Dynamic Expert System Design for the Prediction of Attention Deficit and Hyperactivity Disorder in Childhood

Araştırma Makalesi/Research Article

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Abstract— In this study, for the first time, a Dynamic Expert System was developed to predict attention deficit and hyperactivity impairment in childhood. In this context, the decision-making process, which requires complex and experienced field experts to diagnose the disease, has been transferred to the developed expert system. The subject of the study was determined as prediction of attention deficit and hyperactivity disorder, which is one of the most common psychiatric disorders of childhood. The developed Dynamic Expert System consists of three basic parts, which are the knowledge base, the inference mechanism and the description unit. Data clusters are recorded as attributes and records in the knowledge base. While attributes are determined by field experts, records are composed of clinical patient data received from the Gazi Hospital, Department of Pediatric Mental Health and Diseases. Ensuring the dynamic renewal of the rule base is the most important characteristic of the study using the Naive Bayes Algorithm in the inference mechanism of the developed system. In this way, when the system encounters a new situation that is not previously encountered, it can take advantage of the existing rules and guess which class the rule belongs to. With real data, the system has been trained; and its performance was tested. As a result of this study, accuracy was determined to be 88.62%; precision was determined to be 89.2%, recall was determined to be 88.6%, f-measure was determined to be 88.6% and ROC area value was determined to be 89.8%. It was observed that the performance of the system was quite high compared to the model performance criteria.

Keywords— expert system, machine learning, Naive Bayes Algorithm, early diagnosis, attention deficit, hyperactivity.

Çocukluk Çağı Dikkat Eksikliği ve Hiperaktivite Bozukluğunun Öngörülmesine Yönelik Dinamik Uzman Sistem Tasarımı

Özet— Bu çalışma ile ilk defa çocukluk çağı dikkat eksikliği ve hiperaktivite bozukluğunun öngörülmesine yönelik çocuk psikiyatristlerinin alan uzmanlığı doğrultusunda tanı çıkarımı yapabilen bir dinamik uzman sistem tasarımı geliştirilmiştir. Bu kapsamda hastalığın tanısına yönelik alan uzmanlarının karmaşık ve deneyim gerektiren karar verme süreci, geliştirilen uzman sisteme aktarılmıştır. Çalışmanın konusu gereksinim analizi yapılarak çocukluk çağının en sık görülen psikiyatrik bozukluklarından olan dikkat eksikliği ve hiperaktivite bozukluğu olarak seçilmiştir. Geliştirilen sistem bilgi tabanı, çıkarım mekanizması ve açıklama birimi olmak üzere üç temel kısımdan oluşmaktadır. Veri kümeleri, nitelikler ve kayıtlar olmak üzere bilgi tabanına kaydedilmiştir. Nitelikler alan uzmanları (çocuk psikiyatristleri) tarafından belirlenirken, kayıtlar Gazi Hastanesi Çocuk Ruh Sağlığı ve Hastalıkları Anabilim Dalından alınan kliniksel hasta verilerinden oluşmaktadır. Geliştirilen sistemin çıkarım mekanizması kısmında Naive Bayes algoritması kullanılarak, kural tabanının dinamik olarak yenilenmesinin sağlanması çalışmanın en önemli ayırt edici özelliğidir. Bu sayede sistem, daha önceden kayıtlı olmayan yeni bir durum ile karşılaştığında; mevcut kurallardan faydalanarak yeni kuralın hangi sınıfa ait olduğunu tahmin edebilmektedir. Gerçek veriler ile sistem eğitilmiş ve performansı test edilmiştir. Çalışmanın sonucunda, doğruluk değeri %88.62, kesinlik değeri %89.2, duyarlılık değeri %88.6, f ölçütü %88.6 ve ROC değeri %89.8 bulunmuştur. Sistemin performansının model başarım kriterlerine göre oldukça yüksek olduğu görülmüştür.

