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Attention-Deficit Hyperactivity Disorder Prediction by Artificial Intelligence Techniques

Rasha H. Ali[1], Wisal Hashim Abdulsalam[2]*

[1]*Computer Science Department, College of Education for Women, University of Baghdad, Baghdad, Iraq*
[2*] *Computer Science Department, College of Education for Pure Science/Ibn-Al-Haitham, University of Baghdad, Baghdad, Iraq*

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Abstract

Attention-Deficit Hyperactivity Disorder (ADHD), a neurodevelopmental disorder affecting millions of people globally, is defined by symptoms of hyperactivity, impulsivity, and inattention that can significantly affect an individual's daily life. The diagnostic process for ADHD is complex, requiring a combination of clinical assessments and subjective evaluations. However, recent advances in artificial intelligence (AI) techniques have shown promise in predicting ADHD and providing an early diagnosis. In this study, we will explore the application of two AI techniques, K-Nearest Neighbors (KNN) and Adaptive Boosting (AdaBoost), in predicting ADHD using the Python programming language. The classification accuracies obtained were 96.5% and 93.47%, respectively, before applying balancing to the data. In addition, 98.59% and 97.18%, respectively, after applying the balancing technique The extreme gradient boosting (XGBoost) technique had been applied to selecting the important features and the Pearson correlation for finding the correlation between features.

Keywords: Prediction, Attention Deficit Hyperactivity Disorder (ADHD), Artificial Intelligence, KNN, AdaBoost, XGBoost, Pearson correlation.

التنبؤ باضطراب فرط الحركة وتشتت الانتباه باستعمال تقنيات الذكاء الاصطناعي

رشا حسين علي[1], وصال هاشم عبد السلام[2*]

[1]قسم علوم الحاسوب, كلية التربية للبنات, جامعة بغداد, بغداد, العراق
[2*] قسم علوم الحاسوب, كلية التربية للعلوم الصرفة/ ابن الهيثم, جامعة بغداد، بغداد، العراق

الخلاصة

اضطراب فرط الحركة ونقص الانتباه هو اضطراب في النمو العصبي يصيب ملايين الأشخاص في جميع أنحاء العالم. يتميز بأعراض مثل فرط النشاط والاندفاع وعدم الانتباه، والتي يمكن أن يكون لها تأثير كبير على حياة الفرد اليومية. يعد تشخيص اضطراب فرط الحركة ونقص الانتباه عملية معقدة تتضمن مجموعة من التقييمات السريرية والتقييمات الذاتية. ومع ذلك ، فقد أظهرت التطورات الحديثة في تقنيات الذكاء الاصطناعي نتائج واعدة في التنبؤ باضطراب فرط الحركة ونقص الانتباه وتوفير التشخيص المبكر. في هذه الدراسة ، سوف نستكشف تطبيق تقنيتين من تقنيات الذكاء الاصطناعي ، وهما (K–Nearest Neighbors (KNN)، و(Adaptive Boosting (AdaBoost) في التنبؤ باضطراب فرط الحركة ونقص الانتباه

*Email: wisal.h@ihcoedu.uobaghdad.edu.iq

باستعمال لغة بايثون البرمجية. كانت دقة التصنيف التي تم الحصول عليها 96.5٪ و 93.47٪ على التوالي قبل تطبيق الموازنة على البيانات. بالإضافة إلى ذلك ، 98.59٪ و 97.18٪ على التوالي بعد تطبيق تقنية الموازنة. تم تطبيق تقنية تعزيز التدرج الشديد (XGBoost) لاختيار الميزات المهمة، وعلاقة بيرسون لإيجاد الارتباط بين الميزات.

1. Introduction

Attention-Deficit Hyperactivity Disorder (ADHD) is a neurodevelopmental disorder characterized by difficulty focusing, motor control, adjusting behavior to fit certain situations, and controlling impulsive actions. It is a very frequent disorder [1] and affects nearly 5% of children in the world. Elevated ADHD symptoms, even when time-limited, can beget risks for serious impairments such as school failure and conflict with family members. The diagnosis of ADHD involves several time-consuming and costly tests, which may not always be accurate and can be prone to bias [2]. AI techniques have shown promising results in different uses, such as academic student performance prediction [3], predicting COVID-19 [4], prediction of DNA binding sites [5], breast cancer detection [6], speech emotion recognition [7], and emotion recognition from different channels [8]. These techniques provide faster and more accurate results. According to current work, K-Nearest Neighbor (KNN) and adaptive boosting (AdaBoost) were utilized to predict ADHD and then find total efficiency and accuracy to predict if a human will suffer from this disease or not. Current work aims to help specialists make a more accurate and effective diagnosis of ADHD, which leads to improved treatment outcomes and quality of life for those affected by the disorder. The contributions of this paper are:

1- The use of AI in the prediction of social and behavioral diseases depends on the statements of the survey, which are written by specialists.
2- The dataset of ADHD had been constructed based on the survey answered by the parents, not the images of the intrinsic time-scale decomposition signal.
3- The features of the dataset have been constructed depending on the specialists, and then two techniques of AI are used for classifying the features of ADHD.
4- The importance of features has been computed using the XGBoost technique, which means which features affect the appearance of ADHD, and then the correlation between features has been computed using Pearson correlation.

The structure of this paper is as follows: the associated research is discussed in Section 2. Section 3 displays the materials and methods employed in the paper. Section 4 highlights the details of the proposed model. Section 5 outlines the results and discussion, and concluding remarks on the suggested method and future work can be found in Section 6.

