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Unveiling Teaching Quality: A Hybrid Approach with Factor Analysis and Machine Learning

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Abstract: This study investigates the teaching effectiveness within the educational institution utilizing machine learning models and factor analysis methods. Feedback data collected from students is analyzed to predict faculty performance, employing algorithms such as Lasso, Ridge, Decision Tree, Random Forest, etc. Yielding R2 test score of 0.94 with the weighted average ensemble model. Additionally, factor analysis is employed to uncover underlying constructs influencing teaching quality with correlation matrix and reliability and validity being examined using KMO and Bartlett's Test. This is also verified with Principal Component Analysis and Verimax Rotated solution. Results showcase the predictive capabilities of machine learning models and offer insights into the multifaceted factors shaping student perceptions of faculty performance. The integration of diverse analytical techniques provides a comprehensive framework for assessing and enhancing teaching effectiveness.

Keywords: *factor analysis, correlation matrix, reliability, validity, machine-learning, ensemble, feedback system, bartlett's test, SHapley Additive exPlanations*

1 Introduction

Student feedback in higher education serves multiple purposes. Feedback from students provides valuable insights into effectiveness of teaching, course materials, curriculum relevance and overall learning experiences. Feedback systems helps the institutions for demonstrating their commitment to students' satisfaction and well-being. The educators can evaluate the extent to which students are achieving desire learning outcomes based on the students' feedback. The institution can also identify trends, patterns and areas of concern that require attention. This in-turn fosters a culture of continuous improvement where adjustments are made based on evidence and stakeholder input.

Hattie and Timperley (2007) have given the meaning of feedback:" A conventional view is to see feedback as information provided by an agent, for example, a teacher, peer or self, about aspects of performance or understanding. In recent years, education researchers are concentrating more on student feedback return analysis. The analysis are related to accountability and transparency, faculty development, accreditation, institutional regulation and student success metrics.

Nicol and Macfarlane-Dick (2006) identified seven broad principles of good feedback practice. Graham Hibbs (2006) outlined the ways to address the specific weakness of student feedback system. Margaret Price and Berry O' Donovan (2006) have evolved a constructivist approach for making improvements in students learning and performance. Constructivist Assessment cycle is given in the following figure 1.

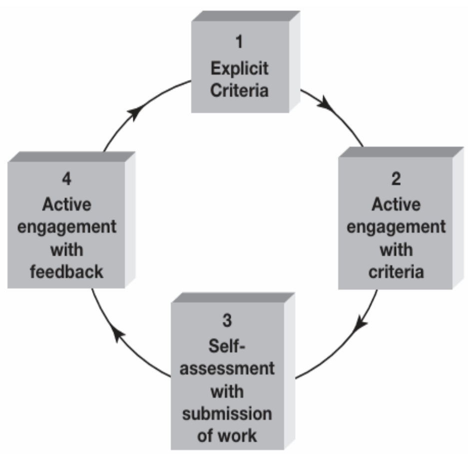

Fig 1. Constructivist Assessment Cycle

David Carless et.al., (2011) have attempted to study in detail development aspects in respect of sustainable feedback practises based on sample of award-winning teachers in the University of Hong Kong.

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Boud and Molloy (2013) have outlined a curriculum approach to feedback analysis. Based on Carless (2015) view on old paradigm, Henderson et.al.,

(2019) conceptualized the interaction between old and new paradigm and the same is given in the following figure 2.

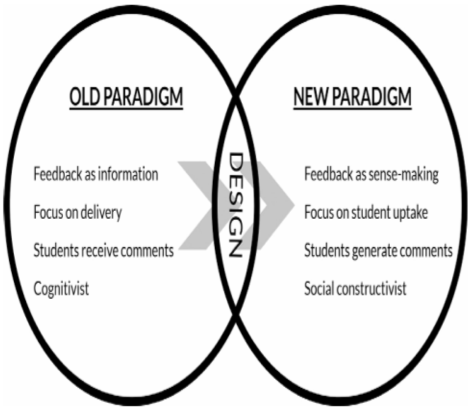

Fig 2. Old and New paradigms of feedback

Objective of the study:

The objectives of the study are:

i. To construct a correlation matrix for studying the inter relation between variables in respect of feedback.
ii. To test the reliability and validity of the feedback data structure.
iii. To extract the variance explained by the factors (Unrotated Factor Solution and Varimax Rotated Solution).
iv. To identify the factors of the feedback evaluation systems.
v. To build/apply machine-learning models for prediction of overall rating of faculty for the respective subject/course.