Anahtar Kelimeler—uzman sistem, makine öğrenmesi, Naive Bayes Algoritması, erken tanı, dikkat eksikliği ve hiperaktivite.

1. INTRODUCTION

Attention Deficit Hyperactivity Disorder (ADHD) is characterized by attention deficit and extreme mobility symptoms that arise in different environments causing difficulties in social, academic and work performance [1], which are the most common and frequently occurring psychiatric disorders in childhood and adolescence [2, 3]. One of the reasons that make ADHD an important issue is its prevalence [4]. The prevalence of it was reported as 3-9% in pediatric age group [5]. The second reason is that it continues to be available at a rate of 60-80% in adolescence and 40-60% in adulthood [6]. ADHD, which begins in childhood, continues in adulthood at a high rate [5]. The prevalence of ADHD is very high in 5 to 20% of the general school population [7]. This means that there may be at least 1-2 ADHD students in each class.

ADHD is one of the major problems of society and health services in terms of its various negative effects on interpersonal relationships, life, school and business. ADHD affects not only the child’s life, but also the lives of the family and the people in the social environment, and it is difficult to overcome it. For this reason, early diagnosis and appropriate holistic treatment approaches of ADHD in childhood are important both for individual health and for community health [8].

Although ADHD is among the most common psychiatric disorders of childhood, it continues in childhood and adolescence, causes social problems when untreated and is therefore considered as one of the most striking issues of child psychiatry [9]. No expert system study has been found for predicting whether or not the ADHD condition is present in an individual. Early diagnosis and treatment of ADHD is critical to the child’s future. The search for helping early diagnosis is very old [10]. In recent years, especially expert systems, machine learning techniques, decision support systems and data mining methods such as intelligent systems are widely used in medicine and psychiatry in order to help early diagnosis [11- 13].

Expert system and Naive Bayes Algorithm in psychiatry, early diagnosis of psychological disorders such as psychotic disorders, anxiety disorders, mood disorders, antisocial personality, multiple personality and dependence [14], the method of psychologists used to determine the patient’s level of stress and personality interest by integrating the rules into the system to provide solutions and suggestions for stress management [15], and developing an expert system which will assist in the early detection of symptoms of schizophrenia [16] are used for the purposes of identifying dependencies between borderline personality disorder and its findings [17], for predicting child abuse [18] and predicting nicotine dependence using genetic data [19].

It is observed that the expert systems developed in the field of psychiatry have not reached the desired target yet. It is also observed that the developed systems contain only specific small medical information and that they have been developed independently from the field specialists. It is controversial how reliable the studies developed independently from field experts. Studies for ADHD diagnosis are limited to clinical level. There is no software for the prediction of ADHD. It is thought that this Dynamic Expert System, which is developed in line with the field expertise of child psychiatrists in order to predict whether ADHD is present in a child, will give an idea to other medical specialty areas as well as meeting the need for the model.

In this study, a dynamic expert system model was designed for the first time in line with the field expertise of child psychiatrists; and an early warning system was developed that could predict the ADHD status in the child. Forward and backward chaining methods are often used in the inference mechanism of specialized systems [20-24]. In this study, a different method (Naive Bayes Algorithm) was tried in the inference mechanism. The reason for using this method was to make sure that the expert system could predict which class the new rule belonged to by making use of the existing rules when a new rule was encountered on the basis of a rule that was not previously registered. In conclusion, in this study, different methods in the inference mechanism of the expert system and the use of the expert system were examined in attention deficit and hyperactivity disorder as an innovation to the studies in terms of both expert systems and psychiatry discipline.

2. THEORETICAL BACKGROUND

2.1. Naive Bayes Algorithm

The Naive Bayes Algorithm is also called as an Independent Feature Model which deals with the simple classification based on Bayes Theorem. It predicts the various sets of probabilities based on the condition values in particular class. The independence assumption is a strong base of classification in Naive Bayes, the values of the attributes are independent irrespective of the other attributes of the variable class [25]. It is used when the dimensionality of the inputs is high [26].

