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AN IMPROVED BREAST CANCER DETECTION MODEL BASED ON CONVULUTIONAL NEURAL NETWORK

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ABSTRACT
Cancer is one of the diseases that causes deaths eventually to women worldwide, that need urgent need for more reliable diagnostic method for early detection to reduce the rate of mortality, many researchers have explode some technologies like machine learning and others techniques for classification of cancer but still several gap has remained, this articles investigate the potential of deep learning especially CNNs techniques for classification of malignant and benign which outperform the traditional classification method like traditional neural network and SVM, mammography, ultrasound and magnetic resonance image. The study identify that all the traditional method of classification of cancer are plague with several limitation which hinder their effectiveness, but using technique like CNN The study have achieve a remarkable success with high performance with accuracy of 98.5%, recall of 98.2 precision of 97.6, and F1-score of 98.0, the study gives an insight overview of deep learning offer crucial information to researchers medical professional of how to improved cancer classifications using CNN technique.

Keywords: Breast cancer, Machine learning, Deep learning, Convolutional neural networks

INTRODUCTION
The era of computer intelligence (CI), particularly deep learning, has recently change the medical imaging diagnostic CNNs, a type of deep learning technique, that shown an exceptional ability to analyze complex medical pictures such as MRI scans, ultrasounds, and mammograms (Ciobotaru *et al.*, 2025). These algorithms make it possible to detect abnormalities more quickly and efficiently by automatically detecting patterns and features in imaging data (Wang *et al.*, 2021). With these there is need to increase the accuracy and efficacy of breast cancer screening. Humayun *et al.* (2023) research state that deep learning algorithms has classify breast cancer from mammograms with high performance levels surpassing or better than those of experienced radiologists (Ciobotaru *et al.*, 2025). CNNs have also been effectively used to assess MRI scans and classify breast masses in ultrasound pictures, showing encouraging results in terms of both sensitivity and specificity (Tian *et al.*, 2023). Despite these achievements, there are several limitations in the application of deep learning to classify breast cancer, the lacks of larger datasets scale for deep learning model training and validation is the big issues and also the quality and diversity of the training data are crucial to these models' efficacy, and current datasets often fail to accurately reflect a range of demographic groups, imaging modalities, and many types of cancer (Lan *et al.*, 2021).

Furthermore, even though CNNs have shown a lot of potential, more studies state that there is to improve their structures for specific diagnostic method, particularly in the classification of breast cancer, the improved CNN model performance can be remarkably influence by the selection of network depth, layer configurations, and hyper parameters; though, these factors have not been well look into in the present literature. Given this defiance, there is still need for researchers to study the ethical and practical implications of using deep learning models in real-world clinical circumstance in addition to pushing the models' technological perimeter. By improving the architecture of the CNN-based model that is particularly designed for cancer classification, and stunning some extension in CNN addressing the problem in existing techniques. This has improved the accuracy, precision, dependability, of breast cancer classifications, in the final analysis it has improved the patient outcomes and reducing the rate of mortality.

The impact of this study depends on its ability to make some changes or new development that revolutionized breast cancer classification by developing an improved

CNN-based model that addresses the limitations of traditional screening methods. The improved model is designed to particularly improved classifications accuracy, reduce false positives and negatives, and improve the overall efficiency of breast cancer classifications. By manipulating the advanced techniques such as batch-normalization, dropout, and ReLU activation functions, the model aims to achieve higher performance compared to existing methods, particularly in challenging cases such as dense breast tissue or early-stage tumors. Wang *et al.* (2021) state that the accumulation the CNN model into a Computer-Aided Detection (CAD) system, which has the potential to assist radiologists in clinical practice, reduce classifications in-balanced, and improve patient results. The computerized interpretation of medical images with good or exceptional accuracy and efficacy, computer intelligence (CI) and deep learning have displayed extra-ordinary changes in classification of breast cancer (Zabihollahy, 2020). Researchers frequently use machine learning (ML) and computer intelligence (CI) to develop complex systems that can do complex tasks that reduce human intervention.

