School of Computer Science and Engineering

CERTIFICATE

The project report entitled "**Human Resource Analytics and Employee Churn Prediction**" is prepared and submitted by **Nithya Sharma(19MIA1028) and Yuvashree R (19MIA1053).** It has been found satisfactory in terms of scope, quality and presentation as partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology – Computer Science and Engineering** in Vellore Institute of Technology, Chennai, India.

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Human Resource Analytics and Employee Churn Prediction

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ABSTRACT: Employee turn-over otherwise known as "employee churn" is a costly problem for companies. The cost of replacing employees for most employers remains significant. This is due to the amount of time spent on the interviews and find a replacement, sign-on bonuses, and the loss of productivity for several months while the new employee gets accustomed to the new role.

In this project "Human Resource analytics and Employee Churn Prediction" we plan to start off with Descriptive Analytics and Exploratory data analysis and then apply predictive modelling in an attempt to solve our problem statements.

KEY WORDS: *employee churn - time spent – interviews – replacement – bonuses – productivity – Descriptive – Exploratory- predictive modelling*

1. INTRODUCTION

Understanding why and when employees are most likely to leave can lead to actions to improve employee retention as well as possibly planning new hiring in advance. We will be using a step-by-step systematic approach using a method that could be used for a variety of ML problems. This project would fall under what is commonly known as "HR Analytics", "People Analytics".

In this Project, we will attempt to solve the following problem statement is:

- What is the likelihood of an active employee leaving the company?
- What are the key indicators of an employee leaving the company?
- What policies or strategies can be adopted based on the results to improve employee retention?

Given that the dataset consists of data on former employees, this is a standard supervised classification problem where the label is a binary variable, 0 (active employee), 1 (former employee). In this project, the target variable Y is the probability of an employee leaving the company.

In this project, a HR dataset was sourced from IBM HR Analytics Employee Attrition & Performance which contains employee data for 1,470 employees with various information about the employees. The dataset used to predict when employees are going to quit by understanding the main drivers of employee churn.

As stated on the IBM website *"This is a fictional data set created by IBM data scientists"*. Its main purpose was to demonstrate the IBM Watson Analytics tool for employee attrition.

2. LITERATURE REVIEW

An evidence-based study by Janet et al. (2017) has combined the already published scholarly reviewed literature on HR Analytics and has concentrated on answering major questions on HR Analytics, how it works, its outcome, and why there is a need for HR Analytics to flourish? They have stated that the interest of people in analytics in the HR domain for the past few years has gradually increased.

Later, the authors concluded that the inclusion of HR Analytics in various organizations is very low and proofs on this topic are scattered, hence suggested areas for future research. Many firms or departments say Marketing, Finance, Supply Chain Management organizations today draw insights from the huge data collected from the employees so that they can stay in this competition. The Human Resource department generates massive amounts of data on employee turnover, Return on Investments, and Cost per hire, but somewhere they still face a harder time relating these data with the organization's performance. They should create reports on past performances, administrative tasks, and generate compliance reports to understand the employee’s contribution to the organization. HR applications followed by today’s organization can act as a mediator between planned HR practices in an organization and the positive outcomes of employees. Hence, Innocenti et al. (2012) have proposed a model that uses survey data that has been collected from over 6000 employees working in almost 37 Italian organizations, and the outcome variables are employee commitment and their job satisfaction. By using the maximum likelihood estimation method and calculating the correlations between different variables it was reported that, there is always a positive effect of experienced HR practices on both affective engagement towards organization and job satisfaction factors. Line managers are considered the assets of that particular organization, so it's necessary to keep them engaged so that they can add value to any organization. Few semi-structured interviews were performed by Sana et al. (2016), to understand the experience and perceptions of the line managers on the level of support and help provided by the HR professionals of their organization. Further, they have stated that the line managers have raised concerns and have suggested ideas for improving few areas like perceptions regarding policies, workload, inadequate training, and HR practices, which we need to pay attention to during any research on the factors related to employee attrition or turnover. There have been several studies on identifying the parameters that play a role in job satisfaction of the employees and predicting the attrition rate. Many Data Analytics techniques and classification models have been used to predict turnover. In any organization, innovation can be seldom duplicated but once a group of productive employees leaves, that place cannot be replicated easily. So, to retain these employees and predict the turnover rate, a Neural Network, with a 10-fold Cross-Validation was designed for a small Midwest manufacturing company to a greater accuracy. Among Layoffs, Discharges, Unavoidable separation, it was identified that voluntary separation from an organization always proves as the most difficult area because the particular organization loses its investment on talent to its competitors out there. On this same note, Fan et al. (2012) in their study, focused on why technology enterprises in Taiwan are unable to retain their talented employees and they have discussed ways so that the organizations can increase the competitiveness among themselves. Techniques like clustering analysis, hybrid artificial neural networks and other machine learning techniques were applied to forecast the patterns of employee’s turnover rate. Again, many Classification models have been used for prediction purposes, on a HR analytics dataset from Kaggle, an online community data site. Correlations between different attributes were evaluated by Sisodia et al. (2017) in their paper. A comparison between different classifiers was drawn using parameters like Accuracy, Precision, True Positive Rate, F-Measure, and few others. Weighted TPR-TNR has been proposed as another performance metric to evaluate the performance of various classifiers, as it especially focuses on the imbalance ratio of any dataset and assigns different weights to