2. Related Works

The following is a presentation of previous studies related to our current research:
T. Chen et al. [9] Ongoing efforts have led to the development of a hybrid AI algorithm for diagnosing adult ADHD. It combines a machine learning (ML) model with a knowledge-based model. The algorithm is currently being tested in a clinical trial conducted by the largest national health service in the UK. Additional data has become available, totaling 501 anonymized records as of July 2022. This prompted researchers to retrain and optimize the ML algorithm for improved accuracy. The study also explores the effectiveness of variables other than the diagnostic interview for ADHD in adults, which is costly and relies on trained clinicians. Results show that the newly trained model achieves 75.03% accuracy when using all features, while the hybrid model achieves 93.61% accuracy. Additionally, a rule-based ML

model alone achieves 65.27% accuracy, highlighting the potential for cost-effective models in the future.

S. Saini et al. [10] analyzed the classification performance of three ML algorithms (Naïve Bayes, KNN, and logistic regression) applied to the dataset (of 157 children, out of which 77 were ADHD patients and 80 were healthy) collected from open source. KNN showed the highest accuracy of prediction with 86%, followed by Naïve Bayes (52%), and logistic regression (66%).

Ghaderyan P et al. [11] proposed a new interdependence electroencephalography (EEG) feature, dynamic frequency wrapping, based on dynamic analysis of frequency fluctuations as a hybrid feature extraction step; a new EEG classifier using sparse coding was developed to detect ADHD. Testing the method with EEG recordings of 14 ADHD children and 19 healthy controls during resting state and a time-reproduction task, the accuracy rate was 99.17%.
Liu, S. et al. [12] proposed a deep learning model that incorporates spatiotemporal feature extraction to extract the features of the fMRI and a classifier. To reduce the spatial dimension of rs-fMRI and extract 3D spatial features, the nested residual convolutional de-noising auto-encoder was used. Simultaneously, the 3D convolutional-gated recurrent unit was employed to extract both spatial and temporal features, which were then sent to a sigmoid classifier for classification. The training and testing processes were conducted across five sites of ADHD-200, producing results that indicated this new method could successfully improve classification performance between ADHD and typically developing disorders in cross-site tests from 1.14% to 10.9% in comparison to other methods.

Tor HT et al. [13] developed a novel automated system as an additional tool to help clinicians accurately diagnose ADHD and/or conduct disorder, providing faster treatment for children. EEG signals were broken down with the empirical mode decomposition and discrete wavelet transform. Autoregressive modeling coefficients and relative wavelet energy were calculated on the signals, after which a variety of nonlinear features were extracted. Adaptive synthetic sampling was used to balance the dataset. The sequential forward selection method was then employed to identify the significant features, which were fed into an array of classifiers. The system was tested on 123 children's EEG data using a ten-fold validation strategy, obtaining the highest accuracy rate of 97.88% with the KNN classifier.

3. Materials and Methods

This study used baseline data from surveying parents of children (6–12). One hundred and fifty-three parents consented to participate in the study.

3.1 Classification and Feature Selection

An overview of the used classification algorithms and feature selection methods is provided below.

3.1.1 k-Nearest Neighbor Method

The non-parametric supervised learning algorithm known as KNN is well-known for its ease of understanding. However, it is memory-intensive as it retains the entire training set for classification, resulting in high complexity during test time. KNN saves all the training data and utilizes the complete training set for prediction or classification, simply preserving all values from the dataset. Various metrics like Euclidean distance, Manhattan distance (also known as City Block), and Minkowski distance (which is a generalization of Euclidean and Manhattan) can be employed to compute the distance between the training set and test set [6].

3.1.2 Adaptive Boosting

To create one stronger classifier and improve prediction accuracy, the AdaBoost algorithm might combine several weak classifiers. Its adaptiveness can be seen in the fact that samples that the preceding weak classifier might have misclassified are given more attention, and the weighted data are utilized to retrain the following weak classifier. Every time this model meets a set of requirements, a new weak classifier is added at the same time, and each input sample is given equal weight. Consequently, if one sample is incorrectly identified, its weight should increase. If not, its weight ought to decrease. The following weak classifier is trained using the data whose weights were adjusted. Finally, all weak classifiers combine to form a strong classifier [15].

3.1.3 Extreme Gradient Boosting

Feature selection is a fundamental part of pattern recognition and ML, as it removes irrelevant, noisy, and extraneous data from the raw features, which enhances the effectiveness of prediction models. In this study, feature importance scores were derived with the XGBoost algorithm, which is employed in ML. It computes an importance score for each feature based on its contribution to decisions made with boosted decision trees [16].

3.2 Correlation Coefficient

The most well-known linear correlation coefficient is Pearson. It is a statistical indicator of how much two variables' values vary from one another and shows how strongly two variables are linearly connected. The correlation coefficient, which measures the linear correlation between two discrete-time signals, is defined in Eq. (1) [17]:

$$P_{x,y} = \frac{Cov_{x,y}}{\sigma_x \sigma_y} \tag{1}$$

where x and y stand for the standard deviations of x[n] and y[n], respectively, and $Cov_{x,y}$ denotes the covariance of two signals. The correlation coefficients, x and y, range in value from -1 to +1. There is no linear relationship between the two signals if the value is equal to zero. A significant positive correlation between the two signals corresponds to a value near +1 for the x and y, and a strong negative correlation to a value close to -1.

