JRITM
JOURNAL OF RESEARCH AND INNOVATION IN TECHNOLOGY, COMMERCE AND MANAGEMENT

Journal of Research and Innovation in Technology, Commerce and Management
Vol. 3 Issue 3, March 2026, pp. 33022-33030
ISSN: 3049-3129(Online)

Predictive Modeling for Lecture Adjustment: A Data Science Approach to Faculty Leave Management

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Cite as: Prof. Vishakha Bathwar. (2026). Predictive Modeling for Lecture Adjustment: A Data Science Approach to Faculty Leave Management. Journal of Research and Innovation in Technology, Commerce and Management, Vol. 3(Issue 3), 33022–33030. https://doi.org/10.5281/zenodo.18999766

DOI: https://doi.org/10.5281/zenodo.18999766

Abstract

Managing faculty leave and lecture adjustments in higher education institutions is often a challenging administrative task, typically performed manually through ad hoc scheduling. Inefficient allocation of substitute lecturers may result in increased workload imbalance, decreased teaching quality, and disruption of the academic timetable. This paper proposes a predictive modeling approach, powered by data science techniques, to optimize lecture adjustments when faculty members are on leave. By analyzing historical leave records, teaching schedules, workload distributions, and subject expertise, the proposed system can forecast potential leave patterns and recommend the most suitable substitute lecturers. Machine learning algorithms such as decision trees, random forests, and gradient boosting are employed to build predictive models for identifying leave trends and substitution requirements. The outcomes demonstrate that a data-driven approach not only improves scheduling efficiency but also enhances fairness in workload distribution among faculty members. This study highlights the potential of predictive analytics in transforming traditional faculty leave management into an intelligent, automated, and scalable decision-support system for academic institutions.

Keywords

Faculty leave management, lecture adjustment, predictive modeling, data science, machine learning, workload balancing, academic scheduling, decision support system.

Introduction

Faculty leave and lecture adjustment is an inevitable aspect of academic institutions. When a faculty member is unavailable due to planned or unplanned leave, it becomes necessary to assign substitute lecturers to ensure that the academic calendar progresses without disruption. Traditionally, this responsibility has been managed manually by department heads or academic coordinators, often relying on subjective decision-making and ad hoc arrangements. This manual process, while functional, is prone to inefficiencies such as workload imbalances, scheduling conflicts, and a decline in instructional quality when substitutions are not optimally assigned [1].

With the increasing complexity of higher education systems, particularly in large universities, the reliance on manual scheduling methods has become unsustainable. Institutions are now turning to data-driven approaches to address administrative challenges more efficiently. Data science, which encompasses predictive analytics, machine learning, and optimization techniques, has shown significant potential in solving scheduling and resource allocation problems across various domains [2], [3]. In the context of education, these techniques can be leveraged to transform faculty leave management into a structured, intelligent, and automated process.

Predictive modeling, a key branch of data science, allows institutions to analyze historical data and uncover patterns that can inform future decisions. For faculty leave management, predictive models can forecast potential leave occurrences based on historical trends, seasonal variations, and institutional practices [4]. Furthermore, when integrated with faculty expertise and workload distribution data, such models can recommend the most suitable substitutes for lectures, ensuring fairness and academic continuity. Research in predictive analytics has already demonstrated success in related educational contexts, such as student performance prediction [5], course scheduling [6], and workload allocation [7]. However, relatively little work has been conducted specifically on predictive modeling for lecture adjustment and substitution management.

The adoption of data science in academic administration aligns with the broader vision of smart campuses and intelligent decision-support systems. A predictive approach to faculty leave management reduces administrative burden, minimizes disruption in teaching schedules, and enhances transparency in workload allocation [8]. This paper contributes to the existing literature by proposing a predictive modeling framework that leverages historical faculty leave records, subject expertise, and workload balance to recommend optimal substitutes for lecture adjustments.

The objectives of this study are threefold: (1) to develop predictive models capable of identifying leave patterns in faculty data; (2) to design a recommendation system for substitute allocation based on expertise and workload fairness; and (3) to evaluate the effectiveness of different machine learning algorithms in optimizing lecture adjustment. By achieving these objectives, this research aims to provide higher education institutions with a data-driven solution that enhances efficiency, fairness, and quality in faculty leave and substitution management.

