# MACHINE LEARNING MODEL FOR EMPLOYEE ATTRITION PREDICTION

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**Abstract:** The Employee attrition is a significant issue and concern for numerous organizations and management teams globally. Attrition has negative effect on the company productivity. Due to its effect, it has attracted many research works. This study aimed at developing employee attrition predictive model. The study adopted IBR HR dataset obtained from kaggle.com repository; it consists of 1470 instances and 34 features. PCA was used for feature reduction. The predictive model was created utilizing RF, BILSTM, SVM and LSTM. The result of the attrition model developed shows the accuracy score of RF, BILSTM, SVM and LSTM to be 86%, 87%, 88% and 87% respectively. Also, the Precision values of 0.87, 0.87, 0.91 and 0.90 for RF, BILSTM, SVM and LSTM respectively. The model also demonstrated high recall value and F1 score. The confusion matrix analysis of the model shows that 221 samples were classified as TP, 4 samples were identified as TN, 34 samples were classified as FP and 35 were identified as FN. The study concluded that SVM perform better than BILSTM RF and LSTM in terms of the validating metric used. The future work can be done using another dataset and other deep learning methods can be employed. The future study can be treated as regression problem to see the performance. The study recommended that the model can be used to assist in decision making as regards attrition issues.
**Keywords:** Employee Attrition, BILSTM, machine learning, deep learning

## Introduction

Benefits of employee to the any organization cannot be overemphasis. The Employee attrition is a crucial challenge and concern for numerous organizations management across the globe. Indeed, Attrition is a significant challenge amidst the fierce competition in today's global market. (Smith *et al*., 2018). This would adversely affect both the performance and profitability of any organization. Additionally, high attrition rates heighten the risk of losing valuable employees. (Hussein *et al.,* 2015). There are numerous issues that form the basis for employee attrition (Griffeth *et al.,* 2001). It has been noticed over the time that employees tend to exist an organization more quickly than they become engaged. When an employee departs, his position in an organization, the vacancies cannot be immediately replaced which can lead to loss of revenue for the organization. Analyzing employee attrition rate can provide valuable insights into a company's overall performance. When employees frequently leave an organization this implies a high attrition rate. A high attrition rate results in a loss of organization advantages (Cascio, 2006). To ensure the organization continues to succeed, it is essential to manage the attrition rate effectively. High employee attrition observed in many organizations which is refers to as loss of employees through series of circumstances, such as resignation and retirement due to many reasons. A high attrition rate in any organization resulted in quantity and quality of an organization's manpower reduction. These therefore bring about huge expenditure on human resource, by contributing towards repeated acquisition (Griffeth *et al.,* 2001).

The departure of employees is becoming a growing worry for various businesses. Employee attrition can be expensive for all firms. In today's competitive market, companies need to effectively manage their skilled and experienced workforce. When employees leave any organization, they often take with them a valuable set of skills and qualifications (Harter *et al.,* 2002). So in order to keep employees, the management of the sector needs to concentrate on improving the working condition of the employee by raising wages and other benefits. Team leader managing a large number of personnel encounter various challenges. Many managers lack the training to decrease employee turnover, which is viewed negatively by businesses due to the loss of valuable talent.

Achieving complete alignment between employee and employer interests is unrealistic, meaning some level of voluntary or involuntary departures will always occur. While no organization is flawless and attrition cannot be entirely eliminated, it can be minimized by implementing effective retention strategies (Negi & Gayatri, 2013). Prediction strategy on employee attrition and identifying key factors that contribute to attrition it is essential for organizations looking to improve their human resource strategies.

