Applying Artificial Intelligence To Develop Adaptive Talent Management And Succession Planning Systems In HRM

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Human Resource Management (HRM) is increasingly driven by artificial intelligence, yet many HR analytics models remain static and fail to capture evolving career patterns. This study proposes an adaptive AI framework integrating Deep Neural Networks (DNN) and Long Short-Term Memory (LSTM) models for employee attrition prediction and career-stage progression modeling. Using the IBM HR Analytics dataset, the framework employs weighted feature aggregation, DNN-based classification, and LSTM-driven temporal analysis, alongside an adaptive retraining mechanism. Results show improved performance with 95.58% accuracy, 1.00 precision, 72.34 recall, 83.95 F1-score, and 0.84 ROC-AUC. The model also enhances minority-class recall and PR-AUC under class imbalance. Overall, the framework offers a scalable and intelligent solution for succession planning and data-driven workforce management in dynamic organizational environments.

Keywords: Adaptive Learning, Talent Management, Succession Planning, Employee Attrition, Deep Neural Networks

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1. Introduction

HRM requires talent management and succession planning because these functions provide organizations with stable workforces and continuous leadership [1]. Organizations are increasingly using data-driven methods because they need to manage employee performance and development and retention [2]. The growing availability of employee data has led organizations to implement intelligent technology solutions for their HR operations [3]. Contemporary businesses require intelligent HR solutions which provide them with flexibility to handle their workforce needs [4].

Talent management systems assist organizations in three main functions which include workforce planning and high-potential identification and leadership assessment. Organizations use succession planning to assess employees who will succeed them by measuring their ability to work in the organization [5, 6]. The insights generated through this process enable organizations to make strategic and data-driven decisions regarding their human resources.

Current HR systems lack flexibility, fail to capture complex employee relationships, and may cause biased decisions. Adaptive intelligent frameworks enable dynamic, fair, scalable talent management and succession planning.

1.1. Objectives

The framework uses DNN and LSTM models with IBM HR Analytics data to predict attrition, career progression, leadership readiness, and succession outcomes.

1.2. Paper Organizations

The paper is organized into six sections. Section 1 introduces the research. Section 2 reviews related work. Section 3 explains the methodology. Section 4 describes the experimental setup. Section 5 presents results and discussion. Section 6 concludes the study and suggests future research directions.

1.3. Contribution of proposed work

The AI framework combines DNN, sequential modeling, and adaptive retraining for workforce planning, retention, promotion, and HR decision-making.

2. Literature review

Yanamala et al., [7] proposed an AI-based predictive analytics framework for intelligent workforce planning and strategic talent management. The framework integrates employee data analysis, skill gap identification, dynamic workforce allocation, and proactive succession planning to forecast future competency requirements. By predicting emerging skill demands, resource needs, and leadership development opportunities, the approach supports informed decision-making and improves organizational agility.

Bildiric et al., [8] created a human resource platform with a built-in artificial intelligence system that can help to increase the match between job seekers and employers. The researchers employed the methods of deep learning and natural language processing to match applicants with the skills and competencies, allowing intelligent matching of applicants to the requirements of the employer. Besides optimization during recruitment, the platform also offered personalized learning and development suggestions to fill in the existing identified areas of weakness and, therefore, contributed to the organization of career advancement and capacity building in the workforce.

Vedapradha et al., [9] investigated the application of artificial intelligence in talent recruitment processes within higher education institutions. The study identified perceived usefulness, ease of use, and adaptability as key factors influencing AI adoption. The findings revealed that AI-driven recruitment systems significantly enhance decision-making efficiency, improve candidate assessment accuracy, and support more effective talent identification and selection processes.

2.1. Problem Statement

The HR frameworks that currently exist use static models which lack the capability to adjust to new employee patterns and performance changes and organizational transformations [10]. The operational performance of traditional systems decreases because they need human operators to enter new information at regular intervals to keep the system running [11]. Organizations face difficulties because their traditional methods, including decision trees and logistic regression, cannot complete complex tasks that involve high-dimensional data because these methods only offer limited capabilities [12]. The traditional models face a bias toward predicting non-attrition as the majority class, which prevents the model from accurately identifying employees who have a high risk of leaving [13]. The adaptive AI framework updates predictions using organizational data, learns complex patterns, handles imbalance, and accurately forecasts rare attrition events and career development outcomes.

