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RESEARCH

Integration of feature enhancement technique in Google inception network for breast cancer detection and classification

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Abstract
Breast cancer is a major public health concern, and early detection and classification are essential for improving patient outcomes. However, breast tumors can be difficult to distinguish from benign tumors, leading to high false positive rates in screening. The reason is that both benign and malignant tumors have no consistent shape, are found at the same position, have variable sizes, and have high correlations. The ambiguity of the correlation challenges the computer-aided system, and the inconsistency of morphology challenges an expert in identifying and classifying what is positive and what is negative. Due to this, most of the time, breast cancer screen is prone to false positive rates. This research paper presents the introduction of a feature enhancement method into the Google inception network for breast cancer detection and classification. The proposed model preserves both local and global information, which is important for addressing the variability of breast tumor morphology and their complex correlations. A locally preserving projection transformation function is introduced to retain local information that might be lost in the intermediate output of the inception model. Additionally, transfer learning is used to improve the performance of the proposed model on limited datasets. The proposed model is evaluated on a dataset of ultrasound images and achieves an accuracy of 99.81%, recall of 96.48%, and sensitivity of 93.0%. These results demonstrate the effectiveness of the proposed method for breast cancer detection and classification.

Keywords Breast cancer detection, Deep learning, Convolutional neural networks (CNNs), Google inception network, Feature enhancement, Medical image analysis, Classification

Introduction

Worldwide, according to the Cancer prevision Organization American Institute of Cancer Research 2020 and National Breast Cancer Foundation, INC report [1], breast cancer is the most commonly occurring cancer in women and the second most common cancer overall. In America, according to the American Cancer Society (ACS) 2020, nearly 1 in 8 women are attacked by breast cancer in their lifetime [1], making it imperative that states deliver plans for breast cancer prevention and promote public health and technological involvements to reduce the incidence and mortality rate as a result of breast cancer. The disease hampers all aspects of women's health, including physical, mental, and social life. Besides breast cancer being a major cause of death among cancer-related death in women, it is also a key challenge for medical practitioners and highly influences the society and economy of a country.

In Ethiopia in 2020, the Global Cancer Observatory (GCO) conducted a study on the prevalence of different types of cancers. The research was conducted in collaboration with the World Health Organization (WHO) and the International Agency for Research on Cancer (IARC). According to findings of this research issued in March 2021, in Ethiopia, it is estimated that breast cancer is ranked first among cancer-related deaths followed by Cervix Uteri, and Leukemia cancer. Only in 2020, 16, 133 (31.9%) new cases were estimated where 9, 061 people (more than half) have died of breast cancer, and in the last five years 27, 872 new cases were estimated which accounts for 48.52 proportion per 100, 000 people in all ages [2, 3]. From the figure, one can recognize that there is a high prevalence of breast cancer and as a result, it is explicit that breast cancer is one of the deadly diseases, which affect the mental, physical, and socio-economic growth of an individual and our country in general.

Cancers have a high chance of cure if it is diagnosed early and treated adequately [4]. Once the cancer cell is developed in an individual, the second approach is very important to prevent breast cancer (i.e., the treatment part). If a patient is at moderate to high risk of developing breast cancer, they are offered regular scans of the breast tissues, to screen for cancerous changes. This surveillance method allows for the early detection of breast cancers and a reduction in mortality [4]. A recent meta-analysis found that women who participated in breast screening programs reported a significant 20% reduction in death for women less than the age of 50 and more than 20% in women aged greater than 50 [5]. As a result, it will reduce patients' burden and cost arises because of the case. However, because of various subjective factors as well as limited analysis time and tools, it is quite common for different medical doctors may come up with diverse detection results at different times. It means detecting breast Cancer prone to false positives and false negatives, which vulnerable a patient to additional investigation (for instance biopsy test by a physician), cost, and tension, and also a doctor for additional burden [6].

Thus, to attain a more reliable and accurate breast cancer detection result, recently, varieties of computer-aided detection (CAD) have been developed and provided promising results [7]. However, still CAD system is still not accurate enough as intended as possible. This arises from many factors. One factor is that breast cancer detection is severely dependent on the integration of low-level features and high-level features. Inherently, the morphology (e.g., extent, shape, and position of tissue) and situation (i.e., correlation or de-correlation of neighbor pixels) of breast images obtained by mammography or ultrasound imaging is inconsistent from one individual to another individual and from one mammography/ultrasound images to another mammography/ultrasound of same patient. Due to this situational and morphological variation, CAD approaches are also not strong as possible in providing accurate detection and classification, as it leads some detection results to false values [7]. Therefore, the need of more robust method is still needed.

In the last five years, the promising success of deep learning methods in natural image detection and classification has also presented different medical imaging problems and modalities. A deep convolutional neural network such as the inception model is one of the deep learning models that provide enormous success over the other state-of-the-art methods in various medical image challenges [5]. For instance, in the area of medical imaging , deep learning methods such as Google inception, ResNet, and GAN Net network have achieved better sensitivity and accuracy than human experts and other methods for breast cancer metastases classification [8], achieving noticeable precision performance than humans. Furthermore, authors in [5] introduced a three-dimensional convolutional network to detect lung Cancer and achieved encouraging results, where this model however limited when the issue of memory and time complexity is taken into consideration. However, due to the contextual and morphological variation among nodules pointed out above, the existing breast Cancer detection using deep learning models have not revealed sufficiently accurate and robust outcome for real-time employment. To enhance the detection and classification accuracy feature selection by removing redundant and noisy feature is crucial steps in developing deep learning models [9].

The detection of breast cancer using deep learning (for instance google inception model) depends on the extent of the intermediate output of the model, i.e., the better the intermediate output of the model is designed, the better the model determines better detection results. Using deep learning-based breast cancer detection, the majority of research that were devoted to breast Cancer detection employed different feature fusion strategy with various kernel size. For example, authors in [8] employed canonical feature fusion to enhance the output of CNN, while authors in [10] introduced a weighted CCA feature fusion strategy and authors in [10] employed the Kernel CCA feature fusion strategy to enhance the output of CNN. However, all these feature fusion strategies are conducted by concatenating different features of CNN and applying the transformation function to enhance the final output of CNN [10–12]. However, most of the features are lost in each intermediate output (layer) of CNN, not on some layers of CNN. Due to this, the overall accuracy of CNN-based breast cancer detection is not as intended as possible [13, 14]. In this research, we proposed a feature enhancement method that aims to enhance the intermediate output of CNN. To this end, one of the CNN-based networks, the modified inception network is selected for breast cancer classification by introducing a feature enhancement method called locally preserving projection (LPP). The key contribution of this research is the development of a feature enhancement method called the Google inception model and the model is expected to increase the accuracy of detection and classification tasks. A feature enhancement method integrated into the Google inception network to retain local information that might be lost in the intermediate output of the model. Transfer learning is employed to further improve the performance of the proposed method to detect and classify breast cancer using ultrasound images with high accuracy and sensitivity.

The rest of this paper is organized as follows: Section "Related Work" presents the related work, while section "Methodology" presents the proposed methodology. Section "Experimental Evaluation" presents the experimental evaluation, while results and discussion is presented in section "Results and Discussion". Finally, the paper is concluded in section "Conclusion and Future Work".

Related work

Breast cancer detection and classification have greatly benefited from the advancements in medical imaging technology, including the use of ultrasound imaging. This section aims to systematically review the achievements and performance of ultrasound imaging in the diagnosis of breast cancer. In the past few years, deep learning methods have revolutionized various fields, including image recognition, segmentation, detection, and computer vision. The ability of deep learning models to automatically learn intricate features and patterns from large datasets has significantly advanced the performance of these tasks [15]. Deep learning has been increasingly used in the field of computer-aided design (CAD) to overcome the limitations of traditional approaches [16]. Traditional CAD approaches typically rely on manually developed functions and algorithms, which can be time-consuming may not capture the complexity of certain design problems, and have limited diagnosis accuracy [17]. In recent years, Deep learning models like AlexNet [17], ResNet [18], VGG16 [19], Inception [20], GoogLeNet [21], and DenseNet [22] offer enhanced classification performance compared to models with fewer layers. Specifically, VGG16, ResNet50, and Inception-V3 achieved impressive classification accuracies of 95%, 92.5%, and 95.5% respectively.

Several scholars have worked on the detection and classification of breast cancer to enhance the classification and detection accuracy. Alanazi et al. [3] proposed a method for automatically detecting breast cancer using convolutional neural networks (CNNs). The authors trained a CNN on a dataset of 275,000 50×50 RGB image patches and achieved an accuracy of 87% in detecting breast cancer. This is a significant improvement over the accuracy of machine learning algorithms, which typically achieve accuracies of around 78%. The proposal is based on the observation that CNNs are particularly well-suited for image classification tasks. CNNs can learn the spatial relationships between features in an image, which is important for identifying patterns that are indicative of breast cancer. The authors' method also uses data augmentation to improve the performance of CNN. Data augmentation involves artificially increasing the size of the training dataset by creating new images from the existing images.

Begum et al. [2] proposed a deep learning technique for breast cancer diagnosis that combines a convolutional neural network (CNN) and a long short-term memory (LSTM) network with a random forest algorithm. The CNN is used to extract features from the images, the LSTM is used to detect extracted features, and the random forest algorithm is used to classify the images. The author evaluates the proposed technique on the Breast Cancer Wisconsin (Diagnostic) Database (WDBC). The results show that the proposed technique achieved an accuracy of 94%, a sensitivity of 93%, a recall of 94%, and an F1-score of 93%. These results are better than the results of other traditional models, such as support vector machines (SVMs) and decision trees.

