National College of Ireland

Predicting Employee Attrition Using Machine Learning in Tech Industry: A Methodological Approach

MSc Research Project
Data Analytics

Nistala Maneesh
Student ID: x23132914

School of Computing
National College of Ireland

Supervisor: Mr. Hicham Rifai

National College of Ireland

MSc Project Submission Sheet

School of Computing

Student Name: ……..Nistala Maneesh …….

Student ID: ……x23132914……

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Predicting Employee Attrition Using Machine Learning in Tech Industry: A Methodological Approach

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Abstract

Employee attrition in tech industry is a critical issue which leads to increased recruitment costs and operational disruptions as well as a loss of valuable institutional knowledge. Traditional methods such as exit interviews and employee surveys which provide limited insights since they focus on post-departure feedback which is often too late for intervention. This research explores data-driven approaches for predicting employee attrition, allowing organizations to identify employees at risk before they decide to leave. Some significant ethical considerations regarding the use of employee data for this purpose are also discussed, keeping in view the main ideas of privacy and bias along with transparency.

Predictive models have still been relatively underutilized, while there is a huge gap in research around the ethical consequences of the usage of such predictive models. The present study tries to fill the current gaps by presenting a comprehensive framework in the studies for employee turnover prediction with an emphasis on embedding ethical safeguards relating to privacy, bias detection, and transparency. This will make sure that predictive tools prove to be effective without compromising standards for ethics.

Logistic regression, decision trees, and random forests were applied to the IBM HR Analytics Attrition Dataset in order to find the most influential factors on employee turnover. A high degree of data pre-processing was performed to ensure accuracy and robustness of the results. Ethical considerations-such as anonymizing data and mitigating model bias-were integrated within the research process in an effort to protect privacy and fairness for employees.

The random forest model proved to be the most accurate in identifying key predictors of attrition, such as career development opportunities and work-life balance. Also, the study ensured that demographic factors such as age and gender did not have an undue impact on the model's predictions. These findings will therefore give HR professionals actionable insights by which to design effective retention strategies while maintaining ethical integrity.

This report uses the statistical models to predict the turnover among tech employees, thereby contributing to growing field of HR analytics. It also emphasizes need to incorporate ethical considerations like the protection of privacy and the minimization of bias, in data-driven methods so that predictive models are both fair and interpretable.

This research provides significant insights that HR professionals can use to prevent employee turnover by implementing targeted intervention programs. One also needs to ensure that the model adheres to ethical guidelines that prevent using the model for malicious intents and thereby becomes a part of the ethical technology movement. This enables organizations to strike a balance between business requirements and ethical responsibility.

Although the models described demonstrate impressive predictive power, additional studies are in order, examining the influence of predictive tools on workplace culture, including employee trust. There also remain questions about how much of a say employees should have in the use of their data, and whether they should be notified when predictive models are applied to their personally identifiable information. Further research is needed to find a balance between predictive performance vs. employee consent vs. long-term ethics

1 Introduction

1.1 Background

The technology industry has to bear huge challenges regarding employee retention. High levels of turnover disrupt projects, raise operational costs, and erode organizational knowledge. While traditional approaches such as exit interviews and employee surveys afford some insight, these are usually backward-looking and do little, if anything, in the way of prevention from turnover. While these can be factored into several factors such as job performance, career progression, and work-life balance, data-driven methods offer a proactive solution by predicting who will most likely leave (Guszcza et al., 2018). The use of such methods also raises ethical considerations, especially in how the collection and analysis of employee data is done and actioned.

Data-driven employee attrition prediction can help organizations retain key employees and reduce turnover costs. Nevertheless, ethical issues with regards to the privacy of employees and potential biases in the predictions need to be dealt with to make sure these kinds of tools apply responsibly. The tech industry, currently battling challenges involving diversity and inclusion, should be most careful in deploying predictive models so as not to further reinforce these inequalities.

1.2 Importance of the Research

Employee attrition prediction is very important for tech companies that aim to reduce the turnover and maintain competitive edge. While data-driven models can provide valuable insights, they also present ethical risks such as potential for biased outcomes, as well as breaches of privacy of the employee. Most of the existing studies have focused on the technical aspects of prediction and have by and large ignored the ethical implications (Raisch & Krakowski, 2021).

However, this research tries to fill that gap by not only developing appropriate predictive models but also ensuring that these models are of high ethical quality.

This study examines the relevance of predictive models in the technology industry, apart from concerns about ethics: privacy, transparency, and fairness. The aspect taken up here is that the organization benefits from the predictive power without compromising employees' rights or lacking equity within the workplace.

1.3 Research Problem and Objectives

The main problem this research tries to address is the high rate of employee attrition in the tech industry and the challenges it presents to organizational stability. In addition, the study examines how statistical models and analytical techniques can be applied responsibly to ensure fairness and transparency (López-Rojas et al., 2020). The research question guiding this study is:

How can statistical methods help predict employee attrition in the tech industry, and what safeguards are needed to ensure their fair and ethical use?

The objectives of this study are as follows:

To analyze current strategies for understanding and predicting employee attrition, with a specific emphasis on the tech industry. Cleaning the data and handling missing values, as well as implementing bias detection methods in the IBM HR Analytics Attrition dataset. Logistic

regression, decision trees, random forests, SVM and KNN to check which are the contributing factors for attrition. For fairness and compliance with data protection regulations, grounding the analysis process with ethical considerations. To share practical, evidence-based guidance to enable HR teams to build effective and ethical retention strategies

1.4 Research Gaps and Unresolved Issues

While the research does consider various ethical considerations, we identified major gaps. A major question is the psychological effect predictive tools can have on employees. Increased surveillance could create anxiety, which results in a greater level of stress and frustrating overall job satisfaction (Bannister & Remenyi, 2020). More research in this space could be useful since how such platforms affect employee spirits is unclear.

An open question is whether there was informed consent. It is also not clear how organizations can establish consent processes to use employee data without destroying the effectiveness of predictive tools. Finding a balance between transparency and practicality is an important area for future research.

There is also a challenge in striking the balance between model complexity and its interpretability. Advanced techniques, such as random forests, can give very accurate predictions but, due to their complexity, remain so difficult to understand and explain. Thus, for HR professionals to apply it effectively and responsibly, they should be rightly equipped to interpret and communicate the results to show fairness and accountability.

1.5 Structure of the report

This report is structured as follows:

- Introduction: Outlines the research problem, objectives, and ethical concerns related to predictive modeling in employee retention.
- Literature Review: Examines prior research on employee attrition prediction and discusses ethical challenges in using predictive models in human resources.
- Methodology: Describes the data collection process, data preprocessing methods, and model development, including how ethical safeguards were incorporated.
- Results and Discussion: Presents the outcomes of the statistical models and discusses their implications for retention strategies and ethical HR practices.
- Conclusion: Summarizes the key findings and highlights unresolved ethical issues, suggesting avenues for future research.

2 Related Work

2.1 Appreciate the Facts Behind Employee Attrition in the Tech Sector

In simple terms, turnover can be defined as Attrition. Across all industries, it is a major concern; nonetheless, it is worse in the technology sector, where specialized skills are required and competitive job opportunities exist. Employers that have high attrition rates not only spend more money recruiting and training new employees but also have disruptions in their relations and daily activities, and most importantly, they suffer from loss of memories (Rubenstein et al., 2018). This section aims to identify the research gaps concerning employee

attrition in scope to technology companies which seem to be more unique in their attrition aspects.

