A COLLABORATIVE KNOWLEDGE FRAMEWORK FOR PERSONALIZED ATTENTION DEFICIT HYPERACTIVITY DISORDER (ADHD) TREATMENTS

BY

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ABSTRACT

Attention Deficit Hyperactivity Disorder (ADHD) is a complex mental health disorder that can affect your child's success at school and his/her relationships. The symptoms of ADHD vary and are sometimes difficult to recognize. Many of the individual symptoms of ADHD are normal for children to experience. Evaluating the child under several criteria is necessary to make a diagnosis of ADHD. Generally, the diagnostic will conduct on children by the time they are teens, the average age of diagnosis is 7. Older children exhibiting these symptoms may have ADHD, but they often have exhibited rather than elaborate symptoms early in life. Attention Deficit Hyperactivity Disorder (ADHD) is a complex mental health disorder that can affect your child's success at school and his/her relationships. The symptoms of ADHD vary and are sometimes difficult to recognize. Many of the individual symptoms of ADHD are normal for children to experience. Evaluating the child under several criteria is necessary to make a diagnosis of ADHD. Generally, the diagnostic will conduct on children by the time they are teens, the average age of diagnosis is 7. Older children exhibiting these symptoms may have ADHD, but they often have exhibited rather than elaborate

symptoms early in life. To further explain the above statement, the problems are summarized as follows: 1) lack of analysis framework for ADHD children, 2) lack of tools for recording behavioral symptoms of ADHD children include to and 3) the analysis takes longer time for children under 6 years old. Most of the time they are influenced by surrounding activities. The above diagnosis is rather difficult because the disease is rising gradually over a period, the disease can occur at the age of 3-7 years. For a person who receives a diagnosis of ADHD, the symptoms of inattention and hyperactivity-impulsivity must be chronic or long-lasting, impair the person's functioning and cause the person to fall behind normal development for his/her age. The treatment of ADHD uses behavioral therapy (BT) and medication such as methylphenidate, dextroamphetamine, and pemoline statins for reducing restless children and helping them to concentrate on their studies and work.

The main purpose of this research is to design a collaborative knowledge framework for personalized ADHD treatments. There are two main objectives, which are 1) to design a framework and develop a tool for observing and recording behavioral symptoms of ADHD children that can be used by doctors, parents, and teachers, and 2) to introduce effective algorithms for classifying ADHD types with appropriate individual behavioral therapy and activities recommendation. In our framework, we introduce a combined technique for ADHD classification using a machine learning approach. The expected outcome of our proposed framework is to provide an effective way to classify types of ADHD and to recommend appropriate treatments and therapy based on individual behavior

Keywords: ADHD, Data mining, Machine learning, Classification, Clustering, Neural networks, Data analytics, Reasoning framework, Reasoning prediction, Decision Tree, k- means Clustering, Naïve Bay algorithm, k-Nearest Neighbors algorithm, Collaborative behavior, Knowledge management, Collaborative knowledge Framework, Decision support system, Recommendation system

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CHAPTER 1
INTRODUCTION

Attention Deficit Hyperactivity Disorder (ADHD) is a neurodevelopmental disorder. Its symptoms are noticeable during childhood (before the age of 7), affecting a child's behaviors, emotions, learning activities, and social interactions. ADHD syndrome includes attention deficit, lack of self-control (impassivity), and impairment (hyperactivity). The primary symptoms in some children include temperament and a lack of ability to control themselves. Surprisingly, 3-5% of school children have ADHD syndrome [1,10]. ADHD children commonly experience academic underachievement, interpersonal relationship problems, and low self-esteem. For 40-50% of ADHD children, the disorder appears to continue with varying manifestations into adulthood and leads to unemployment and social dysfunction [2].

From the data collected by the Ministry of Public Health, Thailand, it has been reported that more than 1 million Thai youth (6 - 12 years) have been diagnosed with ADHD (2012 - 2018). It has been confirmed that the current epidemiological prevalence rate of ADHD in Thailand is 8% [3]. This disorder is more likely seen in boys (12%) than girls (4.2%). If ADHD goes untreated, it might be a problem for individuals in the long run as they might be at the risk of other health conditions, decreased quality of social life, unsatisfactory academics, unpleasant relationships, comorbid psychiatric conditions, and much more. Children with ADHD experience far more obstacles compared to any other average students. While most children diagnosed with ADHD receive special school services to make their overall learning environment and experience more pleasant, this might not always be the case.

Consecutively, parents must observe children’s behavior when at home, and teachers can help monitor and evaluate behavior while individuals are at school. For the assessment, teachers and parents use the DSM-IV standard (Thai version) questionnaires, particularly the Vanderbilt Assessment Scale. Teachers are included in the study as they know students personally and academically. There might be a fair chance that the child might be showing ADHD symptoms of any sort, and parents might neglect it by considering it a habit. Therefore, having multiple perspectives and integrating all the results from different informants would be optimal. With the physician's expertise and evaluation of the assessment tests, recommendations can be made to guide teachers and parents. The methodologies and strategies would ensure that if the recommendations were followed, the children could cope with their symptoms.

1.1 Motivations and Research Problems

Attention Deficit Hyperactivity Disorder (ADHD) is a complex mental health disorder that can affect children's school success and relationships. The symptoms of ADHD vary and are sometimes difficult to recognize. Many of the individual symptoms of ADHD are normal for children to experience. Evaluating the child using several essential criteria is necessary for a diagnosis of ADHD. Generally, the diagnosis will be conducted on teen children rather than young age children. The average age of diagnosis is 7 years old [29]. Based on literature reviews and observed problems [27,29,30], we summarize the issues as follows:

1) lacking an effective analytical framework for ADHD children,

2) lacking tools for recording and screening behavioral symptoms of ADHD children, and

3) the screening process takes a long time for children under 6 years old (More than six months) and to diagnose ADHD children, doctors rely on several things, including interviews with the parents, relatives, teachers, or other adults, and personally watching the child or adult AND rating scales that measure symptoms of ADHD Psychological tests[4,5,29].

Therefore, in this research, we aim to overcome the mentioned problems by proposing a methodology and a framework that can be used by teachers or parents to evaluate and screen their children's behaviors and determine if the behaviors are consistent with any type of ADHD. The framework also provides recommendations for appropriate treatments for different types of ADHD children.

We hope that by using the proposed framework and tool for screening of ADHD symptoms and we can use them for young children, then the teacher or parents can use this information to consult with doctors in order to provide appropriate treatments for the child as early as possible. Behavioral therapy (BT) is the recommended treatment of ADHD children. One of the behavioral therapies is medication. Sometimes, medicines are necessary such as methylphenidate, dextroamphetamine, and pemoline statins can be to reduce restlessness in children and help them to concentrate on their studies and work.

1.2 Contributions

This research aims to design a collaborative knowledge framework for a recommendation of personalized ADHD treatments, having two main objectives as follows:

1) to design a framework and develop a tool for observing and recording behavioral symptoms of ADHD children that can be used by doctors, parents, and teachers.

2) to introduce effective algorithms for classifying ADHD types and recommending appropriate individual behavioral therapies and activities. Our framework introduces a combined technique for ADHD classification using machine learning and a rough set approach.

The expected outcome of our proposed framework is to provide an effective way to screen and classify types of ADHD and recommend appropriate treatments and therapy based on individual behaviors.

1.3 Dissertation Organization

The remaining content of the dissertation is organized as follows:

The background knowledge and related is discussed in Chapter 2.

The proposed research methodology, the research framework, the classification technique for ADHD types, and the recommendation system for behavioral therapy is presented in Chapter 3.

In chapter 4, we explain the experimental results of the classification techniques and the recommendation system.

In chapter 5, we summarize and discuss the findings and knowledge obtained from this research and describe further research direction.

CHAPTER 2
BACKGROUND KNOWLEDGE AND RELATED WORKS

2.1 Background Knowledge

This chapter summarizes the important knowledge for this research. The literature reviews presented in this chapter is related topics such as attention deficit hyperactivity disorder (ADHD), the etiology of ADHD, the ADHD symptoms, the diagnostic approaches, the treatments for ADHD children, and the application of machine learning in health care.

2.1.1 Attention deficit hyperactivity disorder (ADHD)

ADHD is a childhood symptom that affects children's behaviors, emotions, learning activities, and social interactions with other children. ADHD syndrome is characterized by a lack of attention, a lack of self-control (impassivity), and impaired judgment (hyperactivity). Some children have the temperament and lack the ability to control themselves. Surprisingly, three to five percent of school-aged children have ADHD [4, 11,25]. ADHD children typically struggle with academic underachievement, interpersonal relationship issues, and low self-esteem. For 40-50% of ADHD children, the disorder appears to persist with varying manifestations into adulthood, resulting in significant underachievement, unemployment, and social dysfunction. [6].

2.1.2 Etiology of Attention Deficit Hyperactivity Disorder (ADHD)

The genetic factor is the primary cause of ADHD for most patients. The main culprits may have been including the dopamine transporter gene, serotonin transporter gene, and gene that codes for Dopamine beta (β)-hydroxylase and other receptors. Other environmental factors that may contribute to ADHD are lead poisoning, maternal smoking, substance abuse during pregnancy, preterm birth, and other complications of pregnancy and childbirth [5, 6, 17, 23,25].

2.1.3 ADHD symptoms

ADHD symptoms do not remain constant. These symptoms can be divided into three categories: inattention, hyperactivity, and impulsivity [8,43,44].

1) Inattention can be witnessed in a person who is disorganized, wanders off task, lacks persistence, has difficulty maintaining focus, and is unorganized. These issues are not the result of defiance or a lack of understanding.

2) Hyperactivity causes a person to move around constantly, with excessive fidgeting, tapping, or talking in inappropriate situations. These symptoms cause extreme restlessness in adults and exhaust others with constant activity.

3) Impulsivity causes a person to act rashly in the heat of the moment, without giving it much thought. These actions may result from a desire for immediate gratification, an intention to cause harm, or an inability to delay gratification. An impulsive person may be socially intruding and excessively interrupting others or they may make important decisions without considering the long-term consequences.

ADHD symptoms are more visible when patients dislike something or are exposed to distracting stimuli. The symptoms are less noticeable in a calm situation, as evidenced by patients' facial expressions. According to the findings of the study, ADHD-affected children may be able to do things that are considered inspirational for a longer period. These include things like playing video games or watching television. Hyperactivity is the most common of the three common symptoms mentioned. Patients who frequently lack concentration were not observed because impulsive behavior is seen in the preschool segment-specific symptoms [9,20].

There are obvious problems when children attend classes. ADHD is a chronic disease that may take several years to improve or disappear some parts of the patient's symptoms. However, up to 60-85 percent of patients will have symptoms until adolescence and 40-50 percent of patients whose symptoms continue through adulthood [23, 24, 43].

There are potential comorbid psychiatric disorders in ADHD patients. Lack of motivation to learn, resistant or aggressive behavior, anxiety, depression, low self-esteem, and social problems are commonly found in patients with ADHD. Other disorders in ADHD-affected patients include opposition defiant disorder, conduct disorder, anxiety disorder, depressive disorder, learning disorder, and tic disorder. ADHD is diagnosed based on the patient's history and the frequency of the occurrence of symptoms. Generally, these symptoms start to appear before the age of seven and do not originate from other psychiatric disorders [8,26,28,44]. According to the Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition-Text Revised (DSM-5 -TR), a standard diagnosis, children with attention deficit and/or hyperactivity and impulsivity develop a more severe behavior than those without ADHD causes problems in social life, self-development, and future endeavors.

2.1.4 Diagnostic and Treatments for ADHD

2.1.4.1 ADHD Standardized Screening Tool

The Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) is used as the standard screening tool for ADHD which was developed by the American Psychiatric Association [5,16,43]. There are many scale-assessing standards for ADHD, including CRS-R (Conners, C. K.,1997), IOWA Conners (Loney., Milich.,1982), SNAP-IV (Wigal et al.,1998), SWAN (Swanson et al., 2001), ADHD RS-IV (DuPaul, G. J., Power., T. J., Anastopoulos, A. D., & Reid, R.,1998), and VADTRS & VADPRS (Wolraich et al., 1998), etc. These standards can be used to distinguish types of ADHD based on different behaviors and criteria [B5]. The main types of ADHD are inattention, hyperactive-impulsivity, and combined type (having both hyperactivity and impulsivity) [14, 31].

