IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

Predicting Employee Performance in Business Environments Using Effective Machine Learning Models

Himanshu Sinha
Kelley School of Business, Indiana University,
Bloomington, Naperville IL United States

Abstract—The management of companies places great emphasis on human resources, seeking to choose highly skilled employees who can perform above and beyond expectations. As managers and decision-makers attempt to devise plans for locating and developing exceptional talent, human resources management (HRM) has become a crucial area of interest. A key concern lies in enhancing the performance of employees through professional skill development programs. The goal of employee performance reviews is to gauge each employee's level of dedication to the business. A company's ability to forecast employee performance is critical to its success. This study's objective was to investigate the factors influencing employee performance prediction in the workplace using ML techniques. This project aims to provide improved employee performance forecast accuracy and performance via the use of state-of-the-art ML techniques. Utilising a Human Resources dataset from Kaggle, the research involves meticulous data preprocessing steps, including balancing is conducted using SMOTE. Two machine learning models—Gradient Boosting and Extra Trees—are implemented and evaluated with hyperparameter optimisation techniques such as Optuna, Bayesian optimisation, and Randomized Search. The comparative analysis reveals that both models achieve high-performance metrics, with Gradient Boosting slightly outperforming with an accuracy0.962, precision0.955, recall0.967, and F1-score0.961. This study offers significant insights for future research, demonstrating an effectiveness of using sophisticated ML algorithms for optimising and forecasting employee performance in human resource management.

***Keywords**—Employee performance, human resources dataset, extra trees, gradient boosting, machine learning, Bayesian optimization, optuna, randomize search*

I. INTRODUCTION

Performance assessment, which comprises departmental, organisational, and individual performance evaluations, is the most important phase of the employee performance management cycle system [1]. The most difficult part of human resource management is performance assessment, which entails checking in on how people are doing right now, picking out the top performers and the worst performers, and giving advice to employees. Numerous organizations do not implement employee performance evaluations in a systematic manner. Consequently, the evaluation technique becomes ineffective and erratic. Regardless of the size of the organization, employees are essential to its operations.[2] Typically, the recruiting process consists of a series of steps designed to optimise the applicant selection. That choice will not necessarily be successful, however, despite the protocols that are followed throughout the interview process. Interviews could be affected by candidates' stress levels, assessment process ambiguities, and other unidentified human-related elements [3]. The performance of employees has previously been assessed in a variety of business sectors, creating a void for the assessment of a particular industry. Additionally, in order to assess employee performance, a variety of firm-level environmental elements and job-related factors have been examined via the particular mediation of employee-related characteristics including commitment, skill level, motivation, flexibility, and adaptability [4]. Assessing the precise mediation function of workers' commitment among their work environment and performance was not possible with this kind of examination. Consequently, looked to employee dedication as a middle ground between work environment and productivity [5].

Machine learning is essential for improving the precision and effectiveness of employee performance forecasting. In the context of forecasting employee performance, data analytics enables the collection and analysis of data from many sources, such as organisational dynamics, performance metrics, demographic information, and employee surveys[6]. By applying statistical techniques, data visualisation, and predictive modelling, business analytics facilitates the identification of patterns, trends, and correlations that influence employee performance outcomes. Further, Machine learning algorithms refine these insights by identifying complex patterns and relationships within the data, enabling more precise forecasting of future performance outcomes[7]. Organizations may better understand their personnel dynamics proactively optimise performance and achieve organisational success with this comprehensive approach [8][9].

The primary goal of this study is to explore and create an effective approach for using ML and data analytics to forecast employees' productivity. This research uses the Kaggle HR dataset to try to fill in some of the blanks left by previous evaluations by looking at workplace climate and performance through the lens of employee commitment. By using hyperparameter tuning techniques like Optuna, Bayesian optimisation, and randomized search in conjunction with sophisticated machine learning models like Extra Trees and Gradient Boosting, the research aims to enhance the precision and dependability of performance forecasts. The ultimate objective of this study is to offer practical advice on how to maximise worker productivity and foster organisational success.

- The research provides new insights into the elements impacting employee productivity by taking a fresh approach by considering employee commitment as a mediator among the working environment and performance.
- The research improves upon conventional techniques of evaluating employees' performance by using advanced ML models such as Gradient Boosting and Extra Trees.
- An use of hyperparameter tuning techniques such as Optuna, Bayesian optimization, and randomized search significantly improves model performance, setting a benchmark for future research in predictive analytics.
- Utilizing the Human Resources dataset from Kaggle, the study provides a thorough analysis of employee performance factors, making the findings applicable and valuable to real-world HR management practices.
- The outcomes of the study offer practical recommendations that can help organizations optimize their employee management strategies, ultimately contributing to enhanced performance and productivity at the workplace.

