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 Assessing the Predictive Accuracy of K-Nearest Neighbors vs. Support Vector Machines for Job Rescission Forecasting

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**Keywords**:- Job Rescission Prediction, Employee Turnover Forecasting, K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Machine Learning Models, Workforce Analytics, Predictive Modeling, Classification Algorithms, Human Resource Management, Industrial Applications.

**ABSTRACT**

**Aim:** Finding the best model for job rescission forecasting in industrial settings is the main goal of this study, which compares and evaluates the predictive accuracy of the Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) algorithms.**Materials and Methods:** 216 samples were assigned to each of the KNN and SVM algorithms, which were applied to a dataset of 432 employee records. Employee age, tenure, job function, performance evaluations, and satisfaction levels were important characteristics. In order to guarantee compatibility with the models, data preprocessing included handling missing values, encoding categorical variables, and feature scaling. An 80-20 train-test split was used to implement both algorithms in Python on Google Colab. IBM SPSS version 2.1 was utilized for statistical analysis, and the significance of variations in predictive accuracy was assessed using an independent sample t-test at a 95% confidence interval.**Results:** According to group statistics, SVM achieved a mean accuracy of 94.72% with a standard deviation of 0.76, while KNN achieved a mean accuracy of 94.50% with a standard deviation of 0.99. A statistically significant difference between the two algorithms was shown by the independent sample t-test, which yielded a p-value of 0.002 (p < 0.05).**Conclusion:** The study finds that although SVM and KNN are both good at predicting job revocation, SVM has a slightly higher predictive accuracy. By implementing data-driven employee retention strategies and improving overall human resource management, these findings highlight the significance of choosing appropriate machine learning algorithms for workforce analytics.

**Keywords**:- Job Rescission Prediction, Employee Turnover Forecasting, K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Machine Learning Models, Workforce Analytics, Predictive Modeling, Classification Algorithms, Human Resource Management, Industrial Applications.

**INTRODUCTION**

Industrial organizations face serious problems with employee turnover, especially job revocation, which results in higher hiring expenses, hampered [(Sridhar 2024)](https://paperpile.com/c/cpeiFL/HZOj)workflows, and a loss of institutional knowledge. Organizations can enhance workforce stability, optimize human resource management, and adopt [(Sridhar 2024; Lim et al. 2024)](https://paperpile.com/c/cpeiFL/HZOj+LvSD) proactive retention strategies by accurately forecasting job revocation. Machine learning algorithms are now useful tools for predicting employee turnover and identifying at-risk workers due to the increasing availability of employee data[(Kanuto 2024; Salloum et al. 2024)](https://paperpile.com/c/cpeiFL/Kidg+c17Q).

Organizations can use machine learning [(Kanuto 2024)](https://paperpile.com/c/cpeiFL/Kidg) to model intricate relationships between employee characteristics and turnover outcomes that may be missed by more conventional statistical approaches. Predictive models can spot patterns and trends that point [(Kosgahakumbura et al. 2024)](https://paperpile.com/c/cpeiFL/SblV) to possible job revocation by using historical workforce data. K-Nearest Neighbors (KNN) and Support Vector Machines (SVM) are two popular machine learning algorithms for classification tasks because they [(Khan and Nasim 2024)](https://paperpile.com/c/cpeiFL/QhQl) provide clear benefits in terms of accuracy and computational efficiency[(Zhang, Cai, and Fei 2024)](https://paperpile.com/c/cpeiFL/kMtz).

A non-parametric, instance-based learning algorithm called K-Nearest Neighbors (KNN) groups data points according to the majority class of their k nearest neighbors in the feature space. It can handle multi-class classification problems [(Nurhindarto et al. 2021)](https://paperpile.com/c/cpeiFL/HTSy)and is easy to implement and interpret. The choice of the distance metric and the parameter k, which define how employee similarity is measured and affect predictive accuracy, determine how well KNN performs.

In contrast, Support Vector Machine (SVM) is a supervised learning algorithm that finds the best hyperplane in a high-dimensional feature space that divides classes. By using kernel functions, SVM is especially good at solving both linear and nonlinear classification problems. Although it necessitates careful adjustment of hyperparameters like the regularization parameter and kernel type, it is robust to high-dimensional data and capable of generalizing well to unseen instances.