3. Proposed model

The proposed AI-based HRM framework, shown in Fig. 1, utilizes the IBM HR Analytics dataset with preprocessing, feature engineering, and DNN modeling for talent and succession prediction [14].

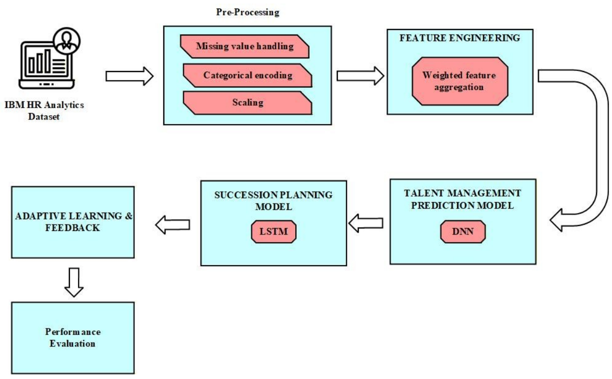

Fig. 1. Proposed AI-Based Adaptive Talent Management and Succession Planning Workflow

LSTM enables succession ranking, adaptive updates, and evaluation of AI-based HRM framework effectiveness. The AI-driven HR framework ensures responsible data management through confidentiality, secure processing, consent, governance policies, and ethical guidelines for transparent decision-making. The preprocessing workflow handles missing values, encodes categorical features, and normalizes numerical attributes to improve feature consistency and model learning effectiveness.

3.1. Feature Engineering

After preprocessing, feature engineering enhances employee feature relevance by considering varied contributions to talent management and succession planning tasks. Weighted feature aggregation uses normalized weights, L2 regularization, adaptive updates, and sensitivity analysis to optimize feature importance and prediction stability.

Weighted feature aggregation computes employee representation z_i (Eq. 1).

$$z_i = \sum_{j=1}^{d} w_j x'_{ij} \tag{1}$$

where w_j represents the importance weight assigned to the j-th feature, and x'_{ij} denotes the standardized (scaled) value of the j-th feature for the i-th employee. Feature weights highlight important employee attributes, improving representation quality, model learning consistency, transparency, and interpretability in DNN-LSTM predictions.

3.2. Talent Management Prediction Model (DNN)

The DNN architecture in Fig. 2 predicts employee attrition using weighted features, nonlinear learning, and sigmoid-based turnover probability estimation.

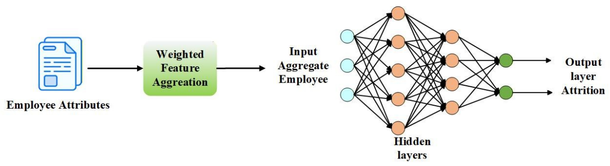

Fig. 2. Deep Neural Network-Based Talent Prediction Model for Employee Attrition

The DNN architecture performs hierarchical learning, extracting complex employee feature patterns through hidden layers to improve attrition prediction accuracy. Binary Cross-Entropy optimization reduces errors through stable convergence, improving probabilistic learning, prediction reliability, and DNN attrition model transparency. DNN classifies attrition risk using Algorithm 1 for workforce planning. Hierarchical representations capture nonlinear employee interactions, enabling intelligent talent analytics, attrition prediction, and adaptive workforce planning beyond traditional methods.

3.3. Succession Planning Model (LSTM)

LSTM models career progression stages to predict succession readiness and identify successors.