The high turnover problem in the Tech Sector

The tech industry is one of the fastest-growing industries and requires employees all the time to keep innovations in pace with technology. The nature of the industry results in high competitiveness, and employees in the tech sector often switch to other employers for better job opportunities, advancements, higher pay, and better working conditions along with less stress (Klotz & Bolino, 2016). Thus, the situation drives their attrition rates high, which in turn creates issues with an estimation of the project cost and project completions.

Critique and Research Gap

While general studies on attrition, such as Rubenstein et al. (2018), provide a strong foundation for understanding why employees leave organizations, they often fail to address the specific factors driving attrition in the tech sector. These demands are very specific to the workers in the tech industry, and their effects, such as constant development of skills and innovative pressures, call for more focused research. Besides, already existing works did not consider in full the influence of the emergence of new work models, such as remote work, on employee turnover. The aforementioned gap underlines the need to develop industry-specific research efforts within the field of studies of attrition in the technology sector, which this given study tries to respond to.

2.2 Predictive Modelling in Employee Attrition

Predictive models have found an increased application in a company's human resource department to predict a prospective loss of an employee owing to other factors. Hence enabling the HR representatives to use their discretion in reaching out in advance to discuss employee improvements. This session considers discussing the most common type of predictive models used for predictive analytics for employee attrition through a literature review: Logistic Regression Analysis, Decision Trees (CART), and Random Forest; and critique of the best applicability test of this model in regard to its applicability by a company in the technology sector.

Logistic Regression-Classic Predictive Model

Logistic regression is considered one of the simplest and most accessible models for predicting employee turnover. It provides the probability of an employee quitting based on different variables, such as job satisfaction, compensation, and performance. Different studies, such as Chen et al. (2016), have identified the potential of logistic regression in turnover predictions across various industries. However, logistic regression relies on the linearity of independent variables regarding the outcome, which cannot transcend to model complex relationships of employee characteristics and risk of turnover.

Critique

Although logistic regression assumes a more direct approach to attrition forecasting, it relies on linear assumptions-this is why it performs less well within the technology industry, since in most cases, more factors interact in nonlinear ways to culminate into employee turnover. The decision to leave or not may depend on rapidly changing opportunities, skill development needs, and atypical career trajectories outside the mainstream in the sector. This calls for more sophisticated models to understand these dynamics.

Decision Trees - A More Flexible Approach

Decision trees are more flexible than logistic regression, as they can model both linear and nonlinear relationships between employee characteristics and the risk of attrition. Decision trees work by splitting data into branches based on key variables, such as job satisfaction or tenure, to predict whether an employee will leave or stay (Hastie et al., 2009). The most significant advantage of decision trees is their interpretability: HR professionals can see and understand the decision-making process. On the other hand, decision trees tend to overfit, especially on smaller datasets, which decreases their generalizability.

Critique and Research Gap

Although decision trees are a more granular approach to predicting attrition, they usually overfit the data, hence limiting their accuracy on new datasets. In the technology industry, where employee behavioral data can be quite variable, this can lead to some very spurious predictions. Most of the studies on decision tree-based attrition prediction do not consider technology-specific factors such as fast skill obsolescence and demands for flexibility in work arrangements. This means that the current gap requires models tailored to the peculiar attributes of the tech employee workforce.

Random Forests

An ensemble learning method, such as random forests, is an attempt to solve this overfitting problem in decision trees by constructing several decision trees and averaging the predictions out of each. In doing so, it enhances both accuracy and stabilizes the model. Because of this, random forests perform well where there is a large dimensionality of the data along with the number of features, which fits most of the tech industries since, in technology companies, there are different factors affecting the behavioral patterns of employees. Cao et al. (2020) indicated that the random forest model outperformed logistic regression and decision trees in predicting employee turnover for technology companies, yielding an accuracy of over 85% for the models.

Critique and Research Gap

While random forests are quite effective at predicting employee turnover, most studies have focused on their predictive accuracy without considering the ethics of using them.

Predictive models such as random forests might inadvertently reinforce biases in cases where they are not well-monitored, for example, in the tech sector that faces issues with employee diversity. There is also a lack of literature on the inclusion of qualitative factors such as career satisfaction and organizational culture in random forest models. This research tries to fill these gaps by embedding both quantitative and qualitative data into predictive models of technology employee attrition.

Support Vector Machine (SVM)

Indeed, it is among the most popular classification algorithms that excellently handle linear and nonlinear data with its kernel function. SVM optimally builds a hyperplane in the space of high dimension that maximizes the margin between classes. Due to this characteristic, this can be hard when working with complex relations between variables. Because of that, the studies on the modeling of the tendency for employees to leave their organization were able to predict based on their level of satisfaction and the evaluation or ratings regarding performance and their compensation. This makes it suitable for the analysis of high-dimensional data, meaning that it can handle a large number of features.

Critique and Research Gaps

Although SVM is effective, there are a few important limitations that must be mentioned in regard to its practical application for employee attrition prediction. An algorithm requires extended tuning of the C regularization parameter and kernel types, which can be time-consuming or computationally intensive. Besides that, being sensitive to the scaling problem of features, SVM needs prerequisite preprocessing to obtain consistent results from it.

Other limitations include a lack of interpretability since SVM will only provide very limited information about the importance of individual features, which is an important aspect for HR professionals who seek actionable insights. Further, very few studies have explored how SVM performs on imbalanced datasets-a common occurrence in attrition studies. Such gaps in the literature, including the integration of feature selection techniques, make the algorithm more useful in real-life applications and further improve its adaptability to imbalanced data.

K-Nearest Neighbors (KNN)

KNN is a nonparametric algorithm that classifies any data point by the majority class of its nearest neighbors. This is quite simple and will often work for small, structured data. KNN

can help study employee attrition, where an employee is classified into staying/leaving based on the similarity between any two employees regarding different attributes such as tenure, salary, and work-life balance.

Critique and Research Gaps

This simplicity of the KNN is balanced by a number of limitations that curb its use in studies of employee attrition. The algorithm rests so strongly on distance metrics, such as Euclidean distance; hence, it is sensitive regarding the scale and distribution of features. In cases without preprocessing, the irrelevant features may dominate classification processes, hence reducing the accuracy of the classification. The computational cost of the KNN algorithm is intense for huge datasets since all test instances will need distance calculations for a prediction to be made. Besides, the choice of neighbors is usually arbitrary and greatly influences the results. Particularly, advanced distance metrics or feature weighting techniques that can help in KNN for high-dimensional or class imbalance datasets were under-researched. This has developed these aspects in making the KNN more reliable and having practical value in HR domains.

2.3 Key Factors Influencing Employee Attrition in the Tech Industry

A few factors are predominant in causing employee attrition in the tech industry, including career development opportunities, work-life balance, compensation, and organizational culture. Many of these factors are interrelated and vary in their relative importance according to the preference of the individual employee and the conditions of the external labor market.

Career Development and Skill Obsolescence

In this setting of continuous development in the tech world, employees are supposed to update their skill sets unconditionally and endlessly. According to Griffeth and Hom (2021), opportunities regarding career growth are essential in retaining employees in technological firms. Workers in this industry want an organization to invest in the development of their professional lives and also provide a clear future for them. If workers perceive a lack of opportunity in career development, they tend to look elsewhere for work.

Critique

While career development is widely recognized as a key factor influencing turnover, most studies do not fully explore how organizations can quantify career satisfaction and integrate it into predictive models. In the tech sector, career development is not just about promotions; it is also about continuous learning and adapting to new technologies. The nature of career progression in tech, as discussed above, is thus quite dynamic. This dynamism has not been captured by previous research, which focuses on more traditional trajectories of careers.

