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## **Integrating Machine Learning with HRIS to Optimize Workforce Management**

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### **ABSTRACT**

The operation of HRIS & their key influence on organizational employee record handling and data informed decision-making in HRIS are of a noteworthy importance. Organization efficiency improvement, especially in organizational resource distribution, possible through forecasting employee performance and turnover metrics, is possible through HRIS utilization and ML (machine learning) application. Therefore, this research is motivated in part by trying to improve the capabilities of HRIS through the development of a proposed optimized model, SHROF (Smart HR Optimization Forest). The research makes use of the employee records of a given organization. The data is subjected to Z Score Normalization in the preprocessing stage in order to scale the numerical attributes, which in this case are salary and performance. To achieve this, PCA (Principal Component Analysis) is utilized. The SHROF model has made noteworthy gains in terms of accuracy Improvement in prediction, thereby facilitating effective decision making and improved employee performance. Regulatory submissions indicate SHROF to be 99.3% accurate, 92.7% precise, with 78% and 84% of the F1 score corresponding to 92.7% recall, thereby shining a spotlight on the model to predict the above metrics with considerable accuracy which strengthens its adaptability to a broad class of HRD (high dimensional HR data to be derived. This with the added competence of employee attrition to optimize HRD (high dimensional data) to improve resource utilization and the overall efficiency of the managerial decision making in the HR domain Determining the competence of the model, SHROF predict employee turnover providing a clear pathway in the refinement of effective HR D (High dimensional HR data). Overall SHROF provides a clear pathway to the refinement of effective organizational HRIS.



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**Keywords:** Organizational Efficiency, Machine Learning, Random Forest, Employee Turnover Prediction

### Introduction

In the current digitally transforming business ecosystem, the Human Resource Information System (HRIS) has become a necessary technology for the management and administration of workforce activities. HRIS and technology and functions automation human resource of range wide and out a applied software is comprehensive. It allows organizations to store, manage, and process all employee-related records. This pertains to functions like recruitment, payroll and benefits management, and performance and compliance management and administration [1].

Traditionally, HR departments employed manual paperwork and autonomous siloed systems. Workforce spatial increased complexities, and systems digitized integrated needed for grew rapidly, the demand across HR activities. Employee onboarding, attendance, performance, and ad hoc report creation are several activities, of HRIS all modern systems. These systems help manage salary, training, employee engagement, and analytics management systems [3][21].

Operational efficiency is increases significantly and chance manual errors is decreased automation of processes routine. It offers organizations greater organizational changes, faster decision, and an are more role to assist. System filters and due dates, tax compliance, employee contracts and compliance are processed statutory, providing ensures processes automation [6][16].

One of the most notable benefits of HRIS is the ability to lower operational expenditures. It removes physical records and optimizes administrative tasks to redistribute resources more effectively [18][12]. This enables HR to move on from transactional administrative tasks to more important strategic functions like organizational talent development.

To improve an organization's efficiency, it is necessary to incorporate systems and practices that improve output by reducing time, cost, and resources spent [8][10]. Integrating employee data and automating HRIS functions culminates in the system's ability to provide analytics to assist in evidence-based decision-making. This enables HR Managers to identify trends in employee performance, gauge employee satisfaction, and take measures to mitigate the risk of turnover.

Furthermore, the field of HRIS has also improved due to the implementation of machine learning. ML systems attribute valuable functions to HRIS such as predictive employee attrition, recruitment funnel optimization, individualized learning path construction, and augmentation of succession planning. These predictive and adaptive functions attribute HRIS as an important resource in the development of human capital for workforce planning [17][4].

HRIS has transformed from a basic system to a valuable tool for managing an organization's most important assets. It enables the organization to not only enhance administrative efficiencies, but also align employee skill sets with the organization's strategies. Given the complexities of today's workforce, as well as the increasing competition for business, a well configured HRIS is essential to achieving sustained growth and performance.

### Literature Review

There has been a focus study concerning the combination of computational intelligence and human resource management. There has particularly been a focus in three areas: evaluation of employees' performance, prediction of employees' attrition, and decision support systems. Several studies focused on the use of computational intelligence to



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predict behavior of employees and enhance HR planning [5]. Most of these studies use some combination of ensemble learning models, which utilize multiple classifiers, to predict behavior of employees and enhance HR planning. These models can include Decision Trees (DT), Naive Bayes (NB), and Fuzzy Logic. Furthermore, some studies use Text Sentiment Analysis (TSA) to derive meaning from the sentiments of employees from unstructured testimonials. The studies that have been accomplished have shown versatility of the ensemble systems through consistency, robustness, and interpretability of results that predictive activities can, therefore, be used in any organization.

