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Human Resource Management | Major No. BBA 7

Predicting Employee Performance Using Machine Learning

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1. INTRODUCTION

Human resource (HR) is the department inside an organization that is in charge of managing and administering the human capital or workforce. Human resources specialists are involved in many elements of the employee lifecycle, including recruitment and selection, training and development, performance management, compensation and benefits, employee relations, and overall organizational workforce planning.

In today’s changing and competitive business environment, accurately predicting employee performance plays an important role in strategic decision making, resource allocation, and talent management. With the increasing awareness and use of machine learning techniques and the availability of vast amounts of employee data, many organizations can use this data to create prediction models that identify employees with high potential for success.

This report focuses on using machine learning to predict employee performance with the help of various factors including promotion data, number of awards won, nature and level of schooling, years of experience, average training score, and number of trainings completed.

Previous research by lather, Anu and Malhotra, Ruchıka and Sıngh, Prabhjot and Mıttal, Sarthak (2019) has highlighted the promising outcomes of machine learning algorithms in the domain of human resource management. Machine learning models can uncover patterns and provide accurate predictions by analyzing historical data, including employee demographics, previous performance, and training records. In our study, we explore the predictive power of variables such as the number of awards won, number of trainings completed, level of education, length of service, previous year rating, and total KPIs met during the employee’s tenure.

These characteristics reflect an employee's accomplishments and commitment to self-improvement. Moreover, the impact of an employee’s experience can not be overlooked. Research by Ahmad Faizal Ismail, Norwati Mustapha, Siti Mariyam Shamsuddin (2020) suggests that experience contributes to the enhancement of expertise and proficiency, which impacts and employee’s future performance. We have included years of experience as an important variable in our predictive model, recognizing its importance in determining an individual's growth trajectory and competency.

In addition to experience, number of trainings completed serves as a clear indicator regarding and employee’s dedication to learning and developing skills continuously. Mishra, Manasvi Role of Training in Employee Performance (2020) highlight the importance of training and its influence on employee performance. By including the number of trainings completed by employees each year as a variable, organizations can determine and individual’s commitment to acquiring new knowledge.

Moreover, number of awards won serve as an indicator to an employee's outstanding performance. Ibitomi, T. , Ojatuwase, O. , Emmanuella, O. and Eke, T. (2022) stress the significance of such recognition as a sign of an employee's potential for growth and performance. By using number of awards won as a variable, organizations can detect high performing employees who are more likely to keep excelling in their future roles. An employee's ability to apply knowledge gained is determined both by his or her average training score and by how well he or she did in prior training. The variables assess how well an employee has demonstrated their skills during earlier training sessions, as well as their learning capacities.

Last but not the least, key performance indicators completed during tenure reflect an employee's performance in completing established targets and organizational objectives. Vosloban, Raluca. (2012) provide evidence of an employee's achievements and contributions.

The first section of this paper will present a review of important literature on employee performance prediction and the use of machine learning techniques. The data gathering process will then be described, including characteristics such as number of awards earned, number of trainings completed, years of experience, and average training score. We will go over the measures used to assure data quality, as well as the feature engineering strategies used to derive relevant insights from the promotion data. Following that, we will present the chosen machine learning models as well as the assessment measures utilized to analyze their performance.

1.1 Problem statement

Predicting employee performance has become a big challenge for organizations seeking to optimize resource allocation, talent management, and strategic decision making. While machine learning approaches have shown promise in a variety of sectors, its application in forecasting employee performance based on promotion data is still in its early stages. Furthermore, research on specific variables that significantly impact an employee's likelihood of receiving promotion such as number of awards won, the number of trainings completed, years of experience, and average training scores is scarce.

This study aims to target these gaps by using promotion data and studying its relationship with employee performance prediction using machine learning techniques. By using variables such as total KPIs completed during tenure, number of awards won, number of trainings completed, years of experience etc and by examining historical promotion records, we seek to create a predictive model that can predict those employees for promotion who have the greatest potential for excellent performance in future roles. We aim to determine the predictive power of variables in forecasting an employee's chances of promotion and performance.

By addressing this problem, our research seeks to provide organizations with insights regarding the variables mentioned above and the results will help organizations in making informed decisions related to succession planning, resource allocation, and managing talent. This will ultimately enhance and organization's overall performance and productivity.

1.2 Objectives

The objective of this report is to employ a variety of machine learning techniques to create a vigorous predictive model that can forecast employee performance with utmost accuracy. By using key variables as mentioned in the problem statement, we strive to unveil the relationship between promotion and exceptional employee performance. Through a detailed and careful analysis of these variables and their influence on employee performance and promotion in an organization, our objective is to provide companies with a clear understanding of factors that drive success within their workforce. By attaining this objective, we seek to empower organizations with invaluable information regarding data-driven decision making, effective talent management, and correctly allocating resources while cultivating a culture of excellence, creating a high performing workforce and elevating organizational performance to unprecedented heights.

1.3 Scope of study

The scope of the study encompasses the analysis of historical data and uses these variables to create a predictive model that accurately forecasts employee performance in relation to an employee's promotion. This study includes data collection, pre-prossessing, and engineering processes to ensure accuracy, relevance, and quality of the variables used as input. The selected machine learning models will be trained, validated, and evaluated using suitable metrics to determine their predictive performance.

However, it is necessary to note that this study does not investigate the implementation of the predictive model in an organizational setting or provide recommendations for specific human resource management practices. The project's scope is limited to the development and testing of the predictive model itself, with the purpose of providing insights into the predictive potential of the selected variables for employee performance.

The study acknowledges that factors other than the variables evaluated may have an impact on employee performance. As a result, the scope is limited to the factors chosen and excludes a detailed examination of other potential predictors of employee performance.

Overall, the goal of this study is to provide the framework for future research and potential practical applications in talent management and decision-making by constructing, analyzing, and learning from a predictive model that projects employee performance using the variables indicated.

2. LITERATURE REVIEW

1) **"Artificial intelligence–challenges and opportunities for international HRM: a review and research agenda"** By Budhwar P. Malik, et al., published in The International Journal of human resource management in 2022 . In this research an automated job satisfaction system utilizing an artificial neural network was proposed .Their system analyzed data to ascertain employee satisfaction levels. However, the limitation of this study was that it primarily focused on employee satisfaction and did not consider other critical factors impacting employee performance. It was also noted that the study did not consider the role of individual employee traits and variations in job roles, which are significant elements in any performance evaluation system.
2) **"Artificial intelligence techniques in human resource management a conceptual exploration"** By Strohmeier.S, et al., published in Intelligent Techniques in Engineering Management in 2015.In this research in response to these limitations applied the adaptive neuro fuzzy inference system for a more comprehensive performance evaluation, considering the work goals and achievement of the Saudi Airlines cabin crew. Nevertheless, the study was limited to a specific industry and did not adequately address how the fuzzy linguistic variables could be applied across various professional contexts and industries.
3) **"The role of artificial intelligence in HRM: A systematic review and future research direction** By Basu, S., et al ., published in human resource management review in 2022.In this research the gap in understanding the influence of AI versus human-driven performance evaluation systems on employee perceptions across different professional settings was addressed .However, the study provided valuable insights into the perceptions of underrepresented groups, it did not fully address the actual presence of bias in AI-driven evaluation systems.
4) **"Artificial intelligence and human workers interaction at team level: a conceptual assessment of the challenges and potential HRM strategies"** By Arsalan A, et al., pulished in Journal of Manpower in 2022.In this research the impact of AI on organizational performance evaluation systems, specifically the continuous modernization of AI, was examined to address this gap . While the study provided insights into the adoption of AI during the global pandemic, it relied mainly on secondary data and did not validate its findings with real-time primary data, presenting a significant limitation.
5) **"Artificial intelligence, robotics, advanced technologies and human resource management: a systematic review"** By Vrontis D, et al., published in the international Journal of Human resource management in 2022.In this research it was investigated that the impact of AI techniques on employee well-being and retention, utilizing primary data through hierarchical and correlational regression analysis. However, it was limited in its scope by focusing solely on employee well-being for retention, neglecting other factors that might influence employee retention, such as job satisfaction, salary, and organizational culture.

