Development of Decision Making Algorithm and other Softwares for Neutron & X-ray Imaging Applications

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Brief outline

- Study and design of decision making system for active neutron interrogation based illicit material detection system

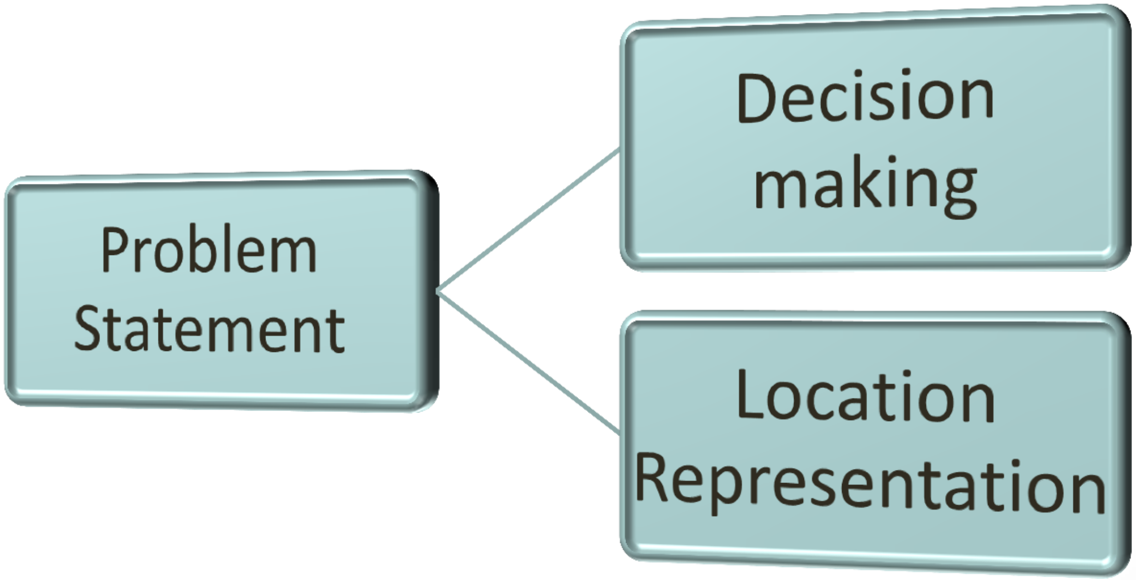
- Design and Development of device controller software for
  - Remote operation of outer gate at Dhruva imaging beamline and
  - 5 kV power supply for ion source

- 3-D Visualisation Software for reconstructed images

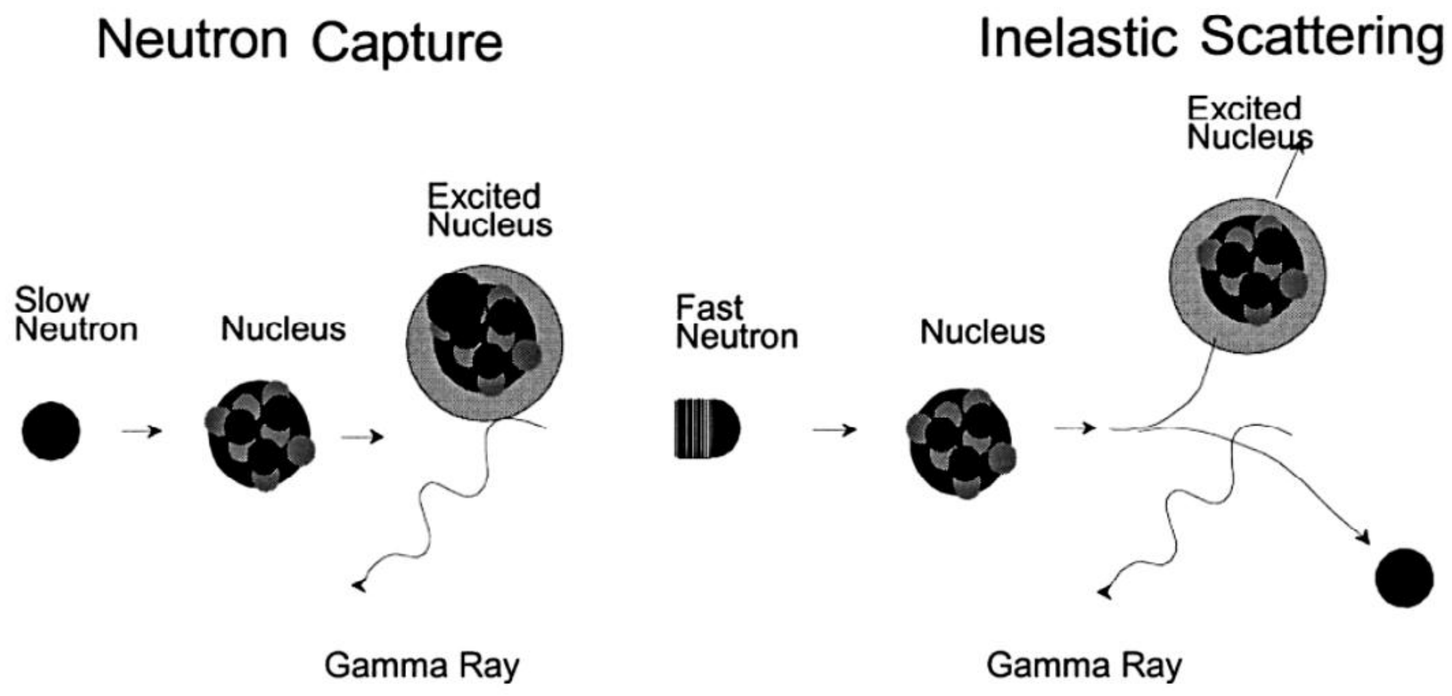
1. Decision Making Software

Problem Description

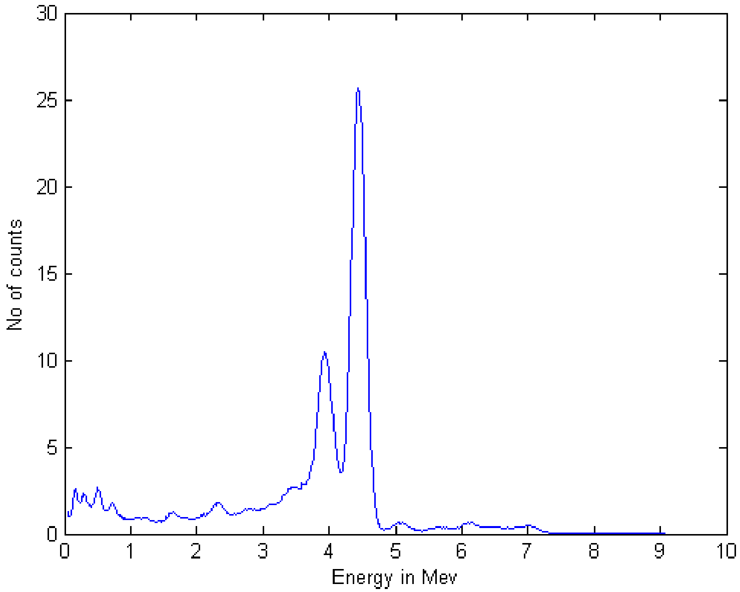
- To design a decision making algorithm, for classifying material under investigation as illicit or benign with a pictorial 3D view of the suspicious material inside a bulk.



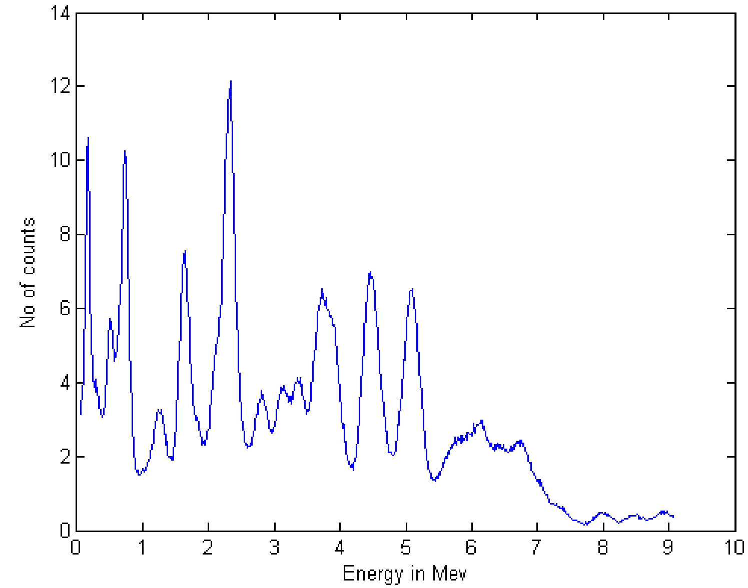
Principle



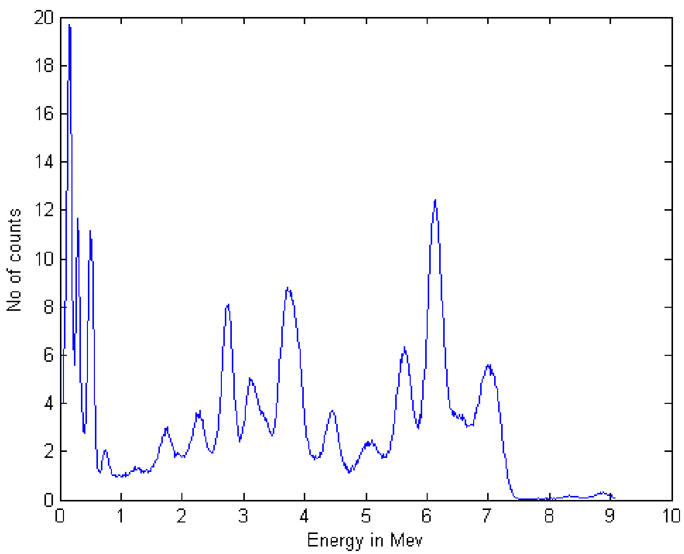
Neutron Capture
Inelastic Scattering
Slow Neutron
Nucleus
Excited Nucleus
Gamma Ray
Fast Neutron
Nucleus
Excited Nucleus
Gamma Ray



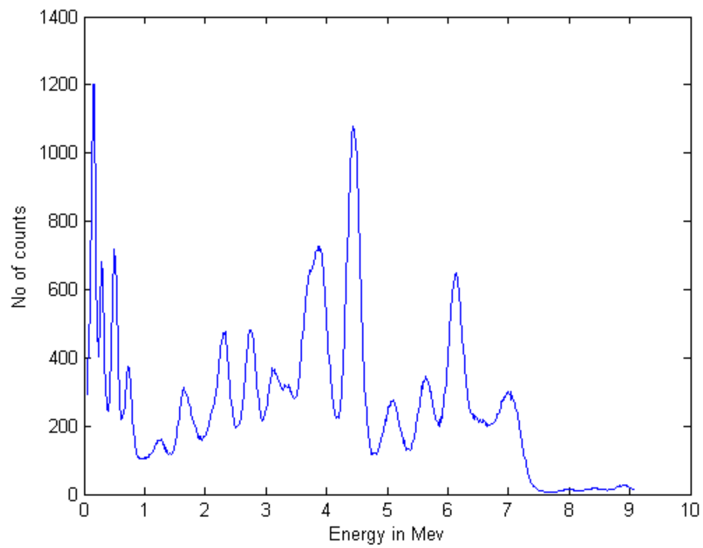
Gamma Spectrum for Carbon



Gamma Spectrum for Nitrogen



Gamma Spectrum for Oxygen



Gamma Spectrum for RDX

Motivation

Density or Ratio	H	C	N	O	Cl	C/O	C/N
Narcotics	High	High	Low	Low	Medium	High, > 3	High
Explosive	Low-Medium	Medium	High	Very High	Medium to None	Low < 1	Low, < 1
Plastic	Medium-High	High	High to low	Medium	Medium to None	Medium	Very High

Table 2.1: Elemental densities and ratios of three classes of substances

- Compositional parameters along with their specific representation decides the nature of the bulk
- A decision making is system is required to carry out this classification.

Name of Compound	C%	H%	N%	O%	Cl%	C/N	N/O	C/O	Cl/C	Cl/H	Nature
Heroin	68.29	6.23	3.79	21.68	0	18	0.18	3.15	0	0	Illicit Drug
Morphine	71.58	6.67	4.91	16.84	0	14.57	0.29	4.25	0	0	Illicit Drug
Codeine	72.24	7.02	4.68	16.05	0	15.43	0.29	4.5	0	0	Illicit Drug
Diphenoxylate	79.65	7.08	6.19	7.08	0	12.86	0.88	11.25	0	0	Illicit Drug
Thebaine	73.31	6.75	4.5	15.43	0	16.29	0.29	4.75	0	0	Illicit Drug
Cocaine	67.33	6.93	4.62	21.12	0	14.57	0.22	3.19	0	0	Illicit Drug
Amphetamin	80	9.63	10.37	0	0	7.71	Inf	Inf	0	0	Illicit Drug
Methamphetamine	80.54	10.07	9.4	0	0	8.57	Inf	Inf	0	0	Illicit Drug
MDMA	68.39	7.77	7.25	16.58	0	9.43	0.44	4.13	0	0	Illicit Drug
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
LSD	74.3	7.74	13	4.95	0	5.71	2.63	15	0	0	Illicit Drug
Ketamine	65.68	6.74	5.89	6.74	14.95	11.14	0.88	9.75	0.23	2.22	Illicit Drug
Salvinorin A	63.89	6.48	0	29.63	0	Inf	0	2.16	0	0	Illicit Drug
Dexomethophan	79.7	9.23	5.17	5.9	0	15.43	0.88	13.5	0	0	Illicit Drug
Ammonium Nitrate	0	5	35	60	0	0	0.58	0	Inf	0	Explosive
Ammonium Picrate	29.27	2.44	22.76	45.53	0	1.29	0.5	0.64	0	0	Explosive
RDX	16.22	2.7	37.84	43.24	0	0.43	0.88	0.38	0	0	Explosive
Ehtlenediamine dinitrate	12.9	5.38	30.11	51.61	0	0.43	0.58	0.25	0	0	Explosive
Nitrocellulose	24.24	2.36	14.14	59.26	0	1.71	0.24	0.41	0	0	Explosive
Nitroglycerine	15.86	2.2	18.5	63.44	0	0.86	0.29	0.25	0	0	Explosive
Nitrotriazolone	18.46	1.54	43.08	36.92	0	0.43	1.17	0.5	0	0	Explosive
PETN	18.99	2.53	17.72	60.76	0	1.07	0.29	0.31	0	0	Explosive
Picric acid	31.44	1.31	18.34	48.91	0	1.71	0.38	0.64	0	0	Explosive
Tetrazene	12.77	4.26	74.47	8.51	0	0.17	8.75	1.5	0	0	Explosive
Tetryl	29.27	1.74	24.39	44.6	0	1.2	0.55	0.66	0	0	Explosive
Trinitro Benzene	33.8	1.41	19.72	45.07	0	1.71	0.44	0.75	0	0	Explosive
TNT	37	2.2	18.5	42.29	0	2	0.44	0.88	0	0	Explosive
TAGN	7.19	5.39	58.68	28.74	0	0.12	2.04	0.25	0	0	Explosive
TATB	27.91	2.33	32.56	37.21	0	0.86	0.88	0.75	0	0	Explosive
C4	20.51	2.56	35.9	41.03	0	0.57	0.88	0.5	0	0	Explosive
Vanilin	63.16	5.26	0	31.58	0	Inf	0	2	0	0	Benign
Triclosam	49.74	2.42	0	11.05	36.79	Inf	0	4.5	0.74	15.21	Benign
Triclocurban	49.45	2.85	8.87	5.07	33.76	5.57	1.75	9.75	0.68	11.83	Benign
Sulfamethoxazolate	45.45	8.33	15.91	18.18	0	2.86	0.88	2.5	0	0	Benign
attrazine	45.18	5.18	32.94	0	16.71	1.37	Inf	Inf	0.37	3.23	Benign
Benzylparaben	73.68	5.26	0	21.05	0	Inf	0	3.5	0	0	Benign
Caffine	49.48	5.15	28.87	16.49	0	1.71	1.75	3	0	0	Benign
Trans cinnamic acid	72.97	5.41	0	21.62	0	Inf	0	3.38	0	0	Benign
Theobromine	46.67	4.44	31.11	17.78	0	1.5	1.75	2.63	0	0	Benign
phenylethylamine	74.23	11.34	14.43	0	0	5.14	Inf	Inf	0	0	Benign
Water	0	11.11	0	88.89	0	Inf	0	0	Inf	0	Benign
Urea	20	6.67	46.67	26.67	0	0.43	1.75	0.75	0	0	Benign
Keratin	50	12	25	10	0	2	2.5	5	0	0	Benign
Cotton/Cellulose	44.44	6.17	0	49.38	0	Inf	0	0.9	0	0	Benign
Polypropylene	85.71	14.29	0	0	0	Inf	Inf	Inf	0	0	Benign
PolyvinylChloride	38.4	4.8	0	0	56.8	Inf	Inf	Inf	1.48	11.83	Benign
Polystyrene	92.31	7.69	0	0	0	Inf	Inf	Inf	0	0	Benign

The System

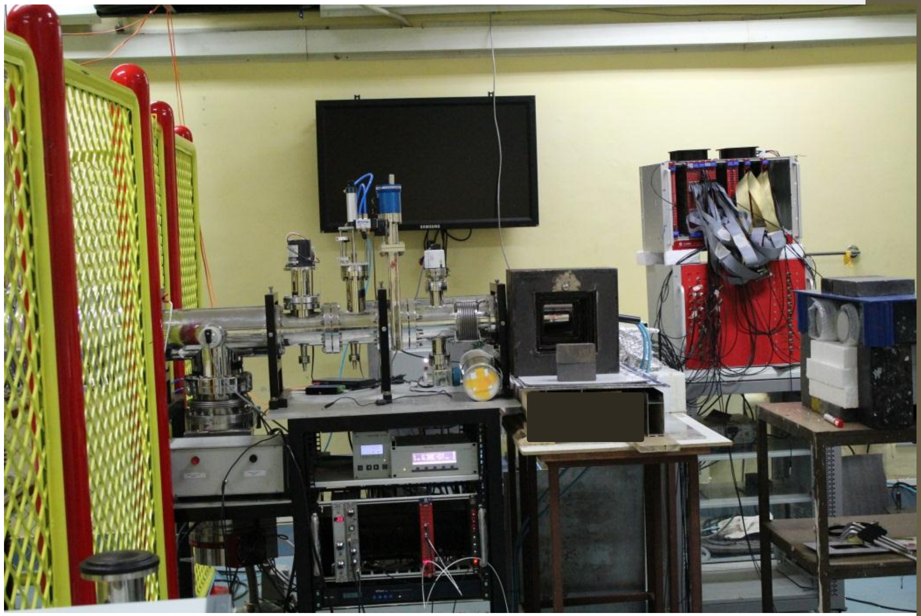
Neutron Generator

Interaction

Gamma Detection

Spectrum Analysis

Decision Making & Representation



$$t = [\text{Alpha Pixel} \quad \text{Gamma Energy} \quad \text{Time of Flight}]$$

