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Breast Cancer Detection Using Deep Learning Algorithms

Mohsin Ali Tariq[1*], Wasif Akbar[1], Saima Ali Batool[1], Muhammad Kamran Abid[1], and Naeem Aslam[1]

[1]NFC Institute of Engineering and Technology, Multan, 66000, Pakistan.
[*]Corresponding Author: Mohsin Ali Tariq. Email: chmohsinali07@gmail.com

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Abstract: The early detection is essential for a more efficient and successful course of treatment in breast cancer. The development of computer-aided detection systems has enabled recent advances in effective and nondestructive cancer diagnosis procedures. This study presents a comprehensive approach to identify the malignant area in mammography pictures. The suggested method is a multi-level method consisting of the grasshopper optimization algorithm integration, the implementation of optimization CNNs for image segmentation and the reduction of image noise. Precision and computing cost are both enhanced by GRASP – Optimization Algorithm, which is used to optimally employ feature extraction and selection. This method is special because it utilizes all CNN-based max segmentation, image noise reduction closely, and novel grasshopper optimization algorithm that maximize breast cancer diagnosis accuracy rate. For illustration, noise reduction image techniques are applied to the procedure in order to elaborate the resolution of mammography images. The standard CNN method with the best partitioning accuracy can describe the adjacent tissues in detail at a must higher level, which makes it easier to find the malignant areas. By integrating a fuzzy grasshopper optimization algorithm, the feature extraction and selection steps will be further accommodated, resulting into higher its accuracy and computational effectiveness. This is their distinction from the traditional techniques because of the uncommon combination of methods. It also proves that the approach is complex and dynamic. The suggested approach demonstrated significant superiority in terms of sensitivity (75%), specificity (97%), positive predictive value (PPV) (99%), negative predictive value (NPV) (45%), and overall accuracy (96%), in a thorough comparison with ten cutting-edge approaches through simulation. The thorough results highlight the efficacy of this novel strategy and establish it as a promising development in the field of breast cancer diagnostics.

Keywords: breast cancer; image segmentation; classification; extraction; grasshopper optimization algorithm.

1. Introduction

Breast cancer represents a noteworthy worldwide health concern, bearing the regrettable distinction of being the leading cause of cancer-associated deaths among women worldwide. There are many different risk factors that contribute to breast cancer, including both genetic and environmental influences. A person's vulnerability to breast cancer can be significantly influenced by important genetic predispositions, such as dense breast tissue, early menstruation, delayed menopause, and family medical history. These hereditary variables significantly increase an individual's overall risk profile for breast cancer and are outside of their control. Understanding how genetic and environmental risk variables are entwined emphasizes the value of thorough screening programs and individualized risk assessment techniques. Informed lifestyle decisions and proactive screening are made possible by education and understanding of these risk factors, which promotes early identification and better results in the fight against breast cancer[1].

These modalities help characterize and distinguish between benign and malignant findings by offering more details about worrisome lesions found on mammograms. A variety of approaches are used as therapeutic techniques for breast cancer, such as radiation therapy, chemotherapy, surgery, and targeted therapies. For this reason it is needed to develop a multidisciplinary model which consists of the participation of radiologists, oncologists, surgeons, and other health care specialists. The teams of experts may give a detailed and personalised treatment plan, containing factors for accurate diagnosis, proper treatment, and supportive care for breast cancer patients in Malaysia and worldwide[2].

The unpredictable nature of breast cancer epidemiology poses the novel problem and the systematic intervention becomes a necessity. The emergence of these dynamic trends poses a real challenge to health care system, and therefore, to address these challenges holistically is vital. these holistic approaches include health education, lifestyle changes, early detection, access to high-quality health care and investigation into the origin of this increase. Recognising and combatting the synergy between internal and external risk factors matters a lot, to minimize the incidence of breast cancer globally and lessening its impact on women[3].

1.2 Background

The microscopic cells that make up the human body are only visible under a microscope. In order to take back the place of aged or dead cells, cells invariably carry on the cycle of division. Usually, cell proliferation unfolds in accordance with a predicted pathway, whereby cells developed in line with the physiological requirements. Nevertheless, an increase in the abnormal cell population that doubles without stopping results in proliferation going out of hand. As a result, it causes malignancy and finally gives birth to a tumor. The main cause of death globally is put down to cancerous tumor development that is mainly associated with organ dysfunction.[4]. Globally, according to GLOBOCAN Data, 18.1 million of cancer case were detected in 2018 and out of these 9.6 million deaths from cancer occurred [5].

