AN EFFICIENT NOVEL APPROACH ON MACHINE LEARNING PARADIGMS FOR ANALYSIS AND PREDICTION OF ACADEMIC PERFORMANCE BASED ON STUDENT BEHAVIOUR APPROACH.

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Abstract:
One of the Pestering issues in these days is suicides in the young generation. For simple reasons, there are more and more suicidal cases observed all over the world as well as in India. Around 35.1 percentage of suicides are between the age group of 18-30 young adults as per NCRB (National Crime Record Bureau) India. Mere Backlogs in education or love failure or unemployment, professional or career problem, or a fall in Social Reputation are some of the reasons for suicides. 3.7 percentages of suicides are noticed in educational graduates. Failure or depression status is based on the way one takes situations. Education should impart the required skills to handle different situations that life brings. It should contribute to the overall development that includes academics, emotional balance, and a positive attitude. Hence, it requires conducting a study analyzing student's reactions to a given situation. Identify the students with poor personality traits provide counseling in time and advise him or her to overcome Problems or Failures or depression situations. Identifying the Personality traits of a student will enable us to counsel the student accordingly. This work aims to classify a student as INTROVERT or EXTROVERT. This works collects 600 records of data from a survey questionnaire designed for Engineering College students on different aspects of personality traits. The ML algorithms like Decision Tree, Random Forest, SVM, KNN, and Naive Bayes were modeled with demonstrative 95 percentage Accuracy.

Keywords— Student Behaviour, Human Personality traits, Introvert, Extrovert, Data Science, Decision tree, SVM.

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INTRODUCTION

The Dictionary of Psychology states that the term behaviour means "the activity of an organism that interacts with its environment". Behaviour refers to the way we exist and behave through observable symptoms. The direction of adaptive behaviour is very important. In general, behaviour can be unambiguously categorized based on various and single parameters such as personality traits, physique, temperament, and disposition. Based on the capacity of attitude, Jung defines Introvert as "An attitude type characterized by the orientation of life by subjective mental content" and Extrovert as "An attitude type characterized by a extroverts and introverts are the main features of several theories about human personality. Extroverts tend to be sociable, talkative, energetic, etc. Meanwhile, introverts tend to be more thoughtful and reserved. The study of behavioural aspects of a student's is needed research; especially in Technical Education where a student must undergo rigorous study, be competitive, have career planning, Work on Innovative Projects so on and so forth, which may lead to failures. Some Introverts may need more guidance, as it is difficult for them to handle the outcomes of failure. Most of the time, they enjoy living alone. This loneliness may become isolation, leading to depression in the case of failure outcomes. Some Extroverts, lack concentrations they have multiple social contacts and there is a high possibility of diversion from their expected goals. This may end up in bad associations or an unsuccessful career. Identifying such students well in advance and sharing this information with the mentor may help guide the students properly.

Introvert: Introvert state to living mostly interested in one's psychological nature. Typically, introverts are sensed as more reticent or thoughtful. Introvert people are characterized by a few popular psychologists as whose energy tends to develop through expression and contract through relations. Characteristics of an Introvert are tending to have a few sets of close associates, being thoughtful, thrilled being unaccompanied, enjoying being alone, increased learning through observations, keeping emotion private, being silent and reserved with strange people or in large groups, feeling exhausted, wish for privacy. Think in their minds rather than speak out, be shy, don't make good leaders, and don't take risks.

Extrovert: Extroverts state on mainly obtains satisfaction from external. They receive enjoyment in actions that involve high social gatherings, like parties, public activities, community demonstrations, or political groups and businesses. An extrovert person is probable to love spending time with others and allocate less time to be alone. Characteristics of an Extrovert are enjoying public location, looking for awareness, being thrilled with unknown people, being friendly with everyone, being sociable, outgoing, optimistic, enjoying working in groups, always being happier, much more confident, starting up a conversation, communicate with strangers freely, and wish to spend time with unfamiliar peoples.

Both or Average: Here some group of people expresses mixed characteristics of introvert-extrovert. For example, a person exhibiting Introvert-Extrovert behaviour may frequently exhibit extrovert character by being social able, Comfortable in large groups but not constantly. Similarly, thrilled to meet unfamiliar people but nervous to address a group of peoples an introvert characteristic. If your close friend is mostly introvert, don't be shocked when he/she does not reject the offer to being loud, takes initiation, and is friendly with strangers. Having these facts can facilitate you keep away from winning the negative response individually.