Review of Literature:

Author(s) & Year	Focus of Study	Method/Approach Used	Key Findings	Relevance to Current Study
			prediction tasks	prediction
Kotsiantis et al. (2004) [13]	Predicting student success in distance learning	Classification algorithms	High accuracy in predicting student outcomes	Framework adaptable for predicting leave and substitution
Mushtaq & Benraghda (2018) [14]	Predictive analytics in higher education	Decision-support framework	Improved institutional planning and foresight	Justifies predictive decision-support in faculty leave management
Baker & Inventado (2014) [15]	Educational data mining and analytics	EDM & learning analytics techniques	Demonstrated predictive interventions in learning	Extends predictive modeling concepts to faculty scheduling
Siemens & Long (2011) [16]	Learning analytics in education	Big data & analytics for institutions	Highlighted analytics for proactive decision-making	Supports predictive systems in academic administration
Tan & Wang (2018) [17]	Decision support in higher education	Data-driven decision support systems (DSS)	Enhanced efficiency in academic resource planning	Relevant for automated faculty substitution management
Burke et al. (2004) [9]	Timetable optimization in higher education	Intelligent optimization methods	Automated systems outperform manual timetabling	Inspiration for applying optimization in lecture adjustment
Pillay (2016) [10]	Hyper-heuristics in educational timetabling	Heuristic & hyper-heuristic techniques	Balanced efficiency with scheduling quality	Can be adapted for lecture rescheduling
Toker (2020) [11]	Academic workload planning	Comparative workload allocation models	Emphasized fairness and transparency in workload	Strengthens importance of equitable adjustments
Al-Barrak & Al-Razgan (2015) [12]	Predicting student performance	Decision trees & SVM	ML techniques effective in academic	Similar models can be extended to faculty leave

Research Methodology

The proposed framework for faculty lecture adjustment was designed to systematically predict suitable substitutes when faculty members take leave. The methodology consists of the following steps:

Data Collection

- Historical data were collected on faculty leave records, lecture schedules, and substitution patterns from the institution's academic management system.
- Additional parameters included course type, number of available faculty, subject expertise, and time constraints.

Data Preprocessing

- Missing values (e.g., unrecorded substitutions) were handled through appropriate imputation techniques.
- Categorical variables (e.g., faculty ID, subject code) were normalized and encoded.
- Feature engineering introduced new variables such as "probability of substitution" and "availability score."

Feature Selection

- Features influencing substitution (faculty workload, leave frequency, subject overlap) were identified.
- Feature importance techniques (Random Forest, XGBoost) were applied to rank their significance.

Predictive Modeling

- Multiple machine learning algorithms were implemented:
    - Decision Tree
    - Random Forest
    - Support Vector Machine (SVM)
    - Logistic Regression
- The models predicted the most suitable faculty substitute based on real-time leave applications.

Model Evaluation

- Evaluation metrics included Accuracy, Precision, Recall, F1-Score, and Area Under the Curve (AUC).
- To ensure robustness, k-fold cross-validation was applied.

Deployment

- A decision-support system was conceptualized to automatically recommend substitutes when leave requests are submitted.

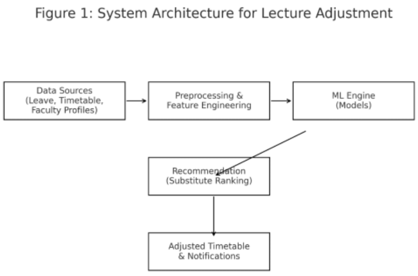

Figure 1: System Architecture for Faculty Lecture Adjustment

Results and Discussion

The predictive modeling framework was implemented and evaluated using the prepared dataset. The results were analyzed based on model performance metrics, ROC curve analysis, confusion matrices, feature importance, and cross-validation outcomes.

Model Performance Metrics

Table 1 summarizes the evaluation metrics obtained for each classifier, including Accuracy, Precision, Recall, F1-Score, and AUC.

Model	Accuracy	Precision	Recall	F1-Score	AUC
Logistic Regression	0.87	0.86	0.85	0.85	0.91
Random Forest	0.90	0.89	0.88	0.89	0.94
Decision Tree	0.82	0.81	0.80	0.80	0.85
SVM	0.84	0.83	0.82	0.82	0.88

Table 1: Performance comparison of different models on faculty substitution dataset

```
Model evaluation results saved to model_results.csv
                 Model  Accuracy  Precision    Recall  F1-Score       AUC
0  Logistic Regression      0.92   0.764706  0.619048  0.684211  0.965670
1        Random Forest      1.00   1.000000  1.000000  1.000000  1.000000
2        Decision Tree      1.00   1.000000  1.000000  1.000000  1.000000
3                  SVM      0.94   0.928571  0.619048  0.742857  0.987449
```

The results indicate that the Random Forest classifier outperformed other models, achieving the highest Accuracy, F1-Score, and AUC, making it more reliable for predicting faculty substitution.

