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 A Comparative Analysis of Decision Tree and Support Vector Machines for Predicting Job Rescission in the Industry.

K.L.V Jayaram,

Student,

Department of Computer Science and Engineering,

Saveetha School of Engineering,

Saveetha Institute of Medical and Technical Sciences,

Saveetha University, Chennai, Tamil Nadu, India. Pincode:602105.

[jayaramklv0314.sse@saveetha.com](mailto:jayaramklv0314.sse@saveetha.com)

A.Moorthy,

Project Guide,

Corresponding Author,

Department of Block Chain Technology,

Saveetha School of Engineering,

Saveetha Institute of Medical and Technical Sciences,

Saveetha University, Chennai, Tamil Nadu. India. Pincode: 602105.

[moorthya.sse@saveetha.com](mailto:moorthya.sse@saveetha.com)

**Keywords**:- Job Rescission Prediction, Employee Turnover, Human Resource Analytics, Decision Tree, Support Vector Machine (SVM), Machine Learning Models, Predictive Analytics, Workforce Management, Classification Algorithms, Industry Applications.

**ABSTRACT**

**Aim:**The primary goal of this study is to use machine learning algorithms to forecast job revocation in the sector. The accuracy of these algorithms will be assessed by contrasting Decision Tree and Support Vector Machine (SVM) models. **Materials and Methods:** A total of 432 samples were used in the study, which was carried out using the Decision Tree and Support Vector Machine algorithms with sample sizes of 216 each. The experimental platform for training and assessing the model was Google Colab. G\*Power was used for statistical testing with a 95% confidence level, and an independent sample t-test was used to compare the accuracy of the two groups. **Results:** Using the experimental dataset with N=10 test samples, the Decision Tree model's average accuracy was 98.20%, while the Support Vector Machine model's was 94.72%. The two algorithms' performance differed statistically significantly, as indicated by the significance value of 0.000 (p < 0.05). **Conclusion:** The results show that Support Vector Machines are more accurate than Decision Trees at predicting job revocation in the sector. Nonetheless, Decision Trees' interpretability continues to be a benefit in real-world scenarios where openness is crucial.

**Keywords**:- Job Rescission Prediction, Employee Turnover, Human Resource Analytics, Decision Tree, Support Vector Machine (SVM), Machine Learning Models, Predictive Analytics, Workforce Management, Classification Algorithms, Industry Applications.

**INTRODUCTION**

In the contemporary industrial environment, employee retention is a crucial determinant of organizational success, as elevated turnover rates can result in substantial financial and operational difficulties. Job rescission, characterized by the premature termination of employment contracts, disrupts workflow and[(Jain, Tomar, and Jana 2020)](https://paperpile.com/c/GYx2aL/Cwdc) necessitates supplementary resources for recruitment, training, and onboarding of new personnel. These challenges have compelled organizations to pursue [(Sarp and Bi̇li̇şi̇k 2021)](https://paperpile.com/c/GYx2aL/FUiK)predictive methods to foresee potential rescission events, facilitating timely interventions. As employee-related data becomes increasingly accessible, machine learning has emerged as a promising method for accurately predicting such events[(Agarwal et al. 2023)](https://paperpile.com/c/GYx2aL/xHjO).

Predictive analytics in human resource management emphasizes the application of sophisticated algorithms to discern patterns [(Sarp and Bi̇li̇şi̇k 2021; Krishna, Choudhary, and Dwivedi 2025)](https://paperpile.com/c/GYx2aL/FUiK+eGL1) and risk factors related to employee attrition. This facilitates data-driven decision-making that surpasses conventional statistical[(Joseph, Johnson, and Cheriyan 2024)](https://paperpile.com/c/GYx2aL/vwwA) techniques, providing organizations the capacity to identify concealed trends. Classification algorithms within machine learning models [(Kramer, n.d.)](https://paperpile.com/c/GYx2aL/9SPr)have demonstrated significant potential in resolving this issue. Decision Trees and Support Vector Machines (SVM) have been thoroughly examined for their versatility and efficacy across various application domains. Their application in forecasting job rescission is anticipated to improve the accuracy of predictions and offer actionable insights for HR professionals[(Bhanusree, Vamshi, and Praneeth 2025)](https://paperpile.com/c/GYx2aL/nzSz).