Nazir et al. [14] proposed a novel hybrid approach for classifying breast cancer in mammogram images. The approach combines two convolutional neural networks (CNNs): a CNN-Inception-V4 network and a CNN-ResNet-50 network. The two networks are first trained separately on a dataset of mammogram images, and then their outputs are fused to produce a final classification. The authors evaluated the performance of their proposed approach on a test set of mammogram images. The results showed that the approach achieved an accuracy of 99.0%, a sensitivity of 98.8%, a specificity of 96.3%, and an F1-score of 97%. These results are comparable to the results of other recent studies on breast cancer classification using deep learning.

Maqsood et al. [23] proposed a new deep-learning model called TTCNN for breast cancer detection and classification in its early stages. The model is based on a two-stream convolutional neural network (CNN) architecture, with one stream for extracting spatial features and the other stream for extracting temporal features. The model is trained on a dataset of digital mammograms, and it is evaluated on a held-out test set. The results of the paper show that TTCNN can achieve state-of-the-art performance in breast cancer detection and classification in the early stages. The model achieves an AUC of 0.97 for breast cancer detection and an accuracy of 97.49% for breast cancer classification.

Chouhan et al. [24] proposed a new method for breast cancer detection using deep learning. The method combines four sets of features: taxonomic indexes, statistical measures, local binary patterns, and dynamically generated features from a deep convolutional neural network (CNN). The features are then classified using a support vector machine (SVM) or an emotional learning-inspired ensemble classifier (ELiEC). The author evaluated the method on the IRMA mammogram dataset, which contains 1,218 images. The results showed that the method achieved an accuracy of 95.4% using the SVM classifier and 96.2% using the ELiEC classifier. This is comparable to the performance of other deep learning-based methods for breast cancer detection.

Ahmad et al. [25] proposed a novel hybrid deep learning model for the detection of metastatic cancer in lymph nodes. The model is a combination of the AlexNet convolutional neural network and the gated recurrent unit (GRU) recurrent neural network. The AlexNet CNN is used to extract features from the images of lymph nodes, and the GRU RNN is used to model the temporal dependencies between these features. The proposed model evaluated the performance of their model on the PCam data set, which contains images of lymph nodes from patients with breast cancer. The results showed that the proposed model achieved a high accuracy of 98.50%, which is significantly better than the accuracy of the CNN-GRU and CNN-LSTM models and the model is computationally efficient, which makes it suitable for use in clinical settings.

Zhang et al. [26] provided a comprehensive review of the use of deep learning for breast cancer detection in radiology. The paper begins by discussing the importance of early detection of breast cancer, and the challenges that radiologists face in detecting cancer on mammograms. The authors then review the different deep learning methods that have been used for breast cancer detection, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and deep belief networks (DBNs). The authors also discuss the different tasks that deep learning can be used for in breast cancer detection, such as image classification, object detection, and image segmentation and the author concludes by discussing the future of deep learning for breast cancer detection. The authors argue that deep learning has the potential to revolutionize breast cancer detection and that further research is needed to improve the accuracy and performance of deep learning models.

Hosseini et al. [27] proposed a new method for breast cancer diagnosis using machine learning. The method, called PSOWNNs-CNN, combines a particle swarm-optimized wavelet neural network (PSOWNN) with a convolutional neural network (CNN). The authors first review the state of the art in breast cancer diagnosis using machine learning. PSOWNN is a type of neural network that is well-suited for image processing tasks. It uses wavelets to decompose images into different frequency bands, which allows it to learn more complex features than traditional neural networks. The CNN is then used to classify the images based on the features that were extracted by the PSOWNN. The authors evaluate the PSOWNNs-CNN method on a dataset of 905 breast cancer images. They compare the performance of PSOWNNs-CNN to other machine learning methods, including support vector machines (SVMs), k-nearest neighbors (KNNs), and CNNs. They found that PSOWNNs-CNN achieved the highest accuracy, with a specificity of 98.8% and a precision of 98.6%.

BitaAsadi et al. [28] proposed a new approach to breast cancer detection using deep learning. The proposed method consists of a cascade network with two stages: a segmentation stage and a classification stage. The segmentation stage uses a UNet architecture to separate the tumor from the background of the image. The classification stage uses a ResNet50 architecture to classify the tumor as benign or malignant. The authors evaluated the performance of their method on a dataset of 2,000 images. The segmentation stage achieved an F1 score of 97.30%, and the classification stage achieved an accuracy of 98.61%. The authors also compared their method to several other deep learning methods for breast cancer detection and found that their method outperformed the other methods in terms of accuracy.

Rathee et al. [29] proposed a new method for automated breast cancer detection in digital mammograms. The method uses a moth flame optimization (MFO) algorithm to optimize the parameters of an extreme learning machine (ELM) classifier. The ELM classifier is a single-hidden-layer feedforward neural network that is trained using a closed-form solution. The MFO algorithm is a global optimization algorithm that is inspired by the behavior of moths. The proposed model performance of their method on a dataset of 1,000 digital mammograms. The results showed that the method achieved an area under the ROC curve (AUC) of 0.952, which is comparable to the performance of other state-of-the-art methods. The authors also found that the method was able to achieve good performance on mammograms of different densities.

Junior et al. [30] proposed a new method for detecting breast cancer lesions in mammograms. The method combines three different approaches: spatial diversity, geostatistics, and concave geometry. Spatial diversity is used to identify regions of the mammogram that are likely to contain lesions. This is done by comparing the intensity values of neighboring pixels in the image. Geostatistics is then used to analyze the spatial distribution of the identified regions. This helps to identify clusters of regions that are likely to be associated with lesions. Finally, concave geometry is used to extract the boundaries of the identified clusters. The performance of the model is evaluated on a dataset of 100 mammograms, of which 50 were known to contain lesions. The method was able to correctly identify 85% of the lesions, with a false positive rate of 10%. This is a significant improvement over the performance of traditional methods for breast cancer detection in mammography.

Ghosh et al. [31] proposed a novel method for mammogram image segmentation using intuitionistic fuzzy soft sets (IFSS) and multi-granulation rough sets. The proposed method is designed to improve the accuracy of mammogram segmentation by handling the ambiguity of lesion and non-lesion pixels. The performance of the proposed model is evaluated by a dataset of mammogram images. The results show that the proposed method achieves higher accuracy than other state-of-the-art methods. First, the proposed model uses IFSS to handle the ambiguity of lesion and non-lesion pixels. This allows for more accurate segmentation of mammogram images. Second, the proposed method uses multi-granulation rough sets to improve the granularity of the segmentation. This results in a more detailed segmentation of the mammogram image. Third, the proposed method is evaluated on a dataset of mammogram images, and the results show that it achieves higher accuracy than other state-of-the-art methods.

Zheng et al. [32] proposed a new method for breast cancer detection that combines deep learning and the AdaBoost algorithm (DLA-EABA). This approach uses a deep convolutional neural network to extract features from breast images. These features are then used to train an AdaBoost classifier. Based on the performance evaluation, the proposed approach on a dataset of breast images achieves an accuracy of 97.2%, which is higher than the accuracy of other methods.

Chen et al. [33] presented a study on the use of transfer learning to improve the classification of malignant and benign masses in digital breast tomosynthesis (DBT). The authors used a deep convolutional neural network (CNN) to train on data from DBT, digitized screen-film mammography (SFM), and digital mammography (DM). They compared two transfer learning approaches: a single-stage approach, in which the CNN was fine-tuned directly with the DBT data, and a multi-stage approach, in which the CNN was first fine-tuned with the SFM data and then fine-tuned with the DBT data. The author concludes that the multi-stage transfer learning approach resulted in a significantly higher area under the receiver operating characteristic curve (AUC) on the test set than the single-stage approach. The AUC for the multi-stage approach was 0.91 ± 0.03, while the AUC for the single-stage approach was 0.85 ± 0.05. The authors also found that the classification performance improved as the training sample size increased. A summary of the literatures reviewed is presented in Table 1.

Breast cancer detection using deep learning with a focus on enhancing the intermediate output of the model, to improve the output of deep learning-based breast cancer detection, the previous researcher employed different feature fusion strategies with various kernel sizes. These strategies involve concatenating different features of the CNN and applying transformation functions to enhance the final output. However, the drawback is that many features are lost in each intermediate output (layer) of the CNN, which may limit the overall accuracy of breast cancer detection. To address this issue, this paper proposes a feature enhancement method called locally preserving projection (LPP) that aims to enhance the intermediate output of the Google Inception network with transfer learning. By incorporating LPP into the modified Inception network, we expect to improve the accuracy of breast cancer detection and classification.

In summary, the research goal is to propose and implement a feature enhancement method, namely locally preserving projection (LPP), in combination with the Google Inception model for breast cancer detection. The proposed approach provides increased accuracy in detecting and classifying breast cancer cases compared to traditional feature fusion strategies. This proposed model contributes to the improvement of breast cancer diagnosis and potentially leads to more effective treatments and outcomes for patients.

