the existing techniques in the field.
- We have to use **training/test from same dataset** to get accurate results.
- We observe that **shape feature is not sufficient** to classify leaf images.

Thesis Outcome

MedLEA

README.md

MedLEA

CRAN 1.0.1 downloads 234/month

The MedLEA package provides morphological and structural features of 471 medicinal plant leaves and 1099 leaf images of 31 species and 29-45 images per species.

Installation

You could install the stable version on CRAN:

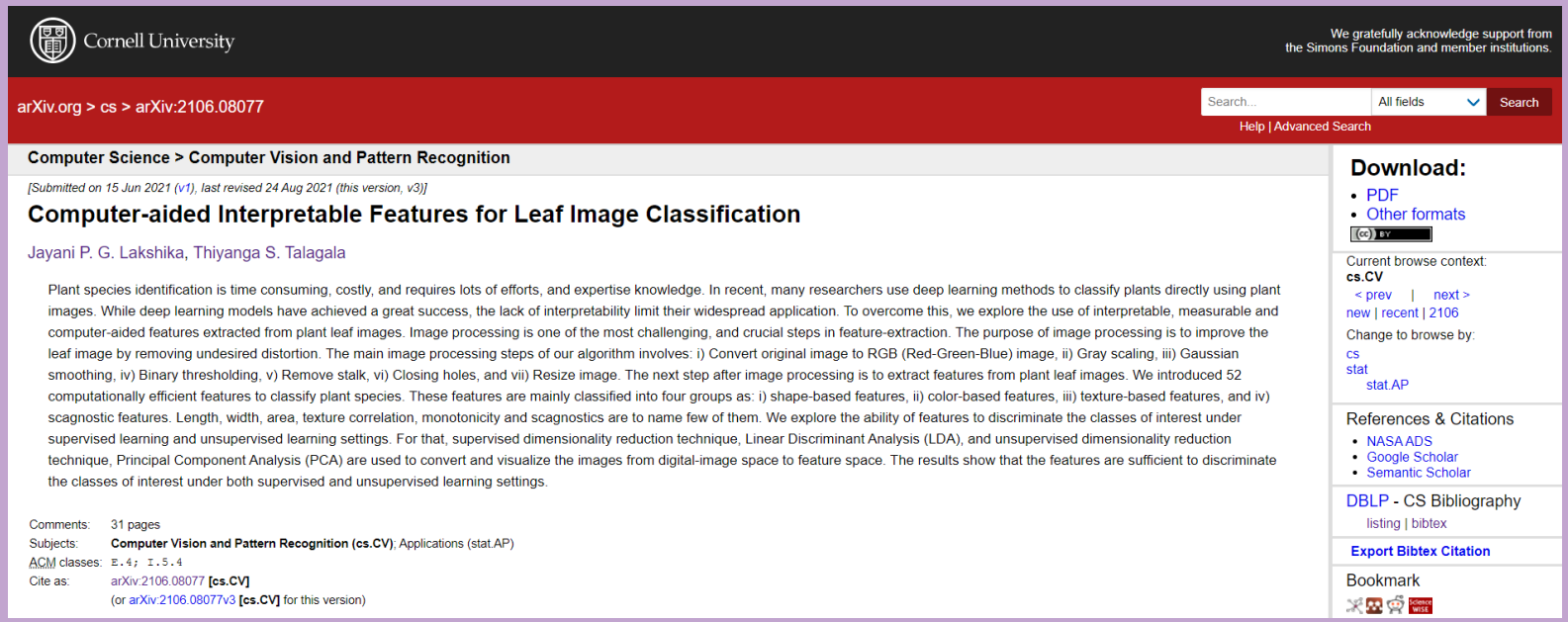
```
install.packages("MedLEA")
```

You can install the development version from GitHub with:

```
# install.packages("devtools")
devtools::install_github("SMART-Research/MedLEA")
```

https://CRAN.R-project.org/package=MedLEA

Research paper



Cornell University

We gratefully acknowledge support from the Simons Foundation and member institutions.

