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Comparative Analysis of Different U-Net Variants for Breast Cancer Detection in Histological Images

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Abstract: One of the most common forms of cancer is breast cancer, and the key to treating it is early detection. First and the most important phases of treating breast cancer is an accurate diagnosis. Numerous studies on predicting the type of breast cancers may be found in the literature. This study used information on breast cancer tumors from the BreCAHAD dataset to predict the types of breast tumors. To discover the region of interest, we used two distinct CNN architectures: U-Net and its variant U-Net++. With 93.15% accuracy, U-Net++ model shows promise for breast image segmentation. Shape and Tetrolet characteristics are used for feature extraction. This study examines how well VGGNet and VGGNet adjusted using Remora Kill Herd Optimization (RKHO) architectures detect breast cancer by analyzing histopathology images. We create reliable and accurate deep learning models by carefully adjusting optimizers and hyperparameters. According to our research, the VGGNet model trained using the RKHO performs exceptionally well in terms of metrics like accuracy, sensitivity and specificity. Corresponding scores obtained are 0.925, 0.915, and 0.929.

Keywords: breast cancer detection; histopathology; deep learning; U-Net; optimization, CNN

1. Introduction

Worldwide, breast cancer is one of the leading causes of death for women, which emphasizes how vital early identification and treatment are [1–3]. In a various medical image processing domains tasks like classification, detection, and segmentation, neural networks have demonstrated outstanding performance, greatly enhancing diagnostic precision and accelerating treatment choices. Transfer learning and data augmentation approaches, which get over issues like incomplete classification and data scarcity are a contributing factor to deep learning's success in medical image analysis [4]. Breast cancer has been identified using a variety of methods, such as self-examination, clinical evaluation, and screening instruments like mammography. Because breast cancer involves a wide spectrum of complex illnesses, diagnosing it can be challenging [5]. One histological diagnostic technique for determining whether a suspicious region is malignant is a biopsy. As a widely recognized and definitive criterion for confirmation, pathologists use a microscope to visually examine histopathological images in order to make their diagnosis [6]. CNNs are now an effective technique for classifying breast cancer and offer special advantages for analyzing medical images [7]. A specialized class of deep learning models called convolutional neural networks, or CNNs, is made especially to perform well on image-related tasks. These are particularly adept in identifying signs of diagnosis of breast cancer by examining histology



and mammogram images CNNs' capacity to automatically extract intricate patterns, features, and pertinent information from complicated medical images is one of their main advantages; it does away with the need for laborious manual feature engineering [8]. This inherent ability improves the precision and dependability of breast cancer classification while lessening the effort for medical personnel. Furthermore, CNNs have demonstrated an impressive capacity for generalization, which allows them to handle various datasets efficiently and adapt to variations in image quality. This is particularly helpful in actual clinical settings where data may be naturally diverse [9]. Despite the effectiveness of these deep learning models, still several problems that need to be fixed in the segmentation of breast images [10]. The most popular deep learning models to segment biomedical images, such as segmenting breast images, are U-Net and its variant U-Net++. They are designed such that spatial information as well as details about the input image's context can be captured. U-Net architecture consists of a contracting path that uses the features it has gathered to rebuild the extracted image and an expanding path is used to get features from the input image. Since its first introduction by Ronneberger et al. in 2015, the U-Net model [11] has gained widespread for a range of medical image segmentation applications, including finding region of interest in breast images.

By investigating the effectiveness of deep learning methods, namely upgraded CNN architectures, in deciphering histopathological pictures, in this work aims to advance the fields of medical imaging and breast cancer detection. In order to support early detection efforts and possibly enhance patient outcomes, we aim to draw attention to the possibilities of these tactics to increase the accuracy and dependability of breast cancer screenings.

The remainder of this research is organized as follows: Section 2 highlights summary of related work in the subject. The dataset description and methodology used in our analysis are presented in Section 3. The execution process's outcomes and the resulting graphs are shown in Section 4. Finally, Section 5 concludes the work.

