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Diagnosis of Breast Cancer with Hybrid Artificial Intelligence Method

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Abstract

According to the data of 2020, it is seen that 1 of every eight cancers diagnosed worldwide and the 5th among cancers that cause death is breast cancer. Cancer can spread to different organs and reach an incurable stage in patients who are not diagnosed and treated at the right time. Therefore, reducing the time taken for breast cancer diagnosis and reducing mortality rates are of great importance for accurate and early diagnosis of the disease. This study aims to improve the accuracy of cancer detection by using various machine learning algorithms and methods for artificial intelligence-based breast cancer diagnosis. By using ultrasonography images taken from 780 people, image information processed with statistical parameters was extracted. Artificial intelligence-based breast cancer detection was performed by applying three different machine learning algorithms and the hybrid machine learning algorithm designed as a combination of these algorithms on the extracted data set. In this way, early detection of cancerous cells will be carried out without creating advanced risks for the individual, and treatment will be possible.

Keywords: Breast Cancer, Hybrid Artificial Intelligence, Image Preprocessing, Feature Selection, Early Diagnosis

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1. Introduction

The most common cancer in women is breast cancer [1]. It is a disease that occurs as a result of a tumor that occurs due to the uncontrolled proliferation of cells in the breast tissue. Although the exact cause of breast cancer is unknown, factors such as genetics, diet, menstrual period, and birth control pills can be mentioned. Its symptoms are usually palpable swelling, deformity, redness, wound, eczema-like skin shedding in and around the breast [2].

There are many studies in the literature for detecting breast cancer [3]–[5]. For the detection of breast cancer, tests deemed appropriate by the physician are performed after the physical examination [6]. Diagnostic methods used in these tests can be classified as laboratory analysis and imaging methods. While blood and biochemistry tests, tumor detection tests and biopsy are included in the laboratory diagnostic methods, imaging is the more frequently used diagnostic method. The most commonly used imaging methods are mammography, ultrasonography (USG), and magnetic resonance (MR) [3]. However, imaging methods do not seem very advantageous because of their low specificity in identifying cancerous cells and their high cost [4],[7]. Today, with the development of technology, the negativities of these methods have been tried to be eliminated, and artificial intelligence systems have started to be used for diagnostic purposes in the field of health [8]. The importance of using artificial intelligence is understood by making the diagnosis and treatment more accurate and faster and benefiting from health services more effectively and easily. The study aims to detect breast cancer faster and more accurately with computer vision.

The study aimed to develop a hybrid artificial intelligence-based prediction process to classify the presence of breast cancer by using the images obtained from radiological examinations of breast cancer. In line with this goal, after the USG images taken from 780 people were transferred to the computerized environment, the balancing process was applied to eliminate the deviation tendency, and its effect on the system performance was lost. For each processed image matrix, 25 feature extractions were performed. After the feature extraction, the feature selection algorithm was applied, the size optimization was achieved in the matrices, and the USG images were classified as cancerous and healthy. Breast ultrasound, which reveals many conditions in the tissue, was preferred in early diagnosis, assuming that the patient is not exposed to radiation and that there is no dense breast tissue.

2. Material and Method

The application steps in Figure 1 were used to classify ultrasonography (USG) images as cancer and healthy. In detail the materials and methods used when conducting the study. The citations you make from different sources must be given and referenced in references.

According to the application flowchart, 25 statistical features were extracted from the USG images. Extracted images were separated as percentages after the feature selection algorithm. The features with low correlation levels were removed from the data set, and maximum performance was achieved by using performance evaluation criteria.

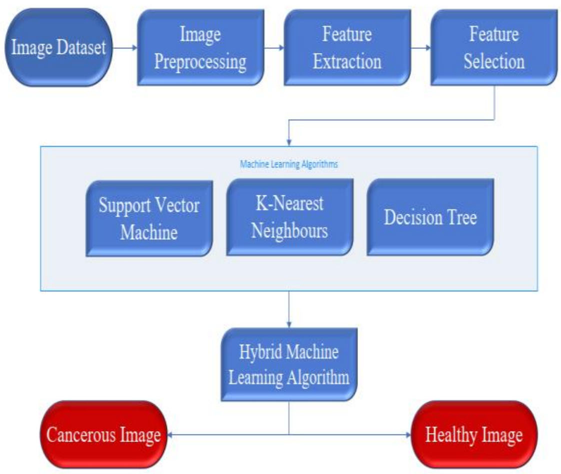

Fig. 1 Flowchart Application

USG images were classified as cancerous and healthy with the feature sets “kNN”, “SVMs”, “DT” and “Hybrid” models.