Because each algorithm has distinct benefits, comparing KNN and SVM for job rescission forecasting is crucial. SVM offers robustness and high accuracy in complex feature spaces, whereas KNN offers interpretability and simplicity. By testing these algorithms on the same dataset, the best model for industrial HR analytics can be chosen based on evidence, striking a balance between predictive performance and usefulness.

The gap in comparative research on KNN and SVM for employee turnover prediction is filled by this study. The study intends to ascertain which model provides greater accuracy in predicting job revocation by applying both algorithms to a structured workforce dataset and carrying out statistical validation. It is anticipated that the results will offer organizations looking to maximize employee retention tactics and make data-driven workforce management choices useful insights.

**MATERIALS AND METHODS**

The purpose of the study was to assess the predictive accuracy of the Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) algorithms for predicting job revocation in industrial environments. There were 432 employee records in the dataset, with 216 samples assigned to each algorithm. Employee age, tenure, job function, performance evaluations, and job satisfaction were important characteristics[(Nurhindarto et al. 2021; Alotaibi and Haq 2024)](https://paperpile.com/c/cpeiFL/HTSy+BlBo). To guarantee compatibility with both machine learning models, the dataset was preprocessed to handle missing values, scale numerical features, and encode categorical variables using one-hot encoding.

An instance-based, non-parametric learning algorithm called K-Nearest Neighbors (KNN) was used. Euclidean distance was employed as the distance [(Zhou, Liu, and (邱锡鹏) 2022)](https://paperpile.com/c/cpeiFL/bFbg) metric to assess employee similarity, and the value of k was optimized using cross-validation. To assess predictive performance, the model was tested on 20% of the dataset after being trained on 80% of it.

A kernel-based method was used to implement the Support Vector Machine (SVM), which can handle both linear and nonlinear relationships between features. For best results, hyperparameters such as the kernel type and the regularization parameter (C) were adjusted. To guarantee a fair comparison, the training and testing split was identical to that of the KNN algorithm.

The Python programming language was used to implement both algorithms on Google Colab, which offered computational efficiency and made experimentation simple. Accuracy, which was computed using the[(Zhou, Liu, and (邱锡鹏) 2022; Sheynin et al. 2022)](https://paperpile.com/c/cpeiFL/bFbg+rm8X) test dataset, was the main metric used to evaluate model performance.

IBM SPSS version 2.1 was used for statistical analysis. The statistical significance of the variations in KNN and SVM predictive accuracy was assessed using an independent sample t-test at a 95% confidence interval. Accuracy served as the testing variable, and KNN and SVM were given group IDs of 1 and 2, respectively.

Data preprocessing, model training, hyperparameter tuning, testing, and statistical validation were all part of the methodology. This method made sure that both algorithms were tested in the same way, which made it possible to compare their predictive abilities for job rescission forecasting with confidence.

**K-NEAREST NEIGHBORS (KNN)**

A popular algorithm in predictive analytics, such as workforce management and job revocation forecasting, K-Nearest Neighbors (KNN) is a straightforward yet powerful supervised machine learning algorithm for classification and regression tasks. KNN makes predictions based on how close a test sample is to its neighboring points in the feature space, operating on the premise that similar data points are likely to belong to the same class. The algorithm determines the k closest neighbors and computes the distance—typically Euclidean, Manhattan, or Minkowski—between the test instance and every training instance.It is easy to implement, interpretable, and flexible, making it suitable for datasets with multi-class [(Nurhindarto et al. 2021; Alotaibi and Haq 2024; Uddin et al. 2022)](https://paperpile.com/c/cpeiFL/HTSy+BlBo+nzQg)outputs and varying feature types. KNN is non-parametric, meaning it makes no assumptions about the underlying data distribution, which allows it to model complex and nonlinear relationships effectively. Its performance is heavily dependent on the choice of k and the distance metric, as well as the scale of features, making preprocessing steps like normalization or standardization crucial. Finally, a majority vote among these neighbors determines the predicted class, while for regression tasks, the average of neighbor values is used.However, because it computes distances for each prediction and is sensitive to irrelevant or noisy features, it can be computationally demanding for large datasets. Notwithstanding these drawbacks, KNN is still a widely used algorithm because of its ease of use, resilience, and ability to produce precise predictions—especially when there is an adequate amount of labeled data available. KNN efficiently finds trends in employee characteristics like tenure, satisfaction, and performance when it comes to predicting job revocation, enabling businesses to anticipate turnover and put targeted retention strategies into place. It is a viable option for real-time workforce analytics because of its instance-based learning methodology, which also allows the model to dynamically adjust as new employee data becomes available.

