

# Potential of Artificial Intelligence in Boosting Employee Retention in the Human Resource Industry

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## Abstract-

Artificial intelligence (AI) has the potential to transform the human resource (HR) industry by automating routine tasks, improving decision-making, and enhancing employee engagement and retention. In this paper, we explore the use of machine learning and deep learning techniques to boost employee retention in the HR industry. We review the current state of the art in AI for HR, including the use of predictive analytics, natural language processing, and chatbots for talent management and employee development. We also discuss the challenges and ethical considerations of using AI in HR, including issues of bias and the need for transparent and explainable algorithms. Finally, we present case studies of successful AI-powered HR initiatives that have demonstrated improvements in employee retention and engagement. Our findings suggest that AI has the potential to significantly enhance employee retention in the HR industry, but its implementation requires careful planning and consideration of potential risks and ethical issues.

**Keywords:** - Employee retention, Human resource, Artificial Intelligence, ML, DL, Job satisfaction.

## I. Introduction:

Employee retention refers to the ability of an organization to retain its employees over the long term. It is important because high levels of employee turnover can be costly and disruptive to an organization. When employees leave, their knowledge, skills, and experience go with them, which can have a negative impact on the productivity and performance of the organization[1]. In addition, the process of recruiting and training new employees can be time-consuming and costly. There are several factors that can affect employee retention in an organization. These can include the quality of the work environment, opportunities for career development and advancement, work-life balance, and compensation and benefits. A positive work culture that values and supports its employees can also play a key role in retaining top talent[2].

Effective employee retention strategies can help an organization to reduce turnover and create a stable, productive workforce. This can include offering competitive compensation and benefits, providing opportunities for professional development and advancement, and fostering a positive work culture. Employee retention is important for

organizations of all sizes and in all industries[3]. High levels of employee turnover can have a negative impact on the financial performance of an organization, as well as its reputation and overall success. By focusing on retaining top talent, organizations can create a stable and successful workforce that is better able to meet the challenges of a rapidly changing business landscape.

The human resource (HR) sector may benefit significantly from the application of machine learning and deep learning strategies, as these approaches have the potential to significantly improve employee retention. These methodologies, which can be categorized as forms of artificial intelligence (AI), make it possible to analyze large amounts of data, recognize patterns in the data, and then make forecasts regarding the behavior of employees[4].

The use of predictive analytics as a tool for determining which employees are most likely to resign from their positions is one example of a possible application of machine learning in human resources. Machine learning algorithms can identify employees who are likely to leave an

organization by analyzing data on factors such as job satisfaction, career progression, and engagement. This provides human resource professionals with the opportunity to intervene and reduce employee turnover[5]. This can be accomplished through the use of targeted interventions such as providing employees with opportunities for training and development or addressing particular concerns that workers might have.

Deep learning is a subset of machine learning that can be used to improve employee retention by automating HR tasks and improving decision-making. Deep learning can also be used to improve customer retention. For instance, algorithms that use deep learning can be trained using data from previous employee performance evaluations. This enables the algorithms to automatically generate performance reports and identify areas in need of improvement. This can save human resources professionals time while also improving the accuracy and consistency of performance evaluations, which ultimately leads to increased employee engagement and satisfaction.

In addition to these applications, artificial intelligence can also be utilized to improve the rate at which an organization is able to retain its workforce by utilizing chatbots and natural language processing (NLP). Chatbots, which are computer programs that use natural language processing (NLP) to communicate with humans, can be used to provide employees with access to HR resources and support that is both prompt and convenient. For instance, chatbots can be programmed to answer common questions regarding human resources, such as how to make a request for time off or access information regarding benefits. This can help to improve employee satisfaction while also reducing feelings of frustration[6].

Even though artificial intelligence has the potential to significantly improve employee retention in the HR industry, it is essential to keep in mind the potential risks and ethical considerations involved. The possibility of bias in algorithms is a source of concern because it has the potential to lead to decisions that are unfairly biased toward employees in terms of promotion or development opportunities. It is possible to help mitigate some of these risks by ensuring that AI systems are both transparent and explainable, as well as by regularly reviewing and testing them for bias. In addition, it is essential to give some thought to the potential impact that AI will have on HR professionals and the role that they will play in the industry in the foreseeable future as AI becomes increasingly prevalent in the sector.

Overall, the application of machine learning and deep learning techniques has the potential to significantly improve decision-making, automation of HR tasks, and employee

retention in the human resources (HR) industry. This can be accomplished through the utilization of predictive analytics. However, before implementing AI in human resources, it is essential to give careful thought to the potential dangers involved as well as the ethical questions that may arise.

