SD-CNN: a Shallow-Deep CNN for Improved Breast Cancer Diagnosis

Fei Gao, Teresa Wu, Jing Li, Bin Zheng, Lingxiang Ruan, Desheng Shang and Bhavika Patel

What is breast cancer? Why should we care?

- Cancer is a disease in which some of the body's cells grow uncontrollably and spread to other parts of the body. When this happens in the breast it leads to breast cancer
- 1 in 8 women will have breast cancer in their lifetime
- Early cancer detection important to avoid fatality

Methods to detect early stage Breast cancer

- Full field Digital Mammography - only clinically accepted method
    - ++ High accuracy 0.75-0.85 in general groups
    - - - Accuracy drops in detection of dense breasts to 0.3-0.5
- Ultrasound and Magnetic Resonance Imaging - adjunct techniques
    - ++ Higher accuracy for dense breasts
    - - - Lower image resolution
    - - - Higher cost
    - - - Lower accessibility and long screening time
- CEDM combines both : injection of iodinated contrast agent along with a mammography examination
    - ++ 4 times faster than MRI with 1/6th the cost
    - ++10 times spatial resolution than Breast MRI
    - - - Yet to be widely accepted

MOTIVATION

- To reduce high false positive recall rate (>10%) in detection by radiologists
- FFDM produces low energy images and used widely.
- The latest technique, CEDM produces low energy images before iodinated agent injection and high energy image after injection. Both are recombined to produce a high resolution image, which can detect even dense breast cancer. But it's low adoption is a major hindrance.
- CNNs can learn non linear mapping of input images to output synthetic images.

Why not use CNN to use FFDM's low energy image to reconstruct a virtual CEDM recombined image?

Lastly we can classify generated recombined image into malignant or benign
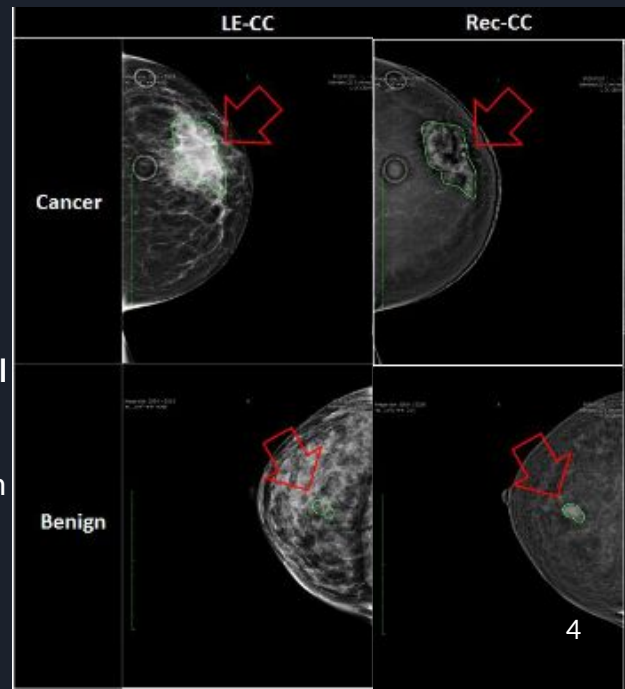
CHALLENGES

- Generating synthetic images requires massive dataset:
  - CEDM examinations from medical center Mayo Clinic Arizona (August 2014-December 2015)
  - Public dataset from INbreast
  - Both contain Low Energy (LE) Images and recombined images
- Annotate regions of tumour through smallest rectangle encompassing tumor. Done manually