Attrition prediction represents a key focus area in today's organizations, and ML techniques have been extensively applied in this domain. Implementing algorithms such as Decision Trees (DT), Logistic Regression (LR), and K-means clustering have uncovered influencing factors including, but not limited to, overtime work, job ranks, and workloads of projects to determine employee turnover [13], [20]. These studies identified factors triggering employee turnover. DT showed the best accuracy, while Random Forest (RF) overall was more precise due to its ensemble nature and overfitting avoidance. Furthermore, the use of DT and RF demonstrated excellent results in the accuracy and precision of employee turnover prediction, respectively. Competency classification, in particular, has been addressed using more lightweight and interpretable models. For example, one study deployed Naive Bayes (NB) and KNN to predict employee's competency levels, based on some skill input parameters [7]. KNN outperformed NB in accuracy, confirming its usefulness on highly structured HR datasets. Simple models, as demonstrated in this study, have the potential to deliver enormous benefits to HR functionalities operating under resource limited conditions.

Optimizing the objectivity and fairness of performance evaluations, an inherently subjective process, is another vital area of study. ML models such as DT and KNN have incorporated Binary Particle Swarm Optimization (BPSO) to tune hyperparameters and boost classification performance [14], [23]. These models have improved predictive robustness assessed by sophisticated measures such as the Matthews Correlation Coefficient (MCC) with confusion matrices. In these studies, KNN prevailed and had the highest F1 scores which indicated its proficiency to mitigate the adverse impact of class imbalance and to finely differentiate employee performance [19], [29].

The optimization of workforce management potential of AI and predictive analytics within human resource information systems (HRIS) and Organizational Management Systems (OMS) through data driven approaches has been addressed in various studies [22]. Similar to resource allocation approaches in IT systems, strategies pertaining to data storage optimization in HRIS remain paramount for handling employee information needed for managing and predictive performance, and performance analytics [23]. Some studies have attempted to incorporate distributed ledger technology (DLT) for data security and transparency of employee data and its use for turnover related predictive analytics and performance data [24]. Consistent with the use of intelligent forecasting systems in the energy sector, machine learned (ML) HRIS systems have been used to predict the future demand for labor in terms of turnover and training costs, which has improved management of HR resources [25].

Improving transparency of predictive models through large language models (LLMs) and explainable AI has begun to impact HR decision making by revealing trends and patterns within employee behavior data [26]. The value of transfer learning, which has been reported in healthcare analytics, also has relevance in employee performance prediction modeling, where past data is taken into account similar to the adaptation of ML models for prediction analytics in HRIS. Predicting employee outcomes, whether successful or



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exiting the company, has become a focal point for organizations [27]. Finally, the integration of advanced contextual comprehension within HR chatbots, which are becoming increasingly prevalent within HRIS, permits deeper and more meaningful exchanges with employees, enriching the employee experience and streamlining the more effective functioning of HR activities [28].

Nonetheless, new models continue to exhibit other challenges as they through additional domain datasets process, interpret, and tune hyperparameters. These problems signal the need for additional predictive ensemble mechanisms which appropriately integrate and harmonize efficiency, performance, and flexibility to meet the demands of modern HR Information Systems.

