An Integrated Detection and Treatment Recommendation Framework for Breast Cancer using Convolutional Neural Network and TOPSIS

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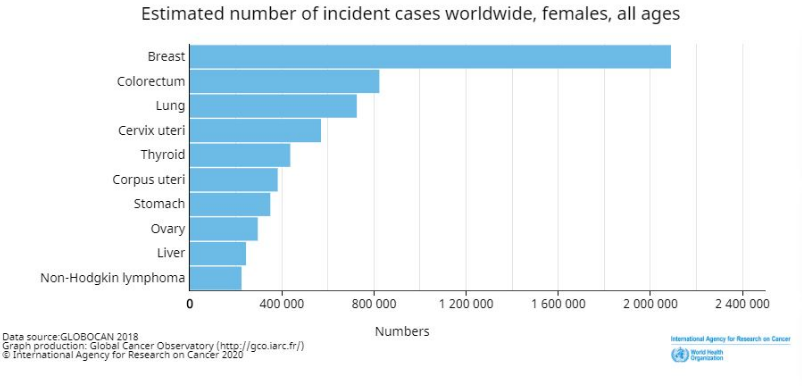
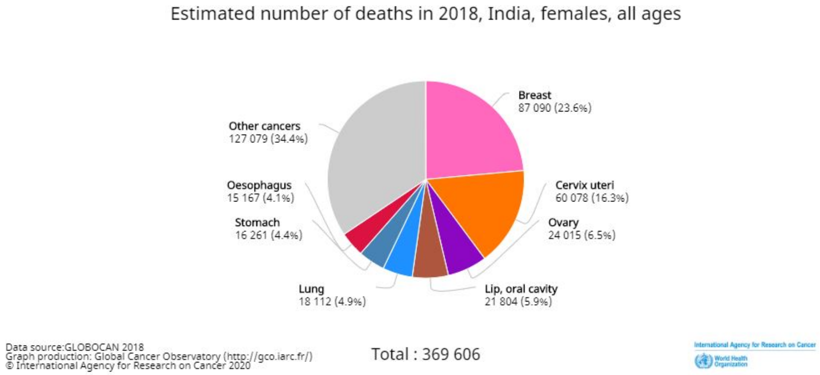
Outline

Introduction

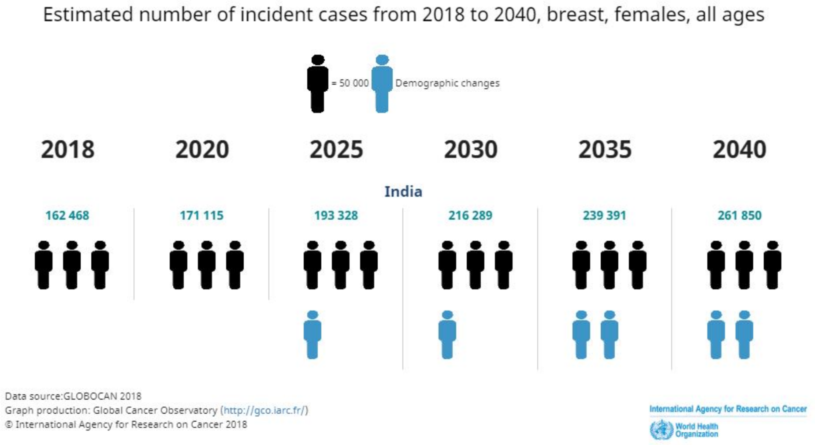
Types of Cancer in Women



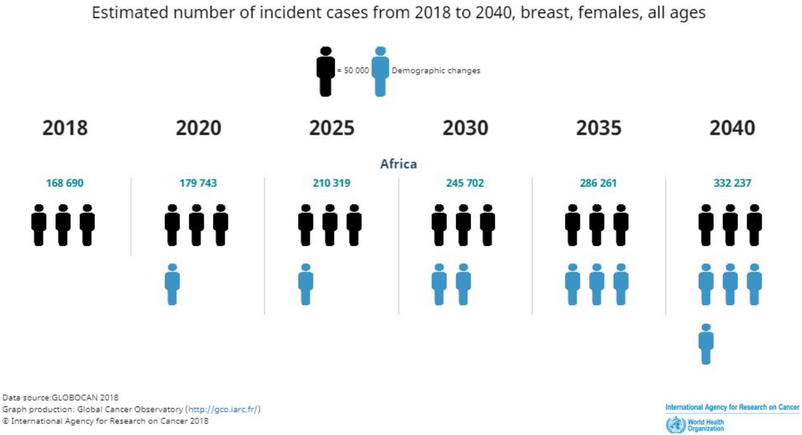
Number of Deaths in India in 2018



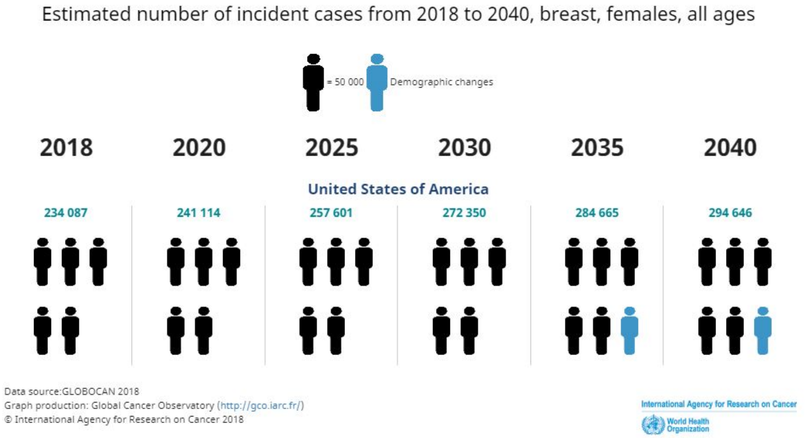
Projected Number of Cases in India through 2040