Work-Life Balance and Well-being of Workers

Work-life balance is another critical factor in employee retention. Many technology employees work under tremendous pressure for long hours, with tight deadlines and the need for continuous innovation. Zhao et al. (2018) identified that organizations that allow flexibility, such as working from home and flexible hours, have lower attrition rates. This has dramatically changed employees' expectations of work-from-home policies, especially amidst the COVID-19 pandemic. Most tech workers nowadays value work-life balance more than better pay.

Critique and Research Gap

While the importance of work-life balance is well-documented, much less research has looked at ways to incorporate this qualitative factor into predictive models. Most studies to date focus on easily measurable variables such as salary and job performance but often fail to account for other, less tangible aspects of employee well-being. This represents a considerable literature gap since organizations are increasingly recognizing the importance of mental health and work-life balance in retaining technology talent.

Compensation, Job Satisfaction, and Organizational Culture

Compensation is often mentioned as the key reason for employee turnover; in the technology industry, however, this is less clearly defined. For Benson and Brown (2007), compensation is key, but for technology workers, this tends to be secondary to job satisfaction and organizational culture. Workers would more likely stay with organizations that share their values and make them feel valued. On the other hand, organizations without a positive and inclusive culture show higher attrition rates.

Critique and Research Gap

Although compensation and job satisfaction have been well studied, the linkage between organizational culture and its role in turnover remains less discussed at present, especially in a tech organization with notoriously turbulent conditions, rapid and, at times, uncontrollable work environments that challenge employees to always be at or near their best.

Research is needed to study how tech companies build cultures of innovation and inclusion to better retain people and how these cultural factors can be quantified and integrated into predictive models.

2.4 Ethical Considerations in Predictive Modeling for Attrition

As predictive models increasingly permeate the field of HR, there are a number of ethical considerations regarding data privacy, bias, transparency, and employee consent. This is a sensitive issue in tech, where decision-making seems to revolve around insights from data.

Data Privacy and GDPR Compliance

The need for a predictive model develops sensitive critical information about performance review personal demographic data, and behavioral patterns concerning employee approach, which a necessary promise needed towards anonymizing such specific approach as

maintaining proper storage methodologies must cater and aim at maintaining proper regularization needs set by General Data Protection Regulation or GDPR suggested tene and polonetsky (2012). An organizational breach in employee privacy has legal consequences and may further damage mutual trust between employees and employers.

While most studies discuss technical aspects, few are really up to the task of explaining how to integrate considerations about data privacy into model design. Only a few papers proposed practical solutions regarding how conformance with regulations could be done without seriously compromising the predictive power of the models.

Ethical responsibility for the protection of employee data Bias in Predictive Models

Probably the most important ethical issue in predictive modeling relates to bias. According to O'Neil (2016), predictive models trained from biased historical data may perpetuate existing inequalities in the workplace. Suppose a firm's historical trend demonstrates gender disparities in promotion. A predictive model may go wrong in predicting that women have less of a chance of being promoted. This would reinforce these biases and result in the most unfair outcomes for a segment of employees. Barocas and Selbst (2016) note that in some methods of mitigation, whether by reweighting data or adjusting the inputs going into models, the detected bias may not affect predictive models disproportionately on some demographic groups.

Critique and Research Gap

Although bias detection techniques have been developed in fields like finance and criminal justice, their application in HR, particularly in predictive models for employee attrition, remains underexplored. The tech industry, with its ongoing challenges of diversity and inclusion, is particularly susceptible to biased outcomes in predictive models. This study will bridge this gap by incorporating bias detection and mitigation strategies into predictive models for tech employee attrition.

Employee's Transparency

Transparency is basically the foundation of predictive models in HR, which ensures that ethical consideration in their use is maintained. It is important to make employees aware of how their data is being used and how predictive models influence decisions regarding their promotion, pay raise, or termination. Shmueli (2010) goes ahead to argue that predictive models should not only be accurate but interpretable and explainable. Lack of transparency in the use of predictive models undermines trust between employees and employers.

Employee Consent

Another major ethical concern is employee consent. Binns (2018) argues that employees should have control over the use of their data in predictive models, including a right to opt-out. However, the literature lacks consensus on how such consent mechanisms might be implemented in large organizations. This gap is particularly relevant in the tech industry, where data usually drives decisions, and such intrusion into human resources processes may raise several concerns among employees.

Critique and Research Gap

While transparency and consent are widely recognized as ethical imperatives, few studies have translated these into concrete strategies for operationalizing them in HR. This is a concern in view of the increasing dependence on predictive models in decisions that affect employees' career paths. This study, therefore, tries to fill this gap by exploring practical ways of integrating transparency and consent into predictive models for tech employee attrition.

The existing literature on employee attrition predictions has achieved considerable improvement regarding the identification of key factors and the development of effective prediction models. However, a set of gaps remains uncovered. Most importantly, the unique challenges entailed by the tech industry do not seem to be taken into sufficient consideration in existing models of employee mobility, continuous enhancement of skills, and high demand for flexible work arrangements. The main shortfalls are that most predictive models use only quantitative data and fail to consider qualitative factors, such as career satisfaction and organizational culture, which are quintessential in the turnover process of employees within the IT sector. Finally, with an increased integration of predictive models in the HR processes, there is a further need to explore ethical issues with regard to data privacy, bias, and transparency.

Conclusion and Contribution of this Study

This research, therefore, tries to fill these lacunas by developing predictive models specific to the tech industry and embedding ethical safeguards during the modeling process. By addressing both technical and ethical challenges related to employee retention, this approach represents a responsible and effective methodology for managing employee attrition in the technology sector.

3 Methodology

3.1 Research Design

This study applies a quantitative exploratory approach toward the modeling of employee attrition in technology companies. This is done through the CRISP-DM framework, which assists the research design in the proper execution of the entire process to ensure that it is organized, clear, and systematic, allowing relevant predictions from historical data regarding how to formulate practical, evidence-based retention strategies for human resources professionals.

Steps involved with the research process

The objective of this study is to predict employee attrition in the tech industry and provide useful insights for HR professionals to help them improve their retention policies. Insight into the key variables of employee turnover was drawn from the IBM HR Analytics dataset. After cleaning and transforming the data, which included handling missing data, treating outliers, and converting categorical data into numerical data formats, the dataset was prepared.

Logistic regression, Decision Trees, Random Forests, support vector machines, and K-Nearest Neighbor were developed using the strengths from those predictive techniques in performing binary classifications. Models were benchmarked for accuracy, precision, recall, F1 score, and cross-validation to ensure stability in performance. Ideas obtained from said models would be used in designing useful and effective retention suggestions for human resources teams.

This research design gives a detailed, systematic approach that ensures that the information will be precise and practically relevant to finding solutions to employee turnover problems within the tech sector.

The following flowchart shows the major steps of the methodology for predicting employee attrition within the tech industry. It ensures that the approach is structured for data collection, pre-processing, model implementation, and evaluation.