1.2 Structure of this paper

The literature review and research gap in Section II form the following section of the study. This approach is described in Section III. A findings and related debates are detailed in Section IV, while the conclusion and potential future research are covered in Section V.

II. Literature Review

Data analytics for optimising and forecasting employee performance has been the subject of prior research, which is summarized in this section alongside:

In [10] focuses on developing problem-solving strategies for identifying great workers for rewards. This approach assigns a weight value to each characteristic before proceeding with a ranking procedure to find a best option for the greatest number of prospective workers. The accuracy level of the employee performance rating was 93% when 193 out of 200 data points were in line with the value derived by the procedure, based on 200 data points from employee appraisals.

In [11] employs a number of ML classifiers, including SVMs, KNNs, DT, RF, and LR, to get the best performance prediction for an employee. As previously mentioned, some of the evaluation measures used to gauge the classifier's performance include precision, accuracy, F1-score, and log loss. Testing outcomes show that RF performs better than other approaches in terms of accuracy (88%) F1-score (0.93) precision score (0.88) and log loss(0.33). Based on the provided data, the RF classifier outperforms other classifiers when it comes to predicting employee performance.

In [12] aims to identify the main factors that influence an employee's decision to leave an organisation by examining the effect of objective variables on employee turnover. In terms of traditional metrics, the findings show that the GNB classifier approach produced the best outcomes for the given dataset. Its highest recall rate is 0.54 and it obtains a total FNR of 4.5 percent since it evaluates a classifier's capacity to recognise every positive event.

In [13] analyzes an approach for making predictions using the characteristics that are used to assess personnel during promotion procedures using ML algorithms like SVM, ANN, and RF. Random Forest outperformed all other methods using the ROS methodology, achieving an accuracy98%, precision96%, recall1.0%, and f1-score values98%.

In [14], optimization involves the use of regularization methods and parameter adjustment to address overfitting problems. Based on the outcomes of a comparison research, an improved SVM model outperformed the other two classifiers (ANN and DT) in terms of accuracy (88.87%) and so was the best model for predicting employee attrition.

Data analytics for optimising and forecasting employee performance are compared in Table 1.

Table 1: Comparative Analysis of data analytics for optimizing and predicting employee performance

Author	Techniques	Dataset	Findings	Limitations & Future Work
[10]	Profile matching method	200 employee appraisal data	Achieved an accuracy level of 93%	Future work could involve exploring more diverse datasets and additional criteria to enhance accuracy.
[11]	SVM, KNN, DT, RF, LR	Employee performance dataset	Random Forest provided the highest accuracy (88%), F1-score (0.93), precision score (0.88), and lowest log loss (0.33)	Limitations include the need for larger datasets and further refinement of hyperparameters for improvement.
[12]	Gaussian Naïve Bayes classifier	IBM analytics dataset with 35 features and ~1500 samples	Overall FNR was 4.5 percent and best recall rate of 0.54 percent.	Future work could include enhancing the recall rate and exploring other classifiers for better performance.
[13]	SVM, ANN, Random Forest	Employee Promotion Evaluation Dataset	The Random Forest model outperformed the others using the ROS method, achieving an accuracy 98%, precision 96%, recall 1.0%, and F1-score 98%.	Limitations involve validating the methodology across different organizational contexts and datasets.
[14]	SVM, ANN, Decision Tree	IBM Human Resource Analytic Employee Attrition and Performance dataset	Optimised, SVM model achieved the highest accuracy (88.87%) compared to other models.	Future work could focus on further optimization techniques and testing with more diverse datasets

III. Methodology

The methodology for this study involves several key steps to ensure effective data handling and model implementation for predicting employee performance. As a first step in data collection, we acquired the HR Data dataset by Kaggle. Data preprocessing follows, which includes reviewing initial records, assessing data shape, and verifying and describing the dataset. Essential preprocessing steps include label encoding to convert categorical data into numerical format, handling missing and negative values to maintain dataset integrity, and using the SMOTE to balance class distribution and address class imbalance issues. Data splitting is then performed, dividing a dataset into 80% for training and 20% for testing. In a proposed model implementation stage, two machine learning models, Gradient Boosting and Extra Trees, are utilized. To assess and enhance the models' ability to forecast employees' performance, the findings and discussion section compares and contrasts them using measures including recall, accuracy, precision, and F1-score; it also makes use of confusion matrices and visual representations.