Some theories like Psychological Contract Theory which emphasize on the unwritten set of expectations between employees and employers. When employees think that their employer has failed in providing for some basic needs such as opportunities for career development, capacity building or supportive work conditions, they may feel deceived and are more likely to leave (Rousseau, 1989). Research on psychological contracts shows that the violations of these expectations can significantly impact the turnover intentions, especially among newer employees (Robinson & Rousseau, 1994). Analyzing some parameters that have effect on attrition; construction of model for predicting employees attrition; developing a performance dataset (gender, income, number of company worked for, and marital status data) and others tasks influence the prediction on employee attrition was the introduction of Machine learning. Machine learning (ML) is a sunset in the field of Artificial Intelligence (AI) which helps machines to learn from past data and predict the future (Gandomi *et al.,* 2022). Presently, machine learning is a vital element of the data science field. The aim of machine learning techniques is to get more accurate results quickly with little time and reduce human error in computation. The machine learning models are used to make decisions. Machines automatically learn through a process. Data is inputted into the machines to train the model and get results which helps make decisions based on new data. Machine learning models aim to discover patterns in data and learn from it without needing explicit programming. The use of machine learning in today’s technology is expanding every day with applications covering a wide range of real-world fields such as Website Trustworthiness Prediction (Alaba *et.al.,* 2021) Stock price prediction (Ogunsanwo *et al.,* 2024), Traffic congestion prediction (Taiwo *et. al,* 2023), Modeling and simulation of river discharge (Aiyelokun *et al.,* 2018), The machine learning models are applied to predict employee attrition (Raza *et al.,* 2022). The followings are the focal contributions of the paper in the perspective of employee attrition prediction:

- The four methods (machine learning-based and deep learning techniques) which are: RF, Bi LSTM, LSTM and SVM were employed to predict employee attrition;
- The comparative analysis of four utilized machine learning models to know which one had the most accurate results;
- We applied Principal Component Analysis (PCA) as an innovation to make the dataset better and improve accuracy compared to other machine learning methods;
- We compared four different models to know how well they performed in terms of accuracy, precision, F1 score, recall;
- The confusion matrix and ROC curve analysis were used to evaluate the performance of these models.

The next sections of this paper are arranged as follows: Related works to our research is studied in Section 2. Section 3 appraised the analysis of the materials and methods used in the research. The results and evaluations of the study are discussed in Section 4. The conclusion of the research study can be found in section 5.

## Related Work

Raza et al. (2022) carried a study on predicting employee attrition using machine learning Approaches. The study employed the use of four machine learning techniques, the proposed optimized Extra Trees Classifier (ETC) and EEDA was also utilized.

Qutub et al. (2021) carried out a study on the prediction of employee attrition using machine learning and ensemble techniques. The study employed the use of ML models (LR, RFR, Adaboost Model, DT, and GB Classifier models) and IBM attrition dataset.

Mansor et al. (2021) carried out a study on ML to forecast employee attrition. The study employed the use of machine namely methods such as ANN, SVM, and DT Classifiers, and choose the best model. IBM human resource analytic employee attrition and performance dataset was use for caparison.

Jain et al. (2020) carried out a study on predicting employees’ attrition using a ML approach. The study employed the use of dataset from Kaggle.com, data exploration using variable identification univariate analysis and Bi-variate analysis. The machine learning technique used for the study includes SVM, DT and Random Forest.

Emmanue- Okereke & Anigbog (2022) carried out a study to predict the perceived employee tendency of leaving an organization. The study employed the use of Naive Bayes (NB) and SVM algorithms.

Fallucchi et al. (2020) worked on a study to predict attrition employee using ML techniques. The study employed the use of IBM, HRM dataset, Gaussian Naïve Bayes, Naive Bayes classifier, Bernoulli NB, Logistic Regression, K-NN, RF, SVC and LSVC.

Harsha et al. (2020) carried out a study on detect early prediction of employee attrition. The study employed the use of IBM Watson Analytics1, data mining approaches from LR, NN and NB to more complicated methods as RF, SVM and other hybrid method.

Irwan et al. (2019) carried out a study to analyze employee attrition using LR. They employed the use of dataset from Kaggle.com, linear regression and model visualization.