4. The Proposed Model

This suggested model contains three stages: preprocessing, feature construction, and classification. As shown below, feature selection has been used to select the important features that have an effect on the classification of ADHD, and the correlation between features has been computed using Pearson correlation. Figure 1 shows the architecture of the proposed model.

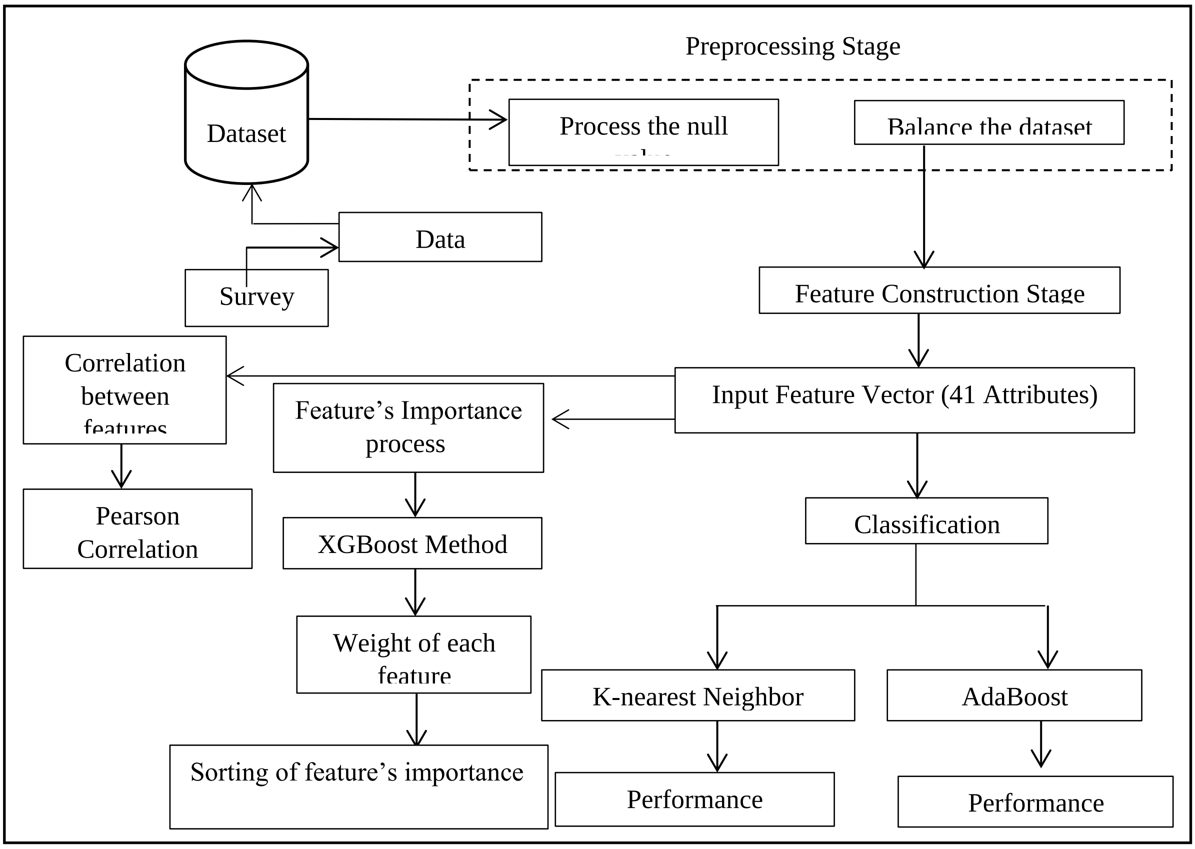

Figure 1: The proposed model architecture

4.1 The Data Collection

The data was collected using a survey, which was filled out by the parents of the children (6–12). The survey contained questions, which were taken by the specialists in ADHD; the statements of the survey were written in the Arabic language and distributed in all the cities in Iraq. The families had answered only one hundred and fifty-three questions. Most responses are from Baghdad. Figure 2 shows the histogram of cities, and Figure 3 shows the histogram of children's age percentage for the dataset.

