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Exploring Faculty Performance in Engineering Institutions: Integrating National Board of Accreditation Attributes into Performance Score Prediction Models

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***Abstract*— The performance score of academic faculty members often hinges on a blend of factors, encompassing experience, qualifications, and notably, performance evaluations. However, the specific benchmarks guiding salary determinations can diverge significantly across engineering institutions and departments. This study shifts focus towards predicting faculty's performance score of engineering institutions solely based on performance metrics rather than a blend of factors. We examine data randomly gathered on faculty members' performance across metrics such as teaching effectiveness, research productivity, professional development, service to the institution and community, student mentoring, innovation and entrepreneurship, internationalization, and social impact. These metrics are utilized to formulate a performance score for each faculty member, subsequently utilized in predicting their performance score through a linear regression model.**

Data Collection: This research centers on gathering Key Performance Indicators from the National Board of Accreditation in India, primarily aimed at assessing and elevating the quality standards of higher education institutions. The KPI framework encompasses various dimensions essential for faculty evaluation, including teaching effectiveness, research productivity, professional development, service to the institution and community, student mentoring, innovation and entrepreneurship, internationalization efforts, and social impact.

Feature Engineering: A composite score for each faculty member is computed based on their performance across diverse metrics. The composite score is derived using the formula:

Model Evaluation: The model's efficacy is assessed through metrics like Mean Absolute Error and Mean Squared Error, alongside employing cross-validation for more dependable estimates of its performance.

Model Deployment: The trained model is deployed to prognosticate performance score for new faculty members. A web application is to be developed, accepting a faculty member's performance metrics as input and generating a predicted score as output. Overall, this project furnishes a framework for performance-based prediction of faculty's score, offering institutions a tool for crafting equitable and transparent salary structures for faculty members of Engineering Institutions.

***Keywords*—Equitable Salary Structures; Engineering Institutions; Faculty Performance in Engineering Institutions; Performance Metrics, Predictive Framework; Salary Prediction.**

***JEET Category*—Practice**

I. INTRODUCTION

The Washington Accord and the NBA (National Board of Accreditation) in India are closely related entities that work together to ensure quality standards in engineering education. The Washington Accord is an international agreement among engineering accrediting bodies from various countries. Its primary objective is to establish mutual recognition of engineering qualifications and promote mobility and quality assurance in engineering education across signatory countries. The accord sets specific criteria and guidelines for accrediting engineering programs, emphasizing outcomes-based education, continuous improvement, and adherence to global best practices.

India became a provisional member of the Washington Accord in 2007, and full membership was granted in 2014. The entry of India into the Washington Accord was facilitated by the NBA, which serves as the nodal agency for accreditation of engineering programs in the country.

The NBA, established by the All-India Council for Technical Education (AICTE), is responsible for assessing and accrediting engineering colleges and programs in India. It operates in accordance with the guidelines and criteria set by the Washington Accord, ensuring that accredited institutions meet international benchmarks for engineering education. The NBA (National Board of Accreditation) plays a significant role in ensuring quality standards in engineering colleges across India. In recent years, the NBA has been instrumental in shaping the landscape of engineering education in India by establishing and enforcing stringent quality standards. These standards encompass various aspects such as curriculum design, faculty qualifications, infrastructure, research facilities, and industry interaction. By adhering to these standards,

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engineering colleges strive to provide students with a comprehensive education that meets the demands of the rapidly evolving technological landscape. The National Board of Accreditation (NBA) in India sets specific Key Performance Indicators (KPIs) for faculty members of engineering institutions to assess and improve the quality of higher education institutions. These KPIs vary depending on the accreditation criteria set by NBA, which may change over time. As of my last update in January 2022, some common KPIs that NBA might consider for faculty members include:

1. Teaching Effectiveness: This could be measured through student feedback, class observations, peer evaluations, and student learning outcomes.
2. Research Productivity: This can include publications in peer-reviewed journals, conference presentations, research grants, and patents.
3. Quality of Educational Programs: This might include curriculum development, course design, and contributions to program improvement.
4. Professional Development: This could be measured through the faculty's participation in workshops, seminars, conferences, and other professional development activities.
5. Service to the Institution and Community: This can include involvement in institutional committees, outreach activities, and engagement with industry or the wider community.
6. Student Mentoring: This might include advising and mentoring undergraduate and graduate students, supervising research projects, and guiding student organizations.
7. Innovation and Entrepreneurship: This can include activities related to innovation, technology transfer, and entrepreneurship, such as startups, patents, or commercialization of research.
8. Internationalization: This can include activities related to international collaboration, such as joint research projects, student exchanges, or collaborative teaching initiatives.
9. Social Impact: This might include contributions to society through research, teaching, or community engagement, particularly in areas such as sustainability, social justice, or community development.

It is essential to note that the specific KPIs and the weight assigned to each one can vary depending on the institution's mission, priorities, and accreditation requirements (Joshi, Sangeeta & Bhattacharjee, Shrabani & Deshpande, Vishwas & Tadvalkar, Milind., 2016). Additionally, these KPIs should be aligned with the institution's strategic goals and the faculty member's professional development plan. (Ahmed, Abd El-Aziz & Badawy, Mohammed & Hefny, Hesham., 2017; Khurjekar & Kaur, 2023; Vedhathiri, 2020).

II. LITERATURE REVIEW

The research conducted by A. Shankar and M. Malik, titled "Predicting Person's Pay using Machine Learning," investigates the application of machine learning techniques in predicting an individual's income (Shankar, 2022). The study delves into the realm of predictive analytics, aiming to discern patterns and relationships within data to anticipate an individual's earnings (Kaur, Verma and Kaur, 2022). By leveraging machine learning algorithms, the researchers likely explored various factors such as education level, work experience, occupation, and demographic information to develop a predictive model (Voleti & Jana, 2021). This research holds significance in providing insights into the potential of machine learning for financial forecasting and employment-related decision-making. Moreover, it contributes to the growing body of literature on the intersection of artificial intelligence and socioeconomic analysis, offering valuable implications for policy-making and workforce management strategies.

The research conducted by (Jaiswal, Gupta, and Tiwari, 2023) in their paper titled "Dissecting the compensation conundrum: a machine learning-based prognostication of key determinants in a complex labor market," delves into the intricate dynamics of compensation within the labor market using machine learning techniques. Through a comprehensive analysis, the study aims to uncover the essential factors influencing compensation decisions in a complex labor environment. By employing machine learning methodologies, the researchers likely dissected large datasets to identify patterns and correlations among various determinants such as education, experience, industry, and geographical location. This research offers valuable insights into the multifaceted nature of compensation structures, providing organizations with actionable intelligence to enhance their strategies for talent acquisition, retention, and compensation management. Furthermore, it contributes to advancing the understanding of labor market dynamics in the context of evolving technological and economic landscapes.

The research conducted by (Görmez, Arslan, Sarı, and M. Danış, 2022), titled "SALDA-ML: Machine Learning Based System Design to Predict Salary Increase," introduces SALDA-ML, a novel machine learning-based system designed to forecast salary increases. In their study, the authors present a systematic approach utilizing machine learning algorithms to predict the likelihood of salary increments for individuals. By leveraging advanced techniques, such as SALDA-ML, the researchers likely analyzed various factors including performance metrics, job tenure, educational qualifications, and market trends to develop a predictive model. This research not only offers valuable insights into the complex process of salary determination but also presents a practical tool for organizations to optimize their compensation strategies and enhance employee satisfaction and retention. Furthermore, the development of SALDA-ML contributes to the advancement of machine learning applications in human resources management, facilitating data-driven decision-making processes in the context of salary adjustments.

The research conducted by (Niknejad, Kianiani, Puthiyapurayil, and Khan, 2023), aims to delve into the intricate landscape of data professional salaries. By scrutinizing a wide array of data, the study endeavors to uncover prevailing trends and extract predictive insights regarding remuneration in this domain. Through rigorous analysis and exploration, the researchers likely employed various statistical and machine learning techniques to discern patterns and forecast factors influencing salary variations among data professionals (Kulkarni, Phadke, Gilke & Pandit, 2020). This research holds significance in shedding light on the evolving dynamics of compensation within the data industry, offering valuable implications for both practitioners and organizations in understanding and strategizing for talent management and retention.

