# Workforce Turnover Prediction Using Machine Learning Algorithms.

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***Abstract*****—** In the age of big data, significant changes are occurring in corporate management. Big data has an impact on human resource management since it is such an essential aspect of the business. The majority of workers quit their existing organizations to gain new skills and expand their competencies. Companies launched various training and development programs in response to this trend, aiming to encourage and thereby keep them. This study uses the working data of business workers as the primary data and analyses it to determine what variables influence worker resignation, the major reasons for resignation, and forecasts of which exceptional people will depart. This project provides a scientific foundation for the accurate management of firms and organizations by predicting indicators using currently popular algorithms (logistic regression, K-nearest neighbor). This project's contents include: analyzing the factors causing worker turnover and mining the influence degree of relevant factors; developing a model using an algorithm and determining the best model parameters to predict which workers will leave; and selecting the best model and parameters through model comparison. We can discover the elements influencing worker turnover through data mining of departed personnel and draw conclusions based on the study results and the real circumstances of the firm.

***Keywords—Big data, machine learning, workforce, logistic regression, KNN (K-Nearest Neighbor).***

## I. INTRODUCTION

The disclosure or departure of an intellectual skill from a sector or organization is referred to as workforce turnover. Another possibility is turnover, which occurs when a member of a population departs. Information regarding the numbers and/or percentage of employees who leave a sector and are replaced by new recruits is provided by workforce turnover. Employers and workers who want to investigate the causes of turnover or quantify the cost of hiring for budgetary purposes may find workforce turnover informative. Retaining qualified employees who support exceeding customer expectations and boosting business productivity is essential to the long-term profitability and health of the organization. Given the evidence of problems in the IT industry, it is crucial for management to implement remedial measures to lower employee turnover. This study will evaluate employee satisfaction levels and probable causes of the high turnover rate in order to achieve this goal. It makes it easier to determine if employees are happy or not, enabling speedy resolution of problems the company is currently experiencing. This makes it simple to lower the turnover rate, which in turn raises the company's total productivity and profitability. Additionally, predicting employee turnover will assist the business in hiring the right candidates for open positions in the future. Additionally, it helps management provide employees with the proper motivation based on their degree of contentment or purpose to quit the organization. Additionally, the business will have the option of changing its goals or plans for growth or productivity. Therefore, estimating the turnover rate is crucial to guarantee the business's ongoing development and progress. Additionally, this will support keeping the company's greater rate of return. We will deal with voluntary turnover in this project, forecast employee turnover using various machine learning algorithms, and examine potential retention tactics for such employees. The Turnover is completed by utilizing a Kaggle dataset and approaching the issue as a classification challenge. By contrasting the effectiveness of the KNN classifier with logistic regression models, the result is achieved.

## II. Literature Review

According to the authors of [1], employee turnover is defined as a scenario in which employees leave the company for a variety of reasons. This has a negative impact on the company's total costs and its capacity to provide the bare minimum of services. When employees leave an organization, it may have an effect not just on the business but also on the workforce. Worker turnover has been a significant concern for researchers, academics, and management due to its depressive effects. Individual aptitude is one of the major determinants of turnover intention. People are more likely to intend to leave their jobs when they have great abilities or when they are not fundamentally good at them and cannot advance them fully in the organization. Individual responsibility is a consideration when considering leaving the company for workers above the age of 30. The less responsibility a person has in the family, such as being the sole provider or being the single parent, the less likely it is that they would leave. This is something we can examine. In other words, each of these individual characteristics has an impact on the intention to turnover, either directly or indirectly through the influence of other variables. The goal of employee turnover is significantly influenced by the interpersonal relationships between the various departments. When there are many sections or small groups within an organization or department with integrated interpersonal relationships, it may be difficult for employees to manage their relationships with managers and coworkers. If they must expend a lot of effort to maintain these relationships, they are more likely to quit their jobs.

Similar research findings revealed that age, gender, ethnicity, education level, and marital status were significant personal or demographic factors in the prediction of voluntary worker turnover. Salary, working conditions, job satisfaction, supervision, progression, recognition, development potential, burnout, and other factors were also studied.