### Research Objectives

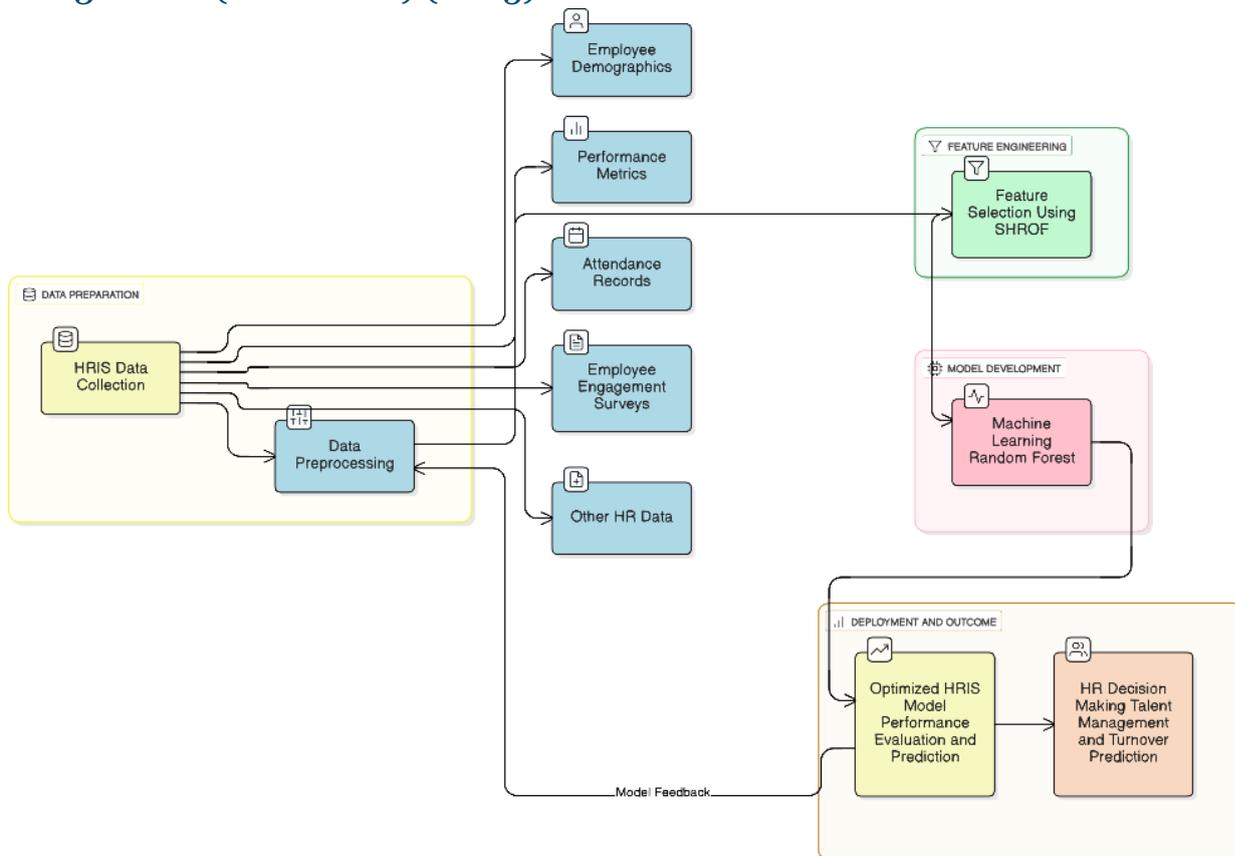
This dissertation revolves around creating and assessing an enhancement to predictive analytics with an integrated estimation model for HRIS named Smart HR Optimization Forest (SHROF) or SHROF. This model aims to improve upon existing capabilities in HR analytics by increasing robustness and efficiencies across various HR functions, including employee turnover forecasting, performance review, and retention planning.

SHROF, to improve employee performance forecasting, combines the Random Forest (RF) classifier with Enhanced Golden Jackal Optimization (EGJO), a metaheuristic optimization algorithm based on the cooperative hunting strategies of golden jackals. EGJO is used to optimize the RF hyperparameters and simultaneously improve feature selection for a better predictive process. The SHROF model combines the best characteristics of features to solve the challenges of predictive human capital analytics.

SHROF will assist in performance evaluations, employee role classifications, talent detection, and early-offboarding prediction, among other additional features of the HRIS. It is built to respond to the urgent necessity of intelligent systems that adapt, as well as advanced, to address the requirements of the industry, as a result of the increasing demand for ‘smart’, ‘adaptive’, and ‘high performance’ HR systems capable of real-time or near real-time complex multidimensional data analysis. Processing complex, high-dimensional data in real-time or near-real-time In this manner, SHROF uplifts both the theoretical side of HR analytics and the practical side of analytics for organizations.

### Methodology

The main focus of the proposed approach of the SHROF (Smart HR Optimisation Forest) model is the improvement of prescriptive analytics in the selective recruitment of HRIS (Human Resource Information System) by integrating enhanced golden jackal optimisation with random forest techniques. The main processes of the proposed methodologies include: 1. data collection; 2. data pre-processing; 3. dimensionality reduction; 4. development of predictive algorithm. Each of these core analytic processes is intended to attain optimum predictive learning efficiencies balance along with accurate predictive capturing of various HR predictive analytics functions, such as employee churn, employee retention and employee performance prediction.