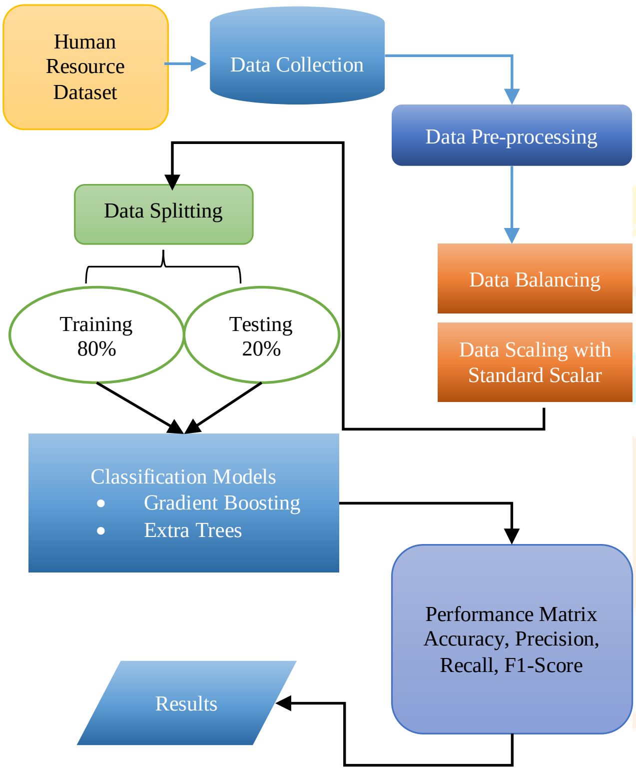

Figure 1: Flow Chart of methodology for employee performance prediction

The following phases of the methodology are shown in Figure 1.

3.1 Data Collection

Information gathering is a first stage in a process of using this method. It was determined that the Human Resource Data dataset, which originated from Kaggle, was utilized in this investigation. Moreover, the collection includes contributions from 311 different individuals.

3.2 Data Preprocessing

Transforming raw data into a ML model that works is called data pre-processing. Numerous pre-processing steps were used in this process, including reviewing a few of the dataset's initial records, assessing the data's shape, verifying information, describing the data, characterizing the data, printing column names with object data type. Other important preprocessing steps are discussed and described in detail below:

- **Label Encoding:** The process of label encoding was used to transform the numerical representation of categorical data. A separate integer value was allocated to each unique category inside the columns of object data types. This conversion made it easier to add categorical variables to the ML models so that the data could be processed and interpreted by the algorithms.
- **Handling missing and negative values:** Both missing and negative values were systematically addressed to ensure the dataset's integrity and reliability.
- **Data Balancing:** The dataset's class imbalance was remedied by using the SMOTE. By using interpolation between existing instances of the minority class, SMOTE is able to produce synthetic examples for that class. This approach helps in creating a more balanced distribution of classes, which is crucial for training robust and unbiased machine learning models.

3.3 Data Splitting

Two distinct sections are used to separate the training and testing components of the dataset.20% of the data will be used for testing, while the remaining 80% will be used for training.

3.4 Proposed Model Implementation

This stage involved applying the two machine learning models, gradient boosting and Extra trees, which are further explained below:

1) Gradient Boosting Model

As a machine learning approach, gradient boosting creates a prediction model by combining many weak prediction models, most often decision trees [15]. An underperforming feature in predicting result Y may be made into a powerful learner using the boosting principle. After finding the regression trees with weak learners, boosting will prioritize the errors among the weak learner's predicted fitted values and the actual values, giving equal weight to every observation. This model uses gradient boosting, which uses the error rate to calculate the gradient of the error function. It then uses the gradient to decide how to adjust the model's parameters such that the error decreases with each iteration. As directed by data scientists, this procedure will be performed m times.

The gradient boosting approach makes the assumption that Y is a real number. With this approach, the weighted sum of functions by weak learners (hi(x)) is attempted to be approximated (F^(x)):

$$\hat{F}(x) - \propto + \sum_{t=1}^{M} \theta_t h_t(x) \ldots\ldots (1)$$

2) Extra Trees:

A cluster of unpruned DTs is generated by the Extra-Trees classifier by following the standard top-down technique. In the end, it comes down to picking characteristics and cutting points at random when dividing a tree node. In its most extreme form, it generates trees with topologies that have nothing to do with the training sample's output values [16]. Unlike previous tree-based ensemble approaches, it uses the whole training set to build trees (rather than a bootstrap replica) and randomly separates nodes using cut points. The ultimate forecast is determined by a majority vote based on the aggregate projections of all the trees. The ETC is built on the premise that reducing variance would be more successful than other techniques that employ a less randomization strategy when the cut-point and attributes are completely randomized and ensemble averaging is used. The goal is to reduce bias by using all of the original training data rather than bootstrap replicas. One of this algorithm's main advantages is its computational efficiency[17][18].

