CLASSIFICATION OF HYPOTHYROID DISEASE WITH EXTREME LEARNING MACHINE MODEL

I. Balikci Cicek, and Z. Kucukakcali

Abstract— *Aim:* In this study, it is aimed to classify hypothyroidism by applying the Extreme Learning Machine model, which is one of the artificial neural network models, on the open access Hypothyroid dataset.

Materials and Methods: In this study, the data set named "Hypothyroid Disease Data Set" was obtained from https://www.kaggle.com/nguyenthilua/hypothyroidcsv. Extreme Learning Machine model, one of the artificial neural network models, was used to classify hypothyroidism. The classification performance of the model was evaluated with classification performance criteria such as accuracy, sensitivity, positive predictive value, negative predictive value and F1-score.

Results: The accuracy obtained from the model was calculated as 0.922, balanced accuracy 0.523, sensitivity 1, positive predictive value 0.922, negative predictive value 1 and F1-score 0.959.

Conclusion: The findings obtained from this study showed that the extreme learning machine model used gave successful predictions in the classification of hypothyroidism.

Keywords— Hypothyroidism, classification, artificial neural networks, extreme learning machine.

1. INTRODUCTION

THE THYROID gland is an endocrine organ located in the front of the neck just in front of the trachea. Its weight is approximately 15-25 grams, each lobe is 2.5-4 cm long, 1.5-2 cm wide, and 1-1.5 cm thick. It is the largest endocrine organ in the human body, its main task is the secretion of thyroid hormones [1]. Thyroid hormones are hormones in protein structure released from the thyroid gland behind the anterior thyroid muscles on the anterior surface of the trachea. They play a fundamental role in growth, development and metabolism [2]. Thyroid hormones have a role in regulating the functions of almost every cell and tissue in our body. A small amount of secretion causes body functions to slow down, and excessive secretion causes body functions to accelerate [3]. Hypothyroidism is a clinical condition characterized by a general slowdown in metabolic events that occurs as a result of thyroid hormone deficiency or when thyroid hormones cannot be effective [4].

The signs and symptoms of hypothyroidism vary according to the rate and severity of the thyroid hormone deficiency and the age at which it occurs. Generally, when thyroid hormone deficiency develops slowly, hypothyroidism has an insidious and slow onset [5]. In adults, it can occur in different pictures ranging from a subclinical course to myxedema coma. Hypothyroidism is a common disease with an incidence of up to 20% [6]. The incidence of hypothyroidism increases with age, especially in women. The prevalence of hypothyroidism is 1.4% in women and 0.1% in men [2]. If left untreated, hypothyroidism can cause more serious complications and even be life-threatening. Serious complications include low metabolism and heart rate, heart failure, severe, life-threatening depression, and coma [7].

Artificial neural networks (ANN) are mathematical models inspired by the functions of biological neural networks. Artificial Neural Networks are computer systems that can learn about events and determine how to react to events coming from the environment by using examples that are products of real brain functions. ANN are information processing systems that have the ability to generate, create and discover new information by way of learning imitating the human brain. ANN can provide nonlinear modeling between input and output variables without the need for any prior knowledge and any assumptions [8]. Today, ANN is effective in many scientific fields due to its superior features such as nonlinearity, learning, generalization, hiding information, producing information about unseen examples, working with incomplete information, classification, adaptability, and error tolerance. At the same time, due to these features of ANN, it has found application place in many scientific fields [9].

Extreme Learning Machine (ELM) is a machine learning technique based on artificial neural networks. ELM algorithm has been developed for machine learning of a single layer feed forward neural network. ELM performs better than traditional feed forward networks in solving many problems [10]. ELM learning algorithm has advantages such as good generalization performance, extremely fast learning ability and low processing complexity [11]. Extreme learning machine using feed-forward neural networks with a single hidden layer have been proposed to solve classification and regression problems. In the basic logic of ELM, input weights and threshold values are assigned randomly and least squares method is used as an algorithm. Randomly assigned input weights and thresholds increase the classification ability of extreme learning machine [10].

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2. MATERIAL AND METHODS

2.1. Dataset

In the study, the data set named "Hypothyroid Disease Data Set" was obtained from https://www.kaggle.com/nguyenthilua/hypothyroidcsv to examine the working principle of the Extreme Learning Machine (ELM) method [12]. In the dataset used, there were a total of 3772 patients, 3481 (92.3%) hypothyroid and 291 (7.7%) negative. The variables included in the dataset are given in Table 1.

