Turkish Journal of Science & Technology
20(1), 29-40, 2025

Research Paper
https://doi.org/10.55525/tjst.1483617

Early Diagnosis of Invasive Ductal Carcinoma Breast Cancer using Deep Learning Framework

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(Geliş/Received: 13/05/2024; Kabul/Accepted: 24/10/2024)

Abstract: This study is aimed to be conducted on invasive ductal carcinoma breast cancer, which is a type of cancer that is common around the world and found in women. Early diagnosis of this disease can be lifesaving. It was aimed to conduct the study to determine the early diagnosis of breast cancer due to its early detection feature. In addition to deep learning techniques, image processing techniques were also used in the study. A dataset consisting of breast cancer images was used. The images in the data set may be complicated or time-consuming when evaluated using traditional diagnostic methods. This is where deep learning models come into play. The models used in the study analyzed breast cancer cells. As a result of the analysis, cells were classified as cancerous or cancer-free. Five different models were used in this study: CNN, SVM, Random Forest, DenseNet and MobileNet. When the results were examined, it was analyzed that the proposed method showed better performance than other methods. The accuracy rates of the models were: CNN (95.1%), SVM (89.87%), Random Forest (93.21%), DenseNet (94.31%), and MobileNet (94.6%). In conclusion, this study reveals the differences between models used in breast cancer diagnosis. In this period when the importance of artificial intelligence increases, it is predicted that it will be an important step in saving breast cancer patients. If the methods are used efficiently and effectively, the rate of early diagnosis will increase and diseases will be prevented.

Key words: Artificial Intelligence, Breast Cancer, Deep Learning, Image Processing, Invasive Ductal Carcinoma.

Derin öğrenme çerçevesini kullanarak invazif duktal karsinom meme kanserinin erken tanısı

Öz: Bu çalışma, dünya genelinde kadınlarda yaygın olarak görülen invazif duktal karsinom meme kanseri üzerine odaklanmaktadır. Erken teşhis, hayat kurtarıcı olabilecek bu kanser türü için kritiktir. Çalışmanın amacı, meme kanserinin erken teşhisini belirlemek için derin öğrenme ve görüntü işleme tekniklerini kullanmaktır. Meme kanseri adlı bir veri seti, geleneksel tanı yöntemleriyle değerlendirildiğinde karmaşık veya zaman alıcı olabilen görüntüler içermektedir. Derin öğrenme modelleri, bu zorlukları aşmak için kullanılmıştır. Çalışmada kullanılan modeller, meme kanseri hücrelerini analiz etmiş ve kötü hücrelere sahip olanları kanserli, iyi hücrelere sahip olanları kansersiz olarak sınıflandırmıştır. Beş farklı model (CNN, SVM, Random Forest, DenseNet ve MobileNet) kullanılmıştır. Sonuçlar incelendiğinde, önerilen yöntemin diğer metodlara göre daha iyi performans gösterdiği görülmüştür. Modellerin doğruluk oranları sırasıyla şu şekildedir: CNN (%95,1), SVM (%89,87), Random Forest (%93,21), DenseNet (%94,31) ve MobileNet (%94,6). Bu çalışma, meme kanseri tanısında kullanılacak modeller arasındaki farklılıkları ortaya koymaktadır. Yapay zekanın önemi göz önüne alındığında, bu çalışmanın meme kanseri hastalarının kurtarılmasında önemli bir adım olabileceği öngörülmektedir. Yöntemlerin etkin ve verimli bir şekilde kullanılması durumunda, erken tanı oranının artması ve hastalıkların önlenmesi sağlanabilir.

Anahtar kelimeler: Yapay Zeka, Meme Kanseri, Derin Öğrenme, Görüntü İşleme, İnvazif Duktal Karsinom.

1. Introduction

Various types of cancer are common worldwide. Breast cancer is among the most common ones. This type of cancer occurs when the cells in the breast turn into harmful cells. There are tools used to diagnose breast cancer and these include mammography. Mammography performs a special X-ray scan and provides detailed examination of the tissues in the breast. It is seen that breast cancer is present if an individual has an abnormal cyst in her breast. Certain symptoms can indicate the presence of breast cancer. Changes seen in the nipple or skin disorders are some of these [1]. Shah and her colleagues also expressed their opinions, claiming that some factors increase the potential of breast cancer [2]. Early diagnosis is crucial as breast cancer can be fatal. After early diagnosis, the correct treatment method is among the major factors in eradicating the disease.

There are many types of breast cancer. One of these types appears to be invasive ductal carcinoma [3]. The type of cancer that we encounter as invasive ductal carcinoma occurs in breast tissues. There are milk ducts in the

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breast tissue. This cancer, as shown in Figure 1, called Invasive Ductal Carcinoma (IDC), is a type that occurs by contacting these tissues as well as the surrounding tissues. IDC is known as the most harmful type of breast cancer. Harmful cells begin to spread into tissues. It occurs when it infiltrates other cells other than the cell in which it is located. Therefore, accurately identifying and classifying IDC plays a vital role in determining treatment options and assembling comprehensive checkups as shown in Figure 1.