Mammography as a technique of finding breast cancer is the main method, often applied together with a clinical breast exam, highlighting the vital importance of this particular method in the early stage detection of the disease. The detection of small lesions or any abnormalities from the breast tissue is aimed at making early intervention which may help enhance the cancer prognosis. Prevention of breast cancer should focus on promoting healthy lifestyles, encouraging screenings on a regular basis, and educating people about the risks. These factors provide the highest chance of good outcomes in breast cancer control[6].

Regardless of this advancement in the early detection of breast cancer, it is just as important to continue to emphasize early identification as it has proven crucial in improving the prognosis and treatment outcomes for patients. Due to its complex origin, breast cancer remains the most dreadful type of cancer; but early detection together with modern treatment protocols bring in a lot of hope of a full recovery. Empowering doctors with tools that are more advanced and that can detect the slightest abnormalities in mammograms can lead to the radical change of the diagnostic conditions. Technological advances can utilize various medical imaging modalities with increased accuracy thus, enabling timely diagnosis and treatment of the patient. While developing and confirming these biomarkers' reliability and effectiveness in clinical settings, as well as to reach the aim of early detection and more efficient patient care, more studies and validation are needed.[7].

Mammography screening at intervals would enable diagnosis of possible cancers at their most incipient stages, typically before they experience palpation or symptoms, particularly for women within the recommended age groups. In addition, advances in mammography technology even improved both the sensitivity and accuracy of breast cancer detection. On the other hand, digital and three-dimensional mammography (tomosynt-hesis) reduced the false negative rate and increased the detectibility of small breast tumours. This role is another important element in the war against breast cancer; it highlights the need for early detection and subsequent timely intervention, both of which are essential elements that can significantly improve the patient's prognosis as well as survival rates[8]. A lot of scientific projects carry out the substantial role of early breast cancer detection since such studies always show that fast diagnosis when treatable increases the survival rate much. The activity of developing non-destructive test has recently grown in detecting breast cancer. Many ways exist for implementing the recommended process without the patient's intervention, but let us look at two of them: image processing and computer programming[9],[10].

Novel approaches to the diagnosis of breast cancer, particularly non-invasive diagnostic instruments, have been discovered in a number of research labs. The techniques used in the methods include optical coherence tomography, multispectral imaging, and dermo copy[11],[12]. The methods discussed in this context each have their own special benefits and drawbacks, and trade-offs are made between precision and efficiency in order to prioritize affordability and usability. Image categorization focuses on assigning the input image to a specific preset category. The accuracy of the final classification depends on how well each processing step accurately sniffs out the cancerous areas, which radiologists use to visually highlight these potential areas. These advances represent a significant advancement in diagnostic capabilities as computer-aided detection raises the rate of cancer detection dramatically[13].

This method helps the radiologist reduce human error by adopting a two-step assured technique to boost the chance of identifying cancer[14],[15]. Mammography is an essential part of cancer detection because the diagnosis depends on the accuracy with which the malignant area is located. Even the most seasoned radiologists occasionally run into difficulties and mistakes when interpreting medical pictures, despite their wealth of knowledge [16] despite the fact that many precautions are taken to prevent human error[17]. In 2016, CCN (CNN) was adapted by Spano et al. to introduce a new method for computer-aided cancer detection from histopathology images[18]. The output from simulation testing gauged the system's precision and compared it to other popular methods.

The significance of false positive reduction as a fundamental component of their inventive methodology[19].