TPR (Sensitivity) and TNR (Specificity), which are majorly considered while comparing ROC curve of any model. A mix of balanced and imbalanced datasets was used to evaluate the performance of 12 classifiers using the above metric. To build and maintain a strong relationship between an organization and its employees, Hebbar et al. (2018), in their study initially implemented Logistic Regression on an IBM Employee Attrition dataset available in Kaggle just to get a basic idea, on which outcome group every individual fall. Later on, a comparative study was done with SVM and Random Forest models, and determined the major characteristics of the dataset performing Exploratory Data Analysis and represented the data using different visualization. With the same dataset (that has been used above), Synthetic Minority Oversampling Technique (SMOTE) was performed by Bhartiya et al. (2019) in their paper, to balance the imbalance dataset, because the count of the "Attrition" parameter with value 0 was greater than "Attrition" with a value of 1. The above technique is often used to generate synthetic data records for that class whose count is very less. Attributes like Gender, Education Field, and Performance Rate were visualized for Attrition parameters thus giving an idea on the relevant features. A comparison between the performance metrics of the classification models provided new insights on improving the work ethics. With redundant data, predicting the correct features becomes a little challenging. So, a superior machine learning model or algorithm called XGBoost gives high accuracy in predicting the attrition rate with fewer running times. Jain et al. (2018) recommend XGBoost as a highly robust model, which easily handles noisy data in a huge dataset, and in their study, it gives an accuracy of about 90% on an online HR dataset. Further, it suggests IT organizations to use this as a top priority, predictive model to identify those employees who are willing to leave in near future and their reasons behind that. A very common issue that today's IT professionals face is stress disorders. Though organizations do offer a nice workplace environment and different activities or workshops to relieve this stress, still the risk increases among the employees. Various machine learning techniques like Boosting and Decision trees were implemented by Reddy et al. (2018) in their study, and have determined that data on family history of illness, gender and health benefits provided by employers plays an important role in evaluating this type of risks. Ensemble method gave the highest degree of accuracy and precision compared to Random Forest. General characteristics like having peers to work with and the financial needs of the employees become critical factors for those who are working for a longer tenure in any business or organization. So, for the hospitality industry in the USA, Self et al. (2011) attempted a qualitative study on identifying various factors that might impact an employee's decision to stay back in a company. By analysing the interview transcripts that were obtained after an in-depth process, four factors were identified: Strong Responsibility towards the company, Financial Requirement, Proper Job Description, and Peers at the workplace has a positive effect on employees.

