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A Comparative Study for the Prediction of Heart Attack Risk and Associated Factors Using MLP and RBF Neural Networks

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ABSTRACT

The aim of this study is to develop a predictive classification model that can identify risk factors for heart attack disease. In the study, patients with a low and high probability of having a heart attack were examined. Variable importance was calculated to identify risk factors. The radial basis function and multilayer perception neural networks were used to compare the classification prediction results. MLP model criteria; Accuracy 0.911, F1 score 0.918, Specificity 0.92, Sensitivity 0.903, while RBF model criteria were obtained as accuracy 0.797, F1 score 0.812, Specificity 0.84, Sensitivity 0.765. The first three most important factors that may be associated with having a heart attack were obtained as trestbps, oldpeak, and chol. According to the prediction results of the heart attack, it can be said that the model created with the MLP neural network has more successful predictions than the model created with the RBF neural network. In addition, estimating the importance values of the factors most associated with a heart attack (obtaining the most important biomarkers that may cause a heart attack) is a promising result for the diagnosis, treatment and prognosis of the disease.

1. INTRODUCTION

HEART attacks are usually caused by a blockage in the coronary artery. Despite improvements in the number of people surviving a heart attack, heart disease still remains the biggest killer. Early recognition of the cardinal symptoms of this disease is important for appropriate management, to prevent poor clinical outcomes [1,2].

Therefore, to shorten the time from heart attack onset to the hospital visit, it is important to improve the public's knowledge of stroke warning symptoms and signs. The symptoms of Myocardial Infarction (MI) include chest pain, which travels from left arm to neck, shortness of breath, sweating, nausea, vomiting, abnormal heart beating, anxiety, fatigue, weakness, stress, depression, and other factors [2,3].

Older age, male gender, lower education level, lack of regular exercise, unmarried status, unemployment, poor economic status, poor health behaviours (high-salt diet, no health screening), poor psychological status (self-perceived high stress and self-perceived poor health), and the presence of hypertension or dyslipidemia independently predicted poorer understanding of Cardiovascular disease (CVD). The heart attack can be prevented by taking earlier action to lower those risks by controlling diet, fat, cholesterol, salt, smoking, nicotine, alcohol, drugs, monitoring of blood pressure every week, doing exercise every day, and loosing body weight. As well as stopping smoking, other important ways of reducing risks are eating healthily, staying within safe limits of alcohol consumption, taking regular exercise and reaching and maintaining an ideal weight. Medication may also be prescribed to lower risks, including ACE inhibitors, antiplatelet therapy, beta-blockers and statins [2,4].

The ability to diagnose the cardiac disease quickly, accurately, and accurately plays a critical role in adopting preventative actions to avoid death. The electrocardiogram (ECG) determines the MI by electrical signals in the heart and damage to the blood supply to the heart muscle. The common blood tests are troponin and creatine kinase (CK-MB). ECG testing is used to differentiate between two types of myocardial infarctions based on the shape of the tracing. An ST section of the tracing higher than the baseline is called an ST-segment elevation myocardial infarction (STEMI) which requires aggressive treatment. The coronary angiography or X-ray of the heart and blood vessels is performed to see the narrowing of coronary arteries. In addition, extensive studies have been made and various machine learning models are used to classify and predict heart disease [1,2].

Data mining is the process of extracting essential information from large datasets in a variety of disciplines, including medicine, business, and education. One of the most rapidly expanding areas of artificial intelligence is machine learning. These algorithms can analyze large amounts of data from a variety of sectors, including the medical field. It is a computer-assisted alternative to traditional prediction modelling for gaining knowledge of complicated and non-linear interactions among various components by reducing errors in projected and actual results. Data mining is the process of analyzing large datasets in order to uncover hidden critical decision-making information for future analysis. Patients' data is abundant in the medical area. These data must be analyzed using a variety of machine learning algorithms. These data are analyzed by healthcare professionals for them to make efficient diagnostic decisions. Through analysis, medical data mining using classification algorithms gives clinical assistance. It puts classification algorithms to the test to predict cardiac disease in patients [5-9].

In this study, Radial Basis Function and Multilayer Perceptron models were established and their results were compared to predict the disease effectively and accurately by identifying heart attack risk factors. In the continuation of the article, Section 2 consists of the materials and methodology used, Section 3 consists of analysis results and findings, and Section 4 consists of discussion.

2. MATERIAL AND METHODS

2.1. Dataset

An open-access data set titled "Health care: Data set on Heart Attack Possibility" is accessible at https://www.kaggle.com/nareshbhat/health-care-data-set-on-heart-attack-possibility.

TABLE I
THE VARIABLES IN THE DATASET AND THEIR DEFINITIONS

Variable	Variable Description
age	age
sex	sex
cp	chest pain type (4 values)
trestbps	resting blood pressure
chol	serum cholestoral in mg/dl
fbs	fasting blood sugar > 120 mg/dl
restecg	resting electrocardiographic results (values 0,1,2)
thalach	maximum heart rate achieved
exang	exercise induced angina
oldpeak	ST depression induced by exercise relative to rest
slope	the slope of the peak exercise ST segment
ca	number of major vessels (0-3) colored by flourosopy
thal	0 = normal; 1 = fixed defect; 2 = reversable defect
target	0= less chance of heart attack 1= more chance of heart attack

The information was collected from heart-attack-possibility. In the data set used, there are 303 patients. While 138 (45.5%) of the patients had a low risk of heart attack, 165 (54.5%) of the patients had a high risk of a heart attack. The variables in the data set and their definitions are given in Table 1.

2.2. Neural networks

Artificial neural networks, or neural networks, are a subset of artificial intelligence. As shown in the taxonomy in Fig. 1, multilayer perceptron or radial basis function is one type of neural network [10].

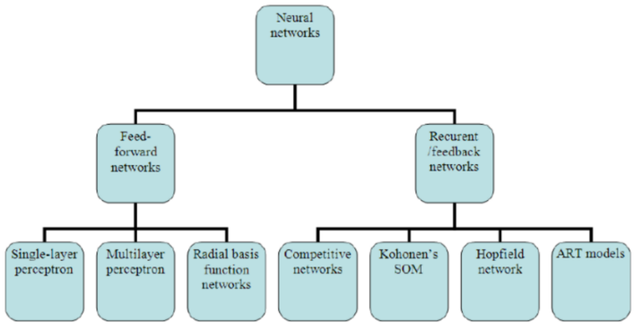

Fig. 1. A taxonomy of neural networks

2.2.1. Radial Basis Function (RBF)

In data analysis and pattern recognition applications, FUNCTIONAL estimation is a critical issue. Radial basis functions (RBFs) have features that make them suited for usage as universal approximators. A weighted sum of kernels can be used to define a continuous function. A kernel decomposition can be used in a two-layer neural network structure, with each kernel implemented by a hidden unit.

The network is given input-output pairs of samples selected from an observation set in supervised learning, and the learning algorithm identifies the rules that describe the given mapping. Because it can approximate any regular function and trains quicker than a multilayer perceptron, the radial basis function neural network (RBFN) can be used for a wide range of applications. The fact that RBFN has only two levels of weights and each layer may be determined sequentially contributes to the faster learning speed. An RBFN has three layers: an input, a middle layer, and an output layer. The pattern classes are represented by the input layer, which corresponds to the input vector space. As a result, determining the middle layer and the weights between the middle and output layers is all that is required to complete the architecture. When the middle layer is determined, the weights between the input and the middle layer are fixed [5,11].

2.2.2. Multilayer Perceptrons (MLP)

The multilayer perceptron, unlike other statistical techniques, makes no assumptions about the data distribution. It can represent extremely non-linear functions and be trained to generalize accurately when given new, previously unknown data. These characteristics make the multilayer perceptron an appealing option for constructing numerical models as well as choosing amongst statistical approaches. The multilayer perceptron has numerous uses in the atmospheric sciences, as will be seen. The multilayer perceptron is a model that represents a nonlinear mapping between an input vector and an output vector. It is made up of a system of basic interconnected neurons, or nodes, as shown in Fig. 2. Weights and output signals connect the nodes, and the output signals are a function of the sum of the node's inputs, modified by a simple nonlinear transfer, or activation, function [5,12].

A multilayer perceptron's construction varies, but it usually consists of many layers of neurons. The input layer serves only to provide the input vector to the network and does not perform any computations. The phrases input and output vectors relate to the multilayer perceptron's inputs and outputs, which can be represented as single vectors in Fig. 2. One or more hidden layers, followed by an output layer, make up a multilayer perceptron. Multilayer perceptrons are fully connected, with each node coupled to every node in the layer above and below it [5].

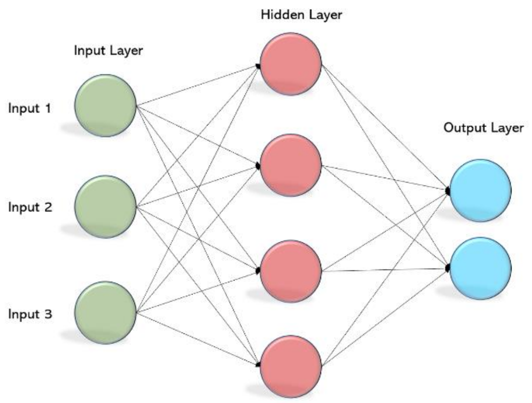

Fig. 2. A multilayer perceptron with two hidden layers.

3. EXPERIMENTAL RESULTS

The classification matrix of RBF and MLP models created in this study to classify heart attacks are given in Table II and Table III, respectively.

TABLE II
CLASSIFICATION MATRIX OF RBF MODEL

Prediction	Reference	
	more chance of heart attack	less chance of heart attack
more chance of heart attack	26	4
less chance of heart attack	8	21

TABLE III
CLASSIFICATION MATRIX OF MLP MODEL

Prediction	Reference	
	more chance of heart attack	less chance of heart attack
more chance of heart attack	28	2
less chance of heart attack	3	23

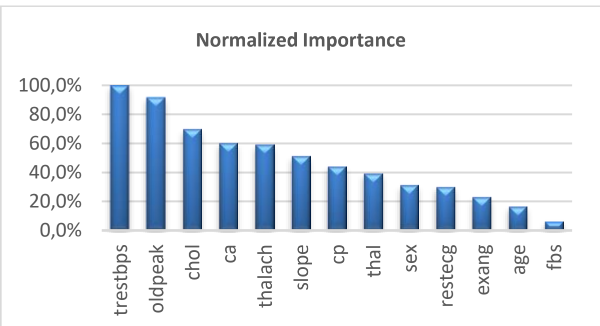

Fig. 3. Variable Importance

TABLE IV
IMPORTANCE SCORES OF FACTORS RELATED TO HEART ATTACK

Factors	Importance
trestbps	0,161
oldpeak	0,147
chol	0,112
ca	0,097
thalach	0,095
slope	0,082
cp	0,071
thal	0,063
sex	0,050
restecg	0,048
exang	0,037
age	0,027
fbs	0,010

When Table IV and Figure 3 are examined; the factors that most effect the risk of having a heart attack were found to be trestbps, oldpeak, and chol.

TABLE V
VALUES FOR THE METRICS OF THE CLASSIFICATIONS PERFORMANCE OF MLP AND RBF MODELS

Metric	**MLP**	**RBF**
	Value	
Accuracy	0.911	0.797
F1-Score	0.918	0.812
Specificity	0.92	0.84
Sensitivity	0.903	0.765
Negative Predictive Value	0.885	0.724
Positive Predictive Value	0.933	0.867

The values for the classification performance metrics of the generated RBF and MLP models are given in Table V. For the MLP model is calculated as accuracy 0.911, F1 score 0.918, Specificity 0.92, Sensitivity 0.903, Negative Predictive Value 0.885 and Positive Predictive Value 0.933. The RBF model is calculated as accuracy 0.797, F1 score 0.812, Specificity 0.84, Sensitivity 0.765, Negative Predictive Value 0.86724. In both models, the ability to distinguish positive cases (i.e., patients with high probability of heart attacks) was better (compared to negative cases). In addition, the MLP model was more successful in classifying heart attacks than the RBF model.

4. DISCUSSION

Ischemic heart disease (IHD) is one of the leading causes of death and morbidity in the world. MI, which is defined as myocardial cell damage induced by persistent ischemia, is one of these disorders. A heart attack is a physiological condition characterized by extreme chest pain and the likelihood of mortality as a result of heart failure caused by a problem in the coronary arteries. A heart attack occurs when the heart's oxygen supply is cut off due to a rapid decrease or interruption in blood flow in the veins that supply it. It can harm or kill the cardiac muscle fed by the blocked vessel to varying degrees.

Heart attack is the most common health concern in affluent countries, as well as a major health issue that is becoming more prevalent in underdeveloped countries. MI is a severe public health issue that affects the productive age group of the population, generates serious complications from post-acute phase issues, and can lead to death. The World Health Organization (WHO) estimates that 16.7 million people die each year as a result of a heart attack. This equates to one-third of all deaths worldwide (13, 14).

The goal of machine learning and deep learning is to filter out undiscovered patterns and relations in data. These patterns are also utilized in the development of various prediction models. Technology advancements have aided in the automation of numerous functional units across multiple disciplines [15].

Health care is one area where many electronic devices provide a large amount of complex connected data about hospitals, patients, and diseases. This unprocessed data can be a valuable resource, but it must be properly processed. These data can be processed to extract important information [16].

The use of machine learning and data mining techniques in the field of health care have ushered in a new era of computing. Various data mining approaches have been extensively used to efficiently diagnose cardiac disease. The fundamental issue with machine learning models is that they frequently require feature engineering for proper implementation, which can be a time-consuming process. Deep learning and neural networks have been employed extensively for various classification tasks in the health area, particularly in cardiovascular disease, to address the aforesaid challenge [17,18].