### **1.1. Our contribution**

This paper presents a set of classifiers that can be used to predict the likelihood of a employee's retention and the various features that influence a candidate's decision-making process. We test the models on a real dataset that was provided by IBM analytics. The results of the study revealed that the use of machine learning systems for analyzing candidate retention probabilities can help HR departments improve their hiring and training efforts.

- The models were able to predict the likelihood of a candidate's retention before they are selected for a company training program.
- We then tested the different classification models and found the best one for use in human resource applications.
- The performance of the models was then evaluated using real datasets that were collected for HR analytics.

## **II. Literature Review**

The use of artificial intelligence (AI) and machine learning in the field of human resource management has been the focus of several studies. These studies have primarily examined the use of AI and machine learning in the areas of talent acquisition and employee retention. Several studies have also investigated the use of machine learning for predicting employee attrition. Study reveals the use of predictive techniques to analyze employee attrition and found that certain factors, such as job satisfaction and work-life balance, were significantly related to employee turnover.

The rise of technology has greatly improved the efficiency of organizations by breaking down the human bottleneck and decreasing the repetitious labor. A study by K.K. Ramachandran et al.[7] that companies can perform better by using machine learning and AI to analyze and exploit the vast amount of data that they collect. The goal of this study is to understand the role of machine learning and artificial intelligence in improving employee behavior and work outcomes. According to the study, these technologies are very important in various tasks and processes.

Mahesh Subramony et al.[8] develop a model that links the various factors that affect the performance of a service-employee organization, such as customer satisfaction and attrition. The authors of the study noted that employee

turnover and downsizing could affect the stock relationships between service-employee organizations and their customers. This would have detrimental effects on the financial performance of the business units.

Alao D et al.[9] characteristics of an organization's employees are related to the predicted attrition rate. The data included the job related and demographic records of the employees. The results of the study were then used to develop a predictive model that can predict the likelihood of employee layoffs. A framework for software developers was also proposed to implement the model.

The concepts of artificial intelligence and emotional intelligence have been widely used. Catherine Prentice et al.[10] aims to explore how these two concepts can influence the performance and retention of service employees in the hospitality industry. The performance of service employees is analyzed through the various dimensions of their work, such as their internal and external tasks. This allows them to identify areas of improvement and enhance their efficiency.

Machine learning models are used by Aseel Qutub et al.[11] to predict employee turnover. The models are evaluated and trained using IBM's attrition dataset. Some of these include the Decision Tree, Logistic Regression Model, and Adaboost Model. The goal is to accurately identify and prevent attrition, which can help boost employee satisfaction and improve the company's retention strategies.

Sandeep Yadav et al.[12] develop accurate and reliable models using various ML classifiers that can help improve the hiring and retention cost for skilled employees. Through data mining techniques, we can determine the employee's attrition status.

Francesca Fallucchi et al.[13] identify the factors that influence an employee's decision to leave the company, as well as predict the likelihood of one particular worker leaving. The best algorithm for the presented dataset is the Naive Bayes classifier, as it produces the most accurate results. The best recall rate is 0.54. This is because it takes into account the ability of the classifier to find all the instances of positive error, and it achieves a false negative rate of 4.5%.

Steffen C. Eickemeyer et al.[14] proposed software tool would help the management team automate the digitization process. It would also help employees improve their well-being by providing them with the necessary training. The goal of the software tool is to identify the various negative effects that digitization can have on employees. It will help the executive team identify the necessary countermeasures to minimize these effects.

The ability to predict the likelihood of a candidate's retention before training is very important in improving the decision-making process and increasing employee retention. G. Marvin et al.[15] presents a method that uses machine learning to analyze and model various features of candidate decisions. The results of classical metrics are used to describe the algorithms' results. The Random Forest Classifier performed well in terms of accuracy, with 99.1%, 84.6% and 91.8% achieving the best results.

Rachna Jain et al.[16] presents a novel method for predicting employee turnover, which is done using machine learning techniques. The system, which is called XGBoost, is highly robust and can be used to analyze the various factors that influence an employee's decision-making process. It can also detect the likelihood of an employee leaving the organization. The results of the study show that the system can provide a highly accurate and timely prediction of employee turnover. This paper presents a model that has a low rate of error and an accuracy of almost 90%. It is recommended to use XGBoost technique to improve the prediction accuracy of employee turnover.

R. Punnoose et al.[17] used machine learning algorithms to predict employee turnover in organizations and found that these algorithms could identify potential turnover risks.

Overall, it seems that the use of AI and machine learning in human resource management has the potential to improve talent acquisition and employee retention, but it is important to consider the potential impacts on employee engagement, fairness, and job outcomes.