Projected Number of Cases in Africa through 2040



Projected Number of Cases in the USA through 2040



World Health Organisation Explains

- Lack of early-detection, patients presenting at later-stage
- Lack of adequate diagnosis and treatment facilities

Problems Identified

- In 2014, patients: oncologists $= 1:\ 2000$
- Detection, consultation and treatment
- Zero to very less outreach in remote areas
- Chance of overlooking
- Affordability
- Limited diagnostic resources
- Problem with evaluating younger patients
- Zero to very few recommendation systems exist

Motivation

- Improve the ratio
- Try eradicating cancer altogether
- Build a system
  - Has good reach
  - Uses the simplest of screening techniques
- Deep learning methods reduce human error rate by 85%

Literature Survey

Literature Survey: Preprocessing

Title and Author	Key Takeaways	Drawbacks
Breast Cancer Detection Using Extreme Learning Machine Based on Feature Fusion With CNN Deep Features (Zhiqiong Wang et. al.)	Subjective and objective feature extraction, actual considerations of doctors are taken into account, use of convolutional neural network for classification	Only classification
A Novel Algorithm for Pectoral Muscle Removal and Auto-Cropping of Neoplasmic Area from Mammograms (Dr M. Handmandlu et. al.)	Novel approach for preprocessing mammograms, tag removal, linear cut-off of pectoral muscle using straight line approximation	Linear approximation of pectoral muscle may lead to full or partial removal of lesion

Literature Survey: Machine Learning vs Deep Learning

Title and Author	Key Takeaways	Drawbacks
Breast Cancer Classification using Machine Learning (Meriem AMRANE et. al.)	Features such as uniformity of cell size and uniformity of cell shape are factored in	K-Nearest Neighbours and Naive Bayes classifiers do not give regard to the spatial and temporal properties of image datasets
Breast Cancer Detection based on Deep Learning Technique (Nur Syahmi Ismail et. al.)	Deep learning models - VGG16 (16 layers) Microsoft's ResNet (152 layers)	Classifies the images as normal or abnormal, fails to address the nature of the tumor, not a regression application

Literature Survey: Recommendation using TOPSIS

Title and Author	Key Takeaways	Drawbacks
Using the AHP and TOPSIS Methods for Decision Making in Best Course Selection After HSC (Varsha T. Lokare et. al.)	Use of Saaty's scale (AHP) to obtain weights, leveraging weights obtained using AHP for recommendation using TOPSIS	Lacks a window for professional opinion on weights, which in cases as sensitive as our application, is of prime interest
An Integrated Neutrosophic-TOPSIS Approach and its Application to Personnel Selection: A New Trend in Brain Processing and Analysis (Nada A. Nabeeh et. al.)	Neutrosophic AHP and TOPSIS overcome the inconsistency and uncertainty found in MCDM problems	Not currently suitable for our application as the number of features considered is relatively less

Literature Survey: Other CAD Research

- *Detection and Classification of the Breast Abnormalities in Digital Detection and Classification of the Breast Abnormalities in Digital (M. A. Al-masni et. al.)*

Key Findings

You Only Look Once (YOLO) based, capable of concurrently detecting and classifying the masses

Literature Survey: Other CAD Research

- *Detection and Classification of the Breast Abnormalities in Digital Detection and Classification of the Breast Abnormalities in Digital (M. A. Al-masni et. al.)*
- *Automatic Segmentation of Pectoral Muscle in Mammogram Images Using Global Thresholding and Weak Boundary Approximation (S. I. Naz et. al.)*

Key Findings

Processing of pectoral muscle using Connected Component Labelling (CCL) based, tags removed using Otsu's thresholding

Other CAD Research

- *The Classification of Mammogram Using Convolutional Neural Network with Specific Image Preprocessing for Breast Cancer Detection (H.-C. Lu et. al.)*

Key Findings

Contrast enhancement done using Contrast Limited Adaptive Histogram Equalization (CLAHE)

Other CAD Research

- *The Classification of Mammogram Using Convolutional Neural Network with Specific Image Preprocessing for Breast Cancer Detection (H.-C. Lu et. al.)*
- *Enhanced Breast Cancer Classification with Automatic Thresholding Using SVM and Harris Corner Detection (M. Taheri et. al.)*

Key Findings

Classification with automatic thresholding utilizing SVM and Harris Corner Detection method

