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Research Article / Araştırma Makalesi

Automatic Diagnosis of Psychiatric Diseases in Adolescents with Machine Learning Methods using DsmV and Various Scales

DsmV ve Çeşitli Ölçekler Kullanılarak Ergenlerde Psikiyatrik Hastalıkların Makine Öğrenmesi Yöntemleri ile Otomatik Teşhisi

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Abstract

Adolescence is a difficult time for both teenagers and their families, they will experience fewer collisions. Teenagers sometimes want to be left alone. During this time, young people need to be recognized and valued. Teenagers are sad and pessimistic. Above all, young people need to feel understood and valued. Otherwise, adolescents need another environment to satisfy these feelings. Adolescence is a difficult time in life and a psychologically difficult period for the individual and the family. Youth is an important factor in the development of a country in all areas. For this reason, puberty should be managed appropriately and a prompt diagnosis/treatment process should be applied if a psychiatric illness occurs. The diagnosis of mental illness is also based on expert observation and requires good expertise. Of course, these systems are decision support systems and the final decision is left to the experts. In this study, we used machine learning to research machine learning for the automated processing of mental illness during the difficult life stages of adolescence. The results obtained are very fruitful and promising in this field and will constitute an important resource for scientists. In our dataset, the TLC+RF machine learning model (accuracy: 82%, ROC area: 0.925, TP: 0.82, FP: 0.037) achieved high classification success rates at all scales, demonstrating that computer-assisted diagnostic systems can be used in the diagnosis of adolescent psychiatric disorders.

Keywords: Psychiatric illnesses in adolescents, Automatic diagnosis, Deep learning, DSMV.

Öz

Ergenlik dönemi hem gençler hem de aileleri için zor bir dönemdir, daha az çarpışma yaşayacaklardır. Gençler bazen yalnız kalmak isterler. Bu dönemde gençlerin tanınmaya ve değer görmeye ihtiyaçları vardır. Gençler üzgün ve karamsardır. Her şeyden önce gençlerin anlaşıldıklarını ve değer gördüklerini hissetmeye ihtiyaçları vardır. Aksi takdirde, ergenler bu duygularını tatmin etmek için başka bir ortama ihtiyaç duyarlar. Ergenlik, yaşamın zor bir dönemidir ve birey ve aile için psikolojik olarak zor bir dönemdir. Gençlik, bir ülkenin her alanda gelişmesinde önemli bir faktördür. Bu nedenle ergenlik uygun bir şekilde yönetilmeli ve psikiyatrik bir hastalık ortaya çıktığında hızlı bir tanı/tedavi süreci uygulanmalıdır. Ruhsal hastalık tanısı da uzman gözlemine dayanır ve iyi bir uzmanlık gerektirir. Elbette bu sistemler karar destek sistemleridir ve son karar uzmanlara bırakılır. Bu çalışmada, ergenlik döneminin zorlu yaşam evrelerinde akıl hastalığının otomatik olarak işlenmesi için makine öğrenimini araştırmak için kullandık. Elde edilen sonuçlar bu alanda oldukça verimli ve umut vericidir ve bilim insanları için önemli bir kaynak oluşturacaktır. Veri setimizde TLC+RF makine öğrenmesi modeli (doğruluk: %82, ROC alanı: 0,925, TP: 0,82, FP: 0,037) tüm ölçeklerde yüksek sınıflandırma başarı oranları elde ederek bilgisayar destekli tanı sistemlerinin ergen psikiyatrik bozukluklarının tanısında kullanılabileceğini göstermiştir.

Anahtar Kelimeler: Ergenlerde psikiyatrik hastalıklar, Otomatik tanı, Derin öğrenme, DSMV.

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1. Introduction

One significant life shift is adolescence. Along with physical changes, this transitory stage also involves emotional and psychological changes. Among the key elements that demonstrate how adolescence will be influenced are early childhood experiences, schooling, parental attitudes, and family history. Adolescents are most likely to suffer from anxiety disorders, depressive disorders, mood disorders, attention-hyperactivity disorders, obsessive-compulsive disorders, behavioral disorders, risky behaviors (such as young pregnancy or behavioral sexual risk), substance use, and eating disorders (Gizli et al., 2022).

Puberty risk factors: Genetic, environmental, and cultural variables have a significant impact. It is commonly known that any mental illness that runs in the family is inherited by the following generation, and that children and adolescents of that generation are at a comparatively higher risk due to their hereditary predisposition to mental disorders. Adolescence is characterized by fast physical growth, including hormonal and physical changes. Along with these hormonal and metabolic changes, self-development is one of the most significant things that happens during adolescence. Conflicts over sexual orientation, sense of belonging, and identity access can develop into identity crises and cause various psychiatric issues if they are not managed appropriately (Palacio-Ortiz et al., 2020).

The brain is still creating new neural connections and areas during adolescence. Because of this, teenagers struggle to control their emotions and make decisions. Adolescents disregard fundamental aspects of their existence, like the value of information, due to adaptive behavior. Parents must so keep in mind the value of their children's individuality. They are all a part of a developmental change. An adolescent's hormonal and mental growth continues even when they appear mature and physically developed. Hormones also affect emotional development, even if parents just pay attention to a child's outward look. Teenagers spend a lot of time analyzing their bodies and appearance in front of a mirror. As they look for who they really are, teenage kids may feel depressed, anxious, angry, or detached from their parents. This is due to the fact that many parents struggle to comprehend their kids during this time of self-discovery. He thinks that as a teenager, he will forge his identity independently of the interactions he had as a youngster. He believes that this relationship will keep going in the same way. Adolescence is actually when identity formation occurs, as many young people diverge from their parents and pursue new interests (Altun, 2018; Ölmez et al., 2014).