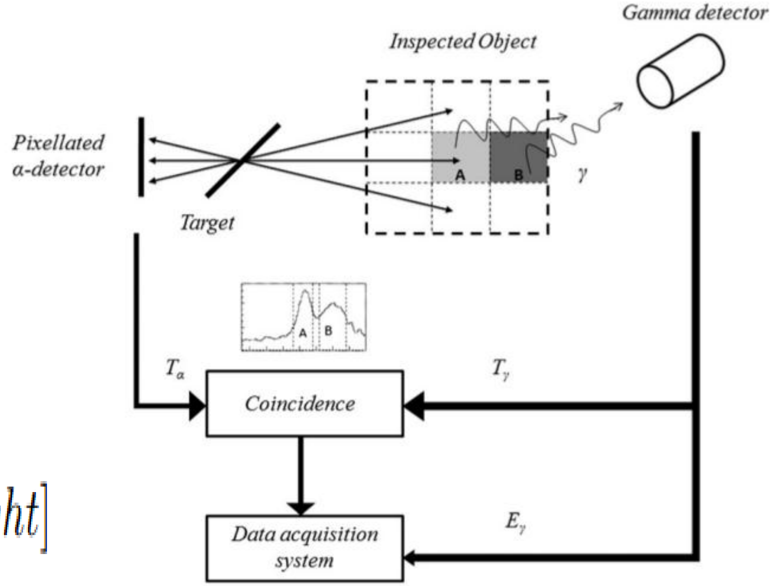
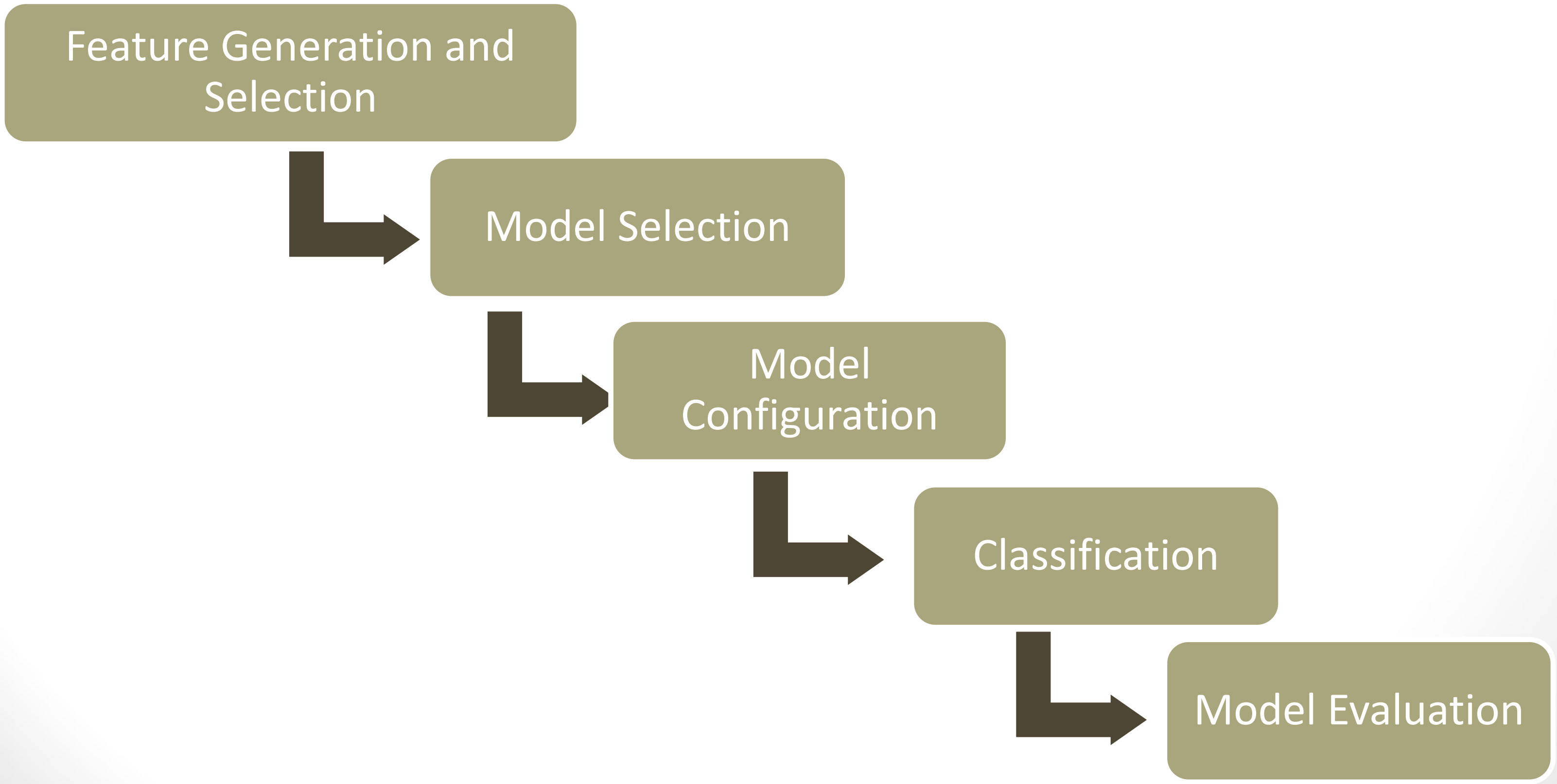


FIG. 1. Schematic of associated particle technique.

As a data mining problem

- Classification problem in a n-dimensional feature space.
- Features are either elemental ratios or fundamental elemental percent or derived parameters from elemental percentage.
- A separating surface/hyper-plane is to be determined which identify the material as Class + (Illicit) or as Class - (Benign).



Data used in the project

- Theoretical data: A list of 60 materials with 15 illicit drugs, 22 explosives and 23 benign material. This dataset is collected with their compositional ratios. This data is used to solve the decision making sub-problem.
- Simulated Data: Generated through n-material interaction for the 60 materials
- Experimental Data: Collected at test facility at NXPS, TPD.

Understanding Feature Vector

- **Feature Vector :** A feature vector is an n-dimensional vector of numerical features that represent some object.
- For the given problem features could be either ratios of elemental percentage or derived compositional parameter.
- Feature vectors may suffer from ‘The curse of dimensionality’
- Larger dimensional feature vectors are not easily comprehendible.
- A thumb rule says that samples must be visually separable in the n-dimensional feature space.
- To visualise the data in 2 or 3 dimensions, a dimensionality reduction is expected.

Steps followed in this classification problem → Feature Generation and Selection → Model Selection → Model Configuration → Classification → Model Evaluation

Possible Feature Vectors

- [C/N , C/O]
- [C/N , N/O]
- [C/N , O/C]
- [O/C , N/C]
- [C/O, N/O]
- [C/O , N/C]
- [N/C ,O/C]
- [N/C ,O/N]

- 5 Ratios (C/N, N/O, C/O, Cl/C, Cl/H)
- 3 Ratios (C/N, N/O, C/O)
- C-N-O percentage

Steps followed in this classification problem
Feature Generation and Selection
Model Selection
Model Configuration
Classification
Model Evaluation

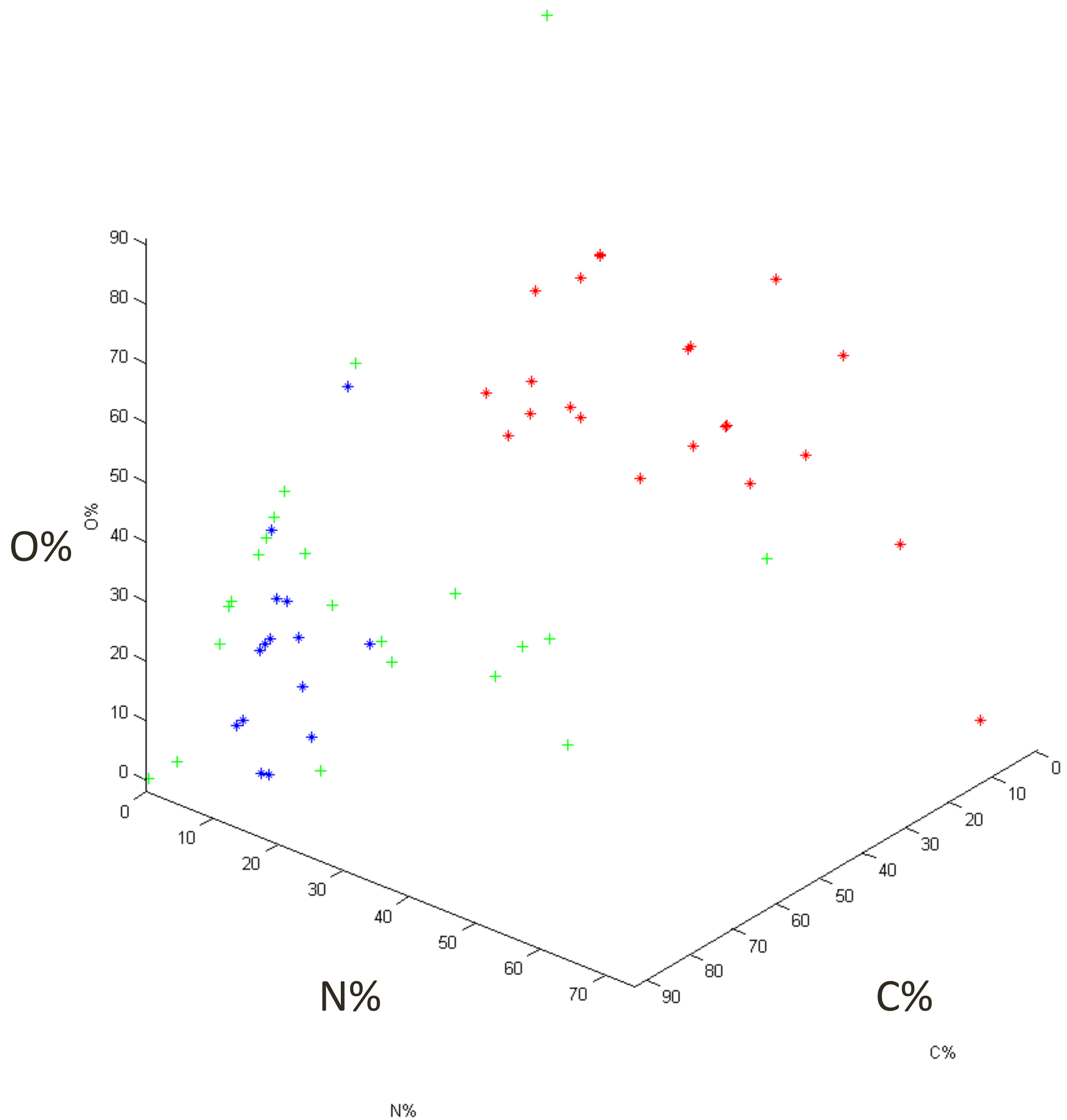
How these Feature vector space look

- A CNO space

Explosive

Illicit Drugs

Benign



Motivation for transformed CNO Space

- Ratios suffers from the infinity problem.
- Elemental percentages loses the ratio information
- A space is needed which can represent both absolute and relative information together.
- In general for such transformation ternary plot is used. But we can't use it

The reason is :

for ternary plot the assumption is

$$X + Y + Z = K$$
$$X \geq 0, Y \geq 0, Z \geq 0 \text{ and } K > 0$$

Actually this is a planner data.

In this case the condition is

$$X + Y + Z \leq K$$
$$X \geq 0, Y \geq 0, Z \geq 0 \text{ and } K > 0$$

This is region inscribed by a irregular tetrahedron

Steps followed in this classification problem → Feature Generation and Selection → Model Selection → Model Configuration → Classification → Model Evaluation

Solution: Transformation

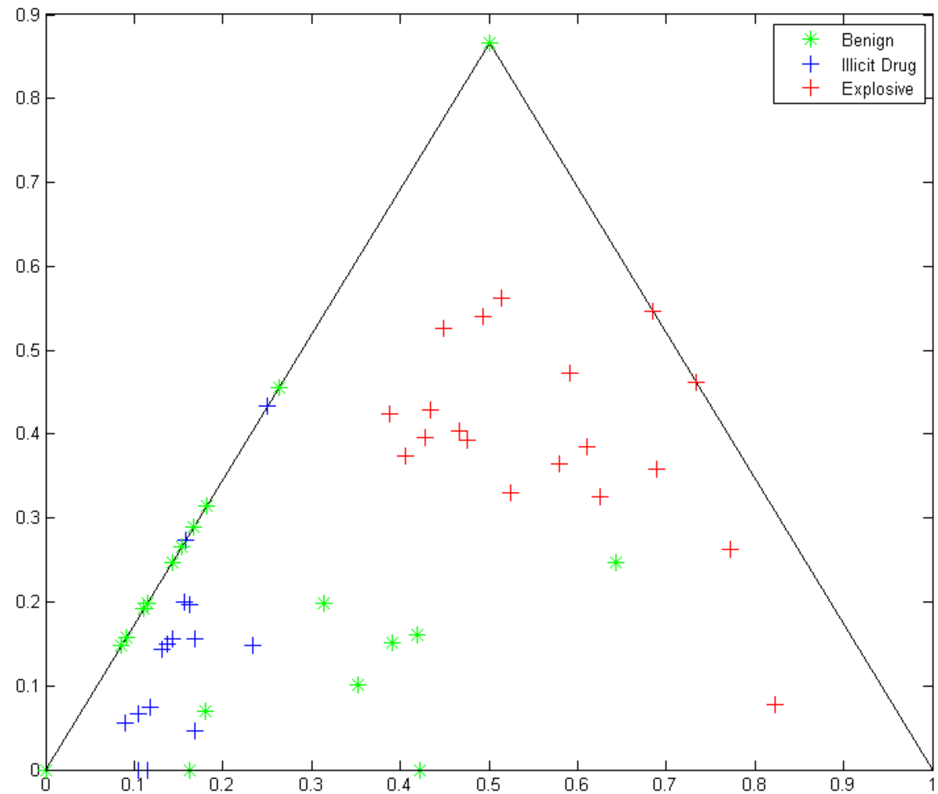
- The transformation will be followed by projection as a 3 D data is to converted into 2-D data

- Properties required:
  - Equal bias to all the principle axis
  - May represent the axis in such a way so that both absolute and relative information be read.
- Such a viewing angle is unit vector with direction cosine as $[1/\sqrt{3}, 1/\sqrt{3}, 1/\sqrt{3}]$

Thus the required transformation is calculated.

$$[U\ V\ W]^T = \begin{bmatrix} 1/\sqrt{3} & 1/\sqrt{3} & 1/\sqrt{3} \\ 1/\sqrt{2} & 0 & -1/\sqrt{2} \\ -1/\sqrt{6} & 2/\sqrt{6} & -1/\sqrt{6} \end{bmatrix} [X\ Y\ Z]^T$$

Transformed Coordinate space



Steps followed in this classification problem
Feature Generation and Selection
Model Selection
Model Configuration
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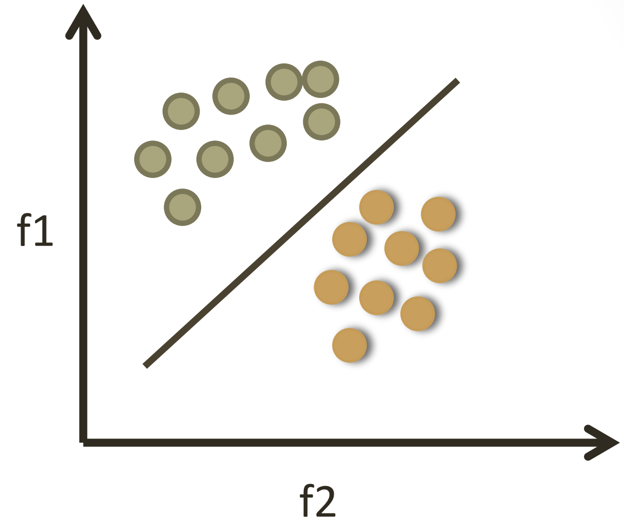
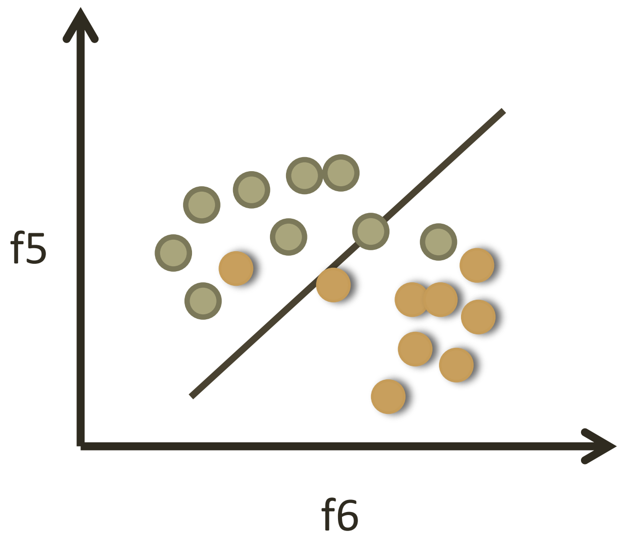
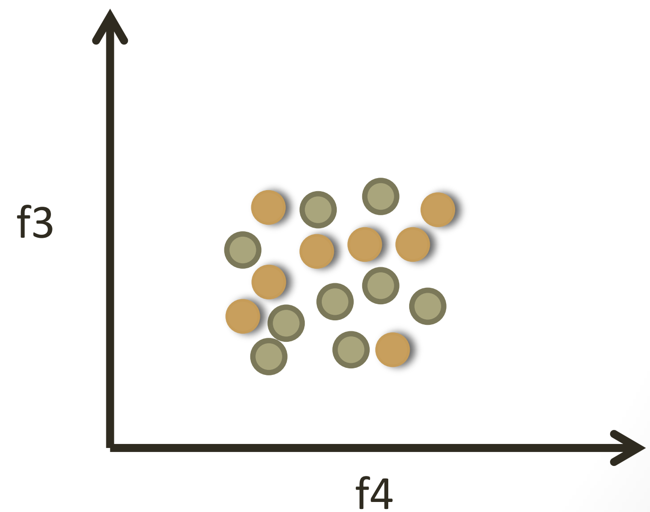
Model Evaluation

Feature Selection criteria

- Correlation
- Mutual Information
- Class separability



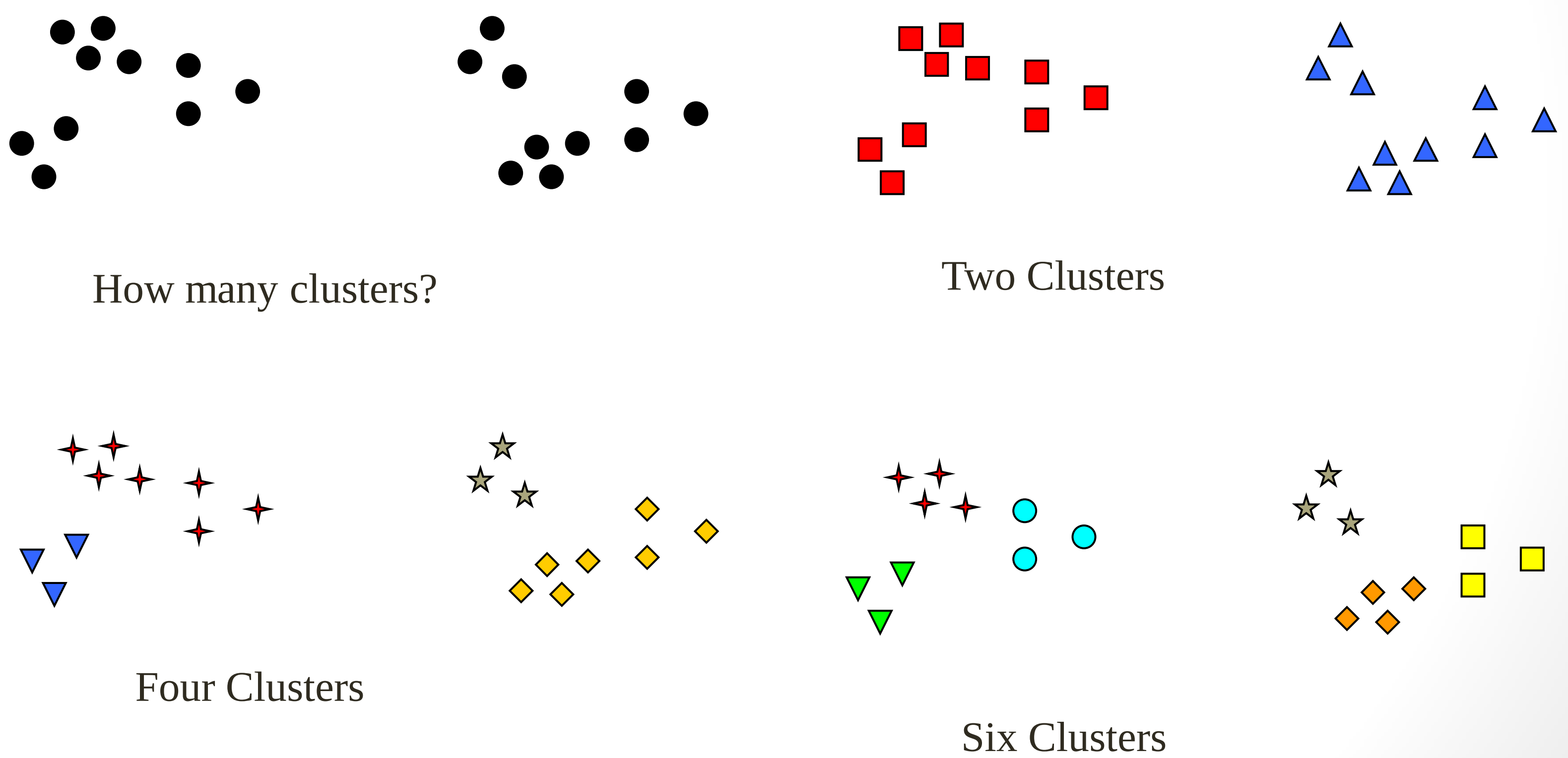


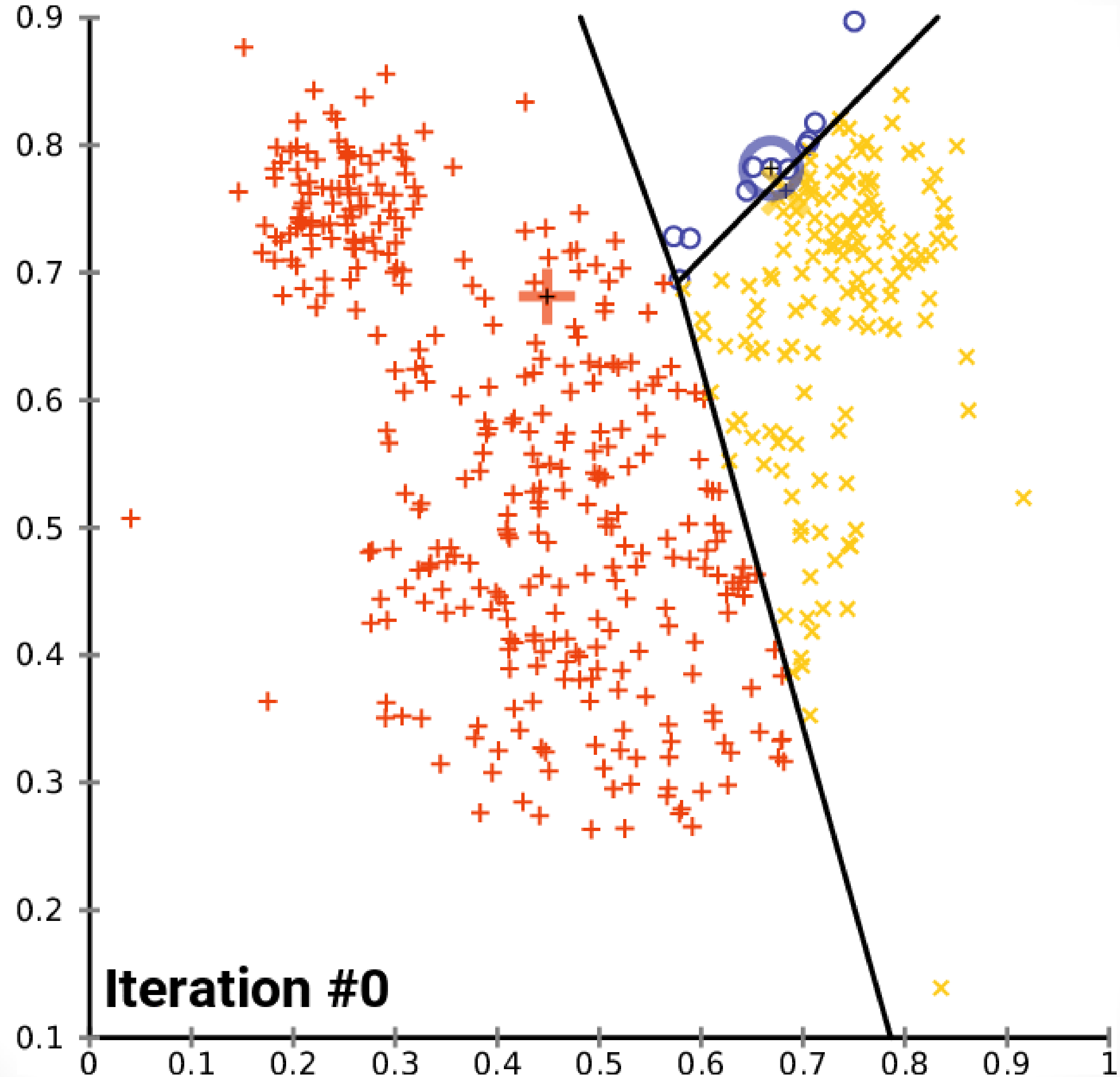


Steps followed in this classification problem → Feature Generation and Selection → Model Selection → Model Configuration → Classification → Model Evaluation

Clustering

- **Cluster analysis** or **clustering** is the task of grouping a set of objects in such a way that objects in the same group (called a **Cluster**) are more similar (in some sense or another) to each other than to those in other groups (clusters).