Using existing medical records for model training and testing, this article presents a proposed model built using current machine learning approaches to detect and predict heart diseases and heart attacks. In this article, MLP and RBF methods were used for classification. In addition, new patterns such as variable importance were discovered from the analysis. After application, 91.1% and 79.7% accuracy of MLP and RBF were obtained, respectively. The model developed in this study can be used to assist medical professionals/practitioners in detecting and predicting heart disease/crisis to minimize deaths in the healthcare industry, given the annual death rate it causes.

In conclusion, the findings from this study showed that the model (MLP) created in the classification of the severity of the probability of heart attack gives successful predictions. In addition, it is thought that by estimating the importance values of the factors associated with heart attack and determining the most important factors, these results will provide benefits to healthcare professionals for diagnosing and treating a heart attack.

REFERENCES

[1] Brice, J. H., Griswell, J. K., Delbridge, T. R., & Key, C. B. (2002). Stroke: From Recognition by The Public To Management by Emergency Medical Services. Prehospital Emergency Care, 6(1), 99-106.

[2] Park, M. H., Jo, S. A., Jo, I., Kim, E., Eun, S. Y., Han, C., & Park, M. K. (2006). No difference in stroke knowledge between Korean adherents to traditional and western medicine–the AGE study: an epidemiological study. BMC Public Health, 6(1), 1-9.

[3] Küçükakçali Tunç, Z., Çiçek Balikçi, İ., Güldoğan, E., & Çolak, C. (2020). Assessment of Associative Classification Approach for Predicting Mortality by Heart Failure. The Journal of Cognitive Systems, 5(2), 41-45.

[4] Küçükakçali Tunç, Z., Çiçek Balikçi, İ., & Güldoğan, E. Performance Evaluation of The Deep Learning Models in The Classification of Heart Attack And Determination of Related Factors. The Journal of Cognitive Systems, 5(2), 99-103.

[5] Çiçek Balikçi, İ., & Küçükakçali, Z. (2020). Classification of Prostate Cancer and Determination of Related Factors with Different Artificial Neural Network. Middle Black Sea Journal of Health Science, 6(3), 325-332.

[6] Çiçek Balikçi, İ., & Küçükakçali, Z. & Çolak, C. Associative Classification Approach Can Predict Prostate Cancer Based On The Extracted Association Rules. The Journal of Cognitive Systems, 5(2), 51-54.

[7] Küçükakçali Tunç, Z., & Çiçek Balikçi, İ. Performance Evaluation Of The Ensemble Learning Models In The Classification Of Chronic Kidney Failure. The Journal of Cognitive Systems, 5(2), 55-59.

[8] Perçin, İ., Yağin, F. H., Arslan, A. K., & Çolak, C. (2019, October). An Interactive Web Tool for Classification Problems Based on Machine Learning Algorithms Using Java Programming Language: Data Classification Software. In 2019 3rd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT) (pp. 1-7). IEEE.Leist, A., & Muniz-Terrera, G. (2021). Symposium: Contextual and life-course determinants of later-life cognitive functioning and dementia.

[9] Yağin, F. H., Güldoğan, E., Ucuzal, H., & Çolak, C. A Computer-Assisted Diagnosis Tool for Classifying COVID-19 based on Chest X-Ray Images. Konuralp Medical Journal, 13(S1), 438-445.

[10] Yegnanarayana, B. (2009). Artificial neural networks. PHI Learning Pvt. Ltd.

[11] Orr, M. J. (1996). Introduction to radial basis function networks.

[12] Karaman, U., & Çiçek Balikçi, İ., Determination Of Cryptosporidium Spp. Risk Factors Using Multilayer Perceptron Neural Network And Radial Based Functional Artificial Neural Network Method. The Journal of Cognitive Systems, 5(2), 83-87.

[13] Després, J. P., Lamarche, B., Mauriège, P., Cantin, B., Dagenais, G. R., Moorjani, S., & Lupien, P. J. (1996). Hyperinsulinemia as an independent risk factor for ischemic heart disease. New England Journal of Medicine, 334(15), 952-958.

[14] McNeer, J. F., Margolis, J. R., Lee, K. L., Kisslo, J. A., Peter, R. H., Kong, Y. I. H. O. N. G., ... & Rosati, R. A. (1978). The role of the exercise test in the evaluation of patients for ischemic heart disease. Circulation, 57(1), 64-70.

[15] Deo, R. C. Machine learning in medicine. Circulation [Internet] 2015; 132 (20). 1920–30.

[16] Sidey-Gibbons, J. A., & Sidey-Gibbons, C. J. (2019). Machine learning in medicine: a practical introduction. BMC medical research methodology, 19(1), 1-18.

[17] Perçın, İ., Yağin, F. H., Güldoğan, E., & Yoloğlu, S. (2019, September). ARM: An Interactive Web Software for Association Rules Mining and an Application in Medicine. In 2019 International Artificial Intelligence and Data Processing Symposium (IDAP) (pp. 1-5). IEEE.

[18] Al'Aref, S. J., Anchouche, K., Singh, G., Slomka, P. J., Kolli, K. K., Kumar, A., ... & Min, J. K. (2019). Clinical applications of machine learning in cardiovascular disease and its relevance to cardiac imaging. European heart journal, 40(24), 1975-1986.

BIOGRAPHIES

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Determination of Knowledge Levels of Nurses Working in the Emergency Department and Intensive Care Units about Evidence-Based Practices in the Prevention of Ventilator-Associated Pneumonia

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ABSTRACT

Objective: The aim of this study was to determine the level of knowledge of nurses working in the Emergency Departments (ED)and Intensive Care Units (ICU)about evidence-based practices in the prevention of ventilator-associated pneumonia(EBP-VAP).

Materials and Methods: This descriptive,two-center study was conducted on nurses working in the EDs and ICUs of two public hospitals in the city center of Malatya.A total of 199 nurses who worked in the ED or ICU for at least one year were included in the study,on voluntary basis.The data were collected by using "Personal Information Form" and the "Information on Evidence-Based Practices for the Prevention of Ventilator-Associated Pneumonia Form"(EBP-VAP).

Results: The mean age of the nurses was 35.92±6.54,58.8% of them were females and 6.7% were undergraduates.The mean total VAP score of the nurses was found to be 4.76±1.57.It was determined that there was a weak positive correlation between the ages of the nurses,their years in the profession,years of working in the emergency room/intensive care unit, and their average total VAP scores ($p<0.05$).It was found that the mean total VAP score of the nurses who received ICU/ventilation training was 5.09±1.32,the mean total VAP score of those who did not receive training was 4.47±1.72,and the difference between the groups was statistically significant ($p<0.05$).The rates of correct answers given by the nurses to the questions on EBP-VAP form were endotracheal intubation type 45.2%,ventilator circuit replacement frequency 50.8%,airway humidifier type 35.2%,humidifier replacement frequency 61.8%,use of an open or closed aspiration system 57.3%,frequency of changing aspiration systems 30.2%,drainage type of subglottic secretions 55.3%, use of kinetic beds 60.3%,and patient positioning 80.4%,respectively.

Conclusion: It was found that the knowledge level of nurses about EBP in the prevention of VAP was moderate.In addition,it was concluded that receiving training about ICU/ventilator,age,working years,and working years in the ED/ ICU were variables that increase the level of knowledge of the nurses about EBP-VAP.

1. INTRODUCTION

VENTILATOR-associated pneumonia (VAP) is a nosocomial lung infection with a high mortality rate, that usually develops 48-72 hours after hospitalization in the ICU [1].

The factors affecting the development of VAP include age, gender, presence of comorbid disease, and invasive procedures performed in the ED or ICU. Since it is among the nosocomial infections, the implementation of hospital surveillance procedures decreases the possibility of the development of VAP. It usually develops 48 hours after invasive mechanical ventilation. In the literature, it has been reported that the possibility of the development of VAP increases 6 to 21 times as the duration of the dependence on mechanical ventilation increases [1,2].

The indicators of the development of VAP include fever exceeding 38.5 ºC, leukocytosis, increased secretions, and an increased infiltration in the chest X-ray. It is classified as early-onset and late-onset VAP. In early-onset cases, Methicillin-susceptible staphylococcus Aureus has been blamed, whereas Pseudomonas auroginosis is blamed in late-onset cases [1-3].

The training of the personnel working in the ED and ICU, about the techniques of approach to the patient, has a very important place in the prevention of VAP. Therefore, it is necessary to update the knowledge of the personnel working in the ED and ICU by providing in-service training and evidence-based guides [4].

The aim of this study was to determine the level of knowledge of nurses working in the Emergency Departments (ED) and Intensive Care Units (ICU) about evidence-based practices in the prevention of ventilator-associated pneumonia (EBP-VAP).

2. MATERIALS AND METHODS

2.1. Study Design, Place and Time

This descriptive, two-centre study was conducted between July 2021 and August 2021 on the nurses working in the ED and ICUs of two public hospitals in the city centre of Malatya. The total number of nurses working in the ED and ICUs in the two mentioned public hospitals was 599, at the time of the study. When power analysis was performed, it was calculated that a sample size of at least 187 nurses was required for 80% power to represent the universe with a 5% error level and 90% confidence interval. All nurses who worked in the emergency room or intensive care unit for at least one year and volunteered to participate in the study were included in the study and the study was completed with 199 nurses. All nurses Included in the study were selected by a simple random sampling method.

2.1. Data Collection Tools

2.2.1. Personal Data Form

The personal data form, which was prepared by the researchers, consisted of 12 questions about socio-demographic characteristics (age, gender, educational status, and perceived income) and working conditions (institution of work, department or unit of work, total working years in the ED or ICU, working type, weekly working hours, number of beds in the department/unit worked, and having an intensive care certificate) of the nurses.

2.2.2. Information on Evidence-Based Practices in the Prevention of Ventilator-Associated Pneumonia (EBP-VAP) Form

The EBP-VAP was developed by Dodek et al. (2004) as an evidence-based practice guide to preventing VAP and a validity study was performed by Labeau et al. (2007) [5,6]. The Turkish adaptation of the form was performed by Akın Korhan et al. (2013) [5-7]. The Evaluation Form consists of titles containing 9 universal measures, including endotracheal intubation type, frequency of replacing ventilator circuits, airway humidifier type, frequency of humidifier replacement, use of open or closed aspiration system, frequency of replacing aspiration systems, drainage of subglottic secretions, use of kinetic beds, and patient positioning. Each question has four multiple-choice answers one of which shows evidence-based correct practice. For each correct answer, 1 point is given and incorrect answers are not scored. The highest score that can be obtained from the form is 9, and the lowest score is 0 [7].

2.3. Data Collection

The data were obtained by using the google form method. Data collection forms prepared online were sent to the chief nurses in the ED or ICUs via WhatsApp application and they were asked to forward the data collection forms to their working groups. The informed consent forms were obtained from the nurses who agreed to participate in the study before they were asked to fill online data collection forms. The data were recorded by the online self-report method. Data collection took approximately 5-7 minutes for each participant.

2.4. Evaluation of Data

The data were evaluated by using the SPSS 24.0 statistical package program. The independent groups' t-test, One-Way ANOVA test and Pearson correlation analysis were used in the evaluation of the data. The descriptive statistics were given as a number, percentage, mean, standard deviation, and min-max. The results were evaluated at the 95% confidence interval and a value of $p<0.05$ was accepted statistically significant.

2.5. Ethical Approval

Ethical approval for the study was obtained from the Inonu University Health Sciences Ethics Committee for Non-Interventional Clinical Research (No: 2021/2177). In addition, institutional permissions from the public hospitals where the study would be conducted were obtained. In addition, the participants were informed about the purposes of the study and they were asked to approve the informed consent forms before the data collection forms were filled.

3. RESULTS

TABLE I
DISTRIBUTION OF NURSES' DESCRIPTIVE CHARECTERISTICS (n=199)

Variable	n	%
Age (Mean±SD) 35.92±6.54		
Total Working Years (Mean±SD)13.50±6.67		
Working Years in the ED/ICU (Mean±SD)9.46±6.00		
Gender		
Female	117	58.8
Male	82	41.2
Educational status		
High school	22	11.1
Associate degree	44	22.1
Undergraduate	113	56.7
Postgraduate	20	10.1
Perceived income status		
Income more than the expenses	22	11.0
Income equal to the expenses	102	51.3
Income less than the expenses	75	37.7
Working unit		
ED	30	15.1
1st degree ICU	41	20.6
2nd degree ICU	48	24.1
3rd degree ICU	80	40.2
Working type		
Shift	45	22.6
Regular hours	64	32.2
Shift and regular hours	90	45.2
Weekly hours of working		
40 hours	116	58.3
>41 hours	83	41.7
Status of receiving training about ED/ICU ventilator		
Yes	93	46.7
No	106	53.3
Total	**199**	**100.0**

The distribution of the descriptive characteristics of the nurses working in the ED and ICUs is given in Table I. The mean age of the nurses was 35.92±6.54, 58.8% of the nurses are women, 56.7% of them are undergraduate. The mean total working year was 13.50±6.67, the mean working year in the ED/ICU was 9.46±6.00 years, and 51.3% of the nurses stated that their income is equal to their expenses. It was determined that 45.2% of the nurses worked in the 3rd level intensive care units, 40.2% of them worked on shifts and daytime work hours, 58.3% worked 40 hours a week, and 53.3% did not receive any intensive care/ventilator training (Table I).