In section 2 we have given a detailed analysis of Factor analysis method and related computations in respect of the study carried out. Section 3 presents the overall procedure for building machine-learning models for overall rating prediction. Findings and conclusions of the study are presented in section 4.

2. Feedback System Evaluation Based on Factor Analysis:

2.1 Factor Analysis: A brief Introduction

Factor analysis is a multivariate statistical technique. It is an important tool in research studies for uncovering underlying patterns and relationships in the data, reducing complexity, summarizing information, assessing construct validity, generating hypothesis, and aiding in variable selection.

The key steps involved in factor analysis are

(i) Data Preparation
(ii) Factor Extraction
(iii) Factor Rotation and
(iv) Interpretation

It also provides researchers with valuable insights into to the structure of the data and helps in making informed decisions in research analysis and interpretation.

2.2 A brief review of Factor analysis relating to Feedback System Evaluation.

Michael Barth (2008) studied the aspects relating to deciphering student evaluations of teaching using the factor analysis method. The author has provided a more refined evaluation of the survey results by analysing the underlying factors that derive the overall rating of the faculty number.

Zainuddin et.al. (2021) examined the factors that contribute to the student's evaluation on instructors by using factor analysis method. The results revealed that five factors namely student's interest, student-instructor relationship, course demands, course organization and instructor involvement are contributing significantly for the overall evaluation.

The details of the application of factor analysis in respect of the study undertaken are presented in detail in sections.

2.3. Data Description

The following variables are considered in the study attempted:

1. Punctuality (PN)
2. Sincerity (SY)
3. Subject Knowledge (SK)
4. Lecture preparation (LR)
5. Communication and Presentation Skills (CPS)
6. Coverage of Syllabus as per Schedule (CS)
7. Controlling of the Classes (CCL)
8. Standard of Test Question (STQ)
9. Discussion of Test Question (DTQ)
10. Fairness in Evaluation (FE)
11. Interaction and Approachability (IA)
12. Helping for Clarification of Doubts (HCD)

A sample of 550 course feedback returns from a higher education institution were selected. The feedback returns are related to the core subjects involving different branches in Computer Science. The total scores of 550 samples for each variable are initially computed. A 5-point Likert scale for evaluation of factors based on the student feedback under the categories viz., Excellent, Very Good, Good, Average and Poor are framed for the analysis. The studies noted above relating to feedback evaluation have extensively used SPSS software for detailed analysis of the data obtained. In the present study SPSS 14.0 version is used for carrying out factor analysis in a detailed manner.

2.3.1 Descriptive Statistics

The results relating t the computation of Mean and Standard Deviation for all the variables in the study and are presented in Table 1.

2.3.2 Correlation Matrix

The correlation matrix computed for the variables under the study is given in Table 2. One can draw meaning conclusions from this table for a detailed understanding relationship among the variables.

Variable	Mean	Standard Deviation
1. Punctuality (PN)	3.90	0.85
2. Sincerity (SY)	2.84	0.73
3. Subject Knowledge (SK)	4.26	0.66
4. Lecture preparation (LR)	2.34	0.93
5. Communication and Presentation Skills (CPS)	2.24	0.84
6. Coverage of Syllabus as per Schedule (CS)	4.40	0.53
7. Controlling of the Classes (CCL)	4.40	0.53
8. Standard of Test Question (STQ)	2.24	0.84
9. Discussion of Test Question (DTQ)	2.28	0.85
10. Fairness in Evaluation (FE)	4.26	0.66
11. Interaction and Approachability (IA)	2.84	0.73
12. Helping for Clarification of Doubts (HCD)	3.90	0.86

Table 1. Mean and Standard Deviation

2.3.3 Reliability and Validity: KMO and Bartlett's Test

The results obtained in respect of KMO and Bartlett's Test are given in Table 3.

Table 3. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.551
Bartlett's Test of Sphercity Approx. Chi-Square	1411.44
df	66
Sig.	0.000

The adequacy of the sample size for carrying out factor analysis is based on the value of KMO. The value of KMO ranges between 0 and 1. The value of KMO closer to 1, indicates the adequacy of the sample size to carry out the factor analysis. Researchers consider KMO value more than 0.5 for carrying out factor analysis reliably. The value of KMO is 0.551 in our study and the same indicates that ther sample size considered in our study is adequate.

Bartlett's test of sphericity is used to test the null hypothesis that the correlation matrix is not an identity matrix. The computed value of the Barlett's test is 0.000, which is < 0.01, hence it is significant. This shows that the correlation matrix is not an identity matrix. The above results justify the application of factor model as an appropriate one in our study.

2.3.4 Communalities of all the variables:

The communalities computed of all the variables in respect of the study are given in Table 4.

