TEMPORAL AND CATEGORICAL FEATURE FUSION FOR EMPLOYEE LAYOFF RISK PREDICTION IN THE IT SECTOR

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Abstract— **In today's scenario, the workforce in IT sector has been experiencing uncertainty because of the changing need of the business, organisational restructuring and changing project need; hence, it is an important area of human resource analytics to predict whether an employee will be laid off or not. Knowing which employes are at risk of layoff helps organisations better plan their workforce, retain employes and make strategic decisions. The methodology developed is based on an employe layoff data set consisting of demographic, organisational, performance, attendance, income, project and work experience features. The steps taken in the preparation pipeline include feature engineering, label encoding, feature normalisation using StandardScaler, and stratified data partitioning to improve data quality for learning and balancing the classes with SMOTE. We comparatively analyse CatBoost, LightGBM, Stacking Classifier, BiLSTM, Hybrid (BiLSTM-CatBoost-LightGBM) and Hybrid (Stacking-BiLSTM) models with the help of accuracy, precision, recall, F1-score and ROC-AUC. Based on the experimental results, the Hybrid (Stacking–BiLSTM) model has the best results in classification with accuracy of 96.4% and ROC-AUC of 0.994. But the one with high deploying performance, high predictive performance and low computational cost is called the Stacking Classifier and is selected for the deployment. To improve transparency and user trust, XAI methods such as LIME, SHAP, PDP and ICE are applied to probe the model predictions and the created web app using Flask allows for layoff risk prediction, confidence estimation, and interactive explanation visualisations, aiding informed human resource decision making processes.**

"Keywords— Employee Layoff Risk Prediction, Human Resource Analytics, Temporal Feature Fusion, Hybrid Machine Learning, Explainable Artificial Intelligence (XAI), Workforce Management."

I. INTRODUCTION

The IT sector has been going thru significant changes due to constant technical innovation, digital transformation, globalisation and changing corporate strategy. Such dynamic changes have radically changed workforce management methods, leading organisations to constantly strive to maximise the utilization of their workforce whilst maintaining operational efficiency and competitiveness. The study of prediction of employees layoff has become an important topic in human resource analytics as there is a greater uncertainty in the workforce now because of the fluctuations in the economy, market demand, organisational restructuring and project-based jobs. Organisations will benefit from proactive workforce planning, optimisation of resource allocation, enhancement of employe retention strategies and informed managerial decision-making, while improving the sustainability and long-term performance of the business [1] [2] if an organisation can detect employees at risk of separation as early as possible.

In recent years, advancements in ML have significantly improved predictive analytics across various HR use cases, such as predicting employee turnover, performance evaluations, and work force planning. However, effectively measuring layoff risk is a difficult task because there are many interrelated demographic, organisational, behavioural and performance factors that impact employe outcomes. The traditional prediction approaches tend to rely on simple features representation or only one learning algorithm, thus lack the ability to model the complex correlation between different employe attributes. Moreover, many prediction systems are so-called black-box models that output prediction results without providing proper explanations about the decision-making process, thus decreasing users' trust, and limiting such systems' application in real organisational scenarios where fairness, accountability and transparency are required [3] [4].

With the growing amount of data collected from organisations, intelligent human resource analytics are created that can help facilitate data-driven workforce management. Both ensemble learning and DL approaches have shown promise in improving the prediction performance by learning complementary patterns from the heterogeneous employe information. In the same way, the rise of XAI has become a key feature of contemporary decision support systems, providing stakeholders with insights into the predictions of AI models and helping them to grasp the variables driving specific decisions. Predictive intelligence combined with explainability enhances prediction accuracy, and fosters the responsible use of AI in organisations, where transparency and trust are essential for effective decision-making in human resource management [5] [6].

Inspired by these problems, this project aims for the creation of an intelligent employe layoff risk prediction platform, which allows for accurate, reliable and interpretable workforce analytics for the IT sector. The proposed design leverages the full employe data set for proactively assessing risk and enhances strategic workforce planning and human resource management. Furthermore, the framework is designed as an interactive decision-support system to support HR professionals with credible prediction results, confidence levels, and interpretable analytical results to support HR decision-making without taking the place of human expertise. The method combines cutting edge predictive analytics with explainable decision assistance in order to increase the adoption of the trustworthy AI within the existing workforce management system [7], [8], [9] and [10].