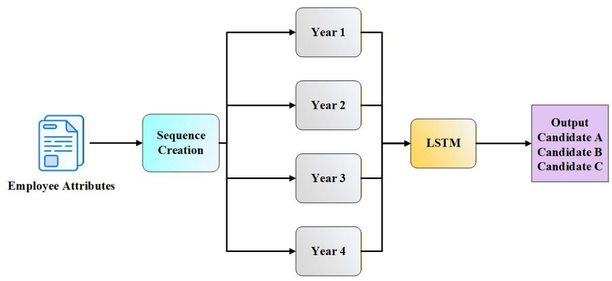

Fig. 3. LSTM-Based Succession Planning Model for Temporal Career Progression Analysis

The succession planning framework illustrated in Fig. 3 models the sequential progression of employee careers through interconnected career stages. LSTM models long-term career dependencies efficiently, making it suitable for HR progression analysis and succession readiness evaluation with smaller datasets. The resulting candidate ranking provides a structured assessment of employee development potential, supporting informed succession planning decisions and the systematic identification of suitable candidates for critical leadership roles.

Sequence representation

Let the career-stage progression sequence of the i^{th} employee, as shown in Eq. (2):

$$\mathrm{X}_i = \left\{\mathrm{x}_i^{(1)}, \mathrm{x}_i^{(2)}, \mathrm{x}_i^{(3)}, \mathrm{x}_i^{(4)}\right\} \tag{2}$$

$\mathrm{x}_i^{(t)}$ represents employee features at career stage t, with $t = 1, 2, 3, 4$ indicating different career periods. Career-stage sequences preserve employee development patterns, enabling longitudinal analytics and accurate succession planning through structured progression modeling.

Forget gate

Forget gate retains relevant employee history and discards outdated patterns (Eq. 3).

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \tag{3}$$

Input gate

Input gate adds updated employee growth indicators into memory (Eq. 4).

$$i_t = \sigma\left(W_i x_t + U_i h_{t-1} + b_i\right) \tag{4}$$

Candidate memory

Candidate memory generates leadership potential using current attributes and hidden states (Eq. 5).

$$\tilde{C}_t = \tanh\left(W_c x_t + U_c h_{t-1} + b_c\right) \tag{5}$$

Cell State Update
Cumulative employee progression representation is constructed across years (Eq. 6).

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{6}$$

Output Gate
Output gate controls readiness information for final prediction (Eq. 7).

$$o_t = \sigma\left(W_o x_t + U_o h_{t-1} + b_o\right) \tag{7}$$

Algorithm 1. DNN Talent Prediction Model

Input: Preprocessed dataset X, labels Y

1. *Initialize DNN weights and biases.*
2. *Compute weighted employee feature representation:*

$$Z_i = \sum_{j=1}^{m} w_j x_{ij}$$

3. *Perform forward propagation through hidden layers using ReLU activation.*
4. *Generate attrition probability using sigmoid output.*
5. *Calculate binary cross-entropy loss and update parameters using backpropagation.*
6. *Repeat training for E epochs and return the trained model with predicted attrition probabilities.*

Hidden State (Temporal Representation)
Hidden state encodes employee progression for readiness scoring (Eq. 8).

$$h_t = o_t \odot \tanh(C_t) \tag{8}$$

LSTM outputs generate succession readiness scores using leadership indicators (Eq. 9).

$$SR_i = \alpha_1 P_i + \alpha_2 C_i + \alpha_3 L_i + \alpha_4 T_i \tag{9}$$

SR_i combines performance, competency, leadership, and tenure factors to rank succession candidates by readiness.

3.4. Adaptive learning

Fig. 4 presents the adaptive HRM framework integrating preprocessing, DNN, and LSTM models for talent and succession planning. The adaptive HR analytics framework is designed to support scalable deployment across organizations of different sizes by continuously incorporating newly available employee data and updating prediction models. This enables efficient talent management, intelligent workforce planning, succession planning, and enterprise-level workforce optimization across diverse organizational environments while maintaining prediction efficiency, operational scalability, low computational overhead, and implementation flexibility. The adaptive retraining framework incorporates drift detection by monitoring prediction error and feature distribution changes over time. Model retraining is initiated when a predefined performance degradation threshold is reached or during scheduled evaluation cycles. Historical training samples are combined with newly acquired employee records during parameter updates to mitigate catastrophic forgetting, preserve previously learned workforce knowledge, and maintain predictive consistency throughout continuous model adaptation.