**Fig.1 Framework Architecture for Integrating Machine Learning with HRIS to Optimize Workforce Management**

The diagram in Figure 1 depicts the methodology for incorporating Machine Learning (ML) into Human Resource Information Systems (HRIS) for workforce optimization. It covers the entire cycle from data training to the HR outcome and illustrates the potential of machine learning in HR functions such as employee retention prediction, performance evaluation, and resource allocation.

At the Data Preparation stage, the process starts with HRIS Data Collection, where the employee information such as demography, attendance, performance, employee engagement surveys and other HR data are archived and retrieved. This diverse data collection serves as the critical inputs for prediction and analysis by the system. The information gets subjected to Data Preprocessing, where the dataset is cleaned, and the raw data is normalized to ensure that the data is consistent and of good quality. Various methods like Z-score normalization and Principal Component Analysis (PCA) are used to scale and reduce the data before passing it to the next stage.

In the feature engineering stage, the data undergoes additional processing depending on the results of the previous stage. Specifically, data undergoes feature selection using the smart HR optimization forest (SHROF)<sup>5</sup>. SHROF is an adapted random forest (RF) model which utilizes additional optimization mechanisms to select features and to make predictions in an optimal manner. Using SHROF prevents additional computations on features that are unlikely to be relevant to the prediction task, which increases the efficiency and effectiveness of the model training.

Each stage in the process model is sequential in nature. In keeping with this business process model approach, the subsequent stage is model development. In this stage the features from the previous stage are used. The features are used as inputs to a machine



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learning model, specifically, a random forest (RF) model in which the RF algorithm is used to train and build a predictive model. The random forest algorithm is also a good candidate for this problem as it is able to manage a large dimension of features and perform robustly on HR predictive analytics, such as predicting employee turnover and employee performance scores. The algorithm is an ensemble of decision trees and gives a prediction with the average of the outputs of the trees to produce a more generalized prediction.

Finally, the Optimised HRIS Model comes into play in the Deployment and Outcome phase. This model, which has additional optimised features, assists many HR functions like performance review, turnover forecasting, and talent management. The model's forecasts guide HR Decision Making, enabling the HR functions to adopt a more analysed approach to workforce planning, employee turnover, and performance management.

The framework demonstrates harmonised machine learning at work to enhance HRIS for better, precise, and more scalable workforce management. This approach improves organisational productivity and employee satisfaction by enabling HR professionals to make more informed decisions through the automated analysis of data, enhancing the prediction of data.

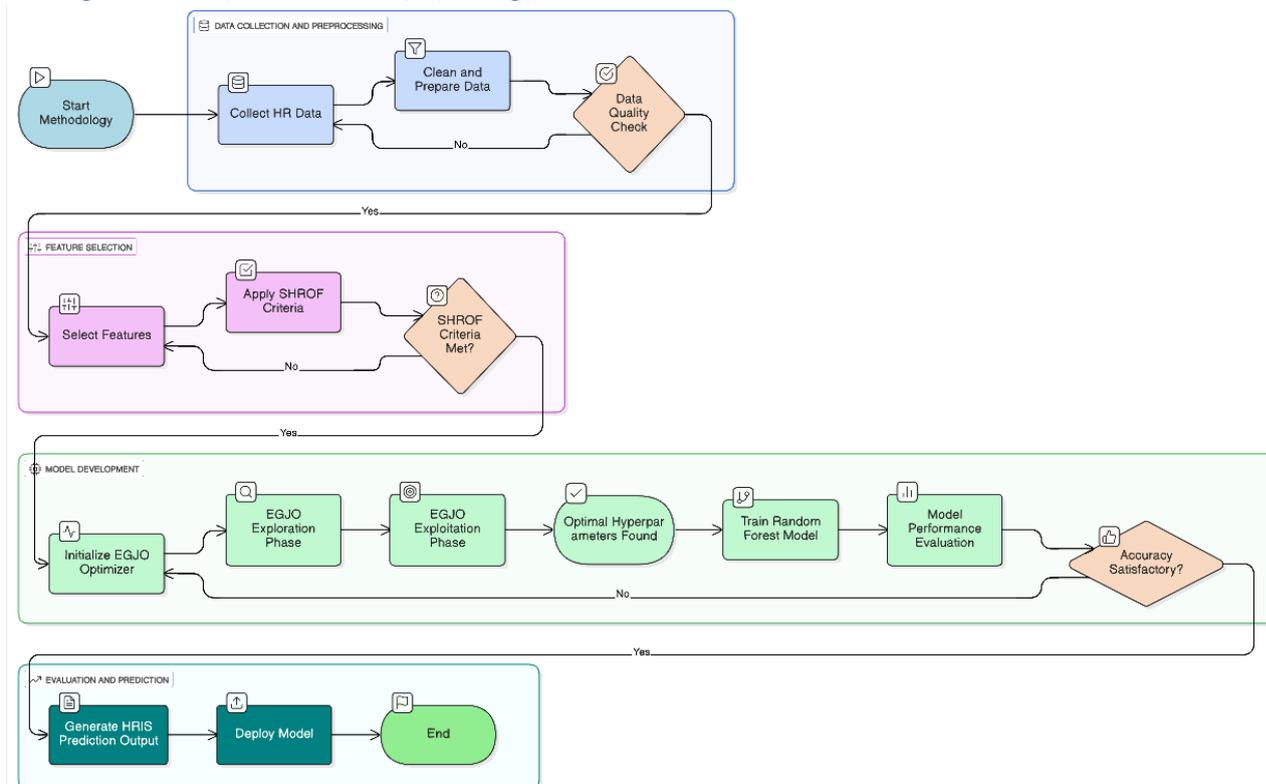
The predictive model developed on an HR dataset published on the digital platform, Kaggle. The dataset contains separable employee records including employee satisfaction score, employee average monthly working hours, the number of projects an employee has been assigned to, last performance score of the employee, evaluation score, promotion status in the last five years, level and classification of salary, and HR department division. The goal of the dataset is to develop a model that predicts employee attrition, as well as performance behaviors.