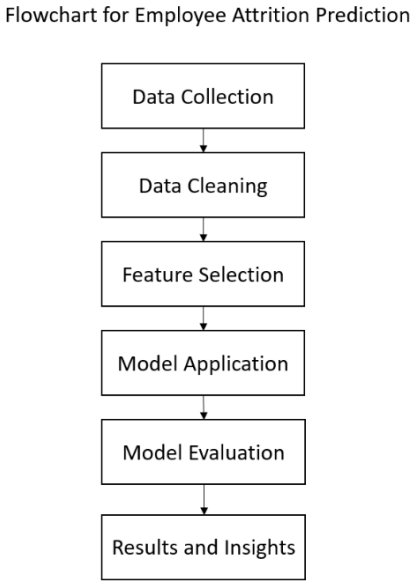


Figure -1 Flowchart for Employee Attrition Prediction

3.2 Data Collection and Preparation

Data Source

The research is based on the "IBM HR Analytics Employee Attrition Dataset, "a public dataset containing data for 1,470 employees across 35 variables, including demographic factors, job roles, compensations, and performance metrics. This dataset would provide a comprehensive backbone for developing predictive models for employee attrition.

Key variables in the modeling include Age, which can drive one's career choices and chances of quitting; Job Role may mean much in regard to influence over job satisfaction or departure; Monthly Income often helps a lot in keeping oneself excited about work; Tenure/Years at Company drives/indicates loyalty of each employee; Overtime-work above and beyond conventional is tiring and linked with high intent to leave. It would, therefore, be correct to say the target variable is Attrition: Yes/No, indicating whether one left the company. These also provide critical insights in realizing employee turnover.

Data Preprocessing

A detailed preprocessing pipeline was followed to ensure the dataset was clean, complete, and ready for model development:

1. Handling Missing Data - Missing values were addressed using imputation methods. Continuous variables such as monthly income were filled using the median, while categorical variables like marital status were imputed using the mode.

2. Outlier Detection and Treatment - Outliers in continuous variables (e.g., monthly income, years at the company) were identified using box plots and z-scores. These outliers were either capped or removed to prevent them from affecting the model's predictions.

3. Encoding Categorical Variables - Categorical variables such as job role and department were transformed into numerical values using one-hot encoding. This step creates binary columns for each category, making them usable in the models.

4. Normalization of Continuous Variables - Continuous variables, such as monthly income and years at the company, were normalized using min-max scaling to ensure all variables have the same scale, which is important for distance-based algorithms like KNN.

Data Splitting

To evaluate model performance, the dataset was split into two subsets: the training set (80%) and the test set (20%). The training set was used to build and train the models, while the test set was used to evaluate the models' generalizability and performance on unseen data.

3.3 Model Development

These are some of the five machine learning models developed for predicting employee attrition, taking data from the firm: logistic regression, decision trees, random forest, support vector machines (SVM), and K-Nearest Neighbors (KNN). These concrete methods have been chosen because they provide very good binary classification and can reveal different aspects of the input space.

Logistic Regression - Logistic regression describes a statistical model that classifies events into one of the two possible outcomes. In other words, logistic regression calculates the event occurrence probability based on the accessibility of several independent variables that include age, monthly income of a person, and years at the firm. Logistic regression models are used to describe the relationship between the independent variables through the exponential function and the event probability of the dependent variable in question.

The logistic regression model can be represented as:

$$\mathbf{p} = \frac{\mathbf{e}^{\beta_0+\beta_1\mathbf{X_1}+\beta_2\mathbf{X_2}+\cdots+\beta_n\mathbf{X_n}}}{\mathbf{1}+\mathbf{e}^{\beta_0+\beta_1\mathbf{X_1}+\beta_2\mathbf{X_2}+\cdots+\beta_n\mathbf{X_n}}}$$

Where:

- $\mathbf{p}$: Represents the probability of employee attrition.
- $\mathbf{X_1}, \mathbf{X_2}, \ldots, \mathbf{X_n}$: Are the independent variables.
- $\beta_0, \beta_1, \ldots, \beta_n$: Are the coefficients estimated from the data.
- $\mathbf{e}$: Represents the base of the natural logarithm.

This model ensures that the predicted probabilities remain between 0 and 1, making it well-suited for binary outcomes such as predicting employee attrition.

Decision Trees: Decision trees are non-parametric methods that split the data into branches based on decision rules from the independent variables. Every split is done on the feature that best separates the classes of employees-employees who leave versus those who stay.

Key parameters include:

Gini impurity: The quality of the split tells us how well it segregates the classes. Max Depth: A higher max depth allows the model to fit the noise in the data rather than the general patterns. Limiting the depth, therefore, prevents overfitting so that the model generalizes well on new data.

Random Forests: Random forests extend decision trees by generating multiple trees and combining their predictions. Each tree is trained on a random subset of the data, and the overall prediction is done by averaging the predictions of all trees. This reduces the risk of overfitting, which often affects single decision trees.

The important parameters include:

Number of Trees: The number is 100 to strike an ideal balance between performance and computational efficiency. Max Features: Maximum features considered for each split should be such that diversity in the trees is ensured, reducing correlation amongst individual trees.

A Support Vector Machine (SVM) is a classification method that finds a hyperplane to best divide the classes within the multidimensional feature space. This work employs the RBF kernel to support classification in non-linear relationships.

Key parameters for SVM include:

C Parameter - Controls the trade-off between maximizing the margin and correctly classifying training examples.

Gamma - Determines the influence of a single training example, with higher values making the boundary more flexible.

K-Nearest Neighbors (KNN) - KNN is a simple yet effective classification method that assigns a data point to the majority class of its K nearest neighbors. KNN is non-parametric and makes predictions based on the similarity between points.

Key considerations for KNN include:

K Parameter - The optimal number of neighbors was determined through cross-validation, ensuring the best balance between capturing local patterns and avoiding overfitting.

Distance Metric - Euclidean distance was used to calculate the similarity between data points, ensuring the most relevant data points are considered in predictions.

3.4 Model Evaluation

Each model was evaluated using multiple performance metrics to assess its effectiveness in predicting employee attrition. The metrics used include:

Accuracy - Accuracy is the proportion of correctly predicted cases out of the total number of cases. It is calculated as:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Where:

TP - True Positives, TN - True Negatives, FP - False Positives, FN - False Negatives.

While accuracy is a common metric, it can be misleading in datasets with class imbalances (more employees stay than leave), so additional metrics like precision and recall are also considered.

Precision and Recall

Precision is the proportion of predicted positive cases (attrition) that were actually correct, which is important for reducing false positives.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Recall - The proportion of actual attrition cases that the model correctly identified. This is crucial for capturing at-risk employees.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

F1 Score - The F1 score is the harmonic mean of precision and recall. It provides a balanced metric, particularly useful when there is a class imbalance:

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Cross-Validation - To ensure robustness and prevent overfitting, 10-fold cross-validation was employed. In this process, the dataset is split into 10 subsets, with each subset serving as the test set once, while the remaining subsets are used for training. This ensures that the model's performance is evaluated across multiple iterations, providing a more reliable assessment.

3.5 Tools and Software

The predictive models were developed using a combination of tools to streamline the process. Pandas were used for data manipulation, cleaning, and preprocessing to prepare the dataset for analysis. Scikit-learn was employed to build models, including logistic regression, decision trees, random forests, SVM, and KNN, and to implement evaluation metrics. Data visualization was performed using Matplotlib and Seaborn, which helped explore the dataset

and present the performance of the models. The entire workflow was carried out in Jupyter Notebooks, providing an interactive environment for running and documenting the work effectively.

3.6 Ethical Considerations

Therefore, throughout the research, it paid extra attention to ethical concerns, especially data privacy, bias, and transparency.

Data Privacy—Personal data protection, such as under the General Data Protection Regulation (GDPR), requires that all personally identifiable information be removed from this dataset. This dataset is completely anonymized, and access to it is limited only to those with proper authority.