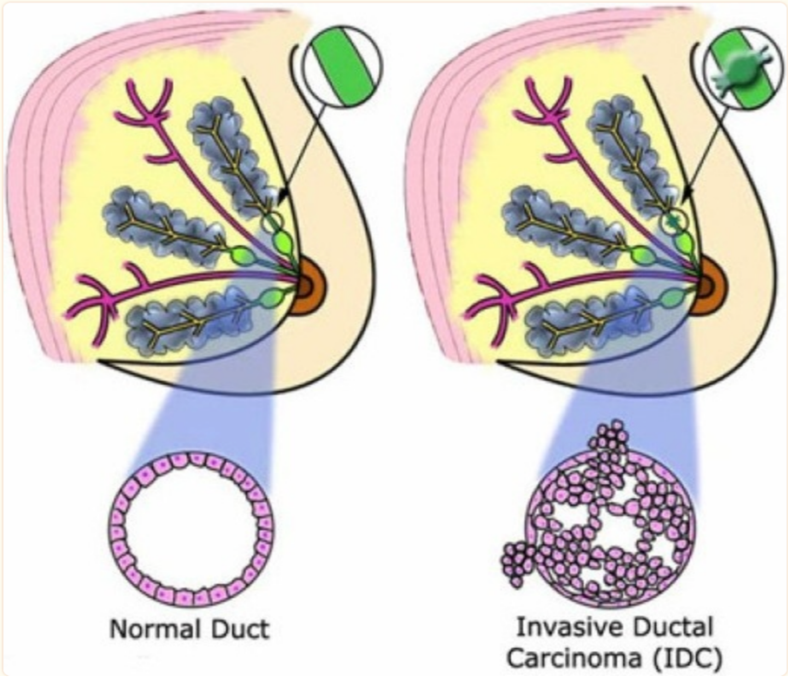


Figure 1. Normal duct and Invasive Ductal Carcinoma (IDC) [4].

Today, diagnosis and classification of breast cancer is usually done manually by pathologists. However, it has great endurance for pathologists who ensure accurate recognition of an aggressive strain such as IDC. Therefore, IDC has a large collection capacity to obtain computer-aided analysis results to accelerate diagnostic support. Therefore, developing a model to recognize IDC using deep learning methods and evaluating its effectiveness by applying this model to large data sets has become an important role. Additionally, it is necessary to explain why these techniques are so important in clinical practice, highlighting the potential impact of deep learning methods in the field of breast cancer diagnosis and classification. This study has the potential to open a new path in the field of breast cancer diagnosis and classification, providing pathologists and clinicians with the opportunity to provide faster and more accurate diagnoses. The unique values of this study or its unique contributions to the literature are described as follows.

Compared to literature studies, a faster approach was presented and results close to the literature were obtained. It can be seen that the study covers the detection and success rate of breast cancer in detail. Inspired by deep learning models, a wide range of investigations and studies have been carried out. The literature review goes beyond previous studies to re-evaluate the effectiveness of pioneering architectures such as Convolutional Neural Network (CNN), Densely Connected Convolutional Networks (DenseNet), and Efficient Convolutional Neural Networks for Mobile Vision Applications (MobileNet) in breast cancer diagnosis and offers a new perspective on this field. Deep learning has become an important technique in artificial intelligence in almost all fields. Its importance was also emphasized in the study and similar studies. It played a helpful role in detecting breast cancer in the study. Thus, it has been seen that it has an important place in the health sector and cancer diagnoses.

2. Background

Studies have been conducted on breast cancer, its diagnosis or classification. In this section, we will examine the studies and approaches. We will examine the proposed methods and what they are, along with their results.

Janowczyk and his colleagues proposed to analyze images and analyze bad cells in breast cancer using deep learning methods. They called the bad cells in breast cancer pathology. While they said that deep learning methods performed well in some cases, they claimed that in some cases it was the opposite. They said that the results were obtained from studies conducted in similar fields and the deep learning methods used in these studies. They proposed and used some techniques to achieve better performing results than these results. They focused on deep learning methods. By talking about a singular network architecture structure, they talked about the framework of this architecture. If we examine the framework in some detail: nucleus segmentation (over 12,000 nuclei, it appeared with an F_1 score of 0.83), epithelial segmentation (1735 regions showed a 0.84 F_1 Score cross score), tubule segmentation (0.83 F_1 score was obtained in 795 tubules).), lymphocyte detection (0.90 F_1 score was obtained in 3064 lymphocytes), mitosis detection (0.53 F_1 score was observed in 550 mitotic events), (f) invasive ductal carcinoma detection (0.7648 F_1 score was seen in 50k test field) and lymphoma classification (0.97 accuracy rate in a total of 374 images). Janowczyk and his colleagues actively used design learning methods and claimed that their study on more than 1200 images was an effective and large study [5].

Shahidi and colleagues conducted a study on the classification of breast cancer histopathology images. They used deep learning methods while carrying out their studies. They made comparisons between the methods they used. In their study, they aimed to investigate the performance of the latest models in this field, which have been little or not studied in the literature, and to offer a new perspective on existing studies. Shahidi and his colleagues claimed that they took important steps in the diagnosis of breast cancer in their studies. They emphasized that deep learning methods and comparisons will help future research [6].

Houssein and his colleagues focused on revealing the current knowledge of machine and deep learning technologies used in detailing and categorizing breast cancer and providing a general evaluation of the developments in this field of research. The focus of the study is to ensure the classification of breast studies with multiple study medical imaging. It has been observed that tumors are presented in some detail to facilitate the classification of non-tumor lesions and dense masses. In addition to the machine learning used in the proposed method, it was seen that different perspectives, different techniques and different thoughts were also included. Following these stages, the breast cancer detection process begins and follows specific architectures in the change process. Provides an overview of different imaging methods. The classification of breast cancers and their detected distributions in this analysis are summarized and summarized [7].