The steps in algorithm are as follows [27]:

1- Here, we have a single class variable c and m attribute variables x_i (for simplicity of exposition, we assume that attributes are discrete). Let c denote a class label and x_i denote a value of an attribute x_i. A Naive Bayes Algorithm thus induces a distribution:

$$Pr(c, x_1, \ldots, x_m) = Pr(c) \cdot \prod_{i=1}^{m} Pr(x_i \mid c) \qquad (1)$$

2- Where we have a class prior Pr (c) and conditional distributions Pr (x_i | c). We can estimate these parameters from data, using maximum likelihood or MAP estimation. Once we have learned a Naive Bayes Algorithm from the data, we can label new instances by selecting the class label c* that has maximum posterior probability given observations $x_1,...,x_m$. That is, we select;

$$c^\star = \underset{c}{\operatorname{argmax}}\, Pr(c \mid x_1, \ldots, x_m). \tag{2}$$

Compared with other classifiers, Naive Bayes Algorithm has the following features [28]:

- When the attributes are mutually independent, this algorithm is accurate.
- Not only a small number of parameters need to be estimated in Naive Bayes Classifier, but it is less sensitive to missing data than Bayes network classifier, so the algorithm of Naive Bayes Classification is relatively simple.
- Naive Bayes Algorithm is based on conditional-independent assumption, and the effect of the attribute value on a given class is independent from other attribute values.

3. METHODS

3.1. Dataset

The subject of the study was determined as ADHD, one of the most common psychiatric disorders of childhood, by conducting a Requirement Analysis. The knowledge base for the prediction of ADHD consists of two parts: attributes and records. Attributes were determined by field experts to analyze the current information obtained from the DSM-V manual published by the American Psychiatry Association. These characteristics include the diagnostic criteria used by field experts when diagnosing ADHD and the thinking processes they follow. The records used in the training and testing of the system consisted of 290 clinical patient data (145 ADHD diagnoses and 145 non-ADHD diagnoses) taken from Gazi Hospital, Department of Pediatric Mental Health and Diseases. Ethics Committee approval was obtained from Gazi Hospital, Department of Pediatric Mental Health and Diseases for the study.

3.2. Division of Data into Training and Test Sets

While the accuracy ratios of classification algorithms are compared, the data in the knowledge base are divided into two groups as training data and test data. The K-Fold Cross Validation Method was used while the dataset was divided into training and test data. In small databases consisting of several thousand or fewer lines, the K-Fold Cross Validation Method can be used where data is divided into k groups. In the K-Fold Cross Validation Method, the data set is randomly divided into k groups. When we examine the literature, it is generally observed that the k value is selected as 10 [29]. Therefore, the k value in the K-Fold Cross Validation Method was determined as 10. While the developed system is trained with the training data, the study is controlled with the test data.

3.3. System Evaluation

The success of the model is related to the number of instances assigned to the correct class and the number of instances assigned to the wrong class. Performance information of the results obtained as a result of the test can be expressed in the confusion matrix. While evaluating the performance of the system, various criteria (model performance criteria) are calculated by these numbers obtained from the confusion matrix [30-31]. The most basic model performance measures used are accuracy, precision, precision and f-measure; and are as follows;

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN} \tag{3}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{4}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{5}$$

$$\text{F-measure} = \frac{2\ x\ Precision\ x\ Recall}{(\ Precision + Recall\ )} \tag{6}$$

While the numbers shown by TP and TN indicates the correct predicted classes, the numbers indicated by FP and FN show the number of wrong predicted samples. While the success of the model is measured, apart from the above-mentioned, accuracy, precision and f-measure, ROC area, kappa statistics and specificity values are also used as measures. When these values are close to 1, this indicates that the success of the system is high [29, 32].

