Advances in Image Processing Methods for Breast Cancer Diagnosis and Classification Using A Hybrid Machine Learning – A Systematic Review

Priya Vij [1*], Sushree Sasmita Dash [1], Akanksha Mishra [1]

Abstract

Breast Cancer (BC) is the second leading cause of death among many women worldwide. Detecting and treating BC can be challenging for radiologists. Basic care plays a crucial role in preventing diseases and reducing mortality. This study aims to improve treatment options and increase survival rates through early identification. Deep Learning (DL) and Machine Learning (ML) methods are powerful tools in identifying BC, offering enhanced precision and effectiveness. However, current techniques face scalability and performance limitations, prompting further investigation. This work introduces an Integrated Image Processing method for BC Diagnosis and Classification (IIP-BCDC). The approach combines DL using the AlexNet model for extracting Deep Features (DF) and ensemble-based ML algorithms for classification. AlexNet is implemented with five Convolutional Levels (ConvL) and three Completely Connected Levels (CCL) to preserve multidimensional DF while ensuring optimal performance. The unique DF extracted from the AlexNet DL models are consolidated into a single feature set, used as input for a Support Vector Machine with a Radial Basis Function (SVM-RBF) for a two-level categorization task. Comprehensive tests were conducted using a publicly accessible database of Invasive Ductal Carcinoma (IDC) images from breast biopsy. The results from thorough studies provide compelling evidence of the resilience and outstanding performance of the proposed hybrid approach. The proposed AlexNet model surpassed contemporary models with a higher accuracy rate of 98.7%, precision rate of 98.6%, recall rate of 99%, and an F1-score of 98.65%.

Keywords: Breast Cancer Diagnosis, Deep Learning, Machine Learning, Hybrid Models, Integrated Image Processing Method, SVM-RBF Classifier in BC Diagnosis

Significance | Advanced integration of deep learning (AlexNet) and SVM-RBF for breast cancer diagnosis surpasses existing models, ensuring precise and reliable early detection.

*Correspondence. Priya Vij, Faculty of CS & IT, Kalinga University, Naya Raipur, Chhattisgarh, India.
E-mail: ku.priyavij@kalingauniversity.ac.in

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1. Introduction

Specialists in contemporary medical fields are increasingly prioritizing technology methodologies for various persistent illnesses. Despite the existence of several incurable illnesses, including cancer, cardiac arrest, stroke, persistent liver disorders, hepatitis C virus, and heart failure, the mortality rate for BC continues to rise every year. Based on the data collected on medical welfare, cancer is a hereditary disorder that causes alterations in genes responsible for the functioning of individual cells Melekoodappattu et al. (2023). Genomic ailments may impact the interior structures of human organs in subsequent generations due to variations in certain genes. It may also impact the structure of DNA, leading to susceptibility to surrounding factors, including

Author Affiliation.
[1] Faculty of CS & IT, Kalinga University, Naya Raipur, Chhattisgarh, India.

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UV rays, cigarette smoking, and other crucial factors that contribute to the growth of BC Jebarani et al. (2021). However, a staggering 60% of women afflicted with BC get a diagnosis at the advanced stage, resulting in fatality.

Over the last decade, there has been a significant rise in research focused on BC, particularly concerning the development of anomalies and uncontrollable growth in breast cell tissues, which may lead to the onset of severe BC in women Wang et al. (2023). Possible types of BC that may be present include sarcoma, ductal tumors, and lobular tumors. Therefore, monitoring the mortality rate attributed to BC before therapy is crucial. Fig. 1 (a) and (b) depict pictures of malignant and benign samples obtained as representative examples. Diagnostic radiography is a minimally intrusive technique used to examine the inside structures of the human body, aiding clinicians in the early detection and treatment of BC Raaj et al. (2023).