In the literature review, one of the studies on breast cancer diagnosis is the study focused on by Zahoor et al. Zahoor and his colleagues aimed to provide better options and a safer source in the study. They used different techniques in the stages of Computer-Aided Diagnosis (CAD) systems (such as pre-processing, segmentation, feature extraction and classification). They presented a report on the detection of breast masses, microcalcifications and malignant cells, including detailed analysis and the use of various techniques. When all these are brought together and examined, it is seen how important early diagnosis is in this type of cancer, as in every type of cancer. By emphasizing this importance, they emphasized the development of the necessary techniques and solutions. They made a brief criticism and said that the segmentation and classification stages have no disadvantages or convenience levels. They said that there would be more optimized and flexible techniques to get accurate results [8].

Zhang and his colleagues also conducted a study on breast cancer. They proceeded by dividing their work into 4 parts. In the first part, they focused on the detection of breast cancer. They then processed the images they obtained. In the next part, pre-processing was done on the images. Then the results were obtained. They discussed the effects of different methods on breast cancer. In addition to supervised and unsupervised learning methods, they also received help from deep learning methods. They evaluated the performance rates of the methods they applied. They evaluated whether the results were breast cancer or not. They emphasized that these studies will guide future studies [9].

Kanojia et al. focused on the early diagnosis and diagnosis of breast cancer and emphasized its importance. They said that breast cancer is very common worldwide and the risk level is high. They said that making a diagnosis on a normal patient takes too much time under normal conditions and in a hospital environment. They said that this waste of time would be prevented with automatic diagnosis systems. They stated that if this type of cancer is diagnosed early, its treatment will be faster and the recovery rate will increase. When these reasons come together, they said that the importance of systems increases even more, considering the concept of time is an important factor in the detection and prevention of cancer. In this context, Kanojia and his colleagues examined breast tissues in their study. They have conducted comprehensive and detailed research on breast cancer with the help of image processing techniques. The main point that Kanojia and his colleagues emphasize is early diagnosis. They aim to make this diagnosis by using relevant techniques [10].

According to Rezaei's study, it was determined that the disease that most threatens the life of women is breast cancer. Rezaei states that in the face of this threat, they stated that this type of cancer will be prevented and the chance of survival will be high. In this context, it is possible to state that various studies have been carried out covering the development of diagnoses and methods for the early diagnosis of breast cancer. In this study, examinations for the diagnosis of breast cancer are carried out with automatic and semi-automatic image-based approaches. The limitation of the research was the image-based diagnosis application journals published between 2016 and 2020 [11].

In their study, Lu and colleagues believe that there is no way to effectively treat breast cancer risk yet. In this context, the point emphasized by Lu et al. is early diagnosis. They point out the importance of correct diagnosis and analysis in breast cancer and say that early detection and diagnosis are the key to reducing the risk of death. Based on medical imaging methods commonly used in the diagnosis of breast cancer, some approaches have been examined to detect breast cancer using computer vision and machine learning techniques. As a result, the data were analyzed by comparing the performances of different methods on histological images and mammography images [12].

In their study, Mashekova and her colleagues, unlike others, predicted that breast cancer is the most common fatal disease in women and that this disease can also affect men. They agreed that the best way to get a quick response during the treatment process of the disease is early diagnosis. Although the screenings for breast cancer today vary, these screenings also have various advantages and disadvantages. Thermography, one of the breast cancer screening methods, is considered safe compared to other methods. This method attracts attention with its smart classification feature and new image processing features. This method has great potential in terms of its low cost, use of contactless technology, and mass screening and continuous monitoring of patients for early diagnosis. This study by Mashekova and her friends emphasized the importance of deep learning fields as well as numerical simulation. It allows a more detailed examination of the studies in the literature covering these areas. It also touches upon the importance of early diagnosis of breast cancer [13].

The literature review focused on comparing and examining the methods used in the research. In addition to these researches, deep learning models are examined and their effects in studies are shown. By combining all these, their effects on the relevant cancer type have been revealed. Its effects and suggestions on current studies are also included. It is thought that it will be an important resource that can support other studies.

3. Material and Methods

Machine learning methods were used in the study. In addition, image processing techniques were also used to make diagnoses. Its further examination and explanation is described in detail.

3.1. Dataset

The dataset moving through the receiver focuses on "IDC", one of the most common subtypes of breast cancer. The dataset includes all cross-sectional images of a total of 162 breast sections scanned with a magnification factor of 40x. 277,524 50x50 segmented patches were extracted from these cross-sectional images. Of these patches, 198,738 represent IDC- negative samples and 78,786 represent IDC+ positive samples as given in Table 1.

Table 1. Detailed View of Number of Datasets.

Class	Magnification	Number of Patches
Invasive Ductal Carcinoma Negative (IDC-)	40x	198,738
Invasive Ductal Carcinoma Positive (IDC+)	40x	78,786
Total	40x	277,524

The filename of each patch is "u_xX_yY_classC.png;" It is formatted as follows. Here, u represents the patient ID, X and Y represent where the patches broke, and C represents the class. Class 0, IDC-; class 1 means IDC+. The figure below describes separating the images in the breast cancer dataset according to their classes and then visualizing randomly selected examples as shown in Figure 2.

