Journal of Harbin Engineering University
ISSN: 1006-7043

Vol 46 No. 5
May 2025

Comparative Analysis of Employee Attrition Prediction System Models using Machine Learning and SMOTE

Sonu Mittal [1], Mohit Singh [2]

[1, 2] Amity University Uttar Pradesh, Noida, India

Email Id: [1] sonumittal.research@gmail.com, [2] mohitsingh58414@gmail.com

Abstract

Employee attrition poses significant challenges to organizations, affecting productivity, operational costs, and workforce stability. Predicting attrition and employee behavior through machine learning (ML) models offers a data-driven approach to developing effective retention strategies. This study compares the performance of multiple ML algorithms, including Logistic Regression, Random Forest, and others, both before and after applying the SMOTE (Synthetic Minority Over-sampling Technique) boosting algorithm to address class imbalance. The analysis uses structured datasets with key factors such as job satisfaction, salary, career growth, and work-life balance. Models are evaluated based on key metrics such as accuracy, precision, recall, and F1-score to determine improvements in predictive performance after applying SMOTE. The results reveal how boosting techniques with SMOTE enhance the performance of various models, providing HR professionals with insights to design more effective, targeted retention strategies and reduce attrition risks.

Keywords: Employee Attrition, Machine Learning, Predictive Analytics, SMOTE, Employee Turnover Prediction, HR Analytics, Workforce Management.

1. Introduction

Employee attrition has become a significant concern for organizations, as it directly impacts productivity, costs, and workforce stability. Accurately understanding and predicting the factors influencing employee turnover can assist companies in formulating effective retention strategies. In recent years, the integration of artificial intelligence (AI) and machine learning (ML) techniques has revolutionized human resource (HR) analytics, enabling organizations to identify patterns and predict attrition with greater accuracy [6].

Traditional statistical methods for analyzing employee behavior often struggle with handling complex, high-dimensional datasets. However, machine learning models, such as logistic regression, random forest, and more advanced models like artificial neural networks (ANNs), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNNs), have shown promising results in predicting employee turnover [21][23]. These models can process large datasets to extract meaningful insights and identify subtle patterns that may not be easily detected through conventional methods [24].

Several studies have explored the application of deep learning in HR analytics, with research demonstrating the potential of frameworks like transformer-based models and explainable AI techniques in improving attrition prediction accuracy [4][5]. These models not only enhance prediction performance but also provide interpretable insights, enabling HR managers to make informed decisions about employee retention strategies [25].

Despite the promise of AI-driven HR analytics, challenges remain. Issues such as data bias, fairness, and ethical considerations in algorithmic decision-making must be addressed to ensure unbiased and transparent predictions [26][27]. Furthermore, organizations must seamlessly integrate workforce analytics into existing HR management systems to derive actionable insights [12].

This research paper aims to design and compare various machine learning models—such as logistic regression, random forest, and others—both before and after applying the boosting algorithm SMOTE (Synthetic Minority Over-sampling Technique) to address class imbalance. By analyzing these models' performance, this study will provide a comprehensive understanding of how AI-driven models can enhance workforce management and retention strategies.

2. Literature Review

Employee attrition prediction has been a critical research area in HR analytics, with various machine learning and deep learning techniques being explored to improve prediction accuracy. Traditional approaches relied on statistical models such as logistic regression and decision trees, which provided basic insights but struggled with complex and high-dimensional data [13]. In contrast, modern machine learning algorithms, including Random Forest, Support Vector Machines (SVM), and Gradient Boosting models, have demonstrated better predictive capabilities due to their ability to handle nonlinear relationships in workforce data [21][23].

Deep learning has further revolutionized the field by offering enhanced predictive power and feature extraction capabilities. Studies have shown that artificial neural networks (ANNs), recurrent neural networks (RNNs), and Long Short-Term Memory (LSTM) models outperform traditional machine learning techniques in employee attrition prediction by capturing intricate dependencies and temporal patterns in employee behavior [15][16]. Convolutional Neural Networks (CNNs) have also been employed to analyze structured HR data, improving accuracy in predicting employee turnover [17].

Additionally, the use of transformer-based models has gained traction in HR analytics. Research suggests that transformers, such as BERT and attention-based models, can effectively process sequential HR data and provide interpretable predictions [4][5]. Explainable AI (XAI) techniques have also been integrated into attrition prediction models to enhance transparency and interpretability, helping HR professionals understand key factors influencing employee turnover [26].