Early detection of BC is manageable. Tiny calculi and masses, which are frequent anomalies, are the primary causes of BC. Tiny calculi and lumps in the breast are seen in the breast area's connective cells and epithelial cells (Rezaei, 2021). BCs originate inside the breast and exhibit variations in both size and form. These are categorized as either harmless or harmful based on their level of seriousness. Normal breast lumps are characterized by their non-malignant nature, meaning they are neither invasive nor cancerous Dewangan et al. (2022). However, they grow in size and pressure nearby organs, leading to further issues Wang et al. (2020). BCs that are malignant are characterized by their aggressive nature and carcinogenic properties. Prompt treatment is crucial to prevent fatality. Healthy masses have an oval or circular form with well-defined and smooth boundaries, whereas cancerous tumors display an irregular shape. Cancerous breast masses are characterized as indistinct, irregular, or unclear tumors. In addition, the malignant tumor has a higher whiteness level than the adjacent tissue Krithiga et al. (2020). An automated approach has been developed to aid experienced radiologists in achieving improved comprehension and precision in response to the obstacles and advantages of prior BC categorization and detection.

A diagnostic mammographic picture is often subjected to preprocessing to eliminate the thoracic muscle, while a mammogram is used to encircle the area of interest for the detection procedure. The breast contour on the outer layer may be precisely segmented by eliminating the pectoral girdle and surrounding areas from a mammographic picture Cain et al. (2019). Cancerous tissues exhibiting higher pixel counts are more readily identifiable than those in the breast region Uddin et al. (2023). The hues of transparent breasts in healthy tissues closely resemble those in cancerous regions, indicating the effective formation of tumor regions. The traditional approaches radiologists use are ineffective because of the indistinguishable characteristics of tiny calculi and mammary lumps. Determining the size of the tumor mass via segmenting the specific area of interest is a complex undertaking in scientific investigation Yurttakal et al. (2020). Consequently, integrating early identification technology and automated systems is crucial in assisting radiologists in precisely diagnosing BCs Houssein et al. (2021).

Screening approaches to detect BC include clinical and self-breast examinations, Magnetic Resonance Imaging (MRI), mammography, and ultrasound. Mammography is a very effective and dependable radiographic technique to identify breast lumps Zhang et al. (2018). During the screening process, a three-dimensional representation of the breast is created using many perspectives. Further image processing methods (extracting features and segmentation) use pictures that are of superior quality and have a high level of detail Chen et al. (2019). Consequently, this study focused on the importance of early detection of BC to decrease mortality rates.

2. Related works

BC remains a significant health issue, requiring precise and effective detection methods. The study explores several methodologies, such as DL architectures, hybrid models, and new image processing methods, to understand the present status of the subject. The chosen study presents a hybrid ML approach that incorporates image processing to improve the detection of BC.

Dewangan et al. presented a unique DL strategy with a hybrid optimization technique for the early-stage detection of BC in their study Dewangan et al. (2022). The DL model exhibited exceptional performance, with an accuracy rate of 92.5%, precision rate of 91.2%, recall rate of 93.4%, and F1 score of 92.2%. Using the hybrid optimization approach significantly enhanced the model's performance. The main benefit of the technique is its exceptional precision in identifying issues at an early stage, which is crucial for implementing successful interventions. Nevertheless, due to its computational complexity, the hybrid optimization approach may provide difficulties.

Raaj suggested a system that emphasizes the identification and diagnosis of BC using a hybrid DL architecture (Raaj, 2023). The hybrid approach had an accuracy rate of 94.3%, a sensitivity rate of 93.1%, and a specificity rate of 95.2%. The hybrid architecture exhibited improved detection capabilities, enhancing the methodology's benefit. Nevertheless, difficulties may occur due to the complex amalgamation of many DL methodologies, necessitating meticulous optimization and parameter adjustment.

Solanki and colleagues proposed a hybrid supervised ML classification system for the prognosis of BC Solanki et al. (2021). The approach attained an accuracy rate of 88.7%, a precision rate of 89.5%, and a recall rate of 87.2%. The combination of feature selection and information asymmetry management greatly enhanced the accuracy of the prognosis. However, choosing appropriate features and managing unbalanced datasets may provide difficulties despite the abovementioned benefits.