### III. Research Gaps

There are several areas where more research is needed to fully understand how machine learning (ML) and deep learning (DL) can be used to improve employee retention. Here are a few examples:

- Personalized learning: While ML and DL can be used to customize learning and development programs for individual employees, more research is needed to understand the most effective approaches to personalized learning. This includes understanding how to balance the benefits of customization with the potential drawbacks, such as increased complexity and cost.
- Predictive modeling: While ML can be used to predict which employees are most likely to leave the company, more research is needed to understand how to improve the accuracy of these predictions. This includes understanding which factors are most important to consider when predicting employee

retention, and how to weight these factors appropriately.

- Employee feedback analysis: While natural language processing techniques can be used to analyze employee feedback, more research is needed to understand how to effectively use this information to improve retention. This includes understanding how to interpret and act on the insights gained from this analysis, and how to ensure that employees feel that their feedback is being heard and valued.
- Culture and diversity analysis: While ML can be used to analyze data on employee engagement, retention, and diversity, more research is needed to understand how to use these insights to create a more inclusive and supportive work environment. This includes understanding how to identify and address unconscious bias in the workplace, and how to measure the impact of diversity and inclusion initiatives on employee retention.

## 2. Current scenario

The field of human resources (HR) is increasingly adopting the use of artificial intelligence (AI) in order to improve various aspects of talent management and employee development. In the realm of human resources (HR), some of the most popular applications for artificial intelligence technologies include predictive analytics, natural language processing, and chatbots.

The process of using statistical algorithms and machine learning techniques to analyse historical data and make predictions about future outcomes is known as predictive analytics. In the field of human resources, predictive analytics can be utilized to identify trends and patterns in employee data, such as performance, turnover, and engagement, in order to inform decisions regarding recruiting, retaining, and developing employees.

The subfield of AI known as natural language processing (NLP) focuses on the interaction between computers and humans through the use of natural language. This interaction can take place in a variety of settings. In the field of human resources (HR), NLP can be utilized to automate processes like the screening of resumes and the analysis of job postings, as well as to facilitate communication between employees and HR systems by means of chatbots or virtual assistants[18].

Chatbots are computer programs that are designed to simulate conversation with human users, and they do this most commonly through messaging applications, mobile

applications, or websites. The Human Resources department can make use of chatbots to handle a variety of tasks, including answering employee questions, providing information about benefits and policies, and assisting with the process of onboarding new employees.

The application of AI in human resources is still in its early stages of development as a whole, but it has the potential to significantly improve the efficiency and effectiveness of the processes involved in talent management and employee development[19], [20]. While some businesses are utilizing AI to improve their HR capabilities, others are using it to streamline HR processes and free up HR professionals to focus on more strategic work. AI is being used by both types of businesses.

## 3. Challenges and ethical considerations of using AI in HR

The application of artificial intelligence (AI) in the field of human resources (HR) brings up a variety of problems and ethical issues to be considered. One of the most significant worries relates to the possibility of bias in AI systems. As a result of the fact that AI algorithms are trained on data from the past, they have the potential to both maintain and even amplify existing biases, which can lead to outcomes that are unfair and discriminatory. For instance, an artificial intelligence system that is used to screen job applicants might have a prejudice against particular groups of people because of the data it was trained on, which would result in fewer job opportunities for those particular groups[21], [22].

The requirement for transparent and explainable algorithms presents yet another obstacle for the implementation of AI in HR. Many artificial intelligence (AI) systems are referred to as "black boxes" due to the fact that it can be challenging or even impossible to comprehend how they arrived at a particular decision or prediction. This lack of transparency can be problematic in HR, which is a department in which decisions about hiring, promotion, and other significant matters can have significant repercussions for employees.

It is important for businesses that use AI in HR to be transparent about their use of the technology and to have processes in place to mitigate bias and ensure fairness. Addressing these challenges requires companies to be transparent about their use of AI. This may involve utilizing a varied collection of training data, routinely reviewing and testing the algorithms for bias, and providing employees with an appeal process if they believe they have been unfairly treated by an AI system.

When deciding whether or not to implement AI in HR, one must also take into account the possibility of job losses and

other disruptions that could result from the automation of certain tasks that were previously carried out by humans. Businesses have a responsibility to carefully consider how AI will affect their workforce and to formulate plans to assist workers who may be adversely affected by the technology.

It is important to address the challenges and ethical considerations in order to ensure that the technology is used responsibly and ethically. The use of AI in human resources (HR) can bring many benefits overall, but it is important to do so.