Khera & Divya (2019) carried out a study to create a prediction model using employee data in order to address the problem of employee leaving their jobs in the Indian IT industry. The study employed the use of HR databases, the models used were RF, SVM, and NB models.

Adarsh et al. (2020) carried out a research to find out which machine learning method is good at predicting which employees might quit their jobs in the organization. The study employs the use of dataset from Kaggle website, four various ML techniques such as DT, KNN, RF, SVM were also used.

## Materials and Method

### *Data Acquisition*

The IBR HR dataset used was obtained from kaggle.com repository. It consists of 1470 instances and 34 features. The sample of the dataset used was shown in Fig.2 Attrition was used as the dependent variable (“yes”= 1 rep employee who left the company, “No” = 0 rep. otherwise. While the other variables are information that is related to the working life and personal bio data of the employees. The work flow diagram of the model are shown in Fig.1

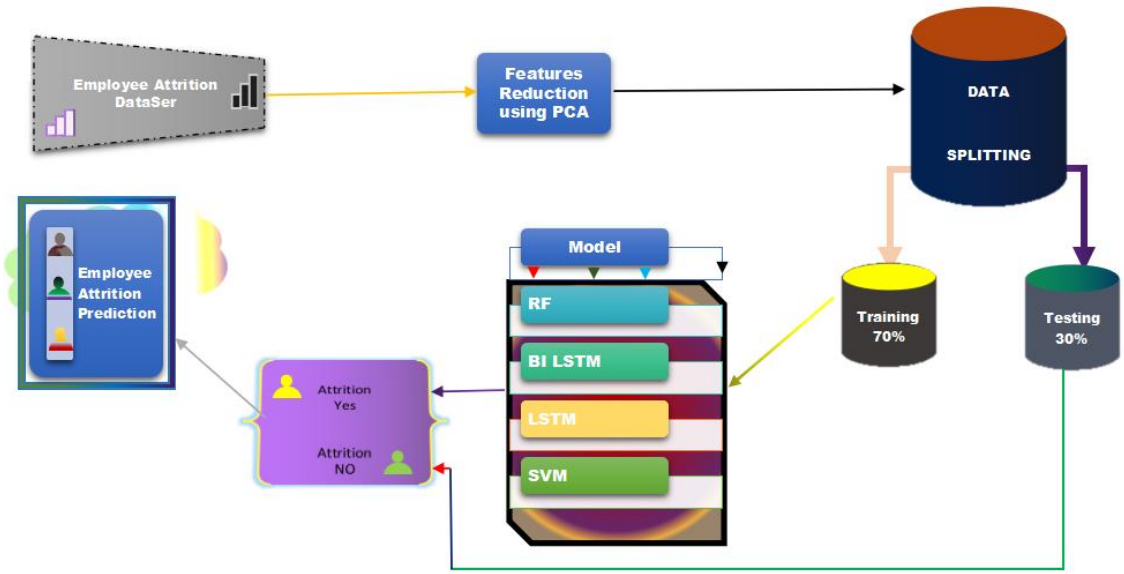


Fig. 1 the work flow diagram of the Model

***Data Preprocessing***

To enhance the model's performance, the dataset was subjected to feature reduction using PCA. The output of the feature reduction done was presented as seen in Fig.3 and Table 1

***Model Development***

The employee Attrition predictive model developed was done using four algorithms which includes: RF, BILSTM, SVM and LSTM.

***Random Forest (RF)***

Random Forest (RF) is an ensemble learning method, majorly utilized for classification and regression challenges. It builds a collection of decision trees, each built from a random subset of the training data, and makes predictions by combining the predictions of individual trees (using majority voting for classification (Breiman, 2001) as seen Eqn. 1

***For classification****:* Each tree in the forest produces a class label, and the final class prediction is made by majority voting

$\hat{y}RF = mode(\hat{y}_1, \hat{y}_2, \dots, \hat{y}_r)$ (1)

Where $\hat{y}_i$ is the predicted class label by tree i , and T is the total number of trees in the forest

***BI LSTM***

BILSTM due to its capability to process the sequence in both directions, it performs better than unidirectional LSTM. BiLSTM can capture dependencies that depend on both past and future elements of the sequence (Graves & Schmidhuber, 2005).