Table 1. Table of Cancerous and Healthy Individuals

Cancerous	Healthy	Total
647	133	780

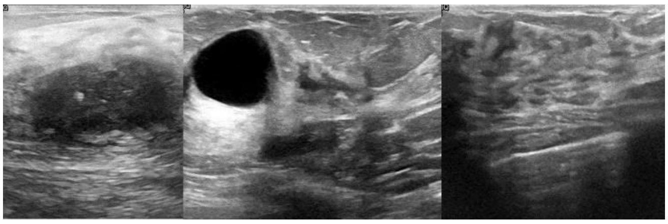

Fig. 2 Sample USG Images

2.1. Feature Extraction

It is necessary to extract information about detecting foreign substances in breast tissue from USG images. Feature selection methods obtain information inference. For this reason, statistical features were extracted from each image in 25-time domains. The feature extraction process was applied to 780 images, of which 647 were patients and 133 were healthy.

2.2. Feature Selection

Feature selection algorithms are a process that is performed in line with the need to extract the features with low correlation values from the dataset and to optimize the matrix size. This study uses the Fisher score algorithm as the feature selection algorithm.

The algorithm calculated correlation values for each feature and correlation levels were determined (Table 2). With these selected values, the ratios of the performance evaluation criteria of different models were created.

Table 2. Representation of Features mathematical and code

Nu	Features	Equation
1	Kurtosis	$x_{karr} = \left(\sum_{i=1}^{n} (x(i) - \bar{x})^4 \right) / ((n-1)S^4)$
2	Skewness	$x_{sle} = \frac{\sum_{i=1}^{n} (x_{\bar{\imath}} - \bar{x})^3}{(n-1)S^3}$
3	* *IQR	$IQR = \mathrm{iqr}(x)$
4	CV	$DK = (S/\bar{x})100$
5	Geometric Mean	$G = \sqrt[n]{x_1 + \cdots + x_n}$
6	Harmonic Mean	$H = n/\left(\frac{1}{x_1} + \cdots + \frac{1}{x_n}\right)$
7	Activity - Hjort Parameters	$A = S^2$
8	Mobility - Hjort Parameters	$M = S_1^2/S^2$
9	Complexity - Hjort Parameters	$C = \sqrt{(S_2^2/S_1^2)^2 - (S_1^2/S^2)^2}$
10	* Maximum	$x_{i_{max}} = max(x_i)$
11	Median	$\tilde{x} = \begin{cases} \frac{x_{n+1}}{2} & = x \text{ odd} \\ \frac{1}{2}\left(x_{\frac{n}{2}} + x_{\frac{n}{2}+1}\right) & = x \text{ even} \end{cases}$
12	* Mean Absolute Deviation	$MAD = \mathrm{mad}(x)$
13	* Minimum	$x_{min} = min(x_i)$
14	* Central moments	CM =moment (x,10)
15	Mean	$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} = \frac{1}{n}(x_1 + \cdots + x_n)$
16	Average Curve Lenght	$CL = \frac{1}{n}\sum_{i=2}^{n} \lvert x_{\bar{\imath}} - x_{\bar{\imath}-1} \rvert$
17	Average Energy	$E = \frac{1}{n}\sum_{i=1}^{n} x_i^2$
18	Root Mean Squared	$X_{rms} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \lvert x_i \rvert^2}$
19	Standard Error	$S_x = S/\sqrt{n}$
20	Standard Deviation	$S = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (x_i - \bar{x})}$
21	Shape Factor	$SF = X_{rus}/\left(\frac{1}{n}\sum_{i=1}^{n} \sqrt{\lvert x_i \rvert}\right)$
22	* Singular Value Decomposition	$SVD = svd(x)$
23	* %25 Trimmed Mean	$T25 = \mathrm{trimmean}(x, 25)$
24	* %50 Trimmed Mean	$T50 = \mathrm{trimmean}(x, 50)$
25	Average Teager Energy	$TE = \frac{1}{n}\sum_{i=3}^{n} (x_{i-1}^2 - x_i x_{i-2})$