Similarly, Fatima and Bilal (2024) have compared a neural network-using (DL) model that classified cancer with traditional machine learning models such as Random Forest, Decision Tree, and Support Vector Classifier (SVC). Age, history of family, genetic changes, hormone therapy, mammography results, breast discomfort, menopausal status, BMI, alcohol consumption, physical activity, smoking habits, identification of breast cancer, frequency of screening, sources of awareness, symptom recognition, screening choices, and geographic location were all examined in the study. Among the classic models, SVC attained 86.36 % accuracy, Decision Tree reached 86.18 %, and Random Forest achieved 86.00 %, emphasizing the capability of deep learning models to surpass traditional methods. The neural network model particularly deep learning surpassed the existing methods by reaching a maximum accuracy of 93 % (Zabihollahy, 2020). AI and ML are extensively utilized in studies focused on creating sophisticated technological systems that can execute intricate tasks with less dependence on human intellect in this context, Rao *et al*. (2022) examine the application of existing image processing and machine learning methods for computer-assisted breast cancer detection through mammogram images, aiming to find efficient techniques that can aid radiologists in their clinical decisions. Studies carried out by Abunasser *et al.* (2023) state that early detection and precise diagnosis of breast cancer (BC) are very important for improving patient results, and survival rates rising by 30 to 50 % (Humayun *et al.*, 2023).

Deep learning has become a very important for handling and analyzing large volumes of X-ray, MRI, and CT images as technology in healthcare continues to advance. Similarly, research by Khalid *et al.* (2023) stated that allot of improvement has been made using CNNs to classified cancer, and some many types of cancer, which helps medical professionals recognize breast cancer using the datasets fetch from the UCI Machine Learning Database, (Islam *et al.* 2020) assessed other supervised machine learning techniques: support vector machines (SVM), artificial neural networks (ANNs) and results have demonstrated that neural network techniques have achieved the highest classification accuracy (Yousaf, 2022). AI models have generally demonstrated a strong capacity to support accurate and timely clinical decision-making. Building on these techniques, Alhussan *et al*. (2023) presented a novel automated computational framework that makes use of the (ABER) Advanced Al-Biruni Earth optimization method to diagnose breast cancer. The system includes improved classification using a (CNN), feature extraction with AlexNet through transfer learning, and data improvement. Evaluation using two publicly available datasets showed that the proposed the classification efficiency has been significantly improved.

MATERIALS AND METHODS

Convolutional Neural Network

CNNs is a branch of DL algorithms which demonstrate to be the number one effective tool in object detection and image classifications in these days (Rosle *et al*., 2025). The CNNs techniques is designed to get inputs datasets and process using different types of layers that are designed to increasingly take out features with abstracts and then perform the classification.

The convolutional layers are the basic module of the CNNs used to filter and fetch features from the pooling layers and input data which gives the output of the convolutional layers sample to decrease the size or measurement of data. The results are flattened after passing through pooling layers and convolutional layers, then fed into a series of fully connected layers, and carry out the classification.

DeepInsight

DeepInsight is a method use to convert a non-picture sample data to a picture form, fetch it to the CNN based architecture for prediction, and detection or classification. It is also illustrated in Fig. 1, where a feature vector *x* consisting of a gene expression value which is transform to a feature matrix *M* by conversion of *T*. The Cartesian coordinates depend on the position of the features and similarity between them. For example, in Fig. 1 features like g1, g3, g6 and gd are very close to each other and when the position of each feature is determined in a feature matrix, the feature values will be mapped, and this will automatically generate a unique picture of each sample data. For instance, *N* samples of *d* features will provide *N* samples of $m \times n$ feature matrices, which 2D matrix form will have all the *d* features. Therefore, after the set of *N* feature matrix is processed the model will provide the prediction.