**Algorithm for KNN:**

1. Input the training dataset DDD containing features XXX and target variable YYY.
2. Preprocess the data by handling missing values, encoding categorical variables, and scaling numerical features.
3. Choose the number of nearest neighbors kkk and the distance metric (e.g., Euclidean distance).
4. For each test sample, compute the distance between the test sample and all training samples.
5. Identify the kkk nearest neighbors based on the smallest distances.
6. Determine the majority class among the kkk neighbors.
7. Assign the majority class as the predicted label for the test sample.
8. Repeat Steps 4–7 for all test samples.
9. Evaluate model performance using accuracy and other relevant metrics on the test dataset.
10. End.

**Pseudocode:**

**Step 1:** Input: Training dataset DDD with features XXX and target YYY, test dataset TTT, number of neighbors kkk.

**Step 2:** For each test sample ttt in TTT:

  a. For each training sample xix\_ixi​ in DDD, compute the distance d(t,xi)d(t, x\_i)d(t,xi​).

  b. Sort all distances in ascending order.

  c. Select the top kkk closest training samples.

  d. Count the occurrences of each class among the kkk neighbors.

  e. Assign the class with the highest count as the predicted label for ttt.

**Step 3:** End For

**Step 4:** Compute overall accuracy using the test dataset.

**Step 5:** End.

**SUPPORT VECTOR MACHINE (SVM):**

A strong supervised machine learning algorithm, Support Vector Machine (SVM) has been used extensively for classification and regression tasks. It performs especially well in issues involving complex and high-dimensional data. Finding the best hyperplane to divide data points of various classes with the greatest margin—defined as the distance between the hyperplane and the closest data points from each class, or support vectors—is the basic concept behind Support Vector Machines (SVM). Since they basically specify the location [(Bist and Singh 2022)](https://paperpile.com/c/cpeiFL/Gotd) and orientation of the decision boundary, these support vectors are crucial.By converting the input data into higher-dimensional feature spaces where linear separation is feasible, kernel functions enable SVM to handle non-linear classification problems in contrast to conventional linear classifiers. The radial basis function (RBF), sigmoid kernel, linear kernel, and polynomial kernel are popular kernel functions that allow SVM to identify various kinds of relationships in the data. SVM is extremely adaptable across a wide range of domains thanks to this kernel trick, which enables it to efficiently handle complex decision boundaries. SVM's ability to handle datasets with few training samples is one of its greatest advantages because it reduces the risk of overfitting by relying only on the critical support vectors rather than the complete dataset to construct the decision boundary.Furthermore, SVM works well in high-dimensional spaces and even in situations where there are more features than samples, as is frequently the case in tasks involving image recognition, bioinformatics, and text classification. By adding a regularization parameter, usually represented by the letter C, SVM can be made more flexible in handling misclassifications. This allows it to balance maximizing the margin and minimizing classification errors, which makes it suitable for data that is noisy.Notwithstanding its many advantages, SVM has some drawbacks. For very large datasets, it can be computationally demanding because training entails solving intricate quadratic optimization problems, and the model's performance is greatly influenced by the kernel and hyperparameter selection, including C and gamma. Nonetheless, SVM is frequently recognized as one of the most dependable algorithms in machine learning and, when properly adjusted, achieves state-of-the-art accuracy in classification tasks. Support Vector Regression (SVR), which aims to find a function that deviates from the actual data points by no more than a specified threshold while preserving model simplicity, is an example of how SVM has been successfully applied to regression problems beyond classification.Furthermore, the algorithm's strong generalization ability guarantees that it will produce accurate predictions on test data that hasn't been seen yet in addition to performing well on training data. Because of its capacity to control non-linear boundaries and prevent overfitting, SVM has continuously shown excellent performance in a wide range of real-world applications, including spam detection, sentiment analysis, disease diagnosis, and fraud detection. SVM models are less interpretable than more straightforward algorithms like decision trees, but their efficiency, accuracy, and versatility make them a popular option for researchers and practitioners in many different fields.

