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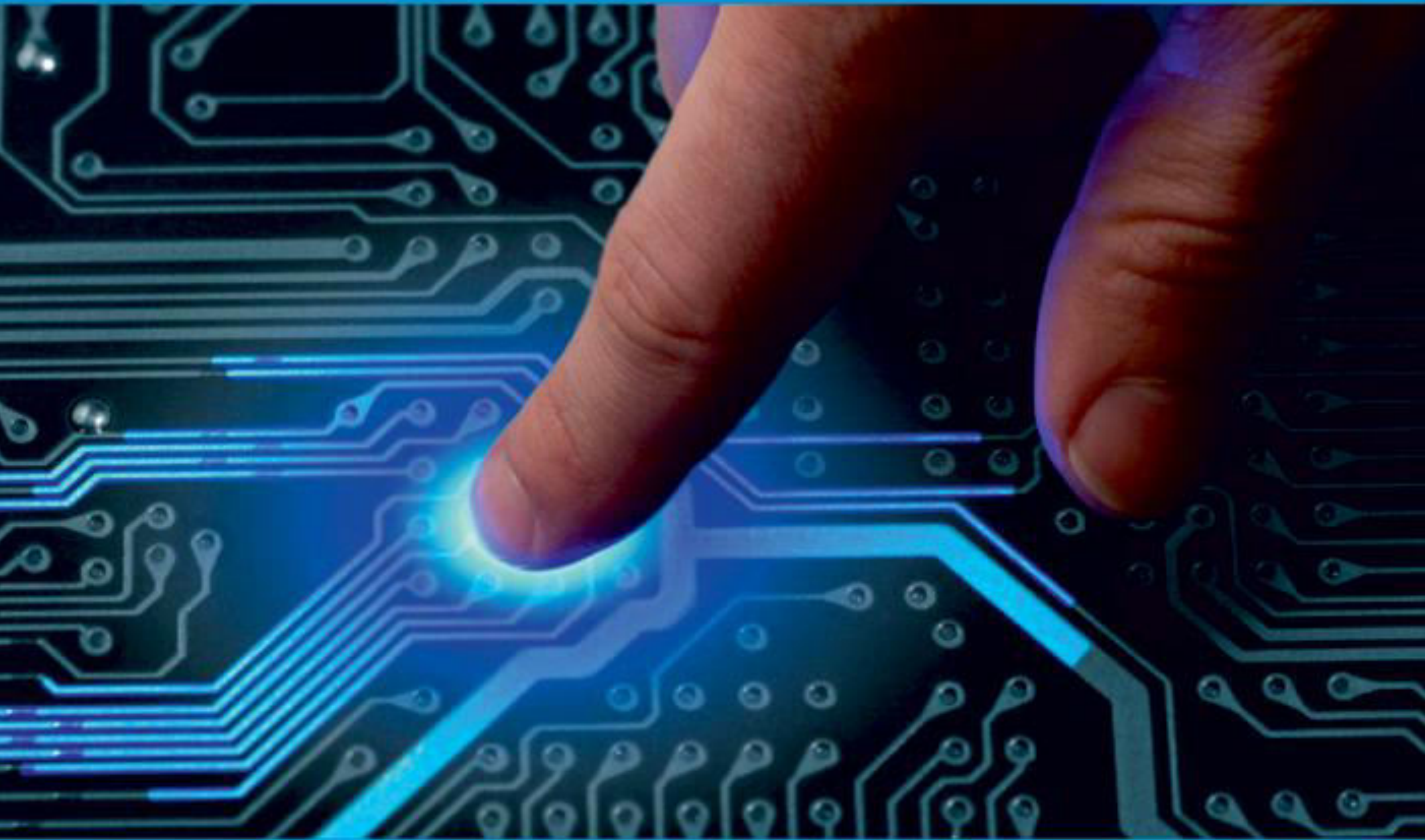

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# Employee Attrition Prediction System using Machine Learning

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**ABSTRACT:** Representative whittling down may be a basic concern for organizations around the world, with noteworthy suggestions for efficiency, assurance, and operational soundness. To address this challenge, this investigate examines the application of machine learning calculations for anticipating representative turnover. By analyzing verifiable worker information including different traits such as socioeconomics, execution measurements, work fulfillment scores, and residency, prescient models are developed and assessed utilizing real-world datasets from different businesses.