arXiv.org > cs > arXiv:2106.08077

Search... All fields Search

Help | Advanced Search

Computer Science > Computer Vision and Pattern Recognition

[Submitted on 15 Jun 2021 (v1), last revised 24 Aug 2021 (this version, v3)]

Computer-aided Interpretable Features for Leaf Image Classification

Jayani P. G. Lakshika, Thiyanga S. Talagala

Plant species identification is time consuming, costly, and requires lots of efforts, and expertise knowledge. In recent, many researchers use deep learning methods to classify plants directly using plant images. While deep learning models have achieved a great success, the lack of interpretability limit their widespread application. To overcome this, we explore the use of interpretable, measurable and computer-aided features extracted from plant leaf images. Image processing is one of the most challenging, and crucial steps in feature-extraction. The purpose of image processing is to improve the leaf image by removing undesired distortion. The main image processing steps of our algorithm involves: i) Convert original image to RGB (Red-Green-Blue) image, ii) Gray scaling, iii) Gaussian smoothing, iv) Binary thresholding, v) Remove stalk, vi) Closing holes, and vii) Resize image. The next step after image processing is to extract features from plant leaf images. We introduced 52 computationally efficient features to classify plant species. These features are mainly classified into four groups as: i) shape-based features, ii) color-based features, iii) texture-based features, and iv) scagnostic features. Length, width, area, texture correlation, monotonicity and scagnostics are to name few of them. We explore the ability of features to discriminate the classes of interest under supervised learning and unsupervised learning settings. For that, supervised dimensionality reduction technique, Linear Discriminant Analysis (LDA), and unsupervised dimensionality reduction technique, Principal Component Analysis (PCA) are used to convert and visualize the images from digital-image space to feature space. The results show that the features are sufficient to discriminate the classes of interest under both supervised and unsupervised learning settings.

Comments: 31 pages
Subjects: **Computer Vision and Pattern Recognition (cs.CV)**; Applications (stat.AP)
ACM classes: E.4; I.5.4
Cite as: arXiv:2106.08077 **[cs.CV]**
(or arXiv:2106.08077v3 **[cs.CV]** for this version)

Download:

- PDF
- Other formats

Current browse context: **cs.CV**

< prev | next >

new | recent | 2106

Change to browse by:

cs

stat

stat.AP

References & Citations

- NASA ADS
- Google Scholar
- Semantic Scholar

DBLP - CS Bibliography

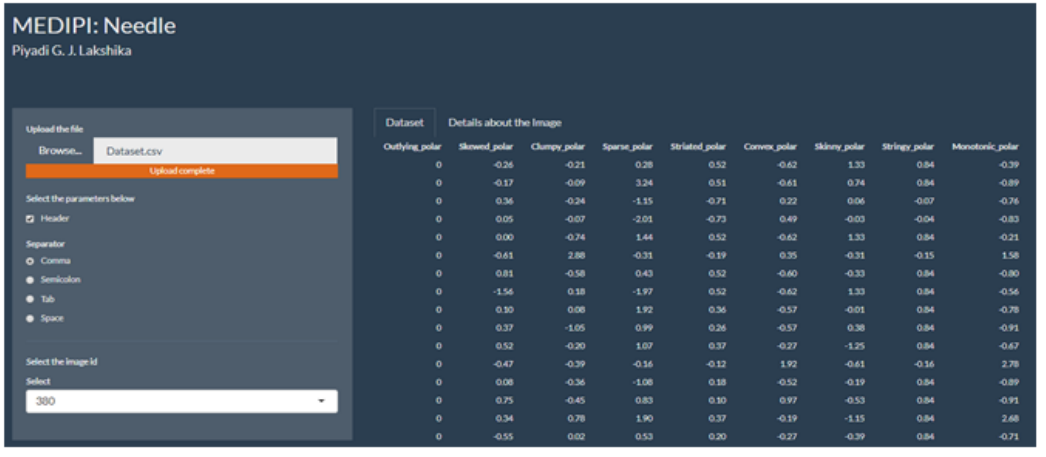
listing | bibtex

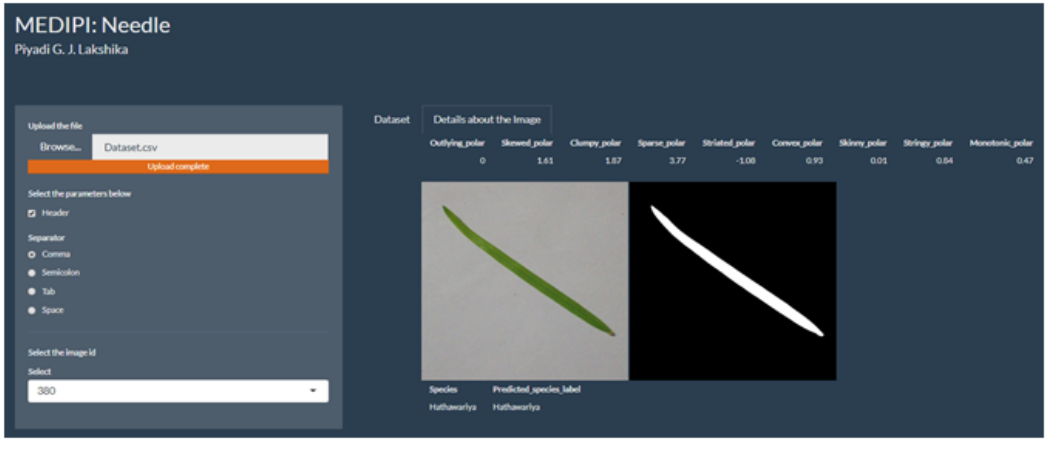
Export Bibtex Citation

Bookmark

https://arxiv.org/abs/2106.08077

Web Application for Leaf Image Identification





OCTAVE

ADVANCED ANALYTICS SYMPOSIUM

FINALIST

Statistical Machine Learning for Medicinal Plant Leaves Classification.

Jayani Lakshika
BSc in Statistics
University of Sri Jayawerdanapura

9.00 AM – 1.00 PM | 30th April 2021

CLICK THE LINK IN THE CAPTION AND REGISTER TO WATCH THE WEBINAR

OCTAVE keells.com/octave/ octave@keells.com

Applied Statistics Conference 2021 (Solvenia)

Statistical Machine Learning for Medicinal Plant Leaves Classification

Jayani P.G. Lakshika[1], Thiyanga S. Talagala[2]

[1] Department of Statistics, University of Sri Jayewardenepura, Nugegoda, Sri Lanka

Introduction

Medicinal plant species identification is costly, time-consuming, and requires lots of effort, and expert knowledge. Recently, many researchers use deep learning methods like CNN (Convolution Neural Network) to classify plants directly using plant images. Even though deep learning models have achieved great success, their interpretability, and transparency of the deep learning models are limited. Also, deep learning models require a large memory space and become computationally prohibitive. To conquer this, we introduce an image feature-based statistical machine learning algorithm.

- **Main Objective**: Develop an automatic algorithm to classify medicinal plants by using statistical machine learning approach.

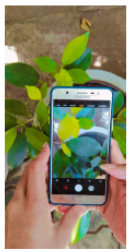


Figure 1: Taking a photograph of a leaf.

- **Significance of the study**: To avoid misidentifying medicinal plants.
- **Why leaf images?** Leaf images are considered as they contain large number of diverse set of features.

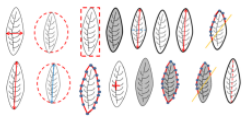


Figure 2: Shape-based features.

- Our classification algorithm operates on the features extracted from the image leaves.

Figure 3: (a) Leaf shape (b) Leaf margin

Methodology

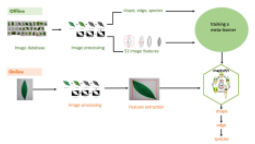


Figure 4: Overview of algorithm.

- **Offline phase** contains 4 main steps: i) Image processing, ii) Feature extraction, iii) Label images, and iv) Trained a algorithm.
- We trained our algorithm using random forest, gradient boosting, and extreme gradient boosting.

Figure 5: Image processing.

- **Online phase**, the pre-trained classification model is used for real-time leaf image classification.