Table 4. Communalities of all the variables

Variable	Initial	Extraction
1. Punctuality (PN)	1.00	0.67
2. Sincerity (SY)	1.00	0.65

3. Subject Knowledge (SK)	1.00	0.69
4. Lecture preparation (LR)	1.00	0.66
5. Communication and Presentation Skills (CPS)	1.00	0.65
6. Coverage of Syllabus as per Schedule (CS)	1.00	0.70
7. Controlling of the Classes (CCL)	1.00	0.77
8. Standard of Test Question (STQ)	1.00	0.64
9. Discussion of Test Question (DTQ)	1.00	0.71
10. Fairness in Evaluation (FE)	1.00	0.74
11. Interaction and Approachability (IA)	1.00	0.60
12. Helping for Clarification of Doubts (HCD)	1.00	0.64

Table 2. Correlation Matrix

Correlation	**1 Punctuality**	**2 Sincerity**	**3 Subject Knowledge**	**4 Lecture Preparation**	**5 Communication & Presentation Skills**	**6 Coverage of the Syllabus as per Schedule**	**7 Controlling of the Classes**	**8 Standard of Test Questions**	**9 Discussion of Test Questions**	**10 Fairness in Evaluation**	**11 Interaction & Approachability**	**12 Helping for Clarification of Doubts**
1 Punctuality	1.000	0.199	0.082	0.244	-0.022	0.310	0.088	0.061	0.149	-0.061	-0.282	-0.068
2 Sincerity	0.199	1.000	0.128	-0.067	-0.328	0.062	0.010	0.063	-0.153	0.1288	0.027	-0.282
3 Subject Knowledge	0.082	0.128	1.000	0.019	0.032	0.103	0.276	0.032	0.228	0.491	0.128	-0.061
4 Lecture Preparation	0.244	-0.067	0.019	1.000	-0.284	0.211	0.171	0.332	0.057	0.248	-0.155	0.093
5 Communication & Presentation Skills	-0.022	-0.329	0.032	-0.284	0.099	1.000	0.000	-0.367	0.411	0.032	0.063	0.061
6 Coverage of the Syllabus as per	0.310	0.062	0.103	0.211	0.099	1.000	.000	0.009	0.196	0.103	0.062	0.310

Schedule												
7 Controlling of the Classes	0.088	0.010	0.276	0.171	0.009	0.000	1.000	0.099	0.196	0.103	0.062	0.310
8 Standard of Test Questions	0.061	0.063	0.032	0.332	-0.367	0.009	0.099	1.000	-0.347	0.032	-0.329	-0.22
9 Discussion of Test Questions	0.149	-0.153	0.228	0.057	0.411	0.151	0.196	-0.347	1.000	-0.023	-0.024	0.204
10 Fairness in Evaluation	-0.061	0.128	0.491	0.248	0.032	0.276	0.103	0.032	-0.023	1.000	0.128	0.082
11 Interaction & Approachability	-0.282	0.027	0.128	-0.155	0.063	0.010	0.062	-0.329	-0.024	-0.128	0.199	1.000
12 Helping for Clarification of Doubts	-0.068	-0.282	-0.061	0.093	0.061	0.088	0.310	-0.022	0.204	0.082	0.199	1.000

The initial values of the communalities of all the variables are unity. The higher the value of the communality of a variable the more the variability explained by the variable. The value obtained in respect of all the variables after extraction is greater than 0.4. Hence it is concluded that the variables considered are useful in the model.

2.3.5 Factor Extraction and the Variance explained by the Factors

The results obtained in respect of factor extraction and the variance explained by the factors are given in Table 5.

Table 5. Total Variance Explained

Variable	Initial Eigenvalues			Extraction Sums of Squared			Rotation Sums of Squared Loadings		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %`**	**Total**	**% of Variance**	**Cumulative %**
1	2.114	17.613	17.613	2.114	17.613	17.613	1.940	16.164	16.164
2	2.039	16.994	34.607	2.039	16.994	34.607	1.601	13.339	29.502
3	1.512	12.602	47.209	1.512	12.602	47.209	1.587	13.223	42.726
4	1.418	11.815	59.024	1.418	11.815	59.024	1.515	12.626	55.351
5	1.059	8.829	67.853	1.059	8.829	67.853	1.500	12.501	67.853
6	.985	8.212	76.065						
7	.697	5.811	81.879						
8	.559	4.661	86.537						
9	.519	4.323	90.860						
10	.503	4.188	95.048						
11	.407	3..9.	98.441						
12	.187	1.559	100.000						

The initial eigen values, extraction sum of squared loading and rotation sums of squared loadings are given in the above Table. It is observed that after rotations the first five variables account for 67.853% of total variance. The table contains eigen values of all the variables. We have retained the only variables

whose eigen values are greater than 1 viz., variables 1, 2, 3, 4, 5.