MAPPING LE TO RECOMBINED IMAGES

- 4 layer shallow CNN
- 2 hidden layers, with 10 7*7 filters in each layer.
- Training with smaller FFDM image "patches" and Recombined image "patches". Final image restitched.
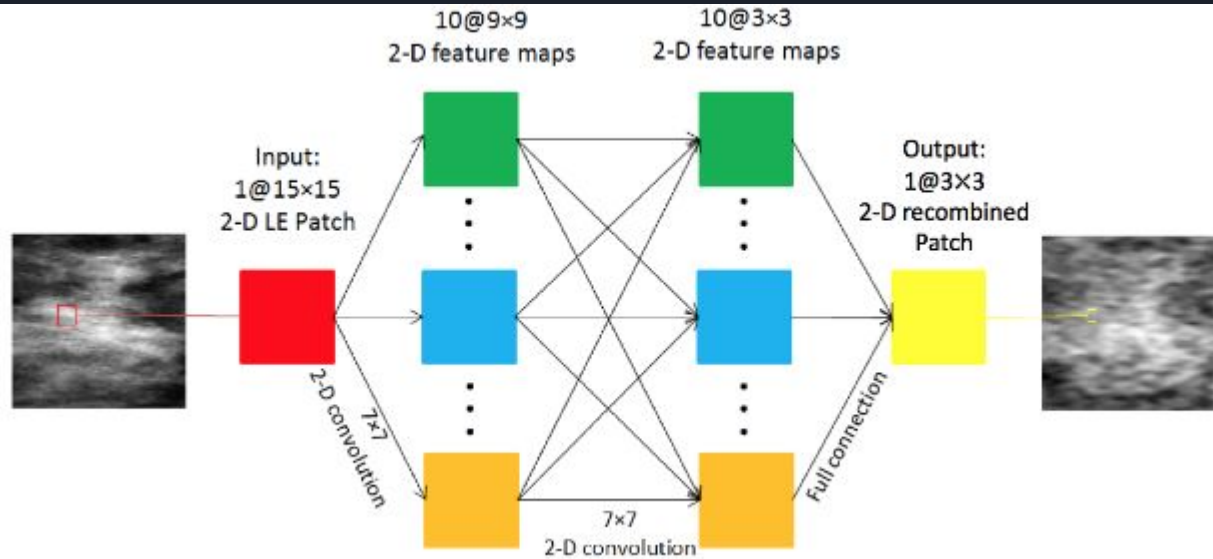
Feature generation from generated recombined image

- The authors use ResNet-50 to extract features from generated recombined image.
- Usually in CNNs gradient tends to vanish as the number of layers increases. ResNet do not suffer higher testing error with larger layers. (because output of basic blocks includes original input)
- Features in different ResNet layers describe the image from different scales and aspects
- From each layer after basic block the extracted features are combined
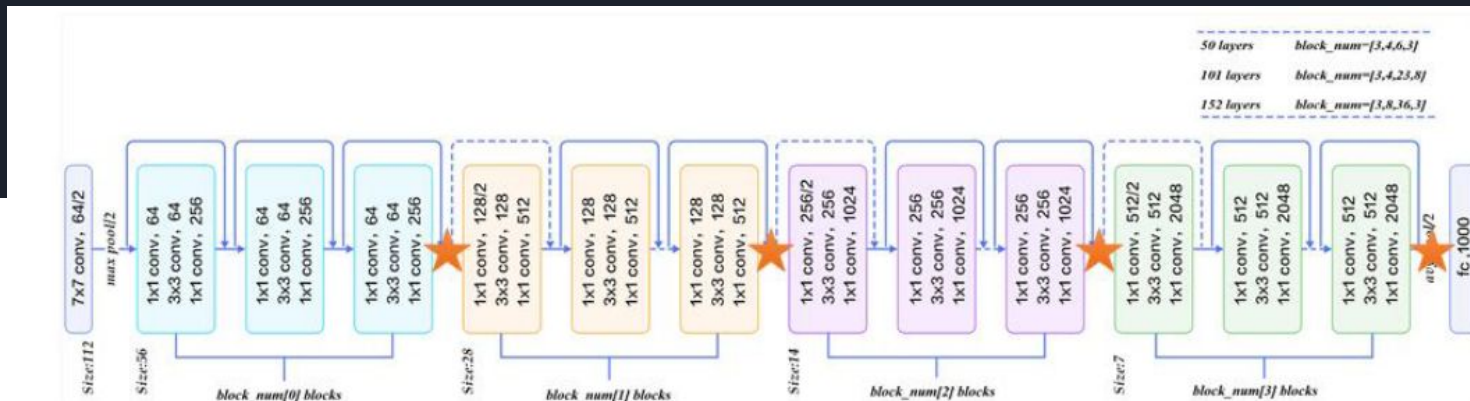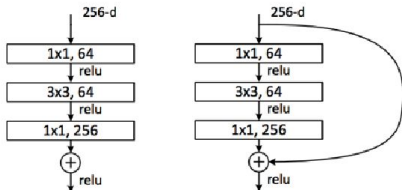
Cancer classification