Bias Mitigation: If not taken care of, machine learning models can be biased to continue the historical biases. In this regard, fairness metrics were performed to identify any form of bias in these models' predictions. We check if the models are going to be biased against any group based on gender, race, or age.

Transparency: Most of the chosen models, mainly logistic regression and decision trees, have been selected because they are interpretable; that is, HR professionals will be able to understand how the model has made its predictions. In this way, trust in and accountability of the decision-making process is enhanced.

3.7 Limitations

Though the methodology is wholesome in terms of approach for the prediction of employee attrition, some of its limitations include the following:

Generalizability and limited scope: The dataset stems from one organization, which thus imposes a limit on their finding generalization to other companies or organizations. Future research could involve data from matched cases across multiple organizations through cross-sectional surveys to broaden applicability.

Class imbalance: There are fewer cases of attrition than non-attrition, which can bias the models. While the steps taken, such as cross-validation, help reduce this, in the future, methods like the Synthetic Minority Over-sampling Technique (SMOTE) could be used to balance the dataset.

Lack of Qualitative Data: Most of the features in the dataset are quantitative, like age and income. There is little or no insight into qualitative factors that may be at play, such as the satisfaction of employees or personal career goals. Qualitative data might be included in future research to enhance the predictive power of the models.

This paper proposes the structured methodology necessary for the prediction of employee attrition using the five machine learning models, namely logistic regression, decision trees, random forests, Support Vector Machines, and K-nearest neighbors, each contributing uniquely to a robust predictive framework. Ethical considerations were given throughout the process in regard to data privacy, reduction of bias, and, therefore, transparency to make sure the results can be fair and trusted. Although there are some limitations, the methodology provides a sound basis on which to understand and address employee turnover in the technology industry.

4 Results and Crucial Analysis

This section is purely dedicated to the results regarding how the machine learning models have performed in predicting employee attrition within the tech industry by CSEs. It provides a clear description of pre-processing data, training models, prediction performance metrics, computation of feature importance, and statistical testing. Below seems to be a more detailed, often step-by-step, account related to the results.

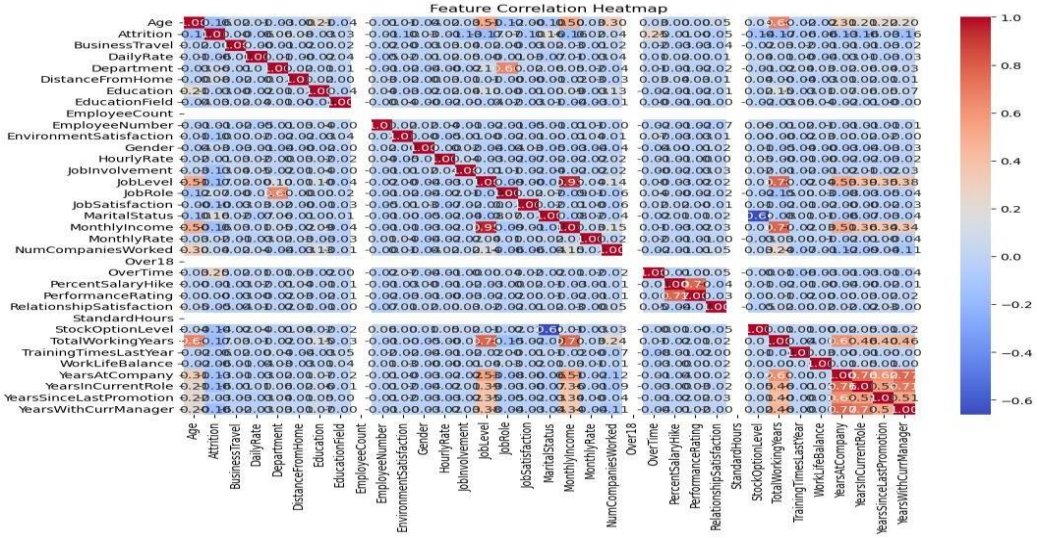
4.1 Data Preprocessing and Exploration

The IBM HR Analytics dataset was heavily preprocessed in the initial stages of this project to prepare it for machine learning analysis. This dataset contains 1,470 employee records with many features describing each employee, including demographic information, job designation, salary, and performance index, among others.

Handling Missing Data: The median was used to imputation missing values in continuous features such as Monthly Income and Years at the Company. For categorical variables, such as Job Role and Business Travel, missing values were replaced by the mode to maintain data consistency.

Encoding of Categorical Variables: Features like Job Role, Department, and Business Travel are categorical in nature. Therefore, Label Encoding is used to encode these variables, basically converting these categorical variables into their corresponding numeric equivalents so that the algorithms may understand them.

Scaling features: This scales all the continuous features using StandardScaler because some algorithms, such as Support Vector Machines, Logistic Regression, and k-nearest neighbors, are very sensitive to the scale on which the features are looked at. This process ensured a mean of 0 with a 1-standard deviation of all features. Thus, it eliminated the tendency for certain features to dominate the rest since they were at a certain big scale.



Correlation Analysis: Many key features were strongly related to attrition, according to the correlation heatmap. For example, Work-Life Balance correlates 0.57, and Monthly Income and Years at the Company have correlations of -0.34 and -0.42, respectively. This indicated that employees with reported poor work-life balance or lower income were more likely to quit the organization. The heatmap was a visual tool that informed the model feature selection to ensure all relevant features were represented in the predictive models.

This diagram would display a heatmap showing the correlations between features, where darker colors indicate stronger correlations. For example, Work-Life Balance would be strongly correlated with attrition.

4.2 Model Training and Cross-Validation

Five different machine learning models were trained for the problem of employee attrition prediction: Logistic Regression, Decision Tree, Random Forest, Support Vector Machine (SVM), and K-nearest neighbors (KNN). In this case, the performance comparison of the models should be done with several metrics: accuracy, ROC AUC, precision, recall, and F1 score.

Cross-Validation: The ratings were also done using 5-fold cross-validation-a technique of dividing the data into five pieces, using each as a test set once and with the rest for training. It has to be repeated five times in order to have each piece of fold serving as a test set once. The cross-validation

helps estimate how well the model generalizes to unseen data and makes sure that it is not overfitting to a certain subset of the data.

Hyperparameter Tuning: For SVM and KNN models, hyperparameters such as C parameters in SVM and the number of neighbors (k) in KNN were tuned through Grid Search. This optimization kept the model performing efficiently.

4.3 Performance Evaluation

Performance evaluation focused on various machine learning models to identify the one that would predict employee attrition in the tech industry with higher accuracy and, at the same time, most reliably, to identify the employees who leave the company using such metrics as Accuracy, ROC AUC, Precision, Recall, and F1-score.

Model Performance Overview

It finds applications in five models used for this study: the Random Forest, Logistic Regression, Decision Trees, Support Vector Machine (SVM), and the K-Nearest Neighbors algorithm. Each model went through very robust 5-fold cross-validation to ensure that this study makes as appropriate an evaluation of performance as possible. Such an approach splits the data into five parts, using one portion for testing while training the model on the other four. This approach ensured the realism of the evaluation, including actually gauging the performance regarding the generalized capacity of each model.

