iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** V **Month of publication:** May 2025

DOI: https://doi.org/10.22214/ijraset.2025.70479

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

Attrition Prediction in Organizations: A Proactive Workforce Management Approach using Machine Learning

Sandesh Parab[1], Kunal Sharma[2], Aditya Vishwakarma[3], Asstt. Prof. Jisha Tinsu[4]
Department of Information Technology Thakur College of Engineering and Technology Mumbai, India

Abstract: Employee attrition remains a major concern for organizations, as it can disrupt productivity, lower team morale, and impact long-term stability. Many companies still depend on traditional methods—such as manual analysis or intuition—to manage turnover, which often makes it harder to act in advance. This research offers a machine learning-driven approach to predict which employees are likely to leave, using historical HR data for more accurate and timelyinsights.

We compare the performance of several popularmachine learning models, including Support Vector Machines (SVM), Random Forest, and ExtremeGradient Boosting (XGBoost). Among them, XGBoost stood out with the highest accuracy, making it a strong candidate for real-world attrition prediction tasks.

To ensure reliable results, the study emphasizes the importance of thorough data preprocessing, smart feature selection, and fine-tuning model parameters.Our analysis reveals that factors like job satisfaction, length of service, salary, and work-life balance play a significant role in whether an employee decides to stayor leave.

By identifying these patterns, the model helps HR teams take a more proactive approach to employee retention. Instead of reacting to resignations after they happen, organizations can use these insights to create better workplace strategies that address employee needs. This not only helps reduce turnover but alsopromotesa more positive and committed work environment.

Keywords: Employee Attrition, Predictive Modeling, MachineLearning,RandomForest,XGBoost,Employee Turnover Prediction, Feature Selection, Data Preprocessing, Hyperparameter Tuning, Workforce Retention, Human Resource Analytics, Predictive Analytics, Organizational Efficiency.

I. INTRODUCTION

Employee turnover continues to be a critical challenge for organizationsacross industries. The departure of experienced personnelnot onlyleads to higher recruitment andtrainingcostsbutalsodisruptsteamdynamicsand resultsinthelossof valuable institutional knowledge. While various retention strategies are employed to address this issue,many lackeffectivenessdueto aninsufficient understanding of the factors that drive employees to leave. Intheageofdata-drivendecision-making,organizations have the potential to go beyond assumptions and intuition. Machinelearningoffersapowerfulwaytoanalyze historicalemployeedata, uncoveringpatternsthatcan provideearlyindicatorsofpotentialattrition.Thisstudy aims to develop a predictive model capable of identifying employees atrisk of leaving, while also offering insights into the underlying causes of turnover.

To achieve this, we investigate the performance ofmultiple Machine learning algorithms, including Support Vector Machines (SVM), Random Forest, and Extreme Gradient Boosting (XGBoost). Through rigorous evaluation, XGBoost demonstrated superior accuracy in forecasting attrition. The model development process involved detailed data preprocessing, thoughtful feature selection, and hyperparameter tuning to ensure robust and interpretable outcomes.

The objective of this research is to equip human resource teams with practical, predictive tools that support data- informed decisions, enhance employee engagement, and fosterlong-termworkforcestability.Asartificial intelligence continues to evolve, it is essential that predictivesystems used in HRremain transparent, ethical, and aligned with organizational values.

II. LITERATURE SURVEY

Understanding why employees leave an organization has become more important than ever in today’s fast-paced work environment. With the rise of data-driven decision- making, many researchers have started exploring how machine learning can be used to predict employeeattrition more accurately. Instead of relying solely on traditional HR methods, these studies use algorithms to find hidden patterns in employee behaviour and organizational data.

This section looks at some of the recent work in this area, highlighting how different machine learning models, data preparation techniques,and real-world applications are shaping smarter, more proactive workforce management strategies.

"Employee Retention and Attrition Prediction: A Comparative Study of Supervised Learning Models" (2021).