3.4. Selection of Classification Algorithm

The most efficient algorithm in the light of model performance criteria is Naive Bayes Algorithm compared to classification algorithms. Therefore, it was decided to encode the Naive Bayes Algorithm in the inference mechanism of the expert system developed.

4. THE COMPONENTS OF THE DEVELOPED DYNAMIC EXPERT SYSTEM

The dynamic expert system developed for the prediction of ADHD consists of three main parts; knowledge base, inference engine and description unit. The flow diagram of the dynamic expert system developed is presented in Figure 1.

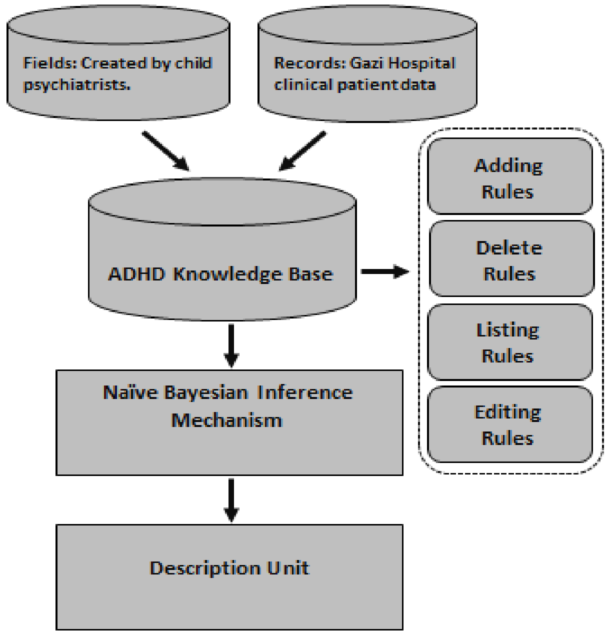

Figure 1. The flow diagram of the dynamic expert system developed

4.1. Knowledge Base

Expert systems are the software used to solve problems that require human expertise. In these systems, the rules used in solving the problems are in the knowledge base [33]. A knowledge base can be established in four different ways [34-35] as a) by converting expert knowledge into belief rules, b) by examining historical data to identify belief rules, c) by using available previous rule base, and d) by creating rules randomly without any prior knowledge.

When previous studies were examined, it was observed that in generating the knowledge base, a) the knowledge of field experts [36-38] and b) past data [39-45] were used mostly. In this study, knowledge of field experts and past data were used while knowledge base was established.

In the dynamic expert system developed, the first "Knowledge Base" option is clicked to develop a data warehouse for ADHD. This section allows the field expert to make the information entry in a more convenient and easy manner and to develop the knowledge base. This section where the ADHD data warehouse is entered is shown in Figure 2.

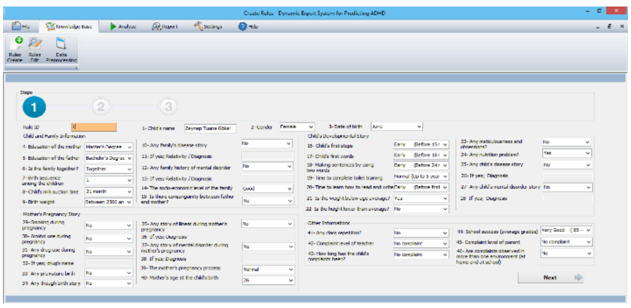

Figure 2. Knowledge base development form

In the study, the ADHD data warehouse entered using the knowledge base form consisted of 290 records. After the data warehouse is developed, the data warehouse can be deleted in Figure 3, the data warehouse display section and new records can be added, existing records can be updated, records can be listed and records of each attribute can be graphically displayed. The field experts can update the knowledge base of the system through a user-friendly interface.