2. Related Work

Computer-aided diagnosis systems use automated models based on machine learning and image analysis methods to help medical practitioners with the diagnostic process. Analyzing nuclei to separate malignancy from benignity is the focus of some research projects. In [12], nuclei in microscopic pictures from tiny needle biopsies were segmented using a range of clustering techniques. In [13] An innovative ensemble deep learning method was presented for the binary categorization of images showing breast histopathology. In [14], the latest developments in deep learning were briefly covered. Numerous recent studies on artificial intelligence based systems for support diagnosis of breast cancer and analysis was automated. They including identification, segmentation and also classification of breast cancers [15,16]. In [17] a dual-view classifier is introduced. It is a pair of classifiers with a single-view where some of the final layers are removed. It is observed that performance is improved by concatenating the outputs for both viewpoints. In [18] when used for a binary classification test, feature fusion of two-view mammograms yielded higher accuracy. Using the best model among those examined in this work on a publicly available database, outperformed [19] in [20]. A study comparing mammography diagnostics with breast cancer biopsy predictions was carried out in [21]. They employed different techniques for classification such as support vector machine, logistic regression, random forest, linear discriminant analysis. In [22], to determine the best solution to predict breast cancer, researchers applied data mining techniques to a number of databases. A reliable technique for forecasting eight cancer forms, including ovarian, lung, and breast cancer, was examined in [23]. In their study, they first normalized datasets using particle swarm optimization, and then they separated features on a normalized dataset using statistical feature selection techniques. A multilayer perceptron neural network was then used for categorization. The contracting path, sometimes called down sampling, and the expanding path, also called up sampling, makes up the U-Net encoding decoding architecture [24]. Ref. [25] Used the AlexNet CNN architecture to apply the TL concept to the "BreakHis" dataset in order to classify the data as non-cancerous or cancerous using HI. Ref. [26] To overcome the problem of limited data availability, "Inception V3" was used to classify breast cancer using augmentation and transfer learning techniques. The accuracy of this model was 89%. Ref. [27] It was suggested that a deep learning architecture be used to recognize and categorize cytology breast images. By using various models of convolutional neural networks like GoogVGGNet, VGGNet and ResNet feature extraction is done. Extracted features were passed to the dense layer for classification [28] Employed four different DL models for the classification of breast tissue histopathology pictures showing carcinoma and non-carcinoma: completely trained VGG-16, VGG-19 which is fully trained, fine-tuned VGG-16 and VGG19. Ref. [29] Proposed a two-phase technique that uses the BreakHis data set to extract features using four pretrained DL models. Two CNN models—VGG-16 and Inception-V3—use a transfer learning strategy in [30]. On the BreakHis database, they used a number of data augmentation methods, including rotation, flip, shift, and zooming.

3. Methodology

This manuscript compares two models for diagnosing breast cancer from histological images. One model is VGGNet CNN architecture trained with an optimization algorithm and second is without using optimization algorithm. Methodology diagram is shown in Figure 1. Initially, input histopathological images are gathered from dataset and then subjected to image de-noising using the gaussian filter to eliminate noise from input images. After denoising the image, the blood cell is segmented by employing U-Net and its variant U-Net++ architectures. U-Net++ architecture is designed such that it enhances the U-Net architecture by inserting set of skip connections, that causes to increase segmentation efficiency tremendously. Hence segmentation output of U-Net++ is considered and shape features namely area, solitary, eccentricity, perimeter, and major axis length along with color features are used to extract features. VGGNet is tuned by the proposed RKHO algorithm. RKHO is established by the integration of ROA [31] and KH [32]. The trained model is employed for detecting breast cancer first. Then detection of breast cancer is performed using VGGNet not trained with optimization algorithm. Performance of these two models is analyzed. And the VGGNet trained with proposed optimization algorithm obtained better performance metrics than the second model.