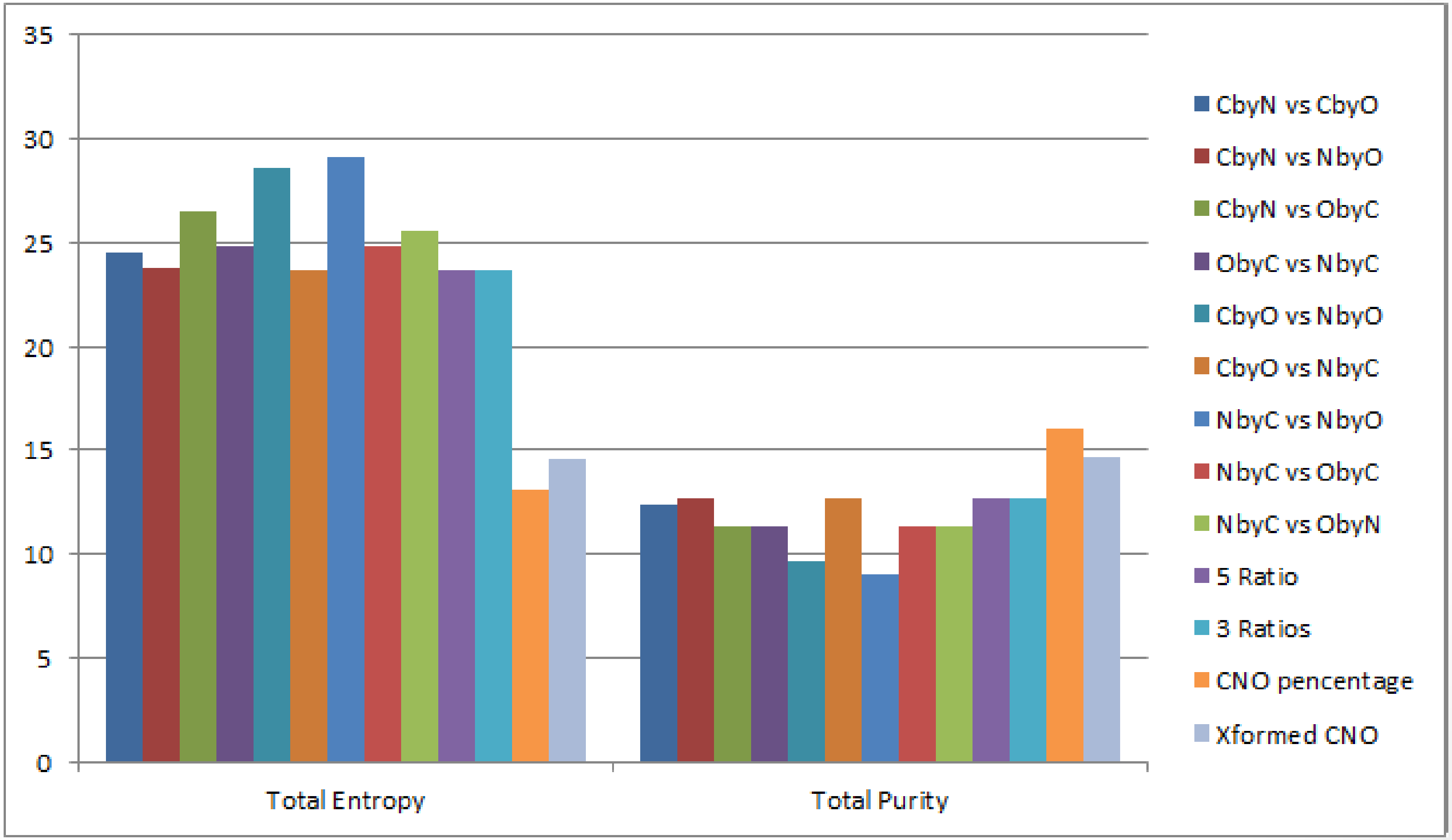
Source: Wikipedia

Supervised Measures of Cluster Validity

- To measure the degree of correspondence between the cluster labels and the class labels.

- Mathematical measure to calculate correspondences are
  - Purity
  - Entropy
  - Rand-Statistics etc.

Comparison of cluster metrics



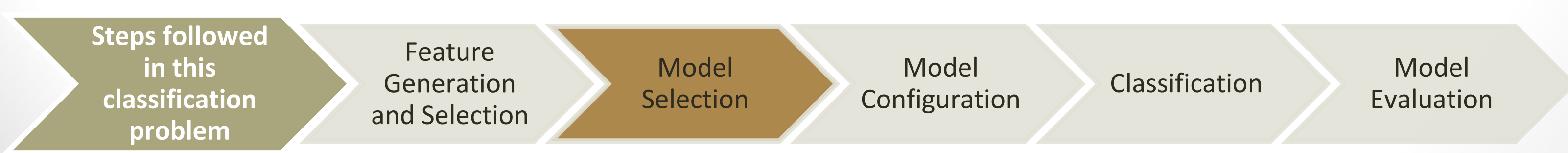
Input formats Used

- 5 ratios (C/N, N/O, C/O, Cl/C, Cl/H)
- 3 ratios (C/N, N/O, C/O)
- Elemental Percentage(C%, N%, O%)
- Transformed elemental percentage space.

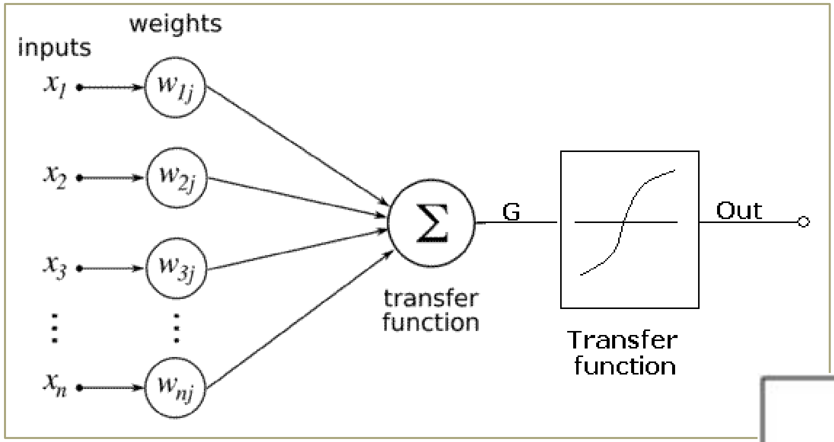
Possible Approaches

- Nearest Neighbour
- Artificial Neural Networks
- Support Vector Machines
- Fuzzy Logic etc.

These are the broad areas of the solution approach, even each of the method can be tuned in many configurations.

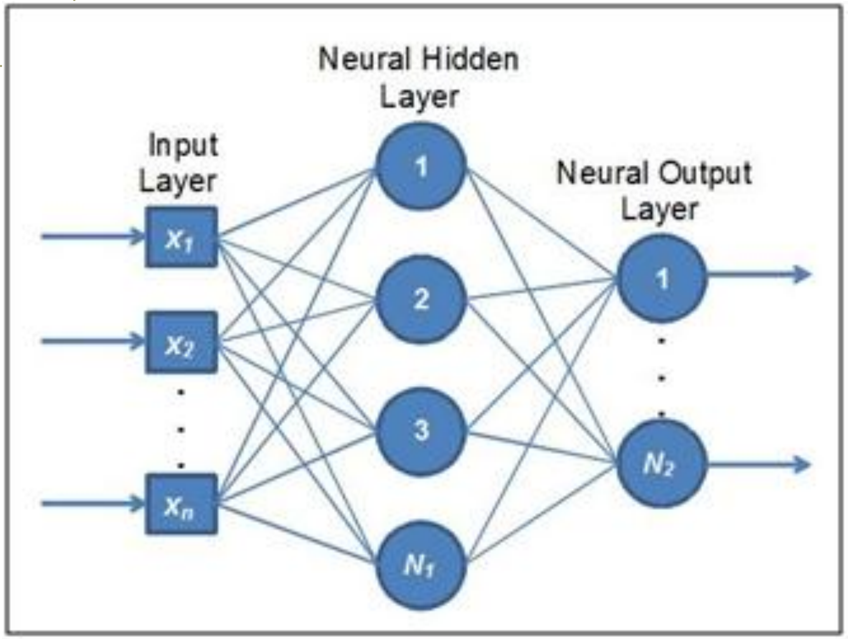


Artificial Neural Network



Micro structure parameters

- Transfer function
- Learning algorithm
- Input and output representation



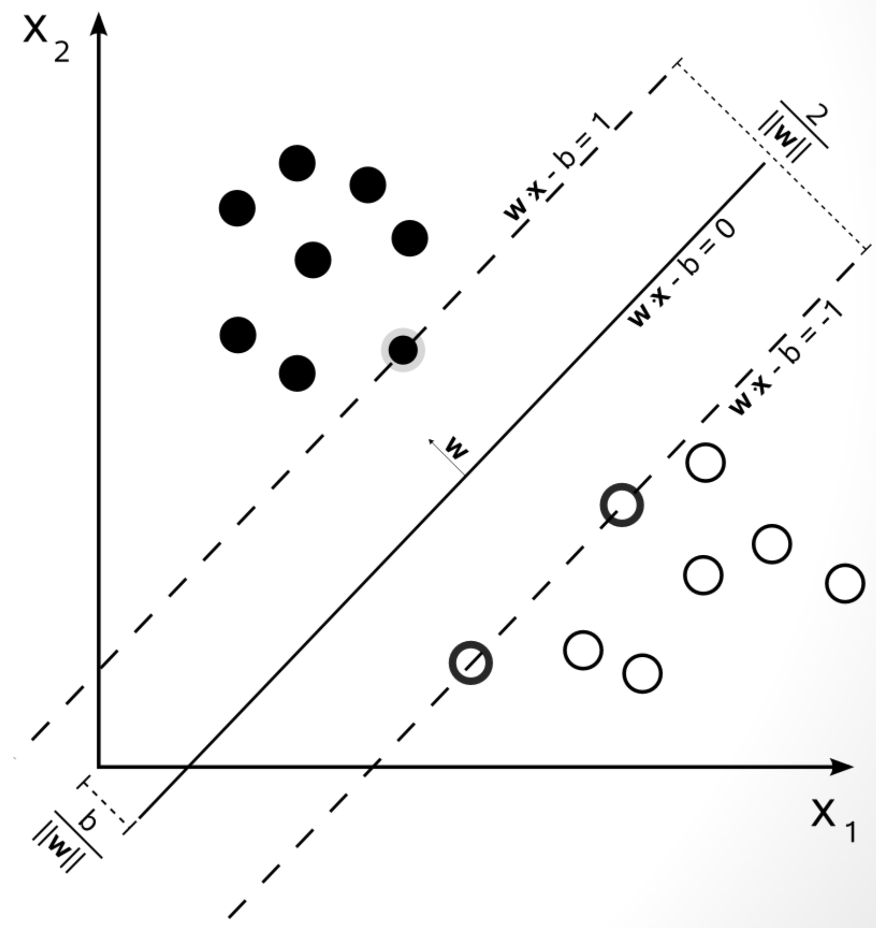
Macro structure parameters

- No of layers
- Size of layers
- Interconnection

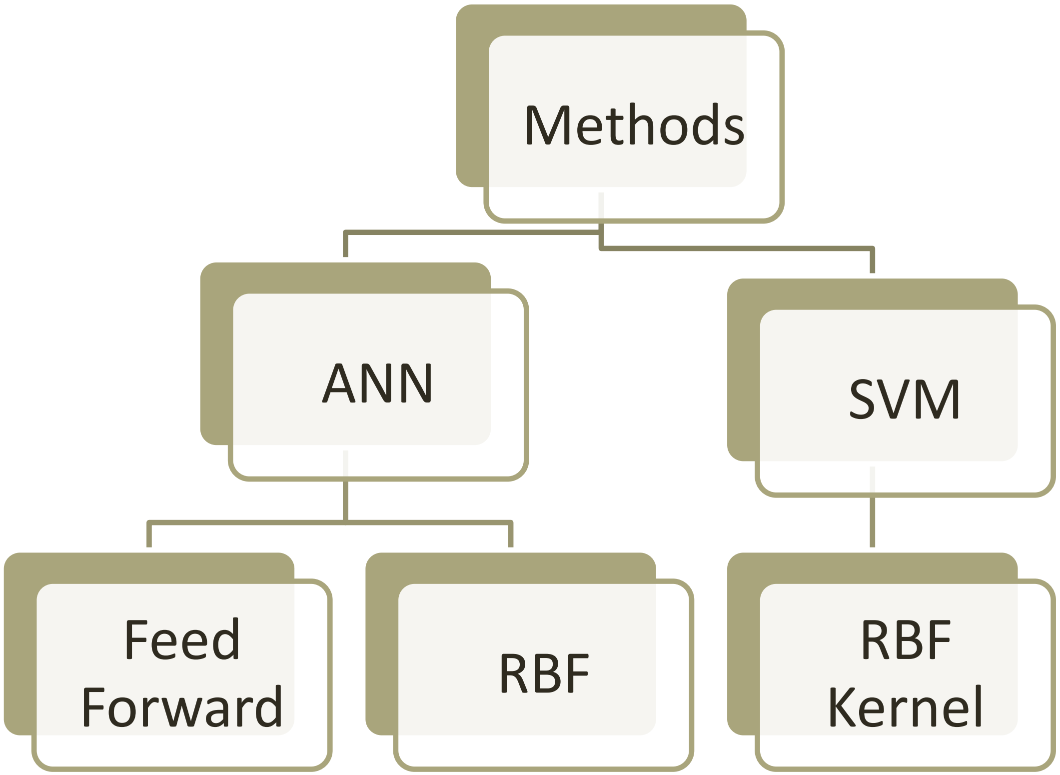
Support Vector Machine

Parameters in support vector machine:

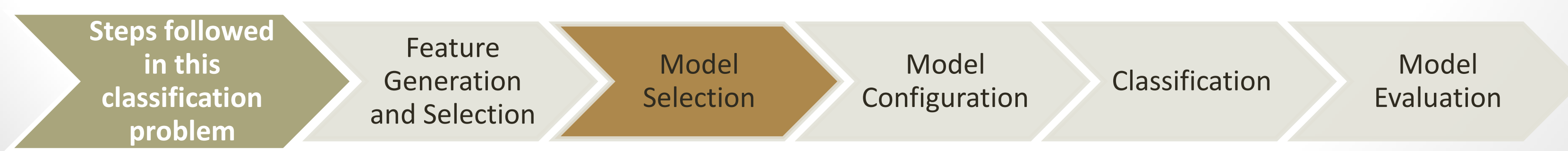
- C, Penalty Factor
- Ɛ, Error Factor
- Kernel
- Kernel Parameters



Methods Adopted for classification



All of them are tested with all the final feature vectors(5Ratios, 3Ratios, CNO and X-CNO)



Goodness of the method

- Performance metrics:
  - ✓ Confusion Matrix

"confusion matrix"
or
"contingency table"

		Actual +	Actual -
Predicted	Y	True positives	False positives
Predicted	N	False negatives	True negatives

✓ Weighted Average of the Confusion Matrix

✓ **Precision** :

$$Precision(P) = \frac{tp}{tp+fp}$$

✓ **Recall**:

$$Recall(R) = \frac{tp}{tp+fn}$$

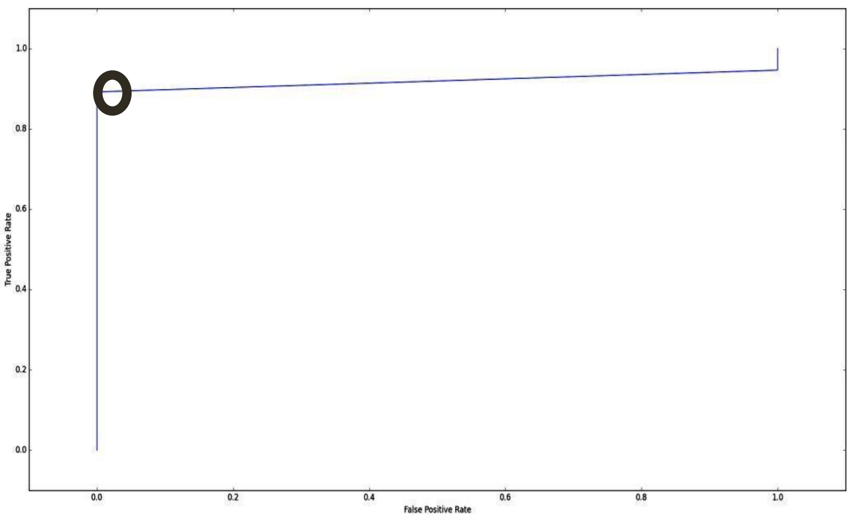
✓ **F-Measure :**

$$F\text{-}Measure(F) = \frac{2*P*R}{P+R}$$

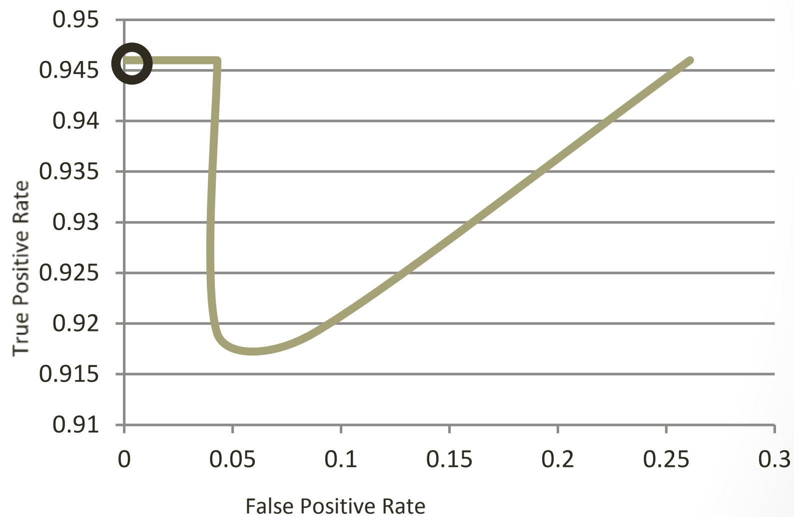
A High F-Measure is desired.