A. Contributions

This research has made the following key contributions:

- A holistic methodology to predict risk of layoff of employees for proactive workforce planning and intelligent human resource decision making based on various employe related information is proposed.
- A robust data preparation technique is adopted to enhance the data quality and predictive learning, which consists of advanced preprocessing and informative feature representation.
- A comparative study of various ML algorithms, Ensemble learning, DL and Hybrid learning model is performed to determine an appropriate prediction model for employe layoff risk assessment.
- Incorporation of XAI principles to ensure transparency of models with explanations that are understandable and lead to user confidence and trustworthy use for decision making purposes.
- An interactive, web-based decision-support system is designed that allows the real-world implementation of the prediction system to provide workforce information to HR professionals that is accessible, reliable, and understandable.

II. Related Work

Advancements in HR analytics have improved HR management, leveraging ML methods for employee retention, attrition forecasting, performance assessments, and workforce planning. Predictive analytics tools have been found to be useful for companies in discovering employees who might be thinking of leaving, and making HR planning and strategic decisions accordingly. Elavarasi and Alagu (2017) conducted an assessment of various ML techniques used in employee retention and layoffs prediction and found that ensemble learning techniques outperformed the traditional clustering techniques when it comes to the prediction. Likewise, Sathiyaprasad et al. integrated layoff prediction with a personalised career advising chatbot demonstrating the real-world application of intelligent decision-support systems for both employes and organisations. While the studies highlighted the importance of predictive intelligence for workforce management, they mostly focused on prediction performance and user experience and spoke less about workforce coverage and explainable decision support [11, 12].

The prediction of employe performance and attrition has been another subject of interest in a number of organisational areas. Ahmed et al. [4] created a ML framework for forecasting employe performance based on structured administrative data and shown that predictive models can be used to help management decision-making thru performance trend analysis. Focusing on the importance of heterogeneity of employe characteristics, similar to Mozaffari et al. who combined quantitative and qualitative organisational data for better predictions of employe turnover in the pharmaceutical sector. The abovementioned approaches yielded good predictive performance however, they were applicable only to certain organisational settings and thus their applicability to the dynamic workforce characteristics and varying operational requirements typically encountered in Information Technology (IT) Industry [13, 14] was limited.

Ensemble learning algorithms have also cemented the role of predictive analytics of structured data in organisations. CatBoost is suitable for processing and reducing the influence of categorical features, and is very suitable for employee-related datasets with a variety of categorical features. LightGBM is an effective and low-cost gradient boosting solution, offering scalable learning without compromising predictive power on large workforce datasets. Although individually these algorithms have demonstrated good capability of classification, relying on one single learning paradigm [15, 16] may limit the possibility of capturing the diverse relationships of demographic, organisational, behavioural and performance-related employe characteristics.

At the same time, the human resource industry is increasingly making use of AI, which has highlighted the importance of model interpretability. XAI methods, like SHAP, offer global explanations by measuring the importance of features across all predictions, while LIME offers local explanations for specific prediction results, thus improving the user's understanding and trust in the AI's decisions. Such methods have been found to be helpful in making forecasting systems more open and accountable, especially in high impact organisational decision making situations. But, many current research on the workforce analytics are still based on only predicting the accuracy without leveraging explainability in real-world decision support.

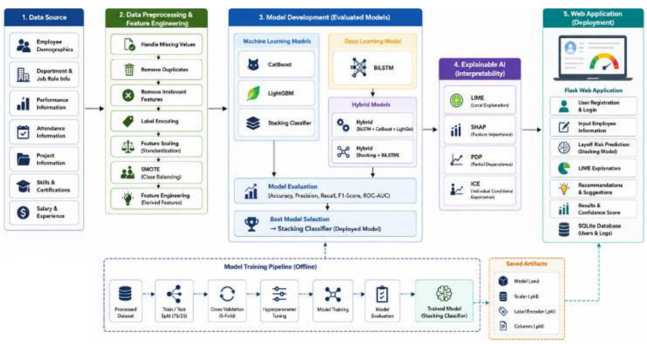
More recent research has examined intelligent workforce analytics more deeply using powerful ML and people analytics approaches. Das and Samal highlighted the significance of predictive analytics in order to anticipate employe attrition using organisational data. Nistala emphasised the importance of the information of the employee in its entirety in the technology-driven organisations to improve the accuracy of the prediction. Such research have hastened the creation of intelligent workforce analytics, with some literature also pointing to persistent issues with feature heterogeneity, generalisability of models, interpretability and implementation in real organisational contexts [19, 20].