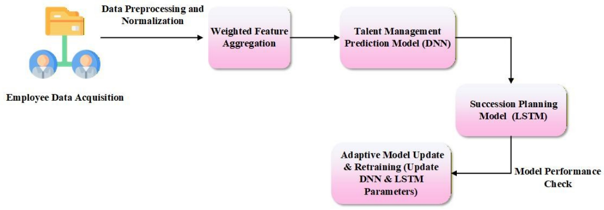

Fig. 4. Adaptive Learning Framework for Talent Management and Succession Planning

4. Experimental setup

4.1. Data Description

Dataset overview

IBM HR Analytics dataset supports adaptive HR model development [14] (Eq. 10).

$$\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N} \tag{10}$$

where $x_i \in \mathbb{R}^d$ denotes the feature vector corresponding to the i-th employee, y_i represents the associated target output, and N indicates the total number of employee records in the dataset. Cross-sectional data is transformed into career sequences for LSTM progression modeling.

Dataset label

The IBM HR Analytics Employee Attrition dataset from Kaggle is used for framework development and evaluation. The IBM HR Analytics dataset is originally cross-sectional in nature. To enable sequence-based modeling, employee attributes such as tenure, job level, performance rating, and training participation are organized into ordered career-stage representations. This transformation creates structured progression patterns that approximate temporal behavior, allowing the LSTM model to learn career evolution dynamics without requiring true longitudinal tracking. The dataset includes employee attributes such as performance, tenure, involvement, training, and advancement for predicting turnover, talent potential, and leadership readiness through AI-based workforce planning.

Dataset splitting

The dataset is divided into 70% training, 15% validation, and 15% testing sets for model training, tuning, and performance evaluation.

Data leakage prevention

Dataset partitioning was completed before preprocessing to prevent data leakage during model development. Missing value imputation, categorical encoding, and feature scaling were fitted exclusively on the training set, and the learned transformation parameters were subsequently applied to the validation and test sets without recalculation. This protocol maintained feature isolation between data partitions, preserved training-validation-test integrity, and ensured unbiased model evaluation with reliable generalization to unseen employee records.

4.2. Data Pre-Processing

The preprocessing phase improves HR data quality through missing value handling, categorical encoding, and feature scaling for deep learning models.

4.2.1. Missing Value Handling

Missing values in numerical features are replaced using mean imputation to preserve data integrity (Eq. 11).

$$x_{ij} = \begin{cases} \bar{x}_j, & \text{if } x_{ij} \text{ is missing} \\ x_{ij}, & \text{otherwise} \end{cases} \tag{11}$$

where x_{ij} denotes the value of the j-th feature for the i-th employee, and $\bar{x}_j$ represents the mean of feature j computed over all available observations.

4.2.2. Categorical Encoding

Categorical features are transformed into binary vectors to support neural network processing without ordinal bias.

4.2.3. Feature Scaling

Min-Max normalization scales numerical features into the range [0,1] for uniform model training.

4.3. Implementation Details

Hardware configuration

Experiments developed DNN and LSTM models using Python, PyTorch, and data libraries on an Intel i5 CPU workstation with 8GB RAM. Hyperparameter optimization was performed using the validation dataset by evaluating multiple combinations of hidden layers, learning rate, batch size, dropout rate, weight decay, optimizer, activation function, and training epochs. The hyperparameter configuration achieving the highest validation performance was selected for the final DNN model, as summarized in Table 1.

Table 1. Optimized Hyperparameter Settings of the Proposed DNN Framework

Hyperparameter	Best Value
Hidden Layers	4
Neurons	128
Learning Rate	0.001
Batch Size	32
Dropout	0.3
Weight Decay	$1e-4$
Optimizer	Adam
Activation	ReLU
Epochs	150

Deployment scalability:

The proposed framework is designed to support enterprise-level deployment by efficiently processing large-scale HR datasets through batch-based model execution and scalable deep learning architecture. The computational requirements remain practical for organizational environments, enabling integration with existing HR information systems and supporting cross-departmental workforce management, continuous model updates, and efficient talent management across complex enterprise infrastructures.