Data

- Five leaf datasets of different countries (i) Flavia 1907 images collected from China, (ii) Swedish 975 images collected from Sweden, and (iii) Kaggle 1584 images collected from United Kingdom (UK), and (iv) MedLEA 1099 images collected from Sri Lanaka.

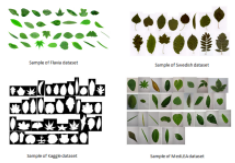


Figure 6: Datasets.

Visualization

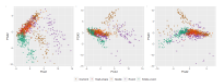


Figure 7: Distribution of Swedish leaf images on the projection space created based on principal component analysis. All projected points are coloured according to their shape labels.

We explore the ability of features to discriminate the classes of interest using PCA and LDA. Under both experimental settings clear separation of classes are visible in their projection spaces (see 2D view).

MedLEA

The MedLEA: Medicinal LEAf package is an open-source R software (https://CRAN.R-project.org/package=MedLEA) for research reproducibility. This repository provides morphological and structural features of 471 medicinal plant leaves and 1099 leaf images of 31 species and 29-45 images per species in Sri Lanka.

MEDIPI

Our medicinal plant classification algorithm is defined as MEDIPI: MEDIcinal Plant Identification (https://github.com/JayaniLakshika/MEDIPI). The MEDIPI is divided into the offline phase and an online phase.

Features

We introduced 52 computationally efficient interpretable features that are useful in leaf classification (Lakshika and Talagala 2021).

Figure 8: Features.

Conclusions

- We introduced 52 computationally efficient interpretable features to classify plant species. These feature are mainly classified in to four groups as (i) shape, (ii) color, (iii) texture, and (iv) scagnostics.
- The model trained with random forest algorithm provides the highest accuracy.
- Our algorithm works as a **hierarchical classification system** which classifies according to shape, edge type (see Figure 3), and plant species. We observed that shape features are more important when classify the leaf images in the first level of the hierarchy. Scagnostic features are more important in identifying leaf species in the bottom level of the hierarchy.
- The **MEDIPI** algorithm yields accurate results to the state-of-the existing techniques in the field.
- We used high dimensional visualization approach as Linear Discriminant Analysis (LDA) to visualize what is happening inside the trained algorithm and provides transparency to our black−box model.

References

Lakshika, Jayani P. G., and Thiyanga S. Talagala. 2021. "Computer-Aided Interpretable Features for Leaf Image Classification." http://arxiv.org/abs/2106.08077.

Thanks!

Slides created via the R package **xaringan**.