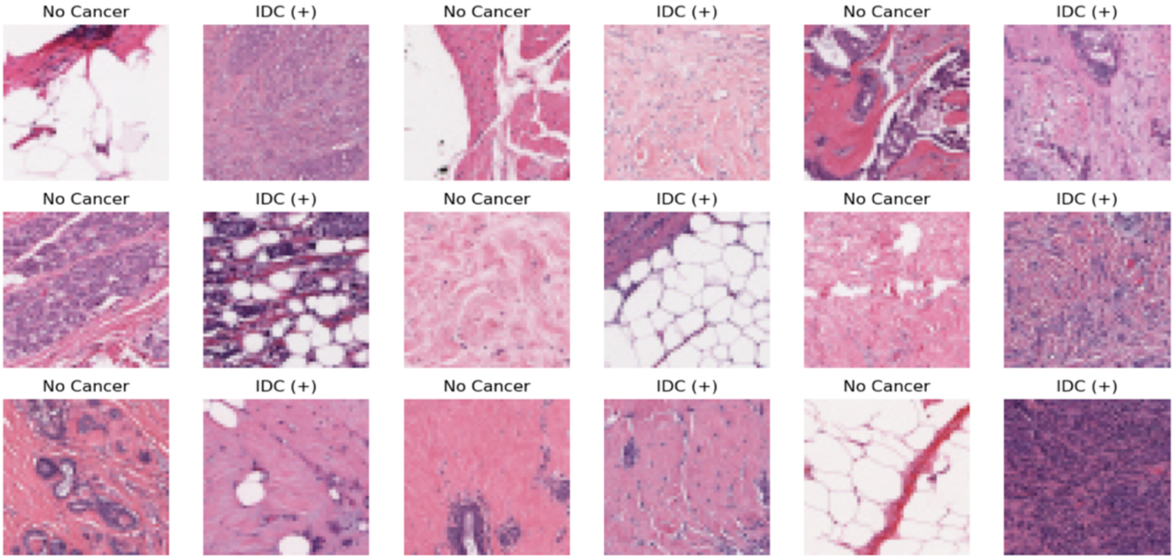


Figure 2. Visualization of IDC+/IDC- (negative and positive) samples.

3.2. Data Preprocessing

Before feeding images to machine learning models, it is critical to pre-process the data for better model performance. Let's examine the data preprocessing stages.

First, images of the IDC+ and IDC- classes were uploaded, then resized and added to the relevant lists to be used in training the model. Additionally, the class label (0 or 1) of each image was determined and this information was added to the relevant list. First, images of the IDC- and IDC+ classes were processed. In both cases, images were first read in color and then resized to 50x50 pixels. The resized images were added to their respective lists along with their tags.

These steps aim to bring the data set into a suitable format that the model can learn from. In other words, a data structure containing images and labels was created, so it was ready to be used for the training process.

Let's see the numbers of data added to the relevant lists during this process. We can see examples of numbers and total numbers belonging to IDC- and IDC+ classes in the chart below.

After this section, a selected subset of the data added to the relevant lists in the previous step was taken and combined. By mixing this data, X and Y data sets were created to be used for training. For each sample, its features (images) were added to dataset x and its labels were added to dataset y. This process enabled him to create a list containing the features and labels of the samples that make up the data set.

Finally, this data set was processed more effectively. The X array contains the image features, while the Y array contains the corresponding class labels. Thus, the data set was brought to a format suitable for training the model and was made ready to be used in the learning process of the model. Our data set after the operations was as shown in Figure 3.

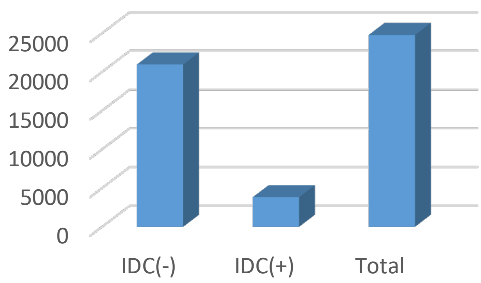


Figure 3. IDC-, IDC+ and total values.

3.3. Analyzing the Performance of Machine Learning Models in Breast Cancer Diagnosis

As for this part of the study, we will focus on the methods used in the diagnosis and diagnosis of breast cancer. The most important of these methods are machine learning and models. Machine learning was used in the study. In addition, different deep learning techniques were also benefited from. It has been observed that techniques such as machine learning and deep learning have been applied in many areas and success has been achieved [14-18]. With the preparation of the data set, the packages were set up step by step. At this stage of the study, both traditional machine learning methods and deep learning models were observed. First, traditional machine learning models such as Support Vector Machines (SVM) and Random Forest (RF) were used to classify the dataset.

SVM a classification algorithm used to separate data into two classes, is considered one of the new supervised machine generator techniques. These models can be accessed by classical multilayer perceptron neural networks. SVMs revolve around a hyperplane that separates two classes of data. This revolves around the term "margin", which creates the largest possible distance between the hyperplane separated by variants in both regions. This has proven effective in reducing the upper bound of expected generalization error [19].