To solve the issues identified throughout adolescence, collaboration between the family and the school is crucial. Mental health practitioners collect data by thoroughly evaluating the family's motivations for pursuing treatment. During treatment, they occasionally employ various exams and scales. Referrals can occasionally result from family issues. A caseworker chooses a strategy to help the teen or family deal with their anxiety based on an evaluation of the problem's timing and intensity. They also take into account how the problem affects young people's functioning (Agnafors et al., 2020).

To lessen or get rid of the symptoms connected to teenage issues, medical procedures may be started. In all circumstances, a mental health expert (psychiatrist) must prescribe the medications. Treatment and psychotherapy can be started at the same time. In order to alleviate symptoms, enhance functionality and adaptability, and promote family and adolescent coping abilities, appropriate psychotherapy approaches and strategies are employed. Families receive education on appropriate behavior and attitudes (de Zambotti et al., 2018; Medhekar et al., 2019).

Scientists are researching applications of artificial intelligence in a variety of domains, with notable results. These range from autonomous systems to the development of expert decision support systems for disease detection. These artificial intelligence accomplishments are currently the subject of theoretical research. A review of the literature reveals that the use of AI/ML techniques in treating children's and teenagers' mental illnesses is less extensive than research on alternative diagnostic techniques (Altun et al., 2022). Since young people are our future's best hope, it is critical that their mental illnesses are identified and treated as soon as possible. All diseases require a quick and precise diagnosis, which calls for an impartial approach. Machine learning-based expert decision support system offers this objective approach, considering the studies in the literature.

DSMV and other scales will be used in this study to automatically diagnose psychiatric illnesses in teenagers. The block diagram for the task at hand is displayed in Figure 1.

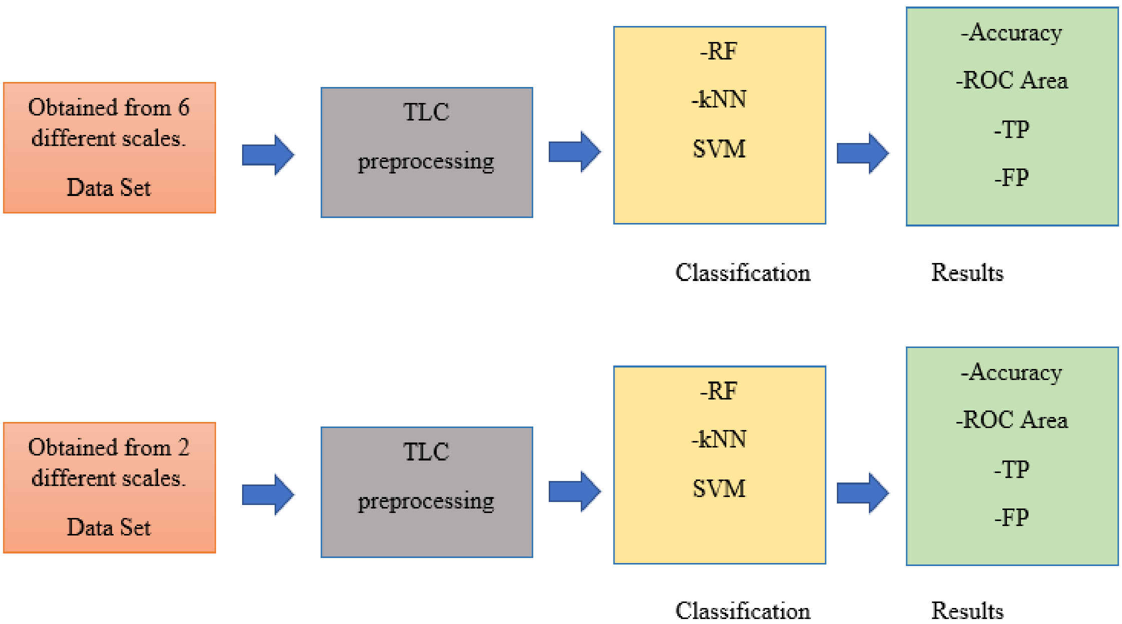

Figure 1. Working block diagram.

1.1. Review

Finding reliable indicators of mental illnesses is crucial for enabling early disease progression prediction. Experiences with asymptomatic psychosis are significant risk factors for subsequent mental health issues and suicidal thoughts and actions. In this work, they looked for neuroanatomical indicators of psychotic events in early and late adolescence using machine learning. In order to categorize teenagers with asymptomatic psychotic experiences in comparison to controls at three time points (time 1: 11–13 years, n = 77; time 2:14), they used elastic network-edited logistic regression and machine learning applied to T1-weighted and diffusion MRI data. An AROC of 0.62 was computed using neuroimaging data that stratified teenagers aged 11–13 who had prior psychotic experiences in comparison to controls. According to Kenney et al. (2022), the greatest discriminating classifier for adolescents with psychotic experiences between the ages of 11 and 13 is the left hemisphere frontal lobe region, particularly the globe region.