The think about utilizes a comparative approach, evaluating the execution of a few machine learning calculations, counting calculated relapse, choice trees, irregular woodlands, bolster vector machines, and neural systems. Through rigorous experimentation and investigation, the inquire about distinguishes the foremost viable calculations and include sets for precisely estimating worker whittling down. Besides, interpretability and adaptability contemplations are inspected to guarantee the commonsense pertinence of the created expectation framework in organizational settings.

The discoveries highlight the adequacy of machine learning procedures in tending to the multifaceted nature of worker whittling down. By leveraging progressed calculations and comprehensive information investigation, organizations can proactively recognize at-risk workers and actualize focused on maintenance methodologies. This enables businesses to cultivate a steady and locked in workforce whereas moderating the negative impacts of turnover on organizational execution.

Generally, this investigate contributes to the growing body of information on representative steady loss expectation by advertising bits of knowledge into the qualities and confinements of distinctive machine learning approaches. By joining these discoveries into organizational hones, businesses can upgrade their capacity to expect and oversee worker turnover viably, eventually driving long-term victory and supportability.

**KEYWORDS:** Python, Employee Attrition, Data Visualization, Data Exploration, ML

## I. INTRODUCTION

Within the energetic scene of cutting edge working environments, worker steady loss postures a noteworthy challenge for organizations over businesses. Whittling down not as it were disturbs operational coherence but moreover brings about considerable costs related with enlistment, preparing, and lost efficiency. Thus, there's a developing basic for organizations to embrace proactive techniques for recognizing and relieving the components contributing to worker turnover. In this setting, the application of machine learning strategies offers promising roads for creating successful employee attrition forecast frameworks.This term paper points to investigate the utilization of machine learning calculations in foreseeing worker steady loss, subsequently empowering organizations to expect and address maintenance challenges more deliberately. By leveraging chronicled information enveloping a assorted cluster of worker traits such as socioeconomics, execution measurements, work fulfillment markers, residency, and career movement, machine learning models can be prepared to observe designs and relationships characteristic of potential turnover dangers. The essential objective of this think about is to explore the adequacy of different machine learning calculations, counting but not constrained to calculated relapse, choice trees, irregular timberlands, back vector machines, and neural systems, in precisely anticipating worker steady loss. Through observational assessment utilizing real-world datasets from different businesses, the inquire about looks for to evaluate the performance of these calculations in terms of prescient precision, affectability, specificity, and by and large demonstrate strength.

Besides, this paper points to dive into the interpretability and noteworthy bits of knowledge determined from machine learning-based whittling down expectation models. By distinguishing the key indicators of steady loss and understanding their relative significance, organizations can tailor focused on intercessions and maintenance procedures to relieve turnover dangers successfully. Furthermore, the consider will investigate the versatility and commonsense

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usage contemplations related with conveying machine learning-based whittling down prediction systems in organizational settings. By and large, this investigate endeavors to contribute to the developing field of prescient analytics in human assets by explaining the potential benefits and challenges of leveraging machine learning for worker whittling down expectation. By tackling the prescient control of progressed analytics, organizations can proactively address maintenance challenges, cultivate worker engagement, and develop a more steady and strong workforce, in this manner driving feasible commerce victory within the competitive worldwide commercial center.

In this study, we investigate the factors that lead an employee to leave a company, aiming to provide timely and effective solutions for the HR department to improve the work environment and enhance incentives for retention. Utilizing a dataset, we identify the key components associated with employee turnover and propose a practical classification system based on thorough data analysis. By employing classification algorithms, HR management can better allocate resources for staff retention within the organization. Our predictive model, tested on real data provided by IBM analytics, comprises 35 features and approximately 1500 samples. Through heatmap analysis of these features, we identify characteristics strongly correlated with employee attrition. Results are presented using standard metrics, with the Gaussian Naïve Bayes classifier yielding the best performance, achieving a recall rate of 0.54 and an overall false negative rate of 4.5%. Our findings highlight the potential of machine learning techniques to support HR departments in staff management. The structure of the paper is as follows: Section 2 reviews relevant issues and existing literature on this topic. In Segment 3, the methodology will be demonstrated, showing the embraced strategy and the information examination. Segment 4 is committed to the demonstrate development stage and received methods are nitty gritty. In Segment 5 we report the comes about of the examination, comparing the execution measurements of the considered calculations. At long last, in Segment 6, conclusions are drawn.