5. Result and discussion

Fig. 5 shows steadily decreasing training and validation losses, indicating stable convergence, effective optimization, minimal overfitting, and strong generalization performance.

Fig. 6 shows the Precision-Recall Curve, where the proposed model achieves the highest AUC for accurate employee attrition prediction.

Fig. 7 presents ROC curves, showing the proposed model achieves strong AUC performance for employee attrition prediction.

Fig. 8 presents the confusion matrix, showing accurate attrition classification with 247 true negatives, 34 true positives, 13 false negatives, and no false positives.

Fig. 9 shows adaptive DNN retraining performance improvements in recall, F1-score, and PR-AUC for dynamic HR decision-making.

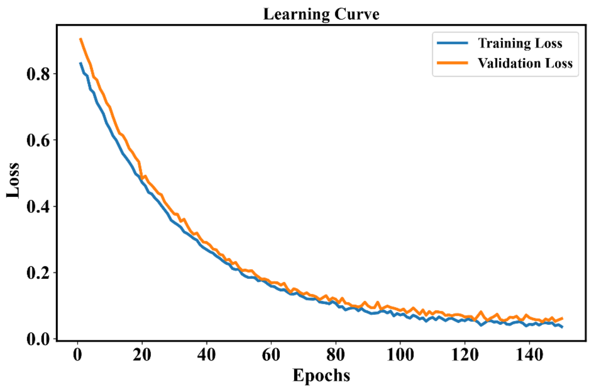

Fig. 5. Learning Curve of the Proposed DNN Model

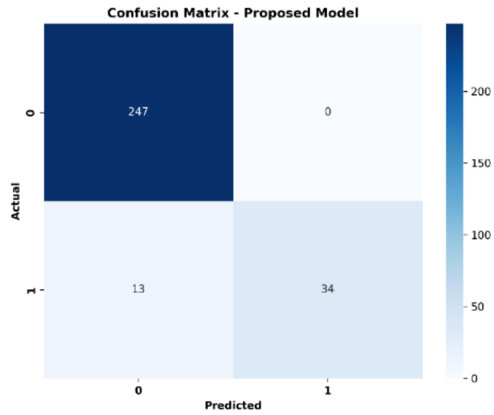

Fig. 8. Confusion Matrix for the Proposed Model

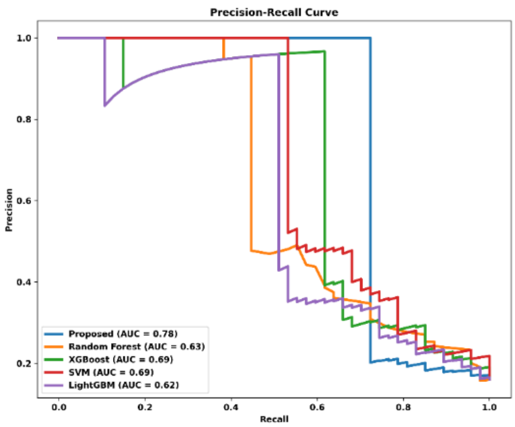

Fig. 6. Precision-Recall Curve

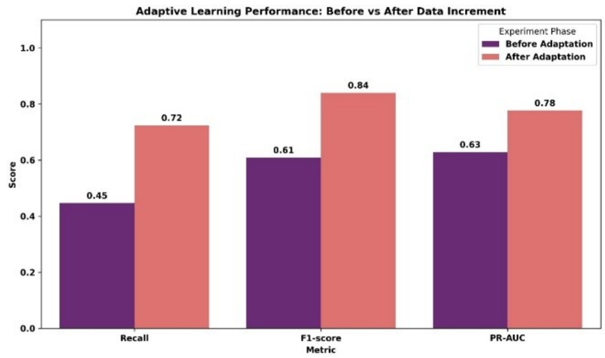

Fig. 9. Adaptive Learning Performance Improvement of the Proposed DNN-Based Attrition Model After Incremental Data Update