3.5 *Model training and evaluation*

The model training process for both Extra Trees and Gradient Boosting classifiers involved hyperparameter optimisation using three methods: Optuna, Bayesian Optimization, and Randomized Search. Utilizing assessment parameters such F1-score, recall, accuracy, and precision, every model's performance was evaluated. To assess an effectiveness and generalization of a model, several metrics were computed for the training and testing sets.

- **Optuna Hyperparameter Optimization:** Optuna uses a trial-and-error approach to explore the hyperparameter space, focusing on refining parameters like the number of estimators, max depth, and learning rate. It efficiently prunes unpromising trials to speed up the optimization process.
- **Bayesian Optimization:** Bayesian Optimization builds a probabilistic model to guide hyperparameter selection, focusing on high-performing regions of the space. It fine-tunes parameters like learning rate, number of trees, and regularization to optimize the model while minimizing computational costs.
- **Randomized Search:** Randomized Search randomly selects hyperparameter combinations from a predefined range, evaluating a fixed number of iterations. It tunes parameters like estimators, max features, and learning rate, offering a quick yet effective method for optimizing models.

IV. RESULTS AND DISCUSSION

Data analytics for predicting and optimising employee performance are compared in this section. The results of ML models implemented on Python simulation tool with Google colab jupyter notebook also included NumPy, pandas, matplotlib sk-learn, and seaborn[19]. That performs on 32 GB of RAM, Intel Core i7 CPU, a 1 TB hard drive, Windows 10, and a 24 GB Nvidia GPU. The investigation involved the description of the dataset, EDA, and an application of many ML models, including the Extra Trees and GB classifier, in addition to the four assessment metrics of F1-score, recall, accuracy, and precision. Each model's classification model and confusion matrix were provided in this. Lastly, a table that compares the machine learning models with the graph is provided.

4.1 *Dataset Visualization*

This Human Resource Dataset was collected from Kaggle. The total number of rows in this dataset, 311, is an acceptable representation for an organisation analysis as it includes inputs from 311 individuals. Data visualisation, plotting, and manipulation without assumption are the fundamental steps of EDA, which is crucial after data collection and pre-processing to assist evaluate a quality of a data and develop models. A following graphs shows the visualisation results of input dataset.

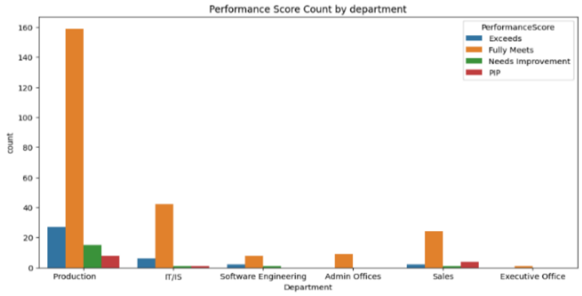

Figure 2: Performance score count by department

The above figure 2, represents how each department performs and gives insights into their productivity rate. The production section is evidently very productive and achieves a perfect score on their performance evaluation.

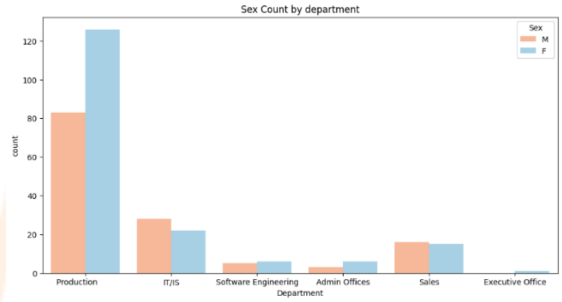

Figure 3: Sex count by department

The above figure 3 is a bar chart that illustrates the count of number of males and females in each department. Compared to the other departments, it is evident that the manufacturing department has the greatest proportion of males and females.