Prior to conducting any model training, data subject to Z-score normalization is to be pre-processed. Z-score is a data normalization technique that transforms all the selected numerical features to a standard numerical range. Salary and performance scores values are a standard numerical range that is within equal distance to the mean, and are thus normalized to prevent such features from dominating the weighted average scores. The normalized  $W'$  value of any selected feature  $w$  is defined in the following equation:

$$W' = (w - \alpha) / \beta \text{ ----- (1)}$$

where  $\alpha$  denotes the mean of the {feature} and  $(\beta)$  its standard deviation. This transformation increases performance and stability of the training of the model by {outlier} mitigation.

In order to overcome the challenges of high dimensionality and feature redundancy, Principal Component Analysis (PCA) {was acquired} for feature extraction. PCA transforms {covariate features} into a set of smaller, mutually orthogonal, and uncorrelated variables termed {principal components} which retain the greatest proportion of variability in the dataset. This approach not only reduces computational load, but also increases the effectiveness of learning in the downstream classifiers by retaining the most salient features of the {data}.



**Fig.2 Flowchart of the Methodology for HRIS Prediction using SHROF**

SHROF, the core prediction model, was constructed{,with} the EGJO metaheuristic algorithm {for} hyperparameter optimization of the RF classifier, after reduction. The EGJO {is} a metaheuristic inspired by the hunting behavior of {golden jackals}. It mimics {two} fundamental behaviors, {Exploration} and {Exploitation}. In the exploration phase, jackals search the space of interest by moving and repositioning themselves:

$$Z_1(t) = Z_n(t) - E * |Z_n(t) - q_1 * Prey(t)| \beta \text{ ----- (2)}$$

The jackal's position  $Z_n(t)$ , random Levy flight vector  $q_1$ , and Position Prey(t), whereby E is the energy level which weakens corresponding to the prey's state, represent the prey position, and prey Position Prey(t). When a solution is discovered, the jackals' positions toward the prey are conver that step in the, exploitation phase, to exploit the position of the prey.

$$Z(t+1) = (Z_1(t) + Z_2(t)) / 2 \beta \text{ ----- (3)}$$

This equation defines the new and refined location of the prey (solution), having been fully surrounded by the jackals and, thereby, proving convergence. The prey, in our case, signifies the best available combinations of HR policy, whereas the jackals represent the diverse, but, in this case, suboptimal, ways of convergence to a solution.

