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HR RECOMMENDER SYSTEM FOR THE IMPROVEMENT OF EMPLOYEE ATTRITION USING DECISION TREE AND WHALE OPTIMIZATION ALGORITHM

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ABSTRACT

This paper presents the design and development of an advanced HR recommender system aimed at mitigating employee attrition; a critical challenge faced by organizations. Employee turnover incurs significant financial costs and negatively impacts productivity and morale. The proposed system combines Decision Tree Analysis with the Whale Optimization Algorithm (WOA) to enhance predictive accuracy in identifying employees at risk of leaving. Decision Tree Analysis serves as a classification tool to analyse historical employee data, pinpointing key factors contributing to attrition, such as job satisfaction, work-life balance, and career growth. Traditional decision tree models often struggle with overfitting and suboptimal performance. To address these issues, WOA, inspired by the hunting strategies of humpback whales, fine-tunes the decision tree model's hyperparameters, improving prediction accuracy and generalization. The system utilizes data from employee surveys, performance evaluations, and organizational metrics, providing a comprehensive view of influencing factors. By leveraging this hybrid model, the HR recommender system predicts potential employee departures and suggests targeted retention strategies, enabling proactive measures such as training and compensation adjustments. The study demonstrates that integrating Decision Tree Analysis with WOA significantly enhances predictive performance, offering a valuable tool for effective employee retention management.

Keywords: Employee Attrition, HR Recommender System, Machine Learnings over employee turnovers, Predictive Modelling, Workforce Management.

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Introduction

Employee attrition presents a significant challenge for organizations, impacting productivity, morale, and operational costs. As companies strive to maintain a stable and engaged workforce, the ability to predict and mitigate turnover becomes increasingly crucial. Traditional methods of addressing attrition often rely on reactive measures and historical data analysis, which may not provide the proactive insights needed for effective retention strategies.

Figure 1.1 employee attrition [14]

This paper introduces the design and development of an HR recommender system specifically aimed at addressing employee attrition. The system leverages the combination of decision tree analysis and the Whale Optimization Algorithm (WOA) to enhance both predictive accuracy and operational efficiency. Decision tree analysis is a powerful tool for identifying and understanding key factors that influence employee turnover. By segmenting data into distinct decision nodes, this method provides a clear visualization of how different variables affect attrition rates.

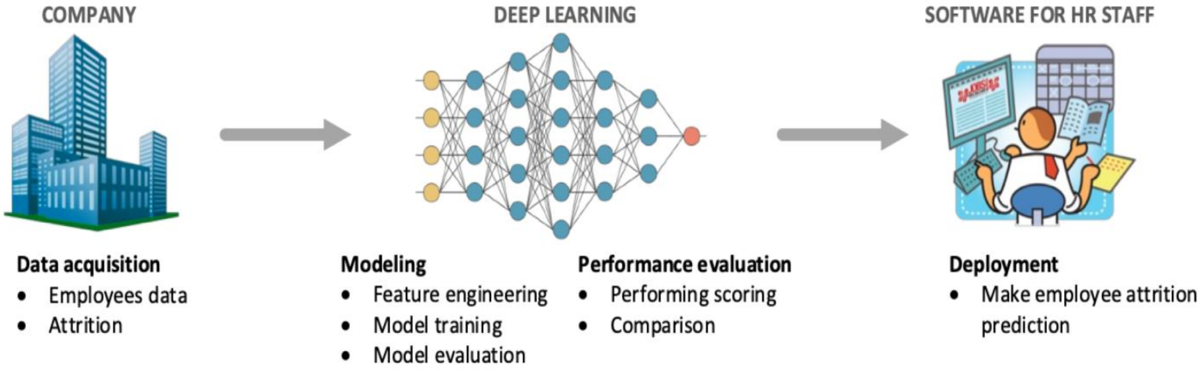

Figure 1.2 HR recommender system for Employee attrition [15]

Traditional methods of addressing employee turnover often rely on retrospective analyses, which can be reactive rather than proactive. In contrast, leveraging machine learning techniques allows for the development of predictive models that can identify at-risk employees before they decide to leave [4,7-9]. Among the numerous machine learning algorithms available, Decision Trees are particularly popular due to their simplicity, interpretability, and effectiveness in classification tasks. Decision Trees can uncover intricate patterns and relationships within data, making them a suitable choice for predicting employee. Figure 1.1 is showing attrition.

The Whale Optimization Algorithm, inspired by the hunting strategies of humpback whales, is used to optimize the parameters of the decision tree model. WOA enhances the model's performance by fine-tuning its predictive capabilities, ensuring that the insights derived are both accurate and actionable. This integration of decision tree analysis and WOA offers a novel approach to predicting employee turnover, enabling HR professionals to develop targeted strategies that address the underlying causes of attrition.

However, the accuracy and reliability of prediction models can be further enhanced through optimization techniques. The Whale Optimization Algorithm (WOA), inspired by the bubble-net hunting strategy of humpback whales, is a metaheuristic optimization algorithm known for its ability to find optimal solutions in complex search spaces. By incorporating WOA, the decision-making process of the recommender system can be refined, leading to improved performance in predicting employee attrition [8-10].

The objectives of this study are twofold: to identify the key factors contributing to employee attrition through detailed analysis and to improve the predictive accuracy of these factors using advanced optimization techniques. The resulting recommender system provides a robust framework for understanding employee turnover, offering organizations a proactive tool for enhancing employee retention and promoting organizational stability.

The rest of the paper is organized as follows: Section 2 presents the Literature Survey. This section presents a review of previous authors' work, covering the historical background, traditional methods, and advanced techniques. It also highlights the research gaps and issues identified in the previous studies.

Section 3 presents the Proposed Methodology. This section outlines the proposed work, where we introduce the use of Decision Tree Analysis and Whale Optimization Algorithm (WOA) to enhance prediction efficiency.

Section 4 presents the Experimental Evaluation and Result Analysis: This section presents the results of the proposed method, including detailed simulation graphs and outputs.

Section 5 presents the Comparative Analysis: This section presents a comparative analysis of the results based on the proposed method.

Section 6 presents the Conclusion & Future Work: This section provides a comprehensive conclusion to our work. It summarizes the key findings and insights derived from the research, reflecting on the effectiveness of the proposed methods and their implications.

Literature Review

This section provides a comprehensive overview of existing research and methodologies related to employee attrition, retention strategies, and the use of recommender systems in human resource management. This chapter aims to contextualize the proposed HR recommender system within the broader academic and practical landscape, highlighting the evolution of ideas, key findings, and gaps in the current body of knowledge.

2.1 Related Work

Historically, HR departments have relied on manual processes and basic statistical models to monitor and assess employee performance, satisfaction, and turnover. Traditional approaches typically involved methods such as employee surveys, exit interviews, performance appraisals, and feedback mechanisms. These data collection techniques provided HR managers with insights into the reasons behind employee attrition and helped identify areas for improvement within the organization.

Basic statistical models, like linear regression, were commonly used to analyses these datasets and discern patterns or correlations between various factors, such as job satisfaction, compensation, and work-life balance, and the likelihood of employees leaving the company.

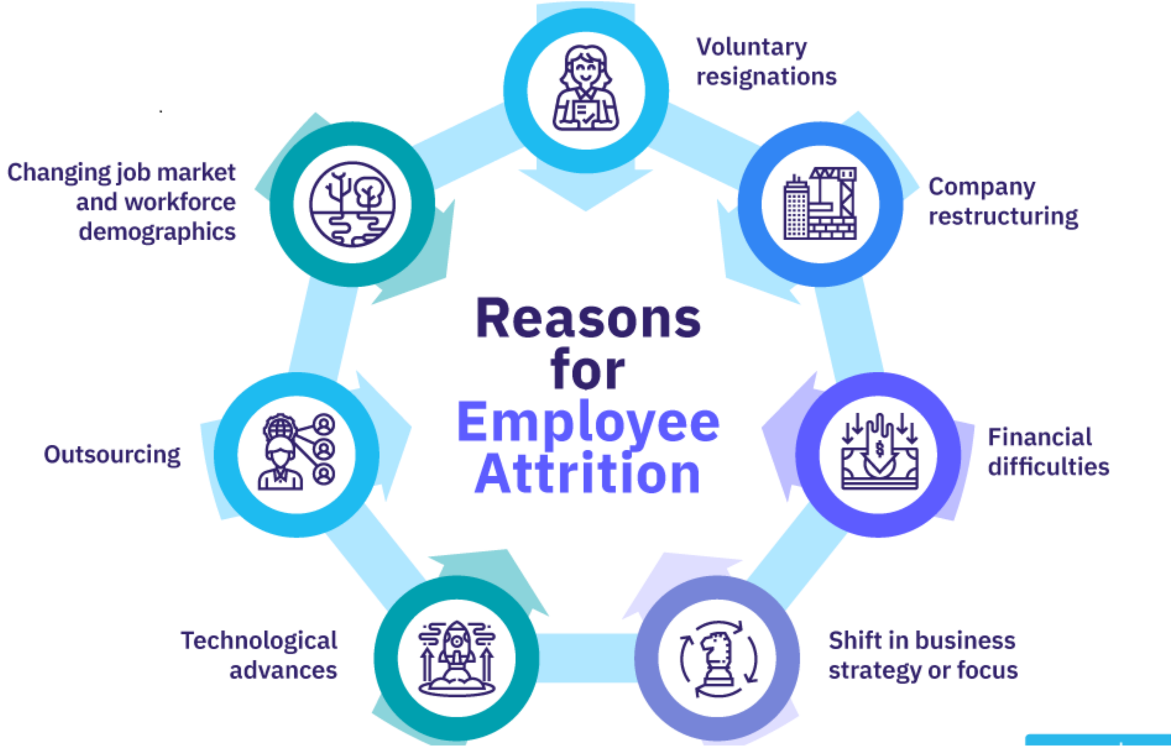
Reasons for Employee Attrition
Voluntary resignations
Company restructuring
Financial difficulties
Shift in business strategy or focus
Technological advances
Outsourcing
Changing job market and workforce demographics

Figure 2.1 Attrition definition, importance & example [15]

One prominent area of research involves the use of predictive analytics to forecast employee attrition. For instance, a study by Kira et al. (2019) [10] highlights the effectiveness of using classification algorithms, such as Random Forests and Support Vector Machines, to predict employee turnover based on historical data and key indicators like job satisfaction and performance metrics. Their findings suggest that machine learning models can significantly improve the accuracy of attrition predictions by analysing patterns and trends in employee behaviour.

