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Harnessing AI for a Comprehensive Student Performance Analysis: A Research Prospect in Educational Data Mining

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Abstract— In the field of education, there are many different criteria and elements used to assess pupils as they go through their career. The responsibility of a learner is to introduce the mechanisms that will enable them to modify the way they shape this process. The process of analysing and developing a system such as student performance analysis may be made easier with the use of a system that incorporates multilabel classification, educational data mining, and the infused AI model. We attempted to do so by using the method of training a neural network with information gathered about the pupils' present educational trajectory. This model will provide multilabel categorization using machine learning techniques by integrating survey data with real-time educational data that is collected within the system. By utilising the OCEAN big five model features, student personality traits may be assessed through the integration of survey data. When developing the more complex models around these ideas, keep in mind Kolb's learning styles as a guide. Gaining a comprehensive knowledge of a student's talents and potential requires evaluating them outside of the usual classroom setting. The traditional measures, which include grades, certificates, attendance records, and proficiency in practical exams, sometimes fall short of capturing the complex character of students' accomplishments. This research also attempts to offer greater insights into characteristics and parameters like study habits, learning styles, home environments, academic relationships, coping strategies, cognitive factors, etc. by integrating multilabel categorization with the EDM framework. It facilitates the development of a tracking system for students' academic progress and aids in navigating the possibilities and difficulties presented by the educational environment.

Index Terms— Multilabel classification, educational data mining, cognitive skills, AI model, Student Profiling, Analysis, Informed Decision Making, Kolb learning styles, Personalized intervention, educational outcome.

I. INTRODUCTION

The technologies been used has increasingly became very prevalent, offering new areas and reflects in understanding and improving the student performance beyond classroom. Such approaches can process the vast amounts of educational data collected from the learner and incorporating technology like artificial intelligence models and using machine learning algorithms which helps in giving an insights and output based on the neural network that we have trained. The educational data mining (EDM) with AI Techniques have gained prominence for their potential recommendations in shaping the student's academic carrier. The approaches of student towards the class environment rely on very grounded and simplistic metrics, subjective assessments, limiting the depth of understanding the behavior of student's ability in different arena, and as a researcher and learner we need to delve more deeper into the nuances of students learning objective, preferences, and challenges. This paper would throw light on the fact that a intersection of the AI models, multilabel classification and EDM with a very focused approach of enhancing the analysis of student's performance. Through this specific source of approach, we collectively understand the diverse data sources, including the survey data, real time educational data and this would help in evaluating them based on learning patterns that have been observed from different streams, discipline or year and level of education they are acquiring. The study also helps in incorporating the validated framework such as OCEAN big five traits for evaluating personality.

By assessing students' personalities using the OCEAN model, educators and administrators can gain valuable insights into individual differences in learning styles, motivations, and behaviours within the classroom. This information can inform instructional strategies, group dynamics, and student support initiatives tailored to meet the diverse needs and preferences of students. For example, students high in openness may benefit from innovative teaching methods and opportunities for creative expression, while those high in conscientiousness may thrive in structured, goal-oriented learning environments. Likewise, understanding students' levels of extraversion and agreeableness can inform group projects and collaborative activities, promoting positive social interactions and teamwork skills. Additionally, identifying students who may score high in neuroticism can facilitate early intervention and support mechanisms to address potential academic and emotional challenges they may encounter. Overall, the OCEAN model provides a valuable framework for enhancing student engagement, satisfaction, and success in the university classroom.

The factors or parameters that we have in the evaluating the students is going to have the simple understanding of the holistic development and not ranging them for the regular basis of the judging criteria and helping them recommend a pathway for the disciplines that want to When it comes to regularise the part where the students can understand the depth of the carrier and the importance, they can actually take this product in hand. A product like website helps in moulding the interest of the students and guide them with the pathway that can help them.