Employee turnover may be seen as an intellectual capital leak or exodus from the hiring organization [2]. Most of the research on turnover divides it into two categories: voluntary turnover and involuntary turnover. An organization will suffer various negative repercussions from high turnover. Employees with specialized skill sets or subject-matter specialists in the corporate world are hard to replace. It impacts the productivity of current employees and their ongoing job. Recruiting and training new personnel has its own costs, such as recruiting and training expenses. Additionally, new hires will experience learning curves as they go towards achieving comparable levels of technical or business competence as an experienced internal employee.

[3] Cox first devised the classic classification approach known as logistic regression in 1958. It uses linear discriminants. A probability that the specified input point belongs to a particular class is the main output. The model establishes a linear border dividing the input space into two sections based on the probability value. One of the most popular classifiers is logistic regression since it is simple to apply and performs well on classes that can be divided into linearly distinct subsets.

A non-parametric approach for classification and regression issues is called K-nearest neighbors. The principle behind classification issues is to find the K training data points that are closest to the new instance, and then categorize the new instance using a majority of its K neighbors. The Minkowski distance, the Manhattan distance, and the Euclidean distance are the three most often used distance measurements in everyday life. The principle behind regression problem is to determine the new instance value by averaging its K neighbors. KNN may perform well when there are few features, but it suffers when feature dimensions grow significantly.

Some elements, such as a staff member's passing or disability, are somewhat out of management's control. In the past, other variables, such as the obligation to care for young or elderly relatives, have been categorized as causes of involuntary turnover. These issues shouldn't be considered involuntary turnover in the modern workplace because business rules and government regulations both provide opportunities for such employees to return to work or work more flexible hours. Depending on employment level, working hours, years spent with the company, and shift work, individual employment features have an impact on the desire to stay in a position.

When making judgments concerning turnover, for example, the administrative staff was more concerned with the work environment and job quality than the employees in the food and beverage department were. Pizam and Thornburg demonstrated the impact of several departments, as well as work status (part- or full-time), and other variables, on judgments about turnover. Individual work profiles, however, had little impact on salary or personal circumstances connected to intent to leave a job.

Together with supervisory leadership, intrinsic motivation is a predictor of the desire to leave. In comparison to the connection to supervisory leadership, the link between turnover intentions and strength was comparatively small. However, neither a clear mention nor a test of the causes of variances in intrinsic motivation was conducted.

The significance of management assistance may lessen this strain because work-life balance is thought to be a factor in turnover. When management supports its employees, employee motivation is higher, which reduces turnover. Because women experience more pressure from work-life balance and are more likely to leave their positions willingly in order to care for their families without effective organization, management assistance has a greater impact on women than it does on men. Because it demotivates workers through inadequate management techniques, a poor central management style may lead to an increase in staff turnover. A code of ethics may affect a company's plans for staff turnover. Corporate philanthropy enhanced organizational and work engagement, which in turn decreased turnover intentions when it was more prevalent in organizations.

However, Yang et al. (2012) cited a number of cultural traits associated with employee turnovers, including factions, intramural conflict, and hostile rivalry. The study concluded that office politics, internal competitiveness, and job pressure all contribute to a toxic culture.

[4] Previous research, including the one by Chan and Kuok (2021), repeatedly demonstrated that promotion was a factor in employee turnover. [2] According to Qiu et al. (2020), promotion is a strategy for increasing employees' intrinsic motivation. As a result, employees were more inclined to quit their occupations when there was little chance to advance their positions, and this result was in line with Yang et al.

In earlier studies, a variety of variables associated with employment were listed. According to Lee and Way different job categories, shifts, and levels have an impact on hotel employees' intentions to leave their jobs. For instance, employees in the food and beverage industry, those in administrative positions, and those on the morning shift showed larger intent to stay on staff at the hotel. Job content had an impact on employee turnover, (Blomme et al), however, these studies did not explicitly state why these elements led to higher job quality.

According to Griffeth et al, compensation and factors connected to pay to have a negligible impact on turnover. Additionally, research that looked at the connection between salary, performance, and turnover was included in their study. They concluded that great achievers leave when they are not appropriately compensated. Jobs that offer sufficient financial incentives increase the likelihood that employees will remain with the company, and vice versa. Poor hiring practices, management styles, a lack of recognition, a lack of a competitive wage structure within the company, and a hostile work atmosphere are other reasons why individuals leave organizations.