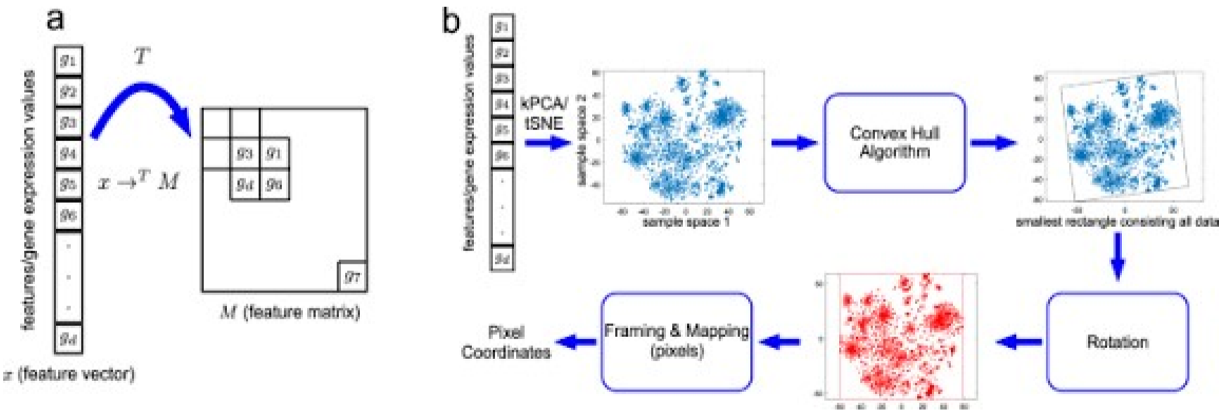

Figure 1: DeepInsight pipeline, which illustrate: (a) Transformation of feature vector to feature matrix; (b) DeepInsight methodology transforming a feature vector to image pixels

