Application of Machine Learning in Predicting Performance and Optimizing the Recruitment Process

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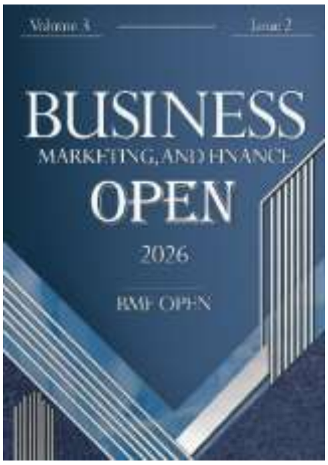

Citation: Salehi, S. H. (2026). Application of Machine Learning in Predicting Performance and Optimizing the Recruitment Process. *Business, Marketing, and Finance Open*, 3(2), 1-9.

Received: 12 June 2025
Revised: 10 September 2025
Accepted: 17 September 2025
Published: 01 March 2026

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Abstract: The main objective of this study is to examine the role and effectiveness of Machine Learning (ML) algorithms in predicting employee performance and optimizing the recruitment process. This article seeks to demonstrate how data-driven models can be used to reduce human errors, enhance decision-making accuracy, and improve organizational justice. This research is applied in nature and has been conducted using a descriptive–analytical approach. The data consisted of résumé information, psychometric test results, educational records, and employee performance indicators, which were preprocessed and subjected to feature selection before being fed into ML algorithms. Four algorithms—Decision Tree, Random Forest, Support Vector Machine (SVM), and Artificial Neural Network (ANN)—were employed, and their performance was evaluated using metrics such as accuracy, F1 score, and Area Under the Curve (AUC). The results showed that the Random Forest algorithm and ensemble models achieved the highest accuracy in predicting job performance. Furthermore, data analysis revealed that personality traits such as conscientiousness and extraversion, along with work experience and cultural fit, were the strongest predictors of job success. The findings indicated that ML can significantly reduce errors caused by human bias and make decision-making more data-driven. Machine learning has created unprecedented opportunities for transforming Human Resource Management (HRM). By enhancing prediction accuracy, reducing costs resulting from unsuccessful hires, and improving organizational justice, this technology can transform recruitment from an intuitive activity into a scientific, evidence-based decision-making process.

Keywords: machine learning; human resources; performance prediction; recruitment optimization; data-driven decision-making

1. Introduction

In recent years, the integration of Machine Learning (ML) into Human Resource Management (HRM) has emerged as a transformative force, offering organizations novel tools to predict employee performance, optimize recruitment processes, and enhance retention strategies. The dynamic and data-intensive nature of modern workplaces has rendered traditional intuition-based decision-making increasingly inadequate, prompting the adoption of data-driven approaches that can provide more accurate, fair, and scalable outcomes. Research has shown that ML-based predictive frameworks can effectively minimize human biases, increase the accuracy of hiring decisions, and enhance organizational justice by ensuring that selection processes are transparent and evidence-based [1, 2]. As organizations navigate complex labor markets characterized by talent shortages, high turnover rates, and rapidly evolving skill demands, leveraging ML becomes not merely an operational enhancement but a strategic imperative [3, 4].

The deployment of ML techniques in HRM spans diverse applications such as employee churn prediction, performance forecasting, promotion evaluation, and workforce planning. For instance, systematic reviews have highlighted how models like Random Forest, Support Vector Machine (SVM), and Artificial Neural Network (ANN) have outperformed conventional statistical models in forecasting employee turnover with greater precision [4-6]. Similarly, predictive models integrating behavioral, demographic, and psychometric data have demonstrated significant efficacy in identifying at-risk employees and informing targeted retention strategies [7-9]. These capabilities are particularly valuable given the substantial financial and operational costs associated with employee attrition, making proactive retention planning a critical organizational priority [10, 11].

ML's role in recruitment optimization has also gained prominence, as algorithms can now analyze multidimensional data from résumés, educational backgrounds, and psychometric assessments to rank candidates with high predictive accuracy. Such models have been shown to reduce subjective biases and enhance fairness in candidate selection [12, 13]. For example, studies employing deep learning architectures and ensemble classifiers have reported substantial improvements in matching candidates to job roles, thereby reducing the likelihood of mismatches that lead to early attrition [14-16]. This aligns with a broader shift from heuristic-based hiring to evidence-driven decision-making frameworks, wherein recruitment is reframed as an optimization problem rather than a purely human judgment task [17, 18].