2.3.6 Scree Plot

We have constructed a Scree Plot and same is given in the following figure 3.

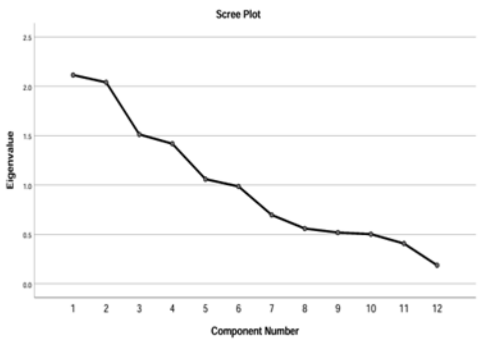

Fig 3: Screen Plot for Eigenvalue and variables

In the Scree Plot X-axis represents the variable number and Y-axis represents the eigen values.

2.3.7 Initial Unrotated Solution

Unrotated Factor Solution is given in Table 6.

Table 6. Component Matrix Unrotated Factor Solution

	Component				
Variable	**1**	**2**	**3**	**4**	**5**
1	-.249	.409	-.458	-.468	.137
2	-.423	.102	.431	-.457	.258
3	.104	.613	.454	-.164	.276
4	-.406	.533	-.286	.277	-.225
5	.732	.024	-.216	-.240	-.080
6	.011	.546	-.149	-.292	-.551
7	.108	.519	-.009	.382	.583
8	-.704	.150	-.114	.337	.033
9	.591	.385	-.352	-.194	.235
10	-.003	.621	.494	.005	-.333
11	.426	-.001	.594	.197	-.157
12	.352	.281	-.165	.638	-.072

Extraction Method: Principal Component Analysis, 5 components extracted.

We note that five factors have been extracted. The factor loadings on each of the five factors are given in the table. It is important to note that this is an Unrotated Factor Solution. This results with some of the variables exhibits their contribution in more than one factor. This has necessitated us to proceed for rotating the factors. Varimax Rotation method is used for rotating the factors.

2.3.8 Rotated Component Matrix: Varimax Rotated Solution

The final solution obtained under Varimax Rotation is given in Table 7.

Table 7. Rotated Component Matrix: Varimax Rotated Solution

	Component				
Variable	**1**	**2**	**3**	**4**	**5**
1	.072	.219	.756	.118	-.192
2	-.195	.081	.041	.146	-.763
3	.111	.375	-.133	.637	-.346
4	-.462	.441	.357	.142	.319
5	.774	.051	.006	-.035	.209
6	.140	.774	.262	-.133	.064
7	-.071	-.072	.066	.843	.202
8	-.756	.028	.249	.081	.070
9	.657	.082	.295	.380	.208
10	-.094	.751	-.302	.254	-.112
11	.186	.157	-.725	.109	.023
12	.013	.094	-.168	.310	.714

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

The solution emerges clearly under Varimax Rotation set-up. The Varimax Rotation facilitates the variable to appear in one and only factor. The identification of variables is primarily based on the maximum factor loading is **0.7** or more. This enables that the factor extracts sufficient variance from that variable. A reduced thershould value of 0.6 and above is considered in the analysis. Based on this criterion, the criterion variables are grouped in each of the five factors viz., Presentation Skills, Commitment of Course, Punctuality, Academic Management and Sincerity**.**

Looking at Tables 8 (i), (ii), (iii), (iv), (v). we note the following:

Table 8 (i). Factor 1: Presentation Skills

Variable		Loadings
5	Communication and Presentation Skills (CPS)	0.774
8	Standard of Test Question (STQ)	0.756
9	Discussion of Test Question (DTQ)	0.657

Table 8 (ii). Factor 2: Commitment of Course

Variable		Loadings
6	Coverage of Syllabus as per Schedule (CS)	0.774
10	Fairness in Evaluation (FE)	0.751

Table 8 (iii). Factor 3: Punctuality

Variable		Loadings
1	Punctuality (PN)	0.756
11	Interaction and Approachability (IA)	0.725

Table 8 (iv). Factor 4: Academic Management

Variable		Loadings
3	Subject Knowledge (SK)	0.637
7	Controlling of the Classes (CCL)	0.843

Table 8 (v). Factor 5: Sincerity

Variable		Loadings
2	Sincerity (SY)	0.763
12	Helping for Clarification of Doubts (HCD)	0.714

The variables viz., Communication and Presentation Skills (CPS), Standard of Test Question(STQ), and Discussion of Test Question (DTQ) are grouped under **Factor 1.** This suggests that Factor 1 is a combination of three variables and this Factor is termed as **Presentation Skills.**

We note that the variables viz., Coverage of Syllabus as per Schedule (CS), Fairness in Evaluation (FE) are grouped under Factor 2. This factor can be termed as Commitment of Course.