Mathematical Formulation for BiLSTM as seen Eqn. 2, 3 & 4

Let $x_t$ be the input at time step t, $h_t^f$ be the forward hidden state and $h_t^b$ be the backward hidden state.

- The forward LSTM processes the input sequence $x_1, x_2, \dots, x_T$ using the standard LSTM

$$h_t^f = LSTM_{forward}\,(x_t\,, h_{t-1}^f) \quad (2)$$

- The backward LSTM processes the reverse sequence $x_T, x_{T-1}, \dots, x_1$:

$$h_t^b = LSTM_{forward}(x_t\,, h_{t+1}^b) \quad (3)$$

At each time step t, the output of the BiLSTM is the concatenation of the forward and backward hidden state:

$$h_t = [h_t^f, h_t^b] \qquad (4)$$

Where [∗] denotes the concatenation operation.

Thus for each tome step t, the final hidden state combines information from both direction capturing both past and future context:

***LSTM***

LSTM networks are brand of recurrent neural network. LSTM study features straight from raw data, these features make it more operative for difficult tasks where patterns and dependencies are not easily feasible (Zhou *et. al.*, 2015).

***Support Vector Machine (SVM)***

SVM is a highly effective classification algorithm. It establishes a vector that separates two classes in a plane by maximizing the distance from both classes (Cortes & Vapnik, 1995). The SVM model generates an optional decision boundary that partitions n-dimensional feature space data into designated classes. To achieve the best-fitting hyperplane and 1reduce error, SVM employs an iterative approach. The separating hyperplane is expressed in Eqn.5. Where M represents weight matrix, P denotes Input feature, and R indicates biased values.

$$\vec{M} \circ \vec{P} + R = 0, \qquad \textbf{(5)}$$

***Validation of the Model***

The followings are the important factors for the validation metrics:

• True Positive: (TP) both the predicted values and actual values are correct;
• True Negative (NP) both the predicted values and actual values are not right;
• False Positive: (FP) predicts a value as correct but the actual value is not right;
• False Negative (FN) predicts a value as not right, but the actual value is correct.

***Accuracy Score***

In order to calculate the accuracy score, the formula equation is expressed in Eqn. 6.

$$Accuracy\ Score = \frac{(TP+TN)}{(TP+FN+TN+FP)} \times 100\% \quad (6)$$

***Precision and Recall***

The mathematical notations to calculate the precision and recall are expressed in Eqn.7
and (8), respectively.

***Precision***

Precision is the number of correct cases returned by the model. The closer the value is to 1, the better the model

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

Recall is the number of positives returned the model. The closer the value is to 1, the better the model. As seen Eqn.5

$$Recall = \frac{TP}{TP+FN} \quad (8)$$

***Specificity***

The specificity is the number of negatives returned by the model. The closer the value is to 1, the better the model as seen Eqn. 9

$$Specificity = \frac{TN}{TN+FP} \quad (9)$$

***F1 Score***

F1score is an evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model into a single metric to gain a better understanding of model performance.as seen Eqn.10

$$F1 = \frac{TN}{TP+\frac{1}{2}(FP+FN)} \quad (10)$$

***Experimental Results***

***Sample Dataset***

The result of Dataset acquired for employee attrition as shown in Fig.2

| | Age | Attrition | BusinessTravel | DailyRate | Department | DistanceFromHome | Education | Educa |
|---|---|---|---|---|---|---|---|---|
| **1465** | 36 | No | Travel_Frequently | 884 | Research & Development | 23 | 2 | |
| **1466** | 39 | No | Travel_Rarely | 613 | Research & Development | 6 | 1 | |
| **1467** | 27 | No | Travel_Rarely | 155 | Research & Development | 4 | 3 | Li |
| **1468** | 49 | No | Travel_Frequently | 1023 | Sales | 2 | 3 | |
| **1469** | 34 | No | Travel_Rarely | 628 | Research & Development | 8 | 3 | |