One of the challenges that the big organizations are facing is, motivating their employees and investing in them for their further development. Understanding the importance of investing in employee development and its final results, is very much needed by the organization. A model proposed by Lee et al. (2003) gives us an interrelationship between perceived investments and other job attitudes and the employee's plan to quit an organization. Factor analysis and Exploratory analysis were conducted for assessing the dimensionality and their insights, respectively. Results suggest that the more the employer spends resources on the development of their employees, the more they will be satisfied at their workplace, hence reducing the possibility of an employee quitting his or her job in that organization. Burnett et al. (2019) propose a few topics on which one can use modern technology or tools to measure both employee engagement and the other HRM practices which can improve the same. Different emotional states of employees affect their engagement at the workplace, either directly or indirectly. Further, they have pointed out that to improve on engagements we need to concentrate on three different levels: individual, team and organizational level and have suggested that with the real-time feedback from employees and rigorous research and analysis on the data will help the HRM department to understand the importance of employee engagement in their respective organization. So, to stay in this competitive market, these technology industries need to continuously evolve in terms of skills and should be ready to embrace the ever-changing products and services. Even employees make themselves proficient in the new skills or technologies and try to search for better job opportunities outside. An analytics-driven approach can help organizations to overcome the situation. Combining the historic record of skills of each employee present in the HR database with the predictive models, Ramamurthy et al. (2015) have proposed an approach that evaluates a set of skills. The algorithm in their study will provide a list of skills to some individuals, where they will fill in their target skills, helping business leaders to find potential candidates and will provide re-skilling offers to them. One can go for Sentiment Analysis to determine the factors affecting employee retention, and organizations can use these models to understand the concepts of People Analytics. A conceptual study was done to identify key indicators to assess the human factors. Six important areas, like performance leadership, employee engagement, learning, workplace dynamics, and overall organizational development have used sentiment analysis to evaluate various insights. The Enron email corpus test case was incorporated to explain how we can predict the digital footprints. Further encourages implementing various data mining techniques or models to analyse the real-time data for predicting more accurate human factor patterns. In addition to this, often interpersonal environment factors provide insights about employee development in any organization. Liu et al. (2019) in their study have concentrated on a state-owned enterprise in China, extracted the related features, and statistically analysed the correlation between employee development in organizations and their interpersonal environment. The results of the predictive model prove that colleagues and classmates have a great impact on the growth of employees in their respective workplaces.