Other CAD Research

- *The Classification of Mammogram Using Convolutional Neural Network with Specific Image Preprocessing for Breast Cancer Detection (H.-C. Lu et. al.)*
- *Enhanced Breast Cancer Classification with Automatic Thresholding Using SVM and Harris Corner Detection (M. Taheri et. al.)*
- *Face Recognition Based on Convolution Neural Network (K. Yan et. al.)*

Key Findings

Location (keypoint) detection, Stochastic Gradient Descent (SGD) optimiser, network consisting of three convolution, two pooling, two fully-connected and one Softmax regression layers

Proposed System

Overview

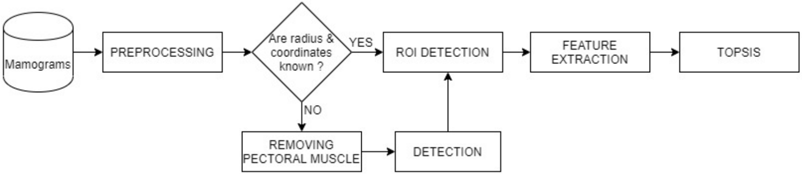


Figure: Block Diagram

Architectural Overview

Architectural Overview

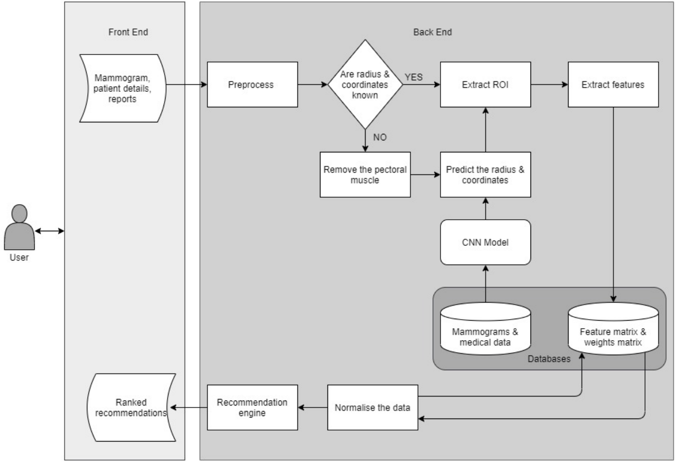


Figure: System

Operational Environment

- Operating system - **Windows 10**
- Hardware - **NVIDIA GeForce MX150, NVIDIA GeForce 940MX**
- Environment - **Anaconda Jupyter Notebook, Google Colab**
- Preprocessing - **OpenCV Python library**
- Pectoral muscle - **OpenCV Python library**
- Locating the region of abnormality (CNN) - **Keras using Tensorflow v2.x backend**
- ROI extraction - **OpenCV Python library**
- Feature extraction - **Pandas Python library**
- TOPSIS - **Numpy Python library**

Methodology

Image Acquisition: Why Mammograms?

- According to World Health Organisation, mammography is the only screening method that has proven to be effective
- Uses low energy x-rays (few kEV)
- Wide availability

Image Acquisition: Description of Mammogram

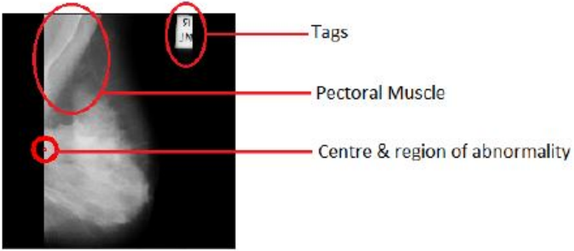


Figure: Mammogram

Image Acquisition: Dataset

- MIAS Database from Kaggle
- 322 mammogram images
- Text file containing -

REFNUM	BG	CLASS	SEVERITY	X	Y	RADIUS
0	G	CIRC	B	535.0	425.0	197.0
1	G	CIRC	B	522.0	280.0	69.0
2	D	NORM	NaN	NaN	NaN	NaN
3	D	NORM	NaN	NaN	NaN	NaN
4	F	CIRC	B	477.0	133.0	30.0