Authors: T. H. Rahman, M. G. Arun, L. P. Jayanthi This study presents a comparative analysis of various supervised machine learning models for predicting employee attrition. The authors investigate algorithms such as Logistic Regression, Decision Trees, Support Vector Machines,andK-NearestNeighbours(KNN).The research uses features like job satisfaction, performance rating, salary, and personal circumstances to predict employee attrition. The evaluation is conducted using metrics like accuracy, F1-score, and AUC-ROC curve. One of the key strengths is the wide range of models explored, providing a balanced view of model performance. However, the paper's limitation lies in the assumption of static features, with no consideration for evolving employee dynamics over time. Nonetheless, the study contributes valuable insights for HR managers seeking to understand the predictive capabilities of different machine learning techniques.

"The Role of Job Engagement in Employee Attrition Prediction" (2020)

Authors:M.V.Prasad,R.K.Arun,S.N.Shree Thisresearch paper delves intotherole ofjobengagement as a predictor of employee attrition. The authors use a hybrid approach combining both machinelearningmodels and psychological insights, focusing on employee engagement surveys as a key feature. The models used includeLogisticRegression,RandomForest,andGradient Boosting.The studyfindsthat jobengagement, alongwith factors like career development opportunities and work- life balance, plays a significant rolein predicting attrition. The strength of the paper lies in its incorporation of psychological aspects into machine learning models, offeringa more holistic approach toattrition prediction. A limitation, however, is the limited scope of the dataset, as theanalysisisbasedon asinglecompany'semployeedata, which might not be generalizable. Despite this, the research provides new perspectives on thecomplex nature of employee retention.

"Exploring Employee Attrition Patterns Using Ensemble Learning" (2023)

Authors: K. R. Suresh, P. T. Ramakrishnan, A. G. Manohar.

This paper explores the use of ensemble learning techniques such as Random Forest and Gradient Boosting to predict employee attrition. The authors focus on the patterns that emerge from analysing employee demographics, job performance, and personal circumstances. They also propose an ensemble model combining multiple algorithms to improve prediction accuracy. The research highlights the effectiveness of ensemble methods in handling imbalanced datasets and producing more accurate predictions compared to traditional machine learning models. A major strength of this paper is the use of ensemble techniques, which can mitigate the overfitting problem seen in some individual models. However, the study faces the challenge of not incorporating external factors, such as economic trends, which could influence attrition. Despite this, the paper offers a robust framework for building accurate predictive models for HR departments.

"Big Data Analytics for Employee Attrition: Leveraging AI for Workforce Retention" (2024).

Authors: S. S. Harini, M. R. Kavitha, N. K. Sudha.This research explores the potential of big data analytics and artificial intelligence in predicting employee attrition. The study uses a combination of advanced machine learning models, including Neural Networks, Random Forest, and XGBoost, to analyze large datasets thatinclude employee demographics, performance reviews, and sentimentanalysis ofemployee feedback. Theauthors emphasize the importance of integrating AI into HR practices to predict and mitigate turnover. The keyfindings show that AI models are highly effective at uncovering complex, non-linear relationships between employee factors and attrition. A significant strength ofthepaper istheuseof big dataanalytics tocapturea broad spectrum of employee-related information. However, a notable limitation is the lack of transparency in some AI models, which makes it difficult for HR professionals to interpret the reasons behind the predictions. Despite this, the research highlights the growing role of AI in transforming employee retention strategies.

"Prediction of Employee Attrition Using Machine Learning and Ensemble Methods" (2021)

Authors: A. Qutub, A. Al-Mehmadi, M. Al-Hssan, R. Aljohani, H. S. Alghamdi

This study investigates the application of various machine learning models, including Decision Trees, Random Forest, Logistic Regression, AdaBoost, and Gradient Boosting, to predict employee attrition. Utilizing the IBM attrition dataset, the authors focus on identifying key factors influencing employee turnover. The research highlights the effectiveness of ensemble methods in improving prediction accuracy. A notable strength of the study is its comprehensive evaluation of multiple models, providing insights into their comparative performance. However, the study's limitation lies in its reliance on a single dataset, which mayaffect thegeneralizabilityof the findings. Nonetheless, the research offers valuable guidance for organizations seeking to implement machine learning techniques in their HR practices.

