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Comparative Study of Employee Turnover Analysis Methods

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ABSTRACT:

In the rapidly evolving landscape of human resource management, understanding and mitigating employee turnover has emerged as a paramount challenge. This research delves into a comparative analysis of various machine learning algorithms applied to the same dataset over several research papers, with the objective of identifying the most effective method for predicting employee turnover. Through a meticulous evaluation based on accuracy, F1 score, and ROC value, this study aspires to identify the best methods for predicting employee turnover.

This study highlights the Artificial Neural Network (ANN) as the top algorithm for predicting employee turnover due to its outstanding performance across multiple metrics, while XGBoost and LGBM Regression are also identified to be highly effective, providing a good mix of efficiency, interpretability, and reliability.

1. Background

Introduction to Employee Turnover Analysis

Employee turnover analysis stands at the forefront of challenges faced by human resource (HR) departments worldwide. As organizations strive to navigate the complexities of retaining talent, the application of analytical tools and methodologies to understand the nuances of turnover has become indispensable.

This analysis not only sheds light on the underlying reasons behind employee departures but also equips organizations with the foresight to implement strategic interventions aimed at enhancing employee retention. [1]

Factors Affecting Employee Turnover

A myriad of factors contributes to employee turnover, ranging from job satisfaction and engagement levels to work-life balance and organizational culture. Moreover, external factors such as market conditions and employment opportunities play a significant role in an individual's decision to leave an organization. Recognizing these variables is crucial in developing a holistic approach to mitigate turnover and foster a supportive work environment [2].

Use of Technology in Employee Turnover Analysis

The advent of technology has revolutionized the approach towards analyzing employee turnover. Machine learning algorithms and data analytics offer a robust framework for predicting turnover, enabling organizations to preemptively identify at-risk employees and devise tailored retention strategies. By leveraging technology, HR analytics transcends traditional boundaries, offering deeper insights into employee behavior and organizational dynamics [2].

2. Objectives of the Study

This study is designed with a multifaceted approach to advance the understanding and application of machine learning algorithms in the prediction of employee turnover. Specifically, this research intends to:

1. Conduct a comprehensive review of existing research on employee turnover prediction using machine learning algorithms.
2. Compare the efficacy of various algorithms on a standardized dataset, based on metrics such as accuracy, F1 score, and ROC value.
3. Identify the most effective algorithm for predicting employee turnover, thereby assisting organizations in enhancing their HR analytics capabilities.

3. Scope of the Study

The scope of this research encompasses a detailed analysis of machine learning algorithms applied to a variety of studies, the majority of which use the "IBM HR Analytics Employee Attrition & Performance" dataset from Kaggle. By focusing on widely recognized research, the study aims to provide a benchmark for algorithm performance in the context of employee turnover analysis. Additionally, this research seeks to offer valuable insights into the factors influencing turnover and the potential of technology to address this pressing HR issue.

The following points outline the specific scope of this research:

1. **Dataset Utilization:** Dataset for this analysis is the "IBM HR Analytics Employee Attrition & Performance" dataset available on Kaggle, which comprises of 1470 instances with 32 features.
2. **Algorithmic Comparison:** The study focuses on a comparative analysis of algorithms including Decision Trees, Random Forest, Support Vector Machines (SVM), Neural Networks (ANN), Gradient Boosting Machines (XGBoost and LGBM), and Naïve Bayes classifiers.
3. **Performance Metrics:** The effectiveness of each algorithm will be assessed based on three key metrics: accuracy, F1 score, and ROC AUC score, which consider not only the overall rate of correct predictions but also the balance between precision and recall, and the model's ability to distinguish between the employee turnover classes.
4. **Application to HR Analytics:** By identifying the most effective ML algorithms for this purpose, the study aims to offer actionable insights that organizations can implement within their HR analytical practices.

4. Limitations of the Study

This study, while comprehensive in its approach to analyzing employee turnover through machine learning algorithms, encounters several limitations that merit consideration:

- **Dataset Specificity**: The primary dataset used, the "IBM HR Analytics Employee Attrition & Performance" from Kaggle, while rich and insightful, represents a specific demographic and organizational setting. The findings and conclusions drawn may not universally apply across different industries or cultural contexts.
- **Dataset Bias**: Machine learning algorithms are susceptible to the biases present in their training data. If the dataset contains inherent biases, the algorithms may inadvertently perpetuate or amplify these biases in their predictions.
- **Dynamic Factors**: Employee turnover is influenced by a multitude of factors, some of which are dynamic and evolve over time. The static nature of the dataset limits the ability to capture these evolving trends and their impact on turnover.
- **Algorithm Selection:** Although the study compares a range of machine learning algorithms, the selection is not exhaustive. There exist additional algorithms and ensemble methods that might offer competitive or superior performance in predicting employee turnover. The choice of algorithms also reflects a balance between model complexity and interpretability, potentially omitting more complex models that could yield insightful but less interpretable results.
- **Performance Metrics:** The evaluation of algorithms is based on accuracy, F1 score, and ROC AUC score. While these metrics provide a robust framework for comparison, they might not capture all aspects of model performance relevant to turnover prediction, such as calibration and the cost-sensitive nature of false positives versus false negatives in real-world HR decision-making.

