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Employee attrition prediction using machine learning models.

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Abstract*– Today's business landscape is characterized by competition and dynamism, which has transformed human resource management into an essential strategic partner for organizations. Employee turnover poses risks that affect productivity and knowledge management. This study focuses on predicting employee turnover using Machine Learning (ML) models. For the training process, a dataset composed of 4410 records and 29 variables was used, in the process of training and evaluation of the ten models, the artificial intelligence (AI) method was followed. The findings showed that the XG Boost Classifier (XGBC) and Random Forest (RF) models achieved the best accuracy and performance rates, with 98.8% and 98.7%. Followed by Decision Tree Classifier (DT) with 97.6%, and the other models, such as Gradient Boosting Classifier (GBC), Ada boost Classifier (AC), Logistic Regression (LR), KN Classifier (K-NNC), SGD Classifier (SGDC), Support Vector Classifier (SVC) and Nu Support Vector Classifier (NuSVC), achieved the following rates: 88.4%, 85.4%, 84%, 82.2%, 83.0%, 83.0%, 55.0%, respectively. Finally, it is concluded that the models are useful and effective in prediction. Their practical implementation in human resource management strategies is recommended for proactive intervention.

***Keywords--* Machine Learning; Artificial Intelligence; Management; Human Resources; Models.**

I. INTRODUCTION

Today's business environment is competitive and dynamic, which has led to the evolution of Human Resource Management, making it a crucial strategic partner [1],[2]. Given the complexity and dynamism of external organizational environments, employee turnover is a constant risk that impacts productivity and knowledge management. Several studies reveal worrying rates of job dissatisfaction and turnover in different countries and sectors, underlining the need to address this challenge. According to the Burnout 2023 study, conducted among workers and HR specialists in five countries in the region, Argentina has the highest burnout rate (94%), followed by Chile (91%), Panama (83%), Ecuador (79%) and Peru (78%) [3]. Similarly, LinkedIn's 2021 report shows a global average turnover rate of 10.9% [4]. According to a report by the Society for Human Resource Management (SHRM) in the U.S., employee turnover can cost up to 50-60% of the replaced employee's annual salary. On average, it can take companies 42-60 days to fill a vacancy, and about 20% of new employees leave within the first 45 days [5]. In addition, a study by the Gallup consulting firm estimates that only 21% of employees worldwide are engaged in their jobs, suggesting a general lack of job satisfaction. The International Monetary Fund (IMF) and the World Bank (WB) also estimate that global unemployment will be 5.3% and 5.2% in 2023 [6],[7]. Therefore, forward-thinking companies are turning to advanced technologies such as AI and data analytics to anticipate potential employee turnover and take preventative measures to minimize its effects [8],[9]. The advancement of technology enables proactive and timely measures to be taken in human resource management, allowing companies to deal with the threat of losing a valuable employee. This is made possible by the intrinsic potential of emerging technologies to address various issues, and they emerge as catalytic agents by enabling the generation of content from pre-existing data [10], [11]. Thus, AI is being adopted by various companies around the world for its ability to perform complex tasks that previously required human intervention. Within the field of AI, we find ML, a branch of AI that focuses on the development of algorithms and models. These models capture patterns and relationships in the data during the training process [12], [13] and are then used to make predictions or decisions about new data [14],[15], [16]. The objective of this research is to predict employee turnover using the following ML models: LR, SVC, NuSVC, XGBC, K-NNC, SGDC, DTC, RF, ABC, and GBC. In addition, the organization of this paper follows the following structure: section 2 presents related work on employee turnover. In section 3, the theoretical foundations underpinning this paper are built. Section 4 presents the training results of ML models. Section 5 discusses the results with findings from related work. Finally, Section 6 presents the conclusions and future work.

