Predicting Employee Attrition with Deep Learning and Ensemble Techniques: A Comprehensive Study

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***Abstract*— Employee attrition is a substantial problem for many organizations, which leads to disruption and high costs. The capability of understanding the reason behind employee departures is necessary for creating an optimistic work environment and enhancing recruitment strategies. This work aims to undertook a comprehensive analysis for predicting employee attrition using a wide range of machine learning models, from standard to advanced levels, which comprise both deep learning and ensemble models. To analyze the features of employee attrition, we initiated our research by evaluating conventional machine learning models, followed by deep learning models, and ultimately exploring ensemble models. Our study revealed Random Forest as the highest achiever with an accuracy of 98.3%, followed by Gradient Boost and XGBoost with an accuracy of 97.9%.**

Keywords: Machine learning, Deep learning, Ensemble models, Recruitment strategies, Random Forest, Gradient Boost, XGBoost

I. INTRODUCTION

Employee attrition is defined as reducing the labour force due to employee exit from the organization for any reason, either forcible or voluntary[1].It is a challenging problem [2]. Any level of attrition can cause operational disruption, increased recruitment costs, and loss of valuable knowledge and experience. As companies are searching to retain talent, it is important to know what factors act as drivers of employee departure in the drive towards improving retention strategies and maintaining a productive workforce. Human resource departments collects employee performance, compensation, absenteeism, and engagement data. Analysing this data can provide valuable insights, especially in predicting employee turnover. Traditional HR practices often miss these com- plex patterns.

Understanding employee behavior is complex, requiring sophisticated ana- lytical approaches. Machine learning tools can predict attrition by uncovering hidden data relationships, providing more accurate predictions. Advanced an- alytics techniques, including machine learning, offer organizations a better un- derstanding of employee behavior.

To meet this requirement, in our current study, we utilized a broad range of machine learning models that predicting employee attrition, from traditional algorithms to current advanced deep learning techniques and ensemble meth- ods.We initiated using traditional models like KNN,SVM, Naive Bayes,decision trees and logistic regression. These methods helped us establish a baseline anal- ysis to better understand the direct impact of factors like job satisfaction, salary, work environment, and attrition outcome.. We learned that these models could not flexibly exhibit complex, non-linear relations and therefore plunged into deep learning techniques.

Some of the deep learning techniques used were Feedforward Neural Networks FNN,CNN,LSTM. The models are highly skilled at realizing delicate patterns and representations from large amounts of data to predict employee turnover

We use ensemble techniques, including Random Forest, Gradient Boosting, XGBoost, CatBoost, AdaBoost, and the Voting and Stacking methods, where the outputs are the consolidations of disparate predictions by a variety of mod- els that negate individual weaknesses to obtain an improved final result[3]

The study underlines the crucial role of advanced analytics in the analysis and prediction of employee attrition. It can thereby identify the root causes of employee exit and further enable organizations to act proactively towards causes of attrition and put effective retention strategies in place. Random For- est emerges as the highest accuracy *achiever* among the models, hence it is a strong choice for this task. The actual brilliance achieved using these machine learning methods is the arming of organizations to have an agile stable work- force, contributing towards success in the long run. This will be a important competitive strategy as the workplace combines new machine learning techniques for attrition prediction.

II. LITERATURE SURVEY

Praphula Kumar Jain et al. [4] applied different machine learning techniques to a human resource dataset. The results display that the best performance was done by RF algorithm among all methods considered in this work. Rahul Y et al. [5] propose that the K-Nearest Neighbours (KNN) classifier can detect employee attrition with a good degree of accuracy so that the HR department may be better prepared to take steps to minimize the risk of employee turnover about those it might predict to leave.

Ali Raza et al. [6] also discuss limitations of his study and outline future directions such as deep learning techniques could be applied to predict employee attrition. In addition, he wants to look more into the feature space of the dataset and utilize deep learning methodologies with even more precision for making predictions.

Norsuhada Mansor et al. [7] identifies important features that lead to the loss of an employee and develops methods such as hyperparameter tuning that may involve search strategies such as grid search or random search, ultimately delivering the best settings of parameters to improve the performance and scalability of the model.