5. Research Methodology

Research Design

The study employs a quantitative approach, focusing on the comparative performance of established machine learning algorithms. This evaluation is conducted through a systematic analysis of existing literature using standardized metrics to ensure an objective assessment of each algorithm's effectiveness.

Data Collection Methods

Data for the study was secondary data, primarily sourced from existing research literature which examines the use of machine learning in HR analytics. Further, performance data for each algorithm was carefully extracted from these sources for a comprehensive comparative analysis.

Data Analysis Methods

This study employed a methodically structured approach to data analysis. Initially, Excel was leveraged as the primary tool for aggregating secondary data derived from an array of research papers. This step was helpful in organizing the gathered information into a coherent table, facilitating straightforward comparison across studies. Furthermore, Excel's pivot table functionality was utilized to calculate average values, thereby forming the preliminary comparative analysis of the algorithms under consideration. Building upon this foundational analysis, the study advanced to employing Power

BI, Power BI's robust data modeling and visualization capabilities enabled the analysis of the dataset under multiple scenarios, offering a dynamic platform for comparing the performance of different algorithms.

Cases- Recognizing the complex nature of algorithmic performance and the diverse criteria by which their effectiveness can be measured, the study is uniquely designed to investigate seven distinct scenarios, each emphasizing different aspects of algorithmic evaluation. This approach is driven by the following considerations:

1. **Diverse Performance Metrics:** The predictive accuracy of machine learning algorithms can be assessed through several metrics, each providing insights into different facets of algorithmic performance. By examining top-performing algorithms across Accuracy, F1 Score, and ROC AUC Score, this study acknowledges the complexity of predictive modeling and seeks to offer a rounded evaluation of each algorithm's strengths and weaknesses.

2. **Comprehensive Evaluation:** To capture a holistic view of algorithmic effectiveness, an overarching analysis considering all relevant performance metrics was conducted. This includes scenarios where algorithms like Ridge and Lasso Classification, which might not have been evaluated against all metrics in existing studies, are given due consideration based on available data. This ensures that the analysis remains inclusive and reflective of the diverse approaches to algorithmic performance in the literature.

3. **Focused Comparisons:** Understanding the limitations and specific applications of each algorithm necessitates focused comparisons under various conditions. By separately analyzing algorithms based on combinations of two metrics (Accuracy and F1 Score) and then on three metrics, including ROC AUC Score, the study delineates the contexts in which certain algorithms excel or falter, providing nuanced insights that are invaluable for practical application.

4. **Identification of Underperformers:** Equally important to identifying the top performers is understanding the algorithms that do not fare as well in predictive tasks. Analyzing the bottom five performing algorithms allows for a critical examination of potential pitfalls and areas for improvement, contributing to the ongoing development of machine learning applications in HR analytics.

Machine Learning Algorithms

The study analyzed a range of algorithms including Artificial Neural Network, Bernoulli Naive Bayes, Decision Tree, Gaussian Naive Bayes, Gradient Booster, J48, K-Means, KNN, KNN (Euclidean), Lasso Classification, LDA, LGBM Regression, Logistic Regression, Naive Bayes, Neural Network (NN), Random Forest, Ridge Classification, SVM, SVM (RBF kernel), XGBoost chosen for their diverse approaches to pattern recognition and prediction.

Evaluation Metrics

The algorithms' performance was assessed using three key metrics [3]:

- **Accuracy:** The proportion of correctly predicted instances to the total instances, providing a general measure of the model's predictive capability.

- **F1 Score:** The harmonic mean of precision and recall, offering insight into the balance between the model's ability to identify true positives and its precision in those identifications.

- **ROC AUC Score:** The area under the receiver operating characteristic curve, evaluating the model's ability to distinguish between classes across various threshold settings.

6. Literature Review

The exploration of machine learning algorithms for predicting employee turnover has yielded varied results across different studies, each highlighting distinct findings relevant to specific sectors and datasets. **P. M. Usha & N. V. Balaji (2021)**[4] highlighted the effectiveness of Naïve Bayes in the IT sector, emphasizing the impact of job security, promotion policies, and work-life balance. Similarly, **Bhuva & Srivastava (2018)**[5] found LDA to be the most accurate in an IBM USA employee database, noting job role, overtime, and job level as significant factors. **Qing Yin (2023)**[6] emphasized the use of the XGBoost model enhanced with SMOTE, demonstrating its utility in addressing unbalanced data sets.