Related works:

The study in [1] divides people into Introvert and Extrovert groups based on their tweets' MBTI scores of their distinct personalities. The open dataset utilized in this study was obtained from Kaggle and consists of 8676 data points that were tweeted. The Support Vector Machine (SVM) classifier was utilized to compare a different subset of features. By conducting an empirical investigation in a dynamically typed learning system over an extended period, the study in [2] improves our knowledge of how gamification impacts both extroverted and introverted participants. The players in the non-gamified version of Feeper are unable to view the gamification features, but the system still awards credits and badges on the organizational stage. This is the only distinction between the gamified and non-gamified variants of Keeper. With the use of this score, we can assess whether students can perceive how the gamification elements attract people. The findings show that gamification, which is especially beneficial to introverted learners and includes aspects like points, badges, and ranking in Feeder, has a good impact on their accuracy.

The example of introverts used in the research [3] are those who have fewer good friends, attend more often than they say, consider before they say, write more effectively than they converse, work slowly and methodically, and can focus on a single task.In the study [4] the distinction between introverts and extroverts in the cerebral processing of stimuli is discussed. Distraction has a significant, though complicated, role to play in this sensitivity. While engaging in simple tasks with distracting stimulation present, introverts' sensory sensitivity is higher than extroverts' at low levels of attention, but it is roughly equal to extroverts at high levels of diversion. The previous Personality Questionnaire was used to measure the personality traits of introversion and extroversion in the study [5]. About introversion and extroversion, two groups of participants were created using the test's mean score as the dividing factor. The findings of this study showed that, in comparison to introverted participants, extroverts were less easily irritated and had superior focus throughout a mental performance in noise. The study in [6] extroversion and introversion can alter people's intentions to pay for social networking site services along with other factors quantify user value and satisfaction views. The responses were investigated the influence of person's mental condition. To check the construct validity, tests for convergent and discrimination validity were performed. Secondly, PLS-Graph Version 3.00 was used to test the theoretical model.

The study in [7] aims to evaluate the social engagement scale's validity and reliability among students in education systems in Finland. Moreover, the interplay between introversion and social engagement and how these factors affect burnout, participation in schooling, and self-esteem. They discovered that the social engagement scale was suited best to a two-factor model. They discovered that introverts with higher levels of social engagement have better levels of self-esteem than those with lower levels. The findings suggested that when introverts participate in group projects in the classroom, they should receive additional support.

The study in [8] examines the Five-Factor Model, which measures extraversion, neuroticism, agreeableness, conscientiousness, and agreeableness, in addition to research studies of several articles that indicate a bias towards introversion. The bias towards introversion has crept into psychology studies, and all these studies are utilized to illustrate the need to buck stereotypes and incorrect data. It is important to look to authors, who are making positive contributions to the study of introversion as role models for others, but addressing this issue will likely take time and deliberate actions on the part of authors and editors to raise standards, reduce bias, and lessen reliance on out-of-date beliefs and stereotypes. They anticipated that social circumstances would serve as a mediator throughout the study in [9] between extraversion and happiness. They found that over time, extroverts report more happiness than introverts, which allowed them to test their theory. To achieve this, a multilevel model (nominal regression) was built using extraversion as the sole independent variable and happiness as the dependent variable. The findings demonstrated that extraversion is a more accurate predictor of happiness.

The Big Five Personality Test and Relationship Assessment Scale were used in the study [10] to examine the association between extraversion and overall relationship happiness. They conclude that extraversion and overall relationship satisfaction are positively correlated. This might be the case because extroverts are energetic, effective communicators, and high on positive impacts. In contrast, introverts are reticent, silent, and thoughtful as well as less talkative. The goals of the study in [11] were to determine which of the students had higher listening scores for English and to see if there were any significant variations in listening scores between introvert and extrovert students. This study used descriptive and comparative methods. The study concludes that introverted learners do better than extroverted pupils in English listening tests.