The demand for information among employees is great. Organizations with effective communication systems had decreased workforce turnover. In jobs where they have some amount of decision-making responsibility, employees feel at ease staying longer. Employees should be fully informed about matters that have an impact on their workplace environment.

## III. Problem Identification & Objectives

### 3.1. PROBLEM IDENTIFICATION

Resignations from the workforce happen in every firm. However, if the issue isn't managed correctly, the departure of essential employees may result in a decline in production. Despite the industry's strong profitability, it may be plagued by a widespread problem of excessive employee turnover, which has an impact on the industry's performance. It may be necessary for the organization to hire new staff members and teach them about the tool in use, which takes time. The majority of

businesses want to know which of their employees could leave.

### 3.2. OBJECTIVES

Because of its negative effects on workplace productivity and long-term growth plans, organizations have highlighted workforce turnover as a major problem. Organizations utilize machine learning approaches to forecast employee turnover to address this issue. The organization will be able to act for employee retention or succession planning with the help of accurate projections. In this project, we will evaluate employee/worker performance, the typical number of hours worked each month, the number of years an employee has been with the organization, and other factors to forecast employee turnover.

## IV. SYSTEM METHODOLOGY

By combining multiple Python libraries to apply machine learning algorithms to historical employee data, we have built the machine learning life cycle forecast employee is leaving the organization or not in this project. The stages we took from the life cycle are depicted in the picture below:

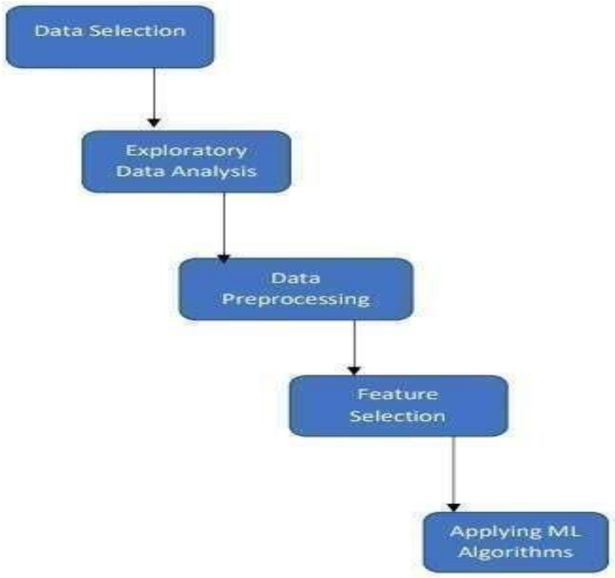


**Fig:** Machine learning life cycle to extract the employee data.

### 4.1. Data Selection

The most important aspect of the endeavor is the gathering of information. The dataset that we 14 will be utilizing ought to have a decent mixture of categorical and continuous variables. We will require at least one continuous outcome variable; every column we utilize in our analysis should be either categorical or continuous. Using a training set, the machine learning technique is trained to grasp the possible link between the explanatory factors and target variables. To verify the effectiveness of the learned connection, a test set is employed. The training set's data should be reflective of the test set as well. The importance of high-quality training data cannot be overstated in machine learning.

Choosing the Data Exploratory Data Analysis Feature Choice Making Use of ML Algorithms Preprocessing of Data Even the most efficient algorithms might become worthless without a base of high-quality training data. When robust machine learning models are initially trained on insufficient, unreliable, or irrelevant data, they might become severely handicapped. The dataset for this research contains about 10,000 entries of information about workers and their working hours. The information includes features such as the satisfaction rating, most recent evaluation, number of projects, average monthly hours, and a few more.

### 4.2. Exploratory Data Analysis

It is a way of analyzing data sets to highlight their key features, frequently utilizing statistical graphics and other techniques for data visualization. It makes it simpler for data scientists to find patterns, identify anomalies, test hypotheses, or verify assumptions by determining how to modify data sources to achieve the answers they need.

EDA helps us comprehend the variables in the data set and their interactions with one another, allowing us to discover what the data may tell us beyond the formal modeling or hypothesis testing assignment. It can also assist in determining the suitability of the statistical methods you are contemplating using for data analysis. EDA methods are still often employed in the data discovery process today. It can assist in finding glaring mistakes, better understanding data patterns, spotting outliers or unusual occurrences, and discovering intriguing relationships between the variables. The dataset will be cleaned in this stage by having null and duplicate values removed. The accuracy of the model would suffer if these values weren't eliminated.

