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Research Article

RoSaT– An Ensemble Architecture of Classification Algorithms to Predict Employee Rating Using SMOTEd IBM HR Analytics

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ABSTRACT

Performance evaluation of the employees reveal their productivity contributing to the growth of the organization they serve. It is therefore crucial for the HR department to ensure that there occurs no bias and the evaluation is done objectively. Machine learning techniques combined with appropriate tools can perform an exploratory data analysis and design a framework that predicts the performance of the employees without any human intervention. In this paper, we propose an ensemble stacking architecture – RoSaT that predicts the performance ratings with maximized accuracy. The dataset obtained was checked for data imputation followed by feature engineering process then training, validating and testing the data against different classification algorithms. The tabulated results along with performance metrics are finally elucidated to prove the efficacy of the proposed architecture.

Keywords: Machine Learning, Classification, Ensemble Learning, Stacking, Performance Rating.

I. Introduction:

Machine learning (ML) is at its zenith in the realm of research. The variety of algorithms developed under supervised, unsupervised, semi-supervised and reinforcement learning coupled with programming tools like Python, Power BI, Orange, R etc., has made decision making process more precise.

Supervised algorithms use labelled data which can be utilized for predictive analytics and classifications to recognize the underlying unseen patterns. They are broadly divided into Classification and Regression algorithms based on the type of output that must be predicted. The variable that needs to be predicted is known as target variables and the other attributes are known as features. If the target is a categorical label (taking values like good or moderate performer in employee performance) it comes under classification and if the target label take numerical values (that are continuous like rating performance of employees between 1-5) they are regression problems.

Ensemble model is a powerful ML technique which combines different algorithms to train and integrate the predictions of all individual models to improve the accuracy, to finally create a robust learner that boost the prediction accuracy of the model. Various ensembling techniques are stacking, voting, bagging and boosting.

Stacking is one of the ensemble learning method that has two stages of model building. The first stage uses different models as Base Model (like KNN, SVM or Decision Tree) in a hierarchical manner. The second stage uses meta model like Linear Regression or Logistics Regression, to further improvise the performance. Thus stacking combines the best features of various models all the while improving the accuracy.

Industry 4.0-the fourth industrial revolution, lays emphasis on embracing digital technological advancements like Artificial Neural Network, Cloud Computing, Deep Learning, Internet-of-Things so on, for sustainable and smart industrial applications. In alignment with this, employee performance evaluation - vital to both employee and the employer, needs to be done without bias, prejudice and in all fairness being strongly objective. Predictive analytics plays a pivotal role in predicting employee performance incorporating AI, ML, Data Analytics and Statistics without any human preconceived notion.

In this paper, we have proposed an ensemble architecture– RoSaT with the objective of utilizing the HR data that is digitally cleansed to remove inconsistencies and train the models to predict performance ratings with utmost accuracy. The model thus developed is evaluated for its performance using various metrics. Finally, we summarize the findings along with their interpretations and recommendations for future work.

II. Literature Review:

An empirical literature review from the year 2020 on/related to the topic "employee performance evaluation", reveals the work done in the arena of HR analytics, their objective(s), methodology adopted, tools and techniques applied, results obtained, limitations and future work. A summary of limited papers are precisely presented in a table below.

Sl #	Author(s)	Algorithm(s) applied	Result(s)	Limitation / Future work
1	Asuquo, D et al., -2020 [4]	C 4.5, RF and NB classifier	RF gives 96.97 & 98.70 % of accuracy for testing & validating	KNN & SVM not applied; 110 data set used
2	T. Li, M. G., et al., -2021 [26]	LR, DT & NB	Two class LR gives 83.4 % of accuracy	21 limited features used
3	Prasetyaningrun , P. T, et al., -2021 [22]	KNN, NB, DT and RF with stacking & bagging.	RF, stacking & bagging gives same 88% of accuracy	Imbalanced data set not considered
4	Y. Jia - 2022 [16]	LR, Nonlinear regression, Regression tree, SVM, RF & Neural network algorithms	RF gives 2.335 as RMSE & 0.906 as R2.	Uses 15 features & attendance variables to predict performance
5	Sujatha . P et al., - 2022 [20]	Gradient Boosting, XG Boosting	XG Boosting gives 92% accuracy	Only 2 models were tried.
6	Zbakh Mourad, et.al., -2022 [18]	KNN	85.71 % of accuracy	Only one model & 311 rows.
7	Toubasi, S. A. - 2022 [29]	J48, NB, SVM, RF, Radial Base Function, Multilayer Perceptron, and with bagging and boosting	J48 with Adaboost gives 99.16% accuracy	Original data set has 15 features. Ensemble models could be tried

Sl #	Author(s)	Algorithms applied	Result(s)	Limitation / Future work
8	Md Abu Jafor et al., -2023 [14]	SVM, LR, ANN, RF , XGBoost, AdaBoost & ensemble model	Ensemble model gives highest accuracy 95.3 %	13 features only used.
9	Gurung, N. N., et al., - 2024 [12]	XGBoost, LR, NB, RF, SVM, LDA, KNN	XG-Boost AUC holdout= 0.86;training data = 0.88; low runtime -16 minutes; max. memory utilization of 12%	Deep learning techniques could have been applied to the 73,115 data set.
10	Nayem, Z., & Uddin, M. A. - 2024 [19]	LR, Gaussian Naive Bayes, DT, KNN & SVM	Accuracy % of RF is 98.2 & Gaussian NB is 61.4	Deep learning & other data set can be tried
11	Youssri, A., et al., - 2024 [30]	RF applied to Oracle EBS data	99 & 98 % of training and testing accuracy respectively	Should verify to rule out overfitting
12	Sinha, H. - 2024 [25]	Gradient Boosting & Extra trees; Optuna, Bayesian optimization and Randomized Search.	Gradient Boosting gives 96% of accuracy	Neural networks & ensemble models can be tried.