The optimized parameters obtained through SHROF are subsequently utilized to train the RF model. RF represents an ensemble learning method wherein numerous decision trees are formed, and their individual outcomes are compiled for predictive purposes. The RF model's ultimate output,  $\hat{y}$ , is the mean value of the individual predictions derived from each of the trees, expressed as:

$$\hat{y} = (1/T) \sum_{t=1}^T f_t(x), \text{ for } t=1 \text{ to } T \beta \text{ ----- (4)}$$

where T refers to the total number of trees and  $f_t(x)$  denotes the output of the  $t^{th}$  prediction from the decision tree. RF is exceptionally robust high-performing classifiers,



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especially when it comes to high dimensional HR data, and is less vulnerable to overfitting because of the ensemble nature of RF.

The SHROF model is implemented with five configurable hyperparameters. These are number of trees, maximum depth of the tree, learning rate, population size, and number of iterations. These hyperparameters were obtained from the EGJO designed optimizer to improve the model's prediction and generalization. The combination of EGJO and RF is therefore a perfect model with great finesse, recall, and simplicity. This is ideal for high-level computational HR applications like performance tracking, retention prediction, and workforce optimization.

### Results and Discussion

In order to assess the predicted utility of the Smart HR Optimization Forest (SHROF) model for predicting HRIS-based outcomes, the experiments were conducted within a virtual environment constituted of Windows 10, 16 GB RAM and Python 3.8.10. Model training and optimization were facilitated through the use of the TensorFlow and Keras Deep Learning libraries. The SHROF model is a hybrid of Enhanced Golden Jackal Optimization (EGJO) and Random Forest (RF) designed to improve accurate predictions of key human resource metrics such as employee turnover and performance rating. The predicted model performance was compared to two other ML models, Decision Tree (DT) and Extreme Gradient Boosting (XGBoost), across a variety of metrics including but not limited to accuracy, precision, recall and F1.

A comparison of the models of interest for accuracy and precision is illustrated in Table I. These metrics become critical in the field of HR concerning the outcome and implications of accurate positive predictions (e.g., employee attrition, high performance) and classification of the outcomes to the organization.

**Table-I Accuracy and Precision Comparison across Models**

Model	Accuracy (%)	Precision (%)
Decision Tree (DT)	99.1	92.1
XGBoost	70.85	68.45
SHROF (Proposed)	99.3	92.7

As illustrated in Table I, SHROF has attained the highest accuracy of 99.3%, slightly better than that of DT at 99.1%, but significantly better than XGBoost at 70.85%. In that order, SHROF also has the highest precision at 92.7%, followed closely by DT at 92.1%, whilst XGBoost lagged at 68.45%. This confirms that the proposed model is the best in terms of predictability, particularly in the context of HR where false positives need to be eradicated to increase confidence in the decision made.

Beyond accuracy and precision, Table II provides the model's comprehensive results which encompasses both recall and F1-score. Recall denotes the model's capability in detecting true positive instances, for instance, predicting an employee's resignation. The F1-score is the best measure to use when precision and recall is to be used, especially with the imbalanced nature of datasets in HR where one of the classes (i.e. the exiting employees) is drastically smaller than the other.



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Table-II Recall and F1-Score Comparison across Models

Model	Recall (%)	F1-Score (%)
Decision Tree (DT)	76.6	83.6
XGBoost	57.55	62.53
SHROF (Proposed)	78	84

As indicated by Table II, compared to baseline models, SHROF has the highest recall score of 78% and F1 score of 84% per the chosen parameter. While DT performs relatively close with 76.6% recall and F1 score of 83.6%, once more, XGBoost has the lowest recall of 57.55% and F1 score of 62.53%, resonating with the underperformance trend. These additional results of SHROF prove further adaptability, especially the borderline retention of F1 score, among models with the balance of overall recall score in biasing towards prominence in efficiency, or in other terms, in the precision of the prediction.