The purpose of the study in [12] is to investigate how personality affects speaking ability. The focus was on an examination of how the student's extrovert and introverted personalities affected their speaking abilities. This study combined a case study technique with a descriptive qualitative research methodology. This study demonstrates that character traits are not a determining factor for spoken English learning success, and it is suggested that students with various personality types use various learning methodologies. When working with pupils with mixed behavioural traits, it might be challenging to tell whether they are interested or boring. When classmates and teachers misinterpret actions resulting from introversion and shyness, students might suffer, which can lead to academic as well as social problems. The study in [14] most classes have one mix of extroverted and introverted students, and that learning outcomes are better when students are given the chance to process new information in their preferred way, faculty may have to provide a balance of tasks and projects that are equally introvert as well as extrovert-friendly inside the classroom.

The study in [15] attempted to compare how introverts and extroverts differ in their capacity for decision-making and to determine which traits are advantageous for making decisions. Extroverts are less effective at making decisions than introverts. Intuition and gut instinct are what introverts rely on. Although it's a positive trait for extroverts to check their facts twice before making conclusions, they still want guidance when it comes to big choices.

"Implementing AutoML in Educational Data Mining for Prediction Tasks" [16–17] is the title of the first work in this group, written by Maria Tsiakmaki, Georgios Kostopoulos, Sotiris Kotsiantis, and Omiros Ragos. Due to the complexity of ML when applied to a specific problem formulation and the need for optimal configuration, this research focuses on investigating the potential use of advanced ML strategies on educational settings from the standpoint of hyperparameter optimisation. With the goal of predicting students' learning outcomes based on their involvement in online learning platforms, the authors analyse the performance of automated ML (autoML), restricting the search space to tree-based and rule-based models.
Numerous trials have been conducted, and the effectiveness of AutoML has been confirmed. With the help of this approach, educators and instructors who work with educational data mining (EDM) can conduct tests with good parameter setups and produce findings that are incredibly precise. The second piece in this collection was written by Raza Hasan, Sellappan Palaniappan, Salman Mahmood, Ali Abbas, Kamal Uddin Sarker, and Mian Usman Sattar and is titled "Predicting Student Performance in Higher Educational Institutions Using Video Learning Analytics and Data Mining Techniques" [18-19].

The authors have developed a system for predicting student's overall performance at the end of the semester using video learning analytics and data mining techniques. They consider video-based learning with flipped teaching to improve student's academic performance. Particularly, the authors applied eight classification algorithms (where random forest obtained the best results) to data collected from the student information system, learning management system and mobile applications. Additionally, they used genetic search, principal component analysis, rule inducer and multivariate projection to improve different aspects of the study.

Problem Statement
Studies reveal that introverts are successful in several aspects but exhibit poor behaviour in group activities [13]. Engineering students need to be active in social association's teamwork and expressing their views. Similarly, extroverts are active in external activities and have chances to lose focus leading to failure. Also, extroverts cannot take decisions on their own. Our study is to identify whether a student is an Introvert/Extrovert well in advance and mentor those students who exhibit poor behavioural traits and guide them to adapt to the relevant standards. The aim is to classify the study Introvert/Extrovert/Average by applying machine learning Algorithms.
Architecture

Research Gap:
When it comes to analyzing and predicting engineering student Behaviour and its relation to academic performance, there are several research gaps that can be identified. These research gaps highlight areas where further investigation and improvement are needed. Here are some potential research gaps in this field.

Data Availability and Quality: Availability of Longitudinal Data: Longitudinal data that spans multiple academic terms or years can provide a comprehensive understanding of student Behaviour and its relation to academic performance. Research could focus on collecting and analyzing long-term data to capture the evolution of student Behaviour over time.

Data Quality and Consistency: Ensuring the quality and consistency of the data used for analysis is crucial. Research could explore strategies for validating and standardizing data collection methods to ensure the reliability of the findings.

Feature Selection and Representation: Identification of Relevant Features: Determining which factors or attributes significantly impact student Behaviour and academic performance is a critical research area. Identifying the most influential features can help build more accurate prediction models.

Representation of Behaviour: Exploring innovative methods to capture and represent student Behaviour is essential. Traditional approaches may not fully capture the complexity and context of student interactions, such as social engagement, collaboration, or online activity.

Research could focus on developing more comprehensive and nuanced representations of student Behaviour.

Contextual Factors and Individual Differences: Contextual Factors: Understanding the influence of contextual factors, such as institution type, curriculum, teaching methods, and student support services, on student Behaviour and academic performance is vital. Research could investigate the impact of these contextual factors to provide a more holistic understanding of student outcomes.