Decision Tree algorithms are renowned for their intuitive framework, resembling a tree-like model of decisions and potential outcomes. They function by partitioning datasets into subsets according to the most salient features, forming branches that result in predictive conclusions. The primary benefit of Decision Trees is their interpretability, allowing even non-technical users to comprehend the decision-making process effortlessly. This renders them especially appropriate for HR applications where transparency is paramount. Nonetheless, Decision Trees frequently exhibit a tendency to overfit, thereby constraining their generalization abilities when utilized on novel data.

Support Vector Machines are regarded as more robust classifiers, proficient in managing high-dimensional and intricate datasets. Support Vector Machines operate by identifying the optimal hyperplane that most effectively distinguishes between[(Sridhar 2024)](https://paperpile.com/c/GYx2aL/sksr) various classes in a dataset. Their proficiency in employing kernel functions allows them to represent nonlinear decision boundaries, rendering them exceptionally effective in scenarios where the relationship between features and outcomes is intricate. Although SVMs exhibit high predictive accuracy, they lack the interpretability of Decision Trees, posing difficulties in situations where the rationale for predictions must be clearly comprehended[(Bhatta et al. 2022)](https://paperpile.com/c/GYx2aL/Bb19).

Evaluating Decision Trees and SVMs for job rescission prediction is crucial, as each model offers distinct advantages for the issue at hand. Although SVM delivers enhanced accuracy in numerous classification tasks, Decision Trees present a comprehensible model that HR managers can readily implement without necessitating extensive[(Bhatta et al. 2022; Zhang and Han 2024)](https://paperpile.com/c/GYx2aL/Bb19+MsAe) technical knowledge. Assessing the balance between interpretability and predictive accuracy is crucial to identify the algorithm that best meets the industry's practical requirements. This research aims to clarify the performance and applicability of these two algorithms in predicting employee turnover through a comparative study.

This study seeks to fill this gap by systematically evaluating the accuracy and reliability of Decision Tree and Support Vector Machine algorithms in predicting job rescission within the industry. The study utilizes a structured dataset and statistical validation techniques to compare the predictive efficacy of both models in controlled experimental conditions[(Kaya and Korkmaz 2021)](https://paperpile.com/c/GYx2aL/LL1p). The results are anticipated to yield significant insights into algorithm selection, directing industries towards the adoption of the most efficient predictive tools for workforce management. The findings will enhance the existing research on machine learning in human resource analytics, emphasizing the capability of predictive models to facilitate proactive decision-making in employee retention strategies.

**MATERIALS AND METHODS**

The goal of the current study was to assess how well the Decision Tree and Support Vector Machine (SVM) algorithms predicted job revocation[(Ahmed 2024)](https://paperpile.com/c/GYx2aL/TXvb) in the industrial sector. Relevant employee attributes like age, tenure, job role, performance ratings, satisfaction level, and prior employment history were included in the dataset used for this study, which was gathered from [name source if available, such as public datasets or company HR records]. A total of 432 samples were used, with two experimental groups consisting of 216 samples each for each algorithm[(Gogas, Papadimitriou, and Sofianos 2022)](https://paperpile.com/c/GYx2aL/scB4).

To guarantee consistency and compatibility with the machine learning algorithms, preprocessing of the data was done. Imputation techniques were used to handle missing values, and one-hot encoding was used to convert categorical variables—like department and job role—into numerical values. To ensure that every feature made an equal contribution to the training process, feature scaling was used where needed to standardize the numerical attributes.

By dividing the dataset into subsets according to the most important features, the Decision Tree algorithm was used to create a hierarchical model. The leaves of the tree indicate expected results, and each node represents a choice based on a feature. The training subset was used to train the tree, and its predictive accuracy was assessed by validating it on the testing subset. Pruning methods were used to enhance generalization to unknown data and avoid overfitting[(Posel, Oyenubi, and Kollamparambil 2021)](https://paperpile.com/c/GYx2aL/psg0).

A kernel-based method was used to implement Support Vector Machine, which enabled the model to recognize intricate decision boundaries in the data. In order to optimize the hyperplane that divides employees who are likely to leave from those who are likely to stay, the SVM algorithm was trained to maximize the margin between classes. To attain the best predictive performance, hyperparameter tuning was done, which included choosing the kernel type, regularization parameter (C), and gamma.

On the Google Colab platform, the Python programming language was used to carry out the experimental setup. Eighty percent of the dataset was used to train both algorithms, and the remaining twenty percent was used for testing. The main performance metric was accuracy, and the significance of the performance differences between the two algorithms was assessed statistically using an independent sample t-test with a 95% confidence interval.