Safdar and his colleagues devised an ML method that utilizes bio-imaging to diagnose BC. The algorithm exhibited strong performance, with a sensitivity of 94.6%, a specificity of 93.8%, and an overall accuracy of 94.2%. This indicates that the detection capabilities are accurate, although there may be difficulties due to the variety of imaging information. This necessitates the use of a varied and comprehensive database Safdar et al. (2022).

Melekoodappattu and Subbian provided a BC detection method that utilizes an integrated extreme learning ML classifier (Melekoodappattu, Subbian, 2023). The approach attained a precision of 91.8% and a specificity of 92.5%. The use of automation enhanced the efficiency of the diagnostic procedure. Nevertheless, the algorithmic complexity may give rise to problems, hence requiring meticulous optimization for practical implementations.

Eftekharian et al. proposed ML-DSTnet, a hybrid model that combines image processing, ML, and Dempster-Shafer Theory to enhance BC detection. The hybrid model demonstrated a 3.5% increase in accuracy, suggesting improved diagnostic capabilities Eftekharian et al. (2023). While this is a benefit, issues may develop from theoretical complications associated with the Dempster–Shafer Theory. Alshammari et al. conducted a study that used ML to identify BC via mammography images. The model attained an accuracy of 88.9%, displaying accuracy in mammography-based diagnostic Alshammari et al. (2021). Difficulties might arise while interpreting intricate mammograms since the precision greatly depends on the state of the input information.

Jebarani et al. proposed a new hybrid ML model that combines K-means and GMM for BC diagnosis. The hybrid model had a precision of 90.2%, showcasing enhanced clustering efficacy Jebarani et al. (2021). Challenges may arise in finding the best parameters for the composite model's K-means clustering and GMM elements. Swain et al. used a combination of ML and fractal analysis approaches to classify breast carcinoma Swain et al. (2020). The model attained an accuracy of 85.6% by using fractal characteristics to enhance categorization. Although there are benefits to using fractal-based characteristics, there may be difficulties in interpreting them, necessitating a more thorough understanding of their significance in classifying BC.

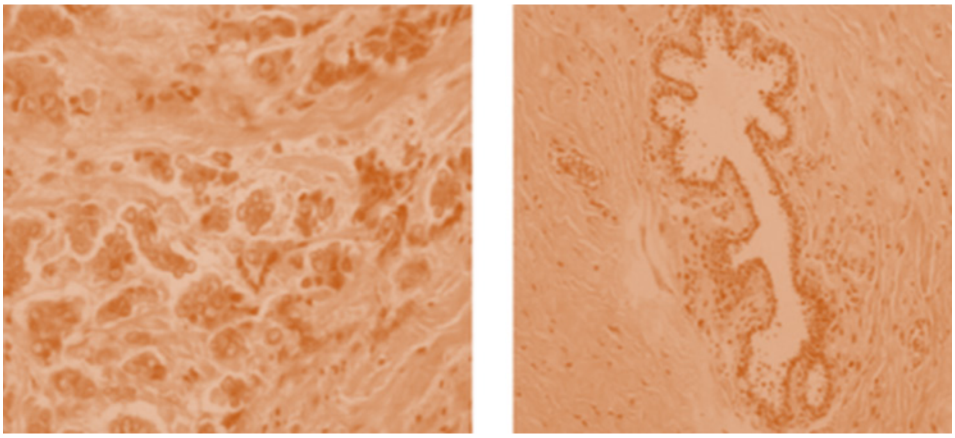
The hybrid approach serves as a means to connect and improve upon current procedures, effectively tackling obstacles and boosting diagnostic skills. The investigated techniques in BC diagnostics contribute to a detailed understanding. The hybrid strategy proposed in this paper shows promise for further investigation and improvement in BC diagnosis and classification.