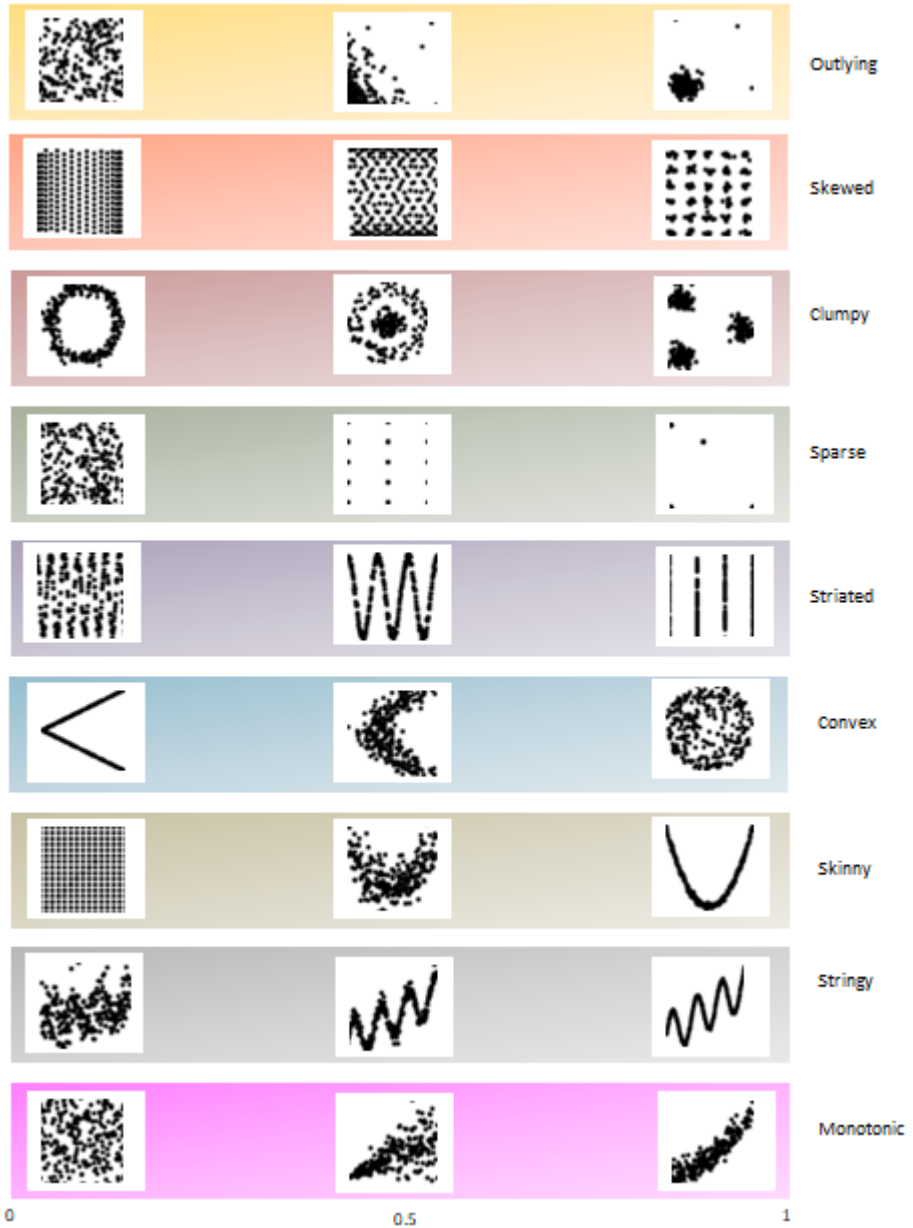
Slides are available at github: https://github.com/JayaniLakshika/Estadistica_2021