A more precise and effective model is required to research teenage populations. Machine learning (ML) algorithms based on a range of clinical demographic, psychometric, and biographical characteristics have been used to predict depression, suicidal thoughts, and suicide attempts in adolescents. In order to determine which machine learning technique best predicted depression and suicidal thoughts in a sizable sample of school-age adolescents, this study tested many approaches. 10,243 Chinese middle and high school freshmen or sophomores were surveyed using ten psychological tests and twenty sociodemographic factors. The random forest (RF), support vector machine (SVM), factor screening, and binary predictor (yes/no) of suicidal thoughts were then determined using these variables. Suicidal ideation was predicted by the RF model with mean accuracy (ACC) = 87.3% (AUC) = 92.4.9% (Huang et al., 2022).

Suicidal thoughts and actions are a significant issue for individuals with major depressive disorder (MDD), particularly those in their teens and early adult years. According to the study, suicide prevention in high-risk patient populations can be enhanced by machine learning algorithms that are able to assess suicide risk at the individual level. 66 teenagers and young adults with an MDD diagnosis were included in the sample for a cross-sectional investigation. FreeSurfer software was used to process each subject's structural T1-weighted MRI data. To distinguish between suicidal ideation without an attempt at suicide and attempted suicide, a classification model was built using the Support Vector Machine – Recursive Feature Elimination (SVM-RFE) method. According to Hong et al. (2021), the SVM model has a cross-validated prediction balance accuracy of 78.59%, a sensitivity of 73.17%, and a specificity of 84.0%, which means it can effectively differentiate between suicidal and suicidal patients.

Adolescence is frequently when depression first manifests, and there is evidence that the symptoms of depression can vary throughout time in long-term patterns. Predicting how teenage depression symptoms will develop can help focus early therapeutic efforts. The Adolescent Brain Cognitive Development Study reports that 4962 participants between the ages of 9 and 10 were monitored for two years. The article describes how latent class growth analysis (LCGA) was used to assess the trajectories of depressive symptoms. To forecast the specified trajectories, they built four different kinds of machine learning models. They also explained that they derived predictive variables from the model that performed the best. Of all participants, 536 (10.80%) were regularly rising, 269 (5.42%) were consistently rising, 433 (8.73%) were continuously falling, and 3724 (75.05%) were consistently falling, according to the LCGA. The best separation performance was attained by the Gradient Boosting Machine (GBM) model. Three functional magnetic resonance imaging data on resting functional connectivity are also said to help classify trajectories, and the most significant variables are sleep quality, parental emotional state, and family financial load (Xiang et al., 2022).

Throughout childhood and adolescence, attention deficit hyperactivity disorder has a detrimental impact on a child's academic career and social interactions. Numerous research have demonstrated the connection between attention deficit hyperactivity disorder and temperamental traits. Expert decision support systems that are semi-automated or fully automated and based on machine learning are frequently utilized in the diagnosis of different illnesses. In order to diagnose attention deficit hyperactivity disorder based on temperamental traits, this study attempts to demonstrate the effectiveness of a semi-automatic expert decision support system. A resource for the possible diagnosis of expert decision support systems for attention deficit hyperactivity disorder is the advanced classification accomplishments attained. The study covers its features and advancements in this regard. A variety of deep learning methods have been applied. Using a lot of photos, the deep learning approach is a model that has performed well in a variety of image processing contests. The continuous wavelet transform was initially used to create the images of the signals in the data set. With an 88.33% classification success rate, the network model outperformed the others in the data set (Altun et al., 2022).

Although they are at risk for suicide, adults are not very good at anticipating suicidal thoughts and actions. In order to find combinations of variables linked to suicide ideation and behavior, machine learning techniques can more effectively analyze several variables at once. To find out how much a variety of behavioral, psychiatric, demographic, and functional neuroimaging factors are linked to suicide thoughts and actions in young adults, the current study employs LASSO regression. 78 young adults (18–25 years old) who were seeking treatment filled out behavioral, psychiatric, demographic, and suicide prevention questionnaires. Additionally, participants refined an implicit neuroimaging paradigm for controlling emotions. Recent reports of suicidal thoughts and behaviors were the dependent variable. Five factors were found using LASSO regression: one neuroimaging variable (left amygdala activity when making sad faces), two psychiatric variables (general psychological distress and depression), and two demographic variables (age and educational attainment). Among other things, suicide ideation and conduct were strongly correlated with amygdala function. The results emphasize the significance of looking at neurobiological indicators and provide guidance for research on suicide ideation and behavior in young adults seeking treatment (Oppenheimer et al., 2021).

In our study, graded scales were not used directly for classification. When the literature is reviewed, it is seen that the Partition Member Ship- Two-Level Classification (TLC) method is widely used to determine the most effective ones for the classification process when there are too many features in the data set. In the graded scales in our study, the most relevant ones were identified and classified using the TLC method. This positively differentiates our study from similar studies in the literature and will contribute to the literature.

2. Materials

The sample for this cross-sectional study was chosen from among the 11–18-year-old patients who applied to the Kahramanmaraş Sütçü İmam University Faculty of Medicine Child and Adolescent Psychiatry Outpatient Clinic and had psychiatric illnesses as defined by the DSM-V. As a retrospective analysis, we scanned the files from 2015 to 2023. A total of 250 adolescents—131 females and 119 boys—were given the tests to construct the data set.