Configuration of model

- Both the models are configured for their free parameters and ROC was generated and using optimum value of ROC the configuration parameters are selected. ROC is plot between true positive rate and false positive rate so, object to have high true positive rate and low false positive rate.



ROC for ANN



ROC for SVM

- **Steps followed in this classification problem**
- Feature Generation and Selection
- Model Selection
- Model Configuration
- Classification
- Model Evaluation

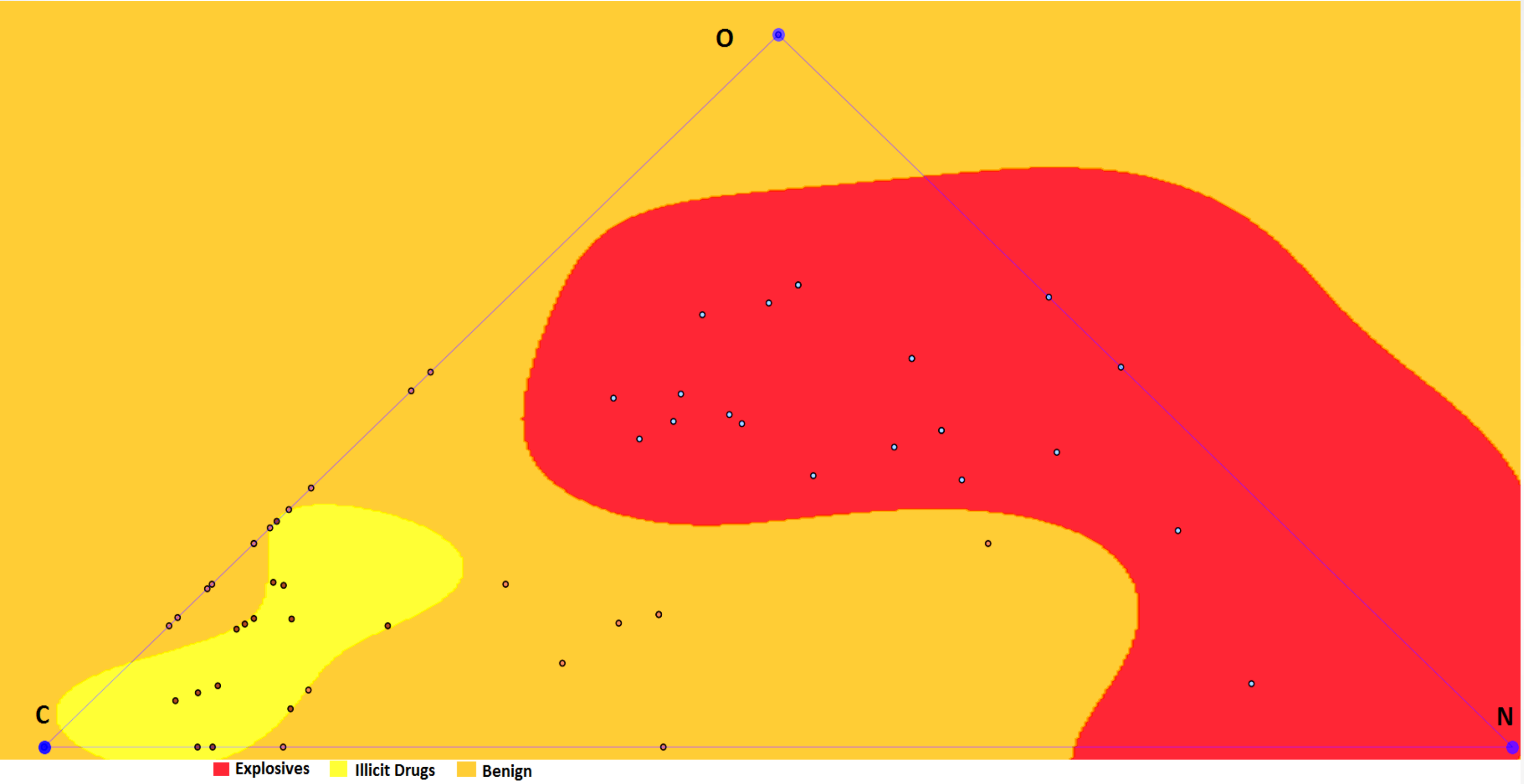
Results and discussion

- Models are configured and result are generated for different inputs and models. A sample result is shown in the table below.

	Trained with 0%						
	Tested with 0 %	Tested with 10%	Tested with 20%	Tested with 30%	Tested with 35%	Tested with 40%	Tested with 50%
FMeasure	0.95	0.95	0.95	0.92	0.92	0.91	0.88
Classification Accuracy	0.93	0.93	0.93	0.9	0.9	0.88	0.85
Discriminant Power	2.87	2.87	2.87	2.38	2.44	2.28	1.87
Error Rate	0.07	0.07	0.07	0.1	0.1	0.12	0.15
FalseNegative Percentage	0.03	0.03	0.03	0.05	0.03	0.03	0.07
FalsePositive Percentage	0.03	0.03	0.03	0.05	0.07	0.08	0.08
Negative Likelihood	16.89	16.89	16.89	10.72	15.28	14.48	7.24
Positive Likelihood	10.88	10.88	10.88	7.05	5.44	4.35	4.1
Precision	0.95	0.95	0.95	0.92	0.9	0.88	0.87
Recall	0.95	0.95	0.95	0.92	0.95	0.95	0.89
Sensitivity	0.95	0.95	0.95	0.92	0.95	0.95	0.89
Specificity	0.91	0.91	0.91	0.87	0.83	0.78	0.78
TrueNegative Percentage	0.35	0.35	0.35	0.33	0.32	0.3	0.3
TrueNegative Rate	0.91	0.91	0.91	0.87	0.83	0.78	0.78
TruePositive Percentage	0.58	0.58	0.58	0.57	0.58	0.58	0.55
TruePositive Rate	0.95	0.95	0.95	0.92	0.95	0.95	0.89

Table 5.1: Results for feedforward network trained with 0% error 5 Ratio theoretical data and tested with 0%, 10%, 20%, 30%, 35%, 40%, 50% random relative error

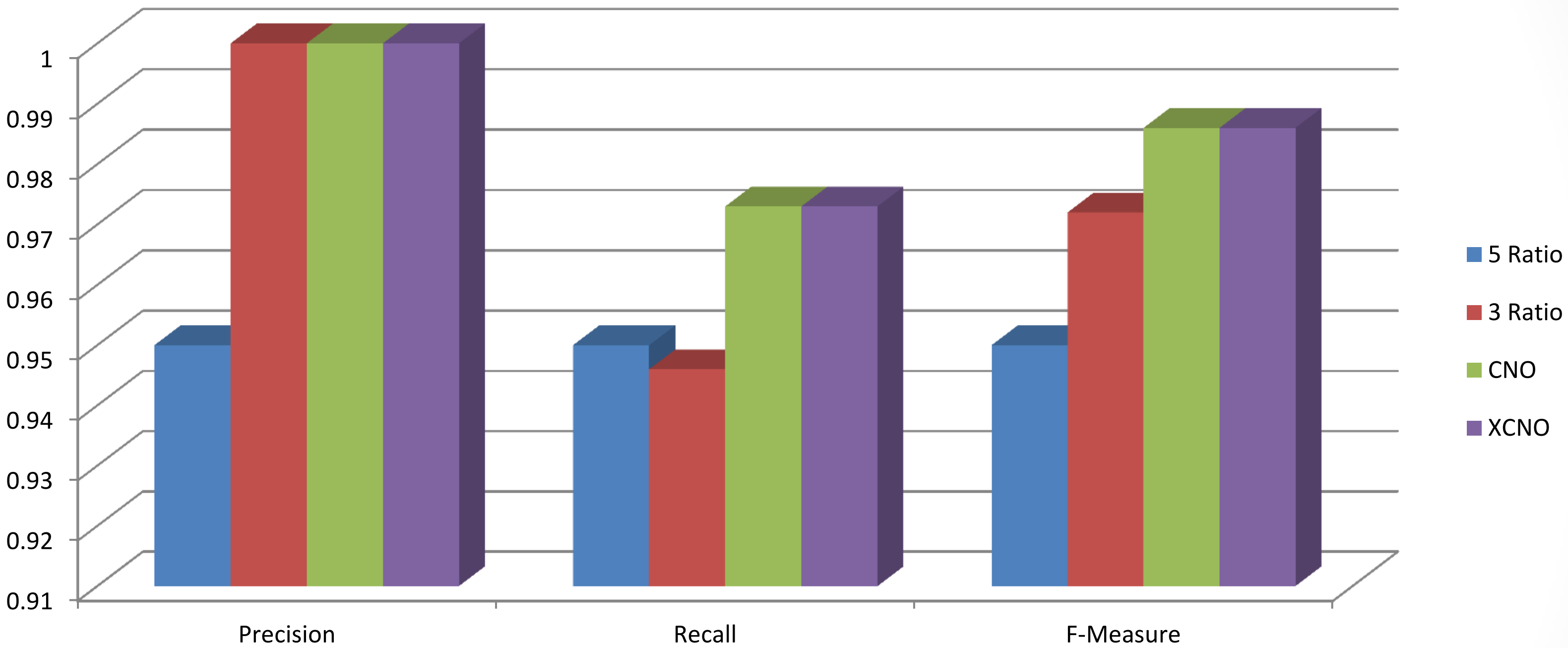
Results and discussion



Classification in transformed CNO space using SVM having RBF kernel.

Results: Theoretical Data(Contd)

- Comparison between different feature vector for Artificial Neural Network with Backpropagation tested with 0 % error data

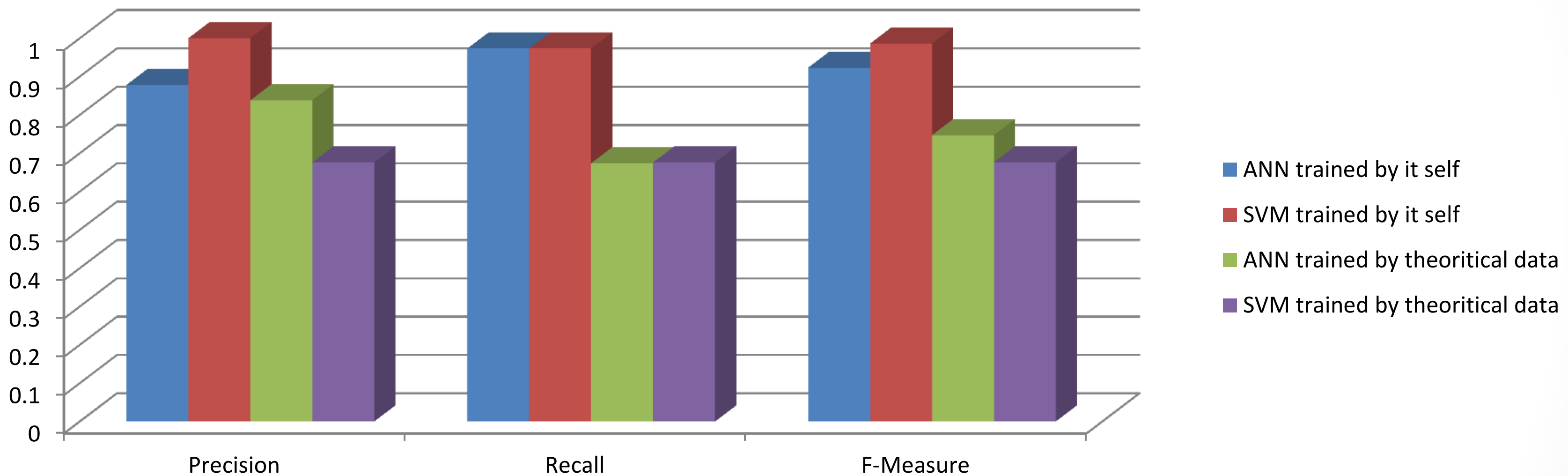


- Clearly Shown that CNO and XCNO over shadows the performance using 5 Ratios and 3 Ratios

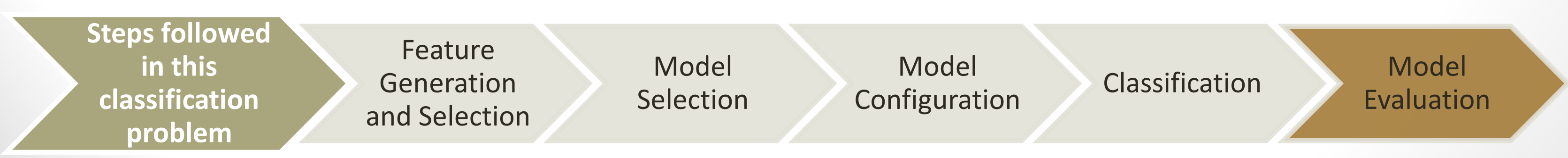
Steps followed in this classification problem → Feature Generation and Selection → Model Selection → Model Configuration → Classification → Model Evaluation

Results: Simulated Data(Contd)

- Simulated data is classified using SVM and ANN using CNO percentage and results are shown as follows



- When trained with itself then the SVM performs better but when trained with theoretical data and tested with simulated data ANN is better.
- Better the data, better the results.



Results: Mixed Material (Contd)

- Till now all the discussion is carried out considering pure materials. Now the classification will be done if a mixture of material is taken in different composition.

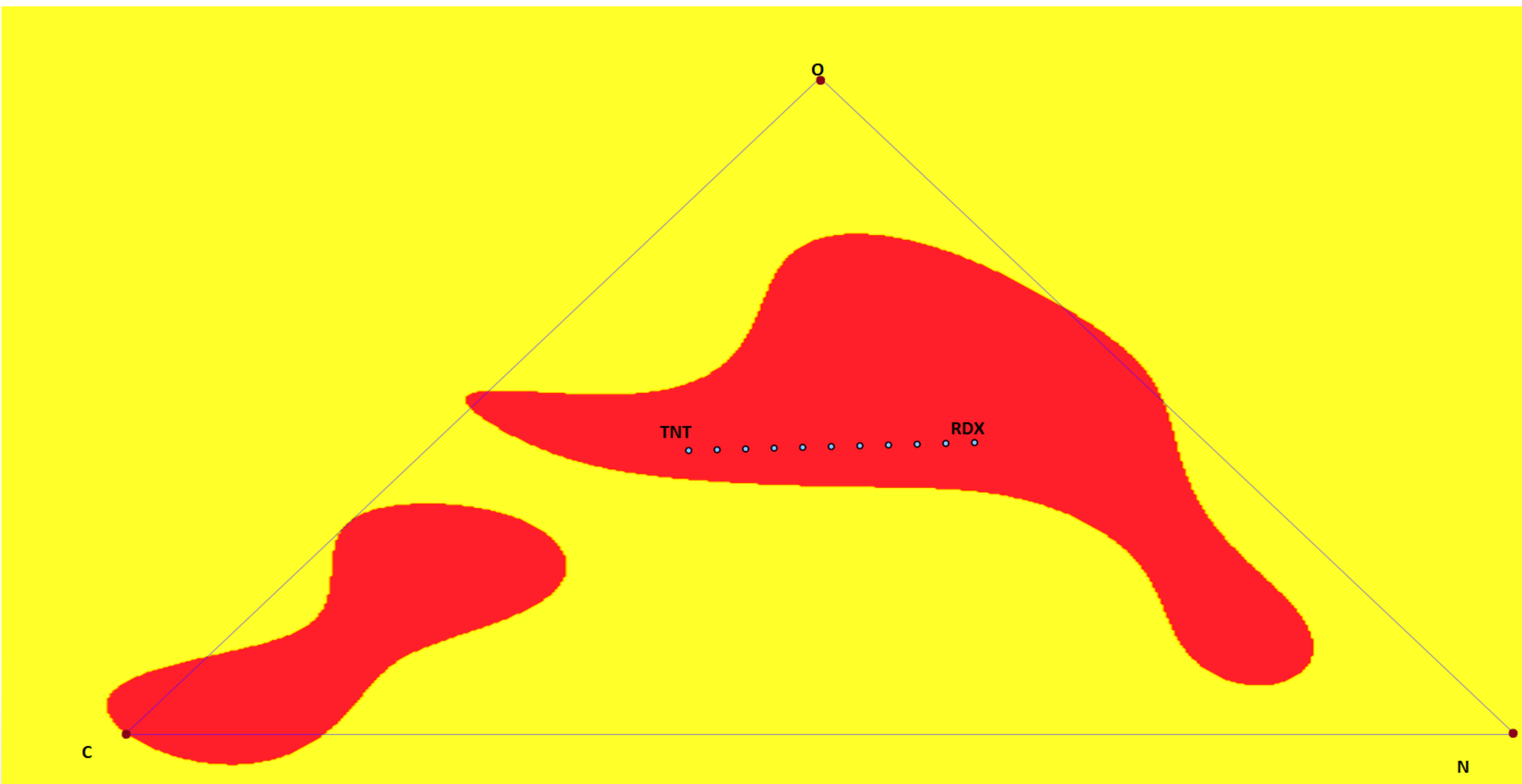
$$P_{Mix} = t.P_X + (1-t).P_Y$$

		Values of t										
Material X	**Material Y**	**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1**
RDX	TNT	+	+	+	+	+	+	+	+	+	+	+
Cellulose	TNT	+	+	+	+	+	+	+	+	+	+	-
Urea	RDX	+	+	+	+	+	+	-	-	-	-	-

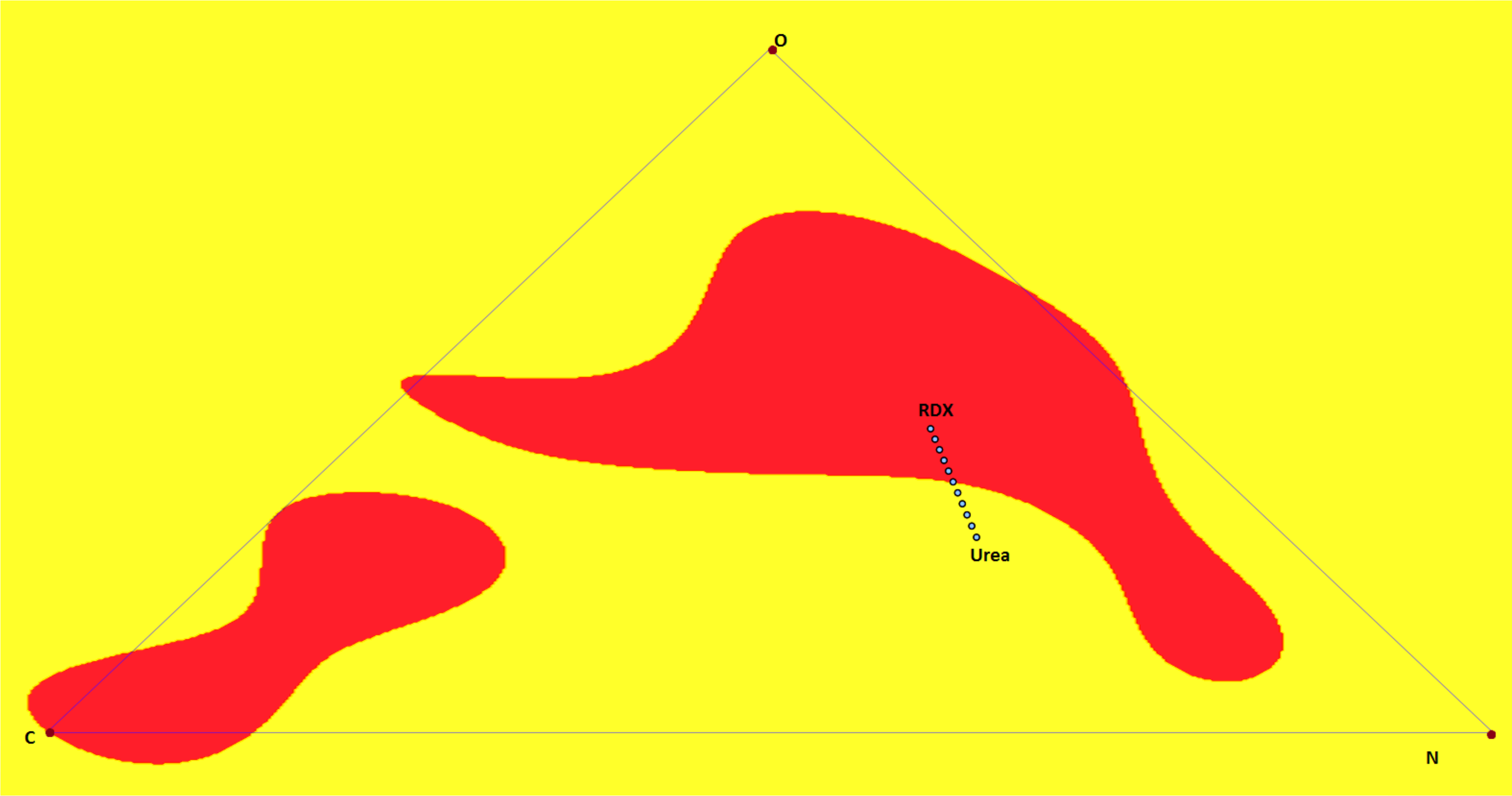
Table 5.19: Results for different composition of material X and material Y using RBF based SVM. Class - depicts the material is classified as benign and class + depicts the material is classified as illicit

Results: Mixed Material (Contd)

- This could easily be understood by visualising the transformed CNO space. The linear interpolation is conserved on the transformation.