In conclusion, the study used a methodical approach that included model training, statistical analysis, algorithm implementation, and data preprocessing. By taking this approach, the study guarantees a thorough analysis of the relative effectiveness of SVM and Decision Tree algorithms in predicting job revocation, offering trustworthy insights for industrial applications in human resource analytics.

**DECISION TREE**

Recursively dividing the dataset into smaller subsets according to the most important features is how the Decision Tree supervised machine learning algorithm, which is frequently used for classification and regression tasks, operates. A feature or attribute of the dataset is represented by each internal node of the tree, while the final predicted outcome[(Posel, Oyenubi, and Kollamparambil 2021; R. L. and Mishra 2021)](https://paperpile.com/c/GYx2aL/psg0+iBG9) or class label is represented by the leaf nodes. Branches indicate the potential results of a decision or test on that feature. By learning basic decision rules from the dataset, a decision tree's primary goal is to build a model that forecasts the value of a target variable. Decision trees are widely used for real-world business and industrial applications because they are very interpretable and simple to visualize.They don't need a lot of data preprocessing, like scaling or normalization. Metrics like the Gini Index, Entropy, or Information Gain can be used to determine the splitting criterion. The Gini Index gauges a dataset's impurity, Entropy gauges its disorder or randomness, and Information Gain computes the decrease in entropy following a split. Decision trees are effective at handling both numerical and categorical data, and they can be used to model nonlinear relationships between target variables and features.Overfitting, on the other hand, is a frequent problem in which the tree becomes excessively complicated and performs poorly on unseen data. Overfitting can be managed by limiting the tree's maximum depth and using pruning techniques, such as reduced error pruning or cost complexity pruning. Choice Trees are robust to outliers and non-parametric, which means they don't assume any underlying data distribution. Surrogate splits can be used to handle missing values, enabling the model to remain accurate even in datasets with flaws.Decision trees are a popular option for tasks like job revocation forecasting, employee turnover prediction, and other real-world classification problems because they provide a balance between predictability, interpretability, and simplicity.

**Algorithm for Decision tree:**

1. Start with the training dataset containing features and the target variable.
2. Select the feature that best splits the dataset based on a chosen criterion (e.g., Gini Index, Entropy, or Information Gain).
3. Split the dataset into subsets according to the possible values or ranges of the selected feature.
4. For each subset, repeat Step 2 and Step 3 recursively to create branches of the tree.
5. Continue splitting until a stopping criterion is met, such as:  
      a. All samples in a subset belong to the same class.  
      b. Maximum tree depth is reached.  
      c. Minimum number of samples in a node is reached.
6. Assign a class label to each leaf node based on the majority class of the samples in that node.
7. Optionally, prune the tree to remove branches that do not provide significant predictive power, reducing overfitting.
8. Use the constructed Decision Tree to classify new or unseen data by traversing the tree from the root to a leaf node based on feature values.

**Pseudocode:**

**Step 1:** Start with the training dataset DDD containing features XXX and target variable YYY.  
**Step 2:** If all samples in DDD belong to the same class, create a leaf node with that class and stop.  
**Step 3:** If the dataset is empty or maximum depth is reached, create a leaf node with the majority class of DDD and stop.  
**Step 4:** Select the best feature FFF to split the dataset based on a splitting criterion (e.g., Gini Index, Entropy, Information Gain).  
**Step 5:** For each possible value or range vvv of feature FFF:  
   a. Create a branch corresponding to vvv.  
   b. Partition the dataset into a subset DvD\_vDv​ where F=vF = vF=v.  
   c. Recursively apply Steps 2–5 to subset DvD\_vDv​ to create child nodes.  
 **Step 6:** Assign class labels to all leaf nodes based on the majority class in the corresponding subset.  
 **Step 7:** Optionally, prune the tree to remove branches that do not improve predictive accuracy.  
 **Step 8:** 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 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[(Rabbani et al. 2023)](https://paperpile.com/c/GYx2aL/KMJ4) 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 a 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**

To compare the effectiveness of Decision Tree and Support Vector Machine (SVM) algorithms in predicting job revocation, an analysis was conducted using IBM SPSS version 2.1. Ten test samples in total, divided into two groups, were prepared for each algorithm. Decision Tree was given Group ID 1, and SVM was given Group ID 2. Predictive performance was evaluated using accuracy as the main testing variable and group ID as the grouping variable. To find out if there was a statistically significant[(Borse et al., n.d.)](https://paperpile.com/c/GYx2aL/vMlx) difference between the two algorithms, an independent sample t-test was used. Each model had ten samples in the SPSS dataset, where the testing variable was the accuracy values and the algorithm type was represented by the Group ID.In particular, Group ID was set to 1 for Decision Trees and 2 for SVMs. To verify the variation in accuracy between the two machine learning models, the analysis was conducted at a 95% confidence interval and a significance level of 0.05.