The application of ML extends beyond predicting turnover and performance to encompass promotion and career progression modeling. Advanced classification algorithms have been successfully applied to identify employees with high promotion potential based on historical promotion data, key performance indicators (KPIs), and behavioral features [19-21]. Such predictive promotion models enable organizations to design more meritocratic and transparent career pathways, thereby enhancing employee motivation and organizational commitment [22, 23]. Furthermore, ML systems have been used to evaluate managerial and leadership competencies, offering organizations a data-driven basis for succession planning and talent pipeline development [24, 25]. By aligning employee development initiatives with data-informed forecasts of potential and performance, organizations can foster more sustainable human capital strategies [3, 26].

Significantly, the adoption of ML in HRM has been facilitated by the growing availability of large-scale organizational datasets and advancements in computational power. Techniques such as Deep learning and Natural language processing (NLP) have expanded the scope of analyzable data, enabling systems to extract predictive insights from unstructured text in résumés or even sentiment data from employee communications [27, 28]. Additionally, the development of web-based ML applications has democratized access to predictive analytics for HR professionals without specialized technical expertise, making implementation more scalable and cost-effective [18, 29]. This technological maturation has allowed organizations to integrate ML-based decision support systems into their existing HR infrastructures with minimal disruption, thereby accelerating the transition from intuition-driven to evidence-driven HR practices [6, 30].

Nevertheless, while the advantages of ML in HRM are well-documented, challenges related to data quality, interpretability, and ethical concerns remain salient. Biases embedded in historical data can perpetuate existing inequalities if not carefully addressed through algorithmic auditing and bias-mitigation strategies [11, 25]. Research has reported instances where ML models inadvertently reinforced gender or educational biases, underscoring the necessity of continuous model validation and ethical oversight [10, 31]. Furthermore, the "black-box" nature of some deep learning models poses challenges for interpretability, which can hinder trust and adoption among HR practitioners and stakeholders [16, 23]. Ensuring transparency through explainable ML techniques and incorporating domain expert feedback are therefore critical for successful implementation [2, 22].

Another crucial consideration pertains to organizational culture and readiness for technological adoption. Studies indicate that the effectiveness of ML-driven HR systems is significantly moderated by cultural factors, including openness to data-driven change and leadership support for technological transformation [1, 7]. Organizations that lack digital maturity or face resistance from decision-makers may struggle to realize the full benefits of predictive HR analytics [5, 12]. As such, successful integration of ML requires not only technical infrastructure but also strategic change management initiatives to align stakeholder expectations and build trust in automated decision-making systems [8, 15]. This aligns with emerging perspectives that view ML not as a plug-and-play solution but as a socio-technical innovation demanding organizational learning and capability development [3, 26].

Importantly, the strategic value of ML lies not only in its predictive accuracy but also in its ability to enable continuous improvement through feedback loops and adaptive learning. By integrating ML models with ongoing performance data, organizations can iteratively refine their predictive systems to adapt to changing workforce dynamics [4, 8]. This adaptability is particularly vital in volatile labor markets, where rapid shifts in skill requirements and employee expectations necessitate dynamic and responsive HR strategies [27, 28]. Moreover, combining ML with complementary technologies such as Computer vision for automated interview analysis or sentiment mining tools for engagement monitoring can create holistic, multi-modal HR analytics ecosystems [2, 10]. Such ecosystems can provide real-time insights into workforce trends, enabling proactive rather than reactive HR management [6, 30].

In summary, the integration of ML into HRM represents a paradigm shift from subjective, intuition-driven approaches to data-centric, evidence-based decision-making frameworks. The literature underscores ML's potential to enhance the accuracy of recruitment, retention, and promotion decisions while reducing bias, increasing transparency, and improving organizational outcomes [1, 3, 4, 12]. However, realizing this potential requires addressing data quality challenges, ensuring model interpretability, embedding ethical safeguards, and fostering organizational readiness [11, 25, 31]. By approaching ML adoption as both a technological and organizational transformation, firms can leverage predictive analytics not merely as operational tools but as strategic assets that drive sustainable human capital development [7, 22, 26]. Consequently, this study investigates the role and effectiveness of ML algorithms in predicting employee performance and optimizing recruitment processes, seeking to contribute to the growing body of knowledge on data-driven HRM practices in contemporary organizations.