Further contributions to the field were made by **Adeniyi et al. (2022)**[7], who showcased the superiority of ANN in predicting employee performance. **Atef et al. (2022)**[8] demonstrated the effectiveness of the KNN algorithm in early turnover prediction, adding to the diversity of approaches explored in the literature. **Zhao et al. (2019)**[9] and **Kovvuri & Dommeti (2022)** [10]discussed the dataset-specific effectiveness of various algorithms, often identifying XGBoost as a strong contender. Additionally, **Emmanuel-Okereke & Anigbogu (2022)**[11], along with **R. Punnoose & Ajit (2016)** [12], highlighted the potential of Naive Bayes and SVM techniques, respectively, in turnover prediction.

In further studies, **Shikha N. Khera and Divya (2019)**[13]and **R. Chakraborty & K. Mridha**[14] emphasized the predictive power of SVM and Random Forest in the Indian IT industry and HR analytics, respectively.

These studies collectively illustrate the broad spectrum of machine learning applications in HR analytics, each contributing unique insights into the capabilities and effectiveness of different algorithms in predicting employee turnover across various contexts.

7. Data Analysis and Interpretations

The comparative analysis of machine learning algorithms in predicting employee turnover was methodically conducted using three pivotal metrics: Accuracy, F1 Score, and ROC AUC.

These metrics provided a holistic view of each algorithm's predictive performance, considering not just the rate of correct predictions but also the balance between precision and recall, and the model's discriminatory capacity. The master pivot table created through excel for the analysis is –

Model	Accuracy	F1 Score	ROC Curve AUC Score	Average
Artificial Neural Network	0.9894	0.9934	0.987	0.990
Bernoulli Naive Bayes	0.794	0.69	0.82	0.768
Decision Tree	0.8354	0.86635	0.8729	0.855
Gaussian Naive Bayes	0.757	0.58	0.72	0.679
Gradient Booster	0.875	0.64	0.98645	0.834
J48	0.8505	0.8873	0	0.869
KMeans	0.7196	0.75	0	0.735
KNN	0.7339	0.329	0.74975	0.602
KNN (Euclidean)	0.5	0	0.52	0.510
Lasso Classification	0.8469	0.914	0	0.880
LDA	0.707967	0.9206	0.74	0.757
LGBM Regression	0.87	0.88	0.8844	0.878
Logistic Regression	0.72072	0.672733	0.758883	0.718
Naive Bayes	0.77245	0.885	0.64	0.769
Neural Network (NN)	0	0	0.778	0.778
Random Forest	0.813322	0.723329	0.866625	0.799
Ridge Classification	0.8503	0.916	0	0.883
SVM	0.90645	0.45	0	0.754
SVM (RBF kernel)	0.6	0	0.68	0.627
XGBoost	0.86825	0.82	0.903431	0.873

Table 1: Comparative Performance Metrics of Machine Learning Algorithms for Employee Turnover Prediction.

Accuracy-based Analysis

Accuracy, defined as the ratio of correctly predicted instances (both true positives and true negatives) to the total instances, served as the primary metric for evaluating an algorithm's overall predictive performance. High accuracy indicates that an algorithm is generally effective in classifying employees as likely to leave or stay. However, accuracy alone can sometimes be misleading, especially in datasets with imbalanced classes, where predicting the majority class could still yield a high accuracy rate.

F1 Score-based Analysis

The F1 Score, the harmonic mean of precision (the ratio of true positives to the sum of true positives and false positives) and recall (the ratio of true positives to the sum of true positives and false negatives), was critically analyzed. This metric is particularly valuable in the study of employee turnover prediction because it accounts for the balance between identifying actual cases of turnover (recall) and the model's ability to only flag genuine cases (precision), making it a crucial metric for datasets where the cost of false positives and negatives varies significantly.

ROC AUC-based Analysis

The ROC (Receiver Operating Characteristic) AUC (Area Under the Curve) Score provides insight into an algorithm's ability to distinguish between classes across all thresholds. A high AUC score indicates that the algorithm has a high probability of ranking a randomly chosen positive instance higher than a randomly chosen negative one. This metric is essential for understanding an algorithm's discriminative power, especially in predicting nuanced behaviors like employee turnover, where the distinction between staying and leaving is not always clear-cut.