2.1. Inclusion criteria for the research

1. Be in the 11–18 age range.
2. Possessing a minimum of one DSM-V psychiatric diagnosis.
3. The child and parents do not have a major intellectual handicap that would make KSADS-PL more difficult.
4. Data from the files containing fully filled-out questionnaire forms.

"Emotional Violence and Schizophrenia Interview for School Age Children - Present and Lifetime - Turkish Cohesion (KSADS-PL) (Mood Disorders and School-Based Schizophrenia Program)" was chosen from the study's files, and the interview technique was used. We looked for psychiatric diagnoses from the DSM-V and the Evaluation of Psychiatric Disorders in Children, Current and Lifetime Versions, KSADS-PL. The Child Depression Scale to Preserve Memory, the Expansion of State and Trait Anxiety Scales for Ventilation, the Smokeless Tobacco/Maraş Otu

Questionnaire to Reduce the Effects of Smokeless Tobacco/Maraş Otu Use, and the Smokeless Tobacco Knowledge Questionnaire to Reduce the Amount of General Knowledge About Smokeless Tobacco. These are your completed files. To lessen the negative impacts, the DSM-IV Symptom Screening Scale was employed in conjunction with the sociodemographic data forms completed by the case's parents, the researcher's demographic data, and the individual's medical history.

The scale values acquired using the forms outlined below were used to construct a data set, and machine learning techniques were used to classify the data in order to diagnose psychiatric disorder in adolescents.

2.2. Sociodemographic Data Form

The researchers developed this form, which was used to gather sociodemographic data about families and adolescents. The information includes the following: the name of the young person, age, gender, education level, number of siblings, residence, parent age, education area, occupation, presence of mental illness, parent-child relationship, monthly income of the child, and psychiatric and other care received by the mother during pregnancy. Issues, therapies, delivery method, prematurity history, family type, other medical history, medications taken, time to first words, length of breastfeeding, presence of a known medical condition, and if any, history of drug use for a medical condition were assessed.

2.3. Interview Schedule for Affective Disorders and Schizophrenia for School-Age Children, Now and Lifetime Version (KSADS-PL)

Kaufman and associates founded KSADS-PL in 1997. Gökler et al. created it, and in 2004 it was translated into Turkish. The Diagnostic and Statistical Manual of Mental Disorders-IV, DSM-IV, and interview style diagnostic criteria were used in an interim investigation to identify current and lifelong psychopathology. Three components make up a shape. General data that can be customized and are not regarded as starting points include introductory data, kid demographics, general health state, prior psychiatric referrals and treatments, family and age relationships, school status, and other school data. The screening questions and an evaluation report detailing the disease-specific psychiatric symptoms are included in the second section of the diagnostic screening. An additional list of symptoms is requested in order to further narrow down the psychopathology if the screening results are positive. The specification structure received ratings of "unusable," "subconscious," and "threshold" during the interviews. The subconscious acquisition level serves as a storehouse for additional research on certain faults but is insufficient to identify errors. Parents and kids from KSADS-PL added to their understanding of what they eventually observed (mother, father, child, school, etc.) based on their interviews and assessments. Parents are the ones who initially get in touch with adolescents. When working with youth, start by having a conversation with them. When isolating information from different sources, the doctor applies their clinical point of view. Psychotic disorders, mood disorders, anxiety disorders, eating disorders, substance abuse, disruptive behavior disorders, excretion disorders, and psychotic disorders are all assessed with KSADS-PL. A general rating scale is employed in the third section to measure the child or young person's degree of functionality at the time of the evaluation (Gökler et al., 20024; Kaufman et al., 1997).

2.4. Smokeless Tobacco Questionnaire Form

Researchers created this standardized questionnaire, which asks patients both closed-ended and open-ended questions regarding their usage of smokeless tobacco. Teenagers are questioned in this survey if they have tried tobacco in other ways, how long and how frequently they use smokeless tobacco, whether family members or close friends use it, and whether they started using it. Properties were assessed, including ingredients, sources of smokeless tobacco, compounds utilized in smokeless tobacco, and willingness to stop smoking.

2.5. Smokeless Tobacco Knowledge Level Questionnaire Form

The 12-question survey was created by researchers to gauge teenagers' familiarity with smokeless tobacco. Participants in the study selected "agree," "don't know, I don't know," or "disagree" in response to questions about them. "Smokeless tobacco is less harmful than tobacco" was the sixth survey question since there are no research that directly compare the effects of tobacco with smokeless tobacco. Due to unclear answers on the usage of smokeless tobacco and its indoor use, the tenth question, "Smokeless tobacco use is not prohibited in closed areas such as schools and hospitals," was not included in the score. It's the opposite of the sixth question. The questionnaire has 12 questions, 10 of which were scored. A perfectly accurate response receives one score, while an inaccurate response receives zero. One can receive a minimum of zero points and a maximum of ten.