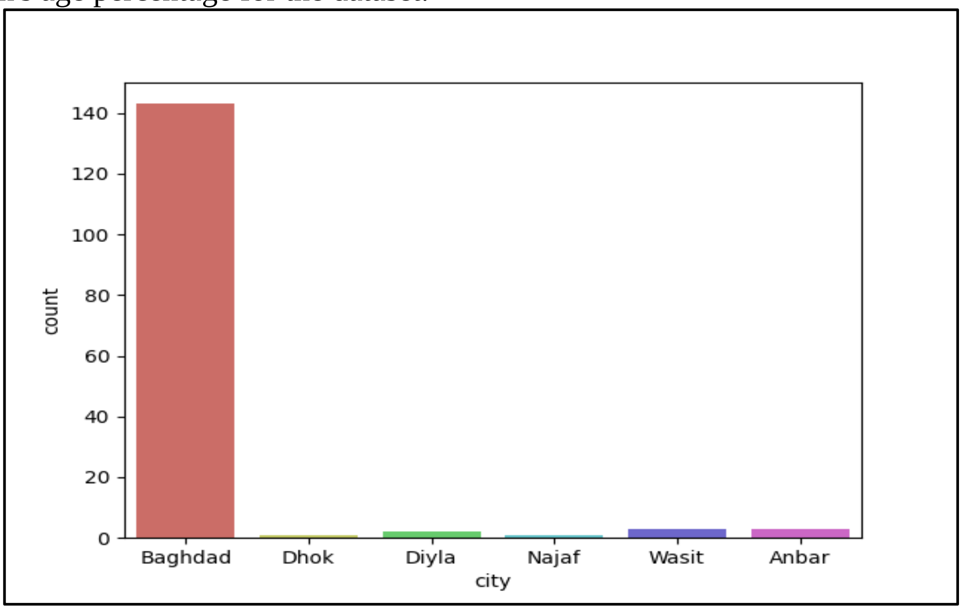

Figure 2: The histogram of cities' percentage

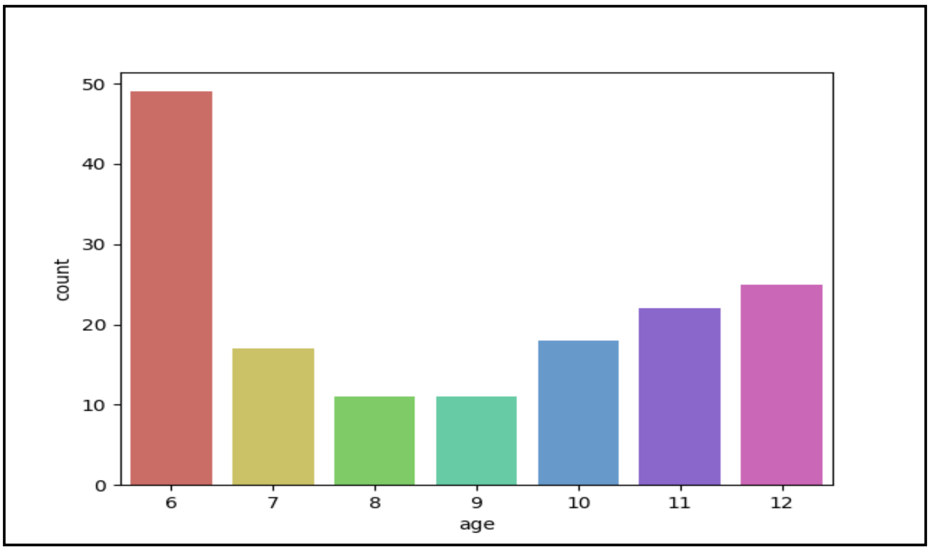

Figure 3: The histogram of age percentages for the dataset

4.2 The Preprocessing Stage

The preprocessing step is vital in the prediction process, as it repairs the data to ensure that it can be employed in feature selection and, hence, the classification stage. Two processes were carried out at this stage. Firstly, the discretization of attributes was conducted. In the questionnaire, each attribute's values were divided into four quartiles (always, often, little, and rarely). The value of scaling digitally is presented in Table 1, while the class label classifies binary classification either as existing or not. The class label was computed by the threshold using Eq. (2) for each instance. In this work, the threshold value was (62). Secondly, process the zero values by taking the mean using Eq. (3). The dataset contains 153 records; it is an imbalanced dataset because it contains 118 zero-class labels and 35 one-class labels. Figure 4 shows the histogram of the class label. Because the dataset was imbalanced, this caused biased results for zero-class labels. The Synthetic Minority Over-sampling Technique (SMOTE) has been used for balancing the dataset. Therefore, the number of the class label after 50% balancing was (177) while the number of zero class labels was (118) and the number of one class label was (59), and the number of the class label after 100% balancing was (236), while the number of zero class labels was (118) and the number of one class label was (118). Figure 5 a shows the histogram of the class label after 50% balancing using the SMOTE technique, and Figure 5 b shows the histogram of the class label after 100% balancing using the SMOTE technique.

$$S = \sum (x)$$

$$T = \frac{\max(S) + \min(S)}{2} \tag{2}$$

$$\mu = \frac{1}{N} \sum_{i=1}^{N} x_i \tag{3}$$

Table 1: The digital value of the attributes

Attribute's value	Digital value of the attribute
Always	3
Often	2
Little	1
Rarely	0