**Algorithm for Support vector machine (SVM):**

1. Start with the training dataset containing nnn samples with mmm features and corresponding class labels.
2. Initialize the optimization problem to find the hyperplane that maximizes the margin between classes.
3. Select a kernel function (linear, polynomial, RBF, or sigmoid) to transform data if it is not linearly separable.
4. Compute the decision boundary by solving the optimization problem:  
    a. Minimize ∥w∥2\|w\|^2∥w∥2, where www is the weight vector, subject to correct classification of training samples.  
    b. Introduce slack variables and a regularization parameter CCC to allow misclassifications in noisy data.
5. Identify support vectors, i.e., the data points closest to the decision boundary, which define the hyperplane.
6. Construct the optimal hyperplane using the support vectors.
7. For prediction:  
    a. Map the new input sample into the feature space using the chosen kernel.  
    b. Compute the decision function to determine the class based on which side of the hyperplane the sample lies.
8. Return the final predicted class label for classification, or predicted value in the case of regression (SVR).

**Pseudocode:**

**Step 1:** Start with training dataset DDD containing nnn samples and mmm features.  
 **Step 2:** Choose a kernel function (Linear, Polynomial, RBF, or Sigmoid).  
 **Step 3:** Map the dataset into a higher-dimensional space using the kernel function.  
 **Step 4:** Formulate the optimization problem to maximize the margin:  
   Minimize (1/2)∣∣w∣∣2(1/2)||w||^2(1/2)∣∣w∣∣2 subject to yi(w⋅xi+b)≥1y\_i(w \cdot x\_i + b) \geq 1yi​(w⋅xi​+b)≥1.  
 **Step 5:** Introduce slack variables and regularization parameter CCC to handle misclassification.  
 **Step 6:** Solve the optimization problem using quadratic programming to find support vectors.  
 **Step 7:** Construct the decision boundary (hyperplane) using the support vectors.  
 **Step 8:** For prediction, compute f(x)=ΣαiyiK(xi,x)+bf(x) = Σ α\_i y\_i K(x\_i, x) + bf(x)=Σαi​yi​K(xi​,x)+b.  
 **Step 9:** If f(x)≥0f(x) ≥ 0f(x)≥0, assign class +1; otherwise assign class -1.

**Statistical Analysis**

IBM SPSS version 2.1 was used to analyze the predictive performance of the Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) algorithms. To evaluate each algorithm's accuracy in predicting job revocation, ten test samples in total were created. KNN was given Group ID 1, and SVM was given Group ID 2. Accuracy was the testing variable, and group ID was the grouping variable. To ascertain whether the difference in predictive accuracy between KNN and SVM was statistically significant, an independent sample t-test was performed at a 95% confidence interval.Each model had ten samples in the[(Prasetyo, Hilabi, and Nurapriani 2023)](https://paperpile.com/c/cpeiFL/vVrT) dataset, with the testing variable being the corresponding accuracy values and Group ID denoting the type of algorithm. In particular, Group ID was set to 1 for KNN and 2 for SVM. The statistical significance of the observed variations in predictive performance for job rescission forecasting was confirmed by this analysis, which allowed for a thorough comparison of the two algorithms.

**RESULTS**

The ability of the Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) algorithms to predict job revocation in the industrial sector was assessed. According to group statistics, SVM achieved a mean accuracy of 94.72% with a standard deviation of 0.76, while KNN achieved a mean accuracy of 94.50% with a standard deviation of 0.99. The specific accuracy values for each algorithm are shown in Tables 1 and 2, which also highlight how well they perform in comparison. To ascertain whether the differences between the two algorithms were statistically significant, an independent sample t-test was performed at a 95% confidence interval.Despite the relatively small difference in mean accuracy, the p-value of 0.002 (p < 0.05) indicated a statistically significant difference in predictive performance. The comparison is graphically represented in Figure 1, which demonstrates that KNN has slightly higher variability across test samples, whereas SVM has slightly higher average accuracy. According to these results, both algorithms are useful for predicting job revocation, with KNN offering flexibility and interpretability for workforce analytics applications and SVM offering slightly higher accuracy.