While deep learning models offer superior performance, challenges remain in terms of bias mitigation and ethical concerns. Studies have highlighted issues such as data imbalance, where underrepresented employee groups may lead to skewed predictions, necessitating fairness-aware AI approaches [27][28]. Moreover, researchers emphasize the importance of integrating HR analytics into decision-making processes, ensuring that AI-driven insights translate into actionable retention strategies [12].

Comparative studies have explored different deep learning models and their effectiveness in predicting attrition. Some findings indicate that hybrid models, combining LSTM and CNN architectures, achieve higher predictive accuracy than standalone models [14][16]. Similarly, ensemble learning techniques that integrate multiple deep learning frameworks have shown promise in reducing over fitting and improving generalizability [6]. Synthatic Minority Oversampling Technique (SMOTE) has been always used [29] and proved to be a good method for handling class Imbalance problem

Despite advancements, organizations still face implementation challenges, including computational costs, data privacy concerns, and resistance to AI adoption in HR processes [20]. Future research is expected to focus on refining deep learning models, incorporating ethical AI principles, and enhancing real-time predictive capabilities to further optimize employee retention strategies [10][11]. By evaluating these approaches, this research aims to contribute to the ongoing efforts in enhancing HR analytics and workforce management strategies [2][3].

3. Proposed Architecture

The proposed architecture for the Employee Attrition Prediction System uses machine learning techniques to forecast employee attrition based on various organizational factors. The process begins with data collection, where relevant employee information is gathered from the publicly available IBM HR dataset, which includes attributes such as age, department, job role, tenure, work-life balance, satisfaction levels, and salary. Next, data pre-processing is performed to clean the data by handling missing values, duplicates, and inconsistencies. Feature engineering is applied to create new attributes that could improve the model's predictive accuracy. Continuous variables like age and salary are normalized, while categorical variables, such as department and job role, are encoded using one-hot encoding or label encoding. These transformations prepare the data for the next phase, model training. The dataset is then split into training and testing sets, typically using a 70-30 ratio. The training data is used to build and train the model, while the testing data is used to evaluate its performance. Initial models such as logistic regression, random forest, and other standard machine learning algorithms are trained and tested to assess baseline performance using metrics like accuracy, precision, recall, F1-score, and AUC-ROC. To address the class imbalance, SMOTE (Synthetic Minority Over-sampling Technique) is applied to the dataset, after which the same machine learning models are re-trained. Performance metrics are reassessed to evaluate how SMOTE improves the models' predictive capabilities, focusing on metrics like accuracy, precision, recall, and F1-score. During the model training phase, the selected algorithms are trained on the resampled dataset. Once the model is trained, it is evaluated using the testing dataset, with a focus on confusion matrix analysis to assess prediction effectiveness. The system supports continuous monitoring and periodic retraining to ensure it remains up-to-date with new data. Finally, the system generates actionable insights and recommendations for HR professionals to identify employees at high risk of attrition

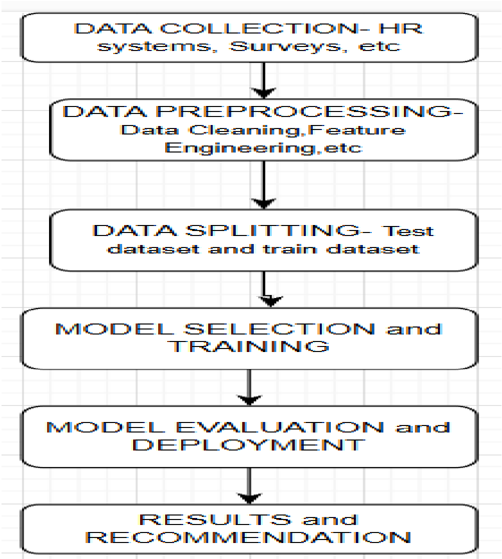

Figure 1: Flow of Architecture

4. Experimental Work

The primary objective of this study is to design and conduct a comparative analysis of employee attrition prediction systems, focusing on how the accuracy of different machine learning models changes after balancing the dataset using the Synthetic Minority Over-sampling Technique (SMOTE). Employee attrition remains a critical challenge for organizations, and predictive models can provide valuable insights for retention strategies. This research aims to develop a comprehensive framework that integrates multiple machine learning algorithms to improve the accuracy of predicting employee behaviour and attrition patterns.