3. PROPOSED METHODOLOGY

The dataset used is a fictional dataset created by IBM data scientists, which contains HR Analytics Employee Attrition & Performance of 1,470 employees with various information about the employees (35 attributes). I will use this dataset to predict when employees are going to quit by understanding the main drivers of employee churn.

```
Index(['Age', 'Attrition', 'BusinessTravel', 'DailyRate', 'Department',
       'DistanceFromHome', 'Education', 'EducationField', 'EmployeeCount',
       'EmployeeNumber', 'EnvironmentSatisfaction', 'Gender', 'HourlyRate',
       'JobInvolvement', 'JobLevel', 'JobRole', 'JobSatisfaction',
       'MaritalStatus', 'MonthlyIncome', 'MonthlyRate', 'NumCompaniesWorked',
       'Over18', 'OverTime', 'PercentSalaryHike', 'PerformanceRating',
       'RelationshipSatisfaction', 'StandardHours', 'StockOptionLevel',
       'TotalWorkingYears', 'TrainingTimesLastYear', 'WorkLifeBalance',
       'YearsAtCompany', 'YearsInCurrentRole', 'YearsSinceLastPromotion',
       'YearsWithCurrManager'],
      dtype='object')
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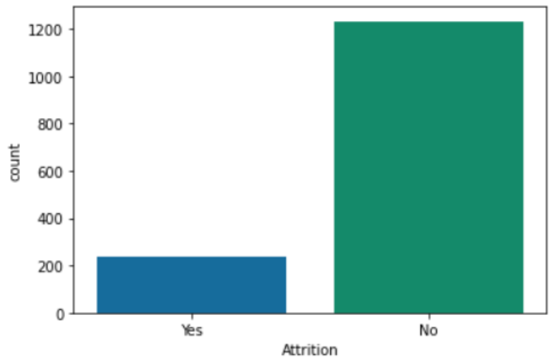
The feature 'Attrition' is what this Machine Learning problem is about. We are trying to predict the value of the feature 'Attrition' by using other related features associated with the employee's personal and professional history.



As shown on the chart above, we see this is an imbalanced class problem. Indeed, the percentage of Current Employees in our dataset is 83.9% and the percentage of Ex-employees is: 16.1%

Machine learning algorithms typically work best when the number of instances of each class are roughly equal. We will also address this target feature imbalance prior to implementing our Machine Learning algorithms.

The analysis and predictions on the data are made using Python in Jupyter Notebook/Colab. Python libraries such as NumPy, pandas, matplotlib, seaborn, scikitlearn and TensorFlow are used for analysis, visualization and model building.

4. EXPERIMENTATION & RESULTS

The project was started off importing libraries such as pandas, openpyxl, numpy ,scipy .etc that is used for data handling and analysis. We also imported seaborn, matplotlib, chart_studio, plotly, etc. for data visualization. For pre-processing we imported sklearn.processing and some sklearn modules for ML Model selection, for performance metrics we have imported confusion_matrix , classification_report, precision_recall_curve,auc, roc_auc_score, roc_curve, recall_score, log_loss,f1_score, accuracy_score, roc_auc_score, make_scorer, average_precision_score

The data provided has no missing values. In HR Analytics, employee data is unlikely to feature large ratio of missing values as HR Departments typically have all personal and employment data on-file. However, the type of documentation data is being kept in (i.e. whether it is paper-based, Excel spread sheets, databases, etc) has a massive impact on the accuracy and the ease of access to the HR data.

Phases required for building employee churn rate prediction model are as follows:

A. Churn Analysis

Each attribute or factor affecting churn are considered in initialization stage. Data integration and data cleaning is done this stage.

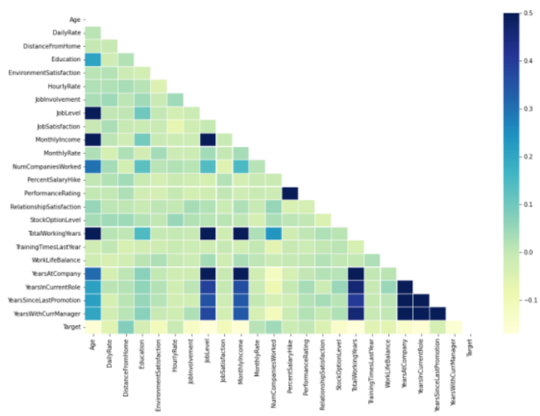
B. Dataset loading and understanding feature

Features assistants to get bigger datasets usually used by the machine learning community for standard algorithms on data that originates from the real world.

C. Exploratory data analysis and Data visualization

The important features and more clear representation of the information visualization.