2.1.4.2 Diagnostic process of ADHD

When behaviors resembling ADHD symptoms are observed during the evaluation process, the children may be taken to the doctor. A child, for example, is much more mischievous than usual. ADHD may cause outbursts and a lack of learning concentration. ADHD should be diagnosed based on an evaluation of learning, behavioral, and emotional issues. When determining the diagnosis of ADHD, it is critical to consider the patient's history as well as current conditions. The required evaluations are described below [46, 47, 51].

A) Patient's history evaluation

Parents have to provide information about their child's past emotional, behavioral, learning and adaptation problems. The severity of the situation with various stress factors, including environmental factors, should all be addressed. The evaluation also covers any information that may be related to the symptoms of ADHD such as a child's development, medical history, physical illness, and family history [15, 18].

B) Patient's current condition evaluation

The child should also be evaluated for overall mental health, ADHD symptoms, and other psychiatric disorders. In any case, the child should be placed in a soothing environment during the evaluation. Because the symptoms are difficult to detect, a similar assessment may be required [29]. Other circumstances, such as additional medical and physical check-ups, may necessitate observing the child's behavior.

C) Evaluation by parents and teachers

This type of evaluation is carried out by both parents and teachers using a questionnaire. The questionnaire must be tailored to address the symptoms of ADHD to provide additional diagnostic information. The information gathered will be useful for research and will be used to track ADHD children. However, data from the questionnaire alone cannot completely screen ADHD children. [16,17].

D) Psychological evaluation

This test is necessary only in some suspected cases for cognitive impairments and learning disorders (LD). Nevertheless, the treatment for ADHD should be improved before the psychological evaluation. The improvement would allow the patient to use his/her full ability for the test. The Continuous Performance Test (CPT) cannot be used to confirm the diagnosis [7, 13, 16].

E) Discussion and recommendation of the treatment

The clinician should identify treatments for patients that aid in the improvement of behaviors or the reduction of symptoms. Most of the time, patients require both medical and behavioral therapies. This would be determined by the type of ADHD [22, 29].

2.1.4.3 Treatments for ADHD

Their pharmacological options for ADHD treatment include presynaptic, dopaminergic, and agonistic agents. Psychosocial treatments, medication, and behavioral therapy are also available. Many ADHD children must take medications in order to maintain self-control and be willing to learn and perform better. This allows them to practice discipline, responsibility, and social skills [10, 16, 29].

ADHD treatments require a combination of methods that are not mutually exclusive (multimodal management) [22]. Ultimately, the treatment must offer knowledge and guidance to help parents and teachers provide support in schools, medication, and solving the impact of ADHD. After diagnosis, parents should attend counseling sessions to understand ADHD treatment plans and the guidelines for chronic diseases that require ongoing monitoring [32, 35, 39, 40]. Moreover, the parents should be provided with psychological help to avoid misunderstanding and misinformation about the issue.

- Symptoms of ADHD are impairments. It is not the intention of the patient to be lazy or harass other people.

- To understand the impact of ADHD and impairments, meet with other patients in various fields, especially if not treated.

- The prognosis for most patients often has symptoms. Chronic and continuous treatments are required for a long time.

Patients should know about ADHD and are advised on how to behave at the developmental level [20].

Medication treatment research evidence has shown the benefits of using drugs in treating ADHD patients. The drug helped patients with self-control and a willingness to learn to perform better, which allows the patients to practice discipline, responsibility, and social skills. The implication for drug usage is obtained through a diagnosis. The patient's ADHD symptoms severity should be assessed for the appropriate choice of therapy, and the parents must be informed about the advantages and disadvantages [20, 22, 32, 43].

2.2 Apply Machine Learning

Contemporary machine learning techniques are used in several healthcare applications. They are employed to predict future diseases for data and offer a desirable decision from the dataset. Many researchers have used machine learning algorithms to indicate diseases such as Liver disease (Logistic Regression with 95.8% accuracy) [19], Breast Cancer (Support Vector Machine with 99% accuracy) [34], and Alzheimer's disease (Neural Networks with 98.3% accuracy) [36].

2.2.1 The Decision Tree Algorithm

A Decision Tree is a supervised learning technique that can be used for both classification and regression problems, but mostly it is preferred for solving classification problems. It is a tree-structured classifier, where internal nodes represent the features of a dataset, branches represent the decision rules, and each leaf node represents the outcome. The information starts at the root, where the point is called the Root node. If the information satisfies the set criteria, it runs to the left side of the Root node, where the point is called the Child node. If the information continues to satisfy the set criteria of the Child node, it runs to the last node called the Leaf node. On the other hand, if the information does not satisfy the criteria at the Root node, it runs to the right to an alternative Child node, which contains another set of criteria. The decision runs in the direction of satisfying criteria until the algorithm finds the answer [49].

The process of the Decision Tree model is shown as follows.

1. It separates data in detail.
2. It selects a variable that best distinguishes the answer class and places it as the first node.
3. After that, other variables are found, and the data is divided into the next hierarchy.
4. The steps are repeated until the data is separated.

2.2.2 The K-Nearest Neighbor (KNN) algorithm

The KNN algorithm classifies data by comparing information of interest to others. The algorithm returns a result based on the information that is most similar to the information of interest. A simulation is created based on this result rather than the training data.

KNN decides the class in which the data is most similar by examining some amount of data (K). The technique is suitable for numerical data and determining the distance between different Attributes.When the decision-making conditions are complex, the KNN approach can be used to develop efficient models. However, the calculation takes time. When there are too many Attributes, errors may occur. This method is limited to nominal data such as gender and occupation [10].

2.2.3 The Naïve Bay algorithm

The Naive Bay algorithm is a data mining classifier. The technique was developed based on the principle of Probably Naïve Bayesian Classification. It is used to analyze the probability of an unprecedented event from occurred events. The procedure of The Naive Bay algorithm process is summarized as follows:[10]

1. Count the total number of transactions and find the resulting class (only 2 answers)
2. Separate the number of results per number of transactions using rule 1.
3. Separate non-answer classes for probability proportions per number of transactions.
4. Results prediction of the information must not exist in the table.
5. Bring the data from Rule 3 to predict the outcome using Rule 2.

2.2.4 The Neural Network Algorithm

This algorithm is one of the data mining techniques. It is a mathematical model for processing information with a connected computation (Connectionist). The algorithm is used to simulate the functioning of neural networks in the human brain to create a tool capable of learning pattern recognition, knowledge extraction (Knowledge Extraction), and the human's brain capabilities.In principle, neurons consist of the same input and output - the simulation assumes that each input has a weight that determines the weight of the input. Each neuron has a threshold that determines how large the total weight of the input must be to transmit its output to other neurons. When the neurons are joined together, they work together logically like a chemical reaction in the brain. The only difference is that everything in the computer simulation comes from numbers.

The function of Neural Networks works as the inputs come to a network. The inputs are multiplied by the weight of each leg. The resulting inputs on all the neuron legs are added together and compared to a predetermined threshold. If the value exceeds the threshold, the neuron sends an output to the other neuron's input as a connection. If the value is less than the threshold, no output will occur. Knowing the weight and threshold values for the computer to recognize is essential. The computer is set to adjust those values by teaching it to recognize the pattern of what we want it to recognize, called "backpropagation". This is a reverse recognition process used to improve the network weight. After each training data format is applied to the network, the network output is compared with the expected results. This error value is then calculated and returned to the network for correction [1, 21, 37, 45].

2.2.4.1 Learning for Neural Networks

1. Supervised Learning is a study in which answers are examined for the neural network to adapt. The dataset used to teach the neural network has answers to check if the network gives the correct answer. If the answer is incorrect, the neural network adjusts itself to provide a better answer. The analogy of teachers teaching students can be used to compare with Supervised Learning.

2. Unsupervised Learning is a lesson without a guide. No right or wrong answers are checked. The neural network organizes its structure by itself according to the nature of the data. The result Neural networks can be used to categorize data. A comparable analogy is when a person could distinguish plants or breed animals according to their appearance without an initial lesson.

Table 2.1 Comparison of advantages and disadvantages of machine learning [10, 21]

No	Classification Technique	Pros	Cons
1	Decision Tree	- Structured data/ Unstructured data - easy implementation	- slight variation in data can lead to a different decision tree - does not work well with small data
2	Naïve Bay	- Structured data/ Unstructured data - easy implementation - high computation efficiency, classification rate, and accuracy.	- precision of the algorithm decreases with fewer data - an extensive number record is required for accuracy
3	KNN	- Unstructured data - suitable for multimodal class - If the decision-making conditions are complex, this approach can create efficient models -a small dataset and the data is noise-free and labeled.	- excessive time to find the nearest neighbors in an extensive training data set - performance of the algorithm depends on the number of dimensions used
4	Neural Network	- Structured data/ Unstructured data - simple to use with a few parameters to adjust - applicable to a wide range of problems in real life	- requires high processing time if the neural network is large - difficult to know the required number of neurons and layers

2.3 Related Works

2.3.1 ADHD standardized screening tool

The first related research shows how the teachers used the DSM-5 standard (Thai version) questionnaire based on the Vanderbilt Assessment Scale. The teachers were selected as candidates because they know students personally and academically. There might be a fair chance that the child might be showing some ADHD symptoms, and parents might neglect it by considering it a habit. Table 2.2 shows the standardized screening tool of the DSM-5 for ADHD Assessment in the English language version and Table 2.3 shows

Table 2.2 Comparisons of the DSM-5 for ADHD Assessment in English language version [14, 48]

No	Scale (Ages) Publisher Reference	Items Factors Scoring (Samples)	Normative Data and Reliabilities for Total Scale & Subscales (Samples)	Validities, Sensitivity & Specificity for Total Scale & Subscales & (Samples)	Cutoff	Other
1	CRS-R (3-17 y) [14]	80 items (parent) 59 items (teacher) 87 items (adolescent) 7 factors (parent) 6 factors (teacher) 6 factors (adolescent) plus: Global index, ADHD index, DSM-IV symptom subscale for parents & teachers 4 points	Normative data available IC: 0.75-0.94 (parent) IC: 0.73-0.94 (teacher) IC: 0.74-0.92 (adolescent) 6-8 wk. TR : 0.13-0.88 (parent) 6-8 wk. TR : 0.47-0.88 (teacher) 6-8 wk. TR: 0.73-0.89 (adolescent) IR : 0.12-0.50 (parent-teacher) IR : 0.13 - 0.53 (adolescent - parent) IR : 0.08 - 0.41 (adolescent - teacher)	DISCRIM: ADHD vs. nonclinical SENS 92% (parent) PPP 94% (parent) SPEC 94% (parent) NPP 92% (parent) SENS 78% (teacher) PPP 90% (teacher) SPEC 91% (teacher) NPP 81% (teacher) SENS 81% (adolescent) PPP 83% (adolescent) SPEC 84% (adolescent) NPP 82% (adolescent) CONV : 0.47-0.81 teacher DISCRIM: ADHD from nonclinical (Total scale) ADHD from ODD (I/O subscale) ODD+ADHD from ADHD and from nonclinical (O/D scale)	93 rd. percentile	Adm: 20-30 min Quick score forms. computer, scoring available Global index to assess treatment French-Canadian translation

No	Scale (Ages) Publisher Reference	Items Factors Scoring (Samples)	Normative Data and Reliabilities for Total Scale & Subscales (Samples)	Validities, Sensitivity & Specificity for Total Scale & Subscales & (Samples)	Cutoff	Other
2	IOWA Connects (6-12 y) [14]	10 items 2 factors 4 points	Limited normative data for teacher report form; no normative data for other report forms IC: 0.89-0.92 (teacher) IC: 0.78–0.87 (counselor) IC: 0.79-0.81 (adolescent) IR: 0.35–0.49 (teacher-teacher) TR: 0.86–0.89 (teacher) TR: 0.84-0.85 (counselor) TR: 0.74-0.83 (adolescent)		11(I/O, K-3rd) 11 (I/O, K-3rd) 9 (I/O, 4th-5th) 9 (O/D, K-3rd) 6 (O/D, 4th-5th) (teacher)	Adm: 5 min
3	SNAP-IV (5-11 y) [14]	90 items full version 31 items (ADHD+ ODD version) 2 factors 7 points	Limited normative data available IC: 0.84-0.95;(teacher) IR: 0.30 (parent-teacher)	No validity data is available	95 th percentile	Adm: 20-30 min (Full version) 5-10 min (ADHD+ODD version)
4	SKAMP (7-12 y) [14]	13 items 2 factors 7 points	No normative data is available 1 day TR: 0.70–0.78	CONV:0.50-0.83	NA	Adm: 5 min
5	SWAN (5-11 y) [14]	26 items 3 factors 7 points	No normative data is available No reliability data is available	No validity data is available	NA	Adm: 5 min

Table 2.2 Comparisons of the DSM-5 for ADHD Assessment in English language version (cont.)

