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Overview Of Online Shopping Through Metaphors During The Pandemic Period

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ABSTRACT

With this study, it is aimed to examine the metaphorical perceptions of the teachers participating in the research regarding the concept of "online shopping" during the pandemic period. In the literature review we conducted, no metaphorical research was found to determine the perceptions of teachers about the concept of online shopping of any person or institution. A total of 138 teachers, who are the teachers of our school as a participant group, constitute the research. The teachers participating in the research were asked to complete the statement "Online shopping is like/similar to………… because……" in order to reach the findings regarding the teachers' use of online shopping during the pandemic period and the metaphors they have regarding the concept of online shopping, through an online form. Of the 138 teachers participating in our research, 131 of the questionnaire forms were evaluated; The metaphors produced by the teachers for the concept of online shopping were first categorized under 2 main headings as positive metaphors about online shopping and negative metaphors about online shopping, and after this categorization, positive metaphors about online shopping were divided into 6 different categories; Negative metaphors were grouped into 3 different categories. According to the results of the research, 70.2 of the metaphors used by teachers for online shopping were in the positive category and 29.8 in the negative category. In the positive metaphor category, food, poetry, friend, need; In the negative category, it was seen that the themes such as swamp, closed box, poison, laziness were emphasized. Qualitative and quantitative research methods were used in the analysis and interpretation of the data obtained at the end of the study. The process of analyzing and interpreting data; It was carried out in five stages: (1) coding and elimination stage, (2) metaphor identification stage, (3) category development and classification stage, (4) validity and reliability stage, and (5) transferring the data to the SPSS package program for quantitative data analysis. After the findings obtained from the research were categorized, they were also evaluated in terms of gender, age and professional experience variables; It has been observed that a total of 9 metaphorical categories, positive and negative, created by teachers regarding the concept of "online shopping" during the pandemic period differ in terms of these variables.

1. INTRODUCTION

After the first coronavirus (Covid-19) case was seen in Wuhan, China, the coronavirus became the agenda in our country, as it was in the whole world, and took its place in the first place. This virus, which is at risk of transmission, has spread to hundreds of countries around the world; It has created significant effects that still continue and leave permanent traces in every aspect of life in Turkey and in the world. So that; It is predicted that the virus, for which important measures have been taken to control it, will cause significant changes in the attitudes and behaviors of individuals. Because predicting the changes in the behavior of individuals in such crisis periods is very important in order to develop a marketing strategy.

Many businesses operating in our country have decided to stop their activities or reduce their production by the state authority or because of the threat to public health. Unfortunately, the coronavirus has turned into a serious crisis for businesses and some businesses that want to overcome this crisis have focused on online sales (sales over the internet). These and similar processes have once again demonstrated the importance of online shopping (online shopping) for businesses [1-4].

There are many scientific studies on online shopping, but; Metaphor study related to online shopping has not been found in the literature. However, it is important to determine what the stereotypical image of online shopping means in people, and whether this image changes the shopping habits of individuals during the pandemic period. In this respect, metaphors are evaluated as expressing a phenomenon or concept with more familiar terms and uncomplicated words in terms of characterization, understanding or explanation [2].

Metaphors that we unconsciously use in our daily lives actually have an important place in our lives. “According to Lakoff & Johnson [5], we cannot think deeply about metaphors that we are not aware of despite their importance and we cannot have more information about their meanings.” Beyond being adorned with fancy words, which are not only used in daily language, metaphors also have much more important functions in human life (Saban, 2004).

A. Coronavirus In Turkey

As explained in the page published by the Ministry of Health of the Republic of Turkey and regularly updated with new data on a daily basis; The first Covid-19 case in Turkey was detected on March 11, 2020[7]. Looking at the statistics as of March 2020, there is a continuous increase in the number of cases and loss of life.

According to the data of the Ministry of Health of the Republic of Turkey, when the current situation of our country is examined, it is seen that the number of tests performed as of 08.01.2021 exceeded 25 million, there were more than 2 million cases and 22,450 deaths. In the light of all these data, the authorities have taken many precautions in public and private institutions from the beginning, announced that education will be carried out over the internet in order to conduct education in a safe and healthy way, and invited the citizens to stay at home during this process. This situation has visibly affected the habits and needs of people to stay at home for a long time, and online shopping is one of these affected habits.

When we look at it in general, the epidemic has increased even more at a time when digital tools, environments and technology are an indispensable part of our lives, and it has made people unable to leave their homes unless it is felt necessary. This situation, in fact, has been included in the quarantine process of the coronavirus, causing the digital transformation, which is seen as an indispensable element of the twenty-first century, which is present all over the world, including our country, and which is called the age of information and communication technologies (mediacat.com).

B. Online Shopping

In a very general way, it can be said that online shopping is to make and manage all commercial relations over the internet virtually, and to describe electronic commerce in short.

Online shopping, using internet technology; It is the buying and selling of many products, goods or services from the social media environment through digital e-commerce sites. Therefore, it can be said that all kinds of buying and selling transactions made using the internet are within the scope of electronic commerce. People who want to shop online can realize the products or services they want to buy from their residence by following various steps on the internet.

C. Online Shopping in Turkey

There is no clear information about how online shopping over the internet became widespread in Turkey, when and how it started. Despite this, the start of online shopping in Turkey is not far behind the online shopping indicators in the World [10].

According to Milong (Cited by: Source, İ. (2020), online shopping is defined as a system in which individuals instantly buy various products and services without the need for an intermediary during shopping with the help of an electronic device connected to the Internet. In the classical sense, individuals who go to the store and shop. With the pandemic process, they have come to prefer online shopping, which is one of the benefits of the internet.”

Turkish Statistical Institute (TUIK) data published in 2019: The proportion of people aged 16-74 who shop online by buying and selling products or services over the internet; It shows that in the twelve months until March 2020, it increased by 2.4% and reached a total value of 36.5%.

In the study, the Covid-19 pandemic period and the place and importance of shopping in our country in this period were mentioned. In the research part of the study, whether the individuals shop online, if they do, the frequency of shopping, whether the shopping made changes in this process and the frequency of the purchased products; In order to reveal what individuals think about the concept of online shopping and their mental impressions, a questionnaire consisting of 138 people was applied online with a google form.

The literature on the subject of the project was searched. Although there have been many scientific studies on online shopping in our country, there has been no metaphor study on the concept of online shopping. It is the first study to examine the factors affecting the attitudes and behaviors of individuals towards online shopping (online shopping) and the concept of online shopping with metaphors during the Covid-19 pandemic period. Based on these, the importance of conducting a research on the concept of online shopping, especially during the pandemic period, has been demonstrated once again. Based on all these information and thoughts, in line with the purposes that form the basis of our research,

In the qualitative part of the research:

What are the metaphors that teachers have and produce about the concept of "online shopping"?

Under which conceptual categories are these metaphors put forward by the teachers participating in the study gathered in terms of common features?

In the quantitative part of the research:

Do the categorized concepts of online shopping show a significant difference according to the gender, age and professional experience of the teachers participating in the study?

What is the rate of online shopping of the teachers participating in the study?

What is the frequency of online shopping of the teachers participating in the study?

Has there been a change in the online shopping behaviors of the teachers participating in the study with the emergence of the Covid-19 virus?

What are the types of products that the teachers who participated in the study most frequently bought from online shopping sites during the Covid -19 outbreak? answers were sought for problem statements such as.

Method this research was carried out using mixed research method. Mixed method (mixedresearch), using both qualitative and quantitative data together; metaphor was used in order to better analyze the concepts.

According to Gay, Mills & Airasian (cited by Hacıfazlıoğlu, Ö, Karadeniz,Ş.,Dalgıç, G. (2011), the mixed method is a combination of both qualitative and quantitative methods collected in accordance with the purpose of the research. It enables a clearer understanding of the subject by using the use of the method." In addition, "Cresswell (cited by Arık, S. (2017) thinks that it will be a more qualified study by bringing together the strengths and weaknesses that may arise in each of the qualitative and quantitative research methods using the mixed method. " [1,11].

D. Data Collection Tools

High school teachers participating in the study were asked to complete the sentence "Online shopping is similar/like because…..." in order to reveal the metaphors in their mental images of the concept of "online shopping". In the literature review, it was stated that different types of tools were used in studies related to metaphor; it is seen that the most preferred one is the semi-structured question form that we used in our research.

A questionnaire was created for the teachers participating in the research to determine gender, age, professional experience, whether they shop online, how often they shop, whether there is any change in their online shopping behavior during the pandemic period, and the frequency of purchasing the purchased products. (Appendix 1: "Survey on Teachers' Online Shopping during the Coronavirus (Covid-19) Pandemic Period and Metaphorical Perceptions of the Concept of Online Shopping", APPENDIX 2:"Permission to Implement the Survey")

In order to analyze the survey results, the answers given were loaded into the SPSS v22 program and the frequency and percentage values of the data were calculated. Comparing the calculated values with the variables given in the research; It was tried to determine whether there was a significant difference between these variables. Chi-square, which is a test of independence analysis, was used for the determination. Content analysis technique was used in the analysis of metaphors. The main purpose of the content analysis technique is to make sense of the metaphor data obtained in the study and to associate it among themselves [9].

E. Working Group

138 teachers working in our school in Yenimahalle District of Ankara province participated in the research. Since the forms of 7 teachers were not filled in accordance with the research, they were not evaluated.

When Table 1 is examined, it is seen that 58.7% and 81 of the teachers participating in the research are female and 41.3% and 57% are male. The finding that the professional experience period of the participant teachers is 11-15 years or more, depending on the concentration of age range of 36-40 years and above; It is a normal result that the school is highly preferred because it is in a central location and a well-established school.

TABLE I
DEMOGRAPHIC CHARACTERISTICS OF PARTICIPATING TEACHERS

Variables	Demographic Features	Frequency (*f*)	Percent (%)
Gender	Female	81	58,7
	Male	57	41,3
	Total	138	100
Age	26-30 years	20	14,5
	31-35 years	23	16,7
	36-40 years	37	26,8
	41-45 years	29	21
	46 years and older	29	21
	Total	138	100
Professional Experience Period	1-5 years	16	11,6
	6-10 years	26	18,8
	11-15 years	28	20,3
	16- 20 years	28	20,3
	20 years and older	40	29,0
	Total	138	100

Considering the assignment according to the service score priority, it can be said that the result is in the expected direction.

TABLE II
"DO YOU SHOP ONLINE?" OF THE TEACHERS PARTICIPATING IN THE RESEARCH. DISTRIBUTION OF ANSWERS TO THE QUESTION

Do you do online shopping?	Frequency (n=138)	Percent (%)
Yes	122	88,4
No	16	11,6

When Table 2 is examined, it is seen that the teachers who participated in the research asked "Do you shop online?" 122 teachers answered yes with 88.4% and 16 teachers answered no with 11.6%.

TABLE III
"HOW MANY TIMES DO YOU SHOP ONLINE PER MONTH ON AVERAGE?" OF THE TEACHERS PARTICIPATING IN THE RESEARCH. DISTRIBUTION OF ANSWERS TO THE QUESTION

How many times a month do you shop online on average?	Frequency (n=122)	Percent (%)
0-2 times	53	43,4
3-5 times	35	28,7
6-8 times	17	13,9
8-10 times	11	9
More than 10	6	4,9
Total	122	100

According to Table 2 (above), the participant teachers' "Do you shop online?" It is seen that 122 teachers answered yes and 16 teachers answered no to the question. In this part of the research, the analysis of the research data was made with the data obtained from the answers given by 122 teachers.

TABLE IV
HAS YOUR ONLINE SHOPPING BEHAVIOR CHANGED WITH THE EMERGENCE OF THE COVID-19 VIRUS?" OF THE TEACHERS PARTICIPATING IN THE RESEARCH. DISTRIBUTION OF ANSWERS TO THE QUESTION

Has your online shopping behavior changed with the emergence of the Covid-19 virus?	Frequency (n=122)	Percentage (%)
Increased	95	77,9
Decreased	0	0
Not changed	27	22,1
Total	122	100

When Table 3 is examined; "How many times do you shop online per month on average?" 53 (43.4%) teachers answered the question 0-2 times; 35 (28.7%) teachers 3-5 times; 17 (13.9%) teachers 6-8 times; 11 (9%) teachers 8-10 times; It was determined that 6 (4.9%) teachers made more than 10 purchases.

When Table 4 is examined, it is seen that the teachers participating in the research asked, “Has there been a change in your online shopping behavior with the emergence of the Covid-19 virus? While there was no teacher who answered the question "There has been a decrease in online shopping behavior; 195 teachers with 77.9% answered yes, there was an increase in my online shopping behavior, and 27 teachers with 22.1% answered that there was no change in my online shopping behavior.

TABLE V.
“WHICH PRODUCT GROUP DID YOU BUY MOST FROM ONLINE SHOPPING SITES DURING THE COVID-19 OUTBREAK?” DISTRIBUTION OF ANSWERS TO THE QUESTION

Determine the frequency of purchasing the products you purchased from online shopping sites during the Covid -19 outbreak.	f	%
Food, greengrocer, delicatessen	20	16,4
Stationery supplies	9	7,38
Baby product	7	5,72
Personal care and cosmetics	26	21,31
Cleaning products	5	4,1
Textile	32	26,23
Electronic	10	8,2
Health equipment (mask, disinfectant, visor, etc.)	4	3,3
Tools, equipment and accessories	8	6,55
Flower	1	0,81
Total	122	100

Looking at Table 5, “Which product group do you buy the most from online shopping sites during the Covid-19 outbreak?” Considering the answers given to the question (the top 3 most purchased answers); Thirty-two (26.23%) of the 122 participants purchased textile products, 26 (21.31%) purchased personal care products and cosmetics, 20 (16.4%) purchased food, greengrocers, delicatessen products. stated that he received it.

F. Analysis of Data

In the research, 138 teachers working in our school were asked to complete the given sentence by producing metaphors about the concept of "online shopping"; However, the answers of 7 teachers, who were determined that there was no relationship between the absence of any metaphor and its subject, were deemed invalid and the research was analyzed with the data obtained from 131 teachers.

The descriptive method was used in the analysis of the quantitative data; The obtained data were transferred to the SPSS v22 program. Chi-square independence analysis was performed by looking at the frequency and percentage distributions of the transferred data and whether there is a relationship between the obtained data.

In the qualitative part of the research, the teachers were asked to use “Online shopping.....similar/like; because……” sentence was given and they were asked to complete it. In order for this activity to be carried out in accordance with the purpose, all necessary explanations about metaphor writing were made to all participants. Teachers were asked to produce metaphors related to the concept of online shopping and to write these metaphors by stating reasons and grounds [12]. It was especially emphasized that they compared the concept of online shopping to something and stated the reason for it.

“Prospective teachers’ conceptions of teaching and learning revealed through metaphor analysis. Learning and Instruction [12]. Metaphor studies, there must be a connection with the target source and reason in the question pattern. The words "like" and "like" in the sentence in the question pattern are generally used to more clearly explain the relationship between the concept stated in the metaphor and the source. In fact, the concept of "because" is also included in the question pattern. The aim here is to base the metaphors produced by the participants on a logical justification.”

Coding the metaphors obtained from the participants, categorizing with categories, making validity and reliability calculations and including the findings are the steps of content analysis [12]. Content analysis method was used in the analysis of qualitative data. The process of analyzing and interpreting data; It was carried out in five stages: (1) coding and elimination stage, (2) metaphor identification stage, (3) category development and classification stage, (4) validity and reliability stage, and (5) data transfer to SPSS v22 program for quantitative data analysis.

G. Coding and elimination phase

The metaphor sentences produced by each teacher were transferred to the Excel program, and the metaphors that appeared in a different column were written and listed in A-Z. Sentences that did not specify a metaphor, and whose reason was not specified even if it was, were determined and eliminated. For such reasons, metaphor sentences of 7 teachers were not included in the study.

H. Metaphor determination phase

After the coding and elimination phase, a new metaphor list was prepared in alphabetical order from A-Z to the metaphors that were clarified to be included in the scope of the research, and each metaphor in the list (emergency room, agent, alcohol, etc.) was sequentially numbered starting from 1. coded. Thus, 60 different and valid metaphors emerged by the participants. Among the coded metaphors, a few sample metaphor expressions that best represent the metaphor were compiled in an original way and these expressions are included in the findings section.

I. Category development and classification phase

At this stage, the metaphor expressions developed by the teachers were examined on the basis of the common features they have for the concept of "online shopping". It was examined how the concept of "online shopping" was categorized according to the sample metaphor list. Metaphors produced by teachers; It has been evaluated how it is related in terms of its subject (online shopping) and its source, in other words, how it is categorized in terms of its qualities by going from the source of the metaphor to the subject of the metaphor. With this point of view, each metaphor is placed under a category. Thus, they were combined under 2 main headings by the teachers as “Positive Metaphors Related to Online Shopping” and “Negative Metaphors Regarding Online Shopping” for the concept of online shopping; Afterwards, positive metaphors were collected in 6 different categories, and negative metaphors were collected in 3 different categories.

J. Validity and reliability stage

It is very important for the reliability of the research to be examined by an expert in the analysis of qualitative data [9]. In order to ensure reliability in this research, the opinion of a field expert was sought to confirm whether the metaphors categorized under a total of 9 conceptual categories reached in the research represent the conceptual category of the aforementioned online shopping. For this purpose, a list consisting of 131 metaphors and 9 different conceptual categories was sent to our counselor and asked to match them. As a result of this matching, numerical data on consensus and disagreements were determined.

The reliability of the study was calculated using the formula of Miles and Huberman (1994: 64) (Reliability = consensus / consensus + disagreement X 100). In studies on the analysis of qualitative data, the fact that the agreement between the evaluations of the field expert and the researcher is 90% and above is an indication that a desired level of reliability has been achieved [8].

TABLE VI.
"DO YOU SHOP ONLINE?" BY GENDER, AGE AND PROFESSIONAL EXPERIENCE OF TEACHERS. DISTRIBUTION OF ANSWERS TO THE QUESTION

Gender			Do you shop online?		Total
			Yes	No	
Female		f	76	5	81
		%	93,8%	6,2%	100%
Male		f	46	11	57
		%	80,7%	19,3%	100%
Total			122	16	138
X2= 5,623	df=1, p=,018				
Age			Yes	No	Total
26-30		f	20	0	20
		%	100%	0%	100%
31-35		f	23	0	23
		%	100%	0%	100%
36-40		f	35	2	37
		%	94,6%	5,4%	100%
41-45		f	27	2	29
		%	93,1%	6,9%	100%
46 years and older		f	17	12	29
		%	58,6%	41,4%	100%
Total			122	16	138
X2=32,746	df=4, p=.000				
Professional Experience			Yes	No	Total
1-5 years		f	16	0	16
		%	100%	0%	100%
6-10 years		f	28	0	28
		%	100%	0%	100%
11-15 years		f	26	2	28
		%	92,9%	7,1%	100%
16-20 years		f	25	1	26
		%	96,2%	3,8%	100%
20 years and older		f	27	13	40
		%	67,5%	32,5%	100%
Total			122	16	138
X2= 24,890	df=4, p=.000				

In line with this information, it was determined by the expert that a total of 7 metaphors out of 9 conceptual categories, which were considered to correspond to 138 metaphors, were not found suitable for the relevant category. Reliability = 138/ (138+7) X 100 = 0.95. In this study, it was seen that the metaphor expressions created were suitable for the categorized ones and a value of 95% was obtained in the reliability study.

The obtained data were arranged in the computer environment and transferred to the SPSS v22 program. Afterwards, the frequency and percentage distributions of the data obtained were tabulated and the X2 (chi-square) independence test was applied to measure whether there was a relationship or difference between the categories according to the gender, age and professional experience of the teachers, and the results were interpreted. In addition, the Mentimeer (https://www.menti.com/) program, one of the Web 2 tools, was used in the preparation of the word cloud. Results within the scope of the research, the relational tables related to the variables determined in the questionnaire form of the data obtained regarding the metaphors produced by our school teachers about the concept of online shopping are given below.

According to the results of the analysis in Table 6, the teachers' "Do you shop online?" Considering the distribution of answers to the question by gender, 93.8% of female teachers stated that they shop online more than male teachers during the pandemic period. As a result of the chi-square analysis, it shows that this difference is significant between male and female teachers (X2= 5.623, p<.05).

According to the table, the teachers' "Do you shop online?" Looking at the distribution of the answers to the question by age, it has been determined that the teachers in the 26-30 and 31-35 age ranges do more online shopping than the teachers in the other age ranges. In addition, it is seen that the rate of online shopping of teachers over the age of 46 is the lowest among all age groups. As a result of the chi-square analysis, it shows that this difference is significant between age groups (X2=32,746, p<.05). According to the same table, teachers' "Do you shop online?" When the distribution of the answers to the question according to professional experience is examined, it has been determined that 67.5% of the teachers with 20 years or more professional experience shop online, and the majority of the teachers with less than 20 years of professional experience prefer online shopping instead of traditional shopping. As a result of the chi-square analysis, it shows that this difference between professional experiences is significant (X2=24,890, p<.05).

According to the results of the analysis in Table 7, the teachers' "How many times do you shop online per month on average?" Considering the distribution of the answers to the question by gender, it is seen that there is no significant difference between female and male teachers (X2= 8,121, p>.05). Again, according to the table, the teachers' "How many times do you shop online per month on average?" Considering the distribution of the answers to the question by age, it is seen that there is no significant difference between male and female teachers (X2= 25,521, p>.05). According to the same table, "How many times do you shop online per month on average?" Considering the distribution of the answers to the question according to professional experience, it is seen that there is a concentration that teachers shop online 0-2 times and 3-5 times a month on average.

TABLE VII.
ACCORDING TO THE GENDER, AGE AND PROFESSIONAL EXPERIENCE OF THE TEACHERS "HOW MANY TIMES DO YOU SHOP ONLINE PER MONTH ON AVERAGE? DISTRIBUTION OF ANSWERS TO THE QUESTION "

Gender		How many times a month do you shop online on average?					Total
		0-2 times	3-5 times	6-8 times	8-10 times	More than 10	
Female	f	27	25	10	10	4	76
	%	35,5%	32,9%	13,2%	13,2%	5,3 %	100,0 %
Male	f	26	10	7	1	2	46
	%	56,5%	21,7%	15,2%	2,2 %	4,3 %	100,0 %
Total		53	35	17	11	6	122
X2= 8,121	df=4, p=0,87						
Age		0-2 times	3-5 times	6-8 times	8-10 times	More than 10	Total
26-30	f	10	4	1	2	3	20
	%	50,0%	20,0%	5,0 %	10,0%	15,0 %	100,0 %
31-35	f	9	5	4	5	0	23
	%	39,1%	21,7%	17,4%	21,7%	0,0 %	100,0 %
36-40	f	10	14	8	2	1	35
	%	28,6%	40,0%	22,9%	5,7 %	2,9 %	100,0 %
41-45	f	12	9	2	2	2	27
	%	44,4%	33,3%	7,4 %	7,4 %	7,4 %	100,0 %
46 years and older	f	12	3	2	0	0	17
	%	70,6%	17,6%	11,8%	0,0 %	0,0 %	100,0 %
Total							
X2= 25,521	df=16, p=.061						
Professional Experience		0-2 times	3-5 times	6-8 times	8-10 times	More than10	
1-5 years	f	10	4	1	0	1	16
	%	62,5%	25,0%	6,3 %	0,0 %	6,3 %	100,0 %
6-10 years	f	11	4	4	7	2	28
	%	39,3%	14,3%	14,3%	25,0%	7,1 %	100,0 %
11-15 years	f	6	11	7	1	1	26
	%	23,1%	42,3%	26,9%	3,8 %	3,8 %	100,0 %
16-20 years	f	9	9	3	3	1	25
	%	36,0%	36,0%	12,0%	12,0%	4,0 %	100,0 %
20 years and older	f	17	7	2	0	1	27
	%	63,0%	25,9%	7,4 %	0,0 %	3,7 %	100,0 %
Total		53	35	17	11	6	122
X2= 29,011	df=16, p=.024						

It has been determined that teachers with less professional experience make more online shopping per month. As a result of the chi-square analysis, when the distribution according to professional experience is examined, it is seen that there is a significant difference between female and male teachers (X2=29,011, p<.05).

TABLE VIII.
ACCORDING TO THE GENDER, AGE AND PROFESSIONAL EXPERIENCE OF TEACHERS "HAS YOUR ONLINE SHOPPING BEHAVIOR CHANGED WITH THE EMERGENCE OF THE COVID-19 VIRUS?"

Cinsiyet		Has your online shopping behavior changed with the emergence of the Covid-19 virus?			Toplam
	f	Increased	Decreased	No Change	
Female	f	65	0	11	76
	%	85,5%	0%	14,5%	100,0%
Male	f	30	0	16	46
	%	65,2%	0%	34,8%	100,0%
Total		95	0	27	122
X2= 6,858	df=1, p=,009				
Age		Increased	Decreased	No Change	Total
26-30	f	13	0	7	20
	%	65,0%	0%	35,0%	100,0%
31-35	f	20	0	3	23
	%	87,0%	0%	13,0%	100,0%
36-40	f	30	0	5	35
	%	85,7%	0%	14,3%	100,0%
41-45	f	21	0	6	27
	%	77,8%	0%	22,2%	100,0%
46 years and older	f	11	0	6	17
	%	64,7%	0%	35,3%	100,0%
Total		95	0	27	122
X2=5,984	df=4, p=.200				
Professional Experience		Increased	Decreased	No Change	Total
1-5 years	f	8	0	8	16
	%	50,0%	0%	50,0%	100,0%
6-10 years	f	25	0	3	28
	%	89,3%	0%	10,7%	100,0%
11-15 years	f	23	0	3	26
	%	88,5%	0%	11,5%	100,0%
16-20 years	f	21	0	4	25
	%	84,0%	0%	16,0%	100,0%
20 years and older	f	18	0	9	27
	%	66,7%	0%	33,3%	100,0%
Total		95	0	27	122
X2= 13,533	df=4, p=.009				

Distribution of Answers to the Question

Has your online shopping behavior changed with the emergence of the Covid-19 virus?

According to the results of the analysis in Table 8, the teachers asked, "Did your online shopping behavior change with the emergence of the Covid-19 virus?" When we look at the answers given to the question, there is no change in the tendency of decreasing according to age, gender and professional experience in the online shopping behaviors of the teachers during the pandemic period; When we look at the distribution by gender, it is seen that 85.5% of female teachers' online shopping behaviors increased during the pandemic period compared to male teachers, and 14.5% of them did not change their online shopping behaviors during the pandemic period. According to the results of the chi-square analysis, it shows that this difference is significant between male and female students (X2= 6.858, p<.05).

Again, according to the table, the teachers asked, "Has your online shopping behavior changed with the emergence of the Covid-19 virus?" Considering the distribution of the answers to the question according to age, it is seen that there is no significant difference between male and female teachers (X2= 5,984, p>.05). According to the same table, "Did your online shopping behavior change with the emergence of the Covid-19 virus?" Considering the distribution of the answers to the question according to professional experience, it is seen that the online shopping behaviors of teachers with 6-10 and 11-15 years of professional experience have increased even more during the pandemic period. As a result of the chi-square analysis, it shows that this difference between professional experiences is significant ($X2=13.533$, $p<.05$).

Metaphors and Distributions of Teachers for the Concept of Online Shopping

138 teachers participated in the research, and the metaphors produced by 131 teachers were evaluated. Responses that did not specify a metaphor, even if it was stated, the reason was not stated, only explanations were not taken into consideration

TABLE IX.
DISTRIBUTION OF METAPHORS PRODUCED BY TEACHERS FOR THE CONCEPT OF ONLINE SHOPPING IN ALPHABETICAL ORDER

Metafor	f	Metafor	f	Metafor	f	Metafor	f	Metafor	f
Emergency Service	1	Discharge	1	Light	2	Magnet	1	Therapy	1
Agent	1	Friend (Dost)	3	Need	7	Music	2	TV Series	2
Alcohol	3	World	1	Medicine	3	Breath	3	Drugs	4
Mother	2	Binoculars	1	Spring	1	Oxygen	3	Virus	5
Friend	4	Education	1	Coffee	3	Game	2	Driving in Rainy Weather	1
Vaccine	1	Bread	1	Coffee House	1	Toy	2	Band-Aid	1
Love	2	Nutrition	2	Closed Box	1	Cake	1	Foreign	3
Swamp	5	Sun	1	Bookshelf	4	Cigarette	3	Lifestyle	4
Nutrients	4	Air Bag	1	Comfortable Life	2	Water	3	Bed	1
Life Saver	2	Life	1	Gambling	4	Poem	1	Meal	5
Raw Chicken	1	Calculator	1	Labyrinth	1	Holiday	1	Saving Time	3
Chocolate	2	Swamp	2	Market	2	Laziness	2	Poison	2
								Total	131

In this part of the research, the metaphors produced by the teachers for the concept of online shopping were combined under 2 main headings as Positive Metaphors Regarding Online Shopping and Negative Metaphors Regarding Online Shopping, and the percentage and frequecy values of these headings are given in Table 10.

TABLE X.
CATEGORIES OF METAPHORS FORMED BY TEACHERS FOR ONLINE SHOPPING

Online Shopping Categories	F	%
Positive Metaphors for Online Shopping	92	70,2
Negative Metaphors for Online Shopping	39	29,8
Total	131	100,0

According to Table 10, 70.2 of the metaphors created by teachers for online shopping were in positive categories and 29.8 in negative categories. After this categorization, positive metaphors for online shopping are in 6 different categories; negative metaphors were collected in 3 different categories and presented in Table 11.

TABLE XI.
SUBCATEGORIES OF METAPHORS CREATED BY TEACHERS FOR ONLINE SHOPPING

Positive Metaphors for Online Shopping						Negative Metaphors for Online Shopping		
Online shopping is a basic and compulsory need	Online shopping makes life easier	Online shopping is entertaining and intriguing	Online shopping is unifying and	Online shopping is relaxing and relaxing	Online shopping is a savior	Online shopping is addictive	Online shopping is dangerous	Online shopping is harmful
Nutrition Food Need Medicine Breath Oxygen Water Lifestyle Meal Life Bread Education Sun	Binoculars Maid Light Bookshelf Comfortable Living	Earth Spring Game Poetry Holiday Toy	Mother Friend Companion Music	Chocolate Discharge Coffee Pastry Therapy Bed	Emergency Vaccine Lifesaving Airbag Band-Aid	Swamp Drugs Coffee- Shop Maze Magnet	Agent Sloth Virus Driving In The Rain Closed- Box	Raw Chicken Gamble Poison

According to the findings in Table 11, positive metaphors online shopping is a basic and compulsory need (13 metaphors), online shopping makes life easier (9 metaphors), online shopping is entertaining and intriguing (6 metaphors), online shopping is unifying and integrative (4 metaphors).), online shopping is relaxing and relaxing (6 metaphors) and Online shopping is savior (5 metaphors); The negative metaphors consist of the categories of online shopping creates addiction (9 metaphors), online shopping is dangerous (5 metaphors), and online shopping is harmful (3 metaphors).

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2. MACATEGORY OF POSITIVE METAPHORS RELATING TO ONLINE SHOPPING

Online Shopping is a Basic and Compulsory Need

In this category, 37 (28.2%) teachers stated that online shopping is a basic and compulsory need: food (f: 4), food (f: 1), need (f: 7), medicine (f: 3), breath (f). :3), oxygen (f:3), water (f:3), lifestyle (f:4), food (f:5), life (f:1), bread (f:1), education (f) 13 metaphors were defined, namely : 1 and sun (f: 1). According to the frequency distribution, the most defined metaphors are need, food, food and lifestyle. As an example of the teachers' sentences in this category;

"Online shopping is like food because you need to consume it regularly to survive." (F;S,13)

“Online shopping is like a breath; because it is necessary for life." (M;Ö,2)

“Online shopping is like life; because you find life in it to be able to live." (K;Ö,24)

“Online shopping is like education; because it is our basic need for our tomorrow.” (F;S,18)

“Online shopping is like water; because I satisfy my vital needs with it.” (F;S,33)

“Online shopping is like bread; because it is the main food source to satisfy our hunger.” (M;S,76)

Online Shopping Makes Life Easier

In this category, 20 (15.3%) teachers voted online shopping makes life easier. 2), market (f:2), assistant (f:3), time saving (f:3), calculator (f:1), 9 metaphors were defined. According to the frequency distribution, the most defined metaphors are library, helper and time saving. As an example of the teachers' sentences in this category;

“Online shopping is like a maid; because it makes our life easier." (K;Ö,112)

“Online shopping is like light; because it gives light when we need it, makes our life easier" (M;Ö,81)

“Online shopping is like saving time; because it allows me to get everything done from where I sit" (F; Ö,131)

“Online shopping is like a library; because it allows me to reach everything I'm looking for easily"(K;Ö,101)

“Online shopping is like binoculars; because it allows me to easily see products that are miles away by zooming in. (M;S,22)

Online shopping is entertaining and intriguing

In this category, 8(6.11%) of the teachers stated that online shopping is entertaining and intriguing: world(f:1), spring(f:1), game(f:2), poetry(f:1), holiday(f) 6 metaphors were defined as : 1 and toy (f: 2). According to the frequency distribution, the most defined metaphors are games and toys. As an example of the teachers' sentences in this category;

“Online shopping is like spring; because in spring, just as nature purifies from its dead cells and blooms, when I shop, I feel different emotions and become happy.” (F;S,99)

“Online shopping is like a game; because it helps to have a pleasant time.” (M;S,54)

“Online shopping is like poetry; because it evokes different emotions in the shopper. (M;P,8)

Online Shopping Is Unifying and Integrative

In this category, 11 (8.4%) teachers gave 4 metaphors as mother (f:2), friend (f:4), friend (f:3), music (f:2) in the category of online shopping uniting and integrating. has been defined. According to the frequency distribution, the most defined metaphors are friend and fellow. As an example of the teachers' sentences in this category;

“Online shopping is like a mother; because it is with me in every moment of my life.” (M;S,44)

“Online shopping is like a friend; because he is always with me in good and bad days” (K;Ö,103)

“Online shopping is like music, because it unites all people in good feelings.” (F;Ö,72)

Online Shopping Is Soothing And Relaxing

In this category, 9 (6.9%) teachers stated that online shopping is relaxing and relaxing: chocolate (f: 2), discharge (f: 1), coffee (f: 3), cake (f: 1), therapy (f: 1), bed (f:1), 6 metaphors were defined. According to the frequency distribution, the most defined metaphors are coffee and chocolate. As an example of the teachers' sentences in this category;

“Online shopping is like chocolate; because it gives relief even in the worst mood swings.” (F;S,31)

“Online shopping is like therapy; because it soothes my soul.” (M;S,65)

“Online shopping is like coffee; because it's the first thing that comes to mind when I feel the urge to relax." (F;Ö,120)

“Online shopping is like a bed; because it takes away my tiredness and relaxes me.” (M;P,124)

Online Shopping is Savior

In this category, online shopping is a savior by 7 (5.34%) teachers in the category: emergency service (f:1), vaccine (f:1), lifeguard (f:3), airbag (f:1), band -aid (f) : 1), 5 metaphors were defined. According to the frequency distribution, the most defined metaphor is lifesaving. as an example of the teachers' sentences in this category;

“Online shopping is a lifesaver; because it saves our lives when we are in a difficult situation.” (F;T,20)

“Online shopping is like an airbag; because it saves lives in the pandemic.” (M;Ö,11) “Online shopping is like an emergency service; because it is always open and serves, it is a savior.” (F;O,109)

3. THE CATEGORY OF NEGATIVE METAPHORS RELATING TO ONLINE SHOPPING

Online Shopping Is Addictive

In this category, 22 (16.8%) teachers stated that online shopping creates addiction: swamp (f:), drugs (f:5), coffee shop (f:1), maze (f:1), magnet (f:1) Nine metaphors were defined, namely, cigarette (f:3), TV series (f:1), alcohol (f:3), love (f:2). According to the frequency distribution, the most defined metaphors are swamp, drugs, cigarettes and alcohol. As an example of the teachers' sentences in this category;

“Online shopping is like a swamp; because once you get inside you can't get out, you always find yourself shopping” (M;T,17)

"Online shopping is like a TV show because you get addicted, you can't stop." (F;S,93)

"Online shopping is like a cigarette because once you inhale it, you can't live without it." (F;Ö,48)

"Online shopping is like a drug; it's addictive, you can't get rid of it." (M;S,21)

Online Shopping is Dangerous

In this category, 10 (7.62%) teachers stated that online shopping is dangerous in the category: agent(f:1), sloth(f:2), virus(f:5), driving in rainy weather(f:1), closed box(f:1), 5 metaphors were defined. According to the frequency

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distribution, the most defined metaphors are virus and laziness. As an example of the teachers' sentences in this category;

" Online shopping is like an agent because I feel like there is always someone trying to reach our information." (F;Ö,6)

" Online shopping is like driving in the rain because it is more dangerous than ever, it involves risk. (F;Ö,51)

" Online shopping is like a closed box because you never know what you're going to encounter." (M;S,118)

" Online shopping is like laziness, because you sit and wait for everything without effort." (M;T,30)

3. Online Shopping Is Harmful

In this category, 7 (5.34%) teachers defined 3 metaphors in the category of harmful online shopping: raw chicken (f: 1), gambling (f: 4), poison (f: 2). According to the frequency distribution, the most defined metaphors are gambling and poison. As an example of the teachers' sentences in this category;

" Online shopping is like gambling because sometimes I worry if the product I want will come as I expect it to." (M;S,75)

" Online shopping is like a poison because it spreads to our whole body in an instant, it takes us prisoner." (F;S,14)

The metaphors that the teachers emphasized the most are seen in the larger font and in the word cloud with more specific fonts.

4. DISCUSSION

With the widespread and more preferred communication tools and the increasing use of online platforms, individuals have begun to meet many of their needs, such as entertainment to socialization, communication to online shopping, through virtual environments.

Especially in recent years, the use of online shopping sites to buy all kinds of equipment has almost surpassed the traditional shopping usage. It is of great importance for both marketers and individuals to determine what influences their purchasing decisions in a sector where people prefer shopping in electronic environment so much. When the literature review is examined, it is seen that privacy and security are the leading factors affecting online shopping behavior. When the results obtained in general are evaluated, 92 of the 131 metaphors produced regarding the concept of online shopping are in the positive category, while 39[1.] metaphors are in the negative category; It shows that people still have concerns about online shopping, and that privacy and security factors negatively affect their online behavior.

When we look at the answers given by the teachers especially during the pandemic period, it has been revealed by the results obtained that women tend to shop online more than men, and that age and professional experience also create a difference in this regard. In addition, it was found that young and middle-aged teachers do more online shopping than older teachers. The findings obtained as a result of our study show similarities with other studies proving that individuals who prefer online shopping are more young individuals [8, 11].

5. CONCLUSION

It is seen that many metaphors are needed to fully express the image of online shopping. When the findings obtained as a result of the research were evaluated, a total of 60 different metaphors were produced by the teachers about the concept of online shopping. These metaphors are positive metaphors for online shopping in 6 different categories; Negative metaphors were grouped into 3 different categories.

It can be said that teachers see online shopping as an important necessity in expressing different situations such as making life easier such as library, helper, comfort, as well as putting life in danger such as laziness, poison, gambling and harming our lives at the same time. At the same time, teachers' definition of online shopping with images such as food, food, oxygen, water and breath that people feel as a basic and compulsory need in their lives and which are more necessary, in fact, emphasizes the importance and necessity of online shopping in our lives, especially during the pandemic period. Based on all these, we can conclude that metaphors carry traces of people's lives and that our lives are shaped accordingly.

Looking at the findings obtained from the research; women's descriptions of online shopping using metaphors such as friends, chocolate, cake, coffee, vacation, love; Men's definitions using metaphors such as game, airbag, driving in the rain, gambling ... seem to be a good example in terms of gender difference. In addition, it is seen that 22 teachers perceive online shopping as an integral part of their lives, beyond virtual shopping, and they are dependent on online shopping.

It is undeniable that, unlike the metaphorical study conducted in the light of the findings obtained at this point, such studies should be conducted in a way that supports, characterizes and explains each other in detail.

As a result; Metaphors help us to show us both surprising and guiding right directions. In this research, quite surprising results were obtained on how effective online shopping is in the lives of teachers, how they attribute to online shopping, how online shopping makes their lives addictive and even how they are connected to online shopping. However, we know that online shopping is a result of digital developments in the age of computers and technology and should be used consciously.

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Evaluation of Performance Metrics in Heart Disease by Machine Learning Techniques

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ABSTRACT

Aim: In addition to affecting the individual sociologically and psychologically, heart disease also poses important problems in health systems. Evaluation of heart disease performances has gained great importance in terms of machine learning method. In the study, performances were compared with the machine learning method for risk methods that classify heart illness.
Materials and Methods: The categorization process Throughout the research made use of the "Heart Disease Dataset," an open access dataset. F1-score, sensitivity, selectivity, accuracy, balanced accuracy, negative and positive predictive values were used to assess the performance of the categorisation model using the machine learning approach. Random forest method, one of the variable selection methods, was used.
Results: According to the relational classification model's classification findings for heart disease, the accuracy, balanced accuracy, sensitivity, selectivity, positive predictive value, negative predictive value, and F1-score values were observed to be 0.997, 0.997, 0.995, 1, 1, and 0.995, respectively.
Conclusion: The relational classification model proposed in the analysis obtained in the web-based open access dataset yielded distinctively successful results in classifying heart disease according to performance criteria.
Keywords: heart disease, classification, relational classification.

1. INTRODUCTION

One of the fields of artificial intelligence known as machine learning allows users to get data on previously collected information without actively programming the system [1].

Heart disease affects both men and women equally across the world. As a result, people must take into account the risk factors for heart disease and adjust their lives accordingly. Heart disease risk factors include several elements including smoking, gender, age, family history, radiation therapy, high blood pressure, obesity, diabetes, stress, elevated blood sugar levels, and unsanitary environments [2].

Artificial Neural Networks (ANN), Deep Learning (DL), Decision Trees (DT), Classification and Regression models (CART, Logistic Regression-LR, K-Nearest Neighbors-KNN), Random Forest (methods like RF), Fuzzy Logic (FL), Genetic Algorithms (GA), and Support Vector Machines are some examples of machine learning techniques (SVM), and Expert Systems (US) are all just a few of the technics used in machine learning algorithms.

These techniques are employed throughout a wide range of the healthcare industry, according to the literature. The WBCD dataset was used to detect breast cancer in patients using methods including SVM, kNN, and NaviBayes. The study's results revealed also that NaviBayes method had a rate of success of 0.702, 0.737 for kNN, and 0.776 for SVM [3].

The use of the variable selection approach in machine learning techniques has been attempted to identify liver failure. Disease identification was carried out with a success rate of Light Gradient Enhancement Machine Classifier-LGBM 82.12%, Multilayer Sensor-MLP 81.13%, DT 81.13%, SVM 77.87%, and Logistic Regression-LR 77.80% in their application on the Indian Liver Patient Dataset (ILPD) [4].

Data mining is best understood as a science that unifies areas that are connected to many other disciplines, such as statistically establishing patterns and using database technology to display data (5).

In terms of resemblance to artificial neural networks, data mining can be described as a method that provides knowledge about the connections between the hidden layers of the variables and how to manage the pattern discovered by these hidden layers in the next phase. focuses on the procedures needed to create an accurate and practical model [6].

2. MATERIAL AND METHODS

2.1. Data set

The whole dataset for cardiac illness used in this study was obtained from the IEEEDataPort database at https://ieee-dataport.org/open-access/. A total of 1190 samples, comprising 629 (52.9%) patients with cardiac disease and 5 61 (47.1%) patients with healthy conditions, were processed in this open access data collection. Table 1 lists the variables from the relevant data set along with their descriptive characteristics.

TABLE I
THE VARIABLES IN THE DATA COLLECTION, TOGETHER WITH A DESCRIPTION OF EACH

Variable	Variable Description	Variable Type	Variable Role
Age	Patient's Age	Numerical	Independent/Predictive
Sex	Patient's Gender	Qualitative	Independent/Predictive
chest pain type	Chest Pain Type	Qualitative	Independent/Predictive
resting bp s	Blood pressure	Numerical	Independent/Predictive
cholesterol	Cholesterol	Numerical	Independent/Predictive
fasting blood sugar	Fasting Blood Sugar	Qualitative	Independent/Predictive
resting ecg	ECG results	Qualitative	Independent/Predictive
max heart rate	Maximum Heart Rate Reached	Numerical	Independent/Predictive
exercise angina	Exercise Induced Angina	Qualitative	Independent/Predictive
oldpeak	oldpeak	Numerical	Independent/Predictive
STslope	STslope	Qualitative	Independent/Predictive
Target	Target	Qualitative	Dependent/Target

2.2. Support Vector Machines

Support vector machines are a machine learning approach that are extensively used in the literature for both classification and regression analysis procedures, even though they are employed for data set classification. Support vector machines are built on a learning model utilised in kernel functions in addition to the supervised learning model, taking into account the type of data being used to test the method. In light of this, it is a strategy that is employed in both linear and nonlinear classification procedures.

Although every data is classed with a hyperplane in classification processes if it is fully decomposable, if the data is in an undifferentiated structure, it is not classified with a single plane. several kernel functions are therefore utilised [7].

2.3. Naive Bayes

The Naive Bayes approach assesses the likelihood of identical situations having the same effects on the outcome.

The Naive Bayes algorithm determines the frequency of occurrence of each output in the training set. A priori probability refers to the result that is taken into account. The total of the calculated probability is one. It displays the result's class in accordance with the highest value attained within the a priori probability [8].

The simplest way to describe naive Bayes is as the sum of all conditional probabilities. according to;

Likelihood Class Prior Probability

$$P(c \mid x) = \frac{P(x \mid c)P(c)}{P(x)}$$

Posterior Probability Predictor Prior Probability

$$P(c \mid X) = P(x_1 \mid c) \times P(x_2 \mid c) \times \cdots \times P(x_n \mid c) \times P(c)$$

2.4. Logistic Regression

It is a technique used to look at the groups to which the data set's observations are categorised. In logistic regression analysis, a classification model is developed by taking into account the information that each class is aware of. New observations or observations that need to be added to the data set are categorised with the aid of the logistic model that was produced. The employment of logistic models is a common strategy in healthcare applications. Risk is variable or processes that show whether the case is visible or not. Input variables. Early diagnosis and disease-causing variables are crucial for variable detection [9].

It is a technique used when the dependant variable is qualitative and contains two or more categories.

Dependent Variable	*Group*
Two-Category (Binominal)	died-living, successful-failed
More than two categories, unorganised (Multinominal)	unemployed-retired-employed, numerical-verbal-equal weight
More than two categories in the sequence (Ordinal)	low-medium-high, ineffective-effective-very effective

The logistic distribution function may be calculated by formulating the distribution function using two-category output variables.

$$P_i = E\left(Y = {}^{1}/_{X_i}\right) = \frac{1}{1+e^{-(\beta_0+\beta_1 X_i)}} \quad (1)$$

$Z_i = \beta_0 + \beta_1 X_i$ in case of conversion;

$$P_i = \frac{1}{1+e^{-Z_i}} \quad (2)$$

The Z_i value is a function known as the logistic distribution function.$-\infty < Z_i < \infty$ takes values in the range and P_i *if its value* $0 < P_i < 1$ takes value between. Z_i equation, so X_i *with* P_i There doesn't seem to be a direct connection between This gap in the linear probability model will be filled if these two relations are offered [10].

2.5. Performance metrics

The performance metrics utilised to compare classification performances were, in order, sensitivity, selectivity, accuracy, balanced accuracy, negative predictive value, positive predictive value, and F_1-score. Table 2 contains the matrix for categorising performance criteria.

TABLE II
PERFORMANCE CRITERION CLASSIFICATION MATRIX

		Actual Value Positive	Actual Value Negative	Total
Estimated Value	**Positive**	True Positive (TP)	False Negative (FN)	**TP+FN**
	Negative	False Positive (FP)	True Negative (TN)	**FP+TN**
	Total	**TP+FP**	**FN+TN**	**TP+TN+FP +FN**

Sensitivity = TP/[TP+FP]
Selectivity = TN/[TN+FN]
Accuracy = [TP+TN]/[TP+TN+FP+FN]
Balanced accuracy = [[TP/(TP+FP))]+[TN/(TN+FN)]]/2
Negative predictive value =TN/[TN+FP]
Pozitive predictive value = TP/[TP+FN]
F_1 – score = [2*TP]/[2*TP+FP+FN]

2.6. Data analysis

When the Shapiro-Wilk test was used to determine if quantitative data were normal, it was found that the data were not symmetrical. The effect size, which was determined by utilizing the median and interquartile range, provided evidence of this. The Mann-Whitney U test and the t-test for independent samples were used to compare the categories of the dependent/target variable, "Normal," and "Heart disease," in order to determine whether there was a difference that was statistically significant (Heart disease). At $p < 0.05$, obtained probability values were deemed statistically significant. The Biostatistics and Medical Informatics Department of inönü University built the open-access web-based http://biostatapps.inonu.edu.tr/ address from which all of the analyses were retrieved.

3. FINDINGS

In Table 3, descriptive statistics are shown for the input variables covered in this study. Age, Blood pressure, Cholesterol, Heart Rate Reached, and old peak variables were statistically different across the groups of the dependent variable ($p < 0.005$).

TABLE III
DESCRIPTIVE STATISTICS FOR QUANTITATIVE VARIABLES

Variable	Normal Median(IQR)	Heart Disease Median(IQR)	p-value	ES
Age	51(13)	57(11)	<0.001	0.077
Blood pressure	130(20)	132(25)	<0.001	0.278
Cholesterol	232(67)	226(148)	0.003	0.364
Heart Rate Reached	154(32)	128(34)	<0.001	0.434
oldpeak	0(0.8)	1.2(1.9)	<0.001	0.375

IQR: Interquartile Range; ES: effect size. ***: Mann Whitney U test, **: Independent samples t-test**

A heart illness dataset was used in the study, and the accuracy values of the classification performances of Support Vector Machines, Naive Bayes, and Logistic Regression models were examined. The model with the best performance was chosen. One of the methods used in machine learning, Support Vector Machines was used to classify the dataset related to heart disease. The classification matrix is seen in Table 4.

TABLE IV
CLASSIFICATION MATRIX FOR THE MODEL

Prediction	Reference Normal	Reference Heart disease
Normal	558	0
Heart disease	3	629

Table 5 provides statistics on the relational classification model's performance in terms of classification. The model's accuracy was 0.997, as were its balanced accuracy, sensitivity, specificity, positive predictive value, negative predictive value, and F1-score. Its negative predictive value was 0.995, and both its positive and negative predictive values were 1.

TABLE V
STATISTICS ON CLASSIFICATION PERFORMANCES OF THE MODEL

Metric	Value
Accuracy	0.997
Balanced Accuracy	0.997
Sensitivity	0.995
Selectivity	1
Positive predictive value	1
Negative predictive value	0.995
F1-score	0.997

The classification matrix utilized in the classification utilizing the dataset for heart disease and the Naive Bayes algorithm, one of the machine learning techniques, is shown in Table 6.

TABLE VI
CLASSIFICATION MATRIX FOR THE MODEL

Prediction	*Reference* *Normal*	*Reference* *Heart disease*
Normal	460	81
Heart disease	101	548

Table 7 provides statistics on the relational classification model's performance in terms of classification. The model's accuracy was 0.847, the balanced accuracy was 0.846, the sensitivity was 0.82, the selectivity was 0.871, the positive predictive value was 0.85, the negative predictive value was 0.844, and the F1-score was 0.835.

TABLE VII
STATISTICS ON THE MODEL'S PERFORMANCE IN CLASSIFYING OBJECTS

Metric	Value
Accuracy	0.847
Balanced Accuracy	0.846
Sensitivity	0.82
Selectivity	0.871
Positive predictive value	0.85
Negative predictive value	0.844
F1-score	0.835

The classification matrix used for the classification utilizing the heart disease dataset and the Logistic Regression model using machine learning techniques is shown in Table 8.

TABLE VIII
CLASSIFICATION MATRIX FOR THE MODEL

Prediction	Reference	
	Normal	Heart disease
Normal	462	82
Heart disease	99	547

Table 9 provides statistics on the model's classification results in relational classification. The model's accuracy was 0.848, along with balanced accuracy of 0.847, the sensitivity of 0.824, specificity of 0.87, positive predictive value of 0.849, negative predictive value of 0.847, and F1-score of 0.836.

TABLE IX
STATISTICS ON CLASSIFICATION PERFORMANCES OF THE MODEL

Metric	Value
Accuracy	0.848
Balanced Accuracy	0.847
Sensitivity	0.824
Selectivity	0.87
Positive predictive value	0.849
Negative predictive value	0.847
F1-score	0.836

4. DISCUSSION AND CONCLUSION

Heart disease, vascular blockage, and the inability to pump blood are some of the symptoms of this particular disease kind. In terms of treatment simplicity, early detection and prevention of heart disease and its many forms become more important. There are numerous drawbacks to technology, which is a part of daily life, as well as novel benefits that influence it. A person's health can be negatively impacted by variables like stabilization, stress, and a bad diet [11].

The extensive use of data mining techniques has been made possible by the rise in the risk of mortality in people with heart disease. To stop people from dying in hospitals after receiving an early diagnosis, serious investigations have been recommended [12].

Data mining is a method that enables information to be extracted from high-dimensional data using a variety of statistical approaches and in circumstances when there is a very low likelihood of guessing the correlations between variables [13]. It is a strategy for analysis that uses data mining to categorize and summarise variables while avoiding information ambiguity. Data preparation is used throughout the data analysis stage to find outliers and extremes as well as to establish the link between the variables. The choice to be made and the definitions that must be made can be guided by it [14].

The prediction of cardiac problems has been the subject of several research in the literature. The maximum success performance was reached with J48 as accuracy (83,732%) in research that compared the performance of approaches used for the identification of heart illness such as J48, K, Nearest Neighbor (KNN) algorithm, Decision tree, and Naive Bayes (NB) [15].

The accuracy performance ratings achieved using machine learning approaches were compared in a different investigation utilizing the same data set. The accuracy rate of Support vector machines (SVM) for classifying heart disease performance, per the study's findings, was 0.897. The SVM accuracy rate for this investigation was determined to be 0.997 [16].

This study made use of the "Heart Disease Dataset," an open-access online resource. The linked data set was subjected to the use of three data mining techniques: Support vector machines, Naive Bayes, and a Logistic Regression Classification Model. The diagnosis of heart illness (the dependent variable) and other relevant parameters (the independent variables) were used to create statistics based on the classification performance of the models of all three data mining techniques.

Sensitivity, selectivity, positive and negative predictive values, accuracy, balanced accuracy, and F1- The score was estimated as 0.997 after taking into account the statistics on classification performances by the analysis results obtained from the open access data set. Estimates with a high degree of accuracy were produced using the Naive Bayes and Logistic Regression approaches.

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Epileptic Activity Detection using Mean Value, RMS, Sample Entropy, and Permutation Entropy Methods

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ABSTRACT

In this study, linear and non-linear signal analysis methods are implemented for epilepsy seizure detection using CHB-MIT EEG data taken from Boston children's hospital. In linear signal analysis, EEG signals are considered linear, although they are not linear. In linear signal analysis methods, root mean square (RMS) and mean of the EEG signals are analyzed. It is detected that the RMS value increased and the mean value moved away from zero in the positive and negative directions during the seizure period. Seizure periods in EEG signals are determined with RMS and mean values with 75 % and 58.4 % accuracy, respectively. Since EEG signals are not linear, the linear analysis is assumed insufficient and so entropy is preferred to linear signal analysis methods. Sample entropy (SmpE) and permutation entropy (PE) are preferred among entropy types. While an increase is observed in the sample entropy values at the beginning of the seizure, a decrease is observed in the permutation entropy values at the same time. When the entropy methods are examined separately, the onset of a seizure is determined with an accuracy of 66.6 % for both methods. However, when the entropy methods are examined together with the increase in the sample entropy value or the decrease in the permutation entropy, the accuracy rate increases to 79.2 % The resultant accuracy rates show that when one entropy method fails to catch the onset of a seizure the other can.

1. INTRODUCTION

Epilepsy has been seen in written sources dating back to 4000 BC. It is defined as the involuntary movement of part or all of the body. The reason for these movements is the electrical discharge in the brain. This electrical discharge can be caused by an infarction, tumor, progressive brain disease (rare), or head injury. However, there are some electrical discharges of unknown cause. Epilepsy is a genetic, non-communicable disease and is not related to age, gender, or race [1,2].

Electroencephalography (EEG) signals have been important in the diagnosis of epilepsy due to the recognition of spikes in EEG signals during epileptic seizures [3]. In epilepsy diagnosis, in addition to EEG, neurological information and neurodiagnostic tests are also used. Electrodes are placed on the scalp in the laboratory environment for EEG recordings. These recordings are classified as ictal, postictal, and interictal. The ictal period is called for during the seizure period, the postictal is called for the post-seizure period and the interictal is for the period between the seizures [4]. Interictal EEG recordings are used in the diagnosis and in the management of the treatment course of epilepsy. In order to diagnose epilepsy, the patient's EEG data, as well as physical examination, seizure history, and neurological tests are taken into account [5]. Of all data, the most important finding is the EEG recordings. Furthermore, having one seizure is not enough to diagnose epilepsy, patients must have at least two or more seizures.

The anti-epileptic drugs are used first in the treatment of epilepsy. The dose of the drug is calculated according to the severity of the seizures of the patient [6]. Drugs can prevent most seizures, however, there are some patients' seizures that cannot be prevented despite using high-dose. Generally, surgical interventions can be a treatment for epilepsy patients. However, there are some cases where surgical intervention is not a solution [7]. Vagus nerve stimulation, in addition to surgical intervention, is a treatment method in which an electrical current is sent to the brain at regular intervals to prevent seizures [8]. Unfortunately, there are some patients who do not respond to any treatment method. In these cases, the moment of seizure should be predicted and it should be ensured that the seizure can be overcome with the least damage. In the diagnosis and treatment stages of epilepsy, it is very time-absorbing to examine long-term EEG recordings by experts and to detect seizures. Therefore, EEG signals are analyzed with linear or nonlinear signal analysis methods in order to detect the epileptic region in EEG. Although EEG signals are not linear, in the linear signal analysis they are considered linear

[9]. In our study, we deal with predicting the moment of the seizure by implementing linear signal analysis methods and nonlinear signal analysis methods of EEG.

In the linear analysis method, EEG signals are analyzed in the time, frequency, and time-frequency domain. In the time domain, energy, power, variance, standard deviation, mean, and root mean square (RMS) of signals are reviewed [9,12,16,17,18,19]. In the frequency domain, spectral power density and subband frequency values are investigated [9,23]. The epileptic region in the signal was identified using the Elman neural network with features extracted in the time and frequency domain [10]. For the diagnosis of seizures in the EEG signal, the signals are separated into subbands by wavelet decomposition and classified by genetic algorithm [11]. A prediction filter has been proposed to show the existence of spikes and sharp waves in seizure regions in EEG signals. In the EEG signals, the seizure region was determined by the increase in the estimation error energy of the filter [12]. The difference between healthy EEG and epileptic EEG signals was shown with the aid of an artificial neural network and genetic algorithm [13]. Furthermore, epilepsy disease was defined by performing EEG signal analysis with a single hidden layer feedforward artificial neural network machine (ELM) in 2012 [14]. The seizure was detected in EEG signals applied to artificial neural networks with multi-stage nonlinear filtering preprocessing [15]. In another study, classifying preictal and interictal EEG signals by using features such as frequency and amplitude in gamma band signal has been shown [16]. Singh et al. classified the EEG signals using the difference in RMS bandwidth and average frequency seen in epileptic zone rhythms [17]. Raghu et al. showed that the epileptic EEG signals have a larger variance, maximum value, wavelet log energy entropy, RMS, and band power properties, while the normal EEG signals have a larger minimum value, wavelet Shannon entropy, and zero-crossing characteristics [18]. Mahapatra et al. classified ictal and interictal EEG signals using the RMS frequency [19]. To distinguish the epileptic region in EEG signals, a feature has been proposed as a time-domain energy-based called exponential energy [20]. In recent studies, the features used for the diagnosis of seizures in the EEG signals were examined. It has been shown that seizures can be determined by using the variance, energy, nonlinear energy, and Shannon entropy calculated in the raw EEG signals or by using the variance, energy, kurtosis, and line length calculated over the wavelet coefficients [21,22]. Ficici et al. analyzed the EEG signals divided into sub-bands with autoregressive coefficients and linear estimation error energy from linear analysis methods, and Shannon entropy and approximate entropy methods from non-linear analysis methods. It has been shown that better accuracy will be obtained with the use of linear and non-linear methods classified as healthy and epileptic EEG signals [23].

In linear signal analysis, EEG signals are considered linear, although they are not linear. For this reason, the preference for nonlinear analysis methods (dimension property, Lyapunov exponents, and entropy) may give better information for the diagnosis of epilepsy [25-45]. In a study conducted in 2019, it was stated that structural changes can be detected early using the Lyapunov Exponents values of EEG signals (non-linear dynamic methods) [24]. One other of these methods, entropy is a thermodynamic concept that gives information about system disorder [9]. It is used to measure the irregularity in EEG signals during an epileptic seizure. Kannathal et al. [25] and Song et al. [26] showed the difference between epileptic and healthy EEG signals using the entropy methods such as Shannon entropy, Renyi's entropy, Kolmogorov-Sinai entropy, sample entropy, and approximate entropy. When the entropy values of the epileptic and normal signals were compared, it was observed that the entropy values of the epileptic signal were higher than the normal ones. This indicated a decrease in the flow of information during the seizure [25,26]. In different studies, EEG signals were decomposed into signal subbands by applying discrete wavelet transform at different levels. These decomposed signals were determined for the seizure by using approximate entropy and spectral entropy [26,27]. EEG signals were classified with the calculated wavelet entropy, spectral entropy, and sample entropy values by repetitive Elman-based neural networks and radial-based neural networks [28]. Song et.al. combined the extreme learning machine with the optimized sample entropy (O-SampEn) algorithm. With this combination, it was determined whether there was a seizure in the EEG signals [29].

Nicolaou et al. and Xiang et al. classified the permutation entropy, fuzzy entropy, and sample entropy values of EEG signals calculated by support vector machine [30,31]. It has been shown that fuzzy entropy has a better seizure detection index than sample entropy [31]. In another entropy method, distribution entropy, the epilepsy signal was segmented in three different ways and entropy values were calculated. Distribution entropy has been observed minimally affected in the parameter selection [32]. Raghu et al. used Shannon spectral entropy to differentiate between two groups of patients with idiopathic epilepsy. They showed that Shannon spectral entropy measured in a specific frequency range can serve to follow the development of patients suffering from idiopathic epilepsy [33]. In another study, EEG signals were separated into subbands by discrete wavelet transform. Of the power spectral analysis in the frequency domain and of the amplitude values in the time domain, the sigmoid entropy was calculated. It was concluded that sigmoid entropy, which has less computational complexity, can be used to analyze epileptic seizure behavior, which also includes brain dynamics [34]. In a recent study, it was shown that the patients can be warned before the seizure by determining the time between the preictal and ictal state by inferring the distribution entropy feature has been stated [35]. Multidimensional sample entropy is proposed and compared with sample entropy. They showed that seizure onset was more notable in the multidimensional sample entropy [36].

Li et al. found that the permutation entropy was more sensitive than the sample entropy for recognizing the nonlinear activity in EEG data and predicting absence seizures [37]. Since permutation entropy is a fast complexity measure in time series, it has been used for seizure detection in online devices. It was observed that the permutation entropy makes a reliable distinction, but the sensitivity of the study could not be measured due to limited data [38]. Jouny et al. proposed that seizure detection was attempted with a combination of eighteen different feature extraction methods, including Shannon entropy, sample entropy, and permutation entropy [39]. In a study in 2012, the permutation entropy was calculated by making different synchronizations of the EEG electrodes. Within the analyzed database, the frontal-temporal scalp areas appeared to be consistently associated with higher permutation entropy levels compared to the remaining electrodes, while lower permutation entropy values were seen in the parieto-occipital areas. It is shown that abnormalities from different parts of the brain were leading to the onset of the seizures [40]. Multiscale permutation entropy (MPE) was proposed to describe the dynamics in EEG recordings and MPE values were classified using linear discriminant analysis. It has been shown that the seizure-free state, pre-seizure, and seizure moments can be differentiated by dynamic features in MPE and EEG. This result supported the opinion that the seizures were predictable from EEG data [41]. Bhanot et al. used four feature vectors for seizure detection: short-term permutation entropy (STPE), STPE gradient (GSTPE), short-term energy (STE), and short-term mean (STM) subtracted from ictal and interictal EEG signals. With these features, RBBoost (Random Balance Boost) algorithm with k-fold cross-validation was used to classify data as ictal and interictal [42]. Peng et al. extracted nine features for each EEG channel, including power spectral density in six subbands, sample entropy, permutation entropy, and spectral entropy. The features of each channel were ordered according to the F-statistic value and the classification results were improved by selecting the most informative features [43]. In a recent study, channel selection has been made in EEG signals to minimize the complexity and computational power of classification. The channels were selected according to their permutation entropy values using the K-nearest neighbor algorithm combined with the genetic algorithm. By channel selection, accuracy, sensitivity, and specificity values in seizure detection were improved. They tried to determine which part of the brain was associated with the onset of seizures for a particular patient and determined that the P7-O1 channel was most effective in the selected patient group. Furthermore, they found that the seizure predictions made by selecting the channel are more accurate and have less computational burden than the seizure predictions made by using all channels [44].

In this study, we prefer to analyze two linear analysis methods, namely the mean of RMS and epileptic EEG signals. We also checked for permutation entropy and sample entropy values for EEG signals, as they have fast complexity measurements in time series. We aimed to predict the seizure moment before a certain time by examining these linear and non-linear methods among themselves.

With this study, the following contributions are made to the ongoing studies on the early detection and diagnosis of seizure activity in EEG signals:

- RMS, mean value, sample entropy, and permutation entropy were used together for the first time for the detection of seizure activity.
- It was determined that the detection rate of seizure activity was higher with non-linear methods.
- It has been determined that using more than one method in detecting seizure activity has higher accuracy than using a single method.
- It has been determined that there are sudden changes before seizure activity.
- It has been shown that sudden changes in EEG signals detected by any method before seizure activity occurs in some methods but not in others. Based on this situation, it has been suggested that using two or more methods for seizure detection will yield better results.

2. MATHEMATICAL MODEL

In the prediction and diagnosis of epileptic seizures, EEG data has an important role. Signal processing of EEG data could be done to detect seizures. It is used to convert features (frequency, energy, power, and complexity of the signal) of EEG signals into numerical data. These features are not clearly visible from the raw EEG data, so they are extracted by linear and non-linear analysis methods [9], which are given in the following sub-sections.

2.1. Linear Analysis Methods

In linear analysis methods, the signal is examined in the time, frequency, and time-frequency domains. In time-domain analysis, statistical properties such as energy, power, mean, standard deviation, variance, and root mean value (RMS) of the signal are generally considered. Of these properties, mean and RMS values are expected to be close to zero if the signal is periodic and sinusoidal. If the signal is not periodic and not sinusoidal, these values are expected to move away from zero, either positively or negatively [45].
The mean (μ) and RMS values of the signal are defined as follows i = 1, 2, .., N for the x signal:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{1}$$

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{2}$$

where N is the number of samples in the data.

One can comment on the complexity of the signal with its mean value of it. If the mean value of the signal is around zero, the signal is assumed a periodic signal. However, if this value is far away from zero, the signal is assumed a complex signal. This situation is also valid for the RMS value. If the RMS value is around zero, the signal is considered to be regular. If it is far from zero, it may indicate that there is confusion in the signal. In this study, we analyzed the mean and RMS values of EEG signals to deal with their complexity of them.

2.2. Non-Linear Analysis Methods

Linear signal analyzes are preferred because of the ease of implementation and simplicity of the theory. In non-linear analysis, more detailed information is obtained about the signal. An essential problem in non-linear analysis is the noise of the signal. For better and more accurate analysis, nonlinear analysis methods should be applied after the signal is eliminated from the noise. Nonlinear analysis methods can be considered into three categories. The first is the dimension property, which gives an idea of how complex a system is; the second is the Lyapunov exponents' property which gives an idea of how predictable a system is; and the third is the entropy property, which gives an idea of how random a system is. In this study, we preferred to analyze the entropy property of the signal to pre-predict the seizure a certain time ago using its irregularity of it [9].

Entropy was used for the first time in thermodynamics to give information about the disorder of a system. It is also a measure of randomness and can be calculated based on the different properties of the signals. In general, all entropies give information about the disorder and regularity of the system [9].

In literature, the researchers performed several types of entropy methods such as Shannon, distribution, approximate, permutation, sample, fuzzy, sigmoid, transfer, and spectral entropy [26-37]. In this study, we preferred the sample and the permutation entropy methods.

2.2.1. Sample Entropy

Sample entropy (SmpE) is a method of measuring the regularity of physiological signals regardless of their length. The SmpE(m,r,n) value can be defined as the negative algorithm of the similarity probability of the tolerance value (r) for the points (m) in any time series of length n. The Sample entropy formula is given as [47]:

$$SmpE(m,r,n) = -log\frac{A}{B} \tag{3}$$

where m is the length of the arrays to be compared, r is the tolerance value to accept matches, and n is the length of the original data. A and B are defined as follows:

$$A = \frac{(n-m-1)(n-m)}{2}A^m(r) \tag{4}$$

$$B = \frac{(n-m-1)(n-m)}{2}\,B^m(r) \tag{5}$$

where Am(r) is the probability that two sequences will match for the m+1 points and Bm(r) is the probability that two sequences will match for the m point. SmpE is consistent for each (m,r) value to be selected [47]. This situation has been effective in the preference of sample entropy in the selection of entropy.

In this study, signals with 256 samples are taken from the data for sample entropy calculation. To calculate sample frequencies, the number of each amplitude repetition is calculated. Then, the possible class probabilities are calculated using the sample frequencies. The resultant probability value is used in the entropy calculation. m is chosen as 1 for this study. Since the sample entropy value increases as the signal become more complex, the sample entropy values will be higher at the beginning of the seizure and during the seizure.

2.2.2. Permutation Entropy (PE)

Another method for evaluating the complexity of the signals in time series is the permutation entropy, which is based on a comparison of neighboring values. In permutation entropy, low noise in the signal does not affect the complexity of the chaotic signal. In this entropy, without requiring pre-processing, robust information can be obtained fast regardless of the size of the data.

The first step in calculating permutation entropy is to convert a one-dimensional time series into a matrix of overlapping column vectors. After, permutation vectors of size M up to M! are generated. Then, the data in each column of the matrix is reconstructed based on the permutation vectors. Reconstructed columns are matched with unique permutations. The relative frequency of each permutation is then determined by dividing the number of times the permutation occurs in the columns by the total number of sequences. Finally, Equation (6) is used to calculate the PE of order M of the signals [48]:

$$PE_M = \sum_{i=1}^{M!} p_i log_2 p_i \tag{6}$$

The embedded parameter, M, should be chosen between 3-7 in order to distinguish the stochastic and deterministic features of the signal. In this study, M is chosen as 3. PE values are in the range of 0-1. In a regular time series, the PE value is close to 0 (zero), whereas in an irregular and random time series, the PE value is close to 1. Since the EEG series becomes regular during the seizure, the PE value is close to zero during the seizure.

3. RESULTS

In this study, CHB-MIT EEG data collected from Boston children's hospital were used. There are 24 subjects; 5 men from 3-22 years old and 18 women from 1.5-19 years old. The EEG data in files 1 and 24 belong to the same person (subject) but they were recorded at different times. EEG signals of 24 patients (subjects) with a 256 Hz sampling rate of 23 channels were recorded as FP1-F7 (1), F7-T7 (2), T7-P7 (3), P7-O1 (4), FP1-F3 (5), F3-C3 (6), C3-P3 (7), P3-O1 (8), FP2-F4 (9), F4-C4 (10), C4-P4 (11), P4-O2 (12), FP2-F8 (13), F8-T8 (14), T8-P8 (15), P8-O2 (16), FZ-CZ (17), CZ-PZ (18), P7-T7 (19), T7-FT9 (20), FT9-FT10 (21), FT10-T8 (22) and T8-P8 (23). The places of electrodes are labeled as FP: frontopolar, F: frontal, T: temporal, O: occipital, C: central, and P: parietal [49]. Fig. 1 shows the electrode diagram of the data and Fig. 2 shows the raw EEG data of a 19-year-old female patient. In this study, the MATLAB program was used for data analysis [50].

In Fig. 3, the RMS value of the P7-O1 channel of a 19-year-old female is calculated. RMS value in the ictal period is higher than it's in the preictal period. Furthermore, the mean value of the same patient moves away from zero in positive and negative directions (Fig. 3). As given in Fig. 4, this situation is also seen in other channels of the same patient.

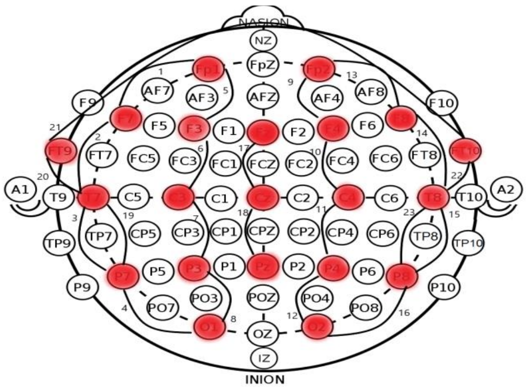


Fig.1. Placement of EEG electrodes for each channel is labeled as red.

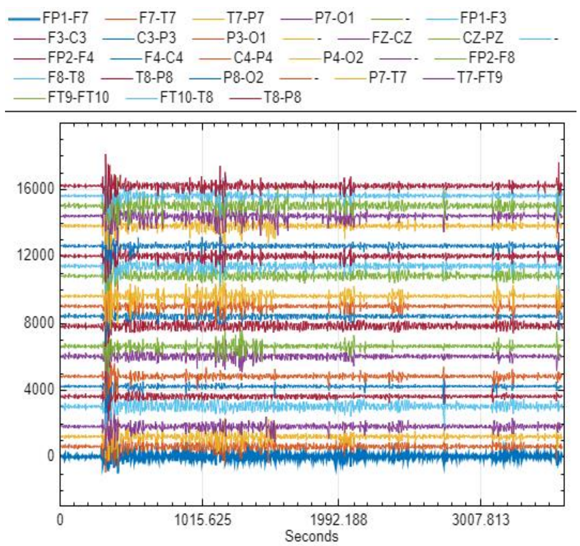


Fig.2. EEG data of a 19-year-old female patient. Each signal is recorded in a specific time period. The signals are separated from each other at 600 μV size.

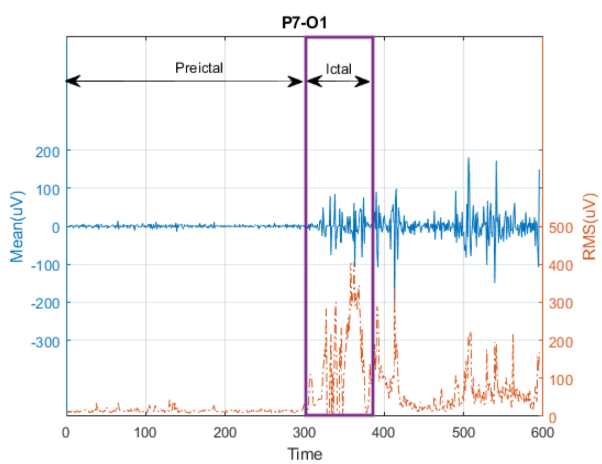
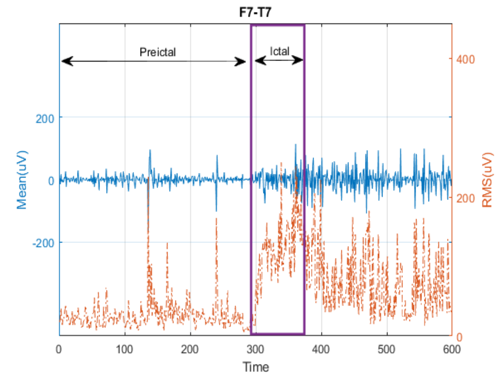
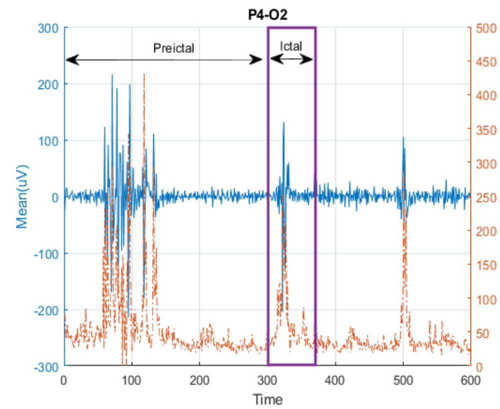


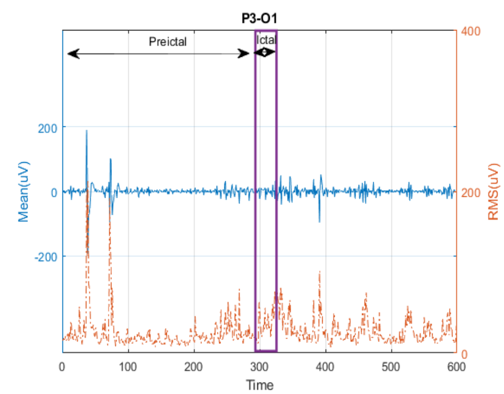
Fig.3. RMS and mean values of the P7-O1 channel of a 19-year-old female patient. The y-axis on the left side of the chart shows the mean values of the EEG signal in µV. The y-axis on the right shows the RMS value of the EEG signal in µV. The X-axis represents the time in s. The ictal state representing the seizure is framed in purple.



(a) F7-T7 channel of a 14-year-old female patient



(b) P4-O2 channel of a 2-year-old female patient



(c) P3-O1 channel of a 7-year-old female patient

Fig. 5. RMS and mean graphs from different channels of different patients.

Fig. 5(a) shows the RMS and mean values of the F7-T7 channel of a 14-year-old female patient. In this graph, it is seen that the RMS value is increased in the ictal state compared to the preictal state, and its mean value is moved away from zero in positive and negative directions when the ictal state is compared to the preictal state. In addition, it is observed that there is a change in the RMS value and the mean value of 50 and 150 seconds before the seizure onset. Fig. 5(b) shows the RMS and mean values of the P4-O2 channel of a 2-year-old female patient. In this patient, an increase in RMS values and a getaway from zero in the mean value are observed in the ictal state compared to the preictal state. More noticeable changes were seen up to 200 seconds before the onset of the seizure. Fig. 5(c) shows the RMS and mean values

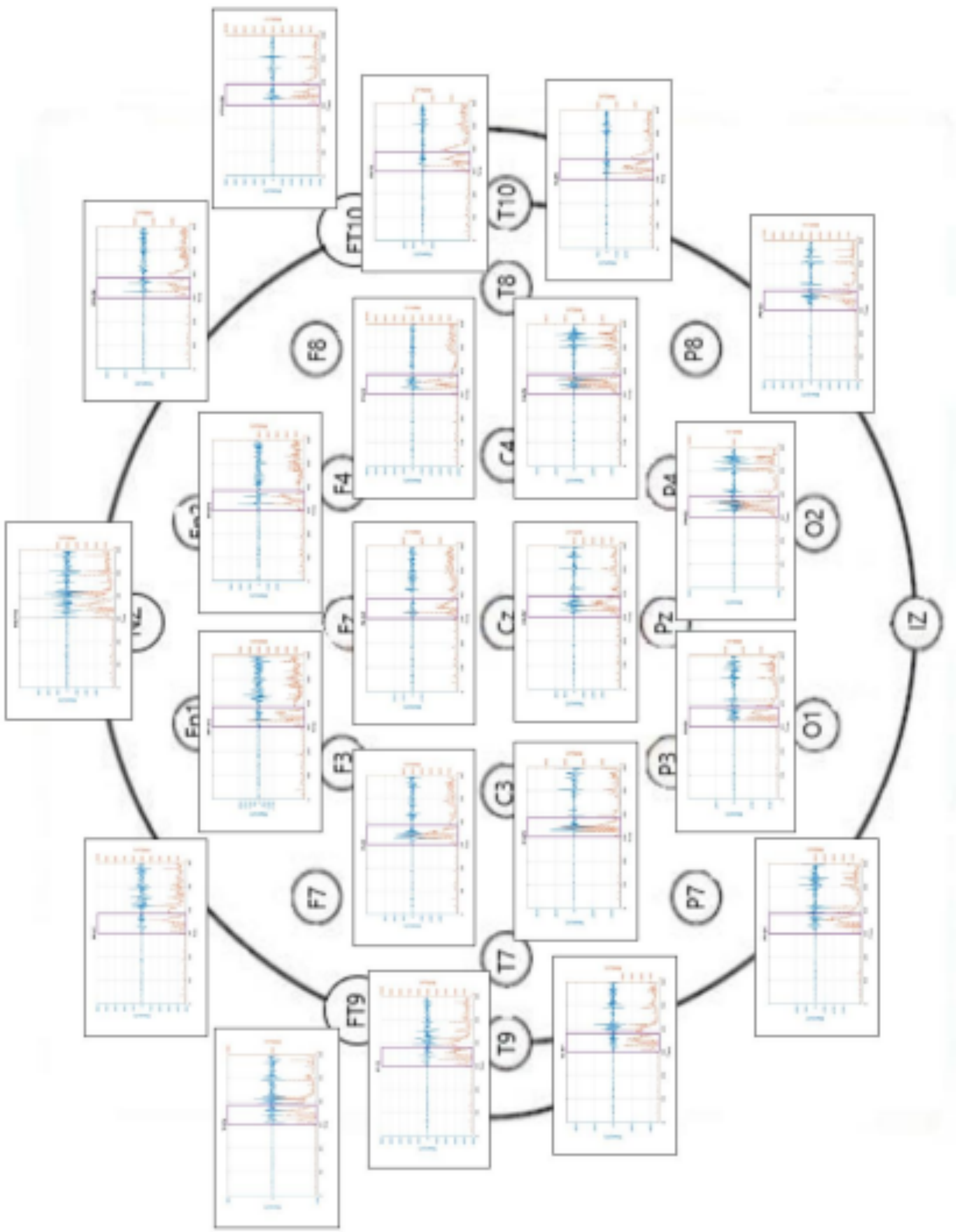
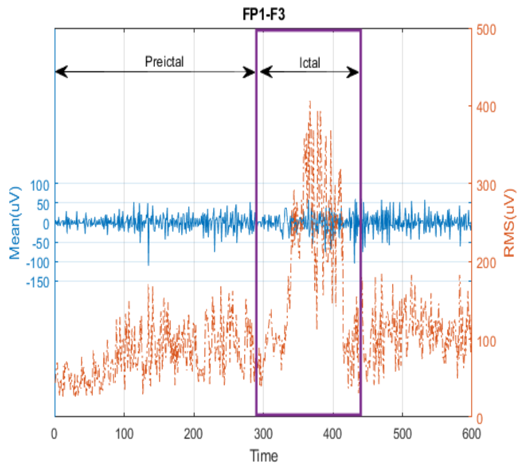
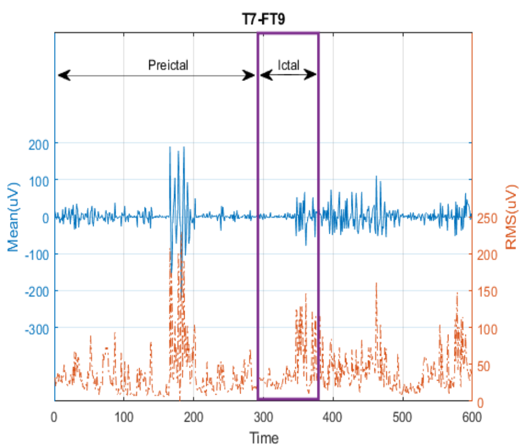


Fig. 4. RMS and mean values of EEG data from all channels of a 19-year-old female patient.

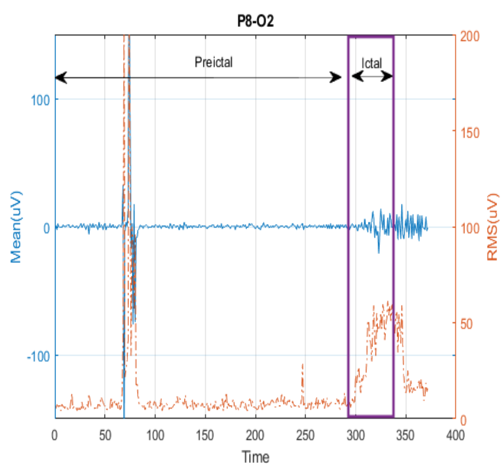
of the P3-O1 channel of a 7-year-old female patient. This patient's RMS and mean values in the ictal state cannot be clearly differentiated from the values in the preictal state. However, an average of 250 seconds before the onset of the seizure, a change is observed in the RMS and mean values.



(a) FP1-F3 channel of another 7-year-old female patient



(b) T7-FT9 channel of a 22-year-old female patient’s



(c) P8-O2 channel of a 18-year-old female patient's

Fig. 6. RMS and mean graphs from different channels of different patients.

Fig. 6(a) shows the RMS and means values of the FP1-F3 channel of another 7-year-old female patient. The RMS value increases in the ictal state compared to the preictal state. The difference between the mean value in the ictal state and the preictal state cannot be distinguished. Fig. 6(b) shows the RMS and mean values of the T7-FT9 channel of a 22-year-old female patient. Towards the end of the ictal region, a change is observed in the RMS and mean values. In addition, changes are observed in both RMS and mean values about 100 seconds before the onset of the seizure. Fig. 6(c) shows the RMS and mean values of the P8-O2 channel of an 18-year-old female patient. In the ictal state, an increase in RMS values and a deviation from zero in mean values are observed. RMS and mean values change about 250 seconds before the seizure. The patient data given in Fig. 5 and fig. 6 were randomly selected to show the changes in RMS and mean values. These states are randomly chosen to show the different states observed in entropy values.

In 18 of the 24 patients' data, it was observed that the RMS values increased in the ictal state compared to the pre-ictal state. Furthermore, the mean value gets away from zero in the ictal state compared to the preictal state in 14 of them. That is, regarding the average and RMS values of the EEG signal, the ictal region was determined at the rate of 58.4% and 75%, respectively.

EEG signals are considered linear while using RMS and mean methods. However, EEG signals are not linear. There is an information loss in the linear analysis of non-linear EEG signals. Nonlinear analysis methods should be used to obtain more comprehensive information about epileptic seizures. In this study, we prefer to analyze the permutation entropy and the sample entropy methods of nonlinear analysis methods.

Permutation entropy is a type of embedded entropy that directly uses the time series to estimate entropy. Sample entropy is a method that measures the regularity of physiological signals regardless of their size.

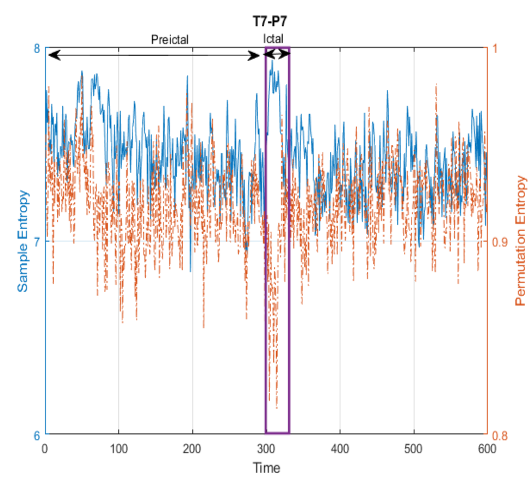


Fig. 7. Sample entropy and permutation entropy values of the T7-P7 channel of an 11-year-old female patient. The y-axis on the left side of the graph shows the sample entropy values. The y-axis on the right shows the permutation entropy values. The x-axis represents the time in s. The ictal state representing the seizure is framed in purple.

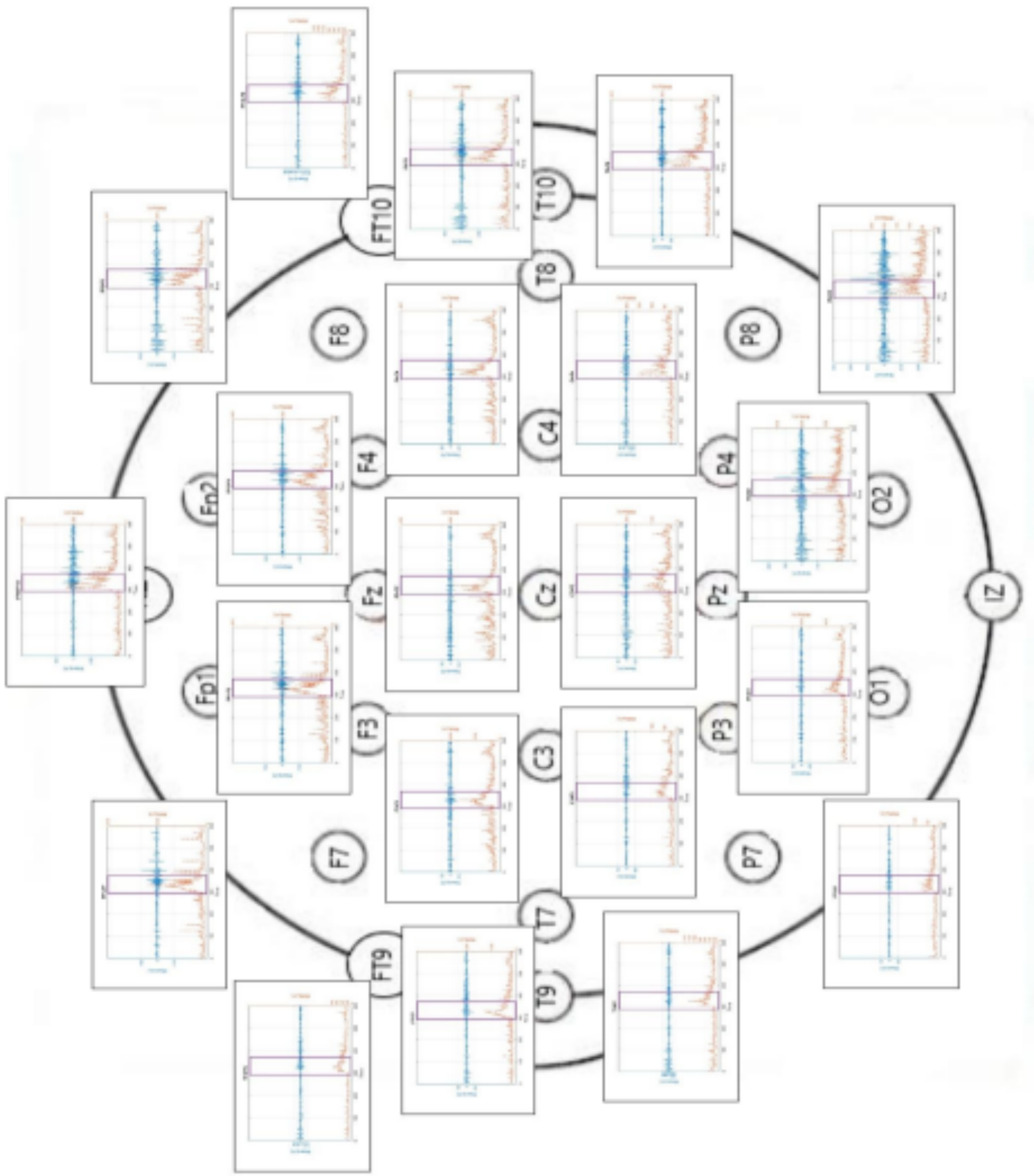
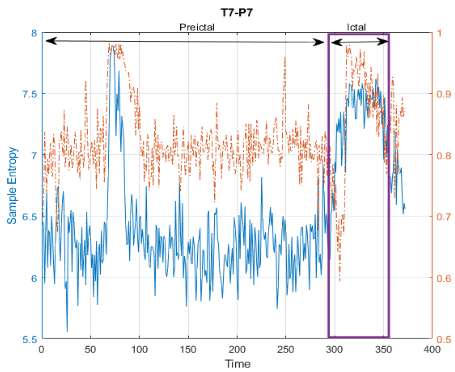
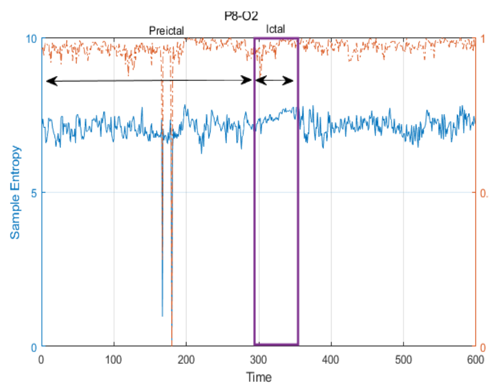


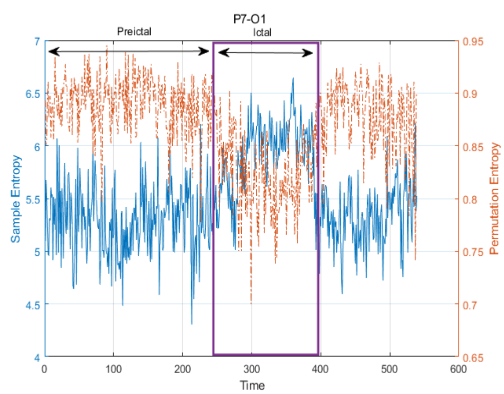
Fig. 8. Sample entropy and permutation entropy values of all channels of an 11-year-old female patient.



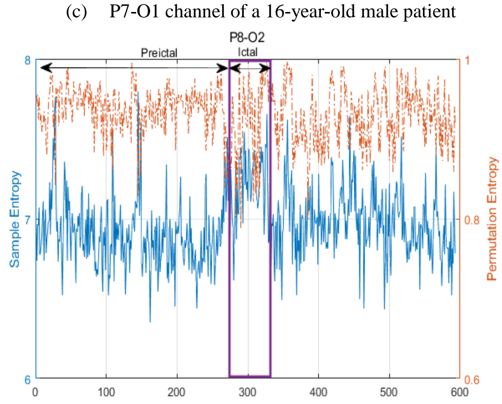
(a) T7-P7 channel of an 18-year-old female patient



(b) P8-O2 channel of a 22-year-old male patient



(c) P7-O1 channel of a 16-year-old male patient



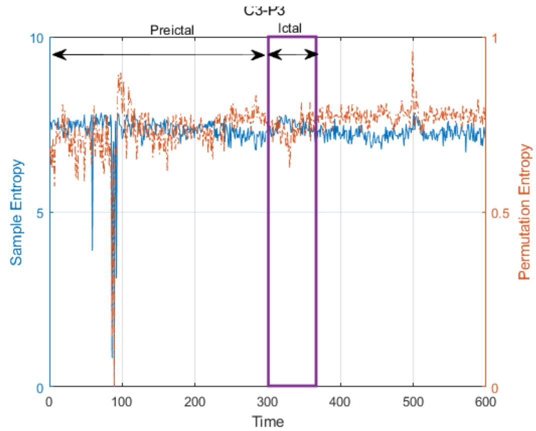
(d) P8-O2 channel of a 12-year-old female patient

Fig. 9. Sample entropy and permutation entropy values of different channels of different patients.

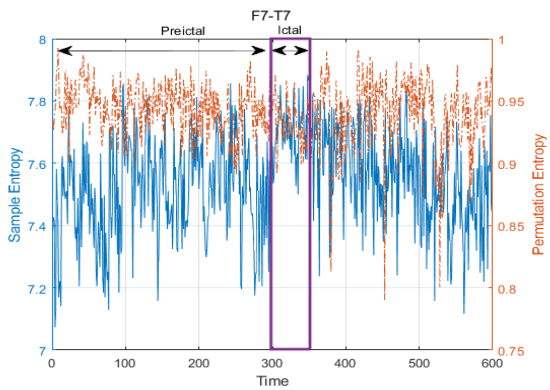
In epileptic seizures, the whole brain is usually affected. In the passage from the preictal state to the ictal state, complexity occurs in the signals. Due to this complexity, it is expected that while the sample entropy value will increase at the onset of the seizure [37], permutation entropy is expected to decrease at the onset of the seizure [40]. In this study, it is observed that the permutation entropy value is decreased in the majority of the patients at the onset of the seizure. In Fig. 7, the sample and permutation entropy values of the T7-P7 channel of an 11-year-old female patient are given. In this figure, it is seen that the sample entropy value increases at the beginning of the seizure, while the permutation entropy decreases. In other words, the ictal region can be determined by regarding the sudden decreases and increases in entropy values. Fig. 8 shows the sample entropy and permutation entropy values of all channels of the same patient.

Fig. 9(a) shows the entropy values of the T7-P7 channel of an 18-year-old female patient. There was an increase in both entropy values in the ictal state compared to the preictal state. In addition, changes in entropy values are observed about 250 seconds before the onset of the seizure. Fig. 9(b) P8-O2 channel values of a 22-year-old male patient are shown. The distinction between the ictal state and the preictal state cannot be seen completely with both entropy methods. However, a sudden change in entropy values is observed up to 120 seconds before the onset of the seizure. Fig. 9(c) shows the entropy values of the P7-O1 channel of a 16-year-old male patient. While the sample entropy value increases in the ictal state compared to the preictal state, it decreased in the permutation entropy value. Fig. 9(d) shows the values of the P8-O2 channel of a 12-year-old female patient. In this patient, while the sample entropy value increases in the ictal state, it is not possible to distinguish between the ictal state and the preictal state in permutation entropy.

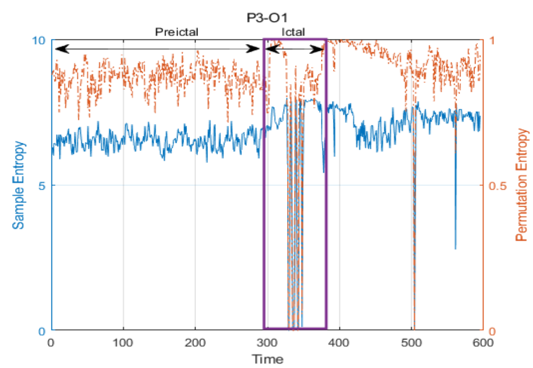
Fig. 10(a) shows the values of the C3-P3 channel of a 2-year-old female patient. In the sample entropy of the ictal state, there is a slight increase compared to the preictal state, while there is a slight decrease in the permutation entropy. In addition, there was a sudden change in both entropy values about 210 seconds before the onset of the seizure. Fig. 10(b) shows the entropy values of the F7-T7 channel of a 3-year-old female patient. The difference between the ictal state and the preictal state cannot be distinguished in both entropy methods. Fig. 10(c) shows the values of the P3-O1 channel of a 19-year-old female patient. While there is an increase in both entropy values at the beginning of the seizure, sudden decreases are observed in both entropy values during the seizure. Fig. 10(d) shows the sample entropy and permutation entropy values of the T7-P7 channel of a 7-year-old female patient. The seizure duration was very short. With both entropy methods, the difference between ictal and preictal states could not be determined. In addition, a sudden change is observed in both entropy methods about 250 seconds before the onset of the seizure. These states are randomly chosen to show the different states observed in entropy values.



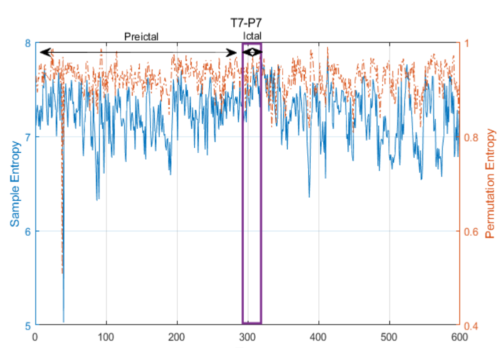
(a) C3-P3 channel of an 2-year-old female patient



(b) F7-T7 channel of a 3-year-old female patient



(c) P3-O1 channel of a 19-year-old female patient



(d) T7-P7 channel of a 7-year-old female patient

Fig. 10. Sample entropy and permutation entropy values of different channels of different patients.

When the sample entropy and permutation entropy values are analyzed one by one, it is observed that the sample entropy value increase in 16 (66.6 %) of the 24 patient data in the ictal state compared to the preictal state. A decrease in permutation entropy is observed at the onset of seizure in 16 (66.6 %) of 24 patients. When both entropy methods are examined together, two different situations emerged. In the first situation, it is observed that during the seizure, the sample entropy value increases, and the permutation entropy value decreases in 13 (54,2 %) patients. In the second situation, during the seizure, the increase in the sample entropy value or the decrease in the permutation entropy is observed in 19 (79,2 %) patients.

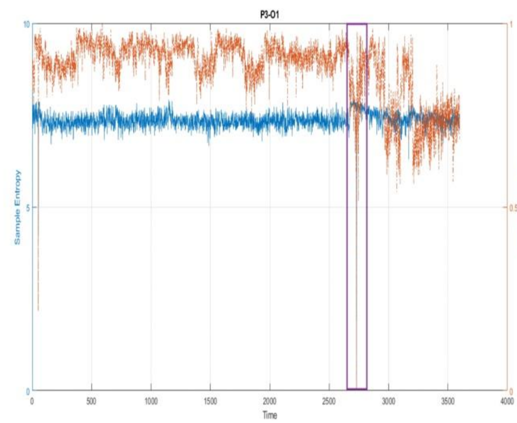


Fig. 11. Sample entropy and permutation entropy values of an hour EEG signals of the P3-O1 channel of a 3.5-year-old male patient.

Sample entropy and permutation entropy values of an hour's EEG recordings of channel P3-O1 of a 3.5-year-old male patient are shown in fig. 11. As seen in this figure, changes in entropy values can be detected in one-hour EEG recordings. The seizure period is seen more clearly in the parts taken 5 minutes before and 5 minutes after the seizure onset.

4. CONCLUISONS

In this study, epileptic EEG signals were examined and the prediction of epileptic seizure onset (ictal region) was investigated. First, EEG signals were accepted as linear. In linear analysis, RMS and the mean value of the signals were calculated. The epileptic seizure onset was determined by RMS and mean value methods with a success rate of 75 % and 58.4 %, respectively. However, since the EEG signals are not linear, these examinations were not considered sufficient, and then entropy methods were used for epileptic region detection. Among the entropy methods, sample entropy is preferred due to its consistency feature, and permutation entropy is preferred because the noise in the signal affects the analysis least. When both entropy methods were preferred separately, the onset of seizure was found with a success rate of 66.6 %. When the entropy methods are considered together, the success rates have changed. When seizure was considered using both sample entropy and permutation entropy, it was determined with a success rate of 54.2 %, while considering sample entropy or permutation entropy, it was determined with a success rate of 79.2 %.

Consequently, when one entropy method could not catch the onset of the seizure, the other might have the possibility to catch it.

In future studies, epileptic EEG signals can be analyzed with more entropy methods. Furthermore, different studies can be carried out to determine the changes that occur before the seizure with different feature extraction methods.

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CONTENTS

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