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Examining Thyroid Cancer Diagnosis: Harnessing Machine Learning for Early Risk Detection

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ABSTRACT

Thyroid cancer is a common type of cancer that begins to form in thyroid gland cells, which has been seen frequently in recent years. Thyroid cancer is a malignancy that develops in the cells of the thyroid gland and is an increasing health problem worldwide. Thyroid cancer grows slowly and usually has no symptoms in the early stages. Therefore, detecting thyroid cancer in the early stages is of great importance. Thyroid cancer is a type of disease with high treatment success when the risk is detected at an early stage, and correct diagnosis and treatment is applied to prevent cancer. Therefore, this study aimed to detect the risk of thyroid cancer at an early stage with the help of computer-aided systems. Thanks to these systems, experts' workloads will be lightened, and the errors experts can make will be minimized. This study used four machine learning methods to determine the risk stage of thyroid cancer. The dataset used in the study is a public data set and consists of 16 features and 383 samples. Different performance measurement metrics were used to evaluate the performance of the models. As a result, when the results obtained in the study were examined, it was shown that machine learning methods achieved competitive results in detecting the risk of thyroid cancer.

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1. INTRODUCTION

Research in the health field is carried out on the correct diagnosis of the disease and the application of the correct treatment. With a suitable treatment method, it is possible to stop the disease and even eliminate its effects. Thyroid disease is among the diseases that can be treated when diagnosed correctly [1]. By integrating artificial intelligence systems into studies in the health field, systems that will support doctors in their decisions are being developed. Sometimes, there may be situations that cannot be noticed by the eye. In this case, performing tests on people other than imaging devices and analyzing them with a decision support system can make the work of specialists easier. In case of early diagnosis, the disease can be overcome with a shorter treatment period. In addition, determining the stage of the disease is also essential at the point of treatment.

Thyroid cancer is one of the most common cancers today, with two different types: papillary and follicular [2]. Physicians may encounter some difficulties during the thyroid cancer treatment phase. Among these difficulties, patients' risk levels can be determined correctly and treatment approaches can be balanced. Preventing overtreatment of patients with low-risk or benign thyroid nodules and ensuring that they receive balanced drug therapy is of great importance for the patient's comfort in life [1].

Artificial intelligence techniques are used to diagnose many diseases to detect thyroid cancer. While these studies can be used separately, such as image processing, data analysis, and classification methods, results can be obtained together. Kim et al. [3] determined the levels of thyroid disease statistically examined them and observed an increase in nodules depending on age. Hall et al. [4] attribute the increase in the disease to the increasing number of tests. Their research stated that the number of tests increased by 18% yearly, as did the detection of asymptomatic nodules. Zhang et al. [5] proposed a method to detect the disease using ultrasound images and computed tomography scans with the CNN model they proposed. Ahmad et al. [6] proposed a model that applies LDA, KNN, and ANFIS to a thyroid disease dataset. In their proposed method, they first reduced the number of features with LDA, then classified them with KNN, and finally diagnosed them with the ANFIS neurofuzzy diagnosis system.

This study focused on the performance of different machine learning methods to detect the risk level of thyroid cancer. The methods and data set used in the study were examined in the rest of the article, followed by the application results, and the article was completed with the conclusion section.

2. BACKGROUND

In this study, machine learning algorithms were used to detect the risk stage of thyroid cancer. Four different techniques were used in this process. The method developed to detect the risk stage of thyroid cancer is presented in Figure 1.

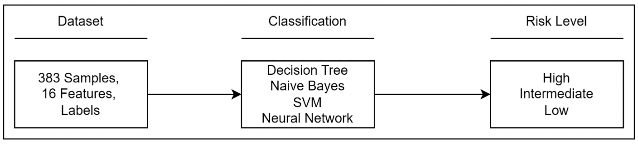

Figure 1. Steps taken to determine the risk stage of thyroid cancer

2.1. Support Vector Machine (SVM):

The SVM algorithm is a machine learning algorithm widely used in classification and regression problems. When classifying data, SVM takes an optimized approach to determine decision boundaries. The aim is to create a decision boundary that maximizes the marginal gap between classes. However, the success of SVM, especially when working with data sets that are not linearly separable, relies on the kernel functions used to transform the data in high-dimensional space. These kernel functions transform the data into the feature space, making it linearly separable. The disadvantage of SVM is that it is costly regarding memory and computing power, especially when working with large data sets [7, 8].