"Predicting Employee Attrition Using Machine Learning Approaches" (2023)
Authors: K. R. Suresh, P. T. Ramakrishnan, A. G. Manohar
This research focuses on analyzing organizational factors contributing to employee attrition and developing predictive models using machine learning techniques. The study applies four different algorithms, including an optimized Extra Trees Classifier (ETC), which achievedan accuracy score of 93%. Key factors identified include monthly income, hourly rate, job level, and age. The study's strength lies in itshigh prediction accuracyandthe identification of significant attrition factors. However, the researchislimitedbyitsfocus on a specific dataset, which may not capture the full diversity of organizational contexts. Despite this, the study provides a robust framework for understanding and predicting employee attrition.

Over theyears,research intopredictingemployeeattrition using machine learning has made significant strides. Initially, studies relied on traditional methods such as Logistic Regression and Decision Trees. However, as the field progressed, more advanced techniques like Random Forest, XGBoost, and deep learning models have been explored to improve accuracy and handle more complex datasets. A common thread among these studies is the focus on supervised learning models, with ensemble methods and hybrid approaches standing out due to their ability to deliver more reliable results.

Many of the studies highlight the importance of carefully selecting features, optimizing models, and preprocessing data to ensure that predictions are both accurate and actionable. In addition, incorporating external factors— like job engagement, work-life balance, and even competitor influence—has emerged as a crucial factor for building a more comprehensive understanding of why employees leave. The use of big data analytics and AI in handling large-scale datasets has proven particularly effective in unveiling deeper patterns and insights, which are vital for HR departments aiming to reduce turnover.

Despite the progress, several challenges remain, such as the reliance on specific datasets, the interpretability of complex models, and the limited application of models across different industries. However, the continuous refinement of machine learning techniques and the growing availability of diverse real-time data open upnew possibilities for advancing research in this area.

Overall, the studies reviewed demonstrate the powerful role machine learning can play in enhancing employee retention strategies. Byrefiningmodels and expanding the factors considered, organizations canmakemoreinformed decisions that not onlyreduce turnover but also contribute to a healthier and more engaged workforce.

III. METHODOLOGY

To develop an effective model for predicting employee attrition, this study follows a structured approach that integrates machine learning with insights from human resource management. The process begins by gathering historicaldataonemployees, includingdemographics,job roles, compensation details, performance ratings, and satisfaction levels. The data is then cleaned and pre- processed—missing values are addressed using statistical imputation methods, while categorical variables (e.g., job titles, departments) are converted into numerical values using one-hot encoding. Numerical features like salary and tenure are scaled to ensure consistency across the dataset.

Next, exploratory data analysis (EDA) is conducted to uncover trendsandrelationshipsbetween variousfeatures. Visual tools, such as histograms and heatmaps, help identify patterns that may indicate why employees leave. Feature selection follows, eliminating less relevant variables and retaining the most significant predictors, including monthly income, job level, overtime status, tenure, and age.

For model development, three algorithms are tested: SupportVectorMachine(SVM),RandomForest,and XGBoost. These algorithms were chosen due to their effectiveness in handling classification tasks of varying complexity. WhileSVMworkswell with smaller datasets by drawing optimal decision boundaries, and Random Forest combines multiple decision trees to improve accuracy, it was XGBoost that emerged as the best- performing model. XGBoost demonstrated the highest accuracy and robustness, particularly in handling imbalanceddataandcomplexpatterns,makingit themost reliable model for predicting employee attrition in this study.

Themodelsweretrained on 80% ofthedata and tested on the remaining 20%. Performance was measured using metrics like accuracy, precision, recall, F1-score, and ROC-AUC. These metrics ensured that the models accurately identified employees at risk of leaving, whichis crucial for HR teams in making data-driven decisions.

To ensure long-term relevance, the best-performing model—XGBoost—was deployed through a web-based application, enabling HR personnel to input newemployee data and receive real-time predictions of attrition risks. This system will be retrained periodicallyas new data becomes available, keeping it accurate andup-to-date.