The parameters that have been used to evaluate the students majorly are study habits, learning styles and OCEAN personality traits. These are the nontraditional ways of producing the result, the statistical measure to lot of such methods helps with the non-cognitive ways and methods. Let us try to understand the learning styles first, the very famous Kolb's learning styles is the helping and guiding light for us when it comes to assess the students based on these styles, since this learning style includes the parameters to assess like- assimilation, converging, diverging and accommodating. The styles work with the simple idea of having these factors listed in the different quadrants and this style helps you assess them based on a questionnaire. We achieved this through conducting the survey through google form and getting a response of about 200 students approximately.

II. LITERATURE REVIEW

The Kolb Learning style Inventory 4.0 (KLSI 4.0) [1], a tool which is used to assess through a lot of different learning theory which includes experimental learning theory (ETL). ETL posits that learning process involves concrete experience, reflective observation, abstract conceptualization, and active experimentation. This also includes 4 divisions of cycle like: accommodating (CE), converging (AC), diverging (SA) and assimilating (AE).

The student who learns best through hands on experiences and enjoys adapting the home environment and mold themselves into the new situations out to be fall under this category. The converging on the other hand is a student who prefers practical applications of knowledge and excel at problem solving using some standard and established methods. Diverging which also includes student approaching more towards the creative sides and ideas and enjoy the brainstorming but sometimes might find it difficult to narrow down or juggle with the pushing themselves into one direction. Assimilating speaks about the student being very value logical and someone who finds giving reasoning and enjoys learning through a very clear explanations and finds a format of approach that is very structured. Psychometric properties also are a prominent feature which helps in the ability to predicting learning a success various educational context. Validity in the terms of research for the KLSI 4.0, includes content validity, construct validity and criterion validity.

Aspect	Key Points
Theoretical Foundation (Experiential Learning)	KLSI 4.0 based on Kolb's ELT cycle: Concrete Experience, Reflective Observation, Abstract Conceptualization, Active Experimentation
Learning Styles	Identifies four styles: Accommodating (CE), Converging (AC), Diverging (SA), Assimilating (AE)

Psychometric Properties (Validity)	Content, Construct, Criterion validity explored
Psychometric Properties (Reliability)	Internal consistency (Cronbach's alpha), test-retest reliability assessed
Research on Validity and Applications (Outcomes)	KLSI 4.0 used to predict learning outcomes in various educational settings
Research on Validity and Applications (Uses)	KLSI 4.0 used for personalized learning experiences, tailoring instruction to learning styles

Table 1. Summary of Kolb's Learning style, highlighting the aspects and key point of the different factors affecting it.

The dynamic approach to learning known as "experimental learning theory" (ELT) places an emphasis on the conversion of experience into knowledge. This effectively integrates experience into a cyclical process that is driven by the resolution of tensions between grasping experience (concrete experience and abstract conceptualization) and transforming experience (reflective observation and active experimentation). These ELT emphasize how crucial experience, introspection, and action are to learning.

Theoretical underpinning: experiential learning theory (ETL) asserts that learning happens when these elements are included, and the validity and applicability are worked on.

Fig.1. The Experimental Learning Cycle in [2]

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The Five Factor Model (FMM), also known as the OCEAN Model, is used in framework to capture personality through five broad dimensions: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. Personality in situations: Going beyond the OCEAN and introducing the Situation Five [2]. Personality traits play a vital role in shaping the behaviour and predicting the outcomes. The authors debate about the environmental circumstances that may influence how personality characteristics show up in conduct and point out certain limitations in their study.