6) **“A Study of Artificial Intelligence and its role in Human Resource Management”** By Yawalkar, et al., published in international journal of research and analytical views in 2019. In this research they conducted a study on the role of AI in enhancing organizational culture and employee engagement. They also Conducted research emphasized the role of AI in fostering a supportive and inclusive work environment. However, their focus was primarily on organizational culture and did not deeply explore the individual differences in employee attitudes towards AI.

7) **“Rethinking strategic HRM. In Human & technological resource management (HTRM): New insights into revolution”** By Malik A Budhwar, et al., published in Emerald Publishing Limited in 2020 . To bridge the gap the previous research in this research they researched the perception of employees towards AI-based performance evaluation. Aforementioned work provided valuable insights into individual attitudes and readiness to accept AI in the workplace. Despite these valuable insights, their study did not explore how AI could be integrated into different organizational processes, such as training and development, which is another essential aspect of performance evaluation.

8) **“Unlocking the value of artificial intelligence in human resource management through AI capability framework”** By Chowdhury S Dey ,et al., published in Human Resource Management Review in 2023 . It was explored in this research the role of AI in training and development programs. It revealed how AI could enhance the learning experience, thus improving overall job performance. However, their study primarily focused on the training aspect and did not consider the potential security concerns associated with using AI in performance evaluation systems.

9) **“Artificial Intelligence in HRM”** By Sipahi E,et al., published in Handbook of research in innovative management using AI in Industry in 2022. In this research they investigated the security aspects of AI-enabled performance evaluation systems. The study highlighted the importance of data privacy and security when using AI in such systems. However, their study was more theoretical and did not provide a practical approach to implementing secure AI systems.

10) **“Artificial Intelligence, Employee Engagement, Experience, and HRM in Strategic human resource management and employment relations: An international perspective”** By Malik A Thevisuthan,et al., published in Springer International Publishing in 2022. In this research they proposed a practical approach for implementing secure AI systems in performance evaluation. They suggested using advanced encryption methods to secure sensitive employee data. Their study significantly contributed to the field by merging theoretical and practical aspects. Nevertheless, it mainly focused on data security and did not consider the ethical implications of using AI in performance evaluation. This presents another gap for future research, emphasizing the need for studies examining the ethical considerations in AI-enabled performance evaluation systems.

11) **“The adoption of artificial intelligence in employee recruitment: The influence of contextual factors”** By Pan Y Froese, et al., Published in The International journal of Human resource Management in 2022. In an attempt to address the ethical implications of AI use in performance evaluation in this research the authors conducted a comprehensive study on the ethical considerations in AI-enabled performance evaluation systems. The study discussed the potential for algorithmic bias and the need for transparency in AI decision-making processes. Despite providing a thorough ethical framework, their study lacked empirical evidence to support their claims and did not investigate the potential effects of AI on employee motivation and productivity.
12) “ **When technology meets people: the interplay of artificial intelligence and human resource management”** By Qamar Y Agrawal,et al., published in Journal of Enterprise Information Managaement in 2021.In this research the authors viewing a gap in understanding the impact of AI on employee productivity conducted a research that focused on how AI in performance evaluation systems could impact employee productivity. It found that well-implemented AI systems could boost productivity by providing more accurate and unbiased evaluations. However, the study did not consider the potential negative impacts of AI, such as employee anxiety related to job security and AI transparency issues.
13) **“’Artificial intelligence in tactical human resource management: A systematic literature review”** By Votto AM Valecha ,et al., published in Journal of Information Management Data Insights in 2021. Addressing aforementioned concerns the authors in this research explored the negative impacts of AI implementation in performance evaluation. The researchers identified that although there were possibilities for enhanced productivity, certain employees faced heightened anxiety regarding job security and the lack of transparency in AI. Nonetheless, it is important to acknowledge that their study was confined to a specific industry, which limits the applicability of their findings to diverse sectors.
14) **“An artificial intelligence algorithmic approach to ethical decision-making in human resource management processes”** By Rodgers W Murray,et al., published in human resource management review in 2023. In this research to expand the scope of the findings, a cross-industry study was conducted by the authors exploring employee perceptions of AI in performance evaluation. The research emphasized the significance of transparency and effective communication during AI implementation to alleviate employee anxiety. However, the study did not delve into potential strategies for the successful implementation of AI in different organizational structures.
15) **“Trends and opportunities of artificial intelligence in human resource management: Aspirations for public sector in Bahrain”** By Abdeldayem. MM ,et al.,Pulished in International Journal of Scientific Technology and Research in 2020 . The authors in this research put forth a series of strategies aimed at facilitating successful AI implementation in diverse organizational

structures. They advocated for an adaptable and personalized approach to AI implementation, considering the specific requirements and limitations of each organization. While their study offers valuable insights for organizations embarking on AI implementation, it does not encompass a longitudinal viewpoint, neglecting to consider how the ongoing advancements in AI technologies could impact the efficacy of their suggested strategies in the future.

The comprehensive literature review detailed above sheds light on various aspects of AI application in performance evaluation, from its potential in enhancing job satisfaction by Budhwar P Malik, et al, to its capacity to ensure fairness in appraisal by Strohmeier.S, et al, reducing biases By Basu, S., et al ., and modernizing performance evaluation systems By Arsalan A, et al. It also underscores the role of AI in employee well-being and retention By Vrontis D, et al , enhancing organizational culture By Yawalkar, et al., understanding individual attitudes towards AI By Malik A Budhwar, et al., and its importance in training and development By Chowdhury S Dey ,et al . While security aspects of AI-enabled performance evaluation systems have been addressed By Sipahi E,et al., practical approaches for secure implementations are still in the exploration phase By Malik A Thevisuthan,et al. Ethical considerations have been discussed By Pan Y Froese, et al. , but the empirical evidence to back up these claims is lacking. The impact of AI on employee productivity By Qamar Y Agrawal,et al., and negative impacts such as employee anxiety By Votto AM Valecha ,et al., have been explored, yet these studies have been limited to specific industries. Cross-industry studies By Rodgers W Murray,et al., and strategies for AI implementation By Abdeldayem. MM ,et al., have been proposed, but these studies lack a long-term perspective.

2.1 Research Gap

However, there is a clear gap in the current literature. None of the above-discussed studies have focused on using AI to predict future employee performance. Most of them have focused on evaluating current performance, assessing employee satisfaction, and reducing bias in performance evaluations. Given this gap, the proposed study's methodology, which utilizes a model **(Name)** to predict future employee performance, is both innovative and necessary. This method will enhance the objectivity of performance evaluations and reduce inaccuracies, leveraging AI's predictive capabilities to forecast future performance parameters. By addressing the gap in the literature, this study can make a significant contribution to the field by demonstrating how AI can not only evaluate current performance but also predict future performance with high precision. This will be a revolutionary step towards automating and enhancing the reliability of performance evaluation systems in various industries.

3. METHODOLOGY

3.1 Data and Sample:

The research commenced with the collection of primary data from the organization of the employees through a survey questionnaire. The necessary permission and authorization has been taken from the organization by keeping employee names anonymous and the response rate in the survey was 25%.The employees from different departments were considered in the survey including sales and marketing, procurement, operations, analytics, HR and technology. According to the gender 98 % males and 2% female respondents participated in the study. The diverse data set contains several fields related to an employee, including Department, Region, Education, Gender, Recruitment channel, Number of trainings, Age, Previous year ratings, Length of service, KPIs met (>80%), Average training score, and Awards won. These variables are mentioned in the table below with a brief description of each.

Table:

Attributes	Description
Department	Contains the name of the current department employee is stationed
Region	Contains the number of employee region
Education	Contains education status of employee
Gender	Contains gender status of employee
Recruitment Channel	Contains source through which employee is recruited
No of Trainings	Contains the number of trainings employee received
Age	Contains number of employee current age
Previous year rating	Contains number of employee previous year rating by the company
Length of service	Contains number of years of employee working in the company
KPI’s met>80%	Contains number of key performance indicators met by employee
Average Training score	Contains number of employee current training score
Awards won	Contains number of awards employee won in the tenure

Each of these features can potentially influence the employee's promotion likelihood, and hence they have been collected for the study. The survey employed a combination of closed ended multiple choice questions allowing for collection of efficient quantitative data for testing. The test train split ratio is 90% for the train data and 10% for the test data. The two types of data training and test data are essential and important parts of machine learning. We assess the performance of our models using training and test data sets, which also shed light on their inner workings. The train data has been collected from github and therefore is secondary data.

3.2 Qualitative research:

To gain a deeper insight of our research on performance evaluation process of employees in the organizations and how machine learning would efficiently solve the issues related to it we also conducted interview from the hiring manager to judge the issues they face during manual performance appraisal of employees. The interview not only cleared the issues they could face but also in what areas our solution of using machine learning would help as human element can not be eliminated completely.

3.3 Data Cleaning and Extraction:

Following data collection, the train secondary data set using MatLab was cleaned and inspected. Initial inspection of the data focused on understanding the dataset's structure, examining missing values, checking data types, and observing the distribution of values across different columns. The data was binned and and divided into sections. As it was a large data set binning helped summarize it so that in detail insights could be gained from the data. Sectioning was done following binning of data set by creating subsets of it based on categories of variables. Through thorough sectioning we could focus on specific parts of the data set more effectively. Missing value handling in this research was particularly interesting because the variable 'previous_year_rating' had missing values for employees with 'length_of_service' equal to 1. Considering that these employees have only been in the service for one year and could not have a previous year's rating, these missing values were filled with zero. Similarly, missing values in the 'education' field are addressed in the context of their 'department'. A mode-based imputation strategy was used, where missing values are replaced with the most common education level in each department. The data pre-processing was done which involved transforming the data set into a form suitable for applying machine learning algorithms. This involved techniques like encoding categorical variables, normalizing numerical variables, handling outliers, and feature engineering to create new variables based on the existing ones.

The test data which is primary data was extracted from the survey filled by employees in the company. The survey questions were designed such that no confidential information of the company was asked directly and questions were indirect so that the employees are not reluctant to answer and the company doesn't have problems with it.

3.4 Five Fold Validation Technique:

A Five Fold Cross Validation had been been done on the data set to assess the functioning and performance ability of the machine learning model. The data set was divided into five equal smaller subsets .The model was trained repeatedly five times and evaluated using different subsets one at a time as a validation set and keeping the remaining four subsets to be gathered as a training set.The five repetitive evaluations were combined to form an average which proved to be a result of how well the model works.

In this study a variety of machine learning algorithms are used to analyze the given data to predict employee performance using machine learning techniques and the following algorithms are utilized for training and testing:

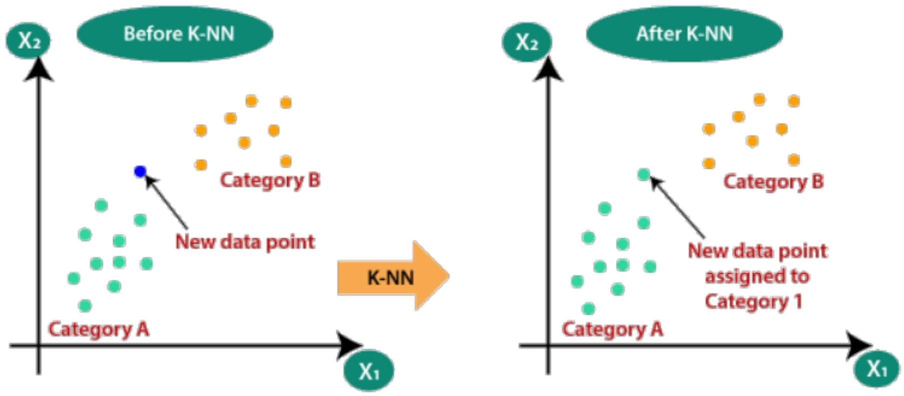
- K-nearest neighbors
- Decision Trees
- Naive bayes
- Random forest
- Gradient boosting

Each algorithm was trained on the data set, hyper-parameters were enhanced using algorithms were evaluated using different metrics such as accuracy, F1 score, precision, and recall using a separate testing set that was created using primary data that was collected according to the details mentioned above.

The above mentioned algorithms are described below:

3.4.1 K-Nearest Neighbors:

The K-nearest neighbors is based on supervised learning technique and is one of the simplest machine learning algorithms. This model is also referred as a memory based learning model as it relies on memory to store all the training data. It is used for classification problems and is a non-parametric algorithm as it does not make assumptions underlying data. This algorithm assigns a new data point to the majority class of its k nearest neighbors in the feature space. During the training phase, this algorithm stores the data set and when it gets new data, it classifies that data into a category that is much similar to the new data. During the training of the KNN classifier, through hyper-parameter training using grid search and cross-validation, the optimal value of k is determined. We used 10% of the data for testing where the accuracy of this model was tested using various metrics such as F1 score, recall, precision, accuracy, and confusion matrix.



3.4.2 Gaussian Naive Bayes:

The Gaussian Naive bayes algorithm uses the probabilistic approach and Gaussian distribution which is normal distribution that describes the statistical distribution of continuous random variables in nature. This model assumes that each parameter has the ability to predict the output variable. Unlike the KNN model, it does not require hyper-parameter tuning when the naive bayes classifier is trained on the training set. The word "naive" is used in its name because it includes features that are independent of each other. So, any changes in the value of one feature has no direct impact on any other features of the algorithm. It is a simple yet powerful model where predictions are made quickly in real-time. This model's accuracy is tested on the testing set using appropriate metrics to gauge its level of effectiveness in predicting employee performance using promotion data.

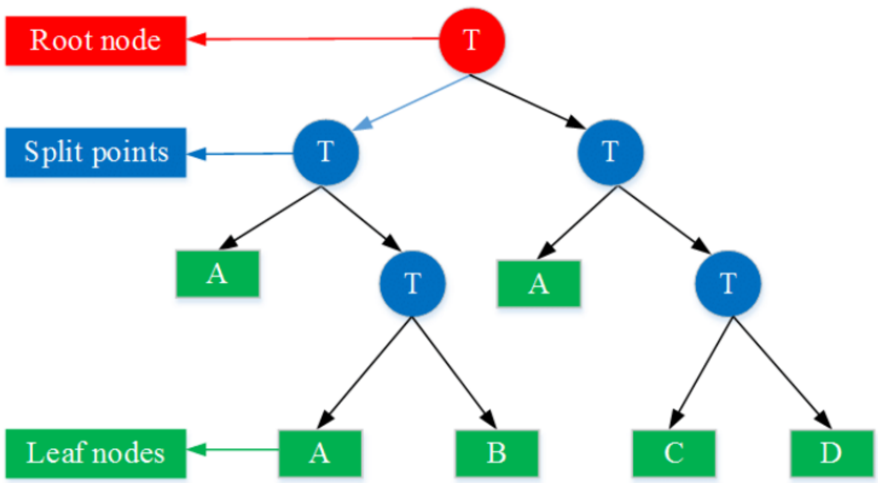
3.4.3 Decision Trees:

The decision tree algorithm is a supervised learning technique that is used to solve classification problems. Decision trees use hierarchical structures that make predictions by dividing the feature space on various attribute conditions. In this algorithm there are two nodes:

- Decision nodes that are used to make any type of decision and have multiple branches.

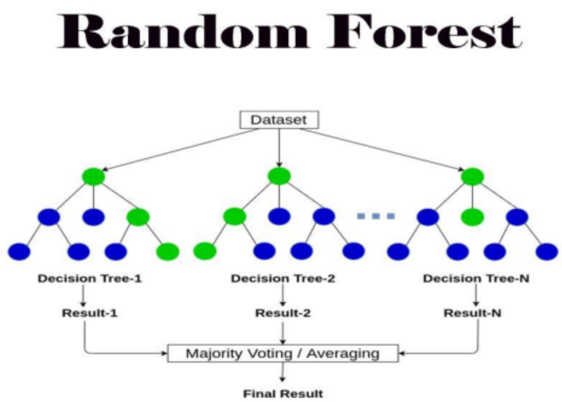
- Leaf nodes are the outputs of decision nodes and do not contain any further branches.

It simply asks a question and based on the answer (yes/no) it splits the tree into sub-trees. On the designated training data set, the decision tree classifier is trained hyper-parameters such as minimum samples split, maximum depth, or criterion are enhanced using cross-validation. In order to assess the predictive capabilities of this model, its performance is evaluated on the testing set and the tests are performed based on the features of the data set.



3.4.4 Random forest:

The random forest algorithm is another supervised machine learning technique and combines multiple decision trees to make predictions. In classification problems it uses a categorical target variable. In this model multiple decision trees are created using various random subsets of data where each tree provides its opinion on how to classify the data. During the training phase, the data set, which consists of features such as employee characteristics, job related factors such as average training score, years of experience, number of awards won etc, and specific performance labels, is used to train the model. The classifier is trained on the training data set and hyper-parameters such as number of trees, minimum samples split or maximum depth are optimized using grid search and cross validation. The random forest algorithm creates a group of decision trees where each tree is trained on a random subset of the data and a random subset of the features mentioned above. Once the training is completed, it can be used to predict the performance of new or unseen employee instances and the models performance is tested on the testing set to evaluate its level of predictive performance.



3.4.5 Support vector machines:

Support vector machines is a supervised machine learning algorithm that aims to find an optimal boundary between the possible outputs. Although it is inherently a binary classifier that can only classify between two classes at a time, but it can be modified to handle multi-class problems using techniques such as One-Vs-One or One-Vs-All strategies. For predicting employee performance using this algorithm a labeled data set containing each employee instance associated with their performance is utilized. All the performance related variables such as years of experience, number of awards won, KPIs met etc are used as relevant features. After splitting the data for training and testing, the model trains to identify decision boundaries in the feature space that separates various performance levels. After training, it can make predictions and the model assigns each instance to a performance level based on the learned decisions boundaries during the training phase and the selected class strategy (One-Vs-One or One-Vs-All).

3.4.6 Gradient boosting:

Gradient boosting combines weak models to create a strong predictive model. The classifier for this model is trained on training data and hyper-parameters such as number of estimators, maximum depth, and learning rate are enhanced using grid search and cross-validation.

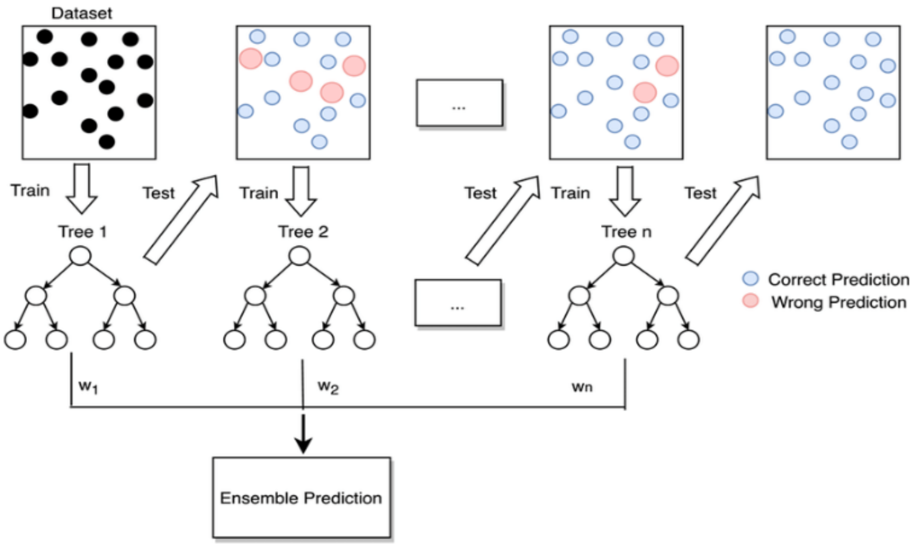
Gradient boosting consists of three main components:

Loss function: It estimates how well the model is making predictions using the data provided.

Weak learner: This component classifies data but does it poorly and has a high error trees.

Additive model: This component adds the weak learner (decision stumps) one by one using an iterative and sequential approach. With each iteration it moves closer to the final model and each iteration reduces the value of the loss function.

In order to evaluate the performance of the testing model a testing data set is used where appropriate metrics are used to evaluate the model's effectiveness.



In this study the metrics used to evaluate the performance of the models applied are as follows:

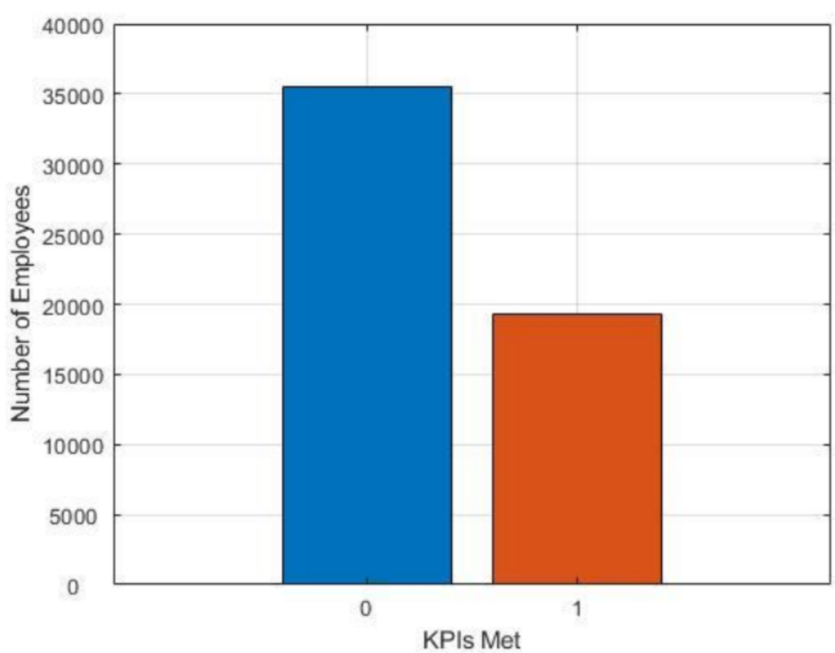
- AUC-ROC metric that helps determine the ability of the applied model to differentiate the classes. It is used to graphically represent the sensitivity and specificity for every cut-off for the tests being performed which means that it depicts the rate of true positives with respect to false positives which highlights the sensitivity of the classifier models applied.

- Confusion matrix which is a basic classification matrix that visualizes truth labels Vs the models predictions in tabular form. It has 4 classes which are true positive that tells the number of correctly predicted positive class samples, true negative that tells the number of correctly predicted negative class samples, false positives which tells the number of incorrectly predicted negative class samples and vice versa for false negative class samples.

4. RESULTS AND DISCUSSION

First looking into the two variables awards won and number of KPIs met during tenure, these two columns directly describe the performance of employees. We investigated the combined impact of the two variables on an employee's likelihood of promotion. KPIs are known as key performance indicators that each employee has met which evaluates their success at reaching targets specified by the organization. We investigated the relationship between the combined KPIs and the number of awards won, as well as an employee's chances of promotion, using statistical analysis and machine learning techniques. We used appropriate predictive models to investigate the predictive power of these variables while accounting for other relevant factors.

In the following case, any employee that has greater than 80% success rate at completing targets has a value of 1 otherwise 0. similarly, number of award won is 1 when an employee has won an award from the company. Out of 40,000 employees, approximately 19,000 employees have met greater than 80% of the key performance indicators which directly describe the employee's performance.

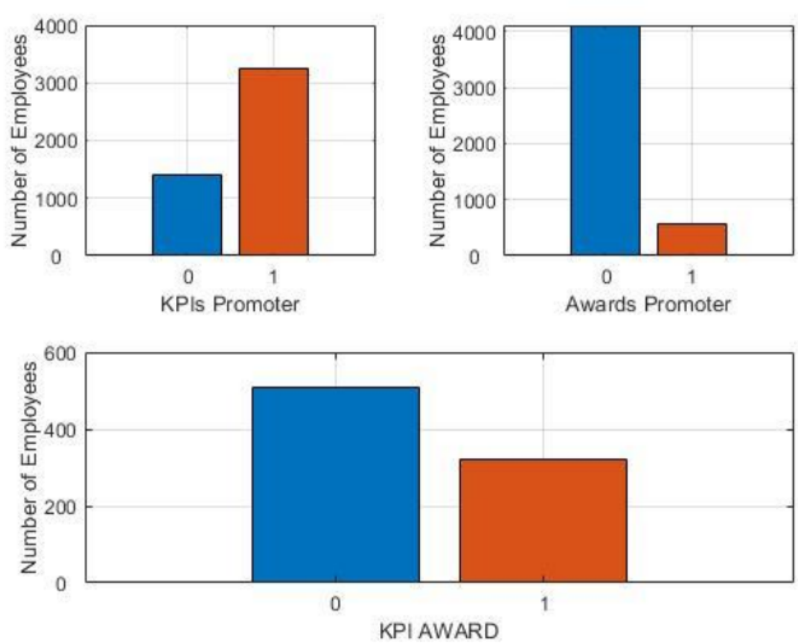


Analysis of the data revealed notable patterns and trends regarding the relationship employee performance, determined key performance indicators and the number of awards won, and their likelihood of promotion. Graph 1 in the set of graphs given below illustrates that a higher number of employees who met KPIs were promoted. This finding suggests a link between meeting KPIs and increased chances of promotion within the organization.

In contrast, graph 2 illustrates that among the employees who won the specific award but did not get promoted while a smaller number are those employees who won the award and got promoted. The graph emphasizes that a signific ant proportion of employees won the award but did not advance in terms of promotion. This finding implies that simply receiving the award does not guarantee promotion.

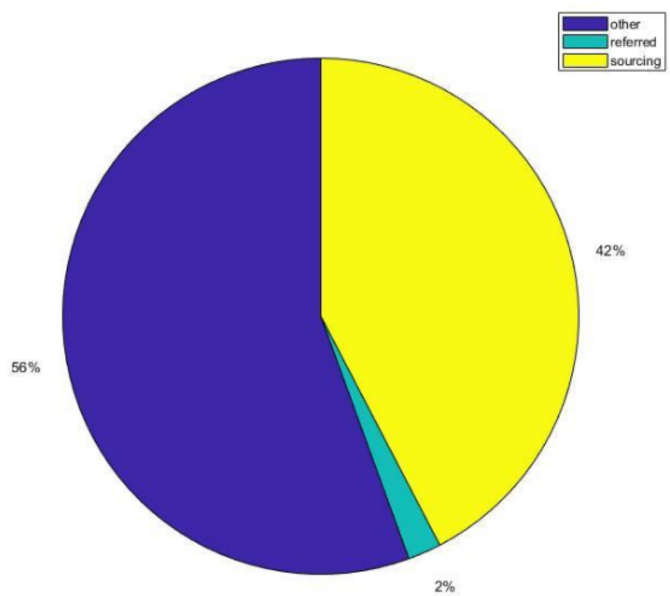
Graph 3 illustrates the combined effect of meeting KPIs and winning awards on getting promoted. Those who did not win any awards or met KPIs did not get promoted. This is higher than those who both, won an award and met their KPIs. This observation clearly highlights the importance of not only winning the award but also meeting KPIs as contributing factors to the chances of an employees advancement in the organization and increased rates of getting promoted.

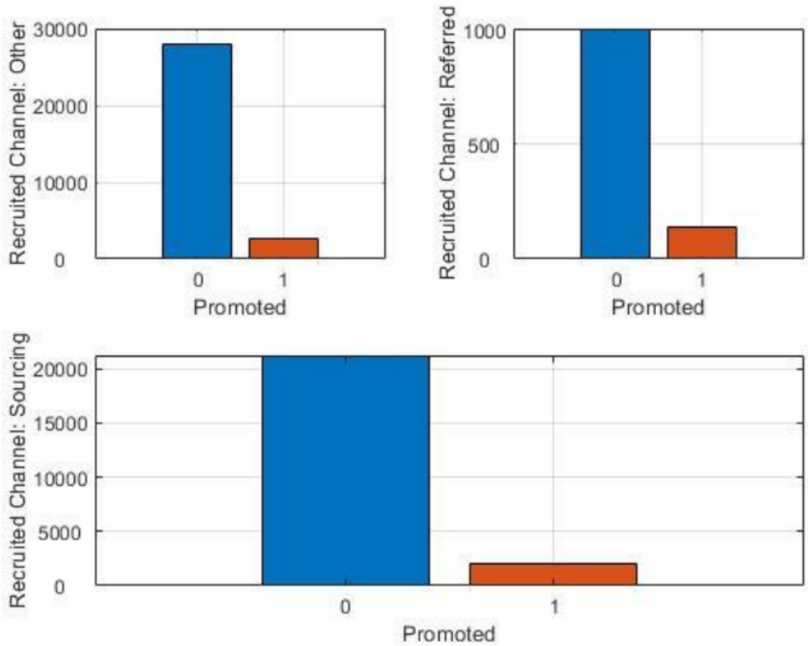
In conclusion, the findings show that attaining KPIs is positively correlated with promotion, but winning an award by itself does not ensure promotion. Employees who achieve both KPIs and the award, however, have a higher chance of being promoted.



Second we look into the impact of the channel of recruitment on an employee's performance i.e the influence of channel of recruitment as a variable on the chances of getting promoted. The analysis showed that a higher proportion of employees who were promoted—around 10% of the promoted people—came from other recruitment channels. This shows that employees hired through sources other than the main recruitment channel had an equal chance of getting promoted. As a result, the data hints that the particular recruitment channel does not significantly affect the results of promotions.

The pie chart below shows the distribution of employees hired from different recruitment channels. Whereas the graph below shows the impact of recruitment channels on promotion.



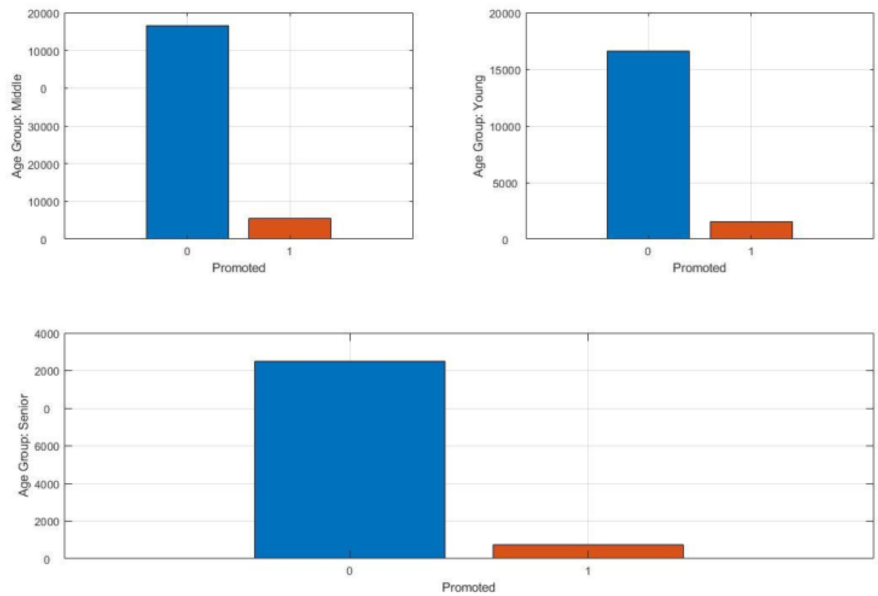


Next, we look at the impact of the variable "age" on employee performance I.e. chances of promotion. In order to enhance the comprehensibility of the data we decided to divide this variable into the following three groups:

- Young: 20 to 30 years old.
- Middle: 30 to 45 years old.
- Senior: 45 and above.

We intended to establish more meaningful divisions that are easier to read than a scatter plot with a wide range of ages (20 to 60 years old) by categorizing the ages into these precise groupings.

From the results below, it can be concluded that middle age group have a 10% chance of getting promoted whereas the age group labeled "young" has 9% chance of getting promoted which is approximately similar to middle age division. And as a senior working for a senior position, employees have a smaller chance of getting promoted. Research on age and promotion suggests that age can influence career advancement. According to several research, younger employees had a higher rate of promotion due to variables such as better energy levels, readiness to take on new tasks, and the possibility of long-term growth within the organization. Younger employees may also have more up-to-date skills and knowledge that correspond to changing job requirements. On the other hand, senior employees may face barriers to promotion such as decreased upward mobility, assumptions regarding retirement plans, or age biases and that is why the number of available roles often decreases as employees advance up the organizational structure, resulting in increased competition for those positions.According to the study conducted by Machado and Portela (2013) which explored the relationship between age and promotion, found that younger employees experience shorter times to promotion than older workers and, therefore, the latter face a smaller likelihood of promotion. This research further supports the results shown in the graphs below:



Next we study the impact of average training score and previous year ratings on an employees performance and their probability of getting promoted. These two variables were combined which gave birth to a new column called, “total score”. The total score could be anything from 0 to lets suppose 710. However, from the data majority of the scores tend to fall within 500s where the remaining scores are outliers. To effectively analyze data, we used the following two approaches:

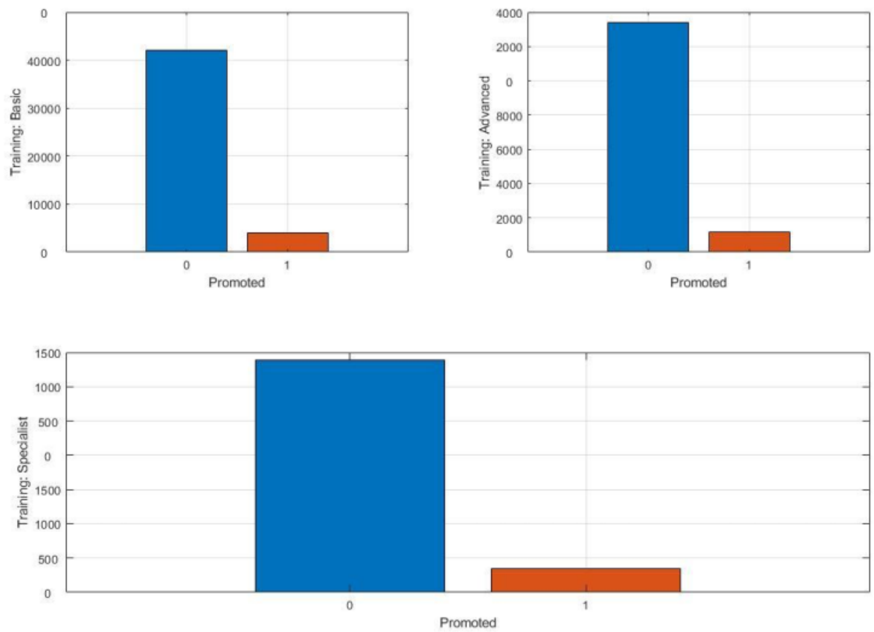
- Binning
- Normalization

With normalization, we changed the total score values into a standardized scale, in order to ensure that the data maintained its relationships and relative proportions. We also incorporated a binning technique where we grouped obtained scores into distinct categories based on predetermined thresholds. The breakdown of the score groups and their training levels are given below:

- Basic training: scores ranging from 0 to 100 or less
- Advanced training: scores greater than 100 and up-to 300
- Specialized training: scores greater than 300 and up-to 400
- Outliers: scores above 400, determined based on data density

By removing the outliers from the data set, we further ensured a more accurate representation of the training score distribution.

From the results given below, it can be concluded that people with specialized training have a higher chance of getting promoted as compared to the other two groups. Training has a significant impact on an employee's performance and does impact his/her chances of promotion. When employees undergo different training, they acquire skills and knowledge with enhances their performance and in turn increases their chances of promotion. The research conducted by Farooq, Mubashar & Khan, Dr. (2011), highlights role of effective training and feedback in improving the quality of task process which ultimately results in the improvement of performance of employees. Therefore it can be concluded that higher training score results in higher chances of getting promoted and people having scores lying in the category of specialized training have better performance and have a higher chance of getting promoted as compared to people having basic to advanced training scores.



The extensive data set led to the following conclusions:

- The performance column which is a combination of number of KPIs met and awards won is a good factor to predict employee performance but it is not the only factor.

- The average training score and previous year ratings have been combined to give total score. Employees with specialized training have a higher chance of getting promoted.

- Gender as a factor has no effect on getting promoted.

- The channel of recruitment as a variable does not significantly effect the results of promotion.

- Department and education do not give much insight into their impact on performance and promotion.

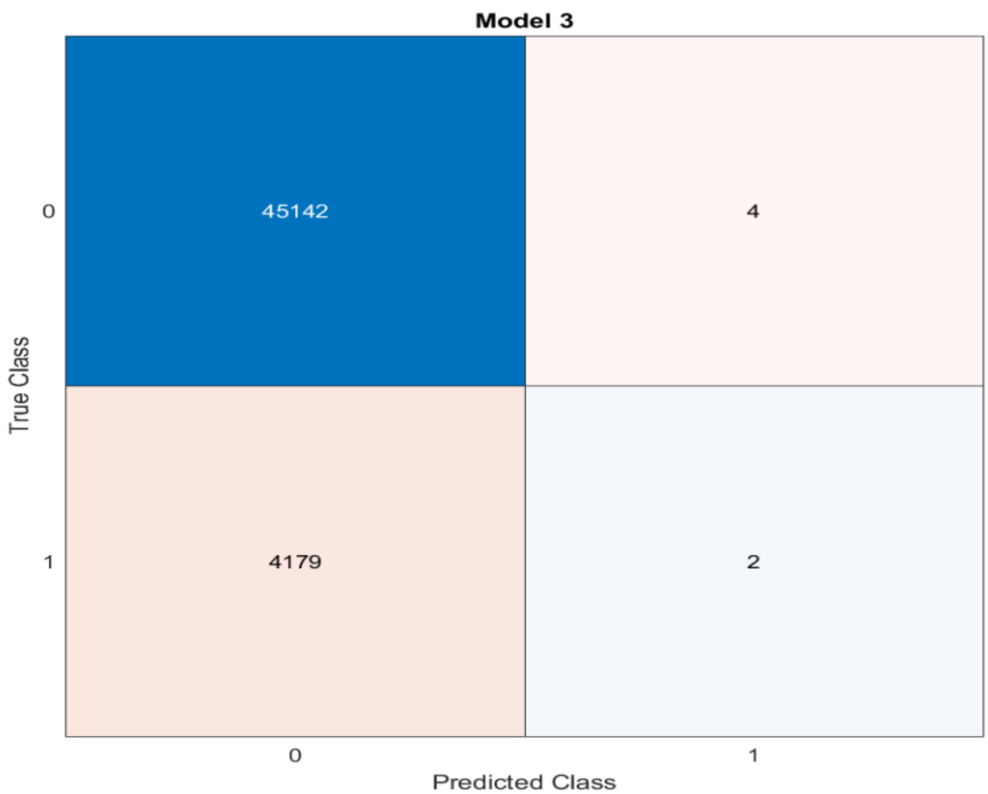
No factor alone has an impact on employee performance and promotion and variables such as performance (KPIs met and awards won), age, and total score can be considered for predictive modeling.

4.1 Testing results:

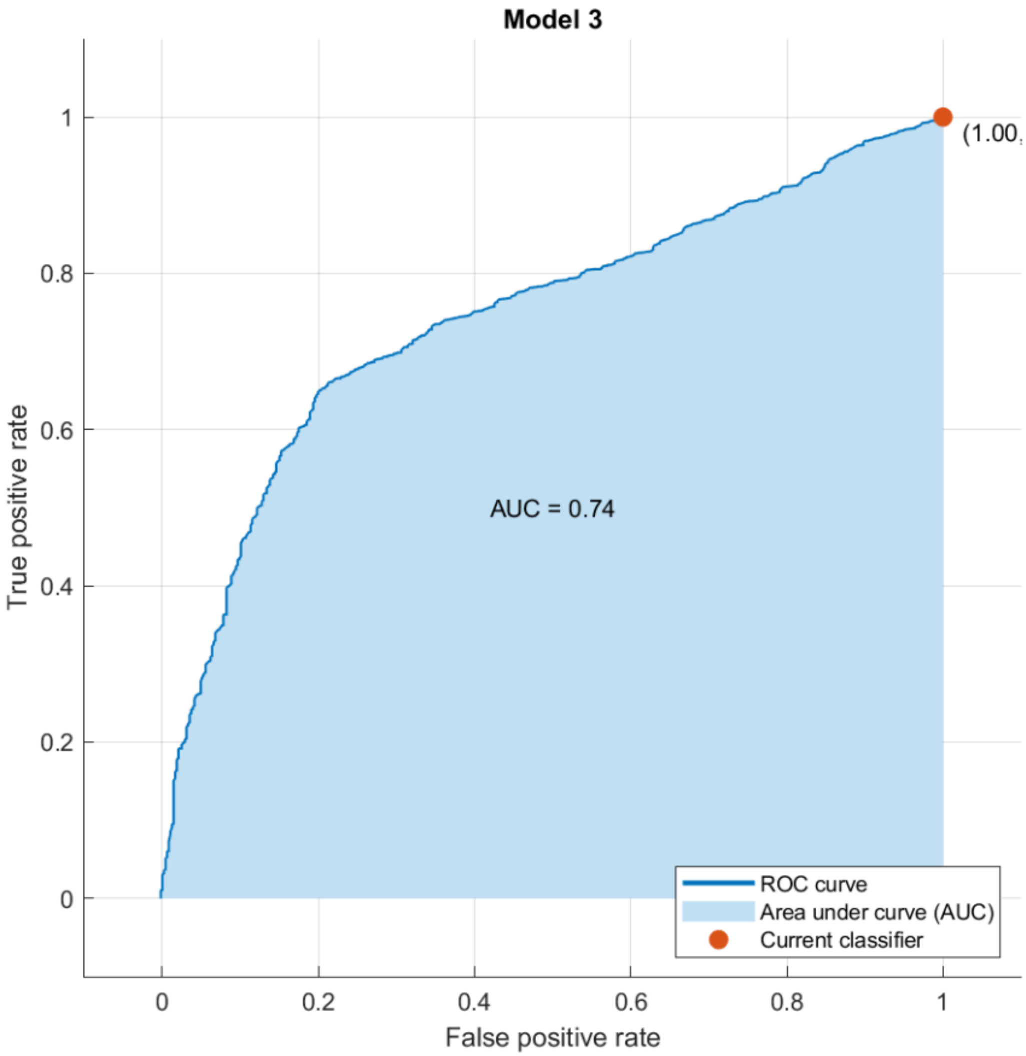
After training the algorithms, the selected models were tested which gave the following results:

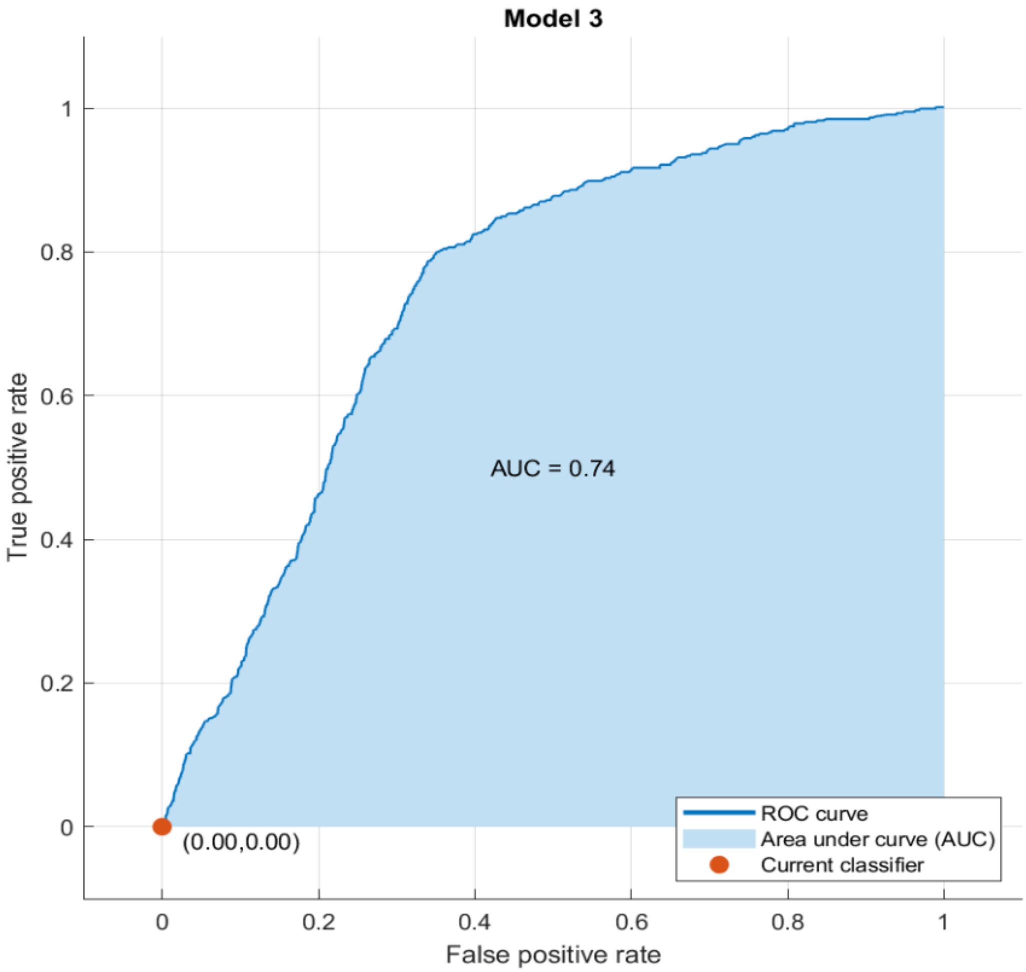
The classification model was trained on a data set of different employers in a firm and used to forecast employers' performance. To evaluate the effectiveness of the model, we constructed a confusion matrix based on the prediction results, which had 0 and 1 as true classes on the vertical axis and predicted classes on the x-axis.

The confusion matrix showed that out of 45,142 actual class 0 instances, 4 were incorrectly classified by the model. Similarly, out of 4,179 actual class 1 instances, 2 were misclassified. The majority of instances were correctly classified, indicating that the model had high accuracy.



A Receiver Operating Characteristic (ROC) curve was also plotted, with the true positive rate (TPR) on the y-axis and false positive rate (FPR) on the x-axis, both varying from 0 to 1. The Area Under the Curve (AUC) for this ROC was 0.74, which suggests a satisfactory level of model performance. The ROC curve started from 0 and gradually increased to 1. Notably, the current classifier stands at the point 1 on the ROC curve.





Another analysis was conducted using a matrix block diagram, with true class instances on the y-axis. The instances in class 0 and class 1 were subdivided into two blocks each. For class 0, 91.5% of the instances were correctly identified (True Positives), while 8.5% were misclassified (False Negatives). For class 1, 66.7% were correctly identified (True Negatives), whereas 33.3% were incorrectly classified (False Positives).

Lastly, the positive predictive value (PPV) or precision, which indicates the proportion of positive results that are true positives, was 91.5% for predicted class 0 and 33.3% for predicted class 1. The false discovery rate (FDR), which is the expected proportion of false positives among all positive findings, was 8.5% for predicted class 0 and 66.7% for predicted class 1. These metrics suggest that the model is highly precise in predicting class 0 but struggles to accurately predict class 1. Future work could focus on improving the precision for class 1 predictions.

5. CONCLUSION

Accurately predicting employee performance is lengthy and time consuming. But it plays a key role in strategic decision making. Humans are bound to make errors and manually calculating performances of each and every employee becomes tiresome and dull. By using machine learning techniques for predicting employee performance and using promotion data, it can make the process fast, help avoid human biases, and allows for fair analysis of employee performance.

From the results it can be concluded that overall, the model correctly classified majority of the instances which proved that the model is showing high accuracy in predicting employee performance. The confusion matrix also had a small number of miscalculations which further strengthened the effectiveness of the models applied.

During the testing phase, after the ROC analysis, the AUC of 0.74 suggested a satisfactory level of performance and the steady increase of the ROC curve towards 1 means that the model has the capability to differentiate between classes. The curve also indicates a high true positive rate and a low high positive rate which means that the models have a strong ability to correctly identify positive instances. The curve is also showing a low false positive rate depicts that the models applied in the study have a low ability to incorrectly predict negative instances as positive.

The matrix blog diagram in the results section of the study showed the distribution of correctly and incorrectly identified instances for each class. Class 0 had a high rate of correct identification i.e. 91.5% which indicated that the model can accurately this class. However, the model struggled to predict class 1 instances as the correct identification rate was only 66.7%

From the positive predictive value it can be concluded that the high PPV value which is 91.5% for class 0, which means that when the models predict an employee as a high performer, it is predicting accurately. The lower PPV of 33.3% on the other hand means that the model has a higher chance of predicting an employee as a low performer incorrectly.

The false discovery rate (FDR) is 66.7% which means that out of all the instances classified by the models as positive, 66.7% of them are incorrect.

From the findings it can be concluded that the models correctly predict class 0 (high performers) instances but struggle to predict class 1(low performers) instances.

Therefore, future research should focus on improving the ability of the models to correctly identify class 1 instances i.e. low performers. This can be done through collecting more representative data, looking into alternative modelling approaches such as feature engineering that could include variables that specifically indicate low performers, use ensemble techniques where multiple models are combined to increase accuracy, cross-sensitive learning, or resampling techniques etc.

In a fast paced world, in order to stay efficient and in touch with the ever changing market trends, it has become a need to stay in touch with the continuously changing and improving technology. By using machine learning techniques to predict organizational factors such as recruitment, attrition, or employee performance help the organizations to boost efficiency, remove the aspect of human biases and error in order to allow fair evaluation of employees using performance data only, and to handle large scale data sets efficiently while saving a lot of time.

The results obtained from this study can be used to verify the performance ratings given by the managers of organizations and can help remove any type of biases or discrimination within the organization. Gaussian Naive bayes and support vector machines prove to be the most suitable in terms of predicting employee performance using promotion data.

6. RECOMMENDATIONS

Based on the findings of this research here are some thorough recommendations to persuade organizations to utilize AI machine learning for improved employee performance evaluation:

1) Decision-makers should receive thorough education and training on the advantages and potential of AI in performance evaluation. To show the beneficial effect of AI on employee appraisal, highlight real-world success stories and case studies. The main concern of the company is also the complexity of AI models for which they can use decision trees as it is a less demanding model and provide good valuable understanding . Gaussian Naïve Bayes as also according to our findings is appropriate for huge datasets or

scenarios with constrained computer resources because it is computationally effective and takes little training time. So companies that don't use AI due to these worries can use these models.

2) To demonstrate the return on investment (ROI), pilot programmes or small-scale installations of AI-based performance appraisal systems should be carried out within the company. The advantages in precision, effectiveness, and employee happiness brought about by the implementation of AI should be measured and presented.

3) Addressing worries and misunderstandings as many organizations might have worries or misunderstandings concerning AI, such as worries about job loss or biases in algorithms. Clear explanations, examples of how AI may enhance human judgement, and the implementation of bias mitigation strategies can all help allay these worries. Companies can use 5-fold validation for accuracy of the model they are using and it reduces bias in model evaluation. You may judge the model's generalization skills more fairly by averaging the performance measures over the five folds. By doing this, it is possible to prevent the unduly optimistic or pessimistic performance estimations that can result from a single train-test split. By including 5-fold validation in the performance evaluation procedure, it is possible to make sure that the machine learning models created by employees are thoroughly assessed, fostering accountability and encouraging the usage of solid and durable methods throughout the organization.

4) Encourage a data-driven culture by highlighting the value of employing factual data and evidence in decision-making processes inside the organization. Encourage staff to keep note of their performance indicators, accomplishments, and feedback so that it can be used as useful data for AI-based appraisal systems.

5) Engage with AI vendors and solution providers who specialize in performance rating systems to collaborate. Work closely with them to comprehend their capabilities for integration, customization, and services. Collaboration with other organizations can allow AI solutions be customized to the unique demands and requirements of the organization. Businesses may look into working with universities, research institutes, or AI startups. These organizations might be open to contributing knowledge or resources to efforts involving performance evaluation in exchange for chances to work together on research, the sharing of data, or other advantageous agreements.

6) Emphasize the fairness and transparency of AI systems in performance evaluation to show that they are just and transparent. Showcase how taking into account a wider range of data sources and objective criteria can help AI

algorithms decrease biases. Share the actions taken to assure responsibility, comprehensibility, and adherence to moral principles.

7) Conduct pilot tests of AI-based performance evaluation systems in particular teams or departments. Then evaluate the results. Gather opinions from the pilot's management, workers, and HR specialists. Before expanding the implementation, use this feedback to improve the system and address any issues or restrictions.

8) Measure performance evaluation success metrics, including their correctness, effectiveness, impact on corporate objectives, and employee happiness. Evaluate the performance of the AI-based systems on an ongoing basis, and inform the stakeholders of the successes.

9) Foster change champions by identifying prominent staff members who are receptive to utilizing new technologies and who will act as change champions. These people may promote AI adoption, offer their good insights, and inspire others to use AI in performance evaluation. AI-based performance appraisal systems and HR team evaluations each have advantages and disadvantages. The objective analysis and scalability of AI technologies, along with the qualitative insights offered by HR evaluations, can be combined to create a thorough and well-rounded approach to performance rating in organizations. Making decisions on employee performance, growth, and organizational objectives requires striking a balance and utilizing the advantages of both approaches.

10) Organizations can use a variety of free and open-source AI frameworks and tools without paying licensing fees because a lot of organizations be small medium enterprises in underdeveloped countries like Pakistan cannot afford to use AI for their performance appraisals. Scikit-Learn, TensorFlow, and PyTorch are among examples of open source tools. These frameworks offer the infrastructure required for putting machine learning models into use and assessing performance. Businesses can use cloud-based AI services rather than spending money on pricey hardware infrastructure. AI services are available from cloud providers like Amazon Web Services (AWS), Google Cloud Platform (GCP), and Microsoft Azure and can be utilized for performance evaluation. These services frequently include pay-as-you-go pricing structures, enabling businesses to utilize AI capabilities as required while staying within their financial limits.

By putting these Recommendations into practice, businesses can foster the adoption of AI in performance evaluation, resulting in more precise, equitable, and data-driven assessments of employee performance.

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