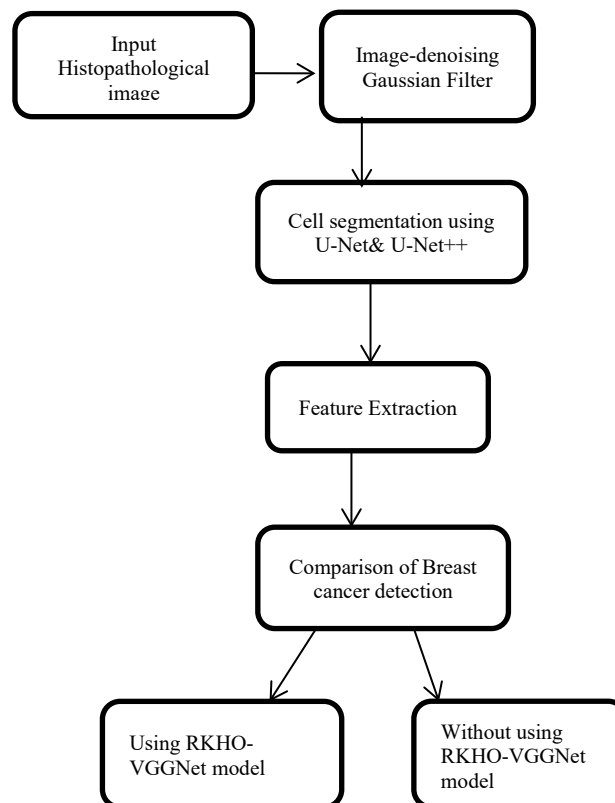


Figure 1. Proposed model methodology.

3.1. Dataset Description

The Breast Cancer detection based on RKHO-CNN model utilizes the BreCaHAD dataset [33] for the disease detection. BreCaHAD dataset is a breast cancer histopathological image dataset especially used for Breast Cancer detection. This dataset includes ground truth images correlated with the original histology images of breast cancer. The dataset's diversity and variability include carefully selected cases with varying patient demographics, imaging characteristics, and illness severity. The excellent quality BreCaHAD and diversity of the dataset served as a helpful basis for evaluating the segmentation models' efficacy and generalizability.

Two .png files, one .zip file, one .json file, and one .xlsx file are among the several files that make up the BreCaHAD dataset. The annotated image shows pink circles displaying non-tumor nuclei, orange or green circles representing mitosis and apoptosis, blue circles displaying tumor nuclei, and yellow circles indicating non-lumen. In this case, the JSON file contains two mitosis and one tumor nuclei annotation. There are three directories in the BreCaHAD.zip file: groundTruth_display, groundTrut, and original pictures. We took into consideration the groundTruth_display and original pictures folders for segmentation purposes.

3.2. Image Acquisition & Pre-Processing

Input histopathological image is taken from the dataset. Gaussian filter is applied to the input histopathological image to eliminate the noise and irregularities exist in the image. The expression for Gaussian filter is

$$g(x, y) = \frac{1}{\sqrt{2\pi}\sigma} e^{- (p^2 + q^2)/2\sigma^2} \quad (1)$$

where p and q are the horizontal and vertical distances from the origin, respectively, and σ is the Gaussian distribution's standard deviation. Augmentation technique is applied to increase dataset size to 10000.

3.3. Segmentation Using U-Net and U-Net++ Architectures

The blood cell from the noise-free image is extracted using U-Net and U-Net++. In this work, the pre-processed output is used as the input U-Net and U-Net++ for performing blood cell segmentation. The U-Net++ model offers improved segmentation results.

U-Net

Designed for image segmentation, U-Net is an architecture built on convolutional neural networks. Although it has been used to numerous fields, including satellite and microscopy pictures, its initial purpose was biomedical image segmentation. The U-Net encoding decoding architecture is comprised of two paths: the contracting path, also known as down sampling, and the expanding path, also known as up sampling. High-level features such as Texture Patterns, Semantic Information etc. from the input image are extracted via the contracting path's several convolutional layers and max pooling layers. Although the image's depth increases, these layers decrease the spatial resolution. By reducing the depth of the image and recovering its spatial resolution, the expanding route is made up of several convolutional and upsampling layers. Through skip connections between the encoding and decoding paths, the network makes use of pixel-level information from the encoder path to improve the results of segmentation achieved through the decoder path. After U-Net processes an image, it produces a segmentation map that names every pixel. A U-Net training dataset of histological pictures of breast cancer together with matching masks is used for breast image segmentation. Which picture pixels are associated with the breast are indicated by these masks. Next, by forecasting the likelihood that every pixel in the image represents a blood cell in the input breast image, then U-Net model which is trained may be applied to dataset images to segment breast cancer images. Architecture of U-Net model is as shown in Figure 2.