2.2. Naive Bayes (NB):

A Naive Bayes classifier is a probability-based classification algorithm based on Bayes Theorem. This algorithm works with the assumption of independence between features. Naive Bayes is used to model the relationship of features with the target variable to be classified. Naive Bayes classifier is simple and fast in model training and prediction processes. Therefore, it is a classifier frequently used in the literature. This classifier produces successful results, especially in small data sets [9, 10].

2.3. Decision Trees (DT):

Decision Tree is an easily understandable and interpretable machine learning algorithm for classification and regression problems. Its primary purpose is to create a set of decision rules to predict or classify the target variable based on the values of features in the dataset. Decision Tree tries to increase the homogeneity in each partition by splitting the dataset using a tree structure. These splits occur at nodes called decision nodes, and a feature value is tested at each node. Each branch represents the decision rule of an attribute value and the journey to the next node [11, 12].

2.4. Neural Network

Neural Network classifiers are a powerful machine learning technique for solving complex classification problems using deep learning models, also known as artificial neural networks. These classifiers are inspired by biological neural networks and contain a set of artificial neurons in a multilayer structure. Each neuron feeds inputs into an activation function and produces output using the weights and slope learned from the input data. In classification tasks, artificial neural network classifiers use layers and connections of these neurons to process input data, learn complex relationships between features, and ultimately predict the correct class label of a given input example [13-15].

2.5. Dataset

The data set used in the study is a Public data set [16]. The relevant data set covers a period of 15 years. Data were generated for each patient by following a minimum of 10 years from the time of surgery and initial diagnosis. There are data of 383 patients in the relevant data set [17]. The features in the data set are presented in Figure 2.

Risk	categorical	3 unique
Age	double	15 .. 82
Gender	categorical	2 unique
Smoking	categorical	2 unique
HxSmoking	categorical	2 unique
HxRadiothreapy	categorical	2 unique
ThyroidFunction	categorical	5 unique
PhysicalExamination	categorical	5 unique
Adenopathy	categorical	6 unique
Pathology	categorical	4 unique
Focality	categorical	2 unique
Risk	categorical	3 unique
T	categorical	7 unique
N	double	0 .. 1
M	double	0 .. 1
Stage	categorical	5 unique
Response	categorical	4 unique
Recurred	categorical	2 unique

Figure 2. Features in the data set

Thyroid cancer risk detection was performed using the features presented in Figure 2. The risk label consists of three classes: Low, Intermediate, and High.

3. RESULTS

The study obtained the application results in the Matlab environment. 70% of the data set was used to train the models. Data other than the data used for training are reserved for testing the models. Different performance measurement metrics were preferred to compare the performances of the models used to determine the thyroid cancer risk level. These metrics are calculated using confusion matrices [18]. An example of a confusion matrix is used in Figure 3.

True Positive (TP)	False Positive (FP)
False Negative (FN)	True Negative (TN)

. **Figure 3.** Confusion matrix example

Performance measurement metrics are presented in Table 1.

Table 1. Criteria for evaluating the performance of models

Sensitivity	SEN = TP / (TP + FN)
Specificity	SPE = TN / (FP + TN)
Precision	PPV = TP / (TP + FP)
False Positive Rate	FPR = FP / (FP + TN)
False Discovery Rate	FDR = FP / (FP + TP)
False Negative Rate	FNR = FN / (FN + TP)
Accuracy	ACC = (TP + TN) / (P + N)
F1 Score	F1 = 2TP / (2TP + FP + FN)

Four different classifiers were used in the study to determine the thyroid cancer risk level. The confusion matrices obtained in these classifiers are presented in Figure 4.