7.1. Top 5 performing algorithms based on Accuracy score

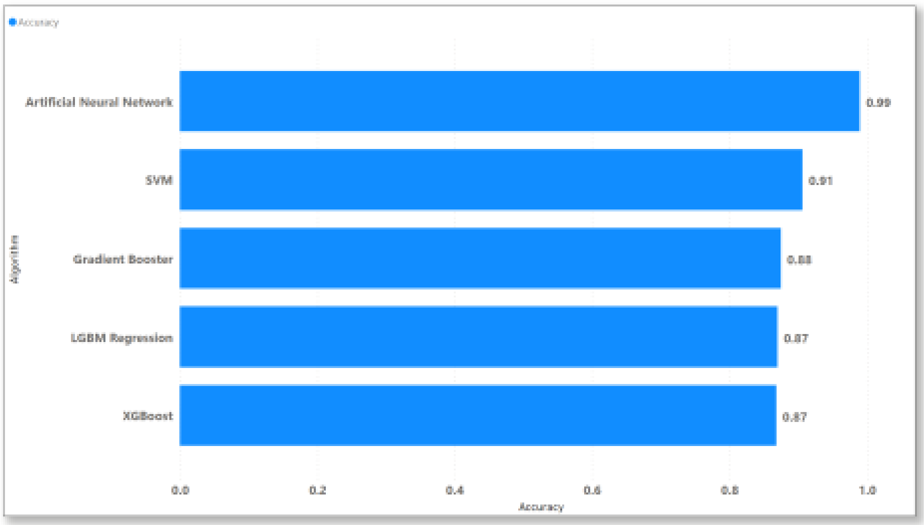

Figure 1: Accuracy scores of top 5 machine learning algorithms

The top five algorithms in terms of accuracy in predictive modeling demonstrate strong capabilities for a variety of tasks. Leading the group is the Artificial Neural Network (ANN) with an outstanding accuracy of 0.99, showing its ability to effectively interpret and use complex data. The Support Vector Machine (SVM) follows with an accuracy of 0.91, excelling at clearly distinguishing between different groups or classes in data.

Ranked third, the Gradient Booster has an accuracy of 0.88 and is praised for its sequential approach to refining predictions. LGBM Regression and XGBoost, both scoring 0.87, are notable for their efficiency and adaptability across large and diverse datasets. These algorithms are essential tools for making highly accurate predictions in fields ranging from HR to scientific research, showcasing their broad applicability and reliability.

7.2. Top 5 performing algorithms based on F1 score

The top five algorithms, ranked by their F1 score, demonstrate their ability to make precise and reliable predictions. The Artificial Neural Network (ANN) leads with an impressive F1 score of 0.99, highlighting its excellent capability to classify data accurately and handle complex patterns.

Following closely are LDA and Ridge Classification, both with an F1 score of 0.92, which excel at separating classes clearly and preventing data overfitting. Lasso Classification scores slightly lower at 0.91, noted for its effective feature selection that simplifies models without sacrificing accuracy.

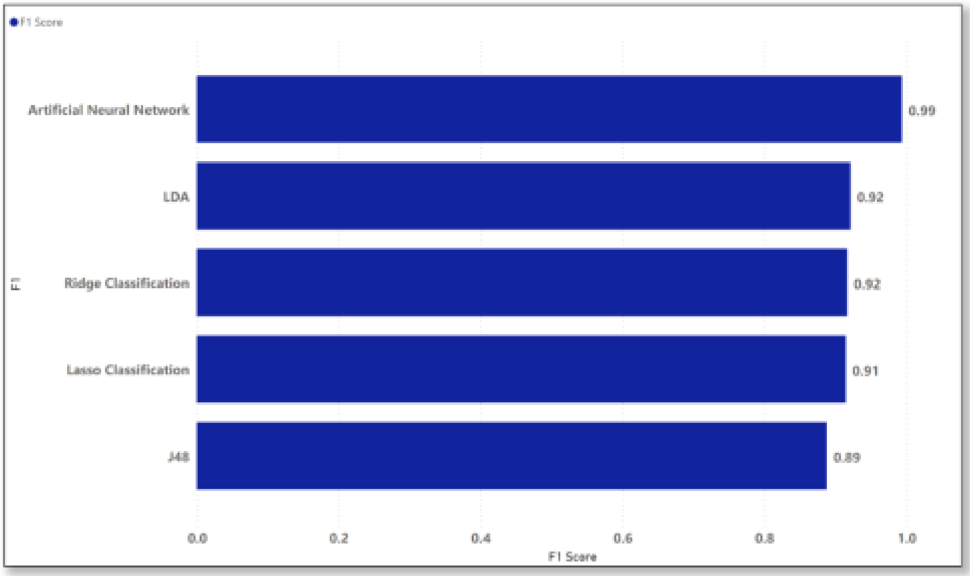

Figure 2: F1 Scores of top 5 machine learning algorithms

Lastly, the J48 decision tree scores 0.89, valued for its straightforward, interpretable approach and versatility in handling different types of data. This lineup showcases each algorithm's strength in maintaining a balance between detecting true positives and avoiding false positives, essential for reliable data analysis across various applications.

7.3. Top 5 performing algorithms based on ROC AUC score

The top five algorithms based on the ROC AUC score demonstrate exceptional ability in distinguishing between different outcomes.

Both the Artificial Neural Network (ANN) and Gradient Booster lead the pack with scores of 0.99, showcasing their near-perfect performance in identifying classes across varied scenarios, thanks to their advanced structures and capabilities. XGBoost follows with a score of 0.90, noted for its strong accuracy and versatility across diverse data types.

