DarkNet-53 CNN for Breast Cancer Detection and Classification

"Turning Pixels into Lifesaving Insights"

Advanced Machine Learning CSCI-575

Presentation Group 9

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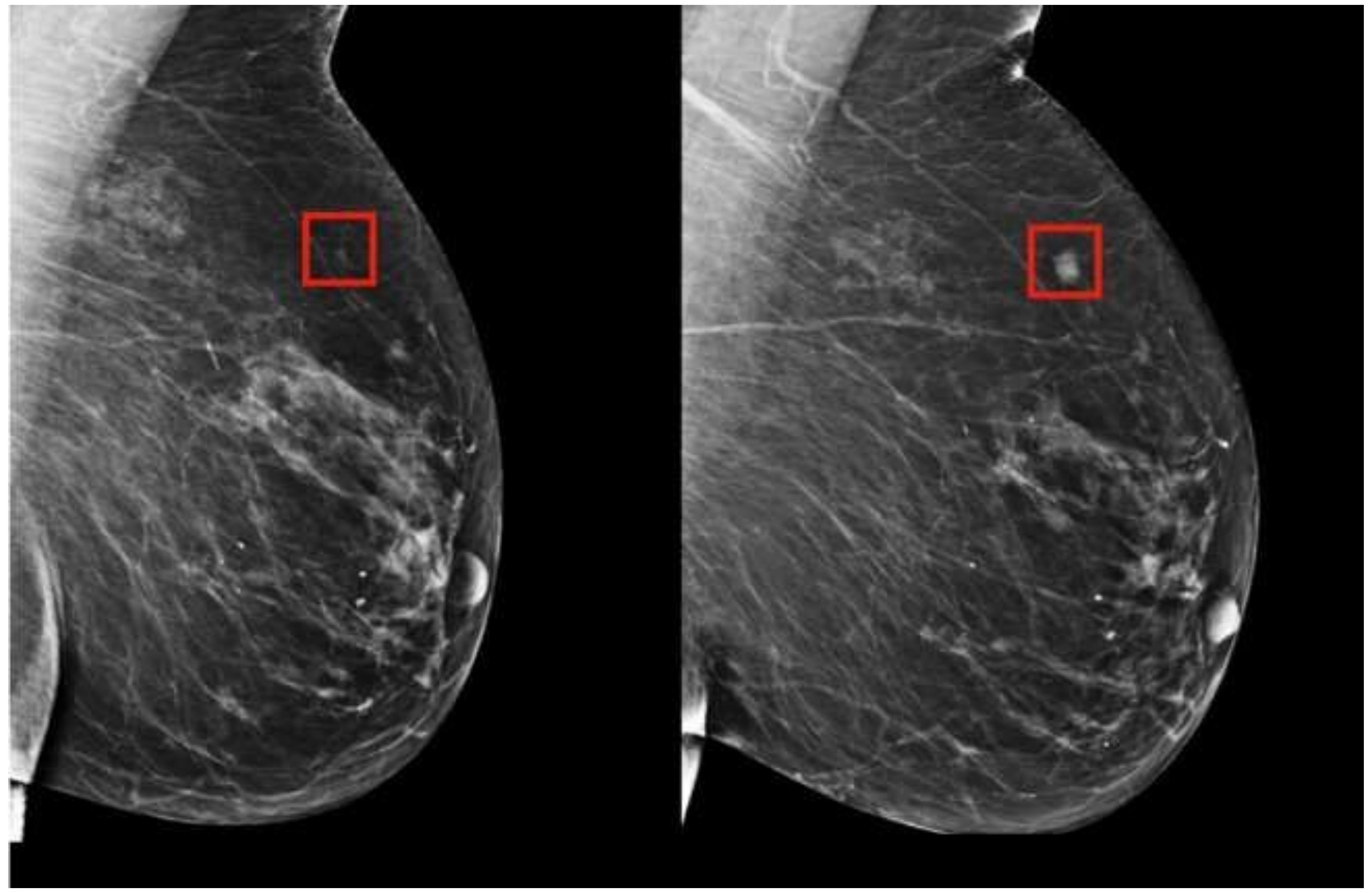
03/04/2025

Reference Research Paper:

DARKNET-53 Convolutional Neural Network-Based Image Processing for Breast Cancer Detection (R. Rajkumar, S. Gopalakrishnan, K. Praveena, M. Venkatesan, K. Ramamoorthy, & J. J. Hephzipah , Trans.). *Mesopotamian Journal of Artificial Intelligence in Healthcare*, *2024*, 59-68. https://doi.org/10.58496/MJAIH/2024/009

1. Introduction: The Challenge of Breast Cancer

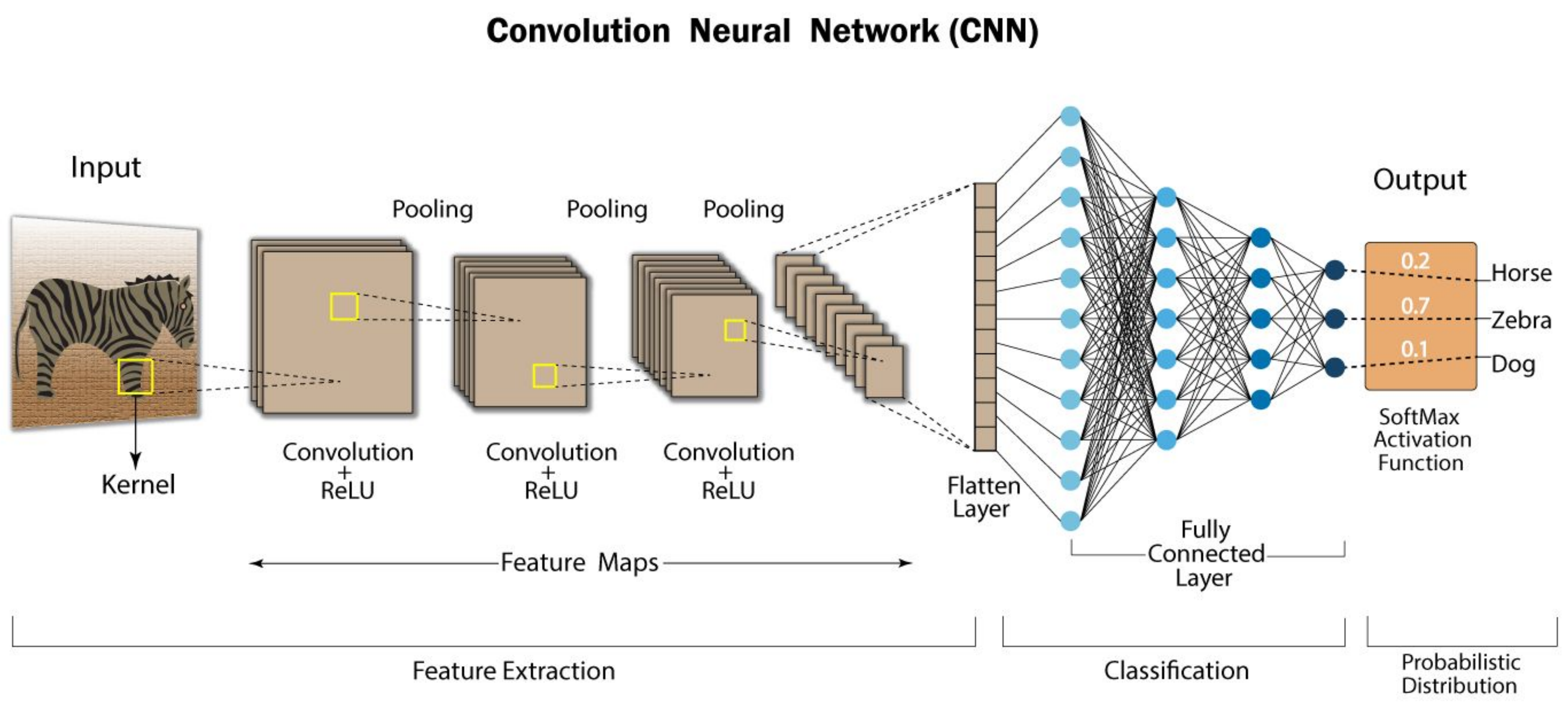
- Breast cancer: a **leading cause of death** for women—**early detection** boosts survival rates up to **90%**.
- Imagine a world where we catch it early **every time**—lives depend on it.
- Doctors rely on **mammograms** and **ultrasounds**, but spotting tiny tumors is tough—like finding a needle in a haystack.
- **CAD** (Computer-Aided Diagnosis) helps, but manual detection takes expertise and still misses too much."