Heatmap to visualize the correlation between Attrition and other attributes.



"Monthly Rate", "Number of Companies Worked" and "Distance From Home" are positively correlated to Attrition;

while "Total Working Years", "Job Level", and "Years In Current Role" are negatively correlated to Attrition.

D. Pre-processing Pipeline

We undertake data pre-processing steps to prepare the datasets for Machine Learning algorithm implementation.

Encoding

Machine learning algorithms can typically only have numerical values as their predictor variables. Hence Label Encoding becomes necessary as they encode categorical labels with numerical values. To avoid introducing feature importance for categorical features with large numbers of unique values, we will use both Label Encoding and One-Hot Encoding.

Feature Scaling

Feature Scaling using MinMaxScaler essentially shrinks the range such that the range is now between 0 and n.

Splitting data into training and testing sets

Prior to implementing or applying any Machine Learning algorithms, we must decouple training and testing datasets from master data frame.

E. Building prediction model using different algorithms

There are machine learning algorithms that could be used for nearly all type of data related issues. We used a range of baseline algorithms (using out-of-the-box hyper-parameters. The algorithms considered in this section are: Logistic Regression, Random Forest, SVM, KNN, Decision Tree Classifier, Gaussian NB.

Logistic Regression is a Machine Learning classification algorithm that is used to predict the probability of a categorical dependent variable. Logistic Regression is classification algorithm that is not as sophisticated as the ensemble methods or boosted decision trees method discussed below. Hence, it provides us with a good benchmark.

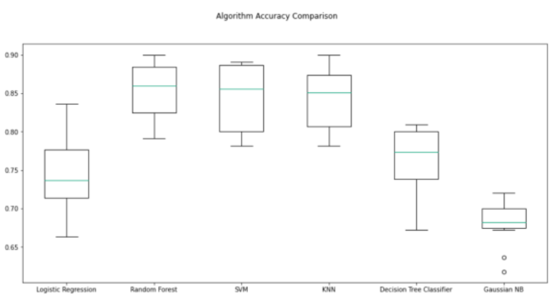
K means algorithm categorizes k number of centroids, and then assigns every data point to the adjacent cluster, while keeping the centroids as small as probable.

Random Forest is a popular and versatile machine learning method that is capable of solving both regression and classification. Random Forest is a brand of Ensemble learning, as it relies on an ensemble of decision trees. It aggregates Classification (or Regression) Trees. A decision tree is composed of a series of decisions that can be used to classify an observation in a dataset.

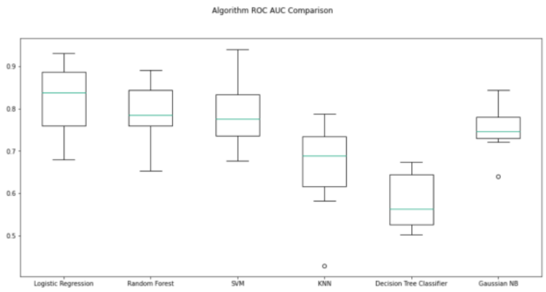
Random Forest fits a number of decision tree classifiers on various sub-samples of the dataset and use averaging to improve the predictive accuracy and control over-fitting. Random Forest can handle a large number of features, and is helpful for estimating which of your variables are important in the underlying data being modelled.

	Algorithm	ROC AUC Mean	ROC AUC STD	Accuracy Mean	Accuracy STD
0	Logistic Regression	82.03	8.06	74.49	5.53
2	SVM	78.88	8.21	84.48	4.18
1	Random Forest	78.86	7.01	85.30	3.75
5	Gaussian NB	75.06	5.10	68.14	3.14
3	KNN	66.42	9.90	84.21	4.04
4	Decision Tree Classifier	58.02	6.23	76.22	4.23

E. Evaluating model performance



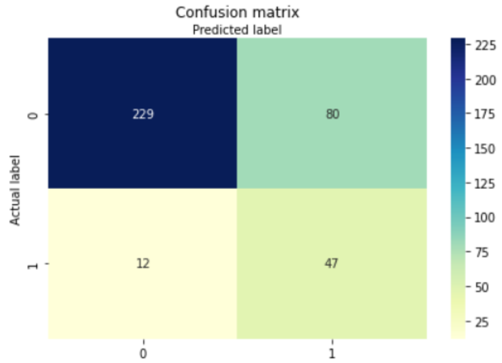
Area under ROC Curve (or AUC for short) is a performance metric for binary classification problems. The AUC represents a model's ability to discriminate between positive and negative classes. An area of 1.0 represents a model that made all predictions perfectly. An area of 0.5 represents a model as good as random



Based on ROC AUC comparison analysis, **Logistic Regression** and **Random Forest** show the highest mean AUC scores. We used these two algorithms for further analysis.