TABLE II
THE RELATIONSHIP BETWEEN THE MEAN TOTAL SCORES OF VAP & AGE, TOTAL WORKING YEARS & WORKING YEARS IN THE ED/ICU (n=199)

Variable	Age	Total Working Years	Working Years in the ED/ICU
VAP Total (Mean±SD) 4.76±1.57	r=0.164 **p=0.021***	r=0.162 **p=0.022***	r=0.204 **p=0.004***

r=Pearson correlation analysis *p<0.05

The mean total VAP score of the nurses was 4.76±1.57. We detected a weak positive correlation between the age of the nurses, the years of working, and the years of working in the emergency room/intensive care unit and the mean VAP total scores; it was found that the knowledge level of the nurses about evidence-based practices in the prevention of ventilator-associated pneumonia increases as the age, working years and working years in the ED/ICU increases (p<0.05; Table II).

TABLE III
COMPARISON OF VAP TOTAL SCORES ACCORDING TO SOME CHARACTERISTICS OF NURSES (n=199)

Variable	VAP Mean±SD	Test and p values
Gender		
Female	4.67±1.68	t= -0.945
Male	4.89±1.42	p=0.346
Educational status		
High school	4.95±1.81	
Associate degree	4.90±1.17	F=0.601
Undergraduate	4.70±1.70	p=0.776
Postgraduate	4.55±1.35	
Working unit		
ED	4.43±1.79	
1st degree ICU	5.12±1.14	F=1.016
2nd degree ICU	4.62±1.49	p=0.425
3rd degree ICU	4.78±1.71	
Status of receiving training about ED/ICU ventilator		
Yes	5.09±1.32	t= -2.835
No	4.47±1.72	**p=0.005***

t=Independent samples t-test F= One-Way ANOVA *p<0.05

It was found that the mean total VAP score of the nurses working in the ED/ICU, who received ED/ICU ventilator training was 5.09±1.32, the mean total VAP score of those who did not receive training was 4.47±1.72; and the difference between the groups was statistically significant (p<0.05; Table III). On the other hand, no significant relationship was found between the gender, education status and units of working of the nurses and the mean total VAP scores (p>0.05).

The rates of correct answers given by the nurses to the questions on EBP-VAP form were endotracheal intubation type 45.2%, frequency of ventilator circuit replacement 50.8%, airway humidifier type 35.2%, frequency of humidifier replacement 61.8%, use of an open or closed aspiration system 57.3%, frequency of changing aspiration systems 30.2%, drainage type of subglottic secretions 55.3%, use of kinetic beds 60.3%, and patient positioning 80.4%, respectively (Table IV).

TABLE IV
THE RATES OF CORRECT ANSWER GIVEN BY NURSES TO THE QUESTIONS ON EBP-VAP FORM NURSES (n=199)

		n	%
1. Oral or nasal route preference in endotracheal aspiration			
×	Oral intubation is recommended	90	45.2
□	Nasal intubation is recommended	9	4.5
□	Both ways are recommended	90	45.2
□	I do not know	10	5.1
2. Frequency of ventilator circuits replacement			
□	It is recommended to be replaced every 48 hours (or as clinically necessary)	58	29.1
□	It is recommended to be replaced every week (or as clinically necessary)	29	14.6
×	It is recommended to be replaced for every new patient (or as clinically necessary)	101	50.8
□	I do not know	11	5.5
3. Airway humidifier type			
□	Heated humidifiers are recommended	9	4.5
×	Heat and humidity exchangers are recommended	70	35.2
□	Both types of humidifiers (heated humidifiers and heat and moisture exchangers) are recommended	85	42.7
□	I do not know	35	17.6
4. Frequency of humidifier replacement			
□	It is recommended to be replaced every 48 hours (or as clinically necessary)	13	6.5
□	It is recommended to be replaced every 72 hours (or as clinically necessary)	42	21.1
×	It is recommended to be replaced for every new patient (or as clinically necessary)	123	61.8
□	I do not know	21	10.6
5. Preference of open or closed aspiration system			
□	Open aspiration systems are recommended	12	6.0
□	Closed aspiration systems are recommended	66	33.2
×	Booth systems are recommended	114	57.3
□	I do not know	7	3.5
6. Frequency of replacement of aspiration systems			
□	It is recommended to be replaced every day (or as clinically necessary)	97	48.7
□	It is recommended to be replaced every week (or as clinically necessary)	29	14.6
×	It is recommended to be replaced for every new patient (or as clinically necessary)	60	30.2
□	I do not know	13	6.5
7. The feature of endotracheal tubes with extra lumen used for aspiration of subglottic secretions			
×	Extra-lumen endotracheal tube reduces the risk of ventilator-associated pneumonia	110	55.3
□	Extra-lumen endotracheal tube increases risk of ventilator-associated pneumonia	21	10.6
□	Extra-lumen endotracheal tube does not affect the risk of ventilator-associated pneumonia	11	5.5
□	I do not know	57	28.6
8. Preference of kinetic or standard beds			
□	Kinetic beds increase risk of ventilator-associated pneumonia	12	6.0
×	Kinetic beds reduce risk of ventilator-associated pneumonia	120	60.3
□	Kinetic beds do not affect the risk of ventilator-associated pneumonia	27	13.6
□	I do not know	40	20.1
9. Patient positioning			
□	Supine position is recommended	19	9.5
×	Semi-sitting position is recommended	160	80.4
□	Patient position does not affect the risk of ventilator-associated pneumonia	6	3.0
□	I do not know	14	7. 1

X=Correct Answer

4. DISCUSSION

Ventilation-associated pneumonia has been defined as pneumonia occurring 48 hours after intubation in a patient who did not have pneumonia before being intubated [8]. The incidence of VAP has been increasing though guidelines have been developed on this subject in recent years.

In the literature, few studies investigate the relationship between VAP and the level of evidence-based knowledge of nurses. Blot et al., found that 46.2% of the nurses working in the ICU had a working experience of 6-10 years [9]. In the study of Akıncı et al, it was found that 44.5% of the nurses had been working in the ICU for less than a year [10]. In our study, the mean working time in the ICU was found to be 9.46±6.00 years.

In the study of Blot et al. [9], it was found that as the working experience of the nurses increased, their EBP-VAP scores increased. Similarly, in our study, a weak positive correlation was found between the level of knowledge of the nurses about evidence-based practices in the prevention of VAP and their age and the years spend in the ICU; as the years in the ICU and age of the nurses increased their EBP-VAP scores increased. This suggests that the experience and the prolongation of the working time in the ICU increase the knowledge of nurses rather than causing boredom.

In the literature, it is emphasized that the personnel working in the ICUs should receive multidisciplinary training programs [9]. Supporting this suggestion, in our study, it was found that the nurses who received training about the prevention of VAP made statistically significant higher scores on EBP-VAS scale.

The most important risk factor in the development of VAP is endotracheal intubation [11]. Therefore, endotracheal intubation should be avoided unless necessary. About half of the nurses participating in our study stated that endotracheal intubation should be avoided in order to prevent the development of VAP.

In the study of Akıncı et al. [10], it was reported that 64.2% of the participants stated that the frequency of changing the humidifier is important in preventing VAP. This rate was found to be 84% in the study of El-khatib et al. [12], and 54% in the study of Blot et al.[9]. In our study, this rate was found to be 61.8%, which is consistent with the literature.

In the study of Akıncı et al. [10], the rate of correct answers to the question regarding the preference of kinetic beds versus standard beds was 41.6% whereas this rate was 48.7% in the study of Blot et al [9]. It is also noted that the position of the patient is related to the frequency of VAP [4]. In our study, the rate of those who knew that kinetic beds reduced the frequency of VAP was 60.3%, and the rate of those who knew that the position of the patient was important was 80.4%

5. CONCLUSIONS

In our study, it was found that the level of knowledge of the nurses working in the ED and ICUs about evidence-based practices in the prevention of VAP was sufficient. Healthcare personnel working in the ED/ICU need to identify strategies to prevent VAP and increase the chances of survival for many patients. We suggest that it can be achieved by forming multidisciplinary teams and providing the healthcare workers with updated training including evidence-based practices.

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REFERENCES

[1] Kapucu, S., Özdemir, G. (2014). Ventilatör ilişkili pnömoni ve hemşirelik bakımı. Hacettepe Üniversitesi Hemşirelik Fakültesi Dergisi, 1(1): 99-110.
[2] Bilici, A., Karahocagil, M. K., Yapıcı, K., Göktaş, U., Yama, G. (2012). Ventilatör ilişkili pnömoni sıklığı risk faktörleri ve etkenleri. Van Tıp Dergisi, 19(4): 170-176.
[3] Coffin, S.E., Klompas, M., Classen, D., Arias, K.M., Podgorny, K., Anderson, D.J. et al. (2008).Strategies to prevent ventilator-associated pneumonia in acute care hospitals. Infection Control and Hospital Epidemiology, 29 (1): 31-40.
[4] Sierra, R., Benítez, E., León, C., Rello, J. (2005). Prevention and diagnosis of ventilator-associated pneumonia: a survey on current practices in Southern Spanish ICUs. Chest, 128: 1667- 1673.
[5] Dodek, P., Keenan, S., Cook, D., Heyland, D., Jacka, M., Hand, L., et al. (2004). Evidence-based clinical practice guideline for the prevention of ventilator-associated pneumonia, Ann Intern Med, 141(4), 304-313.
[6] Labeau, S., Vandijck, D.M., Claes, B., Van Aken, P., Blot, S.I., Executive board of the Flemish Society for Clinical Care Nurses. (2007). Critical care nurses' knowledge of evidence-based guidelines for preventing ventilator-associated pneumonia: an evaluation questionnaire, American Journal of Critical Care, 16: 371-377.
[7] Akın Korhan, E., Hakverdioğlu Yönt, G., Parlar Kılıç, S., Uzelli, D. (2014). Knowledge levels of intensive care nurses on prevention of ventilator-associated pneumonia. Nurs Crit Care, 19(1): 26-33.
[8] Dönmez, N.F., Kanyılmaz, D., Tiryaki, C., Yılmaz, S., Dikmen, B. (2012).Yoğun Bakım Ünitelerinde Çalışan Uzmanlık Öğrencisi Doktorların Ventilatör İlişkili Pnömoninin (VİP) Önlenmesi ile İlgili Bilgi Düzeylerinin Değerlendirilmesi Türk Anest Rean Dergisi, 40(4): 202-211
[9] Blot, S.I., Labeau, S., Vandijck, D., et al. (2007). Evidence based guidelines for the prevention of ventilator-associated pneumonia: results of a knowledge test among intensive care nurses. Intensive Care Med 33: 1463-1467
[10] Akıncı, C., Çakar, C., Ayyıldız, A., Atalan, H.K., Ayyıldız, A. (2010). Evaluation of the Knowledge of Intensive Care Nurses on Ventilator-Associated Pneumonia, Türk Anest Rean Dergisi, 38(1): 45-51.
[11] Zeiher, B.G., Hornick, D.B. (1996). Pathogenesis of respiratory infections and host defences, Curr Opin Pulm Med, 2: 166-173.
[12] El-khatib, M., Zeineldine, S., Ayoub, C., et al. (2010). Critical care clinicians' knowledge of evidence-based guidelines for preventing ventilator-associated pneumonia, American Journal of Critical Care, 19(3): 272-276.

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Detection of Risk Factors of Pcos Patients with Local Interpretable Model-Agnostic Explanations (Lime) Method That an Explainable Artificial Intelligence Model

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ABSTRACT

In this study, it is aimed to extract patient-based explanations of the contribution of important features in the decision-making process (estimation) of the Random forest (RF) model, which is difficult to interpret for PCOS disease risk, with Local Interpretable Model-Agnostic Explanations (LIME).

In this study, the Local Interpretable Model-Agnostic Annotations (LIME) method was applied to the "Polycystic ovary syndrome" dataset to explain the Random Forest (RF) model, which is difficult to interpret for PCOS risk factors estimation. This dataset is available at https://www.kaggle.com/prasoonkottarathil/polycystic-ovary-syndrome-pcos.

Accuracy, sensitivity, specificity, positive predictive value, negative predictive value and balanced accuracy obtained from the Random Forest method were 86.03%, 86.32%, 85.37%, 93.18%, 72.92% and 85.84% respectively. According to the obtained results, the observations whose results were obtained, the values of Follicle (No) L. and Follicle (No) R. in different value ranges were positively correlated with the absence of PCOS. For the observations whose absence of PCOS results were obtained, the variables RBS(mg/dl), bmi_y, fsh_lh, TSH (mIU/L), Endometrium (mm) also played a role in obtaining the results. In addition, for the observations whose results were obtained, the values of Follicle No L and Follicle No R in different value ranges were also found to be positively correlated with PCOS. In addition, beta-HCG(mIU/mL), PRG(ng/mL), RBS(mg/dl), bmi_y, Endometrium (mm), fsh_lh variables also played a role in obtaining the results for PCOS.

When the observations obtained from the results are examined, it can be said that the Follicle (No) L. and Follicle (No) R. variables are the most effective variables on the presence or absence of PCOS. For different value ranges of these two variables, the result of PCOS or not varies. Based on this, it can be said that different values of Follicle (No) L. and Follicle (No) R. variables for PCOS status may be effective in determining the disease.

1. INTRODUCTION

TODAY, tremendous progress in technology has shed light on studies in artificial intelligence (AI) and machine learning (ML). ML methods have achieved great success with predictive models in the analysis of structured data sets in a wide variety of fields, including medical sciences [1]. It is extremely important that ML methods are understandable, explainable and interpretable. However, the inability of researchers to interpret the results of complex models in ML becomes a problem. For ML methods, interpretability is defined as the degree to which the researcher can understand and interpret the prediction of the model created [2].