Figure: Dataset

Image Preprocessing: Flow

- Input - Raw images
- Output - Preprocessed images

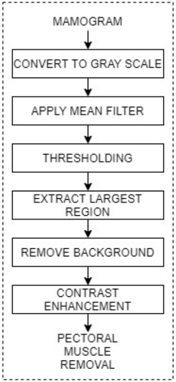


Figure: Preprocessing

Image Preprocessing: Implementation

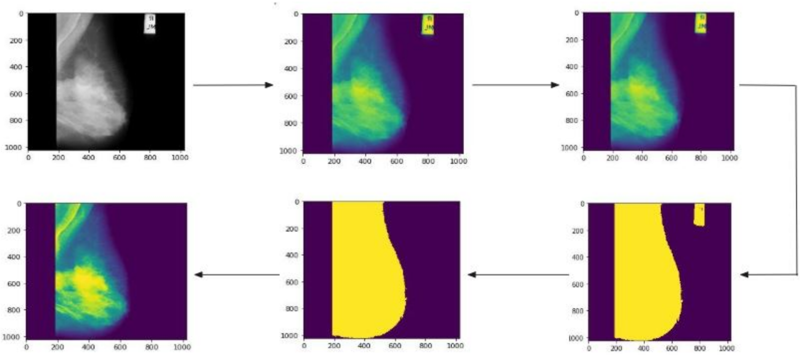


Figure: Preprocessing

Pectoral Muscle: Flow

- Input - Preprocessed images
- Output - Images without pectoral muscle

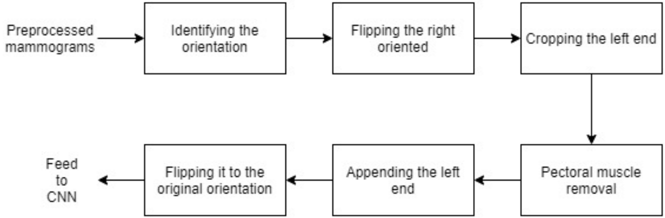


Figure: Pectoral Muscle

Pectoral Muscle: Preprocessing

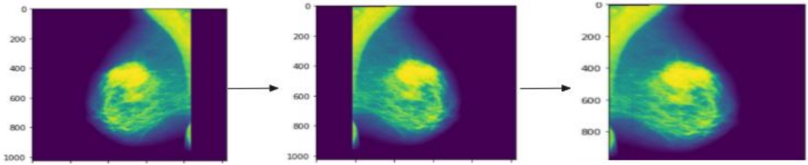


Figure: Flipping and Cropping

Pectoral Muscle: Linear Cut-off

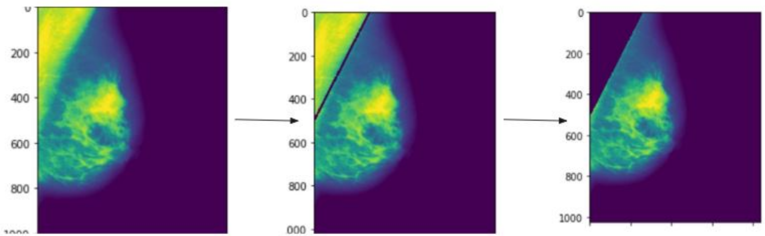


Figure: Existing Method: Linear Cut-off

Pectoral Muscle: Proposed Algorithm

Algorithm 1: Image processing of pectoral muscle

Input: Preprocessed images

Result: Images containing breast mass

Procedure;

for *each image* i **do**

Consider the first $\mathbf{N}$ rows from the top right corner, traverse each row and locate the index $\mathbf{x_j}$ of the last pixel having value greater than threshold $\mathbf{T}$ where;

1. $0 \leq \mathbf{T} < 255$
2. $1 \leq \mathbf{j} < \mathbf{N}$

Consider the first $\mathbf{N}$ columns from the top right corner, traverse each column and locate the index $\mathbf{y_j}$ of the last pixel having value greater than threshold $\mathbf{T}$ where;

1. $0 \leq \mathbf{T} < 255$
2. $1 \leq \mathbf{j} < \mathbf{N}$

Set $\mathbf{X}$ = maximum $(\mathbf{x_j})$ and $\mathbf{Y}$ = maximum $(\mathbf{y_j})$;

Set $\mathbf{Z} = \mathbf{X}$;

for *each row* i *in image such that* $i < Y$ **do**

Select the row and mark the last pixel with pixel value greater than $\mathbf{T}$ having index $\mathbf{k}$ such that $\mathbf{k} \leq \mathbf{Z}$;

Cut off the region along the row from indices 0 to $\mathbf{k}$;

Set $\mathbf{Z} = \mathbf{k}$;

end

end

Pectoral Muscle: Proposed Method

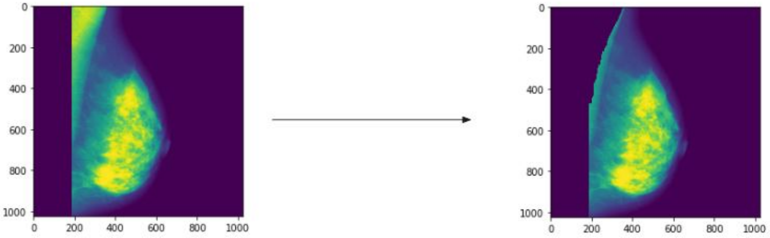


Figure: Proposed Method

Pectoral Muscle: Comparison

Algorithm: Random Forest Classifier to classify dense tissues as normal or abnormal

Linear Cut-off	Proposed System
79.16	83.30

Location Detection: Choosing the Method

Drawbacks of Artificial Neural Network (ANN) -

- ANN has no regard for spatial aspects of data

Implication

Making it unsuitable/ less relevant for image data

Location Detection: Choosing the Method

Drawbacks of Artificial Neural Network (ANN) -

- ANN has no regard for spatial aspects of data
- ANN uses huge number of parameters

Implication

As opposed to Convolutional Neural Networks (CNNs)

Location Detection: Choosing the Method

Convolutional Neural Network (CNN) -

- CNN captures spatial and temporal dependencies
- CNN assigns weights to features
- CNN achieves higher detection accuracy
- CNN delivers quantitative analysis of lesions
- CNN offers lesser number of parameters
- CNN powered CAD finds even the smallest of lesions at early stages

Location Detection: Flow

- Input - Images with no pectoral muscle
- Output - Coordinates and centre of abnormality