The experiment's findings demonstrated increased sensitivity in comparison to current techniques. A noteworthy development in the field was made in 2016 when Gu et al. presented a novel method for the automatic segmentation of 3D ultrasound breast cancer pictures. The method distinguished itself in the classification of breast cancer images by identifying the major tissue components in each image[20]

This particular technique is important because it has the potential to improve the accuracy and consistency of diagnostic abilities in the field of pathology related to breast cancer. Identifying the real nuclei of the cells is major for both diagnosis and prediction of breast cancer. Also, it affects specifically therapy options and extent of influence on patient outcomes. The breast cancer pathophysiology diagnostics' strategy offered by Wang et al. is the step to the development of novel sophisticated instruments. Consequently, there is potential for enhancing diagnostic capacities in the continuous fight against the illness. In the future, the techniques will have a higher potential for success and are more individualized if computational approaches advances, which generally changes the process of diagnosing breast cancer[21]. The use of validation of techniques through well-known databases such as DDSM and MIAS shows the essential role of standardized datasets in advancing breast cancer detection research. These databases constitute a very valuable instrument that enables us to test new methods and to improve the reliability and precision of algorithm development for the study of the breast tissue, which in its turn will make possible the improvement of the diagnostic capabilities of the fight against breast cancer. With the help of these databases, the doctors could be able to carry out more research on and to do improvements in those modalities, and this, in turn, could bring breast cancer diagnosis and medical imaging to a new improved level. The technological intelligence has seen a huge development in the given time.Computational intelligence encompasses various methods such as neural networks,[25],[26], fuzzy techniques[27],[28], and algorithms for optimization[29],[30]. Algorithms for optimization that can improve segmentation and classification techniques include metaheuristics.

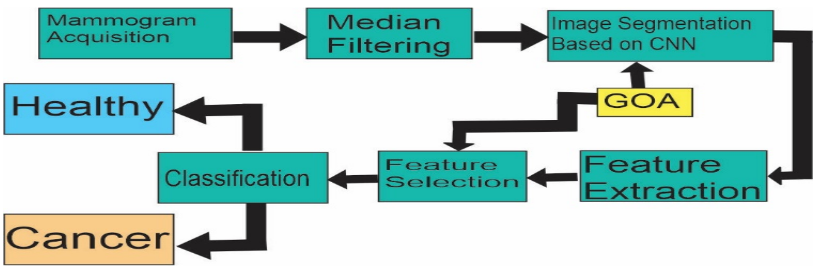

Figure 1. The color figure for the proposed breast cancer diagnosis system

Bhardwaj and Tiwari (2015) presented an improved neural network with a genetic algorithm to create the best breast cancer diagnosis system. According to simulation findings, the studied dataset exhibited a remarkable 100% precision rate[31]. The grasshopper optimisation algorithm (GOA), a revolutionary metaheuristic method, was first presented by Mirjalili and Lewis[32]. Inspired by the swarming behaviors observed in grasshoppers within their natural habitat, the grasshopper optimization algorithm (GOA) has demonstrated favorable outcomes across diverse datasets. This success served as the justification for integrating the GOA into the architecture of a system designed for breast cancer diagnostics, as depicted in Figure 1.1. The objective, as illustrated in the figure, revolves around leveraging the GOA for feature selection and image segmentation, with the ultimate aim of achieving superior outcomes that set it apart from similar endeavors in the field.

2. Literature Review

The information on the relevant previous research is provided in this part. There are essentially two ways to detect breast cancer. Deep learning is the next best thing after machine learning. A great deal of research is done with machine learning. However, Deep learning solves some of the issues with machine learning approaches. Details about deep learning and machine learning techniques are included in this section. Present a machine learning-based hybrid approach concept, providing a unique viewpoint.

2.1 The Problem in Data Initialization

To achieve the best results, this strategy was implemented using four classifiers and MRMR feature selection. The SVM, Naïve Bays, Function tree, and End Meta classifiers were compared by the author. It was found that SVM was a useful classifier[33] In an effort to get better results, a machine learning-based hybrid model was later introduced[34]

This implies that SVM was the best classifier overall, having the highest accuracy. It had carried out the comparison of decision trees, KNN, SVM, and ANN. It was used on the image collection and blood dataset. Consequently, a new classifier was used, but a machine learning model was proposed [35]. As classifiers, the author used ANN, SVM, KNN, and Extreme Learning Machine. To improve the results, the classifier underwent a small tweak. This suggests that the Extreme Learning Machine, the machine learning model that was suggested, yielded better outcomes[36]It employed four classifiers: Naïve Bayes, KNN, CART, and SVM. According to the author, KNN offered better accuracy. SVM has some restrictions. SVM generated better results for binary variables. For this reason, Multi-SVM was applied. completed the analysis of machine learning methods comparison [37]. The Wisconsin Breast Cancer Database served as the dataset, and WEKA was used to do the evaluation. According to the author's evaluation, SVM produced better results in terms of performance measures. Deep learning techniques were developed in response to traditional machine learning as a means of resolving the problem.