Table 1: Employee Performance Evaluation: A review of literature

III. Proposed architecture:

The proposed architecture starts with the pre-processing of IBM data set. An exploratory data analysis (EDA) summarizes the types of features, missing values and its statistical insights.

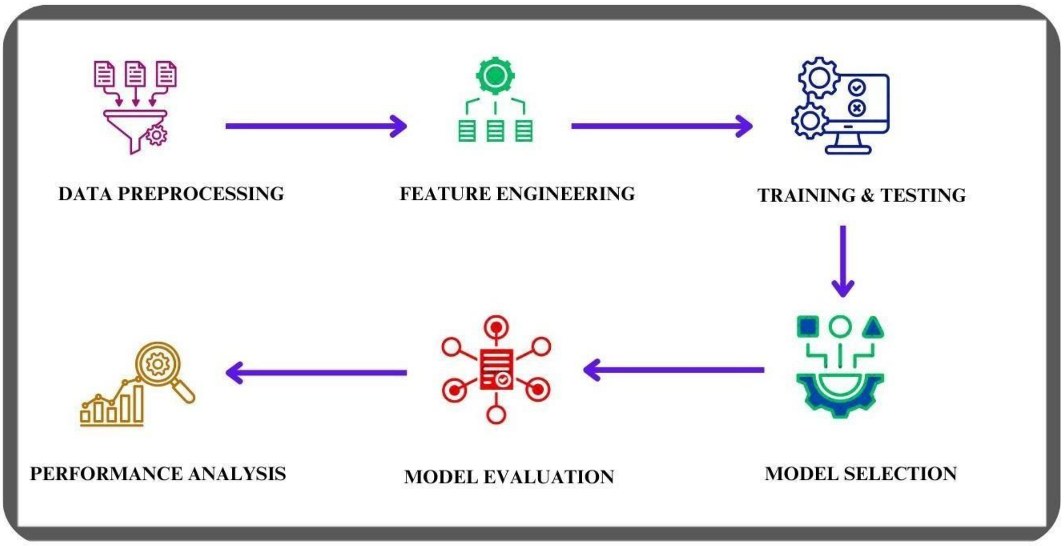

Fig 1: Proposed Architecture

Feature engineering consists of feature selection, feature transformation, feature extraction and feature construction which are performed using techniques like mutual information, normalization, label encoding, log transformation, PCA and constructing new features using the existing ones. The digitally cleansed data is bifurcated into training data and testing data in the ratio 80:20. Various classification models like KNN and Naïve Bayes, SVM, Naïve Bayes and Logistic Regression are trained and their accuracy are tabulated. Metrics like accuracy, precision, recall, F2 score, MCC, log loss and AUC-ROC are evaluated for all the individual models as well as RoSaT. The results obtained are analysed to understand the best performer of all models.

Algorithms used:

KNN- also known as a lazy learner, is the most commonly used algorithm for classification task. It relies on the similarity between the features to make predictions. This aspect of it was useful in this prediction task since there were only two outcomes for performance ratings. In this work we have fixed k = 5.

STEPS:

Store all training data (no learning phase).

For a new data point, calculate the distance (e.g., Euclidean) from all training points.

Pick k nearest neighbours (smallest distances).

Count the class labels of these k neighbours.

Assign the most common class to the new data point.

SVM is a max-margin classification algorithm which aims to find the hyperplane with the largest margin between classes. It can handle both linear and non-linear classification using kernel tricks. In our task we have used kernel= “rbf”, where “rbf” stands for Radial Basis Function (Gaussian kernel) — RBF Kernel enables SVM to find complex boundaries between classes.

STEPS:

Plot data points in space according to their features.

Find the best hyperplane (line/plane) that separates classes with the maximum margin (distance between classes).

If data is not linearly separable, apply kernel trick (e.g., RBF kernel) to map data into higher dimensions.

Use support vectors (key data points near the margin) to define the hyperplane.

Classify new data based on which side of the hyperplane it lies.

Naïve Bayes works on Bayes theorem with the assumption of feature independence. It is a probabilistic generative model and is robust to irrelevant features. It is often used as a baseline model to compare the performance of more complex algorithms.

STEPS:

Calculate prior probabilities for each class (how often each class appears).

For each feature, calculate likelihood of feature value given a class (e.g., using Gaussian distribution for continuous data).

Use Bayes' Theorem to calculate posterior probability for each class.

Choose the class with the highest probability as the prediction.

Logistic Regression is a popular algorithm applied for binary classification. It gives probabilities for class memberships. It assumes a linear relationship between the input features and log odds. In our work we have used C = 5, where C is the inverse of regularization strength, makes the model more flexible.

STEPS:
Initialize weights and bias.
For each data point, calculate weighted sum of features plus bias.
Apply sigmoid function to convert the result into a probability (between 0 and 1).
Compare probability to a threshold (usually 0.5) to decide class (0 or 1).
Optimize weights using gradient descent to minimize the log loss (error).
Repeat until the model converges.

RoSaT classifier (fig 2), is an ensemble stacking model constructed using KNN, SVM and Naïve Bayes as the base models and logistic regression as the meta model.