ID	Sinhala Name	Family Name	Scientific Name	Shape	Arrangements	Bipinnately compound	Pinnately compound	Palmately compound	Edges	Uniform background	Red Margin	Shaded margin
1	Tel kaduru (තෙල් කහුරු)	EUPHORBIACEAE	*Sapium insigne*	2	1	0	0	0	1	1	0	0
2	Telhiriya (තෙල්හිරිය) / Mayura manikkam (මයුර මාණික්කම්)	RHAMNACEAE	*Colubrina asiatica var. asiatica*	2	1	0	0	0	2	1	0	0
3	Thakkali	SOLANACEAE	*Lycopersicon esculentum*	4	2	0	1	0	3	1	0	0
4	Thala	PEDALIACEAE	*Sesamum indicum*	4	1	0	0	0	1	1	0	0
5	Thana hal	POACEAE	*Setaria italica*	4	1	0	0	0	1	1	0	0
6	Thebu (තෙඹු) / Koltan (කොල්ටන්)	ZINGIBERACEAE	*Costus speciosus*	2	1	0	0	0	1	1	0	0
7	Thel kola (තෙල් කොළ)	CONVOLVULACEAE	*Ipomoea littoralis*	1	2	0	0	1	1	1	0	0
8	Thembiliya (තඹිලිය)	MYRTACEAE	*Eugenia bracteata*	2	1	0	0	0	1	1	0	0
9	Thippili (තිප්පිලි)	PIPERACEAE	*Piper longum*	1	1	0	0	0	1	1	0	0
10	Thiththa / Tolol	FLACOURTIACEAE	*Trichadenia zeylanica*	6	1	0	0	0	1	1	0	0
11	Thiththa kinda	MENISPERMACEAE	*Tinospora glabra*	1	1	0	0	0	1	1	0	0
12	Thiththa wel (තිත්ත වැල්)	MENISPERMACEAE	*Anamirta cocculus*	1	1	0	0	0	1	1	0	0
13	Tholabo (තොලබෝ)	AMARYLLIDACEAE	*Crinum asiaticum*	1	1	0	0	0	1	1	0	0
14	Thumba karawila (තුඹ කරවිල) / Mal thumba (මල් කරවිල)	CUCURBITACEAE	*Momordica dioica*	5	1	0	0	0	2	1	0	0
15	Yak erabadu (යක් එරබදු) / Katu kela (කටු කෙල)	FABACEAE	*Erythrina fusca*	2	2	0	0	1	1	1	0	0
16	Yak kapu (යක් කපු)	STERCULIACEAE	*Abroma augusta*	1	1	0	0	0	2	1	0	0
17	Yak kon	MELIACEAE	*Soymida febrifuga*	4	1	0	0	0	1	1	0	0
18	Yakada wel (යකඩ වැල්) / Manorangitham (මනෙරංජිතම්)	ANNONACEAE	*Artabotrys hexapetalus*	4	1	0	0	0	1	1	0	0
19	Yakahalu (යකහළු) / Dummala (දුම්මල)	DIPTEROCARPACEAE	*Shorea oblongifolia*	4	1	0	0	0	1	1	0	0
20	Yakinaran (යකිනාරන්)	RUTACEAE	*Atalantia rotundifolia*	4	1	0	0	0	1	1	0	0
21	Yak eraminiya	RHAMNACEAE	*Ziziphus napeca*	4	1	0	0	0	1	1	0	0
22	Yak komadu (යක් කොමඩු) / Thiththa labu (තිත්ත ලබු)	CUCURBITACEAE	*Citrullus colocynthis*	5	1	0	0	0	3	1	0	0
23	Yaka bendi wel (යකා බැඳි වැල්) / Wellangiriya (වෙල්ලන්ගිරිය)	RUTACEAE	*Paramigniya monophylla*	4	1	0	0	0	1	1	0	0
24	Yakada wel	RHAMNACEAE	*Ventilago madraspatana var. madraspatana*	4	1	0	0	0	1	1	0	0
25	Yakinaran (යකිනාරන්)	RUTACEAE	*Atalantia ceylanica*	4	1	0	0	0	1	1	0	0
26	Yakwanassa (යක්වානස්ස)	LAMIACEAE	*Anisomeles indica*	1	1	0	0	0	2	1	0	0
27	Vanila	ORCHIDACEAE	*Vanilla fragrans*	4	1	0	0	0	1	1	0	0