Situation Five	X^2	*p*	*df*	CFI	TLI	RMSEA	SRMR	Estimator
Outcome-Expectancy	124.44	<.001	27	.98	.97	.097 [.080; .114]	.04	WLSMV
Briskness	107.95	<.001	20	.96	.94	.107 [.087; .127]	.06	WLSMV
Psych. and Phys. Load	116.99	<.001	27	.98	.98	.093 [.076; .111]	.04	WLSMV
Lack of Stimuli	86.50	<.001	27	.99	.99	.076 [.058; .094]	.03	WLSMV
Cognitive Load*	70.94	<.001	16	.98	.97	.094 [.073; .117]	.05	WLSMV
				Study 3				
Situation Five	X^2	*p*	*df*	CFI	TLI	RMSEA	SRMR	Estimator
Outcome-Expectancy	3424.81	<.001	819	.74	.72	.090 [.086; .093]	.09	WLSMV
Briskness	3920.56	<.001	860	.67	.66	.095 [.092; .098]	.10	WLSMV
Psych. and Phys. Load	2270.24	<.001	819	.88	.88	.067 [.064; .070]	.07	WLSMV
Lack of Stimuli	2707.28	<.001	819	.71	.71	.076 [.073; .079]	.09	WLSMV
Cognitive Load	3107.94	<.001	629	.58	.55	.100 [.096; .103]	.11	WLSMV
Big Five	X^2	*p*	*df*	CFI	TLI	RMSEA	SRMR	Estimator
Emotional Stability	42.74	<.001	14	.96	.94	.072 [.050; .095]	.04	MLR
Extraversion	104.60	<.001	25	.91	.88	.090 [.074; .106]	.05	MLR
Openness/Flexibility	59.90	<.001	27	.95	.93	.055 [.039; .072]	.04	MLR
Agreeableness/Team-Orientation	48.56	<.001	18	.89	.83	.065 [.045; .086]	.05	MLR
Conscientiousness	113.69	<.001	27	.88	.84	.090 [.075; .105]	.06	MLR

Model-Fits for the Situation Five and Big Five Models Study 2

Fig.2. The model fits situation Five and Big Five Models in [2]

The fit of two models in two investigations is contrasted in the table:

The fifth scenario model is said to take five elements into account that affect students' results. Students' level of expectation of success in a given scenario is known as outcome expectancy (OE). Students' psychological and physical demands are referred to as psychophysiological needs (PN). The labour or mental effort needed in the circumstance is called the load (LD). The degree of excitement or boredom a student feels in a given circumstance is known as lack of stimulus (LS). The quantity of information processing required in the circumstance is known as cognitive load (CL). The Big Five Model consists of extraversion, agreeableness/team orientation, conscientiousness, openness/flexibility, and emotional stability. Fit statistics (CFI, TLI, RMSEA, and SRMR) for each model are displayed in the table. Better model fit is often indicated by lower RMSEA and SRMR values.

The Person-Situation Interaction (PSI) hypothesis developed by Mischel in 1973 is also emphasised in this work. It suggests that behaviour results from the interaction of a person's (personality) traits with their surroundings. In a similar vein, Bandura's (1986) social cognitive theory recognises the mutual interaction of environmental circumstances and individual traits. Although the model we use provides useful understanding of personality, it is limited in its ability to account for environmental effect. The model may overlook how stable features interact with dynamic conditions by concentrating only on these traits.

III. METHODOLOGY

To help us understand and evaluate the students based on their preferred learning styles and predict the type of personality student holds in a holistic environment, we employed a survey and distributed electronically through *Google Forms* to collect the appropriate educational data. The administration of this survey primarily focuses on capturing the learning styles that are aligned with keeping these styles as a guide like Felder-Silverman Inventory (FSI) and Kolb's Learning style Inventory (KLI). Building a Multi-Factorial Model for Student Performance Prediction.

Data Acquisition

Capturing Learning Styles for designing and collecting the data in gives a brief understanding of potential that students can adapt in the class environment and process of learning becomes crucial for educators, trainers, and researchers alike. This section will give deep insights about designing and collecting the data by the google form survey which is aimed at identifying student's learning styles.

The survey incorporates elements from established learning styles inventories, such as Felder-Silverman (FSI) and Kolb's Learning Style Inventory (LSI), while also covering the aspects like demographics factors which is very specific to evaluating the student's performance.