The variables viz., Punctuality (PN) and Interaction and Approachability (IA) are grouped under Factor 3 and this Factor is named as **Punctuality**.

Subject Knowledge (SK) and Controlling of the Classes (CCL) is grouped under the Factor 4 and this factor is termed as Academic Management.

Sincerity (SY) and Helping for Clarification of Doubts (HCD) is grouped under Factor 5 and this factor is termed as **Sincerity**.

2.3.9 Test Battery

Table 9. Test battery for measuring the Feedback Evaluation System

Factor Group	Variable		Loadings
Presentation Skills	5	Communication and Presentation Skills (CPS)	0.774
Commitment of Course	6	Coverage of Syllabus as per Schedule (CS)	0.774
Punctuality	1	Punctuality (PN)	0.756
Academic Management	7	Controlling of the Classes (CCL)	0.843
Sincerity	2	Sincerity (SY)	0.763

3. Overall Rating Prediction using Machine-learning Models:

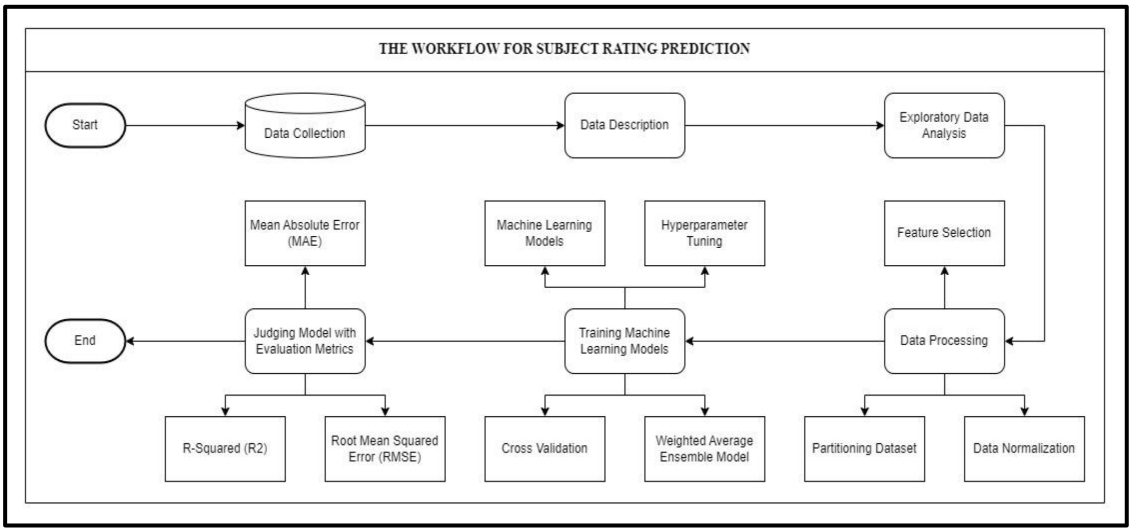

Fig 4: Workflow for Subject/Course Rating Prediction

Figure 4 helps to understand the complete workflow of the study performed. The study commences with data collection followed by exploratory data analysis then data processing and finally training machine learning models also judging the same with evaluation metrics.

3.1 Data Collection

The data acquisition process for this research involves gathering subject-wise feedback from the faculty login of the Academia portal utilized by both staff and students at the College of Engineering and Technology, SRM Institute of Science and Technology, Chennai. This feedback is systematically collected at the culmination of each semester, providing insights into the comprehensive teaching effectiveness of faculty members across 13 distinct parameters. These parameters encompass critical facets such as punctuality, sincerity, subject knowledge, lecture preparation, communication and presentation skills, adherence to syllabus timelines, classroom management, quality of test questions, discussion of assessments, fairness in evaluation, approachability, willingness to address doubts, and the overall knowledge acquisition experience in the subject matter at hand.