### 4.3. Data pre-processing

Making the raw data appropriate for a machine learning model is the procedure at hand. In order to build a machine learning model, is the first and most important stage. Real-world data typically includes noise, and missing values, and may be in an undesirable format, making it impossible to build machine learning models on it directly. Data pre-processing is necessary to clean the data and prepare it for a machine learning model, which also improves the model's accuracy and effectiveness. Before using machine learning or data mining methods, the data's quality should be examined. Data Pre-processing is the process by which the data is altered or encoded to put it in a form that the computer can parse with ease. In other words, the algorithm can now quickly comprehend the data's characteristics. Here, we saw that the majority of the data was in string format. Data is retrieved from each feature, such as days and months from the happiness level in float format and hours and minutes from the time spent company.

### 4.4. Feature Selection

Lowering the quantity of input variables is a step in the feature selection process of a predictive model. In some cases, a model's performance may be improved while its computational cost is decreased by decreasing the number of input variables. The relationship between each input variable and the target variable is evaluated when using statistically based feature selection approaches, and the input variables with the strongest associations are selected. These methods can be rapid and effective even if the choice of statistical measures depends on the data type of both the input and output variables. A machine learning specialist may find it challenging to identify the appropriate statistical measure for a dataset when doing filter-based feature selection. Filter-based feature selection procedures, which grade the correlation or dependence between input variables using statistical measures, choose the features that are most relevant to the situation. Statistical approaches for feature selection must be carefully selected based on the data type of the input variable and the output or response variable. Choosing significant aspects that are more closely connected to the cost is done in this stage. Selected features are given to the group of models. Before preparing our model for prediction, 16 extraneous elements that can impair the model's accuracy are deleted from the predictions provided by other models.

### 4.5. Applying ML Algorithms

You must choose your target variable—the aspect of your data about which you want to learn more—in order to use machine learning to extract insights from it. We will select "department" in this instance as it included it as a feature of its historical dataset when collecting data. To create models that learn from past data by example, we must now apply machine learning algorithms to the dataset. The trained models are then tested using test data that the model has not yet been trained on. We will employ supervised machine learning techniques because our dataset comprises labeled data. Additionally, as our dataset's features include continuous values, we will use regression techniques for supervised learning. To explain the connections between dependent and independent variables, regression models are utilized. Different regression models are applied, and the most accurate one is chosen for finalization.

## V. Overviews Of Technologies

### 5.1. Python

Python is an interpreted, high-level general-purpose programming language. It is a dynamically typed, garbage-collected language. It was produced by Guido van Rossum and made available in 1991. It employs an object-oriented methodology to help programmers create clear, comprehensible code for both little and big projects. It includes a sizable and trustworthy standard library that may be used to build apps. A wide range of applications may be made using it, including web apps, apps with graphical user interfaces, apps for software development, apps for science and math, apps for network programming, games and 3D apps, and other commercial apps. It produces an interface that is user-friendly.

### 5.2. Machine Learning

Artificial intelligence's subtype of machine learning allows a machine to learn from data, get better at what it does based on previous performance, and anticipate outcomes without needing to be explicitly programmed. The phrase "machine learning" was originally used by Arthur Samuel in 1959. In order to build mathematical models and generate predictions based on historical data or prior knowledge, machine learning uses a range of methods. It is used to make choices in a range of sectors, including banking, to find hidden patterns and extract useful information from data, and to resolve complex problems that are challenging for people to handle.

### 5.3. Pandas

An open-source Python package that enables high-performance data processing is called Python Pandas.

It was developed by Wes McKinney in 2008 and is employed for Python data analysis. Compared to other tools, Pandas is a tool that is quicker, simpler to use, and more expressive. NumPy is the foundation for the Python library known as Pandas. Regardless of the source of the data, it can manage the five main procedures needed for data processing and analysis: load, modify, prepare, model, and analyze. This tool allows for the reshaping and pivoting of data collections. It is capable of processing a broad variety of data sets in various formats, including time series, tabular heterogeneous data, and matrix data. Series and Data frame are the two data structures provided by Pandas for processing data.