Presented a convolution neural network model based on deep learning[38]Many models were included in the CNN, however only Mobile Net and Inception V3 were utilized. After comparing the two models, the author concluded that Inception V3 provided superior accuracy. However, there was still hope for treating breast cancer with machine learning[39]. A framework for supervised machine learning is presented. This study used a variety of classifiers, including logistic regression, SVM, and KNN. Performance study was performed on the dataset, which was taken from the UCI repository. With its precision rate of 92.7%, SVM demonstrated its efficacy as a classifier on the Python platform[40] suggested an alternate classifier for a machine learning model.

The Anaconda Platform's Python implantation is now complete. The author claims that Random Forest functioned admirably as a classifier, producing an accuracy rate of 99.76%. When the network with the classifier underwent a small tweak, there was an opportunity to improve accuracy. An SVM classifier was used to analyze the results of this study and assess the effectiveness of the model, looking at the conclusions drawn from building an ANN-based model[41].

According to the author's research, SVM had a precision rate of 91% and ANN had a 97% rate. It was also observed that ANN outperformed SVM alone in terms of accuracy. Depending on the needs of the model, it was suggested that SVM and Grid search be used. The author used SVM in the study at first, then combined it with Grid search for more refinement[42].

After performing a comparison analysis, the author identified the most successful strategy. On the other hand, a new model was developed that achieved higher accuracy by using the grid search technique[43] . proposed a CNN and k-mean GMM model.

Before using the texture feature extraction method, the author first assessed ROI. In the end, the CNN algorithm was utilized to ascertain the better outcomes, attaining a ninety-six percent accuracy in the evaluation. The author used the MIAS dataset to propose the deep learning model[44] The author focused on clustering using Lloyd's approach and classifying using CNN. The accuracy percentage of the recommended methods was 96%. The diagnosis was made using the histopathology images. In the process, explanations on image processing and deep learning were also given[45].

A deep learning algorithm was proposed with the goal of improving histopathology image quality. PCA and LDA were two of the several feature extraction techniques used in this investigation. The author undertook a thorough investigation of machine learning approaches; nevertheless, because large datasets were used, typical machine learning methods did not produce better outcomes. Therefore, deep learning was used.

Table 1. Current Correlated Work

Author & Ref.	Method	Findings	Dataset

Mahmoud Khademi et al. [82].	Probabilistic visual aids and profound belief networks	To determine the greater accuracy, it used manifold learning with a deep belief network and graphical modelling.	Netherlands Cancer Institute dataset, METABRIC breast cancer dataset, Ljubljana breast cancer dataset and WDBC.
Nikita Rane et al. [80]	Method of Machine learning techniques	This suggests that improvements in machine learning produced improved outcomes.	Wisconsin Dataset on Breast Cancer.
Majid Nawaz et al. [74]	Convolution neural network for Deep Learning	Compared to state-of-the-art models, it achieved 95.4% accuracy using the DenseCNN model.	BreakHis Dataset is used
R.Chtihrakkannan, P.Kavitha et al. [78].	Method of Machine learning techniques	It used DNN to reach 96% accuracy.	pictures from mammograms.
Ajay kumar et al. [76].	methods for classification such as Decisioning Tree, KNN, SVM, and Naïve Bayes.	SVM provided 97.89% accuracy when using WBCD32 and 97.13% accuracy while using BCDW11.	The datasets WBCD32 and BCDW11 are from the UCI Repository.
Sri Hari Nallamala et al. [77].	Methods of machine learning	The precision of 98.50% was attained.	Wisconsin Dataset for Breast Cancer.
R. Preetha et al.[73]	Methods of Data Mining	Find the hidden cancer that is related to the classification.	Wisconsin breast cancer dataset.
NareshKhuriwal et al.[75].	Used Deep learning	Using CNN, it reached 98% accuracy.	Mammogram MIAS database.
Shubham Sharma et al. [72]	Naïve Bayes, Random Forest, and KNN.	KNN performed well as a classifier in terms of accuracy.	Wisconsin Breast Cancer dataset from UCI Repository.
PanuwatMekha et al. [81].	Method of Deep learning	The author made a comparison between deep learning and machine learning methods. With deep learning, the accuracy of 96.99% was attained.	Wisconsin dataset on breast cancer.
Weal E.Fathy et al. [79]	Deep learning Technique	It accomplished 82.1% specificity, 99.8% sensitivity, and 96% area under the ROC curve.	Digital Mammography Screening Database dataset.