3.2 Data Description

The dataset comprises 2429 individual reviews sourced directly from students who have completed the respective course over the course of a semester. Each student is required to provide ratings for all 13 parameters listed earlier, utilizing a scale ranging from "excellent" to "poor." Upon submission, the feedback is securely stored within the system, associating each review with a randomly generated unique identifier. Notably, the scale used by students is then standardized, converting the qualitative ratings into a numerical scale ranging from 2 to 10. Under this conversion, "excellent" corresponds to a score of 10, "very good" to 8, "good" to 6, "average" to 4, and "poor" to 2. This standardized approach ensures consistency and facilitates quantitative analysis of the feedback data, enabling comprehensive assessment of faculty performance across the specified parameters.

3.3 Exploratory Data Analysis

In the exploratory data analysis (EDA), we analyze feedback data from College of Engineering and Technology to unveil patterns and insights on teaching effectiveness.

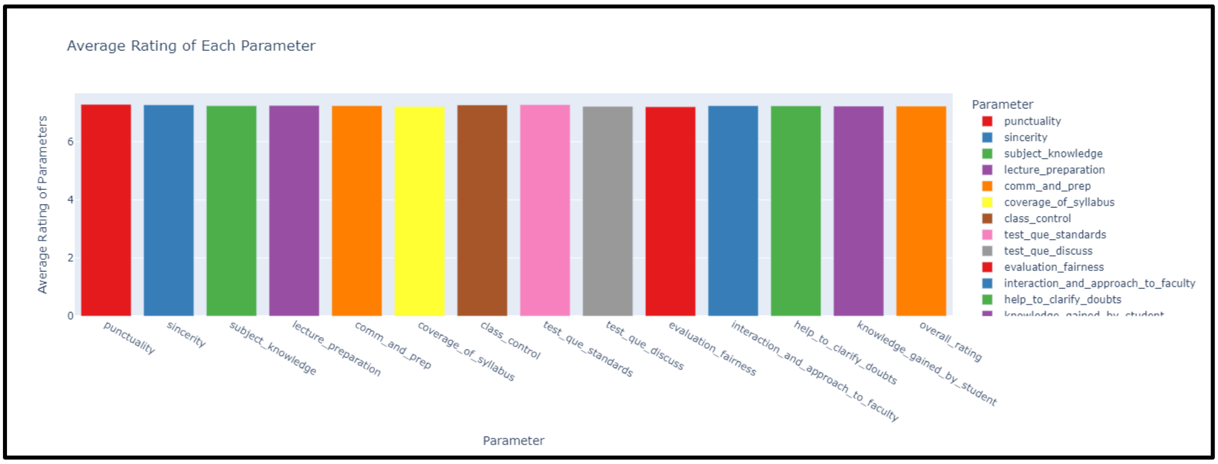

Fig 5: Average Rating of each Parameter

Figure 5, bar charts were generated for each parameter to visualize the average rating, calculated by summing the scores of each parameter and dividing by the total number of feedbacks. This approach provides a succinct overview of the teaching effectiveness across different dimensions. Remarkably, all parameters yielded an average rating close to 7, indicating a consistently positive perception of faculty performance across the board.

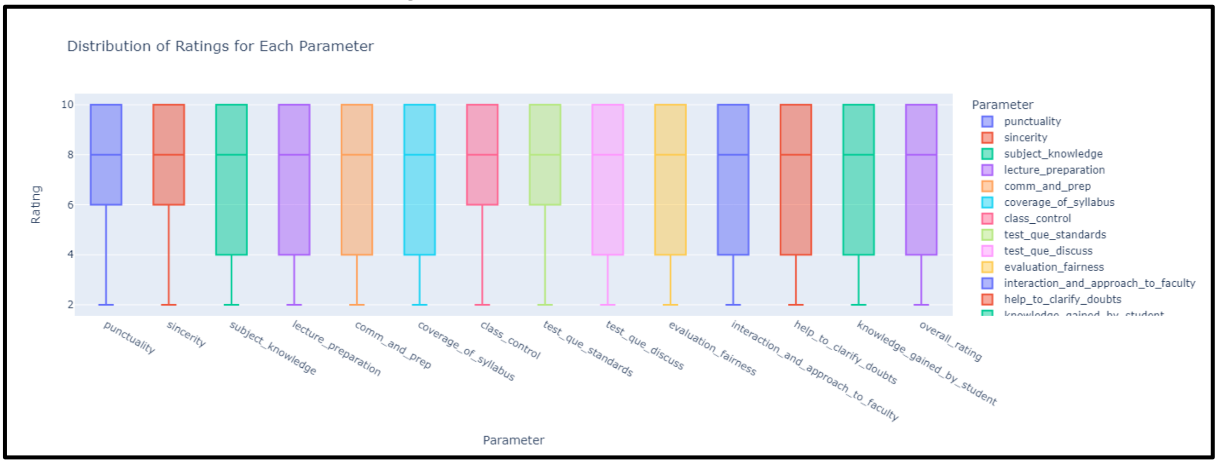

Fig 6: Distribution of Ratings for each Parameter

In figure 6 box plots offer a comprehensive visualization of the distribution of ratings for each parameter, highlighting variations in students' perceptions and experiences. The distinct characteristics of each box plot, such as minimum, maximum, median, and quartiles, provide valuable insights into the range and dispersion of feedback scores across different teaching dimensions, aiding in the identification of outliers and understanding the overall spread of feedback data.