2.6. DSM-4 Disruptive Behavioral Disorders Symptom Screening Scale (DBDSSS)

In 1994, Professor Dr. Prof. Dr. assessed the reliability and validity of the scale created by Atilla Turgay. Eyüp Sabri Ercan et al. conducted the research. The child can be rated for conduct disorder, oppositional defiant disorder, and attention deficit hyperactivity disorder using the scales that are filled out by the child's parents or teachers. Nine questions about attention deficit disorder (1–9). The items included 15 items on behavioral disorders (items 27–45), 8 items on defiant-defiant disorder (items 19–26), and 9 items (items 10–18) on hyperactivity/impulsivity. The total number of items is 41. To describe each symptom, the person filling out the questionnaire is prompted to mark 0, 1, 2, or 3. None = 0, Few = 1, Much = 2, and Much = 3 are the scores assigned to each item. At least six of the nine factors linked to attention deficit must be two or three in order to discuss this symptom. Conduct disorder (DD) requires two or three points in at least three of the fifteen connected categories, while oppositional defiant disorder (ODD) requires two or three points in at least four of the eight associated questions. The DSM-IV Based Disruptive Behavior Disorder Screening and Rating Scale subscale analyses were determined to be sufficiently valid and reliable. Cronbach's alpha coefficients for subscales are 0.88 for Attention Deficit, 0.95 for Hyperactivity, 0.89 for Oppositional Defiant Disorder, and 0.85 for Conduct Disorder (Ercan et al., 2014; Turgay, 1997).

2.7. Depression Scale for Children (DSC)

A validity and reliability research was carried out on the Depression Inventory for Children (DIC), which was translated into Turkish and created by Kovacs in 1981 to gauge the severity of depression in kids and teenagers. It was edited by Oy in 1991. According to reports, the Child Depression Scale is a great tool for assessing depression severity. This self-assessment tool can be used with kids ages 6 to 17. The child reads or fills out the scale. It will take about twenty-five to thirty minutes to complete the application. Each of the 27 points has three possible answers. Kids are asked to select the best expressions from the previous two weeks. For instance: 1. I occasionally feel depressed. 2. I apologize a lot. 3. I apologize all the time. Depending on how severe the symptoms are, each item can be valued zero, one, or two points. The scale assigns inverse scores to opposing items. The elements in question are 2, 5, 7, 8, 10, 11, 15, 16, 18, 21, 24, and 25. For questions with a score of 0, the score is computed to be 2.2 points. 54 is the maximum score that may be achieved using the scale. The severity of the depression increases with the score. It is advised to use 19 pathological cut-off points (9, 10). Oy's study found that the Child Depression Scale's internal consistency was 0.80 and its test-retest reliability was 0.70 (Kovacs, 1981; Spielberger, 1983; Oy, 1991). Annex 6 provides a sample of the scale.

2.8. State-Trait Anxiety Inventory (STAI)

Spielberger et al. created a self-assessment scale in 1970. Each of the two sub-dimensions of the scale, the State Anxiety Inventory and the Trait Anxiety Inventory, includes 20 items. The Trait Anxiety Inventory assesses a person's overall anxiety level regardless of the circumstances, whereas the State Anxiety Inventory assesses a person's anxiety level at a specific moment and circumstance. You can fill out this simple scale on your own (Oner, 1983; Spielberg, 1983). It is possible to use both scales simultaneously. The State Anxiety Scale should be completed in this situation, then the Trait Anxiety Scale. The scale, which can be completed individually or in a group, has no time limit and takes about 20 minutes to complete. The State Anxiety Inventory has four options: 1 for "none," 2 for "somewhat," 3 for "a lot," and 4 for "completely," which correspond to how severe the feelings, thoughts, and behaviors are. You should select the appropriate choice from 1 (never), 2 (sometimes), 3 (often), and 4 (nearly always) on the anxiety trait scale. When scoring, even representations and inverted representations need to be taken into account. Inverses are evaluated by adding them, converting 1 to 4, and converting 4 to 1. Both scales have total scores between 20 and 80. High anxiety is indicated by a high score, and low anxiety is indicated by a low score. The State-Specific Fear Inventory contains two different kinds of statements. Positive emotions are expressed by reverse remarks, whereas negative emotions are expressed by direct words. The State Anxiety Inventory has the following reverse expressions: 1, 2, 5, 8, 10, 11, 15, 16, 19, and 20. article. Items 1, 6, 7, 10, 13, 16, and 19 of the Trait Anxiety Inventory have opposite statements. They are deducted from the total score of the reverse statements once the total scores of the direct and reverse statements have been calculated independently. The direct statement's overall score was calculated. This number has a predefined literal value applied to it. For the State Anxiety Inventory, this fixed number is 50, and for the Trait Anxiety Inventory, it is 35. The application's average score falls between 36 and 41. According to Caci et al. (2003), a score of 0–30 denotes low anxiety, a score of 31–49 denotes moderate anxiety, and a score of 50 and more denotes high anxiety.

3. Method

In the literature, default values are used as hyperparameters in machine learning and deep learning methods. Default values are the closest values to the ideal obtained as a result of testing different data sets. In our study, default values were used in preprocessing and classification methods. Cross validation allows to obtain a more accurate result since it includes all features in the data set in the classification. In the study, classification was performed using 5-fold cross validation method.

3.1. Preprocessing

3.1.1. Partition Member Ship- Two-Level Classification (TLC)

A generalization of attribute-value learning is multi-instance learning. This learning technique performs better in fundamental machine learning application domains like molecular classification and picture classification, but it requires more computing power than feature value learning. Implementing a proposal that converts a data packet into a vector of attribute-value pairs is one way to solve a multi-state learning problem. This allows standard-proposition (i.e., attribute-value) learning algorithms to be used. This method can be used with propositional data and has been used in numerous propositional learning algorithms. The Two-Level Classification (TLC), a variation of the current premise, is empirically examined by Frank and Pfahringer (2013). TLC extracts proposition data using a single decision tree. The version is driven by the possible robustness benefits that can be achieved by using a random forest instead. It uses support vector machines and gains to classify the suggested data and displays results on both synthetic and real data from the two application areas mentioned above (Frank and Pfahringer, 2013).

