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Analysis of changing behavioral patterns in student parent domain using ReinforcementLearning and Machine Learning methods to predict Psychological Disorders

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Abstract

This study takes a critical look at the opportunities and difficulties faced by students in higher education who are moving from adolescence to young adulthood (18 to 25 years old). It integrates interdisciplinary viewpoints from psychology, education, and public health to comprehend and promote students' behavioral well-being. The identification of behavioral patterns, risk factors for scholastic challenges, mental health issues, and novel approaches such as machine learning for early intervention are among the main subjects. K-means, KNN, Clustering, Reinforcement learning, Actor-Critic Method, Multi Linear Regression, and Q-Learning are among the algorithms used.

Keywords: *Interdisciplinary perspectives, Psychology, Public health, K-Means, KNN, Clustering, Multi Linear Regression Reinforcement learning, Actor-Critic-Method, and Q-Learning.*

1. Introduction

To represent the changing student-parent relationship, this study explores the complex dynamics of parental engagement's impact on academic achievement and mental health [1]. Using cutting-edge machine learning and reinforcement learning methods, it investigates how these dynamics impact children's development of mental health issues. To replicate interactive decision-making between parents and children and identify elements that influence the development or reduction of psychiatric problems, this research uses reinforcement learning [2-4]. The study clarifies important elements influencing student behavior in the context of the student-parent interaction using clustering approaches [6-7]. Machine learning methods are also applied to predict the onset of mental illness by analyzing behavioral patterns in the student-parent area [6-8]. The goal of the project is to better understand the intricate interactions that exist between psychological health and student-parent relationships to improve student mental health treatments and support systems [9][12] [17–21].

2. Literature Survey

In their 2023 study, Taru Lintunen, Sami Kokko, and Sanna Palamaa used linear regression modelsand latent class analysis (LCA) [5]. According to their research, there is a significant link between harmful adolescent behavior patterns and a higher chance of anxiety and depression as adults [5–7][11][12][20][21].

The study "Impact of Socio-economic Status on Student Behavior" by Wang and Chen (2022) used structural equation modeling, hierarchical linear modeling, and curve modeling [11]. Their findings demonstrate a strong relationship between students' behavioral problems and their socioeconomic status (SES) [12–14][20].

In their 2021 publication, Johnson et al. employed a meta-analysis to examine the efficacy of Positive Behavior Interventions and Supports (PBIS). Their results showed that the implementation of PBIS enhanced the overall classroom environment and markedly decreased disruptive behaviors [13].
In their 2021 study "Effects of Peer Influence on Student Behavior," Kim and Chang investigated the connection between peer influence and student behavior using statistical methods such as correlation analysis. According to their research, there is a strong correlation between students' behavioral patterns and those of their peers, and peer influence has a significant impact on individualstudent conduct. [16][19].

3. Methodologies Used

Preprocessing operations such as feature scaling and missing value handling were carried out prior to clustering. A 372-observation dataset was subjected to K-means clustering, which sorted the data according to characteristics including "Age," "Mental Issues," and "Parents putting under pressure." The ideal number of clusters (K) may have been found using methods like the elbow or silhouette approaches, with the help of visualizations like labelled clusters and scatter plots with centroids. This method makes use of feature similarity to get insightful conclusions from the data. [9][14]

The summing of squared distances between individual data points and their cluster centroids is known as the within-cluster sum of squares, or WCSS, is what the K-means algorithm seeks to minimize:

$WCSS = \sum_{i=1}^{n} \min_j \| x_i - \mu_j \|^2$ ---→eq1

Non-numeric columns were transformed into factors, and subsequently into numeric variables, for KNN compliance with 70% of training and 30% of testing dataset and obtained an accuracy of 92.66%. This model demonstrated how well it could classify observations according to how similar their features were [1][3][17].

The Actor-Critic Method (ACM) in Reinforcement Learning (RL) continuously modifies actor and critic weights according to features and rewards, guaranteeing consistent decision-making for N=372.To optimize cumulative rewards, post-training weight normalization highlights the significance of features, and helps strike a balance between exploitation and exploration. Actors and critic weights demonstrate perseverance under difficult situations, as shown by high t-values.

Even with a dataset size of N=372, Q-learning is still a useful model-free technique that balances exploration and exploitation over time to optimize decision-making. Q-learning improves decision- making in reinforcement learning tasks by utilizing a Q-table that is updated with observed rewards and state transitions. The effectiveness of Q-learning in dynamic decision-making was demonstrated by a KNN classifier that predicted "Bad habits" based on traits like "Socially Active," "Mental Issues," and "Parents putting under pressure" with an accuracy of 92.66%. An essential method for learning optimum policies in reinforcement learning is the Q-learning algorithm. The following is the Q-learning formula:

$Q(s,a) \leftarrow Q(s,a) + \alpha [r + \gamma \max_{a'} Q(s',a') - Q(s,a)]$ ---------------------------→eq2

Q(s, a) is the notation for the Q-value of a state-action pair (s, a). represents the estimated cumulative reward for action 'a' in the state 's' in Q-learning. The learning rate (α) determines how much the Q- value is adjusted, while 'r' stands for instant rewards.