3.4 Data Processing

Data processing involves refining and preparing raw data for analysis by performing tasks such as cleaning, transforming, and organizing the data to enhance its quality, consistency, and suitability for further analysis or modelling (Abdulaziz Aldoseri et. al.).

- Feature Selection: By selecting only, the parameters relevant to teaching effectiveness and dropping other columns, we streamline the dataset, reducing noise and focusing solely on variables that directly impact our analysis. This step enhances model efficiency and interpretability by excluding irrelevant data points (Davide Cacciarelli et. al.).
- Dataset Partitioning: Partitioning the dataset into training and testing sets with a test size of 30% and a

fixed random state of 42 ensures reproducibility and consistency in model evaluation. This division allows us to train the model on a subset of data and validate its performance on unseen data, thereby assessing its generalization ability and minimizing the risk of overfitting (O. A. Montesinos López et. al.).

- Normalization: Applying the StandardScaler normalization technique exclusively to the training data standardizes the feature values, bringing them to a common scale. This process is crucial for algorithms sensitive to the scale of features, ensuring fair treatment of each parameter during model training and preventing dominance by variables with larger magnitudes (D. Singh et. al.).

3.5 Training Machine-learning Models

Training machine learning models entails feeding labeled data to algorithms, enabling them to learn patterns and optimize internal parameters for accurate predictions on new data.

- **Machine Learning Models:** Utilizing Lasso, Ridge, Decision Tree, Random Forest, Support Vector Machine (SVM), Gradient Boost, and XGBoost algorithms to predict faculty overall ratings on a scale of 10 based on input parameters. Each model offers unique advantages in capturing different aspects of the data, providing a comprehensive approach to prediction.
- **Hyperparameter Tuning:** Employing pipeline and hypergrid techniques with specified hyperparameters and GridSearchCV to optimize model performance. This iterative process systematically explores various combinations of hyperparameters to identify the optimal configuration, enhancing the model's predictive accuracy and generalization ability (L. Yang et. al.).
- **Cross-Validation:** Implementing 10-fold cross-validation to evaluate model performance robustly. This technique partitions the dataset into 10 equal subsets, iteratively training the model on 9 subsets and validating on the remaining subset. By averaging the evaluation metrics across multiple folds, we obtain a more reliable estimate of the model's performance and reduce the risk of overfitting (G. C. Cawley et. al.).
- **Weighted Average Ensemble Model:** Constructing a weighted average ensemble model combining Random Forest and Gradient Boost predictions. This ensemble approach leverages the strengths of both models, mitigating individual model biases and enhancing predictive accuracy through weighted aggregation.

4. Results and Discussions

4.1 Factor Analysis Method

The detailed empirical analysis carried out has identified five factors that are most important once for the effective measurement of the evaluation of feedback system in a higher education institution offering a wide variety of subjects in engineering and technology. The factors in the order of importance resulted in the following.

Identified Factor		Loadings
Academic Management	Controlling of the Classes (CCL)	0.843
Commitment of Course	Coverage of Syllabus as per Schedule (CS)	0.774
Presentation Skills	Communication and Presentation Skills (CPS)	0.774
Sincerity	Sincerity (SY)	0.763
Punctuality	Punctuality (PN)	0.756

4.2 Machine-learning Technique

- Mean Absolute Error (MAE), R-squared (R2), and Root Mean Squared Error (RMSE) Scores: MAE measures the average magnitude of errors between predicted and actual values, while R2 quantifies the proportion of variance explained by the model, with higher values indicating better fit. RMSE represents the square root of the average squared differences between predicted and actual values, providing insight into the model's prediction accuracy (D. Chicco et. al.).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_{actual} - Y_{predicted}\right| \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_{actual} - Y_{predicted}\right)^2} \quad (2)$$

The evaluation of trained machine learning models is based on their Mean Absolute Error (MAE), R-squared (R2), and Root Mean Squared Error (RMSE) scores, as depicted in table 10.