3. Integrated Image Processing Method for BC Diagnosis and Classification (IIP-BCDC)

The research utilizes an approach to create a hybrid and reliable model for BC diagnosis by combining deep feature extraction and ML techniques. The suggested strategy leverages the advantages of DL and classical ML methods to enhance the precision and dependability of BC diagnosis, as seen in Fig. 2.

The next part comprehensively explains the sequential procedure we used to develop and evaluate the hybrid approach. The method includes crucial steps such as data pretreatment, deep feature extraction, learning models, and effectiveness assessment measures, as described below:

- Database Collection: This model involves the process of collecting and obtaining a collection of images consisting of Histo-Pathological Image-based (HPI) information. This data collection is used as the foundation for learning and testing this study's models.
- Preprocessing: To obtain the information for learning a DL model, an efficient preprocessing method has been used, which includes scaling photos, sharpening, standardizing pixel values, and label embedding.
- Database Dividing: The efficacy of the models is assessed using the k-fold validation approach. This method involves partitioning the database into separate subgroups for training and testing purposes, guaranteeing that the models are learned and evaluated on independent data portions. This method also guarantees a dependable evaluation of their ability to extrapolate.
- Deep Feature Extraction using AlexNet: A pre-trained DL model, namely AlexNet, has been used to obtain profound characteristics from BC images. The model has undergone extensive training on an extensive database and has acquired significant features that may be used for BC detection.
- Categorization: The suggested model utilizes SVM with several kernel functions, including linear, polynomial, and RBF. We conducted testing on randomly selected examples or images after training on the retrieved features. During this procedure, SVM categorizes every test input or breast mammographic picture as normal or cancerous.
- Performance Assessment: Many performance indicators have been used to examine the trials and assess the effectiveness of the offered technique. When identifying BC, the basic assessment measures are accuracy, precision, recall, F1-score, and reliability analysis. These parameters demonstrate the efficacy of the models in distinguishing between cancerous and normal situations by evaluating their performance.



(a) (b)