TLC divides the sample space into regions using a heuristic method. After that, a sample bag is advised, with the number of samples falling into each zone being counted. The rationale behind employing this method is that it allows for the description of the sample distribution in the sample space of a bag by segmenting the sample space into regions and measuring the occupancy. How to define regions in the sample space is the question (Frank and Pfahringer, 2013).

All instances from all bags are merged into a single dataset, the bag membership information is removed, and the instances are labeled based on the class label of their bags in order to learn this tree. Each sample in this dataset is 1/|X| x is N/b, where X is the bag from which the sample was taken, N is the number of samples in the combined data, and b is the number of bags in the original dataset. This ensures that the large bags weigh the same as the little bags. For each bag, it creates synthetic multi-sample data with the Boolean attributes x0, x1, and x2, as shown in the example. According to Frank and Pfahringer (2013) and Mark et al. (2009), 100 sample bags were created, with one to ten samples of each bag given an equal chance for each bag size.

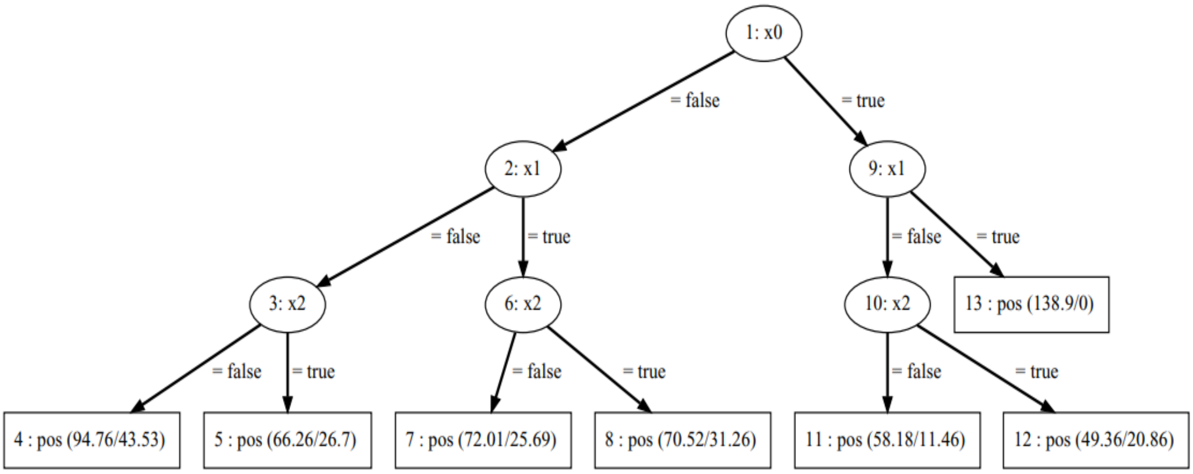

Figure 2. Figure 2. An unpruned decision tree was used for the proposition. where x gives the total weight of all samples in the leaf node and y gives the weight of all misclassified samples (Frank and Pfahringer, 2013).

A bag was classified as "positive" if it had at least one occurrence in which the values of x0 and x1 were both true. The bag was marked "negative" if it contained no samples with this attribute. Although any node in the tree may require it, node 13 is the crucial region in this example problem since a bag is positive if and only if it has an instance in that region. Using the tree in Figure 2, Figure 3 displays an example bag and its propositional variant. The bag is positive in this instance because it belongs to zone 13, even if the class label has been deleted (Frank and Pfahringer, 2013; Mark et al., 2009).

Bag

x0	*x1*	*x2*
false	true	false
false	true	true
false	true	true
true	false	false
true	false	true
true	false	true
true	false	false
true	true	true
false	false	false

⇒

Instance

r1	*r2*	*r9*	*r3*	*r6*	*r10*	*r13*	*r4*	*r5*	*r7*	*r8*	*r11*	*r12*
9	4	5	1	3	4	1	1	0	1	2	2	2

Figure 3. Case of examples and proposal form (Frank and Pfahringer, 2013).

Machine learning techniques (Random Forest, k Nearest Neighbor, and Support Vector Machines) were used in our study to classify our data sets without any pretreatment or Partition Member Ship-Two-Level Classification (TLC) preprocessing. Various preprocessing techniques were also used, however the intended outcome was not achieved.

4. Findings and Discussion

We used the following data set in the study: DSM-5 Disruptive Behavior Disorders Symptom Screening, 27 from the Children's Depression Scale, 40 from the State and Trait Anxiety Inventory (STAI-1 and STA-2), 13 from the Smokeless Tobacco Questionnaire, 12 from the Smokeless Tobacco Knowledge Questionnaire, and 29 from the Sociodemographic Data Form. Of the 162 features in total, 41 are derived from the scale. Every one of the 250 teenagers in the dataset suffers from a mental illness. Attention Deficit and Hyperactivity Disorder, Oppositional Defiant Disorder, Behavior Disorder, Anxiety Disorder, Depression Disorder, Obsessive Compulsive Disorder, Post-Traumatic Stress Disorder, Tic Disorder, Alcohol and Substance Use Disorder, Adjustment Disorder, Mild Intellectual Disability, Bipolar Disorder, Conversion Disorder, Bipolar Disorder, Trichotillomania, Anorexia Nervosa, Psychotic Disorder, and Skin Picking Disorder are the 18 diseases in total. While 250 patients in the DSMV dataset have 70 features and 18 distinct classes, 250 patients in the entire dataset have 162 features and 18 distinct classes.