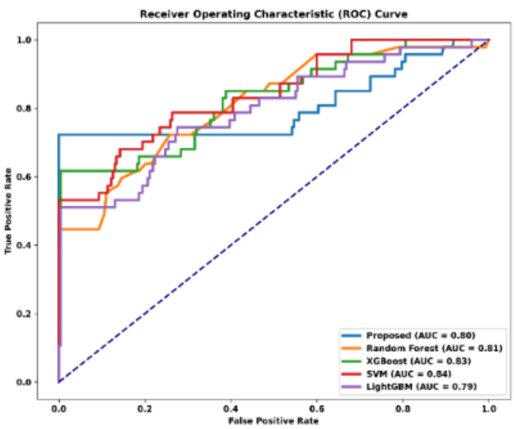

Fig. 7. Receiver Operating Characteristic (ROC) Curve for Comparison of Models

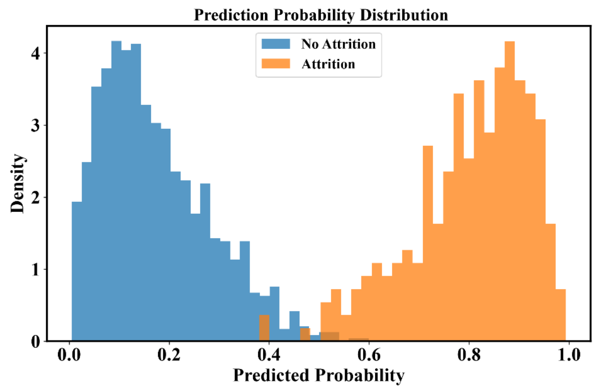

Fig. 10. Prediction Probability Distribution of Employee Attrition

Fig. 10 shows clear separation between attrition and non-attrition prediction probabilities, with minimal distribution overlap, indicating strong class discrimination, reliable probability estimation, and effective employee attrition prediction.

5.1. Performance Comparison

Table 2 compares models, showing the proposed adaptive DNN-LSTM framework achieving superior accuracy and balanced performance.

Table 3 summarizes the performance of the proposed model using multiple evaluation metrics, demonstrating strong classification performance and robust predictive capability for employee attrition prediction.

Table 4 presents fairness evaluation, showing consistent performance across demographic groups with minimal bias in HR decisions.

Table 5 summarizes DNN regularization techniques, including dropout, normalization, and weight control for improved generalization.

Table 6 presents the candidate values considered during the hyperparameter tuning process. The optimal DNN configuration was selected based on the best validation performance obtained from the defined search space.

Table 7 presents the ablation study of the proposed framework by evaluating the impact of removing individual components. The results demonstrate that each component contributes to the overall performance, with the complete model achieving the highest accuracy and F1-score.

Discussion

The DNN-LSTM framework enables talent prediction, career progression analysis, adaptive learning, and strategic succession planning through scalable HR analytics. Prediction transparency is enhanced through Explainable Artificial Intelligence (XAI)-based feature contribution analysis, enabling interpretation of employee-specific prediction outcomes. Important employee attributes, including performance rating, tenure, training participation, and promotion history, provide managerial insight into the factors influencing talent management and succession planning decisions. This improves prediction interpretability, strengthens organizational trust, and enhances accountability in AI-assisted HR decision-making.

6. Conclusion and future enhancement

The study developed an artificial intelligence system which improves talent management and succession planning processes inside Human Resource Management through its DNN employee turnover prediction system and LSTM network-based employee career advancement projection system. The model tested on IBM HR Analytics dataset shows high performance through its 95.58% accuracy achievement and 1.00 precision and 72.34% recall and 83.95% F1-score and 0.84 AUC measurement. The research shows that combining AI systems with adaptive learning systems leads to better human resource decision-making abilities. The framework uses its data processing capabilities to adapt to new information throughout time, which allows organizations to maintain effective employee retention and succession planning predictions throughput time.