Crafting Comprehensive survey:

The fundamental block of this process lies in effectively designing the factors that are to be considered and it captures the diverse learning and development styles of a student. Students confused with their academic pathway will have this as a first-hand tool as it will help them understand better their present and future position. Leveraging the established inventories and drawing inspiration from a well-regarded learning style helps in categorising and gives a better approach to process information and experiences. Kolb's LSI framework focuses on four main categories- Concrete Experience (CE), Reflective Observation (RO), Abstract Conceptualization (AC) and Active conceptualization (AE). This promotes in analysis and applying their knowledge and helps in experimentation or planning. The other aspect which plays important role is question validation with variety of well-rounded survey and incorporate a combination of question types. The question type of categorical choice as a option will have the format of capturing the discrete preferences within a specific learning style dimension. For example- "I learn best by seeing/looking at pictures and diagrams or visuals" or "I prefer to solve problems by trying different approaches". Answering such questions will form a foundation to understand when we incorporate this in the model what kind of result will give a better insight into the performance analysis. When we see at another perspective of dependency of this survey, we found out that demographic section plays an important role includes information like age range, educational background, professional filed, learning context for example traditional classroom and online learning. This helps in exploring the potential correlations between various student's performance. The Tailored Demographic section in this model will help foster the process and ensure the cross-domain factors being used at its potential.

Another important aspect which is highlighted through this model is Pilot Testing and refinement before the process is initialised. With testing with the survey we take this into consideration with help of a small group of individuals. This would promote assess clarity: ensuring the questions that are clear, concise, and easy to understand. Identifying ambiguity that is eliminating any potential words that being referred to the same meaning or confusion in questioning or wording. Another one that comes into notice is gauge time commitment, which is estimating the time required to complete the survey and ensuring it is not much lengthy, the length pf the option and question is not lengthy as it distracts and disinterests the surveyor. With following all the above process, a very important to include should be the maintenance of the test by gathering the feedback of the survey's overall structure, format and ease of use and understanding of the test. These steps will refine the survey and ensure the gathering of the data at much feasibility and reliable data will be collected.

The survey just not only includes the incorporating of the feedback or the pilot testing and etc, with this process it is also important to include the reaching of the right amount and target of people. Once the questionnaire is finalised, before this process the formation of it should always include keeping in mind while designing it. As the most appropriate questions in the survey would be very important. This we have achieved through the means of the email, social media, and most beneficial to be included is learning management systems instructor (LMS), if the researcher is within a specific educational context, instructors can share the link through the LMS platforms.

Feature Encoding

It's vital to bridge the gap between the raw data and categorical variables with the machine learning model that needs numerical features for training and prediction, considering a scenario where we dive into feature encoding with some critical parameters like LMS and the comprehension of FSI. However, these also bring with them certain difficulties in encoding the categorical data. For example, machine learning models work best with numerical data, and they frequently present difficulties when it comes to classifying extremely precise criteria that include scores and marks out of 10 or 20. Thus, it has always been (Yes/No, Agree/, Disagree) while we were classifying learning styles such as accommodating, converging, diverging, and assimilating or other survey replies. These variables or parameters do not have inherent numerical values and cannot be directly fed into the model. Feature encoding comes into the picture as the transformation bridge, this technique helps bridge this gap by transforming into numerical representations that model can understand and give useful results. The also helps model to build a relationship between these features and then target variable. (eg student performance). The technique that come in use here is the label encoding, assigns a unique integer value to each category, while simply assuming a ordinal relationship between categories, which might not always be true (for example- "High" isn't inherently better than "medium"). There is a lot of such categories that comes into picture but always important to categorise and choose the right technique. The optimal encoding technique depends on the specific characteristics of the data, underlying some assumptions about the model, and the desired interpretability of the results. Also, some additional features that come into picture are Number of categories- large no. of categories might favour one hot encoding to avoid the ordinal bias but increase the feature dimensionality. Another approach could be the model type, like in our case we have multi- class classification model, we need to interpret the interactions between features and the target variable, label encoding might offer a simpler representation, although one-hot encoding can also be interpreted through feature importance scores.