## II. RELATED WORKS

In this section, we review the relevant literature pertaining to our research investigation. The literature encompasses previous studies and research findings focused on predicting employee attrition. We specifically selected recent state-of-the-art approaches for our literature review.

One of the reviewed studies proposed the Performance Evaluation of Data Balancing Techniques in classification tasks. The study addressed the challenges posed by imbalanced datasets in various classification problems, such as intrusion detection, fraud detection, and anomaly detection. Different data balancing techniques were examined to improve the accuracy of prediction models, with the research empirically evaluating their performance using imbalanced datasets. The study concluded that data balancing techniques were beneficial in enhancing the performance of classifiers, with no significant performance difference observed among certain balancing methods.

Another study examined the introduction and practical applications of neural network methods. Neural networks, a subset of machine learning, are known for their high-speed processing and parallelism capabilities with large datasets. These methods mimic the information processing patterns of the human brain, consisting of interconnected neurons organized in layers. The study compared various neural network methods, highlighting their performance and challenges. Results indicated that feedforward and backpropagation neural network methods performed effectively with large datasets, addressing real-world problems across various parameters.

A study proposed predicting employee attrition rates using machine learning-based classification algorithms. HR personnel data from Kaggle were utilized for model development, employing machine learning techniques such as K-Nearest Neighbors, Gradient Boosting, Ada Boosting, Decision Trees, neural networks, and Random Forest. Regularization techniques were applied to optimize parameters for predicting employee attrition rates, resulting in an accuracy score of 88%.

Additionally, an automated prediction of employee attrition based on multiple machine learning models was proposed. The IBM HR employee dataset was utilized for model training and evaluation, employing models like AdaBoost, Random Forest Regressor, Decision Tree, Logistic Regressor, and Gradient Boosting Classifiers. The study aimed for accurate detection of employee attrition to aid organizations in maximizing employee satisfaction.

Furthermore, a three-stage framework was proposed for predicting employee attrition, comprising preprocessing, processing, and post-processing strategies. The IBM HR employee dataset was utilized for model training and testing, employing the max-out feature selection method and logistic regression technique for attrition prediction, achieving an 81% accuracy score.

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A comparison of cutting-edge machine learning methodologies was undertaken to forecast employee attrition utilizing the IBM HR employee dataset.. Results were intended to alert managers to update their business strategies, with the Random Forest model proposed as the most effective approach, achieving an 85% prediction accuracy.

Another study proposed predicting employee attrition using a machine learning pipeline, examining factors such as work experience, educational qualifications, gender, and department contributing to attrition. The pipeline integrated gradient boosting and ensemble learning methods, with hyperparameter tuning applied using a randomized grid search method, resulting in state-of-the-art performance.

Moreover, emotional assessment and forecasting of employee attrition rates were suggested utilizing a dataset gathered through a survey containing questions related to attrition.
Classifiers such as Decision Tree, Random Forest, and Support Vector Machine were applied, achieving an 86% precision score in attrition prediction.

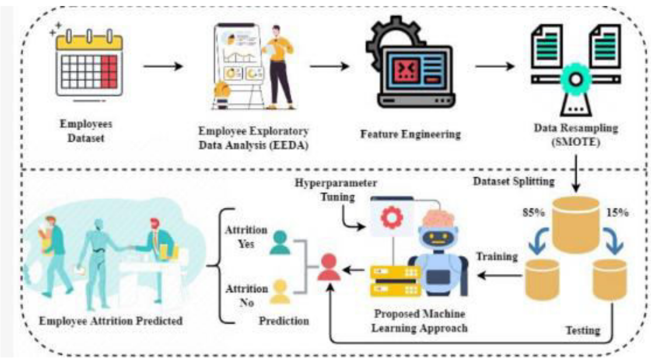
A systematic framework for predicting employee attrition using machine learning methods was proposed, employing models like Naive Bayes, Random Forest, Decision Tree, Support Vector Machine, and K-Nearest Neighbor. The Random Forest model was recommended, achieving an 83% accuracy score, while identifying and mitigating key causes of employee attrition through data analysis.