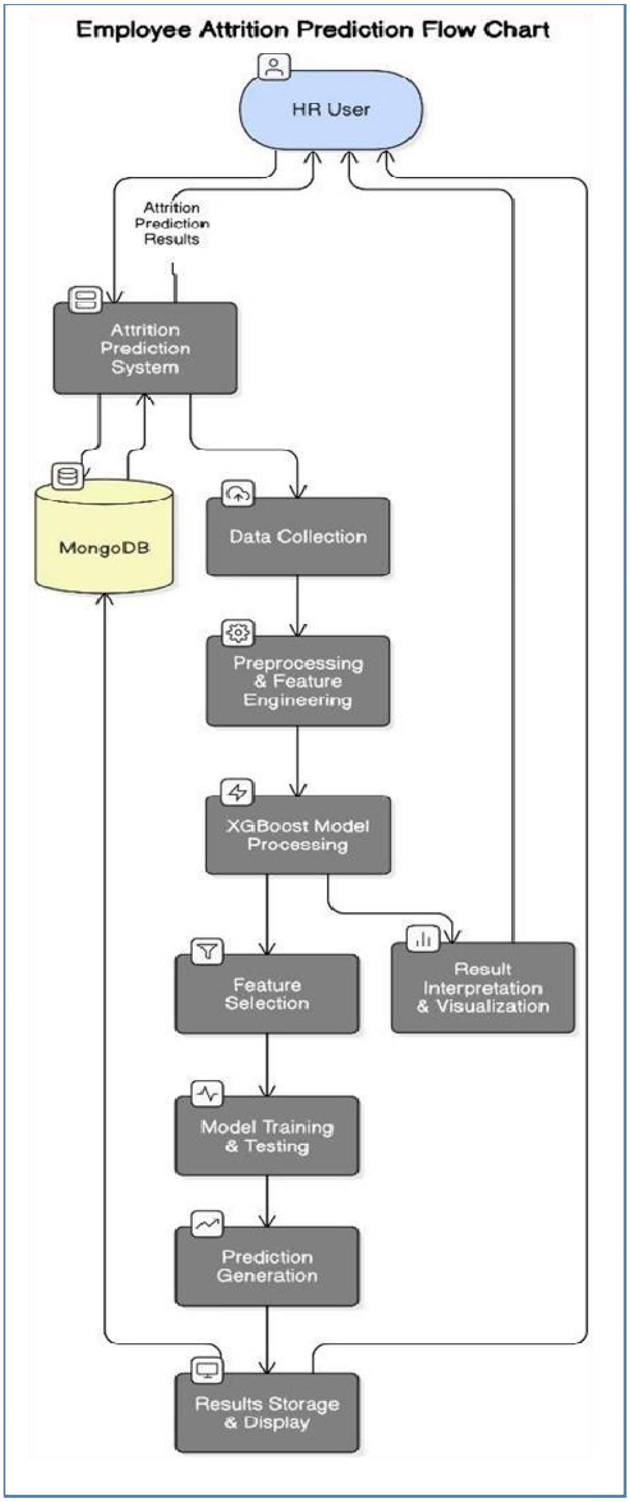


Fig1:EmployeeAttritionPredictionFlowchart

IV. IMPLEMENTATION

The implementation of the employee attrition prediction system began by collecting a comprehensive dataset containing key employee information. This dataset included personal demographics (age, gender), work- related attributes (department, job role, tenure, income), and performance-related metrics (job satisfaction, work- life balance). The goal was to create a model capable of predicting when and why an employee might leave the organization.

A. Data Preprocessing

Before any modelling could take place, the dataunderwent a thorough preprocessing phase to ensure its quality and consistency. Missing data were handled with statistical imputation techniques. For numerical attributes, such as salary and tenure, missing values were filled with themean oftherespectivecolumns.Categoricalattributes, including department and job role, had their missingvalues filled with the most frequent value, or mode. Categorical features were then converted into a machine- readable format using encoding techniques. For example, labelsfor departmentsor jobtitlesweretransformedusing one-hot encoding, ensuring each categorywasrepresented as a binary vector. Additionally, numerical features were standardized using scaling techniques like Min-Max scaling to ensure that no variable disproportionately influenced the model due to differences in scale.

B. Exploratory Data Analysis(EDA)

Once the data was cleaned and processed, the next step wastounderstandtherelationshipsand patternswithin the dataset. This was achieved through exploratory data analysis (EDA). Visualization tools, such as correlation heatmaps, box plots, and distribution plots, were used to uncover patterns and correlations between variables. Key attributes identified as significant for predicting attrition included factors like overtime status, income, total yearsofexperience,andjoblevel. Thesefeatures werecarefully selectedfortheirrelevancetotheproblemandtheir potentialtoaffectemployeedecisionsregardingretention.