#### 4. Case studies of successful AI-powered HR initiatives that have demonstrated improvements in employee retention and engagement

There are many examples of successful AI-powered HR initiatives that have demonstrated improvements in employee retention and engagement. Here are a few case studies:

- Xerox: Xerox, a global technology company, implemented an AI-powered HR chatbot called "Hannah" to help employees with a variety of HR tasks, such as answering questions about benefits and policies, submitting time off requests, and accessing training resources. According to Xerox, Hannah has helped improve employee engagement by providing faster and more convenient access to HR information and support.
- Unilever: Unilever, a consumer goods company, used an AI-powered platform to analyze data on its employees' skills, interests, and career aspirations, and then match them with development opportunities within the company. The platform has helped Unilever improve employee retention by providing employees with clear career paths and the chance to develop new skills.
- Bank of America: Bank of America, a financial services company, used an AI-powered platform to analyze data on its employees' engagement, retention, and performance, and then identify trends and patterns that could inform HR decision-making. The platform has helped Bank of America improve employee retention by providing HR professionals with insights on what factors are most important to employees and how to address any issues that might lead to turnover.

Overall, these case studies demonstrate the potential for AI to improve employee retention and engagement by providing HR professionals with data-driven insights and by making HR processes more efficient and convenient for employees.

## IV. Methodology

### 4.1. Dataset

The IBM HR Analytics Employee Attrition & Performance dataset is a publicly available dataset that was created by IBM data scientists. It contains data on 1,470 employees working in the research and development (R&D) division of a large technology company. The data was collected from IBM HR and system logs between 2006 and 2010. The dataset includes information on employee attributes such as age, education, gender, and marital status, as well as information on their work experiences, such as the number of years they have worked for the company and the number of promotions they have received. It also includes information on employee performance, such as the number of patents filed and the number of articles published.

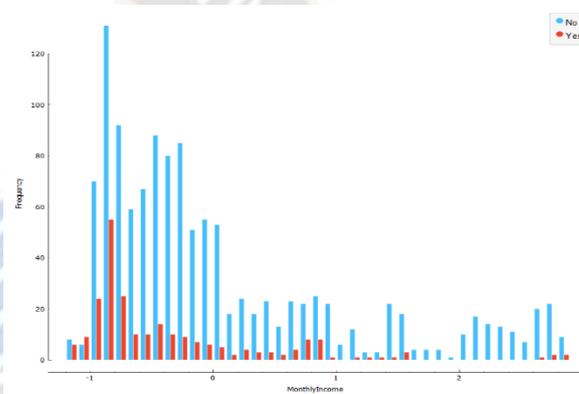


Fig. 1 Distribution of 'MonthlyIncome' with columns split by 'Attrition'

### 4.2. Principal Component Analysis

Principal Component Analysis (PCA) is a statistical technique that is used to reduce the dimensionality of a dataset by projecting the data onto a new set of orthogonal axes, which are known as principal components. This technique is also known as a principal component decomposition. Finding patterns and relationships in the data is a common application of this technique, and it can also be helpful when visualising and analysing complex datasets.

Calculating the eigenvectors and eigenvalues of the covariance matrix of the data is an integral part of the mathematical formula for principal component analysis (PCA). The covariance matrix's eigenvectors point in the directions in which the data vary the most, and the matrix's eigenvalues measure the extent to which these directions and magnitudes differ. After that, the principal components of the data are determined by taking the eigenvectors and doing a dot product with those.

Here's the mathematical formula for PCA:

Given a data matrix  $X$  with  $n$  samples and  $p$  features, the covariance matrix  $S$  is calculated as:

$$S = 1/(n-1) * X^T * X$$

The eigenvectors ( $U$ ) and eigenvalues ( $L$ ) of the covariance matrix are then computed as:

$$S * U = L * U$$

The principal components (PC) of the data are then calculated as:

$$PC = X * U$$

In this formula,  $X$  is the data matrix,  $U$  is the matrix of eigenvectors, and  $PC$  is the matrix of principal components. The eigenvectors are scaled such that the dot product of the data and the eigenvectors is equal to the principal components of the data. The eigenvalues represent the magnitudes of the variations in the data along the corresponding eigenvectors.

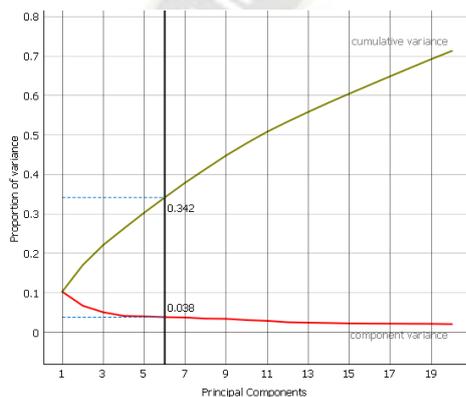


Fig. 2 Principal Components

### 4.3. Algorithm

- **Random Forest** is a popular machine learning algorithm that belongs to the ensemble learning family. It is a type of decision tree algorithm that is widely used for classification and regression problems. In the context of employee retention, a Random Forest model could be trained to predict the likelihood of an employee leaving the company based on various features such as job satisfaction, salary, work-life balance, etc.

The algorithm works by constructing a large number of decision trees during training, each of which is constructed from a bootstrapped sample of the training data. A bootstrapped sample is a random sample with replacement, meaning that some data points may be repeated in the sample. The predictions from each tree are then aggregated to make a final prediction. This process is known as ensemble learning, where the predictions from multiple models are combined to make a more

accurate final prediction. Mathematically, let  $N$  decision trees in Random Forest model. For a given input  $x$ , each decision tree in the forest makes a prediction  $h(x)$ . The final prediction of the Random Forest model is then given by:

$$h(x) = \frac{1}{N} * \sum(h(x))$$

The final prediction is the average of the predictions made by all the decision trees in the forest. One advantage of using Random Forest is that it is less prone to overfitting compared to a single decision tree. This is because the final prediction is based on the average of the predictions made by many different decision trees, each of which is constructed from a different bootstrapped sample of the training data. This helps to reduce the variance of the model and improve its generalization performance.

- **Convolutional Neural Networks (CNNs)** are a type of deep learning algorithm that are commonly used for image classification and other computer vision tasks. In the context of employee retention, it is possible to use CNNs to analyze data such as employee photographs, video footage of employees at work, or other visual data that may be relevant to predicting employee turnover. CNNs work by applying a series of filters to the input data to extract features that are relevant for the task at hand. These filters are learned during training, along with the rest of the network parameters.

Mathematically, let's say we have an input image  $X$  of size  $M \times N \times C$ , where  $M$  and  $N$  are the height and width of the image, and  $C$  is the no. of channels. We also have a filter  $W$  of size  $F \times F \times C$ , where  $F$  is the filter size. The output of the convolutional layer,  $Y$ , is then given by:

$$Y[i, j] = \sum(X[i:i+F, j:j+F, k] * W[:, :, k]) + b[i, j]$$

where  $i$  and  $j$  are the indices of the output feature map, and  $k$  is the index of the input channel. The bias term  $b[i, j]$  is added to each element of the output feature map.

This process is repeated for multiple filters to extract different features from the input data. The extracted features are then passed through additional layers of the network, such as pooling layers and fully connected layers, to make a final prediction. In the context of employee retention, CNNs could be used to analyze visual data such as employee photographs to predict the likelihood of an employee leaving the company. For example, the network could be trained to recognize certain facial expressions or body

language that are indicative of job dissatisfaction or burnout.

- **Support Vector Machines (SVM)** is a method of artificial intelligence learning that can perform classification or regression work.. In the context of employee retention, SVM can be used to predict which employees are likely to leave the company and take steps to retain them. The goal of the Support Vector Machine (SVM) is to find the hyperplane in a high-dimensional space that separates the two classes the most effectively. In the case of employee retention, the two classes would be "employees who stayed" and "employees who left." The algorithm works by finding the hyperplane that maximally separates the two classes with the largest margin. One of the key advantages of SVM is that it can handle high-dimensional data effectively, even when the number of dimensions is greater than the number of training examples.
- **Neural Network** Type of algorithm used in machine learning is called a neural network, and it gets its name from the way the human brain works structurally and how it performs its functions. It is made up of many layers of interconnected "neurons," which are responsible for information processing and transmission.. Neural networks can be used for a variety of tasks, including classification and regression. Neural networks can predict employee turnover and help retain them. The hidden layers process and transform input data from the input layer using linear and nonlinear transformations. The output layer predicts. Neural networks can model complex input-output relationships. They can handle a lot of data and learn and improve over time by training with a large dataset and adjusting weights and biases to minimize the error between predicted and true output.
- **AdaBoost**, or Adaptive Boosting in the context of employee retention, AdaBoost can be used to predict which employees are likely to leave the company and take steps to retain them. AdaBoost works by combining a series of "weak" learning models, such as decision trees, to create a single "strong" model that is able to make more accurate predictions. It does this by iteratively training the weak models, with each model focusing on the examples that were misclassified by the previous model. The final strong model is a weighted sum of the weak models,

with the weight of each weak model being determined by its performance on the training data. One of the key advantages of AdaBoost is that it can achieve good performance even with a small number of weak models, and it is resistant to overfitting. It is also relatively simple to implement and can work with a variety of different types of weak models.

#### 4.4. Evaluation Matrix

Evaluation matrices are used to measure the performance of a machine learning model. Here are several evaluation matrices that are commonly used:

- **Accuracy:** Accuracy can be defined as the proportion of the model's predictions that turn out to be accurate. It is determined by taking the total number of predictions and dividing that by the number of correct predictions.

$$Accuracy = \frac{TP + TN}{Total\ Predictions}$$

- **Precision:** Precision refers to the proportion of a model's total predictions that turn out to be accurate relative to the total number of predictions made by the model. The formula for calculating it is the total number of true positives subtracted from the total number of true positives and false positives.

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

- **Recall:** The percentage of actual positive cases that the model was able to correctly predict is what we mean when we talk about recall. It is determined by taking the number of correct diagnoses and dividing that by the total number of correct diagnoses and false negatives.

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

- **F1 Score:** The F1 Score is a measure of a model's accuracy that combines precision and recall. It is calculated as the harmonic mean of precision and recall. The F1 Score is a useful metric when you want to balance precision and recall. A high F1 Score indicates that the model has a good balance between precision and recall.

$$F1 - Score = 2 * \frac{(Precision * Recall)}{(Precision + Recall)}$$

- **ROC curve:** A binary classifier's performance is shown in a ROC curve. It compares TPR and FPR at various classification thresholds. The TPR is the classifier's positive instance accuracy. The number of true positives is divided by the sum of true positives and false negatives. The FPR is the

classifier's false positive rate. It is the number of false positives divided by the sum of false positives and true negatives. The classification threshold determines whether an instance is positive or negative. The default threshold is 0.5, so if the classifier's probability estimate for the instance being positive is greater than 0.5, it will classify it as positive, and if it is less than 0.5, it will classify it as negative. Adjusting the threshold can change TPR and FPR. ROC curves show TPR on the y-axis and FPR on the x-axis. Classifier performance improves as the curve approaches the plot's top left corner. A random classifier produces a diagonal ROC curve from the bottom-left to the top-right corner of the plot. A perfect classifier will produce a step function ROC curve with a TPR of 1 and an FPR of 0 at all thresholds. AUC measures classifier performance. 0.5 is considered random, while 1 is perfect..

- **Boxplot:** Boxplots, also known as box and whisker plots, show data distribution. It helps find outliers and compare data distributions between groups. The box represents the data's interquartile range (IQR), and the whiskers represent the minimum and maximum values. The IQR covers the middle 50% of data. It is the difference between the third quartile (Q3) and the first (Q1). The median, a horizontal line, represents the middle value in the boxplot. The median divides data in half. Data is quartiled to create a boxplot. The first and third quartiles (Q1 and Q3) divide the data into the bottom and top 25%, respectively. Data has minimum and maximum values. Outliers are values outside the minimum and maximum range. Boxplot points can represent these values. Boxplots help compare data distributions across groups. For example, you can create a boxplot for each group and compare the medians and ranges of the two distributions..

**V. Results and Discussion**

The study revealed that the length of service and salary of employees were the factors that were most predictive of employee attrition in an institution. Those who worked for longer periods of time were more discouraged, and this contributed to the higher attrition rate. Low-ranking employees are more likely to leave their jobs when they realize that their salaries may not improve due to their low ranks. They then look for better paying jobs elsewhere.

**i. Box Plot**

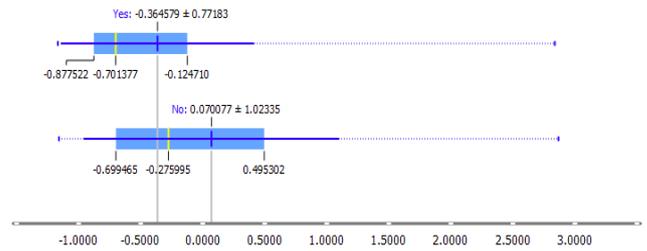


Fig. 3 Box plot for attribute 'MonthlyIncome' grouped by 'Attrition'