- Generated features are classified using Gradient Boosting Trees (A classification algorithm).
- Why GBT? GBT was chosen because it provides importance/weight of each feature in classification
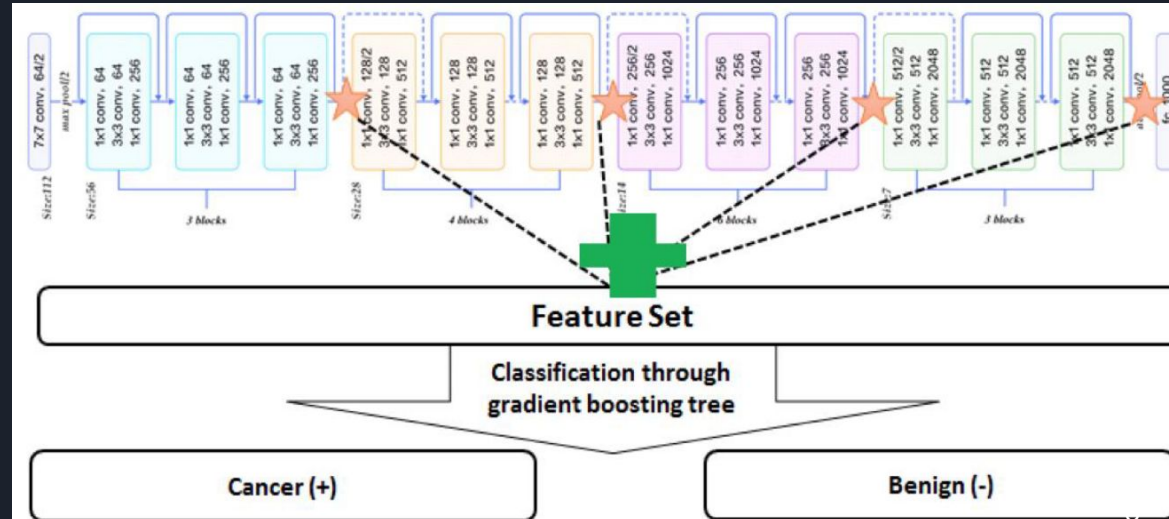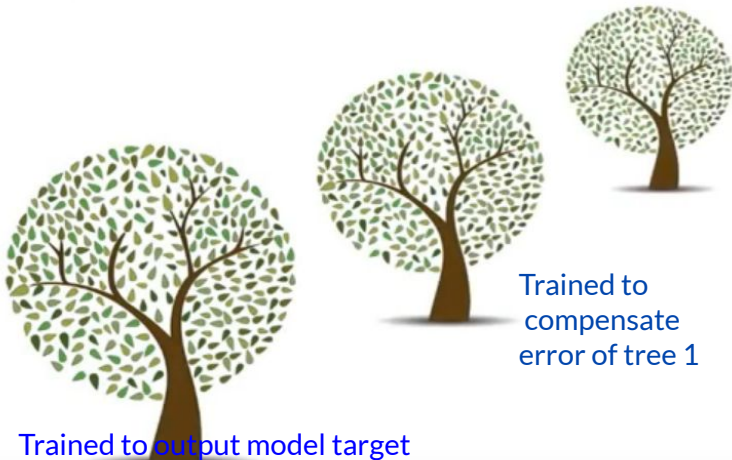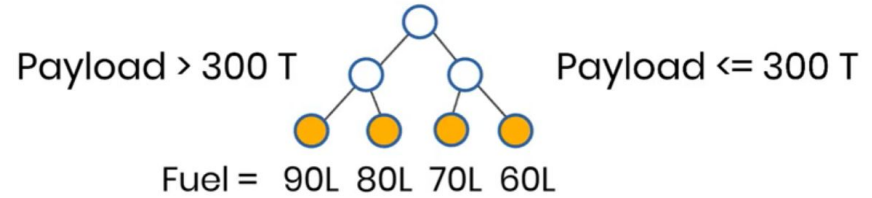

Fig. 7. Workflow of Experiment I

Parameters

Payload	Distance	Duration	Vertical Travel	Operator ID
289	6.2	25	320	16
276	6.1	24	320	16
301	6.2	24	315	18
304	3.9	18	112	18