In breast cancer diagnosis, SVMs offer a powerful option for samples belonging to different categories. The ability to define a distinct margin between different classes makes SVMs particularly effective in scenarios involving parts that are not between data classes.

RF a combinatorial machine learning algorithm, is an ensemble method created by combining multiple decision trees. First, RF is combined into classifying a set of trees, yielding the unit to the most popular class. Then, the obtained data are combined to obtain the final ranking result. RF not only has high classification accuracy but also manages to eliminate noise by detecting inappropriate values. RF is preferred as one of the most popular research methods in data mining and biological fields. RF has a wide range of applications in classification tasks and regression analysis. Since each tree is trained on a subset of the dataset, its generalization capabilities are also high. Additionally, the contributions of each tree are combined to improve the overall performance of the model. This method is especially useful for obtaining effective results on complex and noisy data sets. Advantages of RF include resistance to overfitting, the ability to understand relationships between features, and automatic feature selection. Therefore, using RF to analyze complex medical data sets, such as breast cancer diagnosis, has significant potential for accuracy and reliability [20].

The literature was evaluated on prominent points in the field of deep learning. In this context, deep learning models such as CNN, DenseNet and MobileNet were also investigated. These models have complex architectures that are especially effective in image classification tasks.

In CNN, which is called a type of artificial neural network, the output of each layer is used as the input of the next detailed range. To transform the layer results in a non-linear manner, multi-layer convolution is used and this process continues until the output channel [21].

DenseNet uses denser connections by connecting one layer between connections to previous ones. These dense connections not only alleviate the learning problem but also enable feature reuse. In this context, it is recommended to use various deep learning approaches with denser connections after DenseNet [22].

MobilNet, a network developed to increase the real-time performance of deep learning, provides connections under limited hardware conditions. The most important feature of this network is that it has a very high accuracy rate and can reduce the number of parameters [23].

Each model was tested against the validation dataset for performance evaluation. To measure model performance, measurements were made based on accuracy, precision, recall and F_1 score. It is thought that the performance and prominent features of these models will be a guide for the application of machine learning in the diagnosis of breast cancer.

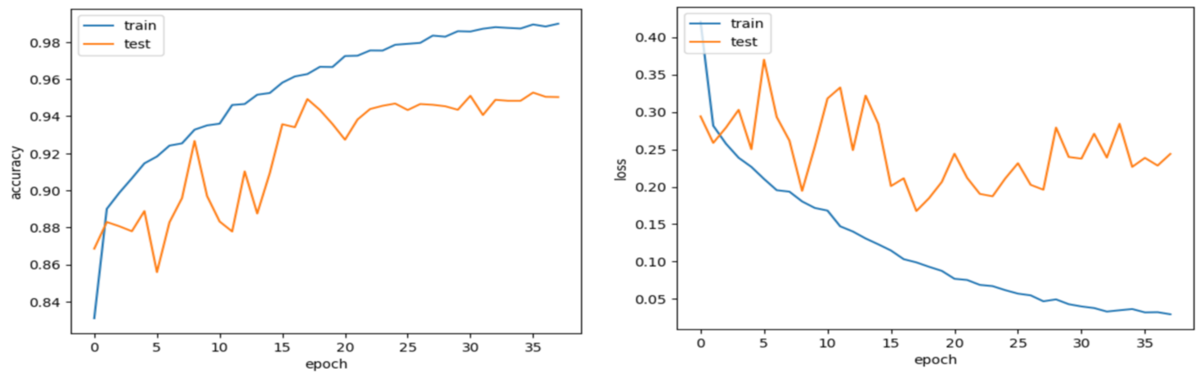
4. Results and Discussion

The aim of this study is to compare machine learning and deep learning models for classification of breast cancer tissues. As a result of experiments using different models such as SVM, CNN, RF, MobileNet and DenseNet, the results of the research were supported as to which model gives more effective results in breast cancer diagnosis.

During the training and evaluation phase of each model, the performance criteria include accuracy rate, sensitivity, freedom and F_1 scores. Additionally, the performance of the models was examined in detail through loss functions and confusion matrices. The analysis in this study allowed us to identify the strengths and weaknesses of each model and find the appropriate model for the categorization task.

As a result of the research, it was determined that the deep learning models MobileNet and DenseNet showed superior performance even under limited hardware conditions. However, it should be noted that each model should be evaluated in the context of its advantages and application. Based on these results, it is predicted that the models developed for the diagnosis of breast cancer can be used as an auxiliary tool that can be preferred in clinical applications.