Lastly, the sudden outbreak of COVID-19 in 2020 resulted in significant business losses globally. In China, governmental measures contributed to economic stability but led to a higher employee attrition rate due to increased unemployment pressure. Studies indicated that workforce stress resulted in job dissatisfaction and burnout, subsequently impacting turnover rates.

In summary, the literature review compared our proposed model with existing machine learning methods and state-of-the-art studies. Our approach incorporated hyperparameter optimization and data balancing techniques, demonstrating superior performance in attrition prediction.

## III. METHODOLOGY

The methodological workflow of our research process is as follows: We utilized the IBM HR employee attrition dataset for our research findings. To gain valuable insights, we conducted Employee Exploratory Data Analysis (EEDA) on the attrition dataset, examining the variables associated with employee attrition. Feature engineering techniques were employed to determine the best-fit parameters through feature correlation for model building and prediction purposes. Feature encoding was conducted during the feature engineering process. Upon analyzing the dataset, we identified an imbalance within it. To address this, we applied the Synthetic Minority Over-sampling Technique (SMOTE) data resampling method. Subsequently, a preprocessed dataset was prepared for model building. The dataset was then split, with an 85:15 ratio for training and testing purposes. The proposed machine learning model was trained on 85% of the dataset and evaluated on the remaining 15%. The chosen machine learning model underwent thorough parameter tuning. Finally, a generalized framework of the proposed model was developed to predict employee attrition by inputting employee details.



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i) Employee Dataset

The IBM HR Employee Attrition dataset was employed to analyze the data and construct a comprehensive machine learning model aimed at predicting attrition among valuable employees. This dataset was curated by IBM data scientists and comprises 35 attributes. Its primary purpose is to investigate the factors contributing to employee turnover. The database contains records for 1470 employees, with a data memory usage of approximately 402.1 KB.

ii) Employee exploratory data analysis

EEDA (Employee Exploratory Data Analysis) was utilized to extract valuable insights from the HR staff dataset, focusing on identifying significant factors contributing to employee turnover. Through EEDA, various graphical representations and time series analyses were employed to thoroughly examine data patterns and determine their impact on employee attrition.

The study examined the relationship between monthly earnings and the total number of years of work concerning employee departure. Monthly income data was plotted on the y-axis against the total years of work on the x-axis. Analysis revealed that within the first year of employment, monthly income tends to be low, coinciding with a higher rate of employee turnover. However, between one to four years of employment, turnover rates decrease. As monthly income rises, employees are less inclined to leave their positions. Furthermore, from the fourth year to the eleventh year, attrition rates remain relatively low, with minimal turnover observed in subsequent years. This analysis underscores the correlation between lower monthly income and shorter tenure with higher employee turnover. Monthly income emerges as a significant factor influencing employee attrition

iii) .Feature Engineering

Feature engineering is a crucial aspect of the learning model as it aims to streamline the data transformation process, ultimately enhancing the accuracy of the learning model. In our study, we employed feature engineering techniques to process the HR dataset features and identify the most suitable ones for the learning model. Through data correlation analysis, we identified the optimal features. By conducting attribute correlation analysis, we eliminated certain features such as Daily Price, Home Distance, Number of Employees, Environmental Satisfaction, Hourly Wage, Job Participation, Job Satisfaction, Monthly Interest, Relationship Satisfaction, Standard Hours, Stock Option Level, Work Destination, Last Year Training Timings, and Personal-Professional Life Balance due to their high negative correlation with other features in the dataset. The selected features were then encoded using a one-hot coding technique. Our research demonstrates that feature engineering techniques have been highly effective in achieving high accuracy.

iv) Descriptive Analysis

The initial step in the descriptive analysis involved examining the distribution of the target variable within the dataset. Out of a sample size of 1,470 employees, 16% (237 employees) had left their jobs, leaving the remaining 84% (1,233 employees) still employed with the company. The distribution of employees across different departments revealed that the research and development department had the highest number of terminated employees, accounting for 133 out of 237 (56.1%). However, it had the lowest attrition rate among its counterparts at 13.8%, compared to the sales and human resources departments with attrition rates of 20.6% and 19%, respectively.