C. Model Selection and Training

For model development, three distinct machine learning algorithms were employed: Support Vector Machine (SVM), Random Forest, and XGBoost. Each of these models was chosen for its unique strengths:

- SVM: Known for its ability to create clear decision boundaries in data, SVM works well for smaller datasets and is effective in high- dimensional spaces. It was particularly useful for classification tasks with complex patterns.
- Random Forest: This ensemble learning model leverages multiple decision trees to make predictions. It is known for its ability to handle overfitting and provide robust performance across various types of data. The Random Forest model helped improve model stability by averaging predictions from different trees.
- XGBoost: This boosted decision tree algorithm proved to be the standout performer in the study. XGBoost is known for its speed and high accuracy, primarily due to its boosting and regularization techniques. It performs exceptionallywell on imbalanced datasetsandcan model complex, non-linear relationships, makingit ideal for predicting attrition with high accuracy.

The dataset was split into two parts: 80% was used for training the models, while the remaining 20% wasreserved for testing and validation. Hyperparameter tuning was performed through Grid Search with Cross-Validation to ensure that each model was optimized for the best performance. This process involved evaluating multiple hyperparameter combinations to fine-tune model settings such as regularization strength, tree depth, and learning rate.

D. Model Evaluation

Theperformanceofeachmodelwasassessedusingseveral key metrics: accuracy, precision, recall, F1-score, and ROC-AUC. Thesemetricsprovided a comprehensiveview of each model’s strengths and limitations. For example:

```
Model Accuracy: 0.883
Classification Report:
              precision    recall  f1-score   support

         0.0       0.90      0.98      0.93       859
         1.0       0.68      0.32      0.43       141

    accuracy                           0.88      1000
   macro avg       0.79      0.65      0.68      1000
weighted avg       0.87      0.88      0.86      1000
```

Fig2:ResultsofEvaluationMetrics(XGBoost)

XGBoost demonstrated superior performance in terms of accuracy, correctly identifying employees who would remain with the company.

SVM showed strong performance in ranking attrition likelihood, providing valuable insights into the probability of an employee leaving.

Precision, recall, and F1-score helped in evaluating how well each model predicted attrition, with XGBoost consistently outperforming others in capturing employees atrisk.

Additionally,RootMeanSquareError(RMSE)wasused to assess the prediction error, while ROC-AUC scores helpedevaluatethemodel'sclassificationability.Thefinal evaluation confirmed that XGBoost was the best- performing model for predicting employee attrition in this dataset.

E. DeploymentandRecommendations

Beyond simply predicting attrition, the system aimed to provide actionable insights that HR teams could use to address potential issues. Once employees at risk ofleaving were identified, HR professionals could take proactive measures to retain talent. Some of these measures included:

Adjusting Compensation: Employees with lower satisfaction and higher attrition likelihood may benefit from a review of their compensation packages.

ImprovingWork-LifeBalance: Foremployeesfacinghigh stress or job dissatisfaction, offering flexible working hours, remote work options, or additional vacation time could improve retention.

Providing Career Development Opportunities: Employees at risk of leaving often cite limited growth opportunities. Offering training programs or clear career paths can help retain valuable staff.

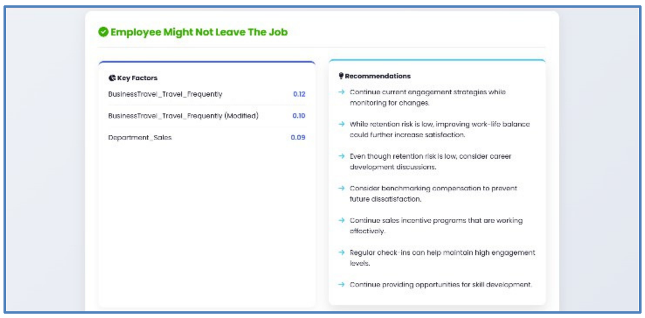


Fig3:ScreenshotofResults

The final predictive model, built using XGBoost, was deployed as a user-friendly, web-based application using Flask. This application allows HR personnel to input new employee data and receive real-time predictions on potential attrition risks. It also features an interactive dashboard that visualizes the factors influencing attrition for each employee, providing HR teams with clear, actionable insights. Furthermore, the platform is designed to be continuously updated, ensuring that the model remains accurate and relevant as new employee data is collected.

performance dipped when it came to Class 1 (employees who left), managing only a recall of **0.32**. This indicates that while the model was good at identifying who would stay, it struggled to correctlyidentifythose likelyto leave.