3. Materials and Methods

This chapter outlines the core idea and suggested approach for Deep Learning Algorithms-Based Breast Cancer Detection.

3.1 Database and Dataset Description

DDSM and MIAS datasets are used in the assessment and testing of the suggested system. The MIAS database is curated in England to support researchers who use mammography pictures. The photographs originate from the National Breast Screening Program me in the United Kingdom and consist of a set of 322 1024 × 1024 digital mammography photos that have been meticulously classified. The University of

Essex's Pilot European Image Processing Archive makes MIAS more accessible. 2620 3000 × 5000 pixel images with a 16-bit grey level are included in DDSM. The intensities in these grayscale pictures range from 0 to 255.To reduce complexity, the photos' native LJPEG format is transformed to JPG format. As a result, the databases had 2942 (322 + 2620) photos in total. Figure 3.1 displays a small selection of DDSM mammography pictures and samples from the MIAS database.

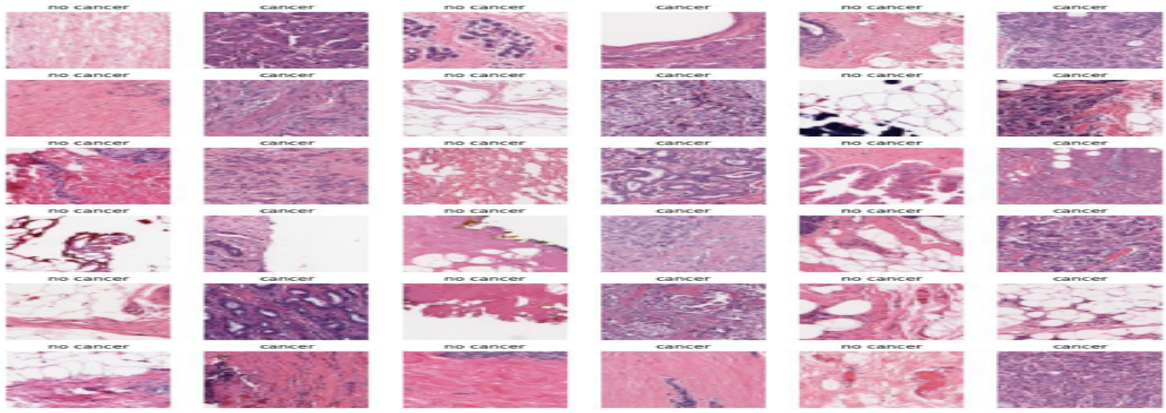

Figure 1. Few Images samples of Breast cancer

3.2 Data Augmentation

Data augmentation is a potent technique that uses unique image processing to artificially increase the amount of data, which improves the model's flexibility.

Rotation, flipping, zooming, and other common data augmentation techniques are used. Seemendra et al. employed these data augmentation strategies in their automated breast cancer categorization studies[72].

3.3 Classification cancer position of the breast

Differentiating between tumor's on the left and right breasts by classifying cancer according to where it is located in the breast. This classification aids in accurate localization, supporting customized treatment plans and enabling a thorough grasp of the distribution of cancer for the best possible patient care.

3.4 Convolutional neural network

The learning technique's primary goal is to produce a few kernel matrices from the mammography image that can be used to extract the key traits of the malignant image. In this work, the backpropagation (BP) technique is used to optimize the weights of network connections. A sliding window is used as the vector in convolution, which makes the dot product and weight addition easier. The rectified linear unit is used to calculate the activation function, which is f(x) = max(x, 0). CNN learning methodology teaches several layers with proficiency. This approach is well-liked and beneficial for many different computer vision applications. The three main layers that shape the CNN network are the convolutional layer, pooling layer, and fully connected layer. Every layer carries out specific tasks. CNN architecture is depicted in Figure 3.4.