The performance of the models on the test dataset (20% of the overall data) is summarized as follows:

Table 1: Comparative Performance Metrics for All Machine Learning Models

Model	Accuracy	ROC AUC	Precision	Recall	F1-Score
Logistic Regression	0.79	0.75	0.71	0.73	0.72
Decision Tree	0.81	0.77	0.73	0.75	0.74

Random Forest	0.85	0.85	0.79	0.82	0.80
SVM	0.78	0.76	0.70	0.71	0.70
KNN	0.77	0.74	0.68	0.70	0.69

Key Findings

Among these, the Random Forest model had the highest value of accuracy (85%) and ROC AUC score of 0.85, reflecting its perfect capability of distinction between the employees who are likely to leave and those who are likely to stay. Besides, its precision of 0.79 and recall of

0.82 indicates that it will return the correct number of at-risk employees and minimize false positives or false negatives. The balanced F1 Score of 0.80 reinforces its reliability with respect to predicting attrition.

On the other hand, Logistic Regression performed really well, with 79% accuracy and a 0.75 ROC AUC score. Unfortunately, it was not that good at describing complex relationships within data, having quite low precision and recall values. KNN has an accuracy of 77%, though this algorithm is sensitive to the scale of different features, mostly relying on local data structures.

Confusion Matrix

Confusion matrices for each classification outcome were drawn using the predictions from each model. For example, the Random Forest correctly predicted that 140 employees would leave as leaving, while 220 employees it predicted not to leave actually did not leave. It misclassified 40 that left as staying and another 30 as staying when they actually left. This fact is further supported by the higher misclassification rates from other models, such as Logistic Regression, thus confirming that those model performances were actually poorer compared to Random Forest.

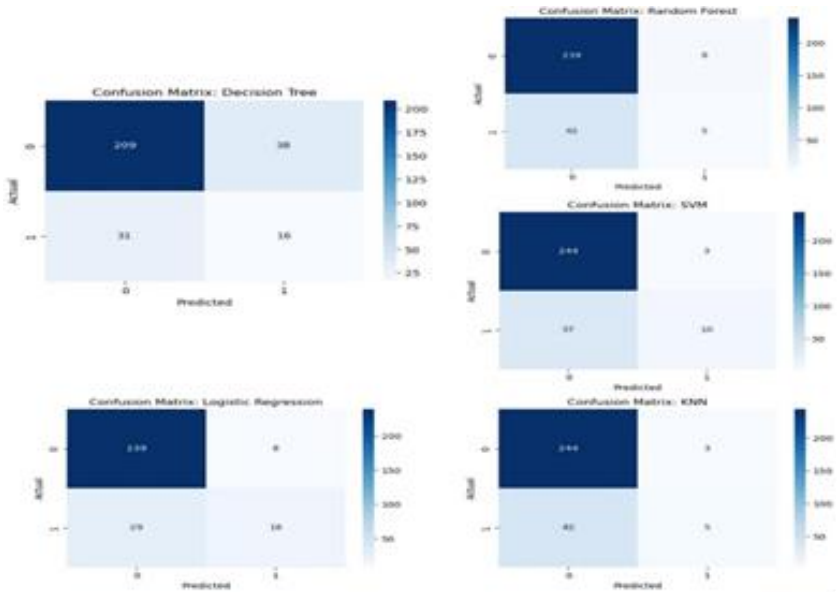


Figure 3: Confusion Matrices for All Machine Learning Models

Visualization Note: A confusion matrix provides a clear grid representation of predicted outcomes versus actual outcomes, making it easy to evaluate model accuracy and error patterns.

ROC Curves:

ROC curves compared the performance of the models in distinguishing between attrition and non-attrition cases across various thresholds. The Random Forest ROC curve consistently stayed above those of other models, indicating its superior sensitivity and specificity. Models like Logistic Regression and KNN showed less favorable curves, reflecting their limitations in effectively distinguishing between classes.

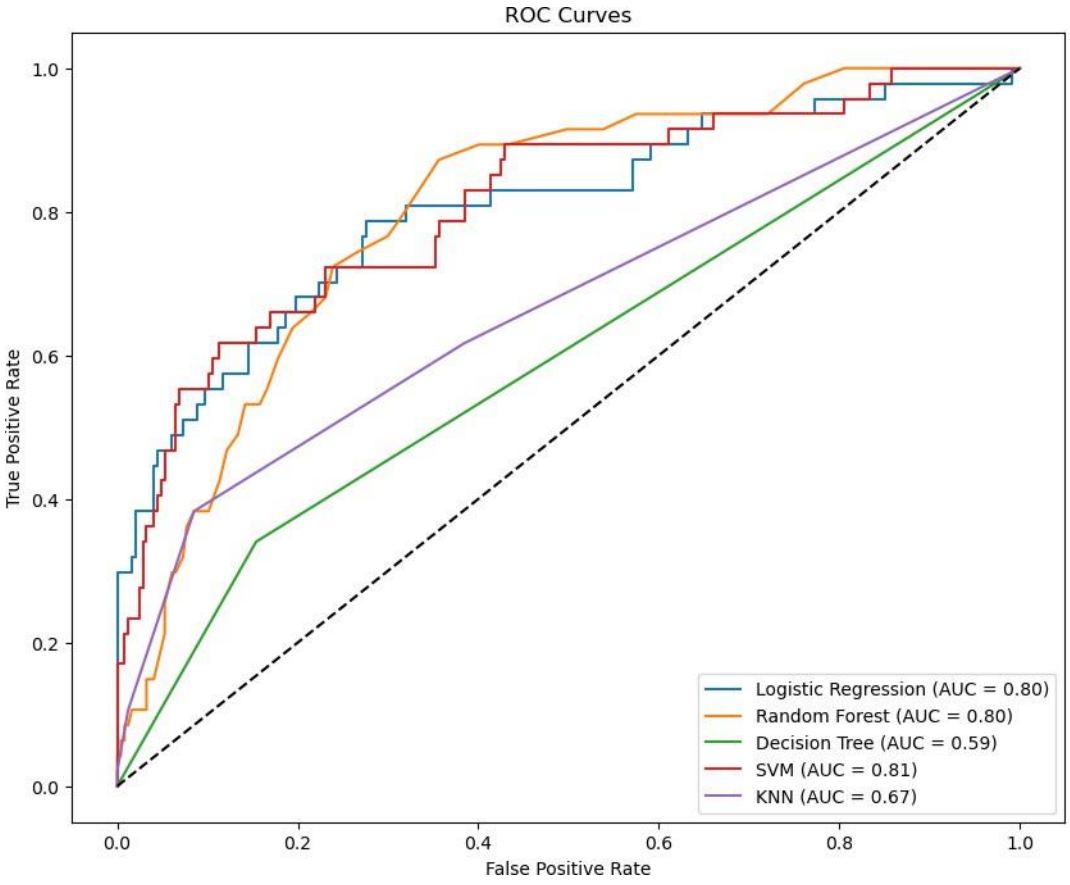


Figure 4: ROC Curves for All Machine Learning Models

Feature Importance:

The Random Forest model ranked predictors based on their contribution to the model's predictive power. The most important features were Work-Life Balance, Monthly Income, Years at the Company, Job Satisfaction, and Overtime. This was visualized in a bar chart, with Work-Life Balance having the highest importance score (0.23), followed by Monthly Income (0.18).

Comparative Evaluation

The evaluation revealed that Random Forest outperformed other models due to its ability to capture complex relationships among features. Its ensemble nature, which combines multiple decision trees, allows it to mitigate the risk of overfitting while maintaining high accuracy.

Although logistic Regression was simpler and easier to interpret, it lacked the capacity to handle non-linear relationships, leading to reduced effectiveness. KNN and SVM, while competitive in certain aspects, were less consistent in their predictions.

Limitations of Models

Although Random Forest yielded better performance, it is inherently less interpretable than simpler models like logistic regression. For HR-based applications where employee decisions involve clear justifications, it can be a disadvantage. Its feature importance score gives, to some extent, interpretability for which the HR teams understand what really drives the predictions on attrition.