No	Scale (Ages) Publisher Reference	Items Factors Scoring	Normative Data and Reliabilities for Total Scale & Subscales (Samples)	Validities, Sensitivity & Specificity for Total Scale & Subscales & (Samples)	Cutoff	Other
6	ADHD RS-IV (5-18 y) [14]	18 items 2 factors 4 points IC: 0.88-0.96 (school)	Normative data available IC: 0.86-0.92 (home) 4 wk. TR: 0.78-0.86 (home) 4 wk. TR: 0.88-0.90 (school) IR: 0.40-0.45 (parent-teacher)	CONV: 035-0.85 DISCRIM: ADHD vs. nonclinical ADHD vs. clinical control ADHD-I vs. ADHD-C SENS 83-84% (home) PPP 54-58% (home) SPEC 49% (home) NPP 77–81% (home) SENS 63-72% (school) PPP 78-79% (school) SPEC 86% (school) NPP 73-81% (school)	80th, 85th, 90th, 93rd percentiles	Adm: 5-10 min Spanish translation
7	VADTRS & VADPRS (6-12 y) [14]	43 items 6 factors 4 points & 5 points	Limited normative data available IC: 0.80–0.95 (teacher) IC: 0.94-0.95 (parent, ADHD subscales) IR: 0.27-0.34 (parent-teacher)	CONC: 0.79 (parent)	85th, 90th, 95th, 97th percentiles (teacher)	Adm: 5-10 min Spanish & German translations

Table 2.2 Comparisons of the DSM-5 for ADHD Assessment in English language version (cont.)

No	Scale (Ages) Publisher Reference	Items Factors Scoring	Normative Data and Reliabilities for Total Scale & Subscales (Samples)	Validities, Sensitivity & Specificity for Total Scale & Subscales & (Samples)	Cutoff	Other
8	ADHD-SRS (5-18 y) [14]	56 items 2 factors 5 points	Normative data available IC: 0.95-0.99 (parent) IC: 0.97-0.99 2 wk. TR: 0.95-0.97 (teacher) IR: 0.18-0.27 (patent-teacher)	CONV: 0.90-0.97 DISCRIM: ADHD vs. nonclinical	85th, 95th percentiles	Adm: 15-20 min Computer scoring available Spanish translation
9	ADDES-2 (4-18 y) [14]	50 items (parent) 56 items (teacher) 2 factors 5 points	Normative data available IC: 0.96-0.98 (parent) IC: 0.98-0.99 (teacher) 30-day TR: 0.90-0.96 (parent) 30-day TR: 0.88-0.97 (teacher) IR: 0.81-0.90 (teacher-teacher) IR: 0.82 (parent-teacher)	CONV: 0.53-0.91 (parent) CONV: 0.42-0.89 (teacher) DISCRIM: ADHD vs. nonclinical	93rd, 98th percentiles	Adm: 10-15 min Computer scoring available Spanish translation
10	ACTeRs (5-13 y) [14]	25 items (parent) 24 items (teacher) 35 items (self-report)	Limited normative data available IC: 0.78-0.96 (parent) IC: 0.92-0.97 (teacher) IC: 0.70–0.88 (self-report) TR: 0.78-0.82 (teacher) IR: 0.51-0.73 (teacher-teacher)		T scores & percentiles	Adm: 5-10min Computer administration & Scoring available Spanish translation

Table 2.2 Comparisons of the DSM-5 for ADHD Assessment in English language version (cont.)

No	Scale (Ages) Publisher Reference	Items Factors Scoring	Normative Data and Reliabilities for Total Scale & Subscales (Samples)	Validities, Sensitivity & Specificity for Total Scale & Subscales & (Samples)	Cutoff	Other
11	BADDS (3-12 y) [14]	4 factors (teacher) 5 factors (parent) 3 factors (self-report)	Normative data available IC: 0.73-0.98 (parent) IC: 0.76-0.98 (teacher) IC: 0.71-0.96 (self, 8-12 y) IC: 0.70-0.95 (self, 12-18 y) 1-4 wk. TR: 0.61-0.93 (parent) 1-4 wk. TR: 0.77-0.93 (teacher) 1-4 wk. TR: 0.87 (self, 12–18 y) IR: 0.40-0.60 (parent-teacher, 3-7 y & 9-12 y) IR: 0.49-0.59 (self-teacher, 8-12 y) IR: 0.39-0.50 (self-teacher, 8-12 y)	DISCRIM: ADHD vs. nonclinical, ADHD vs. LD		Adm: 10-15 min Ready-score forms

NOTE: **ADHD =** attention-deficit/hyperactivity disorder. **ADHD-I** = ADHD inattentive type; **ADHD-C** = ADHD combined type; **ODD** = oppositional defiant disorder; **CRS-R** = Conners Rating Scales-Revised; **SNAP-IV** = Swanson, Nolan, and Pelham-IV questionnaire: **SKAMP** = Swanson, Kotkin, M-Flynn, and Pelham Rating Scale; **SWAN** = Strengths and Weaknesses of ADHD Symptoms and Normal Behavior: **ADHD RS-IV** = ADHD Rating Scales-IV: **VADTRS & VADPRS**: Vanderbilt ADHD Teacher Rating Scale & Vanderbilt ADHD Parent Rating Scale; **ADDES-2** = Attention Deficit Disorder Evaluation Scale-Second Edition; **ADHD-SRS** = **ADHD** Symptoms Rating Scale; **BADDS** = Brown A brown Attention-Deficit Disorder Scales: **LD**= learning disabilities, **I/O**=Inattentive/Overactive; **O/D** = Oppositional/Defiant: **IC** = internal consistency reliability; **TR**= test-retest reliability; **IR** = interrater reliability; **CONV** = convergent validity; **CONC** = concurrent validity; **DISCRIM** = discriminant validity; **SENS** = sensitivity; **SPEC** = specificity **PPP**=positive predictive power; **NPP** = negative predictive power; **Adm** = administration; **NA** = not available

Table 2.3 Comparisons of the DSM-5 for ADHD Assessment in the Thai language version [14, 48]

Description	Evaluation Criteria (DSM-5)					
	Conner's Rating Scales-Revised (CRS-R)	ADHD RS-IV	VADTRS & VADPRS Thai version	SNAP-IV Thai version	KUS-SI Rating Scales ADHD	Thai ADHD Screening Scales
1. Language	English	English	Thai	English	English	Thai
2 Number of items	80 items (P) 59 items (T) 87 items (S)	18 items	43 items (ADHD+ODD)	26 items (ADHD+ODD)	30 items	30 items
3. The age range for diagnosis	3-17 y	5-18 y	6-12 y	4-16 y	6-13 y	3-18 y
4. Education level	Preschool-High school	Elementary-High school	Elementary school	None	Primary School 1- 6	Kindergarten 1-3 Primary School 1-6
5. Evaluation is done by	Teachers & parents	Teachers & parents	Teachers & parents	Teachers & parents	Teachers	Teachers, parents &children
6. Internal consistency Cronbach's alpha value	0.75-0.94 (P) 0.73-0.94 (T) 0.74-0.92 (S)	0.86-0.92 (P)	080-0.95 (T) 094-0.95 (P)	0.93 (P) 0.96 (T)	0.96-0.98 (T)	0.96 (P) 0.98 (T) 0.94 (S)
7.Test-retest Reliability value	NA	NA	NA	NA	NA	0.80-0.90 (P) 0.86-0.91 (T) 0.80 (S)
8.Inter-return Reliability value	0.13-0.53 (S-P) 0.08-0.41 (S-T) 0.12-0.50 (P-T)	0.40-0.45 (P-T)	0.27-0.34 (P-T)	NA	NA	0.54 (S-P) 0.38 (S-T) 0.46 (P-T)
9. Normative data	NA	NA	NA	NA	NA	NA

Table 2.3 Comparisons of the DSM-5 for ADHD Assessment in Thai language version (cont.)

Description	Evaluation Criteria (DSM-5)					
	Evaluation Criteria (DSM-5)	Description	Evaluation Criteria (DSM-5)	Description	Evaluation Criteria (DSM-5)	Description
10. Validities, Sensitivity & Specificity for Total Scale &Subscales & (Samples)	SENS 92% (P) SPEC 94% (P) PV 94% (P) NPV 92% (P)	SENS83-84% (P) SPEC 49% (P) PPV 54-58% (P) NPV77-81% (P)	CONC (0.79 P)	SENS 72% (P) SPEC 75% (P)*	NA	SENS 75% (P) SPEC 55% (P) PPV 80% (P) NPV47% (P)
	SENS 78% (T) SPEC 91% (T) PPV 90% (T) NPV 81% (T)	SENS 63-72% (T) SPEC 86% (T) PPV 78-79% (T) NPV 73-81% (T)	NA	SENS 72% (T)** SPEC 60% (T)**	SENS 65% (T) PPV 62% (T) NPV 54% (T)	SENS 63% (T) SPEC 54% (T) PPV 76% (T) NPV 39% (T)
	SENS 81% (S) SPEC 84% (S) PPV 83% (S) NPV 82% (S)					SENS 57% (S) SPEC 49% (S) PPV72% (S) NPV33% (S) SENS 90% (SPT(-)) SPEC 88% (SPT(+)) PPV B6% (SPT(+)) NPV 55% (SPT(-))

NOTE: P =Parents, T = Teachers, S= Self, Sensitivity& Specificity, Cutoff of 14 scores part hyperactivity impulsivity only.
SPT (-) is the Standard Penetration test (negative) THASS of Parents, Teachers, Self-Sensitivity& Specificity, Cutoff of 10 scores part hyperactivity impulsivity only.
SPT (+) is the Standard Penetration test (positive) THASS of Parents, Teachers, Self of the positive predictive value-PPV.
CONC = concurrent validity
SENS is Sensitivity, **SEC** is Specificity, PPV is positive predictive value and **NPV** is negative predictive value

Table 2.3 shows comparisons of the DSM for ADHD Assessment in the Thai language version. The DSM-5 (Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition) was developed by the American Psychiatric Association [8,14,18] and this research uses the DSM-5 standard rating scale and the Vanderbilt Assessment scale. With ADHD being a neuropsychiatric disorder with high prevalence and long-term impairment, physicians must receive reliable input and conduct proper tests. The most accurate results were consistently provided with the DSM-5 screening system.

The Vanderbilt ADHD Rating Scale (VARS) is another standardized screening tool that aids physicians in making ADHD diagnoses based on DSM-5 standards and assessing comorbid conditions. VARS includes 18 symptoms described in the DSM-5. This tool separates the teachers' (VADTRS) and parents' (VADPRS) versions of assessment forms [52, 53].

VARS contains much more information to make a proper DSM-5-based diagnosis of ADHD and screens for common commodities. VARS has strong scales to its benefit, which allows for measuring comorbid externalizing and aiding in providing proper treatment plans. The only setback is that VARS lacks data validity, data supporting stability, and discriminant validity in evaluation and treatment [14].