A. Research Gap

There are several key limitations to the existing studies and both ML and ensemble learning have been proven to work with employe attrition, retention and layoff prediction. First, studies rely on a restricted range of qualities of the employed or on a static feature representation that does not permit a sufficiently comprehensive characterisation of the behaviour of the workforce and of the organisation. Second, most of the existing approaches only pay attention to improve the prediction accuracy with individual learning algorithm, and there are few systematic evaluation between ML algorithm, ensemble learning algorithm, DL algorithm and hybrid learning algorithm to obtain the most suitable prediction framework. Third, although trustworthy AI is becoming increasingly relevant, explainability is usually treated as a supplementary analysis of the prediction framework, decreasing transparency and users' trust in the decision-making process. Last, many published research focus on the performance of algorithms and not necessarily valid deployment mechanisms that can facilitate enabling real-world human resource operations. To overcome these restrictions, an intelligent employe layoff risk prediction framework with comprehensive workforce representation, comparative forecasting, XAI and interactive decision-support capability was developed to provide accurate, transparent and practically deployable workforce analytics for the IT industry.

III. Materials And Methods

The suggested system is designed to predict the likelihood of layoff of an employee in the variables considered in IT sector (Technological sector) – Demographic, Organisational, Performances, Attendance, Salary, Project, Experience etc. The overall methodology is based on a systematic workflow including the following steps: data preparation, data preprocessing, feature engineering, predictive model building, XAI, and comparative performance, and web-based deployment. At first, the employe dataset is pre-processed for better data quality and learning efficacy via data transformation, feature representation, normalisation and class balancing. Then, several ML algorithms, ensemble learning models, DL models and hybrid learning models are constructed and comparatively analysed to get the best prediction framework. To make more transparent and facilitate trustworthy decision making, we use XAI techniques to provide global explanations and local explanations of the outcome of prediction. Finally, the chosen prediction model is presented through a web application using the Flask library which delivers interactive user interface for prediction of layoff risk, confidence estimation and interpretable decision support for employees.



"Fig. 1. System Architecture"

The system architecture shows the overall flow of the proposed employe layoff risk prediction methodology. Data about employees – including attendance information, project details, salary data, work experience, performance indicators, organizational attributes, and demographic data – are gathered and processed using thru preprocessing, feature engineering, categorical encoding and feature normalisation and class balancing. The processed data are used for comparative learning using ML, ensemble learning, DL and hybrid learning models. Applying XAI techniques to obtain interpretable insights explaining the prediction outcomes. The chosen prediction model is integrated into a web app to deliver layoff risk prediction, confidence estimation and interactive layoff decision-support for HR professionals via the Flask framework.

A) Dataset Collection

The proposed system uses the Employe Layoff Dataset obtained from the Kaggle repository, containing employee related records that have different workforce characteristics. The data comprises of demographic characteristics, department data, job title, education, work mode, professional experience, company tenure, salary, attendance, project workload, overtime data, training activities, performance evaluation, promotion history, managerial assessment, job satisfaction, telecommuting patterns, employe layoff risk labels. Numerous and categorical variables are included in the data set and they provide a detailed representation of workforce behaviour, making them appropriate for predicting employees layoff and HR analytics.

B) Pre-Processing

To enhance data quality, learning efficiency and prediction reliability, a rigorous preprocessing pipeline is used to the employe dataset, including feature engineering, categorical encoding, feature normalisation, visualisation of data, class balancing and dataset division.

Feature Engineering: We construct meaningful workforce metrics using feature engineering on existing employe qualities. Engineered elements like Salary per Experience, Projects per Year, Workload Index, Performance Improved, Attendance Risk, Promotion Gap, High Overtime, and Low Satisfaction help to have a better representation of employe productivity, organisational engagement, workload and career development. The designed properties enhance the ability of predictive models to learn by incorporating relevant workforce features which are not explicitly available in the original data.