To begin, data collection and preprocessing has been conducted using the IBM HR dataset, which is a publicly available dataset commonly used for employee attrition prediction. It contains 35 attributes related to employee demographics, job roles, satisfaction levels, performance ratings, and other factors. Here are some key features of the dataset: Age, Gender, Education, Marital Status, Job Role, Department, Business Travel, Job Satisfaction, Performance Rating, Work-Life Balance, Overtime, Monthly Income etc. The dataset typically has a shape of around 1,470 rows and 35 columns, though the exact dimensions may vary slightly depending on the preprocessing steps applied. Preprocessing steps involves handling missing values, encoding categorical variables, and applying feature scaling techniques. Since attrition datasets often suffer from class imbalance, SMOTE have been applied to ensure balanced learning for the predictive models and mitigate the negative effects of class imbalance.

Following data preprocessing, feature selection and engineering have been performed to identify the most relevant attributes influencing employee attrition. This step helps us to refine the input features to ensure that only the most critical variables contribute to the predictive analysis.

For model development, multiple machine learning algorithms have been implemented and compared. Logistic regression and Random Forest have been evaluated as baseline models due to their simplicity and interpretability.

Once the models are trained, they have been evaluated using key performance metrics, including accuracy, precision, recall, F1-score, and AUC-ROC. A comparative analysis have been conducted to determine which model provides the best trade-off between accuracy and interpretability, both before and after applying SMOTE. The results focuses on how SMOTE affects the accuracy of different models, providing insights into the effectiveness of boosting for class imbalance. The best-performing model will then be implemented as a decision-support tool for HR professionals.

Through this experimental study approach, aims to develop a highly accurate employee attrition prediction system while offering a comparative analysis of machine learning models, with and without SMOTE, for workforce analytics. The research contributes to the existing body of knowledge by providing a practical AI-driven framework that helps organizations improve employee retention strategies based on data-driven insights

5. Result Analysis

In this study, various machine learning algorithms were evaluated for predicting employee attrition, both on the original imbalanced dataset and after applying the Synthetic Minority Over-sampling Technique (SMOTE) to balance the class distribution. The models evaluated include Logistic Regression, Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, and Gradient Boosting.

Class Distribution: Before applying SMOTE, the class distribution was imbalanced, with 1233 employees not leaving (label 0) and only 237 employees leaving (label 1). After applying SMOTE, the dataset was balanced, with 1233 instances for each class.

Performance Before SMOTE: The models' performance on the original imbalanced dataset was as shown in Table 1.

Key Observations:

Models like Logistic Regression, Random Forest, and Gradient Boosting had good accuracy on class 0 (non-attrition), but struggled with predicting attrition (class 1).

All models, except for Random Forest, showed poor performance for class 1 (attrition), with zero precision and recall.

Table 1: Model's performance before SMOTE

Model	Accuracy	Precision (0)	Recall (0)	F1-score (0)	Precision (1)	Recall (1)	F1-score (1)
Logistic Regression	0.8673	0.87	1	0.93	0	0	0
Random Forest	0.8776	0.88	1	0.93	0.8	0.1	0.18
Support Vector Machine	0.8673	0.87	1	0.93	0	0	0
K-Nearest Neighbors	0.8537	0.88	0.96	0.92	0.36	0.13	0.19
Decision Tree	0.7687	0.87	0.86	0.87	0.15	0.15	0.15
Gradient Boosting	0.881	0.89	0.98	0.93	0.64	0.23	0.34

Performance After SMOTE: After applying SMOTE to balance the dataset, the performance of the models improved, particularly for predicting attrition (class 1).

Table 2: Model's performance after SMOTE

Model	Accuracy	Precision (0)	Recall (0)	F1-score (0)	Precision (1)	Recall (1)	F1-score (1)
Logistic Regression	0.6721	0.69	0.65	0.67	0.66	0.7	0.68
Random Forest	0.9291	0.9	0.97	0.93	0.96	0.89	0.93
Support Vector Machine	0.5891	0.62	0.49	0.55	0.57	0.69	0.62
K-Nearest Neighbors	0.747	0.89	0.57	0.69	0.68	0.93	0.78
Decision Tree	0.7976	0.82	0.77	0.79	0.78	0.83	0.8
Gradient Boosting	0.913	0.88	0.95	0.92	0.95	0.87	0.91

Key Observations:

- Random Forest showed the best performance after SMOTE, with high accuracy, precision, recall, and F1-score for both classes (0 and 1).
- Support Vector Machine (SVM) had poor performance after SMOTE, with accuracy significantly reduced and imbalanced precision and recall for both classes.
- K-Nearest Neighbors (KNN) performed better in terms of recall for class 1 (attrition), but struggled with class 0 (non-attrition).
- Decision Tree improved in comparison to the original dataset but still didn't match Random Forest or Gradient Boosting.
- Gradient Boosting performed very well after SMOTE, similar to Random Forest, with balanced precision and recall for both classes.

