

Deep Learning-Based Predictive Analytics for Intelligent Enterprise Management

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Abstract—The problem of reference value in enterprise human resource management performance evaluation data is proposed, and the enterprise human resource management performance evaluation method based on machine learning is proposed. This paper builds an enterprise human resource management performance evaluation system from the three aspects of performance evaluation objectives, subjects and objects. HRM performance measures are chosen and measured in a standardized manner. The organization's employee-related data is analyzed using machine learning algorithms to create an intelligent predictive analytics framework for enterprise management. To enhance the quality and reliability of the data, the methodology proposed is data cleaning, removal of duplicates, noise filtering, One-Hot Encoding, Min-Max scaling, ADASYN data balancing and stratified data splitting. Random Forest (RF) and Extreme Gradient Boosting (XGBoost) methods are applied for predictive analysis and accuracy, precision, recall, and F1 Score are used to verify the performance of the methods. The experimental results show that the proposed RF shows 99.99% accuracy (ACC), 99.97% precision (PRE), 99.98% recall (REC), and 99.96% F1-score (F1), while the XGBoost shows 99.55% ACC, 99.96% PRE, 99.98% REC, and 99.97% F1. The findings show that the proposed models have shown excellent predictive performance and reliability, which can be used to help make decisions based on data and enhance the intelligent enterprise human resource management system.

Keywords—Artificial Intelligence, Business Intelligence Frameworks, Predictive Analytics, Enterprise Decision-Making, Data-Driven Business Strategy.

I. INTRODUCTION

Today, enterprises deal with a highly dynamic environment that is driven by changing market conditions, rising customer expectations, technological advancements, and ever-growing amounts of organizational data. The information coming in is huge and is created from various sources during business activities like customer interaction, financial transactions, production, procurement, sales, logistics, and resource management [1][2][3]. The proper management and interpretation of this information is critical

to increase operational efficiency, decrease costs, optimize the use of resources, and stay competitive [4]. Traditional management methods are based on reports from the past and analytical techniques that are pre-established, and these are limited in their ability to explain the complexities of relationships and to provide insights into future business circumstances [5].

The coordinated management of the functions of finance, marketing, human resources, production, inventory, supply chain and customer relationship management is enterprise management [6]. Today's businesses source data from their enterprise resource planning (ERP) systems, customer relationship management (CRM) systems, financial applications, supply chain databases, cloud storage, and other external market sources. Predictive Analytics can be used for business pattern recognition, anomaly detection, risk analysis, and forecast of future business requirements [7]. Thus, data-driven management can assist companies in making timely decisions, minimizing uncertainty, and ensuring better overall business performance [8][9].

Digital transformation is a phenomenon that has evolved quickly, and has led to the demand for intelligent and predictive enterprise management [10][11][12]. Traditional statistical and rule-based approaches may fail to detect the relationships that are not linear, non-visible patterns, high-dimensional data or abrupt shifts in enterprise data [13][14]. In the supply chain and manufacturing sectors, predictive methodologies can aid in inventory optimization, demand forecasting, production planning, quality control, and logistics management. Predictive quality techniques involve predicting the product outcome based on process and quality data, and taking appropriate action to correct the product in time [15][16][17][18].

Artificial Intelligence (AI) and in particular Machine Learning (ML) and Deep Learning (DL) offer effective solutions to the above challenges. Historical enterprise data can be used for training ML algorithms, and DL models are capable of automatically learning complex features and hidden patterns from large-scale data [19][20]. DL techniques

can be especially useful in capturing temporal dependencies and changing business trends, for demand forecasting, anomaly detection, financial risk assessment and resource management [21][22]. Thus, DL-Based Predictive Analytics for Intelligent Enterprise Management offers a promising approach for converting enterprise data into accurate predictions [23], actionable insights, and improved managerial decisions.