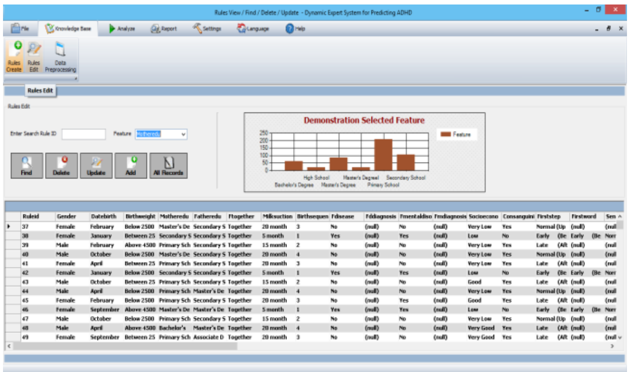

Figure 3. View / delete / update form of the knowledge base

4.2. Naive Bayesian Inference Engine

According to the design of the knowledge base, expert systems are divided into static and dynamic expert systems [33]. While the knowledge base of static expert systems is fixed, the knowledge base of dynamic expert systems can be changed [46]. The Naive Bayes Classification Algorithm was used in the inference mechanism of the dynamic expert system developed. In this way, the rule base became a dynamic structure by renewing itself. When the system encounters a new situation; if there is a rule in the existing rule set, then that rule is executed. If there is no such rule in the rule set, the developed dynamic expert system provides the result by taking advantage of the existing rule set. The inference mechanism of the system is presented in Figure 4:

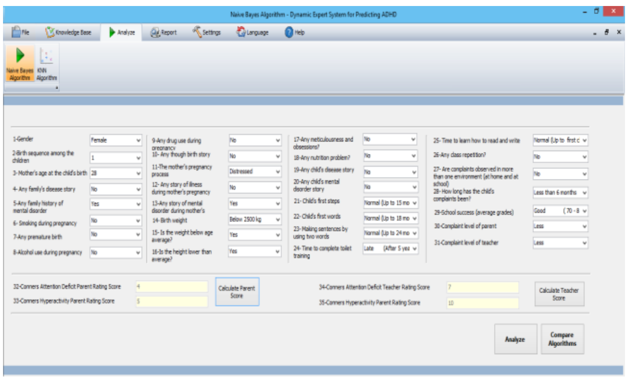

Figure 4. Naive Bayesian inference engine form

Using Naive Bayesian inference engine form, the user can learn the prediction of the system about the child's ADHD status. The most important difference between the existing works of the developed expert system is that the automatic rule base can be formed. The system is first trained with the existing rule base using the Naive Bayes Algorithm. When a new situation is encountered, the current rule base is drawn and the frequency numbers of the attribute values entered for each class (ADHD, Normal) are calculated. The probability of the outcome of each class is multiplied by the probability of all the qualities that affect that result to yield the result of that class. In the Naive Bayes Algorithm, each probability must be greater than zero, otherwise the entire probability will be zero; therefore, the software checks whether each probability is different from zero and adds a value if it is too small to change the result if the probability is equal to 0.

As a result, the probabilities of each class information are compared and the new rule assigns to the "ADHD" class if the likelihood of "ADHD" class information is higher; and to the "Normal" class if the probability of "Normal" class is higher. The results are calculated for each probability and the new rule is assigned to the class with the highest probability. The result is displayed in the user description unit according to the calculated symptom probability. The pseudo code of the inference mechanism in the developed dynamic expert system is given below:

- Calculation of the number of rules for each class
- Calculation of the probability of belonging to each class for each attributes to be calculated
- Elimination of the possibility of zero results
- Calculation of the rates of non-available ADHD symptoms (p) or available ADHD symptoms (q)
- If the p ratio is > q, the rule is assigned to "Normal"; if not, it is assigned to the "ADHD" class.
- Displaying the results to the user in the description unit.

4.3. Description Unit

In the description unit, the results obtained for the prediction of ADHD are forwarded to the users. Whether the ADHD symptoms are observed or not is shown to the user with the form in Figure 5.