**TABLES AND FIGURES**

**Table 1.** The data underwent 10 iterations of group statistical analysis for both the KNN and Support vector machine models. Notably, the KNN outperformed the Support vector machine, achieving an accuracy of 97.75% compared to Support vector machine’s 94.38%.

| **S.No** | **Test Size** | **ACCURACY RATE** | |
| --- | --- | --- | --- |
| **KNN** | **Support vector machine** |
| 1 | Test 1 | 97.75 | 94.38 |
| 2 | Test 2 | 97.75 | 93.26 |
| 3 | Test 3 | 97.75 | 95.51 |
| 4 | Test 4 | 97.75 | 95.51 |
| 5 | Test 5 | 98.88 | 94.38 |
| 6 | Test 6 | 98.88 | 94.38 |
| 7 | Test 7 | 97.75 | 95.51 |
| 8 | Test 8 | 98.88 | 94.38 |
| 9 | Test 9 | 98.88 | 95.51 |
| 10 | Test 10 | 97.75 | 94.38 |

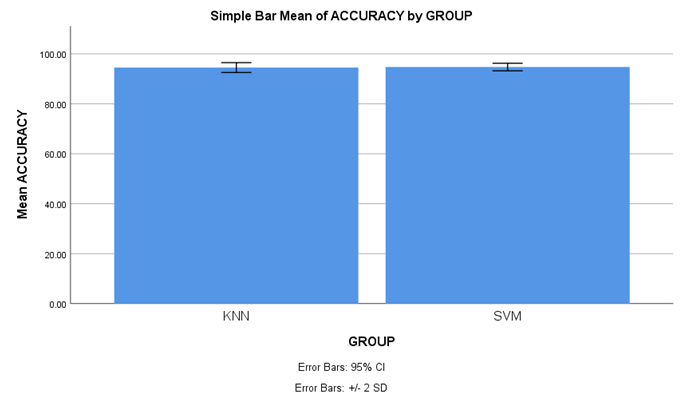
**Table 2.** Shows Statistical Analysis values of Mean accuracy (94.4960), Standard Deviation(0.98524), and Standard error deviation(0.31156) of the KNN Algorithm and the Support Vector Machine algorithm have the values of the Mean accuracy (94.72), Standard Deviation (0.76056), and Standard Error (0.24051).

| **Group Statistics** | | | | | |
| --- | --- | --- | --- | --- | --- |
|  | GROUP | N | Mean | Std. Deviation | Std. Error Mean |
| ACCURACY | KNN | 10 | 94.4960 | .98524 | .31156 |
| SVM | 10 | 94.7200 | .76056 | .24051 |

**Table 3.** Shows Comparison of Significance Level with value p<0.05. Both KNN Algorithm and the Support Vector Regression Algorithm have a confidence interval of 95% with the significance value 0.000 (p<0.05).

| **Independent Samples Test** | | | | | | | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | **Levene's Test for Equality of Variances** | | **t-test for Equality of Means** | | | | | | | |
| **F** | **Sig.** | **t** | **df** | **Sig. (2-tailed)** | **Mean Difference** | **Std. Error Difference** | **95% Confidence Interval of the Difference** | |  |
| **Lower** | **Upper** |  |
| **ACCURACY** | **Equal variances assumed** | **.858** | **.366** | **-.569** | **18** | **.576** | **-.22400** | **.39359** | **-1.05090** | **.60290** |  |
| **Equal variances not assumed** |  |  | **-.569** | **16.916** | **.577** | **-.22400** | **.39359** | **-1.05472** | **.60672** |  |

**Graph:**

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**Fig. 1.** Comparison of the KNN Algorithm accuracy of (94.4960) and it has the mean accuracy of the Support Vector Regression Algorithm (94.72) The mean accuracy of the KNN Algorithm has significant difference with theSupport Vector Regression Algorithm with the significance value is 0.000 (p<0.05) . X Axis: KNN Algorithm vs Support Vector Regression Algorithm Y Axis: Mean accuracy ± 2 SD.