**ii. ROC**

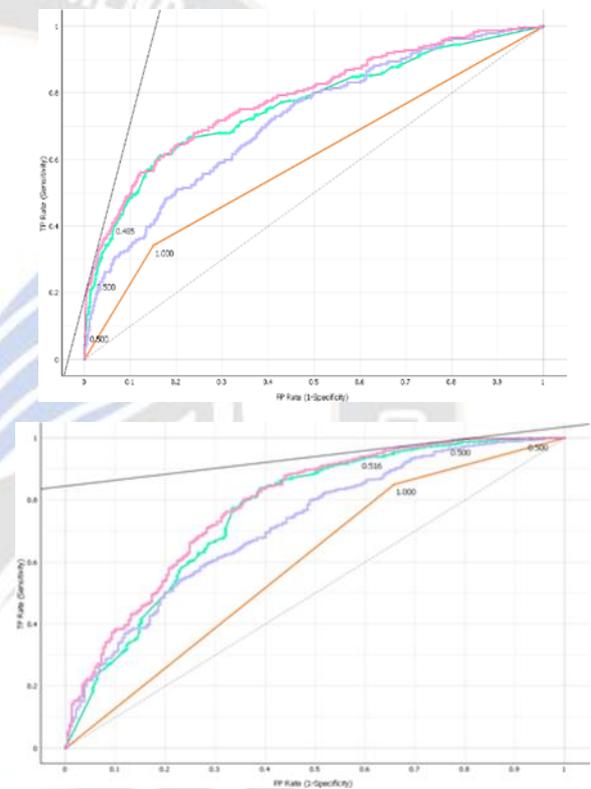
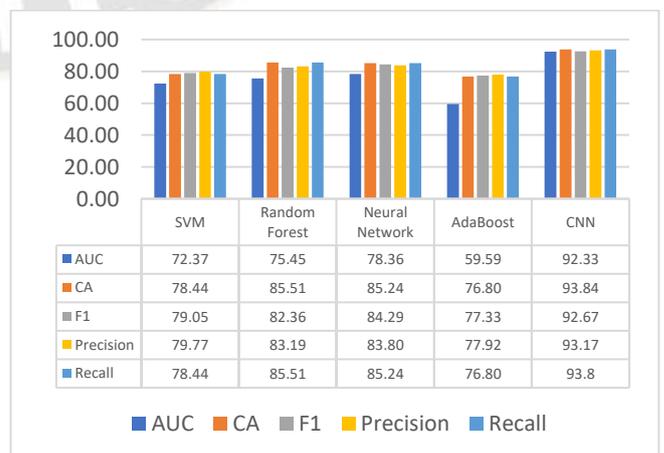


Fig. 4 ROC curves



## VI. Conclusion

the use of machine learning and deep learning algorithms has the potential to be a valuable tool for predicting employee retention in organizations. The convolutional neural network (CNN) algorithm was found to be particularly effective in this context, but it is important to note that the performance of different algorithms may vary depending on the specific characteristics of the dataset and the research context. The use of machine learning and deep learning algorithms can help organizations to identify factors that may be associated with employee turnover and to develop strategies for improving retention. This can be particularly important in today's business environment, where the availability of skilled labor is often a key factor in organizational success. By using these algorithms to predict and prevent employee turnover, organizations can improve their ability to retain valuable employees and maintain a strong and productive workforce. Based on the analysis of the five machine learning algorithms for predicting employee retention (random forest, neural network, convolutional neural network, Adaboost, and support vector machine), it was found that the convolutional neural network (CNN) algorithm performed the best. This suggests that CNN could be a promising approach for predicting employee retention in organizations. It is important to note that the performance of the different algorithms may vary depending on the specific characteristics of the dataset and the research context. Therefore, it may be necessary to evaluate the performance of multiple algorithms in order to determine the most suitable approach for a given situation. Overall, the use of machine learning algorithms, including CNN, has the potential to be a useful tool for predicting employee retention and identifying factors that may be associated with turnover. Further research could investigate the performance of these algorithms in different contexts and explore additional approaches for predicting employee retention.