A. Motivation and Contribution

The motivation of this study is that enterprise data is becoming more complex and extensive, traditional management methods can't effectively solve the problem of data complexity and data volume to make timely decisions. Intelligent predictive analytics is essential for identifying patterns, forecasting future business situations and reducing uncertainties during operation. ML and DL can provide more effective analysis of complex enterprise information and support accurate predictions. Hence, the primary objective of this research is to create a smart predictive analytics solution that helps companies maximize their efficiency, resource utilization and data-driven decision-making. This study has several important contributions:

- Created an intelligent enterprise predictive analytics framework with the use of ML.
- Improved data quality and consistency by applying data pre-processing techniques.
- Addressed class imbalance and enhance model learning using ADASYN.
- Applied Random Forest (RF) and XGBoost in Enterprise Prediction.
- Assessed the performance of the model using ACC, PRE, REC, and F1.
- Showed the promise of using ML for reliable, data-driven decisions in enterprise management.

The justification is based on the requirement of reliable predictive analytics that can assist with effective enterprise human resource management. To enhance the confidence of the prediction, the proposed approach is data pre-processing, class balancing, and ensemble learning. The novelty of it is the combination of the Random Forest and XGBoost algorithms into an intelligent enterprise predictive analytics structure. This way, the approach can help in making accurate, efficient, and data-driven decisions regarding enterprise management. Additionally, it offers a scalable solution for finding valuable patterns in the information related to employees and organizations.

B. Organization of the Paper

The paper is organized as follows: Section II presents related studies, and Section III details the data set, pre-processing, and models proposed. The experimental and comparative results are presented in Section IV and the concluding study, the key findings and future directions are presented in Section V.

II. LITERATURE REVIEW

A comprehensive literature review was carried out to uncover major findings, research methods and gaps in knowledge to guide the development of the proposed study on Intelligent Enterprise (IE) Predictive Analytics.

Matla (2026) the author suggests an AI agent-based predictive analytics system that can be connected to an intelligent dashboard automation system for real-time decision intelligence. The overall approach integrates ML based predictive models, autonomous AI agents and interactive dashboards and provides a single architecture to ingest data continuously, to adapt models on the fly and to execute operational actions automatically. The framework is tested through various business scenarios such as Sales Forecasting, Demand Prediction, Customer Segmentation, and Inventory Automation. These experimental results demonstrate strong predictive performance, with neural network models achieving up to 91% ACC, and AI agents allowing for fast anomaly detection and automated responses, achieving success rates of over 90% [24].

C et al. (2026) present Privacy-Aware FL Framework that provides collaborative performance prediction across the decentralized enterprise systems without violating data sovereignty. It uses the Fed Prox framework with the Fed Prox as the fundamental learning algorithm to overcome the non-IID data problems and homomorphic encryption to ensure safety of model updates in the process of the gradient exchange. Tests with simulated enterprise data of the HR, logistics, finance, and operations departments proved that the proposed model had a global ACC of 96.51, which is much higher than that of local-only (92.13) and centralized baselines (95.73). In addition, the system was fully compliant with GDPR and ISO/IEC 27001, and communication and computation overheads were designed to be deployed in an enterprise[25].

Al-Hashemi et al. (2025) offers a full-featured digital marketing platform that merges sophisticated campaign management, recommendation algorithms, and real-time data to enhance collaboration and decision-making. With an area under the curve (AUC) of 0.95, ACC of 85%, PRE of 87.7%, and REC of 82.6%, the system reliably forecasts the effectiveness of campaigns using ML models [26].

Agrawal et al. (2025) conducts unsupervised clustering to identify operational bottlenecks, and employs supervised and RL for demand forecasting and decision-making, respectively. With the use of predictive analytics, the system can dynamically allocate tasks according to needs, cut down on unused capacity, and make better predictions-based judgments. Quantitatively tested several operational datasets that reflected logistics, personnel planning, and inventory management. In contrast to more conventional methods of management, this one decreased resource wastage by 12.8%, improved operational efficiency by 94.5 percent, and saved 33.4 percent of the budget [27].

Saputro, Nugroho and Patricia (2024) examined talent potential in State-Owned Enterprises (BUMN) using cloud-based ML tools, particularly AWS. The study evaluated employee potential for future leadership and decision-making using BUMN regulatory parameters. Data were processed for training, modeling, and testing on AWS using Python, with Random Forest as the primary algorithm. The study achieved a test ACC of 92.1% [28].

Liu et al. (2023) categorize Chinese firms by industry utilizing business scope texts using DL technologies. Prior to automating the categorization process, data pertaining to business scope texts should be pre-processed according to

their attributes. Next, develop a number of DL models—such as Text CNN, Textron, Extenuate, and fast Text—to categorize Chinese businesses according to the texts that describe their business scope. In terms of text categorization performance, the Text CNN model outperformed the others with a 95.67% ACC rate [29].

Table I summarizes recent studies on Intelligent Enterprise Predictive Analytics, detailing types of models applied, datasets used, key results obtained, and identified limitations.

TABLE I. RECENT STUDIES ON ANOMALY DETECTION FOR CYBERSECURITY USING MACHINE LEARNING TECHNIQUES

Author	Proposed Work	Dataset	Key Findings	Limitations & Future Work
Matla (2026)	AI-agent-enabled predictive analytics framework with intelligent dashboards for real-time enterprise decision intelligence, including sales forecasting, demand prediction, customer segmentation, and inventory automation.	Enterprise data covering sales, demand, customers, and inventory use cases.	Neural networks achieved up to 91% accuracy; AI agents achieved over 90% success in anomaly detection and automated responses.	Requires broader real-world enterprise validation, larger datasets, and further improvement of autonomous AI-agent capabilities.
C et al. (2026)	Privacy-aware Federated Learning framework using Fed Prox and homomorphic encryption for decentralized enterprise performance prediction.	Simulated HR, logistics, finance, and operations enterprise data.	Global accuracy reached 96.51%, outperforming local-only (92.13%) and centralized (95.73%) approaches.	Communication and computational overhead remain concerns; future work can validate the framework using larger real-world enterprise datasets.
Al-Hashemi et al. (2025)	Intelligent digital marketing platform combining machine learning, campaign analytics, recommendation systems, and decision support.	Digital marketing and campaign data.	Achieved 0.95 AUC, 85% accuracy, 87.7% precision, and 82.6% recall for campaign-success prediction.	Larger real-world campaign datasets, deep reinforcement learning, and real-time automated marketing are proposed.
Agrawal et al. (2025)	AI-driven enterprise operations management using supervised learning for demand forecasting, reinforcement learning for decision-making, and clustering for operational bottleneck detection.	Logistics, workforce planning, and inventory-management datasets.	Reduced resource wastage by 12.8%, increased operational efficiency to 94.5%, and achieved 33.4% cost savings.	Requires broader enterprise deployment and validation across diverse operational environments; advanced predictive models can be explored.
Saputro, Nugroho & Patricia (2024)	Cloud-based machine-learning framework for identifying high-potential organizational talent using AWS and Random Forest.	Employee talent-management data from BUMN organizations.	Achieved 92.1% test accuracy and provided visualization for identifying top and nominated talent.	Limited to talent-management applications and Random Forest; future work can investigate deep learning and larger organizational datasets.
Liu et al. (2023)	Deep-learning-based classification of Chinese enterprises according to business-industry categories using business-scope text.	Chinese enterprise business-scope text data.	Text CNN achieved the best performance with 95.67% accuracy.	Focuses mainly on enterprise classification rather than predictive enterprise management; future work can use larger datasets and advanced language models.

Research Gap: Existing studies often address specific enterprise functions rather than providing a unified predictive analytics framework for intelligent enterprise management. There is not much focus on thorough preprocessing, addressing class imbalance and strong feature transformation

for enterprise data. Many approaches are also individual model or application based with limited possibilities for systematic ensemble prediction. A more comprehensive and trustworthy ML platform is required to enable enterprises to make decisions based on facts, data and scale.