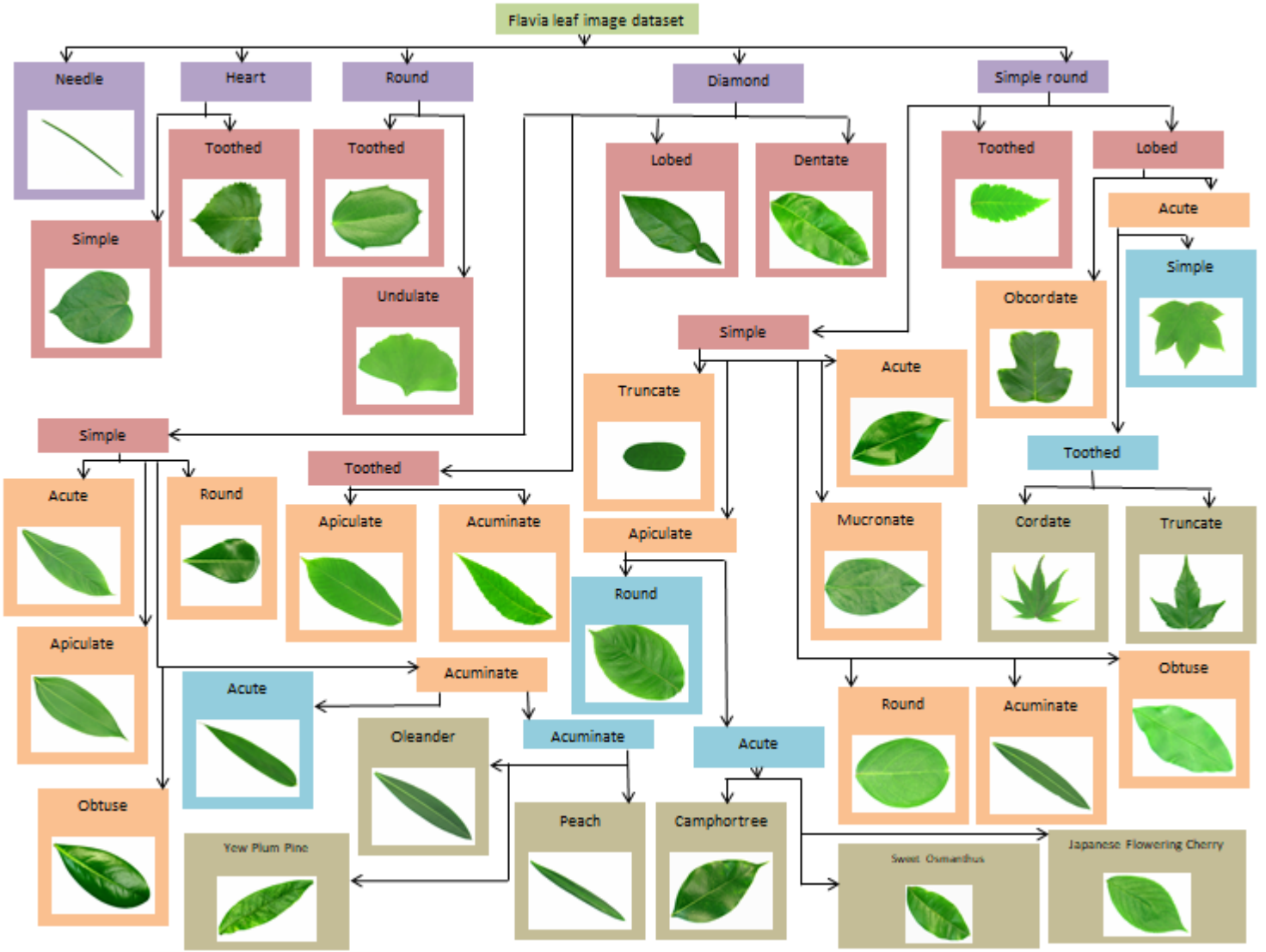
The website "AYURVEDIC MEDICINAL PLANTS OF SRI LANKA" (\url(http://www.instituteofayurveda.org/plants/))

Robust scaling

- If there are input variables that have very large values relative to the other input variables, these large values can dominate or skew some machine learning algorithms (eg: ANN, KNN, SVM etc).
- The result is that algorithm pay more attention to the large values and ignore the variables with smaller values.


Outlying
Skewed
Clumpy
Sparse
Striated
Convex
Skinny
Stringy
Monotonic
0
0.5
1

Flavia hierarchy



Synthetic Minority Oversampling Technique (SMOTE)

- Imbalance dataset is a classification problem where the class distribution is biased or skewed or not uniform. Most machine learning algorithms for classification are designed under the assumption that each class has an equal number of observations. That results, especially for the minority class in the model, has poor predictive performance. Even though minority class is more important, classification errors for minority class is more sensitive than majority class.

- One remedy for class imbalance is to use an over-sampling method. SMOTE is an over-sampling method which creates synthetic (not duplicates) samples for the minority class and makes the minority class equal to the majority class. By selecting similar records and altering that record one column at a time by random amount within the difference to the neighbouring records, SMOTE handles the imbalance problem.

Key Insights

- Most of the research are based on existing databases. Even though researchers used their own database most of the time they didn't define image acquisition process in detail or it was complex. Therefore through this research, we introduced simplest and reliable approach of acquiring leaf images which can be followed without expertise knowledge.

- To classify leaf images, several reliable automatic procedures are used. But we introduced a hierarchical approach which perform better than non hierarchical approaches.

- Random Forest in hierarchical approach
- We have to use training/test from same dataset to get accurate results.

Further Research

- Develop algorithms to identify plant disease in Sri Lanka
- Expand the species collection
- Explore differences in plant features according to spatial distributions and climate conditions (For example, Gotukola leaf in Colombo is smaller than in Anuradhapura)
- Develop an algorithm to handle images with heterogeneous backgrounds