https://dicect.com/2016/08/11/clahe/

2. Research Problem and Approach

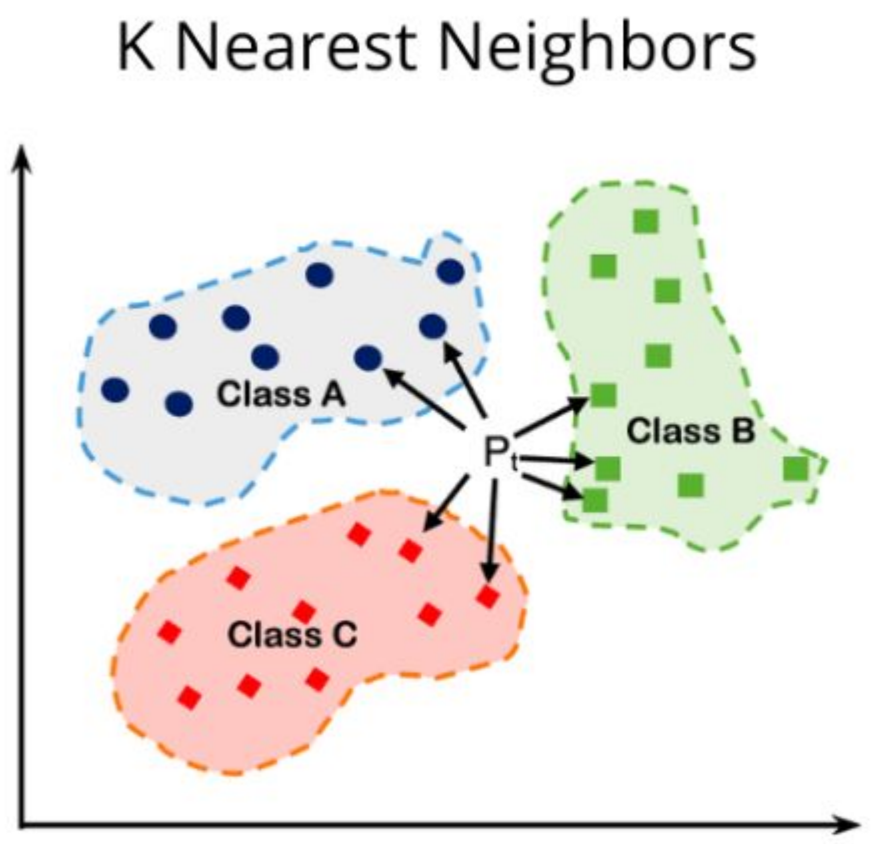
- The puzzle: **Can a machine tell if a blurry breast image hides cancer—benign or malignant?**
- Tumors vary in size and shape, and noisy images make it harder—there's no easy fix.
- Older tools like fuzzy logic or basic CNNs couldn't keep up—too many mistakes.
- We need a smarter detective: **DarkNet-53 steps up to crack the case.**



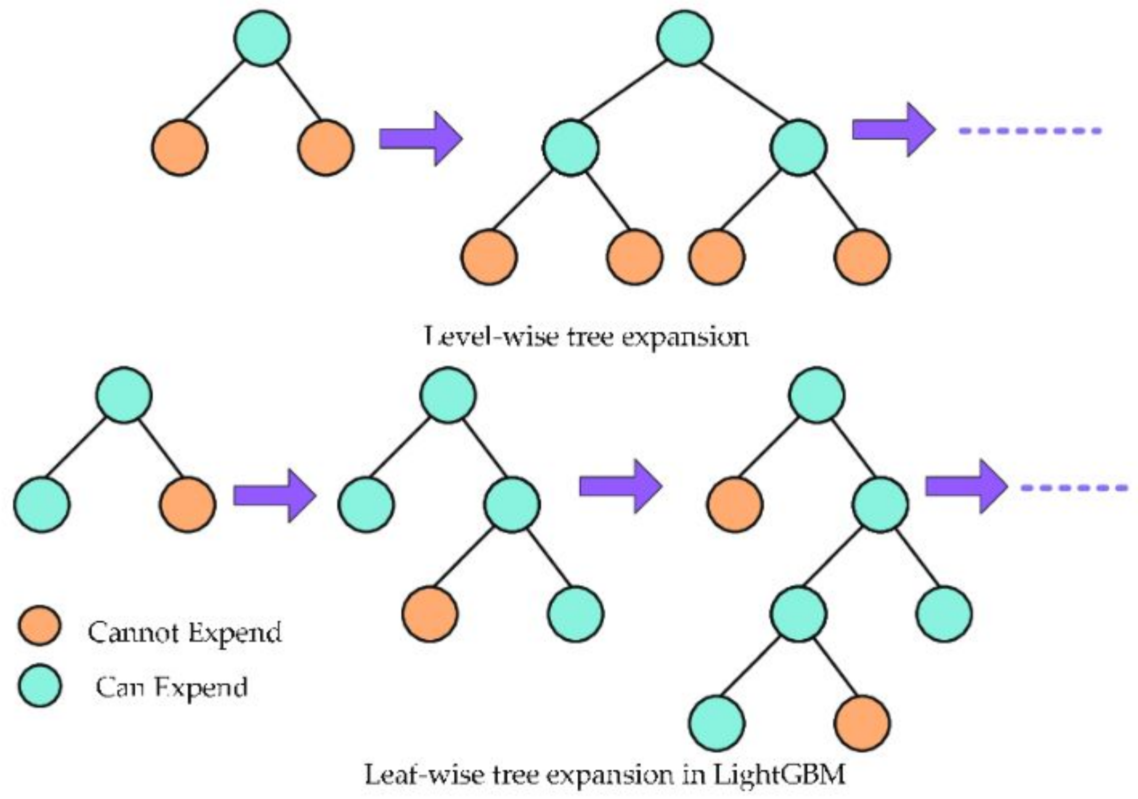
https://www.linkedin.com/pulse/what-convolutional-neural-network-cnn-deep-learning-nafiz-shahriar/

3. Literature review

- Past attempts: Fuzzy logic stumbled on blurry regions; basic CNNs worked for lungs, not breasts.
- DBN tackled histopathology, and LGBM hit 89% accuracy—but still not perfect.
- Table 1: Old methods (e.g., Random Forest, KNN, CNNs, DenseNet161) topped out at 93%—too many gaps.
- **DarkNet-53 promises a deeper look—let's see if it outsmarts the competition.**



https://medium.com/@sachinsoni600517/k-nearest-neighbours-introduction-to-machine-learning-algorithms-9dbc9d9fb3b2



https://medium.com/@venkatyogesh003/unveiling-the-power-of-light-gbm-e3b46743a2b2

TABLE I. IMAGE PROCESSING BASED ON BREAST CANCER PREDICTION

Author/Year	Technique Used	Dataset	Limitation	Accuracy
V. Durga Prasad Jasti/2022 (11)	random forest, and Naïve Bayes	MIAS Mammography	There are currently no effective technologies for the prevention or treatment of breast cancer.	91.6%
Khalid, A /2023 (12)	k-nearest neighbours (KNN) logistic regression (LR)	Exploratory Data Analysis (EDA)	The prognosis and diagnosis of cancer demand exacting attention to segment.	70%
Zakareya, S/2023 (13)	convolutional neural networks (CNNs)	breast histopathology image	Selecting the right kernel size for a convolution operation can be challenging.	93%
Mewada, H / 2024 (14)	DenseNet161 network	Breast Cancer Histopathological Database (BreakHis)	However, multi-class classification may reduce performance	94.65%
S. Gopalakrishnan et al., 2022 (15)	Random Forest (RF)	Chronic Disease Indicators	A major limitation of random forest is that a large number of trees can make the algorithm very slow, resulting in inefficient real-time predictions.	93.8%