TABLE I
HYPOTHYROID DATA SET

Variable	Variable Description
Age	Integer
Sex	Male(M), Female(F)
On thyroxine	False(f), True(t)
Query on thyroxine	False(f), True(t)
On antythyroid	False(f), True(t)
Sick	False(f), True(t)
Pregnant	False(f), True(t)
Thyroid surgery	False(f), True(t)
T131 treatment	False(f), True(t)
Query Hypothyroid	False(f), True(t)
Query Hyperthyroid	False(f), True(t)
Lithium	False(f), True(t)
Goiter	False(f), True(t)
Tumor	False(f), True(t)
Hypopitutory	False(f), True(t)
Psych	False(f), True(t)
Tsh measured	False(f), True(t)
TSH	Real
T3 measured	False(f), True(t)
T3	Real
TT4 measured	False(f), True(t)
TT4	Real
T4U measured	False(f), True(t)
T4U	Real
FTI Measured	False(f), True(t)
FTI	Real
TBG Measured	False(f), True(t)
TBG	Real
Referal source	SVHC, other, SVI, STMW, SVHD
Class	negative, hypothyroid

Among the variables included in the dataset, the variables used and the explanations of these variables are given in Table 2.

TABLE II
VARIABLES USED IN THE DATASET AND THEIR DESCRIPTIVE PROPERTIES

Variable	Variable Description	Variable Type	Variable Role
Class	Negative, Hypothyroid	Qualitative	Dependent/ Target
Age	Age	Quantitative	Independent/ Predictor
Sex	Male (M), Female (F)	Qualitative	Independent/ Predictor
On thyroxine	False(f), True(t)	Qualitative	Independent/ Predictor
On antythyroid	False(f), True(t)	Qualitative	Independent/ Predictor
Sick	False(f), True(t)	Qualitative	Independent/ Predictor
Pregnant	False(f), True(t)	Qualitative	Independent/ Predictor
Thyroid surgery	False(f), True(t)	Qualitative	Independent/ Predictor
T131 treatment	False(f), True(t)	Qualitative	Independent/ Predictor
Query Hypothyroid	False(f), True(t)	Qualitative	Independent/ Predictor
Query Hyperthyroid	False(f), True(t)	Qualitative	Independent/ Predictor
Lithium	False(f), True(t)	Qualitative	Independent/ Predictor
Goiter	False(f), True(t)	Qualitative	Independent/ Predictor
Tumor	False(f), True(t)	Qualitative	Independent/ Predictor
Hypopitutory	False(f), True(t)	Qualitative	Independent/ Predictor
Psych	False(f), True(t)	Qualitative	Independent/ Predictor
TSH	Real	Quantitative	Independent/ Predictor
T3	Real	Quantitative	Independent/ Predictor
TT4	Real	Quantitative	Independent/ Predictor
T4U	Real	Quantitative	Independent/ Predictor
FTI	Real	Quantitative	Independent/ Predictor
Referal source	SVHC, other, SVI, STMW, SVHD	Qualitative	Independent/ Predictor

3. EXTREME LEARNING MACHINE (ELM)

Artificial neural networks has become very easy today to train just like a human brain. Teaching the knowledge that the human brain has acquired through experience to machines by using artificial neural networks has become the main subject of information technologies. An artificial neural network model consists of input layer, output layer and hidden layer. Artificial neural networks are divided into two as feed forward artificial neural networks and feedback artificial neural networks. In feedforward neural networks, neurons are in layers from input to output. Incoming information is transmitted to the input layer, middle layer and output layer respectively. In feedback networks, it is not only given as input to the layer of the cell that comes after it. It can also be connected as input to any cell in its previous layer or in its own layer [10].

Extreme Learning Machine were first introduced by Huang et al in 2006. Extreme learning machine is a fully connected artificial neural network model consisting of three layers as input layer, one hidden layer and output layer [13]. Extreme learning machine are basically similar to artificial neural networks with one hidden layer. For this reason, the working principle of extreme learning machine is to a certain extent the same with the working principles of artificial neural networks. However, in extreme learning machine, the weights in the hidden layer are randomly assigned and these values do not change in the further stage of education. On the other hand, the weights between the hidden layer and the output layer are determined analytically and quickly with the help of a linear model in one go. While activation functions such as Sigmoid, Sinus and Gauss are used in the hidden layer, linear activation functions are used in the output layer. The weights in the input layer of the feed forward neural network do not affect the performance of the network with one hidden layer [14].
ELM has many advantages over classical ANN networks trained with gradient-based learning algorithms. These advantages can be listed as follows; ELM's learning process is extremely fast. This time is usually in the level of seconds, in some applications even less than a second. ELM has better generalization ability than derivative based backpropagation algorithm in many cases. Classical derivative-based training algorithms and other learning algorithms may be faced with many situations such as stuck to local minimums, inappropriate learning rate, excessive learning and memorization. In order to solve these problems, methods such as early stopping, adding regulation parameters, breaking the weight and using validity sets are used. The ELM learning algorithm tends to reach the solution directly without such intermediate processes and is therefore simpler than the learning algorithms used in classical artificial neural networks [15].