Target

Cycle Fuel
98
96
97
56

Decision Trees

Payload > 300 T

Payload <= 300 T

Fuel = 90L 80L 70L 60L
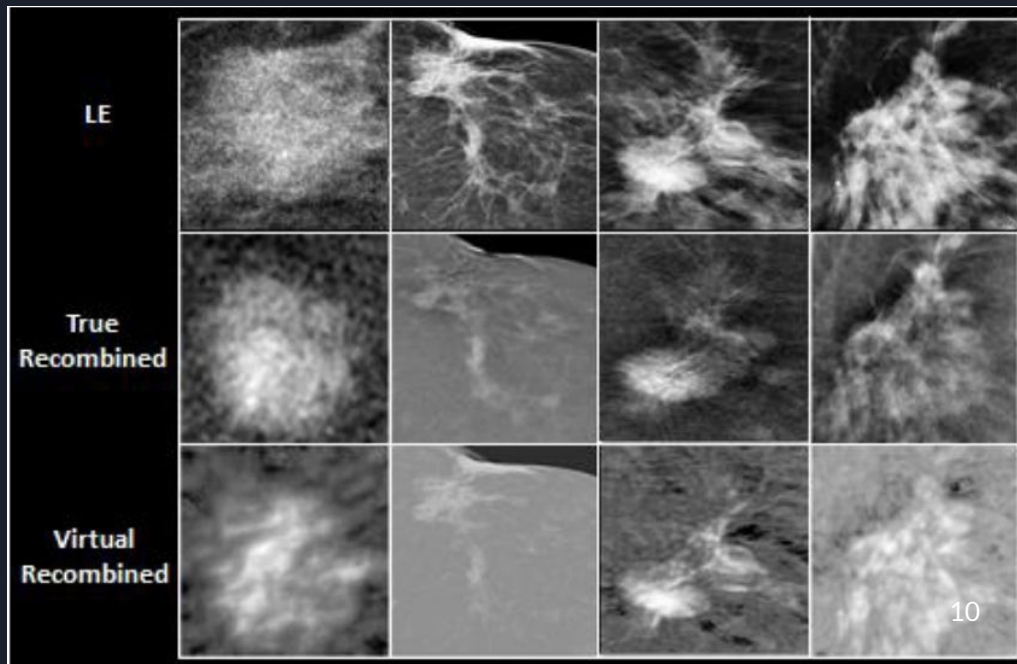
Trained to compensate error of tree 1

Trained to output model target

HOW GOOD ARE VIRTUAL RECOMBINED IMAGES?

- Mean squared error used to measure pairwise squared difference in intensity
- MSE is 0.031
- Standard deviation 0.021

$$MSE = \frac{1}{N} \sum_{i=1}^{N} |TRecombined(i) - VRecombined(i)|^2$$

LE

True Recombined

Virtual Recombined

RESULTS

	LE	LE and True Recombined	LE and Virtual Recombined
Accuracy	0.85	0.89	0.9
Sensitivity	0.89	0.93	0.83
Specificity	0.80	0.86	0.94
AUC	0.84	0.91	0.92

Image Source	No. of Features	Contribution to classification
LE image	56	76.84%
True Recombined image	43	23.16%

Image Source	No. of Features	Contribution to classification
LE image	67	22.33%
Virtual Recombined image	87	77.67%

Region Extraction and Classification of Skin Cancer: A Heterogeneous framework of Deep CNN Features Fusion and Reduction

Tanzila Saba, Muhammad Attique Khan, Amjad Rehman, Souad Larabi, Marie-Sainte

ABOUT SKIN CANCER & DETECTION

- Melanoma - Most dangerous type of skin cancer beginning in pigment cells.
  - 5 year survival ratio of advanced stage is <15%
  - Survival depends on early detection
  - Detected using gel placed on lesion area followed by using a magnifier tool to get illuminated and magnified image of skin
- Non melanoma - less dangerous

- **Motivation:** Interpretation of dermoscopic images is challenging and time consuming. Prone to errors.

 Can we use CNN to classify images as melanoma?

DATASET

- Three famous dermoscopy datasets: ISBI 2016, ISBI 2017 and PH2
- PH2 contains 40 melanoma, 160 non melanoma
- ISBI 2016 challenge contains 1279 images in total with 900 images benign and 379 melanoma
- ISBI 2017 challenge contains 2750 images , 517 melanoma, 2233 benign