Another critical aspect covered in the literature is the integration of recommender systems to suggest retention strategies. Li et al. (2020) [9] presents a hybrid model combining collaborative filtering and content-based filtering to recommend personalized interventions for employees at risk of leaving. Their research emphasizes that tailored recommendations, based on individual employee profiles and historical data, can enhance retention efforts by addressing specific concerns and preferences.

Khanna & Kumar (2020) [8] investigates the primary factors contributing to employee attrition using data from both current and past employees. To address and mitigate employee turnover, the study employs several predictive algorithms—Support Vector Machines (SVM), Logistic Regression (LR), Decision Trees (DT), and Naive Bayes (NB)—to identify key factors that distinguish the top-performing employees within each department. The approach involves selecting a sample of 10 employees and then utilizing these algorithms to categorize them into two groups: top performers and potential churners. Based on the findings, recommendations such as salary increases or bonuses are proposed to retain the top-performing employees. However, this recommendation lacks a detailed exploration of the underlying factors driving the suggested interventions, making it a broad and somewhat generalized solution.

Further, the work by Chen et al. (2021) [7] explores the application of deep learning techniques, such as neural networks, to develop more sophisticated attrition models. Their approach involves analysing large volumes of unstructured data, including employee feedback and social media activity, to gain deeper insights into the factors influencing turnover. This research highlights the potential of deep learning to capture complex patterns and improve the predictive power of attrition models.

In a subsequent study, Raman and Anchal (2022) [3] extends the methodologies used by Khanna & Kumar (2020) by incorporating additional machine learning techniques, specifically Random Forest and AdaBoost (AB). , Raman and Anchal enhances the model by generating new features from the existing dataset, categorizing employees into technical and non-technical departments and further distinguishing them as experienced or fresh based on their tenure, number of projects completed, and recent performance evaluations. To demonstrate the effectiveness of these enhancements, Yadav compares the predictive performance of the model with and without the new feature selections, evaluating the results based on accuracy, precision, F1 score, and recall.

Building on these approaches, Qutub and Mehmedi (2021) [6] also employed Random Forest and AdaBoost but introduce additional methods such as Gradient Boosting and Stochastic Gradient Descent (SGD). They utilize the Receiver Operating Characteristic (ROC) Curve to assess the predictive accuracy of their models. Additionally, they develop hybrid models by combining Decision Trees with Logistic Regression, AdaBoost with Random Forest, and SGD with Gradient Boosting to improve the precision of churn predictions.

In a 2023 study, Musanga [1] evaluates three feature selection methods—Pearson Correlation (PC), Information Gain, and Recursive Feature Elimination (RFE)—using the IBM dataset, which is also utilized in this research. Each feature selection technique is assessed for its effectiveness in improving the performance of various classification algorithms, including Logistic Regression (LR), K-Nearest Neighbors (KNN), Random Forest (RF), Decision Tree (DT), and Gradient Boosting Machines (GBM).

Among the methods tested, Pearson Correlation emerges as the most effective feature selection algorithm. It consistently yields the highest accuracy values across all classification algorithms except for Random Forest. Consequently, PC is selected for use in the preprocessing phase of this study.

Musanga also draws parallels between employee churn and customer churn, noting that while strategies for addressing employee churn focus on retention efforts within organizations, customer churn strategies are aimed at maintaining customer loyalty. To enhance their understanding, Musanga references work by Bach et al. (2021), who address customer churn through a hybrid approach. Bach et al. first employ the k-means clustering algorithm to segment customers into distinct groups. Following this, they use a decision tree algorithm to predict churn probabilities within the clusters that exhibit the highest churn rates. Finally, they perform rule extraction to identify key determinants of churn and offer actionable recommendations to companies based on these insights. This hybrid approach underscores the importance of combining clustering with classification to better understand and address churn issues.

In line to Hybrid approach, Kumar and Gupta (2018) [11] applied a decision tree classifier to HR data to identify the key factors influencing employee retention and turnover, emphasizing the effectiveness of ML models in handling HR-related predictions.

Optimization algorithms, such as Genetic Algorithms (GA) and Whale Optimization Algorithm (WOA), have been employed to enhance the performance of these models by fine-tuning hyperparameters. Sharma et al. (2020) [12] demonstrated how genetic algorithms can be used to optimize recruitment processes by selecting the best-fit candidates based on job requirements and organizational needs.

Moreover, Zhao et al. (2021) [13] incorporated Particle Swarm Optimization (PSO) to fine-tune parameters in a talent recommender system, leading to improved performance and prediction accuracy.

Recent studies also explore hybrid approaches. Goyal and Chhabra (2022) [14] combined Collaborative Filtering and WOA to develop an HR recommender system that accurately matches employees to training programs, showing that optimization algorithms enhance recommendation accuracy compared to traditional techniques. Similarly, Patel and Kaur (2019) [15] used Support Vector Machines (SVM) along with GA to create a robust recruitment recommender system that increased hiring efficiency by reducing bias and improving candidate matching.

The combination of machine learning and optimization techniques continues to transform HR processes by improving efficiency and personalization. These advancements in HR recommender systems demonstrate that the synergy between data-driven approaches and optimization algorithms can lead to better decision-making and improved organizational outcomes.

2.2 Research Gaps Identified

In the field of designing and developing HR recommender systems for employee attrition, based on several author work, several research gaps have been identified. One significant gap is the limited integration of diverse data sources. Many existing systems rely on traditional data, such as basic surveys and performance reviews, which does not fully capture the dynamic and multifaceted nature of employee experiences. This limitation affects the accuracy and effectiveness of predictions and recommendations. Additionally, overfitting remains a challenge, as models often perform well on training data but fail to generalize to new, unseen data, reducing their reliability.

Another critical issue is the lack of explainability and transparency in many advanced machine learning models. The complexity of models like deep learning and ensemble methods makes it difficult for HR professionals to understand and trust the recommendations, which can hinder their practical application. Furthermore, current approaches to feature selection may not adequately address the evolving nature of employee attributes and external factors, leading to suboptimal model performance.

Data imbalance is also a prevalent issue, as attrition datasets often have significantly fewer cases of attrition compared to non-attrition cases. This imbalance skews model predictions and reduces accuracy. The integration of qualitative feedback and sentiment analysis is another area that is often overlooked. Without incorporating employee feedback and sentiment, models may miss critical insights into the reasons behind attrition.

Dynamic adaptation is yet another challenge, as many systems are static and do not adjust to real-time changes in employee behaviour and organizational conditions. This static nature can lead to outdated recommendations that do not reflect current realities. Lastly, ethical and privacy concerns surrounding the use of sensitive employee data need to be addressed. Ensuring robust data protection measures and maintaining ethical standards are crucial for gaining trust and complying with regulations.

With this paper, the research offers several advantages over traditional approaches in machine learning classification:

1. Global search ability, reducing the likelihood of getting trapped in local minima.
2. A better balance between exploration and exploitation.
3. Simplified parameter tuning compared to complex traditional machine learning algorithms.

4. Effective feature selection and hyperparameter optimization.
5. Adaptability to high-dimensional data and flexibility in combining with other models.

Proposed Methodology

This chapter show HR recommender system aims to address the critical challenge of employee attrition through a robust framework that integrates multiple analytical techniques. By leveraging the strengths of Decision Tree Analysis, Random Forests, Hybrid Decision Trees, and the Whale Optimization Algorithm (WOA), the system offers a comprehensive approach to predicting and managing employee turnover effectively.

Proposed Work

The proposed HR recommender system integrates multiple analytical techniques to enhance the prediction and management of employee attrition. It combines Decision Tree Analysis, Random Forests, Hybrid Decision Trees, and the Whale Optimization Algorithm (WOA) to create a comprehensive solution.

Decision Tree Analysis serves as the foundation of the system, offering a clear and interpretable way to identify how various factors, such as job satisfaction or tenure, influence employee turnover. However, to overcome the limitations of a single decision tree, the system incorporates Random Forests, which improve prediction accuracy by aggregating the results of multiple trees, thereby reducing overfitting and handling high-dimensional data more effectively. Further refinement is achieved through Hybrid Decision Trees, which enhance traditional decision trees with advanced methodologies like boosting or bagging, improving overall performance.

To optimize these predictive models, the Whale Optimization Algorithm (WOA) is employed. WOA, inspired by the hunting strategies of humpback whales, fine-tunes the hyperparameters of the decision trees and Random Forests. This optimization process searches for the best parameter configurations to enhance model efficiency and accuracy.