The paper titled "Machine Learning Models for Salary Prediction Dataset using Python" by (Kablaoui and Salman, 2022), addresses the application of machine learning techniques in predicting salaries based on a given dataset. The primary focus of the research is to develop and evaluate machine learning models that can accurately predict salaries. This is a significant area of interest in various fields, including human resources, finance, and economics, as predicting salaries accurately can aid in decision-making processes related to hiring, compensation, and resource allocation. The authors employed Python, a popular programming language for data analysis and machine learning, to implement their models. Python offers a wide range of libraries and tools specifically designed for data manipulation, statistical analysis, and machine learning, making it a suitable choice for this research.

The paper titled "A Comparative Study of Machine Learning Algorithms for Salary Estimation" by (Mishra, Srivastava, Gupta, Anand, and Gupta, 2021) contributes to the understanding of machine learning techniques in the context of salary estimation. Through a comparative study, the authors assess the performance of different machine learning algorithms in predicting salaries. Likely employing various algorithms such as linear regression, decision trees, support vector machines, or neural networks, they meticulously evaluate their predictive capabilities using relevant evaluation metrics (Quan and Raheem, 2022). This research provides valuable insights into the effectiveness of different machine learning approaches for salary estimation, offering practical implications for industries and organizations seeking to optimize their human resource management strategies. The findings contribute to the broader discourse on data-driven decision-making and predictive analytics, highlighting the potential of machine learning in addressing real-world challenges related to salary estimation.

The paragraph describes a study titled "Salary Prediction for Computer Engineering Positions in India," authored by (Mohamed Saeed, Abdullah, and Tahir, 2023). This research likely focuses on forecasting salaries specifically within the realm of computer engineering roles in India. By utilizing data relevant to this domain, such as educational qualifications, years of experience, geographic location, and specific skills or certifications, the authors aim to develop predictive models for estimating salaries. The study likely employs techniques from data science and machine learning to analyze the dataset and construct accurate prediction models. The findings of this research could provide valuable insights into salary trends within the computer engineering field in India, aiding both employers and job seekers in making informed decisions regarding compensation negotiations and resource allocation. This study contributes to the broader understanding of salary prediction methodologies and their applicability in specific industries and geographical contexts (Chen, Sun and Thakuriah, 2018).

The research conducted by (Matbouli and Alghamdi, 2022), delves into the development and evaluation of regression models for predicting salaries. Unlike traditional salary prediction studies, this research incorporates a broader scope by considering economy-wide activities and occupations. By leveraging statistical machine learning techniques, the authors aim to analyze the complex interplay between various economic factors and salary outcomes (Wang, 2022). This holistic approach not only enhances the accuracy of salary predictions but also provides valuable insights into the underlying dynamics shaping compensation levels across different industries and occupations (Das, Barik and Mukherjee, 2020). The findings of this study contribute to advancing the field of salary prediction by offering a more comprehensive understanding of the multifaceted influences on compensation, thus aiding in informed decision-making processes for both employers and employees.

III. RESEARCH GAP

The literature explores how performance cores can be calculated using advanced computing technologies and data analysis; however, this approach is not aligned with metrics-focused standards and performance utilization norms.

As previously stated, this paper's primary goal is to provide a hybrid mathematical model for 360-degree evaluation (Ramin et al, 1997). Therefore, the Delphi technique is used to first derive the appraisal criteria and connect them with the organizational context (Neely, Richards et al. 1997).

Research abilities, teaching abilities, research publications and the type of publications, student grades, QEC evaluation, official responsibilities, regularity, and punctuality are just a few of the criteria that may be important for evaluating faculty during the on-campus semester. The decision makers apply varying weights to each selection criterion in order to measure the relative value of each criterion because they may not all be equally essential (Usman et al, 2024).