Arjun Raj M et al. [8] admit that this paper has some limitation such as data limitation and model assumptions. They emphasized that the solving of these problems will advance understanding of attrition dynamics and help in creating tailored predictive models. Their study underlines the deep influence of machine learning on HR management, offering crucial insights to organizations that wish to push for engagement while at the same time being assured of long-termsuccess.
Matilde Lazzari et al. [9] propose two enhancements to their research. One in- volves refining data weights to a more detailed level. Additionally, they suggest testing causal claims using causal graphs derived from the data through causal discovery algorithms.

III. METHODOLOGY

A. Dataset Description

The dataset utilized is HR Analytics of IBM in Kaggle.This dataset comprises demographics, job attributes, and performance measures. Key attributes in the dataset include Age, Attrition, Job Satisfaction, and Monthly Income.

1) Exploratory Data Analysis

EDA is performed for exploring issues with attrition of employees and factors that influence it.

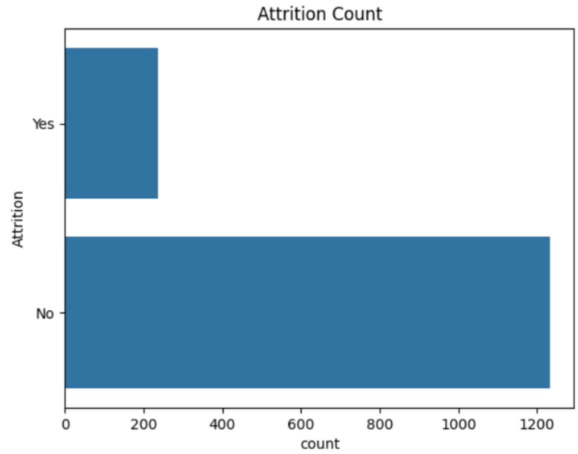

Figure. 1 Count plot

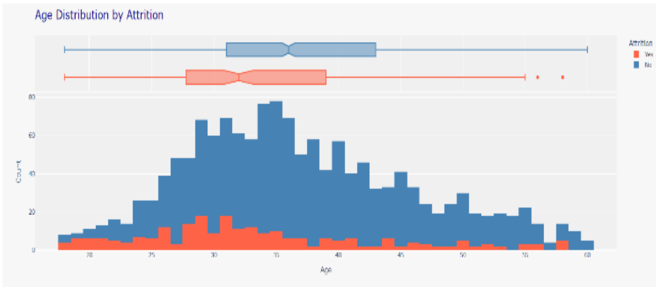

Fig.2 Age vs attrition status Histograms

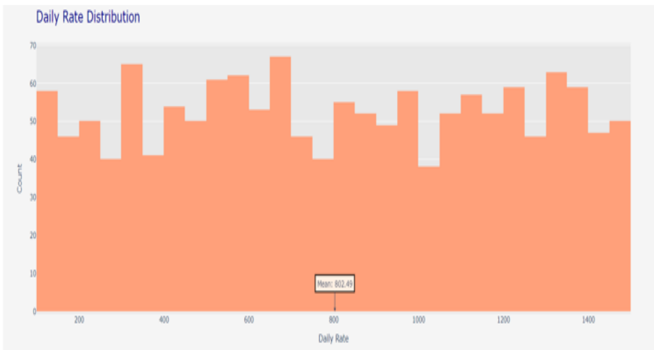

Fig.3 Daily Rate Distributions

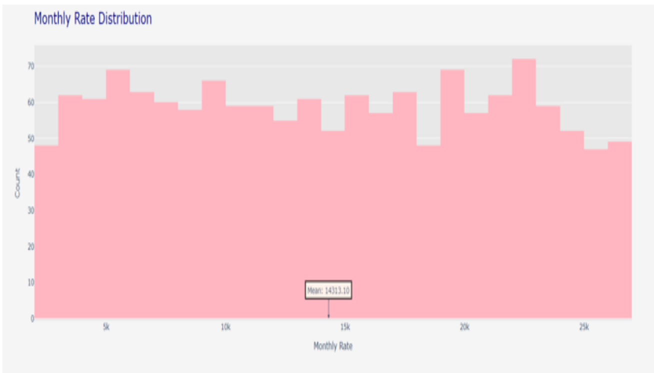

Fig.4 Monthly Rate Distributions

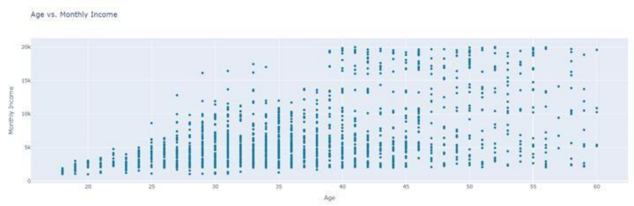

Fig.5 Scatter Plot between age and Monthly income

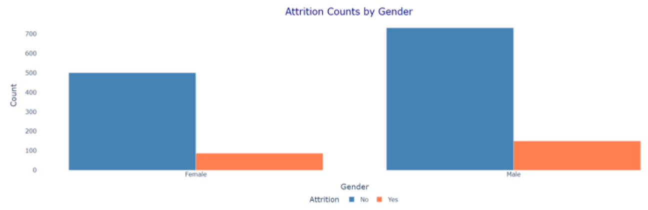

Fig.5 Bar chart of counts by gender

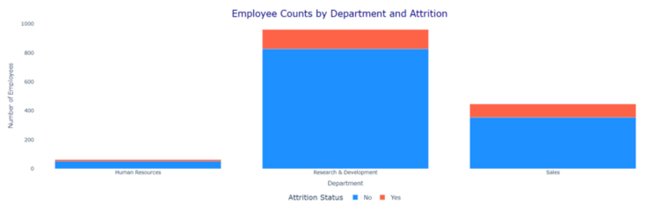

Fig.5 Bar charts of counts by department

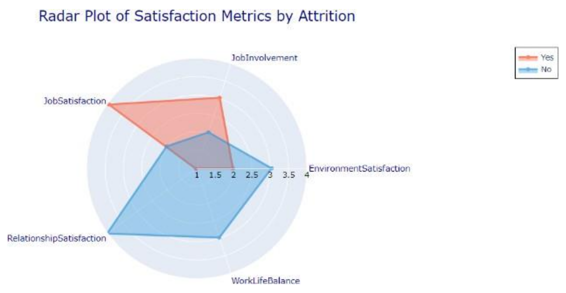

Fig.5 Radar plot

1. Count Plot