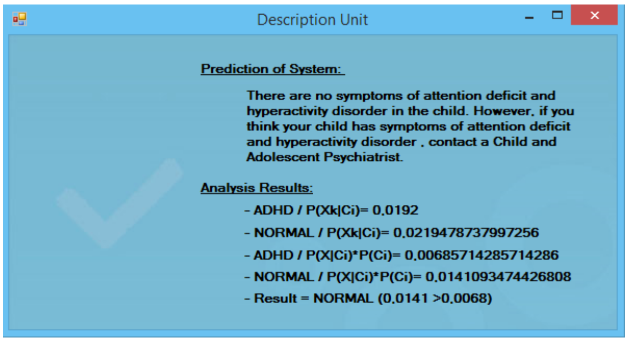

Figure 5. Description unit

5. RESULTS AND DISCUSSION

When similar studies are examined in the literature, it is seen that specialized systems are widely used in the diagnosis of the disease. The studies in the field of psychiatry have reported that effective results are obtained through using expert systems; and expert systems could be used in diagnosis inference [47-51]. In the diagnosis of diseases in other medical fields, it is observed that parallel expert systems are used in the diagnosis of primary headaches [52], early prediction of the bronchopulmonary dysplasia [53], lung cancer [54], breast cancer [55], and thyroid disease [56].

In the present study, an early warning system was developed that predicts ADHD status in the child. 290 clinical patient data in the knowledge base of the dynamic expert system developed by using 10-fold cross validation method were divided into 10 groups randomly. While the system was being trained with the training set, it was controlled with the test set. In addition, the system was validated by field experts.

With the dynamic expert system developed, the results of the most commonly used classification algorithms according to the model performance criteria (K-The Nearest Neighbor (k-NN), Decision Trees (J48), Sequential Minimal Optimization Algorithm (SMO) and RBF Network) [57] are given in Table 1:

Table 1. Comparison of dynamic expert system developed and other classifiers according to model performance criteria

	Classification Algorithms				
	k-NN (k=3)	**J48**	**SMO**	**RBF Network**	**This Study**
Precision	0.86	0.88	0.852	0.87	0.892
Recall	0.848	0.876	0.852	0.869	0.886
F-Measure	0.847	0.875	0.852	0.869	0.886
ROC Area	0.895	0.93	0.852	0.914	0.8984
TP Rate	0.848	0.876	0.852	0.869	0.886
FP Rate	0.152	0.124	0.148	0.131	0.114
Kappa statistic	0.696	0.751	0.703	0.737	0.7724
Accuracy %	84.827	87.586	85.172	86.8966	88.620

The values of TP rate, recall, precision and f-measure, among the model performance criteria, are desired to be close to 1, such as the ROC area value [29-30, 58]. When the comparison table is examined, it is observed that the ROC area, TP rate, recall, precision and f-measure values of all algorithms are greater than 0.80. In addition, when kappa statistical value is between 0.6 and 0.8, this indicates a significant consistency [59].

It was determined that the data tested by the dynamic expert system produced correct results at a very large rate (88.62%). The ROC curve of the study is given in Figure 6. When the ROC value is examined, it is seen that this value is 0.8984. When this value is close to 1, this indicates that the system does not have a random estimation [29, 32].

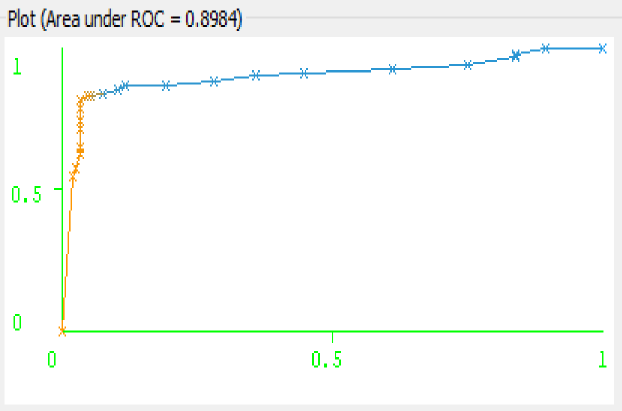

Figure 6. ROC curve of the dynamic expert system developed

The results of the comparison of dynamic expert system and classification algorithms according to sample numbers are given in Table 2.