By integrating these techniques, the system offers a powerful tool for HR departments, providing detailed insights into factors affecting employee attrition and enabling the development of effective retention strategies. This hybrid approach ensures accurate predictions and actionable data, aiding in better decision-making and improving employee retention efforts.

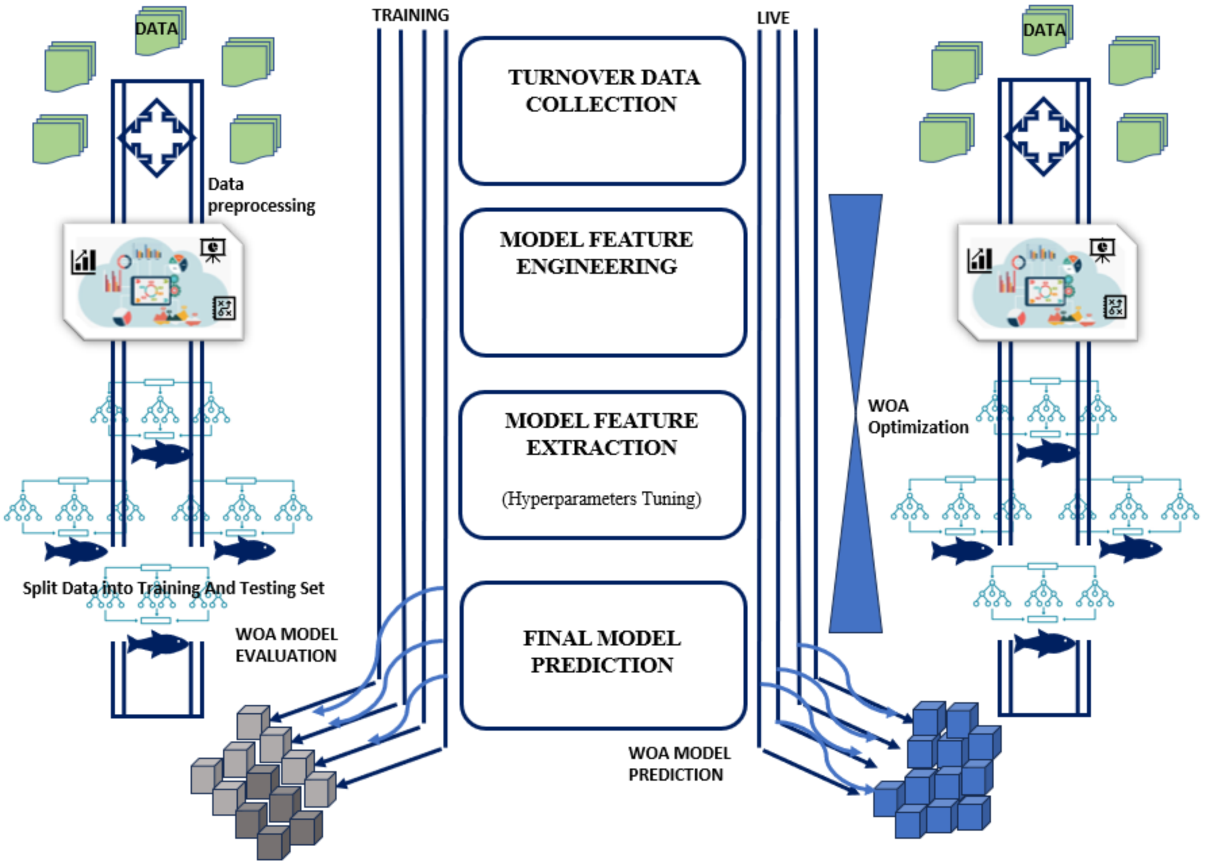

Figure 3.1 System solution design

The methodology is outlined as follows:

1. Decision Tree Analysis

A decision tree is a fundamental model for classification and regression tasks. It splits the data into subsets based on feature values to make predictions. For employee attrition prediction, the decision tree helps identify the most significant factors contributing to turnover. The decision tree can be represented by the following equation:

$$\text{Prediction}=f(X)$$

where X is the input feature vector, and) f(X) represents the decision-making process based on the tree's structure.

2. Random Forest

To improve the performance and robustness of the decision tree, a Random Forest approach is employed. A Random Forest consists of multiple decision trees, each trained on a random subset of the data. The final prediction is made by aggregating the results of all individual trees. The Random Forest prediction is given by:

$$\text{Prediction}_{RF} = \frac{1}{T}\sum_{t=1}^{T} \mathrm{f}_t(X)$$

where T is the number of trees in the forest, and $f_{t(}X)$ represents the prediction of the t-th tree.

3. Hybrid Decision Tree

The Hybrid Decision Tree combines the decision tree with an additional layer of optimization or feature enhancement. This hybrid approach leverages advanced techniques such as feature engineering or parameter tuning to improve the decision tree's performance. In the hybrid model, the decision function can be represented as:

$$\mathrm{Prediction}_{Hybrid} = \mathrm{f}(X, \mathrm{Opt}(X))$$

where Opt(X) represents the optimized or enhanced features derived from the hybrid approach.

4. Whale Optimization Algorithm (WOA)

The Whale Optimization Algorithm is utilized to optimize the parameters of the decision tree or the hybrid decision tree model. WOA mimics the hunting behavior of humpback whales to search for optimal solutions. The algorithm involves the following steps:

1. **Initialization:** Initialize a population of candidate solutions.
2. **Fitness Evaluation:** Evaluate the fitness of each solution based on a predefined objective function.
3. **Update Positions:** Update the positions of the candidates using the following update equations:
   $\mathrm{Position}_i^{new}=\mathrm{Positioni}+A\cdot D$
   where A is a coefficient vector, and D is the distance between the current position and the best position found so far.
4. **Search Behavior:** Implement the exploration and exploitation behaviors of the whales to find the optimal parameter values.

The objective function for WOA in optimizing the decision tree parameters is defined as:

$\text{Objective Function}=\text{Accuracy}_{\text{Model}}$

where $\text{Accuracy}_{\text{Mode}}$l is the accuracy of the decision tree or hybrid model based on the parameters optimized by WOA.

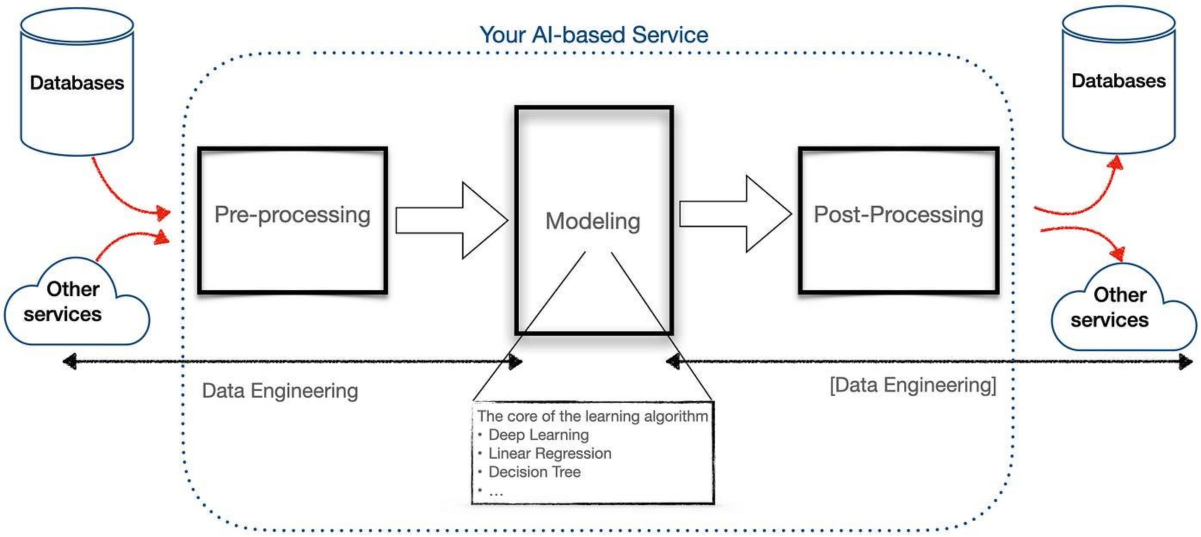

Figure 3.2 System Architecture [18]

In designing and developing an HR recommender system aimed at mitigating employee attrition, the first step is to define the objectives and requirements of the system. The primary objectives include reducing employee turnover and improving retention strategies by leveraging predictive analytics. To achieve these goals, it is essential to outline the requirements for data collection, model accuracy, and overall system performance. This involves specifying the types of data needed, the accuracy metrics that must be met, and the performance standards the system should uphold.

The next phase is data collection, which involves gathering a comprehensive dataset on employee attributes such as job satisfaction, tenure, performance metrics, salary, and work-life balance. This data is sourced from HR databases, employee surveys, and feedback systems, encompassing both historical and current information on employee attrition. Accurate data collection is crucial for building a robust model that can effectively predict and manage attrition.

Following data collection, the preprocessing stage involves several key steps. Cleaning the data is necessary to handle missing values, remove duplicates, and address any inconsistencies in the dataset. Feature engineering comes next, where new features are created to enhance model performance—this might include aggregating performance metrics or developing interaction terms. Normalization is also performed to scale the features appropriately, ensuring that the data is suitable for analysis and model training.

Feature selection is the next critical step, where the most relevant features are identified. Techniques such as Recursive Feature Elimination (RFE) or SelectKBest are employed to determine the importance of various features. A hybrid approach is used to further refine the feature set, integrating these techniques with hybrid decision trees to enhance their effectiveness.