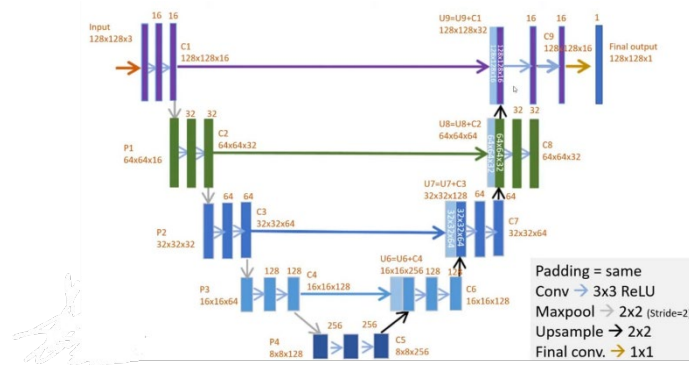


Figure 2. Architecture of U-Net model.

U-Net++

By adding stacked skip connections and dense connections, U-Net++ is a variant designed to enhance U-Net's operating efficiency. Dense skip connections link several U-Net modules, which make up U-Net++ architecture. Two paths that extend and contract with skip connections make up every U-Net module. While the network model can use all of the data gathered from the dataset images to improve segmentation efficiency, U-Net++'s set of skip connections enable the network to obtain features in various measures. Every pixel in the input dataset image is provided a label using segmentation map that U-Net++ produces. A input images and corresponding mask image is trained using U-Net++ for the purpose of segmenting breast cancer image. Next, by forecasting the likelihood that every pixel in the image represents a cell in breast image, the trained model of U-Net++ may be applied on to set of breast images. Architecture of U-Net++ model is as shown in Figure 3.

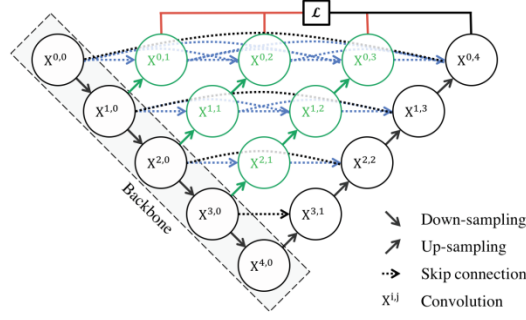


Figure 3. Architecture of U-Net++ model.

3.4. Feature Extraction

Following the segmentation process, features are mined from segmented blood cell. Feature extraction is accomplished by using shape and tetrolet features. The more prominent features in segmented image are retrieved by feature extraction process. These shape features include area, solidity, eccentricity, perimeter, and major axis length.

a) Area: Area is a shape feature. It can be computed as total amount of pixels exist in the boundary.

b) Solidity: Solidity is defined as the ratio among the area and convex region. Further, solidity is computed using the below expression

$$T_2 = \frac{T_1}{C_a} \quad (2)$$

where, C_a signifies convex area and T_2 represents solidity with size 1×1 .

c) Eccentricity: This feature is measured by considering maximum length of the major and minor axes, and eccentricity is represented below

$$T_3 = \frac{2\sqrt{(h_1)^2 - (h_2)^2}}{h_1 h_2} \quad (3)$$

where in, h_1 represents major axis, h_2 indicates minor axis, and T_3 signifies eccentricity with size 1×1 .

d) Perimeter: The length of a given region's boundary is known as its perimeter. Further, the perimeter is signified by T_4 with size 1×1 .

e) Major axis length: The line sector that passes through focus of ellipse is known as major axis. It is stated by T_5 with size 1×1 .