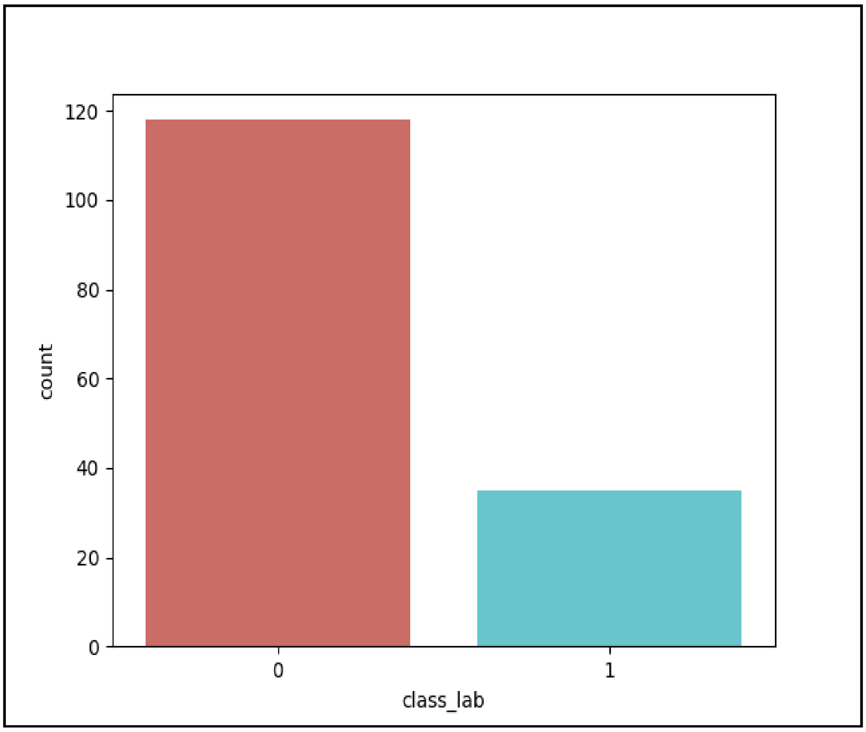

Figure 4: The histogram of the class label

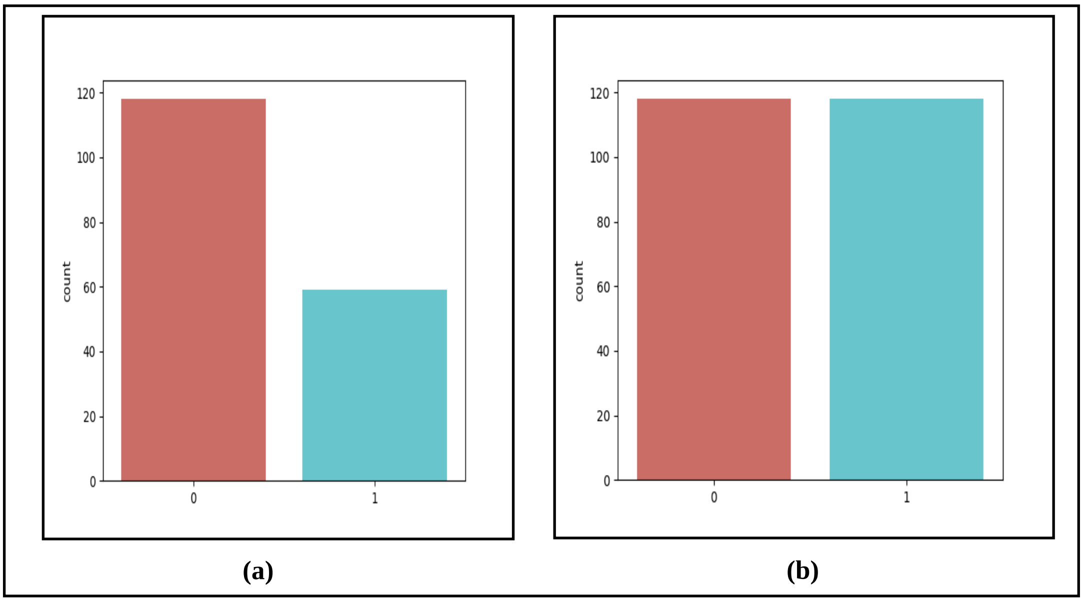

Figure 5: The histogram of the class label after 50% (a) and 100% balancing (b)

4.3Features Construction Stage

In this stage, the attributes are directly selected using the feature selection method. There were 41 attributes in the dataset. By using the questionnaires indicated in the previous section, the families of the children filled out these characteristics. The score of each feature ranges from 0 to 3. Table 2 presents the attribute and its description.

Table 2: The Attribute and its Description

Feature No.	Attribute in English	Arabic
F1	Poor ability to pay attention and focus	ضعف القدرة على الانتباه و التركيز
F2	He suffers from wandering and daydreaming	يعاني من الشرود و أحلام اليقظة
F3	He fails to complete the tasks he starts	يفشل في إتمام المهام التي يبدأها
F4	Moves from one activity to another without justification	ينتقل من نشاط لآخر دون مبرر
F5	Tells stories that are not true or false	يروي قصصا غير حقيقية أو كاذبة
F6	He does not listen or listen to instructions given to him	لا يستمع او يصغي إلى التعليمات التي تقدم إليه
F7	He often preoccupies himself with his fingers, his clothes, and his hair	كثيرا ما ينشغل بذاته بأصابعه ، ملابسه ، بشعره
F8	It is easy to drive than others	من السهل قيادته من الغير
F9	He gets distracted by stimuli in an unusual way	يتشتت انتباهه بسبب المثيرات و بشكل غير عادي
F10	He forgets important things or tools	ينسى أشياء أو أدوات هامة
F11	Exposure to accidents due to lack of attention	التعرض إلى حوادث بسبب نقص الانتباه
F12	Avoids difficult tasks that require mental effort	يتجنب المهام الصعبة التي تتطلب جهدا عقليا
F13	Many annoying and purposeless actions and behaviors	أعمال و سلوكيات كثيرة مزعجة و غير هادفة
F14	He might climb on walls or something like that	قد يقوم بالتسلق على الجدران اومشابه
F15	Damaging and scattering things	إتلاف الأشياء و بعثرتها
F16	Jumping on furniture and things	القفز على الأثاث و الأشياء
F17	Escape from home	الهروب من المنزل
F18	Doing things that are unacceptable to others	القيام بأعمال مرفوضة من الآخرين
F19	He loves to fight with others	محب للعراك مع الآخرين
F20	cruel to animals	قاسي على الحيوانات
F21	He does not get along with his brothers or others	لا ينسجم مع إخوته أو الآخرين
F22	He may not have fun while playing	قد لا يستمتع اثناء اللعب
F23	Not cooperating with others	غير متعاون مع الآخرين
F24	sucking or chewing the thumb, clothing or blanket	يمص أو يمضغ الإبهام أو الملابس أو البطانية
F25	He steals things	يقوم بسرقة الأشياء
F26	He obeys with resentment	يطيع باستياء و امتعاض
F27	Cruel and brutal	قاسي و تصرفاته وحشية
F28	Rebellious, stubborn and disobedient	متمرد و عنيد و غير مطيع
F29	Difficult to make friends and communicate with others	صعب في تكوين صداقات و التواصل مع الآخرين
F30	He denies mistakes and blames others	ينكر الأخطاء و يلوم الآخرين
F31	His words are not clear and different from other children	كلامه غير واضح ومختلف عن الأطفال الآخرين
F32	He can perform anti-social behavior such as starting a fire	يمكن أن يقوم بسلوك مضاد للمجتمع كإشعال النار
F33	Avoids apologizing	يتجنب الاعتذار
F34	Move and impulsively restless	حركي واندفاعي لا يهدأ
F35	He can't control his actions	لا يستطيع السيطرة على أفعاله
F36	His demands must be fulfilled immediately and it is difficult for him to wait	يجب أن تؤدى مطالبه في الحال ويصعب عليه الانتظار
F37	His feelings will soon be hurt	سرعان ما تنجرح مشاعره
F38	He gets bored quickly and gets bored	يضجر بسرعة و يعاني من الملل