Future reward importance is influenced by the discount factor (γ), and the highest Q-value for the next state's″ is indicated by max a′ Q (s′, a′).[2][4].

The process for computing a confidence interval (CI) is determined by the kind of data and statistical distribution. However, the confidence interval for a population mean (μ) may be calculated using the following equation, which is often used when the population standard deviation (σ) is known:[6–8] [11–12][14][16][18][20].

$$CI=\bar{x}\pm z(n\sigma) \dashrightarrow eq3$$

The sample mean is represented by ɫ in this equation, the population standard deviation is denoted by σ, the sample size is indicated by n, and the z-score associated with the selected confidence level (for example, 1.96 for a 95% confidence interval) is shown by z.

4. Block Diagram

The process of the machine learning and reinforcement learning algorithms utilized in our research is shown in the block diagram below.

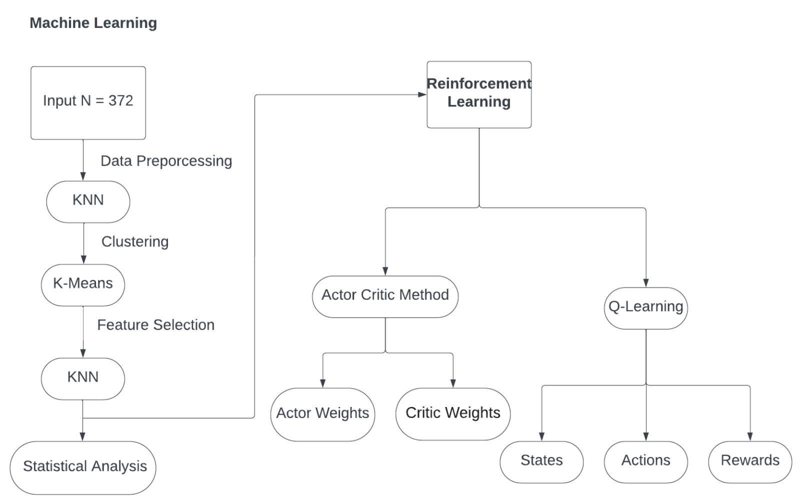

Fig 4.1 Illustrating the workflow of the Machine Learning and Reinforcement Learning

The method of combining reinforcement learning and machine learning is depicted in the block diagram. K Nearest Neighbors and K-means clustering are used in machine learning to preprocess input data (N=372) before statistical analysis. Reinforcement learning refines decision-making based on processed features by utilizing Actor-Critic and Q-learning methodologies. Q-learning iteratively improves judgments by maximizing cumulative rewards, whereas Actor-Critic refines decision- making through weight formation.

5. Outcomes

5.1 Graphs

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This graph illustrates the link between friends' percentage impact on students' decision-making and mental health concerns and parents' pressure on their children.

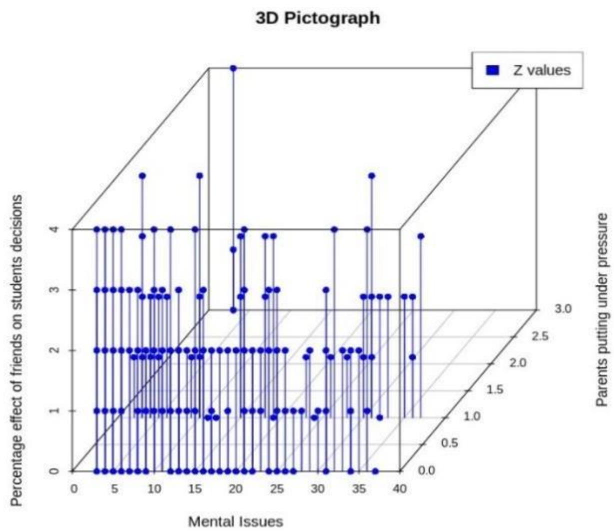

Fig. 5.1.1 3D pictograph illustrating the impact of peers, parental pressure, and mental health conditions on kids' choices.

The relationships between parental pressure, friends' influence, and mental health difficulties are depicted in a 3D pictogram. The blue-highlighted data points (pch=16) have captions for the Z values and axis labels. Known as the "3D Pictograph," a 45-degree rotation that is optionally applied improves visualization for thorough data analysis.

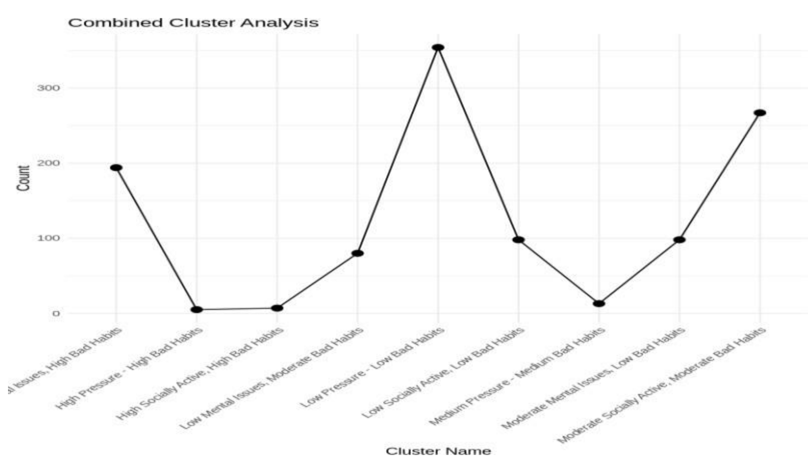

Fig. 5.1.2 The distribution of observations among the dataset's different clusters is shown bythe line graph. The y-axis shows the number of observations in each cluster, and the visualization shows clusters next to the x-axis. Unique characteristics including parental pressure, bad habits, mental health issues, and social involvement levels are briefly described in cluster titles. By linking cluster names to observations, this arrangement facilitates comprehension of the dataset's various profiles and