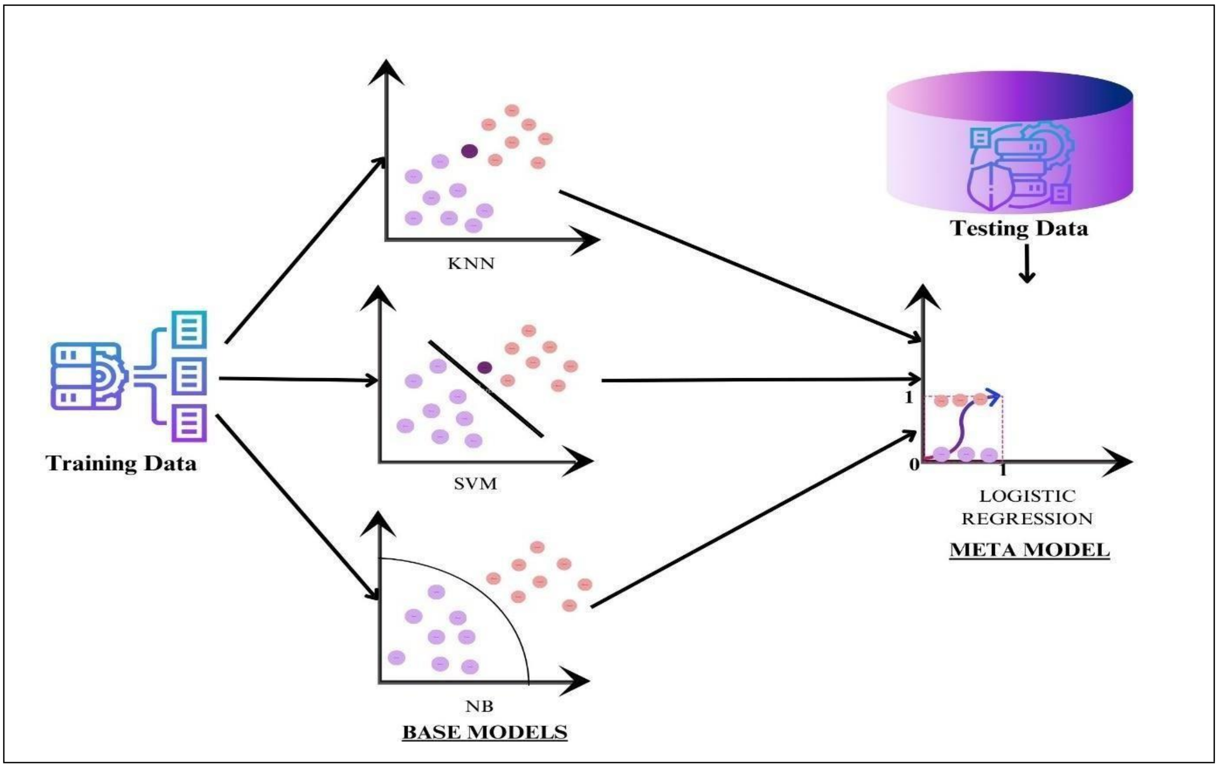

Fig 2: RoSaT Classifier

The training data is split and trains each of the base models-KNN, SVM and NB. Using these models predictions as intermediate predictions, the meta model- Logistic regression, is trained on the testing data.

The accuracy of RoSaT is then compared with the other individual models. To assert the model's overall performance, various metrics are computed and compared.

STEPS:

Input: Dataset D with features X and target y = PerformanceRating_Binary

Output: Predicted class labels for test instances

1. Pre-process the dataset:

a. Handle missing values, standardize if needed.

b. Split D into training set (X_train, y_train) and test set (X_test, y_test).

2. Initialize base models:

a. KNN, SVM, Naive Bayes.

3. Train each base model on X_train, y_train.

4. Generate base model predictions on X_train using cross-validation:

a. For each instance, obtain KNN_pred, SVM_pred, NB_pred.

b. Form new training set for meta-model: Z_train = [KNN_pred, SVM_pred, NB_pred].

5. Train Logistic Regression meta-model on Z_train, y_train.

6. For test instances:

a. Obtain base model predictions: KNN_test_pred, SVM_test_pred, NB_test_pred.

b. Form meta-model input: Z_test = [KNN_test_pred, SVM_test_pred, NB_test_pred].

c. Use Logistic Regression to predict final class labels: y_pred = LogisticRegression(Z_test).

7. Evaluate performance of y_pred against y_test using accuracy, precision, recall, F2-score, MCC, Log Loss, AUC-ROC.

End.

IV. Data pre-processing:

(i) About the data set:

IBM HR Analytics data set taken from Kaggle is utilized in this study. It contains 1470 rows and 35 columns. Exploratory data analysis was performed to gain insights about the data set. There are 26 numerical and 9 categorical features. “PerformanceRating” is set as the target label since our objective is to evaluate the employee performance.

```
Data columns (total 35 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Age                       1470 non-null   int64
 1   Attrition                 1470 non-null   object
 2   BusinessTravel            1470 non-null   object
 3   DailyRate                 1470 non-null   int64
 4   Department                1470 non-null   object
 5   DistanceFromHome          1470 non-null   int64
 6   Education                 1470 non-null   int64
 7   EducationField            1470 non-null   object
 8   EmployeeCount             1470 non-null   int64
 9   EmployeeNumber            1470 non-null   int64
 10  EnvironmentSatisfaction   1470 non-null   int64
 11  Gender                    1470 non-null   object
 12  HourlyRate                1470 non-null   int64
 13  JobInvolvement            1470 non-null   int64
 14  JobLevel                  1470 non-null   int64
 15  JobRole                   1470 non-null   object
 16  JobSatisfaction           1470 non-null   int64
 17  MaritalStatus             1470 non-null   object
 18  MonthlyIncome             1470 non-null   int64
 19  MonthlyRate               1470 non-null   int64
 20  NumCompaniesWorked        1470 non-null   int64
 21  Over18                    1470 non-null   object
 22  OverTime                  1470 non-null   object
 23  PercentSalaryHike         1470 non-null   int64
 24  PerformanceRating         1470 non-null   int64
 25  RelationshipSatisfaction  1470 non-null   int64
 26  StandardHours             1470 non-null   int64
 27  StockOptionLevel          1470 non-null   int64
 28  TotalWorkingYears         1470 non-null   int64
 29  TrainingTimesLastYear     1470 non-null   int64
 30  WorkLifeBalance           1470 non-null   int64
 31  YearsAtCompany            1470 non-null   int64
 32  YearsInCurrentRole        1470 non-null   int64
 33  YearsSinceLastPromotion   1470 non-null   int64
```

Fig 3: Data Description

(iii) Missing Values:

The data set does not have any missing values. It is confirmed via the following heat map.