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II. RELATED WORK

Several studies have successfully explored the use of ML to address employee turnover prediction. The research has highlighted the success of different models, such as Logistic Regression, ensemble models, analysis of different ML methodologies, and the use of deep models to predict employee turnover. In addition, this study builds on research that has successfully used ML to solve various problems. For example, in research [17], a model based on the Logistic Regression algorithm was presented to analyze the probability of employee attrition in an organization. The methodological approach employed consists of the exhaustive application of the Logistic Regression algorithm. This model has shown remarkable results, with an accuracy rate of 84.12%, an accuracy of 84% and a recall rate of 100%. The researchers concluded that the model has significant potential for analyzing the probability of employees leaving an organization. Similarly, in work [18], they analyzed the impact of learning techniques in predicting employee turnover. They applied a nested ensemble model with two layers to a dataset, which achieved an upper accuracy rate of 94.55%, an F1 score of 94.5%, and an AUC of 98.5%. And they concluded that the two-layer nested ensemble model improves the predictive ability of employee turnover prediction. Also, in the study [19], they performed exploratory analysis of different ML techniques for predicting employee turnover. The results obtained with each ML model were compared, and among the different results, the LR model stood out as the most effective model, achieving an accuracy rate of 88% and 85% for the ROC curve. Furthermore, in the study [20], deep ML models were employed to predict employee attrition. The dataset consisted of 35 features and 1470 employee records. Through a series of experiments, the practical value of the research was demonstrated. The deep learning model achieved impressive results, with an F1 score of 94.52%, recall of 94.52%, accuracy of 94.58%, and overall accuracy of 94.52%. These results illustrate the effectiveness of deep learning models in this context. Furthermore, in [21], models were employed to predict whether a particular employee will leave the company, using real data sets provided by IBM analytics. The results are presented in conventional metrics, and the algorithm that demonstrated the best performance was the Gaussian Naive Bayes classifier, with an outstanding recall rate of 0.54. It also achieves an overall false negative rate of 4.5%, indicating a remarkable efficiency in identifying negative instances.

III. METHODOLOGY

In the last decade academics and scholars in human resource management have published work related to the topic of study. For example, the study [22], predicting employee attrition to mitigate employee attrition is a great input for HR managers as it enables them to make timely decisions. For this study, ML LR, SVC, NuSVC, XGBC, K-NNC, SGDC, DTC, RF, ABC, and GBC models were used. Each of these models has its own characteristics and was trained on a dataset from the Kaggle platform consisting of 4410 records and 29 variables.

A. Machine Learning Models

1) Logistic Regression: Logistic regression is a supervised learning model for binary classification. It uses the logistic function to estimate the probability of belonging to a class. Training the model involves fitting its coefficients using optimization techniques such as gradient descent. Although simple and understandable, it may face challenges when dealing with nonlinear data and outliers [23]. The representation of the model is expressed by equation (1).

$$\mathrm{P(Y=1|X)} = \frac{1}{1+\mathrm{e}^{-\mathrm{bo}+\mathrm{b}_1\mathrm{X}_1+\mathrm{b}_2\mathrm{X}_2+\cdots+\mathrm{bnXn}}} \qquad (1)$$

Where:

The probability that Y equals 1, given a vector features X, is denoted as P(Y= ├ 1┤ |X). The coefficients of the model are bo, b1, b2, ..., bn.

These coefficients are modified through an optimization algorithm, such as gradient descent, for the purpose of minimizing the logistic loss function.

2) Support Vector Classifier: The SVM is a supervised learning model applied in classification situations. Its main objective is to find the hyperplane that achieves the best separation between the two classes within the feature space [24]. This model is represented by equation (2).

$$\omega \cdot X + b = 0 \qquad (2)$$

Where:

W: is a vector of weights that defines the direction of the hyperplane.

x: is a feature vector.

b: is the bias.

The hyperplane separates the two classes, and the distance between the hyperplane and the nearest data points is maximized.

3) *Nu Support Vector Classifier*: A variant of the SVC that uses a "nu" parameter instead of the C-regularization. This provides more flexible control over the number of support vectors used and the generalizability of the model [25].