Despite the increasing use of predictive models in the medical sciences, clinicians still find it difficult to rely on these models for various reasons [3, 4]. First, most predictive models target specific diseases, and understanding these models depends on clinicians' domain knowledge [4-6]. Second, most models developed by data scientists focus on the model's accuracy in predicting the disease of interest, but models rarely explain these predictions [6, 7]. This is especially true for complex machine learning models such as

Random Forest, Support Vector Machines and Neural Networks, which are described as black boxes [8, 9].

Approaches focusing on Explainable Artificial Intelligence (XAI) have been used in the medical sciences for over two decades. Explainable ML methods that focus on local interpretation, which can be based, for example, on k-NN or decision trees; It has been frequently used recently for its interpretability in predictive models of health-related conditions, including many types of cancer, chronic diseases such as Alzheimer's or diabetes, knee osteoarthritis, and mortality rates from a particular disease [10, 11].

Local Interpretable Model-Agnostic Explanations (LIME), one of the XAI methods, is a popular technique for describing the predictions of black box machine learning models [12]. Because LIME is designed to be model agnostic, it can be applied to many different machine learning models. The model created by the method determines which features in the data are more important on a patient basis, making the results of the model more interpretable [13].

Although many predictive models have been developed to predict the risk of Polycystic Ovary Syndrome (PCOS), one of the most common health problems affecting women of reproductive age, there are often lacking frameworks to build confidence in their predictions [14-16]. PCOS is basically caused by increased body mass index, cycle length, elevated hormone levels, acne, hair loss, hirsutism, infertility, etc. Since the disease has different factors and symptoms, it is important to evaluate the clinical data of PCOS patients on a patient basis, in the diagnosis and treatment of the disease [17, 18]. Therefore, XAI methods can be used to interpret the relative contribution of clinical features for a patient with suspected PCOS.

In this study, it is aimed to extract patient-based explanations of the contribution of important features in the decision-making process (estimation) of the Random forest (RF) model, which is difficult to interpret for PCOS disease risk, with Local Interpretable Model-Agnostic Explanations (LIME).

2. MATERIAL AND METHODS

2.1. Dataset

The In this study, the data set named “Polycystic ovary syndrome” was obtained from https://www.kaggle.com/prasoonkottarathil/polycystic-ovary-syndrome-pcos address to determine PCOS risk factors and to compare the performances of ANN, MLP and deep learning methods for PCOS diagnosis prediction. In the PCOS data set, there are a total of 541 patients, 364 (67.3%) no and 177 (32.7%) yes.

2.2. Random Forest

An The random forest approach proposed by Breiman is a machine learning algorithm with many decision trees which combination of Bagging and Random Subspaces methods [19-21]. In recent years, this method has demonstrated its effectiveness in both regression and classification problems, and it is one of the best machine learning algorithms utilized in a variety of domains [22]. The data set is first randomly divided into two parts: training data for learning and validation data for testing the learning level in the RF algorithm. Following that, many decision trees are generated at random using "boot-strap samples" from the data set. Randomly picked predictors at node locations determine the branching of each tree. The RF Final estimate is the average of all of the tree's results. As a result, for certain weights, each individual tree has an impact on RF estimation. Because this method shows a "black box" feature, each tree isn't evaluated separately. Because of its ability to randomly accept training data from subsets and create trees with random methods, the RF algorithm outperforms other machine learning algorithms. Furthermore, because training is done on randomly selected different sub-datasets using bootstrap sampling, the random forest algorithm maintains the overfitting level [23, 24].

2.3.Local Interpretable Model-agnostic Explanations

Performance Machine learning and artificial intelligence models are good at prediction accuracy, at process efficiency, and at research productivity. However, current machine learning / artificial intelligence models are often weak in explaining the interpretation process and prediction results. This situation becomes an obstacle in understanding the estimation models created. As a result, clinicians or healthcare workers may think that the results or predictions of a model are not sufficiently descriptive. For this reason, explainable artificial intelligence has started to attract attention recently. In short, explainable artificial intelligence is the totality of methods or techniques that aim to make artificial intelligence applications understandable to users. The purpose of explainable artificial intelligence is to make the computational inferences located behind the decisions of artificial intelligence understandable by researchers. The Local Interpretable Model-Agnostic Explanations (LIME) method is frequently used to ensure the explainability of the artificial intelligence-based models created. The purpose of using LIME is to increase the interpretability and explainability of the created models [25, 26].

In the field of health, the use of classification models to diagnose disease largely depends on the ability to interpretation and explanation of the created models by the researcher. Used for this purpose, LIME provides a patient specific explanation for a particular classification. Thus, it allows any complex classifier to be explained more simply in the clinical setting. LIME, can determine how much each variable in the data contributes to each estimate (patient specific) in the model [27]. Using the LIME method, it can be determined which variables affect each estimation in the model to what degree and in which direction, or which variable has more influence on the results of each estimation in the model compared to other variables. As a result, the LIME method provides explainability for each estimate using any classification model [28].

3. DATA ANALYSIS

Quantitative data are expressed as 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 "no" and "yes" groups, which are the categories of the dependent / target variable (Pcos(Y/N)), and whether there is a relationship, Mann-Whitney U test, Pearson chi-square 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.

4. RESULTS

Descriptive statistics of independent variables included in this study are given in Table 1. According to the results in Table 1; there is a statistically significant difference between the dependent / target variable (PCOS (Y/N)) groups in terms of Hb (g/dl), FSH(mIU/mL), AMH (ng/mL), Follicle No. (L) , Follicle No. (R), Avg. F size (L) (mm), Avg. F size (R) (mm), Endometrium (mm), BMI and Fsh/Lh variables ($p<0.005$).

TABLE I
DESCRIPTIVE STATISTICS FOR INDEPENDENT VARIABLES.

Variables	PCOS (Y/N) No Median (min-max)	PCOS (Y/N) Yes Median (min-max)	p-value*
Hb (g/dl)	11 (8.5-14.8)	11 (9.4-14)	0.025
I beta-HCG (mIU/mL)	13.735 (1.3-32460.97)	70.53(1.92-30007)	0.068
II beta-HCG (mIU/mL)	1.99 (0.99-21084.21)	1.99 (1.65-25000)	0.774
FSH (mIU/mL)	5.01 (0.21-5052)	4.48 (1-65.4)	0.007
LH (mIU/mL)	2.305 (0.02-14.69)	2.22 (0.032-2018)	0.353
TSH (mIU/L)	2.165 (0.04-65)	2.31 (0.05-22.59)	0.715
AMH (ng/mL)	3.2 (0.16-26.8)	5.9 (0.1-66)	<0.001
PRL (ng/mL)	21.17 (0.4-128.24)	22.9 (3.64-111.74)	0.592
Vit D3 (ng/mL)	26.3 (9.01-90)	25.45 (0-6014.66)	0.230
PRG (ng/mL)	0.31 (0.11-85)	0.32 (0.047-1.1)	0.385
RBS (mg/dl)	96 (60-2259	100 (70-350)	0.345
BP Diastolic (mmHg)	80 (8-100)	80 (70-80)	0.470
Follicle No. (L)	4 (0-15)	10 (1-22)	<0.001
Follicle No. (R)	4 (0-16)	11 (1-20)	<0.001
BP Systolic (mmHg)	110 (12-140)	110 (100-130)	0.948
Avg. F size (L) (mm)	15 (0-22)	16 (5-24)	0.009
Avg. F size (R) (mm)	15 (0-24)	16 (0.17-23)	0.026
Endometrium (mm)	8.3 (0-18)	8.9 (4.5-15)	0.005
BMI	23.62 (13.99-38.27)	25.15 (12.42-38.90)	<0.001
Fsh/Lh	2.36 (0.23-1372.83)	2.04 (0.00-327.00)	0.006

***: Mann Whitney U test**

The metrics for the classification performance of Random Forest method in the test phase are given in Table 2. Accuracy, sensitivity, specificity, positive predictive value, negative predictive value and balanced accuracy obtained from the Random Forest method were 86.03%, 86.32%, 85.37%, 93.18%, 72.92% and 85.84% respectively.

TABLE II
VALUES FOR THE METRICS OF THE CLASSIFICATION PERFORMANCE OF RANDOM FOREST METHOD SYSTEMS PARAMETERS.

Method	Metric	Value (%)
Random Forest	Accuracy	86.03
	Sensitivity	86.32
	Specificity	85.37
	Positive predictive value	93.18
	Negative predictive value	72.92
	Balanced Accuracy	85.84

In Figure 1,the findings of the LIME model are given below.

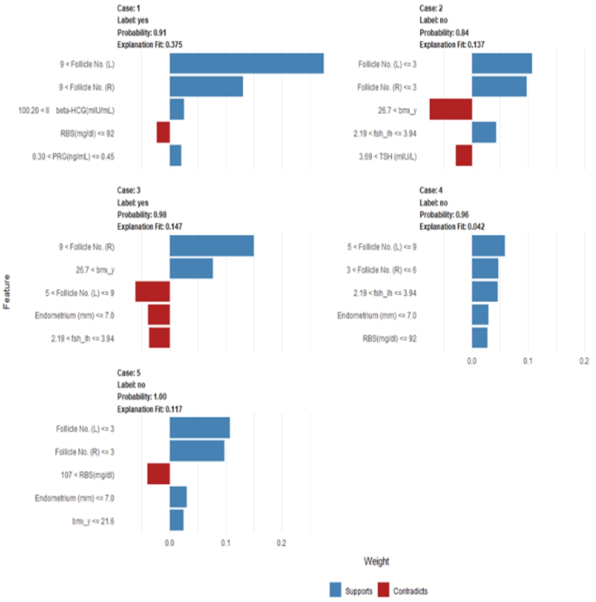

Fig. 1. The findings of the LIME model

For the first patient;

9 <Follicle No. (L) values are positively associated with PCOS status. Likewise, 9<Follicle No. (R) for the values, there is also a positive correlation with PCOS status. 100.20 <II beta-HCG (mIU / mL) values are positively associated with PCOS status. Finally, 30 <PRG (ng / mL)≤ 45 values are also positively associated with PCOS status. However, values with RBS (mg / dl) ≤0.45 are negatively associated with PCOS status. For this patient, 9 <Follicle No. (L) variable is the most important variable in terms of having PCOS.

For the second patient;

Follicle No. (L)≤3, Follicle No. (R)≤3 and 2.19<Fsh/Lh≤3.94 values are positively associated with non-PCOS. However, 26.7<BMI and 2.19<Fsh/Lh≤3.94 values are negatively associated with non-PCOS. For this patient, Follicle No. (L)≤3 and Follicle No. (R)≤3 are the most important variables in terms of not having PCOS.

For the third patient;

9 <Follicle No. (R), 26.7< BMI values are positively associated with PCOS status. However, 5<Follicle No. (L)≤9, Endometrium (mm)≤7 and 2.19< Fsh/Lh ≤3.94 values are negatively associated with PCOS status. For this patient, 9<Follicle No. (R) variable is the most important variable in terms of having PCOS.

For the fourth patient,

5 <Follicle No. (L)≤9, 3<Follicle No. (L)≤6, 2.19 < Fsh/Lh ≤3.94, Endometrium (mm) ≤7 and RBS (mg / dl) ≤92 values are positively associated with non-PCOS status. For this patient, 5<Follicle No. (L)≤9 variable is the most important variable in terms of not having PCOS.

For the fifth patient,

Follicle No. (L)≤3, Follicle No. (R)≤3, Endometrium (mm)≤7 and BMI≤21.6 values are positively associated with non-PCOS. 107<RBS (mg/dl) values are negatively associated with non-PCOS status. For this patient, Follicle No. (L)≤3, Follicle No. (R)≤3 variables are the most important variables in terms of not having PCOS.

5. DISCUSSION

The most frequent endocrine disorder in women of reproductive age is polycystic ovarian syndrome (PCOS). PCOS affects roughly 6–10% of women of reproductive age, depending on the diagnostic criteria used. A combination of clinical indications of menstrual abnormalities or anovulation, clinical or biochemical hyperandrogenism, and polycystic ovaries is used to diagnose PCOS. It is often diagnosed in the reproductive years of life when women with PCOS are meeted with infertility, or because of hyperandrogenism symptoms such as acne, alopecia androgenica, and hirsutism [29]. Because the disease is complex and multifactorial, diagnosing it might be challenging owing to overlapping symptoms. Multiple etiological factors have been implicated in PCOS. Despite these In the care and diagnosis of PCOS, progress has been made [30].

Artificial Intelligence (AI) has gained significant traction in recent years, and if properly handled, it has the potential to exceed expectations across a wide range of application industries [31]. Current artificial intelligence technologies, on the other hand, are often poor at describing the interpretation process and predicting outcomes. This condition makes it difficult to comprehend the estimation models that have been developed. As a result, explainable artificial intelligence has lately begun to gain traction. The goal of explainable artificial intelligence is to make the computational conclusions that underpin AI decisions understandable to ordinary users and academics [32].

LIME (Local Interpretable Model-Agnostic Explanations) is a common methodology for making black box Machine Learning (ML) algorithms more interpretable and explainable. LIME often generates an explanation for a single prediction made by any ML model by learning a simpler interpretable model (e.g. linear classifier) around the prediction by randomly perturbing simulated data around the instance and obtaining feature importance through feature selection. LIME and similar local algorithms have gained popularity due to their simplicity. The LIME approach can be used to discover which variables affect each estimation in the model to what extent and in which direction, as well as which variable has a greater impact on the model's outcomes than other factors. This gives a detailed explanation for each observation, allowing any complex classifier to be explained in a straightforward manner [28].