Individual Differences: Recognizing the individual differences among students is crucial. Personal characteristics, learning styles, and motivation levels may significantly impact student Behaviour and academic performance. Research could explore how individual differences interact with other factors to better predict and understand student outcomes.

Ethical Considerations: Privacy and Data Protection: With the increasing availability of student data, privacy concerns become prominent. Research should address the ethical considerations of data collection, storage, and usage, ensuring that student privacy and confidentiality are maintained throughout the analysis and prediction processes.

Fairness and Bias: Ensuring fairness in predicting student Behaviour and academic performance is important. Research should explore methods to mitigate bias and ensure that the prediction models do not perpetuate inequalities or unfair treatment.

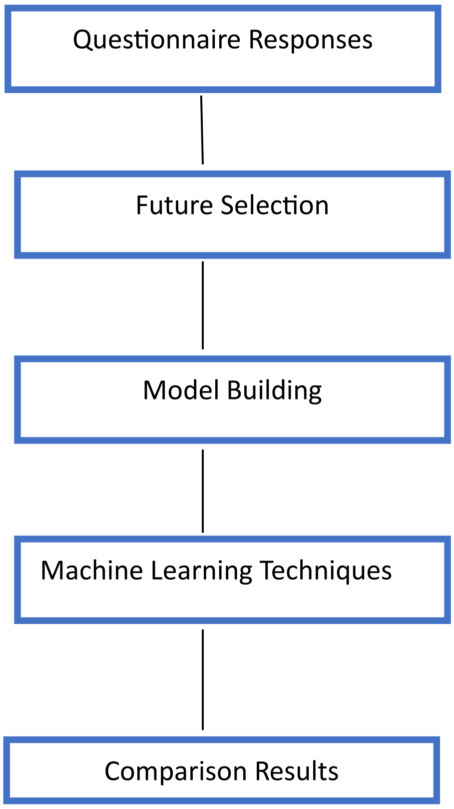

Fig: System Architecture

METHODOLOGY

Data Collection

The data is prepared from the responses of survey questionnaires; the questionnaire, prepared is curetted and tested from benchmark questionnaires on personality traits. The work is guided by practitioner psychiatrists and experienced personnel in the field of Education. The questions are designed based on student Behaviour on a linker scale to collect the responses. The dataset thus collected has 600 records.

Support Vector Machines (SVM), Random Forest, Naive Bayes, and Decision Trees are machine learning algorithms that can be applied to analyze and predict engineering student Behaviour and its relation to academic performance. Here's how each algorithm supports this analysis:

Support Vector Machines (SVM):

SVM is a supervised learning algorithm that can be used for classification tasks. It constructs a hyperplane that maximally separates different classes of data points. In the context of engineering student Behaviour, SVM can be trained on historical data that includes various factors such as attendance, study habits, extracurricular activities, and academic performance. SVM can help identify patterns and relationships between these factors and predict student Behaviour, such as their likelihood of participating in class, engagement in assignments, or overall academic success.

Random Forest:
Random Forest is an ensemble learning algorithm that combines multiple decision trees to make predictions. It can handle both classification and regression tasks. In the analysis of engineering student Behaviour, Random Forest can be trained on a dataset that includes various attributes related to student Behaviour, such as study hours, exam scores, social engagement, etc. Random Forest can provide insights into the most important factors that influence student Behaviour and academic performance. It can also predict the likelihood of a student exhibiting certain Behaviours or achieving certain academic outcomes based on the input attributes.

Naive Bayes:
Naive Bayes is a probabilistic classification algorithm that applies Bayes' theorem with an assumption of independence among features. In the context of engineering student Behaviour, Naive Bayes can be trained on data that includes various attributes such as student demographics, study habits, online activity, etc. Naive Bayes can analyze the relationships between these attributes and predict student Behaviour patterns, such as their likelihood of attending class, submitting assignments on time, or performing well academically.

Decision Trees:
Decision Trees are versatile algorithms that can be used for both classification and regression tasks. They create a flowchart-like structure of decision nodes based on input features to make predictions. In the analysis of engineering student Behaviour, Decision Trees can be trained on a dataset containing attributes such as study time, participation in group projects, exam results, etc. Decision Trees can identify important factors that contribute to student Behaviour and academic performance. By following the decision path, it can predict the likelihood of a student exhibiting specific Behaviours or achieving certain academic outcomes.

