1 week TEQIP-II STTP on

Computer Vision & Pattern Recognition

(CVPR 2014)

June 16 – 20, 2014
NIT, Durgapur, WB

Santosh Chapaneri,
Assistant Professor,
EXTC, SFIT

Outline

- Fundamentals of Pattern Recognition
- Rain Detection & Removal from Videos
- Chaotic Patterns
- Sparse Image Reconstruction
- Sparse Image Denoising
- Color Image Segmentation
- CBIR for Pathology
- Diabetic Retinopathy
- Brain Gliomas
- Language Engineering

Talks Delivered by …

- Dr. Sudipta Mukhopadhyay, **IIT KGP**
- Dr. M. K. Mandal, **NIT Durgapur**
- Dr. S. P. Maity, **IIEST Shibpur** (formerly BESU)
- Dr. D. Nandi, **NIT Durgapur**
- Dr. B. Chakraborty, **NIT Durgapur**
- Dr. U. Roy & Dr. A. Roy, **ISI Kolkata**
- Dr. A. K. Roy, Vice-Chancellor, **IIEST Shibpur**
- Dr. Chandan Chakraborty, **IIT KGP**
- Dr. Utpal Garain, **ISI Kolkata**

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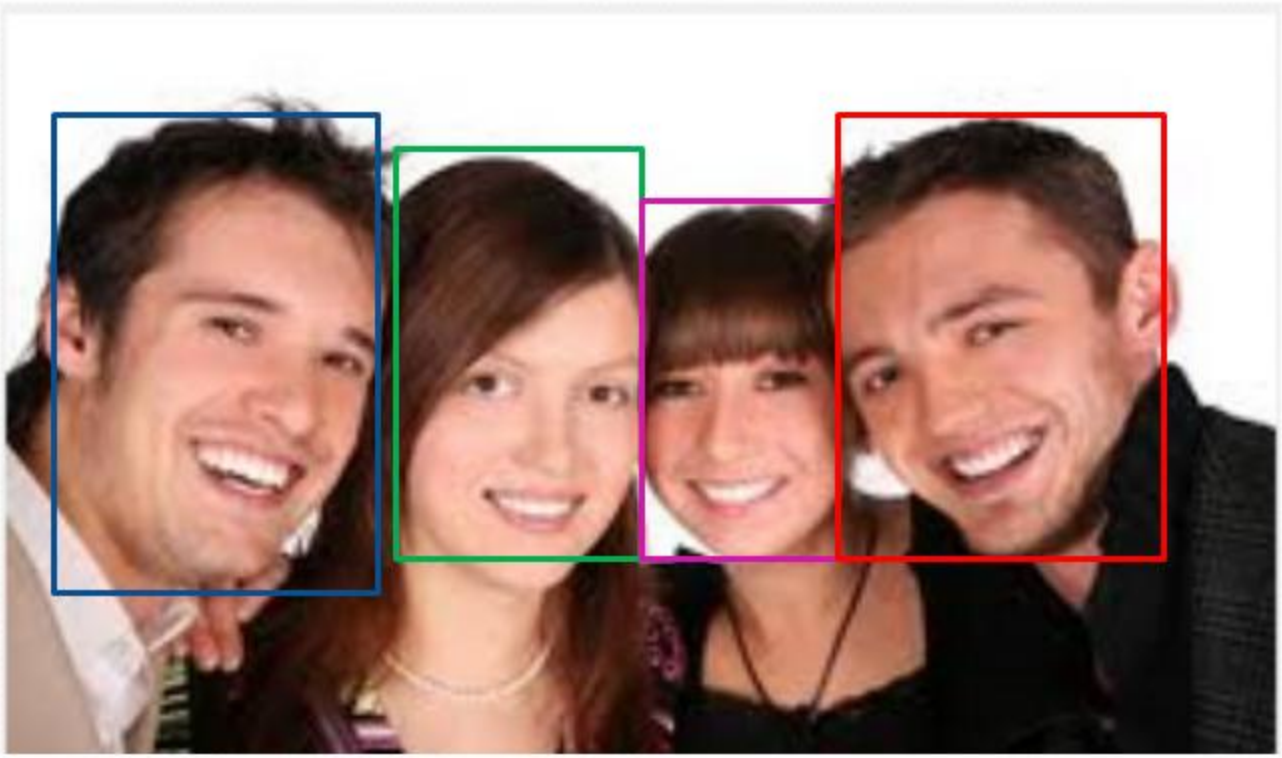
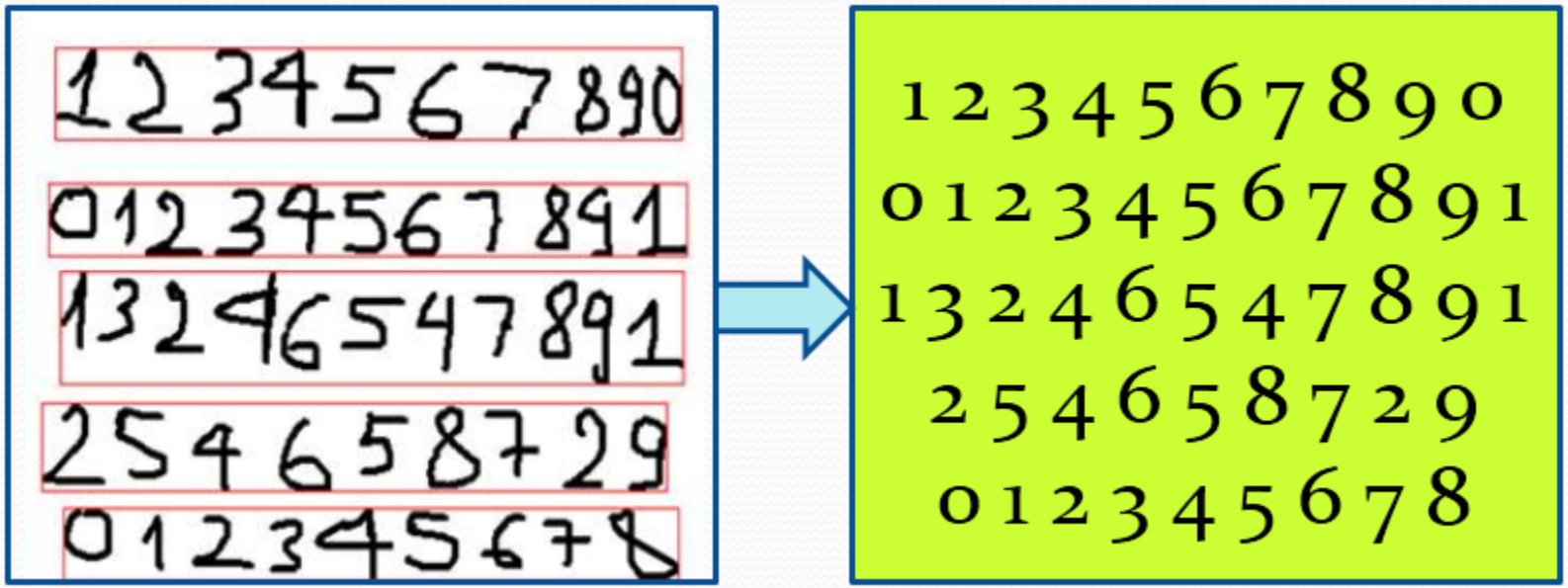
Pattern Recognition (PR)

- Machine Learning for Pattern Recognition
  - Computer Vision
  - OCR
  - Computer Aided Diagnosis
  - Speech Recognition
  - Biometrics
  - Data Mining
  - Bioinformatics

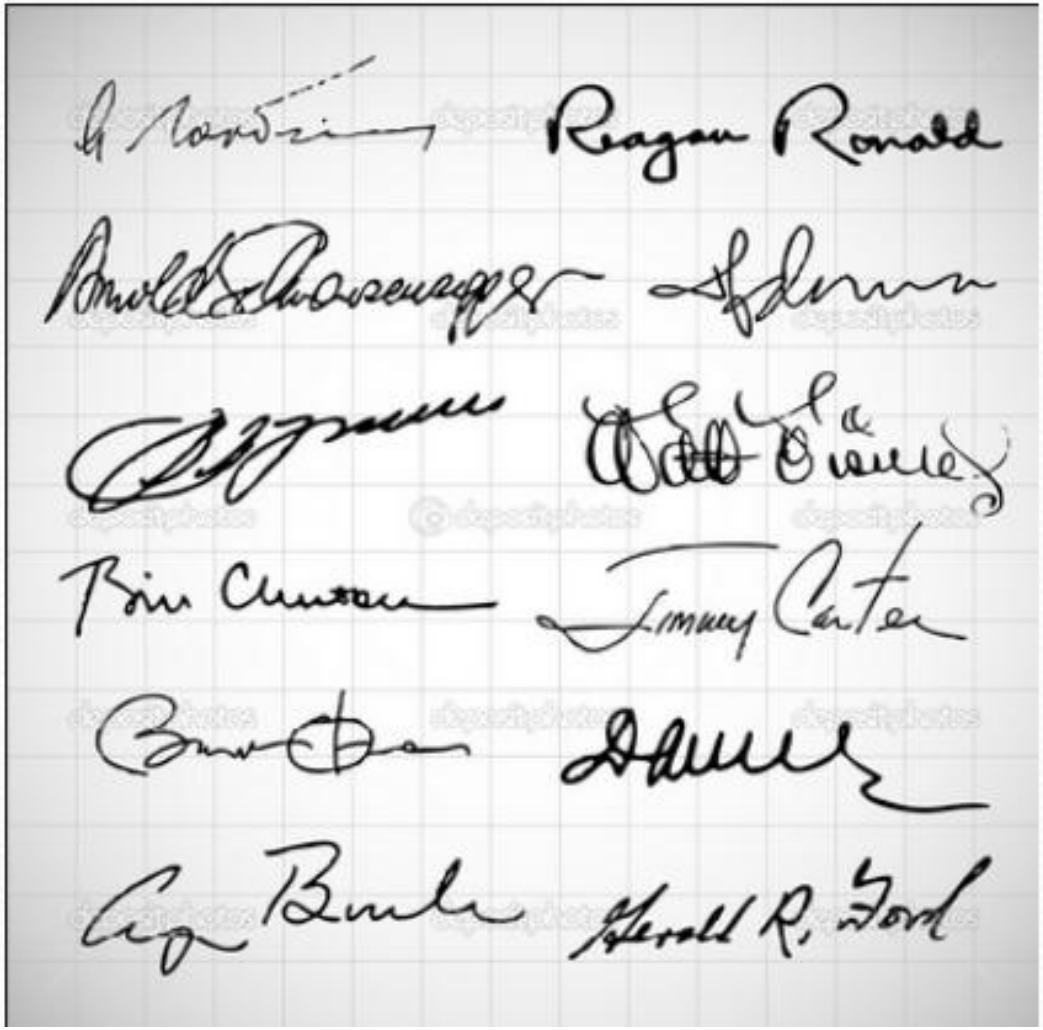
PR – Face Detection/Recognition



PR – OCR

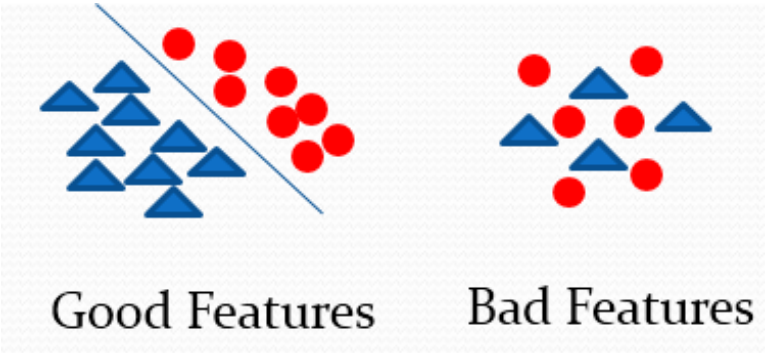

1 2 3 4 5 6 7 8 9 0
0 1 2 3 4 5 6 7 8 9 1
1 3 2 4 6 5 4 7 8 9 1
2 5 4 6 5 8 7 2 9
0 1 2 3 4 5 6 7 8

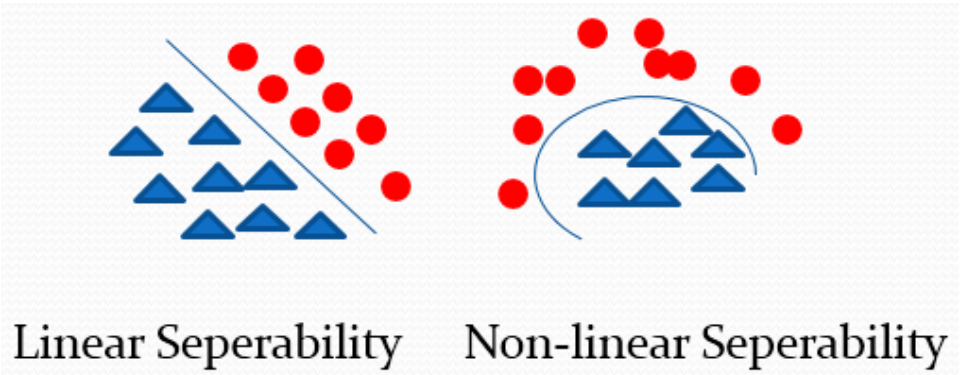
PR – Signature Recognition



Pattern Recognition

- Features, Feature Vectors $\underline{x} = [x_1, ..., x_l]^T \in R^l$





- Feature Extraction & Recognition

- Supervised v/s Unsupervised Learning

Bayesian Classifier

- Baye's Classification rule for (m =) 2 classes

$$If\ P(\omega_1|\underline{x}) > P(\omega_2|\underline{x})\ \ \underline{x} \rightarrow \omega_1$$
$$If\ P(\omega_2|\underline{x}) > P(\omega_1|\underline{x})\ \ \underline{x} \rightarrow \omega_2$$

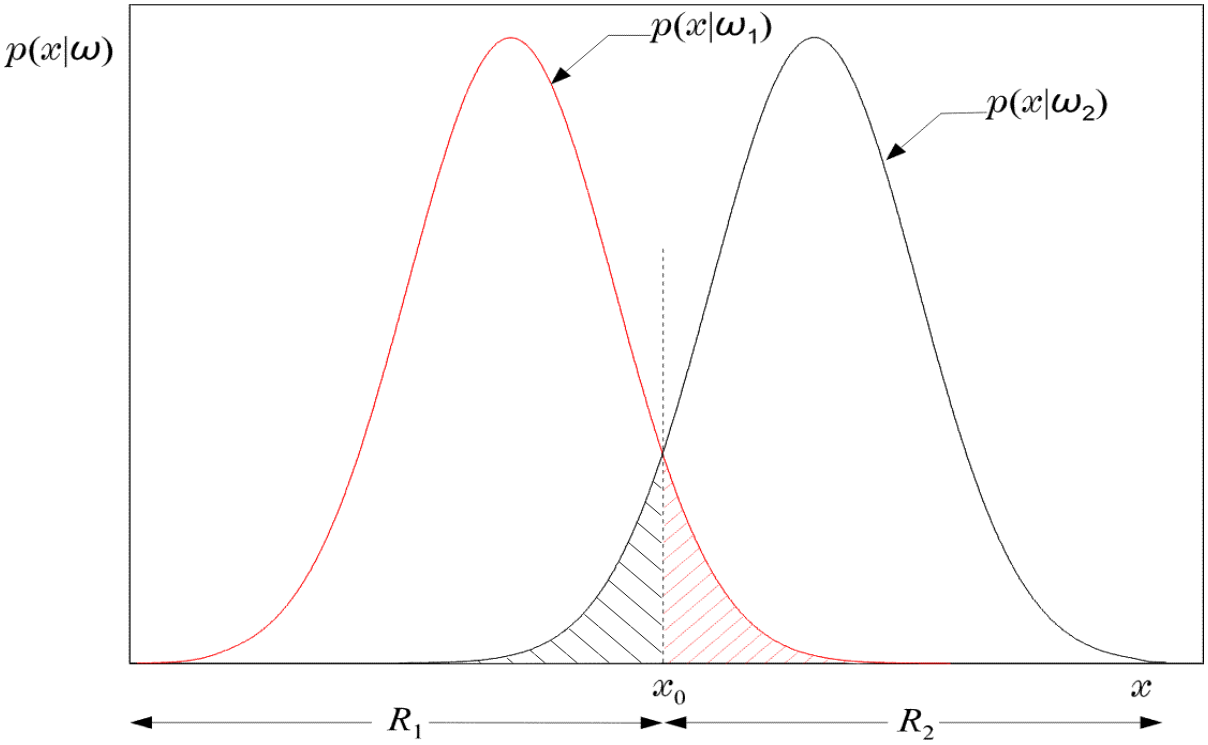
- Equivalently, classify as per rule:

$$p(\underline{x}|\omega_1)P(\omega_1)(><)p(\underline{x}|\omega_2)P(\omega_2)$$

- For equi-probable, this becomes

$$p(\underline{x}|\omega_1)(><)P(\underline{x}|\omega_2)$$

Bayesian Classifier



$$R_1(\rightarrow \omega_1) \text{ and } R_2(\rightarrow \omega_2)$$

$$\text{If } \underline{x} \in R_1 \Rightarrow \underline{x} \text{ in } \omega_1$$
$$\text{If } \underline{x} \in R_2 \Rightarrow \underline{x} \text{ in } \omega_2$$

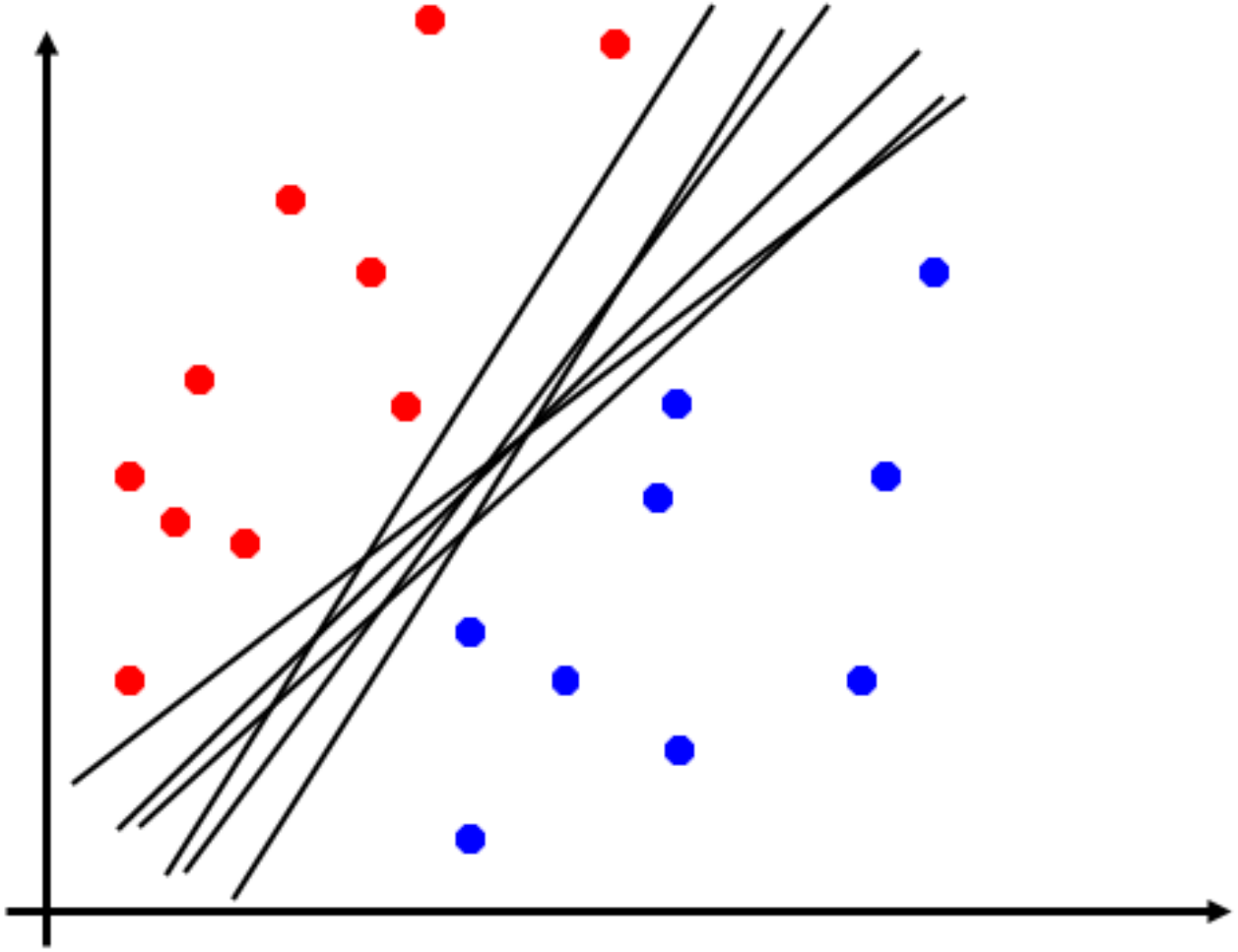
$$P_e = \int_{-\infty}^{x_0} p(x|\omega_2)dx + \int_{x_0}^{+\infty} p(x|\omega_1)dx$$

OPTIMAL wrt minimizing P_e

Types of Classifiers

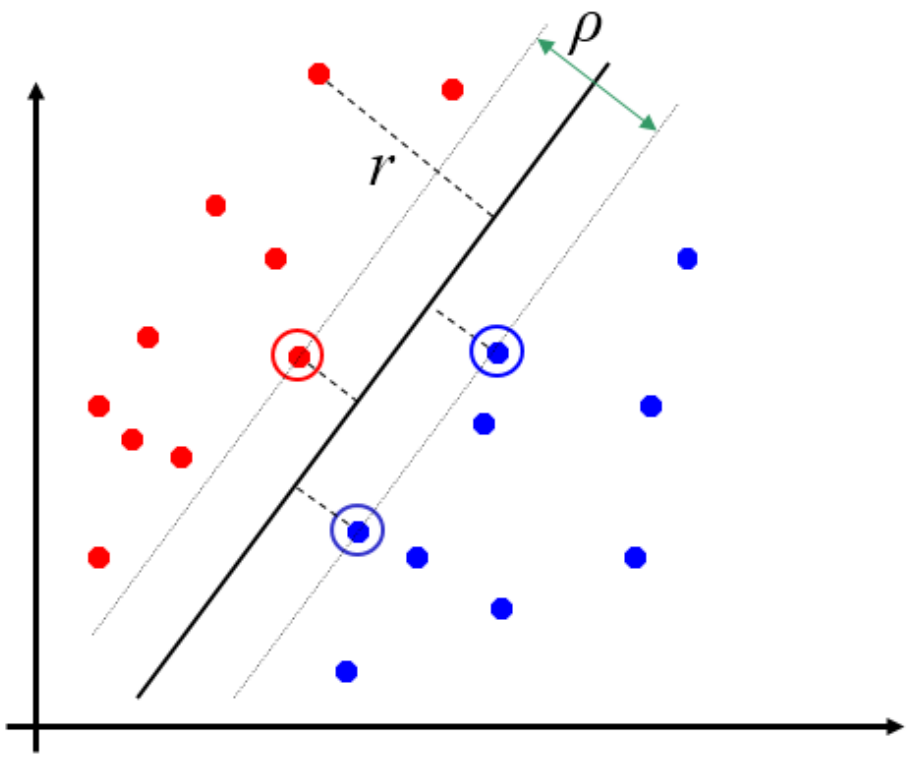
- **Linear Classifiers**
  - Perceptron Algorithm
  - Least Means Square (LMS) Algorithm
  - Support Vector Machines (SVM)
    - ✓Expandable to multi-class
- **Non-Linear Classifiers**
  - Back Propagation Neural Network (BPNN)
  - Probabilistic Classifier
  - Decision Trees

Support Vector Machines

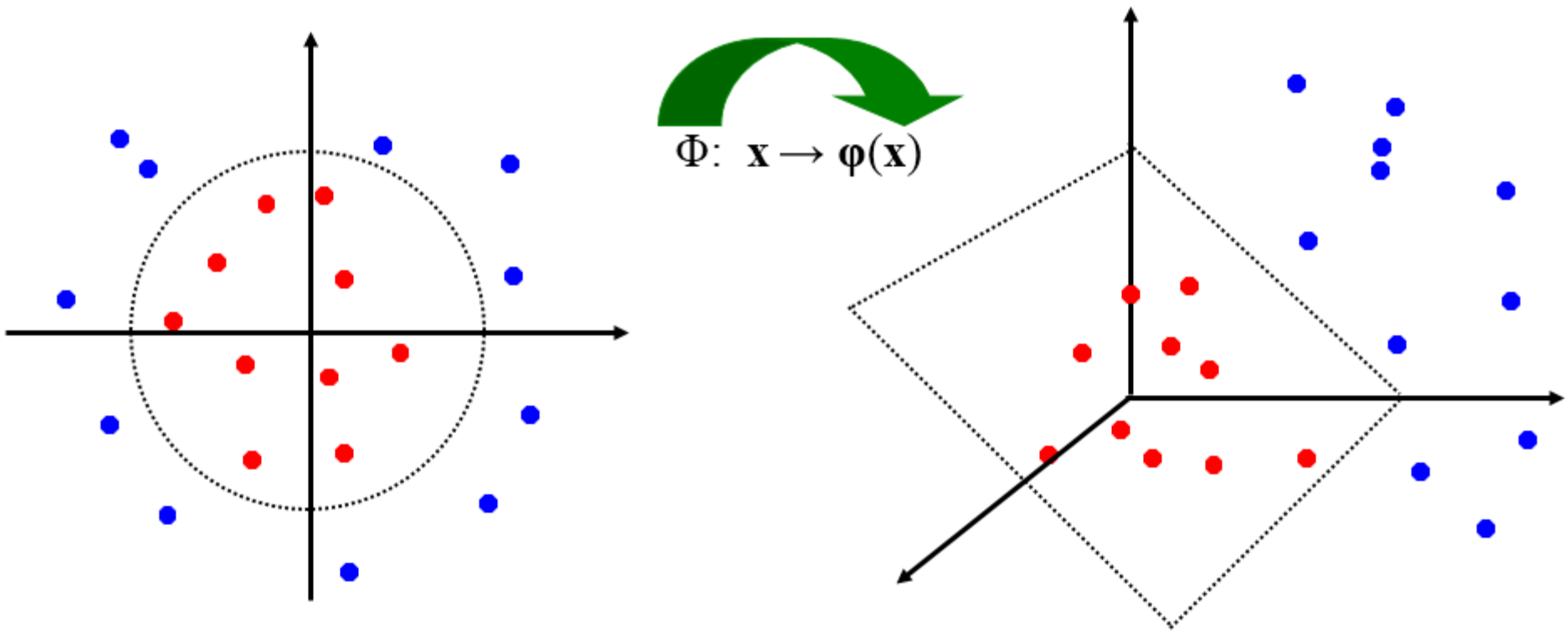


Support Vector Machines

- Distance from example $\mathbf{x}_i$ to the separator is $r = \dfrac{\mathbf{w}^T\mathbf{x}_i + b}{\|\mathbf{w}\|}$
- Examples closest to the hyperplane are ***support vectors***.
- ***Margin*** ρ of the separator is the distance between support vectors.



Support Vector Machines



Fuzzy C-Means Clustering

- Similar to K-Means algorithm
- But membership is fuzzy rather than crisp
- **Iterative clustering** method to produce an optimal c-partition using fuzzy logic
- Each pattern associated with every cluster using DoM (**degree of membership**)

FCM for Retina Blood Vessel Extraction

Ref: S. Silkar, S. P. Maity, “Extraction of Retinal Blood Vessel using Curvelet Transform and Fuzzy C-Means”, *Intl. Conf. Pattern Recognition*, Aug 2014, Stockholm, Sweden (accepted)

- Green Channel Extraction
- Curvelet Denoising
- Matched Filtering
- Vessel Segmentation using FCM clustering

FCM for Retina Blood Vessel Extraction

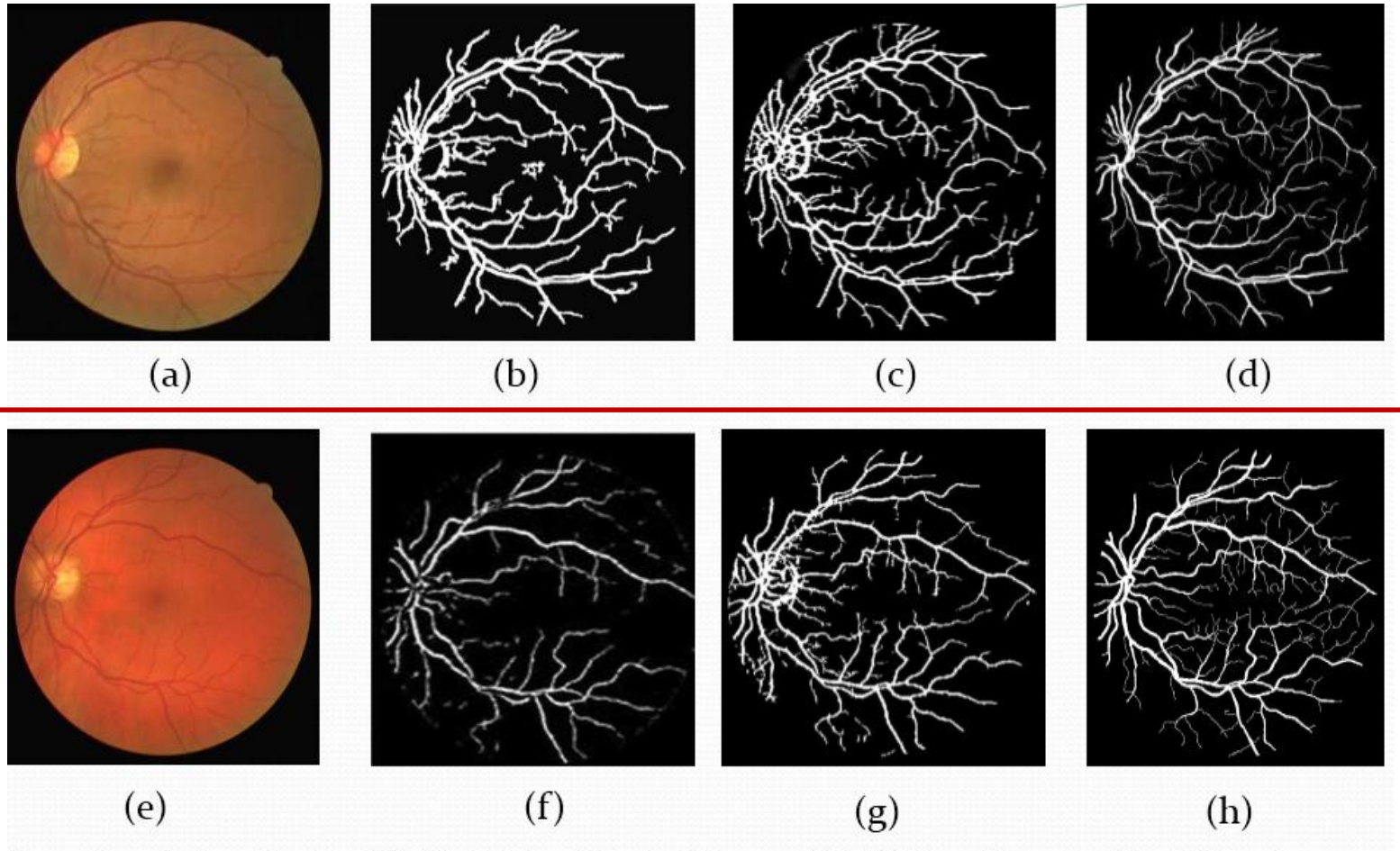


Fig. 1. Simulation Results (a),(d) Original Retinal Image. (b),(f) Vessel Extracted by [13] and [14] ,respectively. (c),(g) Vessel Extracted by Proposed method. (d),(h) Manually Segmented Image

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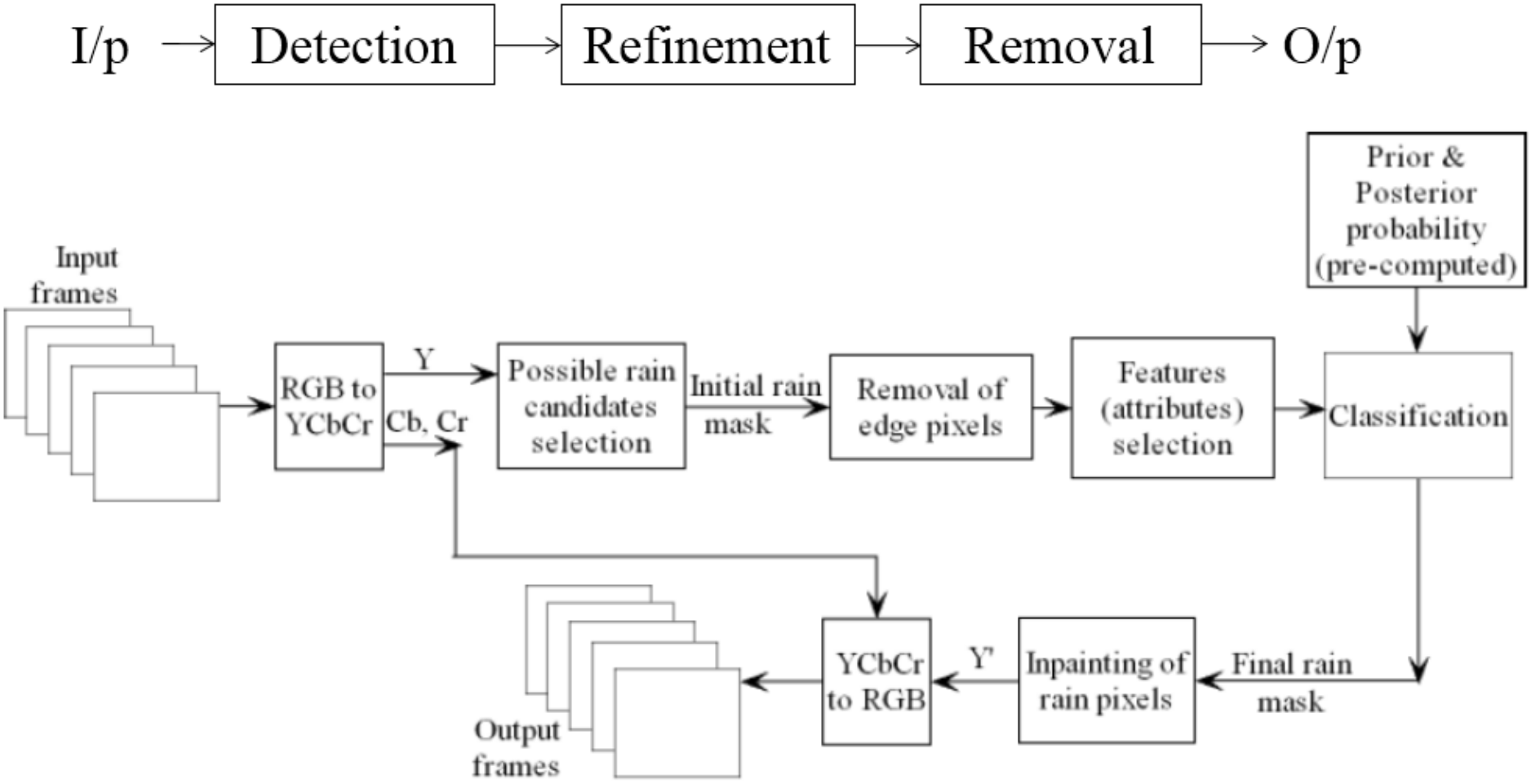
Rain Detection & Removal

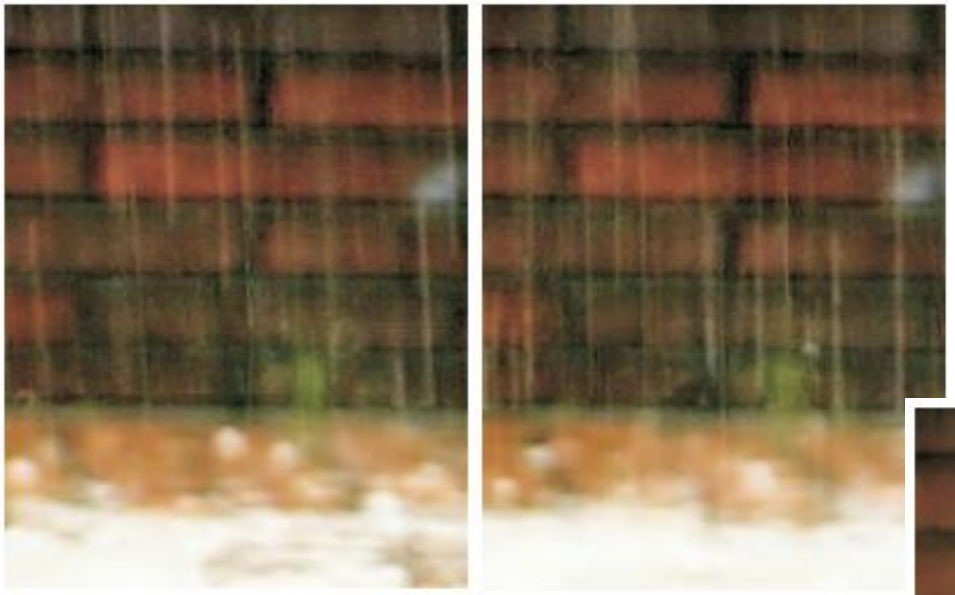
Ref: A. K. Tripathi,and S. Mukhopadhyay,“A Probabilistic Approach for Detection and Removal of Rain from Videos”, *IETE Journal of Research*, (paper communicated)

- Bad weather conditions: Fog, Snow, Drizzle, Rain
- Temporal & Spatio-temporal properties of videos

Rain Detection & Removal



Results of Rain Removal



(a) Frames from the original video

(b) Derained frames

Applications – Rain Removal

- Outdoor Security Video
- Tracking and Navigation apps
- Consumer Electronics
- Film Post Production

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Chaotic Patterns

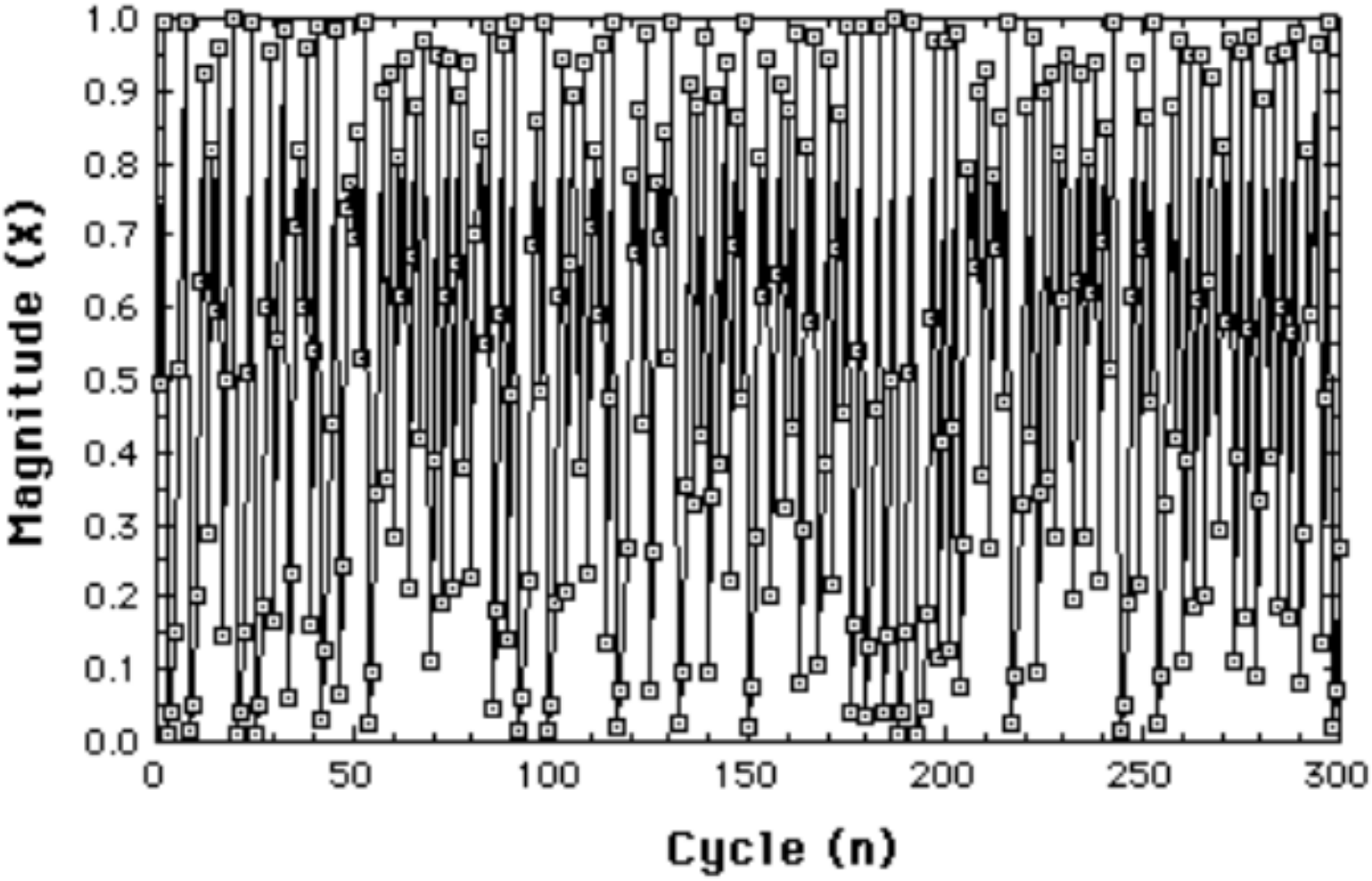
Double Rod Pendulum:
Starting the pendulum from a slightly different initial condition would result in a completely different trajectory.

- Consider a simple 1D equation of Logistic Map:

$$x_{n+1} = r x_n (1 - x_n)$$

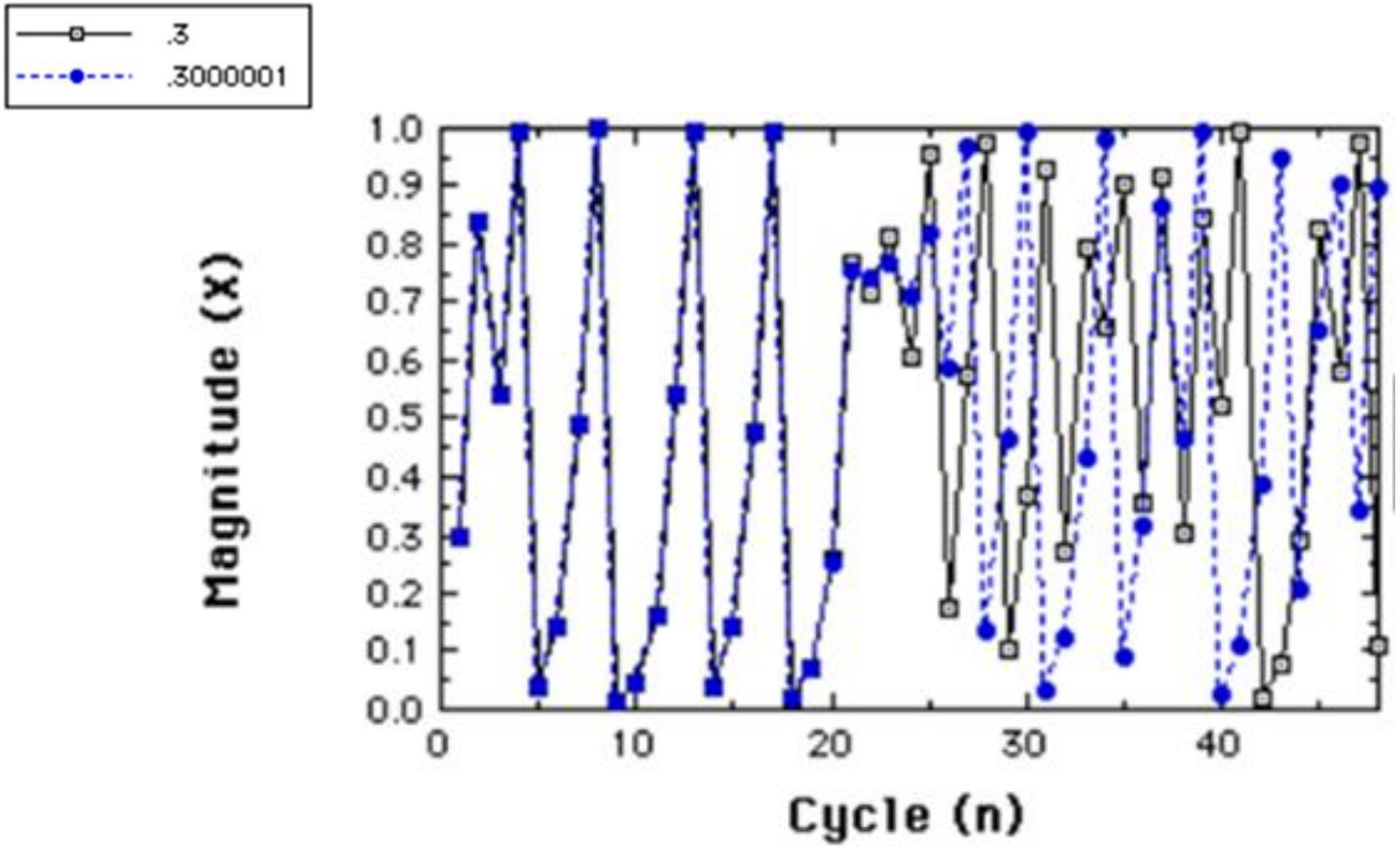
- It produces a "**deterministic random**" sequence of values for parameter *r* in the range (3.57, 4.0).

Chaotic Patterns

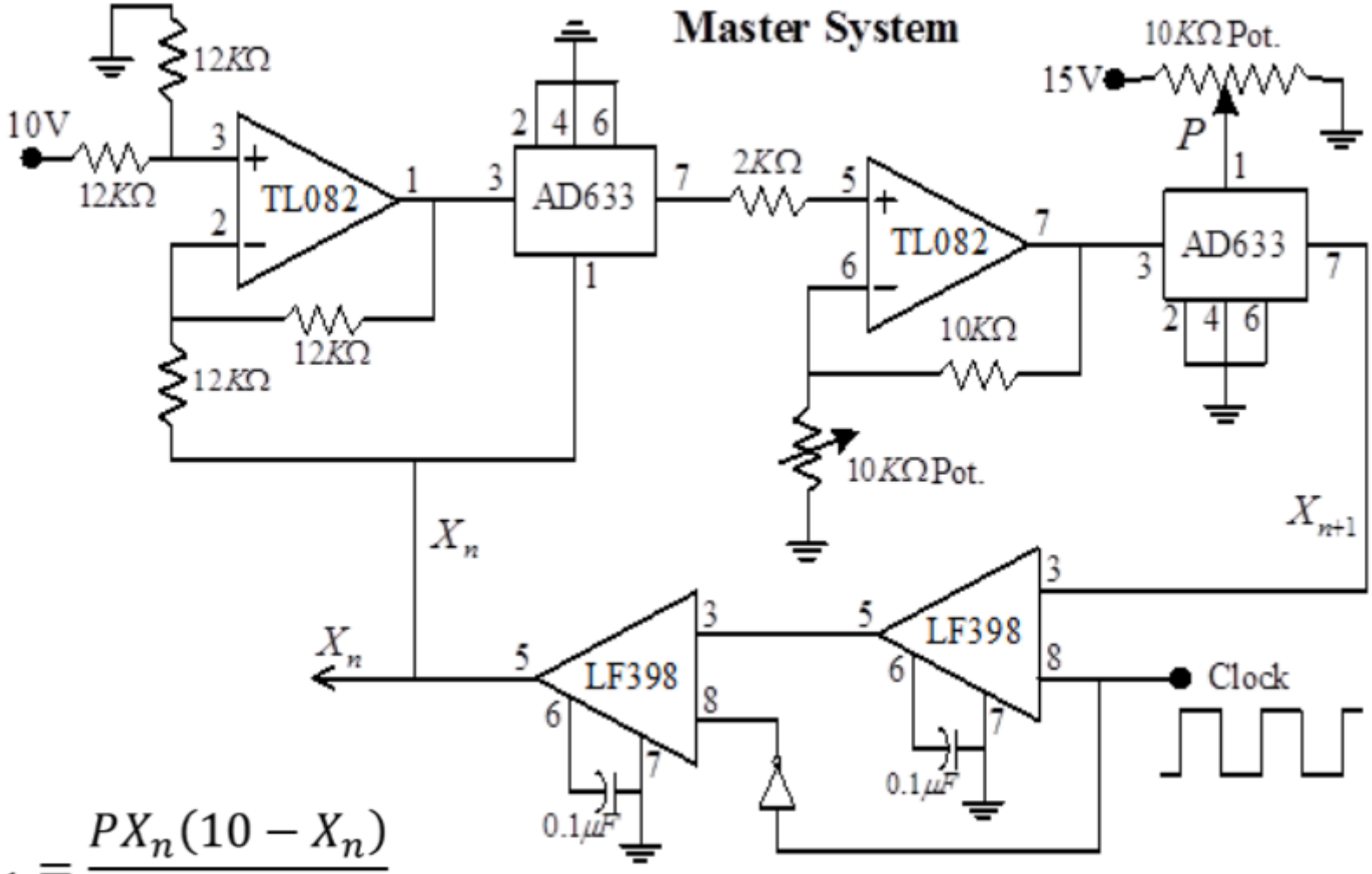


***Chaotic** behavior of the Logistic map at r= 3.99.*

Chaotic Patterns

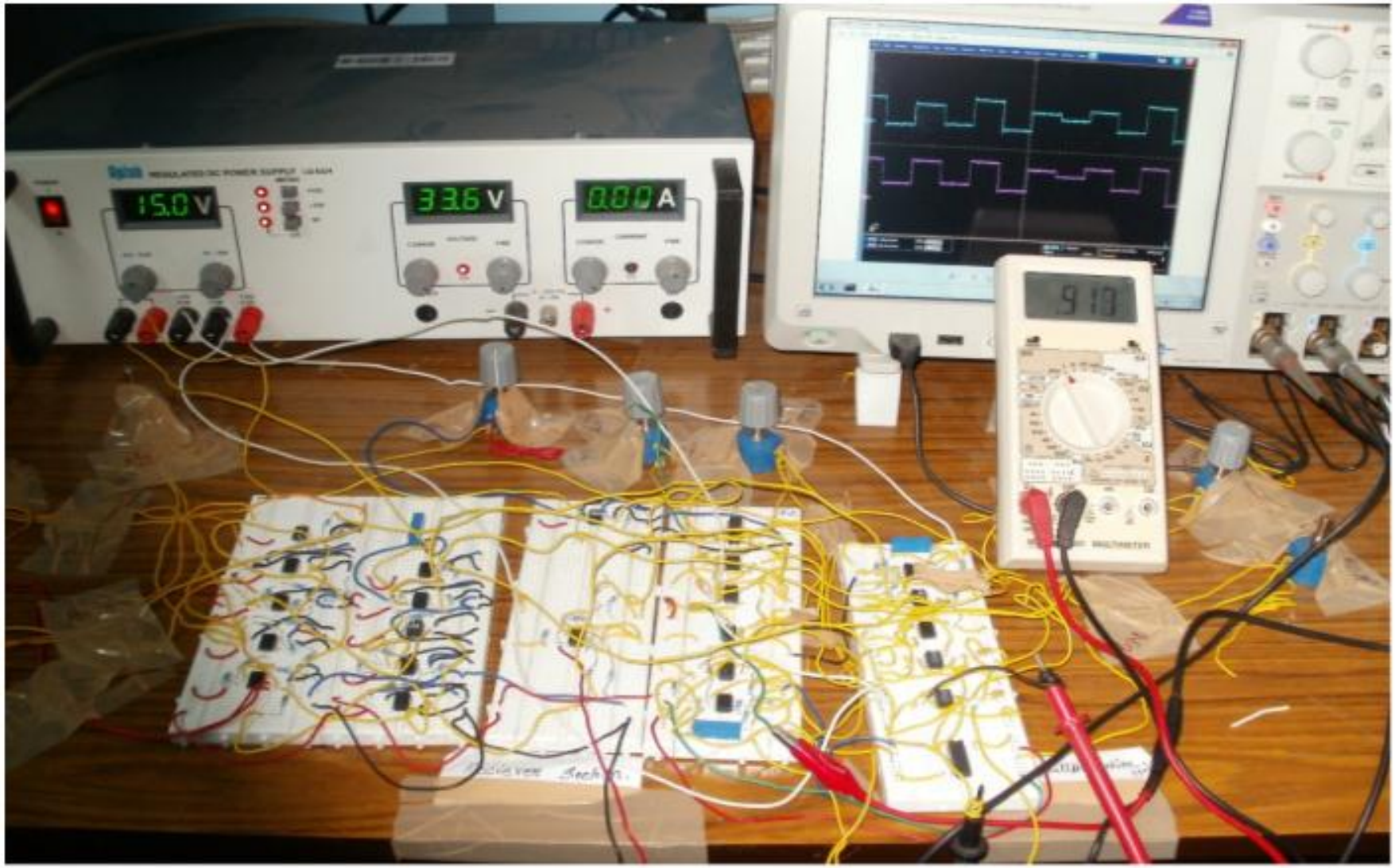


Chaotic Pattern Synchronization

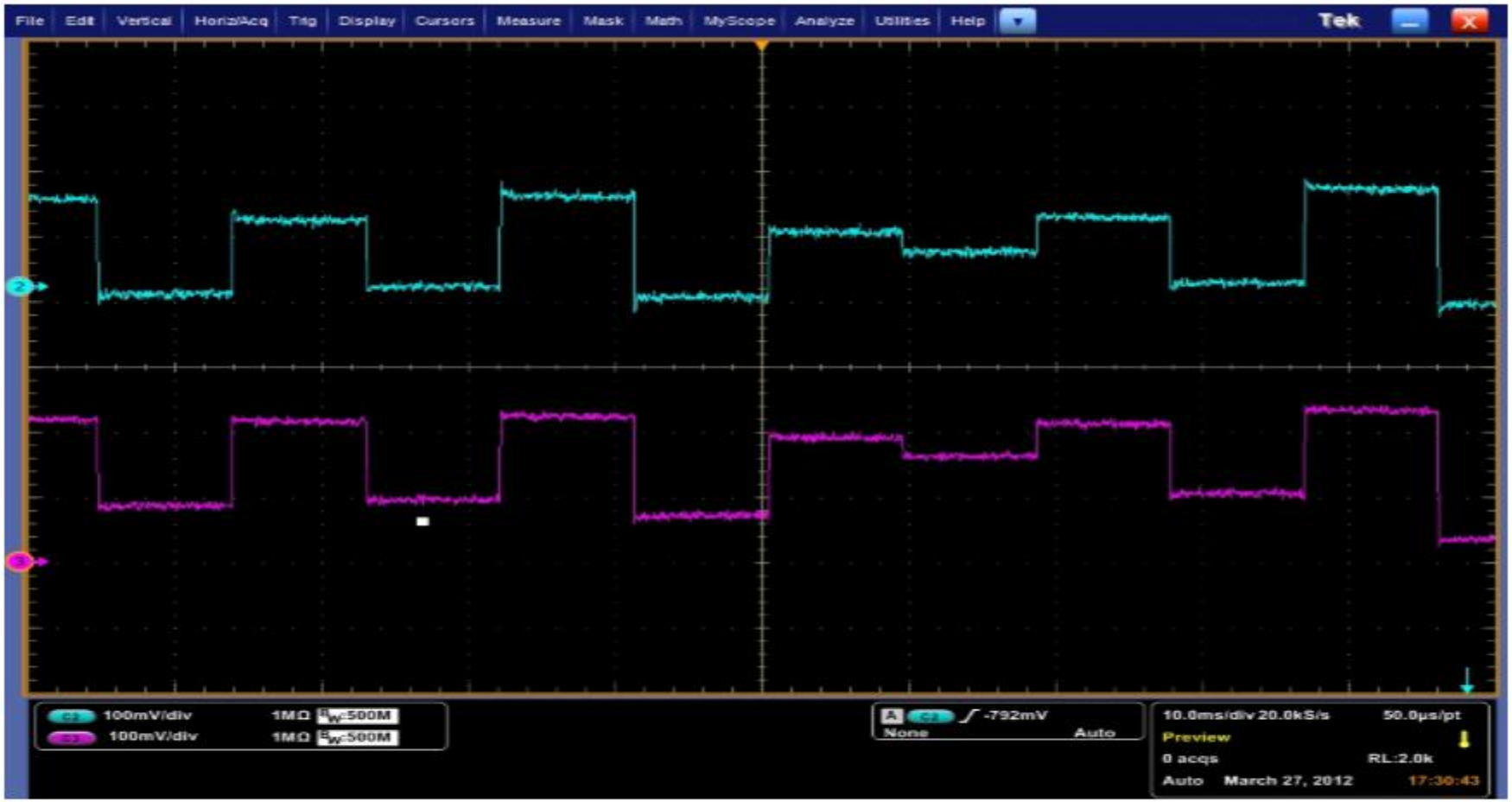


$$X_{n+1} = \frac{PX_n(10 - X_n)}{25}$$

Chaotic Pattern Synchronization



Chaotic Pattern Synchronization



- The result is seen in DPO 5104. The blue signal represent the transmitted signal and the pink one shows the received signal.

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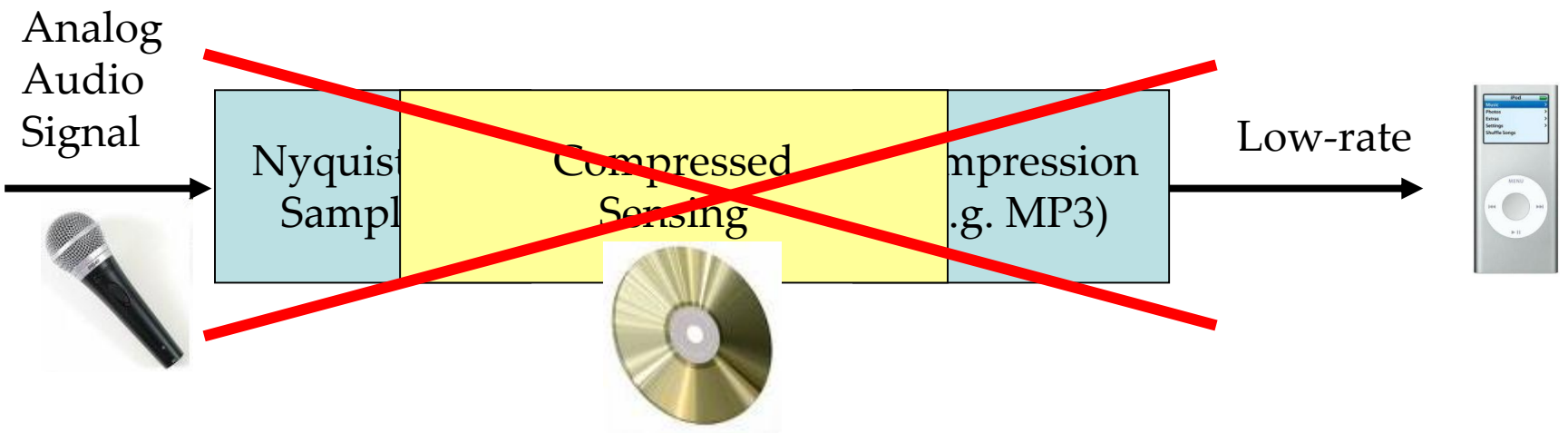
Sparse Image Reconstruction

- Using the concept of **Compressive Sampling**

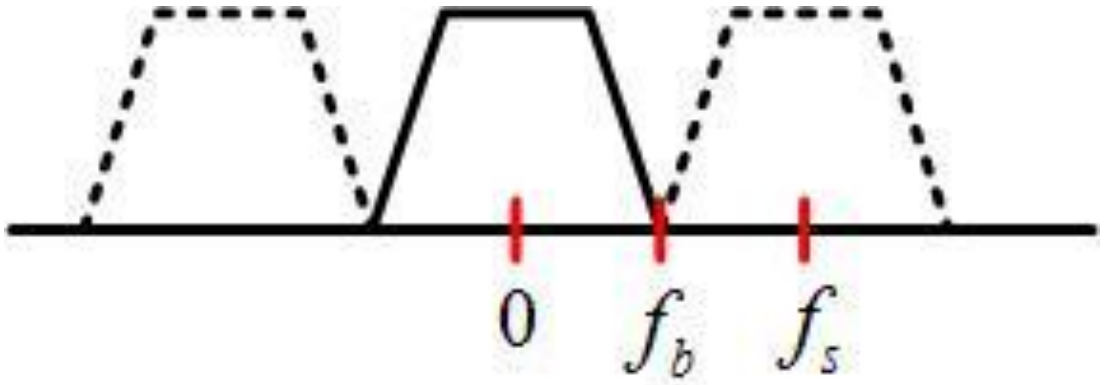
"Can we not just **directly measure** the part that will not end up being thrown away ?"

Donoho



Compressive Sampling

- As per Nyquist's rate, $f_s \geq 2f_b$



- Assume: signal is sparse in some domain…
- e.g. JPEG, JPEG2000, MPEG…

1. Sample with frequency f_s. Get signal of length N
2. Transform signal → K (<< N) nonzero coefficients
3. Preserve K coefficients and their locations

Compressive Sampling

- As per CS theory, sample with rate less than f_s!

	Nyquist's Sampling	**Compressive Sampling**
Sampling Frequency	$\geq 2f_b$	$< 2f_b$
Recovery	Low pass filter	**Convex Optimization**

Sparse Image Reconstruction

- Reconstruction using Convex Optimization techniques
- Relying on **Convergence of Random Variables**

X_n converges *almost surely* to X, denoted by $X_n \xrightarrow{a.s} X$, if

$$\mathbb{P}\left(\lim_{n\to\infty} X_n = X\right) = 1.$$

- Eg. Robbins-Monro **Stochastic Approximation (1951)**
- Iterative stochastic optimization to find extrema of functions, estimated via noisy observations

Sparse Image Reconstruction

1. Undersample

2. Fill in the
l_1 minimi

pes =>
sparsity

4. Add more smaller shapes

5. Iterate to achieve clarity

Results – Sparse Image Reconstruction

Reconstructed Images for different no. of measurement

Original Image

N=50625
TV=64.770

K=5062(10%)
TV= 25.469

K=10124(20%)
TV= 35.273

K= 15186(30%)
TV=41.578

K=25312(50%)
TV= 51.479

TV = Total Variation Regularization

$$J_{\mathrm{TV}} f = \int_{\Omega} \sqrt{\left(\frac{\partial f}{\partial x_1}\right)^2 + \left(\frac{\partial f}{\partial x_2}\right)^2}\, dx_1 dx_2$$

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Sparse Image Denoising

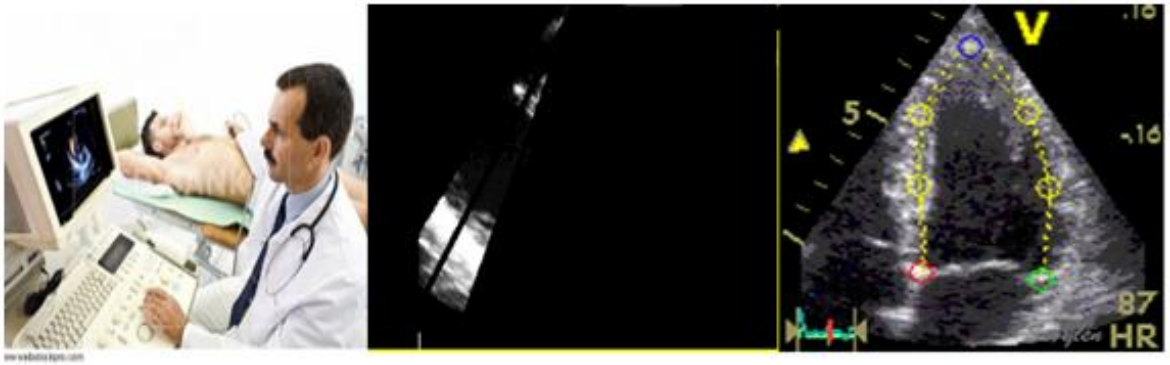
Original image

Noisy image ($\sigma = 25$)

Denoised

Sparse Image Denoising

Ref: D. Nandi, S. Mukhopadhyay, “An improved ultrasound imaging method for speckle reduction”, **US Patent**, June 2013

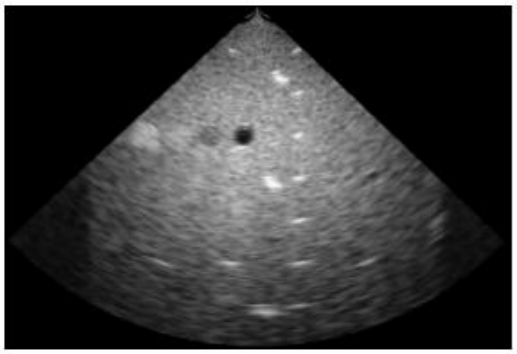


Speckle filtering Scan Conversion in Ultrasound Sector Scanner

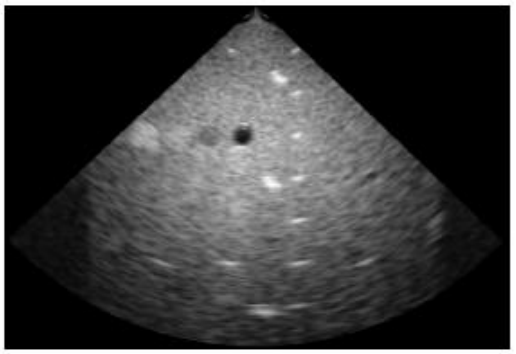
Sparse Image Denoising

- Speckle Noise = most prevalent noise in ultrasound images
- Speckle Noise distorts or hide edges making object detection less reliable
- Take contribution of multiple scatterers from ultrasound device => model as **Random Walk pattern**
- Use **CLT** to result in 2-D Gaussian distribution

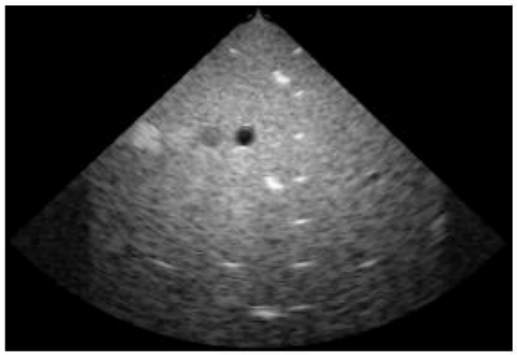
Results – Sparse Image Denoising



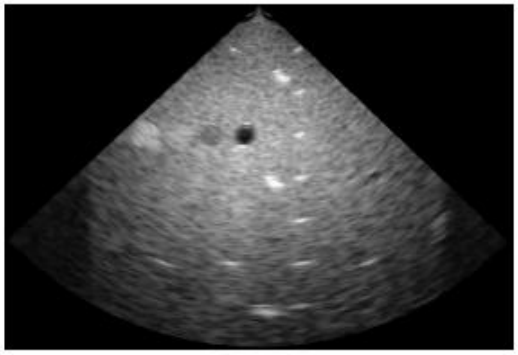
(a) Lee



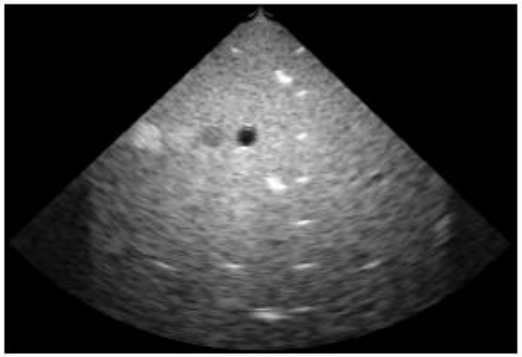
(b) Kuan



(c) Median



(d) AWM



(e) AWM(ANW)

Scan data of real ultrasound machine is obtained from the machine named Ultrasonix Inc. and provided by National Semiconductor.

Data are after pre-processing and before scan conversion with field of view: 90^0, axial data point: 516, no. of lines: 191 and Number of frames: 50.

AWM = Adaptive Weighted Median Filter; ANW = AWM with Negative Weights

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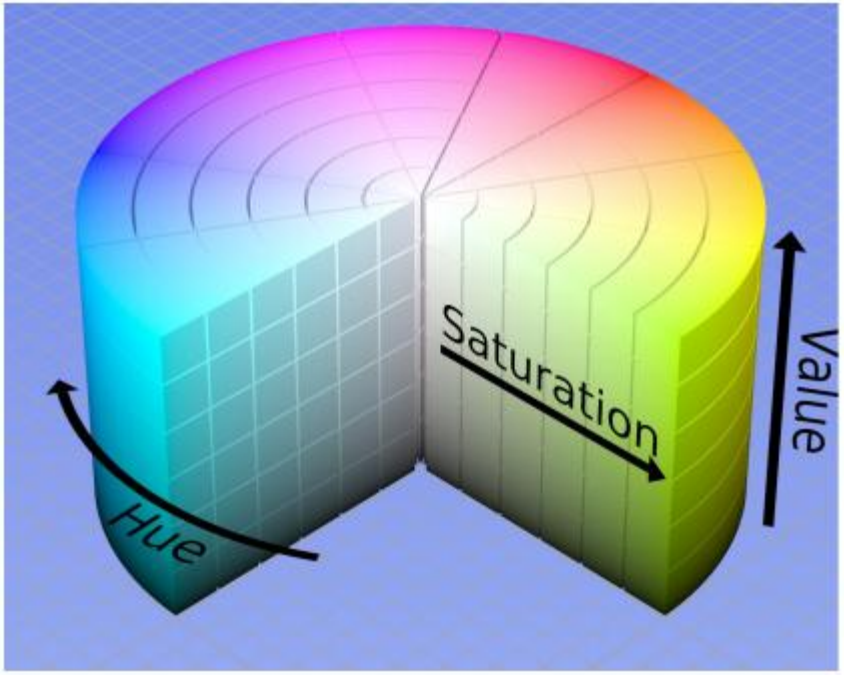
Color Image Segmentation

- To extract text from colored background
- Using HSV color model



Color Image Segmentation

- Hue modeled from **von-Mises (vM) circular distribution**
- Saturation modeled from **Gaussian distribution**

Let a pair of independent random variables be (Θ, X) with $\theta \in [0, 2\pi)$ and $x \in (-\infty, \infty)$. The pdf of vM-Gauss distribution is given by:

$$f(\Theta, X|\mu, \kappa, \nu, \sigma) = f_1(\Theta|\mu, \kappa).f_2(X|\nu, \sigma),$$

Von Mises distribution

Where,

$$f_1(\Theta|\mu, \kappa) = \frac{1}{2\pi I_0(\kappa)} \exp(\kappa \cos(\mu - \theta))$$

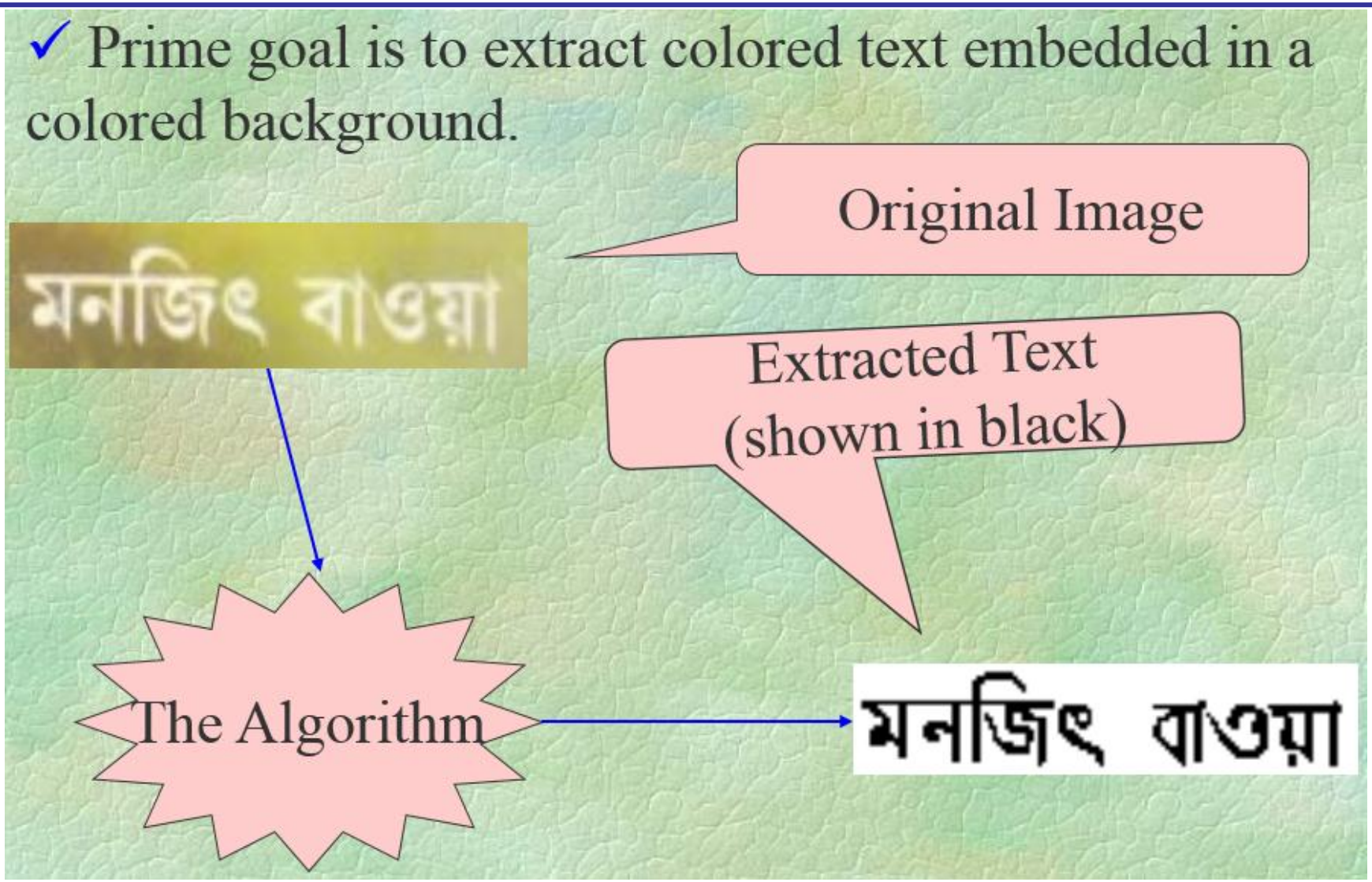
Gaussian distribution

$$f_2(X|\nu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(\frac{-(x-\nu)^2}{2\sigma^2}\right)$$

Clearly Θ and X are independent.

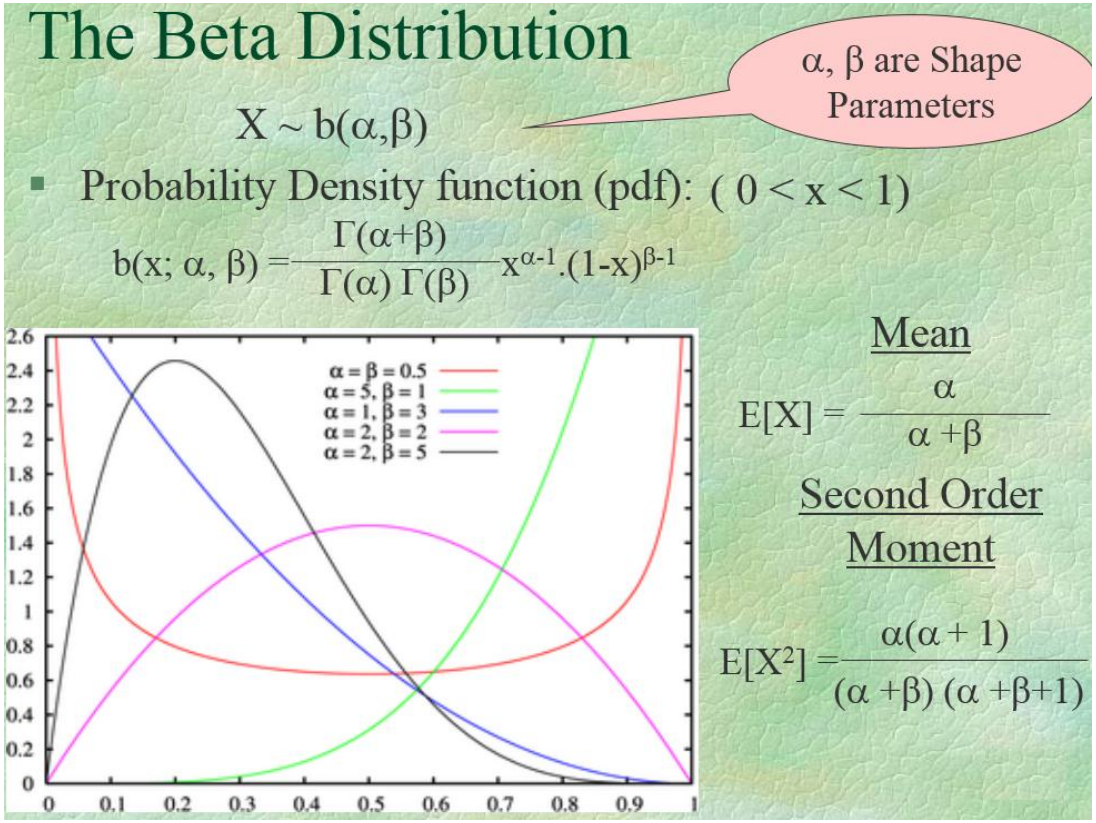
Results – Text Extraction

Text Extraction using BMM



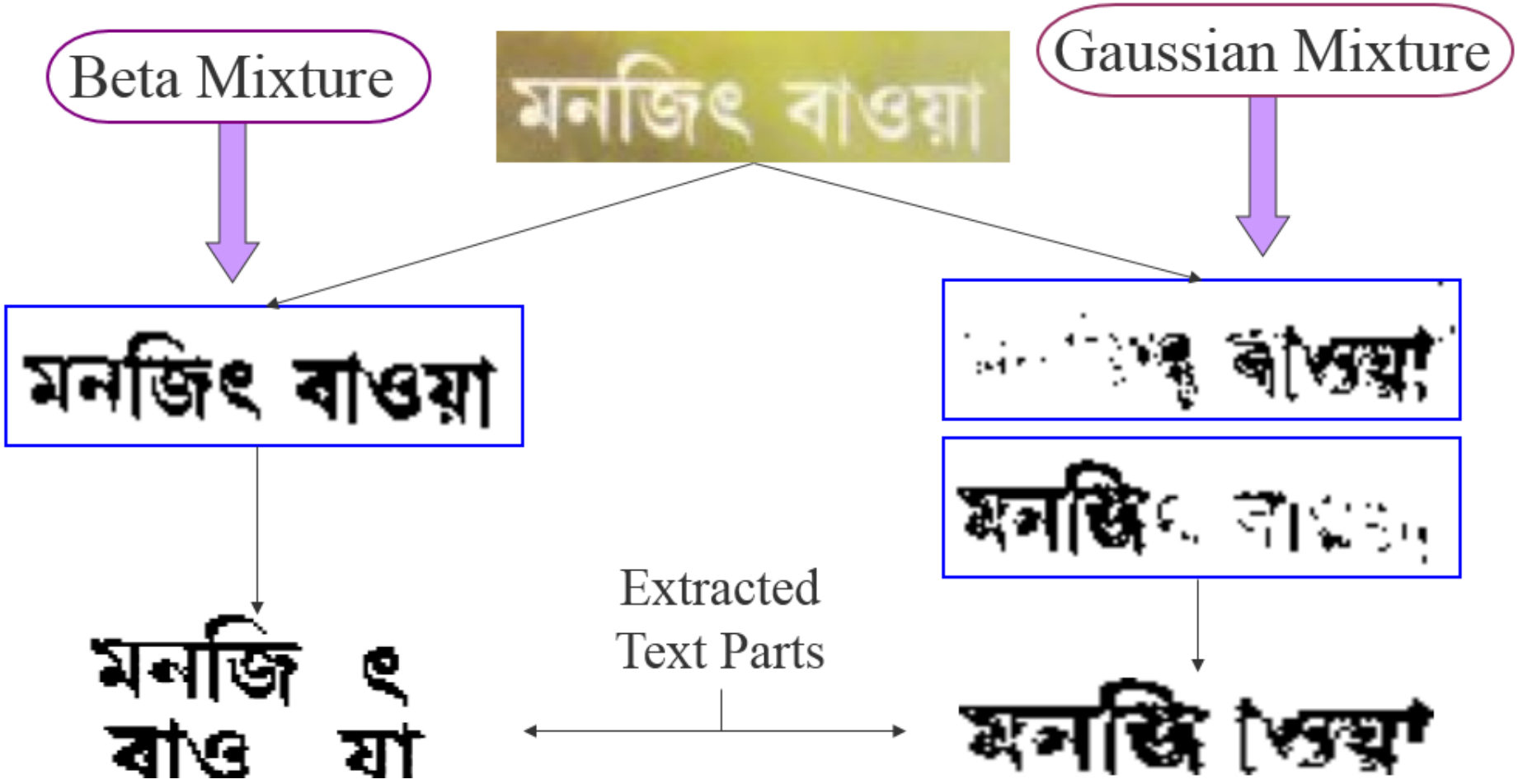
Text Extraction using BMM

- RGB := **tri-variate Beta Mixture Model distribution**



- Parameter estimation using **Expectation Maximization** (EM) algorithm

Results – Text Extraction using BMM



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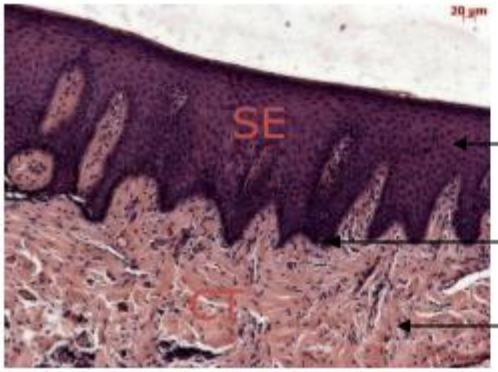
Early Detection of Oral Cancer

- Oral Cancer = 10th most common cancer
- Higher rates of occurrence in India due to **late diagnosis**
- Qualitative assessment by pathologists – **subjective**
- **Automated Diagnosis** => Quantitative assessment
- Via Pattern recognition methods

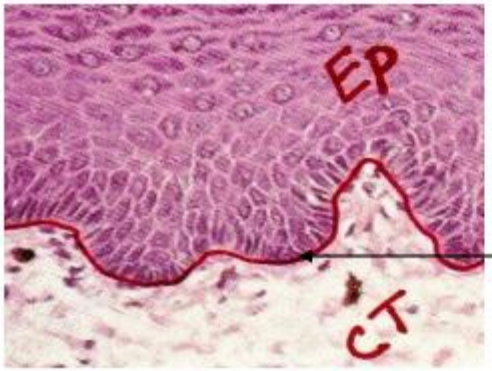
Early Detection of Oral Cancer



Surface epithelium

Basement membrane

Connective tissue

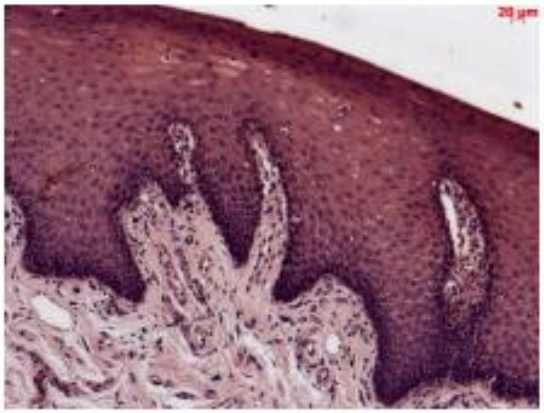


Oral mucous membrane

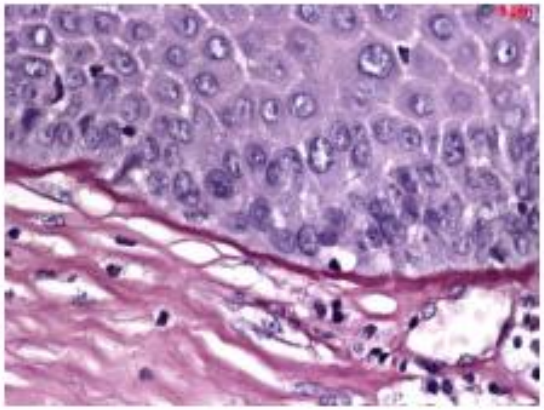
Photo micrograph of normal oral mucosa

Early Detection of Oral Cancer

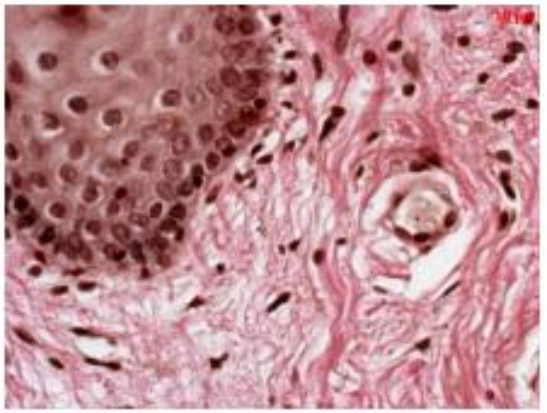
- Imaging of the histopathological slides
  - » Hematoxylin and Eosin (H&E) stained images
  - » Periodic acid-schiff (PAS) stained images
  - » Van Gieson (VG) stained images
  - » Magnifications-10x, 40x, 100x



H&E stained image

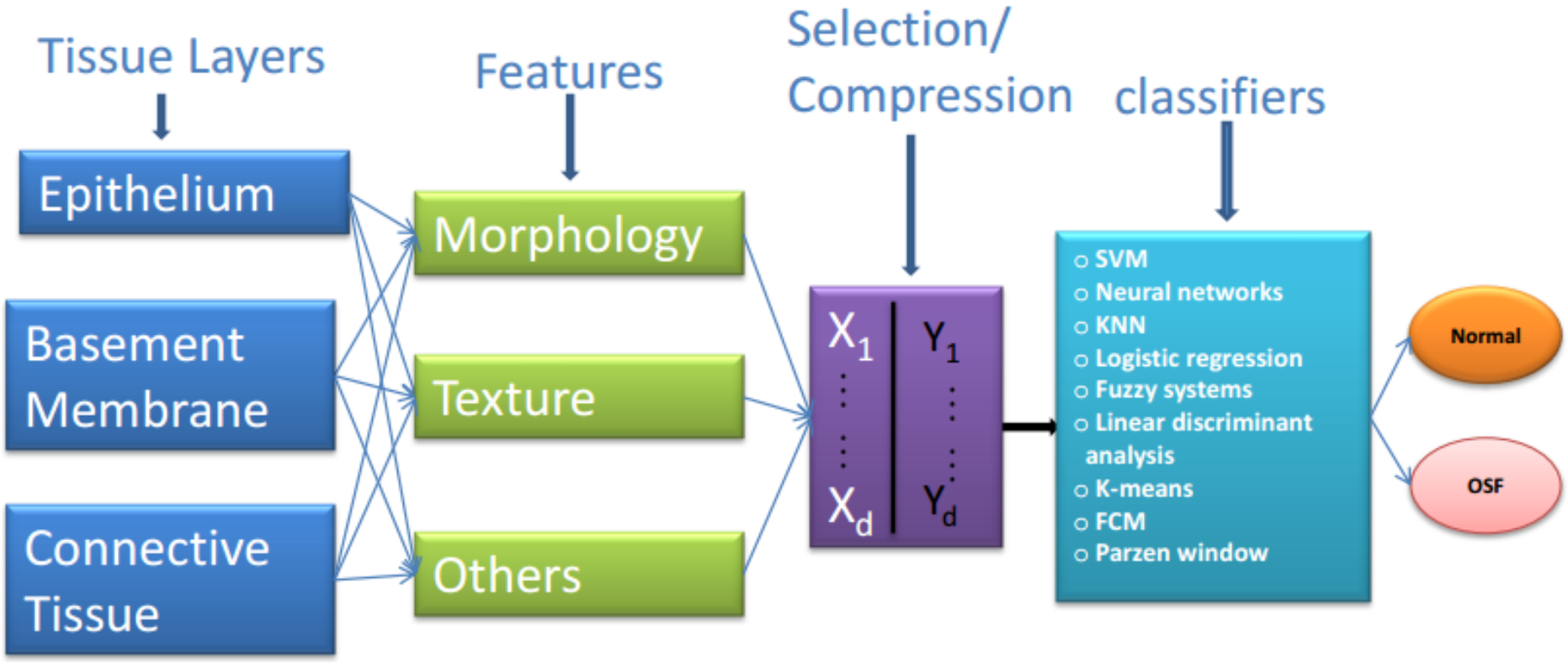


PAS stained image



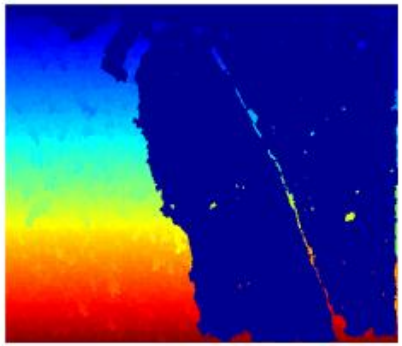
VG stained image

Early Detection of Oral Cancer

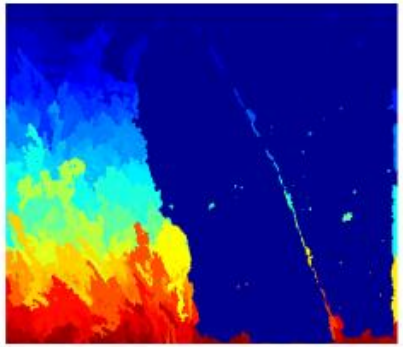


Early Detection of Oral Cancer

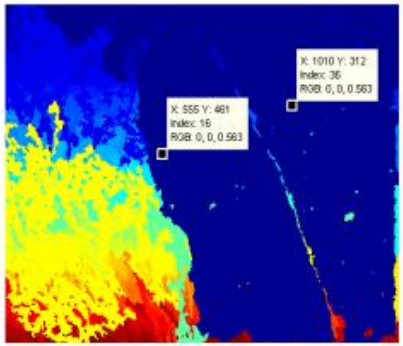
- Otsu's Thresholding & Region Merging with **Hotelling T^2 test criteria** after optimization



Watershed segmentation



Result of first region merging step



Labeled image after multivariate region merging

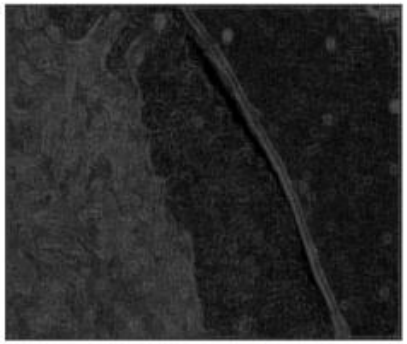
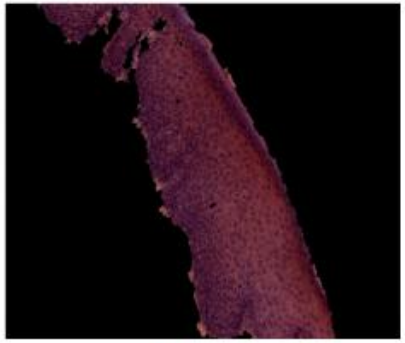


Image after similarity calculation



Segmented epithelial layer

Early Detection of Oral Cancer

- **Multi-scale** Texture Characterization via
  - Fractal Dimension (FD)
  - Gabor Wavelet
  - Brownian Motion Curve
  - Local Binary Pattern (LBP)
  - Principal Component Analysis (PCA)
  - Support Vector Machines (SVM)

Early Detection of Oral Cancer

Comparison between classifiers

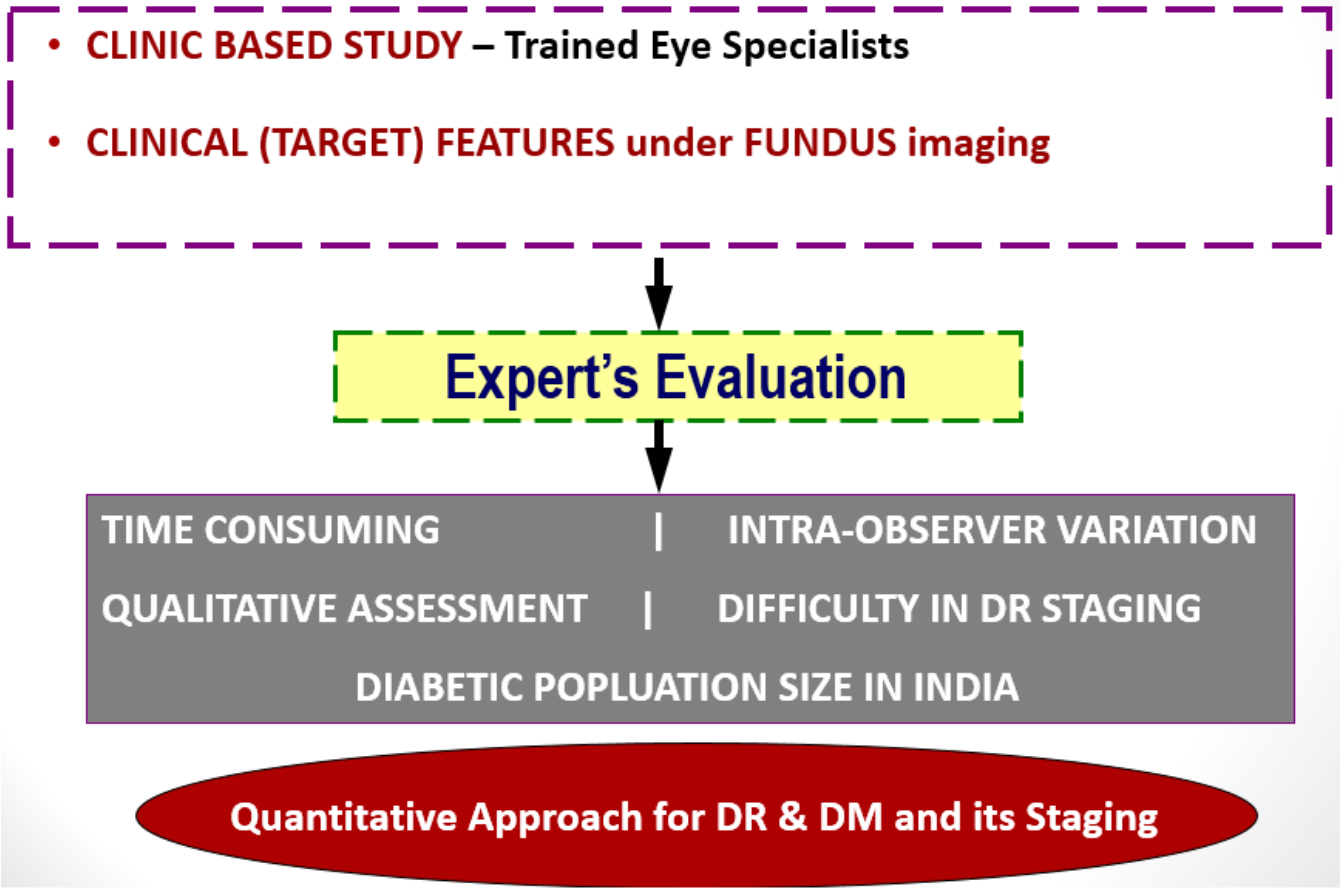
	LDA	BPNN
TP	7	12
TN	17	15
FP	3	0
FN	0	1
Sensitivity (%)	100.00	92.31
Specificity (%)	85.00	100.00
Area under ROC (%)	92.50	96.15
Accuracy (%)	88.89	96.43

Outline

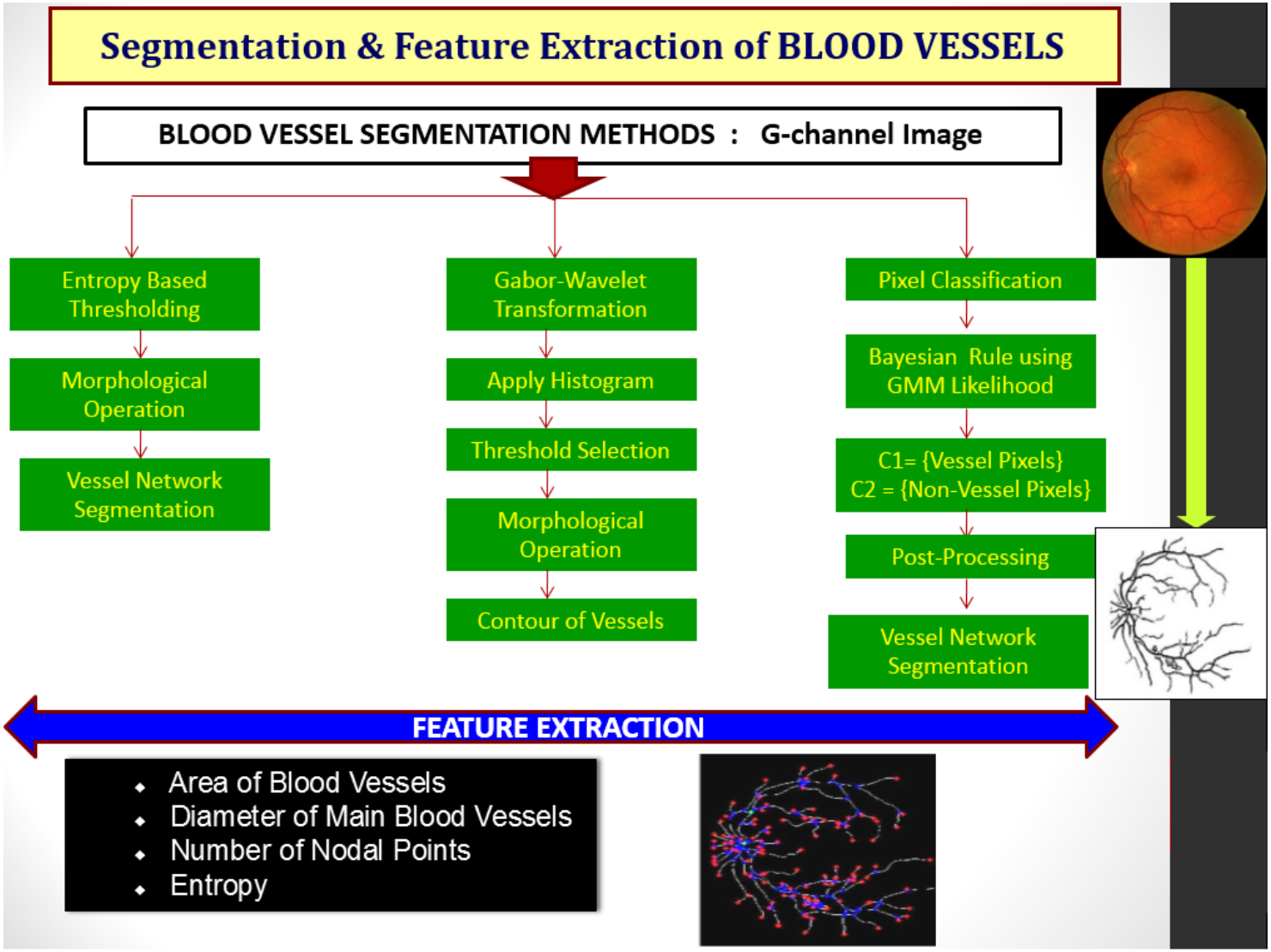
- Fundamentals of Pattern Recognition
- Rain Detection & Removal from Videos
- Chaotic Patterns
- Sparse Image Reconstruction
- Sparse Image Denoising
- Color Image Segmentation
- CBIR for Pathology
- Diabetic Retinopathy
- Brain Gliomas
- Language Engineering

Diabetic Retinopathy

- **Early screening** required to prevent **loss of vision** specially in Indian population

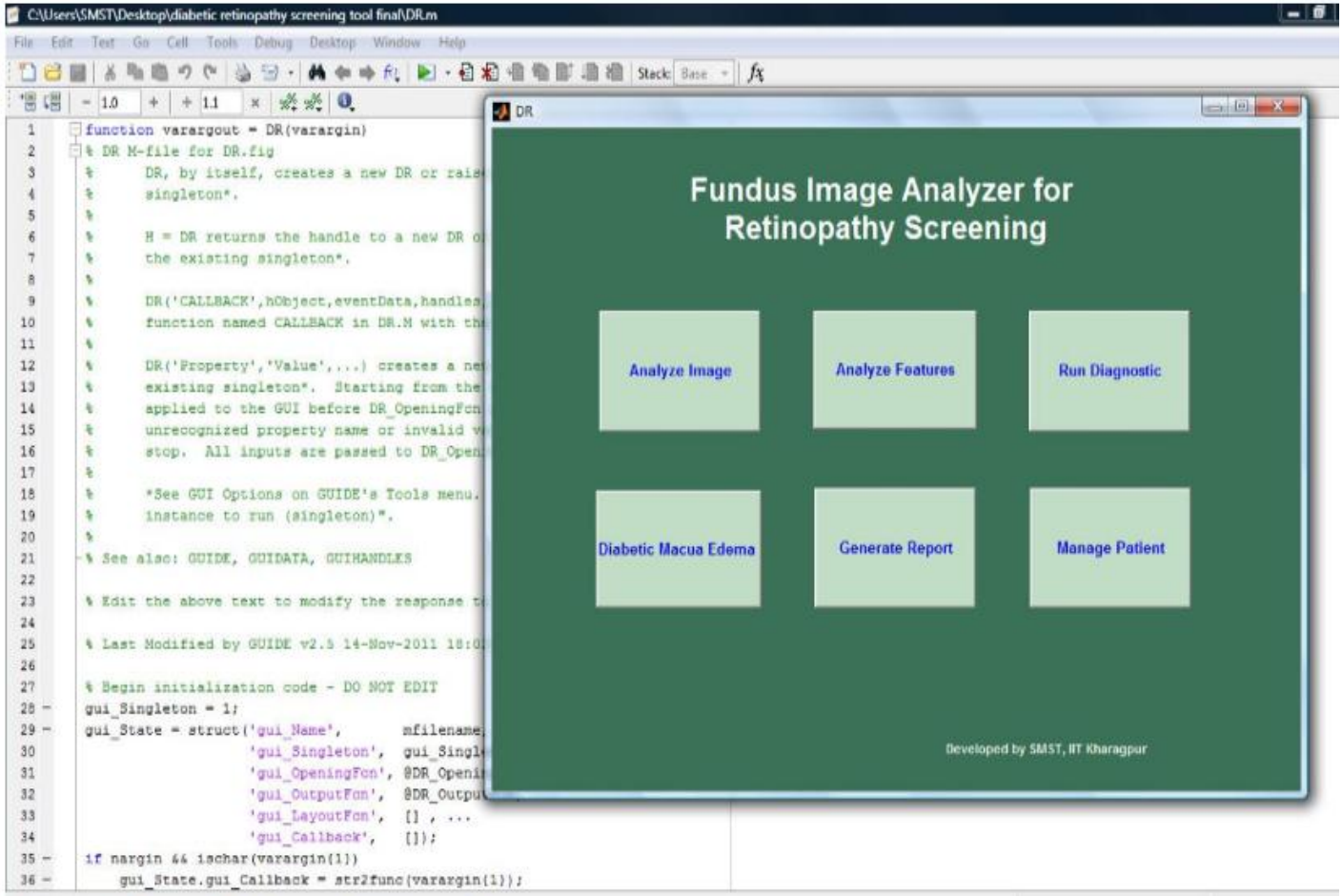


Diabetic Retinopathy

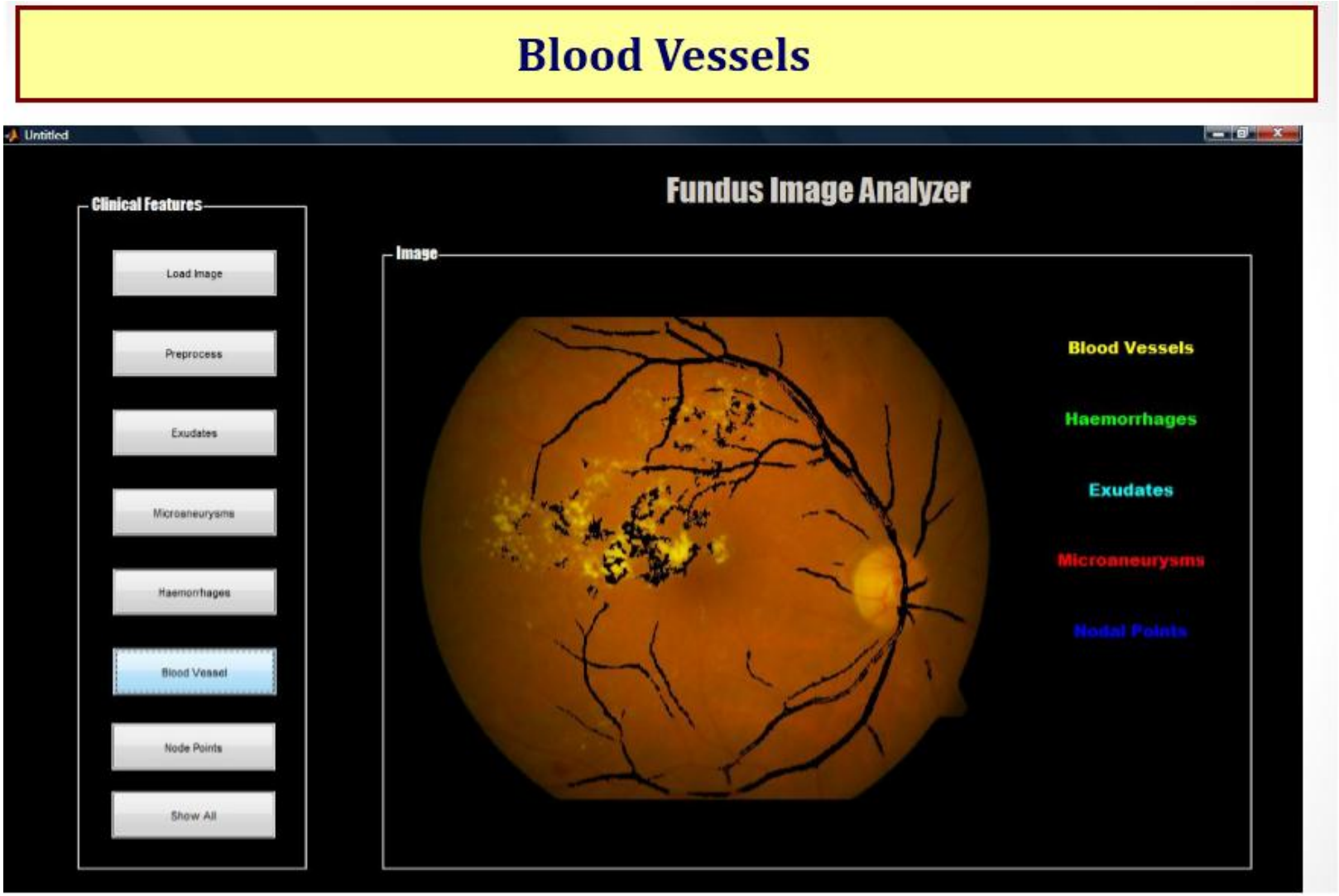


Diabetic Retinopathy

Developed Prototype Software for DR characterization

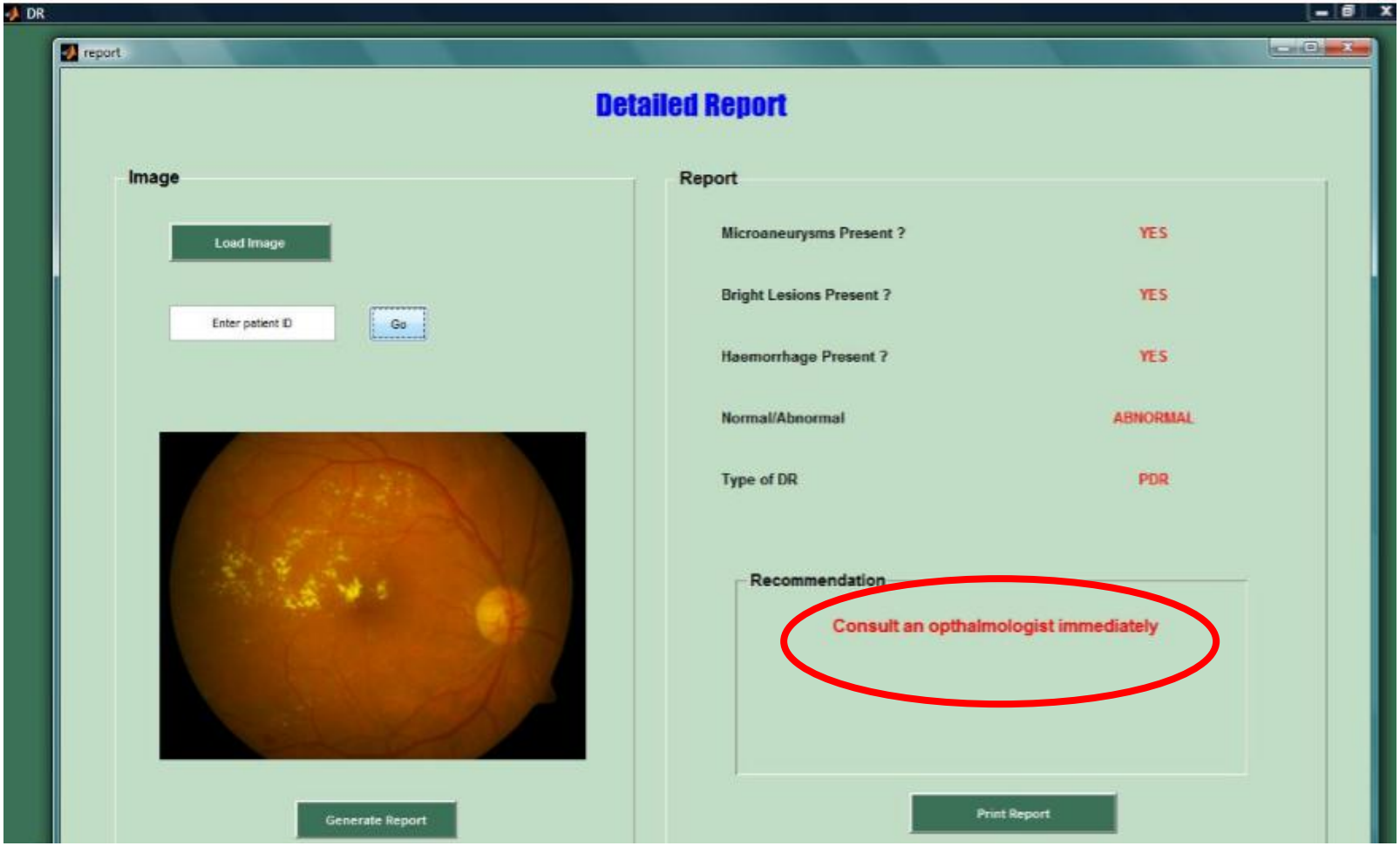


Diabetic Retinopathy



Diabetic Retinopathy

Report Generation for Patients



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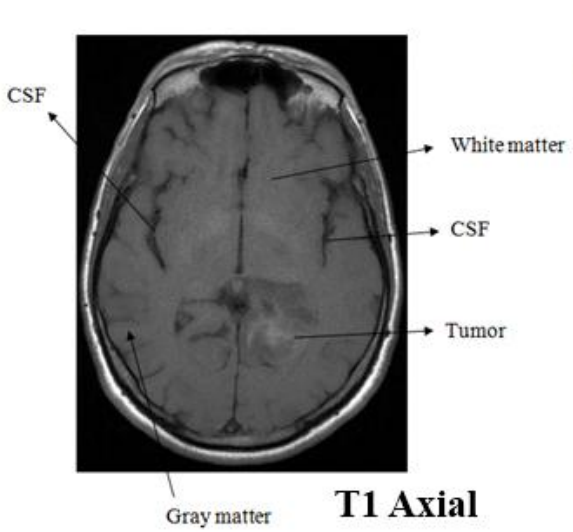
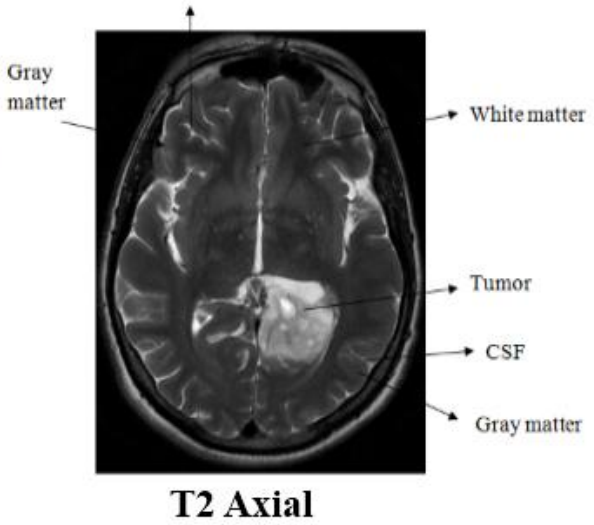
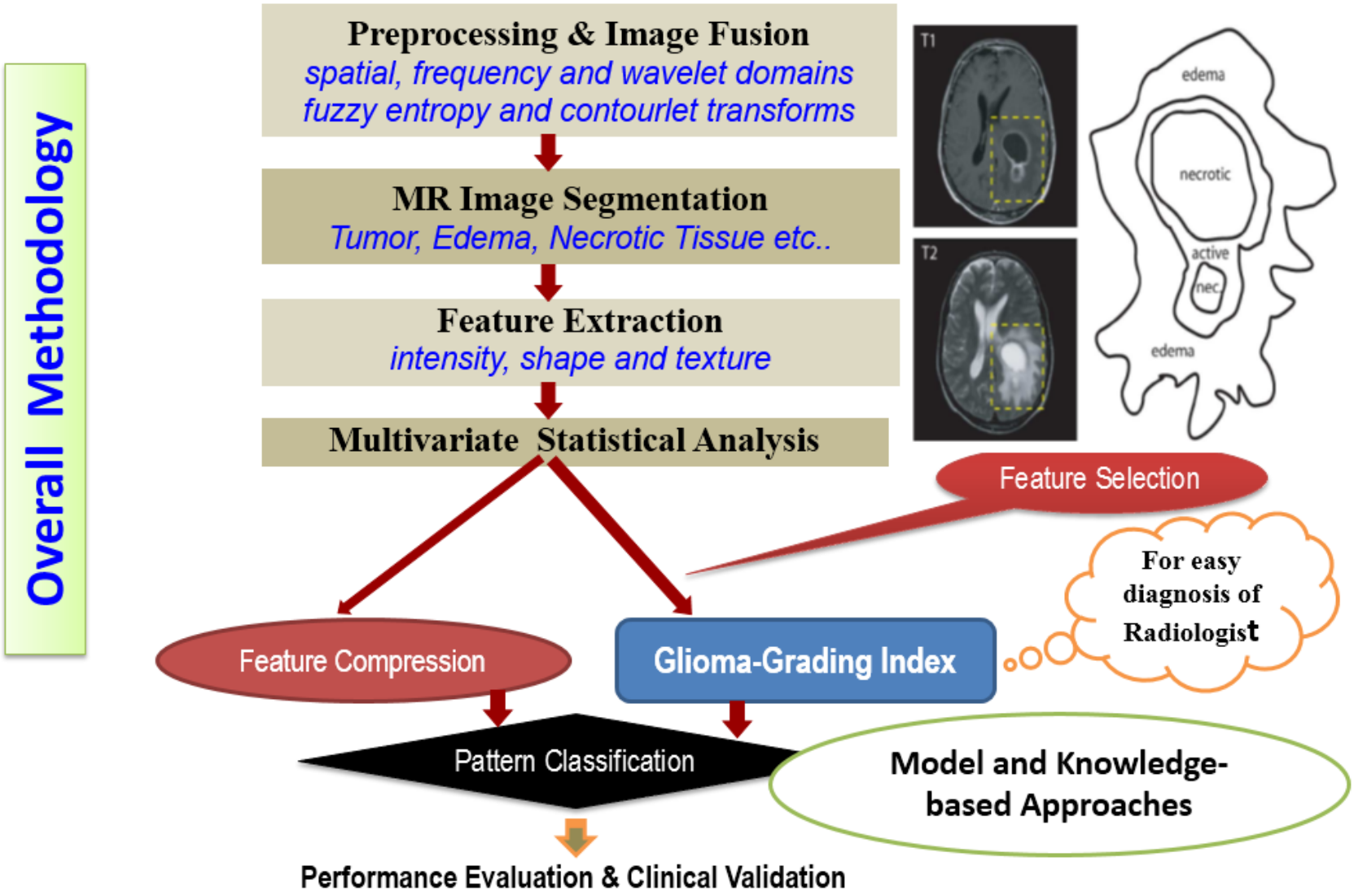
Brain Gliomas – MRI Imaging

- **Characterization and Grading of Brain Gliomas** using MRI images, via computer vision
- Glioma = most common primary **malignant brain tumor**
- Glioma grades I, II, III, IV (WHO 2000)
- 2nd leading cause of cancer deaths in **Male** and **Children**





Brain Gliomas – MRI Imaging



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Language Engineering – Daily Life

- Message/Email => **type in your own language/script**
- No need to write full text = > **Predictive Text**
- “Hinglish” => mera bharat mahan
- Say “Call maa”…your mom’s number will be dialled
- **Scribble** => translated to text
- Press 1 for existing customer, Press 2 … = BORING
  - Say it => **Speech Recognition**

Language Engineering – Daily Life

- How about **Cross Lingual Information Search**?
  - Suppose I want to know what's going on recently in Kerala, pick up local newspaper, but I don't know Malayalam language ☹
  - Give query online in my language
  - Obtain news articles of Kerala in my language ☺

- **Translation**:
  - Don't know French, but can chat with my French friend ☺

Language Engineering

- Language is key to culture, identity
- **Multi-lingual Character of Indian Society**
- Language = both basis for communication + barrier

- Provide **technology in my language**
- My language should play big role in business

- So, who will develop technology for my language?
  - Should we wait for Google or Microsoft to do this??

Language Engineering

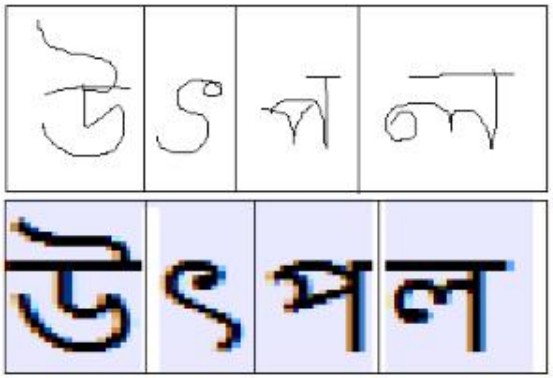
- How do we recognize alphabet?
- Can machine be trained to do the same?
  - Pattern classifiers
  - How to design pattern classifier
    - Structural
      - Shape, shape grammar
    - Statistical
      - Feature vector
      - Distance measure
    - Classification techniques
      - Prototype based
        - » Single prototype
        - » Multiple prototype
      - Machine learning
        - » NN, SVM

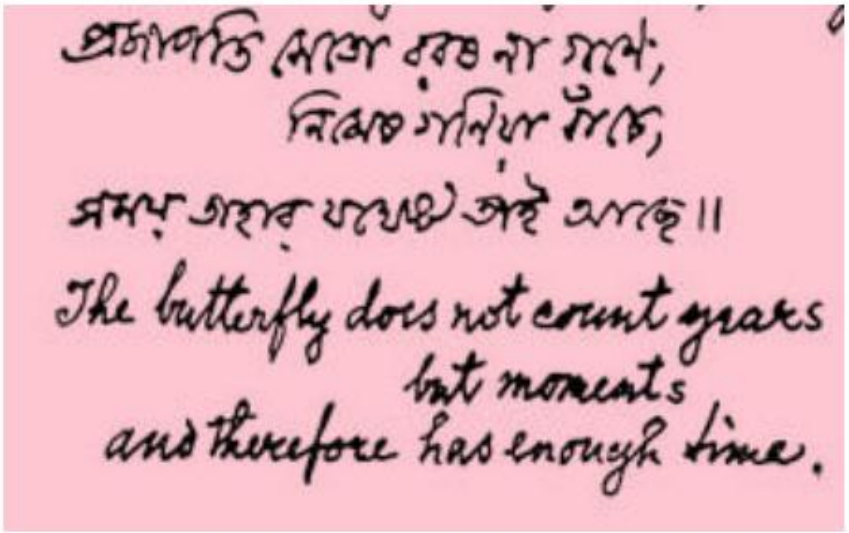
Language Engineering

- Style and size variation
- Machine printed
- Hand-printed
- Handwriting

Stylish Script

The Statesman





Language Engineering

স্যারের বদলি রুখতে মরিয়া গোটা গ্রাম

বাবা মা'কে বুঝিয়ে মেয়েটিকে প্রথম শ্রেণিতে বিদ্যালয়ে ভর্তি করেছিলেন 'মাস্টার।' সেই মেয়ে, রেকসানা খাতুন এ বার উচ্চ মাধ্যমিক দিয়েছে। ফাঁক পেলেই বল নিয়ে মাঠে চলে যেত সাহারুল হোসেন। মাঠ থেকে সাহারুলদের স্কুলে ধরে আনতেন তরুণ মাস্টারমশাই।

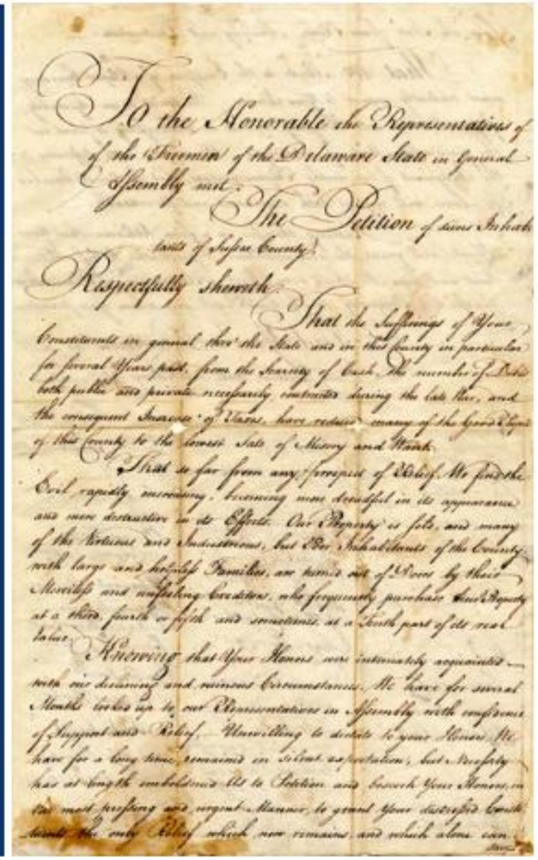
স্যারের বদলি রুখতে মরিয়া গোটা গ্রাম

বাবা মা'কে বুঝিয়ে মেয়েটিকে প্রথম শ্রেণিতে বিদ্যালয়ে ভর্তি করেছিলেন 'মাস্টার।' সেই মেয়ে, রেকসানা খাতুন এ বার উচ্চ মাধ্যমিক দিয়েছে। ফাঁক পেলেই বল নিয়ে মাঠে চলে যেত সাহারুল হোসেন। মাঠ থেকে সাহারুলদের স্কুলে ধরে আনতেন তরুণ মাস্টারমশাই।

স্যারের	বদলি	রুখতে	মরিয়া	গোটা	গ্রাম

Language Engineering

Skew



To the Honorable the Representatives of the Freemen of the Delaware State in General Assembly met. The Petition of sundry Inhabitants of Sussex County

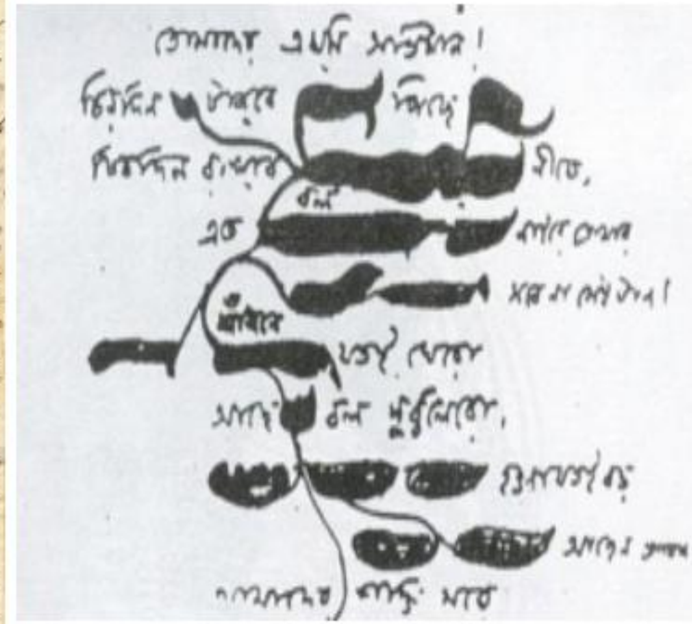
Respectfully sheweth

That the Sufferings of Your Constituents in general thro' the State and in this County in particular for several Years past, from the Scarcity of Cash, the number of Debts both public and private necessarily contracted during the late War, and the consequent Increase of Taxes, have reduced many of the Good People of this County to the lowest State of Misery and Want.

That so far from any prospect of Relief, We find the Evil rapidly increasing, becoming more dreadful in its appearance and more destructive in its Effects. Our Property is sold, and many of the Virtuous and Industrious, but Poor Inhabitants of the County with large and helpless Families, are turned out of Doors by their Merciless and unfeeling Creditors, who frequently purchase such Property at a third fourth or fifth and sometimes at a Tenth part of its real Value.

Knowing that Your Honors were intimately acquainted with our distressed and ruinous Circumstances, We have for several Months looked up to our Representatives in Assembly with confidence of Support and Relief. Unwilling to dictate to your Honors We have for a long time remained in silent expectation; but Necessity has at length emboldened Us to Petition and beseech Your Honors, in the most pressing and urgent Manner, to grant Your distressed Constituents the only Relief which now remains and which alone can

Image quality



Page layout analysis


Backspace
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Shift