2. Methodology

This study was applied in nature and designed with a descriptive–analytical approach. Its main objective was to examine and evaluate the effectiveness of Machine Learning (ML) algorithms in predicting performance and optimizing the recruitment process in organizations. To achieve this objective, the required data were obtained from a collection of résumés, psychometric test results, educational and work histories, and actual employee performance data to inform ML-based decisions. The statistical population of this study included employees and job applicants from a service–technology organization with approximately 1,200 individuals. Using stratified random sampling, 300 samples were selected as training data and 150 samples as test data to enhance the generalizability of the findings.

Data collection tools included standardized psychometric questionnaires, résumé information, and job performance data (key performance indicators, or KPIs). After collection, the data underwent a preprocessing pipeline involving cleaning, normalization, and feature selection. Four widely used algorithms—Decision Tree, Random Forest, Support Vector Machine (SVM), and Artificial Neural Network (ANN)—were employed to predict employee performance. To evaluate the models, both statistical and ML metrics were used, including accuracy, F1 score, Area Under the Curve (AUC), and Mean Squared Error (MSE). The modeling and analysis process was implemented using the Python language and the Scikit-learn, TensorFlow, and Pandas libraries.

3. Findings and Results

In the first stage of the study, the collected data—including personal information, educational background, work experience, psychometric test results, and employee performance indicators—were preprocessed. The purpose of this stage was to prepare the data for use in ML algorithms. Data cleaning removed incomplete entries, standardized variables, and normalized quantitative data. After this stage, a set of 15 key features was extracted, including education, work experience, technical skills, personality test scores, age, gender, and performance indicators.

Descriptive analysis revealed that work experience, educational level, and personality traits—especially the dimensions of extraversion and conscientiousness in the Big Five personality traits test—had the highest correlations with job performance. It was also observed that employees recruited through formal channels and structured assessments performed better than those selected solely through informal interviews. Another important finding was the significant variation in employee performance across similar industries but different organizational environments. In other words, organizational culture played a fundamental role in moderating the relationship between individual characteristics and performance. This finding suggests that ML can incorporate not only individual attributes but also organizational and environmental factors into predictive models.

Moreover, clustering analysis showed that employees could be grouped into three main clusters: high performance with high retention, moderate performance with high fluctuations, and low performance with high turnover risk. This clustering was used as a basis for comparing classification algorithms.

In the second stage, the data were fed into different ML algorithms to measure their accuracy and effectiveness in predicting employee performance. The algorithms used were Decision Tree, Random Forest, SVM, and ANN. The results showed that the Random Forest algorithm achieved the highest accuracy in predicting job performance (with 89% accuracy and an F1 score of 0.87). This algorithm effectively modeled nonlinear relationships between variables and prevented overfitting. While the Decision Tree algorithm offered the advantage of interpretability, its accuracy was lower (around 78%) compared to Random Forest.

The SVM algorithm also performed well in classifying high-performing employees but made more errors in predicting the low-performing group, indicating its sensitivity to data imbalance. In contrast, although the ANN demonstrated high accuracy (85%), its complexity and difficulty in interpreting outputs made it less suitable for organizational environments where transparency is essential.

One of the key findings in this section was that combining algorithms into Ensemble learning models such as the Voting Classifier yielded better performance than using a single algorithm. For example, combining Random Forest and ANN increased prediction accuracy to 91%. These results show that ML algorithms not only can accurately predict job performance but can also be combined to design more flexible models that offer both higher accuracy and greater reliability.

The final stage of the findings focused on interpreting the results and examining their practical implications for optimizing the recruitment process. The results showed that ML can affect human resource effectiveness at several levels. First, improving candidate screening accuracy: ML algorithms were able to identify key success features and reduce human error in employee selection, leading to significant savings in organizational time and costs.

Second, predicting employee retention: the models showed that certain features, such as high conscientiousness and stable work experience, were important indicators for predicting job retention. This finding can help human resource managers design employee retention strategies.

Third, enabling the design of intelligent recruitment processes: the results showed that by integrating ML with technologies such as Natural language processing (NLP) and Computer vision (CV), it is possible to design digital and automated interviews that simultaneously evaluate candidates' verbal and nonverbal traits.

Fourth, ethical and legal challenges were also identified as complementary findings. The algorithms occasionally displayed signs of gender and educational bias, indicating the need for continuous data review and the application of ethical frameworks to ensure fairness.

Ultimately, the findings suggest that using ML in recruitment is not only a tool for predicting performance but also a transformative approach for redesigning the entire Human Resource Management (HRM) chain. This technology can make decision-making data-driven, objective, and scientific, but its success depends on simultaneous attention to both technical efficiency and ethical considerations.