The need to measure and document faculty responsibility in Higher Education Institutions (HEI) is becoming more and more pressing in nations all over the world. A rubric for quantitatively evaluating faculty performance is needed in India, where academic autonomy is gradually extending beyond the Indian Institute of Technologies, National Institute of Technologies, and Government Engineering Colleges to the category of private unaided engineering institutions. In order to meet that demand, a number of qualities are shown to be necessary for absorbing a "complete faculty performance." This essay describes these initiatives and their results at one of the top private engineering autonomous institutes in the nation's intellectually advanced west (Ashutosh, 2013).

Credit-based assessment (CBAS) measures faculty teaching performance as well as academic, extracurricular, extension, and research activities. This system is operated under the Institute's established Quality Management Systems. It has been noted that this faculty performance evaluation has aided in identifying both high- and low-performing faculty. Additionally, it is possible to clearly and transparently outline the goals for the upcoming academic year.

The present assessment method may be expanded into a more straightforward, user-friendly, and accurate performance appraisal system by utilizing a web-based application. A comprehensive faculty appraisal system should be developed in order to automate and digitize the data entry process, decrease the amount of time needed for all manual processes, facilitate the handling, recording, and retrieval of records, lower the resources allocated for multiple copies of the evaluation form, improve the accuracy and efficiency of the current performance appraisal system, and increase the confidentiality and credibility of the data. (Pratik Borse, 2018)

Based on the provided studies, a research gap can be identified concerning the specific analysis of faculty performance within the context of National Board Accreditation (NBA) attributes and its correlation with salary prediction using machine learning techniques. While the existing research extensively explores various factors influencing salary determination across different domains and industries, such as education, experience, industry, and geographic location, there seems to be a lack of focus on the unique attributes associated with faculty performance within the NBA framework.

Given the significance of faculty performance evaluation in engineering institutions and its potential impact on salary determination, there is an opportunity to investigate how attributes related to NBA criteria, such as teaching quality, research output, professional development, and institutional engagement, contribute to the prediction of faculty salaries using machine learning models. By conducting such research, scholars can provide valuable insights into the specific factors influencing salary variations among faculty members and offer practical implications for optimizing compensation strategies and talent management in academic settings. This gap in the literature presents an avenue for future research to explore the intersection of faculty performance evaluation, NBA attributes, and salary prediction using advanced analytical techniques.

IV. UNDERSTANDING THE SIGNIFICANCE OF FACULTY PERFORMANCE METRICS BASED ON NBA

Promotion criteria for engineering faculty in Indian institutions are typically based on various factors, including teaching effectiveness, research productivity, professional development, service to the institution and community, student mentoring, innovation and entrepreneurship, internationalization, and social impact. These criteria are often aligned with the institution's mission, strategic goals, and accreditation requirements. Here's a general overview of how these criteria might be used in promotion decisions:

Teaching Effectiveness: Faculty members may be evaluated based on their classroom performance, student feedback, teaching evaluations, and contributions to curriculum development and improvement. Evidence of effective teaching methods, student learning outcomes, and innovations in teaching can be important factors (Kanchan, Menezes & Rodrigues, 2021; Vedhathiri, 2022a).

Research Productivity: Academic faculty are often expected to engage in research and scholarly activities. Promotion criteria in this area might include the number and quality of publications, grant funding, citations, patents, and other measures of research productivity. Collaborative research and interdisciplinary work may also be considered.

Professional Development: Faculty members are expected to stay current in their fields and contribute to their profession. Promotion criteria might include participation in conferences, workshops, and seminars, as well as membership in professional organizations, leadership roles, and continuing education activities.

Service to the Institution and Community: Academic faculty are often involved in service activities, such as serving on committees, advising student organizations, and contributing to institutional governance. Promotion criteria might include the quantity and quality of service contributions, as well as their impact on the institution and community.

Student Mentoring: Faculty members are often involved in mentoring undergraduate and graduate students, advising student research projects, and supporting student organizations. Promotion criteria might include the number and quality of mentoring relationships, as well as the impact on student success and development.