The shape features, include area, solidity, eccentricity, perimeter, and major axis length obtained are combined to generate feature vector r_1 , which is given by

$$r_1 = \{T_1, T_2, T_3, T_4, T_5\} \quad (4)$$

Tetrolet features: An adaptive Haar wavelet transform is otherwise called Tetrolet transform [33] that provides the effective image detection result. Tetrolet is wavelet transform scheme in which its tetrominoes shapes are created by interconnecting four identical squares. For each level, the low pass image is categorized into 4×4 blocks. From every block the local Tetrolet is computed. For improving the diagnosisability, the Tetrolet transform is considered.

3.5. Breast Cancer Detection Using Proposed RKHO

In our research VGGNet architecture is used to detect breast cancer. The extracted features are inputted to the VGGNet for detecting the breast cancer. Weight parameters of VGGNet are tuned by the proposed RKHO algorithm.

- Training of CNN model using proposed RKHO

The training process of VGGNet is carried out using RKHO, which is the assimilation of ROA [27] and KHO [26] algorithm. To establish this, the weight parameters of VGGNet are adjusted using RKHO algorithm. Remora Optimization Algorithm is a nature inspired algorithm. In this remora present in the

ROA updates their position using two strategies first one is free travel strategy and second is eat thoughtfully. The free travel strategy involving SFO and experience attack strategy, whereas the eat thoughtfully strategy involving WOA strategy followed by host feeding. Moreover, the advantage of WOA is it has high processing speed and quick convergence rate. In KHO, it is a biologically-inspired approach used to resolve the optimization issues. Besides, the KHO algorithm is designed by adapting the herding features of krill individuals. The least distance between every krill and food, and the krill and herd with high density is selected as the objective function of krill's movement. Moreover, the location of each individual krills is based on the three major factors, such as random diffusion, foraging activity and movement induced by the existence of other persons. In order to progress the exploration rate of ROA, the advantage of KHO is adapted to update the locations.

Initialization

The primary step of this algorithm is to initiate the algorithmic parameter and the number of Remoras.

Fitness function

Fitness function is used to evaluate the optimal solution using the Mean Squared Error (MSE), which is expressed as

$$P = \frac{1}{n} \sum_{i=1}^n (ai - bi)^2 \quad (5)$$

Here ai is the expected result and bi is the classified result.

Free travel

The free travel or exploration strategy involves two phases, which are defined as below.

SFO strategy

In this state, the locality or placement of individual is updated based on the elite notion of algorithm, which is modelled as

$$x_{t+1} = x_t + \alpha \cdot (x_{best} - x_t) \quad (6)$$

Here x_t is the position, α is a random number, and x_{best} is the best position.

Experience attack

For evaluating the possibility of changing the host, the tuyu wishes to constantly make a small move nearby the host. This behaviour is modelled as

$$x_{t+1} = x_t + \beta \cdot (x_t - x_{prev}) \quad (7)$$

Here x_{t+1} is the new position, x_t is the current position, β is the tentative step, and x_{prev} is the previous position

Eat thoughtfully

In this step, the location of individual is updated using the following two strategies.

WOA strategy

Based on the standard WOA, the updated position of Remora applied with the Whale is excavated, which is given by

$$x_{t+1} = x_t + \gamma \cdot D \quad (8)$$

Here D is the distance between the prey and the hunter, and γ is a random number.

Host feeding

The exploitation step is partitioned into host feeding such that the best solution is shortened to the location of host area. Thus, the incremental processing can be established as moving or encircle the host, and is formulated as

$$x_{t+1} = x_t + \delta \cdot (x_{host} - x_t) \quad (9)$$

Here x_{host} is the host position and δ is a factor.

Evaluate the feasibility

The feasibility of every solution is calculated at every iteration for updating the best position based on the fitness measure using MSE

Termination

All the above steps explained in this algorithm is continually processed till the best solution is attained.

4. Results and Discussions

The implementation of proposed model for breast cancer detection technique is done in Python Language.

4.1. Performance Metrics

Our research work is detection of Breast cancer. The extracted features are fed into the VGGNet. The proposed RKHO algorithm fine-tunes the weight parameters of VGGNet. Proposed Model detects whether disease is there or not. As it is a binary classification so metrics accuracy, sensitivity and specificity can be applied for performance analysis.