According to the interpreted results, the observations whose results were obtained, the values of Follicle (No) L. and Follicle (No) R. in different value ranges were positively correlated with the absence of PCOS. In addition, these two variables are the most important variables for the absence of PCOS for our observations. For the observations whose results were obtained, the variables RBS(mg/dl), bmi_y, fsh_lh, TSH (mIU/L), Endometrium (mm) also played a role in obtaining the results.

In addition, for the observations whose results were obtained, the values of Follicle No L and Follicle No R in different value ranges were also found to be positively correlated with PCOS. Likewise, the most important variables for PCOS status are Follicle No. (L) and Follicle No. (R) variables. In addition, beta-HCG(mIU/mL), PRG(ng/mL), RBS(mg/dl), bmi_y, Endometrium (mm), fsh_lh variables also played a role in obtaining the results for PCOS.

When the observations obtained from the results are examined, it can be said that the Follicle (No) L. and Follicle (No) R. variables are the most effective variables on the presence or absence of PCOS. For different value ranges of these two variables, the result of PCOS or not varies. Based on this, it can be said that different values of Follicle (No) L. and Follicle (No) R. variables for PCOS status may be effective in determining the disease.

According to the results, the values of Follicle No L and Follicle No R variables tend to increase in the case of PCOS.

REFERENCES

[1] Yu, K. H., Beam, A. L., & Kohane, I. S. (2018). Artificial intelligence in healthcare. Nature biomedical engineering, 2(10), 719-731.

[2] Sokol, K., Santos-rodriguez, R., Hepburn, A., & Flach, P. (2019). Surrogate Prediction Explanations Beyond LIME. no. HCML.

[3] Kononenko, I. (2001). Machine learning for medical diagnosis: history, state of the art and perspective. Artificial Intelligence in medicine, 23(1), 89-109.

[4] Deo, R. C. (2015). Machine learning in medicine. Circulation, 132(20), 1920-1930.

[5] He, D., Mathews, S. C., Kalloo, A. N., & Hutfless, S. (2014). Mining high-dimensional administrative claims data to predict early hospital readmissions. Journal of the American Medical Informatics Association, 21(2), 272-279.

[6] Pederson, J. L., Majumdar, S. R., Forhan, M., Johnson, J. A., McAlister, F. A., & PROACTIVE Investigators. (2016). Current depressive symptoms but not history of depression predict hospital readmission or death after discharge from medical wards: a multisite prospective cohort study. General hospital psychiatry, 39, 80-85.

[7] Futoma, J., Morris, J., & Lucas, J. (2015). A comparison of models for predicting early hospital readmissions. Journal of biomedical informatics, 56, 229-238.

[8] Katuwal, G. J., & Chen, R. (2016). Machine learning model interpretability for precision medicine. arXiv preprint arXiv:1610.09045.

[9] Bastani, O., Kim, C., & Bastani, H. (2017). Interpreting blackbox models via model extraction. arXiv preprint arXiv:1705.08504.

[10] Stiglic, G., Kocbek, P., Fijacko, N., Zitnik, M., Verbert, K., & Cilar, L. (2020). Interpretability of machine learning-based prediction models in healthcare. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10(5), e1379.

[11] Escalante, H. J., Escalera, S., Guyon, I., Baró, X., Güçlütürk, Y., Güçlü, U., ... & van Lier, R. (Eds.). (2018). Explainable and interpretable models in computer vision and machine learning. Cham: Springer International Publishing.

[12] Garreau, D., & Luxburg, U. (2020, June). Explaining the explainer: A first theoretical analysis of LIME. In International Conference on Artificial Intelligence and Statistics (pp. 1287-1296). PMLR.

[13] Hu, L., Chen, J., Nair, V. N., & Sudjianto, A. (2018). Locally interpretable models and effects based on supervised partitioning (LIME-SUP). arXiv preprint arXiv:1806.00663.

[14] Mehrotra, P., Chatterjee, J., Chakraborty, C., Ghoshdastidar, B., & Ghoshdastidar, S. (2011, December). Automated screening of

polycystic ovary syndrome using machine learning techniques. In 2011 Annual IEEE India Conference (pp. 1-5). IEEE.
[15] Denny, A., Raj, A., Ashok, A., Ram, C. M., & George, R. (2019, October). I-HOPE: detection and prediction system for polycystic ovary syndrome (PCOS) using machine learning techniques. In TENCON 2019-2019 IEEE Region 10 Conference (TENCON) (pp. 673-678). IEEE.
[16] Meena, K., Manimekalai, M., & Rethinavalli, S. (2015). Correlation of Artificial Neural Network Classification and NFRS Attribute Filtering Algorithm for PCOS Data. Int. J. Res. Eng. Technol, 4(3), 519-524.
[17] Vikas, B., Anuhya, B. S., Chilla, M., & Sarangi, S. (2018). A Critical Study of Polycystic Ovarian Syndrome (PCOS) Classification Techniques. International Journal of Computational Engineering & Management, 21(4), 1-7.
[18] Kahsar-Miller, M. D., Nixon, C., Boots, L. R., Go, R. C., & Azziz, R. (2001). Prevalence of polycystic ovary syndrome (PCOS) in first-degree relatives of patients with PCOS. Fertility and sterility, 75(1), 53-58.
[19] Breiman, L. (1996). Bagging predictors. Machine learning, 24(2), 123-140.
[20] Breiman, L. (2001). Random forests. Machine learning, 45(1), 5-32.
[21] Ho, T. K. (1998). The random subspace method for constructing decision forests. IEEE transactions on pattern analysis and machine intelligence, 20(8), 832-844.
[22] Izquierdo-Verdiguier, E., & Zurita-Milla, R. (2020). An evaluation of Guided Regularized Random Forest for classification and regression tasks in remote sensing. International Journal of Applied Earth Observation and Geoinformation, 88, 102051.
[23] Prasad, A. M., Iverson, L. R., & Liaw, A. (2006). Newer classification and regression tree techniques: bagging and random forests for ecological prediction. Ecosystems, 9(2), 181-199.
[24] Panov, P., & Džeroski, S. (2007, September). Combining bagging and random subspaces to create better ensembles. In International Symposium on Intelligent Data Analysis (pp. 118-129). Springer, Berlin, Heidelberg.
[25] Shi, S., Zhang, X., & Fan, W. (2020). A modified perturbed sampling method for local interpretable model-agnostic explanation. arXiv preprint arXiv:2002.07434.
[26] Ribeiro, M. T., Singh, S., & Guestrin, C. (2016, August). " Why should i trust you?" Explaining the predictions of any classifier. In Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining (pp. 1135-1144).
[27] Kumarakulasinghe, N. B., Blomberg, T., Liu, J., Leao, A. S., & Papapetrou, P. (2020, July). Evaluating local interpretable model-agnostic explanations on clinical machine learning classification models. In 2020 IEEE 33rd International Symposium on Computer-Based Medical Systems (CBMS) (pp. 7-12). IEEE.
[28] Zafar, M. R., & Khan, N. M. (2019). DLIME: A deterministic local interpretable model-agnostic explanations approach for computer-aided diagnosis systems. arXiv preprint arXiv:1906.10263.
[29] McLuskie, I., & Newth, A. (2017). New diagnosis of polycystic ovary syndrome. BMJ: British Medical Journal, 356.
[30] Khan, M. J., Ullah, A., & Basit, S. (2019). Genetic basis of polycystic ovary syndrome (PCOS): current perspectives. The application of clinical genetics, 12, 249.
[31] Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., ... & Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. Information Fusion, 58, 82-115.
[32] Gunning, D., Stefik, M., Choi, J., Miller, T., Stumpf, S., & Yang, G. Z. (2019). XAI—Explainable artificial intelligence. Science Robotics, 4(37).

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Breast Cancer Diagnosis Based On Thermography Images Using Pre-Trained Networks

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ABSTRACT

Breast cancer is the leading cause of death among women around the world. Because of its low cost and the fact that it does not emit hazardous radiation, infrared thermography has emerged as a viable approach for diagnosing the condition in young women. This study aims to create a computer-aided diagnostic system that can process thermographic breast cancer images and classify breast cancer with pre-trained networks in order to use thermography as a diagnostic method. In this study, an open-access data set consisting of thermographic breast cancer images was used for diagnostic purposes. The data set consists of 179 healthy images and 101 images from patients. The images were converted from .txt format to .jpeg format. The data set is acquired from http://visual.ic.uff.br/dmi/. In this study, various pre-trained networks were used to reduce the training time. Different metrics were employed to assess the performance of the models.The images obtained during the modeling phase were used to display both breasts in the image without distinguishing the right and left breasts, that is, without fragmenting the images. According to the results of the different pre-trained network models after the data preprocessing stages, the best classification performance was achieved for the ResNet50V2 model with an accuracy value of 0.996. In this study, a computer-aided diagnosis system was created by developing an interface for breast cancer classification from thermographic images in addition to experimental findings. The web software based on the proposed models has provided promising predictions of breast cancer from thermographic images. The developed software can help medical and other healthcare professionals easily spot breast cancer.

1. INTRODUCTION

CANCER is one of the most difficult and deadly diseases in the world. Every year, it claims the lives of millions of people. Cancer claimed the lives of 8.8 million people in 2015, according to the World Health Organization (WHO) [1].

Because of somatic cell changes caused by epigenetic or genetic changes, malignant neoplasm or cancer is considered a genetic illness [2]. Cancer affects people of all ages, including men and women, the old and the young, but it is more prevalent in the elderly than in the youth. Different statistics exist for the most common forms of malignancies, and both geographic location and gender have a factor in their occurrence. Breast cancer is one of the most often diagnosed cancers among women and is the leading cause of death among women around the world. It is critical to discover the disease early to improve the odds of people being treated and cured. Because of its low cost and the fact that it does not emit hazardous radiation, infrared thermography has emerged as a viable approach for diagnosing the condition in young women. As a result, research is being conducted to find both diagnostic and therapy methods. In general, the causes of breast cancer are unknown. As of today, doctors and specialists do not have an exact justification for the incidence of breast cancer in some women over others [3]. It is critical to detect breast cancer early to prevent mortality and morbidity [4].

Mammography, ultrasound, and magnetic resonance imaging are the most often used imaging modalities for early breast cancer detection. However, constraints such as x-rays, cost, dense tissue at a young age, false positives (FP), and false-negative (FN) rates prompted researchers and institutions to do an extensive study into other techniques such as thermography. Contrary to other methods, thermography is a non-invasive, non-inclusive, radiation-free, and low-cost technique [5]. Thermography has experienced a surge in popularity in recent years, particularly for breast cancer screening [6]. This is owing to the allure of its low-risk technology, as well as the possibility of future advancements with modern technological innovation. The ultimate goal of current research in this subject is to develop a more accurate and confirmed tumor diagnosis that can be used as a gold standard for breast cancer screening [3]. These innovative approaches, such as thermography, are frequently used in conjunction with computer-aided diagnostic (CAD) systems.

One of the most common applications in breast cancer screening although is thermography, which has not been accepted as the standard procedure. Thermographic imaging is yet to be accepted as the gold standard for this application. Furthermore, even though mammography is not a completely risk-free procedure, physicians prefer it over thermography results. As a result, if thermographic breast cancer screening improves to a satisfactory level, it can be a replacement candidate. The major problem to solve here is the image-processing task. For this reason, computer-aided diagnosis systems should be constructed by applying image processing methods to thermographic breast cancer images and obtaining valid results by processing them [3].

In a clinical study, the approaches for computer-aided diagnosis of breast cancer utilizing thermal imaging are presented in a paper using various Convolutional Neural Networks (CNNs). The accuracy, precision, recall, F1 measure, and Matthews Correlation coefficient of the developed nets were evaluated on a benchmarking dataset. The results reveal that architecture with pre-trained convolutional layers and training freshly added fully connected layers outperforms other architectures. Using transfer learning methods and CNN, 94.3 percent accuracy, 94.7 percent precision, and 93.3 percent recall were obtained [7]. Another work uses convolutional neural networks (i.e., AlexNet, GoogLeNet, ResNet-18, VGG-16, and VGG-19) to identify 440 infrared photos of 88 individuals into two categories: normal and pathological demonstrate that combining deep learning techniques with infrared imagery to help breast cancer diagnosis has a lot of promise for clinical purposes [8]. Additionally, the use of a deep convolutional neural network with transfer learning to automatically classify thermograms into two classes (normal and abnormal) is proposed in a research. A total of 311 female individuals were used to assess the CNN's performance, with one research using a balanced class distribution and the other using a typical screening cohort with a low proportion of aberrant thermograms. The ResNet-101 model exhibited a sensitivity of 92.3 percent and a specificity of 53.8 percent, respectively. These findings imply that the proposed model can accurately categorize abnormal thermograms, indicating that infrared thermography can be used as an auxiliary tool for breast cancer screening [9].

This study aims to create a computer-aided diagnostic system that can process thermographic breast cancer images and classify breast cancer with pre-trained networks in order to use thermography as a diagnostic method.

2. MATERIAL and METHODS

2.1. Dataset

In this study, an open-access data set consisting of thermographic breast cancer images was used for diagnostic purposes. The data set includes a total of 5862 images, including 3504 healthy and 2457 diseased images. Images are in 640*480 jpeg format. The data set consists of 179 healthy images and 101 images from patients. The images were converted from .txt format to .jpeg format. The data set is acquired from http://visual.ic.uff.br/dmi/. Sample images of the data set are given in Figure 1.