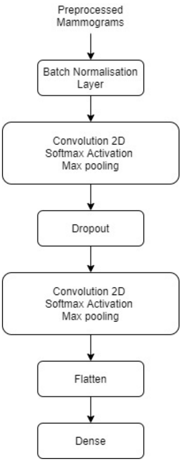


Figure: Location Detection

Location Detection: Dataset Preparation

- Convert images to Numpy array
- Reshape into four dimensions (n, w, h, c) where
  - n is the number of images (322)
  - w is the halved width of each image (512)
  - h is the halved height of each image (512)
  - c is the number of channels (1)

Location Detection: CNN Architecture

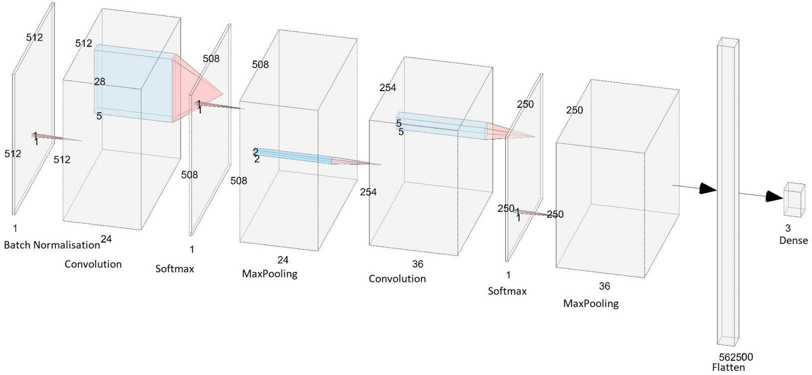


Figure: Architecture

Location Detection: CNN Summary

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
batch_normalization (BatchNo (None, 512, 512, 1)       4
_________________________________________________________________
conv2d (Conv2D)              (None, 508, 508, 24)      624
_________________________________________________________________
activation (Activation)      (None, 508, 508, 24)      0
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 254, 254, 24)      0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 250, 250, 36)      21636
_________________________________________________________________
activation_1 (Activation)    (None, 250, 250, 36)      0
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 125, 125, 36)      0
_________________________________________________________________
flatten (Flatten)            (None, 562500)            0
_________________________________________________________________
dense (Dense)                (None, 3)                 1687503
=================================================================
Total params: 1,709,767
Trainable params: 1,709,765
Non-trainable params: 2
_________________________________________________________________
```

Figure: Summary

Location Detection: Results using Various Optimisers

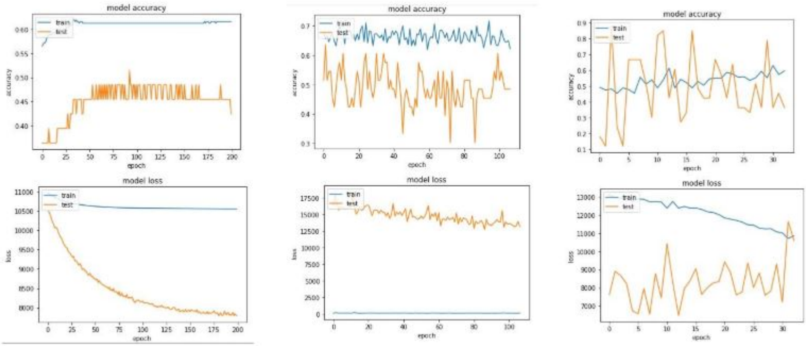


Figure: ADADELTA, Adam, Adamax

Location Detection: Results using Various Optimisers

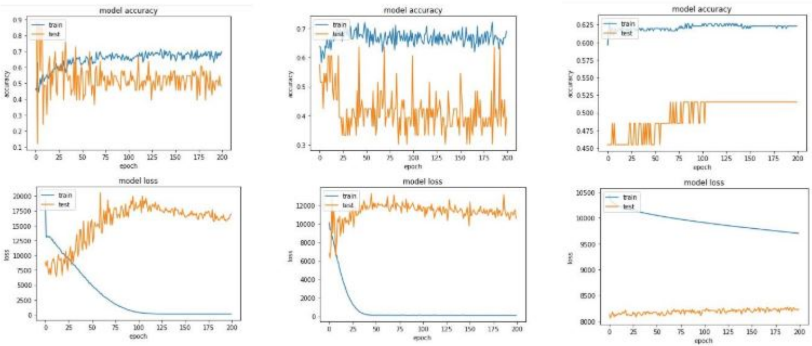


Figure: RMSProp, Nadam, Adagrad

Region of Interest (ROI) Extraction: Flow

- Input - Images, radii and coordinates of abnormality
- Output - Cropped approximate region

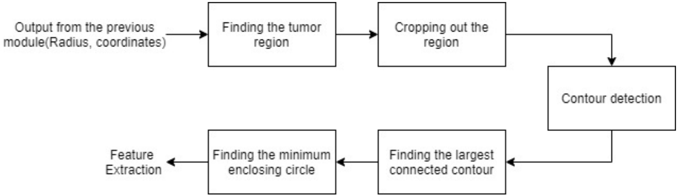


Figure: ROI Extraction

Region of Interest (ROI) Extraction: Cropping the Circular Region

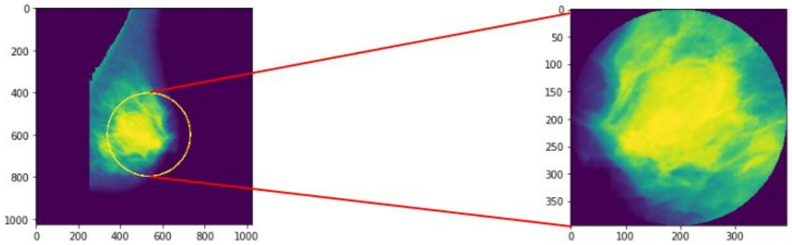


Figure: Extracting ROI

Region of Interest (ROI) Extraction: Automatic Contour Detection

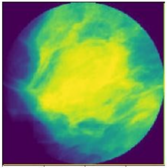


Figure: Region of Abnormality

Region of Interest (ROI) Extraction: Automatic Contour Detection

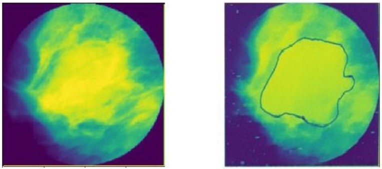


Figure: Lesion Marked by Dr Asawari Lautre, Radiologist at Tata Medical Centre, Mumbai

Region of Interest (ROI) Extraction: Automatic Contour Detection

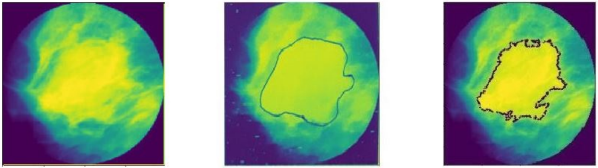


Figure: Contour Detected Automatically

Region of Interest (ROI) Extraction: Automatic Contour Detection

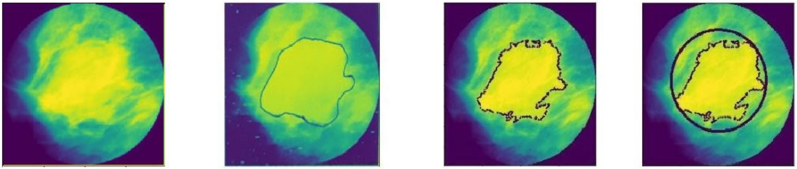


Figure: Minimum Enclosing Circle (MEC)

Feature Extraction: Features