4) *XG Boost Classifier:* It is an extreme gradient boosting algorithm commonly used in classification and regression problems. This model is recognized for its efficiency and speed in making predictions [26]. It is represented by the following equation (3).

$$\mathrm{P(Y=1|X)} = \frac{1}{1+\mathrm{e}^{-(\mathrm{F(X)})}} \qquad (3)$$

Where:

F(X) is a function that combines the output of multiple decision trees.

5) *K-Nearest Neighbors Classifier:* This is a model that classifies data points according to their proximity to nearest neighbors [27].

6) *Stochastic Gradient Descent Classifier:* It is a method used to improve the efficiency of ML models, applicable to various classification algorithms such as LR, SVM, among others. This model optimizes a loss function to make predictions and is iteratively updated [28].

7) *Decision Tree Classifier:* This classification model uses a tree structure to classify data. Although it is easy to interpret and simple, it is crucial to apply controls to avoid overfitting in real-world applications [29].

8) *Random Forest:* It is a powerful and adaptable algorithm that employs multiple decision trees to achieve a more accurate and robust final prediction [30].

9) *Ada Boost Classifier:* The algorithm works by iteratively building a set of classifiers, where each classifier is designed to classify the samples in the data set with a certain degree of accuracy. Typically, each classifier takes the form of a decision tree, which is constructed using a subset of the features in the dataset [31].

10) *Gradient Boosting Classifier:* It focuses on minimizing a loss function, usually through the gradient descent method. This process involves fitting models sequentially with the objective of decreasing the residual error [32].

B. Dataset

This paper uses a dataset from the Kaggle platform, which comprises several factors that can affect or influence employees. It also includes data on employee attrition. The dataset consists of 4,410 records and 29 variables, some of which are Age, Disengagement, Business travel, Department, Distance from home, Education, Educational background, Number of employees, Gender, Total years of employment, Training time in the past year, Years with company, Years since last promotion, Years with current boss, Satisfaction with environment, Satisfaction with job, Work-life balance, and Work involvement. Fig. 1 illustrates the diagram describing the sequence of steps for the formation of the data set.