Table 1. Metrics obtained in the whole data set.

Method Name:	Accuracy:	ROC Area:	TP Rate:	FP Rate:
RF	0,39	0,467	0,392	0,392
kNN	0,476	0,707	0,476	0,203
SVM	0,55	0,763	0,548	0,143
TLC+RF	0,82	0,925	0,82	0,037
TLC+kNN	0,692	0,9	0,692	0,094
TLC+SVM	0,816	0,89	0,816	0,038

Two distinct data sets were used for the machine learning categorization process. The first of them is the data collection that simply includes the DSM-5 Disruptive Behavioral Disorders Symptom Screening Scale (41) and the Sociodemographic Data Form (29) as its components. The dataset that contains all 162 features is the second. This is done in order to compare the effectiveness of the categorization created using all forms with the DSMV scale, which is directly utilized in the diagnosis of mental illness.

The two data sets that would be used in the study were categorized both without and with TLC pre-processing, and the results of these classifications were compared. To further the study and provide a more objective categorization, various data sets are created and raw or pre-processed data is categorized.

Support Vector Machines (SVM), Random Forest (RF), and k Nearest Neighbor (kNN) are popular machine learning techniques for interpreting biological signals and pictures. According to current research, RF has very high effectiveness rates. Furthermore, scientists have been using these algorithms in various studies for a long time. These three approaches will be used to categorize the preprocessed/raw data set in our study, and the results will be compared.

Interpreting the classification findings will require more than just obtaining the accuracy measure in the successful comparison of the classification methods. Machine learning processing of biomedical signals and images frequently uses Receiving over Curve (ROC) metrics with true positive and false positive rates. These metrics provide for a detailed analysis of how accurately or inaccurately the data from the classes in the data set are approximated. The study also computed true positive and false positive rates as well as Receiving over Curve (ROC) measures in addition to the accuracy metric.

The outcomes of our initial data set are displayed in Table 1. Without preprocessing, the categorization method failed, as the table illustrates. All three approaches successfully complete the classification procedure after preprocessing with TLC. Success rates for TLC+RF and TLC+SVM are similar, with TLC+RF achieving the best categorization. Table 2 shows that TLC+RF is superior in other metrics. The approach was able to predict a significant amount of data in the correct class, and its correct prediction rate (TP Rate) was 0.82. Once more, there were very few errors, with the incorrect prediction rate being 0.037.

Table 2. Metrics obtained in the DSMV dataset.

Method Name:	Accuracy:	ROC Area:	TP Rate:	FP Rate:
RF	0,484	0,718	0,484	0,239
kNN	0,448	0,641	0,448	0,231
SVM	0,44	0,676	0,44	0,222
TLC+RF	0,704	0,837	0,704	0,098
TLC+kNN	0,536	0,792	0,536	0,174
TLC+SVM	0,696	0,802	0,696	0,101

Table 1 shows the results obtained from our first data set. As can be seen in the table, the classification process was unsuccessful without preprocessing. When preprocessing with TLC is performed, all 3 methods are successful in the classification process. TLC+RF and TLC+SVM successes are close to each other, and TLC+RF has achieved the most successful classification. The superiority of TLC+RF in other metrics is seen in Table 2. The correct prediction rate (TP Rate) of the method was 0.82, and it was able to predict a large amount of data in the right class. Again, the wrong prediction rate was 0.037, making very few mistakes.

A ROC plot is made by comparing the true positive rate (TPR) with the false positive rate (FPR). The true positive rate is the percentage correctly predicted in favorable cases. The false positive rate is the percentage incorrectly predicted in unfavorable situations. In medical testing, the true positive rate indicates the proportion of individuals who correctly receive a positive test for a given disease. The discrete classifier gives only the predicted class and generates a single point in the ROC area. Probabilistic classifiers allow to obtain a curve by varying the score threshold by presenting the probability of belonging to a certain class. Many discrete classifiers can be transformed into scoring classifiers with sample statistics. For example, a decision tree determines the class based on the proportion of instances at the leaf node.

In order to compare the performance of different classifiers, it may be useful to express the effectiveness of each with a single metric. A common method is to calculate the area under the ROC curve. This indicates the probability that a randomly selected positive sample has a higher ranking than a randomly selected negative sample. When Table 2 is analysed, the area under the ROC curve values in the classification with TLC preprocessing are closer to 1 than in the normal classification. The area under the ROC curve increased more in TLC+kNN and TLC+SVM methods than TLC+RF. However, as can be seen in Table 2, the ideal method for our dataset was not one of these methods, but TLC+RF, which calculated an area under the ROC curve of 0.837.

The data set developed with all forms was more successful than the data set created with only the DSMV and Sociodemographic forms, according to a detailed analysis of Tables 1 and 2. Given that the data set collected with all forms had more specific information about the teenager, this discrepancy can be explained.