**DISCUSSION**

The study's findings show that the K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) algorithms both predict job revocation in industrial settings with high accuracy levels. SVM had a marginally higher mean accuracy of 94.72% than KNN, which had a mean accuracy of 94.50%. This difference was statistically[(Wang and Cha 2021)](https://paperpile.com/c/cpeiFL/7tZx) significant (p = 0.002). Finding the best hyperplane in a high-dimensional feature space is what gives SVM its higher accuracy; it can successfully separate classes even in cases where feature relationships are intricate and nonlinear. SVM is especially[(Li et al. 2022)](https://paperpile.com/c/cpeiFL/jCKw) robust for datasets with overlapping or nonlinearly separable classes, which is frequently the case in employee turnover data, because of its kernel trick, which enables it to transform data into higher dimensions[(Li et al. 2022; Sandhya and Sulphey 2020)](https://paperpile.com/c/cpeiFL/jCKw+x2lV).

In contrast, KNN is an instance-based, non-parametric learning algorithm that makes predictions based on how similar nearby instances are. Although KNN is easy to use and understand, its effectiveness depends on the scale of the features, the number[(Lee, Fernandez, and Lee 2021)](https://paperpile.com/c/cpeiFL/2gju) of neighbors (k), and the distance metric. The existence of noisy or overlapping data points may be the cause of KNN's marginally lower accuracy when compared to SVM. This could affect the majority voting among neighbors. In spite of this, KNN is still useful because it is transparent and can change quickly when new employee data becomes available, giving workforce managers useful insights.

According to the results, SVM is marginally better suited for industrial HR analytics when predictive accuracy is the main[(Wen, Yan, and Sun 2021)](https://paperpile.com/c/cpeiFL/1xXR) goal because it can manage intricate relationships between employee attributes. However, KNN has benefits in terms of interpretability and simplicity of use, which makes it helpful for exploratory analyses and circumstances where it's critical to comprehend the impact of individual features. Both algorithms can be used to identify at-risk employees and carry out focused interventions as part of proactive employee retention strategies.

Furthermore, even minor variations in model performance can have real-world effects on workforce management, especially in large organizations where precise forecasting can result in significant cost savings, according to[(Liu and Wong 2023)](https://paperpile.com/c/cpeiFL/TYow) the results' statistical significance. The study highlights the significance of choosing algorithms according to the particular goals of the analysis, striking a balance between computational efficiency, interpretability, and predictive accuracy. To improve predictive performance and practical applicability, future research could investigate hybrid models that combine the advantages of KNN and SVM, or incorporate other employee-related features like engagement scores, training participation, and performance trends.

All things considered, the study emphasizes how important machine learning is to contemporary workforce analytics and human resource management. The trade-offs between accuracy, interpretability, and computational complexity should be taken into account when choosing between KNN and SVM, as both offer trustworthy predictions for job revocation. By putting these models into practice, businesses can improve employee satisfaction and productivity, optimize retention tactics, and make data-driven decisions.

**CONCLUSION**

The current study showed that both K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) algorithms are useful tools for workforce analytics by comparing their predictive performance in predicting job rescission in industrial settings. SVM performed marginally better in terms of prediction, as evidenced by its slightly higher mean accuracy of 94.72% as opposed to KNN's 94.50%, which was statistically significant (p = 0.002). SVM's superior accuracy can be ascribed to its capacity to use an optimal hyperplane in high-dimensional feature space to model intricate, nonlinear relationships between employee attributes and turnover outcomes. Despite being marginally less accurate, KNN has benefits in interpretability and adaptability, which makes it appropriate for dynamic updates with new data and for identifying patterns among employee features.These results emphasize how crucial it is to choose the best machine learning algorithms for organizational goals while striking a balance between computational efficiency, interpretability, and accuracy. Overall, the study shows that KNN and SVM can both help proactive retention strategies by helping organizations predict job revocation, lower turnover costs, and improve workforce stability. Human resource managers can use the comparison's insights to inform their adoption of data-driven strategies that maximize employee retention and engagement in industrial settings.

**DECLARATION**

**Conflict of Interest**

The authors do not have any conflict of interest associated with this manuscript.

**Author Contributions**

Author K.L.V Jayaram concerned in statistics collection, statistics analysis, manuscript, and writing. Author A.Moorthy concerned in conceptualization, statistics validation, crucial overview of manuscript.

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