5.4. Matplotlib

The Python module Matplotlib offers a multi-platform framework for data visualization based on the NumPy array. It may be used in shells, web applications, Python scripts, and other GUI toolkits. It produces a free and open-source MATLAB-like user interface using Pyplot. Numerous operating systems and graphical user interfaces are compatible with it.

5.5. Seaborn

A Python package called Seaborn makes it possible to view graphical statistical charts. Seaborn offers a variety of color schemes and conventional, attractive designs to enable the creation of multiple statistics charts in Python more visually appealing. It contains dataset-oriented APIs and is built on the foundation of the matplotlib package. Both univariate and bivariate data sets can be visualized with their assistance.

5.6. Operating System

The Python OS module enables communication between the user and the operating system. Basic utility modules for Python cover the OS. A portable method of accessing operating system-specific features is offered by this module. It has a variety of useful OS functions that may be used to carry out OS-related tasks and get operating system-related data. The current working directory can be changed using the chdir() method in the os module.

5.7. Scikit – learn (sklearn)

Sklearn is a useful and comprehensive library. It was initially developed by David Cournapeau under the name scikits. learn. Using a Python consistency interface, it provides a suite of effective machine learning and statistical modeling methods, including classification, regression, clustering, and dimensionality reduction. This package's core components, mostly written in Python, are NumPy, SciPy, and Matplotlib.

## VI. IMPLEMENTATIONS

Get the dataset:

The dataset was obtained from Kaggle, a free online community for machine learning and data scientists.

Source:

https://www.kaggle.com/kerneler/starter-hr-analytics-employee-turnover-e113ec38-2/data.

The dataset consists of 14999 entries and has 10 columns.

Columns in the dataset:

a. **satisfaction_level:** Level of satisfaction of the employee {0–1}.

b. **last_evaluationTime:** Time since last performance evaluation (in years).
c. **number_project:** Number of projects completed while at work.
d. **average_montly_hours:** Average monthly hours at the workplace.
e. **time_spend_company:** Number of years spent in the company.

f. **Work_accident:** Whether the employee had an accident at the workplace {0,1}.
g. **left:** Whether the employee left the workplace or not {0, 1}.
h. **promotion_last_5years:** Whether the employee was promoted in the last five years.
i. **sales:** The department for which the employee works.
j. **salary:** Represents the level of salary {low, medium, high}.

**Dependent variable:** 'left'

**Independent variables:**

'satisfaction_level',

**'**last_evaluation',

‘number_projects’,

‘average_monthly_hours’,

‘time_spend_company’,

‘Work_accident’,

‘promotion_last_5years’,

‘sales’, ‘salary’.

## VII. Algorithms

### 7.1. K – Nearest Neighbors Algorithm

```
from sklearn.neighbors import KNeighborsClassifier
classifier=KNeighborsClassifier(n_neighbors=8)
classifier.fit(x_train,y_train)
```

```
KNeighborsClassifier(n_neighbors=8)
```

```
y_pred=classifier.predict(x_test)
```

Confusion Matrix

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
result=confusion_matrix(y_test,y_pred)
print("Confusion Matrix:")
print(result)
```

```
Confusion Matrix:
[[3306   85]
 [  77  609]]
```

Classification report

```
result1=classification_report(y_test,y_pred)
print("Clasiification Report:",)
print(result1)
```

```
Clasiification Report:
              precision    recall  f1-score   support

           0       0.98      0.97      0.98      3391
           1       0.88      0.89      0.88       686

    accuracy                           0.96      4077
   macro avg       0.93      0.93      0.93      4077
weighted avg       0.96      0.96      0.96      4077
```

Accuracy of KNN

### 7.2. Logistic regression

```
from sklearn.linear_model import LogisticRegression
logistic_reg=LogisticRegression()
logistic_reg.fit(x_train,y_train)
```

```
LogisticRegression()
```

Confusion Matrix

```
y_pred=logistic_reg.predict(x_test)
confusion_matrix(y_test,y_pred)
```

```
array([[3268,  123],
       [ 573,  113]], dtype=int64)
```

Classification report

```
print("Classification Report:")
print(classification_report(y_test, logistic_reg.predict(x_test)))
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.96      0.90      3391
           1       0.48      0.16      0.25       686

    accuracy                           0.83      4077
   macro avg       0.66      0.56      0.57      4077
weighted avg       0.79      0.83      0.79      4077
```

Accuracy of Logistic regression