In model development, a basic decision tree model is initially established to create a baseline and understand preliminary patterns. Random Forest models are then trained to handle high-dimensional data, improving prediction accuracy by combining multiple decision trees. The hybrid decision trees approach is used to further increase robustness and accuracy, incorporating techniques like boosting or bagging.

Optimization of the models is carried out using the Whale Optimization Algorithm (WOA), which fine-tunes the hyperparameters of the decision trees and Random Forest models. WOA mimics the hunting strategies of humpback whales to explore the hyperparameter space efficiently and identify the best configurations. This optimization process ensures that the models are finely tuned to deliver accurate predictions.

Finally, model evaluation involves assessing the performance of the developed models using various metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. Cross-validation techniques are implemented to validate that the models generalize well to unseen data, thereby mitigating overfitting and ensuring that the predictions are reliable and actionable.

Implementation

Setup and Configuration

For setup and configuring machine learning project to perform EDA and generate AI Model, go to the Google Colab site colab.research.google.com and sign in with your Google account. Colab, or ‘Collaboratory’, allows you to write and execute Python in your browser, with Zero configuration required, Access to GPUs free of charge and Easy sharing.

Customization and Integration

Details of each implementation for processing employee attrition data using a Decision Tree and Whale Optimization Algorithm (WOA) are summarized as below.

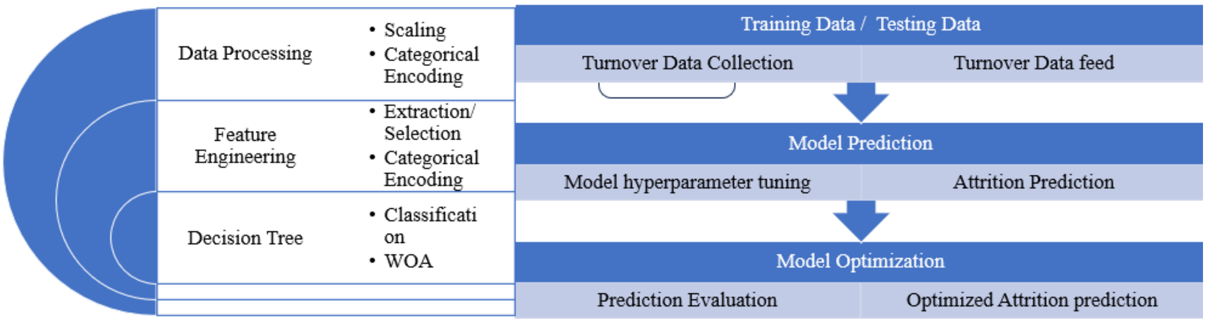

Figure 4.1 System implementation

1. Turnover Data Collection

The dataset used for the purpose of analyzing the patterns in Employee Behavior is IBM HR Dataset, created by IBM data scientists, which is designed to explore factors that lead to employee attrition. It contains a variety of features representing different aspects of employees' personal and professional lives, as well as their satisfaction levels.

2. Initial Data Visualization and Analysis

In this section, we perform an exploratory data analysis (EDA) to understand the structure and distribution of the dataset. We began by performing handling missing Data, clean the dataset by addressing missing values through imputation techniques.

We performed visualizing the key features to observe patterns, trends, and potential outliers. Histograms, bar charts, and box plots are utilized to display the distribution of numerical features such as Age and Daily Rate, while pie charts and count plots provide insights into categorical features like Attrition, Business Travel, and Department. Correlation matrices and heatmaps are employed to identify relationships between variables, helping us detect multicollinearity and understand how features may interact. This initial visualization sets the foundation for deeper analysis by highlighting significant trends and anomalies in the data.

3. Data Transformation and Pre-Processing

To create new features that enhance the predictive power of the model based on existing data.

First, the categorical columns in the dataset are identified. Categorical columns contain non-numeric data, which cannot be directly used in most machine-learning algorithms. Therefore, these columns need to be encoded into numeric formats. The column "Gender" is encoded by replacing "Female" with 0 and "Male" with 1, making it a binary numeric variable.

For the remaining categorical columns, label encoding and one-hot encoding techniques are used. Label encoding is applied to the "Attrition" column, converting its categorical values into numeric values. One-hot encoding is applied to columns such as "BusinessTravel," "Department," "EducationField," "JobRole," "MaritalStatus," and "OverTime." One-hot encoding converts categorical variables into a series of binary columns, each representing a single category. This prevents the model from assuming any ordinal relationship between the categories.

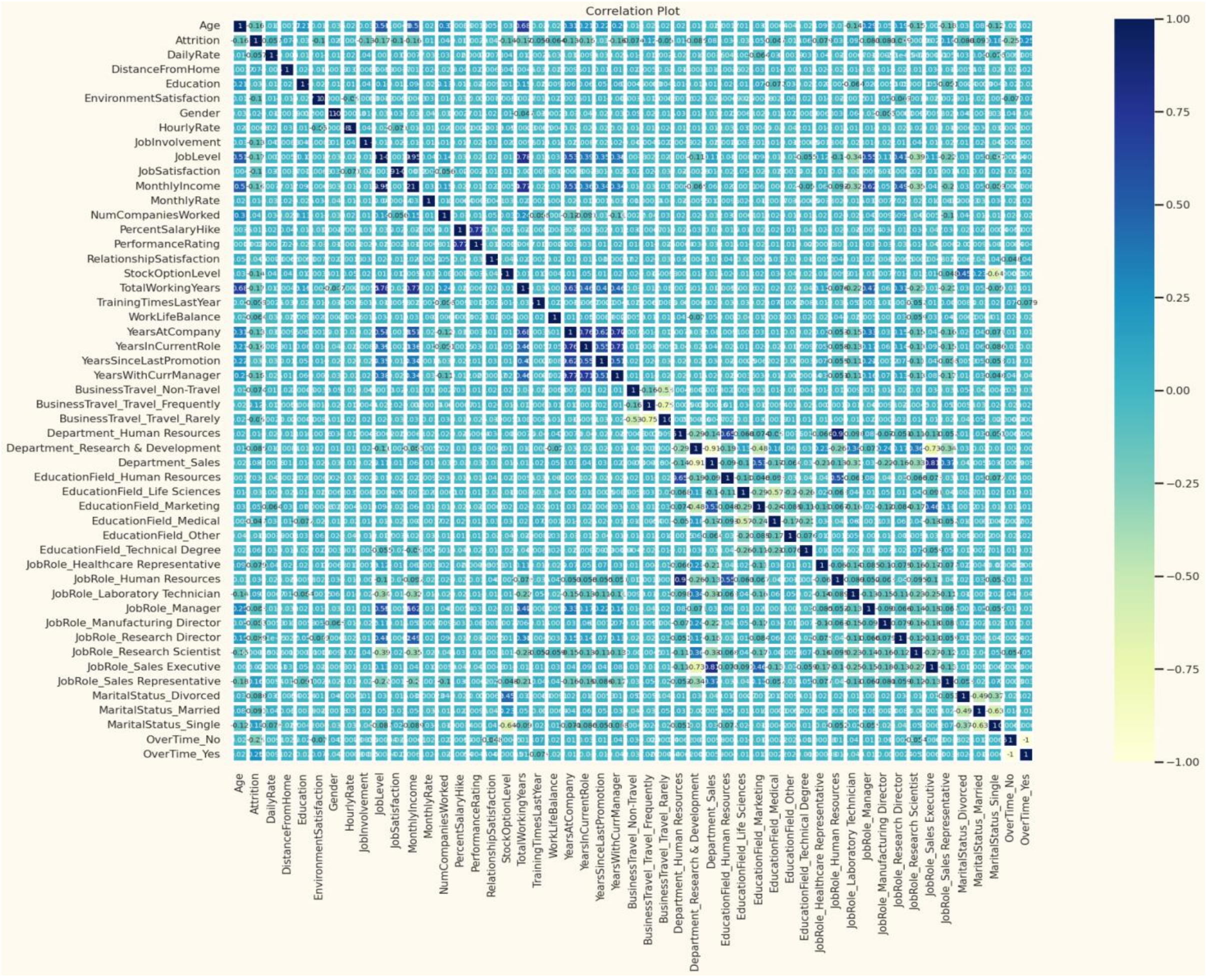

Figure 4.2 snapshot of heatmap

After encoding, the original categorical columns are dropped from the dataset, as they have been replaced by their encoded counterparts. This ensures that all features in the dataset are numeric, which is a requirement for most machine-learning algorithms.

A correlation matrix is then computed to identify the relationships between different features. A heatmap is created to visualize these correlations, highlighting features that are highly correlated with each other. Features with a correlation coefficient greater than or equal to 0.75 are considered highly correlated. Highly correlated features can introduce multicollinearity in the model, leading to redundancy and potentially affecting model performance. Therefore, features such as "JobLevel", "TotalWorkingYears", "PercentSalaryHike," "YearsInCurrentRole" and "YearsWithCurrManager" are identified as highly correlated and are dropped from the dataset.

4. Feature Importance and Extraction

To analyze the importance of categorical features in employee attrition, the Chi-Square test is used. The Chi-Square test evaluates whether there is a significant association between categorical variables and the target variable, in this case, "Attrition." This statistical test is particularly useful for categorical data as it helps identify features that have a statistically significant relationship with the target variable.

First, we select the categorical columns from the dataset and exclude the target variable "Attrition" from this list. The Chi-Square test is then performed for each categorical column to compute the Chi-Square statistic and the p-value. The Chi-Square statistic measures the difference between the observed and expected frequencies, while the p-value indicates the significance of the observed association.