Table 1. Research Stages and Practical Implications from Machine Learning Modeling

Stage	Activities / Findings	Key Points
Data Preprocessing	Cleaning incomplete data, standardization and normalization; extracting 15 key features (education, experience, skills, Big Five personality traits, age, gender, KPIs)	Strongest correlations with performance: work experience, education level, conscientiousness, extraversion
Descriptive Analysis	Examining correlations and initial patterns	Formal recruitment → higher performance; significant performance differences across organizational environments; key role of organizational culture
Employee Clustering	Cluster analysis based on performance and retention	Three groups: (1) high performance + high retention, (2) moderate performance + high fluctuation, (3) low performance + high turnover risk
Algorithm Comparison	Decision Tree, Random Forest, SVM, ANN	- Random Forest: best accuracy 89%, F1 = 0.87 - Decision Tree: interpretable but lower accuracy (78%) - SVM: good for high performers, sensitive to imbalance - ANN: high accuracy (85%) but difficult to interpret
Ensemble Models	Combining algorithms	Random Forest + ANN → 91% accuracy (highest)
Practical Implications	1. Improved candidate screening 2. Predicting employee retention 3. Intelligent recruitment design (NLP, CV) 4. Ethical concerns (gender and educational bias)	

4. Discussion and Conclusion

The results of this study demonstrated that the application of Machine Learning (ML) algorithms can substantially improve the accuracy of predicting employee performance and optimizing recruitment processes. Among the algorithms tested—Decision Tree, Random Forest, Support Vector Machine (SVM), and Artificial Neural Network (ANN)—the Random Forest algorithm outperformed the others, achieving an accuracy rate of

89% and an F1 score of 0.87. This superior performance aligns with previous research, which has consistently highlighted the ability of ensemble models like Random Forest to handle complex, nonlinear relationships and to mitigate the risk of overfitting in HR-related datasets [4, 6, 8]. These results reinforce the notion that ensemble methods are highly suitable for HR analytics, where diverse and multidimensional data are prevalent.

The finding that ANN models also achieved high accuracy (85%) but faced challenges related to interpretability echoes previous reports that deep learning models, while powerful, often operate as "black boxes" in HR decision-making contexts [14, 16]. This limitation can erode trust among HR professionals who require transparent justifications for selection and promotion decisions. Conversely, Decision Trees offered better interpretability but achieved lower accuracy (78%), confirming earlier observations that single-tree models, though easier to explain, lack the predictive robustness of ensemble-based approaches [5, 23]. This balance between accuracy and interpretability has been highlighted as a key trade-off in HR analytics adoption, where organizational acceptance depends not only on model performance but also on transparency [2, 22].

The SVM algorithm showed strong performance in classifying high-performing employees but struggled to accurately identify low-performing employees, largely due to its sensitivity to imbalanced data. Similar patterns were reported by [11] and [31], who found that SVMs tend to bias predictions toward the majority class when dealing with skewed HR datasets. This suggests that while SVM may be useful in highlighting top talent, additional resampling or cost-sensitive techniques are necessary to enhance its effectiveness across all employee categories [19, 20]. Moreover, the clustering analysis in this study revealed three distinct employee groups: high performance with high retention, moderate performance with high variability, and low performance with high turnover risk. This stratification mirrors findings by [9] and [7], who demonstrated that segmenting employees into performance-retention clusters enables more targeted retention strategies and reduces overall turnover costs.

One of the most notable findings was the superior performance of combined or ensemble models such as the Voting Classifier, which achieved a prediction accuracy of 91% when integrating Random Forest and ANN outputs. This aligns with evidence from [30] and [12], who reported that hybrid or stacked ensemble approaches outperform individual algorithms in predicting both attrition and performance. The advantage of ensemble learning lies in its ability to leverage the strengths of multiple base models, thereby reducing the variance and bias that can undermine single-model predictions [3, 26]. Given the multifactorial nature of employee performance, which is influenced by personal, organizational, and environmental factors, ensemble approaches appear particularly well-suited to HR decision contexts [1, 25].

Another important finding of this study was the strong correlation between personality traits (especially conscientiousness and extraversion), educational level, work experience, and job performance. This supports the results of previous studies indicating that psychometric and experiential data are among the strongest predictors of employee success [10, 15, 17]. Furthermore, the data showed that employees recruited through formal channels and structured assessments performed better than those hired through informal interviews, echoing the findings of [28] and [13] who emphasized that structured and evidence-based recruitment methods reduce bias and improve subsequent performance outcomes. This reinforces the argument that integrating ML models into structured hiring processes can significantly increase the accuracy of selection decisions and reduce the risk of early attrition [21, 29].