We used 10-fold Cross-Validation to train Logistic Regression Model and estimate its AUC score. Using GridSearchCV allows to fine-tune hyper-parameters by searching over specified parameter values for an estimator.

Confusion matrix is best method to differentiate between machine learning models with accuracy and error. Performance of classification models is descried by confusion matrix. It provides us with a much more detailed representation of the accuracy score and of what's going on with our labels - we know exactly which/how labels were correctly and incorrectly predicted.



The Confusion matrix is telling us that we have 231+47 correct predictions and 78+12 incorrect predictions. In other words, an accuracy of 75.54%.

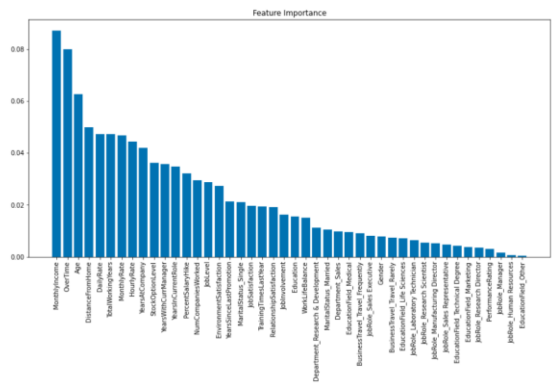
Classification report for the optimised Log Regression:

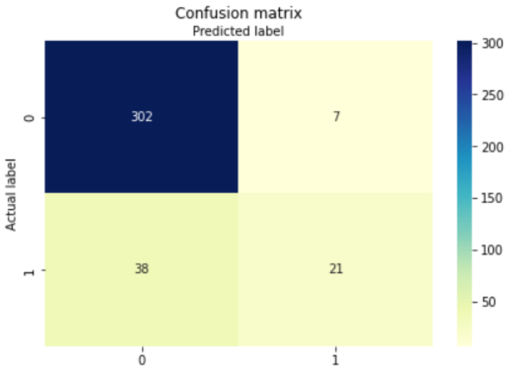
	precision	recall	f1-score	support
0.0	0.95	0.74	0.83	309
1.0	0.37	0.80	0.51	59
accuracy			0.75	368
macro avg	0.66	0.77	0.67	368
weighted avg	0.86	0.75	0.78	368

Next, we fine-tune the Random Forest algorithm's hyper-parameters by cross-validation against the AUC score.

Random Forest allows us to know which features are of the most importance in predicting the target feature ("attrition").

The Top 10 most important indicators : MonthlyIncome, OverTime, Age, MonthlyRate, DistanceFromHome, DailyRate, TotalWorkingYears, YearsAtCompany, HourlyRate, YearsWithCurrManager.





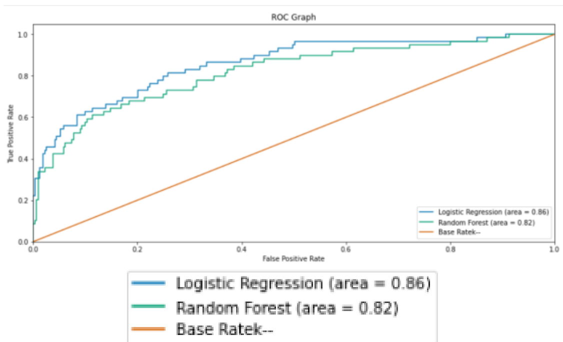
The Confusion matrix is telling us that we have 303+14 correct predictions and 1+52 incorrect predictions. In other words, an accuracy of 86.14%.

Classification report for the optimised RF Regression

	precision	recall	f1-score	support
0.0	0.89	0.98	0.93	309
1.0	0.75	0.36	0.48	59
accuracy			0.88	368
macro avg	0.82	0.67	0.71	368
weighted avg	0.87	0.88	0.86	368

ROC GRAPH

AUC - ROC curve is a performance measurement for classification problem at various thresholds settings. ROC is a probability curve and AUC represents degree or measure of separability. It tells how much model is capable of distinguishing between classes. The green line represents the ROC curve of a purely random classifier; a good classifier stays as far away from that line as possible (toward the top-left corner).



The fine-tuned Logistic Regression model showed a higher AUC score compared to the Random Forest Classifier.

5. CONCLUSION

It was stated which algorithms are performing better than others with their accuracy and reducing error rate using approach of machine learning. Algorithms are performing in predicting the employees; those are possible to leave the respective organization based on their working details and situations.

From the experimental results, Logistic Regression is undoubtedly outclassed remaining classifiers as got in evaluation conditions. The proposed system will be an employee churn rate prediction system that reduces the prediction error and increase the accuracy, to identify the possibility of employee quitting job and take appropriate preventive measures and to enhance company's performance and decrease overall revenue spent on recruitment and training.

Scope

Employee Churn Prediction and Human Resource Analytics allow the company to detect talent gaps, design learning and development programs, retain staff, and plan for succession. It's the expanding use of machine learning in the workplace.
It delivers essential information to enterprises, which they can utilize to make future decisions.
Employee predictive analytics employs correlations, trends, and patterns to anticipate future events and to influence future events and increase the chance of desired outcomes.

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