2.3.2 Apply Machine Learning for ADHD

Table 2.4 Comparison of various works that applied different ML techniques

No	Topic	Classification Algorithm	Accuracy	Method for collecting the data/who assessment	Number of the Data set	Class
1	Diagnosis and evaluation of ADHD using Naïve Bayes and J48 classifiers [35]	1) Naïve Bayes 2) J48 classifiers	1)100% 2)100%	questionnaire (Parents and teachers)	105 data	3 classes 1)ADHDmod 2)ADHDhight 3)NOADHD
2	Classification of ADHD with Deep Learning [33]	MRI and Deep Belief Network	85%	Not collected use ADHD public data	200 data	2 classes 1)ADHD 2) non-ADHD
3	Machine learning approach for the distinction of ADHD and OSA [41]	1) Decision Tree (CART) 2) Decision Three (CHAID) 3) Neural Network	1) 69.1% 2) 70.6% 3) 61.8%	Disruptive Behavior Rating Scale Form (DBRS) /Parents and teachers	227 data training group (70%=149) test group(30%=68)	2 classes 1)ADHD 2)OSA
4	A feature selection method for the classification of ADHD [38]	Feature selection algorithm 1)Relief algorithm (Relief) 2)Verification accuracy (VA-Relief) 3)Minimum redundancy maximum relevance (mRMR)	1) 77.92% 2) 80.52% 3) 98.04%	Not collected use ADHD public data	ADHD-200	2 subjects 1) Patients 2) Normal control Feature Dimension 500,1000,1500,2000,2500 and 2728

Table 2.4 Comparison of various works that applied different ML techniques (Cont.)

No	Topic	Classification Algorithm	Accuracy	Method for collecting the data/who assessment	Number of the Data set	Class
5	A Novel Application for the Efficient and Accessible Diagnosis of ADHD Using Machine Learning [30]	Feature selection algorithm	82.10%	Web-Based Application	50 cases	2 classes 1)Non-ADHD 2)ADHD
6	Efficacy of novel Summation-based Synergetic Artificial Neural Network in ADHD diagnosis, Machine Learning with Applications [45]	Neural Network MRI	72.89%	Not collected use ADHD public data	ADHD-200	2 classes 1)Positive Class 2)Negative Class
7	Heterogeneity of executive function revealed by a functional random forest approach across ADHD and ASD [15]	Random forest MRI	72.70%	DSM-5 ASD+ADHD	67 cases	2 classes 1)ASD 2)ADHD
8	Diagnosis and evaluation of ADHD using MLP and SVM classifiers [49]	1) Support Vector Machine 2)Decision tree algorithms	1)100% 2)100%	NA	NA	2 classes ADHD without ADHD
9	Machine Learning-Based Framework for Classification of Children with ADHD and Healthy Controls [42]	1) SVM 2) Random Forest 3) AdaBoost Classifier(Applied Algorithm)	1)58% 2)82% 3)84%	EEG recordings open-access database	120 children 60ADHD and 60 Healthy	2 classes 1)ADHD and 2)non-ADHD
10	Classification of ADHD with Bi-objective Optimization [50]	Support Vector Machine	92.68%	MRI	ADHD-200	2 classes 1)ADHD and 2)non-ADHD

Table 2.4 compares different machine learning algorithms which were implemented to predict and classify ADHD. In [35], the researchers used Naïve Bayes and J48 Classifier as machine learning techniques and used questionnaires to classify ADHD disease. They achieved a classification accuracy of 100% in their study. The second work used the Deep Belief Network [33], which uses the MRI method to indicate ADHD disease with a classification accuracy of 85%.

The third model used Decision Tree (CART), Decision Tree (CHAID), and Neural Network, which uses the Disruptive Behavior Rating Scale Form (DBRS). They obtained prediction accuracies of 69.1% (Decision Tree (CART)), prediction accuracies of 70.6% (Decision Three (CHAID)), and prediction accuracies of 61.8% (Neural Network) respectively [41].

The fourth model used the Feature Selection algorithm of three methods: the Relief algorithm (Relief), the Verification accuracy (VA-Relief), and the Minimum redundancy maximum relevance (mRMR). They obtained an accuracy of 77.92% (Relief), 80.52% (VA-Relief), and 98.04%(mRMR) [38].

The fifth model also used the Feature Selection algorithm, and they obtained a prediction accuracy of 82.10% [30].

The sixth model used the Neural Network algorithm, which uses the MRI method to indicate ADHD types with a prediction accuracy of 72.89% [45].

The seventh model used the Random Forest algorithm which used data from DSM-IV-TR and predicted ADHD and ASD types with an accuracy of 72.7% [15].

The eighth model used a hybrid approach integrating Support Vector Machine (SVM) and Decision Tree (DT) algorithms that served a classification accuracy and prediction accuracy of 100% and 100%, respectively [49].

The ninth model used Support Vector Machine (SVM), Random Forest, and AdaBoost Classifier (Applied Algorithm) to predict the ADHD type and they obtained an accuracy of 58%, 82%, and 84% respectively [42].

The tenth model used a Support Vector Machine and MRI and obtained an accuracy of 92.68% [50].

From Table 2.4, most of the previous work used supervised machine learning to analyze and predict ADHD classes. Although the accuracies of those works have values of more than 65% their algorithms predicted only two classes. Moreover, those workers used public data set for both unstructured and structured data.

In the case of our work, we aim to examine and find the best algorithm to predict and classify several ADHD types by using the collected and observed data from teachers and parents in real cases. We also propose an effective method for collecting the data. Compared to the previous work in Table 2.4, we use different assessment techniques for screening and predicting ADHD and ODD types. Our input data was obtained by using the standardized screening tool base on the behavior and culture of Thai children (based on the Vanderbilt Rating Scale), which was evaluated by a group of teachers. To evaluate our approach, we compared the models' results with the physicians' diagnoses.

As we show various comparisons of existing works that used different techniques of machine learning algorithms to predict and classify ADHD types and based on their accuracy and pros/cons, we selected the best four techniques from the previous work to test on our data and to find the best approach that can return the best result. For the first algorithm, we chose the Decision Tree that is best for supporting non-linear data and is straightforward to understand, and the results of the trained model are easy to interpret prediction. The second algorithm is the Naive Bay algorithm, which is a data mining classifier, with ease of training, especially with many features and extensive data; can also be used to classify multi-classes.

The third algorithm, the Neural Network algorithm, is simple to use with a few parameters to adjust and flexible. It can simulate any problem and remember a series of input-output pairs that are so complex that they cannot be replicated in a probabilistic way and respond to information that has never been seen.

The fourth algorithm is the latest K-Nearest Neighbor (KNN), which is the most easy-to-understand and straightforward technique to use and classify data.

This research's main purpose is to compare and find the best algorithm to predict and classify ADHD types from data that are obtained from the standardized screening tool, known as the Vanderbilt ADHD Diagnostic Rating Scale. This Vanderbilt screening tool will be evaluated by a group of teachers. ADHD can be seen as a classification problem to discover its various types by analyzing data from the rating scales. The input data is collected from the Vanderbilt Diagnostic Rating Scales and fed into different machine-learning models to find the best algorithm for the highest accuracy. The result of each model was compared with one another, and these results were determined by a consultant from child and adolescent psychiatry and development behavioral pediatrics.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Research Methodology

The chapter presents our proposed research methodology, research framework, classification technique for ADHD types, and the recommendation system based on behavioral therapy and activities for ADHD children.

3.1.1 Literature reviews

In this study, we study related theories and research based on the following topics. The discussion of these related works are explained in chapter 2.

3.1.1.1 Attention Deficit Hyperactivity Disorder (ADHD) Disease

3.1.1.2 Standardized screening tool for ADHD

3.1.1.3 Treatments of ADHD

3.1.1.4 Compare classification techniques

3.1.1.5 Design an algorithm for classifying types of ADHD and treatment and therapy recommendation

3.1.1.6 Others

3.1.2 Design and development of the proposed framework

In this section, we describe the concept of our proposed framework. In this framework, we have three types of participants, which are teachers, parents, and doctors. The framework provides a collaborative tool for all participants to provide collaborative information and the screening tool based on the DSM-IV standard for preliminary assessment.

3.1.2.1 Workflow of the framework

For this framework, we have three types of participants: teachers, parents, and doctors.

Table 3.1 shows roles and responsibilities of each participant in the framework. In this framework, the teacher will evaluation the students using the Vanderbilt ADHD Rating Scale (VARS) and the parents will evaluate their child using the same screening scale. Doctor will determine and validate the results from system and based on the screening results, the doctor may request to have a discussion and consultation with the teacher or parent for appropriate treatment. The system uses recorded information from teachers and parents to perform classification of ADHD types and provide recommended behavior therapy for each student based on his/her ADHD type. The recommended treatments in the recommendation system were pre-input according to the medical recommendations based on different types of ADHD (see Figure 3.1).

Table 3.1 Roles and Responsibilities of activities in the proposed framework

No	Responsibility	Role			
		Parents	Doctors	Teachers	System
1	evaluate students using the Vanderbilt Rating Scale (T.1.1)			y	
2	View the result for evaluation (T.1.2)			y	
3	record behavioral therapy (T.1.3)			y	
4	View recommendation behavioral therapy for ADHD children by type from the system(T1.4).			y	
5	evaluate ADHD children (P2.1)	y			
6	View the result for evaluation from the system (P2.2)	y			
7	View and confirm the results of ADHD classification (D3.1)		y		
8	recommend behavioral therapy for ADHD children by type (D3.2)		y		
9	view, and record discussion (D3.3)		y		

Table 3.1 Roles and responsibilities of activities in the proposed framework (cont.)

No	Responsibility	Role			
		Parents	Doctors	Teachers	System
10	give teachers consultation from the system (D3.4)		y		
11	follow up with ADHD-affected children (D3.5)		y		
12	Classification Type ADHD (SA4.1)				y
13	show the result of classify process(SA4.2)				y
14	confirm the result of classify process (the doctors) (SA4.3)				y
15	view results evaluation by the parents. (SA4.4)				y
16	view activities for ADHD appropriate to type I and II processes (SB4.1)				y
17	request discussion and consultation and view records of these actions from teacher (SB4.2)				y

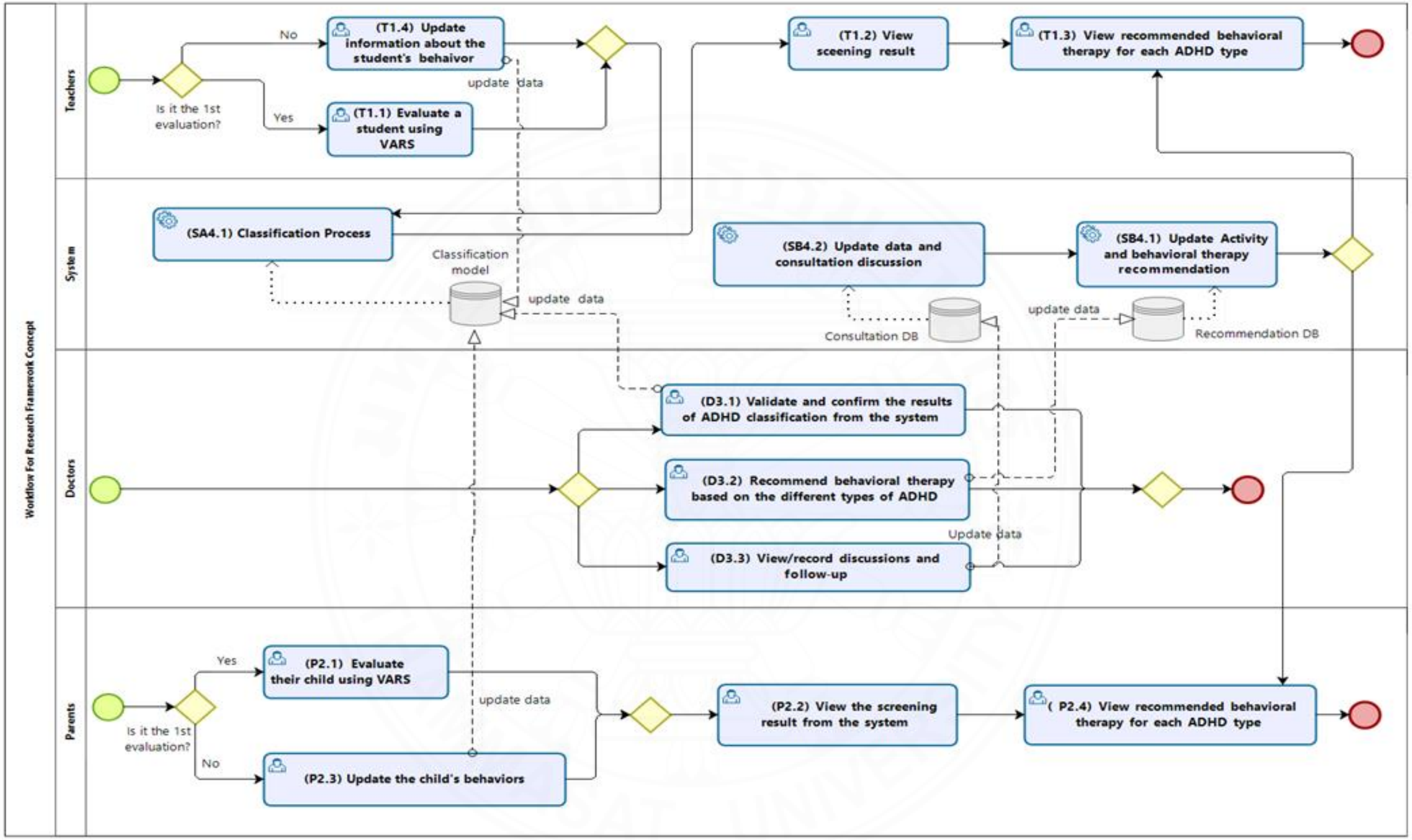

Figure 3.1 Workflow in the proposed framework

Figure 3.1 shows the workflow for this research framework. The arrows indicate the direction of the process. The overall process is described as follows:

1) For the teacher role: the teachers evaluate students using the Vanderbilt Rating Scale (refer to T.1.1 in the framework), view the result for evaluation (T.1.2), record behavioral therapy (T.1.3), consult the doctor, and view recommendation behavioral therapy for ADHD children by type from the system (T1.4).
2) For the parent role: they evaluate their child using Vanderbilt ADHD Rating Scale (P2.1) and view the result for evaluation from the system (P2.2).
3) For the doctor role: they view and confirm the results of ADHD classification from the system (D3.1) and recommend behavioral therapy based on the different types of ADHD (D3.2). They can view, and record discussions (D3.3), and give teachers consultation from the system (D3.4) including follow-up with cases (D3.5).
4) For System:

   Process A: Classification of ADHD Type (SA4.1)

   A1: the system displays the classification results and requests confirmation of the result by the doctor (SA4.2 and SA4.3) and the system displays the evaluation results by the teacher (SA4.4).

   Process B: Activity and behavioral therapy recommendation (SB4.1).

   B1: view activities for ADHD appropriate for type I and II processes (SB4.1).

   B2: request discussion and consultation and view records of these actions from the teacher (SB4.2).

3.1.3 Data Collection and Algorithms Design

In this process, we perform three tasks.

3.1.3.1 Collect data sources from parents, teachers, doctors, and advisors using questionnaires, interviews, focus groups, and social media.

3.2.3.2 Study various algorithms for classifying types of ADHD children based on The Diagnostic Statistical Manual of Mental Disorders (DSM5) Standard [5].

3.3.3.3 Design an algorithm for recommending an appropriate behavioral therapy and treatment activity.

3.1.4 Evaluation and Conclusion

3.1.4.1 Compare the system results with the evaluation based on DSM-5 standard.

3.1.4.2 Compare the system results with the evaluation from the doctor.

3.1.4.3 Conclusion

3.2 Proposed Method

This section provides a detailed explanation of process A in the framework, which mainly concerns the study of various algorithms for classifying types of ADHD children based on the Diagnostic Statistical Manual of Mental Disorders (DSM5) standard. Before starting the process of the research methodology, we approved the ethics via the Human Research Ethics Committee of Thammasat University (Science) (HREC-TUSc)) and the participant recruitment process in Figure 3.2.

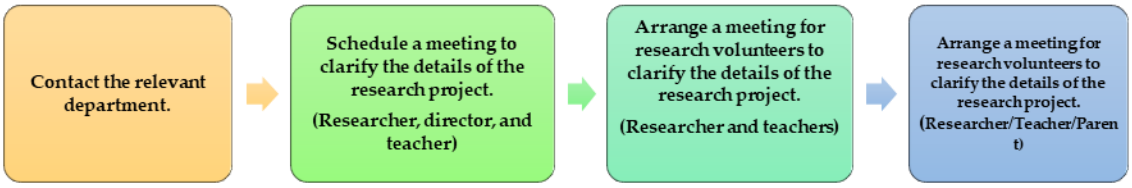

Figure 3.2 Participant recruitment process.

Figure 3.2 describes the selection and recruitment process of volunteers. The steps are as follows:

1. Ban Rat Niyom School (Jor Prayoon Upatham) was contacted with detailed documents about research work. The documents related to research work were presented to the school's director.
2. After receiving approval from the school's director, the researcher arranged a meeting to explain the details of the research process, activities, recruitment, and other information related to conducting research for the upcoming project.
3. Volunteer recruitment for teachers was conducted. After that, an appointment was made to meet and clarify the research implementation requirements. Documents relevant to the study and the activities to take place were presented throughout the research project.
4. The supervised teachers chose students. Then, they sent the parents the participant data sheet and consent letter. If the parents had any doubts regarding student participation, teachers could contact researchers to arrange meetings for clarification.

Participants were selected according to the following inclusion criteria.

(Inclusive criteria for teachers):

- Only homeroom teachers were selected, and they must have the following qualifications.

- The teachers must teach and supervise children of age 6–12 years old who study at the primary level (grade 1–6) at Ban Ratniyom School (Jorprayoon Upatham).
- The teachers have knowledge of and understand information about ADHD in children. They can assess and observe student behaviours in their supervising classes and are able to use a tool to screen behavioral/emotional problems, including the Strengths and Weaknesses Scale (SDQ, Teacher Student Behaviour Assessment Scale).

(Inclusive criteria for students):

- Students must be 6–12 years old and study at the primary level (grade 1–6) at Ban Rat Niyom School (Jor Prayun Upatham). They are in the class of the teachers under the criteria stated above. The participating teachers selected students for this study.

(Inclusive criteria for parents):

- Parents of the selected students, who were willing to participate, were included.

The exclusion criteria for research volunteers are as follows.

- Teachers who cannot participate in activities during the specified period of the research project were excluded.
- Teachers who could not assess and observe students' behaviours in their supervised classes according to the specified criteria and within the duration of the research project were excluded.
- There were no exclusion criteria for students and parents.

3.2.1 Classification of ADHD Types

The classification is proposed based on the use of the Vanderbilt ADHD Diagnostic Rating Scale and machine learning techniques. The result from the classification process is compared with the results evaluated by the consultant in child and adolescent psychiatry and development behavioral pediatrics.

3.2.1.1 Data Collection and Analysis Process

Data collection was carried out in the system by generating the dataset from the teachers, and the processes concerning the teachers are shown in Figure 3.2. The figure depicts the first step in creating the questionnaires and selecting assessment standards from the Vanderbilt ADHD Diagnostic Rating Scale (Thai version). After selecting the standard and the system sends the questionnaires to the participants to fill in the data and then the system generates dataset files.

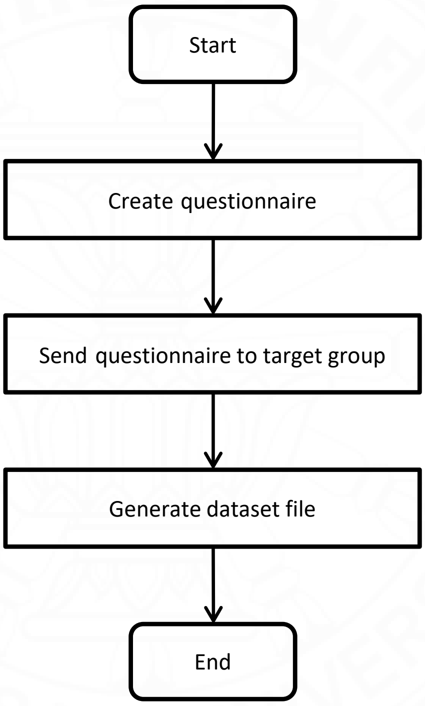

Figure 3.3 Data Collection

3.2.1.2 The Model-Generation Algorithm (Learning Algorithm and model)

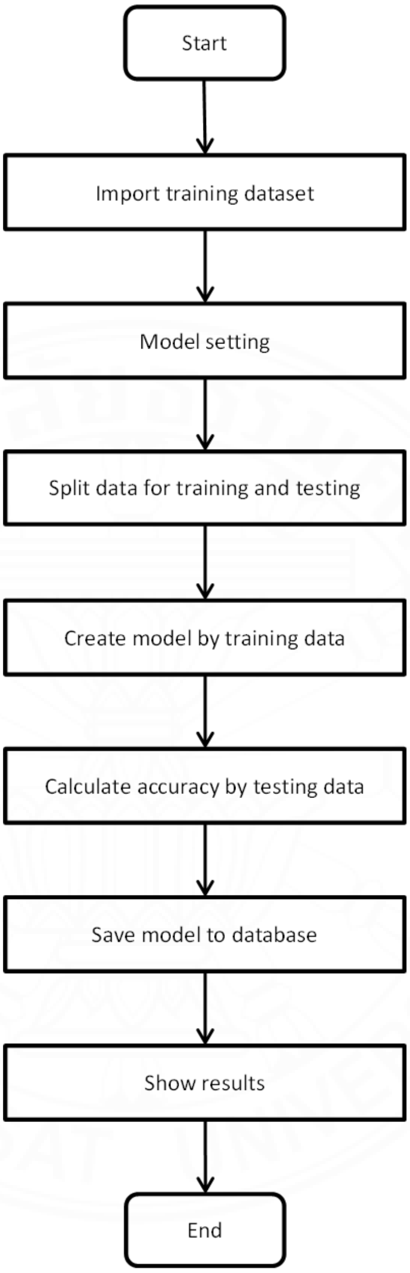

Figure 3.4 The model-generation algorithm

As shown in Figure 3.4, after receiving, recording, and analyzing the desired data from the previous process this process focuses on learning algorithm and model are : (3.1), the system further verifies the data, discards the incorrect data from the dataset, and initiates the sub-process of generating the model. The dataset is imported and split into two parts with a ratio of approximately 80% to train the models and 20% to test. Next, we feed the data to our selected algorithms in question separately, which are Decision Tree, Naïve Bayes, Neural Network, and K-Nearest Neighbor (KNN) algorithms. Consecutively, the accuracy will be obtained from the models and stored in the database.

3.2.1.3 The Prediction Process of the Algorithm (Apply the Model)

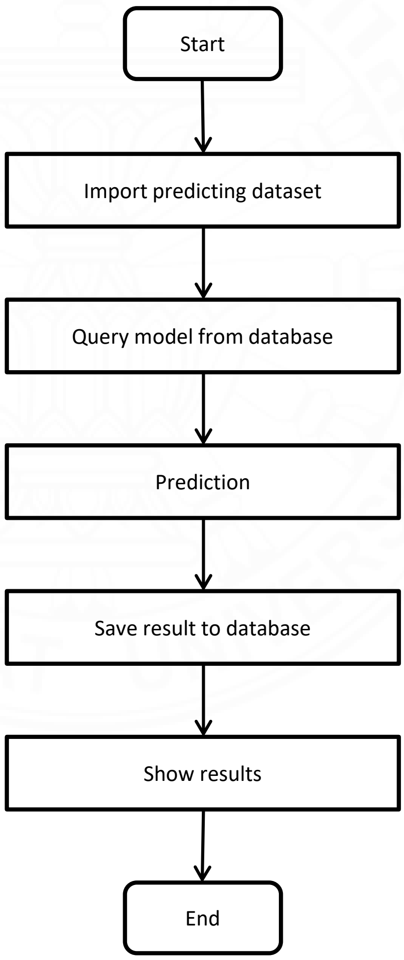

Figure 3.5 The prediction process of the model algorithm

Figure 3.5 illustrates the prediction process of the model to focus on apply the model. In the model-generation algorithm, we prepare and import the dataset to predict, and 2) this subprocess is used to query the model from the database system. After selecting the model algorithm, 3) the system prediction is saved to the database and shows the result of predicting the model algorithm.

3.2.1.4 Verification result of the predicted model

To verify the results from the classification models, we compared the models' results with the reviews and validated results from the doctor, who is a specialist in child and adolescent psychiatry and development behavioral pediatrics. We compared the accuracy and performance of all models and discovered the best classifier for classifying ADHD types for our work.

CHAPTER 4
RESULT AND ANALYSIS

The classification results and the results from the behavior therapy-based recommendation system for ADHD children from our experiments are presented in this chapter.