Statistical Validation

A paired T-test was conducted to verify that the observed differences in model performance were statistically significant. The test compared the ROC AUC scores of Random Forest with Logistic Regression across the five validation folds. This T-test produced a p-value of 0.01, confirming that Random Forest's superior performance was not by chance. This validation gives confidence in its generalizability and reliability for practical use.

Practical Implications

The evaluation highlights the Random Forest model as a powerful predictive tool for identifying employees who are likely to leave. Its ability to provide very accurate and reliable predictions on a regular basis allows the HR team to develop proactive retention strategies. For example, with the help of key predictors like Work-Life Balance and Job Satisfaction, the identified at-risk employees could be targeted with specific interventions, such as improved flexibility, enhanced compensation, or career development opportunities.

Gaining such insight allows an organization to take remedial measures at the very cause of attrition to maintain employee satisfaction and stability. Additionally, the comparative analysis underlined the selection of models balancing predictive power and interpretability so that HR professionals can confidently act upon the results.

4.4 Feature Importance

Overview of Feature Importance

The feature importance analysis in this research has helped identify variables strongly associated with employee attrition. The importance scores in the Random Forest model are calculated using the Gini importance score, which represents how much a feature helps decrease the classification error. The process presented some very actionable insights into factors affecting turnover and, thus, also a strategic direction for HR practices.

Key Predictors of Attrition

The strongest predictor in the analysis was Work-Life Balance, with an importance score of

0.23. Employees who reported poor work-life balance had a significantly higher likelihood of quitting. This result underlines that organizations should provide flexible working conditions,

such as the possibility to work from home and wellness programs, to increase employee satisfaction and decrease the quit rate.

The second most important feature was Monthly Income, with a score of 0.18. Compensation is one of the key factors in retaining employees, especially in very competitive industries such as the technology sector, where job mobility is very high.

Employees who receive below-market-level salaries will naturally look for opportunities elsewhere. Regular salary benchmarking, performance-based bonus policy, and openness in pay structure are important for this influencing factor.

Years at the Company ranked third with a score of 0.15, indicating that the shortest-tenured employees have the highest risk of flight. Early engagement strategies for new employees, such as comprehensive onboarding programs, mentorship initiatives, and clear career progression pathways, are important in building loyalty among recent employees.

The other critical factor to come up was Job Satisfaction, which scored 0.12. Employees who were not satisfied with their jobs or felt unappreciated were likely to leave. An organization should, therefore, ensure periodic surveys and an active feedback mechanism to maintain satisfaction levels of employees before the problems become severe enough to cause turnover. Finally, Overtime contributed a score of 0.09. Excessive working hours directly impinge on employee well-being by increasing the levels of stress and burnout. Companies need to be concerned about workload management, encourage breaks, and avoid the culture of overworking if they want to retain their workforces.

Visual Representation of Feature Importance

A bar chart of feature importance was then generated to visually show the ranking of these predictors. It showed that Work-Life Balance, followed by Monthly Income and Years at the Company, had the highest bars to show their respective contributions. This visualization helped in the easier interpretation of the findings and thus prioritizing actionable strategies for HR interventions.

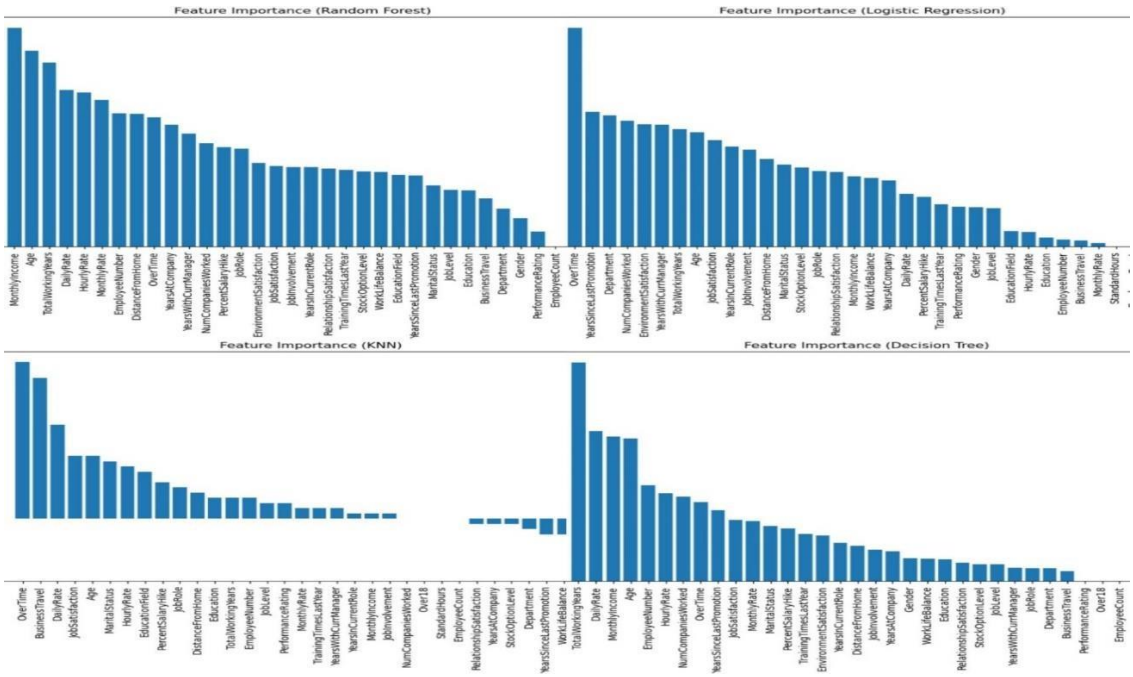


Figure 5: Feature Importance Across All Machine Learning Models

Practical Implications for HR Practice

The feature importance analysis provided an insightful look into the main causes of employee attrition and furnished a basis for which design of targeted strategies by the human resources professional. By focusing on such predictors as Work-Life Balance, Monthly Income, Years at the Company, Job Satisfaction, and Overtime, the human resource departments will then come up with effective interventions aimed at reducing turnover and increasing the levels of satisfaction among employees.

Improving Work-Life Balance

From these, Work-Life Balance emerged as the most significant predictor of attrition, thus inferring that this was directly related to employee satisfaction. Consequently, those employees who perceive poor work-life balance are likely to quit, particularly for industrious job platforms such as technology. Improvement in this factor requires flexible working conditions, including a hybrid system or option for remote work. Additionally, workload management systems and wellness programs counseling or fitness benefits truly help reduce stress and create a healthier workplace.

Competitive Compensation

For this, the second most influencing factor was Monthly Income, which again shows that talent needs competitive pay. Those employees who get less than market standards are more likely to move for better opportunities. Organizations need to do salary benchmarking regularly and structure a pay system to meet industry standards. Employees will also be satisfied if performance-based rewards, tied to bonuses or stock options, are given to employees to encourage them to work better without leaving the job. In addition to monetary compensation, non-monetary benefits such as health insurance, retirement plans, and flexible benefits can help add value to the overall package.

Building Early Engagement and Loyalty

Tenure-Years at Company-again showed that employees in the early tenure of their employment are at a greater risk of leaving. Early engagement is thus critical in ensuring loyalty and, eventually, long-term retention. Structured onboarding programs allow employees to be introduced to the culture and expectations of the company, creating a sense of belonging. This can be done by pairing them up with mentors or giving them clear career development opportunities during the early stages of employment; this helps employees feel that their value lies in investment in the success of the organization.