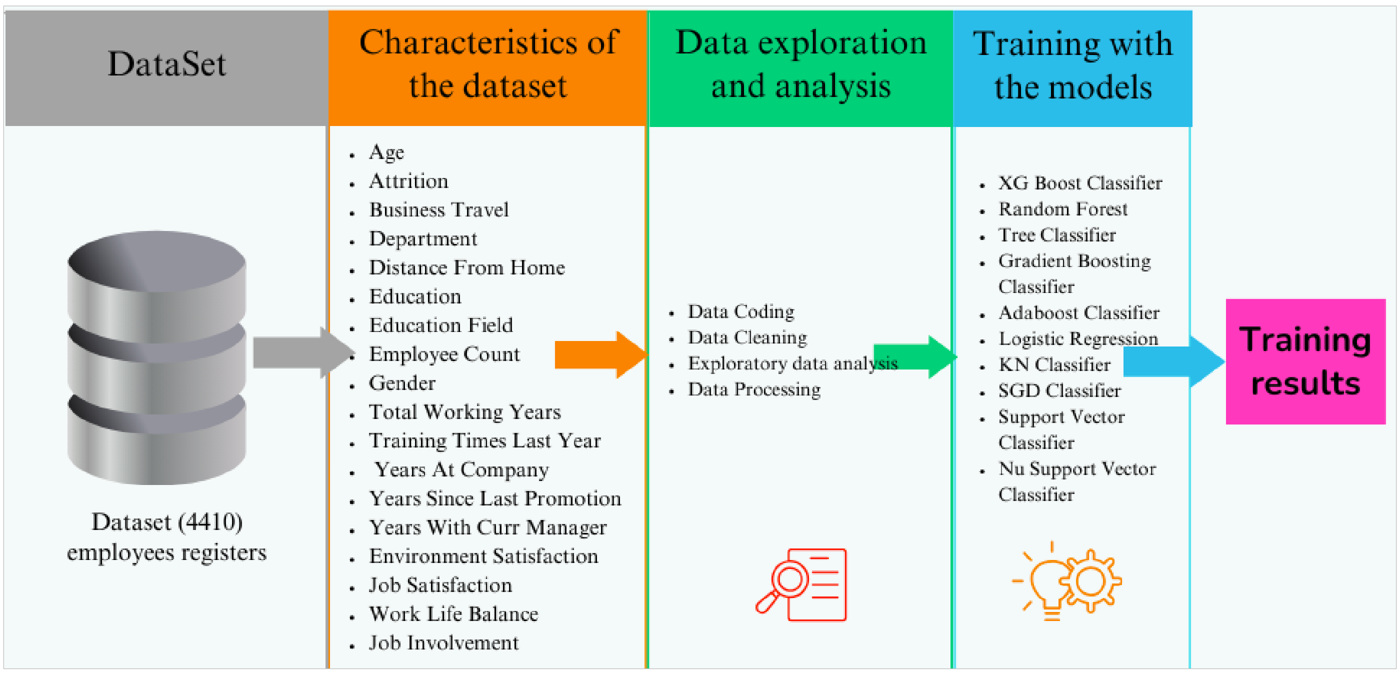

Fig. 1 Data set training development process

C. Data processing

The data preparation process involves several tasks, such as data cleaning, data transformation and data analysis. Initially, the appropriate libraries are imported to load the dataset and perform an exploratory analysis. This allows obtaining information about the type of data for each variable, its content and description. Once the exploratory analysis has been performed, any duplicate, missing or erroneous information is removed. In addition, outliers are checked for accuracy and reliability. Managing missing values and exploring relationships are crucial steps to deepen the understanding of the factors influencing employee attrition. Table 1 shows the attributes of the data set, Table 2 presents a correlation of variables in the context of the workplace.

TABLE 1 DATA SET ATTRIBUTES

#	Age	Attrition	Business Travel	Department	Distance From Home	…	Performance Rating
0	51	No	Travel_Rarely	Sales	6	…..	3
1	31	Yes	Travel_Frequently	Research & Development	10	…..	4
2	32	No	Travel_Frequently	Research & Development	17	…..	3
…..	…..	…..	…..	…..	…..	…..	…..
4408	42	No	Travel_Rarely	Sales	18	…..	3
4409	40	No	Travel_Rarely	Research & Development	28	…..	3

TABLE 2 CORRELATION OF VARIABLES IN THE LABOR CONTEXT

Feature	Work Life Balance	Job Involvement	Performance Rating	Num Companies Worked	Age	Education	.	Attrition
Work Life Balance	1.000000	-0.018435	-0.022920	-0.008910	-0.020524	-0.005610	.	-0.062975
Job Involvement	-0.018435	1.000000	0.010699	0.027887	0.018196	-0.018279	.	-0.015588
Performance Rating	-0.022920	0.010699	1.000000	0.017653	-0.025563	-0.035591	.	0.023403
Num Companies Worked	-0.008910	0.027887	0.017653	1.000000	0.298346	-0.016228	.	0.042301
Age	-0.020524	0.018196	-0.025563	0.298346	1.000000	-0.035706	.	-0.159205
Education	-0.005610	-0.018279	-0.035591	-0.016228	-0.035706	1.000000	.	-0.015111
Distance From Home	0.008305	-0.001837	0.036418	-0.013950	0.006963	-0.008638	.	-0.009730
…	….	….	….	….	….	….	.	….
Attrition	0.062975	0.015588	0.023403	0.042301	0.159205	0.015111	…	1.000000

D. *Exploratory data analysis*

Table 2 presents the correlation between variables. For example, the positive correlation (0.298346) between Age and NumCompaniesWorked indicates that younger employees tend to have worked in more companies throughout their career. This finding highlights the importance of taking age into account when analyzing job stability. In addition, the negative correlation between Attrition and Age (-0.159205) highlights that younger employees may be more likely to leave the company. Satisfaction with the work environment is positively related to overall job satisfaction. Finally, there is a negative correlation between Attrition and Job Satisfaction, indicating that less satisfied employees are more likely to leave the organization. These correlations provide a solid basis for research and strategic decision making in the field of human resource management. In addition, Fig. 2 illustrates the correlation between the number of companies worked for in relation to age, education, and employee satisfaction.

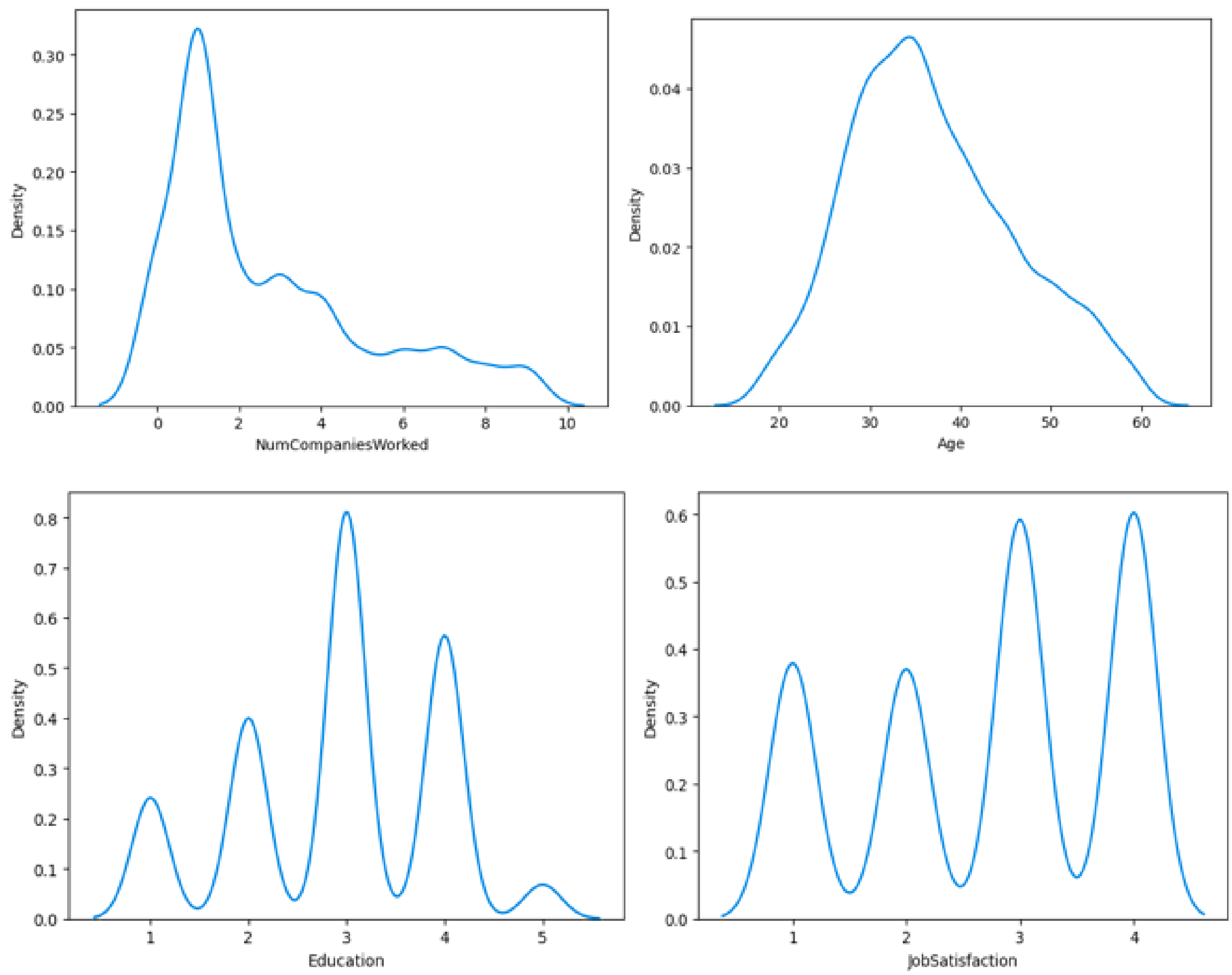

Fig. 2 Exploratory analysis of the variables: # of companies worked, age, education, and employee satisfaction.

E. Training and testing

During training, we proceeded to fit ML models to the training data to generate patterns and relationships in the data, so that it can perform specific tasks such as classification, employee quit prediction. In addition, to start the training, the dataset was split 70% for training and 30% for testing to ensure higher reliability and accuracy in its real-world application.

IV. RESULTS

The following section presents the training results of the ML models (LR, SVC, NuSVC, XGBC, K-NNC, SGDC, DTC, RF, ABC and GBC). The results obtained, measured mainly through the accuracy metric, reveal significant distinctions between the different models evaluated. It can be observed that the Random Forest and XG Boost models present the most remarkable performance in terms of accuracy, with values of 98.7% and 98.8%, respectively. These results highlight the ability of these models to make accurate predictions of employee turnover. Likewise, the Decision Tree Classifier presents a considerably high accuracy, with a value of 97.6%, which positions it as a viable model for application in this specific domain. In contrast, the Nu Support Vector Classifier has an accuracy of 55.0%, indicating certain limitations in its ability to fit the employee turnover prediction data set. Although the Gradient Boosting Classifier (88.4%) and Ads Boost Classifier (85.4%) models show positive accuracy levels, they are lower than the ensemble leaders (Random Forest and XG Boost), however, these results still position them as viable options in predictive analytics, as can be seen in Figure 3, which presents the accuracy rates of the ML models after training.

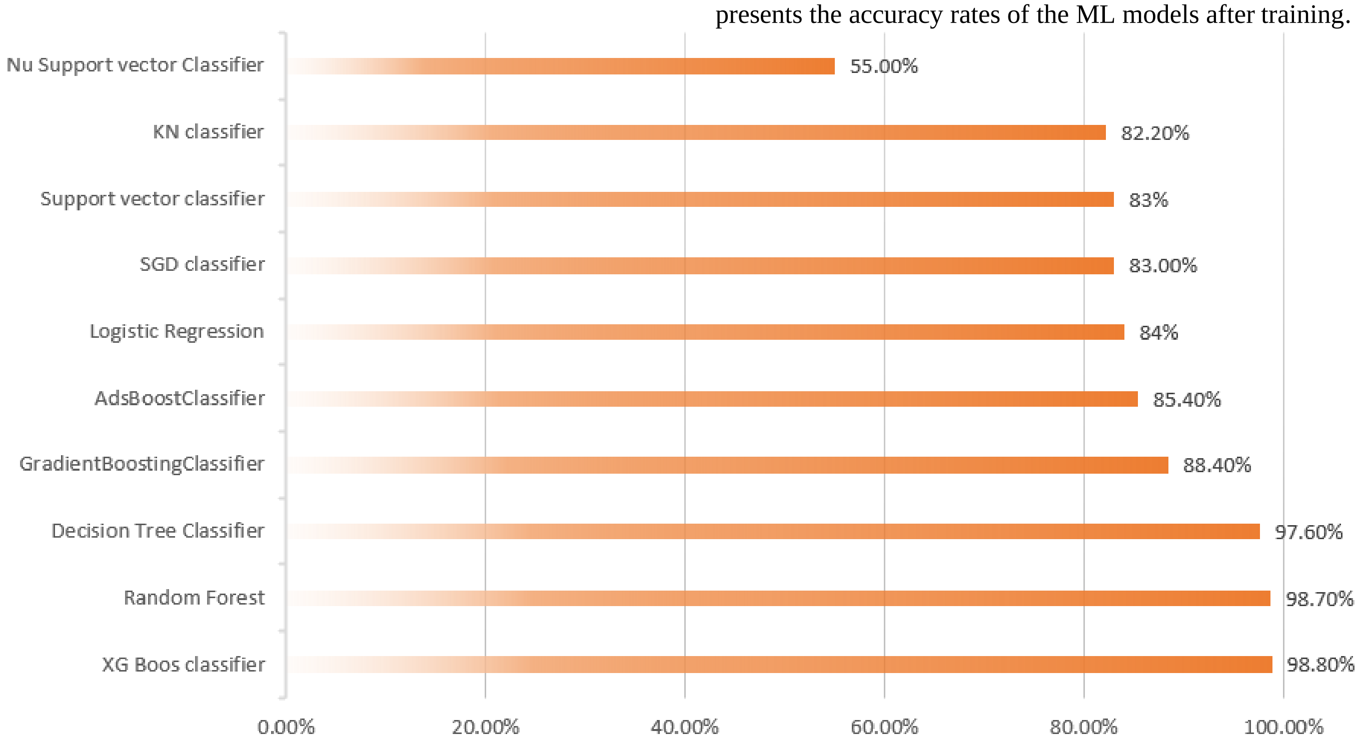

Fig. 3 Accuracy of ML models after training.

V. DISCUSSION

In this work, ten ML models were trained and evaluated using historical employee turnover data, composed of 4410 records and 29 variables. It was observed that the RF and XG Boost models showed the most remarkable performance in terms of accuracy, reaching values of 98.7% and 98.8% respectively.

These findings highlight the ability of these models to make accurate predictions about employee turnover. Also, the decision tree classifier demonstrated a significantly high accuracy of 97.6%, which places it as a viable model for application in this specific field. On the other hand, the Nu support vector classifier achieved an accuracy of 55.0%, suggesting certain limitations in its fit to the employee turnover prediction data set. The Gradient Boosting Classifier and Ads Boost Classifier models showed remarkable accuracy levels of 88.4% and 85.4% respectively, although lower than the leading RF and XG Boost models, which still makes them viable options within predictive analytics. These results confirm the feasibility of using ML for employee attrition prediction, in line with previous research. In the study [18], a deep ML model was developed to accurately predict employee turnover, with an accuracy rate of 94.2%. In addition, a two-layer nested ensemble model was applied to a dataset, resulting in an accuracy rate of 94.5255%, an F1 score of 94.5%, and an AUC of 98.5%. This study contributes to the advancement of employee turnover prediction models, showing originality while validating the results of similar studies employing ML techniques for turnover prediction.

VI. CONCLUSIONS

This paper highlights the effectiveness and usefulness of the Random Forest and XG Boost models, which show the most impressive performance in terms of accuracy, reaching values of 98.7% and 98.8% respectively. These findings demonstrate the ability of these models to make accurate predictions about employee turnover. In addition, the Decision Tree classifier demonstrates a significantly high accuracy rate, reaching 97.6%, which places it as a viable model for application in this specific domain.In addition, the Gradient Boosting Classifier (88.4%) and Ads Boost Classifier (85.4%) models show favorable levels of accuracy, although lower than the leaders of the Random Forest and XG Boost ensemble, they are still considered viable options within predictive analytics. In contrast, the Nu Support Vector Classifier yields an accuracy of 55.0%, indicating certain limitations in its adaptation to the employee turnover prediction dataset. These results corroborate the feasibility of using ML to predict employee turnover. Therefore, its practical application in human resource management strategies for proactive intervention is recommended.

With respect to limitations, the following were evident.

limitations with the data quality due to the presence of biased data, also the selection of relevant features for the model was challenging, also the amounts of computational resources (CPU, GPU, Memory etc.) required by the models.

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