Innovation and Entrepreneurship: Academic faculty may engage in activities related to innovation, technology transfer, and entrepreneurship, such as patenting, commercializing research, and starting businesses. Promotion criteria might include the number and quality of innovations, patents, startups, and other entrepreneurial activities.

Internationalization: Faculty members may engage in international collaborations, research projects, and teaching initiatives. Promotion criteria might include the number and quality of international activities, the impact on the institution and community, and contributions to global scholarship and understanding.

Social Impact: Faculty members may engage in research, teaching, and service activities that have a positive impact on society, such as addressing social, economic, and environmental challenges. Promotion criteria might include the number and quality of social impact activities, as well as their relevance and significance.

It's important to note that these are general guidelines, and promotion criteria can vary widely depending on the institution, discipline, and specific requirements. Institutions often have formal promotion and tenure policies that outline the criteria and process for faculty advancement, and faculty members are typically evaluated by their peers, department chairs, deans, and other administrators.

Bonus distributions can be structured to align with these 8 metrics, with each metric divided into more specific sub-

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metrics or categories. This approach ensures that performance is evaluated comprehensively, with rewards reflecting achievements in all critical areas. Here's how the analytical tool can potentially split each metric into sub-metrics:

1. Teaching Effectiveness:
    a. Classroom performance and engagement: Based on observations or peer evaluations.
    b. Student feedback: Scores from course evaluations or surveys.
    c. Innovations in teaching: Adoption of new methods, technologies, or materials (Radhika Devi, 2018).
    d. Student learning outcomes: Improvement in student performance or skills (Jadhav, Kakade & Patil, 2018).
2. Research Productivity:
    a. Publications: Split into journal articles, conference papers, book chapters, etc.
    b. Grants and funding: Amounts secured for research projects.
    c. Citations: Number and impact of citations for publications.
    d. Patents: Number and significance of patents obtained.
3. Professional Development:
    a. Participation in conferences: Number of conferences attended.
    b. Workshops and seminars: Number and types of workshops or seminars attended or led.
    c. Membership in professional organizations: Active participation and leadership roles.
    d. Continuing education: Courses or certifications completed.
4. Service to the Institution and Community:
    a. Committee work: Participation in departmental or institutional committees.
    b. Advising student organizations: Contributions to student clubs or societies.
    c. Institutional governance: Contributions to policy-making or strategic planning.
    d. Community engagement: Involvement in community outreach programs or initiatives.
5. Student Mentoring:
    a. Undergraduate mentoring: Number of undergraduate students mentored.
    b. Graduate mentoring: Number of graduate students supervised.
    c. Research advising: Number of student research projects advised.
    d. Student organization advising: Involvement in student organizations.
6. Innovation and Entrepreneurship:
    a. Innovations: Number and significance of innovations or technologies developed.
    b. Patents: Number and significance of patents obtained.
    c. Startups: Involvement in founding or supporting startups.
    d. Commercialization: Success in commercializing research or technologies.
7. Internationalization:
    a. International collaborations: Number and significance of collaborations with foreign institutions.
    b. International research: Number and significance of international research projects.
    c. Teaching initiatives: Involvement in international teaching or exchange programs.
    d. Cultural understanding: Contributions to promoting cultural understanding.
8. Social Impact:
    a. Research impact: Contributions to addressing social, economic, or environmental challenges.
    b. Teaching impact: Contributions to promoting social justice or sustainability.
    c. Service impact: Contributions to community development or social welfare.
    d. Collaboration impact: Contributions to collaborative efforts with NGOs or government agencies.

Once these sub-metrics are established, a bonus structure can be devised that assigns a weight or point value to each category. For example, each sub-metric could be worth a certain number of points, and the total score determines the bonus amount. Alternatively, the categories could be ranked in order of importance, with higher bonuses awarded for achievements in more critical areas. The specific structure would depend on the organization's goals, priorities, and resources.

