Artificial Intelligence application in Human Ressources

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1 Application area review

In the field of human resource management, artificial intelligence (AI) is becoming more and more significant. HR-related applications of artificial intelligence (AI) are a touchy subject. On the one hand, because "human" is a part of human resources. However, laws like the upcoming "AI Act" of the European Union legally regard it as an area of application that is distinct from all others.

The initial application of AI was in the field of hiring, where it was used to automate tasks like sorting resumes by keywords. However, its application is not limited there. Managers can assess a job interview with the use of AI-based solutions. The candidate is filmed, and the AI listens to their voice and assesses their mood. Fully automated examinations are used to gauge a candidate's aptitude for tasks like statistical and graphical analysis and software competency.

By looking at applicants' posts, images, and emojis on both personal and work-related social media, AI can also discover more about them. The professor cautions that this "raises significant ethical difficulties and may not always provide very persuasive results." Professionals in human resources are worried about these tendencies.

Companies are increasingly utilizing AI to create job postings that are cognitively neutral and competitive.

AI is also inviting itself to the retention of workers in a situation where labor is becoming scarcer. Many businesses are working to provide technologies that lower the risk of leaving. To create such a tool, Sigma-RH put three years of effort into it. A lot of information about employees is generated by human resources management, including information on absences, tardiness, disciplinary actions, pay raises, evaluations, training, work accidents, etc.

The model performed well in forecasting departure risks that were below 30% or above 90%, but less well in the wide range of departure risks that were in between these two extremes. The project's intricacy was also made clear by the experience. HR managers that believe such a task should be assigned to them personally have been resistant to using Sigma HR.

On the employee side, algorithms are beginning to support workers' personal growth (with matching and suggestions, then), as well as enhance workplace wellbeing. For instance, by bringing up the fact that the employee hasn't taken a day off in a while. Or with recommendations for employer-funded services catered to a particular [employee] profile, such as taking part in childcare or getting a bicycle. Since the health crisis, the application of AI to more accurately comprehend employees' expectations and sentiments has grown significantly.

HR applications of AI do, however, have some restrictions. But it appears that the two fundamental boundaries are morality and the outcomes' comprehensibility. HRDs are more concerned than any other manager with upholding human dynamics in the workplace and the ethics surrounding the usage of AI.

The potential for bias systematization by AI has already been demonstrated by a few examples. Amazon tested hiring algorithms in 2018 with the intention of sorting through resumes and selecting the top applications. However, it undervalued all applications from women and even any resumes that had the term "female" in the title. Amazon had trained its machine using hiring information from the prior ten years. The software naturally tried to mimic this tendency as the majority of its employees were men.

As long as AI serves to expand the capabilities of using already-existing HR data, we don't see any significant resistance to it. On the other hand, more than 70% of respondents regularly oppose AI applications that attempt to replace people in assessment or decision-making jobs. "AI must be ethical, unbiased, and its outputs must be understandable in order to be accepted and integrated into HR processes.

2 Comparison & evaluation of AI techniques

2.1 Talent Acquisition

Talent Identification Recruiting talent is one of the repetitive HR tasks. The hiring process involves attracting talent, screening resumes, tracking and evaluating candidates, scheduling and conducting preliminary interviews, informing candidates of their status, and onboarding. Most recruiters and HR professionals spend the majority of their productive time on this process. The use of AI has significantly decreased these tedious tasks. Talent acquisition software, according to Wislow (2017), has removed about 75% of the labour involved in the hiring process.

With AI, websites like LinkedIn, Glassdoor, Indeed, and Naukri are using machine learning algorithms that provide job recommendations for the candidates based on their resumes, keywords they have used in their job applications, search histories, and connections. Recruitment, which includes posting a job ad in relevant websites and searching for candidates, is a time-consuming process.