Understanding the technical perspective of feature encoding and its impact on model development, we can make some informed decisions when curating the data for the machine learning analysis and achieve optimal results in predicting the student performance.

Model Training and Interpretation

This section delves into the training process, evaluation metrics and potential techniques for interpreting the model's behaviour. Given the condition, multi-class nature of the target variable, for example – predicting a student performance category like "high", "medium", or "low", a multi-layer perceptron (MLP) is a suitable choice for our neural network architecture. MLP's architecture are well-established networks capable of learning complex non-linear relationships between features and the target variable. This process works in different layers in the architecture- input layer- the no of neurons in the input layer will correspond to the number of the Features that we have pre-processed. This includes- encoded learning, normalized OCEAN traits, additional features from LMS data. One or more hidden layers can also be employed to extract the complex patterns from the data. Determining the optimal number of hidden layers and neurons is often achieved by experimentation and validation. Then we have further development through output layer, the number of neurons in the output layer will reflect the number of predicted performances categories. For example, three neurons for "high", "medium" and "low" performance. Activation functions like softmax ensures the output layer produces probabilities for each class, which is summing up to 1.

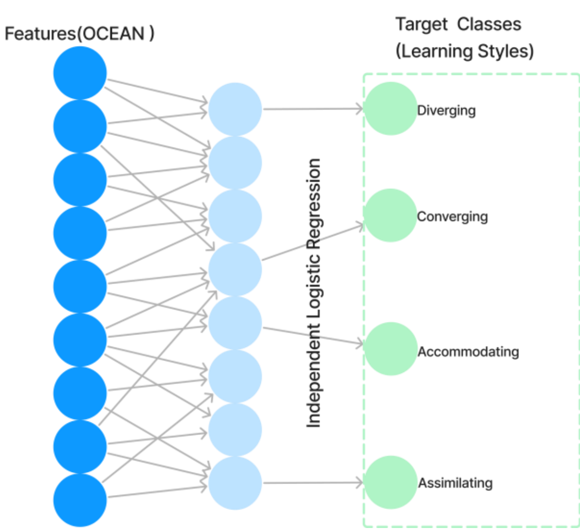

Fig.3. The architecture for parameters and target and classes

The training process includes splitting the pre-processed data into a training set, validation set and a test set. This validation helps us with monitoring the performance and prevent overfitting. The set or the target variable provides an unbiased evaluation of the final model's generalization ability. The Loss function is also a factor that affects the process so the function like categorical cross-entropy, which will be used to measure the difference between the predicted probabilities and the actual performance classification. The model's objective is to minimize this loss function during the training. Optimizer algorithm like stochastic gradient descent (SGD), will iteratively update the weights and biases within the neural network based on the chosen loss function.

Model Evaluation, the classification metric will employ the appropriate multi-class classification metrics to assess the model's performance on the test set. So a very common metrics include- accuracy the overall percentage of correctly classified student into the particular category. The other metric is precision and recall, which enables you to evaluate the model's ability to identify the true positives and avoid false positives/negatives for each performance category.

The F1 score which is harmonic mean of precision and recall, this provides a balanced measure of model performance. Monitoring all these metrics affects the model and improves the performance on the validation set during training helps prevent overfitting. Model Interpretation can be crucial especially if interpretability plays a role in our research. Techniques like permutation importance or SHAP (SHapley Additive exPLanations) can also identify which can help significantly in the prediction performance. Visualizing the decision boundaries or activation patterns that are built within the network can offer insights into how the model separates different performances into categories. These are also limited by the complexity of a multi-layer perceptron architecture. There are also some additional considerations like hyperparameter tuning, tuning of parameters like the learning rate, the number of hidden layers and the neurons that can significantly impact model performance. The grid search or randomized search can be used to optimize the parameters used for training of the model.

IV. RESULTS

The product of the efforts undertaken to understand and analyze student performance data in a deeper, more intuitive way were the actionable insights that we were able to garner from our interactive and useful model. The questionnaire produced a useful result like splitting the parameters into a particular Learning style.