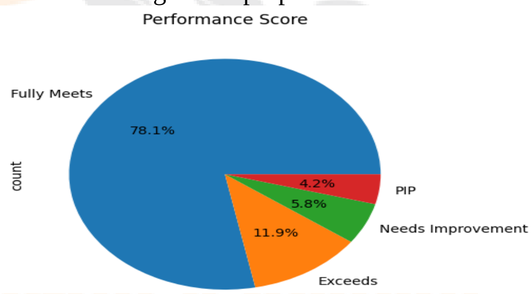

Figure 4: Unique categories in performance score

In Figure 4, the pie chart represents the percentage of unique categories in our target column 'performance score'. There are 4 unique categories in this column namely, fully meets acquiring 78.1%, PIP acquiring 4.2%, Needs improvement acquiring 5.8% and exceeds acquiring 11.9%

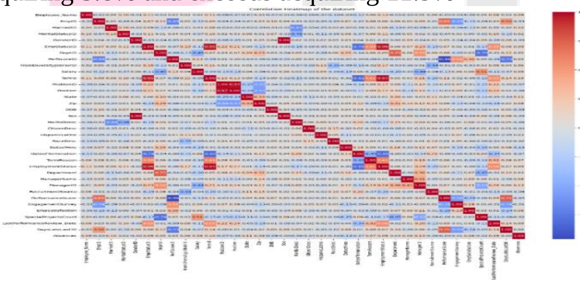

Figure 5: correlation heatmap of the dataset

Figure 5 shows the correlation between the columns of the dataset. A weak association is shown by a lighter color, whereas a deeper color indicates a significant link.

4.2 *Evaluation of Parameters*

An important aspect of developing a model is doing an evaluation of parameters. The classifications are provided in this confusion matrix. Using the performance matrix that is described below, it is possible to identify the optimal model:

1) Confusion Matrix

A machine learning predictive analysis instrument is the confusion matrix. Confusion matrix deployment is implemented to evaluate the functionality of a classification-based ML model. Classifiers and classification models produce confusion matrices, which are summarised tables showing the number of right and wrong predictions. The following confusion matrix evaluate the recall, f1-score, accuracy, and precision.

Accuracy: The accuracy is calculated by adding together the two accurate predictions (TP + TN) and dividing an entire number of datasets (P + N). In the below Equation (2) represents the formula for calculating accuracy.

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FP} \ldots\ldots\ldots\ldots (2)$$

Recall: Recall is measured as a proportion of accurate predictions (TP) to total predictions (P). Another name for it is Recall or Sensitivity (REC). In the given Equation (3) represents formula for calculating recall.

$$Recall \; = \frac{TP}{TP+FN} \ldots\ldots\ldots\ldots (3)$$

Precision: The precision of a forecasting model may be found by dividing the number of correctly predicted outcomes (TP) by the entire number of outcomes (TP + FP). In the given equation (4) represents the formula for calculating precision.

$$Precision = \frac{TP}{TP+FP} \ldots\ldots\ldots (4)$$

F1-Score: The F1-score is a measure of the accuracy of the test. Equation (5) represents formula for calculating F1-score.

$$F1 - Score = \frac{2 \times precision \times recall}{precision \times recall} \ldots\ldots\ldots\ldots (5)$$

Where,

- **TP (True Positive):** The model's prediction and the actual value were both positive.
- **FP (False Positive):** It is untrue and your forecast is positive.
- **FN (False Negative):** Your forecast is inaccurate, and the outcome is likewise false.
- **TN (True Negative):** Even though the model had predicted a negative outcome, the real quantity was negative.

4.3 Proposed Model Results

This section briefly explains the experimental findings of proposed models with hyperparameters tuning on the Human Resource Dataset showed strong performance for the employee performance prediction. These models demonstrated excellent accuracy, precision, recall, and F1 scores during testing phases.

1) Extra Tree Model with hyperparameters tuning

Table 2 shows that the Extra Trees model performs best with Bayesian Optimization, achieving the highest accuracy0.9435, precision0.9445, recall0.9435, and F1-score0.9436. While Optuna and Randomized Search also yield strong results, with accuracies of 0.9230 and 0.9282 respectively, Bayesian Optimization clearly outperforms both in fine-tuning the model's hyperparameters. This makes it the most effective method for optimising the Extra Trees model in this study.

Table 2: Extra Trees Results with hyperparameters.

Parameters	ET with optuna	ET with Bayesian	ET with Randomize search
Accuracy	0.9230	0.9435	0.9282
Precision	0.9282	0.9445	0.9297
Recall	0.9230	0.9435	0.9282
F1-Score	0.9242	0.9436	0.92877

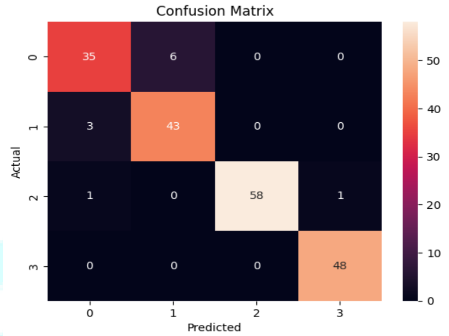

Figure 6: Confusion Matrix for Extra Trees with Bayesian optimisation hyperparameter tuning.