It takes time and effort to screen resumes of candidates and conduct preliminary interviews, especially when there are many candidates for a position. Software businesses can conduct audio or video interviews using AI to complete this process more quickly and efficiently (Hooda, 2018). According to a study by Mondal (n.d.), organizations utilizing AI software for recruiting and associated tasks might cut their cost per hire by 71% and triple the effectiveness of their recruiters (as cited by Min, 2017).

Most businesses struggle with engaging and reengaging prospects because it takes time to do so. Companies usually don't hear back from candidates after they apply for a job or after the interview is over regarding their status. According to Biswas (2018), today's youths anticipate hearing back from the employer within ten minutes of submitting a job application. Therefore, following up with them following a job application or an interview is crucial; otherwise, one risks losing them to more responsive competition. Applicant tracking systems (ATS), customer relationship management (CRM), and chatbots are examples of AI-integrated tools that assist in providing real-time answers to all candidate questions and provide updates on their progress.

Nearly two-thirds of American businesses (63 percent) will invest in artificial intelligence by 2022 for use in hiring new employees. According to Aptitude Research, the Boston-based analysis company that conducted the study "The Power of AI in Talent Acquisition," it is an increase from the 42 percent noted in 2020.

AI-based HR tools have just recently been able to fully develop into the wonderful innovation that they are for our hiring and talent acquisition strategies. As businesses learn more about how beneficial they can be to recruiters who are tasked with identifying the top people in a very competitive employment market, AI is now being widely adopted in the marketplace.

In the recruitment and talent acquisition sector, artificial intelligence is undeniably in the mainstream. It is conclusive evidence that it is possible to thoroughly assess a large number of resumes while reliably excluding the vast majority of resumes that we would otherwise be wasting our time with, leaving us with only the most closely matched and pertinent applicants. In other words, using artificial intelligence makes it easier to find the top candidates.

2.2 Employee Engagement

Every other company's goal is to maintain not just their employees' happiness and satisfaction but also their engagement. Only when it is considered holistically, including numerous factors starting with hiring an employee and ending with his decision to leave an organization, can employee engagement be achieved. Thus, initiatives that promote employee health and wellness as well as programs that clarify roles and provide learning opportunities, rewards, and recognition are all components of employee engagement. With the aid of AI in employee engagement, all of this might be done fairly and evenly. As was previously said, real-time inquiries regarding health and other employee perks, virtual assistants for comprehending business policies, etc., can be accomplished with AI through customized learning and development.

This makes a significant contribution to employee engagement. Al also contributes to the continuing, objective, fact-based feedback system. HR may create and establish measurable objectives for each employee with the aid of AI solutions. This facilitates continual feedback loops and can lead to improved outcomes. The open feedback, suggestions, and concerns shared by thousands of employees via an online survey can also be managed more methodically with AI; AI assists in the analysis of these millions of data points and can forecast not only the present level of engagement but also the future level of engagement, turnover rate, performance level, and more.

There are many tools that would allow AI to improve employee engagement:

- **Predictive analytics and behavior mapping:** Organizations frequently use an annual method to gauge worker satisfaction and productivity, but AI can provide real-time monitoring of employee mental health, behavioral patterns, and engagement levels using data-backed insights. By examining past and present data, finding patterns, forecasting trends, and providing tailored solutions, it aids in gauging levels of participation.insights.
- **Employee Engagement Chatbots:** Employee engagement depends heavily on communication, therefore it's critical that they can express themselves without worrying about being judged. The connection that most employees have to their place of employment is now increasingly influenced by digital interactions and the interfaces that make them possible. Artificial intelligence techniques, including chatbots, are being used to make these discussions more engaging, collaborative, and transparent.
- **Real-time Engagement Feedback Tools:** Real-time engagement feedback surveys are the best method to learn exactly what is going on in your employees' heads, how they are feeling, what they are communicating with the company about most, and what they like and dislike about the workplace. Businesses may gather real-time feedback from their employees

and identify the precise areas where they need to concentrate their efforts to improve employee performance and productivity by using AI-backed feedback platforms.

2.3 AI in job posting

Recruiters shouldn't take any chances in an environment where there is intense competition to land the best talent. And the first step in doing this is publishing a job advertisement online.

The job advertisement is where the applicant's journey begins, despite the fact that it is sometimes skipped. Getting this correctly is crucial since it is frequently the very first representation of your firm that customers see.

The objective is to provide users with data-driven feedback on job advertisements and details on how it will probably perform with a certain audience using a "augmented writing" platform. As a result, businesses will be able to communicate better and consequently get far better feedback.

A company that genuinely recognizes the value of top-notch job listings in attracting the most qualified applicants to your organization is Texio. Ten million job listings are ingested monthly by its system. The software looks for and analyzes linguistic patterns and assesses wording in relation to factors like the number of applicants for a position and the proportion that are qualified for an interview.

The algorithms generate alternatives to phrases to suggest ones identified in the most successful job descriptions using natural language processing (NLP). For instance, substituting "enthusiastic about" for "focused on".

According to Textio, it's essential to include gender-neutral wording in job advertisements to draw in a diverse pool of applicants. Job postings with this type of prejudice are filled 14 days sooner than listings without it.

3 Implementation:

3.1 Diagram

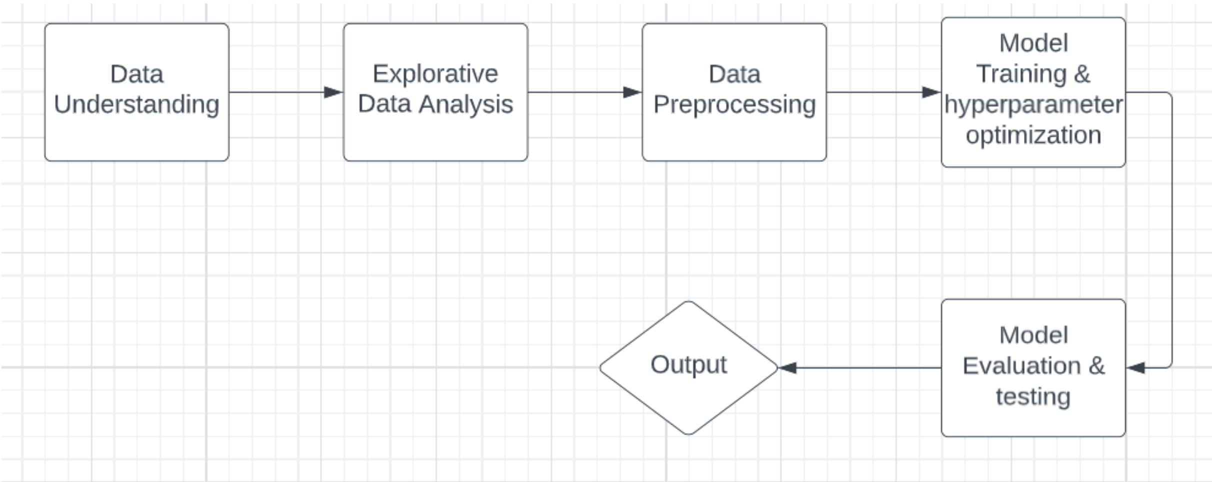

Figure 1: Diagram showing the architecture & steps of the projects

3.2 Input Data

3.2.1 Data format & description

The HR Dataset was designed by Drs. Rich Huebner and Carla Patalano to accompany a case study designed for graduate HR students studying HR metrics, measurement, and analytics.

The CSV revolves around a fictitious company and the core data set contains names, DOBs, age, gender, marital status, date of hire, reasons for termination, department, whether they are active or terminated, position title, pay rate, manager name, and performance score.

This dataset is used to analyze the employee's engagement using predictive analysis and machine learning by classifying whether the employee would be terminated or not (the Target variable is "Termd").

Feature	Description	Data Type
Employee Name	Employee's full name	Text
EmpID	Employee ID is unique to each employee	Text
MarriedID	Is the person married (1 or 0 for yes or no)	Binary
MaritalStatusID	Marital status code that matches the text field MaritalDesc	Integer
EmpStatusID	Employment status code that matches text field EmploymentStatus	Integer
DeptID	Department ID code that matches the department the employee works in	Integer
PerfScoreID	Performance Score code that matches the employee's most recent performance score	Integer
FromDiversityJobFairID	Was the employee sourced from the Diversity job fair? 1 or 0 for yes or no	Binary
Salary	The person's yearly salary. $ U.S. Dollars	Float
Termd	Has this employee been terminated - 1 or 0	Binary
PositionID	An integer indicating the person's position	Integer
Position	The text name/title of the position the person has	Text
State	The state that the person lives in	Text
Zip	The zip code for the employee	Text
DOB	Date of Birth for the employee	Date
Sex	Sex - M or F	Text
MaritalDesc	The marital status of the person (divorced, single, widowed, separated, etc)	Text
CitizenDesc	Label for whether the person is a Citizen or Eligible NonCitizen	Text
HispanicLatino	Yes or No field for whether the employee is Hispanic/Latino	Text
RaceDesc	Description/text of the race the person identifies with	Text
DateofHire	Date the person was hired	Date
DateofTermination	Date the person was terminated, only populated if, in fact, Termd = 1	Date
TermReason	A text reason / description for why the person was terminated	Text
EmploymentStatus	A description/category of the person's employment status. Anyone currently working full time = Active	Text
Department	Name of the department that the person works in	Text
ManagerName	The name of the person's immediate manager	Text
ManagerID	A unique identifier for each manager.	Integer
RecruitmentSource	The name of the recruitment source where the employee was recruited from	Text
PerformanceScore	Performance Score text/category (Fully Meets, Partially Meets, PIP, Exceeds)	Text
EngagementSurvey	Results from the last engagement survey, managed by our external partner	Float
EmpSatisfaction	A basic satisfaction score between 1 and 5, as reported on a recent employee satisfaction survey	Integer
SpecialProjectsCount	The number of special projects that the employee worked on during the last 6 months	Integer
LastPerformanceReviewDate	The most recent date of the person's last performance review.	Date
DaysLateLast30	The number of times that the employee was late to work during the last 30 days	Integer
Absences	The number of times the employee was absent from work.	Integer

Figure 2: Data dictionary

3.2.2 Data Exploration

The statistics, distribution plots, the correlation maps are presented in the report data_exploration_HR.html

3.2.3 Data Preprocessing

Several preprocessing techniques were used in the notebook:

1. **Checking for missing values:**

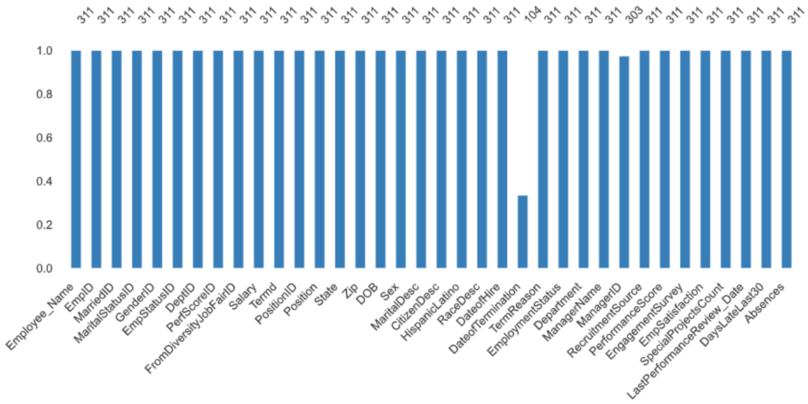

Figure 3: Missing values in the dataset

2. Normalization

- **Standard scaling for numerical features:** by removing the mean and scaling to unit variance. Standardization of a dataset is a common requirement for many machine learning estimators: they might behave badly if the individual features do not more or less look like standard normally distributed data (e.g. Gaussian with 0 mean and unit variance).
- **One Hot Encoding for categorical data**
- **Encoding "date features":** For the features "DOB", "Date of Hire" and "Last Performance Review date"
- **Ordering ordinal feature:** "Performance Score"

4 Testing and evaluating

Several models were trained and optimized for the classification of the termination state of the employees, the results and performances of each of the models are presented below:

4.1 SVC – Support vector classifier

The model was optimized using GridSearchCV by looking for the optimal hyperparameters of the models in ["C", "gamma"]:

The optimized parameters are:

{'C': 100, 'gamma': 0.0001, 'kernel': 'rbf'}

	Precision	Recall	F1 score	Support
Class 0	0.84	1.00	0.91	104
Class 1	1.00	0.62	0.76	52
Macro avg	0.92	0.81	0.84	
Weighted avg	0.89	0.87	0.86	

ROC Score = 0.80, **Accuracy score** = 0.87, **F1 Score** = 0.87

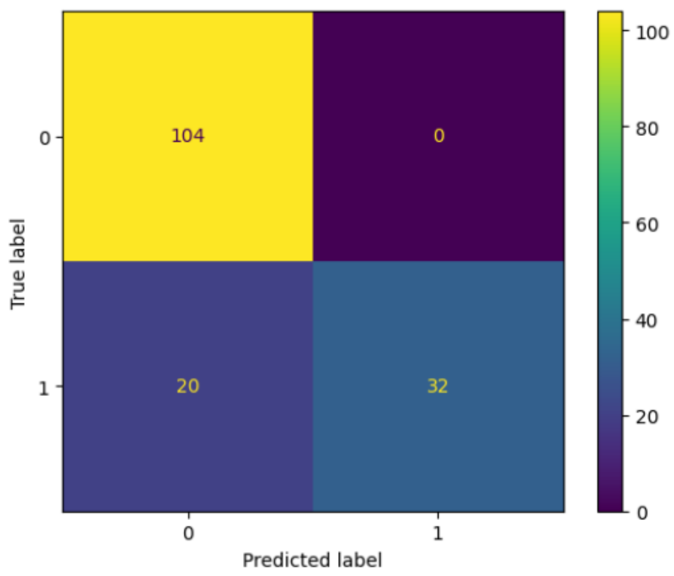

Figure 4: Confusion matrix of SVC

4.2 Random Forest Classifier

The model was optimized using GridSearchCV by looking for the optimal hyperparameters of the models in [“n_estimators”, “max_features”, “criterion”, “max_depth”]

The optimized parameters are:

{'criterion': 'entropy', 'max_depth': 8, 'max_features': 'sqrt', 'n_estimators': 60}

	Precision	Recall	F1 score	Support
Class 0	0.82	0.98	0.89	104
Class 1	0.94	0.58	0.71	52
Macro avg	0.88	0.78	0.80	
Weighted avg	0.86	0.85	0.83	

ROC Score = 0.778, **Accuracy score** = 0.846, **F1 Score** = 0.846

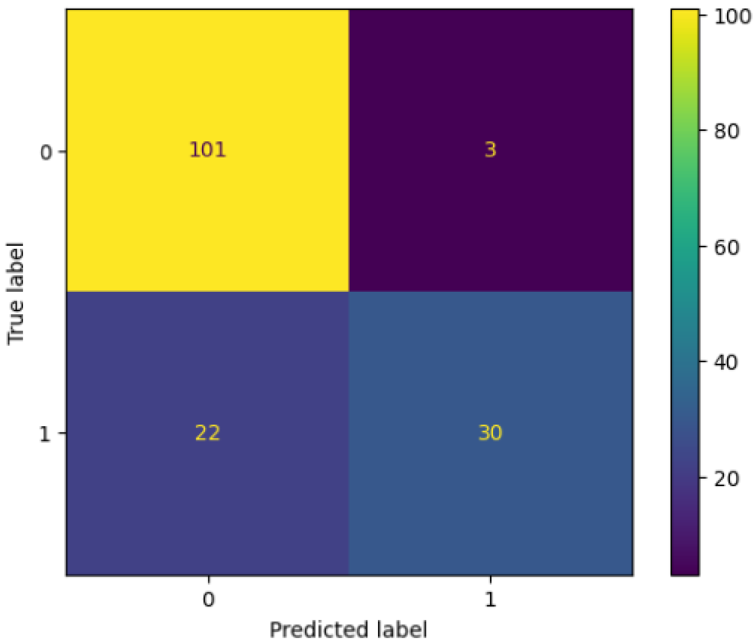

Figure 5: Confusion matrix of Random Forest

4.3 Adaboost

The model was optimized using GridSearchCV by looking for the optimal hyperparameters of the models in [“n_estimators”, “learning_rate”]

The optimized parameters are:

{'learning_rate': 0.1, 'n_estimators': 100}

	Precision	Recall	F1 score	Support
Class 0	0.83	0.92	0.87	104
Class 1	0.80	0.62	0.70	52
Macro avg	0.81	0.77	0.78	
Weighted avg	0.82	0.82	0.81	

ROC Score = 0.769, **Accuracy score** = 0.820, **F1 Score** = 0.820

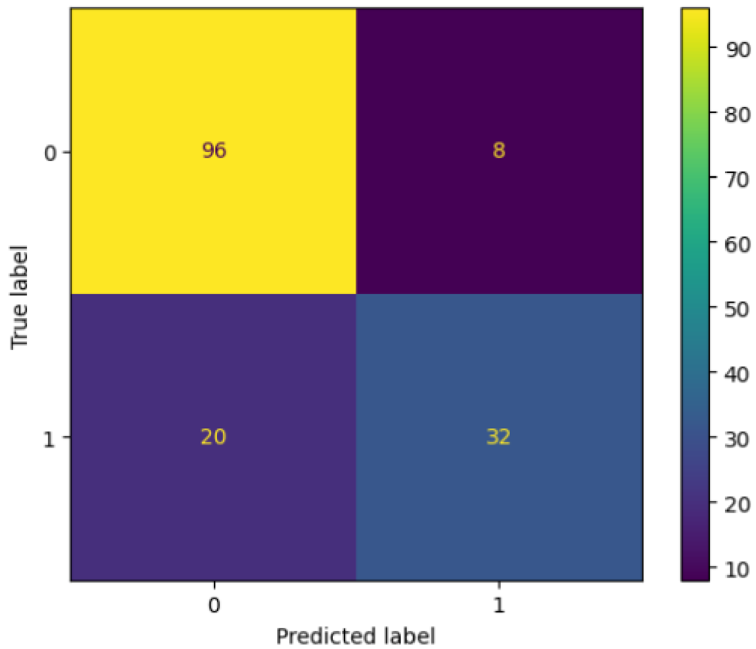

Figure 6: Confusion matrix of AdaBoost

4.4 XGBoost

The model was optimized using GridSearchCV by looking for the optimal hyperparameters of the models in [“n_estimators”, “learning_rate”, “max_depth”]

The optimized parameters are:

{'learning_rate': 0.1, 'max_depth': 3, 'n_estimators': 120}

	Precision	Recall	F1 score	Support
Class 0	0.84	0.97	0.90	104
Class 1	0.92	0.63	0.75	52
Macro avg	0.88	0.80	0.83	
Weighted avg	0.87	0.86	0.85	

ROC Score = 0.802, **Accuracy score** = 0.858, **F1 Score** = 0.858

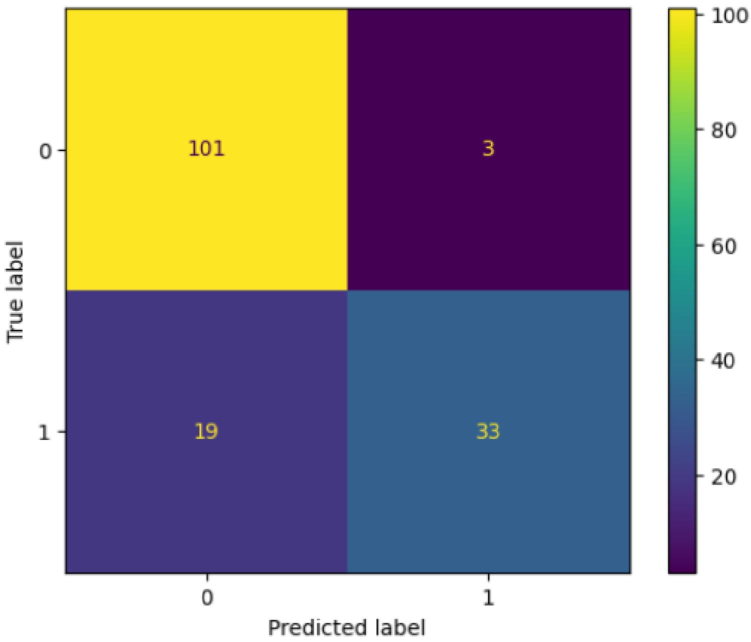

Figure 7: Confusion matrix of XGBoost

The model trained can be used to do prediction for the testing set as showed below for XGBoost

```
In [27]: model = xgb_best
         print('prediction :', model.predict(X_test_proc))

prediction : [1 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 1 1 0 1 0 0 0 0 0 1 0 0 0 1
 0 0 0 1 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0
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 0 1 1 1 1 0 0 0 0 0 0 0 1 0 1 0 0 0 1 0 0 0 0 1 0 0 0 0 1 1 0 0 0 0 0 0 0
 1 0 0 1 1 0 0 0]

In [28]: print('ground truth :', np.array(y_test))

ground truth : [1 1 0 0 0 0 0 1 1 0 0 0 0 0 0 1 1 1 1 1 0 1 1 1 1 0 0 0 0 1 0 0 1 0 0 0 1
 0 0 0 1 0 0 0 1 0 0 0 0 1 1 1 1 0 0 0 1 1 0 0 0 0 0 1 1 0 0 0 0 1 1 0 0 0
 0 0 1 0 1 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 1 0 1 0 1 0 0 0 1 0 1 0 0
 0 1 1 1 1 0 0 0 0 0 0 0 1 1 1 1 0 0 1 0 0 0 0 0 0 0 0 0 1 1 0 1 0 0 0 0 0
 1 0 0 1 1 0 0 0]
```

Figure 4: Prediction vs groundtruth for xgboost

5 Interpretation of the results

Following the metrics that we extracted, we can notice that the SVC Model was the best in all the model trained with an accuracy of 87% and an F1_Score of 87%, which shows that model can perform to detect both classes well.

The model can also safely be deployed in real life since the roc score is quite high which shows that the model is not overfitting and can generate quite well.

The models can be improved furthermore with by improving the quality of the data and having more relevant features and more observations since 311 observations aren't enough, having more can result in better training and thus better performances of the model.

6 Conclusion

All things considered; human resources are crucial to an organization's ability to respond to challenges in the age of artificial intelligence. They can aid leaders and organizations in embracing new technologies, assist employees in adjusting to new work schedules, encourage businesses to embrace technological advancements, and support the creation and modification of national policies and regulations.

In this project, employee engagement has been investigated using artificial intelligence and machine learning tools. We were able to develop predictive models that predict an employee's termination status based on a variety of features. These models can be implemented in a company to help manage employee satisfaction and boost the caliber of work.

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