Breast Cancer Detection with Machine Learning Algorithms

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Introduction

Cancer is a life-threatening disease caused by the uncontrolled division and growth of cells in a specific organ or tissue in the body. Currently, over 100 types of cancer are recognized, classified based on their behavior and response to treatment. A critical aspect of cancer pathology is determining whether tumor cells are benign or malignant, which is essential for accurate diagnosis and effective treatment planning (Cooper, 2000).

Cancer ranks as the second leading cause of death globally, claiming an estimated 9.6 million lives in 2018 alone (MHDF, 2021).

Tumors are masses formed by the uncontrolled growth of cells. While benign tumors remain localized and do not spread, malignant tumors can invade surrounding tissues and spread to other parts of the body. Cancer begins when abnormal cells multiply uncontrollably. In this context, a benign tumor is confined to its original location and does not harm surrounding tissues. In contrast, a malignant tumor invades nearby tissues and attempts to spread beyond its site of origin, often reaching other organs through the lymphatic system and bloodstream. Therefore, early detection plays a crucial role in the effective treatment of cancer (Patel, 2020).

Breast cancer is the most prevalent health issue worldwide. It is a life-threatening disease for women and ranks among the leading causes of death in the female population (Akram et al., 2017).

Cancer is the most commonly diagnosed disease in the majority of countries and is the leading cause of cancer-related deaths in over 100 nations (Bray et al., 2018).

The risk of developing breast cancer in men is just 1% of the risk faced by women. In countries with a low or medium Human Development Index (HDI), the breast cancer mortality rate is 48%, which is four times higher than in countries with a high or very high HDI (Wild et al., 2020).

According to World Health Organization statistics for 2020, 2.26 million people worldwide were diagnosed with breast cancer, and approximately 685,000 women lost their lives to the disease that year (Ariffin, 2022).

Early diagnosis is crucial to increase survival rates in breast cancer, which is a life-threatening disease. Subtypes of breast cancer are directly linked to the treatment process (Uddin & Wang, 2022).

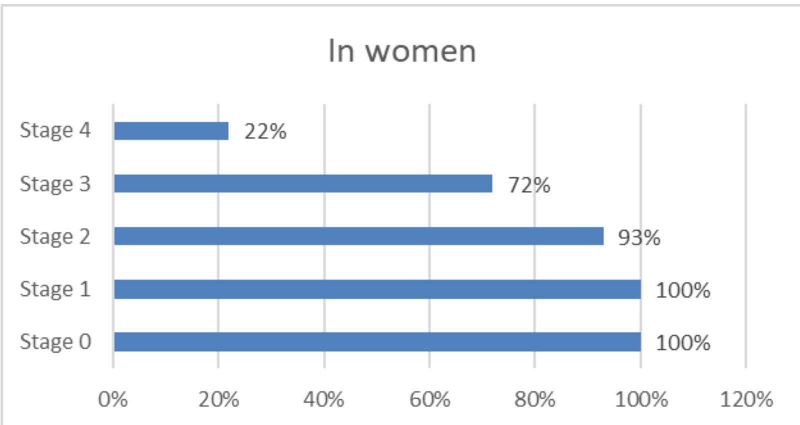
Breast cancer is especially common among women aged 40 to 49 and is the leading cause of cancer-related deaths in women worldwide (Jemal et al., 2010).

Among the 18.1 million cancer cases recorded worldwide in 2018, lung cancer ranked second with 11.6 percent (Bray et al.,2018).

As with all other types of cancer, early detection of breast cancer is crucial in reducing mortality (Tapak et al.,2018).

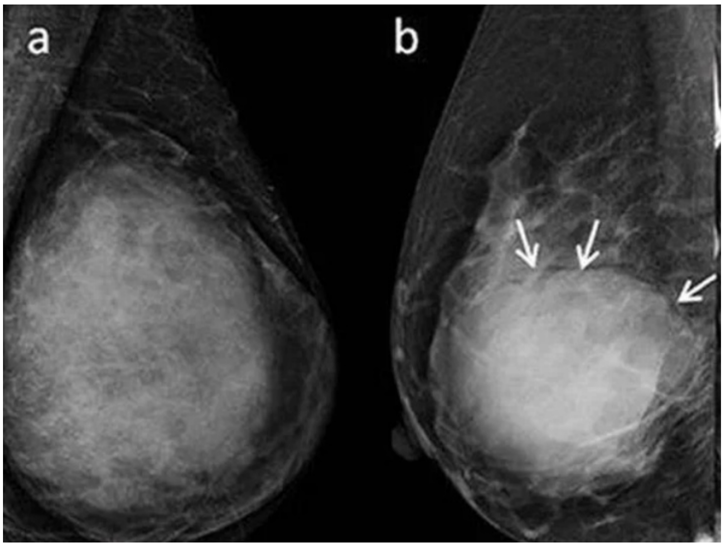
Breast cancer incidence rates have been rising over the past decade in many transitioning countries, with regions in South America, Africa, and Asia experiencing the fastest increases. This may be attributed to demographic factors associated with social and economic development, including high fertility rates, increased obesity and physical inactivity, and limited improvements in breast cancer screening and awareness (Figure 1).

Figure 1
Survival Rates by Breast Cancer Stage



Research indicates that early detection of breast cancer can significantly reduce mortality rates. In breast cancer diagnosis, mammography images examined by radiologists can provide valuable information about the progression of the disease. Figure 2 displays mammograms of benign and malignant breast tissues (Özgür & Keser, 2021).

Figure 2
a) *Mammography Image of a Normal Breast*
b) *A Mammographic Image of a Phylloid Tumor (Özdoğan, 2022).*



Early detection of breast cancer increases the chances of successful treatment and survival. In 61.4% of women, the cancer is diagnosed at stage one, with a five-year survival rate of 98.8% to 100%. For women diagnosed at stage two, the survival rate drops to 93%, for women diagnosed at stage three it drops to 72% and for women diagnosed at stage four it drops to 22%.

It is known that breast cancer occurs in one in every 8 women worldwide and in one in every 9-10 women inTürkiye. As often emphasized, the prognosis for breast cancer is promising when detected early. Table 1 clearly shows the importance of early detection. This situation reveals that new methods are needed to detect even very small malignant tissues (Fear et al., 2002).

Table 1
Relative Chances of Survival According to the Stages of Breast Cancer (Hagness et al., 1998).

Phase	5 Years Relative Survival Chance
0	100%
I	100%
IIA	92%
I B	81%
IIIA	67%
III	54%
IV	27%

Advances in artificial intelligence technologies have led to significant progress in disease diagnosis. Recently, there has been a major breakthrough in the field, particularly with the introduction of deep learning methods and convolutional neural networks. These techniques can even outperform human experts by achieving high performance in classification without the need for predefined feature spaces. Breast cancer diagnosis requires the interpretation of test results, and expert knowledge is essential. With the development of machine learning techniques, successful applications are now being implemented in breast cancer diagnosis (Duggento et al., 2019).

In this context, AI systems can be used as a tool to assist clinicians and radiologists or operate independently. As a result, AI solutions aim to enhance the efficiency of the healthcare system and improve patient outcomes. Recent advances in computer processing power and increased data accessibility have been crucial in the development of computer-aided detection (CADe) and diagnosis (CADx) systems (Hickman, 2021).

The deep learning model developed by Wang et al. (2016) achieved a discrimination accuracy of 87.3% when characterizing microcalcification (calcium deposits in breast tissue) alone.

Liu et al. (2021) developed a deep learning model that combines mammography and clinical variables to predict malignant breast microcalcification in the BI-RADS 4 subgroups evaluated by radiologists. When comparing the performance of radiologists with the combined model in predicting whether breast microcalcification were malignant, they found that the diagnostic capability of the combined model was nearly equivalent to that of a senior radiologist and significantly better than that of a junior radiologist.

By using the least squares support vector machine (LS-SVM) classification algorithm, a 98% success rate has been achieved in breast cancer data (Polat & Güneş, 2007).

Khan et al. (2008) classified breast cancer data using fuzzy decision trees and achieved better results than with independent classifiers.

Delen et al. (2005) developed prediction models using two popular data mining algorithms, artificial neural networks and decision trees, on a large breast cancer dataset. In this study, they achieved an accuracy rate of 93.6% with decision trees and 91.2% with the artificial neural network model.

Akyol (2018) carried out the feature determination process in the breast cancer dataset using the Recursive Feature Selection method and achieved a 98% success rate by applying the random forest algorithm for classification purposes.

Papageorgiou et al. (2015) analyzed the data of 40 patients through a health assistant developed with the fuzzy cognitive map (FCM) method and achieved an accuracy of 95%.

Kolay and Erdoğmuş (2016) classified a breast cancer dataset without any preprocessing using Matlab and Weka software through the K-means method and obtained success rates ranging from 45% to 79% with various parameter changes.

Various results have been obtained based on algorithms, hyperparameters and methods. Using various methods such as decision support machines, decision trees, logistic regression, random forest, K-nearest neighbor, naive bayes and artificial neural networks, accuracy performance between 79.8% and 99% has been achieved (Amrane et al., 2018; Ganggayah et al., 2019; Agarap et al.,2018; Vaka et al., 2021; Akyol, 2017; Sevli, 2019; Mohammed et al., 2020). Despite high success rates, AI-based efforts to optimize breast cancer diagnosis are still ongoing.

The study aims to develop an artificial intelligence model capable of making fast and accurate predictions for the diagnosis of breast cancer, a prevalent disease today. This approach seeks to minimize time and effort in diagnosis while ensuring accurate detection of the disease. Another objective is to train the AI model using diverse and extensive datasets to continually improve diagnostic accuracy. The subsequent sections of the study cover the materials and methods, findings, and conclusions.

Material and Methods

This section explains the proposed model and the steps outlined in the study. First, the algorithm techniques used in the study are described, followed by the process of obtaining and preparing the dataset. Finally, the model-building stages are detailed. To achieve this, the study employed support vector machine (SVM), K-nearest neighbor (KNN), artificial neural network (ANN), random forest, and logistic regression algorithms.

Data Set

The data for this study was obtained from a public platform accessible via the website (URL1). The dataset comprises 2,633 samples, including breast ultrasound images of women aged 25 to 75, collected in 2018. It represents 600 female patients and contains 2,633 images, each averaging 500x500 pixels in PNG format. Both the original and actual images are provided in the dataset, categorized into three classes: normal, benign, and malignant.

The data used in this study consist of benign, malignant, and normal breast ultrasound images. The dataset includes a total of 2,633 breast ultrasound images. A table summarizing the data is provided below.

Table 2

Number and Percentages of Data Used in the Study

Area of Use	Number of Data	Percent (%)
Training	2100	%75
Test	533	%25
Total	2633	%100

Support Vector Machine

SVM is a powerful machine learning algorithm for data classification. It aims to determine a boundary (hyperplane) that maximizes the distance between two classes. To identify this boundary, SVM utilizes data points located on the edge of the classes, known as support vectors. For data that is not linearly separated, it facilitates classification by moving the data to higher dimensions with kernel functions. SVM gives good results, especially for high-dimensional datasets and various classification problems; however, the computational cost can be high for large datasets (Cortes & Vapnik, 1995).

K-Nearest Neighbor Algorithm

In the KNN) algorithm, when adding a new data point, the distance of this point from other points in the existing data set is calculated and its k nearest neighbors are looked at. This technique compares the new data to the existing data, calculates the distance and classifies it. The KNN algorithm is regarded as one of the simplest machine learning algorithms. When a new sample is added to the dataset, its \(k\) nearest neighbors are identified, and the class of the new sample is determined based on these neighbors (Kılınç et al., 2016).

Artificial Neural Network Algorithm

ANNs consist of interconnected elements, like neurons in the human brain. These elements have memories capable of processing information. Artificial Neural Networks (ANNs) are designed to emulate the structure and function of the biological nervous system. They are self-learning algorithmic models capable of learning, memorizing, interpreting, and comparing data (Elmas, 2016).

Random Forest Algorithm

Random Forest, a method introduced by Leo Breiman in 2001, is a model that combines multiple decision trees. When data is processed through N decision trees, the predictions are averaged to make a more accurate overall prediction. Random Forest addresses the issue of overfitting, which is common in traditional decision trees, by splitting the dataset and its attributes into multiple subsets and processing them across different trees (Breiman, 2001).

Logistic Regression Algorithm

Logistic regression is a supervised machine learning algorithm commonly used in classification problems, particularly those involving two classes. Unlike linear regression, it uses the logistic (sigmoid) function to constrain the predicted values between 0 and 1. This ensures that the model's outputs represent probabilities, which can be used in classification tasks. Logistic regression is the preferred method for probabilistic classification and binary decision problems, and it is applied in areas such as disease prediction, customer behavior analysis, and spam detection (Cox, 1958).

Performance Evaluation

Out of the total 2,633 samples, 75% of the dataset was used for training and 25% for testing, with the division being randomized. After training was completed, the classification accuracy was evaluated using the test data. By comparing the classes predicted by the system with the test classes, the proportion of correctly predicted examples determined the overall classification accuracy. In this study, the learning performance was calculated using the confusion matrix, as shown in Table 3. Using the obtained parameters, accuracy, F1 score, precision, and sensitivity values were calculated using the following equations.

Table 3
Confusion matrix

Estimated Values	**Actual Values**	
	Positive	Negative
Positive	True Positive (TP)	False Positive (FP)
Negative	False Negative (FN)	True Negative (TN)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$\mathrm{Re}\,call = \frac{TP}{TP + FN} \tag{2}$$

$$\mathrm{Pr}\,ecision = \frac{TP}{TP + FP} \tag{3}$$

$$F1 = \frac{2\ x\ precesion + recall}{precesion + recall} \tag{4}$$

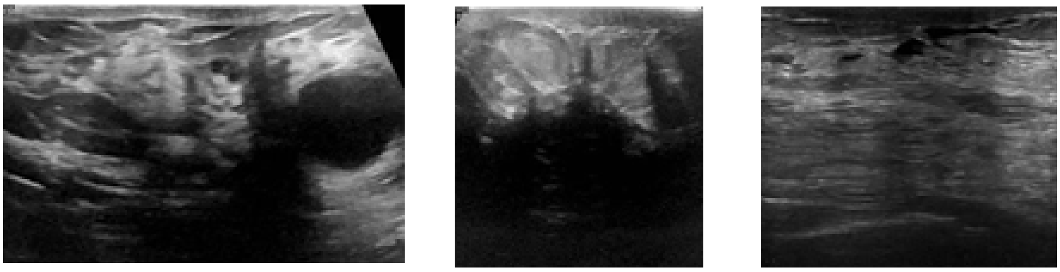
Findings

The model was trained using normal and benign ultrasound images along with images of breast cancer. Therefore, the values of the model's inputs are defined. The input values include normal, benign and malignant ultrasound images. Figure 3 shows examples of the ultrasound images used in the study.

Figure 3

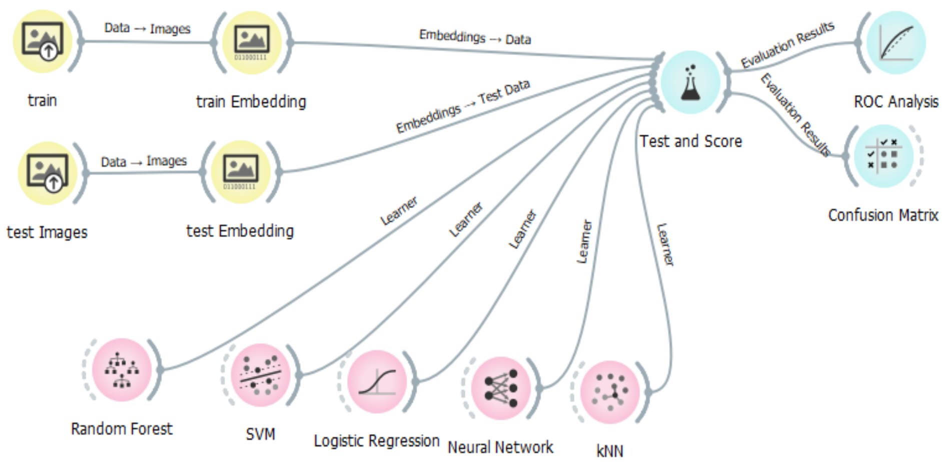
Benign, Malignant and Normal Breast Ultrasounds

Benign *Malignant* *Normal*



The breast cancer detection model used in this study is shown in Figure 4. In the data analysis program, the image data is divided into two groups: training and test data. The input data is processed, and models are then created using three different algorithms. In the "Test and Score" section, the results and performance metrics of these models are presented in tables. Following the Test and Score section, visualizations of the test data are displayed according to the algorithms. These visualizations include the accuracy values of each algorithm as percentages, accuracy and loss graphs for the output layer, and other relevant data.

Figure 4
Breast Cancer Detection Model



The dataset containing breast cancer findings was classified separately using SVMs, KNN, ANN, fandom forest and logistic regression models with 533 samples, which constitute 25% of the total 2633 samples. For each model, a confusion matrix was created, accuracy, classification success, sensitivity, predictive accuracy and precision values were calculated and given in Table 4.

Table 4

Classification Achievements of Models

Model Name	AUC	CA	F1	Precision	Recal
SVM	0.958	0.871	0.870	0.872	0.871
KNN	0.966	0.897	0.894	0.895	0.897
ANN	0.979	0.893	0.892	0.893	0.893
Random Forest	0.959	0.831	0.816	0.849	0.831
Logistic Regression	0.975	0.886	0.884	0.895	0.886

Table 5 shows the confusion matrix values for the algorithms used in the study based on the type of tumor. In these algorithms, it is seen that KNN gives the best percentage results in classification success according to benign, malignant and normal categories. In the KNN technique, 89.9 % benign, 90.2 % malignant and 81.0 % normal were obtained.

Table 5

Confusion Matrix Results of the Algorithm Models Used in the Study

SVM

Actual \ Predicted	benign	malignant	normal	Σ
benign	85.5 %	9.7 %	8.3 %	250
malignant	12.2 %	88.3 %	0.0 %	250
normal	2.3 %	2.0 %	91.7 %	33
Σ	262	247	24	533

KNN

Actual \ Predicted	benign	malignant	normal	Σ
benign	89.9 %	6.7 %	9.5 %	250
malignant	7.0 %	90.2 %	9.5 %	250
normal	3.1 %	3.1 %	81.0 %	33
Σ	257	255	21	533

Random Forest

Actual \ Predicted	benign	malignant	normal	Σ
benign	77.6 %	6.7 %	0.0 %	250
malignant	15.5 %	90.2 %	0.0 %	250
normal	6.9 %	3.1 %	100.0 %	33
Σ	303	225	5	533

Logistic Regression

Actual \ Predicted	benign	malignant	normal	Σ
benign	82.8 %	3.2 %	9.1 %	250
malignant	13.4 %	95.9 %	0.0 %	250
normal	3.8 %	0.9 %	90.9 %	33
Σ	291	220	22	533

ANN

Actual \ Predicted	benign	malignant	normal	Σ
benign	89.9 %	6.7 %	9.5 %	250
malignant	7.0 %	90.2 %	9.5 %	250
normal	3.1 %	3.1 %	81.0 %	33
Σ	257	255	21	533

To classify the data using artificial intelligence, the dataset was split into 75% training data and 25% test data. Machine learning algorithms were applied to the dataset, and their performance was evaluated using the test data.

Figure 5
Accuracy Performance of Algorithms in Breast Cancer Diagnosis

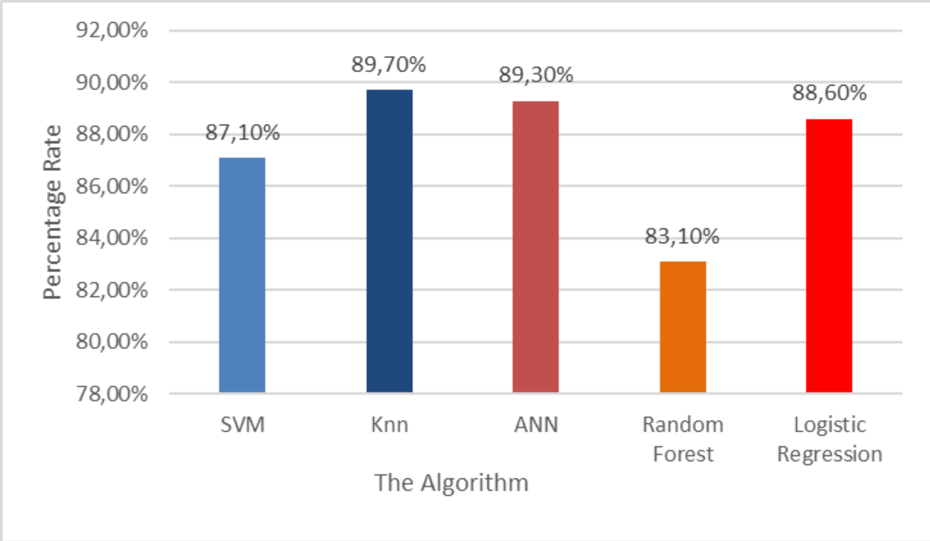


Figure 6 shows the ROC analysis plot of TP and FP plot according to benign breast tomography in diagnosing patients.

Figure 6
ROC Analysis Graph of Benign TP and FP

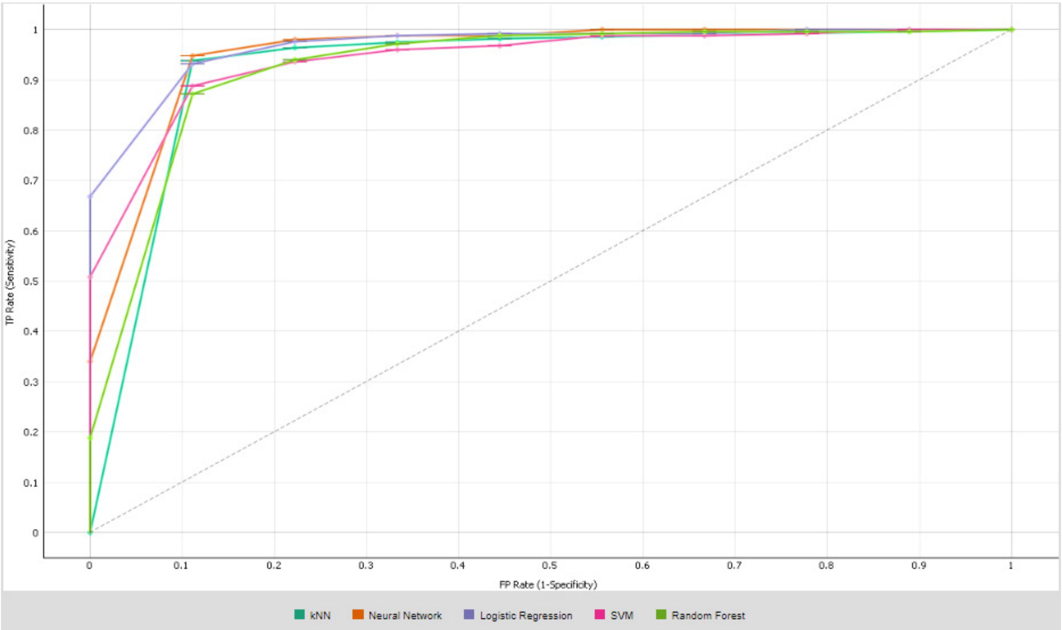


Figure 7 shows the ROC analysis plot of TP and FP plot according to malignant breast tomography in diagnosing patients.

Figure 7
Malignant TP and FP ROC Analysis Graph

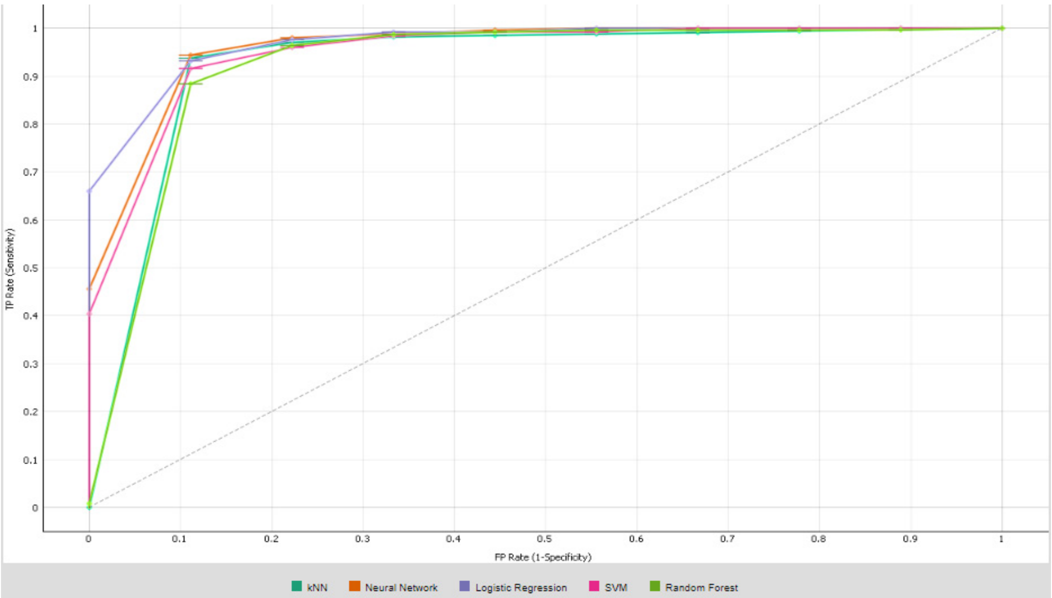
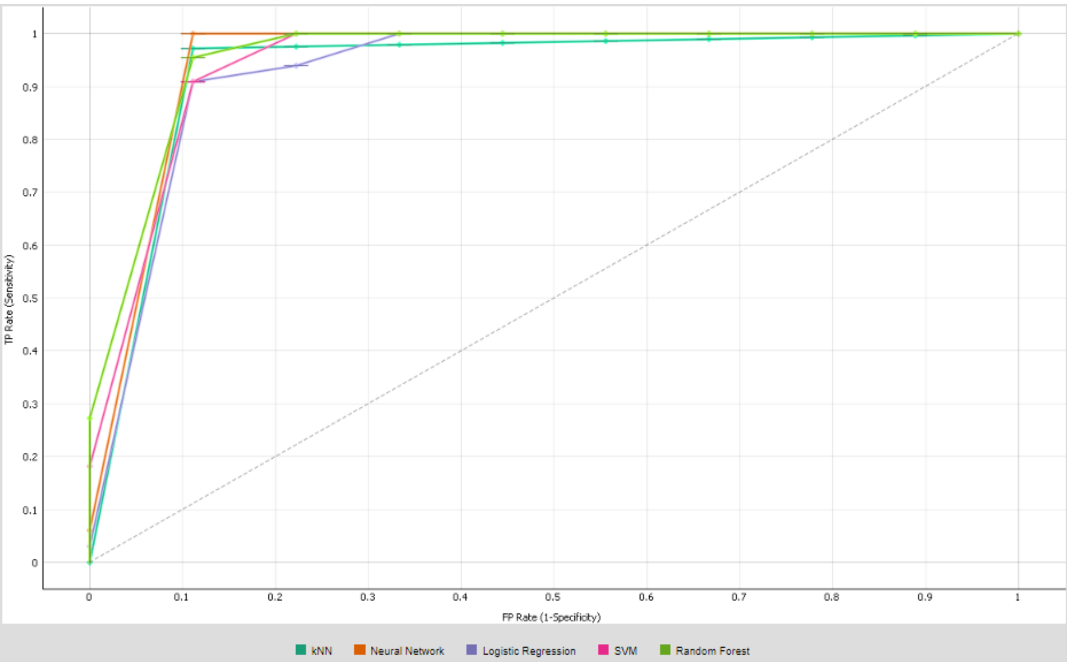


Figure 8 shows the ROC analysis plot of TP and FP graphs compared to normal breast tomography in the diagnosis of patients.

Figure 8
Malignant TP and FP ROC Analysis Graph



When the ROC curve approaches the upper left corner, it indicates a high true positive rate and a large area under the curve. This helps us to understand whether positives are successfully separated from negatives. Analysis of Table 4 reveals that the ANN model outperforms the other models, achieving an AUC value of 0.979.

Results

Tumors that cause cancer disease are divided into multiple classifications as benign, malignant and normal. In this study, benign, malignant and normal tumors that can cause breast cancer were classified. Early diagnosis plays a crucial role in improving the survival rate of breast cancer. In this study, an ANN algorithm is proposed for the early detection of the disease. The proposed model achieved 97.9% AUC, 89.3% CA, 89.2% F1 score, 89.3% precision, and 89.3% recall. Detecting malignant tumors is especially significant in breast cancer diagnosis. An evaluation of the results indicates that the proposed ANN accurately predicts both benign and malignant tumors. These results show that breast cancer can be detected quite successfully based on artificial intelligence. In this direction, it is thought that in future studies, expanding the dataset and learning on larger datasets will provide more successful results.

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