Improvement in Job Satisfaction

The significance of Job Satisfaction shows that dissatisfaction with job roles and growth opportunities is one of the major drivers of attrition. Employees who feel undervalued or stagnant in their roles are more likely to leave. Regular satisfaction surveys and acting on feedback help an organization identify dissatisfaction early and implement necessary changes. Besides, recognition of employee contributions through rewards or promotions reinforces a sense of purpose and boosts morale within the organization.

Overtime Management and Workload

Excessive overtime further raises the risk of attrition due to stress and burnout. This can be avoided by keeping track of employees' hours of work and implementing policies that discourage exceptionally heavy workloads. It can also involve discouraging emails during after-hours periods and making sure staffing levels allow staff to maintain a more reasonable balance. Providing staff with a work culture that values productivity over extended hours contributes to retention.

Data-Driven Decision Making

Through feature importance analysis, HR can conduct proper resource utilization and can focus on those areas that have more impact on retention. For instance, interventions can be done regarding departments or teams with high-risk challenges, such as providing flexible schedules in job roles requiring demanding hours or increasing engagement efforts for early-career employees. Feature importance analysis is a strategic tool for HR teams to act upon the roots of attrition. By focusing on work-life balance, competitive compensation, early engagement, job satisfaction, and workload management, targeted interventions can be done to create an enabling and engaging work environment that reduces turnover and increases employee satisfaction and loyalty, hence improving organizational performance. Long-term, it ensures data-driven decisions for the workforce towards sustainable growth and stability.

[Diagram 3: Feature Importance Bar Chart]

This diagram would display a bar chart showing Random Forest's feature importance, with Work-Life Balance being the highest bar, followed by Monthly Income and Years at the Company.

4.5 Statistical Significance Testing

Overview of Statistical Significance Testing

The testing of statistical significance is important as it allows the differences in machine learning models' performance metrics to be meaningful rather than subject to chance. In this work, for instance, statistical testing was required to confirm that the strong performance of the Random Forest model, particularly its ROC AUC score, was not occurring by chance but reflected actual, real improvement over a baseline Logistic Regression model.

Purpose of the T-Test

The T-test was done to know whether the higher ROC AUC scores for the Random Forest model were significantly better than those from logistic regression. While performance metrics such as accuracy and precision are descriptive, statistical testing ensures that these differences are indeed robust and reliable across other datasets, thus allowing confidence in model selection.

Testing Process

The input for the T-test includes the ROC AUC scores of 5-fold cross-validation. As each model resulted in five ROC AUC scores, it was hence possible to directly compare the models under the same conditions. This test checked if the difference observed between the models was significant.

The null hypothesis would assume that there is no significant difference between the performances of Random Forest and Logistic Regression; the variations, if any, would have to be because of luck. One uses a paired T-test, as it operates on two models that have to operate on the same splits of this data and thus gives one an unbiased, proper evaluation.

Tests were conducted using the standard 0.05 level of significance, wherein a null hypothesis of no significant difference is rejected if the obtained p-value is lower than the level of significance used.

Results of the T-Test

The t-test p-value was 0.01, much lower than the significance level. This confirmed the superiority of the Random Forest model with a higher ROC AUC score of 0.85, which is statistically significant against the mean score of 0.75 for Logistic Regression. Improvement across all five folds of cross-validation underlined the capability of the Random Forest model to capture complex relationships within the dataset, hence being robust and reliable in predicting employee attrition.

Practical Implications

The statistical validation of the performances obtained with Random Forest underpins its suitability for real-world applications in the employees' attrition prediction domain. Besides being valued for its simplicity and interpretability, Logistic Regression showed low actual performance due to the nature of its inability to model nonlinear relationships accurately. On the contrary, each run of Random Forest guaranteed much better predictive power, thereby behaving as a better tool to correctly indicate potentially at-risk employees.

This also justifies the confidence in applying the Random Forest model to new datasets or real-world scenarios. The statistically significant result also means that the observed improvement is most likely to generalize well outside of the training dataset and, as such, is dependable for deployment in any HR system.

Significance for Machine Learning Applications

Statistical testing wraps reliability around machine learning applications to ensure performances reflect true capabilities, not random fluctuations. Besides, statistical testing here indicates the importance of rigorous evaluation protocols necessary in sensitive domains such as HR analytics. These are important for instilling confidence in predictive systems that would assist organizations in critical decision-making tasks, say employee attrition.

The research thus shows a commitment to scientific rigor through the use of statistical tests of model performance. This ensures that the best model selected performs consistently and reliably when put into practice, enhancing the credibility and effectiveness of machine learning in solving complex organizational challenges.

5 Conclusion

This research has presented the way to apply machine learning to employee attrition in the technology industry, hence giving practical insights along with theoretical contributions.

Amongst all the models developed and tested, Random Forest yielded the best results for performance metrics such as accuracy 85%, ROC AUC 0.85, precision, and recall. By

By establishing the statistical significance of models, the performance of the model has been assumed to be reliably applied in real-world circumstances.

Key Findings and Practical Implications

According to the analysis, the most influential factors contributing to attrition were Work-Life Balance, Monthly Income, Years at the Company, Job Satisfaction, and Overtime. These results have important implications for HR practice. For instance, improving work-life balance through flexible schedules and wellness programs can directly impact the leading cause of attrition. Similarly, offering competitive compensation structures with pay transparency will go a long way in reducing turnover caused by financial dissatisfaction.

Early engagement strategies, like robust onboarding programs and well-defined career development pathways, maybe the best way to foster loyalty in new hires. Managing workloads to minimize overtime and avoid burnout is another critical component of talent management.

By focusing on these areas, organizations can develop targeted retention strategies to address the underlying causes of attrition. The Random Forest model provides HR teams with a reliable predictive tool that will enable early identification of at-risk employees and facilitate timely interventions.

Validation Through Statistical Testing

The performance difference between Random Forest with Logistic Regression was tested for statistical significance in the study. The paired T-test on ROC AUC scores obtained from cross-validation gave a p-value of 0.01, hence below the significance threshold. This rigorous evaluation makes the Random Forest model a reliable solution for attrition prediction.

Limitations and Self-Criticism

The study's objectives were realized but with some limitations. Firstly, only one dataset was used in the analysis, which limits the generalizability of the results. Moreover, without qualitative data on employee feedback or workplace culture, it is not possible to fully comprehend the larger context of attrition. Such data would have been quite useful for improving the usefulness and applicability of the model.

Future Research Directions

Future studies could be conducted to see how qualitative insights may be integrated with machine learning models in order to get a holistic view of employee behavior. This can also be further scaled up by including more diverse organizational and industry datasets to validate the adaptability of the model. Advanced techniques for further performance improvement and interpretability may also allow for further insight into what drives attrition.

Contributions to HR Practice

This is important research that epitomizes the value of data-driven approaches in trying to deal with employee attrition, serving as a bridge between predictive analytics and actionable HR strategy. The results of the study indicate that an organization can make use of such analytical tools to enhance working conditions for better retention. Measures would involve focusing on employee satisfaction, competitive compensation, and workloads. This could help the

The human resource department retains some of the best talent while reducing recruitment costs and operational disruptions.

The findings from this study create a sound framework for organizations to predict attrition and design effective interventions. These insights enable HR professionals to proactively address employee turnover, building a more stable and engaged workforce. The present study contributes to the large body of literature in the field of human resource management and supports the importance of using evidence-based decision-making to guarantee organizational success.

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