Morphological

- Roundness
- Acreage ratio

Texture

- Energy
- Entropy
- Contrast coefficient
- Mean
- Variance

Histogram

- Histogram mean
- Histogram variance
- Histogram peak
- Histogram skew

Feature Extraction: Morphological Features

- Roundness

$$r = \frac{p^2}{4\pi A}$$

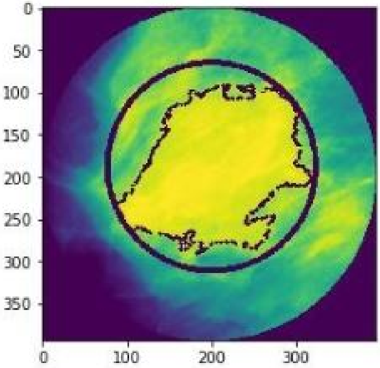


Figure: Tumor along with MEC

Feature Extraction: Morphological Features

- Roundness

$$r = \frac{p^2}{4\pi A}$$

- Acreage ratio

$$a = \frac{Area(Contour)}{Area(MEC)}$$

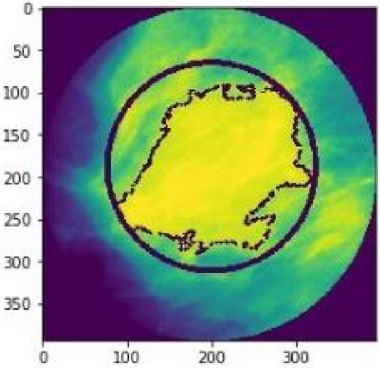


Figure: Tumor along with MEC

Feature Extraction: Texture Features

- Energy

Equation

$$E = \sum P(i,j)^2$$

Feature Extraction: Texture Features

- Energy
- Entropy

Equation

$$S = \sum P(i,j) \cdot (-ln(P(i,j)))$$

Feature Extraction: Texture Features

- Energy
- Entropy
- Contrast coefficient

Equation

$$C = \sum (i - j)^2 \cdot P(i, j)$$

Feature Extraction: Texture Features

- Energy
- Entropy
- Contrast coefficient
- Mean

Equation

$$\mu = \frac{1}{N} \sum P(i,j)$$

Feature Extraction: Texture Features

- Energy
- Entropy
- Contrast coefficient
- Mean
- Variance

Equation

$$\sigma^2 = \sum \frac{(P(i,j) - \mu)^2}{N}$$

Feature Extraction: Histogram Features

- Histogram mean
- Histogram variance
- Histogram peak
- Histogram skew

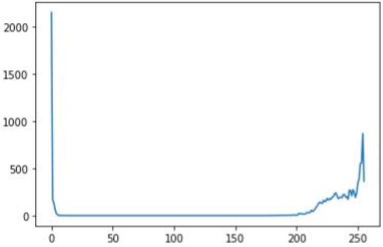


Figure: Histogram

Recommendation: TOPSIS

- Technique for Order Preference by Similarity to Ideal Solution
- Multi-criteria decision making
- Based on Euclidean distance

Recommendation: Flow

- Input - Feature matrix, weight matrix
- Output - Ranked recommendation

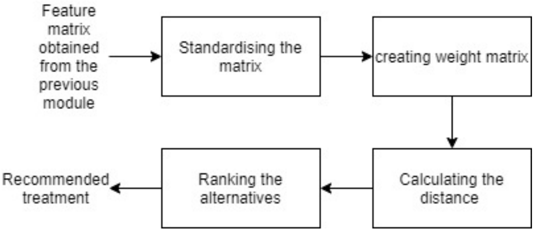


Figure: Recommendation

Recommendation: Implementation Steps

1. Standardise the feature matrix using min-max scaling

Equation

$$X_{sc} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Recommendation: Implementation Steps

1. Standardise the feature matrix using min-max scaling
2. Normalise the weight matrix

Equation

$$X_{inorm} = \frac{X_i}{\sqrt{\sum x_i^2}}$$

Recommendation: Implementation Steps

1. Standardise the feature matrix using min-max scaling
2. Normalise the weight matrix
3. Find Euclidean distance of each alternative from feature tuple

Equation

$$d = \sqrt{\sum (x_i - y_i)^2}$$

Recommendation: Implementation Steps

1. Standardise the feature matrix using min-max scaling
2. Normalise the weight matrix
3. Find Euclidean distance of each alternative from feature tuple
4. Rank the alternatives in accordance with increasing Euclidean distance

Equation

$$d = \sqrt{\sum (x_i - y_i)^2}$$

Recommendation: Implementation Steps

Weight matrix obtained from the radiologist surveyed

	CRITERIA										
ALTERNATIVES	Roundness	Acreage Ratio	Energy	Entropy	Contrast Coefficient	Texture Mean	Texture Variance	Histogram Mean	Histogram Variance	Histogram Peak	Histogram Skew
Reimaging or Other	6	5	7	7	4	6	6	6	5	6	5
Immediate Treatment	0	7	8	8	10	9	8	7	6	10	0