The convolutional layer takes into account several 2D matrices as input and output while classifying images. Using an equal number of input and output matrices is not required. Local features are used to capture the input image's regional peculiarities.

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3.7 Segmentation By Goa-Based CNN

In order to differentiate cancerous patches from the surrounding environment, the best CNN is built in this study using the GOA. The goal of the GOA is to increase efficiency over manual justification by defending the amount of CNN hyperparameters. For this setting, the answer is an integer sequence.

The limitations for minimum (min) and maximum (max) are set at 2 and the sliding window's size, respectively, to prevent system failures. Smaller numbers are not allowed since the maximum value that can be used for max-pooling in this situation is 2.The sliding window's value must be less than the input data due to an inequality restriction in this optimization. As an example, the agents designate 100 as the number of swarms, and they select the CNN hyper-parameters from a range of 10 integer values.

The CNN half-value precision serves as the validation cost function for breast cancer in this study. The architecture is quite computationally intensive since it uses both CNN and GOA, and because BP requires that each CNN swarm agent be trained 1000 times on the breast cancer dataset. Figure 3.5 outlines the specifics.

The process continues until the stop criterion is satisfied after initializing and evaluating the cost of the agents and adjusting the search agents' positions in compliance with the GOA standards.

4. Results

On a laptop running the Anaconda version 2023 and google colab platform, computationally demanding simulations were carried out using an Intel Core i5-4310U CPU backed by 4 GB of RAM.

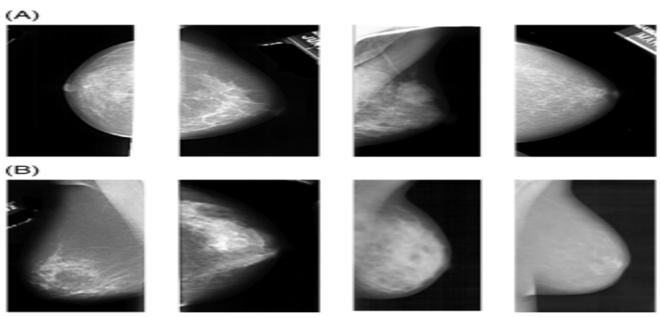

Figure 2. Cancer Area Identification

Here are some examples of cancer area identification using Convolutional Neural Networks (CNNs) in conjunction with the Grasshopper Optimization Algorithm (GOA): The original (A) and improved (B) images.

These simulations were run on the DDSM and MIAS databases with the intention of closely examining the effectiveness of the system. The methodology that has been suggested takes a multifaceted approach. First, careful noise reduction was applied to the input mammography pictures using simple yet efficient median filtering. Second, to accurately distinguish malignant areas from the background, an optimized Convolutional Neural Network (CNN) powered by the Grey Wolf Optimization Algorithm (GOA) was implemented. Then, a variety of elements were carefully taken out of the pictures, which made it easier to convert unprocessed data into organized and meaningful information and less complicated overall. Thirdly, the most insightful and important features were carefully selected using an improved GOA-based process. Last but not least, the condensed and crucial data was expertly trained and smoothly included into a Support Vector Machine (SVM) classifier, skillfully classifying pictures into two distinct groups: malignant and healthy.

Within the developed approach that combined the GOA-driven feature extraction with the improved CNN/GOA model, a standard protocol was established for dataset partitioning, designating 30% for careful testing and 70% for training. To guarantee thorough learning, the painstakingly tuned network was subjected to 10,000 iterations of rigorous training. In order to ensure consistency throughout the study, the training phase was carried out twenty times, averaging the values acquired to consolidate the data. Result for breast cancer detection