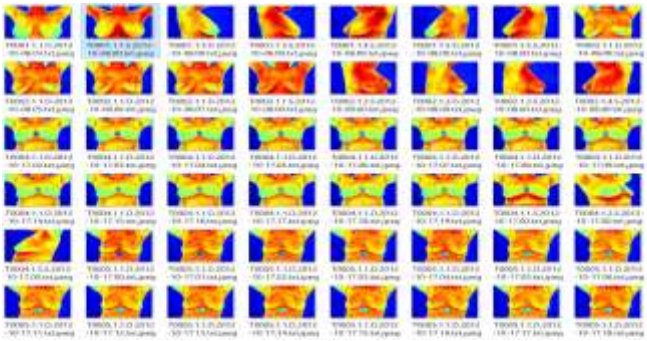

Fig. 1. Sample images of the data set

2.2. Deep Learning

The Deep learning, a subfield of machine learning (ML), has grown in prominence in recent years as computing power has increased dramatically and massive new data sets are being generated daily. Deep learning has produced ground-breaking results in a range of hard tasks, including image classification, object detection, speech recognition, language translation, natural language processing, and games. Deep learning models have outperformed many traditional machine learning approaches in terms of modeling big data sets due to their ability to function on the graphics processing unit. In the processing of medical image and video data, CNN deep learning architecture is commonly utilized. Deep learning algorithms such as CNN have recently been used as a decision support system for breast cancer detection on mammograms, segmentation of liver metastases with computed tomography (CT), brain tumor segmentation with magnetic resonance (MR) imaging, and classification of high-resolution chest CT images of interstitial lung patients [10]. Multiple layers, pooling, local connections, and shared weights distinguish CNN from a typical neural network. The primary idea behind CNN is that input data can be interpreted as images. This can reduce the number of parameters used, resulting in faster processing. Convolutional layers (CLs), pooling layers (PLs), and the rectified linear unit (RLU) are the layers that makeup CNN architecture (ReLU). CLs learn the convolutions and deliver the best data categorization performance. Overfitting is controlled by PLs, which allow for stable conversion and enhance computing performance by lowering the number of structures produced by convolutions. Through the ReLU activation function, ReLU improves the network's nonlinear features. Various study structures have been devised and introduced based on the type of data, image, and objective [11, 12]. In image processing studies with deep learning methods, the model training phase is time-consuming. Furthermore, training a deep learning model requires a lot of data as well as processing time. It is often useful to use pre-trained networks on big datasets lasting days or weeks to train and enhance use-case training. Therefore, in this study, many different pre-trained networks were used to reduce the training time.

2.2.1. Image Processing

Image processing is the process of digitizing an image using various methods and techniques to extract usable information and produce enhanced images. In other words, image processing is a set of computer studies aiming at altering digital picture data using a computer or software in order to meet a certain criterion [13].

2.2.2. Thermography

At certain temperatures, objects inherently generate thermal signals. The type of signals transmitted or radiated, and the temperature range, are determined by the object's features. Under normal circumstances, the human body, like other objects, emits Infrared (IR) signals [14]. Because of the heat, the transmitted IR signals differ from one part to the next. This notion is commonly used in medical tests, particularly for breast cancer screenings. Any malignant growth in the breast is linked to the development of inflammation and blood vessels, both of which have a higher temperature profile. Thermography, often known as thermal imaging, is a non-invasive way of collecting the heat map of a specific limb in medicine. The approach is non-contact, non-destructive, and does not emit radiation, making it suitable for repeated usage. The procedure here uses a thermographic camera to capture a heat map of the breasts and their surroundings to highlight any anomalies [3]. Examples of diseased and healthy breast images are given in Figure 2.

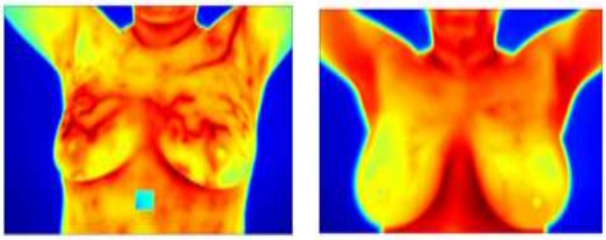

Fig. 2. Examples of the diseased and healthy breast images

Thermography has been recently revived in medical applications. It is evaluated together with image processing methods, especially for use in the diagnosis of breast cancer. Breast thermography takes advantage of the variation in the heat map beneath the skin between healthy and cancerous breasts. The presence of a breast tumor raises the warmth of the tissues that surround it [15]. Asymmetric study of healthy and diseased breasts is generally used by specialists. The process for using thermography to screen for breast cancer is relatively simple. It begins with a physical inspection of the surface of the breasts. This allows the doctor to correlate any unexpected presence to the heat map. Then, the individual needs to stay at room temperature for 15 minutes to acclimate to the environment. This procedure is done in a room where both humidity and temperature are controlled. At the same time, the person will need to undress the upper part of their body from waist to chin. After the body temperature reaches equilibrium, the person is asked to take his hands on his right side so that the relevant surfaces can be viewed. Then the imaging procedure starts to complete the process [3].

2.3. Developed Web-Based Software

The developed web-based interface is designed to classify breast cancer from thermographic breast cancer images. During the development of the interface, Python programming language and additionally Flask [16], TensorFlow [17], Keras [18], Pandas [19], NumPy [20], Scikit-learn [21] libraries were used. A general working diagram is given in Figure 3.

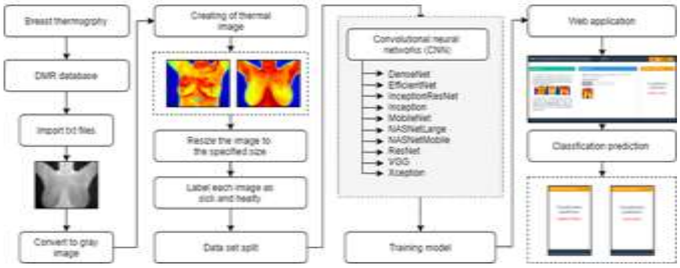

Fig. 3. A general working diagram

2.4. An Illustrative Application in the Developed Web-Based Software

A sample image has been uploaded to the system to show the usability of the developed web-based software. The screen showing classification prediction results of the loaded image is given in figure 4 and it was classified as healthy.

Fig. 4. The screen showing classification prediction results

3. RESULTS

Before classifying the thermographic breast cancer images, the text files were converted into images for visual analysis. For clear and identifiable images, the image pre-processing phase is critical. For this reason, all images were converted to 640x480 jpg format and taken into modeling. The images obtained during the modeling phase were used to display both breasts in the image without distinguishing the right and left breasts, that is, without fragmenting the images. The results of different pre-trained network models after the data preprocessing stages are given in Table 1.

TABLE I
ACCURACY RESULTS FROM MODELS

Model name	Validation accuracy
DenseNet121	0.989
DenseNet169	0.995
DenseNet201	0.995
InceptionResNetV2	0.980
InceptionV3	0.984
MobileNet	0.994
MobileNetV2	0.993
NASNetLarge	0.994
NASNetMobile	0.981
ResNet101V2	0.995
ResNet152V2	0.992
ResNet50V2	0.996
VGG16	0.937
VGG19	0.931
Xception	0.991

According to the results in Table 1, an accuracy value above 0.90 was obtained for all models. The confusion matrix of the

ResNet50V2 model, which gives the highest accuracy of 0.996, is given in Figure 5. After ResNet50V2, the models with the highest accuracy values were DenseNet169, DenseNet201, and ResNet101V2.

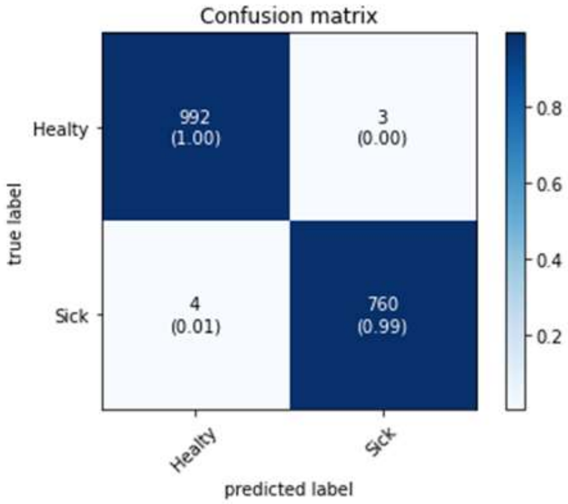

Fig. 5. The confusion matrix of the ResNet50V2 model

The confusion matrices of the next best models are $\begin{bmatrix} 993 & 6 \\ 3 & 757 \end{bmatrix}, \begin{bmatrix} 991 & 9 \\ 5 & 754 \end{bmatrix}, \begin{bmatrix} 991 & 4 \\ 5 & 759 \end{bmatrix}$ respectively.

Performance metrics for the ResNet50V2 model are given with 95 percent confidence intervals in Table 2.

TABLE II
PERFORMANCE METRICS FOR THE RESNET50V2 MODEL

		Testing value(%) (95%CI)	
Metrics	**Value**	**Confidence interval lower limit**	**Confidence interval upper limit**
Accuracy	0.996	0.993	0.999
Sensitivity	0.996	0.990	0.999
Specificity	0.996	0.989	0.999
F1-Score	0.996	0.994	0.999
MCC	0.992	0.988	0.996
G-Mean	0.996	0.993	0.999

4. DISCUSSION

Early identification of breast cancer can help prevent the disease from spreading and becoming lethal. Due to budgetary constraints, lack of convenience, and pain involved with standard screenings such as mammograms, most women neglect the importance of regular breast cancer screening. Thermography can help with some of these issues because it is inexpensive, simple to use, and causes little discomfort to the patient because it is non-invasive and painless. Thermography is a more advanced alternative to mammography, which is known to induce pain and is unsuccessful at detecting breast cancer. The requirement for a mammography exam would be avoided if the thermographic applications could identify cells without cancer. In addition, if the thermogram indicates the presence of a tumor, mammography can be used to validate or refute the allegation. This option may encourage more women to have their breasts evaluated [3, 22]. For these reasons, there is a need for computer-aided diagnostic systems to be obtained by combining thermography with image processing methods. This study aims to demonstrate the feasibility of a computer-aided system through image processing methods to show the usability of thermography instead of the expensive and painful known methods used in the diagnosis of breast cancer. For this purpose, unlike some previous studies, it is aimed to reduce the training time and increase the model performance by using pre-trained networks for image processing in this study [3]. In previous imaging studies with thermographic breast cancer, the breast cross-section was divided into right and left breasts and processed in the studies. However, in this study, image processing was performed by using images of the chest area to cover both breasts, without distinguishing between right and left breasts [3, 22, 23, 24].

According to the results obtained from the different models used in this study, the highest classification performance was obtained with the ResNet50V2 model as 0.996. When previous studies were examined, the highest accuracy was found to be 0.989 in a study that classified thermographic breast cancer images with CNN [3]. In the breast cancer classification study from thermographic images with another CNN method, the highest accuracy was obtained as 0.90 [22].

Finally, unlike other studies, in this study, a computer-aided diagnosis system was created by developing an interface for breast cancer classification from thermographic images in addition to experimental findings. The web software based on the proposed models has provided promising predictions of breast cancer from thermographic images. The developed software helps breast cancer to be easily diagnosed by medical professionals and other healthcare professionals. Thus, the workload of medical professionals can be reduced and a faster consultation system can be created. With the consultation system created, the patient can be directed to a more advanced diagnosis system which can pave the way for early diagnosis and preventing deadly cancer.

REFERENCES

[1] Brookman-May, S. D., Rodriguez-Faba, O., Langenhuijsen, J. F., Akdogan, B., Linares, E., Minervini, A., ... & Marszalek, M. (2017). Challenges, hurdles and possible approaches to improve cancer care in developing countries–A short breakdown of the status quo and future perspective. Advances in Modern Oncology Research, 3(5), 204-212.

[2] Chakraborty, S., & Rahman, T. (2012). The difficulties in cancer treatment. ecancermedicalscience, 6.

[3] Ekici, S., & Jawzal, H. (2020). Breast cancer diagnosis using thermography and convolutional neural networks. Medical hypotheses, 137, 109542.

[4] Li, T., Sun, L., Miller, N., Nicklee, T., Woo, J., Hulse-Smith, L., ... & Boyd, N. (2005). The association of measured breast tissue characteristics with mammographic density and other risk factors for breast cancer. Cancer Epidemiology and Prevention Biomarkers, 14(2), 343-349.

[5] Zuluaga-Gomez, J., Zerhouni, N., Al Masry, Z., Devalland, C., & Varnier, C. (2019). A survey of breast cancer screening techniques: thermography and electrical impedance tomography. Journal of medical engineering & technology, 43(5), 305-322.

[6] Kandlikar, S. G., Perez-Raya, I., Raghupathi, P. A., Gonzalez-Hernandez, J. L., Dabydeen, D., Medeiros, L., & Phatak, P. (2017). Infrared imaging technology for breast cancer detection–Current status, protocols and new directions. International Journal of Heat and Mass Transfer, 108, 2303-2320.

[7] Cabıoğlu, Ç., & Oğul, H. (2020, May). Computer-Aided Breast Cancer Diagnosis from Thermal Images Using Transfer Learning. In International Work-Conference on Bioinformatics and Biomedical Engineering (pp. 716-726). Springer, Cham. 1.

[8] Chaves, E., Gonçalves, C. B., Albertini, M. K., Lee, S., Jeon, G., & Fernandes, H. C. (2020). Evaluation of transfer learning of pre-trained CNNs applied to breast cancer detection on infrared images. Applied Optics, 59(17), E23-E28.

[9] Torres-Galván, J. C., Guevara, E., Kolosovas-Machuca, E. S., Oceguera-Villanueva, A., Flores, J. L., & González, F. J. (2021). Deep convolutional neural networks for classifying breast cancer using infrared thermography. Quantitative InfraRed Thermography Journal, 1-12.

[10] Chartrand, G., Cheng, P. M., Vorontsov, E., Drozdzal, M., Turcotte, S., Pal, C. J., ... & Tang, A. (2017). Deep learning: a primer for radiologists. Radiographics, 37(7), 2113-2131.

[11] Nair, V., & Hinton, G. E. (2010, January). Rectified linear units improve restricted boltzmann machines. In Icml.

[12] Albawi, S., Mohammed, T. A., & Al-Zawi, S. (2017, August). Understanding of a convolutional neural network. In 2017 International Conference on Engineering and Technology (ICET) (pp. 1-6). Ieee.

[13] İnce, Ö., Şenel, İ. K., & Yilmaz, F. (2020). Image Processing and Analysis in Health: Advantages, Challenges, Threats and Examples. Archives of health science and research (Online), 7(1), 66-74.

[14] Tan, J. H., Ng, E. Y. K., Acharya, U. R., & Chee, C. (2009). Infrared thermography on ocular surface temperature: a review. Infrared physics & technology, 52(4), 97-108.

[15] Ibrahim, A., Mohammed, S., & Ali, H. A. (2018, February). Breast cancer detection and classification using thermography: a review. In International Conference on Advanced Machine Learning Technologies and Applications (pp. 496-505). Springer, Cham.

[16] Grinberg, M. (2018). Flask web development: developing web applications with python. " O'Reilly Media, Inc.".

[17] Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., ... & Zheng, X. (2016). Tensorflow: A system for large-scale machine learning. In 12th {USENIX} symposium on operating systems design and implementation ({OSDI} 16) (pp. 265-283).

[18] Akiba, T., Sano, S., Yanase, T., Ohta, T., & Koyama, M. (2019). Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining.

[19] McKinney, W. (2011). pandas: a foundational Python library for data analysis and statistics. Python for high performance and scientific computing, 14(9), 1-9.

[20] Van Der Walt, S., Colbert, S. C., & Varoquaux, G. (2011). The NumPy array: a structure for efficient numerical computation. Computing in science & engineering, 13(2), 22-30.

[21] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... & Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. the Journal of machine Learning research, 12, 2825-2830.

[22] Zuluaga-Gomez, J., Al Masry, Z., Benaggoune, K., Meraghni, S., & Zerhouni, N. (2021). A CNN-based methodology for breast cancer diagnosis using thermal images. Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization, 9(2), 131-145.

[23] Baykara, M. (2021).Performance Analysis of Various Classification Algorithms for Computer-Aided Breast Cancer Diagnosis System Using Thermal Medical Images, Turkish Journal of Science and Technology, vol. 16, no. 1, pp. 65-84,

[24] Kaya, M. O. (2021). Computer-Aided Model For The Classification Of Acute Inflammations Via Radial-Based Function Artificial Neural Network. The Journal of Cognitive Systems, 6(1), 1-4.

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Heart Disease Classification Based on Performance Measures Using a Deep Learning Model

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ABSTRACT

Heart disease, which is one of the most common diseases in the world, is expected to remain the leading cause of mortality on a global scale. Therefore the aim of this study is to classify heart disease using a deep learning approach in an open-access dataset that includes data from patients with and without heart disease.

In this study, a deep learning model was applied to an open-access data set containing the data of patients with and without heart disease. The performance of the method used was evaluated with the performance criteria of specificity, sensitivity, accuracy, positive predictive value, and negative predictive value. Specificity, sensitivity, accuracy, positive predictive value and negative predictive value from the performance criteria obtained from the model were calculated as 0.946, 0.903, 0.9245, 0.9436 and 0.907, respectively.

As a result of the findings obtained from the study, it was seen that the data set we discussed was successfully classified with the deep learning model used. With this obtained high classification performance, the factors associated with the disease can be revealed.

1. INTRODUCTION

HEART disease refers to a set of conditions involving the heart, its vessels, muscles, valves, or internal electrical pathways responsible for muscle contraction. With a more comprehensive definition, heart diseases are complex clinical syndromes that can affect the endocrine, hematological, musculoskeletal, renal, respiratory, peripheral vascular, hepatic, and gastrointestinal systems. According to the Centers for Disease Control, heart disease is one of the leading causes of death worldwide. In addition, despite the advances in modern medicine, it continues to affect millions of people around the world and has high mortality rates [1, 2]. Usually one in four deaths occur as a result of heart disease. Heart disease is common among both men and women in most countries around the world. Therefore, people should consider heart disease risk factors. Although genetics may play a role, certain lifestyle factors significantly influence heart disease. It is predicted that heart disease will continue to be the leading cause of death for a long time globally. For this reason, it is of great importance to estimate the factors associated with the disease by using data mining algorithms with the data of patients diagnosed with heart disease, to take precautions related to the disease, and for physicians to benefit from it [1, 3].

Artificial intelligence is a machine learning that can act like a human, imitate human behavior, make rational decisions, and respond in a meaningful way. While doing these, the basic requirement is education. For years, many scientists thought that computer intelligence was useless without learning.However, this idea has changed and developed rapidly with the advent of machine learning and later deep learning [4]. Machine learning; it is one of the sub-branches of artificial intelligence and has become one of the most important areas to obtain useful, meaningful information from large data sets. Machine learning areas are increasing with the development of today's technologies. This is because the size and complexity of data is increasing day by day. Analyzing large and complex data have becomes even more difficult. In such a case, the use of machine learning has become a necessity for analysis [4, 5].

Deep learning, it contains multiple artificial neural networks and is a sub-branch of machine learning used to obtain new data by analyzing the properties of data such as existing images, audio, with many algorithms including machine learning algorithms [6].

The aim of this study is to classify heart disease using a deep learning approach in an open-access dataset that includes data from patients with and without heart disease. According to the results of this classification model, the factors causing heart disease can be determined and medical professionals will be able to benefit from these results and can be used in preventive medicine.

2. MATERIAL and METHODS

In this study, a data set containing information about patients with and without heart disease obtained from the address "https://www.kaggle.com/asaumya/healthcare-problem-prediction-stroke-patients" was used. The data set used in the study is unbalanced. For this reason, SMOTE, an oversampling method, was used to balance the data set.

It is very difficult to analyze data stacks containing very large and different numerical data using classical algorithms and techniques [7]. In order to solve this problem, data science has made a rapid development in recent years. The importance of data science comes to the fore one more step, especially when considering the ever-growing digital data. As a result of such rapid development of data science, the concepts of data mining, artificial intelligence, machine learning and deep learning have emerged. In order to obtain meaningful patterns from large amounts of data, different algorithms are constantly being developed with data mining. In this sense, the concepts of artificial intelligence, machine learning and deep learning continue to develop in parallel with data mining [8].

Artificial intelligence in literature, transferring the working structure of human intelligence to computers in general; it is defined as the ability of computers to perform tasks that require logic, such as drawing conclusions from human-specific behaviors, finding solutions, making generalizations, understanding the problem, and learning by making use of past experiences [9].

Deep learning is a newer type of artificial neural network algorithm compared to others and is one of the sub-branches of machine learning. Deep learning is an algorithm that has one or more inputs, containing many layers, and one or more outputs at the end. In each layer, it combines the previous information and generates values with complex and meaningful results from this information. In this respect, it is more consistent and powerful than other neural network algorithms. Deep learning models consist of different data transformation stages by considering the properties of the data in the sources and learning them in their hidden layers [10].

The deep learning method learns the distinguishing features itself from a large number of given inputs. This feature learning stages consists of a number of layers. The lower-level layers have less distinctive features, while the higher-level layers, which are a combination of these layers, have more distinctive features. The lower-level layers form the basis of the higher-levels and enable more meaningful features to be produced. Unlike traditional machine learning, it does the learning process on its own instead of calculating the basic features determined by the human [11].

2.1. Data Analysis

Quantitative data were expressed as median (minimum-maximum), and qualitative data as number (percentage). Conformity to normal distribution was evaluated using the Kolmogorov-Smirnov test. Whether there is a statistically significant difference between the "No heart disease" and "Suffering from heart disease" groups, which are the categories of dependent / target variable (heart disease) in terms of independent variables, was examined using the Mann-Whitney U test and Pearson chi-square test. Values of p <0.05 were considered statistically significant. IBM SPSS Statistics 26.0 package program was used for all analyzes.

3. RESULTS

The table showing the distribution of the dependent variable in the data set used in this study is given below.

TABLE I
TABLE SHOWING THE DISTRIBUTION OF THE DEPENDENT VARIABLE

No heart disease		Suffering from heart disease	
Count	Percentage (%)	Count	Percentage (%)
1409	83.6	276	16.4

Descriptive statistics of the independent variables in this study are given in Table 2. According to this table; there is a statistically significant difference between the groups of the dependent variable (Heart Disease) in terms of age, avg glucose level and BMI variables ($p<0.05$).

TABLE II
DESCRIPTIVE STATISTICS TABLE OF QUANTITATIVE INDEPENDENT VARIABLES

Variables	Heart Disease: No heart disease	Heart Disease: Suffering from heart disease	p-value*
	Median (min-max)	Median (min-max)	
Age	47 (0.08-82)	71 (2-82)	<0.001
Avg Glucose Level	93.05 (55.22-267.76)	106.55 (56.31-271.74)	<0.001
BMI	28.3 (10.3-78)	29.8 (19.1-54.7)	0.001

***: Mann Whitney U test**

Table 3 shows that; there is a statistically significant relationship between the gender, hypertension, ever married, work type and smoking status variables and the dependent variable (Heart Disease) groups ($p<0.05$).

TABLE III
DESCRIPTIVE STATISTICS TTABLE OF QUANTITATIVE INDEPENDENT VARIABLES

Variables	Categories of Variables	Heart Disease: No heart disease	Heart Disease: Suffering from heart disease	p-value*
		Number (%)	Number (%)	
Gender	Male	570 (40.5)	163 (59.1)	<0.001
	Female	838 (59.5)	113 (40.9)	
Hypertension	No Hypertension	1258 (89.3)	212 (76.8)	<0.001
	Suffering from Hypertension	151 (10.7)	64 (23.2)	
Ever Married	No	457 (32.4)	32 (11.6)	<0.001
	Yes	952 (67.6)	244 (88.4)	
Work Type	Private	848 (60.2)	158 (57.2)	<0.001
	Self Employed	216 (15.3)	81 (29.3)	
	Govt Job	169 (12.0)	36 (13.0)	
	Children	170 (12.1)	1 (0.4)	
	Never Worked	6 (0.4)	0 (0.0)	
Residence Type	Urban	709 (50.3)	142 (51.4)	0.731
	Rural	700 (49.7)	134 (48.6)	
Smoking Status	Never Smoked	553 (39.2)	90 (32.6)	<0.001
	Formerly Smoked	249 (17.7)	77 (27.9)	
	Unknown	395 (28.0)	48 (17.4)	
	Smokes	212 (15.0)	61 (22.1)	
Stroke	No Stroke	1207 (85.7)	229 (83.0)	0.249
	Suffered Stroke	202 (14.3)	47 (17.0)	

***: Pearson chi-square test**

Table 4 shows the classification matrix for the associative classification model that was used to classify the Heart Disease Dataset in this study.

TABLE IV
DESCRIPTIVE STATISTICS TABLE OF QUANTITATIVE INDEPENDENT VARIABLES

Prediction	Reference		
	No heart disease	Suffering from heart disease	Total
No heart disease	4573	469	5042
Suffering from heart disease	261	4365	4626
Total	4834	4834	9668

Table 5 shows the results of the classification performance criterion for the associative classification model. The model's specificity was calculated to be 0.946, the sensitivity to be 0. 903, the accuracy to be 0.9245, the positive predictive value to be 0.9436 and the negative predictive value to be 0.907.

TABLE V
THE MODEL'S CLASSIFICATION PERFORMANCE CRITERIA'S VALUES

Metric	Value
Specificity	0.946
Sensitivity	0.903
Accuracy	0.9245
Positive predictive value	0.9436
Negative predictive value	0.907

4. DISCUSSION

It is estimated that heart disease, which is one of the most common diseases in the world, will continue to be the most common cause of death on a global scale. It is reported that these deaths tend to decrease in developed countries compared to developing countries. The most effective factor in the reduction of these deaths in the world is the preventability of heart and cardiovascular diseases. Studies such as identifying the factors causing the disease and preventing their emergence have been made possible by developing health services. Recent research has been able to identify risk factors for heart disease, but many researchers agree that more research is needed to use this information to reduce the incidence of heart disease. Heart diseases may be due to different characteristics. Some literature studies have shown that reducing these risk factors for heart disease may actually help prevent heart disease. There are many studies and studies on the prevention of heart disease risk. More studies on heart disease will offer more opportunities to prevent heart disease [1, 12, 13].

With the use of new application areas obtained as a result of developments in computer science in health services, it has been possible to predict disease-related risk factors from patient data. Thus, by determining the factors that cause diseases, important steps are taken in terms of preventability.

Computer and human is one of the interdisciplinary fields of study that deals with the design, implementation and evaluation of interactive technologies. The field of human and computer interaction started to gain momentum in the 2000s and studies in this field are among the areas that have priority today. One of the human and computer interaction fields of study is deep learning, which is a method of machine learning [14]. Deep learning methods are a set of algorithms involved in machine learning; and attempts to model high-level abstractions of data using model architectures that result from multiple nonlinear transformations [15].