CHALLENGES

- Imbalanced/skewed classes - availability of datasets is small - melanoma cases are significantly lesser than non melanoma.
  - Rotate melanoma cases into 4 different angles for data augmentation
- Similar colors of healthy and skin lesions. Change in lesion shapes, textures
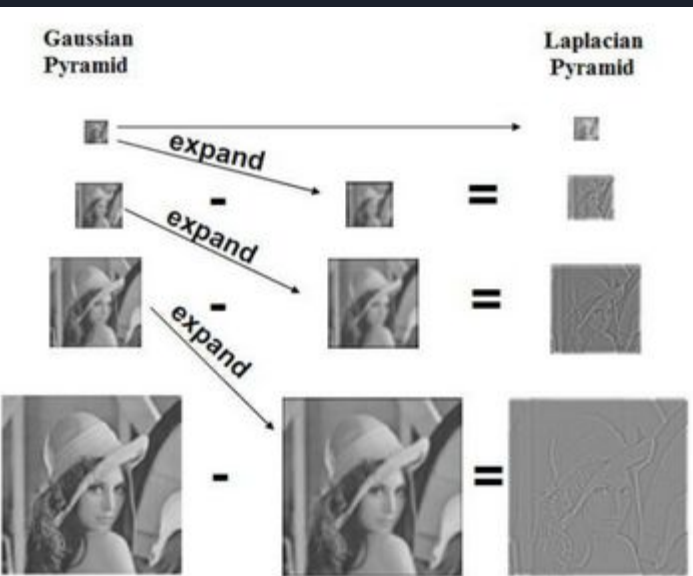- Other artifacts like veins, hair,air bubbles reduce accuracy
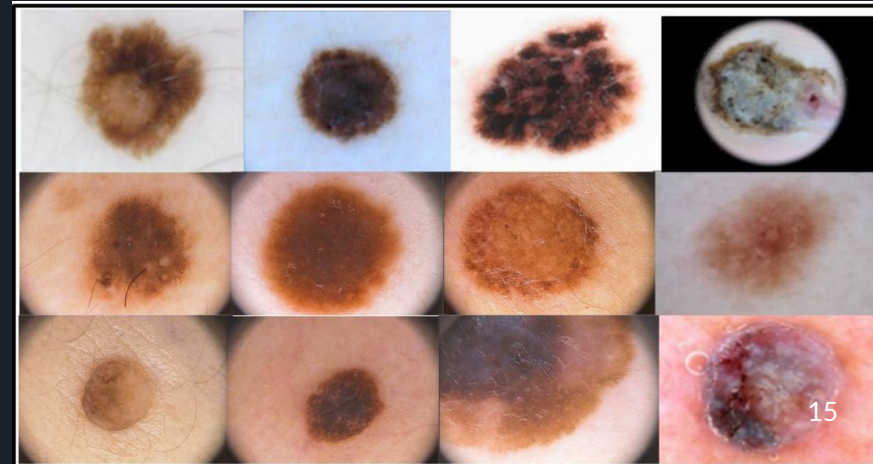
WORKFLOW
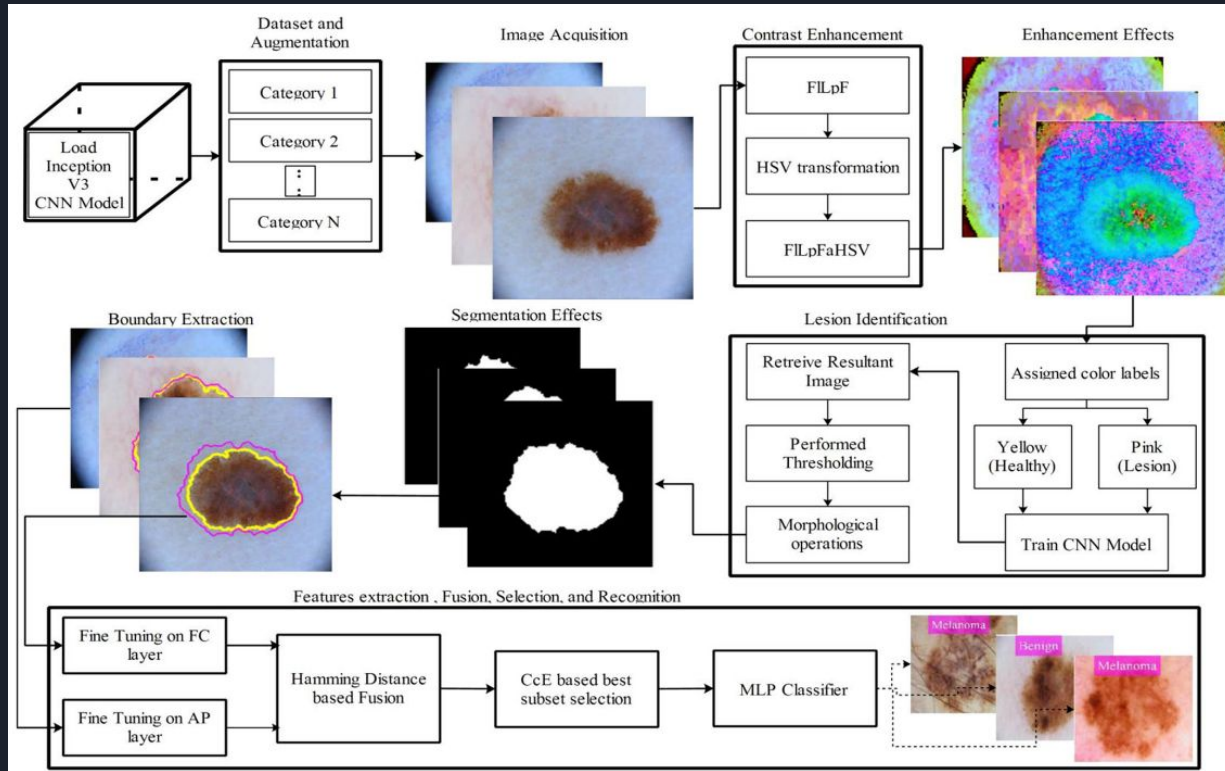
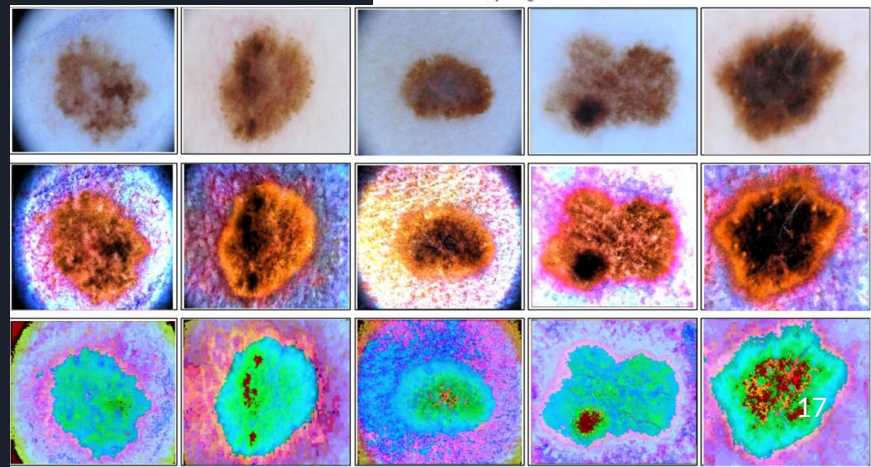# EDGE DETECTION & CONTRAST ENHANCEMENT