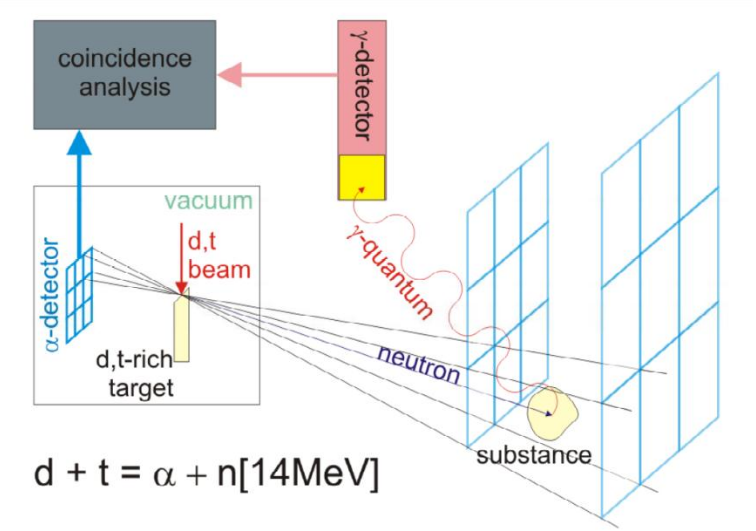
Results: Mixed Material (Contd)



3-D Location

Tagging and API Technique

- To increase the Signal to noise ratio (S/N), Associated Particle Imaging(API) technique is used. In this technique the γ data collection is time gated which provides the data only from specific regions, therefore reducing background. The basis of this techniques is tagging of gamma with associated alpha particle. And using a particular window between the detection of alpha and detection of gamma rays. This fixes area of interest hence increases S/N.



3-D Location

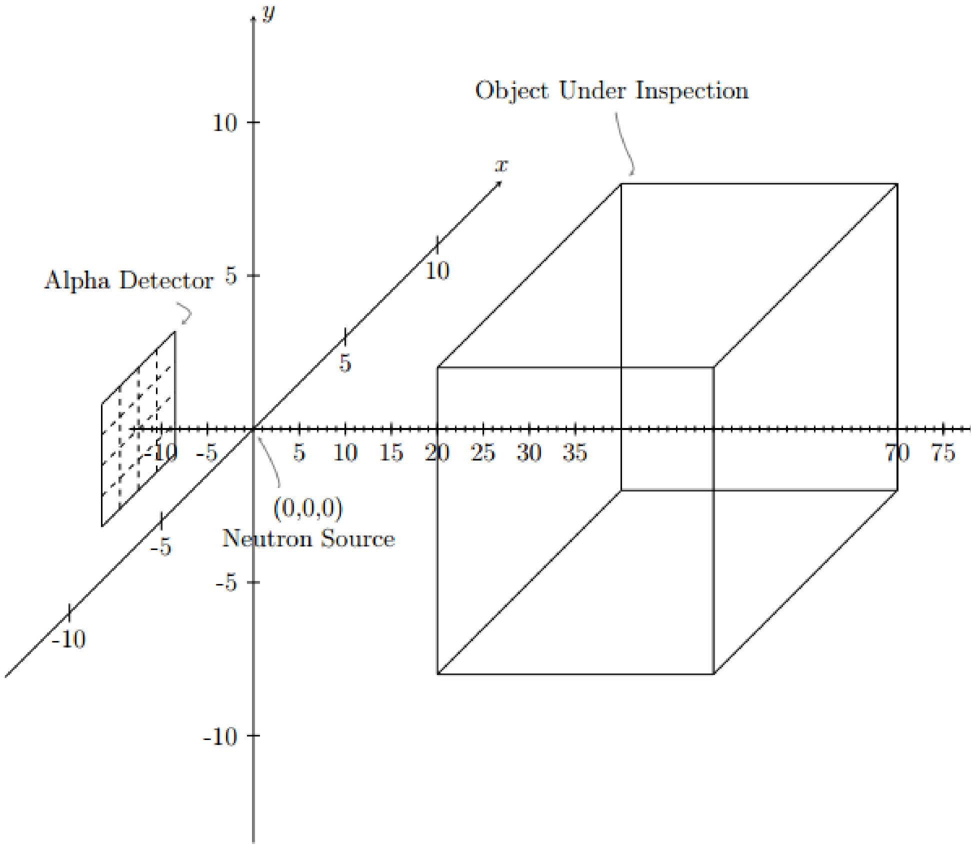


Figure 3.4: Positioning of alpha detector and object in a 3-d coordinate system to be used

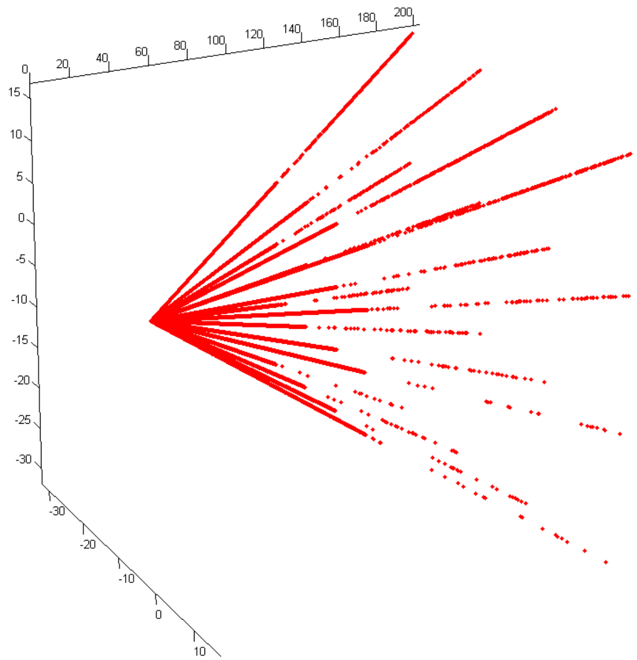
- Point of interaction are calculated as:

$$\hat{U}(i) = \frac{U(i)}{|U(i)|}$$

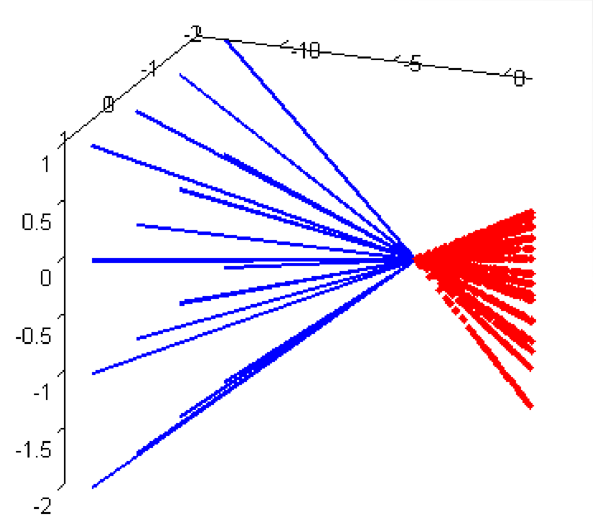
$$L(i) = -k.\hat{U}(i).(TOF(i))$$

- Where L(i) is position vector of point of interaction and U(i) position vector corresponding to the pixel in which alpha is detected.

3-D Location



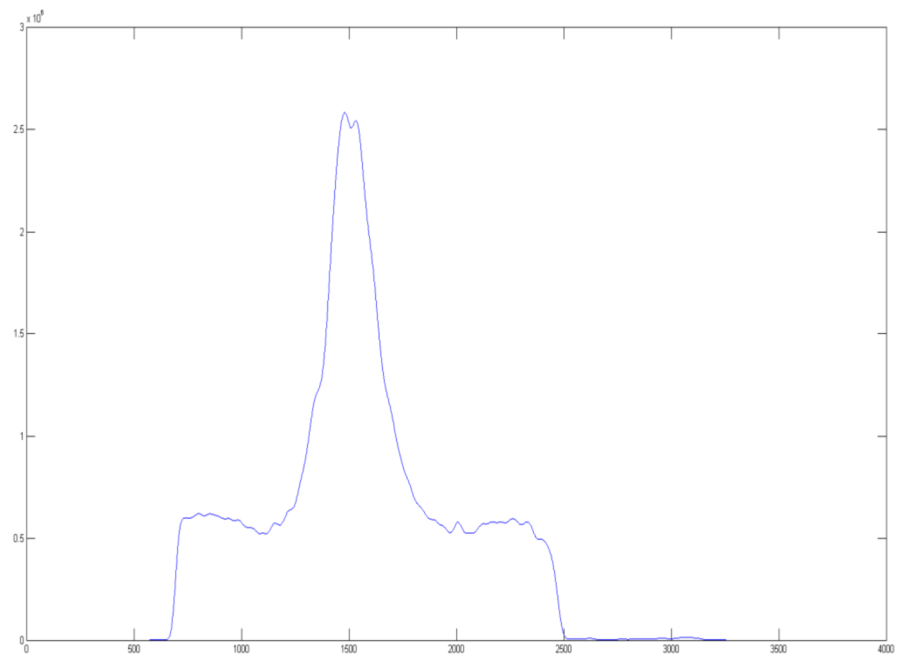
Point of interactions



Point of interactions along with alpha trajectory

- Further to get the location of the material a count density analysis is needed which could be done using an array Q transformed from the experimental data tuple.

$$Q = \sum_{j=1}^{E} C[i][j][1\ to\ T]$$



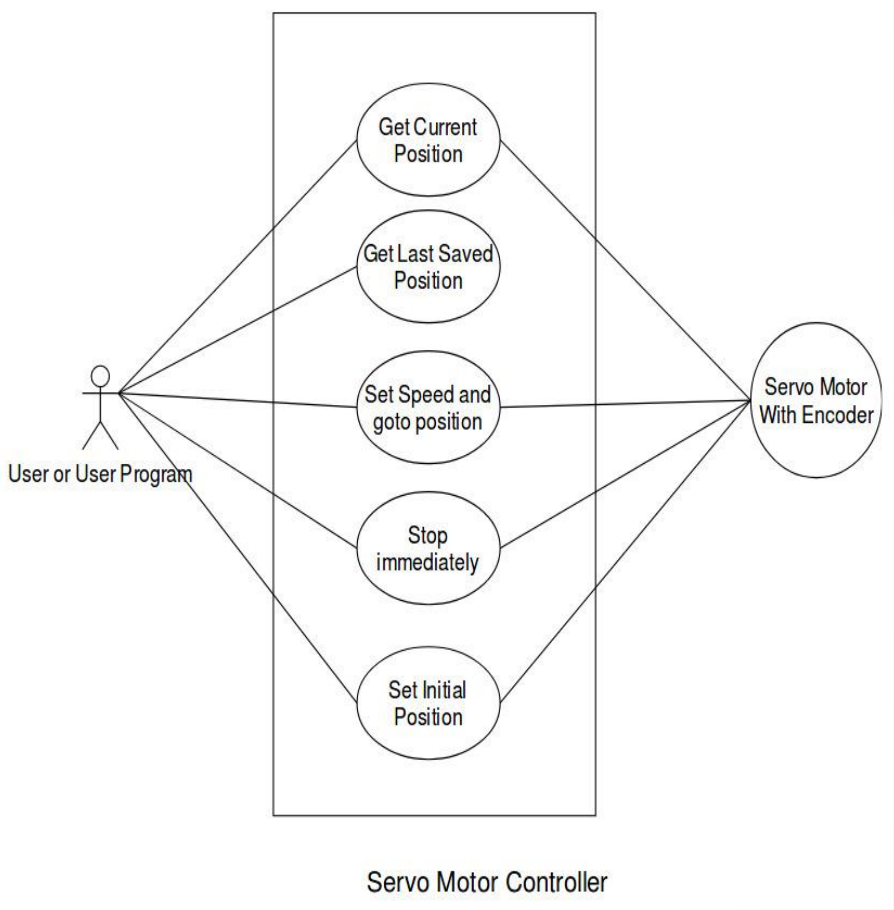
2. Device Controller

Problem Description

- To develop a DC servo motor based control of outer gate of beamline port HS-3018. A device controller of the motor is designed and developed which communicates with PC receives, decodes and responds to device specific commands.
- A computer controlled 5kV power supply for portable penning ion source.

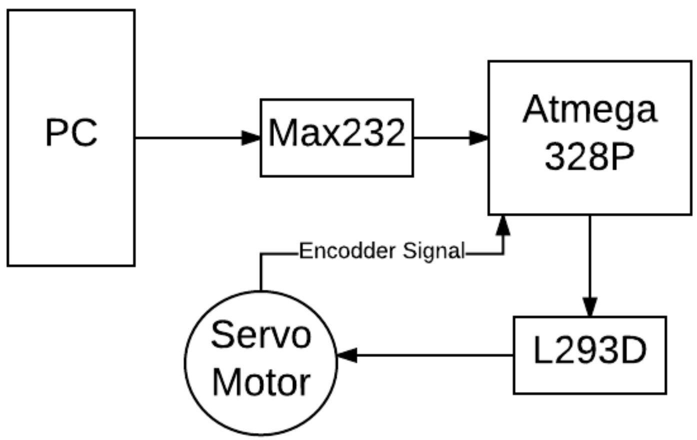
Motivation for Motor device controller and driver

- A neutron imaging beamline has been setup at Dhruva HS-3018 port
- The outer gate of the beamline is to be controlled for the operations
- As advised by research reactor safety committee this door is to be operated remotely, hence a computer controlled motor controller and its corresponding driver is developed.

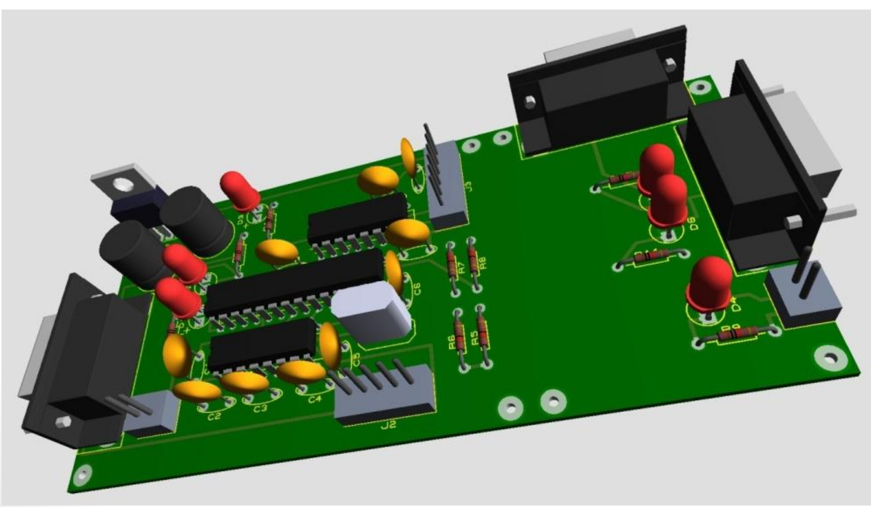


Use Case Diagram for the controller

Tools and platforms used



Block Diagram

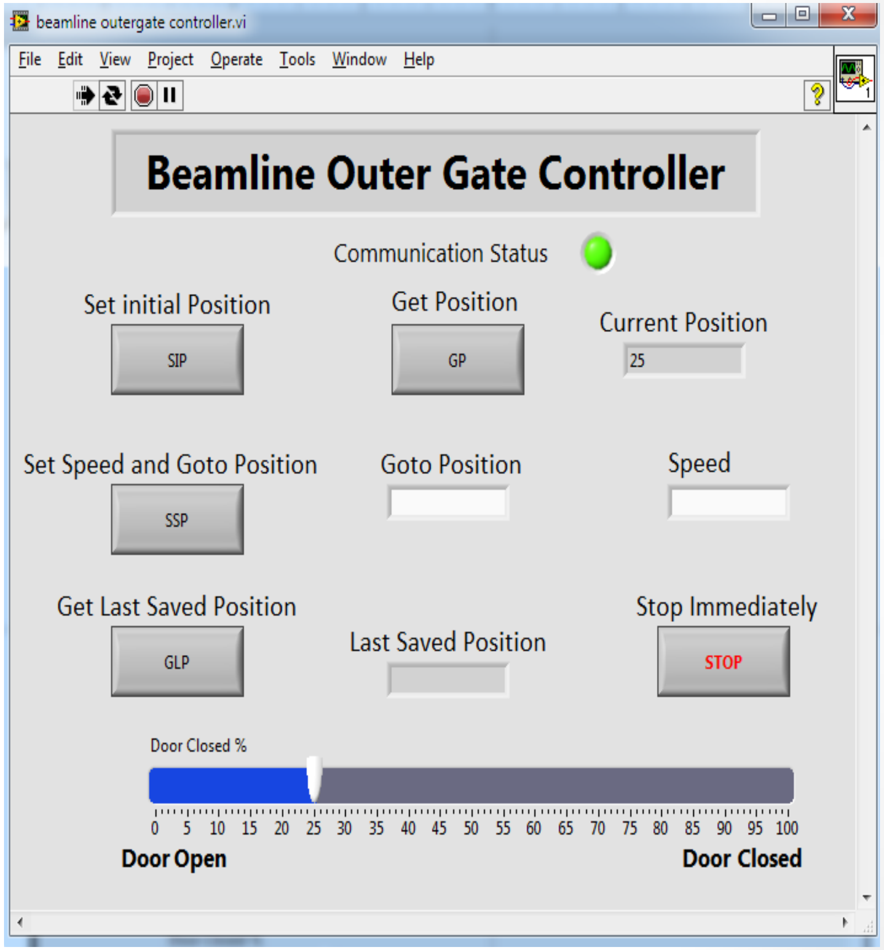


Circuit Diagram

- **Controller**
  - Aurdino Uno (Atmel 328P based development board) used for development
  - Aurdino IDE with wiring framework and C as a language
- **Driver**
  - Labview