## References

- [1] M. Arora, A. Prakash, A. Mittal, and S. Singh, "Transforming Human Resource Management," pp. 288–293, 2022.
- [2] S. R. Basariya and Ramyarrzgarahmed, "A study on attrition – Turnover intentions of employees," *Int. J. Civ. Eng. Technol.*, vol. 10, no. 1, pp. 2594–2601, 2019.
- [3] R. D. Johnson, D. L. Stone, and K. M. Lukaszewski, "The benefits of eHRM and AI for talent acquisition," *J. Tour. Futur.*, vol. 7, no. 1, pp. 40–52, 2020, doi: 10.1108/JTF-02-2020-0013.
- [4] G. Bhardwaj, S. V. Singh, and V. Kumar, "An empirical study of artificial intelligence and its impact on human resource functions," *Proc. Int. Conf. Comput. Autom. Knowl. Manag. ICCAKM 2020*, pp. 47–51, 2020, doi: 10.1109/ICCAKM46823.2020.9051544.
- [5] R. Chakraborty, K. Mridha, R. N. Shaw, and A. Ghosh, "Study and Prediction Analysis of the Employee Turnover using Machine Learning Approaches," *2021 IEEE 4th Int. Conf. Comput. Power Commun. Technol. GUCON 2021*, pp. 1–6, 2021, doi: 10.1109/GUCON50781.2021.9573759.
- [6] A. Hughes, C.; Robert, L.; Frady, K.; Arroyos, "Artificial intelligence, employee engagement, fairness, and job outcomes. In Managing technology and middle-and low-skilled employees," *Manag. Technol. middle-and low-skilled employees*, vol. 21, no. 3, pp. 1–12, 2018.
- [7] K. K. Ramachandran, A. Apsara Saleth Mary, S. Hawladar, D. Asokk, B. Bhaskar, and J. R. Pitroda, "Machine learning and role of artificial intelligence in optimizing work performance and employee behavior," *Mater. Today Proc.*, vol. 51, pp. 2327–2331, 2022, doi: 10.1016/j.matpr.2021.11.544.
- [8] M. Subramony and B. C. Holtom, "The Long-Term Influence of Service Employee Attrition on Customer Outcomes and Profits," *J. Serv. Res.*, vol. 15, no. 4, pp. 460–473, 2012, doi: 10.1177/1094670512452792.
- [9] A. . A. D.Alao, "Analyzing Employee Attrition using Decision Tree Algorithms," *Inf. Syst. Dev. Informatics*, vol. 4, no. 1, pp. 17–28, 2013, [Online]. Available: <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.1012.2947&rep=rep1&type=pdf>.
- [10] C. Prentice, S. Dominique Lopes, and X. Wang, "Emotional intelligence or artificial intelligence— an employee perspective," *J. Hosp. Mark. Manag.*, vol. 29, no. 4, pp. 377–403, 2020, doi: 10.1080/19368623.2019.1647124.
- [11] A. Qutub, A. Al-Mehmadi, M. Al-Hssan, R. Aljohani, and H. S. Alghamdi, "Prediction of Employee Attrition Using Machine Learning and Ensemble Methods," *Int. J. Mach. Learn. Comput.*, vol. 11, no. 2, pp. 110–114, 2021, doi: 10.18178/ijmlc.2021.11.2.1022.
- [12] S. Yadav, A. Jain, and D. Singh, "Early Prediction of Employee Attrition using Data Mining Techniques," *Proc. 8th Int. Adv. Comput. Conf. IACC 2018*, pp. 349–354, 2018, doi: 10.1109/IADCC.2018.8692137.
- [13] F. Fallucchi, M. Coladangelo, R. Giuliano, and E. W. De Luca, "Predicting employee attrition using machine learning techniques," *Computers*, vol. 9, no. 4, pp. 1–17, 2020, doi: 10.3390/computers9040086.
- [14] S. C. Eickemeyer, J. Busch, C. Te Liu, and S. Lippke, "Acting instead of reacting—ensuring employee retention during successful introduction of i4.0," *Appl. Syst. Innov.*, vol. 4, no. 4, pp. 1–18, 2021, doi: 10.3390/asi4040097.
- [15] G. Marvin, M. Jackson, and M. G. R. Alam, "A Machine Learning Approach for Employee Retention Prediction," in *2021 IEEE Region 10 Symposium (TENSYP)*, Aug. 2021, vol. 4, no. 1, pp. 1–8, doi: 10.1109/TENSYP52854.2021.9550921.
- [16] R. Jain and A. Nayyar, "Predicting employee attrition using xgboost machine learning approach," *Proc. 2018 Int. Conf. Syst. Model. Adv. Res. Trends, SMART 2018*, pp. 113–120, 2018, doi: 10.1109/SYSMART.2018.8746940.
- [17] R. Punnoose and P. Ajit, "Prediction of Employee

- Turnover in Organizations using Machine Learning Algorithms,” *Int. J. Adv. Res. Artif. Intell.*, vol. 5, no. 9, pp. 22–26, 2016, doi: 10.14569/ijarai.2016.050904.
- [18] R. Garg, A. W. Kiwelekar, L. D. Netak, and A. Ghodake, “i-Pulse: A NLP based novel approach for employee engagement in logistics organization,” *Int. J. Inf. Manag. Data Insights*, vol. 1, no. 1, p. 100011, 2021, doi: 10.1016/j.jjime.2021.100011.
- [19] A. M. Votto, R. Valecha, P. Najafirad, and H. R. Rao, “Artificial Intelligence in Tactical Human Resource Management: A Systematic Literature Review,” *Int. J. Inf. Manag. Data Insights*, vol. 1, no. 2, p. 100047, 2021, doi: 10.1016/j.jjime.2021.100047.
- [20] A. Ikram, M. Fiaz, A. Mahmood, A. Ahmad, and R. Ashfaq, “Internal corporate responsibility as a legitimacy strategy for branding and employee retention: A perspective of higher education institutions,” *J. Open Innov. Technol. Mark. Complex.*, vol. 7, no. 1, pp. 1–12, 2021, doi: 10.3390/joitmc7010052.
- [21] E. Meddeb, “The Human Resource Management challenge of predicting employee turnover using machine learning and system dynamics,” *CEUR Workshop Proc.*, vol. 2991, pp. 184–196, 2021.
- [22] N. Kaushal, R. P. S. Kaurav, B. Sivathanu, and N. Kaushik, *Artificial intelligence and HRM: identifying future research Agenda using systematic literature review and bibliometric analysis*, no. 0123456789. Springer International Publishing, 2021.