3.1. Performance evaluation metrics

Performance metrics obtained by using the classification matrix (Table 3) given below were used in the performance evaluation of the extreme learning machine model. The classification matrix of performance metrics is given in Table 3.

TABLE III

CLASSIFICATION MATRIX FOR CALCULATING PERFORMANCE METRICS

		Real		
		Positive	**Negative**	**Total**
Predicted	Positive	True positive (TP)	False negative (FN)	TP+FN
	Negative	False positive (FP)	True negative (TN)	FP+TN
	Total	TP+FP	FN+TN	TP+TN+FP+FN

Accuracy = (TP+TN)/(TP+TN+FP+FN)

Sensitivity = TP/(TP+FP)

Positive predictive value = TP/(TP+FN)

Negative predictive value =TN/(TN+FP)

F1-score = (2*TP)/(2*TP+FP+FN)

4. DATA ANALYSIS

Quantitative data are expressed as mean ± standard deviation, median (minimum-maximum), and qualitative data as number (percentage). Conformity to normal distribution was evaluated by the Kolmogorov-Smirnov test. In terms of independent variables, whether there is a statistically significant difference between the "Negative" and " Hypothyroid " groups, which are the categories of the dependent / target variable (class), and whether there is a relationship, Mann-Whitney U test, Pearson chi-square test, Continuity Correction test and Fisher's Exact test it was examined using the chi-square test Values of $p<0.05$ were considered statistically significant. IBM SPSS Statistics 26.0 package program was used for all analyzes.

For the validity of the model, a 10-fold cross-validation method was used. In the 10-fold cross-validation method, all data is divided into 10 equal parts. One part is used as a test set and the remaining 9 parts are used as a training data set and this process is repeated 10 times.

5. RESULTS

Descriptive statistics for the independent variables examined in this study are given in Table 4. According to the findings in Table 4; there is a statistically significant difference between the dependent / target variable groups in terms of TSH, T3, TT4, T4U, FTI variables ($p<0.05$).

According to the findings in Table 5; there is a statistically significant relationship between the sex, onthyroxine, pregnant, queryhypothyroid and referralsource variables and the dependent / target variable (class) groups ($p<0.05$).

TABLE IV

DESCRIPTIVE STATISTICS FOR QUANTITATIVE INDEPENDENT VARIABLES

Variables	Class		**p-value***
	hypothyroid	negative	
	Median(min-max)	**Median(min-max)**	
age	54 (1-455)	55 (1-88)	0.905
TSH	1.2 (0.005-145)	12 (0.015-530)	**<0.001**
T3	2 (0.05-10.6)	1.5 (0.2-4.09)	**<0.001**
TT4	105 (19-430)	77 (2-44076)	**<0.001**
T4U	0.97 (0.25-2.32)	1.01 (0.56-1.65)	**0.005**
FTI	108 (17-395)	77.5 (2-153)	**<0.001**