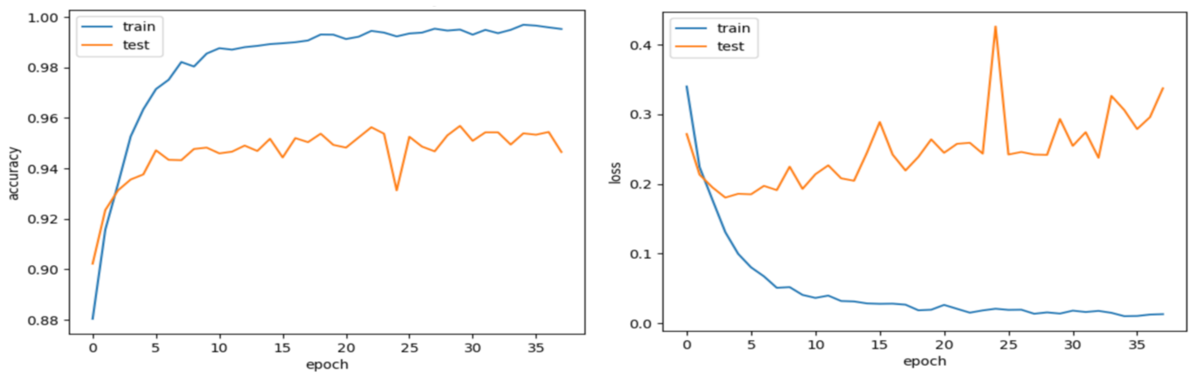
Let’s examine the results obtained in more detail, focusing on the detailed performance analysis of each model. An evaluation was made on the performance of the CNN model. In the evaluation, the model was subjected to test accuracy separately in each period in the training phase, in the graph showing the success. Additionally, the loss graph showing the learning process of the model was also examined. The training accuracy graph shows that the model is achieving increasing accuracy on the training data. The test accuracy graph represents the generalization ability of the model. The similarity between the model's training process and test accuracy shows that the model avoids overfitting and can generalize. When the loss graph was examined, a decrease in training and testing losses was observed. This reduction demonstrates the model's ability to effectively learn and parse data. As a result, we can say that the CNN model has a successful performance in breast cancer diagnosis. The high accuracy values obtained by the model during the training process show its usability as a potential auxiliary tool for breast cancer diagnosis as shown in Figure 4a and Figure 4b.



(a) CNN model accuracy (b) CNN model loss

Figure 4. CNN model a) Model accuracy b) Model loss.

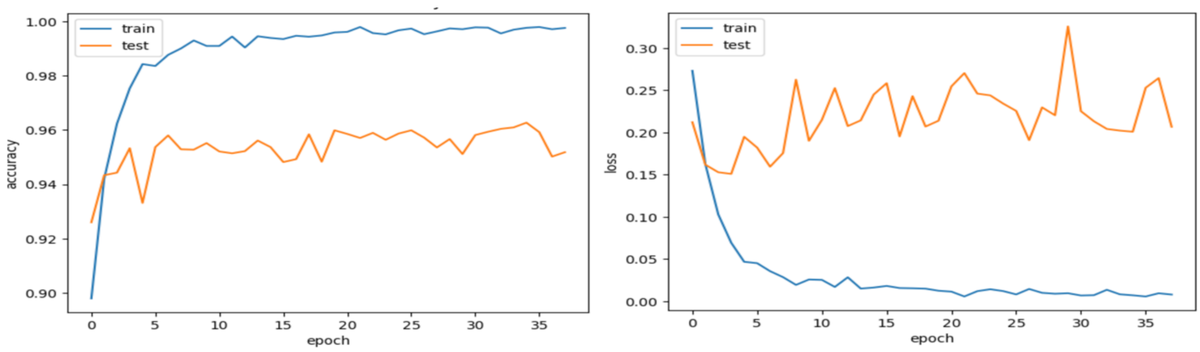
If we talk about the performance of the MobileNet model, as a result of the evaluation, it can be said that the model can achieve a successful result in breast cancer diagnosis as shown in Figure 5a and Figure 5b. The high accuracy values obtained by the model during the training process show its usability as a potential auxiliary tool for breast cancer diagnosis.



(a) MobileNet model accuracy (b) MobileNet model loss

Figure 5. MolineNet model a) Model accuracy b) Model loss.

It can be said that the DenseNet model has an impressive performance in breast cancer diagnosis. The high accuracy values obtained by the model during the training process show that it can be used as a reliable tool for breast cancer diagnosis as shown in Figure 6a and Figure 6b.



(a) DenseNet model accuracy (b) DenseNet model loss

Figure 6. DenseNet model a) Model accuracy b) Model loss.

One of the methods used in the study is SVM. A study was conducted to detect the type of cancer related to the SVM model. SVM results were evaluated. ROC analysis was used to demonstrate its performance. When looking at ROC analysis, is a tool that shows the relationship between the sensitivity and specificity of the model and turns it into a graph. The results obtained with SVM are expressed in orange color on the graph. The part under the curve represents the classification success of the model used. As the value remaining in this section increases, the performance results of the model also increase and are directly proportional. The blue line represents random classification. The fact that the model tested for training is above this line indicates that it achieved a better result than the one tested. As can be seen from Figure 7, the accuracy of the model showed better performance than the accuracy of a randomly selected class.

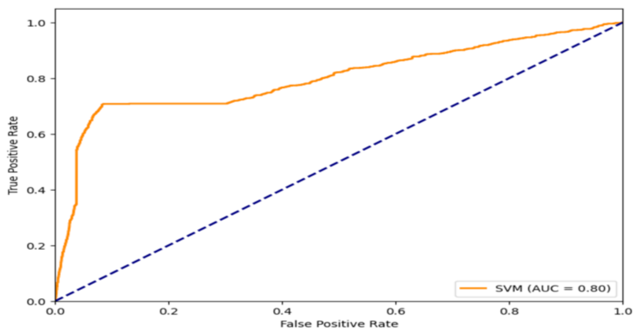


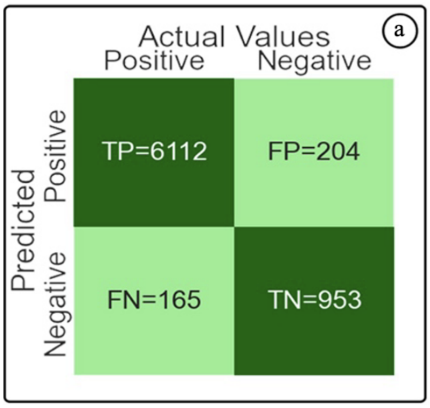
Figure 7. SVM roc curve.