These algorithms can provide valuable insights into engineering student Behaviour and their relation to academic performance. By leveraging historical data and appropriate feature selection, they can help identify patterns, predict outcomes, and guide interventions or recommendations to improve student engagement and success in the engineering domain. It's important to note that the choice of algorithm depends on the specific characteristics of the dataset and the nature of the problem being addressed.

Algorithm: Labeling theory

```
Procedure to label training data:
{
    Let D be the dataset
    Let f be the Features
    Let fi be the set of intro character-related questions
    Let fj be the set of extro character-related questions
    Let pI = nI = pE = nE =0
    for v in f:
        if r(v) belongs to fi:
            if v belongs to fip:
                if r(v) < 3:
                    pI++
            else:
                if r(v) > 3:
                    nI++
        else:
            if v belongs to fjp:
                if r(v) < 3:
                    pE++
            else:
                if r(v) > 3:
                    nE++
        if v belongs to fi:
            if v belongs to fip:
                res(i) = Avg(fip)
            else:
                res(j) = Avg(fin) * nI
        else:
            if v belongs to fjp:
            res(k) = Avg(fjp)
            else:
            res(l) = Avg(fjn) * nE

    if(res(i) > res(l) OR res(j) > res(k)):
        Labeled = Introvert
    elif(res(l) > res(i) OR res(k) > res(j)):
        Labeled = Extrovert
    else:
        Labeled = Average
}
```

In this section, Labeling theory is a sociological perspective that can be applied to the analysis and prediction of engineering student Behaviour. The theory suggests that individuals' Behaviour and self-identity are influenced by the labels assigned to them by others, particularly through social interactions and institutions. Here's how Labeling theory can be used in the context of analyzing and predicting engineering student Behaviour.

Social Labels and Stereotypes: Labeling theory highlights how social labels and stereotypes can shape individuals' Behaviour and self-perception. In the case of engineering students, societal stereotypes or preconceived notions about their intelligence, competence, or social skills can impact their Behaviour within the academic setting.

Stigmatization and Self-Fulfilling Prophecy: According to Labeling theory, individuals who are labeled or stigmatized based on certain characteristics may internalize and conform to those labels, thereby reinforcing the expected Behaviour. In the context of engineering students, if they are labeled as "nerds" or "socially awkward," they may be more likely to exhibit Behaviours that align with those stereotypes.

Differential Treatment: Labeling theory emphasizes that individuals who are labeled or perceived in a certain way may experience differential treatment from others, including teachers, peers, and administrators. This differential treatment can further influence their Behaviour and academic performance. For instance, if engineering students are labeled as "high achievers," they may receive more opportunities and resources that contribute to their success.

Predictive Power: Applying Labeling theory to the prediction of engineering student Behaviour involves considering the impact of labels and stereotypes on their actions and outcomes. By analyzing the labels assigned to engineering students and the subsequent consequences of those labels, it may be possible to predict certain Behavioural patterns or academic performance.

Intervention Strategies: Labeling theory suggests that interventions should focus on challenging and changing the labels and stereotypes associated with engineering students. By promoting positive and inclusive labels, fostering a supportive learning environment, and addressing stigmatization, interventions can help mitigate the potential negative effects of labeling on student Behaviour and academic performance.

Contextual Factors: Labeling theory also emphasizes the importance of considering contextual factors that contribute to the labeling process. Factors such as cultural norms, institutional policies, and social interactions play a significant role in assigning labels to individuals. Analyzing these contextual factors can provide insights into the broader mechanisms that influence engineering student Behaviour.

By incorporating Labeling theory into the analysis and prediction of engineering student Behaviour, researchers and educators can gain a deeper understanding of the social dynamics and processes that shape student experiences and outcomes. This perspective can inform intervention strategies and create more inclusive and supportive environments for engineering students.

Experiment Results and Discussions:

In this section, It constructs a hyperplane that maximally separates different classes of data points. In the context of engineering student Behaviour, SVM can be trained on historical data that includes various factors such as attendance, study habits, extracurricular activities, and academic performance. SVM can help identify patterns and relationships between these factors and predict student Behaviour, such as their likelihood of participating in class, engagement in assignments, or overall academic success.

In the analysis of engineering student Behaviour, Random Forest can be trained on a dataset that includes various attributes related to student Behaviour, such as study hours, exam scores, social engagement, etc. Random Forest can provide insights into the most important factors that influence student Behaviour and academic performance.