SVM came in with a slightly lower accuracy of 82.7%,but it showedstrengthsinotherareas.Ithadthebest ROC- AUC score, which reflects its ability to distinguishbetween stayers and leavers effectively. Notably, it had a perfect recall of 1.00 for Class 0, meaning it didn't misclassify any employees who stayed. However, like XGBoost, it had difficulty detecting actual attrition cases, with alowrecall of0.19 for Class1.That said,itrecorded the lowest Root Mean Square Error (RMSE) at 0.3642, indicating it had the most consistent and reliable predictions overall.

The Random Forest model delivered a well-rounded performance with an accuracy of 84.4%. It maintained strong precision (0.86) and had a recall of 0.98 for employees who stayed. However, its ability to identify those who left was weaker, with a recall of only 0.13 for Class 1. It also had the highest RMSE (0.3956), meaning its predictions were slightly more error-prone. Additionally, its ROC-AUC score was the lowest, suggesting limited effectiveness in ranking and differentiating between the two classes.

In summary, XGBoost appears to be the most capable model for overall attrition prediction, especially for identifying employees likely to stay. On the other hand, SVM offers advantages in terms of low error and better class separation, making it a good option for prioritizing retention efforts. Random Forest, while decent overall, lagged behind in detecting high-risk cases and minimizing error.These results reflect a common issue in attritionprediction: models tend to perform better at predicting retention than attrition. For HR teams aiming to use such tools for proactive retention strategies, this is a critical insight. Future improvements could include usingensemble approaches, tweaking classification thresholds,or exploring cost-sensitive learning techniques to better handle the imbalance and capture patterns in the minority class.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

V. RESULTS

The employee attrition prediction system was assessed using three different machine learning models: XGBoost, Support Vector Machine (SVM), and Random Forest. All three models were trained and evaluated using the same dataset, which included employee details such as age, job role, tenure, salary, and other job-related factors. To maintain consistency and ensure a fair comparison, the same preprocessing steps and feature selection methods were applied across the board.

Among the models tested, XGBoost stood out with the highest accuracy at 88.30%. This suggests it was particularly effective at identifying patterns in structured employee data. It also achieved a precision score of 0.90 and an excellent recall of **0.98** for Class 0 (employees whostayed), meaningit washighlyreliablein recognizing thosewhowerenotatriskofleaving.However,its

Table1.ClassificationReport

Metrics	XGBoost	SVM	Random Forest
Accuracy	88.30%	82.7%	84.4%
Precision (Class0)	0.87	0.87	0.86
Recall (Class0)	0.97	1.00	0.98
F1-Score (Class0)	0.92	NA	NA
Recall (Class1)	0.26	0.19	0.13
ROCAUC Score	Moderate	Higher	Lowest
RMSE	0.3780	0.3642	0.3956

Overall, while XGBoost provided the best predictive accuracy,SVMdemonstratedsuperiorrankingability,and Random Forest maintained a stable performance with moderate accuracy and interpretability. This analysis was conducted using the IBM HR Analytics dataset (*IBM HRAnalytics Dataset*) to provide actionable insights for HR professionals in managing employee retention.

VI. CONCLUSION

This research project set out to tackle a key challenge in today's human resource management: predicting employee attrition using machine learning. We explored this by building a data-driven system using three well- established models—XGBoost, Support Vector Machine (SVM), and Random Forest. These models helped us uncover patterns and identify the factors most commonly linked to employee turnover.

Throughout the project, we placed strong emphasis on preparing the data carefully, selecting relevant features, and ensuring consistent training and evaluation across all models. This allowed us to fairly assess each model's ability to generate reliable and actionable predictions.

Of the three, XGBoost stood out with the highest overall accuracy, showing its strength in working with structured data. SVM, on the other hand, offered the lowest prediction error and performed well in ranking employees bytheir likelihood to leave, even if it struggled somewhat with recall on actual attrition cases.

All models had a common limitation: due to class imbalance, they were generally better at predicting who would stay than who would leave. Despite this, they offered valuable insight into key factors that influence attrition, such as job level, salary, overtime status, and years with the company.