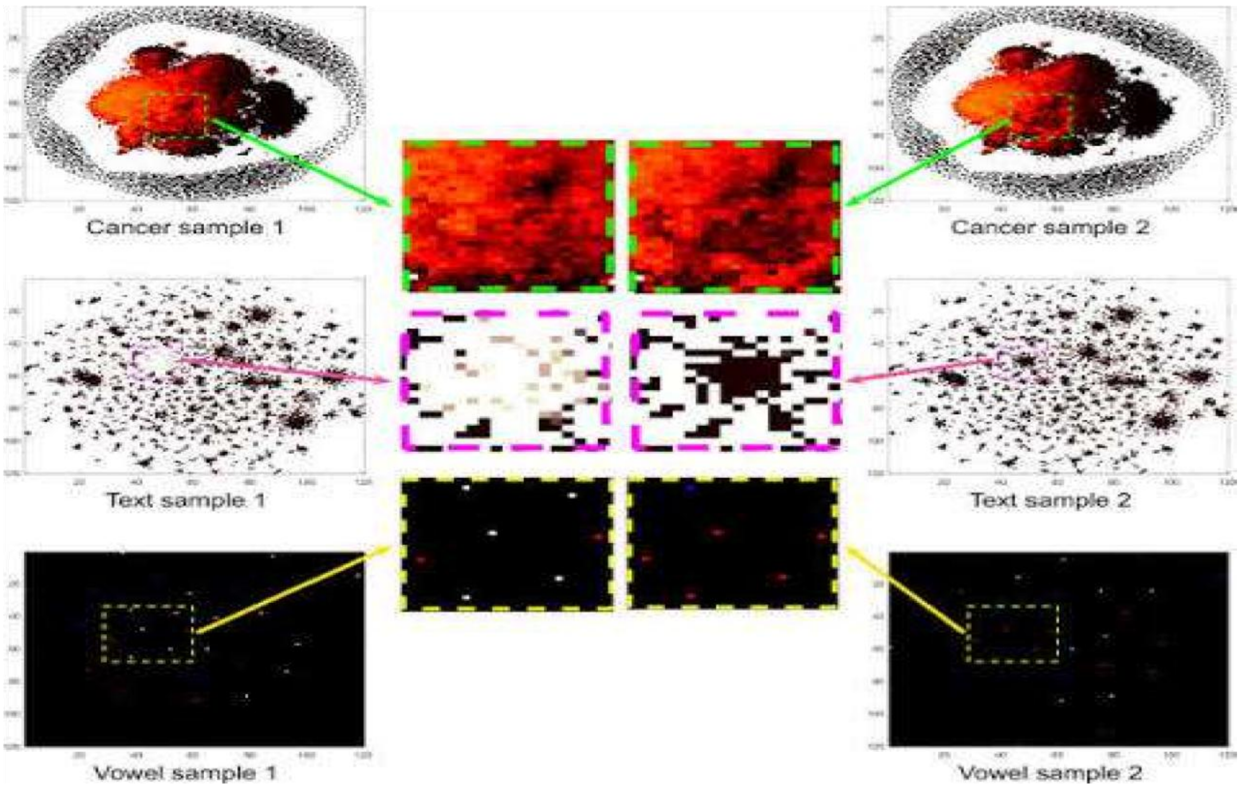

Figure 2: The different pattern archived by DeepInsight

The patterns represented by DeepInsight method, is an illustration that shows the different type of patterns achieved by DeepInsight on different type of cancers, text, and vowels. Each pattern shows a transformed sample; hence, difference between samples can now be noticed directly.

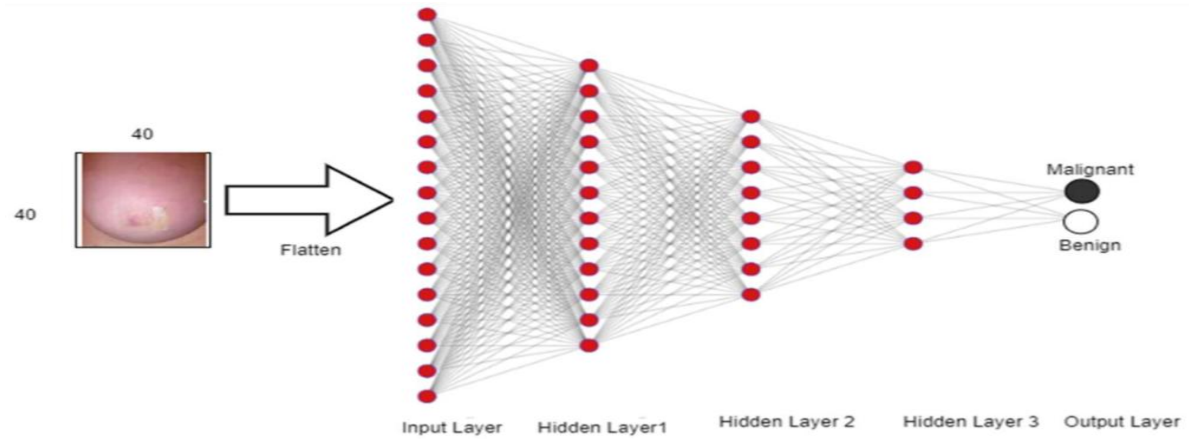

Figure 3: CNN model architecture

Feature Learning

The feature learning is a technique that is used to fetch out features from input data and make the machine to learn from those features automatically. In CNN, there are two components in which features are extracted, which are: Convolution Layer and Pooling Layer

Convolution Layer

The convolution layer is one of the components of feature learning, designed specifically for feature extraction, where it started by applying convolutional function at first for feature extraction and activation on the results of convolution function. There are many more of convolution layers which are used for the feature extraction, such as convolution operation, linear function also known as kernel function, otherwise called filter. The description of an input by tensor I of dimension (m_1 x m_2 x mc) is given bellow:

m_1= height of image
m_2 = width of image
mc = number of images

The filter is applied as (n_1 x n_2 x nc), where the number of channels for the kernel is the same as the input image. The filter moves upon the image from left to right, and perform some multiplication between part of I and K then add the products, where strides determine the step size by which the filter would move upon image. The resultant of I and K is another tensor of dimension (m_1 — n_1 +1) x (m_2 — n_2 +1) x 1

Where

$$dim\ of\ I = m_1 \times m_2 \times m_c$$
$$dim\ of\ k = n_1 \times n_2 \times n_c$$
$$dim\ of\ F = (m_1 - n_1 + 1) \times (m_2 - n_2 + 1) \times 1$$