It can also predict the likelihood of a student exhibiting certain Behaviours or achieving certain academic outcomes based on the input attributes.

In the context of engineering student Behaviour, Naive Bayes can be trained on data that includes various attributes such as student demographics, study habits, online activity, etc. Naive Bayes can analyze the relationships between these attributes and predict student Behaviour patterns, such as their likelihood of attending class, submitting assignments on time, or performing well academically.

In the analysis of engineering student Behaviour, Decision Trees can be trained on a dataset containing attributes such as study time, participation in group projects, exam results, etc. Decision Trees can identify important factors that contribute to student Behaviour and academic performance. By following the decision path, it can predict the likelihood of a student exhibiting specific Behaviours or achieving certain academic outcomes.

Intervention Strategies and Evaluation:

Effective Intervention Strategies: Developing and evaluating effective intervention strategies is crucial for improving student Behaviour and academic performance. Research could focus on identifying interventions that have a significant impact on outcomes and assessing their effectiveness in real-world settings.

Evaluation Metrics: Establishing appropriate evaluation metrics to assess the success of intervention strategies is essential. Research could explore comprehensive evaluation frameworks that consider multiple dimensions of student success, beyond just academic performance. By addressing these research gaps, researchers can advance the field of analysing and predicting engineering student behaviour and its relation to academic performance. This can lead to more effective interventions, personalized support systems, and policies that promote student success in engineering education.

These algorithms can provide valuable insights into engineering student Behaviour and their relation to academic performance. By leveraging historical data and appropriate feature selection, they can help identify patterns, predict outcomes, and guide interventions or recommendations to improve student engagement and success in the engineering domain. It's important to note that the choice of algorithm depends on the specific characteristics of the dataset and the nature of the problem being addressed.

Table: 1 Comparison Results

Model	Accuracy(%)
Navie Bayes	82
Random Frest	87
SVM	92
Decision Tree	96

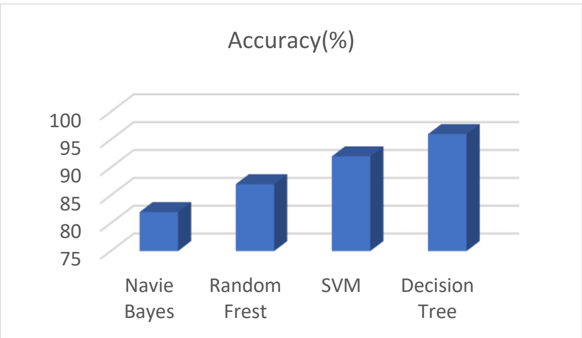

Fig: Comparision results with Accuracy

Fig. 10. demonstrates the accuracy of the models explored in this study to identify Intorvert, Extrover or Mixed behavioural traits for unknown instances in the test dataset. SVM, KNN, RF, NB and DT approaches are studied and compared. The results show that Decision Tree Approach has shown 95% accuracy. When concluding an analysis and prediction of engineering student Behaviour using machine learning techniques, it is important to summarize the findings and highlight the key takeaways. Here are some justifications for the conclusion part.

Accuracy of Predictive Models: Discuss the accuracy and performance of the machine learning models used in predicting engineering student Behaviour. Highlight the evaluation metrics, such as accuracy, precision, recall, and F1 score, to demonstrate the effectiveness of the models in capturing patterns and predicting student Behaviour.

Identification of Important Factors: Emphasize the identification of important factors or features that significantly influence engineering student Behaviour. Highlight the variables that were found to be most predictive of student outcomes, such as study hours, attendance, collaboration, or engagement in extracurricular activities.

Insights into Student Behaviour: Discuss the insights gained from the analysis. Highlight any interesting patterns, trends, or correlations discovered during the investigation of engineering student Behaviour. This can include the impact of certain Behaviours on academic performance or the influence of contextual factors on student outcomes.

Practical Implications: Discuss the practical implications of the findings. Explain how the analysis and prediction of engineering student Behaviour can inform intervention strategies, personalized support systems, or educational policies. Discuss the potential benefits of using machine learning techniques to enhance student success and improve the overall learning experience.

Based on comparison results, Decision trees can be highly valuable in analyzing and predicting engineering student Behaviour. Here's how decision trees support the analysis and prediction of engineering student Behaviour.