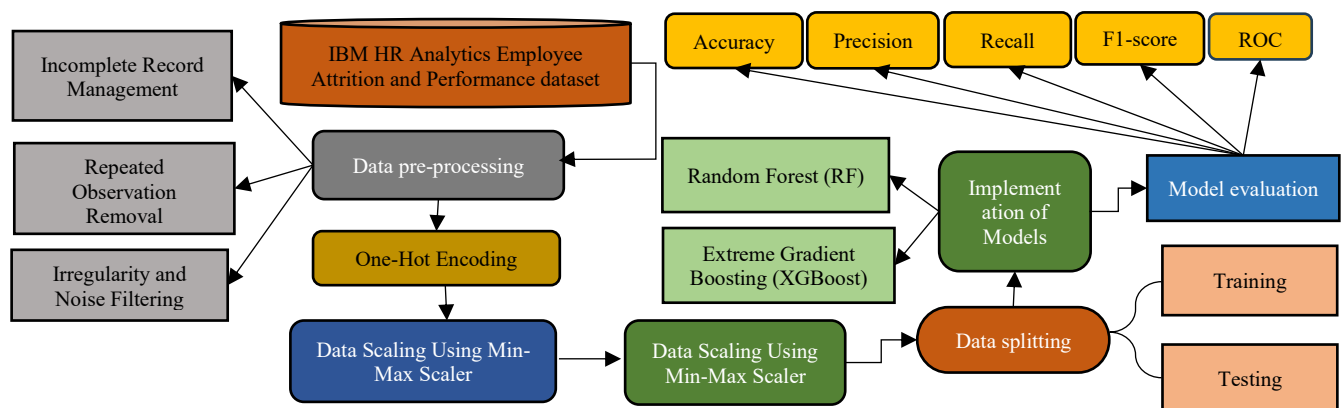


Fig. 1. Proposed Flowchart for Intelligent Enterprise Predictive Analytics using Machine Learning

III. RESEARCH METHODOLOGY

Data collection and data pre-processing, such as handling missing values, removing duplicates, filtering noise, one-hot encoding, Min-Max scaling and class balancing using ADASYN. The balanced data set is split into two groups, a

training set and a testing set, with an 80:20 ratio, stratified. Lastly, the ACC, PRE, REC, F1, confusion matrix, and ROC analysis were used to perform the development and evaluation of the RF and XGBoost models. The proposed Intelligent Enterprise Predictive Analytics using ML techniques is shown in Fig. 1.

This section provides a detailed description of each step of the proposed methodology:

A. Data Gathering and Analysis

IBM HR Analytics Employee Attrition and Performance data is used as a benchmark and is used in this study. There are 1,470 employee records and 35 demographic, professional and organizational attributes. The distributions, relationships and patterns of the features were analyzed using bar plots and correlation heat maps for enterprise predictive analytics:

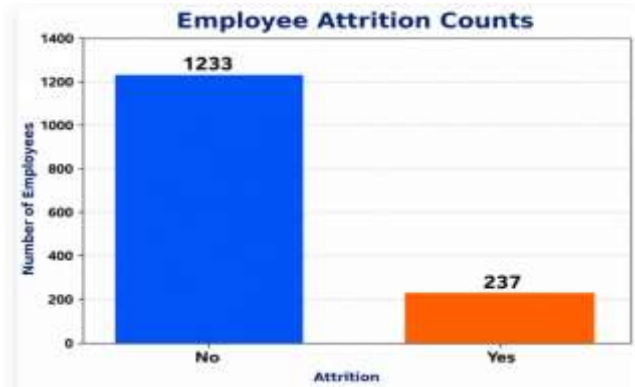


Fig. 2. Bar Graph of Class Distribution

The attrition status of employees is presented in Figure 2. A total of 1,233 employees is represented as not leaving the organization. 237 workers are listed as leaving the organization, in contrast. This graph illustrates the imbalance, with more employees remaining than leaving.

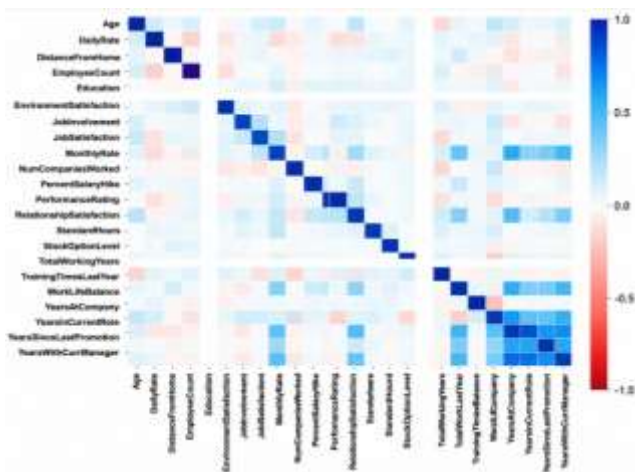


Fig. 3. Correlation Matrix Heatmap

Fig. 3. Correlation Matrix Heatmap shows the correlations between the selected enterprise and employee-related variables. The darker the color, the stronger the (positive or negative) correlation, and the lighter the color, the weaker the correlation. The heatmap identifies significant correlations between job satisfaction, salary, performance and employee tenure characteristics.