Displays the count of the employee by their status on attrition. Since most employees stayed in instead of leaving, it might indicate class imbalance and this would be a challenge to modelling.

2. Age: Histograms of Attrition Status

Age distributions for those leaving with those staying, so it would seem that the younger employee is more likely to leave, suggesting different expectations in the Histogram

3. Daily Rate Distributions

This would give an idea about the variation in salaries for the employees. It would show that low daily rates may have a good deal with high attrition and, therefore, competitive pay policies might be required.

4. Monthly Rate Distributions

As with a daily rate, so too does it indicate that the lower rate of salary in monthly may be associated with higher attrition rates, and fair compensation becomes all the more crucial.

5. Scatter Plot between Age and Monthly Income

Scatter plot will plot an increasing trend of income with age, that is, older- aged workers tend to stay longer perhaps because they have more experience, thus making career development opportunity vital for them.

6. Bar Chart of Counts by Gender

Gender count of Bar chart indicates that men have a higher rate of attrition compared to women, hence, this might suggest retention issues could be gender- specific to some employees

7. Bar Charts of Counts by Department

Department counts of Bar chart focuses on the departments that show the highest rates of attrition hence giving a few pinpointed areas that need focus on departmental areas that would need retention strategies and better working conditions.

8. Radar Plot

It uses the leavers vs. stayers metrics of visual satisfaction thus implies a lower satisfaction level among the leavers, which means it is one of the employee engagement areas where it needs improvement.