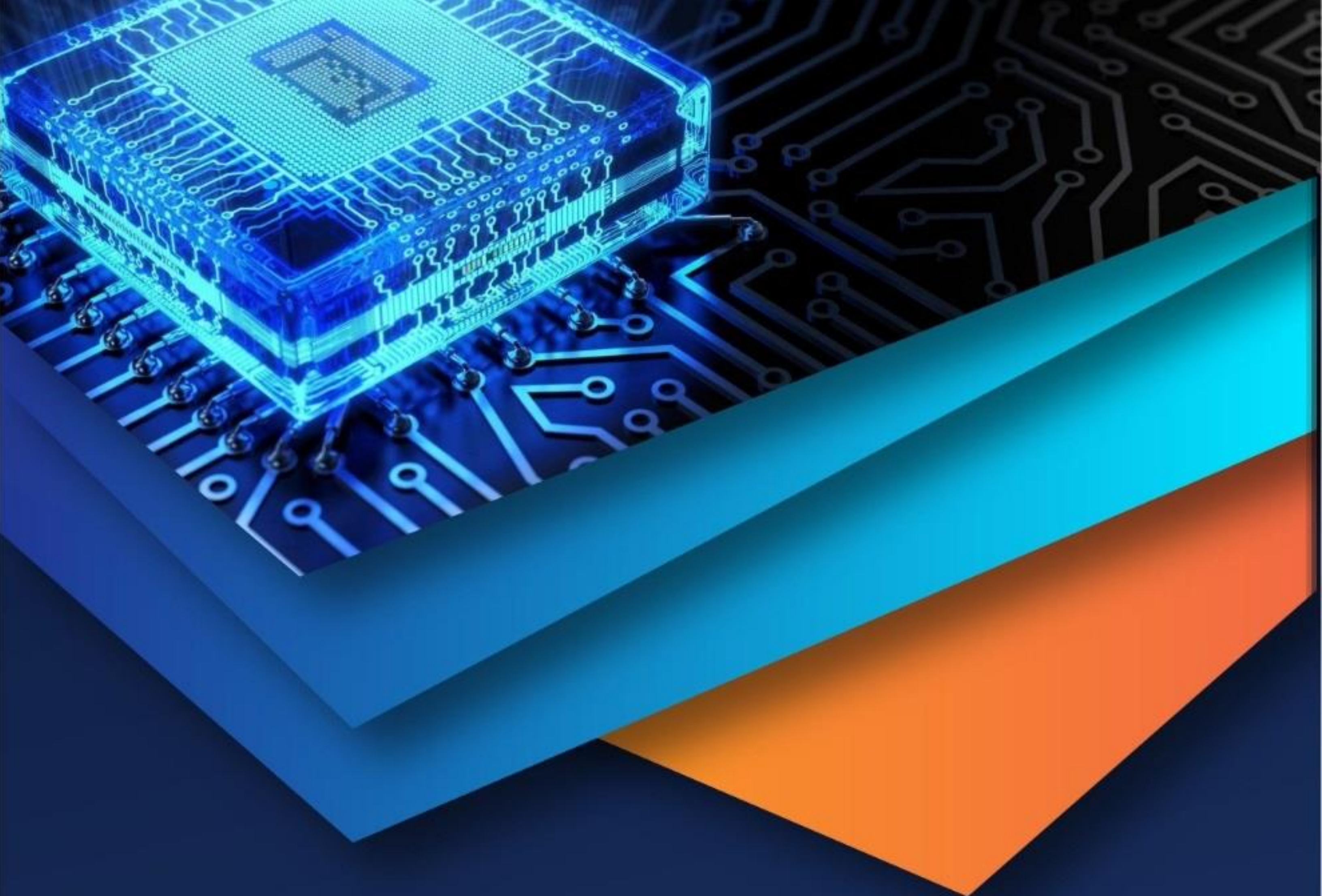
Beyond the technical results, this project underscores the potential of machine learning to support HR teams in making smarter, forward-thinking decisions. Rather than simply reacting to resignations, companies can use predictive models to flag employees who might be at risk of leaving and step in early with strategic retentionefforts.