The above figure 6, displays a confusion matrix of an Extra Trees model with Bayesian optimisation hyperparameter tuning some predicted and actual values for positive and negative. It shows for class 0, there are 35; for class 1, there are 43; for class 2, there are 58; and for class 3, there are 48 correct predicted values.

```
Classification report:
              precision    recall  f1-score   support

           0       0.90      0.85      0.88        41
           1       0.88      0.93      0.91        46
           2       1.00      0.97      0.98        60
           3       0.98      1.00      0.99        48

    accuracy                           0.94       195
   macro avg       0.94      0.94      0.94       195
weighted avg       0.94      0.94      0.94       195
```

Figure 7: Classification Report of Extra trees with Bayesian optimisation hyperparameter tuning

An above figure 7 displays a classification report of Extra Trees with Bayesian hyperparameter tuning. In this, 4 classes are 0, 1, 2 and 3. In class 0, precision0.79, recall0.90, f1-score0.84, and the support value is 41. In class 1, precision0.91, recall0.85, f1-score0.88, and the support value is 46. In class 2, precision1.00, recall0.97, f1-score0.98, and the support value is 60. In class 3, precision0.98, recall1.00, f1-score0.99, and the support value is 48. Overall, the accuracy of all the classes is 0.94, with support values 195.

2) Gradient Boosting Model with hyperparameters tuning

Table 3 shows that Randomized Search yields the best performance for the Gradient Boosting model, with the highest accuracy0.9641, precision0.9645, recall0.9641, and F1-score0.9642. Optuna follows closely with an accuracy of 0.9589, while Bayesian Optimization produces the lowest results across all metrics, with an accuracy of 0.9435. Overall, Randomized Search proves to be the most effective optimisation method for Gradient Boosting.

Table 3: Gradient Boosting Results with hyperparameters

Parameters	GB With optuna	GB With Bayesian	GB with Randomize search
Accuracy	0.9589	0.9435	0.9641
Precision	0.9598	0.9443	0.9645

Recall	0.9589	0.9435	0.9641
F1-Score	0.9592	0.9439	0.9642

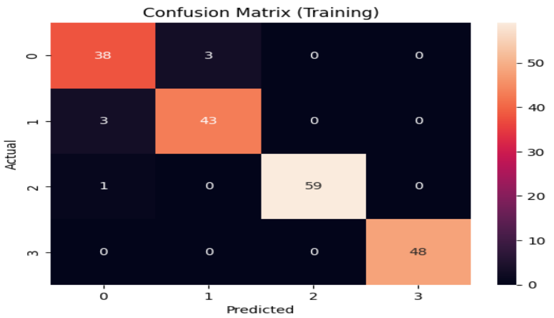

Figure 4: Confusion Matrix for Gradient Boosting with Randomize search hyperparameter tuning

In figure 4 displays a confusion matrix of the Gradient Boosting model with a randomise search hyperparameter tuning some predicted and actual values for positive and negative. It shows for class 0, there are 38; for class 1, there are 43; for class 2, there are 59; and for class 3, there are 48 correct predicted values.

```
Classification report:
              precision    recall  f1-score   support

           0       0.90      0.93      0.92        41
           1       0.93      0.93      0.93        46
           2       1.00      0.98      0.99        60
           3       1.00      1.00      1.00        48

    accuracy                           0.96       195
   macro avg       0.96      0.96      0.96       195
weighted avg       0.96      0.96      0.96       195
```

Figure 5: Classification Report of Gradient Boosting with randomise search hyperparameter tuning

An above Figure 5 displayed a classification report of Gradient Boosting randomised search. There were four classes in all: 0, 1, 2, and 3. For class 0, the support value was 41, the f1-score was 0.92, the recall was 0.93, and the precision was 0.90. Class 1 results show 0.93 precision, 0.93 recall, 0.93f1-score, and 46 support values. Class 2 precision1.00, recall0.98, f1-score0.99, and support is 60. Class 3 has a precision1.00, recall1.00, f1-score1.00, and support value of 48.