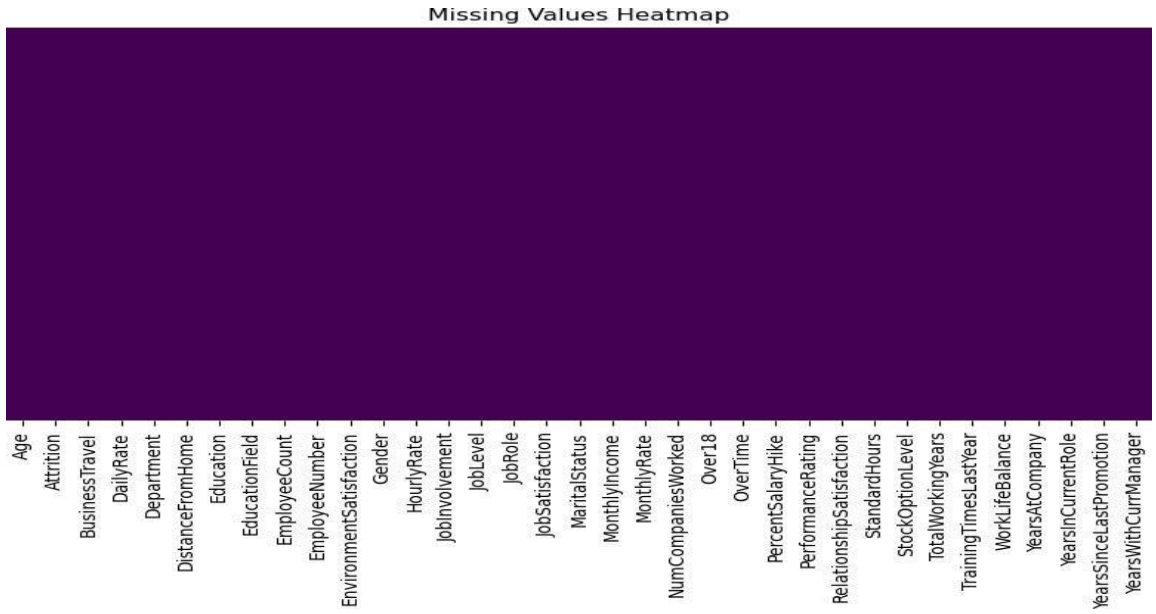

Fig 4: Heat map for missing values

(iv) Summary Statistics:

The table throws light on the statistical implications of the data set and helps us to decide about the features to be selected. For ex., features like EmployeeCount, Over18, StandardHours have the same value and hence can be dropped. EmployeeNumber is a unique identifier and not useful for prediction.

Summary Statistics:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount
count	1470.00	1470.00	1470.00	1470.00	1470.00
mean	36.92	802.49	9.19	2.91	1.00
std	9.14	403.51	8.11	1.02	0.00
min	18.00	102.00	1.00	1.00	1.00
25%	30.00	465.00	2.00	2.00	1.00
50%	36.00	802.00	7.00	3.00	1.00
75%	43.00	1157.00	14.00	4.00	1.00
max	60.00	1499.00	29.00	5.00	1.00

	EmployeeNumber	EnvironmentSatisfaction	HourlyRate	JobInvolvement
count	1470.00	1470.00	1470.00	1470.00
mean	1024.87	2.72	65.89	2.73
std	602.02	1.09	20.33	0.71
min	1.00	1.00	30.00	1.00
25%	491.25	2.00	48.00	2.00
50%	1020.50	3.00	66.00	3.00
75%	1555.75	4.00	83.75	3.00
max	2068.00	4.00	100.00	4.00

	JobLevel	JobSatisfaction	MonthlyIncome	MonthlyRate
count	1470.00	1470.00	1470.00	1470.00
mean	2.06	2.73	6502.93	14313.10
std	1.11	1.10	4707.96	7117.79
min	1.00	1.00	1009.00	2094.00
25%	1.00	2.00	2911.00	8047.00
50%	2.00	3.00	4919.00	14235.50
75%	3.00	4.00	8379.00	20461.50
max	5.00	4.00	19999.00	26999.00

	NumCompaniesWorked	PercentSalaryHike	PerformanceRating
count	1470.00	1470.00	1470.00
mean	2.69	15.21	3.15
std	2.50	3.66	0.36

Fig 5: Summary of statistics

(v) Data transformation:

The next step is encoding: Label encoding binary categorical columns (e.g., Gender: Male=1, Female=0) and One-Hot Encoding for multi-category columns (e.g., Department, JobRole).

(vi) Handling outliers:

Further, outliers are detected using box plot. It was found that 11 features had outliers and they were replaced with median instead of mean.