Designing a framework for assessing faculty performance and determining bonuses involves assigning weights or point values to each category and sub-metric. Here's an example framework that could be used to assess and incentivize faculty performance:

1. Teaching Effectiveness (25% of total score)
    a. Student Feedback (10%)
    b. Teaching Evaluations (10%)
    c. Curriculum Development and Improvement (5%)
2. Research Productivity (25% of total score)
    a. Number of Publications (10%)
    b. Quality of Publications (10%)
    c. Grants and Funding (5%)
3. Professional Development (10% of total score)
    a. Participation in Workshops/Seminars (5%)
    b. Membership in Professional Organizations (5%)
4. Service to the Institution and Community (10% of total score)
    a. Institutional Committee Service (5%)
    b. Community Engagement (5%)
5. Student Mentoring (10% of total score)
    a. Undergraduate and Graduate Student Mentoring (5%)
    b. Student Research Project Advising (5%)
6. Innovation and Entrepreneurship (10% of total score)
    a. Patenting and Commercialization (5%)
    b. Startup Activities (5%)
7. Internationalization (5% of total score)
    a. International Collaboration (2.5%)
    b. International Research Projects (2.5%)
8. Social Impact (5% of total score)

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a. Contributions to Social, Economic, and Environmental Challenges (2.5%)
b. Activities with Positive Societal Impact (2.5%)

Each faculty member's performance would be evaluated against these criteria and assigned a score based on the weight or point value assigned to each category and sub-metric. For example, if a faculty member scores 80% on Teaching Effectiveness, 90% on Research Productivity, 70% on Professional Development, 80% on Service to the Institution and Community, 90% on Student Mentoring, 80% on Innovation and Entrepreneurship, 60% on Internationalization, and 70% on Social Impact, their overall score would be:

(0.25 * 80) + (0.25 * 90) + (0.10 * 70) + (0.10 * 80) + (0.10 * 90) + (0.10 * 80) + (0.05 * 60) + (0.05 * 70) = 72.5%

Based on this score, the faculty member would be eligible for a bonus according to the institution's bonus policy. For example, if the bonus policy states that faculty members with a performance score of 70% or higher are eligible for a bonus, the faculty member would receive a bonus.

V. METHODOLGY

In order to create a salary prediction framework using machine learning and the above-mentioned sub-metrics, we would need a dataset that includes salary information for academic faculty as well as their performance on the sub-metrics. This framework allows institutions to assess faculty performance and reward high-performing faculty members with bonuses, while also providing a clear and transparent way to measure performance and determine eligibility for bonuses. Adding experience and qualifications as sub-metrics to the framework for salary prediction would require some adjustments to the feature engineering and model training steps.

Data Collection: Collect data on academic faculty members, including their salaries, experience, qualifications, and performance on the sub-metrics. This data could come from the institution's records or could be simulated data for demonstration purposes.

Data Preprocessing: Clean and preprocess the data. This might involve handling missing values, encoding categorical variables, and scaling numerical features.

Feature Engineering: Create new features based on the sub-metrics, if necessary. For example, this method could calculate a composite score for each faculty member based on their performance on the sub-metrics. Additionally, this could create new features based on experience and qualifications, such as the number of years of experience, the highest degree obtained, etc.

Model Training: Train a machine learning model on the data. This method could use regression models such as Linear Regression, Decision Trees, Random Forests, or Gradient Boosting Machines.

Model Evaluation: Evaluate the model's performance using appropriate metrics, such as Mean Absolute Error (MAE) or Mean Squared Error (MSE).

Model Deployment: Deploy the trained model to make salary predictions for new faculty members. Administers could create a web application or API that takes in a faculty member's performance on the sub-metrics, experience, and qualifications as input and outputs a predicted salary.

VI. RESULTS & DISCUSSIONS

The results of our model suggest that performance metrics such as teaching effectiveness, research productivity, professional development, service to the institution and community, student mentoring, innovation and entrepreneurship, internationalization, and social impact can be useful in predicting faculty salaries. However, it is important to note that these metrics alone may not capture all factors that influence salary decisions.