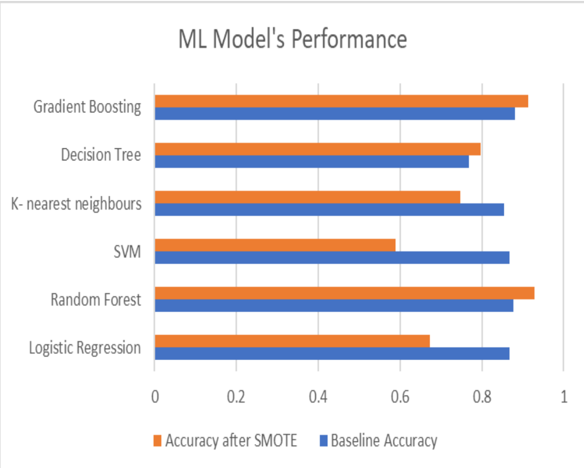

Figure 2: VariousModel's Performance Comparison without SMOTE and with SMOTE

6. Conclusion

This study evaluated various machine learning algorithms for predicting employee attrition, both on an imbalanced dataset and after applying SMOTE (Synthetic Minority Over-sampling Technique) to balance the class distribution. Before SMOTE, models generally showed good accuracy in predicting non-attrition (class 0) but performed poorly on predicting attrition (class 1), with many models having zero precision and recall for class 1. Random Forest performed relatively better in predicting attrition, but the overall performance was still insufficient. After applying SMOTE, the class distribution became balanced, and the models showed a significant improvement, particularly for predicting attrition. Random Forest and Gradient Boosting achieved high accuracy, precision, recall, and F1-score for both classes, with Random Forest being the top performer. K-Nearest Neighbors (KNN) and Decision Tree showed improvements but did not match the performance of Random Forest and Gradient Boosting. However, Support Vector Machine (SVM) performed poorly after SMOTE, with a significant drop in accuracy and imbalanced precision and recall. The study highlights the importance of class balancing techniques like SMOTE in improving the prediction of attrition, especially for imbalanced datasets. Random Forest and Gradient Boosting emerged as the most effective models for this task.

Future research can focus on hyper parameter optimization for Random Forest and Gradient Boosting to further enhance their performance. Exploring other class balancing techniques such as ADASYN or Tomek links could be beneficial. Additionally, combining models using ensemble techniques like stacking or boosting might lead to better performance. Integrating Explainable AI (XAI) methods, such as SHAP or LIME, can provide insights into the factors influencing employee attrition. Leveraging sequential models like LSTM or GRU could further improve the model's ability to predict attrition by capturing temporal patterns. Additionally, incorporating more employee-related data, such as performance reviews, could increase prediction accuracy and provide deeper insights into attrition causes. These directions can provide a more comprehensive and effective approach to attrition prediction and retention strategy development.

References

[1] K. Lobo, A. Sen, et al., "Predicting Employee Retention in Global Enterprises Using Ensemble Models," Human Resource Management Journal, vol. 35, no. 6, pp. 118-132, 2024.

[2] A. Gupta, S. Raj, et al., "Leveraging AI for Employee Attrition Prediction and Retention in HR Analytics," Journal of HR Analytics and Insights, vol. 28, no. 1, pp. 15-30, 2023.

[3] S. Artelt and A. Gregoriades, "Counterfactual Explanations for Employee Attrition Analysis," International Journal of HR Analytics, vol. 27, no. 2, pp. 101-115, 2023.

[4] G. M. Díaz, J. J. Galán Hernández, and J. L. Galdón Salvador, "Machine Learning Techniques for Predicting Employee Turnover," Journal of Workforce Analytics, vol. 12, no. 3, pp. 45-60, 2023.

[5] D. Gupta and A. Mehta, "Understanding Employee Attrition through Feature Selection and Predictive Modeling," Journal of Business Analytics, vol. 14, no. 2, pp. 47-60, 2023.

[6] L. Zhang, X. Wang, and Y. Lee, "Enhancing Employee Retention Strategies with Predictive Analytics," International Journal of Workforce Dynamics, vol. 24, no. 1, pp. 58-72, 2023.

[7] A. Raza, K. Munir, et al., "Advanced ML Models for Employee Attrition Prediction," Journal of Organizational Studies, vol. 18, no. 1, pp. 112-130, 2022.