Deep learning methods, with the increase in processing power and the advancement of graphics processors, many more applications such as big data analysis, image classification, voice identification, generic visual recognition, face recognition, pedestrian detection, natural language processing, handwriting recognition, multiclassification, regression problems, time series estimation, etc. started to take place in a wide variety of fields [15, 16].

In this study, a deep learning model was applied using an open-source dataset containing information about patients with and without heart disease, and it was aimed to classify the output variable and to obtain information about the factors associated with the disease. Specificity, sensitivity, accuracy, positive predictive value, and negative predictive value from the performance criteria obtained from the model as a result of classification were calculated as 0.946, 0.903, 0.9245, 0.9436, and 0.907, respectively.

As a result of the findings obtained from the study, it was seen that the data set we discussed was successfully classified with the deep learning model used. This successful classification performance will give medical professionals an idea about the risk factors that may be associated with heart disease and will be decisive for preventive medicine practices.

REFERENCES

[1] Özmen, Ö., Ahmad, K. H. D. R., & Engin, A. V. C. I. (2018). Sınıflandırıcıların Kalp Hastalığı Verileri Üzerine Performans Karşılaştırması. Fırat Üniversitesi Mühendislik Bilimleri Dergisi, 30(3), 153-159.

[2] Felman, A. (2018). Everything you need to know about heart disease. Medical News Today.

[3] Yaşar, B. Kalp Hastalıkları Sindirim Sistemini Etkiler mi?.

[4] Zencirli, K. (2020). Bipolar parsiyel protez uygulanmış kalça kırıklı hastalarda makine öğrenme yöntemleri ile perioperatif prognoz ve maliyet analizi.

[5] Perçin, İ., Yağin, F. H., Arslan, A. K., & Çolak, C. (2019, October). An Interactive Web Tool for Classification Problems Based on Machine Learning Algorithms Using Java Programming Language: Data Classification Software. In 2019 3rd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT) (pp. 1-7). IEEE.

[6] Doğan, F., & Türkoğlu, İ. (2019). Derin öğrenme modelleri ve uygulama alanlarına ilişkin bir derleme. Dicle Üniversitesi Mühendislik Fakültesi Mühendislik Dergisi, 10(2), 409-445.

[7] Najafabadi, M. M., Villanustre, F., Khoshgoftaar, T. M., Seliya, N., Wald, R., & Muharemagic, E. (2015). Deep learning applications and challenges in big data analytics. Journal of big data, 2(1), 1-21.

[8] Hajkowicz, S., Karimi, S., Wark, T., Chen, C., Evans, M., Rens, N., ... & Tong, K. J. (2019). Artificial Intelligence: Solving problems, growing the economy and improving our quality of life.

[9] Nabiyev, V. V., & Zeka, Y. (2010). Seçkin Yayıncılık, 3. baskı.

[10] SAKARYA, Ş., & YILMAZ, Ü. (2019). Derin öğrenme mimarisi kullanarak bist30 indeksinin tahmini. European Journal of Educational and Social Sciences, 4(2), 106-121.

[11] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," nature, vol. 521, pp. 436-444, 2015.

[12] M. E. TAŞÇI and R. ŞAMLI, "Veri Madenciliği İle Kalp Hastalığı Teşhisi," Avrupa Bilim ve Teknoloji Dergisi, pp. 88-95, 2020.

[13] Kolaç, N. K. Vardiyalı Çalışanlarda Uykusuzluk ve Kalp Hastalıkları Riskleri: Sistematik Derleme. Arşiv Kaynak Tarama Dergisi, 30(1), 13-21.

[14] Tüfekçi, M., & Karpat, F. Derin Öğrenme Mimarilerinden Konvolüsyonel Sinir Ağları (CNN) Üzerinde Görüntü İşleme-Sınıflandırma Kabiliyetininin Arttırılmasına Yönelik Yapılan Çalışmaların İncelenmesi.

[15] Bılgıç, A., Kurban, O. C., & Yildirim, T. (2017, May). Face recognition classifier based on dimension reduction in deep learning properties. In 2017 25th Signal Processing and Communications Applications Conference (SIU) (pp. 1-4). IEEE.

[16] Yağin, F. H., Güldoğan, E., Ucuzal, H., & Çolak, C. A Computer-Assisted Diagnosis Tool for Classifying COVID-19 based on Chest X-Ray Images. Konuralp Medical Journal, 13(S1), 438-445.

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Is Turing Test Still Proficient and Operative at Present State of the ART?: Beyond Turing Test For The Next Generation AI Frameworks

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ABSTRACT

The problem of consciousness in terms of artificial intelligence is a difficult and big problem. With the test he put forward, the efficiency of artificial intelligence was discussed and tested. Some scientists have criticized the inability to distinguish between humans and robots with the Turing Test. Problems such as how sufficient this is and how it is possible to compare the intelligence of a human with the intelligence of a robot have been handled philosophically. The main purpose of this article is to address the adequacy of Turing testing and to question artificial intelligence tests and tools that can shed light on shaping the design of next-generation AI architectures. Searle's Chinese room experiment has been reconsidered by Turing by addressing the subjectivity-objectivity problem of Qualia philosophers and giving place to criticisms that can be directed to this test and countercriticisms that can be made to these criticisms. In addition, the role of the new generation Turing test in modeling concepts such as artificial consciousness and machine self-awareness and evaluating their performance is discussed.

1. INTRODUCTION

ALAN M. TURING, one of the most important mathematicians of the century by putting forward his ideas that will form the basis of computers, said, “Can machines replace humans? “How can we show it, whether it can or not?” He is known as the architect of the Turing test looking for answers to his questions. We can summarize Turing's thought experiment as follows. A computer stays out of sight with a human. The tester asks questions and tries to understand which is a human and which is a computer-based answer to the questions. If it cannot be determined which is which, the machine has passed the test. It was able to disguise itself, so this computer can be called artificial intelligence.
The machine in the Turing test processes input data internally and provides outputs to evaluate behaviors. This corresponds to the concept of mind in the tradition called Functionalism in the history of philosophy. [1] In summary, being in a mental state is being in a functional state [2]. As it is seen, Turing evaluates the intelligence of the machine in his test as a functional tool. With similar logic, the mind also processes input information that is received by sensory stimuli and generates output as a result of a behavior [3, 4]. When these outputs are considered, the final feature of the being, which has a function between the input and the output as a result of behavior determined by observation will be the behavior, in which the presence and absence of a mind, consciousness, and intelligence, and if any, how humanoid it is. However, the mind and consciousness cannot be considered as consisting of behaviors. According to the concept of logical behaviorism, which Gilbert Ryle put forward in his book [5], the behaviors exhibited by the machine are only a reflection of the concepts of mind and consciousness. Functionalism does not see the behavior itself as the mind, hence the concept and/or problem of the mind as a pseudo-problem. It does not take an attitude that reduces the mind to behaviors [2]. This is the biggest feature that distinguishes it from behaviorism.

Concerning this approach of functionalism, Searle, in his consciousness and language, mentions Turing as follows: “Instead of accepting that consciousness is essentially a subjective and qualitative phenomenon, the most people mistakenly assume that the essence of consciousness is a control mechanism as a bunch of abilities or skills regarding behaviors." [6] Searle states that the Turing test fails and proposes a thought experiment, just like Turing, to explain what the error of the Turing test is. The famous Chinese room experiment. To sum up, someone who doesn't understand anything in Chinese is locked in a room with lots of Chinese symbols and a program to answer Chinese questions. Let the input of the system consist of Chinese symbols in the form of questions. The output should consist of Chinese symbols in the form of answers to questions. In this case, we can assume that the program will give the questions to a native Chinese speaker. However, neither the person nor the system (the machine) inside the room can understand Chinese [7].

According to Searle, what we call artificial intelligence performs operations just like the Chinese in the experiment. But he never understands these processes. Searle does not treat the mind as something supernatural (the soul). With a materialistic approach, he states that the mind (just like photosynthesis, digestion, etc.) is a biological phenomenon. The machine in the Turing test has no consciousness. The machine is not aware of what it is doing. Just having zeros and ones is not enough to provide conscious or unconscious mental content [6]. This is where Searle opposes the Turing test and thinks that the test is leading us to error. Therefore, he states that it is not possible for 0 and 1's to have the human abilities we call understanding and awareness.

However, we can criticize Searle in many ways. The first criticism will be a criticism of the experiment. Even if the person who is closed in the Chinese room does not understand Chinese, that room is full of Chinese resources. Here, it will be not just the person that takes the input and outputs it, but the entire room the person is in [8]. Therefore, it is not so important how much this person knows or understands Chinese. In addition, especially nowadays, programs and machines that simply take an input and output an output are quite simple. Now, these systems have been overcome and much more complex systems have taken their place. “A chat program that is sophisticated enough to give the impression of intelligence should not have lists of input/outputs, but rather complex real-world models with which it can match elements in dialogue.” [9]. Another study on this subject belongs to Thomas Nagel. This problem, known as the "Qualia" problem, is to show that consciousness cannot be reduced to a physical state. Therefore, individual subjective experiences can never be realized objectively [10].

2. BEYOND TURING TEST FOR THE NEXT – GENERATION AI FRAMEWORKS

Despite some shortcomings, the Turing Test is still valid in many ways. Both the Turing-NLG, GPT-2, and GPT-3 (Generative Pre-trainer Transformer), which Microsoft introduced in February 2020, still carry the underlying idea of the Turing Test. A language that can use deep learning to produce content similar to texts written by people was modeled as GPT-3 in June 2020 [11]. But if there is to be a question of consciousness, it is required a different paradigm beyond the Imitation Game.

With the new Turing Tests, artificial intelligence must go beyond imitation. What we call consciousness is much more than imitating human intelligence, it is the self-perception of itself and its environment without any human behavior or thought [3, 4]. It should detect new information, store old information, and of course reuse it when necessary.

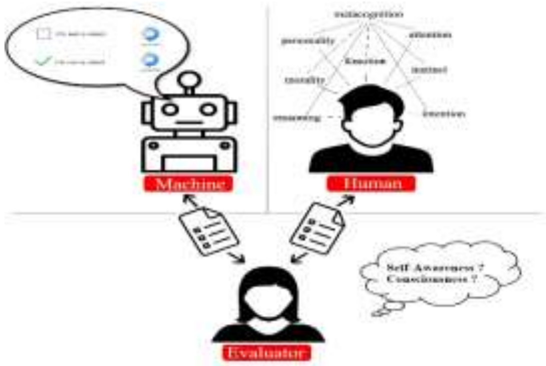

Fig. 1. Evaluation of the Turing test dealing with attributes of the human mind.

To summarize, they should act according to the goals they set themselves, without being programmed to set and make their own goals. Even if a smart vehicle that goes from point X to point Y goes in the desired orbit, it cannot go beyond doing what it is told. The only way to overcome this stage is that the current Turing test should evolve beyond logical intelligence to evaluate human mental activities such as emotion, attention, intention, values/morality, instinct, awareness, meta-cognition, responsibility, regret, reasoning/inference so that the next-generation artificial intelligence models evaluated by these evolved testing tools are developed.

3. CONCLUSIONS

In terms of the theory of mind and human cognition, this article discusses how the Turing test may evolve to shape the next generation of AI models in the future. This article also includes studies that criticize the conventional form of the Turing test dealing with logical intelligence. Searle's Chinese room experiment and the Qualia problem are just two of the criticisms that can be leveled against the Turing approach. According to these ideas, the conventional form of the Turing test dealing with logical intelligence should be improved so that self-aware autonomous machines (humanoids, UAV/UGV, etc.) with next-generation AI (super artificial intelligence) which can be expressed as artificial general intelligence (AGI) or technological singularity can be realized.

REFERENCES

[1] Priest, S. (2018). Zihin Üzerine Teoriler (Dereko, A., Trans.). Istanbul: Litera, pp.205
[2] Bailey, A. (Ed.). (2013). Philosophy of mind: The key thinkers. A&C Black, pp.148.
[3] Daglarli, E. (2020). Computational Modeling of Prefrontal Cortex for Meta-Cognition of a Humanoid Robot. IEEE Access, 8, 98491-98507.
[4] Daglarli E., (2020). A Cognitive Integrated Multi-Modal Perception Mechanism and Dynamic World Modeling For Social Robot Assistants, The Journal of Cognitive Systems, 5(2), 46-50.
[5] Ryle, G. (2011) Zihin Kavramı (Çelik, S. Trans.) Istanbul:Doruk
[6] Searle, J. (2005). Bilinç ve Dil. (Macit, M. & Ozpilavcı, C., Trans.) Istanbul: Litera, pp. 29-30
[7] Searle, J. (2014). Zihnin Yeniden Keşfi. (Macit, M., Trans.) Istanbul: Litera, pp. 70.
[8] Heil, J. (2020). Zihin Felsefesi Çağdaş Bir Giriş (Bilgili M., Akbıyık S. Trans). Kure, pp. 187.
[9] Say, C. (2021). 50 Soruda Yapay Zeka. Istanbul: Bilim ve Gelecek Kitaplığı, pp. 164.
[10] Nagel, T. (2012). Mind and Cosmos: Why the Materialist Neo-Darwinian Conception of Nature Is Almost Certainly False. New York: Oxford University Press.
[11] Floridi, L., & Chiriatti, M. (2020). GPT-3: Its nature, scope, limits, and consequences. Minds and Machines, 30(4), 681-694.

BIOGRAPHY

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