5 rows × 35 columns

Fig.2 Sample of the dataset

4.1.2 The Result of PCA done on the dataset Attrition Employee prediction as shown in Table 1 and Fig.3

Table 1

| | principal component 1 | principal component 2 |
|---|---|---|
| 0 | -0.297903 | -1.650685 |
| 1 | 0.567731 | 2.541670 |
| 2 | -2.478634 | -1.142014 |
| 3 | -0.881883 | -0.154870 |
| 4 | -1.906462 | -1.065404 |

PC

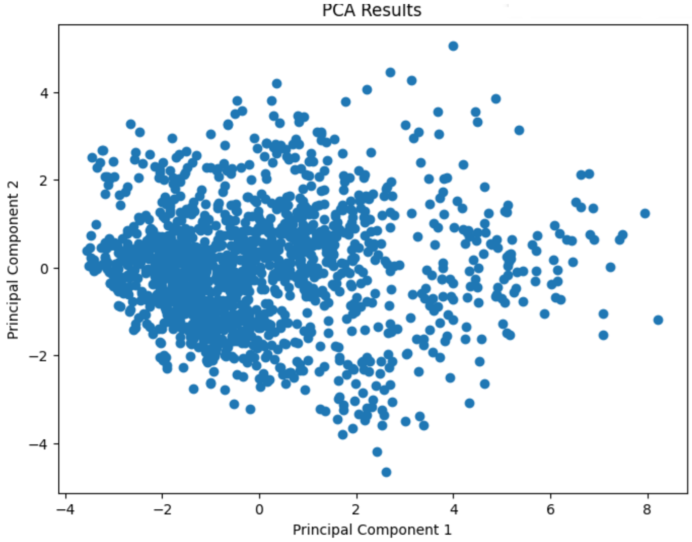


Fig 3 PCA

***Model Development***

The result of the dataset used was divided into 70% training and 30 % testing as shown in Fig 4

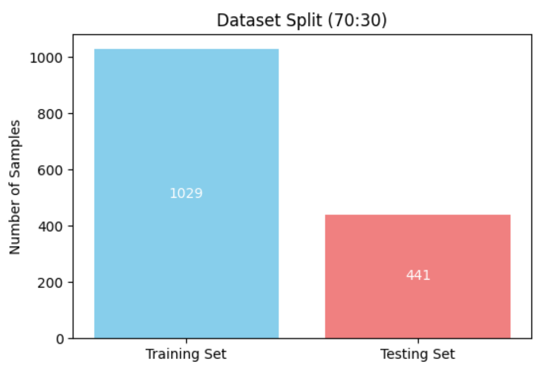


Fig 4 Dataset Split 70:30

***The Result of Random Forest Clasiisfier***

The Employee Atrition predictive model developed using RF using the following validation metric such as Accuracy, Precision, Fi Score Recall and confussion matrix are shown in Fig.5 and Table 2

Table 2 RF Analysis

| RF ACCURACY:= 86% | | | | |
|---|---|---|---|---|
| Category | Precision % | Recall % | F1 Score % | Support Score |
| 0 | 87 | 99 | 93 | 380 |
| 1 | 56 | 8 | 14 | 61 |
| Average | 83 | 86 | 82 | 441 |