F39	It is easy for him to scream or cry	من السهل ان يصرخ او يبكي
F40	We often find him upset and frowning	غالبا نجده مستاء وعبوس
F41	He gets himself involved in matters that have nothing to do with him	يقحم نفسه في أمور لا علاقة له بها

4.4 Classification Stage and Performance Evaluation

As mentioned in the previous subsection, the feature vector was constructed from the responses to the survey. The total number of features is 41. Two techniques that have been used for classifying the feature vector are the KNN and AdaBoost. The dataset contained 153 instances before the balancing step and 177 and 236 instances after the 50% and 100% balancing steps, respectively. The dataset was split into 70% for training and 30% for testing. The proposed work is evaluated using the following equations [18].

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \quad (4)$$

where TP = true positive, FN = false negative, FP = false positive, and TN = true negative.
A recall is the ratio of correctly predicted positive observations to all observations in an actual class, as shown in Eq. (5) below:

$$Recall = TP/(TP + FN) \quad (5)$$

Precision: is the ratio of correctly predicted positive observations to the total predicted positive observations, as shown in Eq. (6) below:

$$Precision = TP/(TP + FP) \quad (6)$$

The F1-score is a measure of a test's accuracy. It considers both the precision and the recall of the test to compute the score, as appears in Eq. (7) below:

$$F1\text{-}score = 2 * (Recall\ /Precision + Recall) \quad (7)$$

4.5The Importance of Features

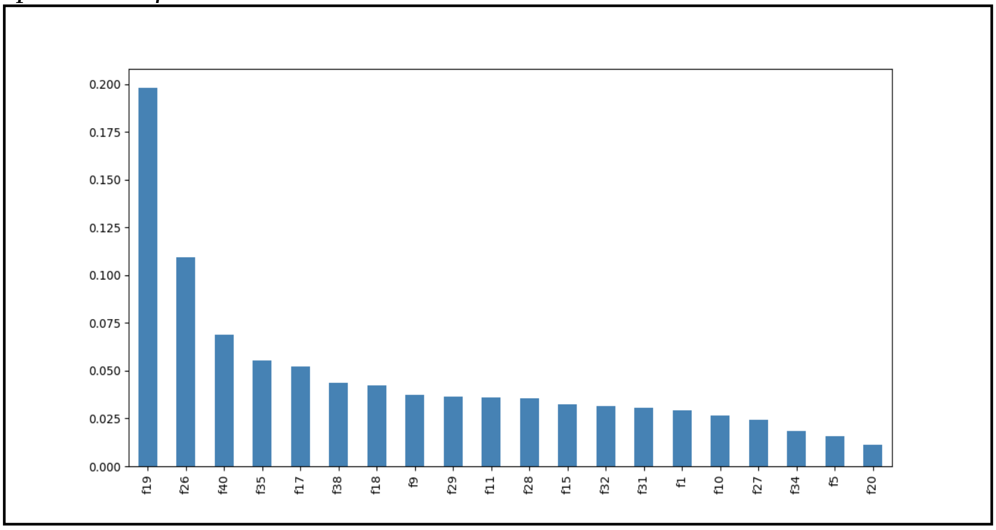

Figure 6: The top twenty important features using XGBoost

The XGBoost had been used to locate the importance of features by computing the gain for each feature. Therefore, each feature had a score and weight, while the gain type showed the average gain across all splits where the feature was used, and the weight showed the number of times the feature was used to split data. Figure 6 shows the top twenty important features. Table 3 shows the value of importance for each feature.

Table 3: The score of each attribute using XGBoost

Feature No.	Feature score	Feature No.	Feature score
F0	0.02927	F21	0.00000
F1	0.00000	F22	0.00000
F2	0.00387	F23	0.00000
F3	0.00000	F24	0.00000
F4	0.01598	F25	0.10951
F5	0.01056	F26	0.02410
F6	0.00000	F27	0.03549
F7	0.00674	F28	0.03665
F8	0.03741	F29	0.00781
F9	0.02643	F30	0.03078
F10	0.03587	F31	0.03149
F11	0.00772	F32	0.00232
F12	0.00000	F33	0.01842
F13	0.00595	F34	0.05518
F14	0.03258	F35	0.00000
F15	0.00702	F36	0.00000
F16	0.05203	F37	0.04361
F17	0.04242	F38	0.00000
F18	0.19812	F39	0.06903
F19	0.01146	F40	0.00342
F20	0.00876		

4.6 Correlation of Features

The correlation between features had been computed using Pearson correlation for understanding the relationship between features and finding if the attribute depends on one or multiple features. The correlation had been computed using Eq. (1). The positive correlation between two or more features has a value greater than zero, which is represented by a small cell in Figure 7. The positive correlation means any increase in the value of one feature causes an increase in the value of the correlated feature.