The chart in Fig. 4 illustrates the distribution of certain key employee attributes by performance rating. It highlights differences in demographics, employment, satisfaction, income, experiences, and work-life across the performance levels. These distributions tell us something about how employee attributes are associated with the level of performance.

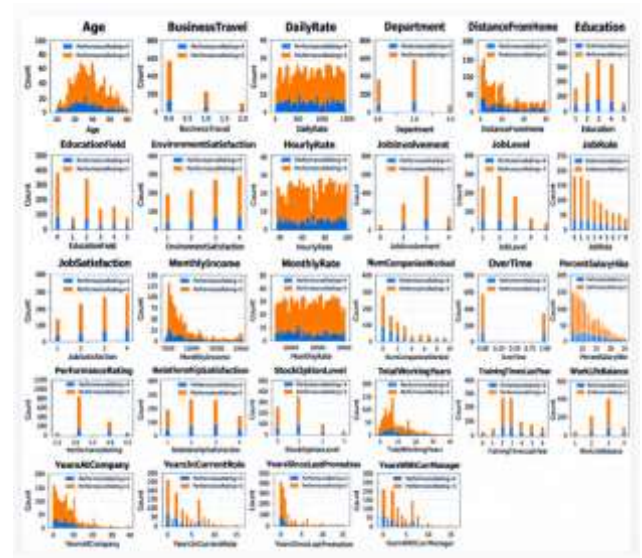


Fig. 4. Histogram of Each Feature Depending on Performance Rating

B. Data Pre-Processing

The dataset from IBM HR Analytics was prepared in a systematic manner through data integration, data cleaning, data transformation and data structuring. The goal was to enhance consistency in data, remove unreliable observations, and format the raw data into a suitable format for the ML process. The major phases in the process of data preparation are described as follows:

- **Incomplete Record Management:** Missing or incomplete observations were discussed within the dataset to determine whether they could impact analysis. Records were “cleaned” of missing data, and proper methods of imputation were used if needed.
- **Repeated Observation Removal:** Duplicate and unnecessary records were identified and removed to ensure data uniqueness (Repeated Observation Removal). This avoided the situation where employee information could reappear in the analysis and bias the model.
- **Irregularity and Noise Filtering:** The dataset was examined for inconsistent, abnormal and irrelevant data, which may interfere with the learning process. The observations were filtered and corrected to ensure consistency and reliability of the data and model.

C. One-Hot Encoding

These categories are then converted to a binary vector representation using One-Hot Encoding, giving each category its own binary feature. This method removes the need to establish an ordinal link between categories when numerical zing categorical data.

D. Data Scaling Using Min-Max Scaler

Data processing techniques often use feature scaling as one of their phases. Dataset feature counts can range greatly, according to studies. The characteristics must be resized accordingly to bring their magnitudes closer to each other. The Minmax scaler is a method for scaling features. The feature sizes are adjusted within a predetermined range, either from -1 to 1 or from 0 to 1, as stated in the study report, using the minmax scaler. Follow this link for the Equation (1):

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

in where X is the feature's initial value, X' is its normalized value, X_{min} is its lowest value, and X_{max} is its highest value.

E. Data balancing using ADASYN

Data balancing is the process of correcting class imbalance in a dataset, which occurs when one class has considerably less samples than the others, in order to enhance ML model performance and dependability. This study used the ADASYN approach to obtain a more equal distribution of classes by generating synthetic samples for the underrepresented classes. For instances belonging to minority classes, ADASYN adaptively creates synthetic samples according to their learning difficulty, doling out more synthetic samples to those instances in close proximity to samples from other classes. The samples are produced by extending the distance between examples of the minority class and their closest neighbors. To even out the class distribution and enhance the model's capacity to pick up on minority-class tendencies, these simulated data sets are subsequently included in the training dataset.