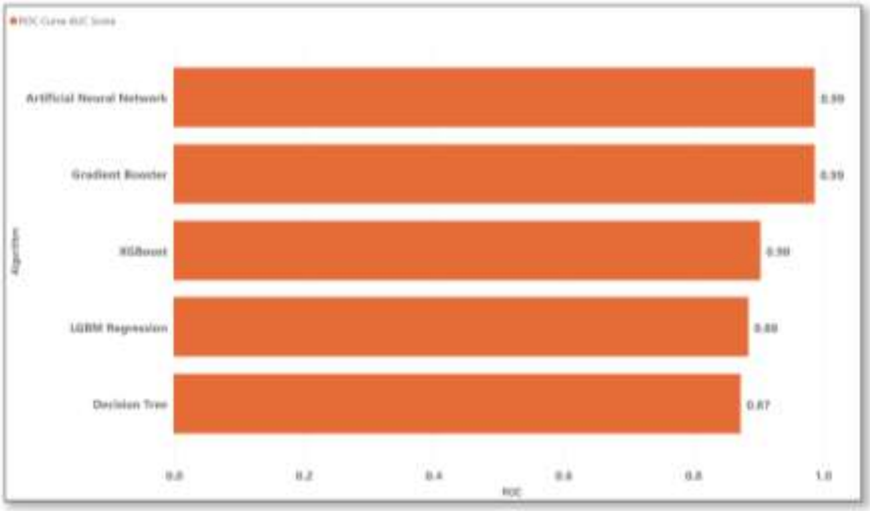

Figure 3: ROC AUC scores of top 5 machine learning algorithms

LGBM Regression scores 0.88, excelling in handling large datasets and complex features efficiently. Finally, the Decision Tree, with a score of 0.87, offers solid performance in a user-friendly format, making it accessible for less technical applications. These algorithms excel in reducing errors in classification, crucial for sectors where accurate prediction is of prime importance.

7.4. Top 5 overall performers across all metrics

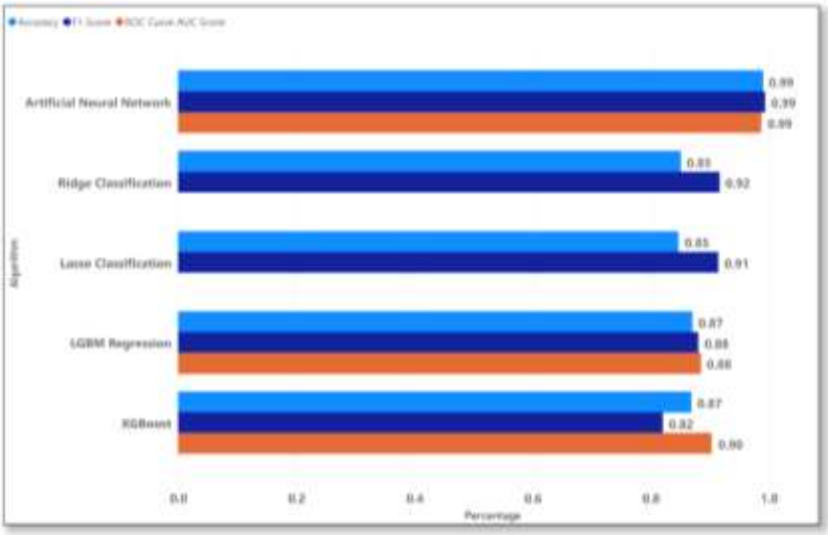

Figure 4: Performance overview of top 5 machine learning algorithms

The top five performing algorithms overall, based on various metrics, showcase their robustness in predictive accuracy and reliability. The Artificial Neural Network (ANN) excels with scores of 0.99 in both Accuracy and F1 Score, demonstrating superior ability to classify data points accurately and maintain balance between precision and recall, ideal for complex analyses.

Ridge and Lasso Classifications also perform well, each achieving an Accuracy of 0.85 with F1 Scores of 0.92 and 0.91 respectively, indicating strong predictive performance and balance, though their capabilities in class distinction aren't measured due to the absence of AUC Scores.

LGBM Regression delivers solid results with an Accuracy of 0.87 and an F1 Score of 0.88, complemented by a good AUC Score, proving its efficiency in handling large datasets and minimizing overfitting.

XGBoost matches this with comparable Accuracy and a robust AUC Score of 0.90, reflecting its versatility and effectiveness across different data scenarios. Overall, ANN stands out for its exceptional precision, while LGBM Regression and XGBoost also highlight their comprehensive strengths in varied predictive tasks.

7.5. Top 5 algorithms based on Accuracy and F1 score

The top five algorithms evaluated based on Accuracy and F1 Score highlight their strong predictive capabilities, particularly useful in HR analytics for tasks like employee turnover prediction. The Artificial Neural Network (ANN) leads with near-perfect scores in both metrics, demonstrating its superior ability to recognize complex patterns and balance precision with recall. Ridge Classification follows with excellent accuracy and a high F1 score, benefiting from its ability to prevent overfitting, making it highly effective for accurate turnover predictions.