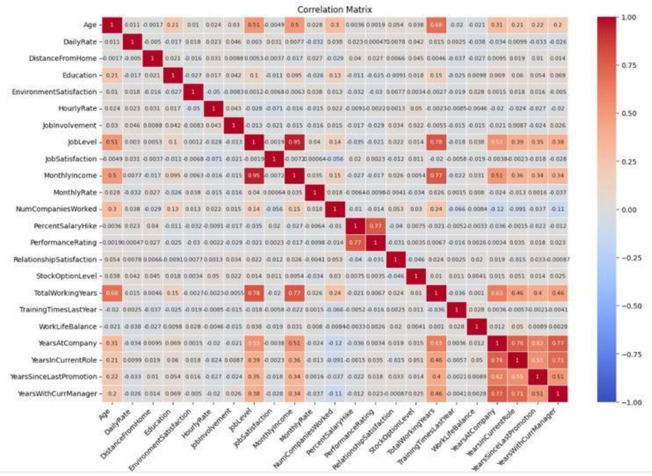

Figure. 2 matrix of correlation

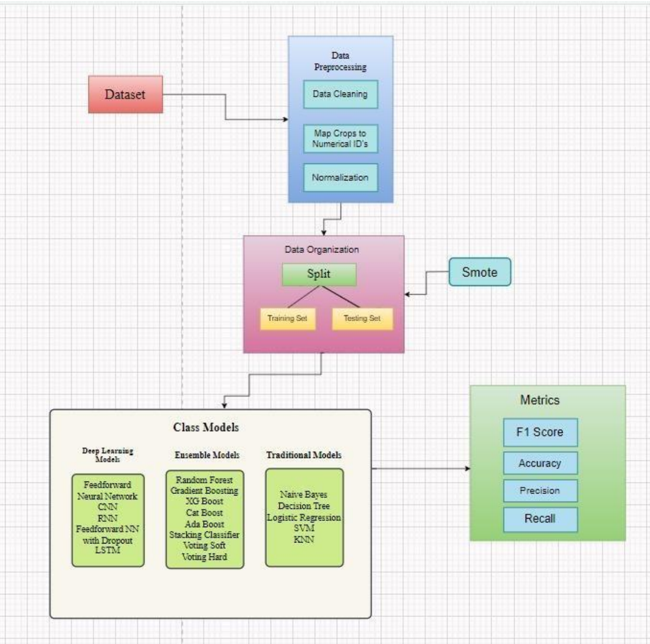

Figure. 3 Proposed Architecture

B. *Preprocessing Techniques*

1) *Handling Missing Values*

Exploratory analysis was conducted prior to this step, including data type inspection and identification of missing values. This provided an overview of the dataset's structure and highlighted columns requiring further processing.

2) *Removal of Irrelevant Columns*

Several columns were dropped from the dataset due to their lack of meaningful contribution to predictive modelling:

Over18: This attribute is always true and, therefore, not useful as a predictor.

Employee Number: This attribute does not contribute to data interpretation.

Employee Count: This attribute remains constant across all records. Standard Hours: This attribute exhibits no variation.

The removal of these irrelevant columns effectively reduced noise in the data, thereby improving model performance.

3) *Encoding Categorical Varibles*

To prepare categorical features for modelling, we applied two encoding methods based on the number of unique values:

For binary categorical variables such as **Attrition**, **OverTime**, and **Gender**, we utilized LabelEncoder to convert categories into a numerical format (e.g., converting ['Yes', 'No'] to [1, 0]).
For categorical variables with multiple unique levels (e.g., **BusinessTravel**, **Department, JobRole**), we employed one-hot encoding using pd.get dummies. This approach creates binary columns for each category, avoiding the creation

4) *Scaling Numeric Features*

To ensure equitable contributions from all numeric features during training, we applied Min-Max scaling using **MinMaxScaler** , to scale down with a range of [0, 1]. This normalization technique is commonly used in machine learning, especially when feature attributes exhibit widely varying magnitudes, to enhance model convergence and performance.

5) *Addressing Class Imbalance with SMOTE and implementing RFE*

The attrition have associated with class imbalance, we applied (SMOTE). SMOTE creates synthetic samples for the minority class (e.g., employees who left) to balance the dataset This balancing improves ability of model by learning from classes like under present, so that it improves predictive performance overall. The dataset is splitted into testing and training applying an 20:80 ratio and there by applying feature recursive elimination.

C. *Models Initilization*

1) Logistic Regression

Logistic regression is applied to predict binary outputs by leveraging the logistic function to model the probability of the target variable.

$$P(y = 1/Z) = \frac{1}{1+e^{-(\beta 0+\beta 1Z1+\cdots+\beta nZn)}}$$

2) K-Nearest Neighbors (KNN)

KNN is a label for a data point which depends on the majority class of its closest 'k' neighbour's, calculated using distance metrics .

$$d(q, q') = \sqrt{\sum_{i=1}^{n}(q_i - q_i')^2}$$

3) Support Vector Machine (SVM)

SVM separates classes by finding the hyperplane with the largest possible margin between the data points of each class.

$$f(x) = b + w^T y$$

4) Naive Bayes

Naive Bayes applies Bayes' theorem with an independence assumption be- tween predictors to classify data.

$$P\left(\frac{C}{Q}\right) = \frac{P(Q/C)P(C)}{P(Q)}$$

5) Decision Tree

Decision Trees split data at decision nodes to categorize it, using measures

$$Gini = 1 - \sum_{i=1}^{n} q_i^2$$

6) Long Short-Term Memory (LSTM)

LSTMs represent a RNN utilizing memory cells to learn long-term dependencies, overcoming the problem of vanishing gradients in standard RNNs.

$$h_t^{\alpha} = o_t^{\beta} \cdot \tanh(C_t^{\gamma})$$

$$f_t^{\delta} = \sigma(b_f^{\epsilon} + W_f^{\zeta} \cdot [h_{t-1}^{n}, x_t^{\theta}])$$

$$C_t^{l} = C_{t-1}^{k} \cdot f_t^{\lambda} + i_t^{\mu} \cdot [\tilde{C}_t]$$

$$i_t^{\zeta} = \sigma([h_{t-1}^{\pi}, x_t^{\rho}] \cdot W_i^{\sigma} + b_i^{T})$$

$$o_t^{P} = \sigma(W_o^{X} \cdot [h_{t-1}^{\psi}, x_t^{\omega}] + b_o^{\varphi})$$

7) Convollutional Neural Network (CNN)

CNNs are applied to process and analyse images. CNNs employ convolutional

layers that automatically learn spatial relationships within input images.

$$S(p, q) = (I * K)(p, q) = \sum_a \sum_b I(a, b)K(p - a, q - b)$$

8) Recurrrent Neural Network (RNN)

RNNs are tailored for predicting sequences, utilizing an internal hidden state to retain information from earlier inputs, enabling them to forecast outcomes based on sequential data.

$$h_t = \sigma(b + W_h \cdot h_{\{t-1\}} + W_r \cdot r_t)$$

9) Feedforward Neural Network (FNN)

A FNN is a kind of neural network [10]characterized by one-way connections without cycles. Data flows from input nodes, passes through hidden nodes, finally it reaches the output nodes.

$$a^{(l)} = f(z^{(l)}) = f(b^{(l)} + W^{(l)}a^{(l-1)})$$

10) Feedforward Neural Network with Dropout

Dropout is a regularizer that prevents overfitting by randomly setting some neurons to zero during training, allowing the network to learn robust features.

$$a^{(l)} = f(z^{(l)}) = f(b^{(l)} + W^{(l)}a^{(l-1)}) \cdot r$$

11) Random Forest

Random Forest creates numerous decision trees[11] while training process and gives the most (common class) of classification or average prediction of (regression) as its output.

$$\hat{y} = \frac{1}{N}\sum_{i=1}^{N} f_i(q)$$

12) Gradient Boosting

Gradient Boosting constructs a series of models where each new model ad- dresses the mistakes made by the preceding one, using gradient descent to minimize the loss function.

$$\hat{y} = \hat{y}_{-1} + \eta f_t(x)$$

13) Extreme Gradient Boosting(XGBoost)

XGBoost is gradient boosting but advanced version in terms of speed and performance, incorporating regularization to prevent overfitting.

$$\hat{y} = \sum_{t=1}^{T} \eta f_{t(x)}$$

.

14) AdaBoost (adaptive Boosting)

AdaBoost combines several weak classifiers into one strong classifier, assigning

more weight to misclassified instances in subsequent classifiers.

$$\hat{y} = \sum_{t=1}^{T} \alpha_t f_t(x)$$

15) CatBoost (Categorical Boosting)

CatBoost handles categorical features natively, preventing overfitting with ordered boosting.

$$\hat{y} = \sum_{t=1}^{T} \eta f_{t(x)}$$

16) Stacking

Stacking combines multiple models (base learners) by training a meta-learner on the predictions of the base models.

$$\hat{y} = q(p_1(x), p_2(x), \dots, p_n(x))$$

17) Voting

Voting combines multiple classifiers to make a single prediction, using either soft voting on predicted probabilities or hard voting on class labels. Soft Voting

Formula:

$$\hat{y} = \arg\max \left(\frac{1}{N}\sum_{i=1}^{N} P_i(y/x)\right)$$

D. Model Performance Evaluation

1) Confusion Matrix

Definition: A confusion matrix is summarizing counts a table of actual vs. predicted classifications; this serves as a guide to model performance in solving a classification problem. Four metrics are commonly incorporated: (FN),(TP),(FP),(TN)

2) Accuracy

Accuracy measures the ratio of both correctly identified positive outcomes and correctly identified outcomes which are negative—related to the total number of predictions made.

$$Accuracy = \frac{M + N}{M + N + O + P}$$

3) Precision

Precision is correctly identified outcomes which are positive out of the total number of outcomes which are predicted positive , or how many of the actual positive outcomes were identified as positive.

$$Precision = \frac{M}{M + O}$$

4) Recall

Recall is number of correctly identified outcomes which are positive out of the actual outcomes which are positive, or how many of the actual positive outcomes were identified as positive.

$$Recall = \frac{M}{M+P}$$

5) F1 score

It is simply a measure wherein recall and precision combined into a single metric that can provide a fair check as to how well the classifier performed.

$$F1 = \frac{2 \times (\frac{M}{M+O}) \times (\frac{M}{M+P})}{(\frac{M}{M+O}) + (\frac{M}{M+P})}$$

Here:

M: Correctly classified as positive

N: Correctly classified as negative

O: Incorrectly classified as positive

P: Incorrectly classified as negative

IV. Interpretation and Test Results

A comparison of several models metrics are discussed among that best algorithm for employee attrition prediction is the Random Forest classifier with an accuracy of 98.3%. Such robust performance can definitely be attributed to the ensemble learning technique used by Random Forest, where it is possible to aggregate the predictions from multiple decision trees in order to enhance the overall accuracy and avoid overfitting.[12]

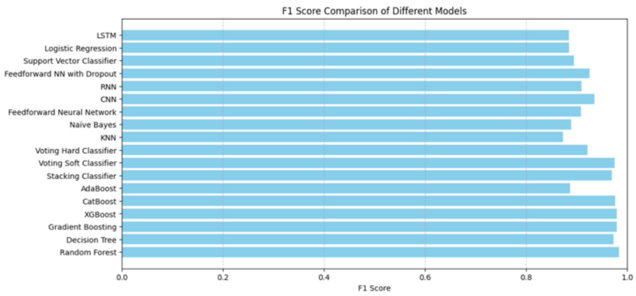

Figure 4: Comparison of Different models F1 Score for balancing precision, recall to better understand classification of employees that are at risk

There are numerous reasons why the model was able to represent high-dimensional data and capture complex interactions among features in an efficient way, which led to its successful prediction of employee attrition in a significant way. Here are metrics of evaluation for different model.