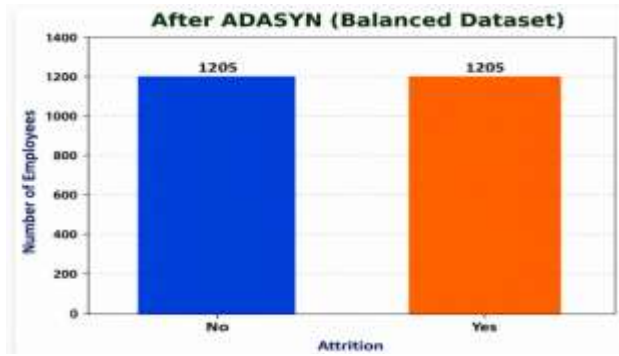


Fig. 5. Bar Graph of Class Distribution After ADASYN

The class distribution of the dataset after applying ADASYN is shown in Fig. 5. There is an even split between the two classes, with 1205 employees in each. This balancing minimizes the impact of the majority class during model training. Consequently, it helps improve the fairness, reliability, and predictive performance of the proposed models.

F. Data Splitting

The dataset was divided into training and testing subset with an 80:20 ratio and stratified sampling technique was used. This method preserved the relative distribution of each target class in both subsets, allowing for a representative class composition and enabling sound model evaluation.

G. Implementation of Models

The implementation phase resulted in two proposed ML models: RF and XGBoost for intelligent enterprise predictive analytics. Both models were trained and evaluated to accurately identify enterprise outcomes and provide reliable predictive performance.

H. Proposed Random Forest (RF) Model

Random Forest (RF) is an ensemble ML method, which is a chain of decision trees, and it can limit the overfitting effect and increase the classification ACC. The model produces

multiple decision trees from randomly sampled subsets of training data and attributes. All trees make a separate prediction, and the overall classification result is based on the majority of predictions made by all the trees. The RF prediction function can be represented as Equation (2).

$$\hat{Y} = \text{mode}\{T_1(X), T_2(X), T_3(X), \dots, T_N(X)\} \quad (2)$$

where $\hat{Y}$ stands for the last projected class, $T_i(X)$ suggests the i th decision tree's prediction, X is the input feature vector, and n is the total forest tree count. The ensemble learning mechanism of RF enhances model stability, improves generalization capability, and provides effective classification performance for Intelligent Enterprise Predictive Analytics. The probability estimation in the RF classifier is calculated by aggregating the outputs of all individual trees, which can be expressed as Equation (3):

$$P(Y = c|X) = \frac{1}{N} \sum_{i=1}^N I(T_i(X) = c) \quad (3)$$

where $P(Y=c|X)$ represents the probability of class c , N is the number of decision trees, and $I(\cdot)$ is an indicator function that returns 1 when the condition is satisfied. This probability-based decision mechanism enables RF to accurately distinguish between Intelligent Enterprise Predictive Analytics. The hyperparameters are set to estimators = 100, max_depth = 10, min_samples_split = 2, min_samples_leaf = 1, and random state = 42 to provide stable and effective ensemble classification.

I. Proposed Extreme Gradient Boosting (XGBoost) Model

XGBoost is a decision-tree based ensemble learning method. By minimizing a loss function that measures the difference between the actual and anticipated target values, it may be used to regression situations. This is the mathematical paradigm that XGBoost regression follows: Equation (4):

$$y = f(x) \quad (4)$$

in where $f(x)$ is the XGBoost model that uses x to forecast y , y is the expected property price, and x is a vector of input characteristics like space, number of bedrooms, etc. When calculating $f(x)$, XGBoost uses a network of decision trees trained to minimize the loss due to the mean squared error (MSE). To attain a final forecast, the model integrates the outputs of several decision trees. Here is the generic version of the XGBoost regression model Equation (5)

$$y = \sum_{k=1}^K f_k(x) \quad (5)$$

The forecast of the k^{th} DT is denoted as $f_k(x)$, and K is the total number of decision trees in the ensemble. Each tree's forecast is a weighted average of the values learnt for its leaves during training.