5. Data Modeling

For understanding patterns and relationships within data, various machine learning models have been implemented. This step involves fitting the model to the training data, `x_train` and `y_train`, which prepares the model. Once the model is trained, it predicts the outcomes for both the training and testing datasets (`x_train` and `x_test`), generating predictions (`x_train_pred` and `x_test_pred`) and probabilities (`y_test_prob`) for the testing data.

The function then calculates various performance metrics. Accuracy scores for both training and testing data indicate how often the model makes correct predictions. Precision and recall metrics provide insight into the model's performance concerning positive predictions: precision measures the correctness of positive predictions, while recall measures the model's ability to identify all actual positives. The ROC AUC score assesses the model's ability to distinguish between classes, providing a single measure of performance across different threshold values. The F1 score harmonizes precision and recall into a single metric. Cohen's kappa score evaluates the agreement between predicted and actual values, accounting for the possibility of agreement occurring by chance, and the balanced accuracy score provides a balanced measure of accuracy, accounting for class imbalances.

5.1. Logistic Regression Model

The logistic regression model serves as a valuable statistical tool for predicting binary outcomes, making it particularly suitable for addressing employee attrition in the Human Resources (HR) domain. The dataset utilized for this analysis comprises historical employee records that include several attributes related to employee demographics, job characteristics, performance metrics, and workplace environment.

Model Training

Once the data was preprocessed, the logistic regression model was trained on the dataset. The training process involved splitting the dataset into training and testing subsets, typically using an 80-20 split. The training subset was utilized to fit the model using the following logistic regression equation:

$$P(Y=1|X)=\frac{1}{1+e^{-(\beta_0+\beta_1X_1+\beta_2X_2+...+\beta_nX_n)}}$$

Where:

P(Y=1|X) is the probability that an employee will attrite (leave the organization) given the input features X.

β0 is the intercept term.

β1, β2, …, βn are the coefficients of the predictor variables X1, X2, ..., Xn.

The logistic regression algorithm optimizes the coefficients β through maximum likelihood estimation, which seeks to maximize the likelihood of observing the given data under the model.

5.2. The K Nearest Neighbors (KNN)

The K Nearest Neighbors (KNN) model serves as a robust classification technique for predicting employee attrition in Human Resources (HR) by analyzing the proximity of employee data points in the feature space. This non-parametric method relies on the idea that similar employees exhibit similar behaviors and characteristics, allowing for effective attrition prediction based on historical employee data.

The model utilizes a comprehensive dataset containing various employee attributes, including demographic information, job-related factors, performance metrics, and workplace environment variables.

Model Training and Evaluation

The K Neighbors Classifier model is trained on a subset of the data, typically using an 80-20 split for training and testing. The model predicts employee attrition based on the "K" nearest neighbors within the feature space. The optimal value of K is determined through techniques such as cross-validation, where various K values are tested to identify the one that yields the highest accuracy.

5.3. Naive Bayes

The Gaussian Naive Bayes model was applied to predict employee attrition based on various employee-related features. This section provides an evaluation of the model's performance using key metrics such as accuracy, precision, and recall.

Gaussian Naive Bayes assumes that the features follow a normal (Gaussian) distribution. The likelihood of the features given a class C is modeled using the Gaussian probability density function (PDF):

$$P(x_i|C) = \frac{1}{\sqrt{2\pi\sigma_C^2}} \exp\left(-\frac{(x_i - \mu_C)^2}{2\sigma_C^2}\right)$$

where:

- xi is the feature value.
- μC is the mean of the feature for class C.
- σ2C2 is the variance of the feature for class C.
- P(xi ∣C) is the likelihood of observing xi given class C.

The model then applies Bayes' theorem to compute the posterior probability for each class:

$$P(C|x) = \frac{P(C)\prod_{i=1}^{n} P(x_i|C)}{P(x)}$$

where P(C∣x) is the posterior probability of class C given the input features x= (x1, x2, ..., xn), and P(C) is the prior probability of class C.

5.4. Decision tree

The Decision Tree model was evaluated on the Employee Attrition Data to assess its performance across several metrics, such as accuracy, precision, recall, and the ROC AUC score.

5.4.1. Accuracy of the Decision Tree

The accuracy of the model is the proportion of correctly classified instances over the total number of instances. It can be calculated as:

$$\text{Accuracy} = \frac{\text{True Positives (TP)} + \text{True Negatives (TN)}}{\text{Total Number of Samples}}$$

In this evaluation:

- The model achieved 100% accuracy on the training data, which is a sign of overfitting, where the model memorizes the training set.
- On the testing data, the accuracy was approximately 85%, indicating that while the model performs well on unseen data, it still overfits the training data.

5.4.2. Precision and Recall

Precision and recall help to measure the model's performance in identifying the relevant instances (employees at risk of attrition) and avoiding false positives.

- Precision is defined as: Precision indicates the proportion of true attrition cases among all the cases the model predicted as attrition. A balanced precision means the model is not prone to false positives.
- Recall (or sensitivity) is defined as: Recall measures the proportion of actual attrition cases that the model correctly identified.

The model's precision and recall scores are balanced, which means it performs well in both predicting employee attrition and avoiding false positives.

5.4.3. ROC AUC Score

The ROC (Receiver Operating Characteristic) AUC (Area Under the Curve) score is a metric that measures the model's ability to distinguish between classes (i.e., employees who will leave vs. those who will stay). It is calculated by plotting the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings.

$$\text{AUC} = \int_0^1 \text{TPR}(FPR)\, d(\text{FPR})$$

- where TPR is the true positive rate, and FPR is the false positive rate.

For this Decision Tree model, the ROC AUC score is 0.848, which indicates strong discriminatory power. A score of 1 indicates perfect classification, while a score of 0.5 indicates random guessing.

5.5. Using Whale Optimization

In this evaluation, the Whale Optimization Algorithm (WOA) is integrated with the Decision Tree model to optimize its performance on predicting employee attrition. WOA helps to fine-tune the hyperparameters of the Decision Tree, improving its predictive power and generalization. Here's an overview of the evaluation with equations:

5.5.1 Whale Optimization Algorithm (WOA) Overview

The Whale Optimization Algorithm is inspired by the bubble-net hunting strategy of humpback whales. WOA mimics the foraging behavior of whales to find the optimal solution in a search space. In the context of Decision Trees, WOA optimizes parameters like maximum tree depth, minimum samples per leaf, and criterion for splitting nodes.

WOA uses the following steps for optimization:

- **Encircling prey:** Whales move towards the best solution by adjusting their positions.
- **Bubble-net attack:** Whales exploit local solutions by spiralling towards prey, simulating a shrinking circle.
- **Exploration:** Whales randomly search for new solutions globally to escape local optima.

The optimization process is represented by:

$$\mathbf{X}(t+1) = \mathbf{X}^*(t) - A \cdot |C \cdot \mathbf{X}^*(t) - \mathbf{X}(t)|$$

where:

- X(t+1) is the updated position,
- X∗(t) is the position of the best solution found so far,
- A and C are control parameters that influence exploration and exploitation.

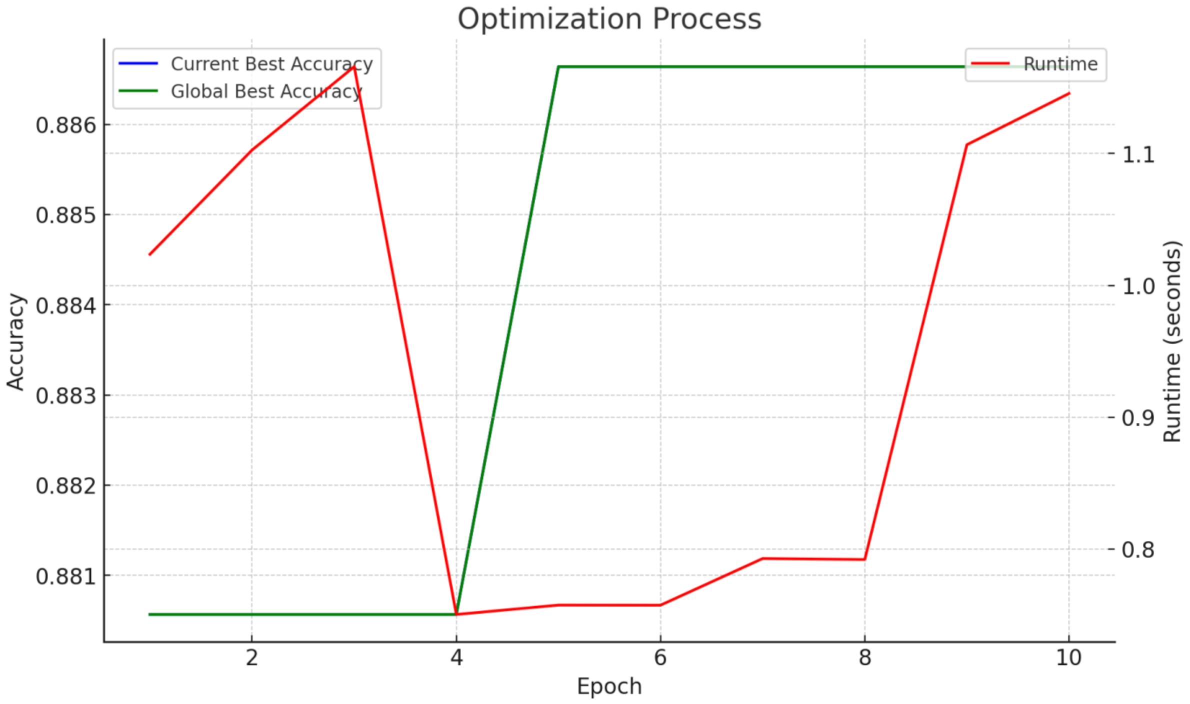

Figure 4.3 WOA optimization on Decision tree

Best agent: id: 2153, target: Objectives: [0.88663968], Fitness: 0.8866396761133604, solution: [6.72668832 61.24362074]

Best solution: [6.72668832 61.24362074]

Best accuracy: 0.8866396761133604

Best parameters: {'max_depth': 6.726688321958532, 'min_samples_split': 61.243620739410204}

5.6. Random Forest

The evaluation of the Random Forest model on the Employee Attrition Data shows its performance in predicting whether employees will leave or stay.