4.1 Analysis of the result of the classification technique for ADHD type

This section presents the classification results of the selected techniques.

4.1.1 Attribute Selection

In this work, we have data from 420 cases used as input data sets to the system. The data set was pre-processed to remove duplicates, missing data, and inconsistencies. We used the Vanderbilt ADHD Diagnostic Rating Scale, which has 52 attributes (general data, criteria) for the data set. We utilized the feature extraction approach to use the SelectPercentile module from the scikit-learn tool to decrease the number of attributes; select only important features (Selection) or convert features (Transformation) to reduce dimensions. After the data is declined dimensionally, it is processed for classification or processing. The performance of the models, we have created will be tested with datasets. By specifying the percentage of properties to be chosen rather than the number of properties to be determined. We selected the top n% percentile to acquire the whole ten properties procedure is summarized as follows:

1.Set SelectPercentile = N %

2. No. of the remaining attributes <= N%

3. Update a set of attributes based on SelectPercentile

4. Return the attribute selection result

Based on the above procedure, we can reduce the matrix dimension by using SelectPercentile equal to 40% for optimization because if it is too little, the attributes utilized to create the model will be less, making it unable to accurate data extraction. Still, too much will make the model structure too complex. From the experiment, the value of 40 gave the best result, with eight remaining attributes significant for the experiment results. The eight attributes are name, gender, age, education level, R1(Result1), R2(Result2), R3(Result3), and the projected class or output class (see Table 4.1). The classification technique detects and deletes data to improve model construction performance.

Table 4.1 ADHD attributes for the data set after processing the feature selection.

No	Attribute	Description
1	Name	Name of student ex, A1, A2
2	Gender	1.1 Boy = 160 cases 1.2 Girl = 260 cases
3	Age	6 years -12years = 420 cases
4	Education level	Grade 1-6 = 420 cases
5	R1(Result1)	Question V1-V9 (Inattention type) The total score of the answers from questionnaires by instructors in questions 1-question 9 and performance evaluation score 4 or 5 from Q36-Q43 is less than one 1. R1: yes/no
6	R2(Result2)	Question V10-V18 (Hyperactivity-Impulsivity type) The total score of the answers from questionnaires by teachers in questions 10-question 18 and performance evaluation score 4 or 5 from Q36-Q43 is less than one 1. R2: yes/no
7	R3(Result2)	Question (V19-V28) (Oppositional defiant disorder) The overall score of the answers from surveys by instructors in questions (V19-28) and performance assessment scores 4 or 5 from Q36-Q43 were less than one 1 question. R3: yes/no
8	Predicted class	0 =Mix (Mix Type) 1 =Non-ADHD (No) 2 =ODD (Oppositional defiant disorder) 3 =hyperactivity (Hyperactivity-Impulsivity type) 4 =inattention (Inattention type)

4.1.2 The diagnostic criteria of the Vanderbilt Assessment Scales

The Vanderbilt Assessment Scales [7, 8] used in this work are based on the DSM5-standard screening tool. The criteria for the Vanderbilt Assessment Scales are shown in Table 4.2. Based on diverse behaviors and characteristics, these standards can distinguish different kinds of ADHD. ADHD is classified into three types: inattention, hyperactivity-impulsivity, and mixed type (having both hyperactivity and impulsivity).

Table 4.2 The Criteria of the Vanderbilt Assessment Scales.

Description	Evaluation Criteria (DSM)
1. The number of diagnostic criteria	43(items)
2. To assess the inattention type	Q1-Q9
3. To assess hyperactivity-impulsivity type	Q10-Q18
4. To assess Oppositional defiant disorder	Q19-Q28
5. Assessment Scale (for Parents)	Require 6 (Score 2 or 3) or more conducted behavioral from(Q1-Q9) for indication of inattention type and performance assessment score 4 or 5 from Q48- Q55 less than one 1 question Require 6 (Score 2 or 3) or more conducted behavioral from(Q10-Q18) for indication of the hyperactivity-impulsivity type and performance assessment score 4 or 5 from Q48-Q55 less than one 1 question Require 4 (Score 2 or 3) or more conducted behavioral from(Q19-Q28) for indication of the hyperactivity-impulsivity type and performance assessment score 4 or 5 from Q48-Q55 less than one 1 question

Table 4.2 The Criteria of the Vanderbilt Assessment Scales(cont.).

Description	Evaluation Criteria (DSM)
6. Assessment Scale (for Teachers)	Require 6 (Score 2 or 3) or more Conducted behavioral from(Q1-Q9) for indication of inattention type and performance assessment score 4 or 5 from Q36-Q43 less than one 1 question Require 6 (Score 2 or 3) or more conducted behavioral from(Q10-Q18) for indication of the hyperactivity-impulsivity type and performance assessment score 4 or 5 from Q36-Q43 less than one 1 question Require 3 (Score 2 or 3) or more conducted behavioral from(Q19-Q28) for indication of the hyperactivity-impulsivity type and performance assessment score 4 or 5 from Q36-Q43 less than one 1 question

4.1.3 Confusion Matrix

In classification works, a confusion matrix is widely used for performance measurement. The confusion matrix is a table of size *n* by *n* was given *n* classes. If the incident is positive and classified as such, it is considered a true positive (TP). It is considered a false negative if it is labeled as negative (FN). If the incident is negative and characterized as such, it is considered a real negative (TN). If it is classed as positive, it is considered a false positive (FP).

A confusion matrix for a two-classes classification problem is shown in Table 4.3. The numbers along the diagonal, from upper-left to lower-right, reflect correct decisions, whereas the numbers outside of this diagonal represent errors.

Table 4.3 Confusion matrix of two classes

Predicted Class			
True/Actual		A1	A2
	A1	TP	FN
	A2	FP	TN

The True Positive and True Negative values estimate a classifier's overall accuracy. Other aggregated performance indicators are calculated using recall (sensitivity), specificity, and the F-measure. As defined below, many performance measurements are calculated.

$$\text{Classifier Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{4.1}$$

$$\text{True Positive Rate (TPR)} = \frac{TP}{TP+FN} \tag{4.2}$$

$$\text{True Negative Rate (TNR)} = \frac{TN}{TN+FP} \tag{4.3}$$

$$\text{Recall (RC)} = \frac{TP}{TP+FN} \tag{4.4}$$

$$\text{Precision (PR)} = \frac{TP}{TP+FP} \tag{4.5}$$

$$\text{F1-score (F1)} = \frac{2*(\text{Precision}+\text{Recall})}{(\text{Precision}+\text{Recall})} \tag{4.6}$$

$$\text{Average Accuracy} = \frac{\sum_{i=1}^{l} \frac{TP_i + TN_i}{TP_i+FN_i+FP_i+TN_i}}{l} \tag{4.7}$$

The classifier accuracy (Equation 4.1) is a measurement used to assess which model is best at recognizing correlations and patterns between variables in a dataset based on inputs (or training data). The good classification model should have high accuracy.

Equation (4.2) shows True Positive Rate or Sensitivity, which refers to the probability of a positive test, conditioned on truly being positive.

Equation (4.3) shows True Negative Rate or Specificity, which refers to the probability of a negative test, conditioned on truly being negative.

Equation (4.4) shows recall (sensitivity or true positive rate), which is a measure of our model correctly identifying True Positives.

Equation (4.5) shows precision, which is a ratio between the True Positives and all the Positives.

Equation (4.6) shows F1-score, which is a metric that takes into account both precision and recall precision. (from 0 to 9, 0 being the lowest and nine being the highest) is a mean of an individual's performance in the model)

Equation (4.7) shows the average accuracy, which is the average effectiveness per class of the classifier.

Tables 4.4 to 4.7 show the confusion matrix of four classifiers using 84 cases of test data.

Table 4.4 The Confusion Matrix of the Decision Tree Classifier

	Vanderbilt	Predicted				
True / Actual	Decision Tree	Mix-type	Non-ADHD	ODD	hyperactivity	inattention
	Mix-type	46	0	0	0	1
	Non-ADHD	0	7	0	0	0
	ODD	0	0	3	0	0
	hyperactivity	0	0	0	8	0
	inattention	0	0	0	0	19

Table 4.4 shows the test data that was returned by using the Decision Tree Classifier. The results consist of five classes: 1) Mix-type (46 cases) and incorrect (inattention 1 case), non-ADHD (7 cases), ODD (3 cases), hyperactivity (8 cases), and inattention (19 cases).

Table 4.5 The Confusion Matrix of the KNN Classifier

True / Actual	Vanderbilt	Predicted				
	KNN	Mix-type	Non-ADHD	ODD	hyperactivity	inattention
	Mix-type	44	0	0	0	3
	Non-ADHD	0	7	0	0	0
	ODD	0	0	3	0	0
	hyperactivity	0	0	0	8	0
	inattention	0	0	0	0	19

Table 4.5 shows the test data that was returned by using the KNN classifier. The results consist of five classes: 1) Mix-type (44 cases) and incorrect (inattention 3 cases), non-ADHD (7 cases), ODD (3 cases), hyperactivity (8 cases), and inattention (19 cases).

Table 4.6 The Confusion Matrix of the Naïve Bay classifier

True / Actual	Vanderbilt	Predicted				
	Naïve Bay	Mix-type	Non-ADHD	ODD	hyperactivity	inattention
	Mix-type	34	0	0	0	13
	Non-ADHD	0	7	0	0	0
	ODD	0	0	3	0	0
	hyperactivity	0	0	0	8	0
	inattention	0	0	0	0	19

Table 4.6 shows the test data returned from using the Naïve Bay classifier. The results consist of five classes: 1) Mix-type (34 cases) and incorrect (inattention 13 cases), non-ADHD (7 cases), ODD (3 cases), hyperactivity (8 cases), and inattention (19 cases).

Table 4.7 The Confusion Matrix of the Nerul Network Classifier

True / Actual	Vanderbilt	Predicted				
	Nerul Network	Mix-type	Non-ADHD	ODD	hyperactivity	inattention
	Mix-type	46	0	0	0	1
	Non-ADHD	0	7	0	0	0
	ODD	0	0	3	0	0
	hyperactivity	0	0	0	8	0
	inattention	0	0	0	0	19

Table 4.7 shows the test data returned from using the Naïve Bay classifier. The results consist of five classes: 1) Mix-type (46 cases) and incorrect (inattention 1 case), non-ADHD (7 cases), ODD (3 cases), hyperactivity (8 cases), and inattention (19 cases).

4.1.4 Cross-Validation Summary and Accuracy

Table 4.8 shows the Cross-Validation Summary of the four classifiers and Table 4.9 show statistical data analysis of the ADHD classes. It also shows a comparison of outcomes between the system results and the validated results from a doctor who is a specialist in the field of child adolescent psychiatry and development behavioral pediatrics. For this experiment, we used 336 records of training data (80%), 84 records of test data (20%), and 420 cases for doctor-confirmed outcomes.

Table 4.8 The Cross-Validation Summary of the four Classifiers.

No	Type of ADHD	Vanderbilt Rating Scale	
		Validated and Confirmed Results by Doctor	Test Data
0	Mix -Type	235	47
1	Non-ADHD	35	7
2	ODD	15	3
3	hyperactivity	40	8
4	inattention	95	19
Total(cases)		420	84

The validated results from the doctor are categorized into classes as follows; 1) Mix-type (47 cases), non-ADHD (7 cases), ODD (3 cases), hyperactivity (8 cases), and inattention (19 cases).

Table 4.9 Statistical data analysis of the ADHD classes.

No	Type of ADHD	Data	Number of data	%	All data
0	Mix -Type	train	188	80	235
		test	47	20	
1	Non-ADHD	train	28	80	35
		test	7	20	
2	ODD	train	12	80	15
		test	3	20	
3	hyperactivity	train	32	80	40
		test	8	20	
4	inattention	train	76	80	95
		test	19	20	

Table 4.10 A comparison of results of four classifiers.