Table 2. Result for breast cancer detection

Metric	CNN + GOA
PPV	99%
NPV	45%
Accuracy	96%

4.1 Model Accuracy Diagram

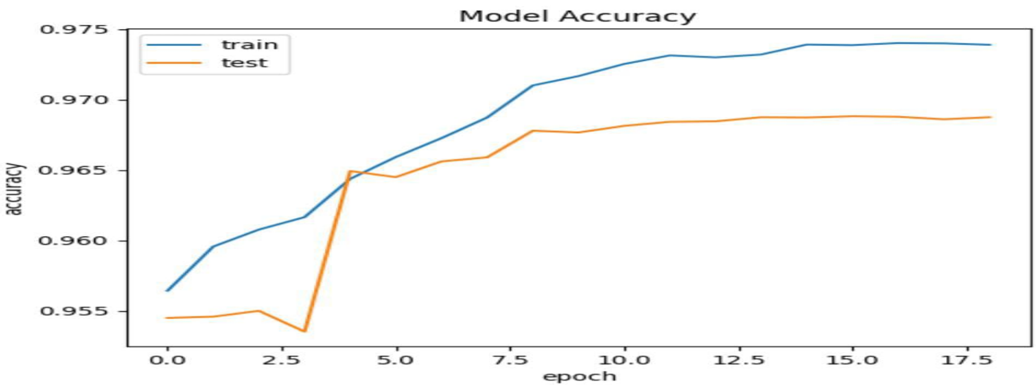

Figure 3. The Accuracy of Model Trains

5. Discussion

A comparative bar graph demonstrating the increase in PPV, NPV, and accuracy performance of the CNN model with incorporation of GOA optimization.

5.1 Enhanced Positive Predictive Value (PPV)

The CNN+GOA method produced an astounding 99% PPV. This means that, in comparison to the CNN base model, there were substantially fewer false positives—99% of the detected positive cases were real positives.

5.2 Challenges in Negative Predictive Value (NPV)

45% of the indicated negative cases may have been actual negatives, despite the NPV being just 45%. To decrease false negatives and increase the model's capacity to accurately detect negative cases, further work must be done.

5.3 Substantial Accuracy Improvement

The accuracy of the model reached 96% once GOA optimization was incorporated into the CNN architecture. This represents a significant improvement in the model's overall prediction accuracy when compared to the original CNN model.

5.4 Clinical Relevance and Applicability

In clinical settings, where precisely identifying actual positive cases is essential to preventing misdiagnosis and guaranteeing prompt response, a PPV of 99% is very encouraging.

Although NPV is still a problem, a 96% accuracy rate suggests that breast cancer detection is generally quite reliable.

5.5 CNN/GOA Model

This subsection presents a graphical comparison of different models with the CNN/GOA model that is suggested. These graphics provided an overview of the comparison of previous studies through debate and literature. The figures below show comparisons between accuracy and the PPV measure: -