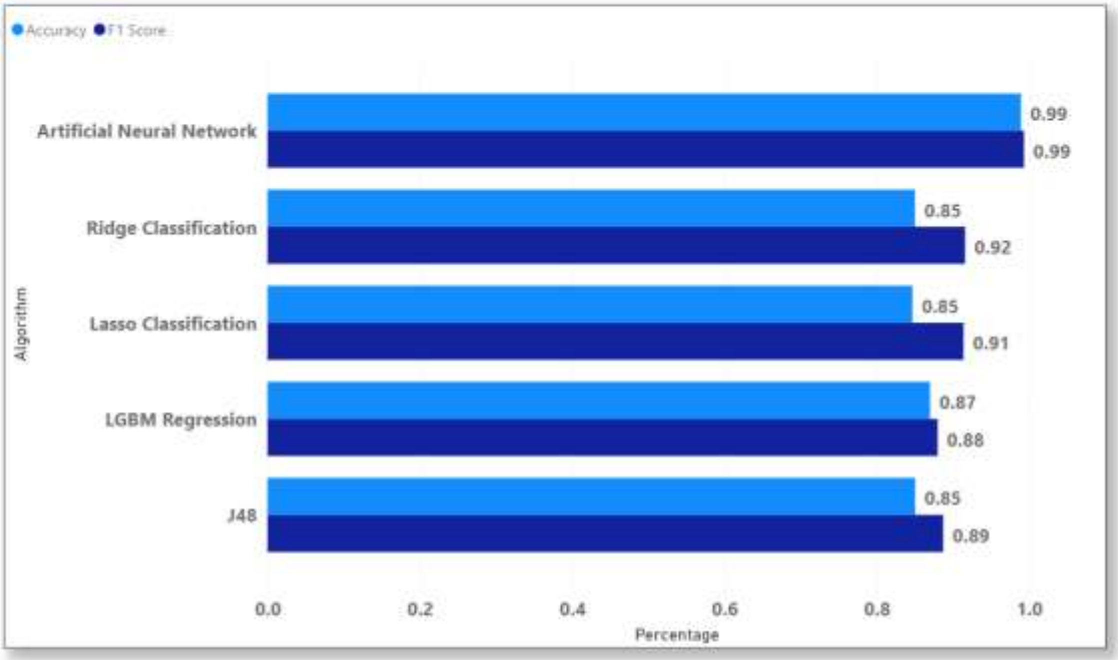

Figure 5: Top 5 algorithms by Accuracy and F1 score

Lasso Classification also shows strong performance, particularly in simplifying the model while maintaining high predictive accuracy. Light Gradient Boosting Machine (LGBM) Regression excels in handling large datasets efficiently, reflecting in its impressive accuracy and F1 score. Lastly, the J48 Decision Tree provides good accuracy and F1 score, offering an interpretable model that helps HR departments make informed decisions about employee turnover. Together, these algorithms demonstrate robustness and versatility, making them invaluable tools in predictive modeling within HR settings.

7.6. Top 5 algorithms in a full-metric analysis (AUC score required):

Top 5 performing algorithms across three metrics: Accuracy, F1 Score, and ROC AUC score-