- Fast local laplacian filtering to highlight the edges
- Then HSV color transformation applied to enhance contrast. Highlighted edges of lesion are further improved

$$H' = \begin{cases} \text{undefined}, & \text{if } C = 0 \\ \frac{G-B}{C} \bmod 6, & \text{if } M = R \\ \frac{B-R}{C} + 2, & \text{if } M = G \\ \frac{R-G}{C} + 4, & \text{if } M = B \end{cases}$$

LESION IDENTIFICATION

- XOR operation between HSV transformed image and laplacian filtered image
- After computing boundary, internal lesion pixels are profiled
- Through a probability value pixels with intensity 0-0.4 best represent lesion pixels
- Lesion and healthy pixels segregated into two groups
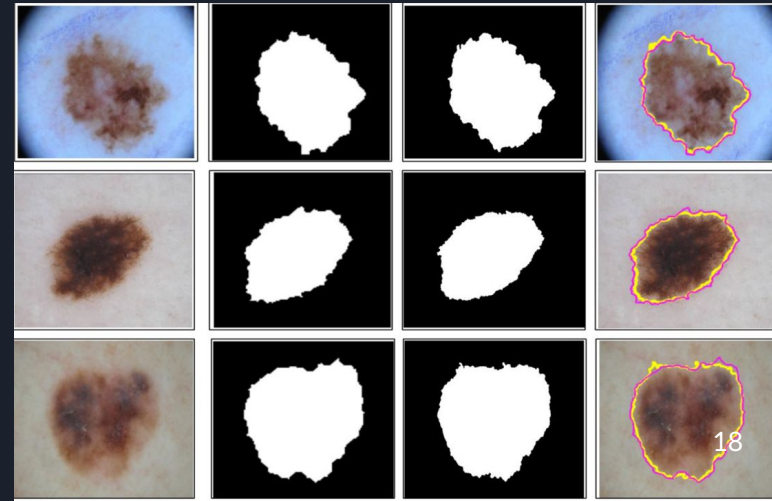
FEATURE EXTRACTION & CLASSIFICATION