I learn by	When I learn	O	C	E	A	N	AE	CE	RO	AC	Learning Style
Doing	I am active	14.0	14.0	13.0	13.0	13.0	3.0	1.0	0.0	1.0	Diverging
Thinking	I evaluate things	17.0	16.0	14.0	11.0	17.0	1.0	0.0	0.0	4.0	Converging
Doing	I am active	13.0	17.0	13.0	9.0	14.0	3.0	1.0	0.0	1.0	Diverging
Thinking	I get involved	7.0	16.0	12.0	11.0	17.0	0.0	2.0	1.0	2.0	Accommodating
Thinking	I get involved	18.0	16.0	15.0	12.0	17.0	1.0	1.0	1.0	2.0	Converging

Fig.4. Dataset with Label and binary Encoding

The dataset already assigns categorical labels to participants based on their dominant learning style (e.g., "Accommodator," "Converge," "Diverge," "Assimilator"), and have implemented label encoding. This process assigns a unique numerical value (e.g., 1, 2, 3, 4) to each learning style category.

And helps categorize these parameters on a scale out of 5. The dataset includes Kolb Learning Style Inventory (KLSI) scores, which represent people's preferences on the four ELT aspects. Based on the circumstances, [Insert a statement here describing how the data is encoded in your dataset]. For example, a new binary variable "High_CE" based on the original CE score might be established if the focus is on comparing students with high and low preferences for Concrete Experience (applicable if scenario 2 is relevant).

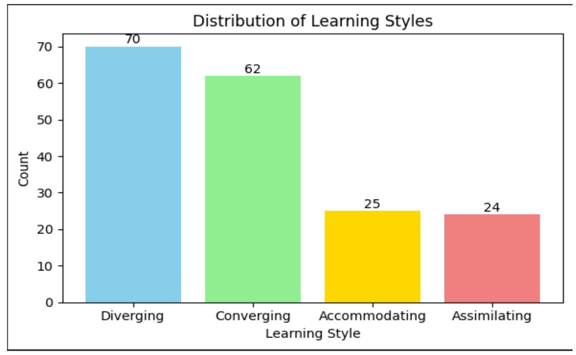

Fig.5. Distribution of Learning Style

This graph depicts the learning style that we have categorized and hence obtained a specific result. The dataset incorporates scores from the Kolb Learning Style Inventory (KLSI), reflecting individuals' preferences on the four dimensions of Experiential Learning Theory (ELT).

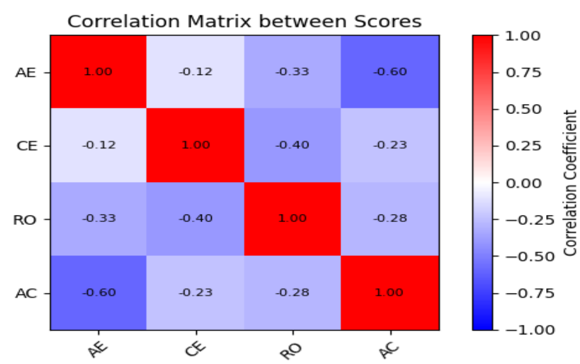

Fig.6. Correlation Matrix between scores.

The values of correlation: The matrix cells show the individual correlation coefficients for every pair of scores. Perfect positive correlation is represented by a value of +1, perfect negative correlation by a value of -1, and no correlation is shown by a value of 0.

Interpretation: The correlation values and colour map might help you understand how the various learning styles relate to one another. For instance, a large positive association between AC and CE may indicate that people with high abstract thinking scores also have a propensity to favour concrete experiences.

Next Actions: The associations between KLSI scores are shown in a snapshot form via the correlation matrix. Regression models and other advanced analysis might be used to investigate the ways in which different learning styles affect student results or other pertinent factors in your study.