Figure 1. (a) Malignant and (b) benign samples from breast image

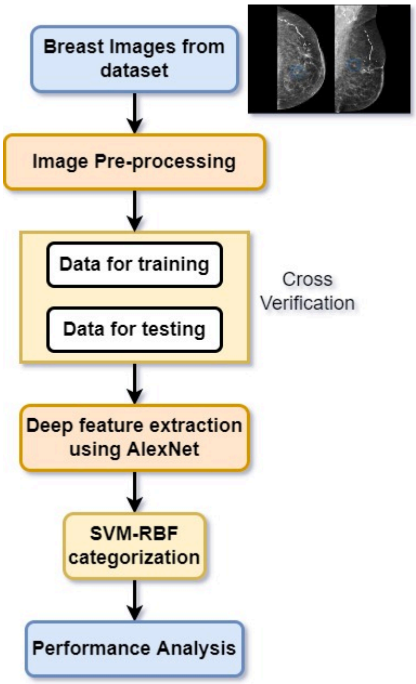


Figure 2. Architecture of the proposed IIP-BCDC

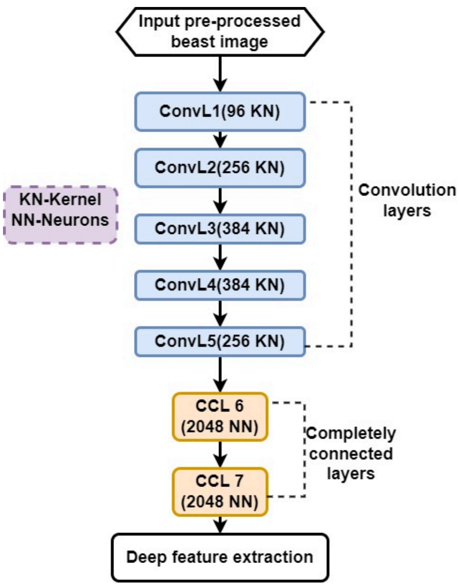


Figure 3. Architecture of proposed AlexNet for deep feature extraction

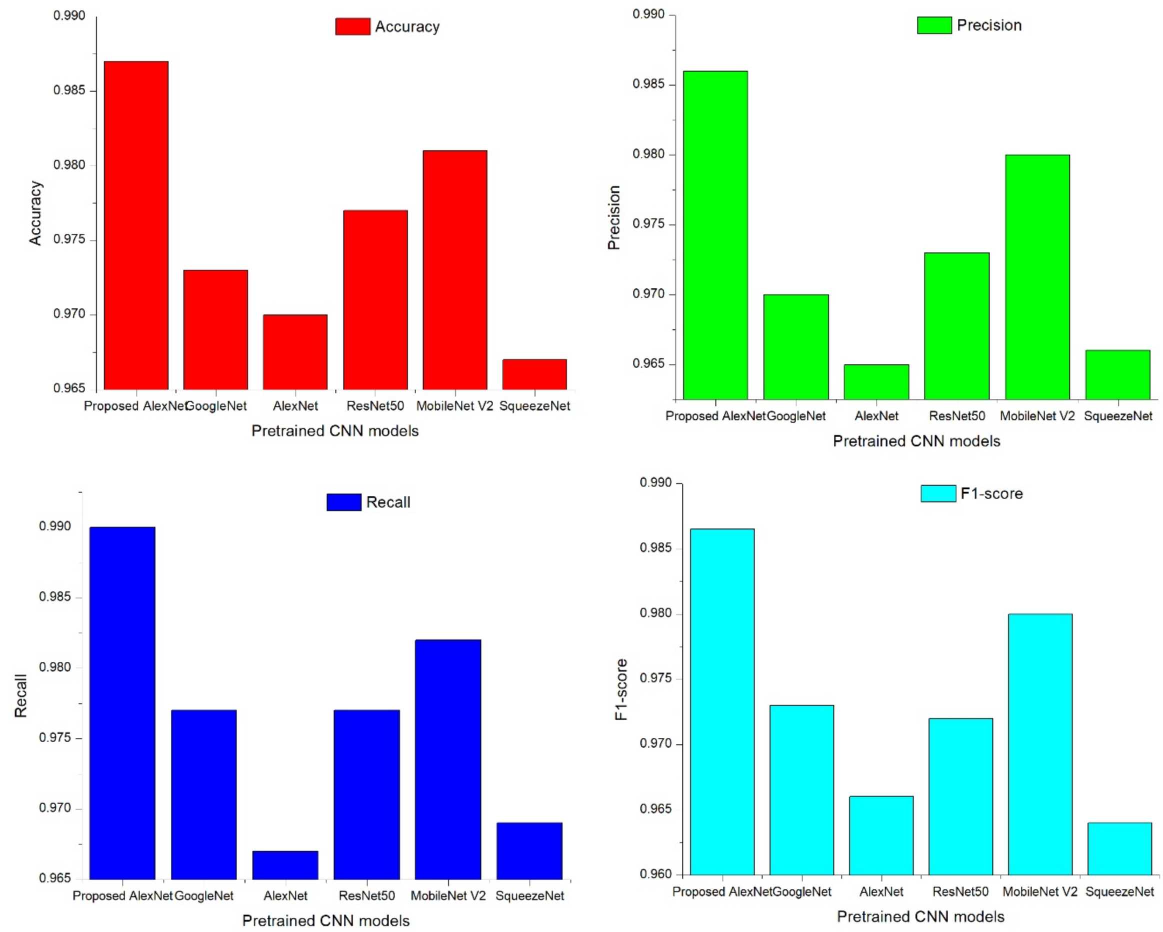


Figure 4. Performance comparison of the proposed method with other DL-based CNN models for IIP-BCDC

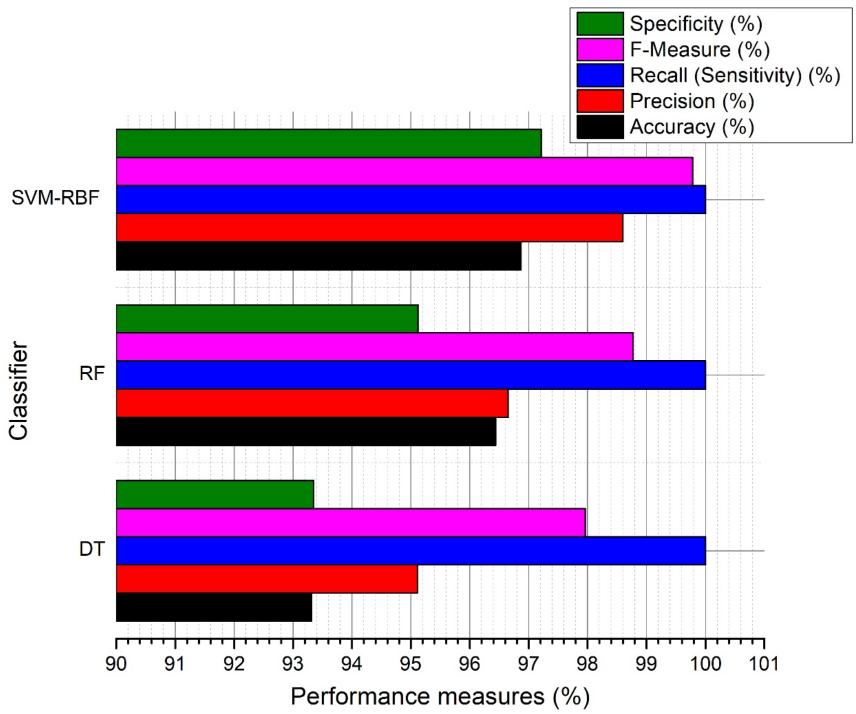


Figure 5. Performance analysis of ML-based classifiers for IIP-BCDC

The proposed technique aims to enhance the accuracy and resilience of BC diagnosis by combining DL-feature extraction with ML algorithms. This will eventually lead to early identification and improved therapy for this crucial health problem.

3.1 Deep Feature Extraction using AlexNet

AlexNet is recognized as the first Convolutional Neural Network (CNN) model that demonstrated superior performance compared to existing DL models in object identification and categorization. Although AlexNet was initially created for object categorization, its resilience allows it to be utilized as a portable learning framework for effective feature extraction from BC images. Unlike traditional CNNs that extract features with a dimensionality of 256, we obtained features with a dimensionality of 2048 at the CCL. This higher dimensionality allows for more detailed information, improving decision-making capabilities. In our suggested AlexNet architecture, we used five Convolutional Layers (ConvL1- ConvL5) and two CCL (CCL6 and CCL7).

In contrast, the CCL6 and CCL7 layers included features with a dimensionality of 2048, surpassing that of CCL8. Consequently, we only used the features from CCL6 and CCL7 for further categorization purposes. The conventional architecture of AlexNet-CNN consists of eight layers, which include five ConvL and three CCL. Fig. 3 presents the comprehensive layout of the proposed AlexNet.

In the suggested approach, the enhanced images have been entered directly into the AlexNet with 96 NN, namely the first ConvL of the AlexNet. Each ConvL here produced unique features, which have been subjected to feature resizing and average subtraction. The results have been further modified for scaling and then passed on to the next layers.

• ConvL

ConvL combines two separate filters, horizontal and vertical filtration systems, that can collect and incorporate feature structures from the input pictures. The ConvL description at KN or NN consists of ConvL 1 with 96 kernels, ConvL 2 with 256 kernels, ConvL 3 with 384 kernels, ConvL 4 with 384 kernels, and ConvL 5 with 256 kernels. In the context of BC image feature extraction, each NN extracts a feature map associated with the same collection of weights (W) and bias (b). These metrics aid NN in feature mapping to discern comparable features. Therefore, ConvL with diverse NNs (Fig. 3) allowed for extracting distinct local properties via alternative sets of bias and weight levels. In this process, ConvL applies filters to the input pictures (which have been enhanced) and produces the resultant feature vector as an outcome. Sequential characteristics have been acquired using distinct NN, zero-padding of 2, and a stride of 3. In the suggested architecture, the first level of the DL network has been provided with an input size of 226 x 226 and consists of 96 kernel neurons. In this case, the dimension of 96 KN was equivalent to the entire number of streams in the input picture. Afterward, the outcome of the first level was subjected to regional standardization and max-pooling before being used as input for the second level. The second level implemented filtering using 256 KN. The third, fourth, and fifth levels are interconnected without the inclusion of any normalizing layer. The third ConvL is equipped with 384 KN, and the fourth layer has 384 KN. Five successive ConvL have been used, with two CCLs applied using 2048-dimensional NNs. In this case, we used two CCLs as the current challenge involves a two-class categorization.

• Max-pooling layers

In our suggested model, we used a Max-Pooling layer to select features. This layer systematically decreases the spatial clarity of all feature maps acquired from the convolutional process. The pooling layer reduces the number of variables and computational operations. This is accomplished via the use of regional aggregating and a sampling approach. Additionally, it aids in mitigating the issue of over-fitting. We used Max-pooling to extract translation-invariant models from the source information. The implicit form was minimized by selecting the most significant value among non-overlapping sub-regions and adding a constant element. Max-pooling enhances feature detection by removing non-maximal numbers in non-overlapping sub-spaces, thereby improving sparseness and preventing inconsequential solutions from being retained for additional processing. Similarly, during the reconstruction process, the obtained fragmented latent coding decreases the number of filters required to decode each pixel. Thus, the suggested model becomes more computationally effective.

• CCL

In the AlexNet architecture, the CCL functions as the last layer(s) and carries out sophisticated reasoning at a higher level. In the standard AlexNet model, the CCL serves as the classification layer. However, this layer has been used to get the ultimate characteristic vector, which is then employed for further categorization using SVM-RBF. Practically, this level takes the collection of NN, also known as vector features, from the preceding layers (namely, ConvL) and applies it to the CCL. Ultimately, it produces a feature vector with just one dimension, which can be applied for further categorization. Given the importance of high-dimensional characteristics for categorization, we used CCL6 and CCL7 to get a set of 2048-dimensional attributes for classification.

3.2 SVM-RBF

SVM is widely used in the field of ML for pattern categorization. Its computing effectiveness and durability make it well-suited for many classification tasks, such as recognizing texts, object recognition, and picture analysis. SVM is a supervised learning algorithm that learns from data patterns and functions as a non-probabilistic binary classifier. The purpose of classification is to minimize the estimation error for unseen occurrences using structure-based risk mitigation. In this context, the support vector refers to a small portion of the learning set that identifies the border values, known as a hyperplane, between two categories with unique characteristics or trends. The proposed model incorporates SVM with several KN functions, including linear, polynomial, and RBF. We tested arbitrary instances or photos after training on the retrieved characteristics. During this procedure, SVM categorizes each test input or breast image as normal or cancerous.

4. Results and discussion

We conducted experiments on a high-performance system with eight cores, 64 GB of RAM, and a 100 GB drive. In addition, we used the TensorFlow and Keras libraries to harness their advanced DL abilities for our study. The framework consisted of essential components and archives tailored to model training for Transfer Learning. Using this condensed environment was essential in effectively executing the tests and allowing the evaluation and verification of the suggested strategy for diagnosing BC. This research used the IDC database, representing the most common subgroup among all BC. The collection comprises 162 whole-mount sliding pictures of BC samples captured at an enlargement factor of 50x.

Fig. 4 depicts the performance comparison of the proposed method with other CNN models for IIP-BCDC. The suggested AlexNet model has exceptional performance, achieving an accuracy rate of 98.7%, a precision rate of 98.6%, a recall rate of 99%, and an F1 score of 98.65%. This suggests an almost flawless equilibrium in recognizing positive instances and reducing incorrect identifications. GoogleNet, albeit significantly less efficient, nevertheless demonstrates strong performance with an accuracy rate of 97.3%, precision rate of 97%, recall rate of 97.7%, and an F1-score of 97.3%. The original AlexNet model exhibits worse metrics than the suggested AlexNet, achieving an accuracy of 97%, precision of 96.5%, recall of 96.7%, and an F1-score of 96.6%. The ResNet50 model, characterized by its increased depth, achieves an accuracy rate of 97.7%, a precision rate of 97.3%, a recall rate of 97.7%, and an F1 score of 97.2%. MobileNet V2, developed explicitly for mobile and integrated image applications, has exceptional performance with an accuracy of 98.1%, precision of 98%, recall of 98.2%, and an F1-score of 98%. Lastly, SqueezeNet, despite its small size, demonstrates impressive performance with an accuracy of 96.7%, precision of 96.6%, recall of 96.9%, and an F1-score of 96.4%. The findings demonstrate the efficacy of the proposed AlexNet model in detecting and classifying breast cancer, surpassing other well-recognized CNN designs.

Fig. 5 shows the performance analysis of ML-based classifiers for IIP-BCDC. The Decision Tree (DT) classifier has an accuracy rate of 93.31%, a notable precision rate of 95.11%, and an exceptional recall (sensitivity) rate of 100%. The F-measure, a combination of accuracy and recall, is 97.96%, and the specificity is 93.35%. This demonstrates a robust capacity to discern both positive and negative instances accurately but with a somewhat lower overall precision when compared to other models. The Random Forest (RF) classifier has a superior accuracy rate of 96.44%, a precision rate of 96.65%, and a recall rate of 100%. The F-measure of the model is 98.77%, indicating a high level of accuracy in categorizing BC cases.

Additionally, the model's specificity is 95.12%, suggesting a well-balanced performance in accurately identifying negative instances. The SVM-RBF has the maximum performance compared to the other two methods, with an accuracy of 96.87%, precision of 98.6%, and recall of 100%. The F-measure has an exceptionally high accuracy of 99.78%, while the specificity exhibits an exceptionally high value of 97.21%. The results indicate that SVM-RBF is proficient in differentiating breast cancer instances with little inaccuracies, making it a possibly dependable instrument in BC diagnostics.

5. Conclusion

This study aims to introduce an Integrated Image Processing Approach for Breast Cancer Diagnosis and Classification (IIP-BCDC). The technique integrates the functionalities of DL by using the AlexNet model to extract Deep Features (DF) and utilizes ensemble-based ML algorithms for categorization. To ensure the preservation of multidimensional data frames while optimizing speed, the implementation of AlexNet includes five levels of convolutional processing and three levels of CCL. We obtained the distinct DF using the DL models of AlexNet. The characteristics mentioned above have been integrated into a unified set of attributes, which was then used as input for an SVM-RBF for a two-tier classification assignment. We conducted extensive examinations using a publicly available repository of IDC pictures acquired from a breast biopsy. The database included specimens of diverse sizes. The findings obtained from rigorous investigations provide compelling evidence of the durability and outstanding performance of the suggested hybrid strategy. The AlexNet model, as presented, demonstrated superior performance compared to other models of its time, achieving an accuracy rate of 98.7%, a precision rate of 98.6%, a recall rate of 99%, and an F1-score of 98.65%.

Author contribution

P.V., S.S.D., A.M. wrote, reviewed and edited the article. All authors read and approved for publication.

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Competing financial interests

The authors have no conflict of interest.

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