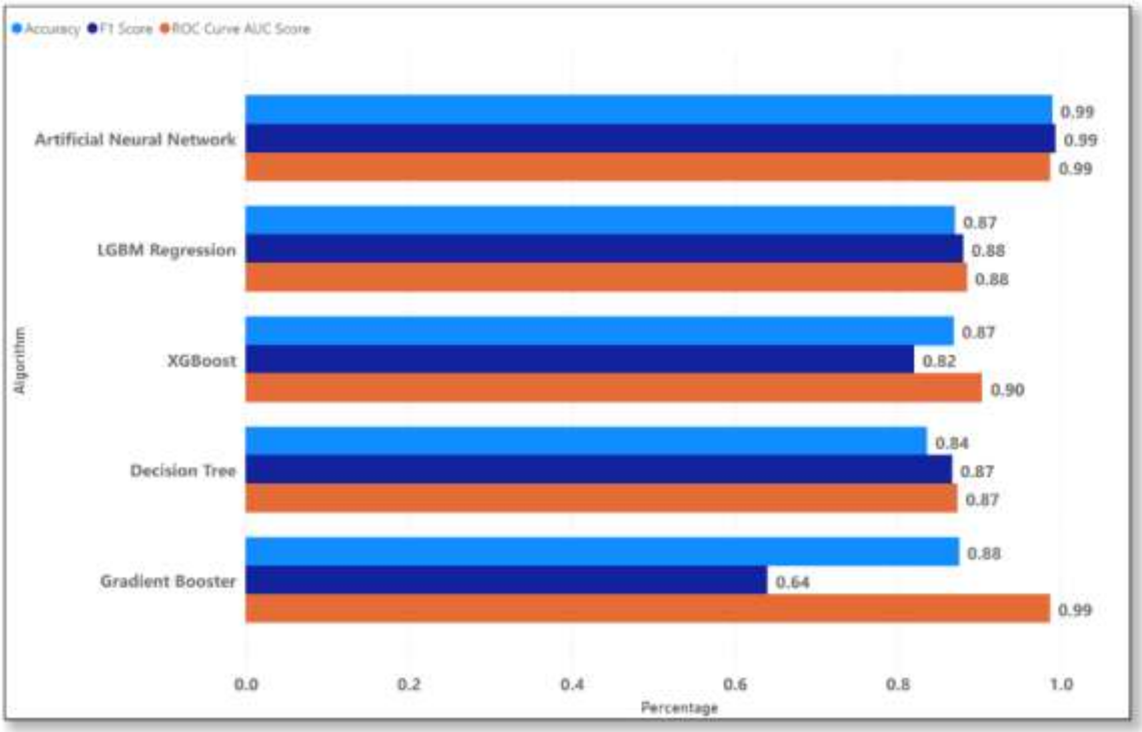

Figure 6: Full-Metric performance analysis of top 5 algorithms

The top five algorithms evaluated on three key metrics—Accuracy, F1 Score, and ROC Curve AUC Score—demonstrate their robustness in predictive modeling. The Artificial Neural Network (ANN) leads with exceptional scores of 0.99 in all metrics, illustrating its outstanding ability to accurately classify data, maintain precision and recall, and effectively differentiate between classes.

LGBM Regression also performs strongly with scores around 0.87-0.88, showcasing its capability in managing large datasets and maintaining high precision. XGBoost, with similar accuracy and a notable AUC Score of 0.90, excels in reliable class distinction and predictive accuracy.

The Decision Tree presents solid performance with scores just slightly lower, emphasizing its effectiveness in clear and interpretable classification. Gradient Booster, though with a lower F1 Score of 0.64, impresses with high accuracy and an AUC Score of 0.99, indicating its strength in enhancing predictive precision over successive iterations.

Overall, these algorithms provide powerful tools for various predictive tasks, with ANN standing out due to its versatility and high performance across all evaluated metrics.

7.7. Low performing algorithms across key metrics

The bottom five algorithms in the study—Logistic Regression, Gaussian Naive Bayes, SVM (RBF kernel), and two variations of KNN (including Euclidean)—demonstrate varying levels of performance in predicting employee turnover. Logistic Regression, known for its simplicity and interpretability, offers moderate performance but struggles with complex patterns due to its linear nature.

Gaussian Naive Bayes, while achieving higher accuracy and AUC scores, falls short in the F1 Score, suggesting issues with balancing precision and recall. Both versions of KNN display decent accuracy and AUC scores, yet their performance dips in F1 Score, indicating difficulties in equally maintaining precision and recall.

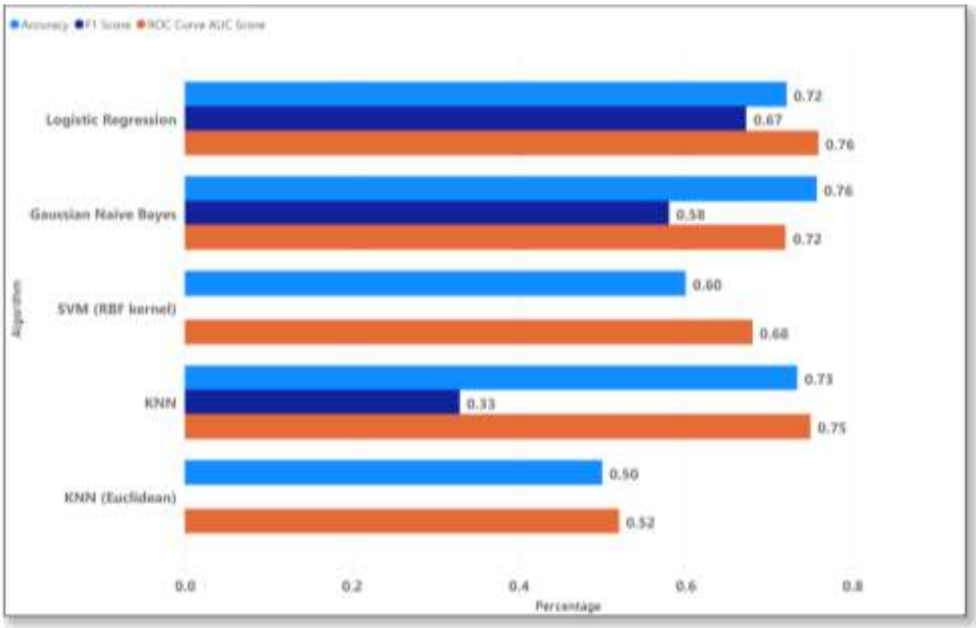

Figure 7: Performance overview of the bottom five algorithms

These findings highlight important considerations for refining algorithm selection and optimizing models within HR analytics, even among those not performing at the top.