No	Type of ADHD	Test	Decision Tree				KNN				Naive Bayes				Neural Network			
			Cor	%	Inc	%	Cor	%	Inc	%	Cor	%	Inc	%	Cor	%	Inc	%
0	Mix-type	47	46	97.87	1	2.13	44	93.62	3	6.38	34	72.34	13	27.66	46	97.87	1.00	2.13
1	Non-ADHD	7	7	100.00	0	0.00	7	100.00	0	0.00	7	100.00	0	0.00	7	100.00	0.00	0.00
2	ODD	3	3	100.00	0	0.00	3	100.00	0	0.00	3	100.00	0	0.00	3	100.00	0.00	0.00
3	hyperactivity	8	8	100.00	0	0.00	8	100.00	0	0.00	8	100.00	0	0.00	8	100.00	0.00	0.00
4	inattention	19	19	100.00	0	0.00	19	100.00	0	0.00	19	100.00	0	0.00	19	100.00	0.00	0.00
Total (case)		84		99.57		0.43		98.72		1.28		94.47		5.53		99.57		0.43
% Total Cases			99.57				98.72				94.47				99.57			

Ps: Cor =%Correct ,Inc=%Incorrect

Table 4.11 Performance comparison of four classifiers.

No	Type of ADHD	Decision Tree						KNN						Naive Bayes						Neural Network					
		TPR	TNR	PR	RC	AC	F1	TPR	TNR	PR	RC	AC	F1	TPR	TNR	PR	RC	AC	F1	TPR	TNR	PR	RC	AC	F1
0	Mix-type	0.98	0	1	0.98	0.99	0.99	0.94	0	1	0.94	0.96	0.97	0.72	0	1	0.72	0.85	0.84	0.98	0	1	0.98	0.99	0.99
1	Non-ADHD	1	0	1	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1
2	ODD	1	0	1	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1
3	hyperactivity	1	0	1	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1
4	inattention	1	0.02	0.95	1	0.99	0.97	1	0.05	0.86	1	0.96	0.93	1	0.2	0.59	1	0.85	0.75	1	0.02	0.95	1	0.99	0.97
Average Accuracy		0.996						0.984						0.94						0.996					

Ps: TPR= Rate of True Positive, FPR =True Negative, PR= Precision, Rc=Recall and AC=accuracy

Table 4.10 shows a comparison of the four classifiers' results. The Decision Tree method and the Neural Network algorithm provide 99.57% of accuracy. The K-Nearest Neighbor (KNN) algorithm achieves up to 98.72% of accuracy. The Naive Bay algorithm achieves 94.47% of accuracy. Therefore, based on the results in Table 4.9, The Decision Tree and the Neural Network models provide the highest accuracy for our data set.

Table 4.11 shows a performance comparison of four classifiers. The average accuracy of Decision Tree methods and the Neural Network algorithms is 99.6%. The K-Nearest Neighbor (KNN) has an average accuracy of 98.40% and the Naive Bay technique has an average accuracy of 94.00%.

4.1.5 Discussion and Conclusion The result of the classification technique for ADHD type

In this work, we aimed to find the best classifier for classifying ADHD types. We used 420 cases for our data set, and we applied four machine learning algorithms for result comparisons. The algorithms are Decision Tree, Nave Bayes, Neural Network, and K-Nearest Neighbor (KNNs). We validate the classifiers' results with the validated data obtained from the doctor, who is a specialist in child and adolescent psychiatry and development behavioral pediatrics. We also tested the models' performances based on the five classes recommended in the Vanderbilt standard. The five classes of ADHD are Mix-type, Non-ADHD, ODD, hyperactivity, and inattention.

The average accuracy of the classification is 99.60% by the Decision Tree and the Neural Network models. The K-Nearest Neighbor (KNN) provides average accuracy of 98.40%, whereas the Naive Bay provides average accuracy of 94.00%. Furthermore, as shown in Table 4.10, the Decision Tree and the Neural Network models produce the same values of TPR is 100%, FPR is 0.02%, and Recall, Precision, and F1-score for five classes. The value of TPR, Recall, and F1 scores are greater than 97% The precision is 95% and the FPR is 0.02%, indicating the probability of true negative testing negative is lower.

(Number 0 to 9, which 0 being the lowest and nine being the highest, is a mean of an individual's performance in the model)

The classification results of the K-Nearest Neighbor (KNN) algorithm are as follows: The TPR shows 100% for all cases but 0.94% for the Mix-type, FPR shows 100% for all cases but 0.05% for the inattention, Recall shows 100% for all cases but 0.86% for the inattention, Precision shows 100% for all cases but 0.94% for the Mix-type, and F1-score of five classes has value greater than or equal to 93%. The FPR of KNN in this experiment is greater than the FPR values of other algorithms.

4.16 Using the algorithm experiments, the activity recommendation process

From the previous experiments to find the best classifier for classifying ADHD types. The average accuracy of the classification is 99.60% by the Decision Tree and the Neural Network models. We chose the decision tree algorithm because the value of the F1 score is greater than 97% The precision is 95% and the FPR is 0.02, indicating the probability of true negative testing negative is lower. From several data sets experiments, we found that the decision tree algorithm gave prediction accuracy close to the results of each experiment. However, the main reason that we chose Decision Tree is because we found that it also provides better computation time compared to the neural network model. Table 4.12 shows an example of computation time offered by the Decision Tree and neural network from our experiments.

Table 4.12 Comparison of model time between the DT and neural network models.

No.	Computation Time	
	Decision Tree Model	Neural Network
1	0.031229	1.040929
2	0.055537	1.110908
3	0.061133	1.175104
4	0.051996	2.634261
5	0.074594	1.068259
6	0.052359	1.24145

Table 4.12 Comparison of model time between the DT and neural network models (cont.).

No.	Computation Time	
	Decision Tree Model	Neural Network
7	0.050016	1.313238
8	0.047997	1.392138
9	0.073211	1.600991
10	0.078132	2.092879
11	0.058697	1.389741
12	0.057674	1.334164
13	0.062324	1.848112
14	0.082012	1.639582
15	0.091128	1.899683
16	0.070998	1.397739
17	0.044996	1.257645
18	0.058901	1.204572
19	0.045997	1.127632
20	0.056571	1.180286
21	0.049337	1.2724
22	0.063612	1.046959
23	0.064478	1.25124
24	0.063231	1.501523
25	0.063992	3.656594
26	0.083996	1.15601
27	0.058533	1.216549
28	0.050994	1.071333
29	0.048935	1.203264
30	0.048	1.352984
31	0.047018	1.296979
32	0.081719	1.195881
33	0.045019	1.038161
34	0.052759	1.117537
35	0.048993	1.120578
36	0.063812	1.11737
37	0.053889	1.229534
38	0.054619	1.55222
39	0.050994	1.119644
40	0.060458	1.255233
41	0.051103	1.493202
42	0.050003	1.005049
43	0.05909	1.304165

Table 4.12 Comparison of model time between the DT and neural network models (cont.).

No.	Computation Time	
	Decision Tree Model	Neural Network
44	0.052995	1.251586
45	0.061735	1.457659
46	0.050007	1.086125
47	0.052067	1.379029
48	0.051687	1.133587
49	0.050996	1.049925
50	0.044999	1.177412
51	0.064901	1.06846
52	0.056602	0.970769
53	0.051998	1.345009
54	0.046708	1.189245
55	0.047584	1.125525
56	0.089003	1.555476
57	0.0625	2.134213
58	0.086094	2.15842
59	0.068346	1.812286
60	0.059886	1.31289
61	0.0644	1.274483
62	0.053056	1.663544
44	0.052995	1.251586
45	0.061735	1.457659
46	0.050007	1.086125
47	0.052067	1.379029
48	0.051687	1.133587
49	0.050996	1.049925
50	0.044999	1.177412
51	0.064901	1.06846
52	0.056602	0.970769
53	0.051998	1.345009
54	0.046708	1.189245
55	0.047584	1.125525
56	0.089003	1.555476
57	0.0625	2.134213
58	0.086094	2.15842
59	0.068346	1.812286
60	0.059886	1.31289
61	0.0644	1.274483

Table 4.12 Comparison of model time between the DT and neural network models (cont.).

No.	Computation Time	
	Decision Tree Model	Neural Network
62	0.053056	1.663544
63	0.077142	1.632083
64	0.084134	2.141111
65	0.074552	1.464199
66	0.057663	1.094026
67	0.048291	1.640016
68	0.044992	1.486279
69	0.049449	1.069333
70	0.046227	1.450437
71	0.063584	1.509127
72	0.075065	1.465219
73	0.047998	1.345517
74	0.047002	1.229406
75	0.056996	1.622626
76	0.048608	1.10312
77	0.046375	1.286845
78	0.047895	1.19502
79	0.054994	1.117199
80	0.074998	1.395097
81	0.05399	1.271263
82	0.053778	1.882056
83	0.065562	1.208384
84	0.055619	1.22781
85	0.047999	1.047544
86	0.048203	1.251664
87	0.04885	1.160577
88	0.050631	0.874186
89	0.055177	1.260275
90	0.049021	1.201123
91	0.044018	1.254685
92	0.046995	1.244649
93	0.047016	1.05943
94	0.052024	0.944234
95	0.042279	1.299954
96	0.059698	1.503714
97	0.047133	1.13383
98	0.060916	1.063454

Table 4.12 Comparison of model time between the DT and neural network models (cont.)

No.	Computation Time	
	Decision Tree Model	Neural Network
99	0.047019	0.98657
100	0.05708	1.087645
Average computation time	0.057146	1.348791

In this section, we compare the output to the decision tree plot in Figure 4.1, define the parameter in the tree, and produce the three graphs in the following step.

Step 1: Calculate the Gini Impurity before extracting the target column. (Buying costumes)

Gini as a whole = 1 - (probability of not) ^{2} - (probability of yes) ^{2}

Step 2: Select Properties to calculate the Gini Split (amount of impurity for a specific split).

Step 3 - Calculate Gini Gain (Amount of Impurity Removed using Characteristic Isolation)

Tree splitting begins with the Node - Gender columns. Data repartitioning continues until each region in the leaf partition has a higher Gini Gain (relatively higher Gini Gain is specific property extraction). There is only one target value in the decision tree (single regression value or single class). A pure tree leaf is one that has all data points that have the same target value.

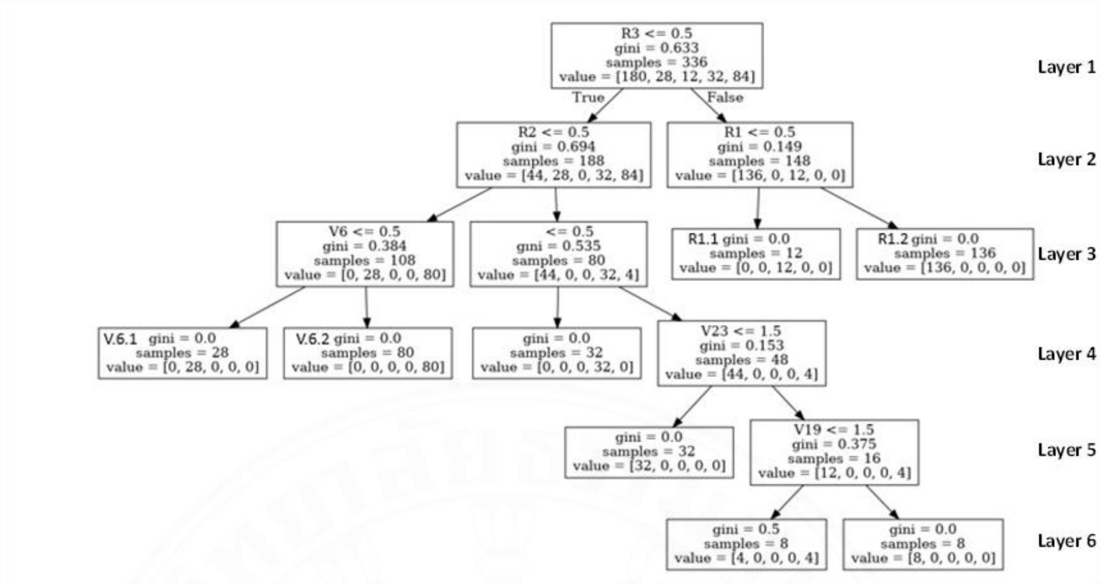

Figure 4.1 The decision tree graph

The parameter in the tree graph

1) Samples Parameter is the number of data items compatible with that node, so as the decision moves down the depth of the tree, the number of samples of a node in each layer tends to decrease over time.