4. Methodology

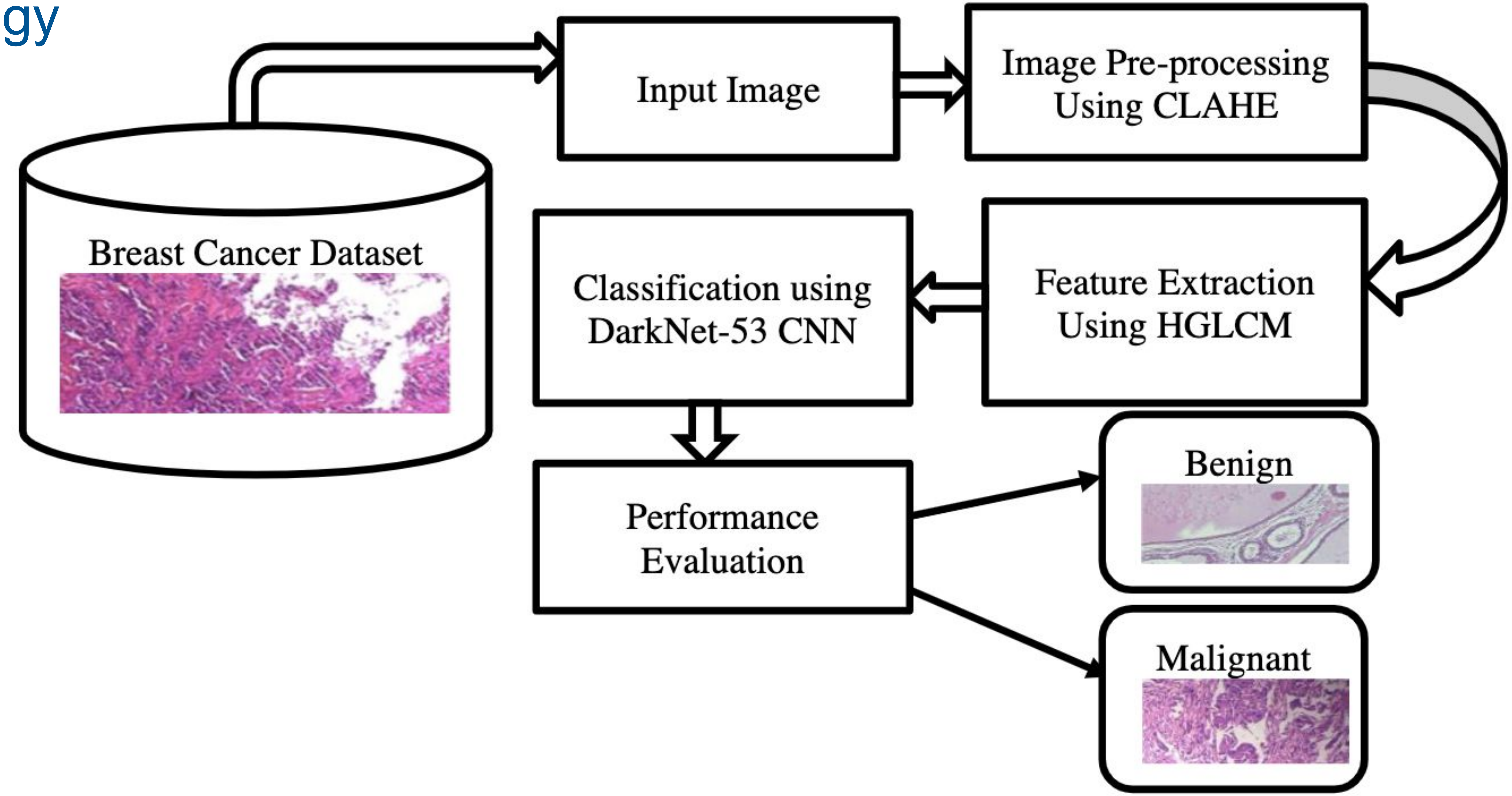
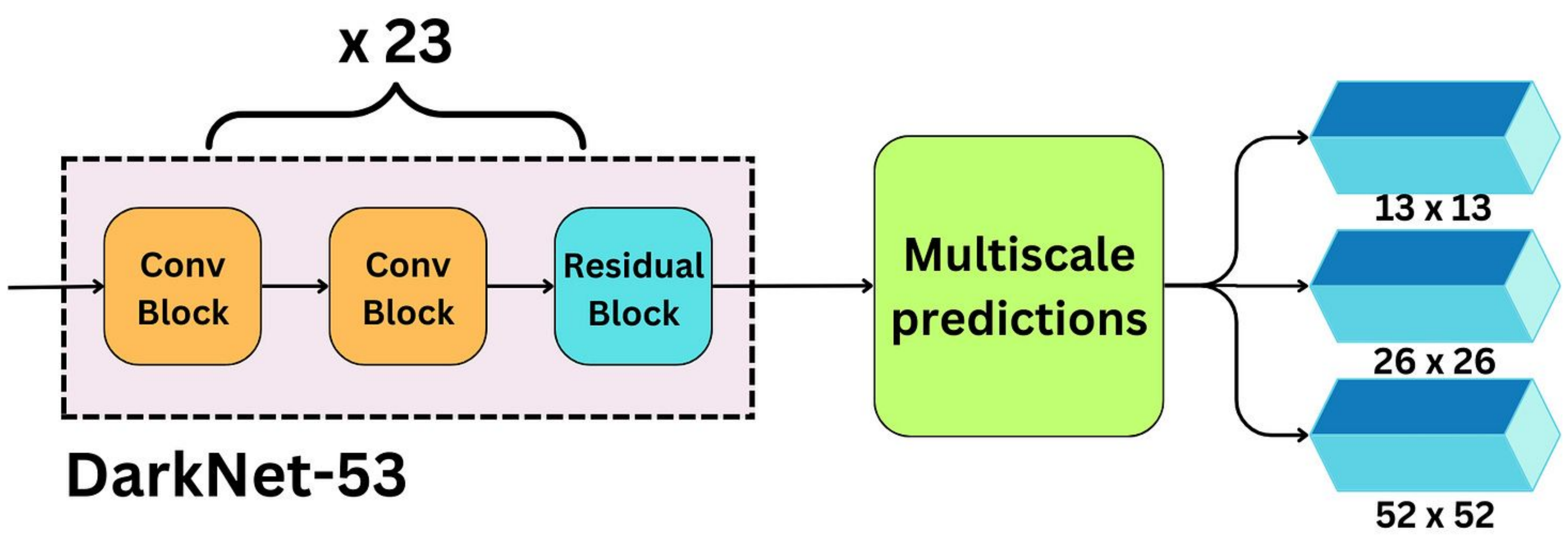


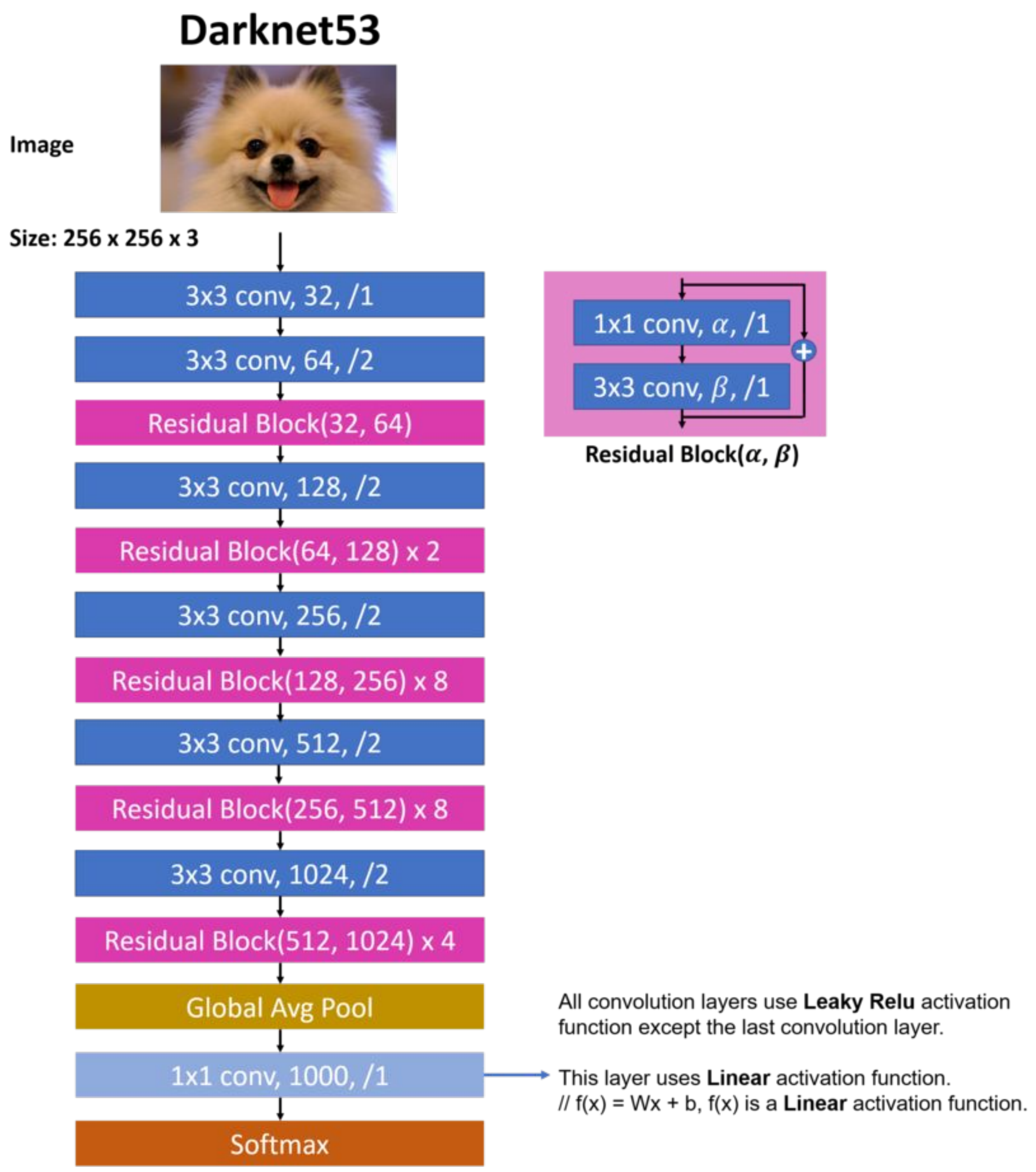
Fig. 1. The Proposed Architecture Diagram for DarkNet-53 CNN

4.1 Architecture

- Meet DarkNet-53: a clever network to see through breast image chaos.
- **Step 1**: Clean up—**CLAHE** acts like a photo filter, making faint tumors pop.
- **Step 2:** Dig deeper—**HGLCM** maps pixel patterns.
- **Step 3:** Decide—DarkNet-53 trains on **thousands** of images.



https://newsletter.theaiedge.io/p/deep-dive-how-yolo-works-part-1-from

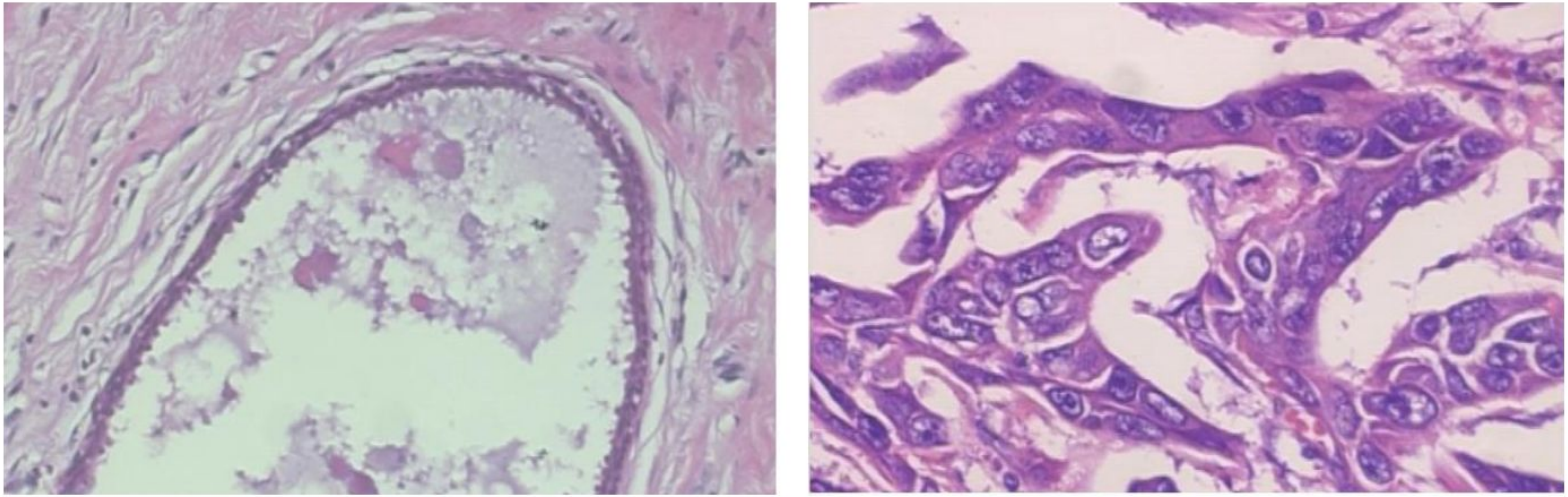


https://github.com/developer0hye/PyTorch-Darknet53

4.2 Dataset Collection

- Dataset from **Kaggle**: **7783** breast cancer histopathology images.
- 82 patients.
- Classification: **5304** malignant, **2479** benign.
- [Link to Dataset]

https://opendatascience.com/10-tips-to-get-started-with-kaggle/

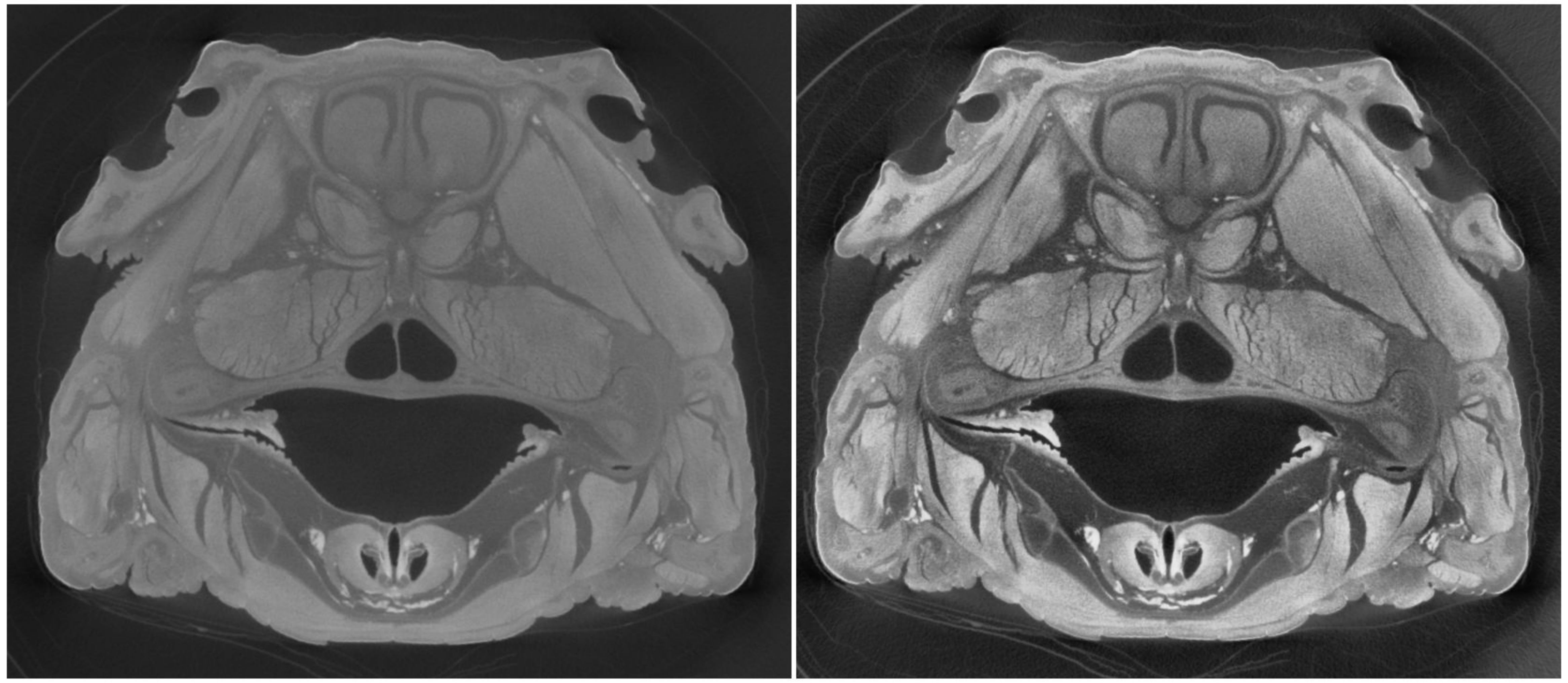


(a) Benign (b) Malignant

Fig. 2. The Breast Cancer Image Dataset collection

4.3 Image Preprocessing

- **CLAHE** (Contrast-Limited Adaptive Histogram Equalization).
- Enhances image quality and reduces noise.
- Analyzes **pixel-by-pixel** grey-level measurements.
- Improves **local contrast** by analyzing pixel distribution.
- Analyzing grey level relative to the total pixel count in image —> Optimizing value of the transfer function —> I**mage quality improved**
- Equations 1-6



http://dicect.com/2016/08/11/clahe/

Calculate the grey level corresponding to the total number of pixels in the histopathology image (Equation 1)
Where q = total pixels histopathology image, q_1 = pixel number, t_1 = grey level, r = random variable

$$m_t(t_l) = \frac{q_l}{q} \tag{1}$$

Calculate the grey levels of the input and output images as random variable probability density functions of the areas of the original image histogram and the processed histogram (Equation 2)
$m_w(w)$ and $m_t(t)$ = probability of density function, t = grey level input image, and w = output image

$$m_w(w) = m_t(t)\,\frac{c_t}{c_w} \tag{2}$$

Estimate the grayscale transfer function of the integrated dummy variable (Equation 3)
s = integral dummy variable

$$w = r(t) = (k-1)\int_0^t m_t(s)\,c_s \tag{3}$$

Estimate the grey level transfer function based on the combined characteristics described (Equations 4 and 5)

$$\frac{c_w}{c_t} = \frac{c_r(t)}{c_t}(K-1)\frac{c}{c_r}\left[\int_0^t m_t(s)\, c_s\right] = (k-1)m_t(t) \tag{4}$$

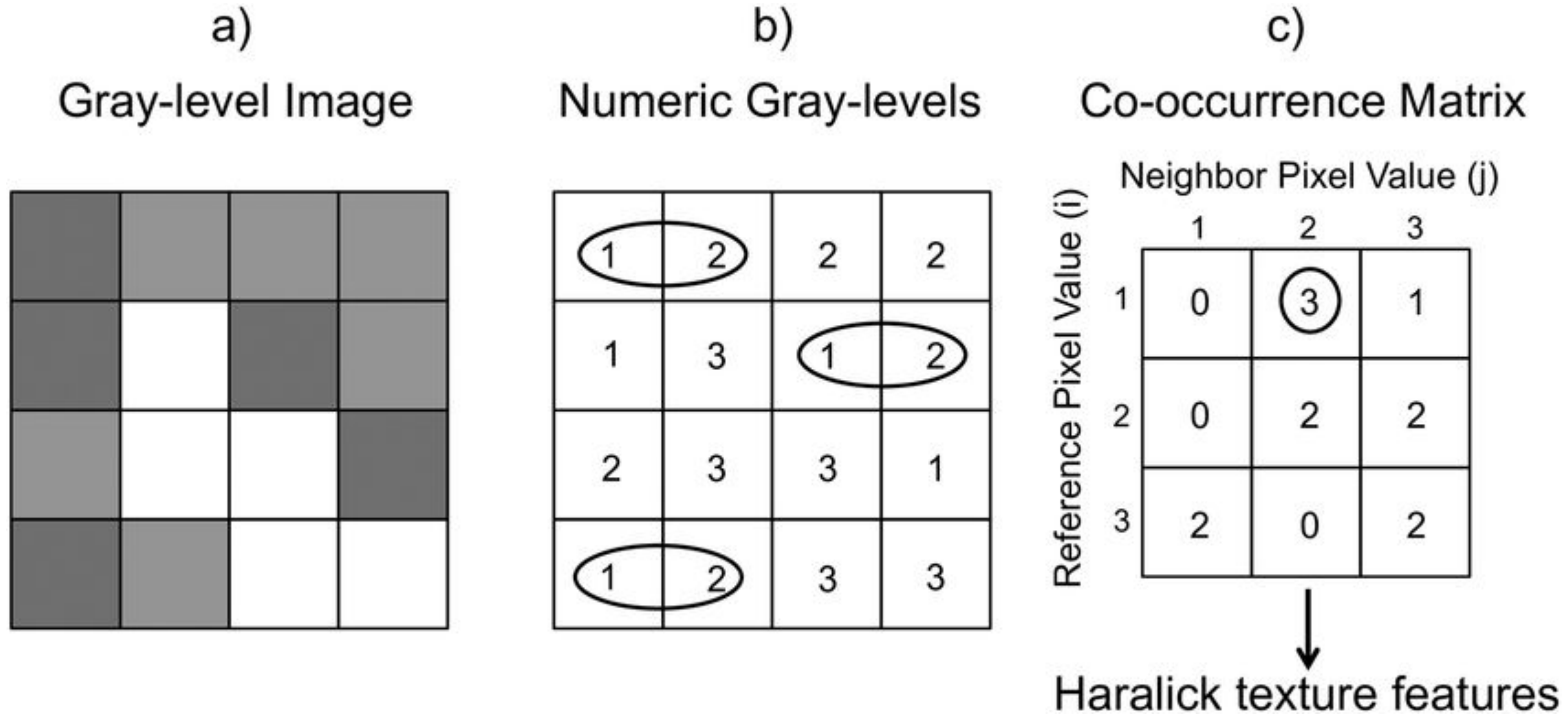
$$m_w(w) = m_t(t)\left|\frac{c_t}{c_w}\right| = m_t(t)\left|\frac{1}{(k-1)m_t(t)}\right| = \frac{1}{k-1}, \qquad 0 \leq w \leq k-1 \tag{5}$$

Adaptive histogram equalization can improve the quality of breast cancer images compared to full histogram equalization using the grayscale remapping function (Equation 6)

$$w_l = r(t_l) = (k-1)\sum_{y=0}^{l} m_t(t_y) = \frac{k-1}{q}\sum_{y=0}^{l} q_y, \qquad l = 0,1,2,\dots,k-1 \tag{6}$$

4.4 Feature Extraction

- **HGLCM** (Haralick Grey-Level Co-Occurrence Matrix).
- Analyzes pixel value **intensity levels** and **spatial relationships**.
- Extracts and evaluates Haralick features.
- Measures **spatial** and **local** information elements.
- The intensity of the gray levels between pixels can be determined by evaluating the **ratio of co-occurrences**, which shows a linear dependence of the gray values.
- Equations 7-11



https://www.linkedin.com/pulse/what-convolutional-neural-network-cnn-deep-learning-nafiz-shahria

Each GLCM element calculates the neighbouring units of measure diagonally. (Equation 7)
H = homogenity, N = dimension image, M = matrix, Cn = number of Co-occurrence matrix image, i and j = pixel value.

$$H = w_l \sum_{p=1}^{P} \sum_{q=1}^{Q} \frac{d_q(x,y)}{1+(x-y)^2} \tag{7}$$

Application of entropy in assessing irregular or unpredictable patterns in breast cancer images. (Equation 8)
E = entropy

$$E = -\sum_{p=1}^{P} \sum_{q=1}^{Q} d_q(x,y)\, lqd_q(x,y) \tag{8}$$

The areal uniformity of the grey level is calculated using the second moment of energy angle. (Equation 9)
En = energy

$$E_n = \sqrt{\sum_{p=1}^{P} \sum_{q=1}^{Q} d_q^2(x,y)} \tag{9}$$

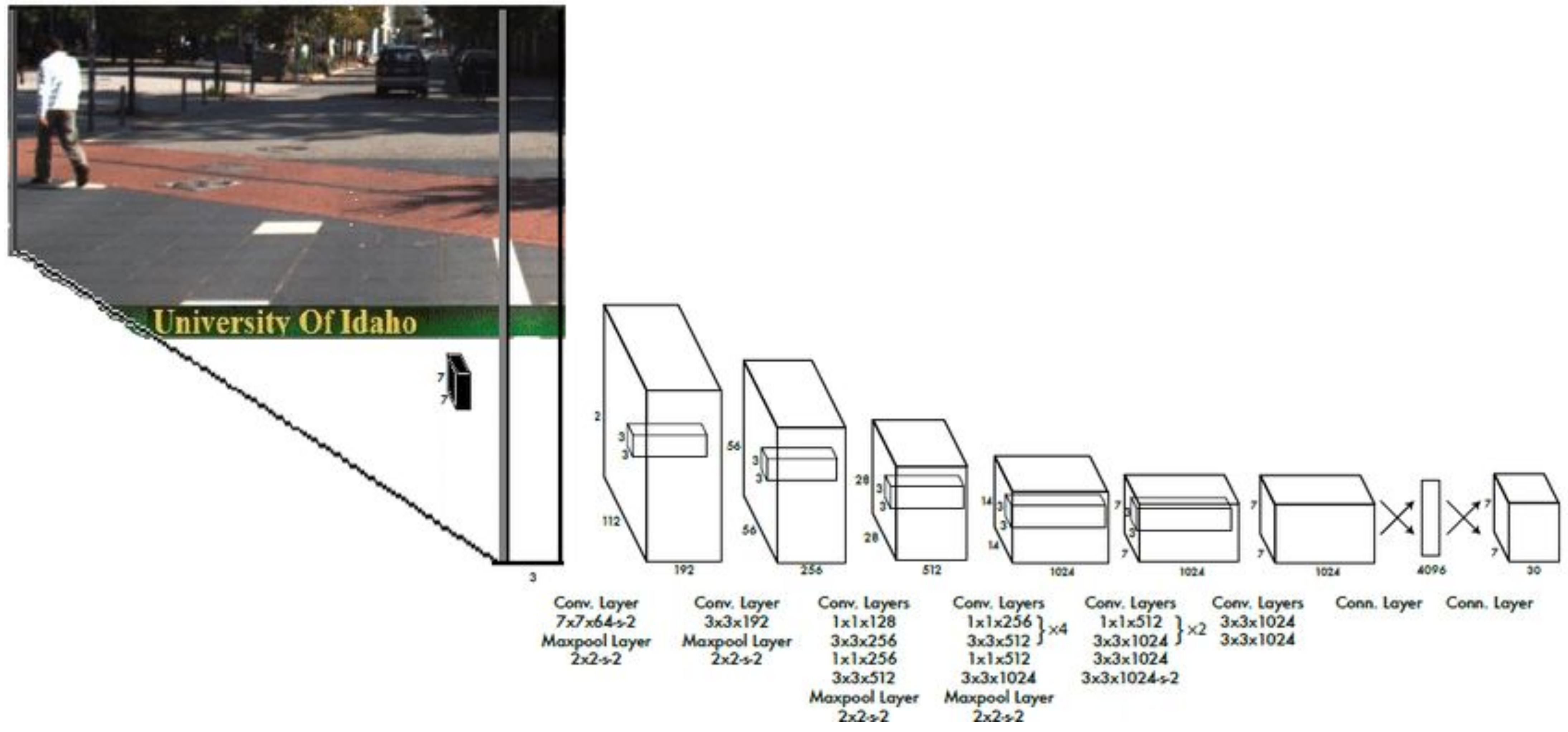
Calculate the aspect ratio of the co-occurrence matrix showing the linear dependence of the gray value (Equations 10 and 11) Analysis of the mean and standard deviation matrix along the long horizontal and vertical spatial planes can predict the intensity level of breast cancer images. $\sigma_i\sigma_j$ and $\mu_i\mu_j$ = long horizontal and spatial plane, C = correlation.

$$C = \sum_{p=1}^{P} \sum_{q=1}^{Q} d_q(x,y) \frac{(x-\mu_i)(y-\mu_j)}{\sigma_i\sigma_j} \tag{10}$$

$$C = \sum_{p=1}^{P} \sum_{q=1}^{Q} (x,y)^2 d_q(x,y) \tag{11}$$

4.5 Darknet CNN Details

- Classifies images as **benign** or **malignant**.
- Feature **vector analysis** using multiple convolution kernels.
- **ReLU** (Rectified Linear Unit) activation layers.
- Fully connected layers for feature synthesis.
- A fully connected layer consists of a **configurable number of neurons** for each neuron in the previous layer and can **classify breast cancer** using typical neural network features.
- Equations 12-17



The breast cancer image is convolved with several convolution kernels to generate feature maps and calculate the convolutional operation. (Equation 12)

m = convolutional kernel, upq = separate feature map, n = represent layer, ∗ = convolutional operation, ix = feature vector, y = element

$$u_p^q = C \sum_{y \in i_x} u_y^{q-1} * j_{y_p}^q + O_p^q \quad (12)$$

Compute the average standard deviation of all output layers and the scaling factor. The output normalized through volume normalization to match the distribution of the eigenvalue coefficients. (Equation 13)

u_{out} = convolutional output layer, ∝ = scaling factor, ∂ = mean output, ω = input varience, φ,γ = represente constant offset, a_{out} = batch normalization.

$$u_{out} = \frac{\propto\left(u_p^q - \partial\right)}{\sqrt{\omega^2 - \varphi}} + \gamma \quad (13)$$

The static parameters of the input values in a network utilising a pooling layer. (Equation 14)

In addition, pooling layers can be used to reduce the network weight.

j_y, i_y = activation value, b_i = fixed parameter interval

$$i_y = \begin{cases} j_y & \text{if} u_{out} \geq 0 \\ \frac{j_y}{v_y} & \text{if} u_{out} < 0 \end{cases} \quad (14)$$

The convolution function used to improve the model representation of the image features by the ReLU activation function of the convolutional layer. (Equation 15)
i(x,y) = output of convolutional operation, L = Kernel, x = image.

$$i(x, y) = (X * L)(xy) = \sum_p \sum_q X\,(x + p, y + q).\, L(p, q) \tag{15}$$

Breast cancer can be classified in a neural network using a normal function that inputs each dimension from the output of a dense layer of a fully connected layer. (Equations 16 and 17)
$i^{(c)}$ = input batch normalization layer, c = dimension, b = variable, $\gamma^{(c)}$ = scaling factor dimension, $\beta^{(c)}$ = shifting factor dimension, ε = varience, s = weight matrix, v = bias vector, i = input vector, h = activation function.

$$\widehat{i^{(c)}} = \frac{i^{(c)} - g[i^{(c)}]}{\sqrt{b[i^{(c)}] + \epsilon}} * \gamma^{(c)} + \beta^{(c)} \tag{16}$$

$$j = h(s_i - v) \tag{17}$$

5. Results

Performance Evaluation: **Darknet-53 CNN**

- Dataset split: **Training** - 5149 images, **Testing** - 2634 images, Table II
- Table III details the true positive, true negative, false positive, and false negative measures used in **performance evaluation** to classify pictures of breast cancer as benign or malignant

TABLE II. SIMULATION PARAMETER

Simulation	Values
Dataset Name	Breast Cancer Dataset
Number of Images	7783
Training	5149
Testing	2634
Language	Python
Tool	Jupyter

TABLE III. PERFORMANCE EVALUATION

Matrices of Performance	Formula
Precision	$\frac{T_P}{T_P + F_P}$
Sensitivity	$\frac{T_P}{T_P + F_N}$
Specificity	$\frac{T_N}{T_N + F_P}$
Accuracy	$\frac{T_P + T_N}{T_P + T_N + F_P + F_N}$

- <u>Specificity</u>:

DarkNet-53 CNN (79%)
vs.
LGBM (77%)
KNN (74%)
CNN (71%),

(Figure 3)

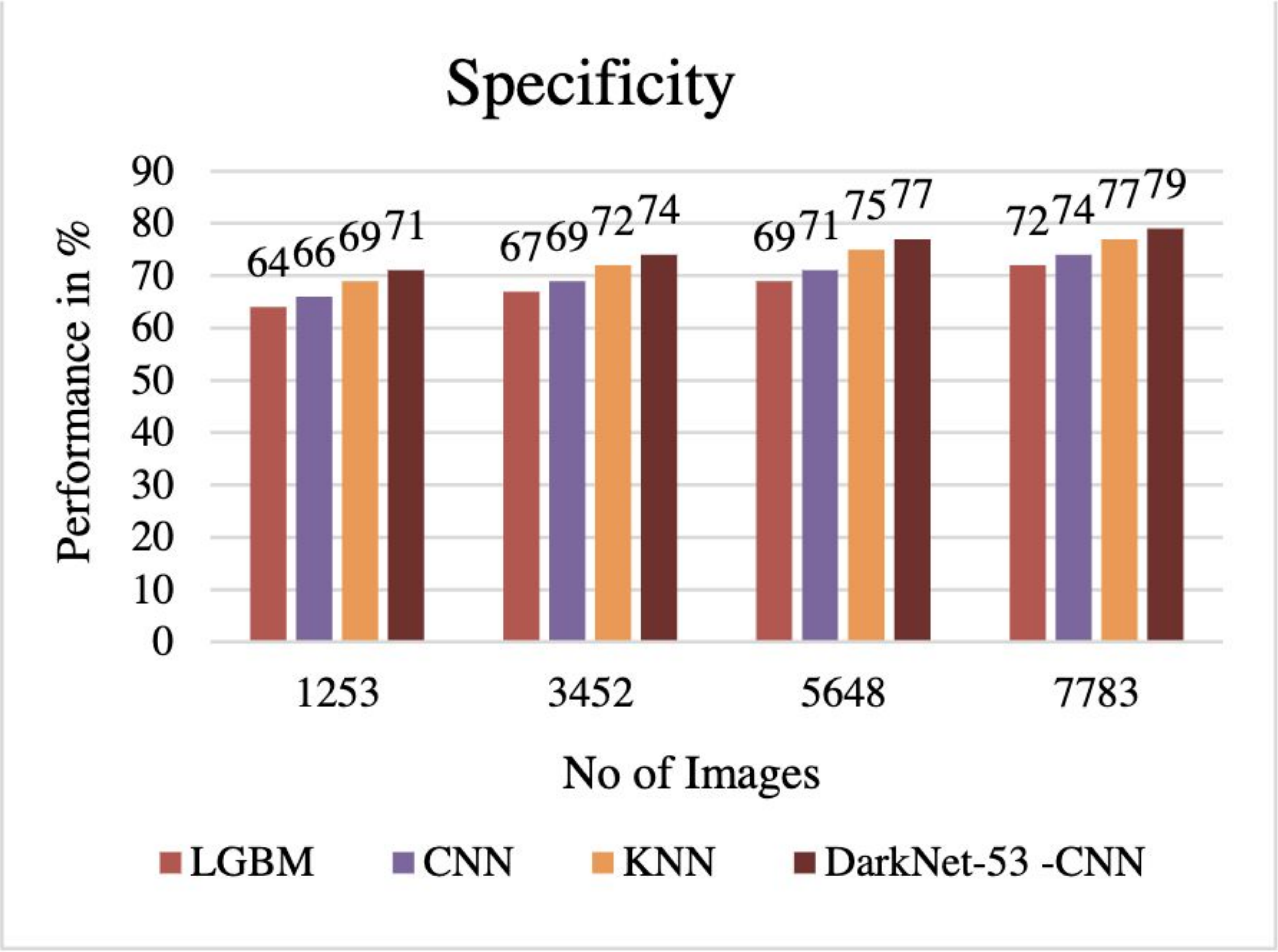


Fig. 3. Analysis of Specificity

- <u>Sensitivity</u>:

DarkNet-53 CNN (85.36%)
vs.
CNN (82.34%)
LGBM (79.64%)
KNN (77%)

(Figure 4)

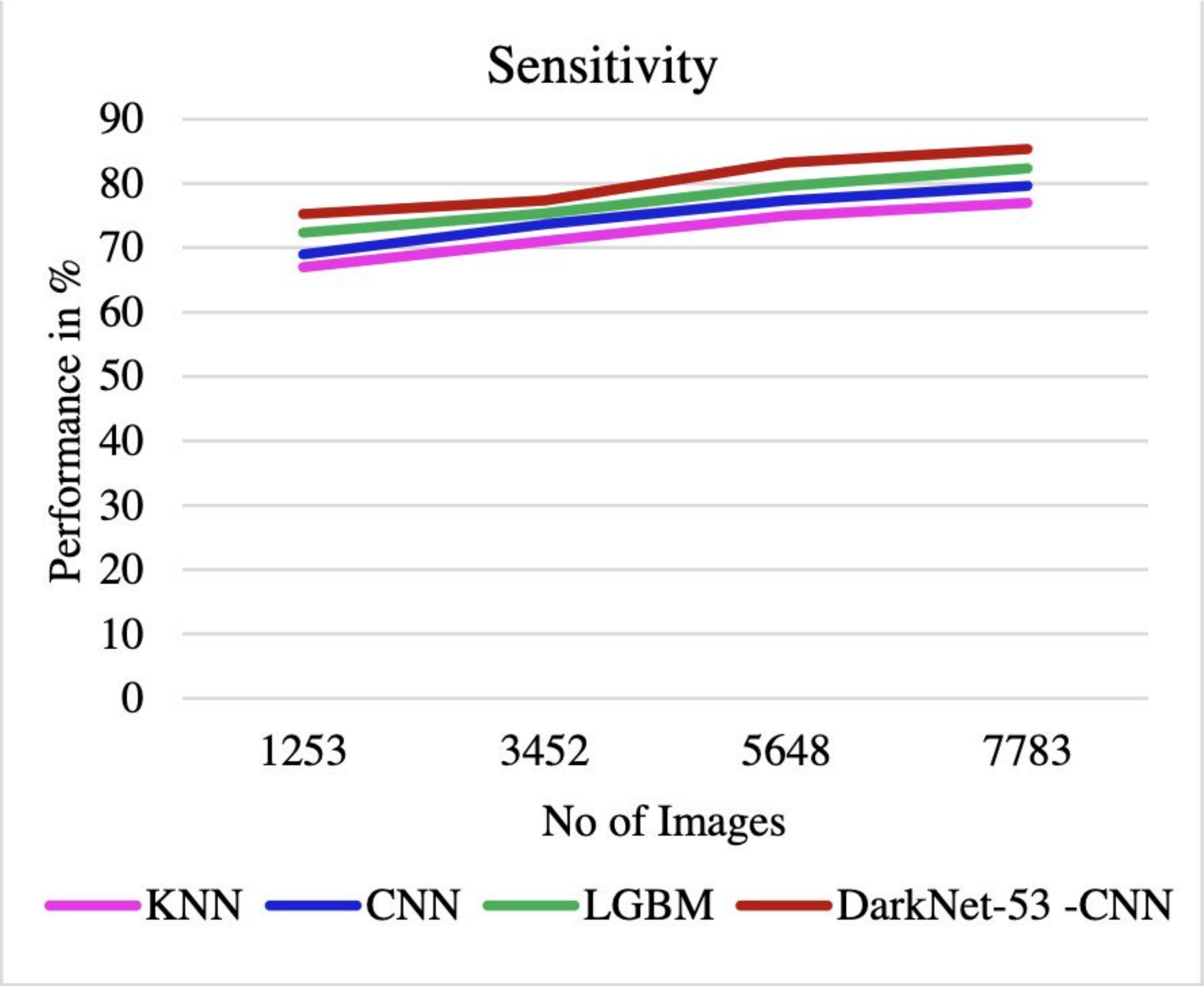


Fig. 4. Analysis of Sensitivity

- Precision:

DarkNet-53 CNN (89.14%) vs.