Fine Tree		High	Intermediate	Low
True Class	High	4	1	1
	Intermediate		18	3
	Low		4	45
		Predicted Class		

SVM		High	Intermediate	Low
True Class	High	5		1
	Intermediate		20	1
	Low		4	45
		Predicted Class		

BNN		High	Intermediate	Low
True Class	High	5		1
	Intermediate		19	2
	Low		4	45
		Predicted Class		

NB		High	Intermediate	Low
True Class	High	4	2	
	Intermediate		19	2
	Low		1	48
		Predicted Class		

Figure 4. Confusion matrices of classifiers

When the confusion matrices presented in Figure 4 are examined, it is seen that the Fine Tree classifier predicted 67 correct and 9 incorrect predictions out of 76 test data. The accuracy value obtained in the Fine Tree classifier is 88.2%. The SVM classifier, used to detect the thyroid cancer risk process, predicted 70 of 76 test data correctly and 6 incorrectly. The accuracy value obtained in the SVM classifier is 92.1%. BNN correctly predicted 69 of the same number of test data. The number of data that BNN predicted incorrectly is 12. The accuracy value obtained in the BNN classifier is 90.8%. Among the methods used in the study to determine the risk of thyroid cancer, NB was the most successful method. NB incorrectly predicted 5 out of 76 test data. The accuracy value obtained in the NB classifier is 93.4%. The ROC curve of the NB model is presented in Figure 5.

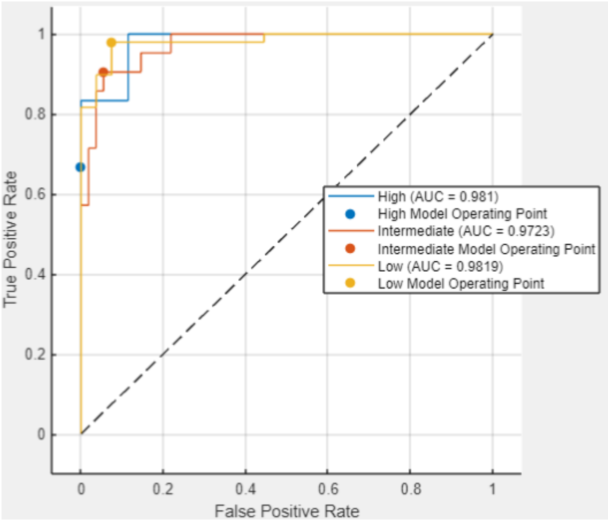

Figure 5. ROC Curve of NB

Performance measurement metrics of the NB classifier are in Table 2.

Table 2. Performance metrics of NB (%)

	SEN	SPE	PPV	FPR	FDR	FNR	ACC	F1
High	100	97,22	66,66	2,77	33,33	0	66,66	80
Intermediate	86,36	96,29	90,47	3,7	9,52	13,63	90,47	88,37
Low	96	96,15	97,95	3,84	2,04	4	97,95	96,96

The values obtained in the study show that the thyroid cancer risk level of the NB classifier can be determined. Some limitations of the study can be mentioned. The number of data used in the study is small, and the data were collected from the same region. Our goals are to obtain more data from people living in different regions and to develop an artificial intelligence-based model that produces more successful results.

4. CONCLUSION

With the development of technology in recent years, machine learning methods have produced successful results in many fields, especially in health. This study used machine learning methods to determine the thyroid cancer risk level. Four different machine-learning methods were used in the study. Among the methods used, the most successful results were obtained with the NB classifier. An accuracy value of 93.4% was achieved on the test data in the NB classifier. This value shows that machine learning methods can be used to determine the risk level of thyroid cancer. The model used in the study can be used for preliminary diagnosis in non-expert places and will alleviate the experts' workload.

Competing interests

The authors declare that they have no competing interests.

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