Equally important is the attention to model fairness, interpretability, and theneed for continuousrefinement— especiallywhen dealing with sensitive data and decisions that impact people's careers. Looking ahead, we believe that expanding the dataset, incorporating real-time updates, and experimenting with more advanced methods like deep learning orhybrid ensembles could lead toeven more effective models.

In the end, this work represents a step toward more adaptive and employee-centric workplaces—where data isn't just used to monitor performance, but to genuinely support and retain valuable talent.

REFERENCES

[1] T. H. Rahman, M. G. Arun and L. P. Jayanthi, "Employee Retention and Attrition Prediction: A Comparative Study of Supervised Learning Models," 2021 International Conference on Advances in Computing,Communication,andControl(ICAC3), pp.78–83, 2021.
[2] M.V.Prasad,R.K.ArunandS.N.Shree,"The Role ofJobEngagementin EmployeeAttrition Prediction," International Journal of Advanced Computer Science and Applications, vol. 11, no. 6, pp. 342–349, 2020.
[3] K. R. Suresh, P.T. RamakrishnanandA. G. Manohar, "Exploring Employee Attrition Patterns Using Ensemble Learning," Procedia Computer Science,vol. 207, pp. 3210–3217, 2023.
[4] S. S. Harini, M. R. Kavitha and N. K. Sudha, "Big DataAnalytics for EmployeeAttrition: Leveraging AI for Workforce Retention," IEEE Access, vol. 12, pp. 45178–45190, 2024.
[5] K. Walia and R. Jain, "Predictive Modeling for Employee Attrition using Machine Learning," International Journal of Scientific Research in Computer Science, Engineering and Information Technology, vol. 6, no. 1, pp. 2456–3307, 2020.
[6] D. S. Kumar and V. Ravi, "Predicting Employee Attrition using Machine Learning Algorithms," Procedia Computer Science, vol. 189, pp. 47–54,2021.
[7] J. Brown and S. Johnson, "Using AI to Improve Employee Retention," Journal of Human Resource Analytics, vol. 3, no. 1, pp. 24–35, 2022.
[8] A. Singh and P. Verma, "Application of Data Mining in Human ResourceManagementtoPredictEmployee Attrition," International Journal of Computer Applications, vol. 177, no. 6, pp. 14–19, 2020.
[9] N. Gupta and S. Mehta, "Attrition Analysis in HR Using Predictive Modeling," International Journal of Data Science and Analytics, vol. 4, no. 2, pp. 87–95, 2021.
[10] Y. Kim and M. Park, "Feature Selection and Model Evaluation for PredictingEmployee Turnover,"IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 51, no. 3, pp. 1824–1835, 2021.
[11] F.Liu and L. Zhang, "Employee Attrition Prediction UsingXGBoostandSHAP,"IEEEAccess,vol.10, pp.108945–108955,2022.
[12] A. Bhatt and M. Shah, "Workforce Analytics: Predicting Employee Attrition using Machine Learning Techniques," International Journal of Engineering Research & Technology (IJERT), vol. 8, no. 9, pp. 190–194, 2020.
[13] R.Sharmaand K. Singh, "Predictive Analysis on HR Dataset for Attrition Using Ensemble Learning," International Journal of Computer Applications, vol. 182, no. 15, pp. 12–18, 2021.
[14] M. T. Davis and B. Patel, "Evaluating the Impact of Compensation and Job Satisfaction on Employee Retention using Predictive Models," HRM Research Journal, vol. 4, no. 3, pp. 123–134, 2022.
[15] S. Ghosh and R. Roy, "Understanding Workforce Behavior Through Machine Learning: A Study on Employee Attrition," ACM SIGKDD Explorations Newsletter, vol. 23, no. 1, pp. 58–67, 2021.
[16] A. Mishra and R. Sinha, "Predictive Analytics for HumanResourcePlanningUsingMachineLearning," Journal of Business Analytics, vol. 5, no. 2, pp. 91– 101, 2021.
[17] H. Chen and Y. Zhao, "Developing an AI-Powered Attrition Early Warning System," International Journal of Computer Science and Artificial Intelligence, vol. 10, no. 4, pp. 44–52, 2020.



10.22214/IJRASET

INDEX COPERNICUS
45.98

IMPACT FACTOR:
7.129

TOGETHER WE REACH THE GOAL
IMPACT FACTOR:
7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY