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EMPLOYEE PROMOTION PREDICTION USING IMPROVED ADDITIVE REGRESSION CLASSIFIER ALONG WITH ANN (ARTIFICIAL NEURAL NETWORKS)

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ABSTRACT
Employee development is an important component of human resource management that facilitates human development within the organization. The purpose of the this study is to develop a machine learning algorithm to predict employee growth. For a realistic increase prediction, a modified Additive Regression Classifier is mainly used. Modified Additive Regression Classifier is primarily used for automatic campaign forecasting, and its performance is compared to other devices study design such as Additive Regression Classifier, XGBoost (XGB), Support Vector Machines (SVM), Dispatch Systems regression (LR), random forest (RF), and artificial neural networks (ANN). Monitoring the effectiveness of these Machine learning algorithms for predicting professional development are evaluated through a comprehensive evaluation process which applies analytical metrics to employee analytics data management. The results show that compared to the normal machine learning methods, artificial neural network (ANN) and additive regression classifier models are employed alright. In addition, a modified additive regression classification strategy with an accuracy of 95.30% is proposed. It outperforms all other measures considered.
Keywords: Additive Regression Classifier, Machine Learning, Predictive Systems, Employee Development

I. INTRODUCTION

There are many factors involved in the process of promoting employees within an organization, especially in large organizations with many divisions. Each department, including IT, Marketing, Research and Development, Accounting, Human Resources, and. have a specific role in production and the day-to-day operations of the company. Human Resources (HR).[1] The

department is one of the most important because they are responsible for recruitment. dismissal and promotion of employees. Identifying progress is important for HR and employees Precisely because they have not only monetary rewards but social status, career interests, as well inspiration. But the process of incentives, especially in large organizations, is complex.

A decision that is sometimes compounded by a lot of paperwork and the need to sew data from different sources. Promotions are affected by many variables, and organizations may have different priorities These are the parts. Innovation, efficiency or performance, seniority or experience, courtesy, punctuality, performance Qualifications, education and ethnic influences are common factors.[2] Because of its positive impact a Company's reputation and profitability, innovation tends to be highly regarded. An employee's performance is. Efficiency determines whether they are good enough to be promoted, and how well their seniority and experience may prove Problems can be solved. A collaborative working environment is created through altruistic behavior and professionalism It makes the organization successful, and punctuality is a mark of trust. Race and extracurricular play increased promotion rates are generally associated with specific ethnic groups and increase different levels of education.[3]

Machine learning techniques have been applied in research on professional development, including predictive models to analyze various characteristics and aspects that influence development.[4] These models consider characteristics such as age, gender, education level, work history, emotional intelligence and communication style. Some studies emphasize long-term contributions, dedication, loyalty, and punctuality as reasons for promotion; Others focus on core traits and relationships. Effective recruitment strategies are also essential to identify qualified candidates and reduce attrition of job roles. However, several obstacles can be overcome to create an effective campaign forecasting system, such as analyzing variables, protecting data, preserving the integrity of data collection, and reducing bias.[5]

II. LITERATURE REVIEW

Employee turnover is the major barrier to organizational growth as it has a negative impact in the long run process and yield. The advantages of the Extreme Gradient Boosting (XGBoost) method for This study used data from HR information systems to examine determinants of employee turnover (HRIS). The results showed that XGBoost outperformed the other methods in terms of accuracy and uptime efficiency and use of memory. They create post characteristics and core interpersonal features, too.[6] When analyzing the relationship between traits and achievement, there are two main components to the prediction approach. Moreover, random forests were shown to outperform other models when relevant attribute validation, while GINI was used to analyse promotional attributes. Skilled employees must be retained if an organization is to succeed and remain stable. In this study, a machine learning approach with three main functions for resolving wasteful workers.[7]

Initially, Random Forest, K-Nearest Neighbours (KNN), and Support Vector Machine (SVM) techniques were used to train the class-imbalanced dataset.[8] After balancing the dataset, the Adaptive Synthetic technique was used, and the previously discussed techniques were subsequently used for retraining. In order to establish class balance, manual undersampling was finally carried out.[9-12] Effective human resource management (HRM), which makes use of big data and artificial intelligence technologies to evaluate various professional traits and improve organisational devotion and work happiness, must prioritise fostering talent and ensuring employee contentment.[13]

Due to high turnover rates, business organisations gain from reducing repetitive duties such regularly issuing job circulars and holding recruiting campaigns. By identifying qualified applicants who are likely to stay with the company, predictive modelling with binary classification lowers recruitment expenses and lessens the chance of sudden turnover.[14] This model predicts applicants' chances of long-term commitment by taking into account key traits such as mental and physical skills.[15]

III. PROPOSED FRAMEWORK

To further clarify the steps involved in data collecting, preprocessing, and feature engineering, we have divided our explanation into many subsections. First, we provide the baseline models that are used to forecast employee promotions. Next, we go into great detail about our suggested model, which is illustrated visually in Figure 1.

A. Dataset: To carry out our investigation and examine the relevant variables impacting promotions, we used the "Employees Evaluation for Promotion" dataset from Kaggle.To improve prediction accuracy, we extracted major and minor characteristics using a feature extraction approach. Notably, resampling procedures were required to create balance because the dataset was previously uneven. The dataset was then split into training and testing sets in a 3:1 ratio so that we could train and assess our suggested machine learning model.

B. Gathering the Raw Dataset: We used a sizable dataset from Kaggle for our research, called the "Employees Evaluation for Promotion" dataset. This dataset includes a variety of employee characteristics, including role, creativity, loyalty, and experience, among others. There was enough of data for analysis in this dataset, which included 54,808 items and 13 characteristics.

C. Preprocessing: "Is promoted," which indicates if an employee received a promotion, was the only target variable out of all the attributes in the dataset.Our prediction system is centred around this binary variable, where values of 1 indicate a promotion and values of 0 indicate no promotion. We indicated these numbers as "YES" and "NO," respectively, for clarification.[16]

D. Balancing Dataset: We used the Synthetic Minority Oversampling Technique (SMOTE) to rebalance the data in order to correct for the imbalance present in the original dataset. To improve model generalization is then it divided the data set into small groups for testing and training purposes.

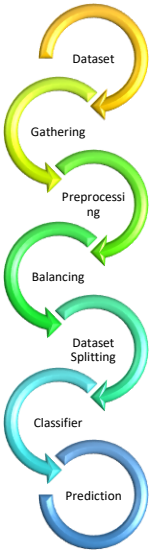

Figure 1: Proposed model workflow

E. E. Feature Engineering: We scrutinized the features of the data set associated with employee amplification Factor Analysis Tool (FAT). As shown in Figure 2, we were able to identify important features Accurate prediction by comparative analysis.

F. F. Major and Minor Removal: Effectiveness of Our learning algorithm relied heavily on feature extraction. It was important to assure positive results for a thorough examination of major and minor features. The extraction procedure was guided by appropriate methods Correlational analysis, which focused on qualities such as creativity, experience and professionalism and others that they thought were most important for the accuracy of forecasting.

G. G. Proposed Approach: To predict actual growth, we first used basic categories such as endorsement vector machines (SVM), logistic regression (LR), artificial neural networks (ANN), random forest (RF), and XGBoost (XGB). For accuracy, we then combined ANNs and provided a unique model classification using Additive Regression Classifications. Our final prediction model is It was developed using an iterative process combining an ANN classifier and an additive regression classifier.[17]

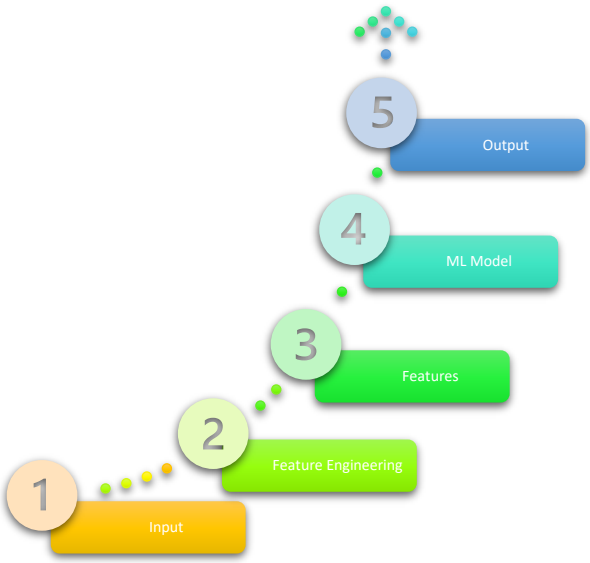

Figure 2: Critical elements in feature engineering

IV. RESULT AND DISCUSSION

a. Experimental design: In this section, we formulate the necessary procedures for designing and conducting our proposed experiment approach. All test systems have an Intel (R) Xeon (R) CPU, 13 GB RAM, 512KB cache, a CPU clock of 2249.998 MHz. It was also introduced as an AMD EPYC 7B12 model. There were specific parameters The choices for our proposed model were: random condition = 0, number of studies = 1, n estimators = 50, base estimator = SVM.

b. Evaluation metrics: Training and testing consist of accuracy, accuracy score, recall score, and F1 score Analytical metrics used with great care to predict employee growth in our machine learning-based analytics. The main features of these coefficients, which are obtained with the illusion matrix are true positive (TP), true negative (TN), false positive (FP), and false negative (FN).

Figure 3 shows confusion matrix and figure 4 shows evaluation metrics

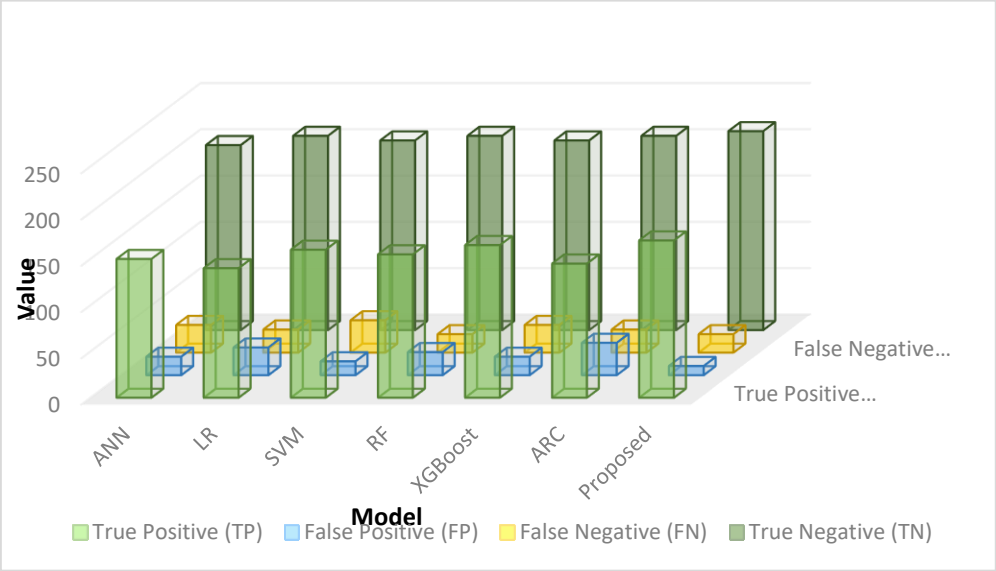

Figure3: Confusion Matrix

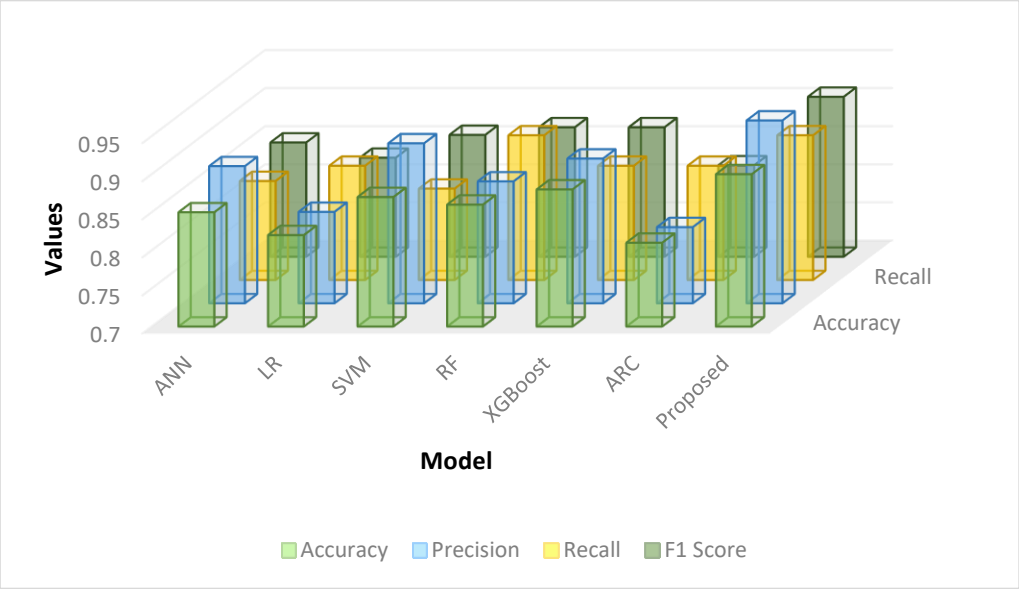

Figure 4: Evaluation Metrics

c. Analysis of the Results: We compared the accuracy, precision, recall, and F1-score of our suggested strategy with those of other conventional machine-learning models. Our suggested model performs better than conventional models, with the greatest accuracy of 95.30%. Notably, with an accuracy of 92.16%, the Additive Regression Classifier model also exhibits good performance. While ANN and SVM have comparable precision rates, LR has the lowest precision of all the models. Moreover, our suggested model is superior in every category except recall, where the LR model is somewhat superior. The effectiveness of various categorization models is depicted by a Receiver Operating Characteristic (ROC) curve, which highlights the higher performance of our suggested model over conventional techniques. Furthermore, our suggested technique outperforms previous efforts on the same dataset. Figure 5 shows the True Positive Rate (TPR) and False Positive Rate (FPR) for different machine learning models

Figure 5: the True Positive Rate (TPR) and False Positive Rate (FPR) for different machine learning models

V. CONCLUSION AND FUTURE WORK

It has become clear from this research how important it is to forecast employee promotions in the human capital development process. In this work, we performed a comparative analysis using five popular advanced machine learning techniques: ANN, LR, SVM, RF, and XGBoost. Real firm data was used to create training datasets, which were then painstakingly analysed to guarantee correctness. After making a prediction using a modified Additive Regression Classifier, the effectiveness of well-known supervised machine learning techniques was assessed using numerical measures. ANN stood out amongst the other models with a better F1 score. The ANN model's Precision and Recall compared favourably to the model with the highest ratings, while not having the greatest percentages of any other model. These outcomes highlight how well Artificial Neural Networks (ANN) perform on this dataset. Our research's conclusions can help organisations reduce employee churn by offering guidance on how to strategically promote staff members.

Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding the present study

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