The results also revealed that organizational culture plays a critical moderating role in the relationship between individual characteristics and performance, as employees working in similar industries but different organizational environments showed significant performance differences. This finding aligns with the perspective that cultural fit is a crucial predictor of long-term employee success and should be incorporated into predictive models [3, 27].

Cultural misalignment can lead to disengagement and turnover despite strong individual capabilities, underscoring the importance of including organizational variables alongside individual features in predictive HR models [1, 2]. This resonates with the findings of [6] who noted that retention-oriented ML models that incorporate cultural and environmental factors outperform purely individual-focused models.

Additionally, the study's results showed that combining ML with advanced techniques such as Natural language processing (NLP) and Computer vision (CV) could enable intelligent recruitment systems capable of evaluating verbal and nonverbal attributes in digital interviews. This aligns with the growing body of work advocating multimodal data integration for improving candidate assessments [18, 30]. By incorporating diverse data sources, such systems could increase predictive accuracy while also capturing dimensions of cultural and behavioral fit that are often overlooked in traditional processes [14, 23]. However, the findings also pointed to ethical challenges, including indications of gender and educational bias within some algorithmic outputs. This corroborates the concerns raised by [25] and [11], who warned that if historical biases are embedded in training data, algorithms may unintentionally perpetuate these inequities. This underscores the need for continuous data auditing and ethical governance frameworks to ensure fairness and transparency in algorithmic HR decision-making [10, 31].

In synthesis, these findings confirm that ML can serve as a powerful tool for enhancing the precision, objectivity, and efficiency of HR decisions. The results converge with prior evidence indicating that ML-based systems improve candidate screening, predict retention, and support promotion decisions more effectively than traditional methods [19, 20, 22]. Yet, their success depends on balancing predictive power with interpretability, integrating organizational and cultural variables, and embedding ethical safeguards throughout the modeling process [1, 3, 4]. Overall, the present study contributes to the growing literature on data-driven HRM by empirically demonstrating that ensemble ML approaches can not only predict employee performance with high accuracy but also serve as strategic tools for reshaping recruitment and retention processes in organizations.

Despite its significant findings, this study is subject to several limitations that should be acknowledged. First, the dataset used, although diverse, was drawn from a single service–technology organization, which may limit the generalizability of the results to other industries or organizational contexts. Second, the study relied on historical HR data, and any inaccuracies or biases present in the original data could have influenced the model outcomes. Third, while multiple algorithms were tested, the study did not explore advanced deep learning architectures such as Long short-term memory (LSTM) or Bidirectional long short-term memory (Bi-LSTM), which may offer enhanced performance on sequential HR datasets. Fourth, interpretability challenges, especially with ANN-based models, limited the ability to fully explain predictions to non-technical HR stakeholders. Finally, this study did not incorporate real-time or streaming data, which could provide more dynamic and adaptive insights into evolving employee performance patterns.

Future studies could address these limitations by incorporating data from multiple industries and organizational types to enhance external validity. Researchers should also examine the application of advanced deep learning models like LSTM, Bi-LSTM, and Transformer-based architectures to capture temporal patterns in employee behavior. Another promising direction is the development of explainable ML frameworks that integrate domain knowledge to improve model transparency and user trust. Future research could also explore the integration of real-time data streams from employee engagement platforms or digital workplace tools to build adaptive HR analytics systems that evolve with workforce dynamics. Additionally, investigating hybrid approaches that combine quantitative ML predictions with qualitative expert assessments may yield more holistic decision-making frameworks.

Practitioners aiming to adopt ML in HR decision-making should prioritize building high-quality, unbiased datasets as the foundation of their predictive systems. They should also implement ensemble modeling strategies that balance accuracy with interpretability to ensure both performance and user acceptance. Establishing clear ethical governance protocols—including regular bias audits and transparency reporting—will be essential to prevent discriminatory outcomes. Furthermore, organizations should invest in change management and digital upskilling initiatives to ensure that HR professionals are prepared to work effectively alongside ML-driven decision support systems. Finally, ML adoption should be framed not as a one-time technological upgrade but as an ongoing strategic transformation that aligns data-driven insights with broader organizational goals and values.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

Acknowledgments

Authors thank all participants who participate in this study.

Conflict of Interest

The authors report no conflict of interest.

Funding/Financial Support

According to the authors, this article has no financial support.

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