The Random Forest model achieved perfect accuracy on the training data with a score of 100%, indicating that the model has learned the training data extremely well, which suggests overfitting. On the testing data, the model achieved an impressive accuracy score of approximately 92.91%, showing strong generalization to unseen data.

RESULTS AND DISCUSSION

Perform an exploratory data analysis (EDA) to understand the structure and distribution of the dataset. We begin by visualizing key features to observe patterns, trends, and potential outliers. Histograms, bar charts, and box plots are utilized to display the distribution of numerical features such as Age and DailyRate, while pie charts and count plots provide insights into categorical features like Attrition, BusinessTravel, and Department. Correlation matrices and heatmaps are employed to identify relationships between variables, helping us detect multicollinearity and understand how features may interact. This initial visualization sets the foundation for deeper analysis by highlighting significant trends and anomalies in the data.

Visualizing the Employee Attrition Rate

In this section, we aim to provide a clear picture of the employee attrition rate within the dataset. To achieve this, we use following charts to visualize the data effectively.

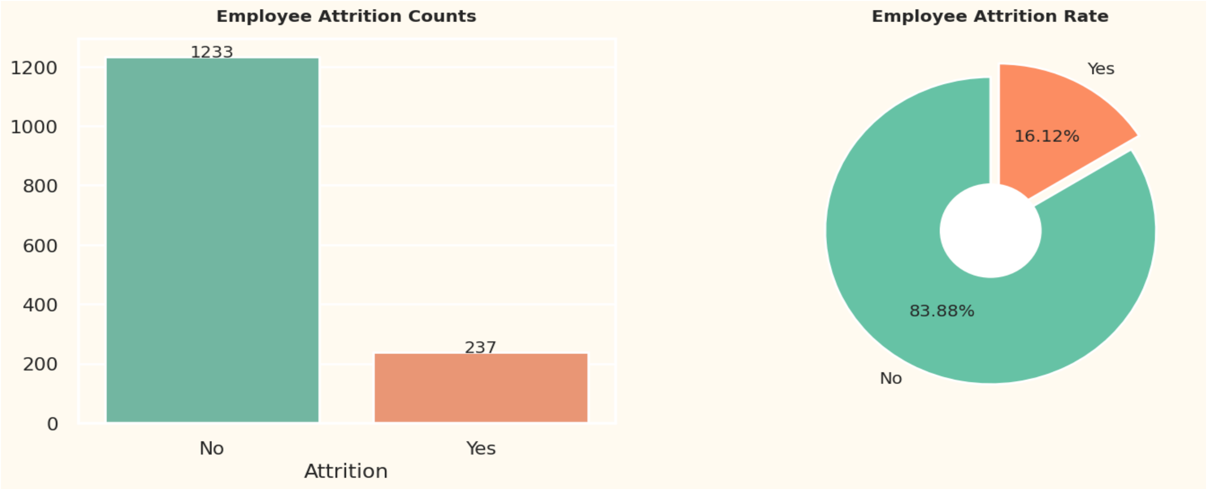

Figure 5.1: Employee attrition rate

Graphs showing the percentage of employees who have left (16.12%) versus those who have stayed (83.88%). The trends that we see are that the attrition and attrition rate is much lower than the number of employees that stay.

Analyzing Employee Attrition by Department

In this section, we analyze the impact of department affiliation on employee attrition rates to identify any department-specific trends or issues.

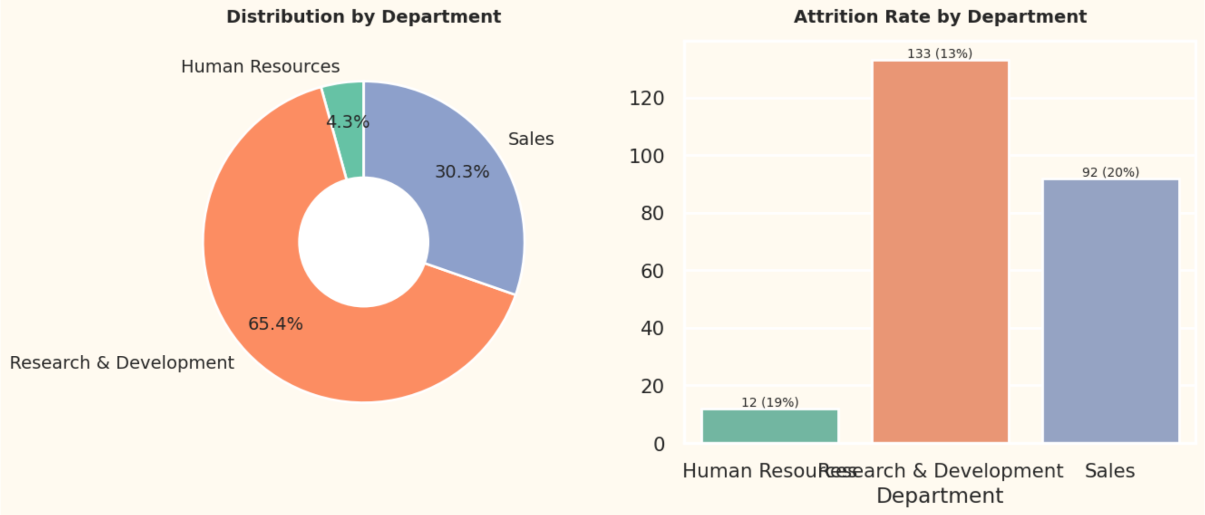

Figure 5.2: Employee attrition by Department

The data reveals that the Sales department has the highest attrition rate at 20%, followed closely by Human Resources at 19%, while Research & Development has the lowest attrition rate at 13%. These figures suggest that employees in Sales and Human Resources are more likely to leave the company compared to those in Research & Development.

Analyzing Employee Attrition by Job Satisfaction

In this section, we investigate the relationship between employees' job satisfaction levels and attrition rates to understand how satisfaction influences employee turnover.

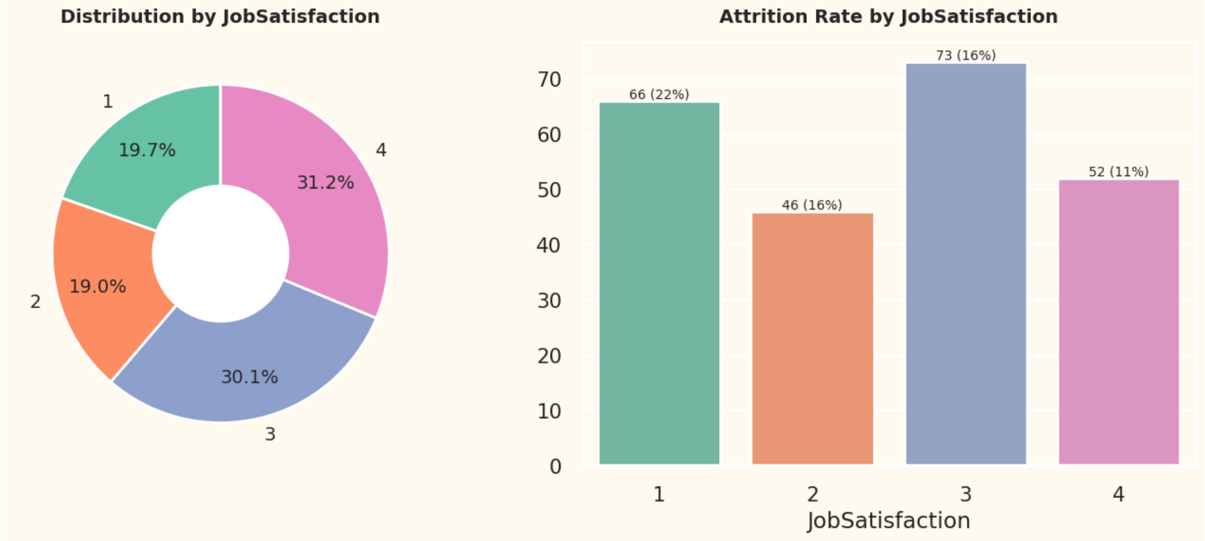

Figure 5.3: Employee attrition by Job Satisfaction

The data reveals the following attrition rates: employees with a job satisfaction level of 1 (Low) have the highest attrition rate at 22%, those with a satisfaction level of 2 (Medium) and 3 (High) both have an attrition rate of 16%, while employees with a satisfaction level of 4 (Very High) have the lowest attrition rate at 11%.

Analyzing Employee Attrition by Over Time

This section examines how working overtime impacts employee attrition rates, providing insights into whether extended working hours influence employees' decisions to leave the company.