A descriptive analysis of dataset characteristics was conducted by examining their association with the target variable "Attrition". Focus was placed on the five most significant features. The primary factor contributing to employee attrition was financial, with "MonthlyIncome" being the leading indicator. This trend could be attributed to inadequate compensation practices, as attrition rates gradually decreased with higher wages. Notably, the highest attrition rates were observed in lower salary ranges, particularly between \$1,000 and \$3,000, while salaries exceeding \$10,000 experienced a reversal in this trend.

Additionally, analysis of age demographics indicated that younger employees (aged 18-23) were more likely to leave the company, with an attrition rate of approximately 44%. However, as employees aged, their attrition rates decreased. Conversely, the age group most affected by attrition in absolute terms was 29-33 years, exhibiting a rate of 28.7%, significantly higher than other age groups.

Furthermore, attrition rates appeared to be higher among employees living closer to the company premises. Employees with less work experience were also more prone to leaving, with attrition rates ranging from 15.6% to 23.6% among those with 0-11 years of total employment. Attrition decreased gradually as the tenure with the company increased, with the lowest rates observed in employees with 12-14 years of tenure.

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For part-time workers, attrition rates were evenly balanced between those who left and those who remained. However, overtime employees experienced a significantly higher turnover rate, exceeding 30%, while non-overtime employees had a lower turnover rate of 10.4%.

**1. Machine Learning Models**

Machine learning calculations play a significant part in foreseeing worker steady loss. Let's dive into a few common machine learning calculations utilized in this setting:

- Logistic Regression:

Depiction: Logistic Regression may be a factual strategy utilized for twofold classification assignments, making it reasonable for anticipating whether an worker will remain or take off the organization.
Working: It models the likelihood of a twofold result based on one or more free factors. Within the setting of representative whittling down, autonomous factors might incorporate components such as work fulfillment, execution appraisals, residency, compensation, etc.
Points of interest: Logistic Regression is straightforward, interpretable, and computationally productive. It gives likelihood gauges for results, making it valuable for hazard evaluation.
Restrictions: Logistic Regression assumes a linear relationship between the independent variables and the log-odds of the outcome. However, it may not effectively capture complex interactions among variables.

- Decision Trees:

Depiction: Decision Trees parcel the include space into disjoint districts, making consecutive choices based on the values of input highlights to classify occasions.
Working: Within the setting of worker whittling down, choice trees part the data based on worker properties such as work part, fulfillment level, and residency. Each hub within the tree speaks to a choice based on a highlight, driving to a last forecast at the leaf hubs.
Preferences: Decision Trees are known for their simplicity in interpretation and visualization. They are capable of handling both numerical and categorical data, making them versatile in various data scenarios. Additionally, Decision Trees naturally perform feature selection, which can be advantageous in reducing the dimensionality of the dataset.
Confinements: Decision Trees are inclined to overfitting, particularly with complex datasets. They may not generalize well to inconspicuous information without fitting regularization methods.

- Random Forests:

Depiction: Random Forests are an ensemble learning technique that combines multiple decision trees to improve prediction accuracy and reduce overfitting.
Working: Random Forests construct numerous choice trees utilizing irregular subsets of the preparing information and arbitrary subsets of the highlights. The ultimate forecast is made by amassing the expectations of person trees (e.g., by averaging or taking a larger part vote).
Preferences: Random Forests are vigorous against overfitting and tend to generalize well to inconspicuous information. They are exceedingly versatile and can handle expansive datasets with tall dimensionality.
Impediments: Random Forests can be computationally costly and may not be as interpretable as single choice trees.

- Support Vector Machines (SVM):

Depiction: Support Vector Machines are administered learning models used for classification and relapse assignments.
Working: SVMs point to discover the hyperplane that best isolates the classes within the highlight space. Within the setting of worker steady loss forecast, SVMs classify employees into "remain" or "take off" based on their highlight vectors.
Focal points: SVMs are compelling in high-dimensional spaces and are less inclined to overfitting, particularly in cases where the number of highlights surpasses the number of tests.
Confinements: SVMs can be touchy to the choice of part work and parameter tuning. They may not perform well with loud or covering classes.