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}$$

Fig.7. Pearson's Correlation Coefficient

r	=	correlation coefficient
x_i	=	values of the x-variable in a sample
$\bar{x}$	=	mean of the values of the x-variable
y_i	=	values of the y-variable in a sample
$\bar{y}$	=	mean of the values of the y-variable

Correlation coefficient of Pearson (Figure 7), the Pearson correlation coefficient between the AE and AC scores is computed by the code. The linear link between these two variables' strength and direction is indicated by this coefficient. The correlation strength is represented by the resultant number, r = {correlation:.2f}, which ranges from -1 (perfect negative correlation) to +1 (perfect positive correlation). There is no linear connection when the value is 0.

Trendline and Scatter Plot: The link between the AE and AC scores is graphically shown by the scatter plot that the code creates. The scatter plot's data points each represent a person's score on both dimensions.

The model can be used as a tool in a project called "Student Performance Analysis System" [11] as it presents a holistic approach to understand student's performance through accurate data analysis and prediction. The combined output from all the data engineering pipelines may provide for a novel solution that provides a better performance than existing technologies[12].

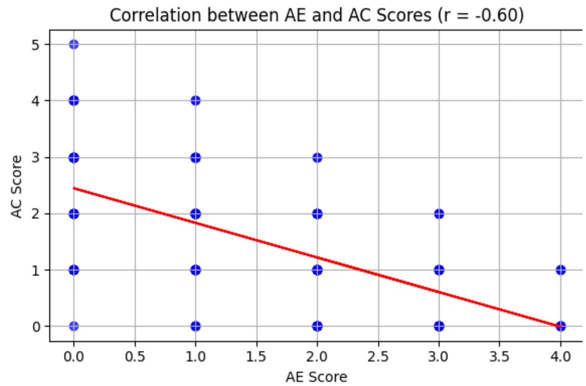

Fig.8. Correlation between AE and AC scores.

The data density is visually represented by the colour map, which is probably blue with an alpha of 0.7. greater AE scores (desire for applying theories) are positively correlated (r > 0) with greater AC scores (propensity for abstract thinking) in people. A negative connection (r < 0) suggests that those who have a higher inclination towards applying theories (high AE) also have lower abstract thinking scores (low AC).R is not correlated (≈ 0): This suggests that the AE and AC ratings in our analysis do not have a distinct linear connection. The scatter plot's best-fit trendline, as determined using linear regression, is indicated by the red line. The general direction and degree of the correlation between the AE and AC scores are illustrated by this line.

Fig. 9. Visualizing the output

Ultimately, the model is integrated with a web – based application that visualizes the independent features and the dependent target classes through radar charts (top left and top right) and bar graphs (bottom left and bottom right). Figure 9 explains this implementation.

CONCLUSION

This study explored a diverse strategy to analyse the elements impacting student performance. To provide a more thorough knowledge of the learning experiences and results of students, we looked at the impact of both situational features and individual personality factors. The results demonstrate the possible advantages of taking situational aspects into account in addition to personality traits. The findings indicate that the Big Five personality model (Extraversion, Conscientiousness, Openness, Agreeableness, Neuroticism) may not be as good a predictor of student performance in the settings of our studies as the Situation Five model, which accounts for social pressure, uncertainty, novelty, goal clarity, and time pressure. This suggests that the unique requirements and features of learning settings may have a greater impact on students' achievement than generic personality traits, maybe even surpassing them.

These results are consistent with the expanding understanding of how context influences learning outcomes. Researchers and educators can create treatments that are more successful by recognising the interaction between environmental circumstances and personality traits. Prospective Courses: this study offers room for more investigation. Subsequent research might: Examine how particular situational elements and personality qualities combine to affect how well students succeed. Creating and verifying a thorough model that incorporates personality and environmental factors. Make use of these discoveries to create customised learning settings that meet the requirements of various learning contexts as well as the unique needs of each learner. This study's result highlights the value of a comprehensive strategy for comprehending student achievement. Understanding the impact of environmental elements as well as personality characteristics can help us get towards growth of the student’s academic carrier.

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