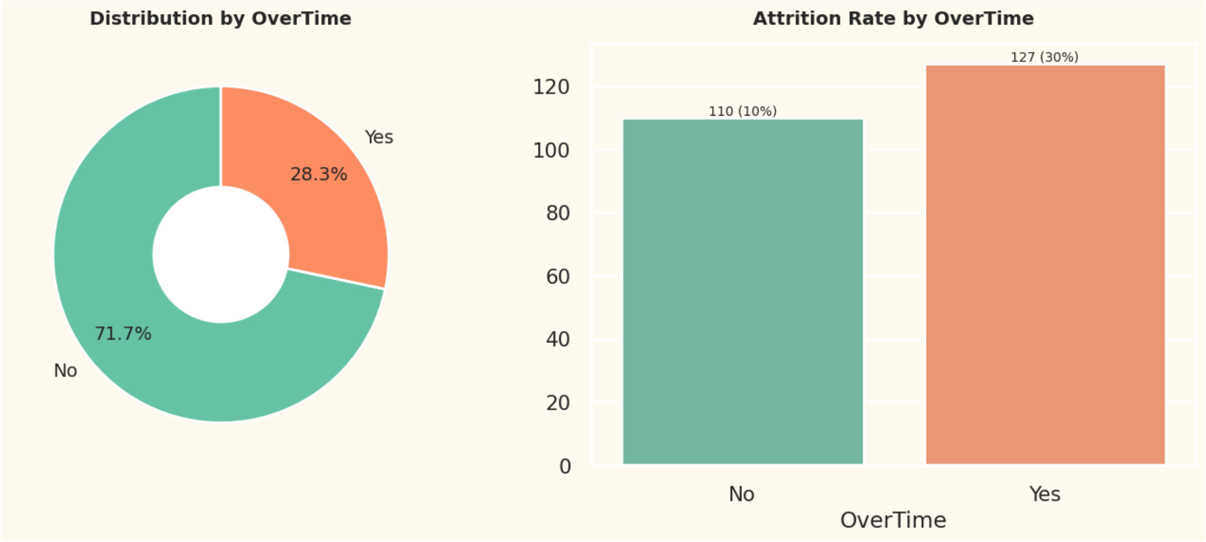

Figure 5.4: Employee attrition by Over Time

The data reveals that employees who do not work overtime have an attrition rate of 10% (110 employees), whereas those who work overtime have a significantly higher attrition rate of 30% (127 employees).

Analyzing Employee Attrition by Job Roles

Analyzing employee attrition by job roles reveals significant variations in turnover rates across different positions within the organization.

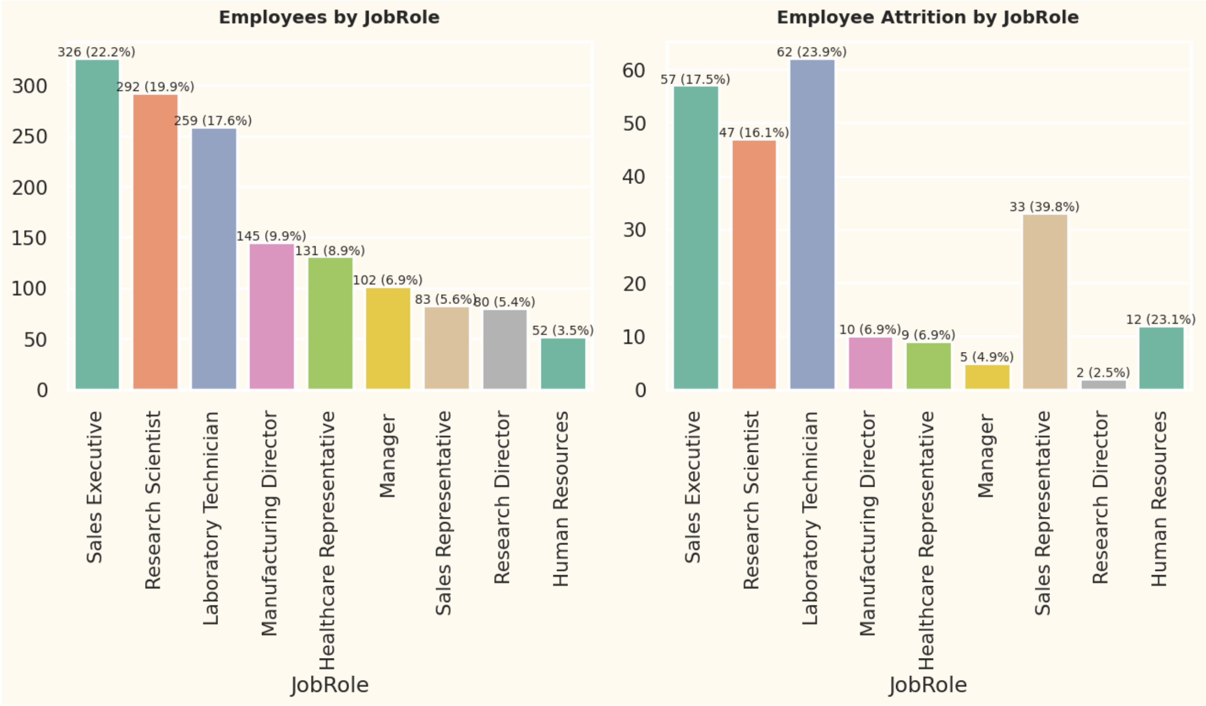

Figure 5.5: Employee attrition by Job Roles

Data Modelling

Decision Tree

The Decision Tree model evaluation for the Employee Attrition Data reveals several insights into its performance. The Decision Tree model achieved perfect accuracy on the training data, scoring 100%. This indicates that the model has perfectly memorized the training data, a classic sign of overfitting. On the testing data, the model achieved an accuracy score of approximately 84.82%, suggesting it correctly predicted the attrition status for around 85% of the instances.

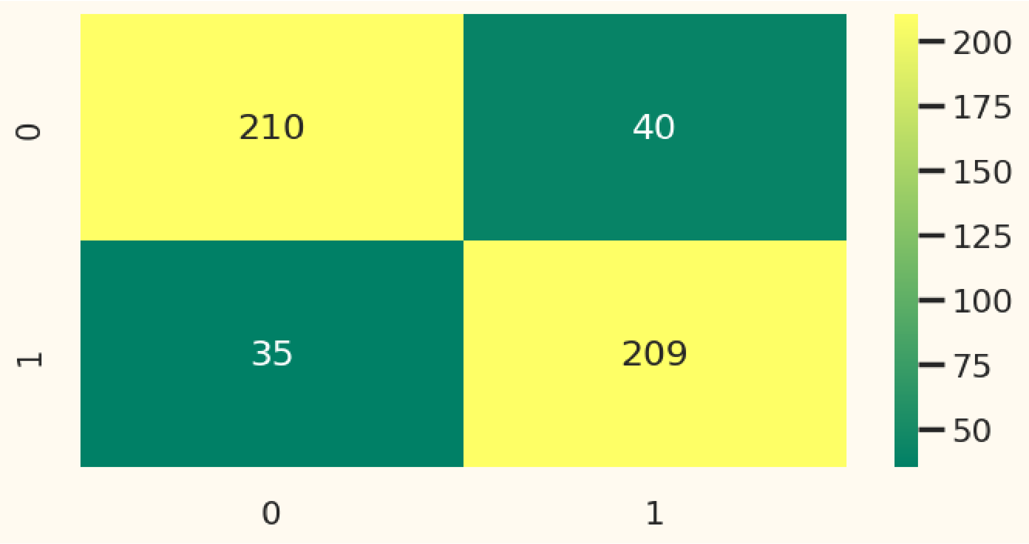

Figure 5.6: Decision Tree model evaluation

The precision score of 0.84 (or 84%) for the positive class indicates that when the model predicts an employee will leave, it is correct 84% of the time. The recall score of approximately 85.66% suggests that the model successfully identifies around 86% of the employees who actually leave. The balanced precision and recall values suggest the model is equally good at identifying employees who will leave and at avoiding false alarms.

The ROC AUC score of 0.848 (or 84.83%) reflects the model's ability to distinguish between employees who leave and those who stay. This score indicates a strong overall performance in ranking employees by their likelihood of attrition.

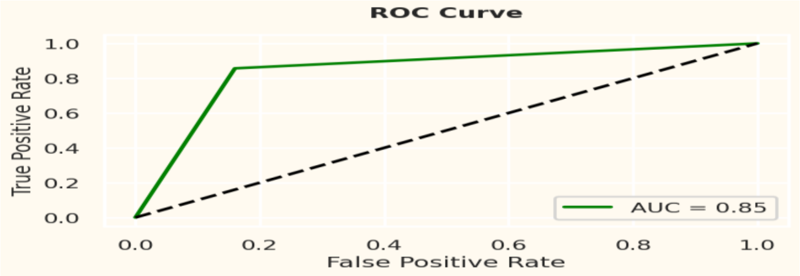

Figure 5.7: Decision Tree ROC AUC

The classification report provides additional insights into the model's performance for each class. For the non-attrition class (0), the precision is 0.86, recall is 0.84, and the F1-score is 0.85. For the attrition class (1), the precision is 0.84, recall is 0.86, and the F1-score is 0.85. This indicates a well-balanced performance across both classes, with similar precision, recall, and F1-scores.

The key points from this evaluation are:

- The Decision Tree model exhibits perfect accuracy on the training data, which suggests overfitting.
- Despite overfitting, the model performs well on the testing data with an accuracy of approximately 85%.
- Precision and recall scores are balanced, indicating the model's good performance in both predicting employee attrition and avoiding false positives.
- The ROC AUC score of 0.848 suggests strong discriminatory power.