Interpretability: Decision trees provide a clear and interpretable representation of the decision-making process. Each node in the tree represents a feature or attribute, and the branches represent possible decisions or outcomes. This makes it easier to understand the factors that influence engineering student Behaviour.

Feature Importance: Decision trees can identify the most important features or attributes that significantly contribute to engineering student Behaviour. By examining the structure of the decision tree, researchers can identify the key factors that influence student Behaviour, such as attendance, study habits, collaboration, or extracurricular involvement. Prediction of Behaviour Patterns: Decision trees can be trained on historical data that includes various attributes related to engineering student Behaviour. Once trained, the decision tree can predict the Behaviour patterns of new students based on their input attributes. For example, it can predict the likelihood of a student attending classes regularly, actively participating in group projects, or seeking help from instructors.

Identification of At-Risk Students: Decision trees can help identify students who are at risk of exhibiting certain Behaviours or facing academic challenges. By analyzing the decision paths in the tree, researchers can pinpoint the attributes or combinations of attributes that are associated with poor academic performance or disengagement. This information can be used to identify at-risk students early and implement appropriate interventions.

Personalized Interventions: Decision trees can guide the development of personalized intervention strategies for engineering students. By understanding the attributes that lead to desired Behaviours or outcomes, educators can tailor interventions based on individual students' needs. For example, the decision tree can suggest specific strategies for improving time management, study techniques, or engagement in class.

Evaluation of Intervention Effectiveness: Decision trees can help evaluate the effectiveness of intervention strategies by comparing the predicted Behaviours of students before and after the implementation of interventions. This allows researchers to assess the impact of specific interventions on engineering student Behaviour and academic performance.

Actionable Insights: The insights gained from decision trees can inform educational policies and practices. By understanding the factors that influence engineering student Behaviour, educators and administrators can implement targeted initiatives to promote positive Behaviours, enhance student engagement, and improve academic outcomes.
Overall, decision trees provide a versatile and intuitive approach to analyze and predict engineering student Behaviour. They offer insights into the key factors influencing Behaviour, enable personalized interventions, and support evidence-based decision-making in education.

CONCLUSION

Overall, the conclusion should summarize the findings of the analysis and prediction of engineering student Behaviour using machine learning techniques, emphasizing the accuracy of predictive models, insights gained, practical implications, and areas for future research. It should provide a clear and concise summary of the main outcomes and highlight the significance of the study in improving student outcomes and informing educational practices. The suicidal cases in young people with issues of career failure, failure of affairs, or a mere backlog in a course so on and so forth are pestering issues. Identifying students with low personality traits so comes with the need to study the attributes of students and identify the characteristics that lead to a depressed situation. This work conducts a survey and collects data from an authorized source and performed a study of machine learning models built on the survey data. 96% Accuracy is observed with Decision Tree and 92% using SVM. Decision trees can help identify students who are at risk of exhibiting certain Behaviours or facing academic challenges. By analyzing the decision paths in the tree, researchers can pinpoint the attributes or combinations of attributes that are associated with poor academic performance or disengagement. This information can be used to identify at-risk students early and implement appropriate interventions. Decision trees can guide the development of personalized intervention strategies for engineering students. By understanding the attributes that lead to desired Behaviours or outcomes, educators can tailor interventions based on individual students' needs. For example, the decision tree can suggest specific strategies for improving time management, study techniques, or engagement in class.
Decision trees can help evaluate the effectiveness of intervention strategies by comparing the

predicted Behaviours of students before and after the implementation of interventions. This allows researchers to assess the impact of specific interventions on engineering student Behaviour and academic performance. Overall, decision trees provide a versatile and intuitive approach to analyze and predict engineering student Behaviour. They offer insights into the key factors influencing Behaviour, enable personalized interventions, and support evidence-based decision-making in education.

Future Directions: Identify areas for future research and improvement. Highlight any limitations or research gaps encountered during the analysis and suggest ways to address them. This could include exploring additional factors, expanding the dataset, considering longitudinal studies, or incorporating more advanced machine learning techniques.

Ethical Considerations: Discuss the ethical considerations that need to be addressed when utilizing machine learning techniques for analyzing and predicting student Behaviour. This can include privacy concerns, bias mitigation, and ensuring fairness and transparency in decision-making.

Generalizability: Comment on the generalizability of the findings to other engineering education settings or student populations. Discuss whether the conclusions drawn from the analysis can be extended to other institutions or if there are specific contextual factors that may influence the results.

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