- Neural Networks:

Portrayal: Neural Networks are a class of deep learning models that draw inspiration from the organization and operation of the human brain.
Working: Within the setting of representative whittling down expectation, neural Networks comprise of connected layers of neurons that prepare input highlights, learn representations, and make expectations. They are able of capturing complex connections within the information.

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Preferences: Neural Networks exceed expectations at learning intricate designs from huge and complex datasets. They can naturally extricate pertinent highlights and adjust to non-linear connections.
Restrictions: Neural Networks require a large amount of information and computational assets for preparing. They can be inclined to overfitting, particularly with inadequately information or insufficient regularization.

**2. Interpretation and Insights**

Elucidation and experiences allude to the method of understanding the comes about of a machine learning show and extricating meaningful information from them. Within the setting of foreseeing representative steady loss utilizing machine learning, translation and experiences include understanding why the demonstrate makes certain forecasts, recognizing key components contributing to steady loss chance, and inferring noteworthy bits of knowledge for organizational decision-making. Here's a point by point clarification of elucidation and bits of knowledge in this setting:

- Understanding Demonstrate Forecasts:

Interpretability is significant for picking up believe in machine learning models, especially in delicate spaces like HR. Organizations ought to get it why the demonstrate predicts an representative is likely to take off or remain.
Strategies such as highlight significance investigation, fractional reliance plots, and SHAP (SHapley Added substance exPlanations) values can offer assistance clarify the commitment of each highlight to the model's expectations.
For case, on the off chance that the show relegates tall significance to components like moo work fulfillment, constrained development openings, or later execution issues, it shows these factors altogether impact whittling down chance.

- Distinguishing Key Indicators of Whittling down:

Elucidation includes distinguishing the foremost persuasive highlights or indicators related with representative steady loss.
Factual procedures like coefficient investigation in direct models or highlight significance rankings in tree-based models can highlight which factors have the most grounded affect on steady loss expectations.
Bits of knowledge gathered from these examinations can help HR experts prioritize intercession methodologies to address the foremost basic variables driving steady loss inside their organization.

- Revealing Designs and Patterns:

Machine learning models can reveal covered up designs and trends in representative information that will not be clear through conventional investigation.
Clustering strategies like K-means clustering can distinguish unmistakable bunches of workers with comparable characteristics and attrition risks.
Time arrangement investigation can uncover worldly designs in steady loss rates, such as regular changes or long-term patterns.
By understanding these designs, organizations can tailor maintenance methodologies to distinctive worker fragments and expect steady loss vacillations more successfully.

- Approval and Calibration:

Translation moreover includes approving and calibrating the model's expectations to guarantee they adjust with real-world perceptions.
This may include comparing anticipated steady loss rates with chronicled turnover information or conducting A/B testing to assess the effectiveness of maintenance activities proposed by the show.
Calibration strategies like unwavering quality charts or calibration bends can survey the model's exactness and alter forecasts to make strides arrangement with watched results.

- Noteworthy Experiences for HR Procedure:

Ultimately, the objective of elucidation and experiences is to infer significant proposals for HR procedure and decision-making.
Insights produced from the show can educate focused on retention initiatives, such as progressing representative engagement, giving career advancement openings, or tending to working environment disappointment.
By deciphering show yields into significant intercessions, organizations can proactively moderate whittling down risk and cultivate a more steady and locked in workforce.
In rundown, elucidation and experiences in worker steady loss expectation include understanding show forecasts, distinguishing key indicators of whittling down, revealing designs and patterns in employee data, approving

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demonstrate yields, and inferring noteworthy proposals for HR procedure. Successful translation and experiences empower organizations to form educated choices, execute focused on intercessions, and eventually decrease whittling down rates whereas cultivating a positive work environment.

### 3. Challenges and Future Prospects

**Challenges:**

- Data quality and availability:

Limited availability of high-quality staff turnover history can hinder the development of accurate predictive models.
Incomplete or inconsistent data, such as missing values or outdated records, can cause bias and reduce the reliability of the forecasting system.

- Interpretability and explainability:

Many machine learning algorithms, especially complex ones such as neural networks, lack interpretability, which makes it difficult to understand the factors influencing wear prediction.
HR professionals may be hesitant to rely on black-box models without clear explanations of how to make predictions, limiting the adoption of advanced machine learning techniques.