When the literature is examined, Table 3 is obtained. As can be seen in Table 3, the use of machine learning in child and adolescent mental health is increasing, with random forest (RF) models being particularly prominent. Usta et al. (2020) reported 85% accuracy with the RF model in predicting the development of disorders in adolescence from early childhood symptoms. Tate et al. (2020) reported AUC values of 0.74 with RF and SVM, based on parental reports from a large cohort. Na ve ark. (2020) achieved very high accuracy with RF when predicting the persistence of oppositional behaviour. Altun & Altun (2025) developed RF classification using scalogram-based features. This study, on the other hand, achieves and surpasses the performance ranges in the literature with an AUC of 0.925 in a challenging context where 18 diagnostic classes are predicted simultaneously.

Table 3. Comparison of the success of the study

Study Name	Sample / target variable	Data	Methods	Performance	Reference
Proposed	250 adolescents, 18 diagnostic categories	Scale + Sociodemographic	RF, kNN, SVM + TLC	Accuracy=0,82; AUC=0,925	-
Usta et al., 2020	116 children	BITSEA & CBCL	RF, SVM, et al.	RF: %85,2 accuracy; AUC=0,79	Usta et al., 2020
Tate et al., 2020	7.638 children	Symptoms + record data	RF, SVM, XGB, et al.	AUC ~ 0,74	Tate et al., 2020
Na et al., 2020	1.323 children	Behavioral scales	RF	Accuracy=0,955; AUC=0,982	Na et al., 2020
Altun & Altun, 2025	Psychiatric adolescents	Scalogram images	RF, SVM	Accuracy= %91	Altun & Altun, 2025

5. Conclusions and Recommendations

Adolescence, sometimes referred to as the Storm Stress Period, is a challenging time between the ages of 11 and 21. Teenagers believe they do not fully experience the feeling of being understood, and families find it difficult to comprehend them, making adolescence a challenging time for both parties. The more parents are aware of their children's physical, sexual, social, and emotional differences during this time, the less conflict between them will occur. Adolescents experience varied emotions throughout this time, and they frequently find it challenging to identify with themselves. Young people go through a highly rich and strong emotional experience throughout this time. Compared to earlier times, his tone, accent, and facial expressions more effectively convey his feelings. Compared to other times, he has more intense dreams and occasionally loses touch with reality. These dreams could be about the other sex or involve future goals. Sometimes, teenagers want to be alone themselves. Young people should not worry that they are in major trouble if they lock themselves in their rooms and declare that they want to be left alone. Teenagers may feel that they must be left alone and take ownership of their experiences. Adolescents should be identified and assessed during this period. Young people can get support from a variety of friend groups if their families are unable to provide for these requirements.

Depression rises during this period. Issues with self-worth, gender, education, or family may be the cause. This normally passes quickly and doesn't need to be addressed. Teenagers experience sadness and guilt. She can carry on with her everyday activities, though. Adolescents may have developed suicide ideas in circumstances of true depression. He felt absolutely useless. resentment from family members, interest in dying, loneliness, lack of affection in infancy, separation from death, painful experiences, etc. for various reasons. Aside from this, teenagers may occasionally have angry outbursts. Talking is pointless right now. You ought to hold off till things settles down. Another issue is eating problems. Teenagers struggle with eating too much, eating too little, and believing they are overweight all the time. Teenagers must, above all, feel appreciated and understood. If not, they require a different setting to satiate their emotions. Young people should listen with objectivity and deference and look for areas of agreement on a range of topics.

Adolescence is a stressful time in a person's life and a psychologically taxing time for the family as well as the individual. It can leave the adolescent with long-lasting psychiatric difficulties if it is not properly addressed. The psychological pain of the individual may worsen in the future as a result of these problems. It might so reach a point where it could endanger both its surroundings and itself. In every aspect of a nation's development—economic, artistic, cultural, etc.—young people play a crucial role. Adolescence must therefore be appropriately managed, and if a psychological disorder has developed, prompt diagnosis and therapy should be implemented.

Autonomous systems start to show up in different domains, including disease diagnostic and treatment procedures, and theoretical research is implemented. The diagnosis of psychiatric disorders necessitates strong competence and is also based on the expert's observations. Inaccurate diagnosis might result in inappropriate therapy, which can exacerbate the illness. Objective methods are required because this circumstance is never desired. Large amounts of data can be used to train computer-aided diagnosis systems, which can produce more objective results than a specialist's subjective approach. Naturally, though, these are decision support systems, and the expert has the last say.

In this study, we used machine learning to automatically treat psychological disorders that are prevalent throughout the challenging adolescent stage, which is a significant time in people's life. Since young people represent every society's future, it is crucial to diagnose and treat psychological illnesses in them as soon as possible. This is important for both the individual and the entire community. Results from various scales were used as a data set in the study. These data sets have also been thoroughly examined. The outcomes are highly promising and successful in the field, and scientists will find them to be a valuable resource. The TLC+RF (Accuracy: 82%, ROC area: 0.925, TP: 0.82, FP: 0.037) machine learning model demonstrated significant classification success in the data set we generated utilizing all scales, demonstrating the potential of computer-aided diagnosis systems for the identification of psychological disorders in teenagers.

Authors' Contributions

S.A.: %70

H.A.: %30

Statement of Conflicts of Interest

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The author declares that this study complies with Research and Publication Ethics.

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