***: Mann Whitney U test**

TABLE V
DESCRIPTIVE STATISTICS FOR QUALITATIVE INDEPENDENT VARIABLES

Variables		Class: hypothyroid	Class: negative	p-value
		Number(%)	**Number(%)**	
sex	female	2265 (67.8)	215 (76.8)	**0.002***
	male	1077 (32.2)	65 (23.2)	
onthyroxine	false	3026(86.9)	282 (96.9)	**<0.001***
	true	455 (13.1)	9 (3.1)	
onantithyroidmedication	false	3439 (98.8)	290 (99.7)	0.254***
	true	42 (1.2)	1 (0.3)	
sick	false	3345 (96.1)	280 (96.2)	1**
	true	136 (3.9)	11 (3.8)	
pregnant	false	3428 (98.5)	291 (100.0)	**0.032*****
	true	53 (1.5)	0 (0.0)	
thyroidsurgery	false	3430 (98.5)	289 (99.3)	0.433***
	true	51(1.5)	2 (0.7)	
I131treatment	false	3427 (98.4)	286 (98.3)	0.804***
	true	54 (1.6)	5 (1.7)	
queryhypothyroid	false	3286 (94.4)	252 (86.6)	**<0.001***
	true	195 (5.6)	39 (13.4)	
queryhyperthyroid	false	3259 (93.6)	276 (94.8)	0.484**
	true	222 (6.4)	15 (5.2)	
lithium	false	3464 (99.5)	290 (99.7)	1***
	true	17 (0.5)	1 (0.3)	
goitre	false	3447 (99.02)	291 (100.0)	0.107***
	true	34 (0.98)	0 (0.0)	
tumor	false	3393 (97.5)	283 (97.3)	0.971**
	true	88 (2.5)	8 (2.7)	
hypopituitary	false	3480 (99.97)	291 (100.0)	1***
	true	1 (0.03)	0 (0.0)	
psych	false	3305 (94.9)	283 (97.3)	0.107**
	true	176 (5.1)	8 (2.7)	
referralsource	SVHC	375 (10.8)	11 (3.8)	**0.002***
	other	2028 (58.3)	173(59.5)	
	SVI	937 (26.9)	97 (33.3)	
	STMW	105 (3.0)	7 (2.4)	
	SVHD	36 (1.0)	3 (1.0)	

***: Pearson chi-square test, **: Continuity Correction test, ***: Fisher's Exact test**

The classification matrix for the Extreme Learning Machine model used to classify the hypothyroid dataset in this study is given in Table 6 below.

TABLE VI
CLASSIFICATION MATRIX FOR THE EXTREME LEARNING MACHINE MODEL

Prediction	Reference: hypothyroid	Reference: negative	Reference: **Total**
hypothyroid	485	41	526
negative	0	2	2
Total	485	43	528

Values for the metrics of the classification performance in the testing phase of the model are given in Table 7. The accuracy obtained from the model was calculated as 0.922, sensitivity 1, positive predictive value 0.922, negative predictive value 1 and F1-score 0.959.

TABLE VII
VALUES FOR THE METRICS OF THE CLASSIFICATION PERFORMANCE IN THE TESTING PHASE OF THE MODEL

Metric	**Value**
Accuracy	0.922
Sensitivity	1
Positive predictive value	0.922
Negative predictive value	1
F1-score	0.959

6. DISCUSSION

Inability of the thyroid gland to produce as many hormones as necessary is called hypothyroidism. Patients with hypothyroidism experience weight gain, tendency to sleep, reduced exercise capacity and cold intolerance. In more severe patients, constipation, thickening of the voice, hair loss, broken nails, increased cholesterol levels, myxedema, cretinism, skin dryness and goiter are seen. The most common cause of hypothyroidism is iodine deficiency [16]. Cardiovascular, gastrointestinal and metabolic diseases (such as sinus bradycardia, altered gastrointestinal secretion and motility) are the main known clinical symptoms of hypothyroidism. These symptoms can cause anatomical disorders, cardiovascular and cerebrovascular diseases. In addition, it causes delay in skeletal development and mental disorders [17].

ANN can establish a relationship between inputs and outputs determined depending on various parameters of a system by using the properties of biological nervous systems [18]. Feedforward ANNs are widely used for function approach in many fields due to their distinctive features [19]. When evaluating ANN as a classifier, the number of neurons in the hidden layer, the values of the weights between the input layer and the hidden layer and between the hidden layer and the output layer and the selection of the learning algorithm play an important role. The biggest disadvantage of ANN is the use of gradient descent algorithm to adjust weights and parameters during the training process, which makes the performance of the model time consuming and increases the computational burden [20].

ELM is a feed forward ANN algorithm with a single hidden layer. In ELM, unlike conventional feed forward ANNs, the input weights and the latent threshold value are given randomly, and the weights of the neurons in the output layer are calculated. In this approach they suggest, performing all processes without repetition during training enables the learning phase to be completed in a very short time for most applications. Also, studies have shown that ELM has a better classification performance than most gradient-based learning [21].

In this study, an extreme learning machine model, which is an artificial neural network method, was applied to the open source dataset named "Hypothyroid Disease Data Set". Among the performance criteria obtained from the extreme learning machine model, accuracy was calculated as 0.922, sensitivity 1, positive predictive value 0.922, negative predictive value 1 and F1-score 0.959.

As a result, in the study conducted with hypothyroid dataset, the extreme learning machine model used yielded successful results in the classification of hypothyroidism.

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