For a specific input x , the prediction of the XGBoost model is computed as the sum of the predictions from all the decision trees in the ensemble. The hyperparameters are set to estimators = 100, max_depth = 6, learning rate = 0.1, subsample = 0.8, colsample_bytree = 0.8, and random state = 42 for efficient gradient-boosting classification.

J. Evaluation metrics

The models proposed were tested with various well-known classification performance measures. The confusion matrix was created to show the number of correct and incorrect predictions made for each class. The matrix contains the values of True Positive (TP), False Positive (FP), True

Negative (TN), and False Negative (FN). These values were then applied to computing other evaluation measures, such as ACC, PRE, REC and F1, which are shown below:

Accuracy: The number of instances that are correctly classified by the trained model divided by the total number of instances in the input samples (data set). It is given as Equation (6)-

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (6)$$

Precision: PRE measures how well a model predicts positive cases relative to all positive instances. It suggests PRE. It is possible to describe the classifier's ACC in predicting positive classes as Equation (7)-

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

Recall: The proportion of correctly predicted positive events relative to the total number of instances that should have been positive is this statistic. It may be expressed mathematically as Equation (8)-

$$Recall = \frac{TP}{TP+FN} \quad (8)$$

F1 score: It is a combination of harmonic mean of PRE and REC, which helps to balance REC and PRE. Its range is [0, 1]. From a mathematical perspective, it is represented as Equation (9)-

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (9)$$

Receiver Operating Characteristic Curve (ROC): The ROC curve is a graphical representation of the model's classification performance over various decision thresholds, with TPR on the y-axis and FPR on the x-axis. TPR is the same as sensitivity or REC, while FPR is defined as 1 – specificity.

IV. RESULTS AND DISCUSSION

The experimental setup is described and the performance of the proposed models for intelligent enterprise predictive analytics is evaluated in this section. The experiments were performed to test the effectiveness of RF and XGBoost MB for enterprise classification tasks. To process the data efficiently and train the models, the models were implemented in Python on a Windows 11 system with 128 GB of RAM. The proposed RF presented 99.99% ACC, 99.97% PRE, 99.98% REC, and 99.96% F1 as shown in Table II. The proposed XGBoost achieved 99.55% ACC, 99.96% PRE, 99.98% REC, and 99.97% F1. The models yielded nearly identical classification results with all evaluation metrics. The overall results verify the effectiveness and reliability of the proposed models for intelligent enterprise management.

TABLE II. CLASSIFICATION PERFORMANCE IN INTELLIGENT ENTERPRISE ANALYTICS

Matrix	Proposed Random Forest (RF)	Proposed Extreme Gradient Boosting (XGBoost)
Accuracy	99.99	99.55
Precision	99.97	99.96
Recall	99.98	99.98
F1-score	99.96	99.97

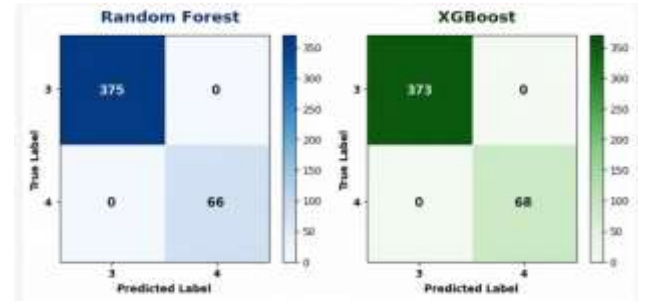


Fig. 6. Confusion Matrix for the Proposed Model

The classification ACC of the proposed Random Forest and XGBoost models are shown in Fig. 6. There are no incorrect predictions, and the RF model correctly predicts 375 and 66 instances. Likewise, XGBoost has no wrongly classified instances for a classification of 373 and 68 instances. There are no off-diagonal values, which represents very good predictive performance of both models. The overall confusion matrices show that both models provide very accurate and reliable classification performance.