2) Gini indicates the "purity" of a Node, where Gini = 0 means that all data items in the node belong to the same class. In comparison, Gini = 0.5 standards that data items in the node belong to two similar types, represented through values such as value R1= value [136,0,12 0, 0] in the child node to the right of the root node, meaning that out of 148 entries satisfying this node condition. If the answer is false (child node left R1) value [0,0,12 0, 0], There are 12 entries in Class ODD, but if the answer is true value [136,0,0,0,0] (child node right R1) and 136 entries in Class Mix-Type. It assumes that data that meets this node's condition is in class ODD and Mix-type.

3) Value is indicated class of predicted activities by ADHD type. The activities of the five classes are;1) Mix-type (index [0]), non-ADHD (index [1]), ODD (index [2]), hyperactivity (index [3]) and inattention (index [4]).

Table 4.13 Decision tree structure

No	Node	Gini Value	Left node	Right node	sample	Value				
						Mix-type index [0]	Non-ADHD (index [1])	ODD (index [2])	hyperactivity (index [3])	inattention (index [4])
1	R3	0.633	R2	R1	336	180	28	12	32	84
2	R2	0.694	V6	R1_2	188	44	28	0	32	84
3	R1	0.149	R1.1	R.1.2	148	136	0	12	0	0
3.1	R1.1	0.0	no	no	12	0	0	12	0	0
3.2	R.1.2	0.0	no	no	136	136	0	0	0	0
4	V6	0.384	V6.1	V6.2	108	0	28	0	0	80
4.1	V6.1	0.0	no	no	28	0	28	0	0	0
4.2	V6.2	0.0	no	no	80	0	0	0	0	80
5	R1_2	0.535	R1_2.1	V23	80	44	0	0	32	4
5.1	R1_2.1	0.0	no	no	32	0	0	0	32	0
6	V23	0.153	V23.1	V19	48	44	0	0	0	4
7	V19	0.375	V19.1	V19.2	16	12	0	0	0	4
7.1	V19.1	0.5	no	no	8	4	0	0	0	4
7.2	V19.2	0.0	no	no	8	8	0	0	0	0

Table 4.11 shows the structure of a decision tree. The end result has six layers: 1) The first layer is made up of a root node, R3, a left node (R2), and a right node (R3) (R1). The second layer is made up of R2 (if the response is yes) and R1 (if the answer returns false).

The third layer is made up of V6 (if the response is true), R1 2 (if the answer is false), R1.1 (left node R1), and R1.2 (right node R1). The fourth layer is made up of V6.1 (left node V6) and V6.2 (right node V6), R1 2.1 (left node R1), and V23 (right node R1);

the fifth layer is made up of V23.1 (left node V23) and V23.2 (right node V23) (right node V23). V19.1 (left node V19) and V19.2 make up the six-layer (right node V19)

4.2 Behavioral therapy recommendation for ADHD children

This section explains how the system recommends activities and behavioral therapy for ADHD children based on a different types of ADHD.

4.2.1 Activity recommendation process

In this process, the system will recommend appropriate activity and behavioral therapy based on the classified type of ADHD child. Table 4.13 shows various activities recommended for each ADHD type.

Table 4.14 Recommending activities and behavior therapy for different ADHD types

No	ADHD Type	Activities	Description
1	Mix-type	AOCD and AMOD	Organization and Discipline Activities and Medication Activities
2	hyperactivity	AOCD	Activities Organization/ Discipline Activities
3	inattention	AMOD	Activities Medication Activities
4	ODD	ACB	Activities Control Behavioral
5	Non-ADHD	NO- Activities	Non-ADHD

Table 4.13 shows recommended activities for ADHD children by type as defined below. (Recommend by the doctor)

1. Mix-type is symptom hyperactivity-impulsivity and inattention type of ADHD; the activities focus on organization and discipline activities (AOCD) and medication activities (AMOD).
2. Hyperactivity is a symptom of a hyperactivity-impulsivity type of ADHD; the activities focus on organization and discipline activities (AOCD).

3. Inattention is a symptom of a lack of concentration; the activities focus on increasing concentration activities (AIC).
4. ODD is Oppositional defiant disorder ADHD; the activities focus on control behavior (ACB).

Table 4.15 Confusion matrix of the Decision Tree classifiers (Recommend Activities)

		Predicted				
	Decision Tree	Mix- (AOCD+ AMOD+ ACB)	hyperactivity (AOCD)	inattention (AIC)	ODD (ACB)	Non-ADHD (No)
True / Actual	Mix-type (AOCD+ AMOD+ ACB)	46	0	1	0	0
	hyperactivity (AOCD)	0	8	0	0	0
	inattention (AIC)	0	0	19	0	0
	ODD (ACB)	0	0	0	3	0
	Non-ADHD (No)	0	0	0	0	7

According to Table 4.13, the Decision Tree classifiers return test data. The outcomes are divided into five categories: 1) There are 46 cases of mix-type (AOCD+ AMOD+ ACB) and 1 case of incorrect (inattention (AMOD)), 8 cases of hyperactivity (AOCD), 19 cases of inattention (AMOD), and 7 cases of non-ADHD (No).

Table 4.16 Performance Metric of The Decision tree classifiers

No	Type of ADHD	Decision Tree					
		TPR	TNR	PR	RC	AC	F1
0	Mix-type (AOCD+ AMOD+ ACB)	0.98	0	1	0.98	0.99	0.99
1	hyperactivity (AOCD)	1	0	1	1	1	1
2	inattention (AIC)	1	0	1	1	1	1
3	ODD (ACB)	1	0	1	1	1	1
4	Non-ADHD (No)	1	0.02	0.95	1	0.99	0.97
Accuracy average		0.996					

Table 4.15 displays the Performance Metrics of the Decision Tree algorithms, which produced TPR, FPR, Recall, Precision, and F1-score (five class) values greater than 0.97. (TPR, Recall, and F1-score). Nonetheless, the precision is 0.95, the FPR is 0.02, the probability that a true negative will test negative is low, and the average accuracy is 0.996.

4.2.2 Discussion and Conclusion

This is a continuing study, and the data reported in this section represent the second round of results from activities prescribed experiments. We selected three decision algorithms for processing activity recommendations suitable for ADHD children. The extraction of decision trees does not tend to equalize or standardize features. Furthermore, the Decision Tree method performs best for features that span scales and have a smart, continuous blend of constituents. The main disadvantage of decision trees is that they are pruned at an early stage. However, it is frequently overcrowded and has poor summation performance. As a result, in most applications, ensemble methods are used instead of single decision trees.

The results are returned. The precision is 0.95, the FPR is 0.02, the probability that a true negative would test less minor, and the average accuracy is 0.996. In the future, we intend to expand the data set and conduct more tests with others to construct and create an efficient plan of sub-activities that will benefit individuals with ADHD in the long term.

CHAPTER 5
CONCLUSION AND FUTURE WORK

5.1 Conclusion

In this research, we aim to overcome the mentioned problems by proposing a methodology and a framework that teachers or parents can use to evaluate and screen their children's behaviors and determine if they are consistent with any ADHD. The framework also provides recommendations for appropriate treatments for different types of ADHD children. 1) to design a framework and develop a tool for observing and recording behavioral symptoms of ADHD children that doctors can use for parents and teachers. 2) to introduce practical algorithms for classifying ADHD types and recommending appropriate individual behavioral therapies and activities. Our framework introduces a combined technique for ADHD classification using machine learning and a rough set approach.

The expected outcome of our proposed framework is to provide an effective way to screen and classify types of ADHD and recommend appropriate treatments and therapy based on individual behaviors.

Our proposed research methodology, literature reviews, design and development of the proposed framework, Data Collection, algorithms design and evaluation, and conclusion. This is an ongoing study with two experiments. 1) In the first experiment, we used machine learning to classify ADHD types using four algorithms: Decision Tree, Nave Bayes, Neural Network, and K-Nearest Neighbor (KNNs) algorithms with doctor-verified criteria and criteria from the ADHD Standardized Screening Tool; the Vanderbilt Assessment Scale and selected the best techniques to classify types of ADHD.

The result shows in Table 4.9 of four Vanderbilt ADHD Diagnostic Rating Scale classifiers (chapter 4). The classification accuracy average of 99.60% was achieved by the Decision Tree and the Neural Network algorithms. Still, The K-Nearest Neighbor (KNN) approach had a classification accuracy average of 98.40 %, whereas the Naive Bay technique had a classification accuracy average of 94.00%. Therefore, we used the Decision Tree and the Neural Network algorithms for our classification in our framework. For the activity and behavioral therapy recommendation part, we also use the Decision Tree for recommending suitable activities and behavioral therapies for each type of ADHD child because based on many experiments and performance metrics, the Decision Tree showed the best performance and robustness. From several data sets and experiments, we found that the Decision Tree algorithm gave prediction accuracy close to the results of the investigation by doctors.

5.2 Future work

To improve our framework, we would like to generate and expand the data collection and conduct further experiments to design and build more efficient plan of sub-activities based on different ADHD type. Although the current work can achieve high accuracy for classifying ADHD types, but some cases still need to be improved (e.g., classifying an Inattention type and Mix-type). For future work, we plan to train the model for different scenarios and try to enhance the model's accuracy and UX/UI design based on feedbacks from users (e.g., teachers and doctors).

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APPENDIX

APPENDIX A

CERTIFICATE OF APPROVAL FROM THE HUMAN RESEARCH ETHICS COMMITTEE OF THAMMASAT UNIVERSITY(SCIENCE), (HREC-TUSC)

ScF 03_01 (Eng)

The Human Research Ethics Committee of Thammasat University (Science), (HREC-TUSc) Room No 110, Piyachart Building, 1st Floor, Thammasat University Rangsit Campus, Prathumthani 12121 Thailand, Tel: 0-2564-4440 ext.7358 E-mail: ecsctu3@tu.ac.th

COA No. 061/2565

Certificate of Approval

Project No. : 032/2565
Title of Project : Development of an Application for Screening and Providing Care Information for ADHD Children
Principle Investigator : Miss Pornsiri Chatpreecha
Place of Proposed Study/Institution: Sirindhorn International Institute of Technology, Thammasat University

The Human Research Ethics Committee of Thammasat University (Science), Thailand, has approved the above study project in accordance with the compliance to the Declaration of Helsinki, the Belmont report, CIOMS guidelines and the International practice (ICH-GCP).

Signature: Jinda Wzblul	Signature: Laksana Lakt
(Assoc. Prof. Jinda Wangboonskul, Ph.D.)	(Assoc. Prof.Laksana Laokiat, Ph.D.)
Chairman of the Human Research Ethics Committee of Thammasat University (Science).	Secretary of the Human Research Ethics Committee of Thammasat University (Science).

Date of Approval: July 27, 2022 **Approval Expire date:** July 26, 2023
Progressing Report Due: June 27, 2023

The approval documents including
1) Research proposal
2) Patient/Participant Information Sheet and Informed Consent Form
3) Principal Investigator's Curriculum Vitae
4) Development of an Application for Screening and Providing Care Information for ADHD Children
5) Vanderbilt ADHD diagnostic rating scale

ScF 03_01 (Eng)

The approved investigator must comply with the following conditions:

1. Researcher fully understand that it is unethical to collect studied data before the protocol has been approved by The Human Research Ethics Committee of Thammasat University (Science), (HREC-TUSc).
2. The research protocol activities must be ended on the approval expired date. If require to extend the approval, application should be done along with research progress report not less than one month prior to expiry date.
3. The researcher(s) must strictly conduct the research activities as mentioned in the proposal.
4. The researcher(s) must submit the progress report according to schedule (ScF 09_01 Progress Report Form).
5. Use only the participant information sheet, consent form, research tools, advertising leaflet (If any) that have been approved and stamped by the HREC-TUSc's seal of approval.
6. Report to HREC-TUSc for any serious adverse events within 5 working days (ScF 10_01)
7. Report to HREC-TUSc if any changes of the protocol for approval prior to continue the activities (ScF 08_01 Protocol Amendment Form).
8. Submit the final report (ScF 11_01 Protocol Final Report Form) within 30 days after the completion of the research.

BIOGRAPHY

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Publications

Chatpreecha, P., & Usanavasin, S. (2023, July). A Design of a Collaborative Knowledge Framework for Personalized Attention Deficit Hyperactivity Disorder (ADHD) Treatments. In *Children* (ISSN 2227-9067) on 23 July 2023

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