Let's move on to the confusion matrix analysis of the models we used in our study. Confusion matrix analysis means that it shows the confusions between classes of each model as shown in Figure 8. These analyses allowed us to perceive and better understand the advantages and disadvantages of the models. The analyses and percentage equivalents of these models are shown below, respectively.

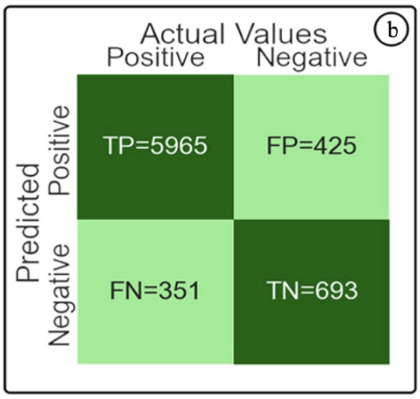
The study evaluated the performance of deep learning models used in breast cancer diagnosis and treatment. Various models such as CNN, SVM, RF, DenseNet and MobileNet have been trained and subjected to various tests. The analysis results are as follows as shown in Table 2:

- CNN Model: It has a 95.1% accuracy rate. F_1-Score, Recall and Precision values were measured as 0.95, 0.95 and 0.95, respectively.
- SVM Model: It has a 89.87% accuracy rate. F_1-Score, Recall and Precision values were measured as 0.89, 0.90 and 0.89, respectively.

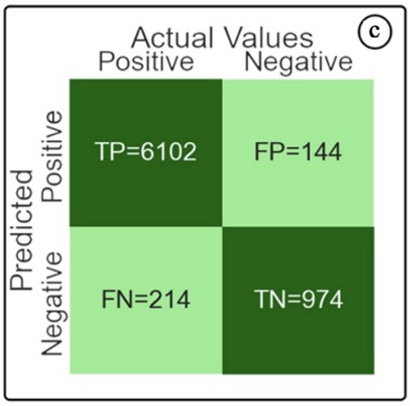
- Random Forest Model: It has a 93.21% accuracy rate. F_1-Score, Recall and Precision values were measured as 0.93, 0.93 and 0.94, respectively.
- DenseNet Model: It has a 94.31% accuracy rate. F_1-Score, Recall and Precision values were measured as 0.95, 0.95 and 0.95, respectively.
- MobileNet Model: It has a 94.6% accuracy rate. F_1-Score, Recall and Precision values were measured as 0.94, 0.95 and 0.95, respectively.



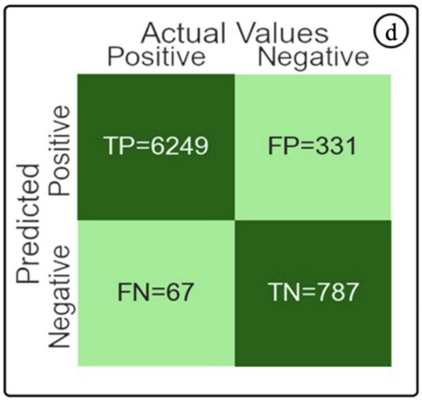
(a) Confusion matrix, CNN.



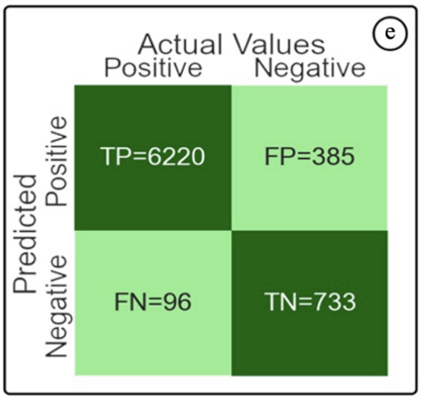
(b) Confusion matrix, SVM.



(c) Confusion matrix, DenseNet.



(d) Confusion matrix, MobileNet.



(e) Confusion matrix, RF.

Figure 8. (a) CNN, (b) SVM, (c) DenseNet, (d) MobileNet, (e) RF Confusion matrices.

The results are shown in a detailed analysis covering the performances of various deep learning models used in the diagnosis and treatment of breast cancer. Different models such as CNN, SVM, RF, DenseNet and

MobileNet were evaluated based on accuracy rates and classification metrics. The findings reveal the advantages and limitations of each model; It has been observed that models such as CNN and DenseNet have high accuracy rates and balanced F_1-Score, Recall and Precision values.

These results shed important light on understanding and improving the effectiveness of deep learning models for breast cancer diagnosis and treatment. However, other models such as SVM also appear to be effective in certain situations. The analysis can guide future research and clinical practices and inspire studies to obtain more precise and reliable results in disease detection and treatment planning.

Table 2. Experimental results.