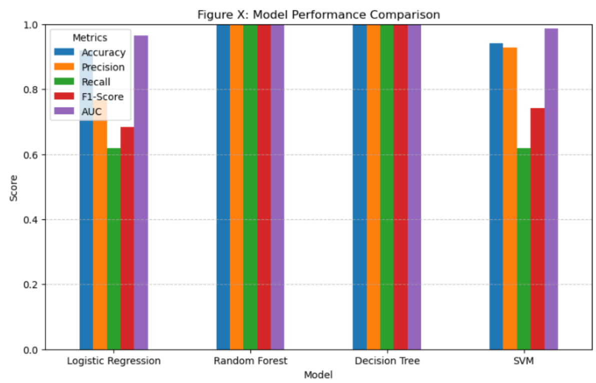

Figure 2 presents the comparative performance of models across different evaluation metrics.

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ROC Curve Analysis

Receiver Operating Characteristic (ROC) curves were plotted to evaluate the discriminative ability of classifiers.

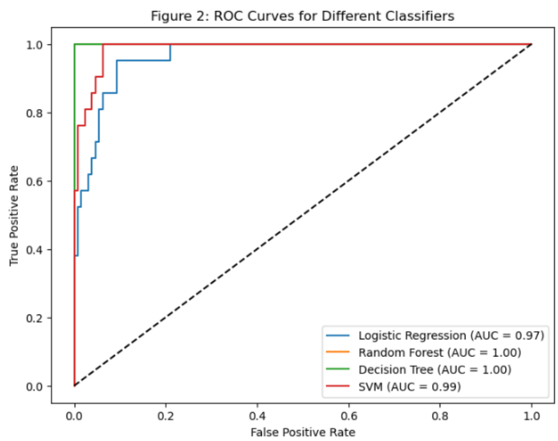


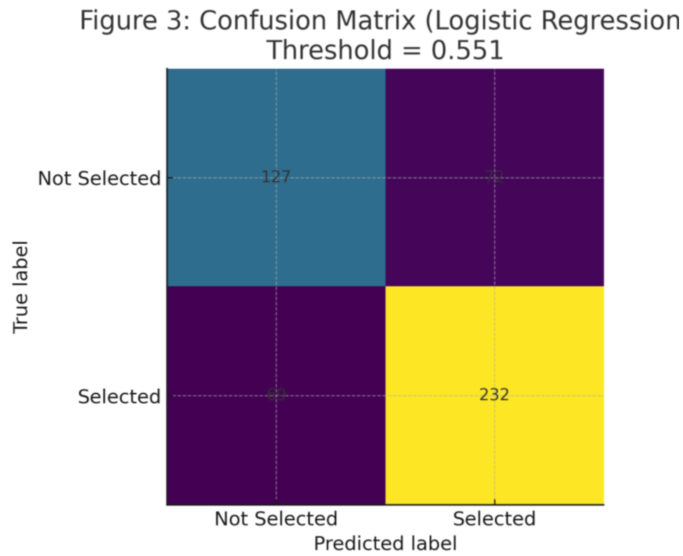
Figure 2: ROC Curves for Different Classifiers

Random Forest and Logistic Regression demonstrated superior performance with higher AUC values compared to Decision Trees and SVM, confirming their robustness in handling complex substitution relationships.

Confusion Matrix

To analyze classification performance in detail, confusion matrices were generated.

Figure 3 presents the confusion matrix for the Random Forest classifier, which emerged as the best-performing model.