Table 3. Selected properties table

Level	Percent	Feature Count	Feature Number	Fischer Score
1	5	1	14	0.0604
2	10	3	12	0.0359
			1	0.0197
3	15	4	23	0.0197
4	20	5	24	0.0195
5	25	6	10	0.0181
6	30	8	13	0.0174
			18	0.0162
7	35	9	25	0.0147
8	40	10	16	0.0119
9	45	11	19	0.0107
10	50	13	15	0.0065
			6	0.0062
11	100	25	4	0.0057
			5	0.0052
			7	0.0047
			21	0.0039
			17	0.0031
			9	0.0027
			11	0.0026
			22	0.0023
			8	0.0022
			3	0.0019
			2	0.0016
			20	0.0006

2.3. Performance Evaluation Criteria

There is a need for systems that work with reliable accuracy in detecting cancerous cells. The higher this ratio, the higher the diagnostic reliability will be. Different processes have been processed so far in line with the study's objectives. By optimizing the USG image matrix size with feature extraction, only 11 of 25 features were selected with the Fisher score algorithm. The performance value of each level was calculated with the classification processes applied to the remaining dataset. It will be possible to determine which algorithm shows maximum performance. Performance monitoring was performed by separating the data set as %80 training and %20 testings. The six performance evaluation criteria are accuracy rate, sensitivity, specificity, f-measurement, kappa and AUC value. A high level of performance is desired. This shows the success rate when the accuracy rate is %100 or around, and the other criteria are 1 or close to 1. Performance indicators for each classification model are given in Table 3. In line with these criteria, it is evaluated that breast cancer diagnosis can be made with a hybrid algorithm with an accuracy rate of %99.248 at level 7 in the table 4.

3. Results

The study aims to detect the disease by processing USG images of individuals suspected of breast cancer. While making the determination, DT, SVMs, k-NN and Hybrid model algorithms were used. The Fisher feature selection algorithm was used to facilitate image processing. Models were created using the Fischer score values specified with 11 levels and different feature numbers (Table 2).

k-NN, SVMs, DT and Hybrid models were used. The hybrid model effectively increases the performance of the first three models by combining these models. The selected features were created using 11 levels. Twenty-five features have been removed. The percentages of the extracted feature numbers are shown in the table 3.

The performance evaluation criteria of the hybrid model increased at every level and reached their highest values at level 7. For example, all healthy people were found with the specificity value of 1 at level 7. Other values are very close to 100 and 1. The accuracy rate value is 99.24; sensitivity, specificity, f-measurement, kappa and AUC values were 0.98, 1, 0.99, 0.98 and 0.99, respectively. The values close to 1 indicate that the hybrid model is successful.

4. Discussion and Conclusion

This study aims to screen for breast cancer by using USG images in artificial intelligence. In the images in the dataset, there are three separate labels: healthy, benign and malignant tumour. K-NN, SVMs, DT and Hybrid model algorithms were used. The data will be analysed more effortlessly and accurately by comparing the outputs obtained from machine learning algorithms.

The images obtained using the LOGIQ E9 US system and the LOGIQ E9 Agile tool are the results of the algorithms; Accuracy, sensitivity, specificity, F-measurement, Kappa and area under the ROC curve AUC performance evaluation criteria were used and evaluated according to these criteria [9].

Different feature extraction algorithms such as time domain, texture and frequency have been used in the literature. This study developed a statistical-based feature extraction process, unlike the literature. This way, an independent feature extraction process from the data set was preferred.

Some studies in the literature prefer the PCA algorithm for feature reduction. In this study, the feature selection process is preferred over applying a transformation to features. This is because, in models created after PCA, all features need to be extracted again in each diagnostic process. With the feature selection process, only the relevant features are extracted. In this way, the performance of the process will be improved.

The number of studies conducted with deep learning algorithms in the literature is increasing daily. In these structures, feature extraction and selection processes are carried out by deep learning. However, the training period takes quite a long time. It helps re-evaluate the algorithm selection at points where the training process is essential. This study developed a hybrid model with single classifiers to shorten the training time and increase the performance to deep learning levels [10], [11]. This way, the performance rate (%99-100) reached the deep learning performance values in the literature, while the training process was considerably shortened.

When classical machine learning algorithms are used in the literature, segmentation structures are frequently used. In this study, unlike in the literature, segmentation was not performed.

Table 4. Performance Evaluation Table

Level	Model	Performance Evaluation Criteria					
		AR	Sen	Spe	F-Ms	Kappa	AUC
1	DT	57.895	0.731	0.424	0.537	0.156	0.578
	kNN	62.406	0.672	0.576	0.620	0.248	0.624
	SVMs	57.895	0.731	0.424	0.537	0.156	0.578
	Hybrid	75.940	0.925	0.591	0.721	0.518	0.758
2	DT	55.639	0.478	0.636	0.546	0.114	0.557
	kNN	54.135	0.433	0.652	0.520	0.084	0.542
	SVMs	60.150	0.522	0.682	0.592	0.204	0.602
	Hybrid	81.203	0.881	0.742	0.806	0.624	0.812
3	DT	60.902	0.582	0.636	0.608	0.218	0.609
	kNN	61.654	0.597	0.636	0.616	0.233	0.617
	SVMs	61.654	0.537	0.697	0.607	0.234	0.617
	Hybrid	90.977	0.925	0.894	0.909	0.819	0.910
4	DT	57.895	0.806	0.348	0.487	0.155	0.577
	kNN	65.414	0.627	0.682	0.653	0.309	0.654
	SVMs	65.414	0.612	0.697	0.652	0.309	0.654
	Hybrid	78.195	0.836	0.727	0.778	0.564	0.782
5	DT	61.654	0.597	0.636	0.616	0.233	0.617
	kNN	65.414	0.642	0.667	0.654	0.308	0.654
	SVMs	63.158	0.552	0.712	0.622	0.264	0.632
	Hybrid	95.489	0.955	0.955	0.955	0.910	0.955
6	DT	58.647	0.522	0.652	0.579	0.173	0.586
	kNN	63.910	0.597	0.682	0.637	0.279	0.639
	SVMs	59.398	0.582	0.606	0.594	0.188	0.594
	Hybrid	90.977	0.955	0.864	0.907	0.819	0.909
7	DT	54.135	0.313	0.773	0.446	0.086	0.543
	kNN	64.662	0.612	0.682	0.645	0.294	0.647
	SVMs	66.165	0.657	0.667	0.662	0.323	0.662
	Hybrid	99.248	0.985	1.000	0.992	0.985	0.993
8	DT	54.135	0.403	0.682	0.507	0.085	0.542
	kNN	65.414	0.642	0.667	0.654	0.308	0.654
	SVMs	58.647	0.657	0.515	0.577	0.172	0.586
	Hybrid	93.985	0.896	0.985	0.938	0.880	0.940
9	DT	57.143	0.448	0.697	0.545	0.144	0.572
	kNN	64.662	0.612	0.682	0.645	0.294	0.647
	SVMs	57.143	0.403	0.742	0.522	0.145	0.573
	Hybrid	93.233	0.881	0.985	0.930	0.865	0.933
10	DT	54.887	0.299	0.803	0.435	0.101	0.551
	kNN	65.414	0.627	0.682	0.653	0.309	0.654
	SVMs	55.639	0.448	0.667	0.536	0.114	0.557
	Hybrid	91.729	0.836	1.000	0.911	0.835	0.918
11	DT	62.406	0.552	0.697	0.616	0.249	0.625
	kNN	63.158	0.582	0.682	0.628	0.264	0.632
	SVMs	60.902	0.627	0.591	0.608	0.218	0.609
	Hybrid	99.248	0.985	1.000	0.992	0.985	0.993

A: Accuracy, Se: Sensitivity, Sp: Specificity
F-Ms: F-Measurement

In this way, the segmentation workload is reduced. Even if there is no segmentation in terms of performance, high performance in the deep learning process has been achieved (Table 4 - %99-100) [9], [10].

The study aims to increase the performance of these data by using the data obtained from cancerous and healthy people. According to the results we obtained, the ones with the best performance were selected from the images of breast cancer patients in the USG screening process. AUC performance evaluation criteria were used. k-NN, SVMs, DT and Hybrid algorithms were used. Some of the innovations obtained according to the literature review are as follows. (1) Performance has been increased using model performance evaluation criteria. (2) The best performance values were established using the hybrid model.

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