And,

$$F[i,j] = (I * K)_{[i,j]}$$

The ij-th entry of the features map is given as below:

$$\boldsymbol{f}[\boldsymbol{i},\boldsymbol{j}] = (\boldsymbol{I} * \boldsymbol{K})[\boldsymbol{i},\boldsymbol{j}] \sum_{x}^{m1} \sum_{y}^{m1} \sum_{z}^{m1} \boldsymbol{K}[\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}]\, \boldsymbol{I}[\boldsymbol{I} + \boldsymbol{x} - \boldsymbol{1}, \boldsymbol{j} + \boldsymbol{y} - \boldsymbol{1}, \boldsymbol{z}]$$

We have taken the following sample of a 5x5x1 dimensional image being convoluted with a kernel of 3x3x1 and the stride s= 1 has been used.

$$\begin{array}{c|ccccc} & -2 & -1 & 0 & 1 & 2 \\ \hline -2 & 1 & 0 & 1 & 1 & 0 \\ -1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 1 \\ 2 & 1 & 0 & 0 & 1 & 1 \end{array} \quad * \quad \begin{array}{c|ccc} & -1 & 0 & 1 \\ \hline -1 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 1 & 1 & 0 & 1 \end{array} \quad = \quad \begin{array}{c|ccc} & -1 & 0 & 1 \\ \hline -1 & 4 & 2 & 3 \\ 0 & 2 & 2 & 2 \\ 1 & 4 & 1 & 3 \end{array}$$

Image **Kernel** **Feature map**

The ij-th entry of feature map is given by following general formula:

$$f[i,j] = (I * K)[i,j] = \sum_{x}^{m1} \sum_{y}^{m1} \sum_{z}^{m1}$$

We compute the 11-entry of the feature map in above sample:

$$f[i,j] = \sum_{x=1}^{m1} \sum_{y=1}^{m2} \sum_{z=1}^{mc} K_{[x,y,z]} I_{[I+x-1,j+y-1,-z]}$$

$$f[1,1] = \sum_{x=1}^{5} \sum_{y=1}^{5} K_{[x,y]} I_{[I-x,1-y]}$$

$$= \sum_{x=-2}^{5} K[x,-2]\ I[1-x,3] \sum_{x=-2}^{5} K[x,-1]I[1-x,2] + \sum_{x=-2}^{5} K[x,0]I[1-x,1] + \sum_{x=-2}^{5} K[x,1]I[1-x,0] + \sum_{x=-2}^{5} K[x,2]I[1-x,-1]$$

The entries which are not available are substituted zero.

$$f[1,1] = 0 + 0 + 0 + 0 + 0 + 0 + (1 \times 1) + (0 \times 1) + (1 \times 0) + (0 \times 1) + 0 + 0 + (1 \times 0) + 0 + 0 + 0 + 0 + (1 \times 1) + 0 + 0 + (1 \times 1) + (0 \times 1) + (1 \times 0) + (0 + 1) + 0$$

$$f = [1,1] = 3$$

Pooling Layer

The convolved features' spatial dimensions are reduced in the pooling layer. This method enables us to extract the image's primary feature and result produced by the convolution layer is subject to the pooling operation in the pooling layer.

$$Conv(I, K) = C$$
$$P = \Theta_p(C)$$
$$Where\ \Theta_p is\ a\ pooling\ function$$

The dimension of pooled part is given as

$$\dim of\ P = \left(\frac{d1 + 2p - n}{s}\right)\left(\frac{d2 + 2p - n2}{s}\right) \times mc$$

$$Where,$$
$$d1 \times d2 = the\ dimension\ of\ input\ image$$
$$n1 \times n2 = the\ dimension\ of\ padding$$
$$S, stands\ for\ stride\ and\ P, stands\ for\ paddind$$

Fully Connected Layer

The flattened vector is received by the fully linked layer, which transforms it into a new vector. It is also possible for one class to appear more frequently than another model. In order to solve this issue, the pooling portion is mixed with the balanced weights, and a biased term was added, then activation function is used. The following is the mathematical explanation:

$$X = \sum_{i} wiPi + b'$$
$$z = g(X)$$
$$Where\ g\ is\ an\ activation\ function\ for\ fully\ connected\ layer$$

Performance Evaluation

Assessment of the CNN model efficiency for breast cancer classifications, several evaluation metrics were used. Thus, matrices chose for the study provides a comprehensive knowledge of the model's effectiveness in classifying breast cancer cases as malignant or benign. The following metrics were chosen.