(vii) SMOTE process:

Initially the distribution of the target label “PerformanceRating” has skewness 1.9199, which indicates that the data is positively skewed. When Undersampling, Oversampling also known as SMOTE, and hybrid – Undersampling + SMOTE were applied, SMOTE and Undersampling has skewness as zero. However, Undersampling has only 452 rows and 1018 rows from the original table are removed. SMOTE has totally 2488 rows ie., 1018 rows augmented which also helps in training the models with more data. Therefore, the SMOTEd data set was used for further processing of the model.

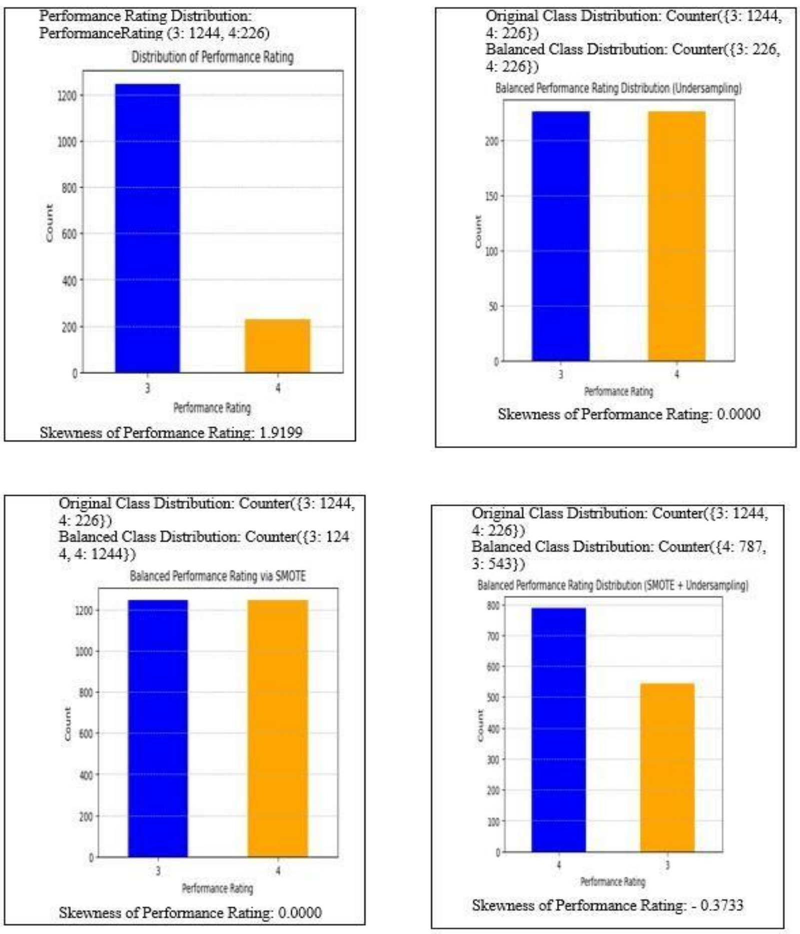

Fig 6: Skewness comparison of original data, Undersampling, SMOTE & hybrid

V. Feature Engineering:

PCA visualization:

Fig 8 shows that the data set contains only 3 & 4 for performance ratings. Hence it was considered as a classification problem of rating employees as moderate & good performers.

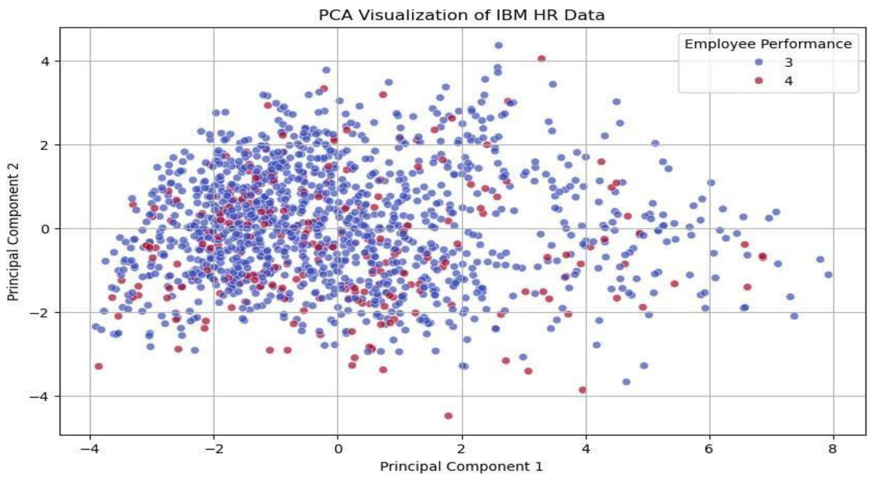

Fig 7: PCA visualization

```
df = pd.read_excel(file_path)

# Convert PerformanceRating into binary classification
df['PerformanceRating_Binary'] = df['PerformanceRating'].apply(lambda x: 0 if x == 3 else 1)
```

Fig 8: Converting PerformanceRating into binary value

The above converts Performance rating into a binary classification.

Mutual Information:

The graph shows that PercentSalaryHike with the maximum MI score implying that it is the most influential feature for predicting the target.

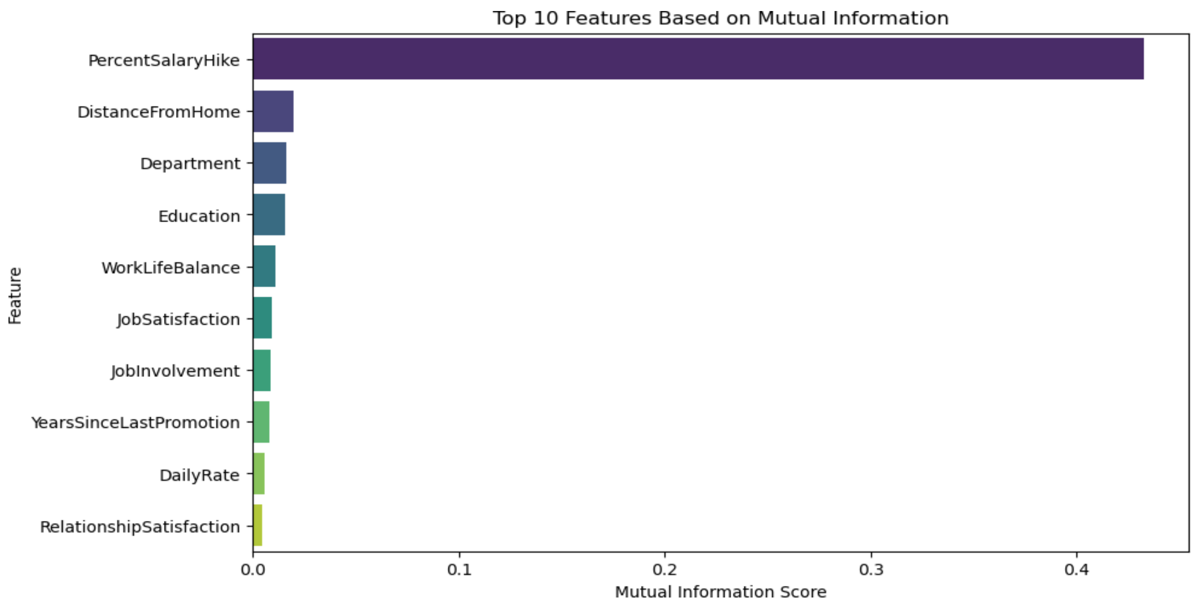

Fig 9: Mutual Information Score

The modified data after pre-processing and feature selecting, extracting and transforming was ready for model training. The data set was then split into training and testing data and applied to the ensemble stacking model – RoSaT. The predictions of RoSaT were then validated using various metrics.

VI. Evaluation of Metrics:

Metrics are crucial to assess, analyse and reveal the hidden pattern in the data set. Evaluation metrics for classification, measures the performance of models. Various metrics their formula, significance and interpretation are listed below.

1. $Accuracy = \frac{Correct\ Predictions}{Total\ Predictions}$ It measures the overall correctness of the model and is useful

when the dataset is balanced. Higher accuracy means better model performance.

2. $Precision = \frac{True\ Positives}{True\ Positives\ +\ False\ Positives}$ It tells us how many of the predicted positives are

actually positive. High precision means fewer false positives.

3. $Recall = \frac{True\ Positives}{True\ Positives\ +\ False\ Negatives}$ It measures how many actual positives the model

correctly identified. High recall means fewer false negatives.

4. $F2\ Score = 5\ X\ (\frac{Precision\ x\ Recall}{4\ x\ Precision\ +\ Recall})$ It is useful when false negatives (FN) are more critical

than false positives (FP). Higher F2 score indicates that model prioritizes recall (fewer false negatives); lower F2 score indicates that model fails to identify actual positives correctly.

5. *AUC-ROC (Area Under the Curve - Receiver Operating Characteristic)* = $\int_0^1 TPR\ d(FPR)$

Measures the ability of the classifier to distinguish between classes. Higher AUC means better overall model performance.

6. *Log Loss (Logarithmic Loss)* = $-\frac{1}{N}\sum_{i=1}^{N}[y_i\ log\ log\ (P_i)\ + (1 - y_i) log\ (1 - P_i)]$

Used in probabilistic classification, where models predict probabilities. Lower Log Loss means better model performance.

7. *Matthews Correlation Coefficient (MCC)* = $\frac{(TP\ X\ TN) - (FP\ X\ FN)}{\{(TP+FP)\ (TP+FN)\ (TN+FP)\ (TN+FN)\}}$

Used to evaluate binary classification. If MCC = +1 it's a perfect classification; 0 implies just a random guessing (like tossing a coin); -1 indicates completely wrong classification.

Metric evaluation of RoSaT classifier with other algorithms:

The proposed ensemble stacking classifier– RoSaT was evaluated against the individual models and the results are tabulated as follows:

Model	Accuracy (%)	Precision (%)	Recall (%)	F2 Score (%)	MCC	Log Loss	AUC ROC (%)
KNN	94.38	94.02	94.78	94.63	0.8876	0.1804	99.01
SVM	98.19	97.24	99.2	98.8	0.964	0.035	99.95
Naive Bayes	97.19	98.35	95.98	96.45	0.944	0.071	99.74
Logistic Regression	96.99	96.43	97.59	97.36	0.9398	0.1135	99.54
RoSaT	98.59	98.4	98.8	98.72	0.9719	0.0444	99.95