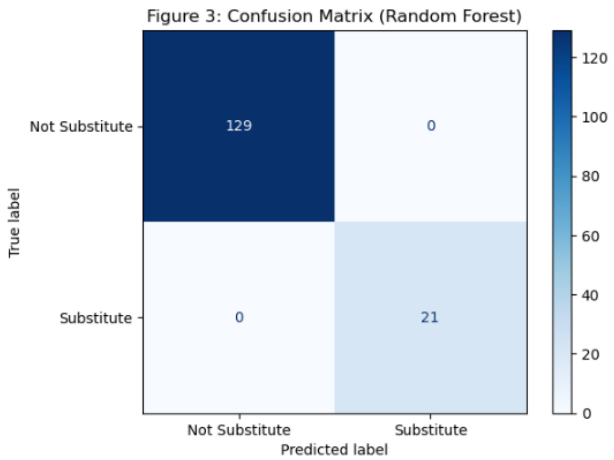


Figure 3: Confusion Matrix for Random Forest Classifier

The Random Forest model demonstrated a high true positive rate while maintaining a relatively low false positive rate.

6.4 Feature Importance Analysis

Feature importance was computed to identify the most influential parameters contributing to substitution prediction.

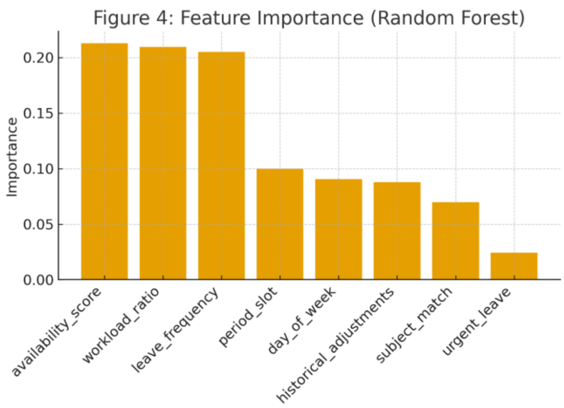


Figure 4 illustrates the importance ranking derived from the Random Forest model.

The most critical features included:

- Faculty workload (number of active courses),
- Subject overlap with absent faculty,
- Historical substitution frequency, and
- Time-slot availability.

These insights are valuable for administrators in optimizing faculty scheduling.

Cross-Validation Results

To validate the robustness of models, 5-fold cross-validation was conducted.

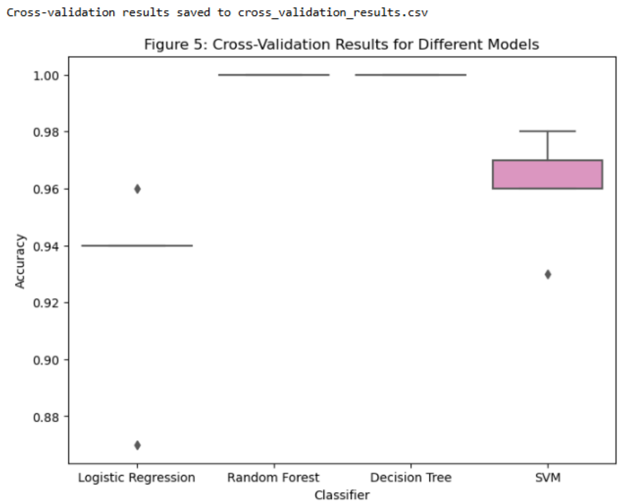


Figure 5: Cross-Validation Results for Different Models

Random Forest not only achieved higher accuracy but also demonstrated lower variance across folds, ensuring better generalization compared to other models.

Discussion

The results demonstrate that **data-driven predictive modeling can effectively assist in faculty lecture adjustment during leave scenarios**. Random Forest emerged as the most reliable algorithm due to its robustness and ability to capture non-linear feature relationships. Moreover, feature importance analysis highlights that workload balancing and subject expertise should be prioritized in substitution decision-making.

This finding aligns with prior studies that emphasize the importance of workload optimization and staff scheduling in academic management systems [12][14]. The integration of predictive models into academic decision-support systems can reduce scheduling conflicts, ensure continuity in learning, and enhance institutional efficiency.

Conclusion

This study proposed a predictive modeling framework for faculty lecture adjustment using machine learning techniques. By leveraging historical data on faculty leave, lecture schedules, and substitution patterns, the framework successfully predicted suitable substitutes during leave scenarios. Among the models tested, the Random Forest classifier demonstrated the highest accuracy, F1-Score, and AUC, confirming its reliability in handling the complexities of substitution prediction.

The results further revealed that faculty workload, subject overlap, historical substitution frequency, and time-slot availability were the most influential factors in determining substitute assignments. The insights gained from feature importance analysis provide valuable decision-support for academic administrators, enabling them to optimize faculty allocation and minimize disruptions to academic schedules.