Label Encoding: Label encoding is a technique used for categorical employe attributes to convert them to numeric form. Organisational information is represented as department, job role, education level, work mode and performance categories, which can then be efficiently managed by predictive learning algorithms and for which the mapping of categories is assumed to be the same in the training and deployment contexts.

Feature Normalization: Feature normalisation uses StandardScaler to scale numerical properties of the employees to a common scale. This procedure reduces the fluctuations among the magnitudes of features, boosts the convergence in the process of model training, and helps to stabilize ML and DL approaches.

Data Visualization: We do exploratory data visualisations to learn statistical properties of employe data set. Correlation analysis, distribution visualisation of features, and class distribution analysis give insights on attribute correlations, the potential redundancy and class imbalance, which are useful for pre-processing and model construction.

Data Balancing: Using the SMOTE to balance the employe layoff data set addresses the class imbalance issue. Synthetic minority cases are created to improve class representation during training, which leads to reduction of the prediction bias towards the majority class, and better model robustness, fairness and generalisation.

C) Training and Testing:

The pre-processed balanced dataset is subsequently split into training and testing datasets using a Stratified Sampling method which preserves the original class distribution. This way, the performance can be evaluated objectively and the results of the experiments can be more reliable and repeatable. Comparative assessment of the constructed prediction models for the efficiency in employe lay-off risk prediction is done based on the Accuracy, Precision, Recall, F1-Score and ROC-AUC.

D) Algorithms

CatBoost Classifier: CatBoost is a gradient boosting algorithm that captures complex relationships between categorical and numerical employee properties, reduces prediction bias and improves classification accuracy.

LGBM Classifier: LightGBM constructs optimised gradient-boosted DT ensembles for efficient learning with reduced computational costs and decent prediction quality under a large scale scenario.

Stacking Classifier (Random Forest, Gradient Boosting, XGBoost with Logistic Regression Meta-Classifier): RF, Gradient Boosting and XGBoost are used as base classifiers and LR is used as meta-classifier in the Stacking Classifier. This ensemble learning method is used to strengthen the predictions of the classifiers so as to make the predictions more resilient, stable and enhance the overall classification performance.

Bidirectional Long Short-Term Memory (BiLSTM): The Bidirectional LSTM network can model different feature relationships in a complicated manner by leveraging information in both forward and backward directions, enabling the network to accurately simulate complicated feature dependencies in employe layoff prediction.

Proposed Hybrid Model (BiLSTM + CatBoost + LGBM): The hybrid learning framework is the integration of BiLSTM, CatBoost and LightGBM with deep feature learning and gradient boosting learning, which can complete each other's learning procedures so as to achieve better predictive ability.

Extension Hybrid Model (Stacking + BiLSTM): In the Hybrid (Stacking–BiLSTM) model, the ensemble learning and DL are combined together by combining the Stacking Classifier and BiLSTM. This hybrid model is able to improve the stability of prediction, learning diversity and classification performance by adopting the complementary decision boundaries learned by the ensemble and neural network architectures.

IV. EXPERIMENTAL RESULTS

The created employe layoff risk prediction framework is evaluated using conventional classification measures, such as accuracy, precision, recall, F1-score, and ROC-AUC. All together, these measures assess the models' predictive capabilities, robustness and generalisation performance.

Accuracy: It is the ratio of correctly classified employe instances to the total number of instances considered and it measures the overall prediction performance of the classification model.

$$Accuracy = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{FP}+\mathrm{TN}+\mathrm{FN}} \tag{1}$$

Precision: Precision is the number of real positive employes divided by the number of employes predicted to be at risk of layoff; is a measure of reliability of a positive prediction.

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \tag{2}$$

Recall: Recall is the measure of how well the prediction model can categorise the employes belonging to the layoff-risk class properly, by comparing correctly predicted positive instances with all the actual positive instances.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \tag{3}$$

F1-Score: It will be the harmonic mean of Precision and Recall so F1-Score will be a good indicator of the categorisation performance, particularly in the case of class imbalance.

$$F1\ Score = \frac{2 \times (Recall \times Precision)}{Recall + Precision} \tag{4}$$

ROC-AUC: ROC-AUC measures the discrimination of the layoff-risk employes and the non-layoff employes at various classification levels. ROC-AUC values closer to 1 are indicative of better discrimination.

$$AUC = \sum_{i=1}^{n-1} (FPR_{i+1} - FPR_i) \cdot \frac{TPR_{i+1} + TPR_i}{2} \tag{5}$$