Accuracy: this performance evaluation matrix, measures the proportion of correctly classified instances out of the total instances. It is calculated as:

$$\text{Accuracy} = \frac{TP + TN}{TP+TN+FP+FN}$$

Precision: this is the proportion of true positive predictions which measure out of all positive predictions. It can be calculated as:

$$\text{Precision} = \frac{TP}{TP\ FP}$$

Recall: is the proportion of true positive predictions measured out of all actual positive's predictions. And it is also calculated as:

$$\text{Recall} = \frac{TP}{TP+FN}$$

The F1 score: refers to the harmonic mean of precision and recall, which measures the balance performance of the model; also calculated as:

$$\text{F1 Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

The matrices were chosen because of the study's objectives of developing an high accurate and reliable breast cancer classifications model, especially precision and recall are essential in medical diagnosis. The F1 score have provide a balanced evaluation, ensuring that the improved CNN model for cancer classification performs well across all metrics.

Datasets and Evaluation Metrics

The source of the dataset used for the study was chosen from the UCI Breast Cancer Wisconsin (Diagnostic) Dataset, is popularly known in machine learning community specifically for cancer classifications, its extensive feature set, which is produced from digital images of fine needle aspirates (FNA) of breast lumps. The dataset is ideal for training a CNN models used for cancer classification since it comprises features that characterize the cell nuclei contained in the images. Each 569 cases in the dataset represents a breast mass, thirty real-valued features including mean, standard error, and worst (biggest) values for ten important cell nucleus characteristics radius, texture, area, smoothness, compactness, concavity, concave spots, symmetry, and fractal dimension are used to define each occurrence. There are two classes in the binary dataset: benign (357 cases) and malignant (212 instances). Although the imbalance between the two classes may need to be handled carefully during model training, this distribution represents the actual prevalence of benign and malignant breast tumors. The model was built with Google COLAB and tested on breast cancer dataset. The computer used for the development of the model is an Intel Core i5 processor and 4GB of RAM was used for the testing.

In this study, machine learning classifiers like SVM (Support Vector Machine) and KNN (K-Nearest Neighbors) were used for breast cancer detection in order to evaluate the suggested approach and compare it with cutting-edge machine learning algorithms in terms of performance. The features that are chosen for the training, dictate which classifiers are used. And also, a set of measures were taken to contrast the results between machine learning classifiers and evaluate the detection rate. Table 1 presents a recap of various metrics components.

Table 1: the comparison the improved model and the existing model

Metric	Improved CNN Model	Existing System (kNN)	SVM-Based System
Accuracy	98.5 %	94.0 %	95.5 %
Precision	97.8 %	92.5 %	94.0 %
Recall	98.2 %	93.0 %	94.5 %
F1 Score	98.0 %	92.7 %	94.2 %

FINDINGS AND DISCUSSION

The matrices used in this study to test the improved CNN model performance were precision, recall, accuracy and F1 score, gave an in-depth evaluation of the model's capacity that differentiate between benign and malignant condition. An improved CNN model was compared with the existing models such as SVM, and KNN models, in which the improved CNN model's performance showed a good result shown in Table 1. With the high performance of the accuracy of 98.5 %, which outperformed the SVM-based system (95.5 %) and the existing neural network (NN) system (94.0 %). The low rate of false positives features of the model performance were essential for cancer cell diagnosis to save undesired biopsies as indicated by its precision of 97.8 %. The recall of 98.2 % shows that the improved model can classify the majority of malignant cases without mistake, and reduced the rate of missed diagnosis. The model has successful classified cancer, as shown by the F1 score of 98.0 %, which balanced the performance between precision and recall.