Methodology

This research is focused on breast cancer detection and classification by introducing a locally preserving projection in the inception model. As is explained in the background part, because of the variable kernel size employed in a deep learning model, there is a loss of information in the intermediate output of those models. Due to this phenomenon, various researchers have introduced several feature enhancement methods such as canonical correlation analysis (CCA) and weighted canonical correlation analysis (WCCA). However, these methods fail in preserving local information (the dependence on neighbor pixels or neighbor information), and with only global information, it is not performing well in preserving intended local information. Thus, to alleviate this problem, this research is planned to introduce the locally preserving features in one of the deep learning models called the Google inception model. The selection of the Google inception model is: (1) it has fewer parameters compared to other deep learning models such as VGG Net [7], and ResNet [8], (2) the Google inception model provides higher accuracy than almost the majority of deep learning model (for instance, inception net outperforms top one error over VGG Net, Alex Net, ResNet, Google Le Net, and several others). Based on suggestions from reviewers, Mobile Net will be considered and compared with the inception network. From reviewing different documents, we have also found that mobile net has fewer parameters, better accuracy, and good latency. Hence, the mobile net is considered in this work. Figure 1 shows the comparison of different deep learning models. As one can observe from the figure, the inception model (particularly inception. (3) outperforms almost all of them in terms of top-one accuracy, employing a smaller number of parameters. In this work, did not directly use this model, but modified the network since it has some drawbacks by itself [36]. Once the network is modified, we introduced the feature enhancement model called LPP followed by the classifier function. Here Soft max is selected as a classifier.

What makes this research different from others are:

- The deployment of a modified Google inception model that serves for the automatic detection and classification of breast cancer in women.
- The insertion of LPP enhances features that will vanish in the intermediate output of the inception model and helps preserve local information.
- The joint use of online datasets and clinical datasets through transfer learning, where the use of transfer learning is employed to tackle problems concerning the shortage of data sets.

Locally preserving projection

Locally preserving projection is a simple mathematical method that is applied to many image processing applications. It is presented as follows:

Assume $X = \{x_1, x_2, \ldots, x_k\}$ and $x_j \in R^{dim}\,(j = 1,2,\ldots,k)$ where k is the size of sample points and dim refers to the dimensionality of the instances where dimensionality reduction aims to determine a transformation T from R^{dim} to R^{dim} such that $y_k = T\,(x_j)$, $y_j \in R^{dim}$, and dim is much less than dim. By the assumption that it is leaner mapping, a matrix $M \in R^{dim}$ x dim~ is obtained by $y_j = M^T x_j$ [17].

In locally preserving projection, any affinity graph W is built to exploit the local nearby structure of an instance. With, LPP determines a sub-space with a low dimension

Table 1 Summary of related works

Author	Research Objective	Methods/Approaches	Results	Limitation
Alanazi et al. [3]	Developed an automatic breast cancer detection system using convolutional neural networks (CNNs)	Uses CNN to extract features from WSIs and then classifies the images as either cancerous or non-cancerous	The model trained a CNN on a dataset of 2,000 50×50 RGB image patches and achieved an accuracy of 87% in detecting breast cancer.	It requires a large dataset of WSIs to train the CNN. The method is computationally expensive to run. The method is not yet fully automated and requires some human intervention.
Begum et al. [2]	Proposed a deep learning technique in combination with a convolution neural network (CNN) and long short-term memory (LSTM) with a random forest algorithm to diagnose breast cancer.	CNN is used for feature extraction, and LSTM is used for extracted feature detection. A random forest algorithm is used for classification.	The proposed model achieved an accuracy of 97.8%, a sensitivity of 98.0%, and a specificity of 97.6%.	The dataset consisted of only 100 images. Performance of the model on two classes of breast cancer: benign and malignant
Nazir et al. [14]	Develop a novel hybrid approach to identify breast cancer mass images as benign or malignant.	The proposed approach combines two convolutional neural networks (CNNs): Inception-V4 and ResNet-50. The Inception-V4 network is used to extract features from the images, and the ResNet-50 network is used to classify the images.	The proposed approach was trained on a dataset of 450 benign and 450 malignant mammogram images from the CBIS-DDSM dataset. The approach achieved an accuracy of 99.0%, on the test set.	The approach was evaluated on a small, independent dataset. The approach only classifies the disease as benign, and malignant
Maqsood et al. [23]	Developed a deep learning-based method for breast cancer detection and classification using digital mammograms	Used a Transferable Texture Convolutional Neural Network (TTCNN) to extract features from mammograms and classify them as malignant or benign.	The TTCNN was trained on a dataset of 10,240 mammograms, and its performance was evaluated on a test set of 2,048 mammograms. The TTCNN achieved an accuracy of 97.49% in classifying mammograms as malignant or benign	However, the TTCNN is not yet able to detect small or subtle tumors, and it may not be as accurate for early-stage breast cancer.
Chouhan et al. [24]	Developed an automatic breast cancer detection system using deep convolutional neural networks (CNNs)	Used a hybrid approach that combines static features, such as taxonomic indexes, statistical measures, and local binary patterns, with dynamically extracted features from a CNN. Train the system using an emotional-learning-based ensemble classifier (ELiEC).	The proposed system was trained using the IRMA mammograms dataset with 2796 images. The results showed that the method achieved an accuracy of 95.4% using the SVM classifier and 96.2% using the ELiEC classifier.	Requires a large dataset of mammogram images to train the CNN. It is not yet clear how well the system would perform on images from different databases. The system is not able to provide a diagnosis of breast cancer. It can only classify mammogram images as normal or abnormal. Not detection is performed.

Table 1 (continued)

Author	Research Objective	Methods/Approaches	Results	Limitation
Ahmad et al. [25]	Developed a novel hybrid deep learning model for metastatic cancer detection.	The proposed model combines convolutional neural network GRU (CNN-GRU), CNN long short-term memory (CNN-LSTM), and the proposed AlexNet-GRU.	The proposed model was trained on a dataset of 450 lymph node (LN) images, 225 of which were positive for metastatic cancer and 225 of which were negative for metastatic cancer. The model achieved an accuracy of 96.5% on the test set.	The proposed model was only trained on a relatively small dataset. It is possible that the model would not perform as well on a larger, more diverse dataset. Additionally, the model was not evaluated on a large, independent dataset. This means that it is not yet clear how well the model would perform in a real-world setting.
Hosseini et al. [27]	Developed a breast cancer diagnosis using machine learning	The author proposed a swarm-optimized wavelet neural network (PSOWNN) with a convolutional neural network (CNN).	The authors evaluate the PSOWNNs-CNN method on a dataset of 905 breast cancer images. They compare the performance of PSOWNNs-CNN to other machine learning methods, including SVMs, (KNNs), and CNNs. They found that PSOWNNs-CNN achieved the highest accuracy, with a specificity of 98.8% and a precision of 98.6%.	The researcher uses PSOWNN wavelets to decompose images into different frequency bands, which allows it to learn more complex features than traditional neural networks.
Asadi et al. [28]	Developed a deep learning model for efficient breast cancer detection.	The authors used a cascade deep learning network with a UNet architecture for segmentation and a ResNet backbone for classification.	The proposed model achieved a high accuracy of 98.61% with an F1 score of 98.41%.	The model was only trained and tested on the INbreast dataset, so it is not clear how it would perform on other datasets.
Rathee et al. [29]	Develop a CAD system for breast cancer detection	Extract features from mammogram images using LWT, reduce dimension using PCA and LDA, train an ELM classifier	AUC of 0.952, sensitivity of 87.0%, specificity of 88.4%	Can produce false positives and false negatives, tested on a relatively small dataset
Junior et al. [30]	Developed a method for breast cancer detection in mammograms	Use spatial diversity, geostatistics, and concave geometry Use SVM as a Feature extraction	Detection Accuracy of 91.63% on the MIAS dataset, 87.50% on the DDSM dataset	The method is not robust to noise in the images. The method is not able to distinguish between different types of breast cancer.
Zheng et al. [32]	To develop a deep learning-based algorithm that can improve the accuracy of breast cancer detection and early diagnosis.	The DLA-EABA algorithm combines a deep convolutional neural network (CNN) with the AdaBoost algorithm. The CNN is used to extract features from breast images, and the AdaBoost algorithm is used to combine these features to make a classification decision.	The DLA-EABA algorithm achieved an accuracy of 97.2% on a test set of breast images. This is a significant improvement over the accuracy of traditional machine-learning algorithms for breast cancer detection.	The DLA-EABA algorithm is still under development, and there are some limitations to its performance. For example, the algorithm is not as accurate for small or poorly-defined breast masses. And it is not yet clear how it will perform in clinical settings.

Table 1 (continued)

Author	Research Objective	Methods/Approaches	Results	Limitation
Sorkhabi et al. [34]	Evaluated the effectiveness of PEPMED on a heart disease dataset and make EHR data more suitable for mining for the development of new generations of medicine, such as precision medicine.	The researcher used a three stage PEPMED preprocessing approach. These are cleaning, data engineering and data integration stages.	The study showed that PEPMED dramatically improved the accuracy of four subgrouping methods on the heart disease dataset with 90% accuracy of Random forest Algorithm.	The authors only evaluated PEPMED on a single heart disease dataset. It is important to evaluate PEPMED on other datasets to confirm its effectiveness.
Ayana et al. [35]	Investigated the effectiveness of ViTs for breast ultrasound image classification.	CNN-based methods and Vision transform-based methods. The researcher uses Pre-trained a ViT model on the ImageNet dataset. Then, they fine-tuned the pre-trained model on the BUSI dataset.	The proposed model achieved an accuracy of 95.9% in the detection of breast cancer using ultrasound images.	The researcher only used transfer learning approaches to use a pre-trained model to fill the gap of the dataset but doesn't include feature enhancement techniques on CNN-enabled Google Net algorithm
Proposed Model	Developed an automatic breast cancer detection and classification method using the Google Inception network.	Integrate feature enhancement techniques on the Google inception network (inception V3) and Transfer learning. We use the pre-trained ImageNet model to locally preserve projection feature enhancement methods to enhance the accuracy of breast cancer detection and classification. We use a local dataset for testing the proposed model.	Our proposed system achieved 99.81% accuracy in the detection and classification of breast cancer.	

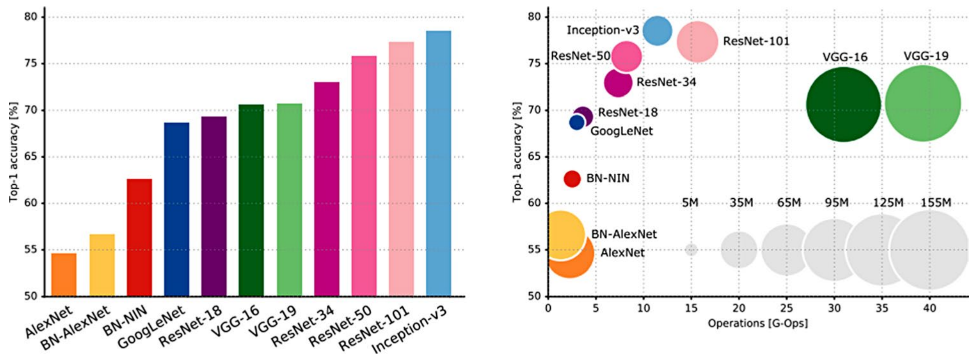

Fig. 1 Various comparisons of deep learning models in terms of parameters, and top 1 accuracy

where the nearby information contained in X can be preserved. In the LPP problem, if x_j and x_i are close (in the context of Euclidian distance) the closeness of y_j and y_i are ensured by solving the following objective function:

$$min\sum_{ji}\|y_j - y_i\|^2 W_{ji} = min\sum_{ji}\|M^T x_j - M^T x_j\|^2 W_{ji} \tag{1}$$

where W_{ji} is affinity between x_j andx_i. If x_j is one of the nearby of x_i and vice versa, then

$$W_{ji} = e^{\frac{|x_j - x_i|\vee^2}{s}} \tag{2}$$

With s a pre-specified parameter. If we want simplicity one can set $W_{ij} = 1$ for x_j and x_i nearby neighbor and $W_{ij} = 0$ otherwise.

From leaner algebra, the objective function (1) is solved by transforming the equation into a generalized Eigen decomposition problem as

$$X^T L X z_j = \lambda_j X^T D X z_j \tag{3}$$

where $L = D - W$ is a matrix with D diagonal matrix, whose$i$ th diagonal element is $\sum_i W_{ji}$ and λ_j is the smallest j th value corresponding to z_j for $j = 1,2,\ldots,dim$

The final low-dimensional embedding can be expressed by

$$Y = M^T X \tag{4}$$

where $M^T = [z_1, z_2, \ldots, z_j]^T$

The fused low-dimensional vector Y preserves the local important information of the original deep features and will be used as the final input features of the classifier. A softmax classifier will be used considering the deep features. Overall, in this research, a modified inception network is used as a feature extractor, LLP serves as the feature refiner, and softmax will be used as a classifier.

With this explanation and justification, LLP has the following advantages:

1. LPP is employed to preserve local information. When convolution, pooling, upsampling, and down sampling are applied to images or image features, obviously there is trade-off information. As the number of hidden layers increases in deep learning models, the model better extracts deep features, however, the loss of

information will increase. Thus, to alleviate this challenge, the LPP is going to be introduced in this research.

2. LPP is used for feature enhancement: Once features are affected by those mentioned operations, it is used to recover local information. This may be one of the interesting parts of the technique especially when we come to medical images in which each piece of information is so important in analyzing and treating a disease.

Since LPP is a feature transformation method, it is not a separate task during training and testing an instance, the training and testing of the model can be in an end-to-end fashion.

Data collection

Breast Mammography is a golden standard for breast cancer detection and classification. Next to Breast mammography images, the breast ultrasound image is highly used. In our country, it is hard to get mammography images [37]. Thus, we focused on breast ultrasound images. This dataset was collected from Assosa general hospital, Felege-Hiwot Hospital, and Gondar University Hospital. According to a preliminary survey we made, the above all mentioned hospitals are dealing with breast cancer considering ultrasound images.

After the data is collected, it goes through some preprocessing stages such as noise removal, quality enhancement, size correction, format correction, etc. With the help of medical experts wherever and whenever necessary, those images may go again under preprocessing such as cancer labeling, removing ambiguous images, etc.

Data pre-processing

Pre-processing the data in a way that will improve the network's ability to learn is essential before training an Inception network [34]. For Inception networks, some of the most popular data preprocessing methods are discussed in sections "Image Normalization" to "Image Augmentation".

Image normalization

Image normalization is a straightforward but efficient method for enhancing the efficiency of Inception networks [38]. It involves splitting each image by the standard deviation after taking the mean pixel value out of each one. As a result, the distribution of pixel values becomes more uniform and the pixel values are helped to center around zero.

normalized_pixel_value = (pixel_value - mean) / standard_deviation

For the entire training dataset or each class of images, the mean pixel value and standard deviation was determined. The images will all be scaled to the same value if the mean pixel value and standard deviation are determined for the full training dataset. If the training dataset's picture images span a large range of brightness and contrast, this may be useful. Each class of photos will be standardized to a different scale if the mean pixel value and standard deviation are determined for each class of photographs. This is useful if the brightness and contrast of the images in each class vary.

Image augmentation

Since almost all deep learning model needs large dataset during training, we use the online freely available dataset and train the proposed model. Then taking the trained model as a per-trained model, we again retrain the model with the collected dataset [39]. In addition to this, we use data augmentation to increase the size of the collected dataset and train the proposed model. For this purpose, we implement filliping and rotation at 45, 90, 135, 180, 270, and 360 degrees to each collected dataset. Augmentation techniques were used in this stage. This technique of training is called transfer learning in deep learning models. For the online dataset, we used ultrasound images released by the Kaggle data science bowl [17]. This dataset has 266 normal, 421 malignant, and 891 benign ultrasound images. However, for the proposed model, this size of the dataset may not be sufficient. Hence, we applied the data augmentation method mentioned. This is a common method whenever we encounter a shortage of datasets. Accordingly, through filliping, and rotation at 45, 90, 135, 180, 270, and 360 degrees, we increased the size of the normal dataset from 266 to1862, the malignant dataset from 421 to 2947, and finally the size of the benign dataset from 891 to 6237. Then, we divided it into training, validation, and test datasets and transfer the learned parameters with the locally collected dataset [14]. In addition to the Kaggle dataset. There are different data augmentation techniques such as cropping, adding noise, translation, rotation, and filliping. But to increase the size of the data set, filliping, and rotations are commonly used [40]. Other introduce extra or reduced information from the original raw data, and hence, rotation and clipping are selected.

Modified google inception network

To integrate the locally preserving projection (LPP) technique into the Google Inception Network for breast cancer detection and classification, modifications need to be made to the network architecture [32]. The modified architecture will incorporate the LPP-enhanced features to improve the network's discriminative power. To add LLP-enhanced features there should be an original Google Inception Network which serves as the starting point for the modified architecture [41]. In this research, we use the mobile net inception network as the base Google inception network which serves as the starting point for the modified architecture and it consists of multiple inception modules, each comprising of parallel convolutional layers of varying filter sizes, followed by pooling and concatenation operations. The base network extracts rich and hierarchical features from the input ultrasound images. After we select the base Google inception network, the locally preserving projection (LPP) feature enhancement technique is integrated to enhance the discriminative power of the features. The LPP algorithm is applied to the feature maps obtained from the Inception V3 base network and computes the within-class and between-class scatter matrices based on the extracted features and projects them into a lower-dimensional subspace. Finally, the LPP-enhanced features capture the underlying structure and discriminative information present in the ultrasound images [42]. After LLP feature enhancement techniques are applied the LPP-enhanced features are concatenated with the original features obtained from the base network which aims to preserve both the enhanced discriminative information and the original representation captured by the base network and the concatenation operation combines the feature maps of the LPP-enhanced features and the original features, resulting in a combined feature representation. Following the feature concatenation, the modified network integrates a classifier to perform breast cancer detection and classification [43–52]. In this paper, we use SoftMax classifiers and trained on the combined features, enabling it to learn the discriminative patterns and make accurate predictions.

Proposed architecture

As we have mentioned earlier, a modified inception model is used in this research. In addition, a feature enhancement mechanism called locally preserving projection is going to be introduced. Overall, the architecture of the proposed framework is presented in Fig. 2. The figure has four parts, the preprocessing part, the feature extraction [49] part by the inception model, and feature enhancement part by the LLP and the classifier part by SoftMax function.

From the proposed system architecture in Fig. 2, the proposed enhanced feature inception network or the modified Google Inception network with the locally preserving projection can be divided into the following key components:

- **Input Layer**: The input layer of the network takes ultrasound breast cancer images dataset as input. These images are preprocessed to ensure a standardized format and pixel intensity range.
- **Convolutional Layers**: The initial layers of the modified Inception network consist of convolutional layers with varying filter sizes (1×1, 3×3, 5×5). These layers perform feature extraction by capturing low-level patterns and local features from the input images.
- **Inception Module**: The core of the modified network comprises Inception modules, which are responsible for multi-scale feature extraction. Each Inception module consists of multiple parallel convolutional branches with different filter sizes (1×1, 3×3, and 5×5) and a max-pooling branch. This design allows the network to capture features at different scales and capture both fine-grained and high-level information.
- **Locally Preserving Projection Layer**: Locally preserving projection is a feature enhancement technique applied to the Google inception network to enhance the quality and increase the accuracy of the model. After the Inception modules, a locally

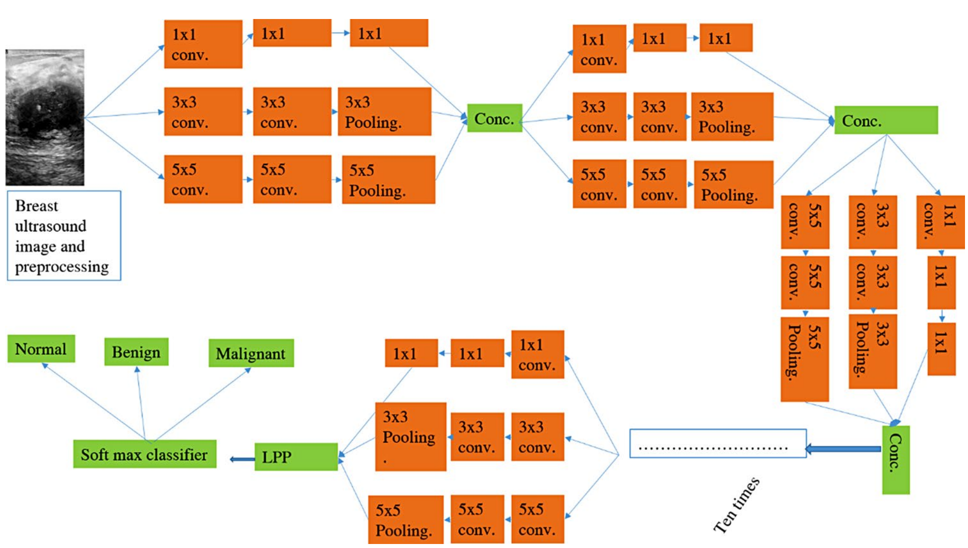

Fig. 2 Proposed enhanced feature inception network

preserving projection layer is inserted into the network architecture. This layer applies the locally preserving projection technique to the feature maps extracted by the Inception modules. The locally preserving projection enhances the compactness and separateness' of the feature representations, leading to improved discriminative power.

- **Fully Connected Layers**: After LLP feature enhancement techniques are integrated into the Inception Network, fully connected layers are added to the network to perform high-level feature aggregation and transformation, leading to the final feature representation for breast cancer classification The fully connected layers in the modified Google Inception network are responsible for high-level feature aggregation and transformation. These layers take the output of the convolutional layers and map it to the desired classification output.
- **Output Layer**: The output layer of the modified network consists of a SoftMax activation function for multi-class classification. In this case, the network is trained to classify ultrasound image datasets into malignant, benign, and Normal classes: benign and malignant.

Transfer learning

In addition to feature enhancement techniques pre-trained models to accelerate training and improve performance on the detection and classification of breast cancer. In the context of the modified Google Inception network for breast cancer detection and classification, transfer learning can be employed to benefit from the knowledge learned from a large-scale image recognition task, such as ImageNet [44]. During the training, we use a limited number of labeled datasets and to enhance the performance of the proposed model we use a pre-trained model through transfer learning techniques [45]. Pre-trained models are deep neural networks that have been trained on a large dataset, typically ImageNet, which contains millions of labeled images from thousands of classes. These models have learned to extract general visual features and patterns that apply to various image-related tasks and Transfer learning offers several advantages when integrating a modified Google Inception network for breast cancer detection and classification:

- **Reduce Training Time**: By utilizing pre-trained models, the network starts with a set of learned features that are relevant to image recognition tasks. This reduces the time required for training from scratch.
- **Improved Generalization**: Pre-trained models have already learned robust and generalized features from a large and diverse dataset. By leveraging these features, the modified network can benefit from the model's ability to generalize well to unseen mammogram images [46].
- **Effective Feature extraction**: The pre-trained model's architecture, such as the Google Inception network, is designed to capture meaningful and discriminative features. By utilizing these learned features, the modified network can focus on learning task-specific features and reduce the risk of overfitting.

Implementation details

We train the modified Google Inception network with the locally preserving projection using popular deep learning frameworks called Tensor Flow. The implementation also includes regularization techniques like dropout and weight decay to prevent overfitting during training. By integrating the locally preserving projection technique into the Google Inception network, we aim to improve the network's ability to detect and classify breast cancer accurately. The modified network architecture captures both local and global features and leverages the power of multi-scale convolutional filters to enhance the discrimination of malignant and benign cases in ultrasound images. In addition, pre-trained weights of the original Google Inception network can be loaded into the corresponding layers of the modified network. The initial layers can be frozen, while the locally preserving projection layer and subsequent layers are fine-tuned using the target Ultrasound dataset. This can be achieved using deep learning frameworks such as TensorFlow which provide APIs for loading and fine-tuning pre-trained models. Transfer learning with the modified Google Inception network allows for efficient training and improved performance in breast cancer detection and classification by applying the knowledge learned from a pre-trained model, the network can benefit from rich and generalized feature representations, leading to more accurate and robust predictions.

Experimental setting

Four experiments were conducted to evaluate the proposed model. The first experiment was conducted to compare the performance of the proposed model in three deep learning models (AlexNet). The second experiment, Google Inception Network from scratch was compared with the proposed transfer learning model. This experiment aims to determine whether training the Google Inception network from the beginning is better suited for classifying breast ultrasound images compared to using a pre-trained network on pre-trained datasets before applying it to the task of breast ultrasound image classification. The third experiment is performed to choose the transfer learning approaches appropriate for the proposed model. Finally, the fourth experiment is conducted to compare the performance of the Proposed model (modified Google inception-based transfer learning) with other deep learning-based transfer learning for breast cancer detection and classification.

Evaluation metrics

Many medical image detection performance evaluations have been proposed by researchers. Among those metrics, accuracy, recall, and specificity are commonly employed. We also employed these metrics to see how our model will perform on the testing set. These metrics are defined as follows

$$Accuracy = \frac{(tp + tn)}{(tp + tn + fp + fn)} \tag{5}$$

$$Sensetivity = \frac{tn}{(tn + fp)} \tag{6}$$

$$Recall = \frac{tp}{(tp + fn)} \tag{7}$$

where $tp, fp, fn,$ andtn , denote the number of true positives, false positives, false negatives, and true negatives, respectively.

Experimental evaluation

In this section, we experimented with and present the performance of our proposed model in comparison with models developed using the Google inception network without feature enhancement, Google inception Network with feature enhancement and transfer learning techniques, and using deep learning algorithms Like Alex Net CNN deep learning algorithms and with the state of the art.

Experimental evaluation with AlexNet CNN

To evaluate the performance of the implemented proposed model for breast cancer detection and classification, we conducted a series of experiments. The experiments aimed to assess the model's accuracy, and sensitivity in comparison to baseline models or existing state-of-the-art approaches. In this study, we develop a model for breast cancer detection and classification AlexNet, which uses its ability to learn hierarchical features from breast ultrasound images, helping to identify patterns indicative of benign, malignant, or normal. The model development process involves obtaining a labeled dataset, preprocessing the data, constructing the AlexNet architecture, training the model, tuning hyper parameters, evaluating the model's performance, and potentially fine-tuning it for better results. To develop the model using Alex Net for breast cancer detection and classification, we use five convolutional layers as AlexNet architecture (CONV1 to CONV5) and two fully connected layers (Fully connected layer 6, and fully connected layer 7) as shown in Fig. 3. In the first the first convolutional layer (Conv2D) to the model. It has 96 filters, each with a kernel size of 11×11. The stride is set to (4, 4), meaning the filters move 4 pixels at a time. The activation function used is ReLU (Rectified Linear Unit). The input shape parameter specifies the shape of the input images (image_width, image_height, and num_channels). After each convolutional layer, we add a max pooling layer (MaxPooling2D) is added. It performs down sampling by taking the maximum value within a pooling window. In this case, the pool size is set to (3, 3), and the stride is (2, 2), meaning a 3×3 pooling window moves 2 pixels at a time. Then we add additional convolutional and max pooling layers, following the same pattern as the previous layers. The number of filters in these layers is 256, 384, and 256, respectively.

After the convolutional and pooling layers, the feature maps are flattened into a 1D vector using the Flatten () layer. The flattened features are then fed into two fully connected layers (fc6 and fc7) with 4096 neurons each. These layers extract higher-dimensional features that capture more comprehensive information about the input. Each fully connected (dense) layer has 4096 neurons and uses ReLU activation. The dropout layers are added after each dense layer with a dropout rate of 0.5. Dropout helps prevent overfitting by randomly setting a fraction of inputs to 0 during training. The AlexNet-CNN model architecture is presented in Fig. 3.

The design shows the extraction of more comprehensive and nuanced features that often retrieve 256-dimensional features. By utilizing two fully connected layers (fc6 and fc7), which have 4096-dimensional features, the model gains more depth information, enhancing its decision-making capabilities. In this experiment the pre-processed images are fed into the Alex Net with Conv2D (96, (11, 11), strides= (4, 4), activation='relu', input_shape= (image_width, image_height, num_channels), name='conv1'): This line adds a convolutional layer (Conv2D) with 96 filters of size 11×11. The stride is set to (4, 4), meaning the filters move four pixels at a time. The activation function is ReLU

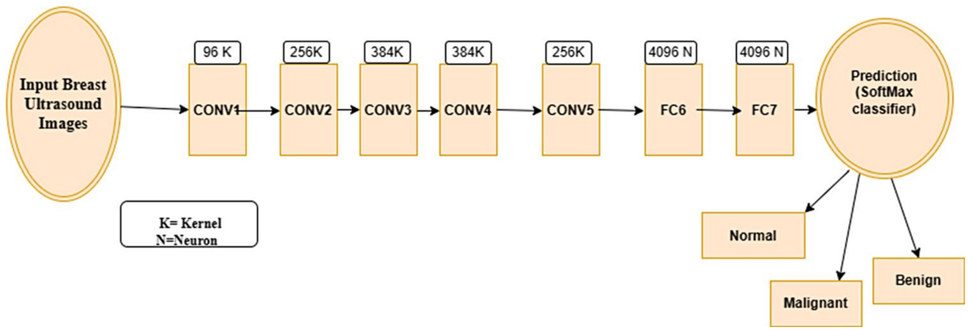

Fig. 3 AlexNet-CNN Model architecture

('relu'), and the input_shape specifies the shape of the input images. MaxPooling2D (pool_size= (3, 3), strides= (2, 2), name='pool1'): After the first convolutional layer, a max pooling layer (MaxPooling2D) is added. It performs down sampling by taking the maximum value within a pooling window of size 3×3. The stride is set to (2, 2), meaning the window moves two pixels at a time. Similar patterns of adding convolutional layers and max pooling layers are repeated for subsequent layers (conv2, pool2, conv3, conv4, conv5, and pool3) with 256,384,384, and 256 respectively. Each layer applies a convolution operation and then performs down sampling using max pooling. Finally feed in the Fully Connected Layers with Dense (4096, activation='relu', name='fc6'): This line adds a fully connected layer (Dense) with 4096 neurons and ReLU activation. It receives the flattened feature maps as input. Dense (4096, activation='relu', name='fc7'): Dense (num_classes, activation='softmax', name='predictions'): The last fully connected layer (predictions) has several neurons equal to the number of classes (num_classes). The activation function is softmax, which outputs class probabilities of Normal, malignant, and benign. The parameters are further presented in Fig. 4.

Based on the experiment conducted to assess the effectiveness of the model developed by Alex Net CNN, a training accuracy of 0.909%, test accuracy of 0.72%, and validation accuracy of 0.73% was achieved as shown in Fig. 5.

Experimental evaluation using google inception network (inception v3)

To achieve the objective of this research, we experimented to assess the performance of the Google Inception Network, specifically the Inception V3 architecture, on a given task. The Inception V3 model is a deep convolutional neural network architecture widely used for image classification and recognition tasks. This evaluation aims to analyze its accuracy and effectiveness without making any modifications to the original algorithm or without adding feature enhancement techniques. The model is developed using inception V3 architecture with 7 convolutional (CONV1-CONV7) layers and 3 fully connected layers using the Tensor flow library. The pre-processed data is fed into the first convolutional layer with input input_shape = (224, 224, and 3): This defines the input shape of our images as a tuple of height, width, and channels (RGB) with 64 filters of size 1×1, 3×3 5×5 and ReLU activation and adds a max pooling layer with a pool size of 3×3, 5×5 to downsample the output of convolutional layer 1 and the model is compiled with Adams optimizer with softmax classifier. In this model, 5,382,945 total parameters are generated and 5,374,113 are trainable 8,832 are non-trainable parameters. Based on the experiment we get a test accuracy of 0.93% with a test loss value of

Layer (type)	Output Shape	Param #
conv1 (Conv2D)	(None, 55, 55, 96)	34944
pool1 (MaxPooling2D)	(None, 27, 27, 96)	0
conv2 (Conv2D)	(None, 27, 27, 256)	614656
pool2 (MaxPooling2D)	(None, 13, 13, 256)	0
conv3 (Conv2D)	(None, 13, 13, 384)	885120
conv4 (Conv2D)	(None, 13, 13, 384)	1327488
conv5 (Conv2D)	(None, 13, 13, 256)	884992
pool3 (MaxPooling2D)	(None, 6, 6, 256)	0
flatten (Flatten)	(None, 9216)	0
fc6 (Dense)	(None, 4096)	37752832
fc7 (Dense)	(None, 4096)	16781312
predictions (Dense)	(None, 2)	8194

Total params: 58,289,538
Trainable params: 58,289,538

Fig. 4 Alex-Net CNN parameters and convolutional layer block

0.179 which means the developed model correctly detects and classifies the breast cancer disease is 93.0%. The developed model using the inception V3 algorithm summary is depicted in Fig. 6(a) and (b).

Experimental evaluation using google inception network with feature enhancement techniques

To enhance the accuracy of the model developed using the Google Inception Network, such as InceptionV3, we propose the incorporation of feature enhancement techniques known as locally preserving projection. These techniques aim to improve the overall performance of the model by preserving the local structures and relationships within the data. In this study, we propose the integration of locally preserving projection techniques into the Google inception network (Inception V3) model, and we refine the representation of features, leading to more precise predictions and better overall performance. The breast cancer ultrasound image dataset is divided into training, validation, and test datasets. Once the dataset is divided preprocessing technique is applied. Filliping and rotation data pre-processing techniques are applied in this study to increase the size of the dataset. To conduct the experiment the researcher uses an input layer, Convolutional layer, inception Module, feature enhancement layer using a Locally Preserving Projection Layer, fully connected layer, and output layers with a Softmax activation function for multi-class classification.

Pre-processed data are inserted into the convolutional layer with the input shape of the image input_shape = (224, 224, 3) as a tuple of height, width, and channels (RGB). Then the convolutional layer creates a 2D convolutional layer with filters of size (1×1, 3×3, and 5×5) and softmax activation. It takes the input layer as input. Then the

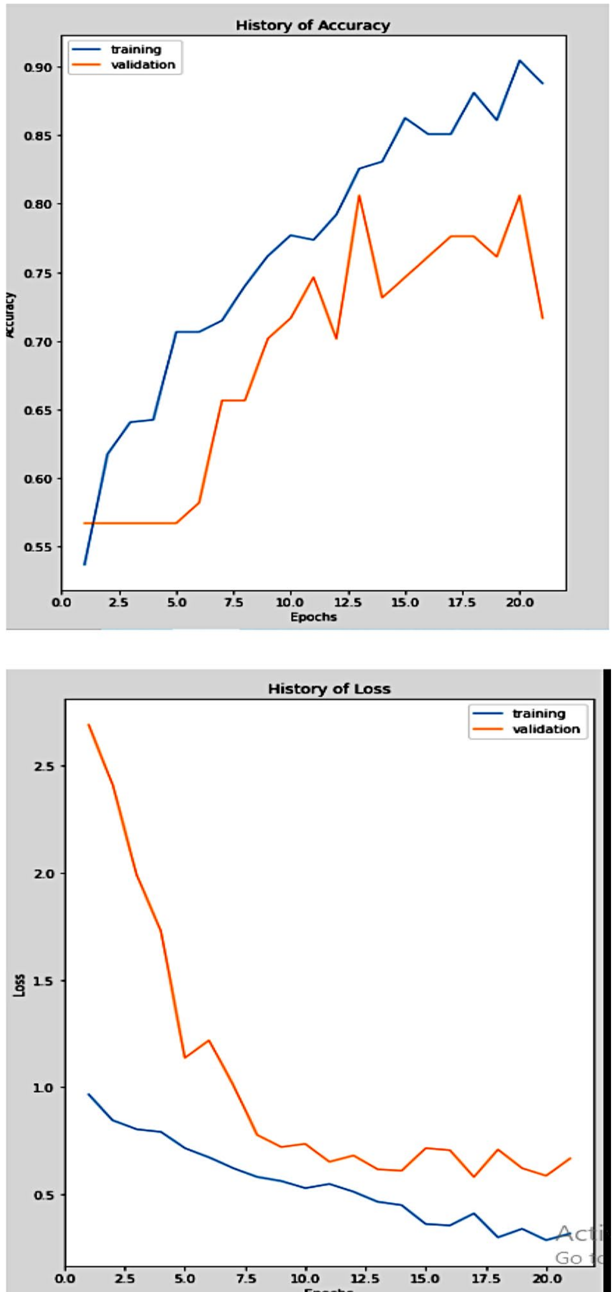

Fig. 5 Accuracy of the AlexNet Model for breast cancer detection and classification

convolutional layer is concatenated with the inception module with 1×1, 3×3, and 5×5, the inception module with filter size 1×1, 3×3, and 5×5 modified with LLP feature enhancement techniques to enhance the accuracy of the model, the modified inception model concatenated with the fully connected layer. Finally, the output layer of the modified network consists of a SoftMax activation function for multi-class classification. In this case, the network is trained to classify ultrasound image datasets into malignant, benign, and Normal classes: benign and malignant.

The model developed by Google using the Inception Network with feature enhancement techniques achieved an accuracy of 0.95% as shown in Fig. 7. An accuracy of 0.95%

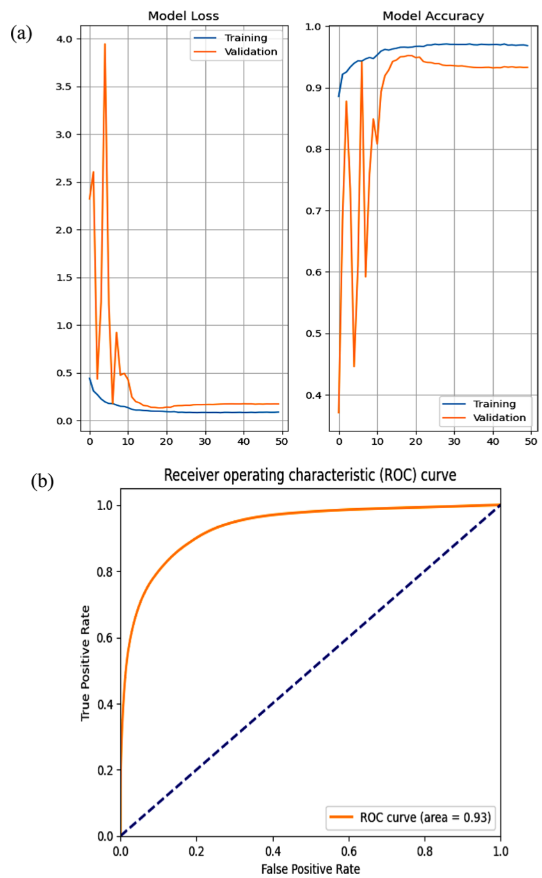

Fig. 6 (**a**) Accuracy and Loss value (**b**) Model developed by Google Inception Network (Inception V3)

indicates that the model is performing well and has a high level of accuracy in predicting the correct labels for breast cancer ultrasound images.

The performance of the model developed by Inception Network with feature enhancement techniques is summarized in Table 2.

When we compare the performance of the model developed with the Inception Network with feature enhancement techniques to the original Inception V3 and AlexNet CNN models, it was observed that the enhanced model outperformed both of them in terms of accuracy. This suggests that the feature enhancement techniques used in the model improved its ability to detect, classify, and make accurate predictions of breast cancer disease with an accuracy of 0.95% to the inception model and AlexNet model and make accurate predictions.

Experimental evaluation using google inception network with feature enhancement techniques and transfer learning

After experimenting with the Modified Google Inception Network (Google inception network with LLP feature enhancement techniques) we also integrated transfer learning techniques to improve the accuracy of the proposed models. To tackle the problem concerning the shortage of the dataset, we used both the online dataset and clinical dataset through transfer learning. After we integrated transfer learning techniques on Experimental Evaluation using Google Inception Network with Feature enhancement Techniques, we got an accuracy of 99.081%. Figure 8 presents the accuracy and loss value of

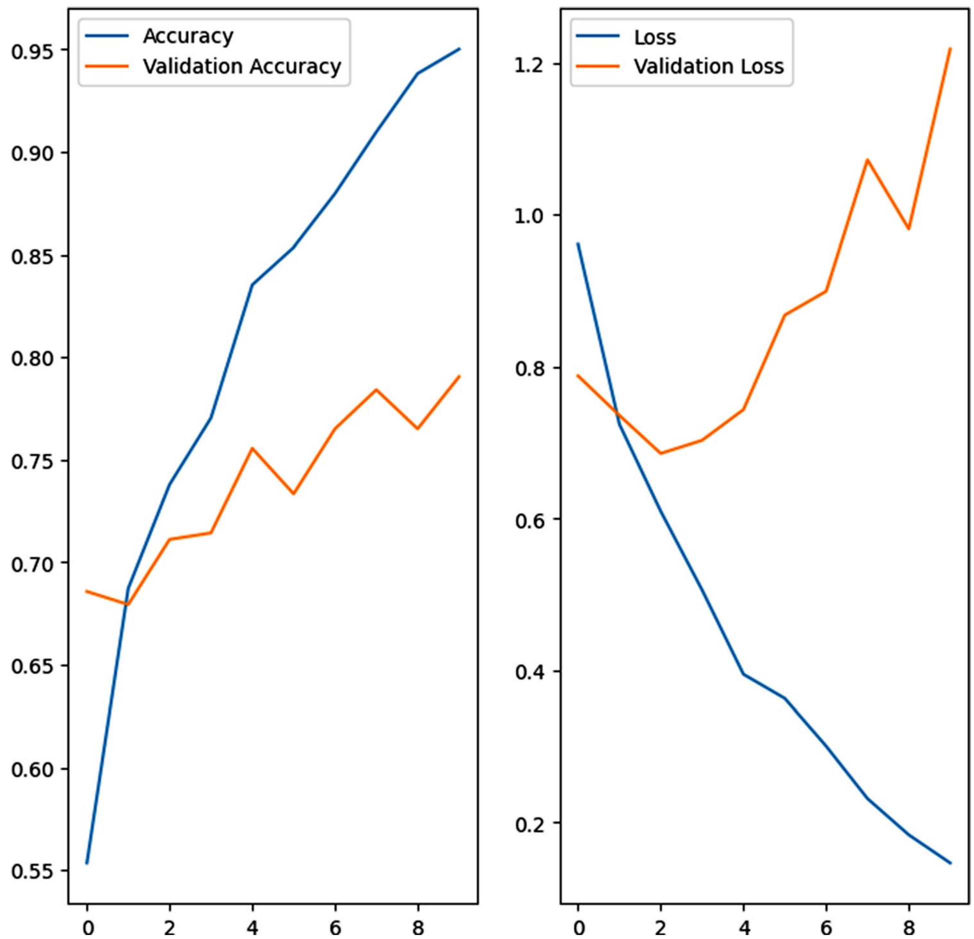

Fig. 7 Accuracy and loss Value of Model developed by Google Inception Network with Feature Enhancement Techniques

Table 2 Accuracy, recall, and sensitivity value of the model developed using Inception Network with feature enhancement, Google Inception Network (Inception V3), and Alex Net CNN.

Model	Accuracy	Precision	Sensitivity	Execution Time
Inception Network with feature enhancement	0.95%	0.80%	0.85%	1.23 m
Google Inception Network (Inception V3)	0.93%	0.75%	0.78%	3 m
Alex Net CNN	0.73%	0.70%	0.712	4 m

the model developed using Google Inception Network with Feature Enhancement Techniques and Transfer Learning.

The model developed by using Google Inception Network with Feature enhancement Techniques and transfer learning is summarized and compared in Table 3.

When we compared the performance of the model developed using Inception Network with locally preserving projection (LPP) feature enhancement with transfer learning and the Inception Network with locally preserving projection (LPP) feature enhancement techniques, the original Inception V3 and AlexNet CNN models, it seems that the enhanced model with transfer learning outperformed both of them in terms of accuracy. It suggests that the feature enhancement techniques used in the model with transfer learning have improved its ability to detect, classify, and make accurate predictions

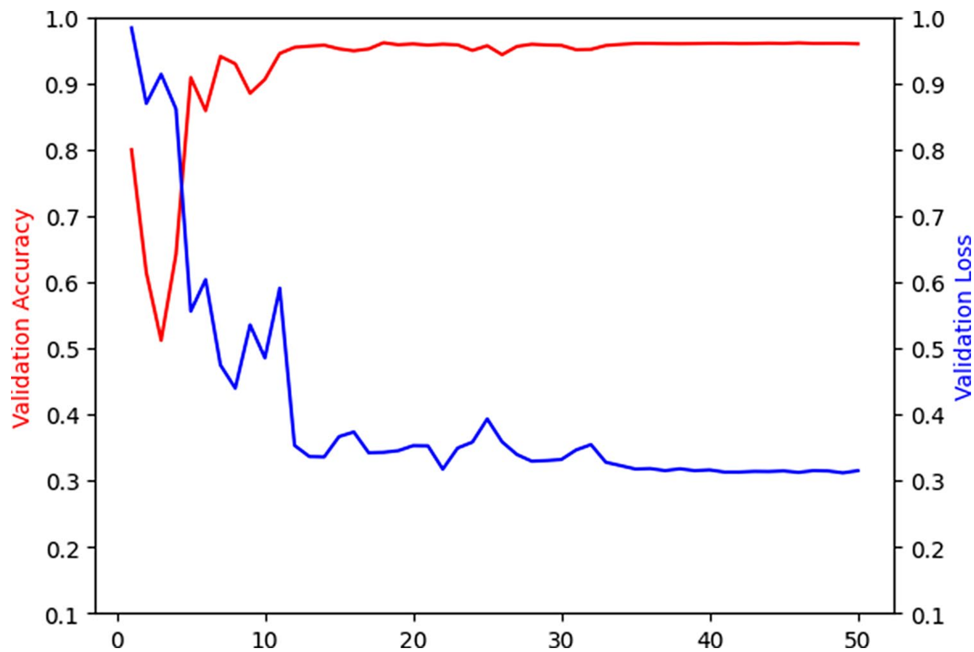

Fig. 8 Accuracy and loss value of the model developed using Google Inception Network with Feature Enhancement Techniques and Transfer Learning

Table 3 Accuracy value of the model developed using Inception Network with feature enhancement with transfer learning, Inception Network with feature enhancement, Google Inception Network (Inception V3), and Alex Net CNN.

Model	Accuracy
Inception Network with feature enhancement with transfer learning	0.9981%
Inception Network with feature enhancement	0.95%
Google Inception Network (Inception V3)	0.93%
Alex Net CNN	0.73%

of breast cancer disease with an accuracy of 99.81% to the inception model and AlexNet model and make accurate predictions.

Results and discussion

In the study, we aim to investigate the effectiveness of integrating a feature enhancement technique into the Google Inception network for breast cancer detection and classification. The experiments aimed to assess the performance of the proposed model in comparison to baseline models and state-of-the-art deep learning architectures commonly used in medical image analysis tasks. To achieve this, we obtained a breast cancer dataset comprising of annotated Ultrasound images from Hospitals and online sources. The dataset was carefully curated to ensure accuracy and quality of the annotations. We partitioned the dataset into training, validation, and testing sets while maintaining the class distribution. The proposed model was implemented by integrating the locally preserving projection (LPP) feature enhancement technique, into the Google Inception network and by applying transfer learning Techniques. The proposed model architecture was designed to accommodate the integration of the locally preserving projection (LPP) feature enhancement technique while ensuring compatibility with the input size and channel requirements of the ultrasound images. During the model training phase, we initialized the model with appropriate weights and biases and utilized the training set to update the model's parameters through backpropagation. The progress of the training process was monitored using the validation set, and early stopping was applied if necessary to avoid overfitting. The modified proposed model includes InceptionV3 Inception Network as the base Google Inception Network. This base network consists of multiple inception modules, which consist of parallel convolutional layers with different filter sizes, pooling, and concatenation operations. The base network is responsible for extracting rich and hierarchical features from the input ultrasound images. Then LPP feature enhancement technique is integrated into the base network to enhance the discriminative power of the features. The LPP algorithm is applied to the feature maps obtained from the InceptionV3 Inception Network. It computes within-class and between-class scatter matrices based on the extracted features and projects them into a lower-dimensional subspace. This process captures the underlying structure and discriminative information present in the ultrasound images. After applying the LPP feature enhancement technique, the LPP-enhanced features are concatenated with the original features obtained from the base network. The concatenation operation combines the feature maps of the LPP-enhanced features and the original features, resulting in a combined feature representation. This step aims to preserve both the enhanced discriminative information and the original representation captured by the base network. Then a classifier is integrated into the modified network. In this paper, SoftMax classifiers are used, and they are trained on the combined features. This enables the classifier to learn the discriminative patterns and make accurate predictions for breast cancer detection and classification.

Integrating the LPP feature enhancement technique into the Google Inception Network architecture helps to enhance the network's discriminative power by using both the original features extracted by the base network and the enhanced features obtained through the LPP algorithm. This modification allows the network to capture and utilize the underlying structure and discriminative information in ultrasound images integrated with transfer learning, ultimately improving the accuracy of breast cancer detection and classification. The proposed model performs an accuracy of 99.81%.

Model comparison in terms of accuracy, sensitivity, and recall

To further demonstrate the proposed model we compare the performance of AlexNet CNN, Inception V3, Modified Inception Network (inceptionV3) with LPP feature enhancement techniques, and Inception Network with LPP feature enhancement with transfer learning and we discuss each model and their relative performances based on the experiments. AlexNet was one of the first CNN architectures to widely adopt the rectified linear unit (ReLU) as its activation function and uses the dropout regularization technique to address the issue of overfitting. We compared the detection performance with those proposed by other researchers. It was observed that metrics such as accuracy, recall, and specificity are commonly employed. We also employed these metrics to see how the developed model performs on the testing set. As shown in Table 4, the proposed model, which combines the Inception Network with LPP feature enhancement using transfer learning achieved a high accuracy of 99.081% for breast cancer detection and classification.

Table 4 Model comparison in terms of accuracy, sensitivity, and recall

Model	Accuracy	Recall	Sensitivity	Execution Time
Inception Network with feature enhancement with transfer learning	0.9981%	0.9648%	0.930%	1.5 m
Inception Network with LPP feature enhancement	0.95%	0.80%	0.85%	2 m
Google Inception Network (Inception V3)	0.93%	0.75%	0.78%	3.5 m
Alex Net CNN	0.73%	0.70%	0.712	4 m

Table 5 Comparative analysis of the proposed model with related works

Author	Models used	Accuracy	Recall	Sensitivity
[15]	VGG16 with Transfer Learning	97.35%	92%	93%
[23]	Transferable Texture Convolutional Neural Network (TTCNN) with Google Net	97.49%		86.78%
[33]	CNN-based transfer learning with AdaBost Classifier	96.2	-	97.3%
[47]	InceptionV3	97.816%	94%	96.75%
Proposed Model	**Inception Network (V3) with LPP feature enhancement with transfer learning**	**99.81%**	**96.48%**	**93.0%**

The LPP feature enhancement techniques help the inception network to enhance performance and transfer learning allows the model to use pre-trained weights and knowledge from different datasets, which can enhance its performance to detect and classify the breast cancer. By incorporating these techniques, the model can learn more representative and discriminative features for breast cancer detection, resulting in higher accuracy (99.081%) as compared to Inception Network with LPP feature enhancement, Google inception Network (Inception V3), and Alex Net CNN.

Comparative analysis of the proposed model with state of the art models

We compared the performance of our proposed model with traditional methods and state-of-the-art deep learning architectures using the breast cancer dataset in Table 5. We measure various evaluation metrics, including accuracy, sensitivity, and recall.

As shown in Table 5, the quantitative comparison table demonstrates that the proposed approach for breast cancer detection using ultrasound images achieved impressive results. The accuracy of 99.8% indicates that the model is making correct predictions. Furthermore, the recall of 96.96% highlights the model's ability to identify the majority of positive cases correctly and the sensitivity of 93.19% further emphasizes the model's capability to correctly identify true positive cases. This metric indicates the model's ability to minimize false negatives, which is crucial in preventing misdiagnosis and ensuring that potential cases are not overlooked. Mohanty et al. [48] produce better performance with a model accuracy of 98.3% but, our model has better accuracy than other algorithms with an accuracy of 99.81%. Authors in [47] slightly produced a better accuracy, but the proposed model has greater accuracy and recall than other algorithms.

Conclusion and future work

Over the past five years, deep learning methods, including deep convolutional neural networks (CNNs), have demonstrated remarkable success in image detection and classification tasks. These advancements have also been extended to the field of medical imaging, where deep learning models have shown great promise in addressing various medical image challenges across different modalities. For instance, in the area of medical imaging , Google inception, ResNet, and GAN Net networks have achieved better results in terms of sensitivity and accuracy than human experts and other methods of breast cancer metastases classification. Furthermore, we introduced a 3D CNN for lung cancer detection which achieved promising results. Deep learning models for breast cancer detection in recent times have not yet achieved sufficient accuracy and robustness for real-time applications, due to the morphological variability in nodule appearance. The detection of breast cancer using deep learning (for instance google inception model) depends on the extent of the intermediate output of the model, i.e., the better the intermediate output of the model, the better the model achieves better detection results. Using deep learning-based breast cancer detection, the majority of research that were devoted to breast cancer detection employed different feature fusion strategies with various kernel sizes. For example, to enhance the detection and classification of breast cancer using CNN canonical feature fusion which enhances the output of CNN, we introduced a weighted CCA feature fusion strategy and the Kernel CCA feature fusion strategy to enhance the output of CNN. However, all these feature fusion strategies are conducted by concatenating different features of CNN and applying the transformation function to enhance the final output of CNN. However, most of the features are lost in each intermediate output (layer) of CNN, not on some layers of CNN. Due to this, the overall accuracy of CNN-based breast cancer detection is not as intended as possible.

The development of breast cancer detection and classification algorithms using deep learning techniques can be of great assistance to radiologists and medical professionals in enhancing medical image analysis and the models have the potential to significantly impact the field of radiology and improve the efficiency and accuracy of breast cancer diagnosis. In this research paper, we proposed a feature enhancement method that aims to enhance the intermediate output of the proposed model. To this end, the modified inception network, CNN-based networks (InceptionV3), is selected for breast cancer classification by introducing a feature enhancement method called locally preserving projection (LPP). The LPP algorithm is utilized on the feature maps acquired from the Inception V3 base network. It calculates the scatter matrices within the same class and between different classes using the extracted features. These matrices are then projected into a lower-dimensional space. Ultimately, the LPP-enhanced features effectively captures the inherent structure and distinguishes between information found in the ultrasound images. After applying the LPP feature enhancement technique, the LPP-enhanced features are combined with the original features obtained from the base network. The objective is to preserve both the enhanced discriminative information and the original representation captured by the base network. The concatenation operation merges the feature maps of the LPP-enhanced features and the original features, resulting in a unified feature representation. Following the feature concatenation, a modified network integrates the classifier that facilitates breast cancer detection and classification. In this paper, SoftMax classifier was employed and trained on the combined features. This allows the classifier to learn the discriminative patterns present in the data and make accurate predictions. The proposed model is expected to increase the accuracy of the detection and classification of breast cancer. To evaluate the performance of the proposed model, an extensive testing on the held-out testing set was conducted. We also conducted an experiment to compare our proposed model with other approaches .

During the experiment, we compared the results of different model settings like Inception Network with feature enhancement with transfer learning, Inception Network with LPP feature enhancement, Google Inception Network (Inception V3), and Alex Net CNN models. We used various evaluation metrics, including accuracy, sensitivity, and recall, which assess the model's ability to detect the cancer disease as malignant, benign, and normal. The experimental results were analyzed and compared with the performance of baseline models and state-of-the-art deep learning architectures. The proposed Inception Network (V3) with LPP feature enhancement with transfer learning model demonstrates improved performance in terms of accuracy, sensitivity, and recall, 99.81%, 96.4%, and 93.0% respectively compared with Inception Network with LPP feature enhancement with evaluation metrics of 95% accuracy, 80% recall, and 85% precision, while Google inception Network (Inception V3) achieved an accuracy of 93%, recall of 95% and precision of 78%. Alex Net CNN achieved an accuracy of 73%, recall of 70%, and precision of 71.2% . Based on the analysis and evaluation carried out in this study, the integration of the LLP feature enhancement technique in the Google Inception network holds promise for enhancing the accuracy and effectiveness of breast cancer detection and classification. The findings from the experiments provide valuable insights into the potential clinical relevance and interpretability of the model's predictions. In conclusion, our experiment validates the effectiveness of integrating a feature enhancement technique in the Google Inception network for breast cancer detection and classification.

Future work

This work contributes to the advancement of medical image analysis and has implications for improving early detection and patient outcomes in breast cancer diagnosis. In the future, the authors hope to evaluate the proposed model with a larger and diverse dataset, and incorporate domain knowledge from radiologists into the model to improve its interpretability and clinical relevance.

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Author contributions
Wasyihun Sema Admass: Conception and design, Data acquisition, Analysis and interpretation, Drafting and critically revising the manuscript. Yirga Yayeh Munaye: Conception and design, Data acquisition, Analysis and interpretation, Drafting and critically revising the manuscript. Ayodeji Olalekan Salau: Conception and design, Data acquisition, Analysis and interpretation, Drafting and critically revising the manuscript.

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Data availability
The datasets generated during and/or analysed during the current study are not publicly available but are available from the corresponding author on reasonable request.

Code Availability
Not applicable.

Declarations

Conflict of interest
The authors declare that they have no conflict of interest.

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