Table. 1. Performance Evaluation

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
CatBoost	91.8	91.3	92.3	91.8	97.2
LGBM	94.1	93.8	94.5	94.1	98.5
Stacking Classifier	96.2	95.9	96.6	96.3	99.4
Bidirectional LSTM (BiLSTM)	95.6	95.3	96.1	95.7	99.1
Hybrid (BiLSTM–CatBoost–LGBM)	94.9	94.8	95.0	94.9	98.8
Hybrid (Stacking–BiLSTM)	96.4	96.0	96.8	96.4	99.4

The relative performance of ML models, ensemble models, DL and hybrid learning models implemented are shown in Table 1. The Hybrid (Stacking–BiLSTM) model outperforms all other models in terms of overall classification performance 96.4% Accuracy, 96.0% Precision, 96.8% Recall, 96.4% F1-Score, and 0.994 ROC-AUC, which makes it the most efficient for employe layoff risk prediction. Similarly, the Stacking Classifier accomplishes very competitive results (96.2% Accuracy, 0.994 ROC-AUC) with less computing complexity and faster inference. For this reason, the Stacking Classifier is selected as deployment model due to its excellent trade-off between predictive performance, computational efficiency and model complexity, and its appropriateness for use in real-time web-based decision assistance.

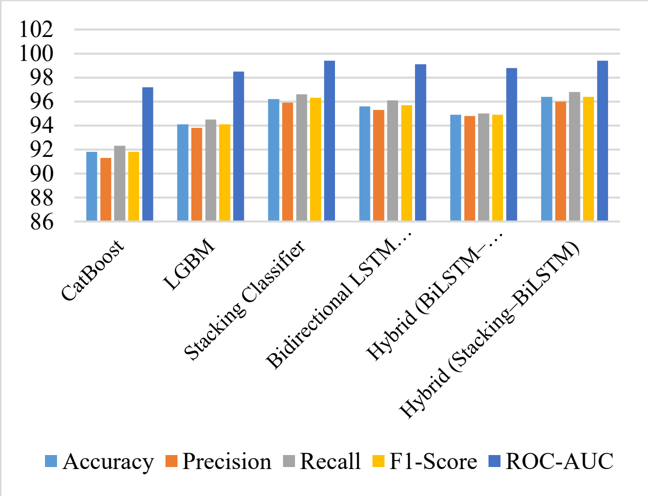


Fig. 2. Comparison Graph

The performance comparison of CatBoost, LightGBM, Stacking Classifier, Bidirectional LSTM, Hybrid (BiLSTM–CatBoost–LightGBM), and Hybrid (Stacking–BiLSTM) is shown for the Accuracy, Precision, Recall, F1-Score, and ROC-AUC parameters. As seen from the overall performance, the Hybrid (Stacking–BiLSTM) model exhibits the best performance with similar deployment efficiency confirming that it is suitable for the deployed web application.

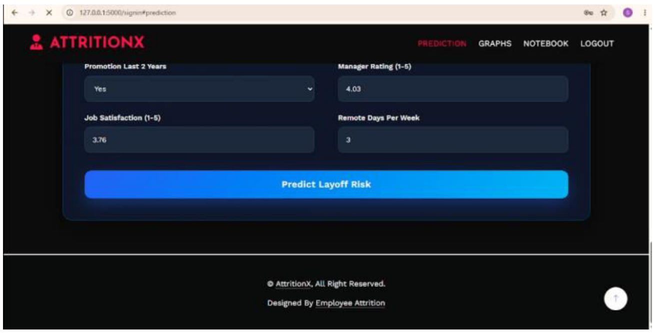


Fig.3 Enter the Data

Figure 3 displays the employe information input interface of the built Web application. Users input the required details of demographics, organisations, attendance, performance, income, projects and experience with an interactive interface that allows them to predict employee layoff risk.