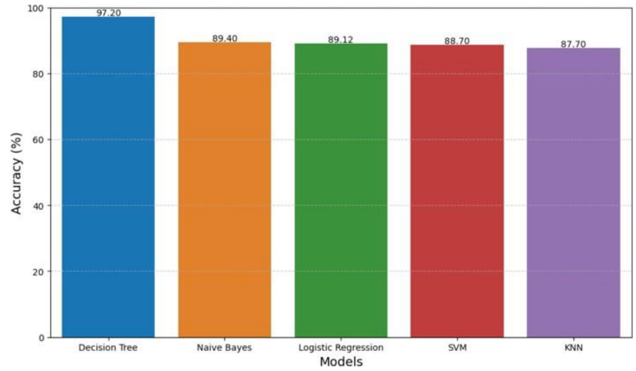

Figure. 5 Conventional Models Accuracies

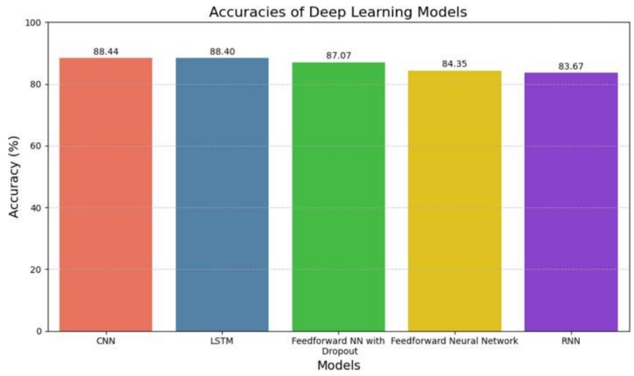

Figure. 6 Deep Learning Models Accuracies

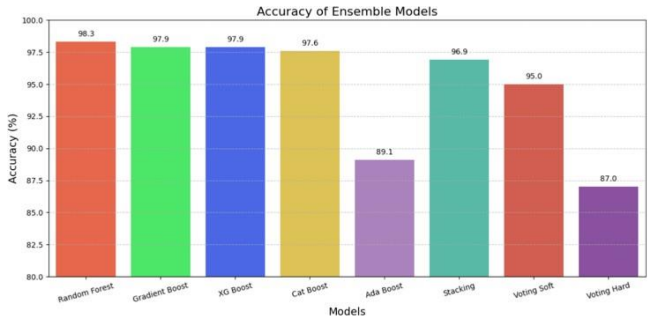

Figure. 7 Ensemble Models Accuracies

The following confusion matrix clarifies further on performance by representing Correctly classified as positive, Correctly classified as negative, Incorrectly classified as positive, Incorrectly classified as negative for top accuracy achiever RF model

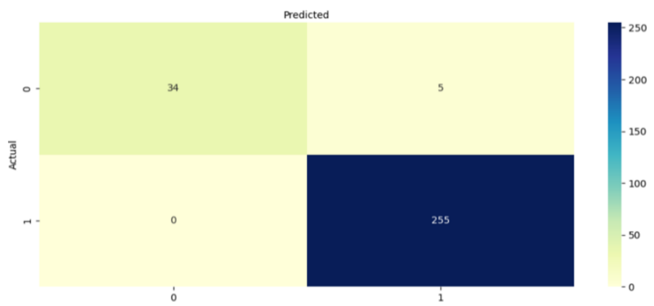

Figure. 8 Confusion Matrix of Random Forest

Table 1: Derived Model Accuracy, Precision, and Recall

Model	Accuracy	Precision	Recall
Random Forest	0.9830	0.9833	0.9830
Decision Tree	0.9728	0.9728	0.9728
Gradient Boosting	0.9795	0.9794	0.9795
XGBoost	0.9795	0.9794	0.9795
CatBoost	0.9761	0.9758	0.9761
AdaBoost	0.8911	0.8826	0.8911
Stacking Classifier	0.9693	0.9690	0.9693
Voting Soft Classifier	0.95	0.98	0.97
Voting Hard Classifier	0.87	0.98	0.87
KNN	0.8775	0.8684	0.8776
Naïve Bayes	0.8945	0.8841	0.8946
Feedforward Neural Network	0.843537	0.887160	0.930612
CNN	0.884354	0.880866	0.995918
RNN	0.836735	0.845614	0.983673
Feedforward NN with Dropout	0.870748	0.887640	0.967347
Support Vector Classifier	0.8878	0.9006	0.8878
Logistic Regression	0.8912	0.8776	0.8912
LSTM	0.8844	0.8844	0.8844

V. CONCLUSION

In conclusion this study underlines the important role of accurately predicting employee attrition in an organization to improve organizational sustainability and performance. Using a variety of classification algorithms, this study displayed that the Random Forest model got an impressive accuracy of 98.3% with regard to employee attrition prediction. Such high accuracy underscores the capability to identify complex patterns in the data even amidst inherent noise. Indeed, through this study, it becomes evident that implementation of the Random Forest classifier will help organizations to provide proactive identification of at-risk employees, thus enabling opportunity for timely intervention and retaining employees. Ultimately, this contributes valuable insights into human resource management by focusing on how advanced analytics has the potential to provide a committed and stable workforce.

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