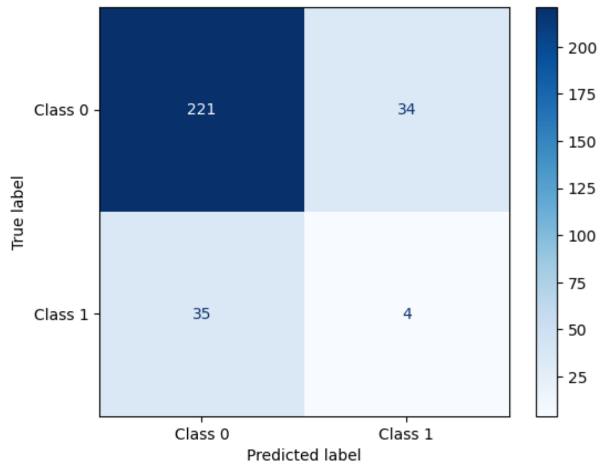


Fig. 5 Confusion Matrix

***The Result of BI LSTM Clasiisfier***

The Employee Atrition predictive model developed using BILSTM using the following validation metric such as Accuracy, precision, F1 Score Recall and confussion matrix are shown in Fig.6 and Table 3

```
Epoch 7/10
33/33 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.9071 - loss: 0.2664
Epoch 8/10
33/33 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9028 - loss: 0.2448
Epoch 9/10
33/33 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9058 - loss: 0.2423
Epoch 10/10
33/33 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.9108 - loss: 0.2307
14/14 ━━━━━━━━━━━━━━━━━━━━ 2s 8ms/step - accuracy: 0.8884 - loss: 0.3400
Accuracy: 0.875283420085907
14/14 ━━━━━━━━━━━━━━━━━━━━ 2s 49ms/step
              precision    recall  f1-score   support

           0       0.91      0.96      0.93       380
           1       0.57      0.38      0.46        61

    accuracy                           0.88       441
   macro avg       0.74      0.67      0.69       441
weighted avg       0.86      0.88      0.86       441

[[363  17]
 [ 38  23]]
```

Fig 6 BI LSTM Model

Table 3 BILSTM Analysis

| BI LSTM ACCURACY:= 87% | | | | |
|---|---|---|---|---|
| Category | Precision % | Recall % | F1 Score % | Support Score |
| 0 | 87 | 96 | 93 | 380 |
| 1 | 57 | 38 | 46 | 61 |
| Average | 86 | 88 | 86 | 441 |

***The Result of SVM Classifier***

The Employee Attrition predictive model developed using SVM using the following validation metric such as Accuracy , precision , Fi Score Recall and confusion matrix are shown in Fig. 7 and Table 4

```
Accuracy: 0.8866213151927438

Classification Report:
              precision    recall  f1-score   support

          No       0.91      0.97      0.94       380
         Yes       0.65      0.39      0.49        61

    accuracy                           0.89       441
   macro avg       0.78      0.68      0.71       441
weighted avg       0.87      0.89      0.87       441


Confusion Matrix:
[[367  13]
 [ 37  24]]
```

Fig 7 SVM Model simulation

Table 4 SVM analysis

| SVM ACCURACY:= 88% | | | | |
|---|---|---|---|---|
| Category | Precision % | Recall % | F1 Score % | Support Score |
| 0 | 91 | 97 | 94 | 380 |
| 1 | 65 | 39 | 49 | 61 |
| Average | 87 | 89 | 87 | 441 |

***The Result of LSTM Classifier***

The Employee Attrition predictive model developed using LSTM with sigmoid activation using the following validation metric such as Accuracy, precision , Fi Score Recall and confusion matrix are shown in Fig. 8 and Table 5

```
Epoch 9/10
33/33 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.8981 - loss: 0.2699
Epoch 10/10
33/33 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.9020 - loss: 0.2471
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8784 - loss: 0.3358
Accuracy: 0.8707482814788818
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step
              precision    recall  f1-score   support

           0       0.90      0.96      0.93       380
           1       0.55      0.34      0.42        61

    accuracy                           0.87       441
   macro avg       0.73      0.65      0.68       441
weighted avg       0.85      0.87      0.86       441

[[363  17]
 [ 40  21]]
```