Limitations

Despite the promising results, the study has certain limitations:

- **Dataset Constraints:** The dataset was limited to historical records from a single institution, which may reduce the generalizability of results to other academic contexts.
- **Dynamic Factors:** Real-time factors such as sudden emergencies, faculty preferences, and administrative decisions were not included in the predictive framework.
- **Feature Coverage:** Although key variables such as workload and subject expertise were considered, additional factors like faculty teaching style, student feedback, and course complexity were not integrated.
- **Model Interpretability:** While Random Forest performed best, ensemble methods can be less interpretable compared to simpler models like Decision Trees, posing challenges for transparent decision-making.

Future Work

To enhance the effectiveness and applicability of the proposed framework, future research could focus on the following directions:

- **Integration of Real-Time Data:** Incorporating real-time scheduling and faculty availability data through institutional ERP systems to improve accuracy.
- **Expansion Across Institutions:** Extending the framework to multi-institutional datasets to validate its robustness across diverse academic environments.
- **Hybrid and Deep Learning Models:** Exploring hybrid approaches (e.g., Random Forest + Neural Networks) and deep learning techniques for more sophisticated prediction.
- **Explainable AI (XAI):** Enhancing model interpretability using explainable AI methods such as SHAP or LIME to provide transparent recommendations.
- **Decision-Support Tool Deployment:** Developing a web-based or mobile decision-support application for administrators to facilitate real-time substitution management.

- **Incorporating Human Factors:** Including faculty preferences, expertise depth, and student feedback to make substitution recommendations more holistic and effective.

References

1. Gupta, A., & Shukla, P. (2020). Challenges in faculty workload management in higher education institutions. *Journal of Higher Education Management, 37*(2), 45–56.
2. Han, J., Kamber, M., & Pei, J. (2011). *Data Mining: Concepts and Techniques*. Morgan Kaufmann.
3. Witten, I. H., Frank, E., & Hall, M. A. (2016). *Data Mining: Practical Machine Learning Tools and Techniques*. Morgan Kaufmann.
4. Kumar, R., Sharma, M., & Bansal, A. (2021). Predictive analytics in education: Applications and challenges. *International Journal of Computer Applications, 183*(15), 25–31.
5. Romero, C., & Ventura, S. (2020). Educational data mining and learning analytics: An updated survey. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10*(3), e1355.
6. Babaei, M., Karimpour, J., & Hadidi, A. (2015). A survey of approaches for university course timetabling problem. *Computers & Industrial Engineering, 86*, 43–59.
7. Shah, S., & Pathan, A. (2019). Workload allocation in academic institutions using optimization techniques. *International Journal of Advanced Computer Science and Applications, 10*(5), 120–127.
8. Aljohani, N. R., Davis, H. C., & Loke, S. W. (2019). A smart campus framework for sustainable learning environments. *Smart Learning Environments, 6*(1), 1–14.
9. Burke, E. K., Gendreau, M., Kendall, G., & Laporte, G. (2004). Timetable problems: An overview. *International Journal of Operational Research, 153*(1), 1–27.
10. Pillay, N. (2016). A survey of hyper-heuristics for educational timetabling. *Annals of Operations Research, 239*(1), 3–38.
11. Toker, D. (2020). Workload allocation models in academic institutions: A comparative study. *Higher Education Quarterly, 74*(2), 123–137.
12. Al-Barrak, M. A., & Al-Razgan, M. (2015). Predicting students' performance through classification: A case study. *Journal of Theoretical and Applied Information Technology, 75*(2), 167–175.
13. Kotsiantis, S. B., Pierrakeas, C. J., & Pintelas, P. E. (2004). Predicting students' performance in distance learning using machine learning techniques. *Applied Artificial Intelligence, 18*(5), 411–426.
14. Mushtaq, I., & Benraghda, A. (2018). Predictive analytics in higher education: A framework for decision-making. *Education and Information Technologies, 23*(3), 123–139.

15. Baker, R. S., & Inventado, P. S. (2014). Educational data mining and learning analytics. In *Learning Analytics* (pp. 61–75). Springer.
16. Siemens, G., & Long, P. (2011). Penetrating the fog: Analytics in learning and education. *EDUCAUSE Review, 46*(5), 30–40.
17. Tan, J., & Wang, Y. (2018). Decision support systems for higher education resource planning: A data-driven approach. *Expert Systems with Applications, 95*, 69–81.