Accuracy: Accuracy is the correctness of cases that are correctly detected as normal or diseased. The accuracy is determined based on the true positive and true negative of normal and diseased cases based on the extracted features.

$$I_{acc} = \frac{a + b}{a + b + d + e} \quad (10)$$

Here a, b, d, e indicates the True Positive, True Negative, false positive and false negative.

Sensitivity: The correctly identified abnormal cases are determined by term specificity, which is computed as

$$I_x = \frac{a}{a + e} \quad (11)$$

Specificity: The correctly identified normal cases are determined by the term specificity, which is computed as

$$I_y = \frac{b}{b + d} \quad (12)$$

4.2. Experimental Results

Figure 4 refers to a sample input image from the dataset. The image 4 (a) is an example pathological image in the BrecaHAD dataset and the image 4 (b) is the masked image. Like this for all input images corresponding ground truth images are available in dataset.

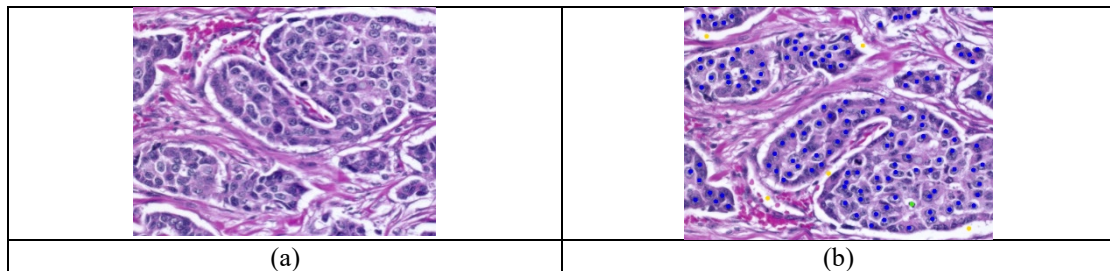


Figure 4. (a) Input image. (b) Ground truth display image.

The U-Net model's segmentation results are displayed in Figure 5. The model has successfully identified and located the region of interest in the target object, as demonstrated by the results, which show that the comparison between the segmented result and the ground truth mask is almost identical. These output results imply that the bias and variance are balanced by trained model successfully and is efficient in precisely segmenting the target item. We have computed two evaluation metrics for segmentation.



Figure 5. Segmentation results of U-Net Model.

- i) Dice coefficient

$$Dice\ coefficient = 2 \times (\text{Area of Overlap}) / \text{Total Area}$$

ii) Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (13)$$

where

TP is pixels correctly predicted as objects

TN is pixels correctly predicted as background

FP is pixels incorrectly predicted as objects

FN is pixels incorrectly predicted as background

Dice coefficient of segmentation using U-Net model is 0.891 and accuracy of the U-Net model derived from the data is 85.70%.

The U-Net++ model's segmentation output is displayed in Figure 6. U-Net++ model has done a good job of accurately segmenting the target item. We can observe high degree of similarity between the segmented output and the ground truth mask from the results. These output results shows target object is segmented correctly by the trained model. Dice coefficient of segmentation using U-Net++ model is 0.929 and accuracy of the U-Net++ model obtained is 93.15%. U-Net++ model obtained more accuracy and Dice coefficient values than U-Net model. Hence we considered the features extracted from U-Net++ Model to detect breast cancer.

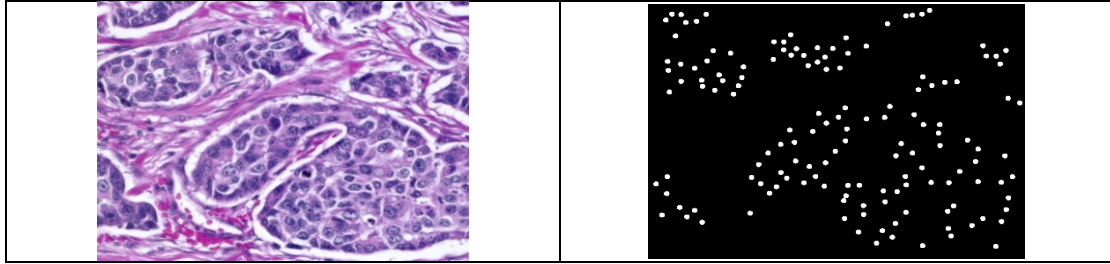


Figure 6. Segmentation results of U-Net++ Model.

Features are extracted from the output of U-Net++ model. These features are used to detect breast cancer using RKHO-VGGNet.

4.3. Comparative Performance Analysis

Aim of this research is to compare Breast cancer detection using RKHO-VGGNet optimization and without using RKHO-VGGNet optimization methods. Hence comparative graphs are presented for RKHO-VGGNet optimization and without using RKHO-VGGNet respectively. The analysis of performance for the RKHO-VGGNet is done by considering the percentage of learning data and evaluation parameters.

The performance of RKHO-VGGNet for breast cancer is exhibited using result analysis graphs. The accuracy measure of RKHO-VGGNet is given in Figure 7. Figure 7a is graph showing the accuracy of the VGGNet model across different learning data percentages without using optimization, for various epoch settings. Figure 7b is a graph showing the accuracy of VGGNet with optimization over different epochs as a function of learning data percentage. It is observed that for each epoch setting, the optimized model consistently outperforms the non-optimized model, showing higher accuracy at each level of learning data. The accuracy gap between the optimized and non-optimized versions widens as both learning data percentage and epoch increase, demonstrating the impact of optimization on model performance over time and with more data.

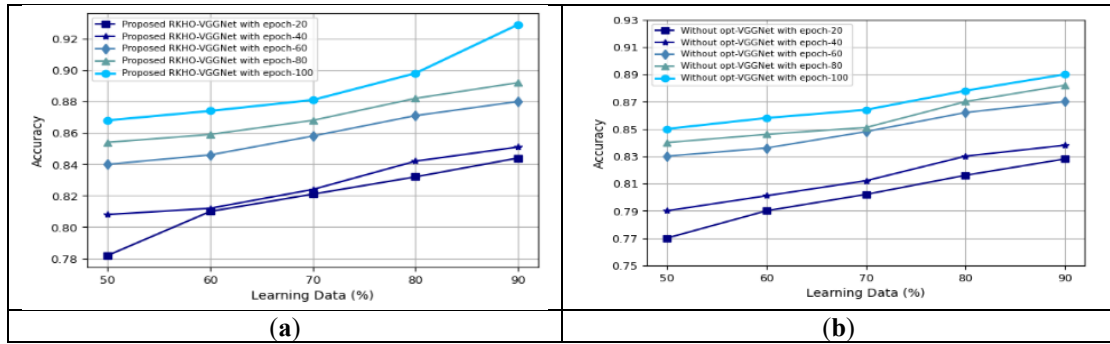


Figure 7. (a) Accuracy of RKHO-VGGNet with Optimization. (b) Accuracy of RKHO-VGGNet without Optimization.

The sensitivity measure of RKHO-VGGNet is given in Figure 8. Figure 8a is graph showing the sensitivity of the VGGNet model across different learning data percentages without using optimization, for various epoch settings. Sensitivity improves gradually with more learning data and epochs. Figure 8b is a graph showing the sensitivity of VGGNet with optimization over different epochs as a function of learning data percentage. Sensitivity improves consistently with higher learning data percentages and more epochs, indicating better true positive rate with optimization. It is observed that sensitivity values are more for optimized model than model without optimization.

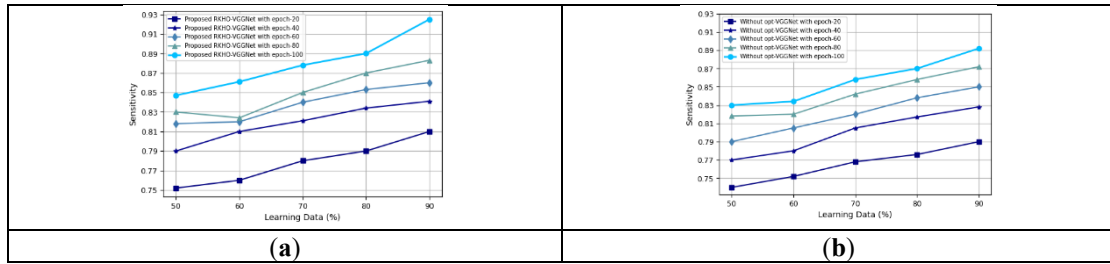


Figure 8. (a) Sensitivity of RKHO-VGGNet with Optimization. (b) Sensitivity of RKHO-VGGNet without Optimization.

The specificity measure of RKHO-VGGNet is given in Figure 9. Figure 9a is graph showing the specificity of the VGGNet model across different learning data percentages without using optimization, for various epoch settings. Figure 9b is a graph showing the specificity of VGGNet with optimization over different epochs as a function of learning data percentage. Specificity graph shows a steady increase with higher learning data and more epochs, indicating improved true negative rate due to optimization.

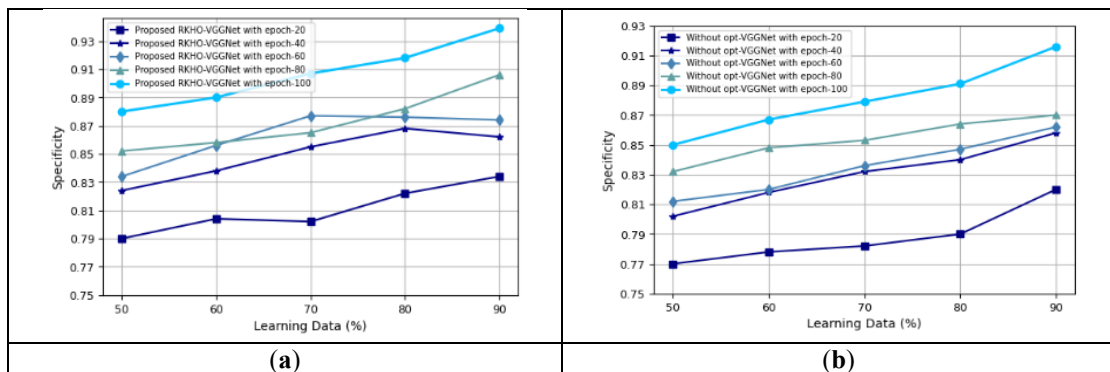


Figure 9. (a) Specificity of RKHO-VGGNet with Optimization. (b) Specificity of RKHO-VGGNet without Optimization.

5. Conclusion

This paper proposes comparative analysis of two CNN models RKHO-VGGNet and VGGNet not trained with RKHO optimization algorithm for diagnosing the breast cancer from the histological images. The input image is pre-processed using Gaussian filter that eliminates the noise from the images. The

blood cell segmentation is accomplished using U-Net++ which separates the blood cells from the pre-processed images. Moreover, the significant features, like shape features and Tetrolet features are extracted that significantly aim to progress the detection performance. Consequently, the extracted feature is prosecuted to detect the breast cancer using VGGNet. Performance of the model is measured. And then weights of VGGNet are tuned by the RKHO algorithm, which is the assimilation of ROA and KHO algorithm. Performance of RKHO VGGNet models is computed and observed that proposed optimization algorithm helps to enhance the accuracy of breast cancer detection. The effectiveness of experimental result is validated in accordance with the metrics, sensitivity, specificity and accuracy. The visualization clearly demonstrates the advantage of using optimization techniques to enhance model performance.

Author Contributions

Eliganti Ramalakshmi contributed in identification, conceptualization of the research problem and also worked towards methodology & implementation. Dr Loshma Gunuseti and Dr Sumalatha Lingamgunta contributed towards Supervision and guidance of the research work.

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Conflict of Interest Statement

The authors declare no conflicts of interest.

Data Availability Statement

BreCaHAD dataset from kaggle repository.

Acknowledgment

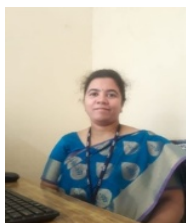
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