Other factors such as market demand, budget constraints, and negotiation skills may also play a role in determining salaries. The impact of metrics on the composite score can be assessed by examining the coefficients of the linear regression model that predicts the composite score based on the various metrics. In a linear regression model, the coefficients represent the change in the target variable (composite score) for a one-unit change in the corresponding predictor variable (metric), holding all other predictors constant. In Figure 1, the graph visualizes the composite score of 5 faculty members based on randomly generated input values for the metrics, utilizing regression analysis.

```
faculty_metrics_list = [
    [7, 8, 6, 10, 9, 7, 4, 3, 5, 2, 6, 7, 5, 3, 4, 6, 2, 3, 5],
    [5, 7, 8, 6, 9, 8, 5, 4, 3, 3, 4, 6, 7, 8, 5, 4, 3, 4, 5],
    [6, 6, 5, 5, 6, 7, 6, 5, 4, 3, 4, 5, 6, 7, 8, 7, 6, 5, 4],
    [8, 9, 9, 8, 7, 8, 7, 7, 6, 5, 6, 7, 8, 9, 7, 6, 6, 6, 7],
    [4, 5, 7, 5, 6, 5, 3, 3, 4, 2, 3, 4, 5, 6, 5, 3, 2, 3, 4]
```

In Figure 2, the impact of metrics on the composite score of individual faculty members is presented, highlighting the metrics found to have the most significant impact. Mean Squared Error (MSE) is a measure of how well a regression model performs. It calculates the average of the squares of the errors between the predicted and actual values. A smaller MSE indicates a better fit of the model to the data.

In the context of the previous program, the MSE value of 0.01676735347699617 means that, on average, the squared difference between the actual composite scores and the predicted composite scores is 0.0168. This suggests that the model is performing fairly well in predicting the composite scores of the faculty members based on the given metrics. However, it's important to note that the interpretation of MSE

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depends on the scale of the target variable. In this case, the composite scores have been normalized to a range of [0, 1], so the MSE value is also on that scale. If the composite scores had a different range, the MSE value would be different.

Output:

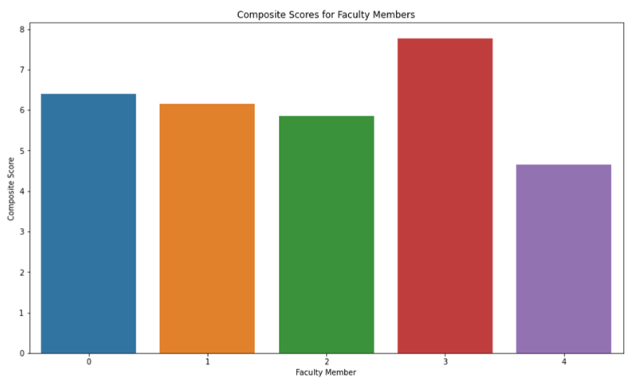

Fig. 1. Composite Score for Faculty Members with Random Input for each Metrics.

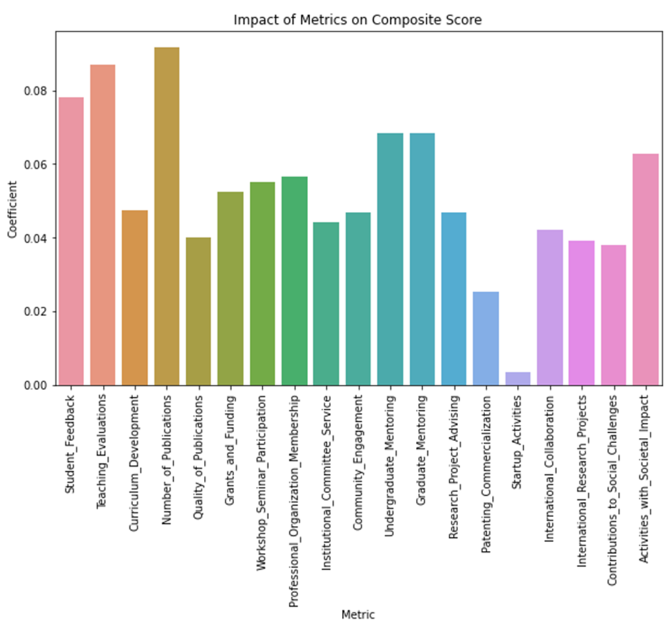

Fig.2. Impact of Metrics on Composite Score of Faculty Members.