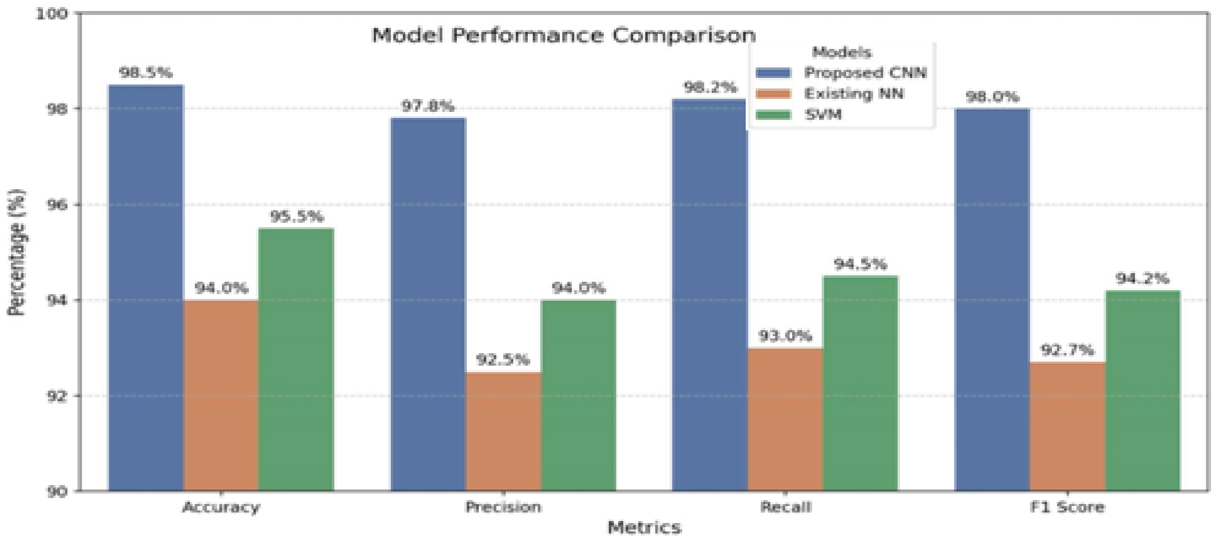

Figure 4: Model performance comparison 1

The improved convolutional neural network model's performance is compared with the existing systems in the Fig 2 above. The understanding of the model's performance especially with regard to true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN), a confusion matrix was created.

Table 2 confusion matrix

	Predicted malignant	Predicted benign
Actual malignant	208 (TP)	4 (FN)
Actual benign	3 (FP)	354 (TN)

Table 2 shows True Positives (TP): 208 malignant cases were correctly classified as malignant, True Negatives (TN): 354 benign cases were correctly classified as benign, False Positives (FP): 3 benign cases were incorrectly classified as malignant, in these cases, the model predicted cancer when none was present potentially resulting in needless biopsies, and False Negatives (FN): 4 malignant cases were incorrectly classified as benign.

CONCLUSION AND FUTURE WORK

By prevailing the weakness of traditional screening method including mammography, ultrasound, and MRI, this study was effectively designed and evaluates an improved breast cancer detection model using Convolutional Neural Networks. The improved CNN model performed remarkably success, of a very result of current neural network (NN) and SVM-based systems with an accuracy of 98.5 %, high precision (97.8 %), and recall (98.2 %). The results have proven that model's performance to accurately classify cases of breast cancer while keeping away of false positives and false negatives, which is necessary for improving early detections and cutting down the effectiveness of medical treatments. The study shows how deep learning, particularly CNNs, might change breast cancer early detection; the study also improved the field of medical diagnostics. With the highlighting of improved CNNs capacity to automatically classifying patterns from medical imaging datasets and generalize effectively to new data has shown a promising development in clinical applications. Even with a very large or short dataset, the model has shown a strong performance by utilizing sophisticated approaches including data batch normalization, dropout and augmentation. The study did have a number of drawbacks, though, including as the dataset's modest size and feature-based structure, which would limit the model's applicability to larger populations and unprocessed imaging data. In order to further improve the model's diagnostic capabilities, future research should concentrate improving the model’s interpretability so that the clinicians can trust and comprehend the model predictions which is essential for adoption in clinical practice and testing it on bigger, more varied datasets, combining it with raw imaging modalities like mammograms and MRI images, and investigating multimodal techniques.

Conflict of interest: The authors declare no conflicts of interest.

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