Fig 10: Metrics evaluation of all models

VII. Findings:

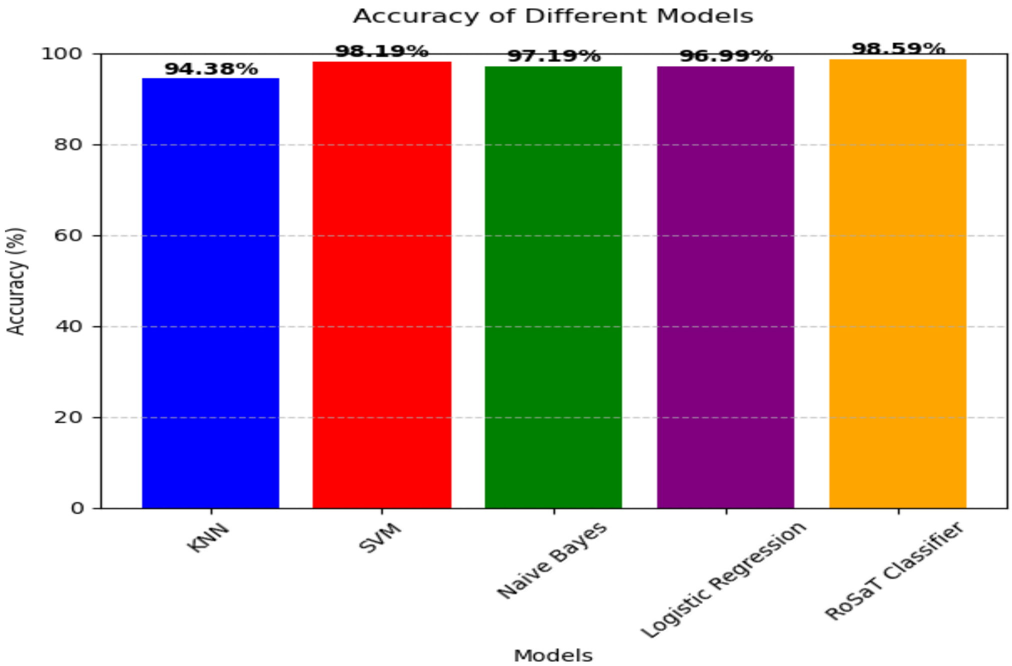

Fig 11: Accuracy comparison

RoSaT algorithm has yielded an accuracy rate of 98.59 % by using KNN, SVM & NB as base models and Logistic regression as meta model. The percentage of precision is also the highest amongst all other models. SVM has given highest F2 score and has the same value as that of RoSaT for AUC-ROC but has less accuracy and precision. KNN has given the least prediction.

VIII. Takeaways for HR Managers:

It is imperative that HR data set will contain all the personal and professional information about the employees. But when utilizing predictive analytics or any software, it must be noted that not all attributes are required to predict employee performance.

RoSaT used data set wherein features like over 18, employee count were dropped. Performance ratings should not be biased on gender. Also it is evident from fig 9 that salary hike influences performance. The results manifest underlying implications of the work environment. Like, attrition can be analysed from this, if their ratings happen to be high.

Therefore, it is mandatory that HR managers accept and adopt AI, ML, Data Analytics practices for the overall wellbeing of the employees and organization.

IX. Future work:

Real time monitoring of employee performance can be done by incorporating real time input from different units such as wearable devices, IoT sensors, streaming data and mobile apps. The objective can be broadened as multi-objective research by developing models that can incorporate productivity, employee safety, employee satisfaction etc. Bespoke models could be developed by considering personality traits, learning rate and career goals.

X. Conclusion:

Employee performance evaluation is a routine vital task that must be carried out by HR mangers periodically not only to appraise and reward the employee but to identify their strength and recommend for career succession. Growth of the organization will be expedited when the employees are motivated and encouraged for their contributions. Predictive analytics can automate the entire task using ML algorithms. RoSaT is one such algorithm which has proven to predict the performance rating of the employees with high accuracy and precision.

XI. References:

[1] Adeniyi, J. K., Adeniyi, A. E., Oguns, Y. J., Egbedokun, G. O., Ajagbe, K. D., Obuzor, P. C., & Ajagbe, S. A. (2022). Comparison of the performance of machine learning techniques in the prediction of employee. ParadigmPlus, 3(3), 1–15. https://doi.org/10.55969/paradigmplus.v3n3a1

[2] Amarnath Bhimanatham, Subramaniam Seshan Iyer (2024) The Role of HR Analytics in Optimizing Employee Performance in Information Technology Firms. Library Progress International, 44(2), 525-530.

[3] Anjum, A. A., Majumder, S., Islam, S., & Rabiul Alam, M. G. (2022). A decentralized employee performance appraisal framework for recruitment, performance prediction and ranking using Permissioned blockchain and machine learning. *2022 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE)*, 1-6. https://doi.org/10.1109/csde56538.2022.10089340

[4] Asuquo, Daniel; Umoh, Uduak A.; Okokon, Edikan W. and Osang, Francis B. (2020), Performance Evaluation of C4.5, Random Forest and Naïve Bayes Classifiers in Employee Performance and Promotion Prediction, Afr. J. MIS, Vol. 2, Issue 4, pp. 41 - 55 .

[5] Atiku, S. O., & Obagbuwa, I. C. (2021). Machine learning classification techniques for detecting the impact of human resources outcomes on commercial banks performance. Applied Computational Intelligence and Soft Computing, 2021, 1–16. https://doi.org/10.1155/2021/7747907

[6] Bian, K., & Priyadarshi, R. (2024). Machine Learning Optimization Techniques: A survey, classification, challenges, and future research issues. Archives of Computational Methods in Engineering. https://doi.org/10.1007/s11831-024-10110-w

[7] Chukwuka, & Dibie. (2024). Strategic role of Artificial Intelligence (AI) on human resource management (HR) employee performance evaluation function. International Journal of Entrepreneurship and Business Innovation, 7(2), 269–282. doi:10.52589/ijebi-het5styk

[8] Deo, A., Mahfouz, Y., Implementation of machine learning algorithm for the prediction of IT industry employees performance. (2023). International Research Journal of Modernization in Engineering Technology and Science, 5(2), e-ISSN: 2582-5208. https://doi.org/10.56726/IRJMETS33849.