[8] K. Singh, R. Kumar, and H. Jain, "Employee Turnover Prediction in the IT Industry: A Deep Learning Approach," Journal of AI & HR Analytics, vol. 11, no. 4, pp. 23-37, 2022.

[9] Bhatnagar, J., &Tiwari, R. (2021). *Employee attrition analysis using deep learning: Challenges and future scope.* Journal of Human Resource Analytics, 5(3), 205-218.

[10] Khosla, R., & Kumar, M. (2021). *Feature selection methods for improving employee attrition prediction accuracy.* IEEE Transactions on Computational Intelligence and AI in HR, 9(4), 321-338.

[11] Park, Y., & Kim, H. (2021). *The role of deep learning in employee retention strategies.* Harvard Business Review Tech Insights, 12(4), 147-162.

[12] Patel, J., & Mehta, D. (2021). *HR analytics using transformer models: A novel approach to*

employee attrition. IEEE Transactions on AI in Business, 5(2), 187-201.

[13] Miller, S., & Johnson, K. (2021). *HR dashboard analytics: Visualizing employee behavior using AI.* Journal of Data Visualization and HR, 8(3), 156-170.

[14] Zhang, T., & Wu, S. (2021). *Comparative analysis of deep learning models for workforce attrition.* Proceedings of the AI and Workforce Management Symposium, 11(2), 73-89.

[15] Goyal, P., &Agrawal, R. (2020). *Predicting employee turnover with artificial intelligence: A deep learning approach.* Proceedings of the IEEE International Conference on AI and Business Analytics, 1(1), 67-74.

[16] Brown, C., & Wilson, J. (2020). *The impact of deep learning models on HR decision-making: An empirical study.* HR Technology Journal, 4(2), 56-72.

[17] Hassan, M., & Ahmed, K. (2020). *Explainable AI for HR analytics: A case study on employee attrition prediction.* Journal of AI Ethics, 3(1), 75-88.

[18] Choudhary, V., & Banerjee, A. (2020). *Real-time employee attrition prediction: Challenges and implementation.* International Conference on AI and Business Innovation, 9(1), 112-125.

[19] Rahman, A., &Sinha, P. (2020). *Workforce analytics: Using AI to predict employee turnover.* Journal of Organizational Management and AI, 5(4), 199-212.

[20] Chen, Y., &Xu, R. (2020). *A systematic literature review on AI applications in HR analytics.* AI and Human Capital Management, 4(3), 142-158.

[21] Kaur, P., Sharma, M., & Singh, G. (2019). *A comparative analysis of machine learning algorithms for employee attrition prediction.* International Journal of Advanced Computer Science and Applications, 10(6), 123-130.

[22] Gupta, S., & Sharma, P. (2019). *Employee retention and attrition: The role of machine learning in HR analytics.* Springer Lecture Notes in Data Science, 2, 89-104.

[23] Zhao, L., & Li, X. (2019). *Understanding employee attrition using ANN and LSTM models.* International Conference on Machine Learning Applications in Business, 6(1), 98-112.

[24] Singh, R., &Yadav, P. (2019). *Evaluating the performance of CNN and LSTM for predicting employee turnover.* Springer Advances in Computational HR Analytics, 10(3), 231-245.

[25] Kim, J., & Lee, D. (2019). *Addressing bias in AI-driven HR analytics: A fairness approach.* Ethical AI and HR Management, 7(1), 83-97.

[26] Fischer, M., & Roberts, J. (2019). *Using SHAP for explainable AI in employee attrition models.* International Journal of AI in Business Intelligence, 6(4), 204-220.

[27] Rajan, S., &Verma, T. (2018). *Deep learning for HR analytics: Predicting employee behavior and attrition.* Journal of Business Intelligence, 7(2), 44-59.

[28] Williams, D., & Smith, L. (2018). *The ethical challenges of AI in HR decision-making: A review.* Journal of Business Ethics and AI, 6(2), 62-78.

[29] Mirza S., Mittal Sonu et. al. (2020) "*Effective Prediction of Type II Diabetes Mellitus Using Data Mining Classifiers and SMOTE*", by Springer Nature Singapore Pte Ltd. 2020 book ISBN 978-981-15-0221-7, H. Sharma et al. (eds.), Advances in Computing and Intelligent Systems, Algorithms for Intelligent Systems (ISSN: 2524-7565) https://doi.org/10.1007/978-981-15-0222-4