provides information on how these parameters differ throughout groups.

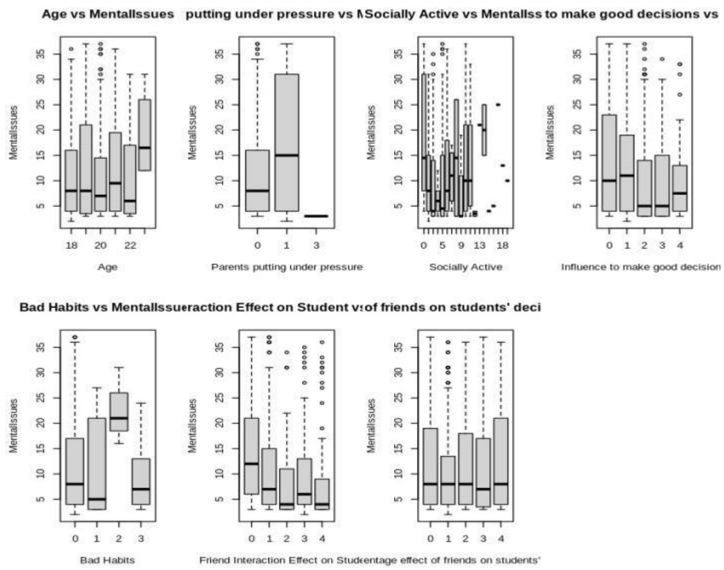

Fig.5.1.3 The predictor variable coefficient estimates in a multiple linear regression model are displayed in this bar graphic.

The length of the bar shows the size of the coefficient estimate, and each bar represents the predicted coefficient value for a predictor variable. The names of the predictor variables are shown on the x- axis, and the coefficient estimates are shown on the y-axis. The central tendency and distribution of "Mental Issues" within the different categories of each independent variable are shown visually in these charts.

Table:

Table.1 Key descriptive and statistical analysis metrics that are commonly used in data analysis areshown in this table.

	Z-Score	F-Score	T-Score	Probability	C.I	Chi-square
Parents Pressure	0.18279570 .4802568	0.23065	0.1827957	0.1424731	0.1338326 0.2317588	445.98
Socially Active	5.76819413 .7568189	14.114	5.768194	0.1455526	5.384660 6.151728	642.35
Mental Issues	11.8145161 9.8334105	96.696	11.81452	0.05913979	10.81198 12.81705	764.13
Good decisions	4.11900646 319513e-17	0.8185972 00043297	25.45074	0.2455253	0.9872587 1.0000000	84.586
Bad habits	2.559395e-17	4.275387	4.855941	0.8575413	0.08176152 0.192432	904.02
Friends	6.023647e-17	2.404255	21.20777	0.1844086	0.09197149 0.3920441	57.677

Social activity and mental health show significant deviations from the mean when z-scores, F-scores, t-scores, probability values, confidence intervals, and Chi-square tests are examined. On the other hand, variables such as parental pressure, judgment, habits, and peer pressure exhibit marginal deviations or no statistically significant variances, pointing to a lack of patterns or relative consistency. Other factors in the dataset show less variation overall, with social activities and mental health issues standing out for their significant variances.

6. Conclusion

Variables like friendships, parental influence, negative behaviors, social media use, and mental health issues were investigated using a variety of techniques, such as clustering and multi-regression analysis. Different patterns emerged from clustering, with age, mental health, and parental influence among the characteristics that affected the decisions. The substantial positive effects of friendships and sound judgment on students' mental health were demonstrated by regression analysis. The great accuracy of K-nearest neighbors (92.66%) suggests that parental pressure has a significant impact on mental health, namely on anxiety, stress, and depression. The importance of students' mental health in decision-making was highlighted by Reinforcement Learning algorithms, while Q-Learning focused on how favored behaviors influence decisions. This thorough analysis highlights the critical role that mental health plays in decision-making and the well-being of students.

7. Further Research

Subsequent investigation may entail examining the effects on student behavior and mental health of variables such as eating habits, sleep patterns, physical health, and academic stress. Further research and analysis of pertinent aspects may be required to enhance prediction capabilities, maybe utilizing sophisticated approaches like Support Vector Machines (SVM), MPMC, and other Artificial Intelligence techniques. With the help of these sophisticated techniques, one can gain a greater understanding of the intricate relationships between different factors and how they affect the behavior and psychological health of students.

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