Analysis of each scenario to suggest the top-performing algorithms:

Most Consistent Performers: The Artificial Neural Network (ANN), LGBM Regression, and XGBoost excel as the most consistent performers across three key metrics: Accuracy, F1 Score, and ROC Curve AUC Score. ANN not only achieves high scores in all categories but is especially notable for its effective handling of various aspects of the predictive process. Both LGBM Regression and XGBoost show impressive capabilities, particularly in their ability to distinguish between different classes, as evidenced by their high ROC AUC Scores. This trio's robust performance across diverse metrics underscores their reliability and effectiveness in complex predictive tasks.

High Scorers: In the analysis considering overall performance across all metrics, the Artificial Neural Network (ANN), Ridge Classification, and Lasso Classification stand out as high scorers. ANN and Ridge Classification both reach near-perfect scores in Accuracy and F1 Score, demonstrating their precision and balance in handling predictive tasks. Lasso Classification, despite a slight lag in accuracy, still performs commendably well, showcasing its strength in balancing precision and recall. This group's performance highlights the high effectiveness of these algorithms in delivering accurate and reliable results.

Top Performers: When evaluated specifically on Accuracy and F1 Score, the Artificial Neural Network (ANN) and Ridge Classification distinguish themselves as top performers, thanks to their exceptional scores in these metrics. The inclusion of the J48 decision tree algorithm in this context emphasizes its capability to provide balanced and precise outcomes, making it a notable choice in scenarios that prioritize accuracy and a robust precision-recall balance.

This analysis reaffirms the strengths of these algorithms in providing precise and dependable predictions, crucial for tasks that require high accuracy and the effective management of false positives and negatives.

8. Conclusion

After analyzing the performance of various machine learning algorithms across different metrics such as Accuracy, F1 Score, ROC Curve AUC Score, and considering evaluations based on specifically two and over all three metrics, the overall conclusion points towards identifying the best-performing algorithms for predictive modelling tasks. Given the comprehensive analysis across multiple facets, here’s an overall conclusion and recommendation:

Identification of Strong and Weak Algorithms

The assessment of machine learning algorithms showed a range of performances. Artificial Neural Networks (ANN), Ridge Classification, and LGBM Regression stood out as strong performers, excelling across Accuracy, F1 Score, and ROC Curve AUC Score, with ANN particularly noted for its accuracy and precision-recall balance. Conversely, Logistic Regression and Gaussian Naive Bayes struggled with lower accuracy and F1 scores, highlighting difficulties in precisely predicting employee turnover.

Comparison of Algorithms

Comparative analysis revealed varied strengths among the algorithms. ANN was exemplary across all metrics, proving effective for complex employee turnover patterns. Ridge and Lasso Classifications were notable for their feature selection, enhancing accuracy.

LGBM Regression and XGBoost were proficient in managing large datasets and demonstrated strong discriminative abilities. Simpler models like Decision Trees, while easily interpretable, fell short in predictive power and accuracy.

Recommendations for best performing algorithms:

- For General Predictive Modelling Tasks: ANN emerges as the best overall choice given its superior and consistent performance across all metrics. Its deep learning capabilities make it particularly adept at capturing complex, nonlinear relationships within large and diverse datasets.
- For Tasks Requiring Precision and Interpretability: XGBoost and LGBM Regression are highly recommended. Both offer an excellent balance of accuracy, efficiency, and the ability to provide insights into feature importance, making them ideal for applications where both performance and understanding of the model's decision-making process are crucial.
- When Model Reliability and Class Separation are Key: Gradient Booster, with its high ROC Curve AUC Scores, is a strong candidate. It is particularly beneficial in scenarios where distinguishing between classes with high confidence is important.

Contributions to existing research

This study adds to the body of HR analytics by providing a detailed comparative analysis of machine learning algorithms in the context of employee turnover prediction. It contributes to existing research by providing a comprehensive comparison of machine learning algorithms specifically tailored to employee turnover prediction.

Scope for future research

Future research could explore the integration of dynamic factors into the predictive models to reflect the evolving nature of the workforce and workplace. Additionally, investigating the deployment of these algorithms in real-world HR systems could provide valuable feedback loops for further refining the models.

Exploring advanced machine learning models and hybrid approaches could also offer new perspectives on employee turnover prediction.

Additionally, future studies could delve into the practical implications of implementing these algorithms in real-world HR analytics, considering ethical considerations, model interpretability, and the integration of predictive models into organizational decision-making processes. This research lays the groundwork for continued exploration and innovation in leveraging machine learning to address the complex challenge of employee turnover.

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