- Imbalanced data:

Employee turnover datasets frequently encounter class imbalance, characterized by a situation where the number of employees leaving (considered the minority class) is significantly smaller compared to the number of employees staying (considered the majority class).

- Model Generalization:

Machine learning models trained for one dataset or organization may not generalize well to different contexts or industries.
Models that work well in one organization may not account for the unique factors that affect friction in another organization, requiring retraining or adaptation for each implementation.

**Future Directions:**

- Integration of Qualitative Data:

Future research could explore the integration of qualitative data sources such as employee surveys, exit interviews and sentiment analysis of employee feedback to enrich predictive models with deeper insights into employee attitudes and motivations.

- Explainable Artificial Intelligence (XAI):

Advances in explainable artificial intelligence techniques aim to improve the interpretability of complex machine learning models, enabling HR professionals to more easily understand and trust attrition forecasts.
Future research could focus on developing interpretable machine learning models specifically tailored to predict employee turnover, prioritizing transparency and comprehensibility.

- Handling unbalanced data:

Research could explore methods to reduce the effect of class imbalance in output datasets, such as oversampling minority **8**methods designed for unbalanced data.

- Domain Adaptation and Transfer Learning:

Domain adaptation and transfer learning methods offer valuable approaches to enhance the generalizability of wear prediction models across various organizations or industries.

- Ethical and Fair Artificial Intelligence:

As attrition prediction systems become increasingly common in HR decision-making, ensuring fairness, transparency and accountability in model development and implementation are essential.
Future research should address ethical considerations such as bias detection and mitigation, fairness-aware modeling and ethical guidelines for using predictive analytics in the HR context.
By addressing these challenges and exploring future directions, researchers and practitioners can advance the development of machine learning based employee prediction systems, enabling organizations to proactively manage workforce retention and improve organizational resilience.

## IV. CONCLUSION

Employee attrition presents significant challenges to organizations across industries, affecting productivity, morale and overall business continuity. As organizations strive to create and maintain a stable and engaged workforce, developing effective predictive systems to prevent and mitigate aging has become a key goal. In this study, we explored the

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utilization of machine learning methods to forecast employee turnover, aiming to offer insights and suggestions for enhancing workforce stability.
Through a comprehensive literature review, we examined previous research on predicting employee turnover and identified the limitations of traditional approaches such as rule-based systems and manual analysis. Machine learning offers a promising alternative, using advanced algorithms to analyze vast amounts of employee data and uncover hidden patterns that indicate aging risk. By automating the forecasting process through machine learning, organizations can proactively identify at-risk employees and implement targeted retention strategies.

In our research, we explored Several machine learning algorithms, including logistic regression, decision trees, random forests, support vector machines, and neural networks, were employed in the analysis to predict employee attrition. Through rigorous testing and benchmarking, we evaluated the performance of these algorithms using real data sets from different organizational contexts. Our results highlight the effectiveness of machine learning techniques in accurately predicting employee turnover, with certain algorithms demonstrating excellent predictive accuracy and reliability.

The interpretation and insights from our analysis provide valuable guidance for decision makers and HR professionals in organizations. By understanding the factors driving attrition predictors and uncovering hidden patterns in employee data, organizations can tailor retention strategies to meet specific challenges and effectively reduce attrition risks. In addition, integrating qualitative data sources such as employee surveys and opinion polls enriches forecasting models with deeper insights into employee attitudes and motivations, improving their predictive power and practical utility.
Despite the promise of machine learning in predicting employee turnover, there are several challenges and opportunities for future research. Issues such as data quality, interpretability, unbalanced data and model generalization require further clarification and innovation. Additionally, ethical considerations, including bias detection and fairness-aware modeling, are critical To ensure responsible and ethical utilization of predictive analytics in HR decision-making.
Taken together, the results of this study highlight the potential of machine learning to transform workforce management and improve organizational agility. With advanced algorithms and deep data analysis, organizations can proactively identify attrition risks, implement targeted retention strategies and foster a stable and engaged workforce. As the field of predictive analytics evolves, continued research and collaboration are essential to harness the full potential of machine learning to drive workforce stability and organizational success in the digital age.

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