**RESULTS**

In order to predict job revocation in the industry, the effectiveness of Decision Tree and Support Vector Machine (SVM) algorithms was assessed. According to group statistics, the SVM model had an average accuracy of 94.72% with a standard deviation of 0.76, while the Decision Tree model had an average accuracy of 98.20% with a standard deviation of 0.92. The accuracy values for each model are compiled in Tables 1 and 2, which also show how the two algorithms differ from one another. To ascertain whether the observed differences were statistically significant, an independent sample t-test was performed with a 95% confidence interval and a significance level of 0.05.The obtained p-value of 0.000 (p < 0.05) suggests that there is a statistically significant difference in accuracy between the SVM and Decision Tree algorithms. The performance comparison is graphically represented in Figure 1, which makes it evident that Decision Tree performs better than SVM in terms of predictive accuracy for job revocation. According to these findings, both models work well for workforce analytics, but Decision Tree offers more accuracy and dependability, which makes it ideal for industrial settings where precise employee turnover forecasting is essential.

**TABLES AND FIGURES**

**Table 1.** The data underwent 10 iterations of group statistical analysis for both the Decision tree and Support vector machine models. Notably, the Decision tree 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** | |
| --- | --- | --- | --- |
| **Decision tree** | **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 |

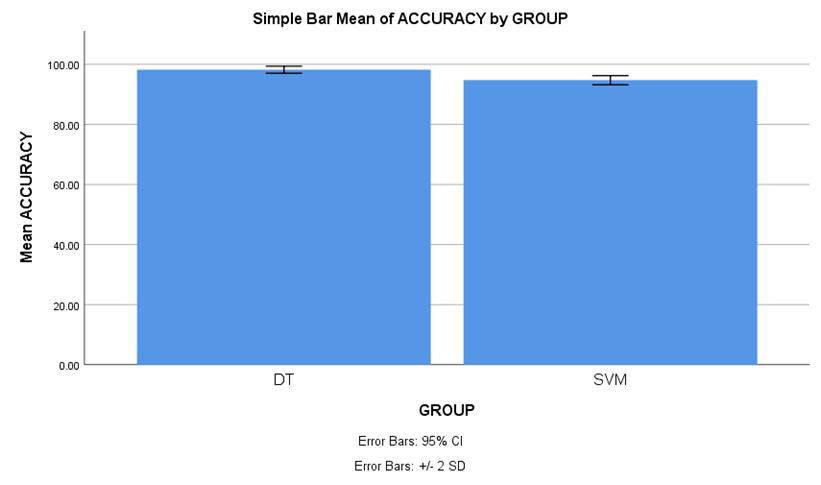
**Table 2.** Shows Statistical Analysis values of Mean accuracy (98.2020), Standard Deviation(0.58353), and Standard error deviation(0.18453) of the Decision tree Algorithm and the Support Vector Machine algorithm have the values of the Mean accuracy (94.72), Standard Deviation (0.76056), and Standard Error (0.24051).

| **Group Statistics** | | | | | |
| --- | --- | --- | --- | --- | --- |
|  | **GROUP** | **N** | **Mean** | **Std. Deviation** | **Std. Error Mean** |
| **ACCURACY** | **DT** | **10** | **98.2020** | **.58353** | **.18453** |
| **SVM** | **10** | **94.7200** | **.76056** | **.24051** |

**Table 3.** Shows Comparison of Significance Level with value p<0.05. Both the Decision tree 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** | **.541** | **.471** | **11.486** | **18** | **.000** | **3.48200** | **.30314** | **2.84512** | **4.11888** |  |
| **Equal variances not assumed** |  |  | **11.486** | **16.869** | **.000** | **3.48200** | **.30314** | **2.84205** | **4.12195** |  |

**Graph:**

**Fig. 1.** Comparison of the Decision tree Algorithm accuracy of (98.2020) and it has the mean accuracy of the Support Vector Regression Algorithm (94.72) The mean accuracy of the Decision tree Algorithm has significant difference with theSupport Vector Regression Algorithm with the significance value is 0.000 (p<0.05) . X Axis: Decision tree Regression Algorithm vs Support Vector Regression Algorithm Y Axis: Mean accuracy ± 2 SD.