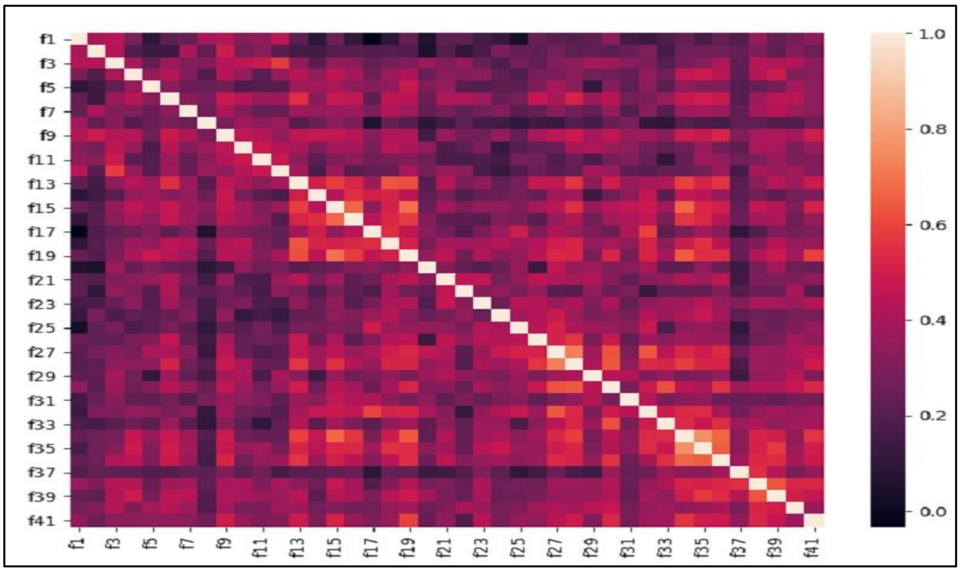

Figure 7: The correlation between features

As shown in Figure 7, there is more than one feature that is correlated. The feature (he fails to complete the tasks he starts) is correlated. So, the existence of one of them can be dispensed with for the other correlated feature. The same thing applies to features (19) and (15).

5. Results and Discussion

This work was carried out using the Python (V.3.5) programming language and the Jet Brains Pycharm (V.2018.2) framework. As mentioned, this work contained three main stages. Firstly, the data preparation involves answering the survey, balancing the data, and processing the null value. Secondly, constructing a feature vector by selecting all features for classification in the next stage Finally, the classification stage was carried out using two techniques (KNN and AdaBoost) for classifying the feature vector.

Two models had been applied to the imbalanced dataset and to balancing the dataset using the SMOTE technique. The accuracy of classification using KNN and AdaBoost techniques was 96.5% and 93.47%, respectively, for the unbalancing dataset, 98.14% and 93.5%, respectively, for the 50% balancing dataset, and 98.59% and 97.18%, respectively, for the 100% balancing dataset. Figure 8 shows the difference in accuracy between the proposed models using KNN. Figure 9 shows the difference in accuracy between the proposed models using AdaBoost.