LGBM (87.36%)

KNN (83.47%)

CNN (81.6%)

(Figure 5)

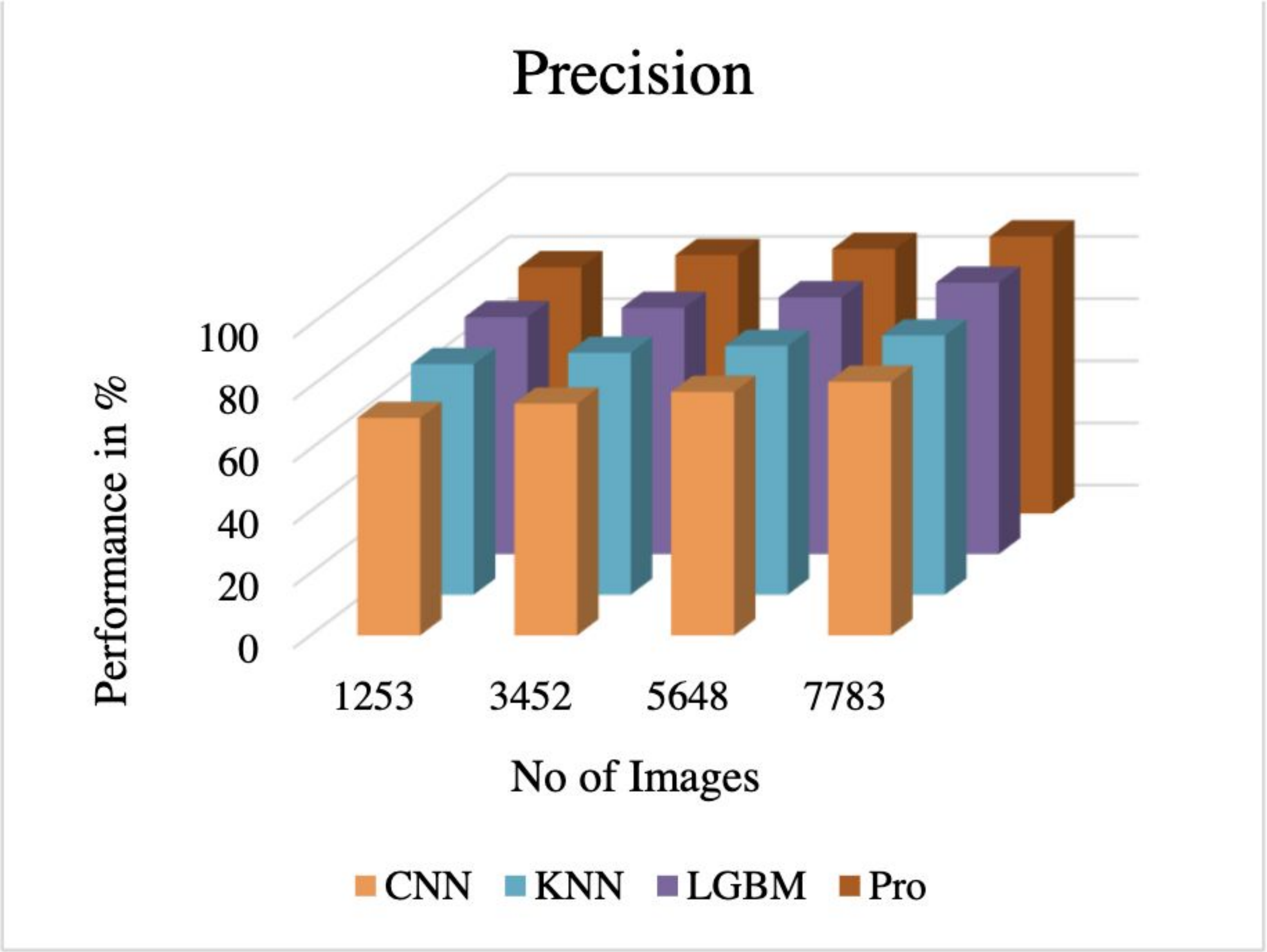


Fig. 5.Analysis of Precision

• <u>Accuracy</u>:

DarkNet-53 CNN (96.2%)

vs.

KNN (93.15%)

LGBM (89.14%)

CNN (86.4%)

(Figure 6)

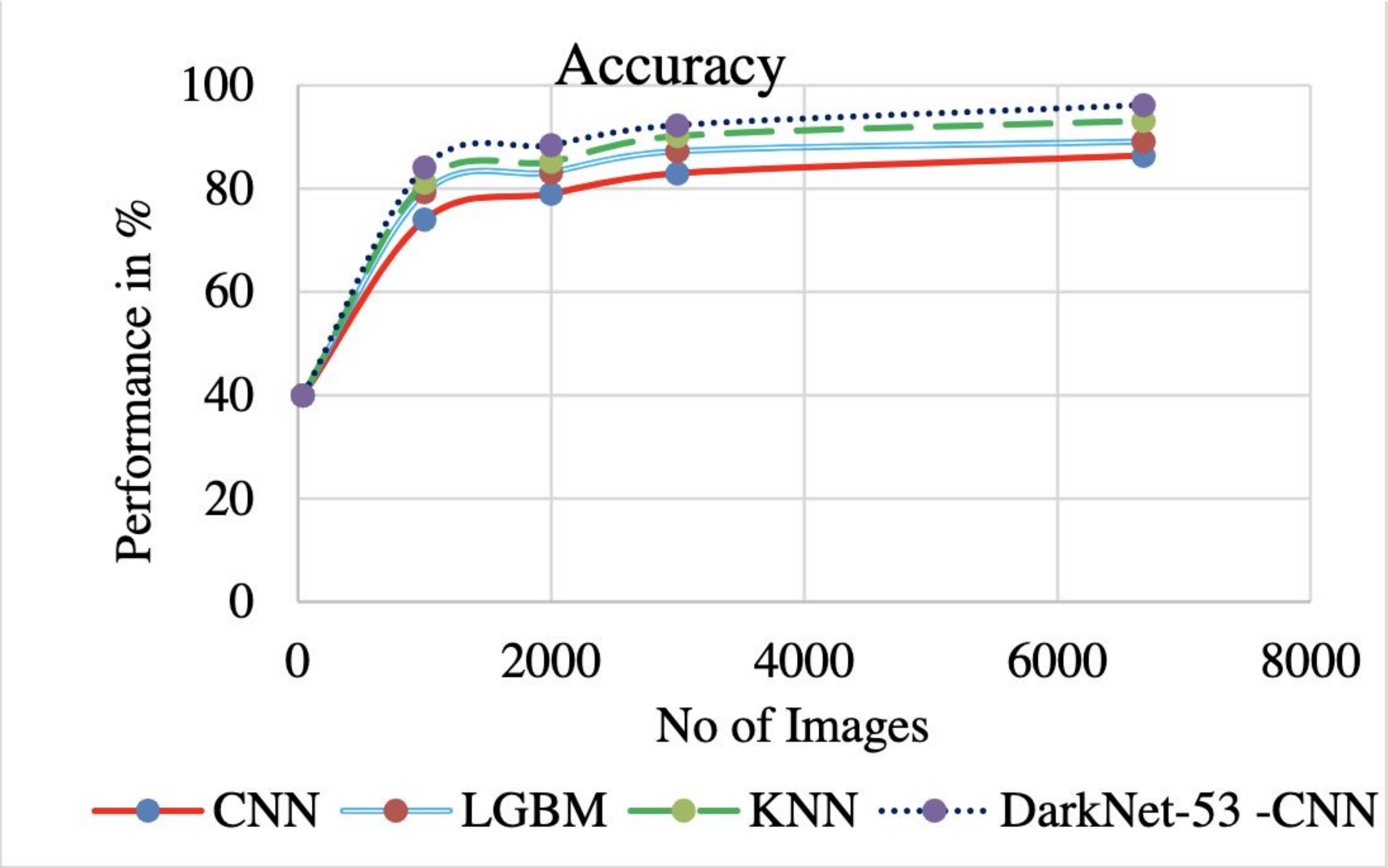


Fig. 6. Analysis of Accuracy

6. Discussion and Analysis

- DarkNet-53 CNN **significantly improves** accuracy, sensitivity, specificity, and precision compared to other methods (CNN, KNN, LGBM).

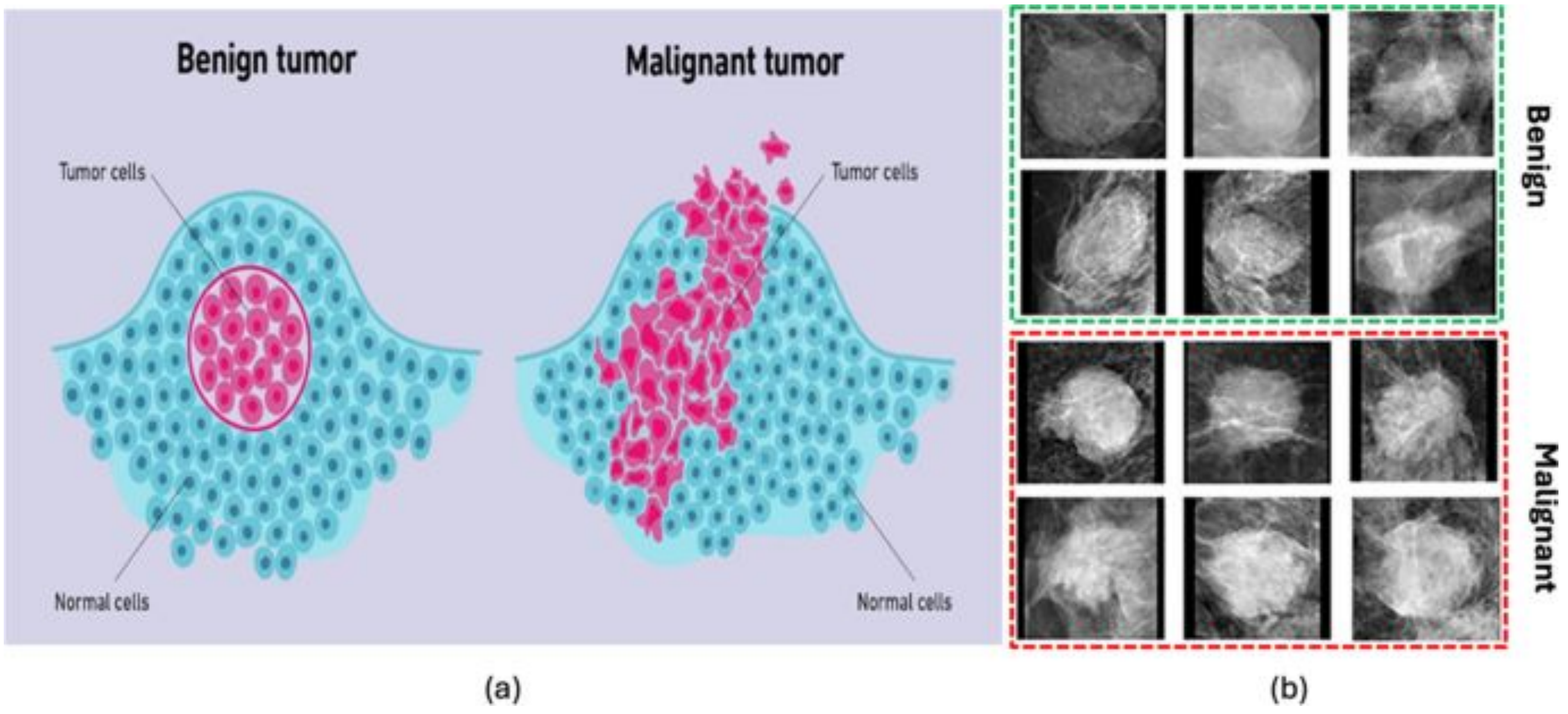
- **Noise reduction** and **overall image enhancement** can be achieved by pre-processing with CLAHE.