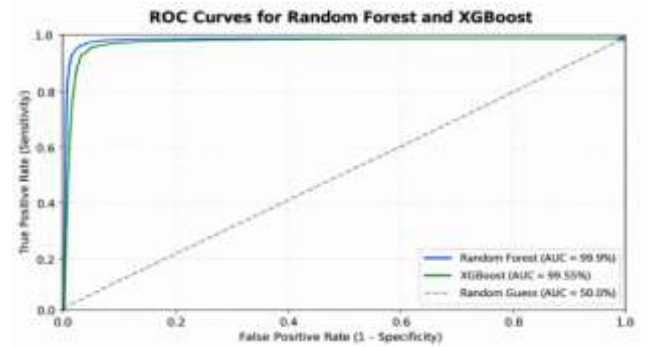


Fig. 7. ROC Curve for Proposed Model

The classification performance of the proposed models (RF and XGBoost) is shown in Fig. 7. The ACC of both the Random Forest and XGBoost models is very high with AUC values of 99.99% and 99.55% respectively, showing their excellent discriminatory power. All of the ROC curves are near the top left corner, which represents a very high true positive rate and low false positive rate. The outcomes from the results indicate that both models can effectively differentiate the target outcomes. In general, the models showed high reliability and predictive ability by the ROC analysis.

A. Comparative analysis

A comparative performance evaluation was provided with the existing ML models in order to evaluate the effectiveness of the proposed models, as shown in Table III. The comparison is done with other classifiers like LR, MLP, SVM, and the proposed classifiers RF, and XGBoost. The proposed RF was found to be the highest in terms of ACC (99.99%), PRE (99.97%), REC (99.98%), and F1 (99.96%). Likewise, the proposed XGBoost model obtained 99.55%, 99.96%, 99.98%, and 99.97% ACC, PRE, REC, and F1 respectively. LR, MLP and SVM performed worse on the evaluation metrics. The results prove the superiority of the proposed models in terms of classification ACC for the purposes of intelligent enterprise predictive analytics.

TABLE III. COMPARISON OF DIFFERENT MACHINE LEARNING MODELS FOR INTELLIGENT ENTERPRISE PREDICTIVE ANALYTICS

Model	Accuracy	Precision	Recall	F1-score
LR[30]	84.6	83.1	81.7	82.4
MLP[31]	87.76	61.70	61.70	61.70
SVM[32]	92.7	92.7	92.8	92.7
Proposed RF	99.99	99.97	99.98	99.96
Proposed XGBoost	99.55	99.96	99.98	99.97

The proposed RF model had the highest ACC of 99.99% and the XGBoost model had an ACC of 99.55%, clearly showing good predictive ACC. Both models show very high level of reliability in classification and consistency in enterprise outcome identification. These high scores suggest good learning of complex patterns and relationships in the data. The proposed models can provide accurate and efficient solutions for intelligent enterprise predictive analytics in general.

V. CONCLUSION AND FUTURE STUDY

Digital technologies and the new technologies of the MLSSS have opened up new possibilities for organizations to increase their efficiency, competitiveness and knowledge management strategies. This research explores the use of ML and predictive analysis methods with organizational data related to employees for intelligent enterprise management. The proposed methodology involves data preprocessing, One-Hot Encoding, Min-Max scaling, ADASYN data balancing, and stratified data splitting to enhance the quality and reliability of predictive analysis. As per the experimental results, the proposed RF ACC 99.99% and XGBoost models recorded an ACC of 99.55%, which is significant as compared to LR (84.6%), MLP (87.76%) and SVM (92.7%). The results show that the ensemble learning models proposed in this study can successfully learn complex patterns from enterprise data and provide very accurate predictions. So, the incorporation of ML in smart business administration can help in data-driven decision-making, boost the organization's efficiency, and strengthen the effectiveness of predictive analytics.

The study has limitations because it was based on a single benchmark enterprise dataset, which could limit the generalizability of the results to other organizations and industries. In this evaluation, the primary focus is on RF and XGBoost, so comparisons are limited to a broader selection of more sophisticated predictive models. The framework can be validated by future studies with larger, diverse, and real-time enterprise datasets.

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