Model	Accuracy (%)	F_1-Score	Recall	Precision
CNN	**95.1**	0.950712	0.950363	**0.951150**
SVM	89.8	0.894132	0.895615	**0.892930**
Random Forest	93.2	0.931609	0.933818	**0.935169**
DenseNet	94.3	0.952440	0.951843	**0.953322**
MobileNet	**94.6**	**0.943427**	**0.946462**	**0.945463**

This study provides an in-depth evaluation on a wide range of models, including various machine learning models. The results obtained were compared with the performance rates in different studies. The table below provides a comprehensive evaluation of the various metrics used when measuring the performance of these models as presented in Table 3.

Table 3. Comparison results.

Article	Model	Accuracy (%)
Proposed approach	CNN	**95.1**
	SVM	89.8
	Random Forest	93.2
	DenseNet	94.3
	MobileNet	94.6
A Dataset for Breast Cancer Histopathological Image Classification [24]	1-NN	91.5
A Dataset for Breast Cancer Histopathological Image Classification [24]	Random Forest	92.3
Convolutional Neural Network for Classification of Histopathology Images for Breast Cancer Detection [25]	CNN	93.5
Detection of Breast Cancer Using Histopathological Image Classification Dataset with Deep Learning Techniques [26]	SVM	86.1
Detection of Breast Cancer Using Histopathological Image Classification Dataset with Deep Learning Techniques [26]	K-NN	76.1
BRACS: A Dataset for BReAst Carcinoma Subtyping in H&E Histology Images [27]	WSI	70.3
An SVM approach towards breast cancer classification from H&E-stained histopathology images based on integrated features [28]	SVM	91.0
An SVM approach towards breast cancer classification from H&E-stained histopathology images based on integrated features [28]	Random Forest	85.0
Breast cancer detection from histopathology images with deep inception and residual blocks [29]	ResNet	79.0
Breast cancer detection from histopathology images with deep inception and residual blocks [29]	SVM	83.0

Since the highest accuracy rate was obtained with the CNN algorithm, the training and hyperparameters of this algorithm are given in Table 4 as follows.

Table 4. Selected hyperparameters for CNN model.

Layers	Dropout	optimizer	Learning rate	Loss function	Early stop	Activation function	Test split	Total params
10	.3	Adam	1e-4	Binary crossentropy	5 epochs	Relu - softmax	.3	3.36e6

The table above shows the models used in studies conducted on similar data sets regarding breast cancer and their success rates. In this article, the performances of the used models were analyzed in detail by comparing them with the results of previous studies in the literature. The results obtained reveal important similarities and differences between the prominent models of this study and the models in other literature. This comparison serves as an important resource for the current evaluation in the development of models for breast cancer diagnosis and treatment.

In this context, the analysis results show that deep learning models have the power to be used effectively in the diagnosis of breast cancer. Especially CNN and DenseNet models stand out with their high accuracy rates and classification metrics. The findings encourage further exploration of deep learning models in clinical applications.

5. Conclusion

This study focuses on the early diagnosis of invasive ductal carcinoma (IDC), the most common and aggressive type of breast cancer found in women globally. IDC poses a significant threat to women's health, and early detection is critical to improving survival rates and reducing mortality. Traditional diagnostic methods, such as mammography, often face challenges in accurately detecting early-stage cancer due to the complexity and time required for image interpretation. To address these limitations, this research leverages deep learning techniques, which have the potential to provide faster and more accurate diagnostics through automated image processing.

The primary objective of this study is to explore the effectiveness of deep learning models in the classification of IDC-positive and IDC-negative breast cancer cells. A dataset comprising thousands of breast cancer histopathology images was used, and image processing techniques were applied to prepare the data for model training. Five state-of-the-art deep learning models were utilized: Convolutional Neural Network (CNN), Support Vector Machine (SVM), Random Forest, DenseNet, and MobileNet. Each model was trained to analyze and classify the breast cancer images, distinguishing cancerous cells from non-cancerous cells.

The results of the analysis demonstrated that all models performed well, but some outperformed others in terms of accuracy and efficiency. CNN and DenseNet emerged as the top-performing models, with accuracy rates of 95.1% and 94.31%, respectively. MobileNet also exhibited strong performance with an accuracy rate of 94.6%, followed by Random Forest with 93.21% and SVM with 89.87%. These findings highlight the strength of deep learning models in accurately diagnosing breast cancer compared to traditional machine learning models. The superior performance of CNN and DenseNet, in particular, suggests that they have the potential to be integrated into clinical practice to assist pathologists in making faster and more accurate diagnoses. In addition, comparisons were made with models in studies conducted with artificial intelligence in the field of health [30], further validating the robustness and applicability of these models in medical diagnostics.

In conclusion, this study provides a comprehensive evaluation of multiple deep learning models in the context of breast cancer diagnosis. The comparative analysis of these models offers valuable insights into their strengths and weaknesses. CNN and DenseNet, with their high accuracy and robust classification metrics, show significant promise for clinical applications, especially in assisting with early diagnosis where time and precision are of utmost importance. This research underscores the potential of artificial intelligence to revolutionize cancer diagnosis, offering more reliable and efficient diagnostic tools that can significantly impact patient outcomes. Future research should focus on optimizing these models for real-time clinical use, expanding the dataset to include more diverse samples, and exploring ways to reduce the computational complexity of deep learning models to facilitate their integration into everyday medical practice. If these methods are applied efficiently, they could lead to earlier detection, more effective treatment planning, and ultimately, a reduction in breast cancer mortality worldwide.

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