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Research Article

DARKNET-53 Convolutional Neural Network-Based Image Processing for Breast Cancer Detection

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ABSTRACT

Breast cancer is a common type of cancer in women, denoted by the uncontrolled growth of cells in breast tissue. Thus, manually detecting breast cancer is time-consuming and necessitates automated systems. Existing breast cancer screening methods often have limited efficacy and may delay detection and complicate the individual treatment planning process. However, early detection of breast cancer can be costly and impact the accuracy of diagnosis. To address this issue, we introduce a Darknet-53 Convolutional Neural Network (darknet-53CNN) approach for classifying breast cancer images and improving precision. Furthermore, we utilise the Contrast-Limited Adaptive Histogram Equalization (CLAHE) technique to pre-process breast cancer images to enhance image quality. Furthermore, we evaluate the intensity level of pixel images by feature extraction using the Haralick Grey-Level Co-Occurrence Matrix (HGLCM) technique. Finally, the DarkNet-53 CNN method improves the accuracy of detecting breast cancer and classifying images as benign or malignant. The proposed algorithm evaluates the specificity, sensitivity, accuracy and precision of predictive test results based on the classification of breast cancer images. Moreover, the accuracy of the proposed method has increased to 95.6% compared to the methods obtained from previous approaches.

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1. INTRODUCTION

One of the main causes of death for women and the second most common cause overall is breast cancer. To lower the death rate from breast cancer, early detection is crucial. Moreover, image-based non-invasive techniques in BC provide early detection and treatment options, with radiologists also offering Computer-Aided Diagnosis (CAD) solutions for informed decision-making. Imaging technology plays an important role in detecting breast abnormalities and detecting breast cancer before invasive surgery. Screening methods based on imaging data, such as X-rays, mammography, and ultrasound, can help detect breast cancer more quickly. To identify breast cancer, mammography and ultrasound are the most often employed imaging techniques [1].

Breast tissue cells grow, multiply uncontrollably, and invade nearby healthy tissue to cause cancer. After invading healthy breast tissue, breast cancer cells go on to other parts of the body. Histopathology and magnetic resonance imaging (MRI) are two methods that can be used to obtain clinical images [2]. They analyze the cellular structure and presence of cancer cells using a high-resolution microscope, and the stained tissue is cut into small pieces by a pathologist. Furthermore, CAD technology is being implemented to assist pathologists and improve accuracy in breast cancer diagnosis.

However, detecting cancer manually from mammography images is a challenging task that demands expertise. However, early detection of breast cancer is difficult with screening mammograms because the number of nodules that may be present throughout the breast is not large. Despite advances in medical imaging technology, the accuracy of tumour classification remains a challenge. Imaging issues and variations in tumour size can complicate the process of accurately identifying and classifying different tumour types [3].

This paper presents the implementation of the DarkNet-53 CNN method for breast cancer detection and classification of images benign or malignant. The breast cancer dataset collected from Kaggle is a valuable resource for obtaining breast cancer images needed to train and test models. Furthermore, the use of image pre-processing techniques such as CLAHE effectively improves the quality of breast cancer images by reducing noise. Likewise, feature extraction using HGLCM techniques can estimate the pixel intensity level in an image, thus facilitating a detailed analysis of the data set.

2. LITERATURE REVIEW

So far, fuzzy logic methods have been used to classify lung disease prognoses, but they face challenges such as difficult identification of segmented regions and incorrect output. To resolve the challenges, a CNN methodology was deployed. It is commonly used for tasks such as lung disease prognosis and identification because it can detect complex details in cluster data [4]. The impact of different pre-treatment modality combinations on the distinction between benign and malignant breast lesions was diagnosed. Furthermore, lesion detection is facilitated by the fact that all image-processing algorithms employ information gathered from the mini-MIAS database [5]. A novel [6] suggested classifying and identifying breast cancer in histopathological images using Deep Belief Network (DBN) technique. Unsupervised pre-training and supervised fine-tuning phases were used to extract features. They developed the Light Gradient Boosting Machine (LGBM) approach, which combines several finite feature techniques to increase the model's high accuracy in differentiating between benign and malignant tissues [7]. Additionally, features were chosen by the Convolutional Neural Networks (CNN) model's classification. Nevertheless, while assessing the challenges associated with cancer diagnosis, more importance needs to be focused on improving prediction [8].

Nevertheless [9], while many Deep Learning (DL)-based techniques have been established for accurate breast cancer prediction and classification, few methods provide a comprehensive overview of lesion segmentation. Neural networks utilising Auto Encoders (AEs) combine the processing techniques required to classify various features [10].

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%

As shown in table 1, the application of image processing for breast cancer prognosis prediction can be achieved by analyzing datasets collected from the literature to determine its scope and accuracy.

Nonetheless, it is necessary to define the variables affecting breast cancer patient's chances of survival. Furthermore, the Symbiotic Organism Search (SOS) technique for feature extraction and optimal hyper parameter tuning with the EfficientNet-B0 model can be used to identify breast cancer [16]. Furthermore [17], the RetinaNet model was tested on the Inbreast dataset, a small mammography dataset, using CNN and image processing techniques.

3. PROPOSED METHODOLOGY

In this section, we present the DarkNet-53 CNN method for breast cancer detection and classifying breast cancer images as benign or malignant. The performance model is evaluated by testing its accuracy on a breast cancer dataset obtained from Kaggle. Furthermore, to further improve the quality of breast cancer images, a pre-processing step was implemented including the CLAHE method to reduce noise and improve overall image quality. Additionally, to efficiently extract features from images, the HGLCM technique is used to facilitate the measurement of pixel intensity patterns and spatial relationships within images. Furthermore, the assessment of the suggested methodology enhances the accuracy of identifying breast cancer and offers a significant understanding of clinical imaging data.

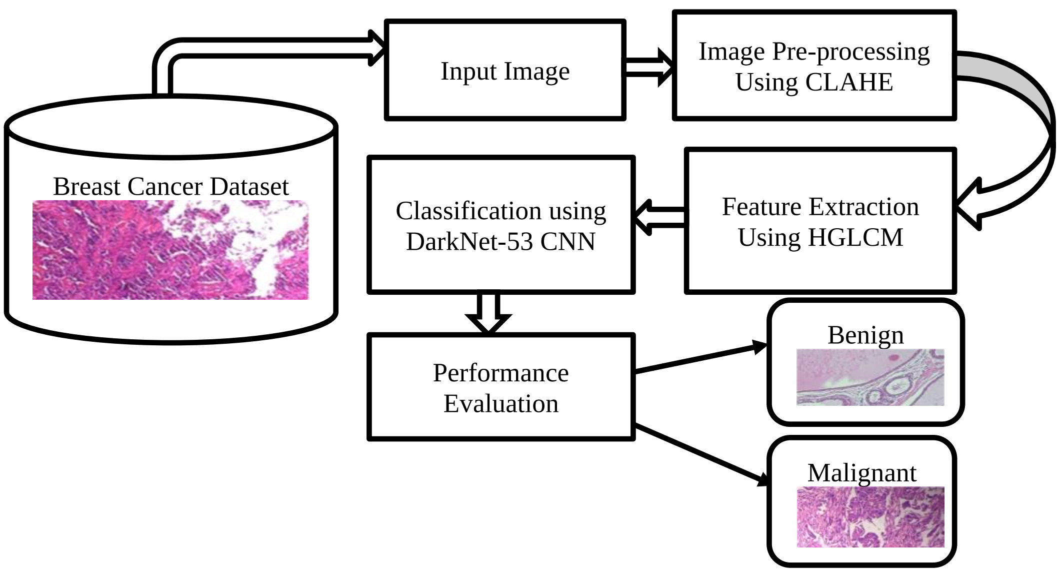
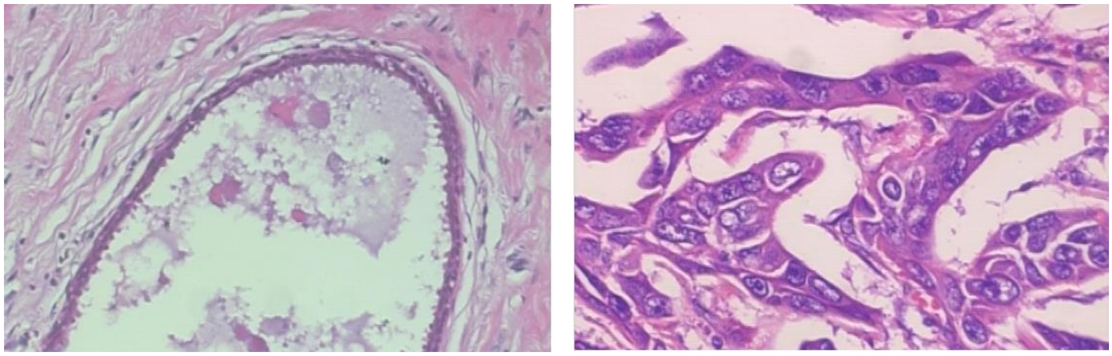


Fig. 1. The Proposed Architecture Diagram for DarkNet-53 CNN

The suggested architecture diagram for DarkNet-53 CNN can be used to identify breast cancer and categorise images of the disease as benign or malignant, as seen in figure 1. It can also identify image intensity levels and enhance the quality of breast cancer images Moreover; the assessment of the proposed methodology enhances the precision of identifying breast cancer and offers significant perspectives into clinical imaging information.

3.1 Dataset Collection

In this section, we use a dataset collected from Kaggle to enhance the accuracy of 7783 breast cancer histopathology images obtained from 82 patients. Additionally, these can be used to classify breast cancers using the website https://www.kaggle.com/datasets/anaselmasry/breast-cancer-dataset?select=BreaKHis_Total_dataset. Furthermore, the classifier for benign and malignant images in the dataset can identify 5304 files as malignant and 2479 files as benign. Breast cancer images in breast cancer datasets are classified into two categories, offering a valuable tool for clinicians.



(a) Benign (b) Malignant

Fig. 2. The Breast Cancer Image Dataset collection

Figure 2 shows the proposed methods to identify images as benign or malignant using a dataset that was acquired via Kaggle. Additionally, the Breast Cancer dataset enables medical professionals to enhance the precision and effectiveness of image categorization.

3.2 Contrast-Limited Adaptive Histogram Equalization (CLAHE)

In this section, utilising a CLAHE, image pre-processing can enhance image quality and eliminate noise in breast cancer images. The CLAHE method proposed has been widely utilized for enhancing the contrast of histopathological images. In addition, pixel-by-pixel grey-level measurements of breast cancer images can be analyzed using CLAHE. Estimate the input and output image grey levels of the random variable's original and processed breast cancer image histogram regions. To improve breast cancer image quality, the CLAHE technique analyses pixel distribution to enhance local maps.

Calculate the grey level corresponding to the total number of pixels in the histopathology image, as shown in equation 1. Furthermore, a histogram is defined by converting the input image to the output image of an increasing function. Let's assume q- total pixels histopathology image, q_l −oixel number, t_l −grey level, r-random variable.

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

As stated in equation 2, 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. Let's assume $m_w(w)$ 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 as indicated in equation 3. Where s-integral dummy variable.

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

The grey level transfer function is estimated based on the combined characteristics described in equations 4 and 5.

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

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

As described in equation 6, adaptive histogram equalization can improve the quality of breast cancer images compared to full histogram equalization using the grayscale remapping function.

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

By analyzing the grey level relative to the total pixel count in the histopathology image, image quality can be improved by optimizing the value of the transfer function.

3.3 Haralick Grey-Level Co-Occurrence Matrix (HGLCM)

In this section, feature extraction was performed employing the HGLCM technique to analyze the pixel value intensity levels in the breast image. Furthermore, a useful method for extracting and evaluating Haralick features is for analysing the correlation between the brightness of neighbouring pixels. Furthermore, the HGLCM method reveals the relationship between the intensity of a particular pixel and its neighbouring pixels. Additionally, images have features that measure important spatial and local information elements. Based on the HGLCM technique, the intensity levels of dimensional images can be assessed. Therefore, HGLCM technology can be used to analyze the intensity levels of pixel values in breast cancer images.

As demonstrated in equation 7, each GLCM element calculates the neighbouring units of measure diagonal. Let’s assume H-homogenity, N-dimension image, M-matrix, C_n −number of Co-occurrence matrix image, i and j-pixel value.

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

Equation 8 demonstrates the application of entropy in assessing irregular or unpredictable patterns in breast cancer images. Let’s assume E-entropy,

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

Equation 9 shows that the areal uniformity of the grey level is calculated using the second moment of energy angle. Where E_n −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 as indicated in 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. Let’s assume $\sigma_i\sigma_j$ and$\mu_i\mu_j$ −long horizontal and spatial plane, C −correlation.

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

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

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.

3.4 DarkNet-53 convolutional neural network (DarkNet-53-CNN)

In this section, the proposed DarkNet-53 convolutional neural network technique can be utilized to classify images as benign or malignant, assisting in the detection of breast cancer and enhancing accuracy. DarkNet-53-CNN method is the basic method for breast cancer image detection and classification. It involves feature vector analysis of the input image using multiple convolution kernels, generating discrete feature maps and normalizing the output to obtain a consistent coefficient distribution. The DarkNet-53-CNN architecture incorporates a ReLu layer as part of its design. Fully connected layers with an adjustable number of neurons facilitate feature synthesis and nonlinear transformations. By integrating dense layers in neural networks, the classification accuracy of benign and malignant breast cancer images can be improved significantly.

As described in equation 12, the breast cancer image is convolved with several convolution kernels to generate feature maps and calculate the convolutional operation. Let’s assume m-convolutional kernel, u_p^q −separate feature map, n-represent layer, $*$ −convolutional operation, i_x −feature vector, y-element,

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

In equation 13, compute the average standard deviation of all output layers and the scaling factor. The output is normalized through volume normalization to match the distribution of the eigenvalue coefficients. Let’s assume u_{out} −convolutional output layer, $\propto$ −scaling factor, ∂ −mean output, ω −input varience, φ, γ −represente constant offset, a_{out} −batch normalization.

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

Equation 14 shows the static parameters of the input values in a network utilising a pooling layer. In addition, pooling layers can be used to reduce the network weight. Let's assume j_y, i_y −activation value, b_j −fixed parameter interval,

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

Equation 15 shows that the convolution function is used to improve the model representation of the image features by the ReLU activation function of the convolutional layer. Let's assume $i(x, y)$ −output of convolutional operation, L-Kernel, x-image.

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

Equations 16 and 17 show that 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. Let's assume $i^{(c)}$ −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.

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

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

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.

4. RESULT and DISCUSSION

In addition, using a dataset collected from Kaggle, the size of histopathology images can be predicted to be 463.8 kB for benign cases and 520.18 kB for malignant cases. Furthermore, the CLAHE approach can improve the quality of breast cancer images presented with breast cancer by utilising image pre-processing. Additionally, a test analysis can be used to assess the accuracy, sensitivity, specificity, and precision of the suggested procedure.

TABLE II. SIMULATION PARAMETER

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

As shown in table 2, the accuracy of breast cancer can be improved by using the simulation parameters using the Python language-based Jupyter Notebook. Additionally, this dataset can be used to classify test-5149 and training-2634 breast cancer images and provide performance evaluation.

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	$\frac{T_P + T_N}{T_P + T_N + F_P + F_N}$

Table 3 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.

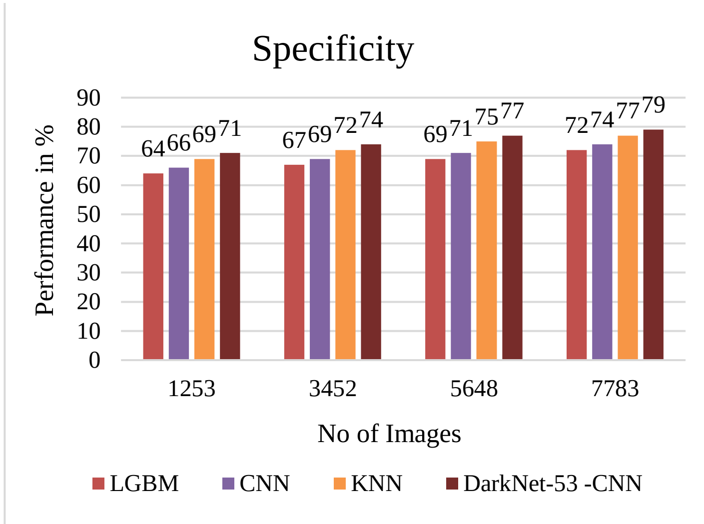


Fig. 3. Analysis of Specificity

The classification of breast cancer employing the suggested DarkNet-53 –CNN method based on the specificity analysis is depicted in figure 3. Furthermore, when analysing the specificity using methods such as CNN and KNN, the accuracy of LGBM is increased (71%, 74%, and 77%) for predicting breast cancer images. Additionally, the accuracy of the proposed DarkNet-53 –CNN method in specificity analysis was improved to 79% compared to the conventional method.

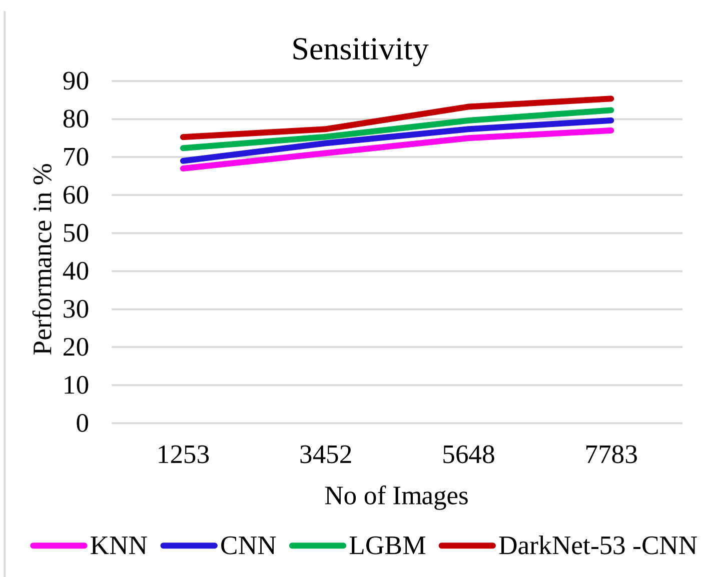


Fig. 4. Analysis of Sensitivity

Figure 4 shows the breast cancer classification using the suggested DarkNet-53 –CNN approach based on sensitivity analysis. In addition, sensitivity analysis using methods such as CNN and LGBM outperforms KNN (77%, 79.64% and 82.34%) in the accuracy predict breast cancer images. Furthermore, the sensitivity analysis accuracy of the proposed DarkNet-53 –CNN method was enhanced to 85.36% compared to the previous method.

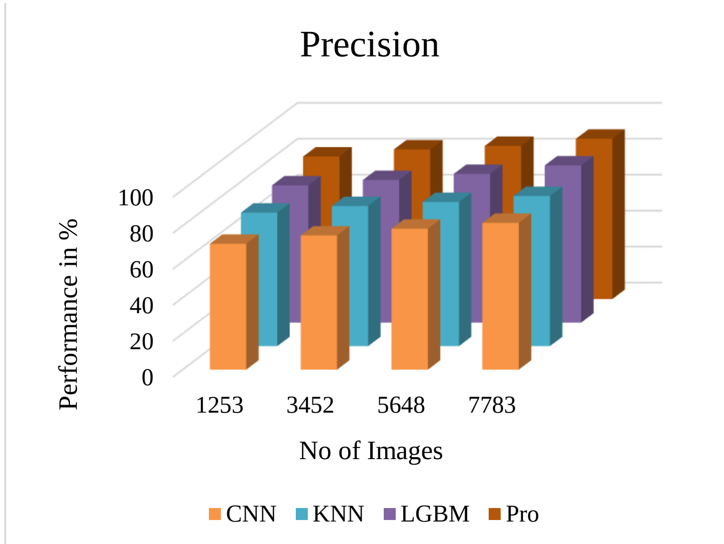


Fig. 5.Analysis of Precision

In Figure 5, the classification of breast cancer using the proposed DarkNet-53 –CNN method, based on the precision analysis, is described. By combining approaches like LGBM-87.36% and CNN-81.6% for precision evaluation, the predictive accuracy of KNN-83.47% in identifying breast cancer images is enhanced. Moreover, in precision analysis, the proposed DarkNet-53 –CNN method achieved an improved accuracy of 89.14% compared to previous methods.

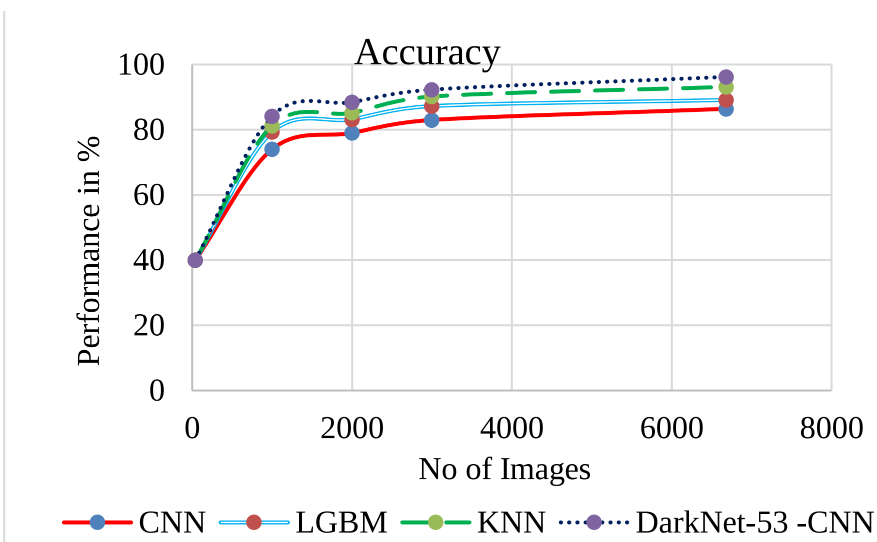


Fig. 6. Analysis of Accuracy

As shown in Figure 6, the classification of breast cancer utilizing the proposed DarkNet-53 –CNN method is detailed, emphasizing accuracy analysis. Through the integration of approaches such as LGBM-89.14% and CNN-86.4% to estimate accuracy, the predictive ability of KNN-93.15% in detecting breast cancer images can be significantly improved. Moreover, compared to the previous methods, the accuracy of the proposed DarkNet-53 -CNN method increased to 96.2% in classifying breast cancer images.

5. CONCLUSION

In conclusion, this paper emphasizes the assessment of the new DARKNET-53 CNN model in breast cancer classification. To improve the quality of breast cancer images, pre-processing can be done using the CLAHE technique for noise reduction and overall image enhancement. In addition, the GLCM method can be manipulated to analyze the pixel intensity levels for useful feature extraction. By combining the DarkNet-53 CNN approach for breast cancer detection and image classification into benign or malignant categories, the accuracy of test results can be improved. Additionally, we evaluate the specificity, sensitivity, accuracy, and precision of the proposed method to predict test results based on the classification of breast cancer images. Therefore, the combination of methods such as LGBM-89.14% and CNN-86.4% by performance evaluation to measure the accuracy and using KNN-93.15% to find the predictive capabilities in detecting breast cancer images can significantly improve the prediction models. In addition, analyzing the proposed DarkNet-53 CNN approach, the accuracy in classifying breast cancer images increased to 95.6% and outperformed previous methods.

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Conflicts Of Interest

The author's disclosure statement confirms the absence of any conflicts of interest.

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