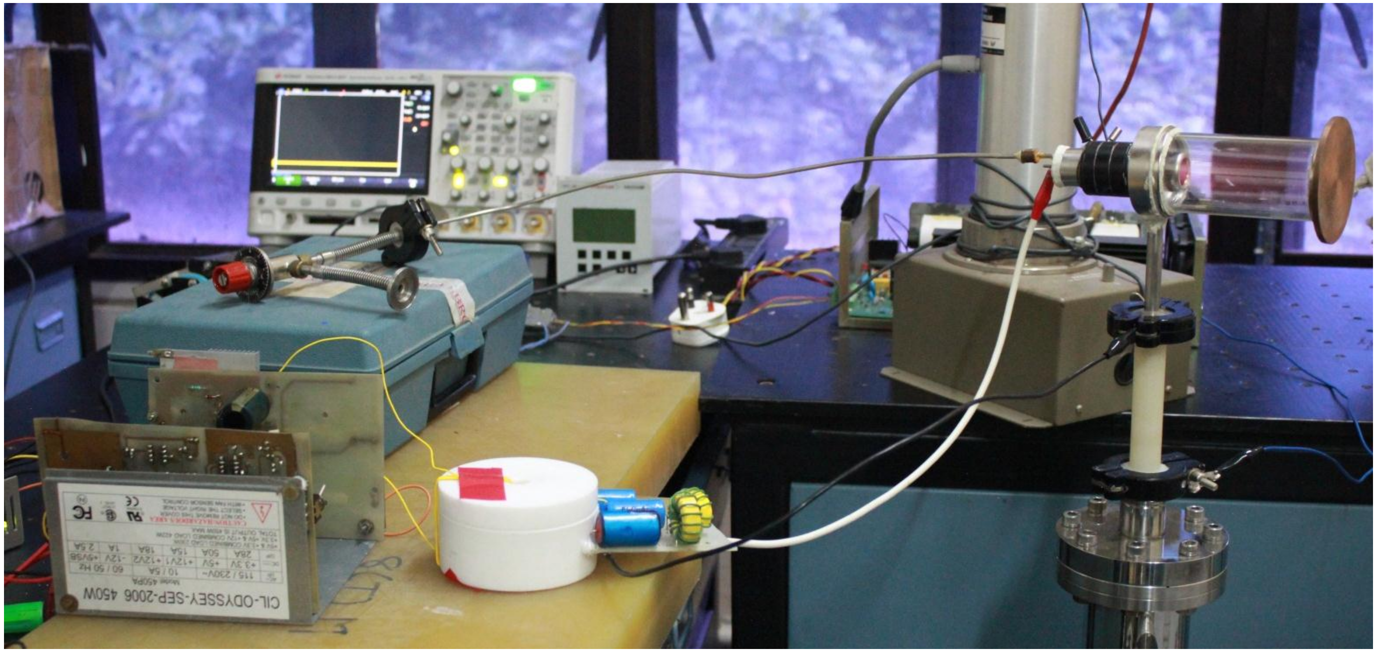
GUI for the Program

Outer gate of Dhruva Imaging beamline



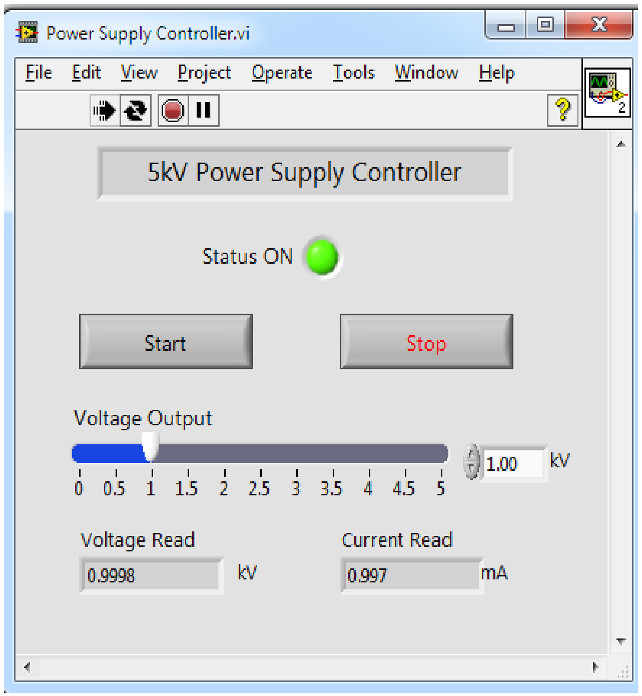
Power Supply control

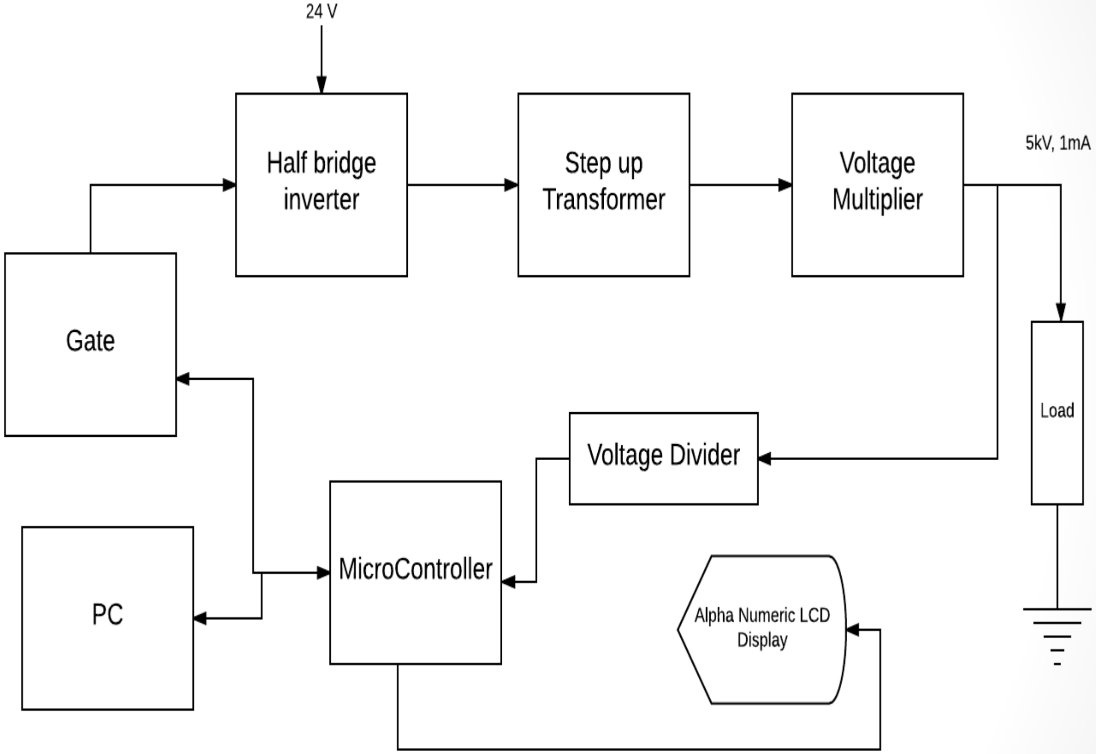
- It controls the voltage output for the power supply 0-5kV
- It can set the value of output voltage, and get the current and voltage parameters
- It also displays the system parameters to a Alphanumeric LCD



5 kV Power Supply

Block Diagram for the Power Supply

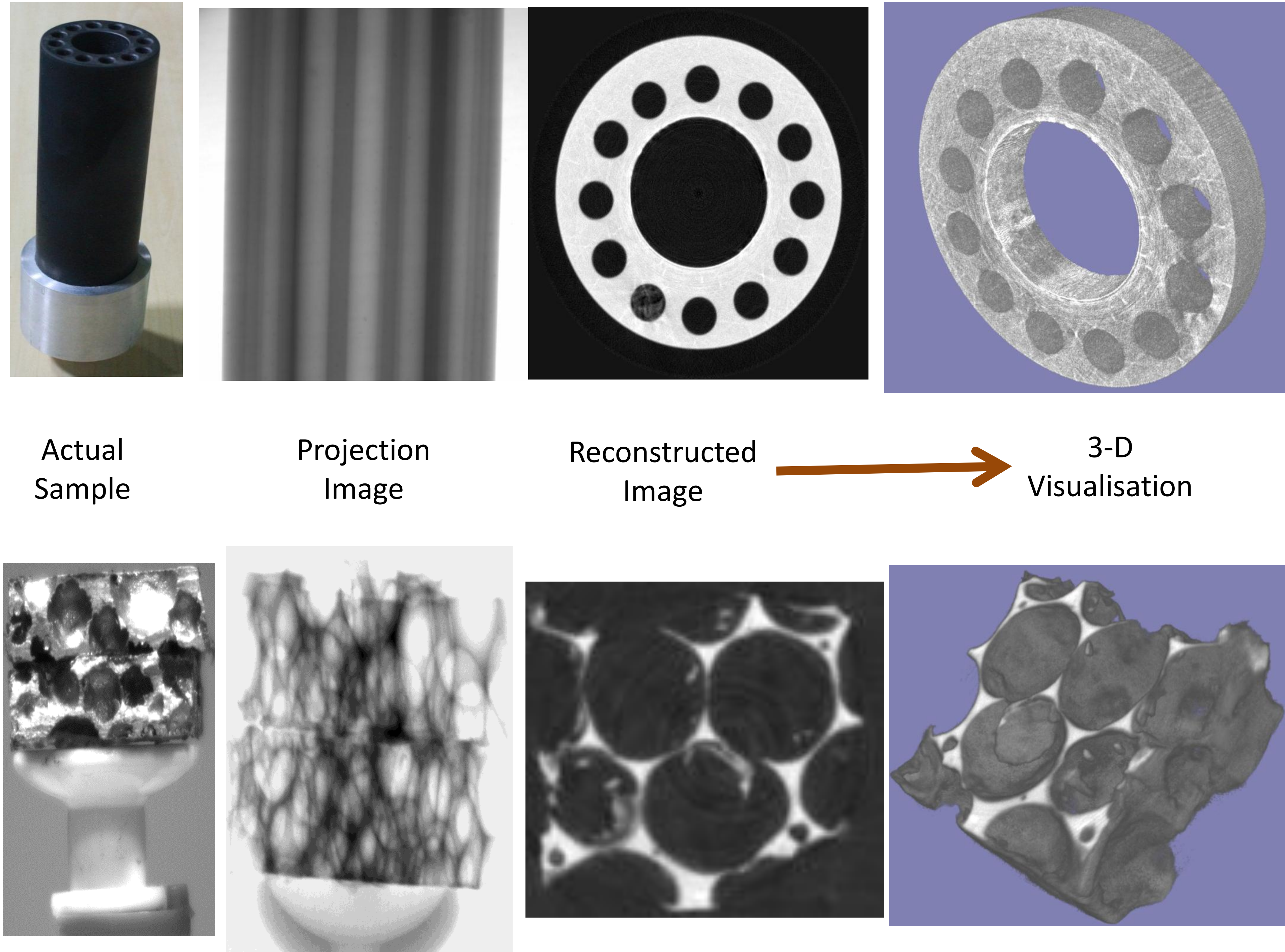




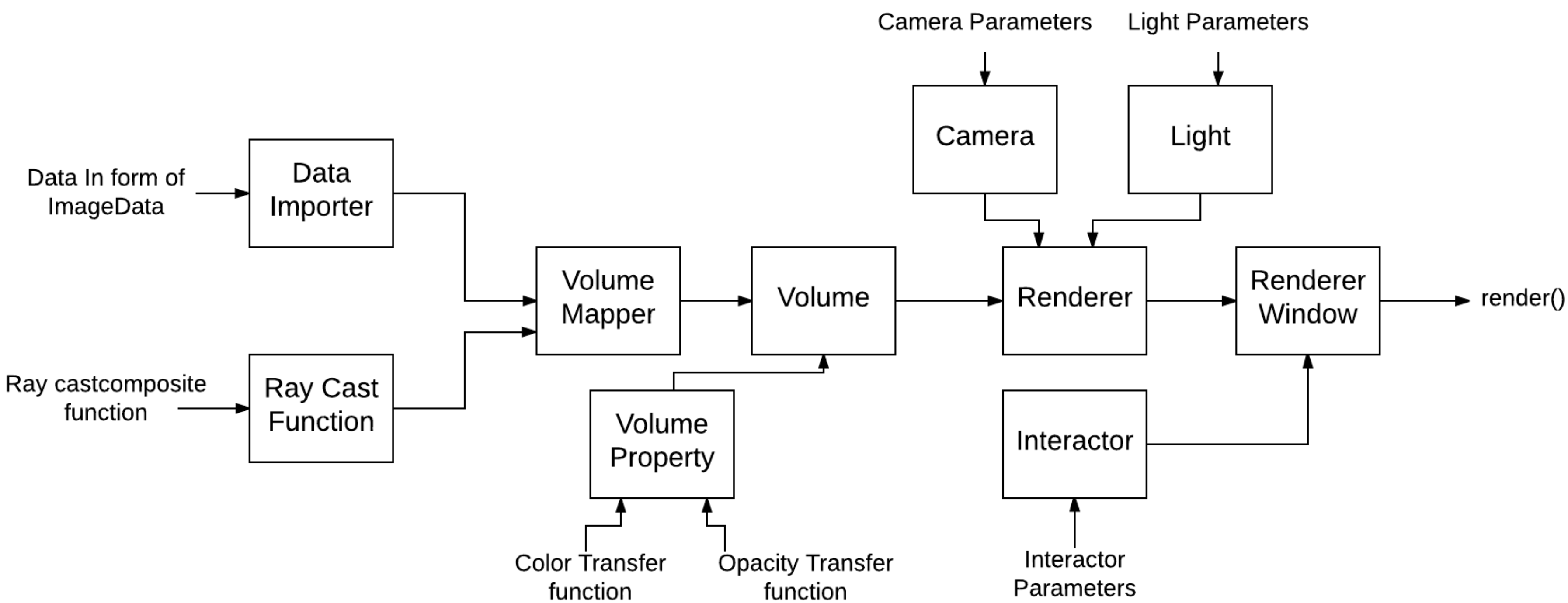
3. 3-D Visualisation Software for Reconstructed Images

Motivation

- Various tomography systems are present in NXPS
- An exhaustive end to end software is intended to be developed
- A software is to be developed which takes reconstructed images as input and produces an interactive 3-D representation

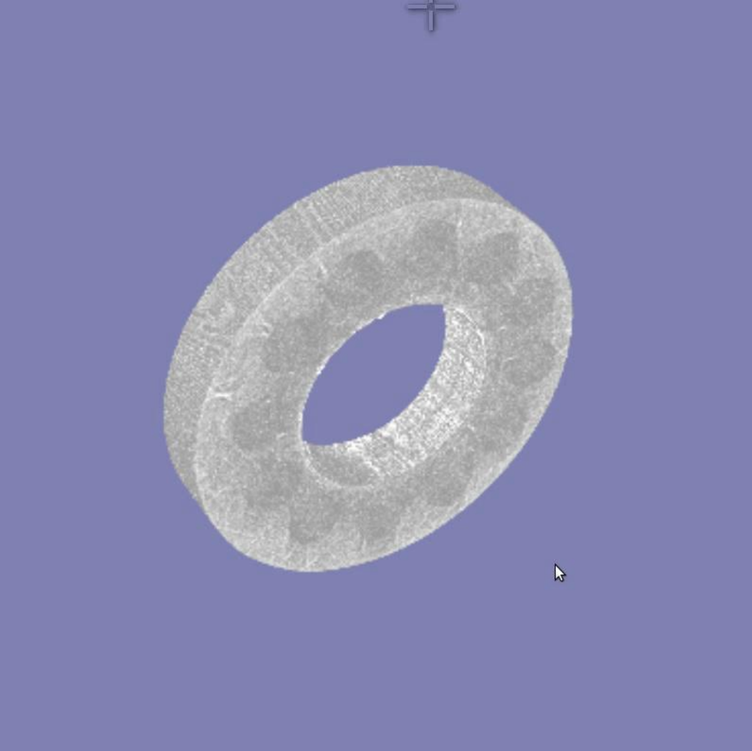
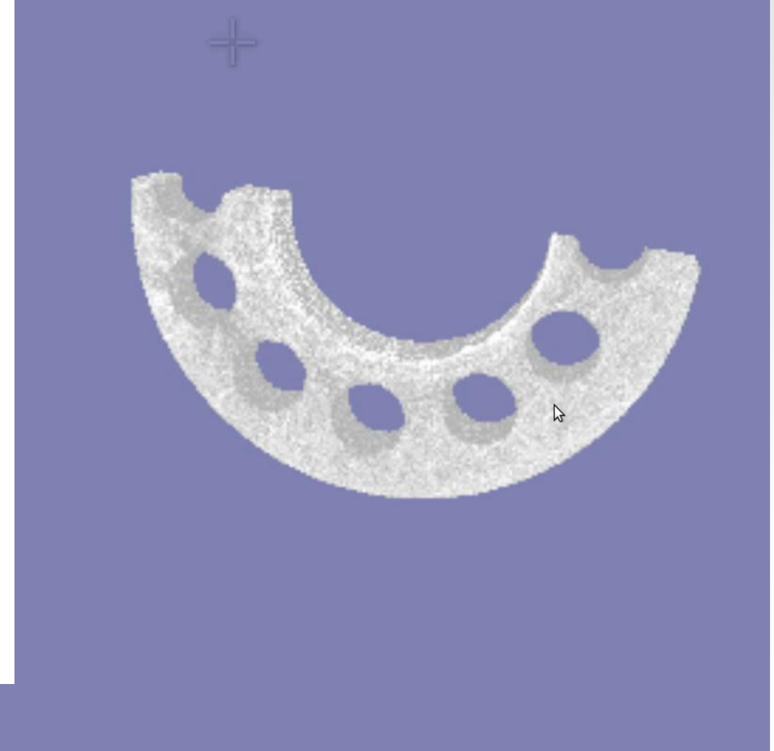
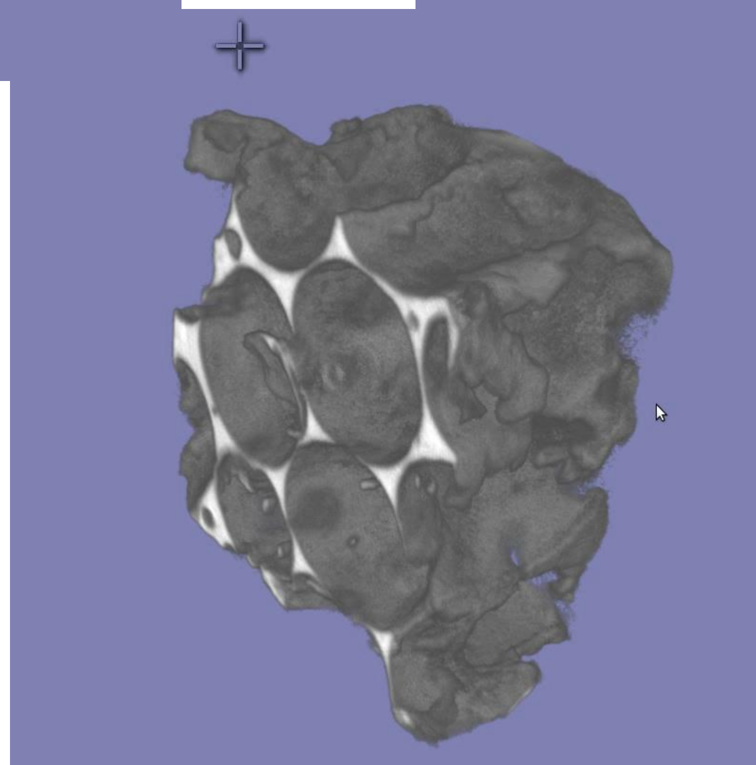

Actual
Sample
Projection
Image
Reconstructed
Image
3-D
Visualisation

Block Diagram



Visualisation Software for Reconstructed Images

- It can plot scalars with various color and opacity transfer functions
- It can cut plane, clip the data set and also perform extrusion
- It can import in form of images
- It can run on both Linux and Windows environment
- Python is used as the language and the Visualisation Tool Kit (VTK) is used.

Highlights and Future scope

- Decision Making Algorithm

  Using Supervised Cluster Validation for feature selection criteria is a novel contribution

  Future Scope: Validation of decision algorithm with experimental data

- Device Controller

  Future Scope: More Functionalities will be implemented as per the user requirements

- 3-D Visualisation Software

  Basic module with importing image set and visualization with simple modalities have been incorporated.

  Future Scope: GUI with advanced such as mouse based crop, See and edit the properties for each graphic object in a convenient, consistent property editor, print visualization, save visualization in standard formats etc.

THANK YOU

Appendix – A Transformation Matrix

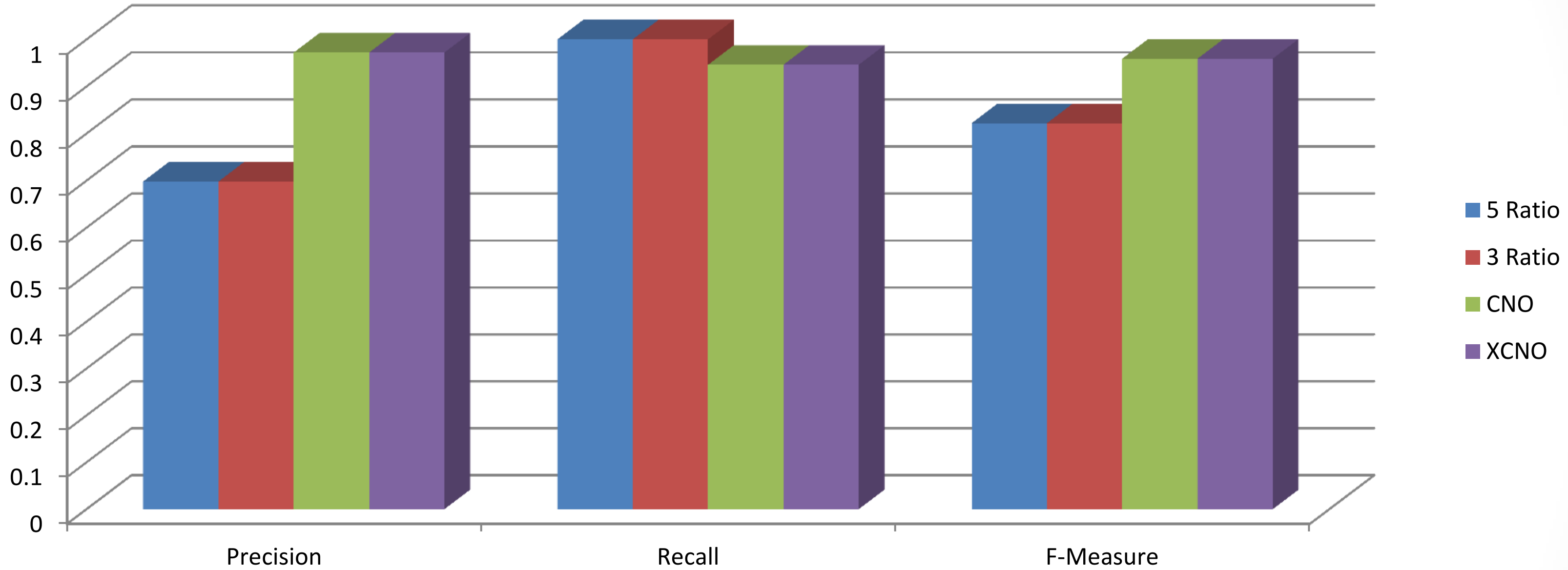
- An Affine transformation is needed for rotation.

$$[\,U\ \ V\ \ W\,]^T = \begin{bmatrix} 1/\sqrt{3} & 1/\sqrt{3} & 1/\sqrt{3} \\ 1/\sqrt{2} & 0 & -1/\sqrt{2} \\ -1/\sqrt{6} & 2/\sqrt{6} & -1/\sqrt{6} \end{bmatrix} [\,X\ \ Y\ \ Z\,]^T$$

- After the affine transformation a projection on plane Z=0.
- Although results may be drawn in this space also, but for a good visualization a bit rotation is required in XY plane.