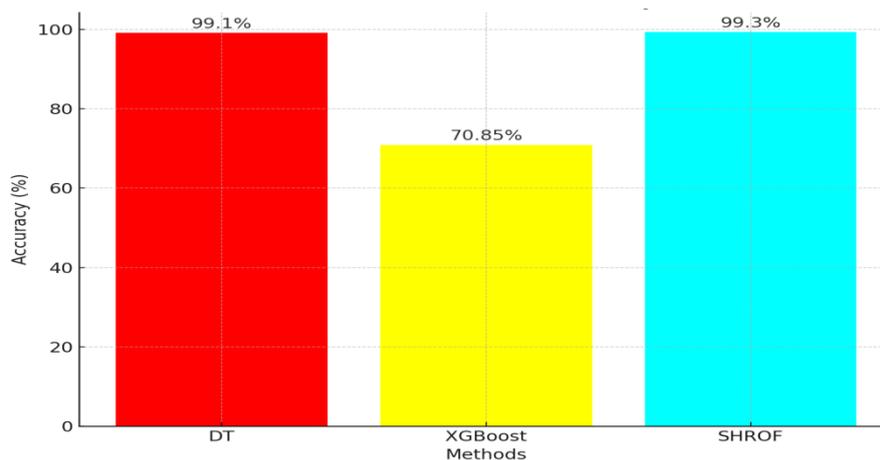
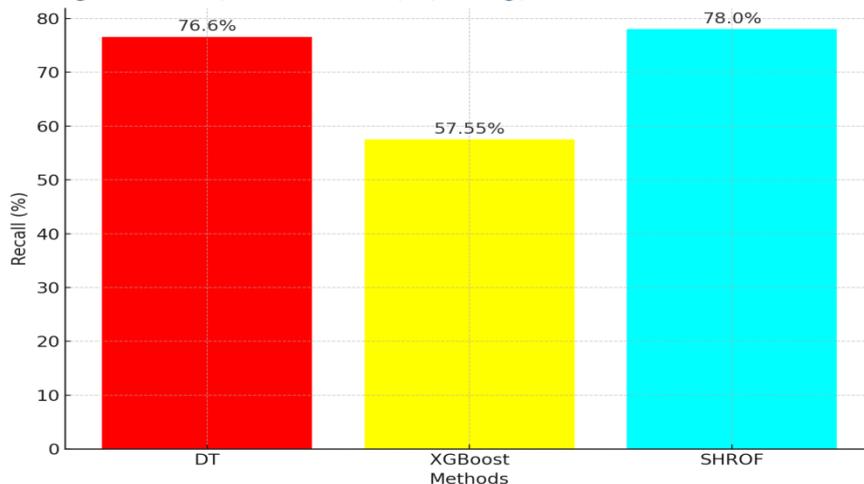


Fig.3 Results based on Accuracy for SHROF comparisons

All four metric results returning improvements overall validated the capability of SHROF model in the context of HRIS prediction. With the bounded parameter space, EGJO's hyperparameter tuning integration leaves a positive determination on feature selection, rate of convergence, Random Forest classifier's overall effectiveness on highly dimensional, complex HR datasets, if not all in the consolidation by the ensemble. Plus, the combined exploration-exploitation behavior EGJO with the ensemble of RF offers a markedly generalized model as per results aligned with the desire in the opposite of overfitting to remain the model in range of reliable, consistent, prediction showing across diversified HR indicators.



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**Fig.4 Results based on Recall for SHROF comparisons**

Conclusively, the operational efficiency of SHROF model in the rapid prediction of the highly accurate results in performance evaluation of HR functions and retention planning, workforce optimization as continuum in performance evaluation of workforce to provide more HRIS functions with data-driven support, shaping the strategic decision with streamlined model to the identified range of Human Capital in the organization, depicting organizational efficiency greatly.

**Conclusion**

We derived the SHROF model from the Enhanced Golden Jackal Optimization with Random Forest optimization. This hybrid model attempts to improve the efficiency and prediction powers of human resource information systems. Most human resource information systems face challenges with predicting employee turnover and the human resource performance evaluation systems. Most of the data sets used in this domain are public. For this study the data public resource in human resources information systems was used. Data pre processing was executed with Z score methodologies. Principal Component Analysis was utilized to retain pertinent data while expediting the processing speed of the model.

EGJO refined the hyperparameter tuning and feature selection to set another record in the performance of the RF classifier. SHROF can make data driven and predictive human resources decisions and significantly improve organizational performance by achieving 99.3% accuracy, 92.7% precision, 78% recall, and 84% F1 score. Most prediction systems in human resources using Decision Trees and XGBoost are outperformed by this prediction model.

While the current research works with a single data set, it must be, albeit reluctantly, accepted that the findings of this research work may not be widely accepted and, consequently, not be generalizable to different organizations. Further studies should be conducted with the assistance of multiple, larger and more heterogeneous data sets, enabling the incorporation of different variables and parameters, and utilizing the data sets in real time in order to adapt the data toward a more heterogeneous multiple ensemble approach. In addition, further work on the EGJO tuning process should result in faster speeds of convergence, allowing a more extensive application of the research to more generalized and other branches of human resources such as recruitment, workforce management and succession planning.



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