Table 10: MAE, R2 and RMSE Scores of Machine-learning Models for Overall Rating

	MAE Train Score	MAE Test Score	R2 Train Score	R2 Test Score	RMSE Train Score	RMSE Test Score
Lasso Regression	0.30	0.27	0.89	0.90	0.87	0.83
Ridge Regression	0.30	0.27	0.89	0.90	0.87	0.83
Decision Tree	0.22	0.28	0.92	0.87	0.73	0.94
Random Forest	0.21	0.26	0.94	0.90	0.65	0.83
Support Vector Machine	0.31	0.34	0.91	0.89	0.79	0.87
Gradient Boost	0.21	0.29	0.94	0.88	0.63	0.90
XGBoost Classifier	0.35	0.37	0.91	0.89	0.79	0.85
Ensemble of Random Forest & Gradient Boost	0.18	0.20	0.97	0.94	0.53	0.68

By analysing the MAE, R2 and RMSE scores, it is clear that, Ensemble model performs the best among all the other models as mentioned in table 1. Now, let us have a look at the individual parameter impact on ensemble model output with the help of SHAP plot.

- SHAP Plot: SHAP (SHapley Additive exPlanations) plots visualize the contribution of each feature to the model's output prediction for individual samples. They offer valuable insights into feature importance and the impact of specific variables on the model's decision-making process, aiding in the interpretation and explanation of model predictions (S. Lundberg et. al.).

Figure 7 illustrates the SHAP plot, delineating the contribution of each parameter to the model's predictions.

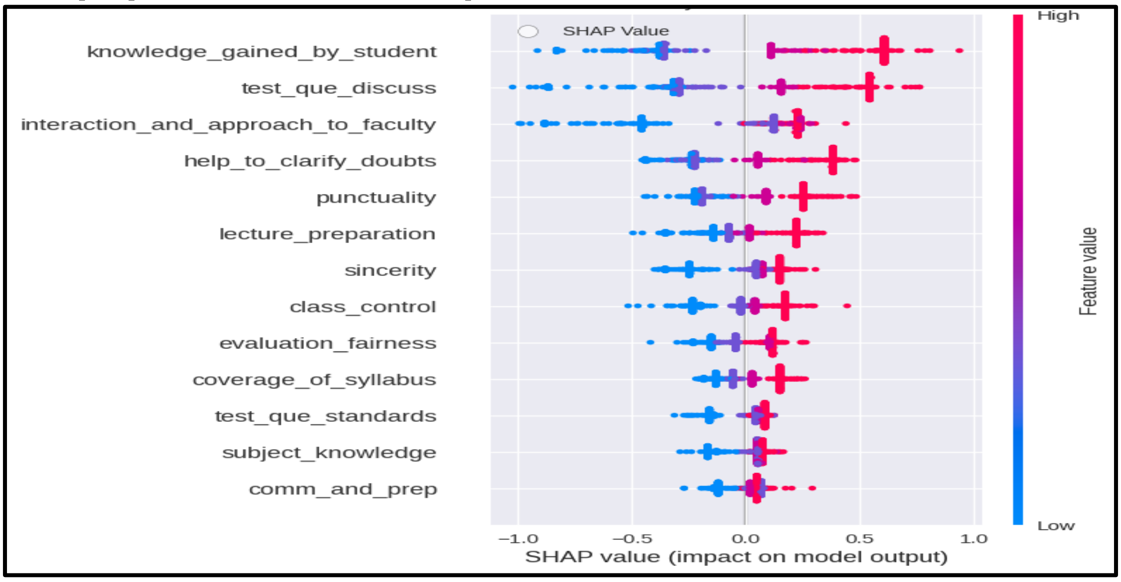

Fig 7: SHAP Plot of Ensemble Model for Overall Rating

4.2 Conclusion of the Study and Future Work

In conclusion, this research leveraged both machine learning models and factor analysis methods to comprehensively analyze and predict faculty performance based on feedback data. The integration of diverse analytical techniques facilitated a nuanced understanding of the multifaceted factors influencing teaching effectiveness within the College of Engineering and Technology. The results demonstrated the efficacy of machine learning algorithms in predicting faculty ratings, while factor analysis provided valuable insights into underlying constructs and patterns driving student perceptions.

For future work, further exploration could focus on refining and optimizing the predictive models by incorporating additional variables or refining feature selection techniques. Additionally, a deeper investigation into specific factors identified through factor analysis could offer actionable insights for targeted interventions aimed at enhancing teaching quality and student satisfaction. Moreover, longitudinal studies could be conducted to assess the stability and effectiveness of predictive models over time, facilitating ongoing improvement and adaptation to evolving educational contexts.

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