4.4 Comparative analysis

Table 4 presents a comparison of several bases and proposed models for predicting employee performance on the house prediction dataset. The support vector machine and KNN' models are compared in this section with the proposed model extra tree classifier and gradient boosting using the parameters f1-score, recall, accuracy, and precision. A comparison of these models with a parameter is displayed in this Table 8 below.

Table 4: Comparative between base and proposed models for the prediction of House Prediction Dataset.

Parameters	**Base Models**		**Proposed Models**	
	SVM [20]	**KNN** [21]	**Extra Trees**	**Gradient Boost**
Accuracy	0.87	0.90	0.94	0.96
Precision	0.87	0.84	0.94	0.96
Recall	0.87	0.98	0.94	0.96
F1-Score	0.87	0.90	0.94	0.96

In Table 4, the comparative analysis of base and proposed models for house price prediction highlights the significant advancements introduced by the Gradient Boost model. This model stands out as the best performer among the proposed models, achieving the highest accuracy of 0.96, compared to 0.87 for SVM, 0.90 for KNN, and 0.94 for Extra Trees. The Gradient Boost model also excels in precision, with a top score of 0.96, surpassing the base models' precision values of 0.87, 0.84, and 0.94. It leads to recall with a perfect score of 0.96, while the base models show recall rates of 0.87, 0.98, and 0.94. Additionally, the Gradient Boost model achieves the highest F1 score of 0.96, outperforming the base models' F1 scores of 0.87, 0.90, and 0.94. Among the base models, KNN demonstrates the highest accuracy and recall but falls short in precision and F1-score compared to the Gradient Boost model. Overall, the Gradient Boost model is identified as the best model, offering superior predictive performance across all evaluated metrics.

V. CONCLUSION AND FUTURE WORK

This research investigates an effectiveness of ML models, namely Gradient Boosting and Extra Trees, in forecasting employee performance using the Kaggle HR Data dataset. The analysis demonstrated that both models are effective in predicting employee performance, with Gradient Boosting generally outperforming Extra Trees according to F1-score, recall, accuracy, and precision. Among a hyperparameter tuning methods tested—Optuna, Bayesian, and Randomized Search—Gradient Boosting with Randomized Search achieved the highest accuracy of 96.41%, showcasing its superior capability in handling the dataset's complexity. The comparative analysis with base models like SVM and KNN further emphasises the robustness of the proposed models in providing accurate and reliable performance predictions. This study underscores the critical role of advanced ML techniques in enhancing employee performance management systems and highlights the potential for these methods to drive organisational success through improved predictive insights.

To expand on this study's conclusions, future research may concentrate on a number of topics. To enhance the generalisation and robustness of the model, the dataset might be enlarged to include a wider range of different samples. Additionally, exploring other ML and DL algorithms, such as neural networks or ensemble methods, might yield further insights and enhancements in prediction accuracy. Incorporating additional features like employee sentiment analysis or external factors like market conditions could provide a more comprehensive view of performance predictors. Further, examining the integration of these models into real-time performance management systems could offer practical benefits and validate their effectiveness in dynamic organisational environments. Finally, investigating the potential of transfer learning and domain adaptation techniques might address challenges in applying these models across different sectors and industries.

REFERENCES

[1] N. Dewi, R. H. Laluma, Gunawansyah, E. Garnia, D. Saepudin, and N. Hendajany, "Employee performance assessment system design based on 360 degrees feedback and simple multi-attribute rating technique method integration," in *Proceeding of 14th International Conference on Telecommunication Systems, Services, and Applications, TSSA 2020*, 2020. doi: 10.1109/TSSA51342.2020.9310873.

[2] A. S. Lather, R. Malhotra, P. Saloni, P. Singh, and S. Mittal, "Prediction of employee performance using machine learning

techniques," in *ACM International Conference Proceeding Series*, 2019. doi: 10.1145/3373477.3373696.

[3] F. Guerranti and G. M. Dimitri, "A Comparison of Machine Learning Approaches for Predicting Employee Attrition," *Appl. Sci.*, 2023, doi: 10.3390/app13010267.

[4] A. D. Diamantidis and P. Chatzoglou, "Factors affecting employee performance: an empirical approach," *Int. J. Product. Perform. Manag.*, 2019, doi: 10.1108/IJPPM-01-2018-0012.

[5] G. Zhenjing, S. Chupradit, K. Y. Ku, A. A. Nassani, and M. Haffar, "Impact of Employees' Workplace Environment on Employees' Performance: A Multi-Mediation Model," *Front. Public Heal.*, 2022, doi: 10.3389/fpubh.2022.890400.