- Inception V3 CNN pretrained model is used to extract features from the lesion identified image patches.
- Features are extracted from the activation following the FC and AP layer. These features are fused together
- Fused feature vector is K-means clustered (k=2). Entropy of each cluster is calculated and highest value features chosen through weights posterior probability assignment
- Then this chosen feature subset is classified using SVM,KNN and neural network
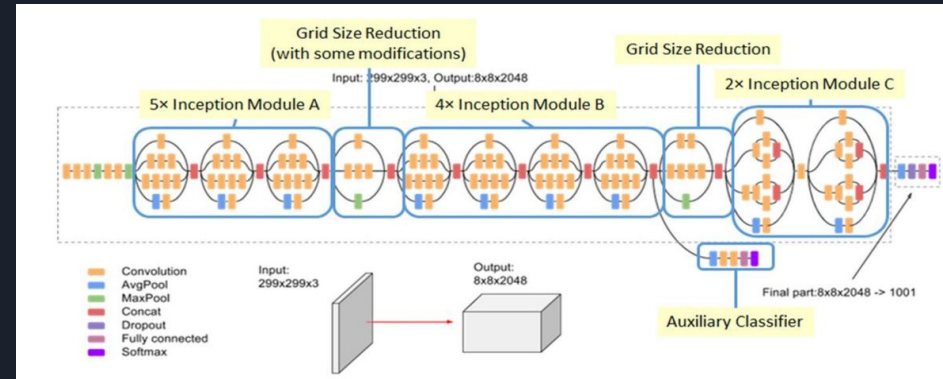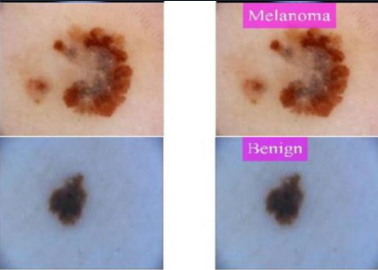
RESULTS

| Classifier	Method						Measures						
	CT		ST				Sen (%)	Spec (%)	Prec (%)	F1 M (%)	AUC	Acc (%)	FPR	Time (sec)
Trees	✓						90.5	90	90.5	90.5	0.93	90.8	0.095	13.68
			✓				91.5	94	92.0	91.69	0.91	91.8	0.085	9.34
Discriminant	LDA		QDA				Measures							
	✓						88.5	83	89	88.75	0.92	88.5	0.115	9.58
			✓				88.0	91.5	91.5	89.72	0.94	91.4	0.085	8.39
Support Vector Machine	LSVM	CSVM	QSVM	MGSVM	CGSVM		Measures							
	✓						94.0	91.0	94.0	94	0.98	93.8	0.06	9.84
		✓					92.5	93.0	92.5	92.5	0.97	92.4	0.15	8.70
			✓				91.5	92.0	92.0	91.75	0.98	91.8	0.08	8.75
				✓			92.0	90.0	92.5	92.25	0.97	92.1	0.08	8.50
					✓		89.0	83.0	89.5	89.25	0.96	88.8	0.11	8.37
K-Nearest Neighbor	FKNN	MKNN	Cosine	Cubic	W-KNN		Measures							
	✓						86.0	90.0	90.5	88.20	0.90	89.8	0.10	8.59
		✓					87.5	78.0	89.5	88.5	0.96	87.8	0.125	8.03
			✓				86.0	90.5	91.0	88.42	0.97	90.8	0.095	8.59
				✓			89.5	83.0	90.0	89.75	0.96	89.5	0.105	10.67
					✓		89.0	81.0	90.5	89.75	0.96	89.1	0.105	7.97
Neural Network	**MLP**						**95.0**	**95.0**	**95.0**	**95.0**	**0.98**	**95.1**	**0.05**	**6.97**
EBT	Baggage tree						92.0	91.0	92.5	92.25	0.97	92.1	0.08	20.59