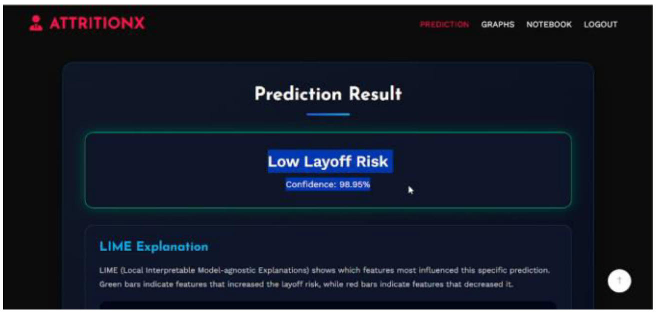


Fig.4 Predicted Result

Figure 4 shows an example of prediction outcome for a Low Layoff Risk employe. The system generates local explanations based on LIME, along with the prediction result and the confidence score, which helps identify the most influential features to contribute to the prediction, thereby increasing the transparency of the system and supporting better human resource decisions based on the predictions.

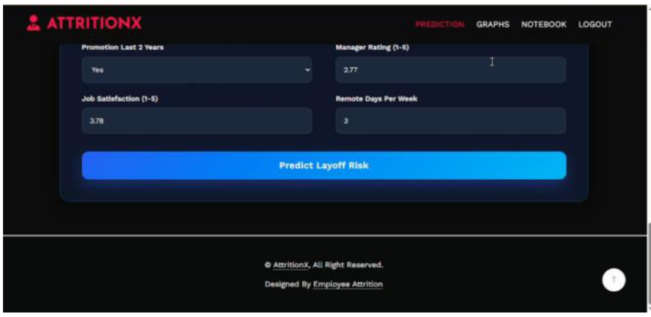


Fig.5 Enter the Data

An example of another employe information input for prediction framework with different workforce characteristics prior to layoff risk assessment is presented in Figure 5.

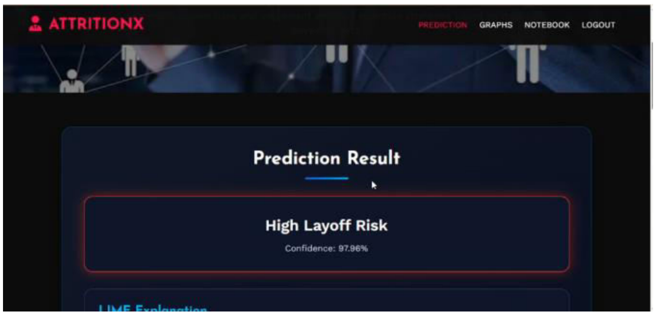


Fig.6 Predicted Result

The forecast result for an employe with High Layoff Risk is shown in figure 6. The created approach presents the anticipated risk category, confidence score and feature-level interpretability via the LIME explanations to assist HR managers to grasp the major causes behind the prediction and make transparent workforce planning choice.

V. Conclusion

The proposed employe layoff risk prediction framework is an effective and interpretable decision support tool for workforce analytics in the IT sector. The comprehensive employe information including demographic, organisational, performance, attendance, salary, project, experience, etc. attributes are used in the framework to accurately identify employes at risk of layoff and for the pro-active planning of workforce and strategic human resource management. The detailed preparation pipeline with feature engineering, categorical encoding, feature normalisation and class balancing improves the quality of the data and consequently the predictive learning. This comparative study of different ML, ensemble learning, DL and hybrid learning models shows the applicability of the proposed model for the prediction of layoff risks amongst the employees. Among the models evaluated the Hybrid (Stacking – BiLSTM) model gets the best overall prediction performance (96.4% accuracy and 0.994 ROC-AUC). The Stacking Classifier is chosen for deployment for its strong predictive performance, computational efficiency, inference speed and deployment suitability. Additionally, the use of XAI techniques like LIME, SHAP and PDP and ICE can enhance the model's transparency by offering insightful explanations for the prediction results. The web app developed with Flask makes the application more usable in practice by offering the output of the forecast of employees layoff risk, confidence estimation and interpretation of analytical results interactively. In summary, the framework developed is a comprehensive, transparent and achievable approach to data-informed workforce planning and decision-making.

Future research should look to include larger datasets of employes from a variety of organisations and other workforce variables such as employe engagement, skill development, career progression, learning activities, and organisational feedback in an effort to further increase the dependability of predictions. The framework can be further developed with integration with enterprise HRM platforms, deployment in the cloud, real time monitoring of the workforce, and privacy protecting learning approaches. Furthermore, using adaptive learning approaches that can continually update predictive models as the organization's trends and workforce evolve can help to increase its scalability, resilience and applicability across various industrial settings.

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