[6] R. Jayadi, H. M. Firmantyo, M. T. J. Dzaka, M. F. Suaidy, and A. M. Putra, "Employee performance prediction using naïve bayes," *Int. J. Adv. Trends Comput. Sci. Eng.*, 2019, doi: 10.30534/ijatcse/2019/59862019.

[7] A. Pathak, C. K. Dixit, P. Somani, and S. K. Gupta, "Prediction of Employees' Performance Using Machine Learning (ML) Techniques," in *Designing Workforce Management Systems for Industry 4.0: Data-Centric and AI-Enabled Approaches*, 2023. doi: 10.1201/9781003357070-11.

[8] I. Adeoye, "Unveiling Tomorrow's Success: A Fusion of Business Analytics and Machine Learning for Employee Performance Prediction," *SSRN Electron. J.*, 2024, doi: 10.2139/ssrn.4729244.

[9] M. G. T. Li, M. Lazo, A. K. Balan, and J. De Goma, "Employee performance prediction using different supervised classifiers," in *Proceedings of the International Conference on Industrial Engineering and Operations Management*, 2021. doi: 10.46254/an11.20211188.

[10] Safrizal, L. Tanti, R. Puspasari, and B. Triandi, "Employee Performance Assessment with Profile Matching Method," in *2018 6th International Conference on Cyber and IT Service Management, CITSM 2018*, 2019. doi: 10.1109/CITSM.2018.8674256.

[11] P. Sujatha and R. S. Dhivya, "Qualitative Assessment of Machine Learning Classifiers for Employee Performance Prediction," in *Lecture Notes in Networks and Systems*, 2021. doi: 10.1007/978-981-16-3153-5_37.

[12] F. Fallucchi, M. Coladangelo, R. Giuliano, and E. W. De Luca, "Predicting employee attrition using machine learning techniques," *Computers*, 2020, doi: 10.3390/computers9040086.

[13] K. Sahinbas, "Employee Promotion Prediction by using Machine Learning Algorithms for Imbalanced Dataset," in *2022 2nd International Conference on Computing and Machine Intelligence, ICMI 2022 - Proceedings*, 2022. doi: 10.1109/ICMI55296.2022.9873744.

[14] N. Mansor, N. S. Sani, and M. Aliff, "Machine Learning for Predicting Employee Attrition," *Int. J. Adv. Comput. Sci. Appl.*, 2021, doi: 10.14569/IJACSA.2021.0121149.

[15] S. Mathur., "Supervised Machine Learning-Based Classification and Prediction of Breast Cancer," *Int. J. Intell. Syst. Appl. Eng.*, vol. 12(3), pp. 0–3, 2024.

[16] R. K. Vinita Rohilla, Sudeshna Chakraborty, "Random Forest with harmony search optimisation for location based advertising," *Int J Innov Technol Explor Eng*, vol. 8, no. 9, pp. 1092–1097, 2019, [Online]. Available: https://scholar.google.com/citations?view_op=view_citation&hl=en&user=zlcFgwEAAAAJ&citation_for_view=zlcFgwEAAAAJ:WF5omc3nYNoC

[17] N. Mahendran, P. M. Durai Raj Vincent, K. Srinivasan, V. Sharma, and D. K. Jayakody, "Realizing a Stacking Generalization Model to Improve the Prediction Accuracy of Major Depressive Disorder in Adults," *IEEE Access*, 2020, doi: 10.1109/ACCESS.2020.2977887.

[18] H. Alghamdi and G. Amoudi, "Using Machine Learning for Non-Invasive Detection of Kidney Stones Based on Laboratory Test Results: A Case Study from a Saudi Arabian Hospital," *Diagnostics*, vol. 14, no. 13, 2024, doi: 10.3390/diagnostics14131343.

[19] Y. M. Mohialden, R. W. Kadhim, N. M. Hussien, and S. A. K. Hussain, "Top Python-Based Deep Learning Packages: A Comprehensive Review," *Int. J. Pap. Adv. Sci. Rev.*, vol. 5, no. 1, pp. 1–9, 2024, doi: 10.47667/ijpasr.v5i1.283.

[20] A. Raza, K. Munir, M. Almutairi, F. Younas, and M. M. S. Fareed, "Predicting Employee Attrition Using Machine Learning Approaches," *Appl. Sci.*, 2022, doi: 10.3390/app12136424.

[21] S. S. Alduayj and K. Rajpoot, "Predicting Employee Attrition using Machine Learning," in *Proceedings of the 2018 13th International Conference on Innovations in Information Technology, IIT 2018*, 2018. doi: 10.1109/INNOVATIONS.2018.8605976.