No Treatment	10	1	2	2	1	2	1	2	1	2	10

Recommendation: Implementation Steps

Normalised weight matrix

	CRITERIA										
ALTERNATIVES	Roundness	Acreage Ratio	Energy	Entropy	Contrast Coefficient	Texture Mean	Texture Variance	Histogram Mean	Histogram Variance	Histogram Peak	Histogram Skew
Reimaging or Other	0.6	0.7	0.7	0.7	0.4	0.6	0.7	0.7	0.7	0.6	0.5
Immediate Treatment	0	0.86	0.72	0.72	0.92	0.79	0.77	0.71	0.73	0.82	0.89
No Treatment	0.84	0.11	0.18	0.18	0.09	0.17	0.09	0.2	0.12	0.16	0

Recommendation: Implementation Steps

Tuple from feature matrix

Roundness	Acreage Ratio	Energy	Entropy	Contrast Coefficient	Texture Mean	Texture Variance	Histogram Mean	Histogram Variance	Histogram Peak	Histogram Skew
0.599662	0.544823	0.185483	0.884496	1	0.187019	0.448059	1	1	1	0.944063

Recommendation: Implementation Steps

Subtraction of tuple values from normalised weight matrix

Roundness	Acreage Ratio	Energy	Entropy	Contrast Coefficient	Texture Mean	Texture Variance	Histogram Mean	Histogram Variance	Histogram Peak	Histogram Skew
0.599662	0.544823	0.185483	0.884496	1	0.187019	0.448059	1	1	1	0.944063

ALTERNATIVES	CRITERIA										
	Roundness	Acreage Ratio	Energy	Entropy	Contrast Coefficient	Texture Mean	Texture Variance	Histogram Mean	Histogram Variance	Histogram Peak	Histogram Skew
Reimaging or Other	0.6 - 0.599662	0.7 - 0.54482	0.7 - 0.18548	0.7 - 0.88449	0.4 - 1	0.6 - 0.18701	0.7 - 0.44805	0.7 - 1	0.7 - 1	0.6 - 1	0.5 - 0.944063
Immediate Treatment	0 - 0.599662	0.86 - 0.54482	0.72 - 0.18548	0.72 - 0.88449	0.92 - 1	0.79 - 0.18701	0.77 - 0.44805	0.71 - 1	0.73 - 1	0.82 - 1	0.89 - 0.944063
No Treatment	0.84 - 0.599662	0.11 - 0.54482	0.18 - 0.18548	0.18 - 0.88449	0.09 - 1	0.17 - 0.18701	0.09 - 0.44805	0.2 - 1	0.12 - 1	0.16 - 1	0 - 0.944063

Recommendation: Implementation Steps

Subtraction of tuple values from normalised weight matrix

ALTERNATIVES	CRITERIA										
	Roundness	Acreage Ratio	Energy	Entropy	Contrast Coefficient	Texture Mean	Texture Variance	Histogram Mean	Histogram Variance	Histogram Peak	Histogram Skew
Reimaging or Other	0.000338	0.15518	0.51452	-0.1845	-0.6	0.41298	0.25194	-0.3	-0.3	-0.4	-0.44406
Immediate Treatment	-0.599662	0.31518	0.53452	-0.1645	-0.08	0.60298	0.32194	-0.29	-0.27	-0.18	-0.05406
No Treatment	0.240338	-0.4348	-0.0055	-0.7045	-0.91	-0.017	-0.3581	-0.8	-0.88	-0.84	-0.94406

Recommendation: Implementation Steps

Squared values

		CRITERIA										
		Roundness	Acreage Ratio	Energy	Entropy	Contrast Coefficient	Texture Mean	Texture Variance	Histogram Mean	Histogram Variance	Histogram Peak	Histogram Skew
ALTERNATIVES	Reimaging or Other	1.14E-07	0.02408	0.26473	0.03404	0.36	0.17055	0.06347	0.09	0.09	0.16	0.197192
	Immediate Treatment	0.359595	0.09934	0.28571	0.02706	0.0064	0.36359	0.10365	0.0841	0.0729	0.0324	0.002923
	No Treatment	0.057762	0.18907	3E-05	0.49631	0.8281	0.00029	0.12821	0.64	0.7744	0.7056	0.891255

Recommendation: Implementation Steps

Sum of values for each alternative