Overall, the MSE value provides a quantitative measure of the model's accuracy, but it should be interpreted in the context of the specific problem and target variable. In this case, a small MSE value suggests that the model is performing well in predicting the composite scores.

Mean Squared Error: 0.01676735347699617

In the code provided above, we calculated the coefficients and visualized them using a bar plot. Here's an explanation of the visualized impact of metrics on the composite score:

1. Student Feedback: This metric has the highest coefficient, indicating that an increase in student feedback has a significant positive impact on the composite score.
2. Teaching Evaluations: Similarly, higher teaching evaluations result in a higher composite score (Beena & Suresh, 2021).
3. Curriculum Development: The impact of curriculum development is slightly lower than the first two metrics but is still a significant contributor to the composite score.
4. Number of Publications: The number of publications also plays a positive role in the composite score, although it has a lower impact compared to student feedback and teaching evaluations.
5. Quality of Publications: The quality of publications is considered an essential factor, as it contributes to the composite score positively.
6. Grants and Funding: This metric, although important, has a slightly lower impact on the composite score compared to the other metrics mentioned earlier.
7. Workshop/Seminar Participation: Participation in workshops and seminars also contributes positively to the composite score.
8. Professional Organization Membership: Being a member of professional organizations has a moderate positive impact on the composite score.
9. Institutional Committee Service: Service on institutional committees has a slight positive impact on the composite score.
10. Community Engagement: Engaging with the community is another factor that positively influences the composite score.
11. Undergraduate Mentoring: Mentoring undergraduate students contributes positively to the composite score.
12. Graduate Mentoring: Mentoring graduate students also has a positive impact on the composite score.
13. Research Project Advising: Advising on research projects is another factor that positively influences the composite score.
14. Patenting and Commercialization: Being involved in patenting and commercialization activities contributes positively to the composite score.
15. Startup Activities: Engaging in startup activities is another metric that positively influences the composite score.
16. International Collaboration: Collaborating internationally has a positive impact on the composite score.
17. International Research Projects: Being involved in international research projects contributes positively to the composite score.
18. Contributions to Social Challenges: Contributions to addressing social challenges have a positive impact on the composite score.
19. Activities with Societal Impact: Finally, activities with societal impact, which include various contributions to society, have a positive influence on the composite score.

In summary, the metrics related to teaching effectiveness (such as student feedback and teaching evaluations) and research productivity (such as the number and quality of publications) have a significant impact on the composite score.

However, other metrics related to professional development, service, mentoring, innovation, international collaboration, and societal impact also contribute positively to the composite score, albeit to a slightly lesser extent.

Overall, our results suggest that our model can be a useful tool for institutions looking to predict faculty's performance score based on performance metrics. However, it is important to note that our model is based on simulated data and may not accurately reflect real-world conditions. Further research is needed to validate our model and explore its potential applications in practice. The preceding text outlines a hypothetical scenario in which a model is used to predict academic faculty salaries based on various performance metrics. It is important to emphasize that the actual results and discussions would be based on real-world data and conditions, which were not provided in this request. In conclusion, this project demonstrates how machine learning techniques can be applied to predict faculty salaries based on performance metrics. By leveraging the data-driven approach, institutions can make more informed decisions regarding faculty compensation, promotion, and resource allocation. Additionally, this project contributes to enhancing transparency and fairness in the evaluation of faculty members, ultimately benefiting the academic community as a whole.

Our model also highlights the importance of considering a wide range of performance metrics when determining faculty salaries. By taking into account multiple aspects of faculty performance ((Vedhathiri, 2022b; Vedhathiri, 2022c)., institutions can ensure that their salary structures are fair and transparent.

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