Table 2. Comparison of dynamic expert system developed and other classifiers according to numbers of instances

	Classification Algorithms				
	k-NN (k=3)	**J48**	**SMO**	**RBF Network**	**This Study**
TP Instances	110	119	122	123	120
FN Instances	35	26	23	22	25
FP Instances	9	10	20	16	8
TN Instances	136	135	125	129	137
Correctly Classified Instances	246	254	247	252	257
Incorrectly Classified Instances	44	36	43	38	33

When Table 2 is examined, it is seen that the classifier with the highest number of correctly classified samples is the developed expert system (Naive Bayes Algorithm is used in the inference mechanism). When the confusion matrix (TP, TN, FP and FN values) of the developed expert system is examined, it is seen that the TP-classified number of samples is 120, the FP-classified number of samples is 8, the TN-classified number of samples is 137 and the FN-classified number of samples is 25. It was determined that the total number of correctly classified samples is 257 and the number of misclassified samples is 33.

When the studies on the classification of ADHD are examined, it has been observed that the classification is usually based on neuroimaging biomarkers such as EEG, MRI, and fNIRS [60-61]. Tenev et al. (2014), in their study on 117 adults (67 ADHD, 50 Non-ADHD) patient data, classified the individual's ADHD status and ADHD subtypes based on EEG signals [62]. Mohammadi et al. (2016) propose an approach to distinguish ADHD children from normal children using EEG signals when performing a cognitive task [63]. Similarly, Peng, Lin, Zhang and Wang (2013) used machinery learning classification algorithms to classify ADHD using MRI data [64]. However, field experts do not want these neuroimaging biomarkers for each patient when diagnosing ADHD. In fact, it is not possible for field experts to request these markers, in many ways, such as time, cost-effectiveness and usability for each patient.

6. CONCLUSIONS

In this study, in line with the field expertise of child psychiatrists, the performance of classification algorithms was compared with a pre-warning system and with a dynamic expert system; and the results of this system were developed using the ADHD Knowledge Base. In this context, an “ADHD knowledge base” containing 290 clinical patient data has been developed, which includes diagnostic criteria such as age, gender, academic achievement of the child, level of teacher and parent complaints, developmental characteristics of the child, etc. used by field professionals when diagnosing ADHD.

New rules can be added to the knowledge base of the developed expert system, existing rules can be deleted, edited and graphically displayed, which means that the system can be trained so that the performance of the system can be improved.

When learning with the system training dataset, the success with the test dataset was tested. A comparative analysis of the expert system developed by the most widely used classification algorithms in the literature based on model performance criteria was made on the ADHD knowledge base. All of the classification algorithms used were found to be greater than 0.80 percent success rates. It was observed that the highest performance of the comparison classifiers belonged to the dynamic expert system in which the Naive Bayes Algorithm was used in the inference mechanism (88.62%).

When the ROC area, recall, precision and f-measure values from model performance criteria are close to 1, this indicates that the system developed does not have a random estimation [29, 32]. Table 1 indicates that all the values in question (ROC area=0.898, recall=0.886, precision=0.892, f-measure=0.886) are close to 1. This finding indicates that there is a significant consistency, and that the developed expert system does not have a random estimation. It is shown that the constructed Naive Bayesian inference engine exhibits a higher performance than the other model predicting ADHD. In the estimation of ADHD, the Naive Bayesian inference engine was used for the first time in this study.

As a result, an early warning system that predicts whether the child has ADHD or not has been developed with the dynamic expert system. The system can be used to help field professionals to generate a database of complaints and diagnostic information for individuals with ADHD, and to support the early diagnosis of ADHD. The developed expert system can be adapted to the solution of different problems by changing the rules in the knowledge base.

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