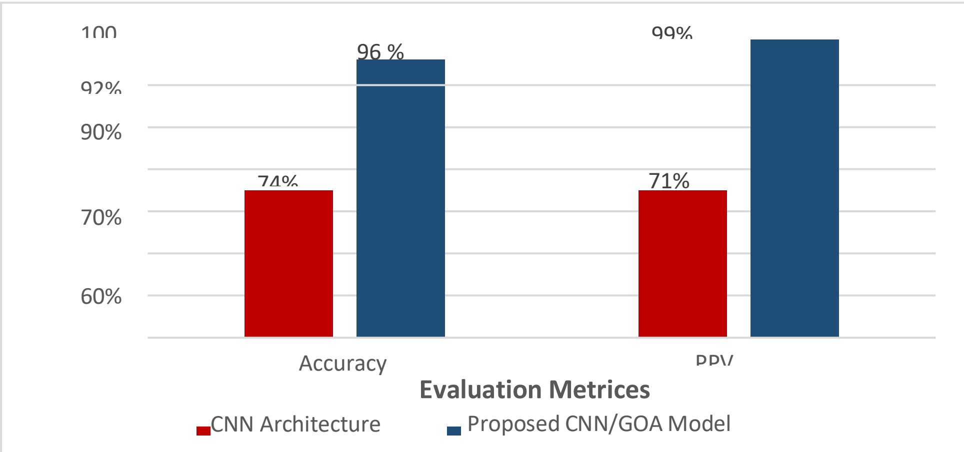

Figure 4. Comparison of CNN Architecture with Proposed CNN/GOA Mode

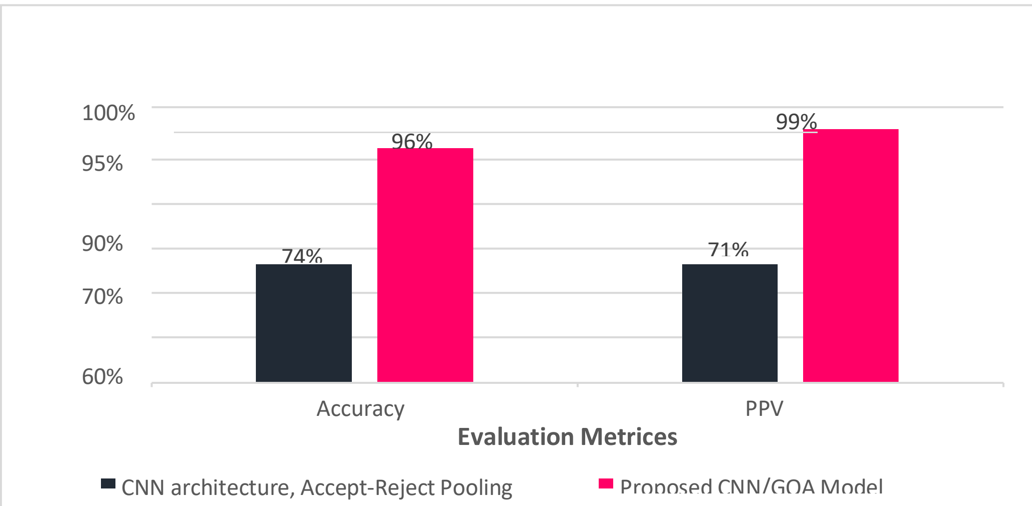

Figure 5. Comparison of CNN Architecture with Proposed CNN/GOA Model

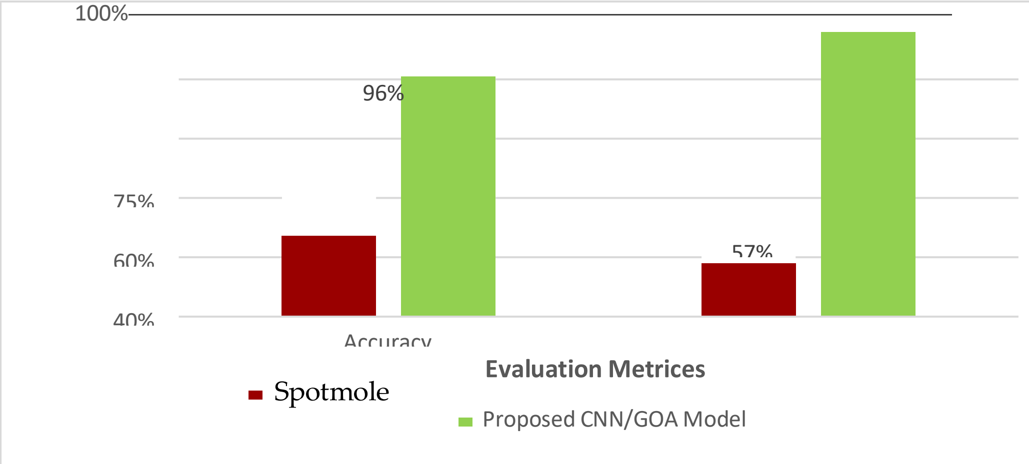

Figure 6. Comparison of Spotmole with Proposed CNN/GOA Model

6. Conclusions

This study provided a comprehensive method for the most precise mammography-based breast cancer diagnosis. After utilizing a median filter to remove noise from the raw photos, CNN-based optimum image segmentation was utilized to distinguish the cancerous region from the surrounding backdrop. In order to reduce computing costs and increase precision, a number of features were extracted. To remove the unnecessary features and choose the best traits for extracting pertinent information, an ideal method was used to trim the features. These attributes were then used to train an SVM classifier, which was used to distinguish between photos that were cancerous and those that were not. The relatively new GOA optimized feature selection and image segmentation. To assess the efficacy of the suggested system, ten different cutting-edge approaches were compared using simulations run on the MIAS and DDSM breast cancer databases.. In comparison to other approaches, the results revealed 75% Sensitivity, 97% Specificity, 99% PPV, 45% NPV, and 96% accuracy. Subsequent studies in the field of breast cancer diagnosis may investigate different strategies to improve the efficacy of CNN and the Grasshopper Optimization Algorithm (GOA) combination. First, by analyzing the effects of different CNN designs and hyperparameter combinations, the model's performance can be enhanced.

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