Cancer type	Cancer type	
	Benign	Malignant
Benign	**98%**	2%
Malignant	9%	**91%**
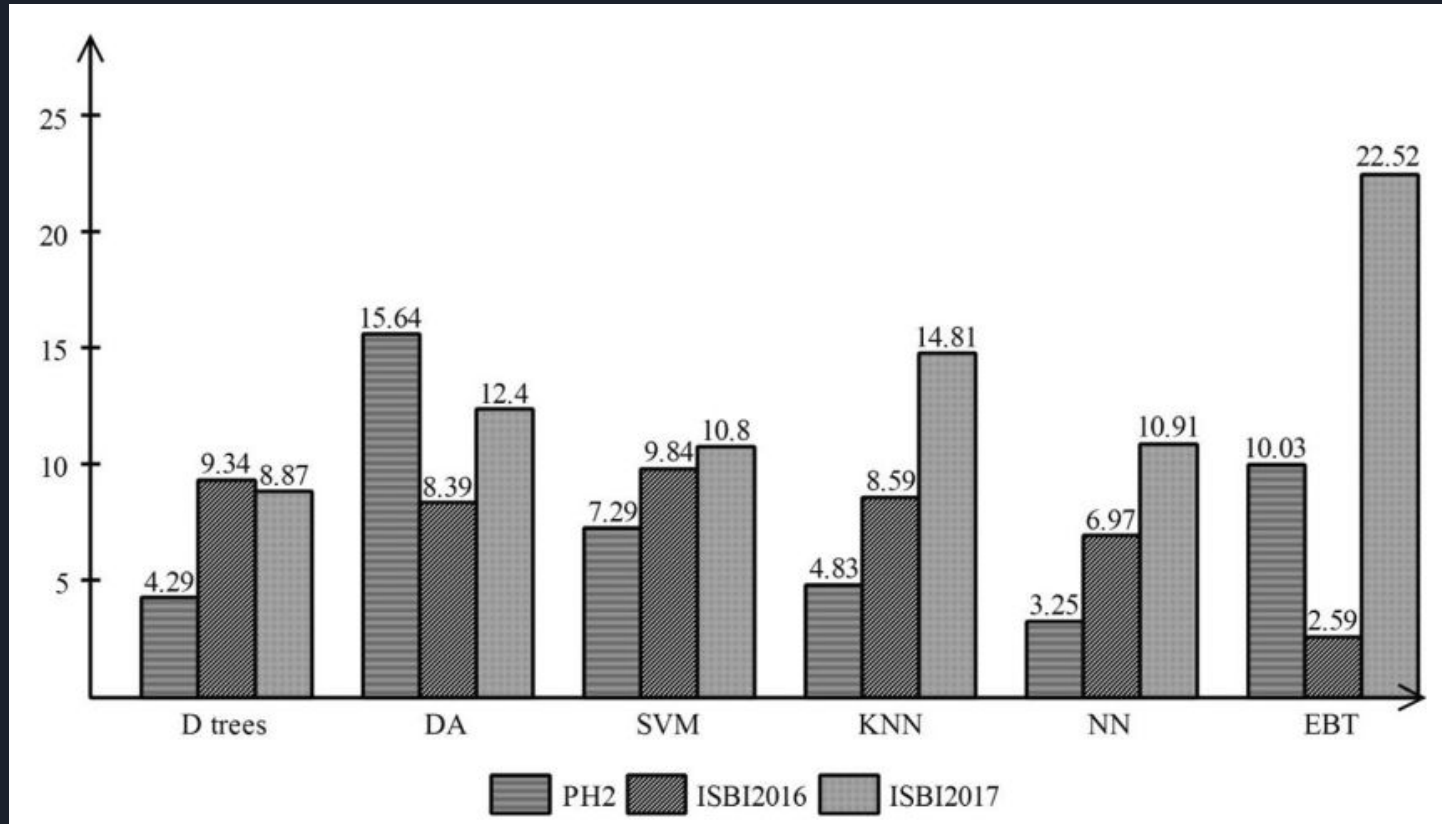
KEY TAKEAWAYS

- The proposed recognition process is evaluated on ISIB 2016, 17, and PH2 datasets and attained the best accuracy of 95.1%, 94.8%, and 98.4%, respectively
- The selection of the most relevant pixels of lesion regions provides good segmentation results that later affect the recognition process which makes results better than state of the art
- Selection of the best subset of features reduces the overall system execution time
- Neural network with Multilayer Perceptron MLP technique outperforms the other techniques by classification accuracy and execution time.

RELATED WORK

Deep embedding convolutional neural network for synthesizing CT image from T1-Weighted MR image. Xiang L, Wang Q, Nie D, Zhang L, Jin X, Qiao Y, Shen D.

Lung Cancer Detection and Classification with 3D Convolutional Neural Network (3D-CNN)

Wafaa Alakwaa, Mohammad Nassef, Amr Badr

Deep learning-based bone suppression in chest radiographs using CT-derived features: a feasibility study Ren G, Xiao H, Lam SK, Yang D, Li T, Teng X, Qin J, Cai J.