- HGLCM method contributes to **improved performance** by analyzing pixel intensity levels for useful feature extraction.

https://www.linkedin.com/pulse/what-convolutional-neural-network-cnn-deep-learning-nafiz-shahriar/

7. Conclusion

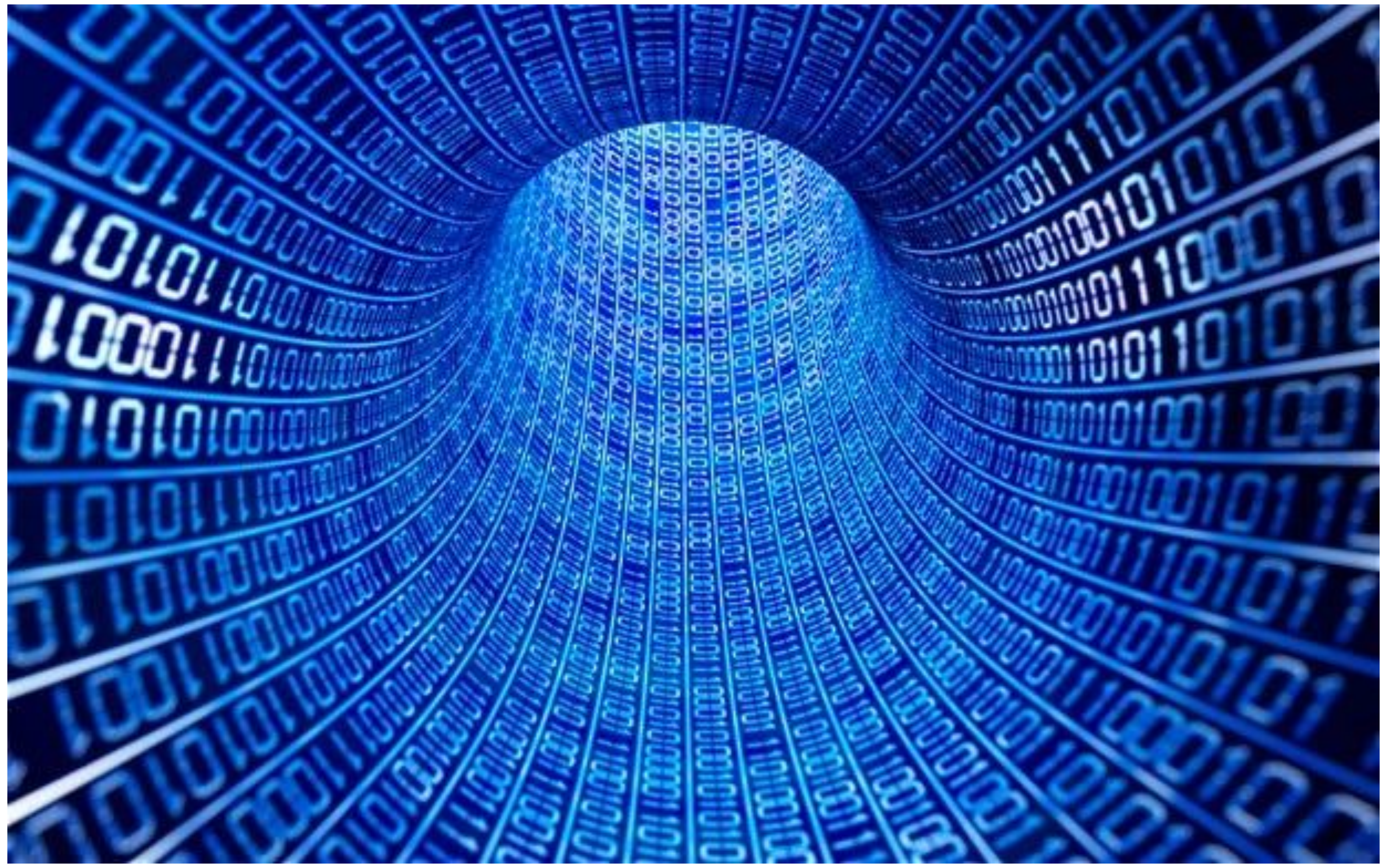
- DarkNet-53 CNN shows **excellent performance** for breast cancer detection and classification.
- Analyzing the proposed DarkNet-53 CNN approach, the accuracy in classifying breast cancer images **increased to 95.6%** and **outperformed** previous methods
- Implications: **Improved diagnostic accuracy** can lead to **better patient outcomes** in terms of breast cancer detection and preventive measures.



https://www.nature.com/articles/s41598-024-57740-5

8. Future Directions

- Test on **larger** and more **diverse** datasets.
- Explore **other** CNN architectures.
- Investigate the use of different **pre-processing** techniques.
- Evaluate the model's **performance** on different imaging modalities (mammography, ultrasound).



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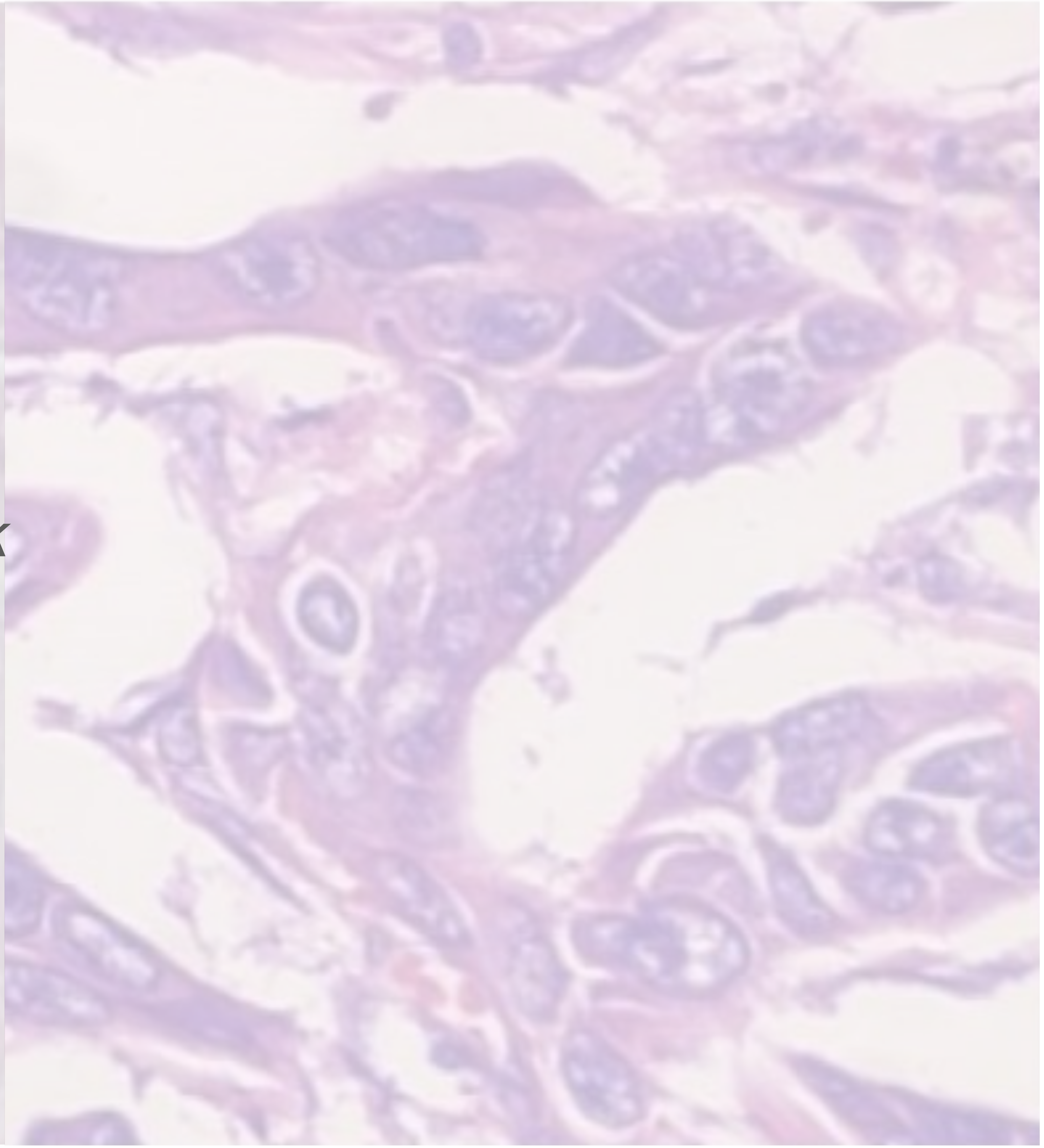

Thank You