		CRITERIA											
		Roundness	Acreage Ratio	Energy	Entropy	Contrast Coefficient	Texture Mean	Texture Variance	Histogram Mean	Histogram Variance	Histogram Peak	Histogram Skew	SUM
ALTERNATIVES	Reimaging or Other	0.0000001	0.02408	0.26473	0.03404	0.36	0.17055	0.06347	0.09	0.09	0.16	0.197192	1.45407
	Immediate Treatment	0.3595945	0.09934	0.28571	0.02706	0.0064	0.36359	0.10365	0.0841	0.0729	0.0324	0.002923	1.43765
	No Treatment	0.0577624	0.18907	0.00003	0.49631	0.8281	0.00029	0.12821	0.64	0.7744	0.7056	0.891255	4.71103

Recommendation: Implementation Steps

Taking square root and assigning ranks

		CRITERIA												
		Roundness	Acreage Ratio	Energy	Entropy	Contrast Coefficient	Texture Mean	Texture Variance	Histogram Mean	Histogram Variance	Histogram Peak	Histogram Skew	SQRT SUM	RANK
ALTERNATIVES	Reimaging or Other	0.0000001	0.02408	0.26473	0.03404	0.36	0.17055	0.06347	0.09	0.09	0.16	0.197192	1.20585	2
	Immediate Treatment	0.3595945	0.09934	0.28571	0.02706	0.0064	0.36359	0.10365	0.0841	0.0729	0.0324	0.002923	1.19902	1
	No Treatment	0.0577624	0.18907	0.00003	0.49631	0.8281	0.00029	0.12821	0.64	0.7744	0.7056	0.891255	2.17049	3

Recommendation: Significance of Alternatives

- Re-imaging or other methods

Implication

- Magnetic Resonance Imaging (MRI) or Ultra Sonography (USG)
- Breast captured has a high tissue density
- Image is not clear

Recommendation: Significance of Alternatives

- Re-imaging or other methods
- Immediate treatment

Implication

- The case is of utmost seriousness
- The case is benign but needs to be addressed

Recommendation: Significance of Alternatives

- Re-imaging or other methods
- Immediate treatment
- No treatment

Implication

The case does not need immediate attention

Recommendation: Validation

The radiologist looked into each of 119 cases independently and labelled.

Results

Accuracy

- Training accuracy - 85.43%
- Testing accuracy - 73.49%

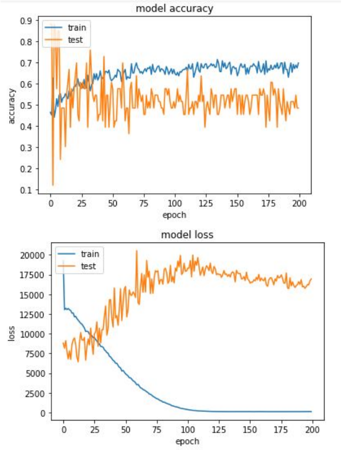


Figure: RMSProp

Performance

97 out of 119 cases
81.5%

Applications and Future Scope

Applications

1. Web application
2. Pathological labs
3. Outreach in the most remote of places

Future Scope

- Room for integrating other features (criteria)
- Room for integrating other methods of screening
- Streamlining of treatment methods (alternatives) with appropriate criteria
- Neutrosophic set in place of traditional fuzzy set theory

Conclusion

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3. A wide window for adding new criteria (features) and alternatives (treatments)
4. Flexible
5. Weights can be modified
6. Uses the most common method of imaging i.e. Mammography
7. Can be easily extended for other types of cancer

Disadvantages

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4. Image processing of pectoral muscle requires high precision
5. Weights are not set as learning quantities

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Q & A

Thank You