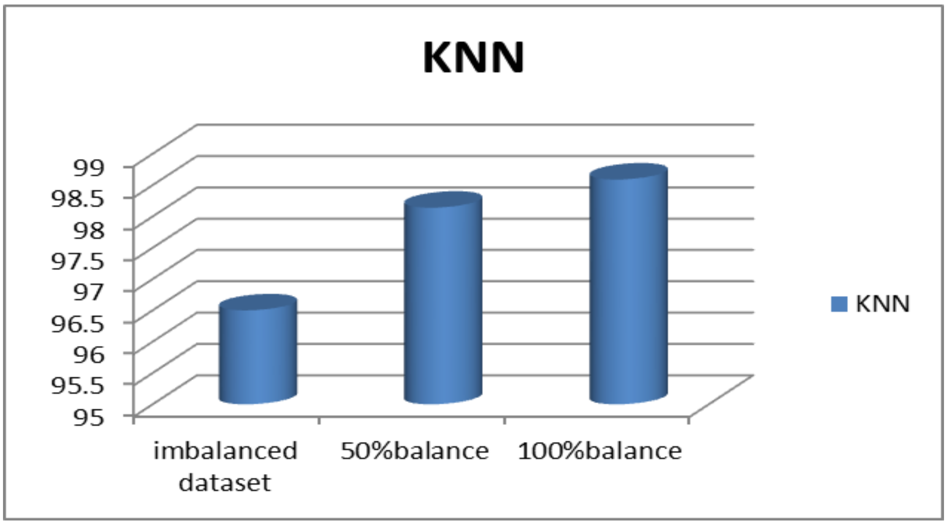

Figure 8: The accuracy of the proposed models using KNN

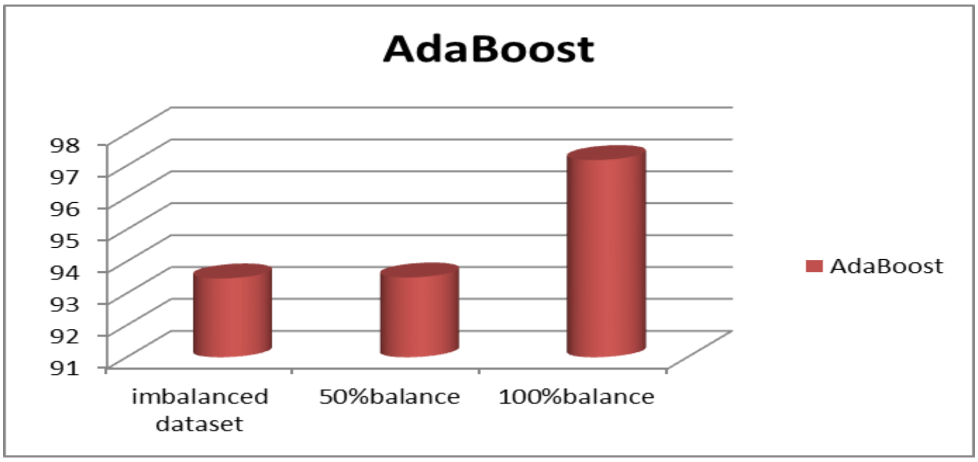

Figure 9: The accuracy of the proposed models using AdaBoost.

As shown in Figure 8, the accuracy of the imbalanced dataset was good but less than that of the fifty percent balanced dataset and the hundred percent balanced dataset, but we can't measure the accuracy only in this case because the dataset was imbalanced. So, the classification report had been measured. Also, as shown in Figure 9, the accuracy of the imbalanced dataset was good but less than that of the fifty percent balanced dataset and the hundred percent balanced dataset, but we can't measure the accuracy only in this case because the dataset was imbalanced. So, the classification report had been measured. Generally, the value of F1_score is the value for showing the bias of the accuracy in the class label (zero) and class label (one). Tables (4), (5), and (6) show the classification report for each technique before balancing and after balancing for 50% and 100%, respectively, for KNN and AdaBoost classifiers.

Table 4: The classification report of each technique before balancing

Technique	Precision	Recall	F1-score	Support	Class label
KNN	0.97	0.97	0.97	36	0
	0.90	0.90	0.90	10	1
			0.96	46	Accuracy
Ada Boost	0.97	0.94	0.96	36	0
	0.82	0.90	0.86	10	1
			0.93	46	Accuracy

Table 5: The classification report of each technique after balancing for 50%

Technique	Precision	Recall	F1-score	Support	Class label
KNN	1.00	0.97	0.99	36	0
	0.95	1.00	0.97	18	1
			0.98	54	accuracy
AdaBoost	0.92	0.97	0.95	36	0
	0.94	0.83	0.88	18	1
			0.93	54	accuracy

Table 6: The classification report of each technique after balancing 100%

Technique	Precision	Recall	F1-score	Support	Class label
KNN	0.97	1.00	0.99	35	0
	1.00	0.97	0.99	36	1
			0.99	71	Accuracy
AdaBoost	1.00	0.94	0.97	35	0
	0.95	1.00	0.97	36	1
			0.97	71	Accuracy

In general, as shown in the previous results, the accuracy of the KNN technique for three cases (imbalance, 50%, and 100%) in the dataset was good compared with the AdaBoost technique for the same cases. Because the dataset was imbalanced and balanced, the classification report is very important for clarifying the results, especially the F1-score. Table 4 showed the value of the F1-score was 0.97 for the class label (zero) and 0.90 for the class label (one) when using KNN. The difference between these values is because the number of the class label (zero) is greater than the number of the class label (one). Also, the value of

F1_score was 0.96 for the class label (zero) and 0.86 for the class label (one) when using AdaBoost because the dataset was imbalanced.

Table (5) showed the value of the F1-score was 0.99 for the class label (zero) and 0.97 for the class label (one) when using KNN. This means there is an approximate value for the F1-score for a two-class label because of balancing the dataset at 50%. And there is an enhancement for the value of the F1-score when using AdaBoost for the same reason, where the F1-score was 0.95 for the class label (zero) and 0.88 for the class label (one).
Table (6) showed the value of F1_score was 0.99 for the class label (zero) and 0.99 for the class label (one). When using KNN, the values of F1_score were the same. Also, the values of F1_score were the same when using AdaBoost, which were 0.97 for the class label (zero) and 0.97 for the class label (one).

6. The Conclusion and Future Works

ADHD is a neurodevelopmental disorder that affects a significant number of children and adults worldwide. The diagnosis of ADHD involves several time-consuming and costly tests. The diagnosis of ADHD contains medical tests and behavioral tests. This paper concentrated on behavioral tests.

Recently, AI techniques have been used for predicting behavioral and social diseases as well as medical diseases. Therefore, the current study used the Python programming language to examine the possibility of having ADHD symptoms using AI techniques. One hundred fifty-three Iraqi parents of children (6–12 years old) filled out an online survey, which contains statements about ADHD, to investigate the degree of severity of different emotional and mood states such as sadness, boredom, little enjoyment/interest, and disrupted behaviors such as verbal and physical aggression and opposition. The proposed model used two techniques: KNN and AdaBoost; the classification accuracies obtained were 96.5% and 93.47% for unbalanced data and 98.59% and 97.1% for balanced data, respectively; the XGBoost technique was applied for selecting the essential features; and the Pearson correlation was used for finding the correlation between features.

In future works, hybrid features can be used in predicting ADHD by analyzing social and behavioral factors and medical images of the brain using the techniques of soft competition. In addition, AI techniques can be used for other social and behavioral diseases, such as post-traumatic stress disorder (PTSD).

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