```
accuracy=logistic_reg.score(x_test,y_test)*100
print('Accuracy of Logistic Regresssion is: {:.2f}'.format(accuracy))
```

```
Accuracy of Logistic Regresssion is: 82.93
```

```
result2=accuracy_score(y_test,y_pred)
print("Accuracy of KNN is:{:.2f}".format(result2*100))
```

```
Accuracy of KNN is:96.03
```

## VIII. Results And Discussion

### 8.1. Algorithms

#### 8.1.1. K Nearest Neighbors Algorithm

The non-parametric k-nearest neighbors' algorithm (K-NN) is used for classification and regression. In both scenarios, the input consists of varied k nearest training points that are used to choose n neighbors from the training data, forecast their class, and assign the neighboring point to the class that is determined by the mode of the classes for that point.

Confusion Matrix

The performance of a forecasting model on a set of test data for which the real values are known maybe described using a confusion matrix.

```
Confusion Matrix:
[[3306   85]
 [  77  609]]
```

Classification report

```
Clasiification Report:
              precision    recall  f1-score   support

           0       0.98      0.97      0.98      3391
           1       0.88      0.89      0.88       686

    accuracy                           0.96      4077
   macro avg       0.93      0.93      0.93      4077
weighted avg       0.96      0.96      0.96      4077
```

Accuracy of KNN

Based on the input, and training data, accuracy is the metric used to indicate which is best at finding links and patterns between variables in a dataset.

| Name | Accuracy |
|---|---|
| K Nearest Neighbors Algorithm | 96.03 |

#### 8.1.2. Logistic Regression

Confusion Matrix

```
array([[3268,  123],
       [ 573,  113]], dtype=int64)
```

Classification report

```
Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.96      0.90      3391
           1       0.48      0.16      0.25       686

    accuracy                           0.83      4077
   macro avg       0.66      0.56      0.57      4077
weighted avg       0.79      0.83      0.79      4077
```

Accuracy of Logistic regression

| Name | Accuracy |
|---|---|
| Logistic regression | 82.93 |

This project 's main goal is to reduce workforce turnover by identifying the most effective factors to consider when a valuable employee resigns, according to assessments of the workforce turnover prediction data. Prior to this, it was essential to forecast the employee portfolio data in order to identify the employees who would be departing soon. According to employee statistics, the following indicators are responsible for predicting turnover: most recent assessment, number of projects, average monthly hours worked, time spent at the firm, work-related accidents, departures, promotions during the past five years, sales, salary, and level of satisfaction. Additionally, it's important to know which employees to invest in in order to manage the personnel management budget.

Decision-making models must be created in order to choose valuable personnel. It was necessary to collect information in order to determine the elements influencing employee value and workforce turnover in order to complete this project. The machine learning algorithms that were employed in the project were examined in order to choose the one that offered the most accuracy. The employee prediction and the method that produced the most accurate results were determined using the dataset gathered from Kaggle and chosen data training techniques including Logistic regression and KNN.

| Name | Accuracy |
|---|---|
| K Nearest Neighbors Algorithm | 96.03 |
| Logistic regression | 82.93 |

Last but not least, it should be highlighted that the results and discussion only cover how to utilize data mining techniques to understand staff turnover rather than how to minimize it.

## IX. Conclusions

This strategy for predicting staff turnover has been put out utilizing common machine learning techniques. Comparing the goal of this machine learning technique to statistical and other consistency algorithms, it is evident that it is successful. The literature review demonstrated how near to a prediction-type problem this issue is. This sparked a conversation on how to approach this issue and choose relevant features. The feature selection approach determines which factors are the best choice for accurately predicting employee turnover. In order to forecast employee turnover, the algorithm with the best performance was kept.

## X. Future Scope

Overall prediction accuracy might be assessed and maintained for future prediction improvement. Additionally, this method might be used to make a variety of other intriguing predictions, such as those about motivation, pay, and sick leave. Staff turnover is a crucial indicator of the efficiency of a program's or organization's overall management as well as the success of its human resources management system. Additionally, those that are eager to get down and dirty with their business may learn a great deal about employee morale, which is awonderful predictor of how long a worker could stay on the job. By using a machine learning model to predict worker turnover, businesses may be able to begin the hiring process early and therefore reduce the productivity hit when moving between old and new personnel.

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