**DISCUSSION**

The study's findings demonstrate how well machine learning algorithms predict job revocation, a crucial aspect of workforce management. Both algorithms achieved high levels of predictive accuracy, according to a comparison of [(Singh et al. 2024)](https://paperpile.com/c/GYx2aL/rIhb)Decision Tree and Support Vector Machine (SVM) algorithms. But with a mean accuracy of 98.20% as opposed to SVM's 94.72%, Decision Tree performed noticeably better than SVM. An independent sample t-test was used to statistically validate this difference, and a p-value of 0.000 indicated that it was significant.

The ability of Decision Trees to efficiently handle both numerical and categorical data while capturing intricate relationships through hierarchical splitting is one of the primary factors contributing to their superior performance[(Garigipati, Raghu, and Saikumar 2022)](https://paperpile.com/c/GYx2aL/jy8W). HR managers can better comprehend the factors influencing job revocation thanks to Decision Trees' interpretability, which makes it simple to visualize decision paths. SVM needs careful parameter tuning, including kernel selection and regularization, to achieve optimal performance, despite its robustness and ability to handle high-dimensional datasets. The lower performance seen in this study may be partially explained by improper tuning, which can lower predictive accuracy.

Decision Tree's higher[(Bhatta et al. 2022)](https://paperpile.com/c/GYx2aL/Bb19) generalization capability is a result of its ensemble-like behavior through recursive splitting and its capacity to concentrate on the most important features. Additionally, it is less susceptible to missing values and outliers, which are frequent in actual HR datasets. However, despite its strength, SVM can be computationally demanding and difficult to interpret, which restricts its usefulness in workforce analytics where openness is essential[(Zambelli, Marcionetti, and Rossier 2024)](https://paperpile.com/c/GYx2aL/CiPt).

Because feature importance can be extracted to identify important factors influencing employee turnover, the results show that Decision Trees offer both actionable insights and higher predictive accuracy. This enables businesses to create proactive retention plans, like focused training courses, workload modifications, and employee engagement campaigns. Although SVM is still a dependable algorithm, its somewhat reduced accuracy and restricted interpretability imply that it might work better in situations where making predictions [(Bhatta et al. 2022; Aggarwal et al. 2022)](https://paperpile.com/c/GYx2aL/Bb19+fL4z)is more important than comprehending decision paths.

All things considered, the study shows that decision trees are a very useful tool for forecasting job revocation in industrial settings. It is especially useful for HR analytics because of its accuracy, interpretability, and robustness. The study emphasizes how crucial it is to choose algorithms based on their practical applicability as well as their predictive performance. Future research could look into different machine learning models or hybrid approaches that combine SVM and Decision Trees[(Hernandez and Enriquez 2021)](https://paperpile.com/c/GYx2aL/fAWA) to improve forecasting accuracy and decision-making support in employee retention strategies.

**CONCLUSION**

Both models are useful for predicting employee turnover, but there are some significant differences between them, according to the current study's successful comparison of the effectiveness of Decision Tree and Support Vector Machine (SVM) algorithms in predicting job rescission in the industrial sector. With an average accuracy of 98.20% as opposed to 94.72%, Decision Tree performed noticeably better than SVM. This difference was statistically significant with a p-value of 0.000, indicating superior predictive ability. Decision Tree's hierarchical structure and recursive feature splitting enable it to efficiently handle both categorical and numerical variables while capturing intricate relationships in workforce data.HR managers can identify important factors influencing job revocation thanks to its interpretability through visual decision paths and resilience to missing values and outliers, which are common in real-world HR datasets. SVM requires careful hyperparameter tuning, which may have contributed to its somewhat lower performance even though it is very effective at handling high-dimensional data and nonlinear relationships. Actionable workforce strategies are further supported by Decision Tree's feature importance ranking, which enables businesses to carry out focused interventions and enhance employee retention.According to the study, choosing a machine learning algorithm for HR analytics requires careful consideration of both predictive accuracy and model interpretability. Decision trees provide a useful compromise between these factors. These results highlight how effective data-driven strategies are at lowering turnover costs, raising employee satisfaction, and facilitating well-informed decision-making in business environments. In order to further enhance predictive performance, the study also recommends that future research investigate hybrid models or include bigger datasets and more workforce characteristics. All things considered, the study offers empirical proof that Decision Trees are the best option for precise, comprehensible, and trustworthy job revocation predictions, greatly advancing workforce management and HR analytics.

**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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