[9] G. Dharani Devi; S. Kamalakkannan, "Prediction of Job Satisfaction from the Employee Using Ensemble Method", 2022 International Conference on Advanced computing Technologies & Applications (ICACTA), Mar. 04 – 05, 2022, DOI: 10.1109/ICACTA54488.2022.9753135

[10] Gaurav Sharma, "A literature review on application of Artificial Intelligence in Human Resource Management and its practices in current organizational scenario", Proceedings of the Fifth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC) 2021, IEEE Xplore Part Number: CFP21OSV-ART; ISBN: 978-1-6654-2642-8, DOI: 10.1109/I-SMAC52330.2021.9640954

[11] Gupta, A., Chadha, A., Tiwari, V., Varma, A., & Pereira, V. (2023). Sustainable training practices: predicting job satisfaction and employee behavior using machine learning techniques. Asian Business & Management, 22(5), 1913–1936. https://doi.org/10.1057/s41291-023-00234-5

[12] Gurung, N. N., Gazi, N. M. S., & Islam, N. M. Z. (2024). Strategic Employee Performance Analysis in the USA: Deploying Machine learning Algorithms Intelligently. Journal of Business and Management Studies, 6(3), 01–14. https://doi.org/10.32996/jbms.2024.6.3.1

[13] Haidari, M. (2022). A conceptual Artificial intelligence application framework in performance appraisal. In Advances in human resources management and organizational development book series (pp. 1–16). https://doi.org/10.4018/978-1-6684-5575-3.ch001

[14] Jafor, M. A., Wadud, M. A., Nur, K., & Rahman, M. M. (2023). Employee promotion prediction using improved AdaBoost machine learning approach. *AIUB Journal of Science and Engineering (AJSE)*, *22*(3), 258-266. https://doi.org/10.53799/ajse.v22i3.781

[15] J. Katyayani,N. A. Saira Banu (2024) Predictive Analytics in Talent Management. Library Progress International, 44(3), 20399-20408.

[16] Jia Yuan, "Research on Employee Performance Prediction Based on Machine Learning", 2022 IEEE 5th International Conference on Electronics Technology (ICET), DOI: 10.1109/ICET55676.2022.9824477

[17] Mishra, S., Mallick, P. K., Tripathy, H. K., Jena, L., & Chae, G. (2021). Stacked KNN with hard voting predictive approach to assist hiring process in IT organizations. International Journal of Electrical Engineering Education. https://doi.org/10.1177/0020720921989015

[18] Mourad, Z., Noura, A., & Mohamed, C. (2022, May 18). Towards a new method for classifying employee performance using machine learning algorithms. 2022 International Conference on Intelligent Systems and Computer Vision (ISCV). Presented at the 2022 International Conference on Intelligent Systems and Computer Vision (ISCV), Fez, Morocco. doi:10.1109/iscv54655.2022.9806118

[19] Nayem, Z., & Uddin, M. A. (2024). Unbiased employee performance evaluation using machine learning. Journal of Open Innovation Technology Market and Complexity, 10(1), 100243. https://doi.org/10.1016/j.joitmc.2024.100243

[20] P. Sujatha; R.S. Dhivya, "Ensemble Learning Framework to Predict the Employee Performance", 2022, IEEE, Second International Conference on Power, Control and Computing Technologies (ICPC2T), DOI: 10.1109/ICPC2T53885.2022.9777078

[21] Pathak, A., Dixit, C. K., Somani, P., & Gupta, S. K. (2023). Prediction of Employees' Performance using Machine Learning (ML) Techniques. In CRC Press eBooks (pp. 177–196). https://doi.org/10.1201/9781003357070-11

[22] Prasetyaningrun, P. T., Pratama, I., & Chandra, A. Y. (2021). Implementation of machine learning to determine the best employees using Random Forest method. IJCONSIST JOURNALS, 2(02), 53–59. https://doi.org/10.33005/ijconsist.v2i02.43

[23] S Roshini; Sanjana Prakash; J Shilpha Dharshini; M N Saroja; J Dhivya, "Decision Tree and KNN Analysis for HR Analytics Data", International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA) | 2021 IEEE | DOI: 10.1109/ICAECA52838.2021.9675616

[24] Sabuj, H. H., Nuha, N. S., Gomes, P. R., Lameesa, A., & Alam, M. A. (2022). Interpretable garment workers' productivity prediction in Bangladesh using machine learning algorithms and explainable AI. RESEARCH GATE, 236–241. https://doi.org/10.1109/iccit57492.2022.10054863

[25] Sinha, H. (2024). Predicting employee performance in business environments using effective machine learning models. doi:10.5281/ZENODO.13771036

[26] T. Li, M. G., Lazo, M., Balan, A. K., & Goma, J. D. (2021). Employee performance prediction using different supervised classifiers. *Proceedings of the International Conference on Industrial Engineering and Operations Management*. https://doi.org/10.46254/an11.20211188

[27] Tanasescu, L. G., Vines, A., Bologa, A. R., & Vîrgolici, O. (2024). Data Analytics for optimizing and predicting employee performance. Applied Sciences, 14(8), 3254. https://doi.org/10.3390/app14083254

[28] Thabet, H. H., Darwish, S. M., & Ali, G. M. (2024). Measuring the efficiency of banks using high-performance ensemble technique. Neural Computing and Applications, 36(27), 16797–16815. https://doi.org/10.1007/s00521-024-09929-y

[29] Toubasi, S. A. (2022). A Combined Approach for Predicting Employees' Productivity based on Ensemble Machine Learning Methods. Informatica, 46(5). https://doi.org/10.31449/inf.v46i5.3839

[30] Youssri, A., Abdelbadea, E., Raslan, A., Mosallam, I., Aly, T., Amin, E. A., Gheith, M., & Khater, A. (2024). The future ERP systems: Improve employee performance evaluation using Machine Learning. In Lecture notes on data engineering and communications technologies (pp. 13–21). https://doi.org/10.1007/978-3-031-71619-5_2