The research will investigate balance solutions for the attrition dataset by testing the effectiveness of SMOTE and cost-sensitive learning methods. The model's explainability requires enhancement through SHAP and LIME methods which will help HR professionals understand model predictions better. The research will test how real-time data integration enables continuous model updates and validation across multiple industries to

improve system scalability and operational capacity. The development work will maintain framework functionality while supporting HR departments through their changing requirements.

Declarations

Data availability

No dataset found.

Conflicts of interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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Author contributions

Zhu Lin contributed to the conceptualization of the study, methodology design, data analysis, and manuscript drafting.

Shuai Dong supervised the research, contributed to the research design, validation of the analytical framework, and manuscript review and editing.

Table 2. Performance Comparison of Attrition Prediction Models

Reference	Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)
Rana et al., [15]	Traditional ML	84.3	0.78	0.74	0.76	0.77
Li et al., [16]	Transformer Encoder	85.07	0.79	0.70	0.78	0.75
Proposed	DNN + LSTM + Adaptive Learning	95.58	1.00	72.34	83.95	0.84

Table 3. Comprehensive Performance Metrics of the Proposed Model

Metric	Proposed
Accuracy	95.58
Precision	1
Recall	72.34
F1-score	83.95
ROC-AUC	0.84
PR-AUC	0.78
MCC	0.81
Cohen Kappa	0.83
Balanced Accuracy	86.17
G-Mean	84.61
Specificity	100
NPV	95.01

Table 4. Algorithmic Fairness Evaluation Across Demographic Groups

Group	Accuracy	FPR	TPR	Demographic Parity
Male	95.7	2.8	73.2	0.19
Female	95.4	2.9	72.5	0.2
Age<30	95.2	3.1	71.6	0.21
Age30-45	95.8	2.7	73.4	0.19
Age>45	95.5	2.8	72.8	0.2
Married	95.6	2.7	73.1	0.19
Single	95.5	2.9	72.3	0.2

Table 5. Regularization Techniques Used in the Proposed DNN Framework

Regularization Technique	Parameter Value
Dropout Rate	0.3
Batch Normalization Momentum	0.9
Batch Normalization Epsilon	1×10^{-5}
Early Stopping Patience	15 epochs
Early Stopping Minimum Delta	0.001
Weight Decay (L2 Penalty)	1×10^{-4}
L2 Regularization Coefficient	1×10^{-4}
Gradient Clipping	1

Both authors read and approved the final manuscript.
Ethical Approval
This research does not involve human participants, animals, or any personal identifiable data.
Therefore, ethical approval was not required for this study.

Table 6. Hyperparameter Search Space for DNN Optimization

Parameter	Candidate Values
Learning Rate	0.0001,0.0005,0.001,0.005
Hidden Layers	2,3,4,5
Batch Size	16,32,64
Optimizer	Adam,SGD,RMSProp
Dropout	0.2,0.3,0.4
Weight Decay	1e-5,1e-4,1e-3

Table 7. Ablation Study of the Proposed Framework

Configuration	Accuracy	F1
Full Model	95.58	83.95
Without Weighted Aggregation	93.74	80.82
Without DNN	90.61	76.44
Without LSTM	92.46	79.28
Without Adaptive Learning	91.58	77.91

Consent to participate

Not applicable.

Consent to publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

Code availability

Not Applicable.

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References

[1] D. Hudiyah, B. Sutarto, L. Marthalia, G. Prayudo, and P. Prihatini, (2025) *"The Role of Human Resource Management in the Succession Planning Process"* **Research Horizon** 5(3): 751–762. DOI: 10.54518/rh.5.3.2025.630.

[2] A. M. Căvescu and N. Popescu, (2025) *"Predictive Analytics in Human Resources Management: Evaluating AIHR's Role in Talent Retention"* **AppliedMath** ***5***(3): 99. DOI: 10.3390/appliedmath5030099.

[3] J. Roul, L. M. Mohapatra, A. K. Pradhan, and A. V. S. Kamesh, (2024) *"Analysing the Role of Modern Information Technologies in HRM: Management Perspective and Future Agenda"* **Kybernetes** ***54***(14): 7409–7434. DOI: 10.1108/K-11-2023-2512.

[4] Z. Yifan, (2025) *"Innovation and Optimization Path of Flexible Human Resource Management in Projects in the Digital and Intelligent Era"* **Journal of Business Economics Research** ***1***(7): DOI: 10.63887/jber.2025.1.7.6.

[5] I. S. Coffie, R. Müller, M. Marfo, E. C. Ocloo, and N. de Klerk, (2024) *"Succession Planning Practices and Succession Success in Family-Owned Businesses: The Role of Leadership Style as Internal Branding Mechanism"* **Journal of Family Business Management** ***15***(3): 684–704. DOI: 10.1108/JFBM-09-2024-0207.

[6] S. Mahabub, M. R. Hossain, and E. Z. Snigdha, (2025) *"Data-Driven Decision-Making and Strategic Leadership: AI-Powered Business Operations for Competitive Advantage and Sustainable Growth"* **Journal of Computer Science and Technology Studies** ***7***(1): 326–336. DOI: 10.32996/jcsts.2025.7.1.24.

[7] K. K. R. Yanamala, (2024) *"Strategic Implications of AI Integration in Workforce Planning and Talent Forecasting"* **Journal of Advanced Computer Systems** ***4***(1): 1–9. DOI: 10.69987/JACS.2024.40101.

[8] F. Bildirici, T. D. Medeni, I. T. Medeni, D. Soylu, and I. E. Kökdemir, (2025) *"Artificial Intelligence Supported Career Platform Model: A Proposal for Adaptive Development in Companies and Talents"* **Kamu Yönetimi ve Teknoloji Dergisi** ***7***(2): 209–230. URL: https://dergipark.org.tr/en/pub/kaytek/article/1763861.

[9] R. Vedapradha, R. Hariharan, E. Sudha, and V. Divyashree, (2024) *"Artificial Intelligence – Talent Acquisition in HEIs Recruitments"* **International Journal of Information and Learning Technology** ***41***(3): 230–243. DOI: 10.1108/IJILT-09-2023-0176.

[10] L. O. Arini, D. N. Ardillah, and S. Shaddiq, (2025) *"Aligning Human Resource Information Systems with the Imperatives of Society 5.0: A Strategic Framework for Digital Talent Management in the Indonesian Banking Sector"* **Jurnal Riset Multidisiplin Edukasi** ***2***(7): 300–322. DOI: 10.71282/jurmie.v2i7.656.

[11] J. Barach, (2026) *"Enhancing Ransomware Resilience in Cloud-Based HR Systems Through Moving Target Defense"* **Computers, Materials & Continua** ***86***(2): 1. DOI: 10.32604/cmc.2025.071705.

[12] R. K. Ramasamy, M. Muniandy, and P. Subramanian, (2025) *"A Predictive Framework for Sustainable Human Resource Management Using tNPS-Driven Machine Learning Models"* **Sustainability** ***17***(13): 5882. DOI: 10.3390/su17135882.

[13] F. Guerranti and G. M. Dimitri, (2023) *"A Comparison of Machine Learning Approaches for Predicting Employee Attrition"* **Applied Sciences** ***13***(1): 267. DOI: 10.3390/app13010267.

[14] IBM. *IBM HR Analytics Employee Attrition & Performance*. Dataset. 2026. URL: https://www.kaggle.com/datasets/pavansubhasht/ibm-hr-analytics-attrition-dataset.

[15] M. S. Alshiddy and B. N. Aljaber, (2023) *"Employee Attrition Prediction using Nested Ensemble Learning Techniques"* **International Journal of Advanced Computer Science and Applications** ***14***(7): DOI: 10.14569/IJACSA.2023.01407101.

[16] W. Li, (2023) *"A Transformer-Based Deep Learning Framework to Predict Employee Attrition"* **PeerJ Computer Science** ***9***: e1570. DOI: 10.7717/peerj-cs.1570.