Overall, the Decision Tree model provides a robust performance for predicting employee attrition, with balanced metrics and high accuracy, though the perfect training accuracy indicates a need for regularization or pruning to prevent overfitting and improve generalizability.

Using Whale Optimization

Figure 5.8 shows, the best agent (ID: 3230) in the optimization process achieved an objective (accuracy) of 93.32% with a fitness score of 0.9332. The best solution for this agent involved using 185.42 estimators and a learning rate of 0.7066. This configuration yielded the highest model accuracy of 96.32%. These parameters (n_estimators and learning_rate) were optimized through the Whale Optimization Algorithm (WOA), providing the best model performance in this case.

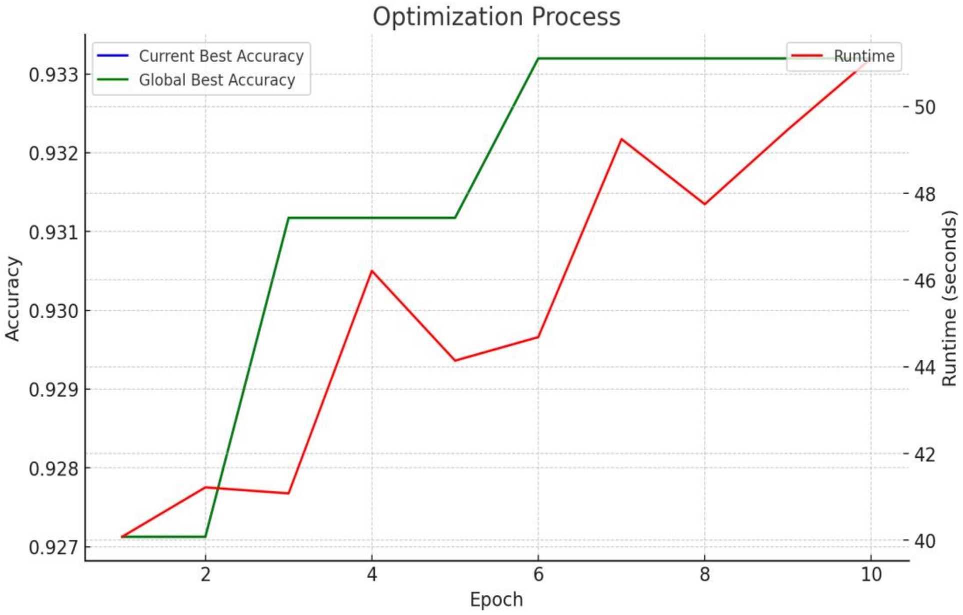

Figure 5.8: Optimized result using Whale Optimizations

Random Forest

The evaluation of the Random Forest model on the Employee Attrition Data shows its performance in predicting whether employees will leave or stay:

The Random Forest model achieved perfect accuracy on the training data with a score of 100%, indicating that the model has learned the training data extremely well, which suggests overfitting. On the testing data, the model achieved an impressive accuracy score of approximately 92.91%, showing strong generalization to unseen data.

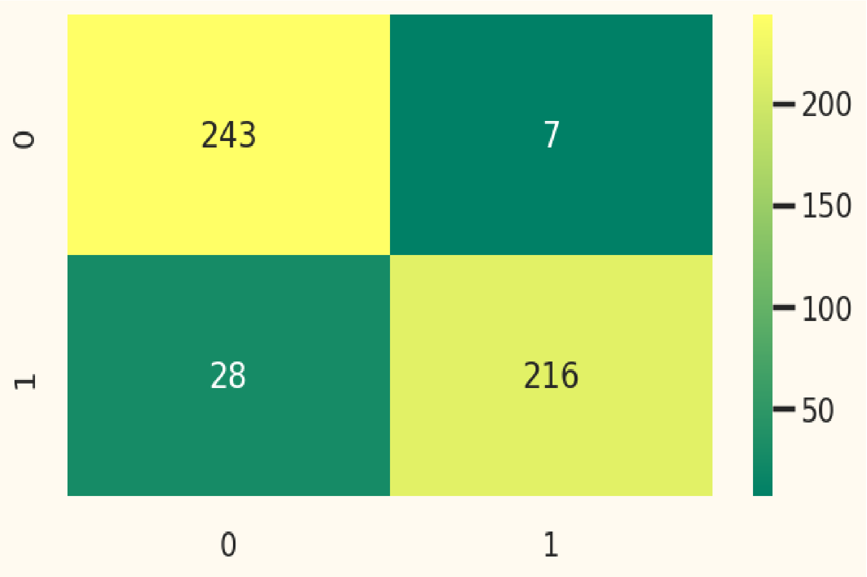

Figure 5.9: Random Forest data modelling

The precision score of 0.969 (or 96.86%) for the positive class indicates that when the model predicts an employee will leave, it is correct 96.86% of the time. The recall score of approximately 88.52% indicates that the model successfully identifies around 88.52% of the employees who actually leave. This high precision is valuable as it means fewer false positives, and the high recall indicates good sensitivity in identifying actual leavers.

The ROC AUC score of 0.980 (or 97.96%) reflects the model's exceptional ability to distinguish between employees who leave and those who stay. This near-perfect score indicates that the model performs extremely well in ranking employees according to their likelihood of attrition.

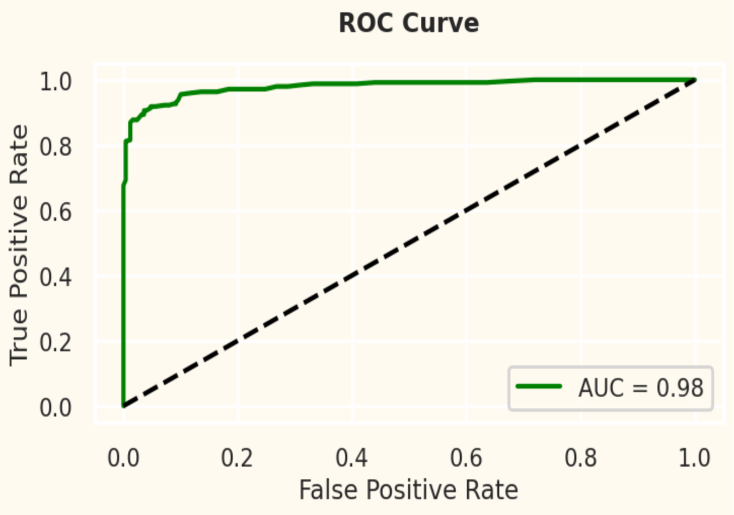

Figure 5.10: Random Forest data modelling

The classification report offers further detail on the model's performance across both classes. For the non-attrition class (0), the precision is 0.90, recall is 0.97, and the F1-score is 0.93. For the attrition class (1), the precision is 0.97, recall is 0.89, and the F1-score is 0.93. These metrics are very high and balanced, indicating strong performance across both classes.

Key points from this evaluation are:

- The Random Forest model shows perfect accuracy on the training data, indicating overfitting.
- Despite this, the model performs exceptionally well on the testing data with an accuracy of approximately 92.91%.
- The precision and recall scores are high and well-balanced, showing the model's effectiveness in predicting both classes.
- The ROC AUC score of 0.980 indicates an excellent ability to discriminate between employees who will leave and those who will stay.

Comparison with Existing Solutions

S. No.	Algorithm	Accuracy
1	Decision Tree	85%
2	Random Forest	92.91%
3	Ada Boost	93.10%
4	XG Boost [34]	95.14%
5	Proposed (Decision Tree+ Whale Optimization)	96.31%

Given table compares the accuracy of various algorithms, highlighting improvements made by the proposed method. The Proposed Method (Decision Tree + Whale Optimization) achieved the highest accuracy of 96.31%, outperforming XGBoost (95.14%), Ada Boost (93.10%), and Random Forest (92.91%). The traditional Decision Tree algorithm performed the lowest with 85% accuracy. This shows the significant performance boost gained through optimization techniques in the proposed method.

CONCLUSION

The HR recommender system designed using the decision tree analysis combined with the Whale Optimization Algorithm (WOA) provides valuable insights into the factors influencing employee attrition. The findings from the decision tree analysis, optimized through WOA, highlight several key predictors of turnover.

Processing employee attrition data using a Decision Tree and Whale Optimization Algorithm (WOA) offers several advantages. Decision Trees are intuitive and easy to interpret, allowing HR professionals to visualize factors driving attrition, such as age, gender, tenure, or job satisfaction. They efficiently handle both numerical and categorical data, making them suitable for HR datasets. Incorporating WOA for hyperparameter tuning enhances model accuracy by optimizing parameters like tree depth and split criteria, leading to better predictions. WOA mimics whale behavior for global and local search, improving optimization over traditional methods like grid search.

However, Decision Trees can be prone to overfitting, especially with smaller datasets, leading to less reliable predictions on unseen data. While WOA improves parameter tuning, it may require considerable computational power and time for large datasets, limiting its efficiency in real-time applications. Furthermore, Decision Trees are less effective with imbalanced datasets—common in employee attrition data—where attrition is rare compared to retention.

This research can be applied in various HR tasks, such as predicting employee turnover, identifying at-risk employees, and improving retention strategies. It can also aid in optimizing hiring processes by forecasting the longevity of new hires. These insights enable HR professionals to develop personalized retention strategies, ultimately reducing operational costs associated with attrition.

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