Results and discussion

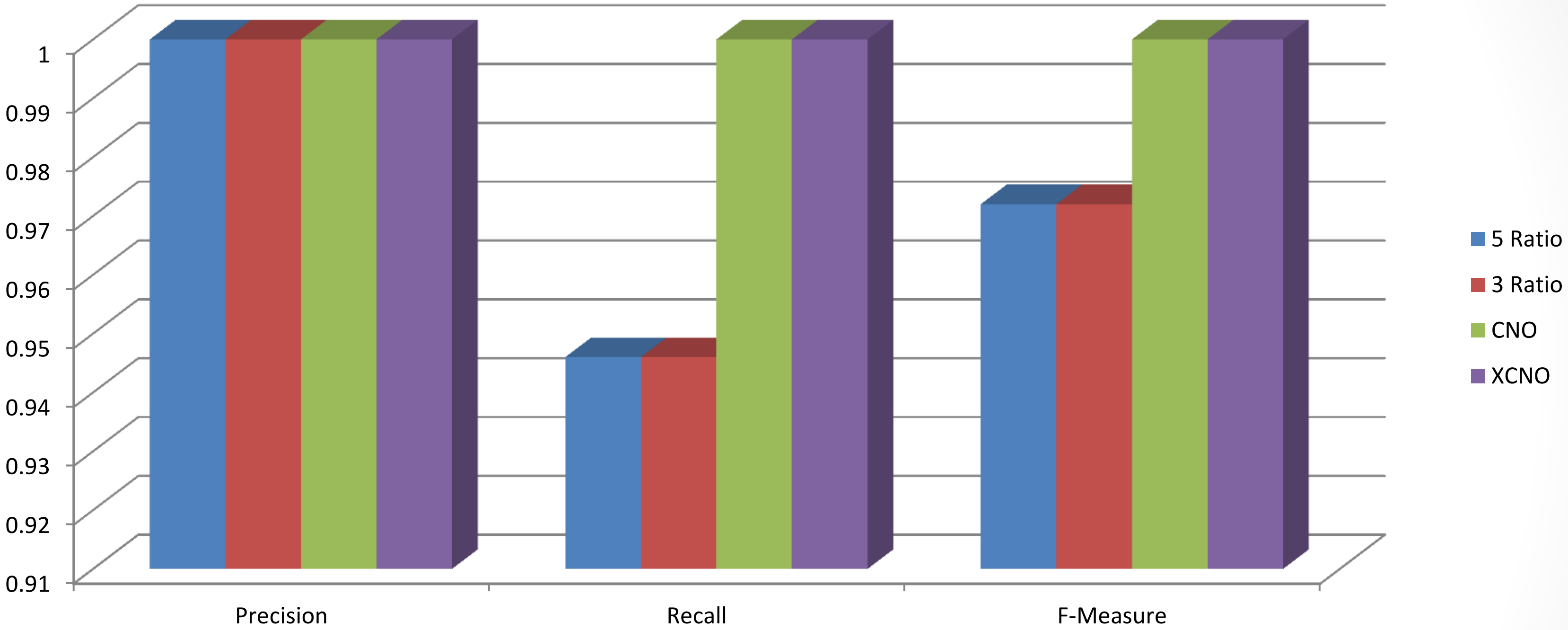
- Comparison between different feature vector for RBF ANN tested with 10% error data.



- RBF ANN gives zero error on training data. So tested with 10% error

Results and discussion

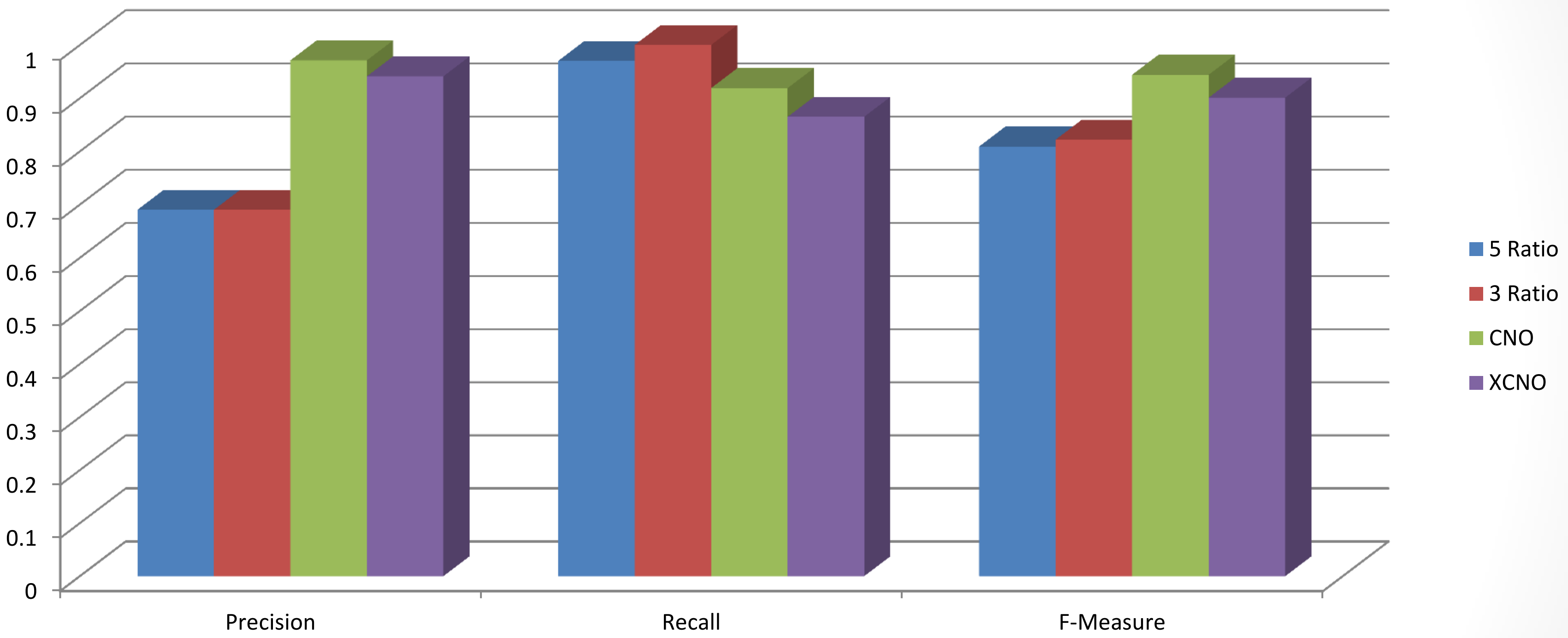
- Comparison between different feature vector for SVM with RBF kernel tested with 0% error data.



- Clearly Shown that CNO and XCNO over shadows the performance using 5 Ratios and 3 Ratios

Results and discussion

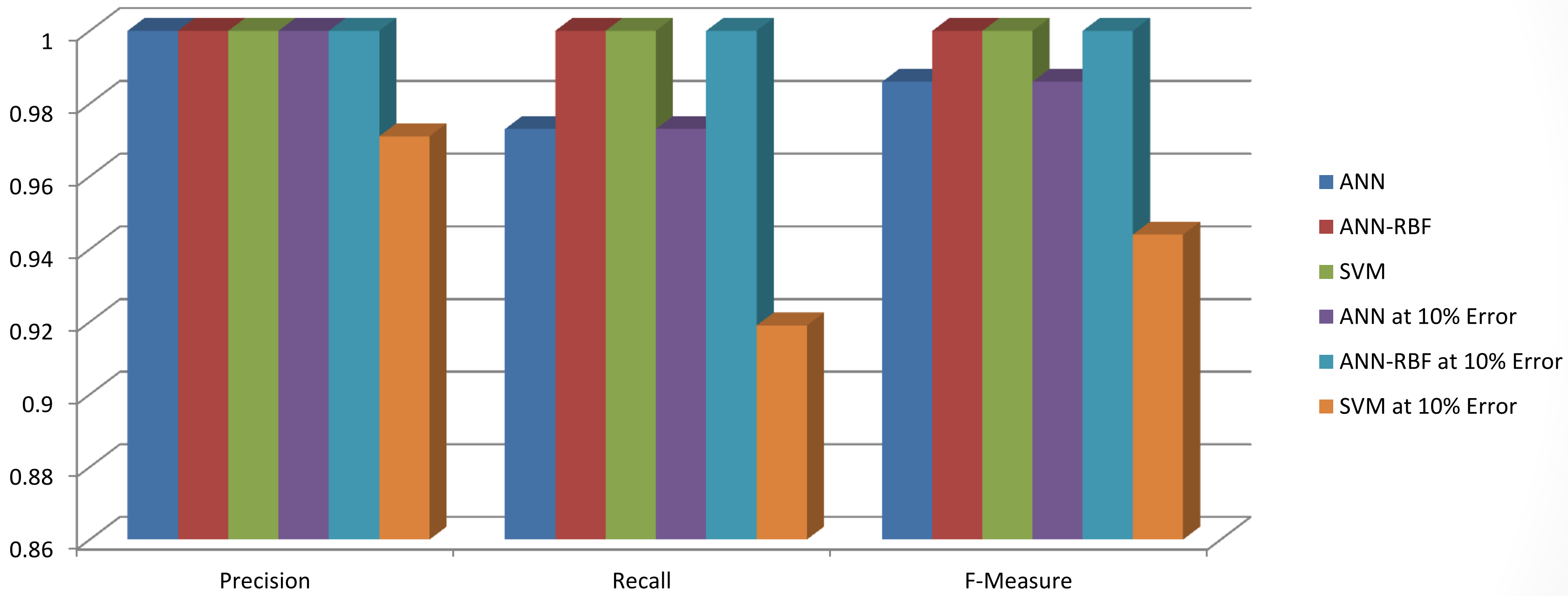
- Comparison between different feature vector for SVM with RBF kernel tested with 10% error data.



- Clearly Shown that CNO and XCNO over shadows the performance using 5 Ratios and 3 Ratios

Results and discussion

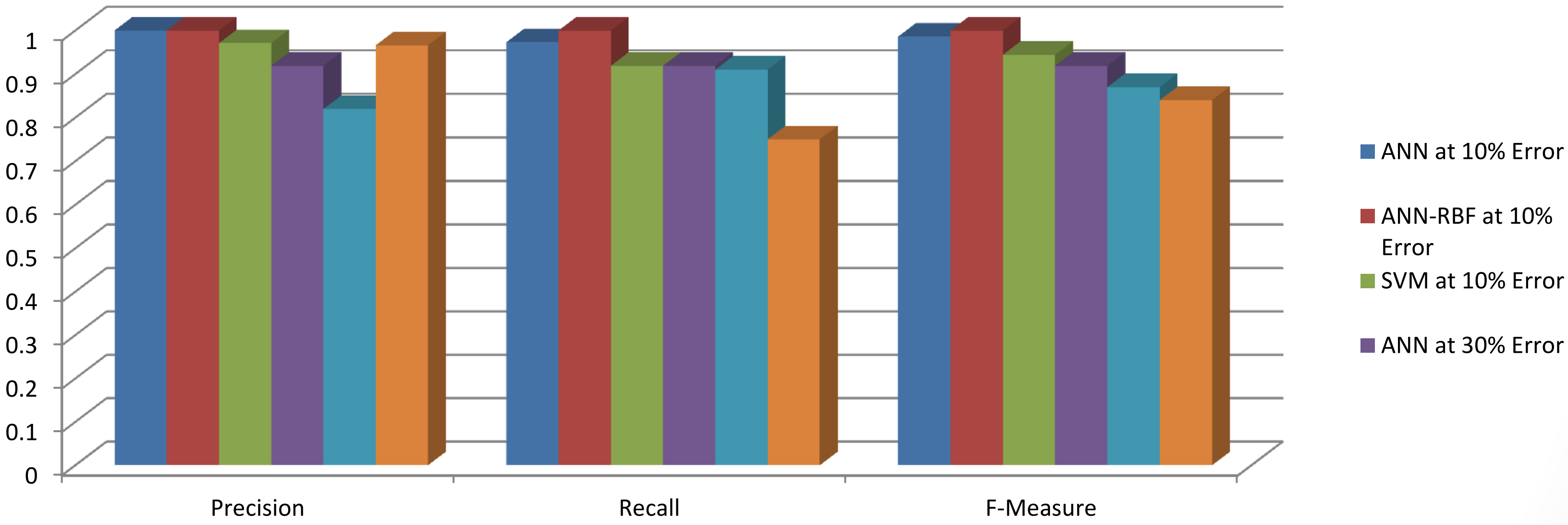
- Comparison between models for CNO Space tested with 0% and 10% error data.



- ANN may not give zero error for the training data but is more fault tolerant. Whereas SVM gives zero error at training data but not so fault tolerant.

Results and discussion

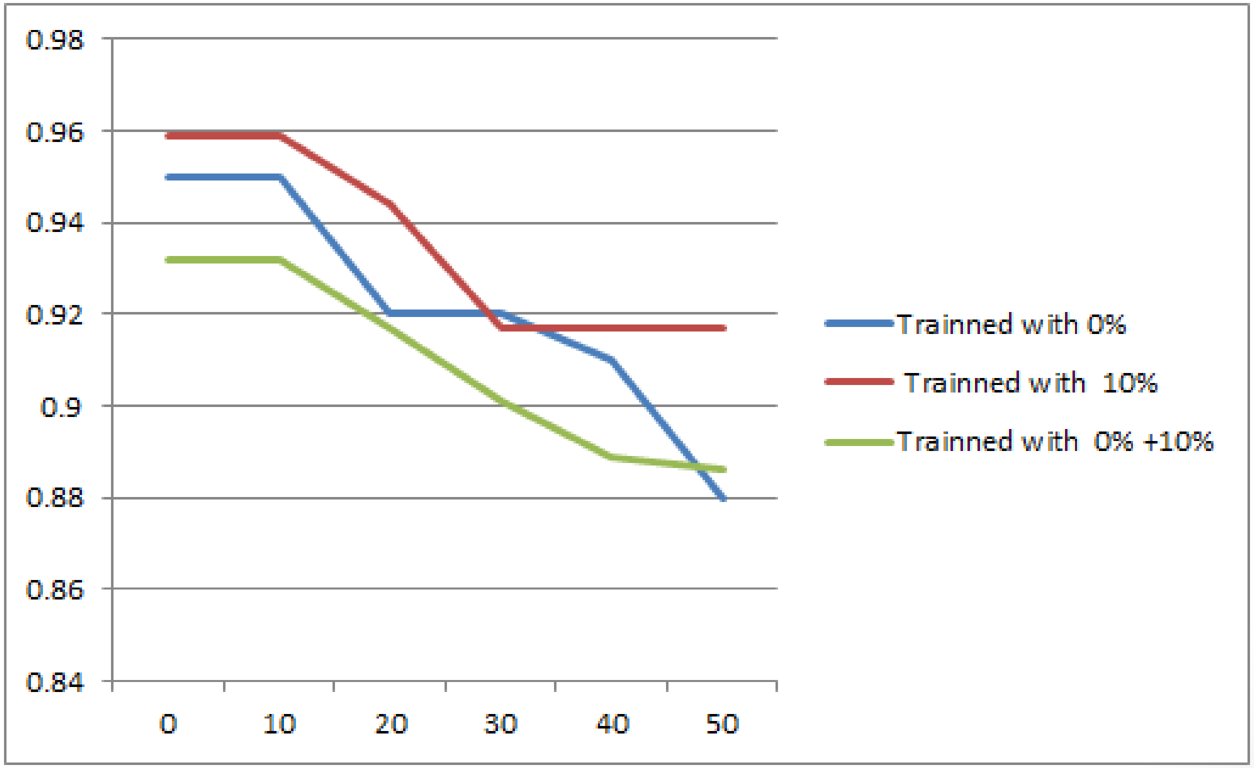
- Comparison between models for CNO Space tested with 10% and 30% error data.



- ANN is fault tolerant even at higher errors.

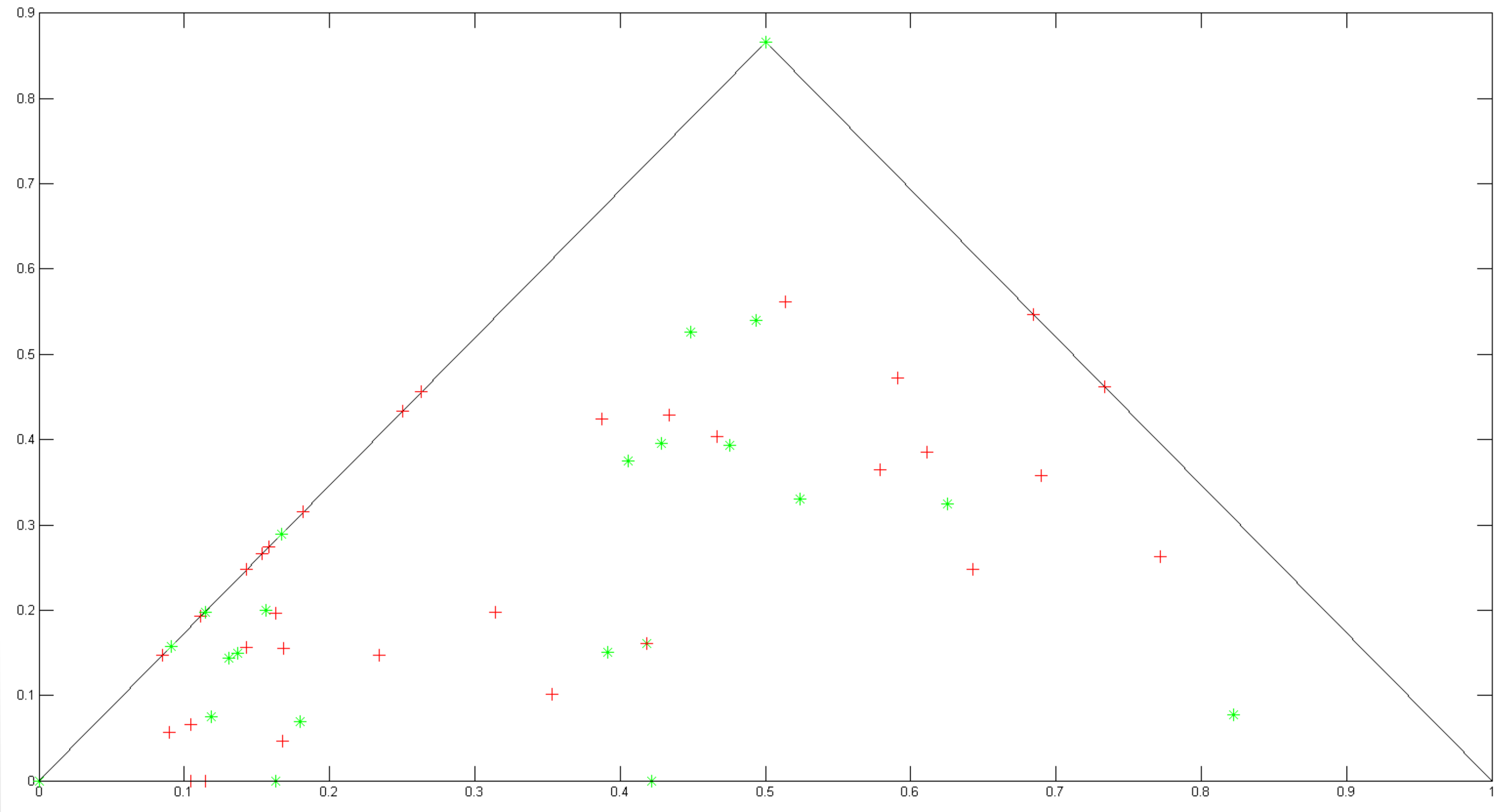
Results and discussion

- When trained with data which have error in itself the robustness of the system increases but the performance is less than that of the no error data.

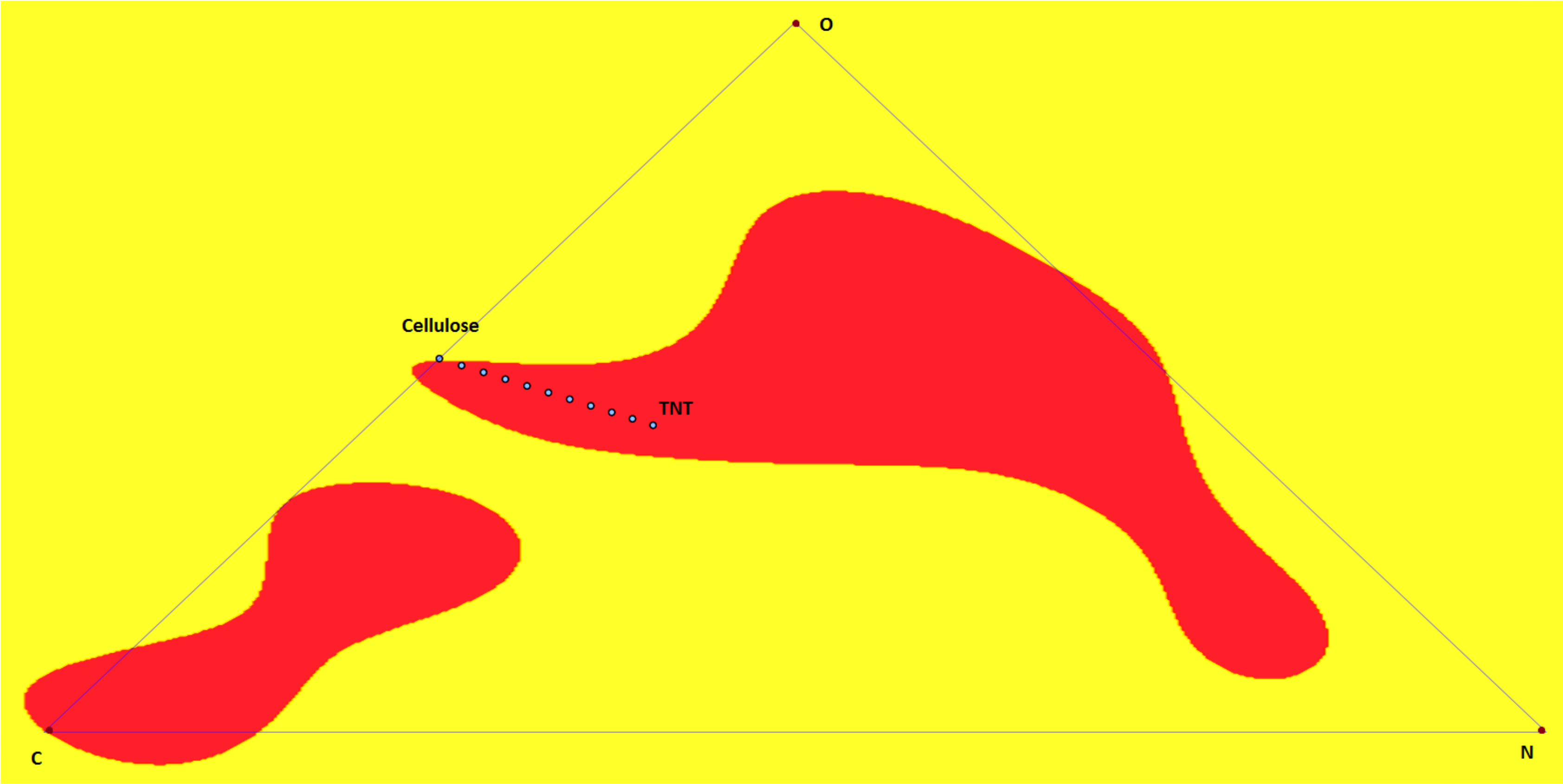


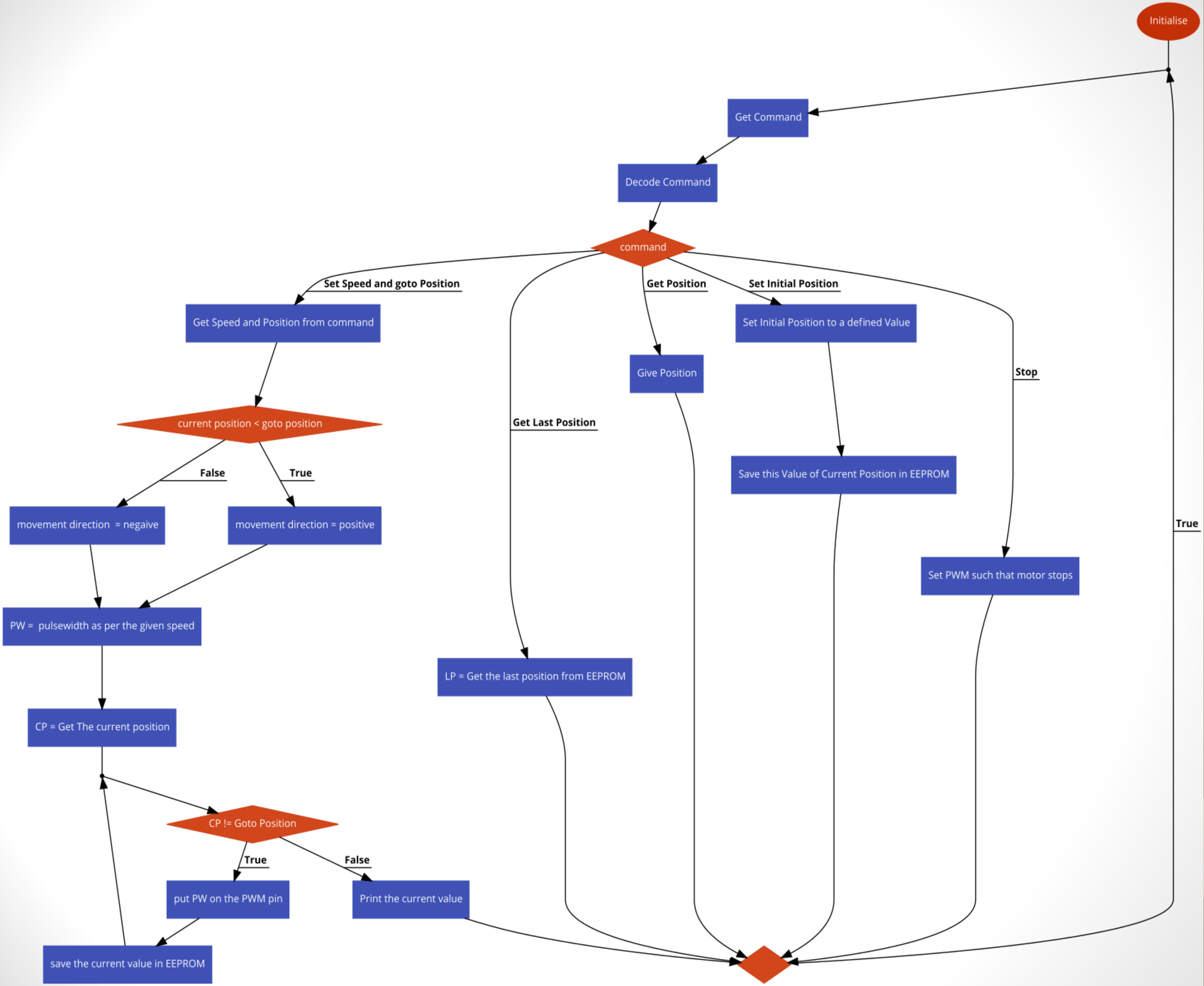
Results for Simulated Data

- Simulated data is having error of the RMS upto 30 %



Results for Mixed Data




Initialise
Get Command
Decode Command
command
Set Speed and goto Position
Get Position
Set Initial Position
Get Speed and Position from command
Give Position
Set Initial Position to a defined Value
Stop
current position < goto position
Get Last Position
Save this Value of Current Position in EEPROM
False
True
movement direction = negaive
movement direction = positive
True
Set PWM such that motor stops
PW = pulsewidth as per the given speed
LP = Get the last position from EEPROM
CP = Get The current position
CP != Goto Position
True
False
put PW on the PWM pin
Print the current value
save the current value in EEPROM

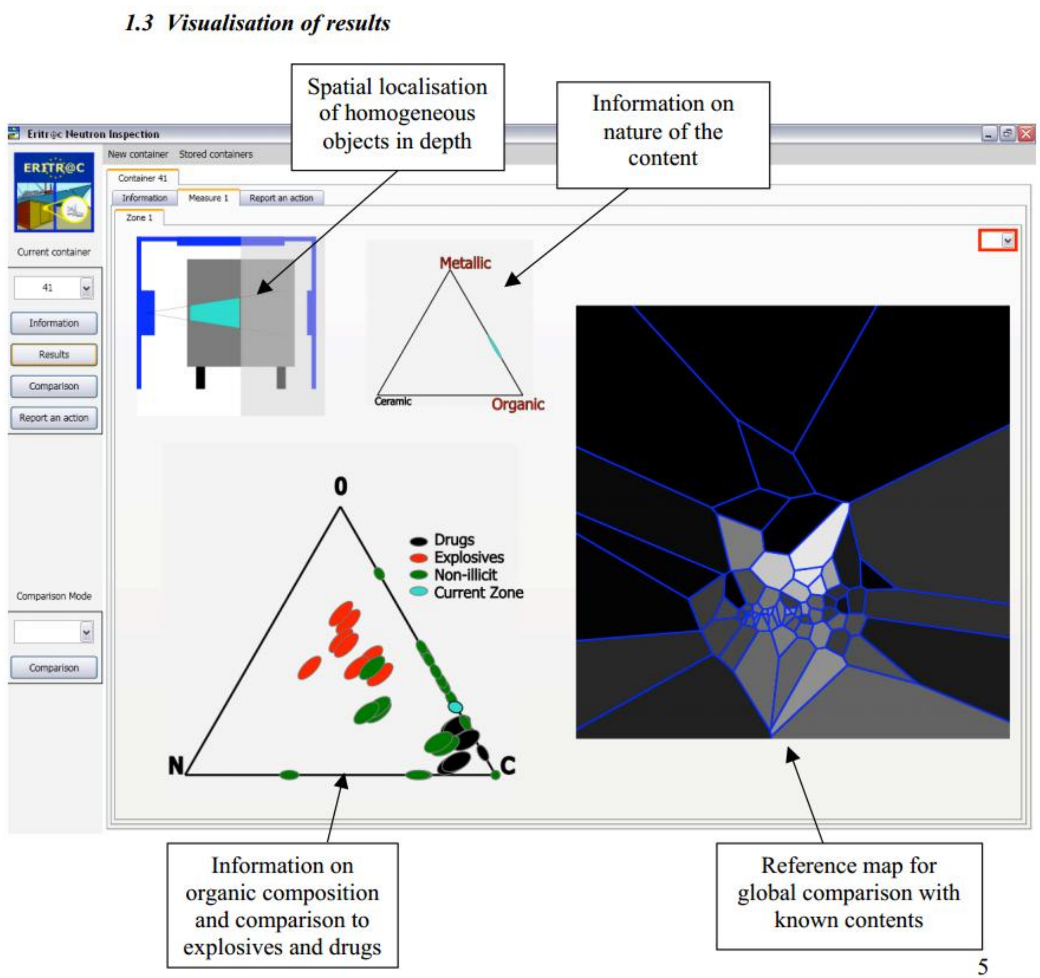
Conclusion

- For feature selection the criteria used is class separability and as a mathematical formulation of the separability, supervised cluster metrics are used
  This feature selection process also complies with results drawn.
- CNO and XCNO over shadows the performance using 5 Ratios and 3 Ratios
- ANN is fault tolerant even at higher errors.
- When trained with data which have error in itself the robustness of the system increases but the performance is less than that of the no error data.
- When trained with itself then the SVM performs better but when trained with theoretical data and tested with simulated data ANN is better.

Conclusion

- Although CNO space have better metric as according to feature selection process than transformed CNO space, so is also shown by the results. Yet transformed CNO improves the **understandability** of the problem where CNO stands for the **explainability** of the problem.
- It is not only error which is responsible for the misclassification but also the direction of error.

Euritrack Software

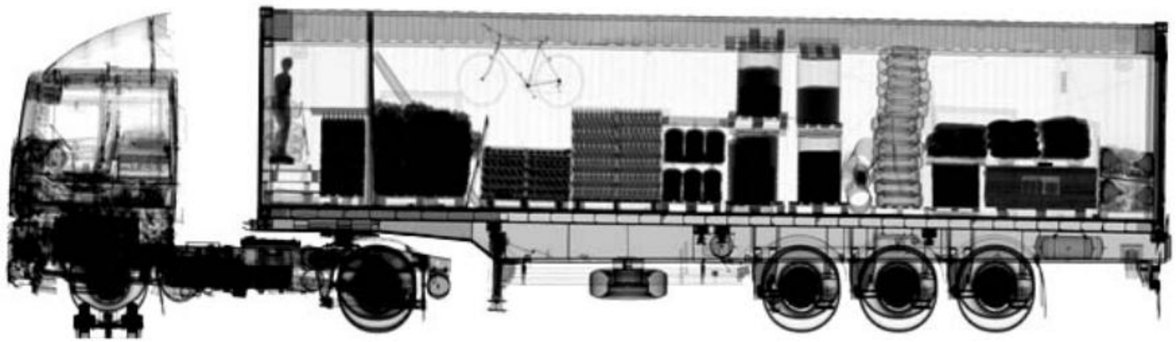


Final Product

Figure 1: General view of the EURITRACK Tagged Neutron Inspection System.

General X-Ray Scan

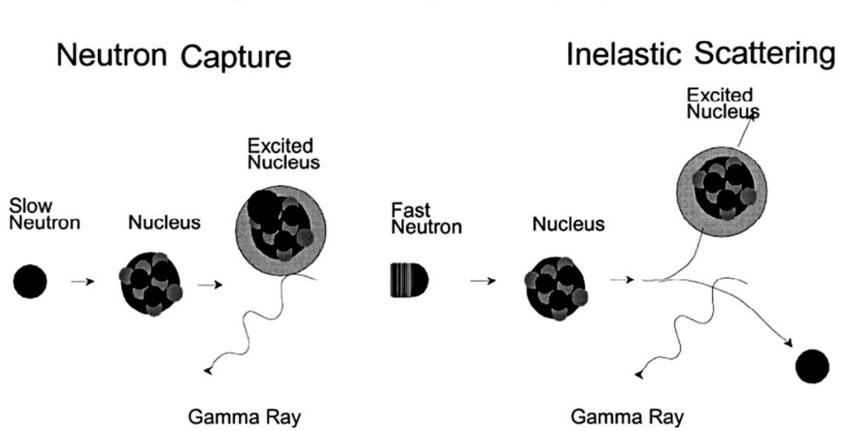
Typical X-ray results



X-Ray systems provide limited information even when extended to the higher energies needed to penetrate fully loaded cargo containers: they can only give an idea of the shape and of the density of the objects and can not fully characterize the chemical elements present inside the container. Several threat materials such as explosives have indeed density very close to benign items and can be prepared in any shape.

Principle

- Explosives (TNT, RDX, C-4, etc.) are composed primarily of the elements hydrogen, carbon, nitrogen and oxygen. Many innocuous materials are also primarily composed of these same elements. These elements, however, are found in each material with different elemental ratios and concentrations.
- In principle, a fast neutron impinging on an object can initiate one of several nuclear reactions with the elements of which the object is composed.
- The result is emission of characteristic *γ*-rays of unique energies. These *γ*-rays are the fingerprints of the elements contained



- Basis for taking these elements is a PCA analysis shown in the paper ‘Analysis of containerized cargo in the ship terminal’ by Jasmia Obhodas

Measure of class separability

- Using **Supervised measures cluster validity** as a measure
- As k-means clustering ensures the linearly separable data.
- If the value of purity is 1 and entropy is 0 then that means the points in that cluster all belongs to same class.
- If value of purity is not unity but close to it that means although data is not linearly separable but if classified with linear classifier, not much misclassifications will be there and vice-versa.
- So better the value of entropy and purity → lesser misclassification
- But individual cluster's purity does not make any sense so total purity and entropy are taken.

Clustering

- K-means clustering always results in linearly separable clusters.
- Classifier can be given by the bisector of the line joining the centeroid of the two clusters.
- Motivations for such an analysis are the comparison of clustering techniques with the ground truth or the evaluation of the extent to which a classification process can be automatically produced by just by cluster analysis

---

Algorithm 1 Basic K-means Algorithm.

1: Select K points as the initial centroids.
2: **repeat**
3:     Form K clusters by assigning all points to the closest centroid.
4:     Recompute the centroid of each cluster.
5: **until** The centroids don't change

Supervised Measures of Cluster Validity

- To measure the degree of correspondence between the cluster labels and the class labels.

Mathematical measure to calculate correspondences are entropy, purity, Rand-Statistics etc.

- **Entropy** The degree to which each cluster consists of objects of a single class. For each cluster, the class distribution of the data is calculated first, i.e., for cluster j, p_{ij} is calculated, the probability that a member of cluster i belongs to class j as $p_{ij} = m_{ij}/m_i$, where m_i is the number of objects in cluster i and m_{ij} is the number of objects of class j in cluster i. Using this class distribution, the entropy of each cluster i is calculated using the standard formula,

$$e_i = -\sum_{j=1}^{L} p_{ij} \log_2(p_{ij}) \tag{4.9}$$

where L is the number of classes. The total entropy for a set of clusters is calculated as the sum of the entropies of each cluster weighted by the size of each cluster, i.e.,

$$e = \sum_{i=1}^{K} (m_i/m) e_i \tag{4.10}$$

where K is the number of clusters and m is the total number of data points.

Supervised Measures of Cluster Validity

Purity: Another measure of the extent to which a cluster contains objects of a single class. Using the previous terminology, the purity of cluster i,

$$p_i = \max_i p_{ij} \tag{4.11}$$

the overall purity of a clustering is

$$purity = \sum_{i=1}^{K} (m_i/m) p_i \tag{4.12}$$

Artificial Neural Network

- In machine learning and cognitive science, artificial neural networks (ANNs) are a family of models inspired by biological neural networks and are **used to estimate or approximate functions** that can depend on a large number of inputs and are generally unknown. Artificial neural networks are generally presented as **systems of interconnected "neurons"** which exchange messages between each other. The **connections have numeric weights** that can be **tuned based on experience**, making neural nets adaptive to inputs and capable of learning.

Source: Wikipedia

Steps followed in this classification problem → Feature Generation and Selection → Model Selection → Model Configuration → Classification → Model Evaluation

Support Vector Machine

- In machine learning, support vector machines are **supervised learning models** with associated learning algorithms that analyze data used for **classification and regression analysis**. Given a set of training examples, each marked for belonging to one of two categories, an SVM training algorithm **builds a model** that assigns new examples into one category or the other, making it **a non-probabilistic binary linear classifier**.
- SVMs can efficiently perform a non-linear classification using what is called the **kernel trick**, implicitly mapping their inputs into high-dimensional feature spaces.

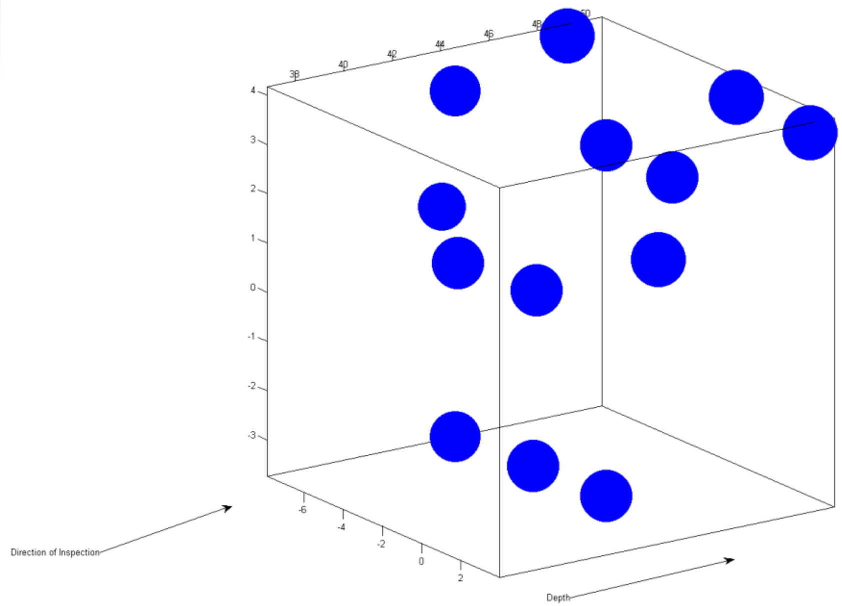
Source: Wikipedia

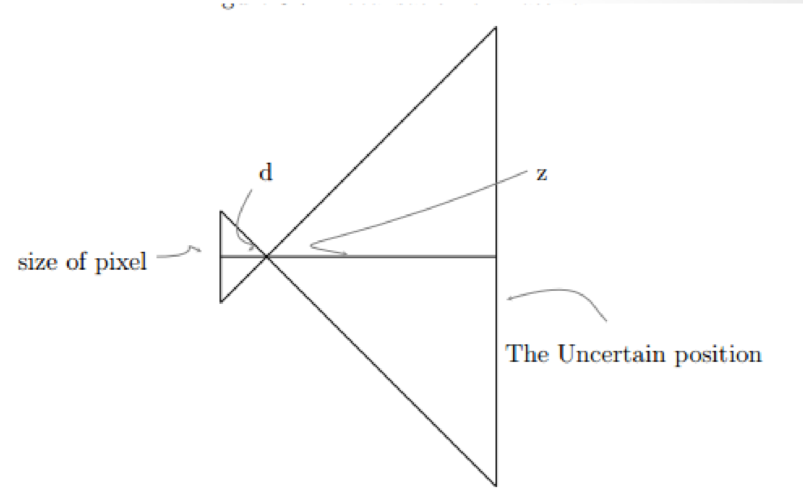
Steps followed in this classification problem → Feature Generation and Selection → Model Selection → Model Configuration → Classification → Model Evaluation

Results for Mixed Data

- Although CNO space have better metric as according to feature selection process than transformed CNO space, so is also shown by the results. Yet transformed CNO improves the **understandability** of the problem where CNO stands for the **explainability** of the problem.
- There is always a trade-off between the explainability and understandability of the problem.
- It is not only error which is responsible for the misclassification but also the direction of error.

3-D Location





$$\frac{s}{d} = \frac{z}{u}$$
$$\implies u = \frac{z.d}{s}$$

Uncertainty in location

- As along the depth the uncertainty in position increases and is given as above

- For a distance of 3 meters in depth, with the present experimental system it gives a voxel size of 1 x 1 sq-ft