Fig 8 LSTM Model

Table 5 LSTM analysis

| Category | Precision % | Recall % | F1 Score % | Support Score |
|---|---|---|---|---|
| 0 | 90 | 96 | 93 | 380 |
| 1 | 55 | 34 | 42 | 61 |
| Average | 85 | 87 | 86 | 441 |

Table 6 Comparison of the Accuracy Model

| S/No | Model | ACCURACY % |
|---|---|---|
| 1 | RF | 86 |
| 2 | BI LSTM | 87 |
| 3 | SVM | 88 |
| 4 | LSTM | 87 |

Table 7 Comparison of the Precision and F1 Score Model

| S/No | Model | Recall% | F1 Score % |
|---|---|---|---|
| 1 | RF | 99 | 93 |
| 2 | BI LSTM | 96 | 93 |
| 3 | SVM | 97 | 94 |
| 4 | LSTM | 96 | 93 |

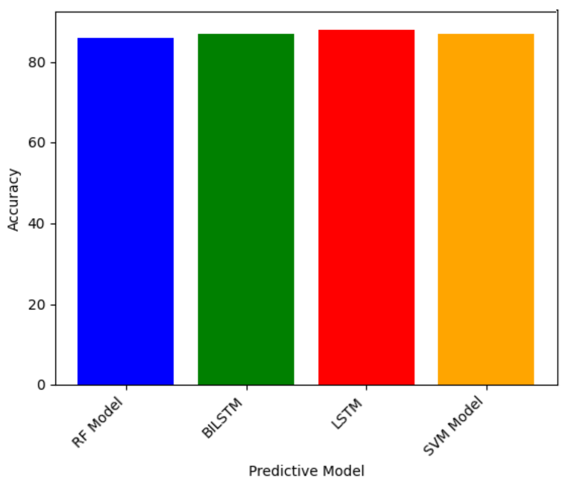


Fig 9 Accuracy Comparison of four Models


Fig 11 Training and validation Loss

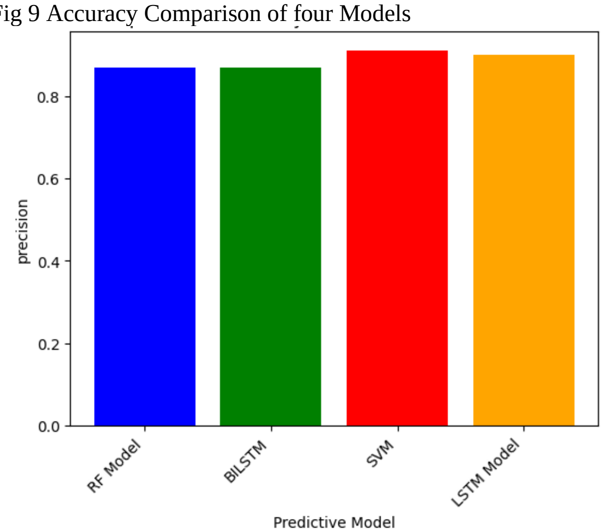


Fig 10 Precision Comparison of four Models

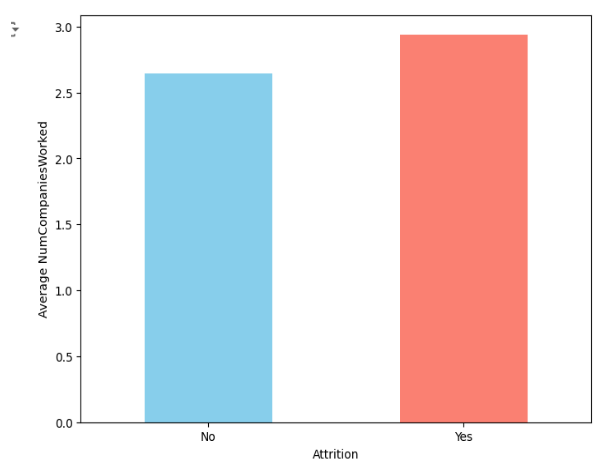


Fig.12 Average Number Company worked with Attrition

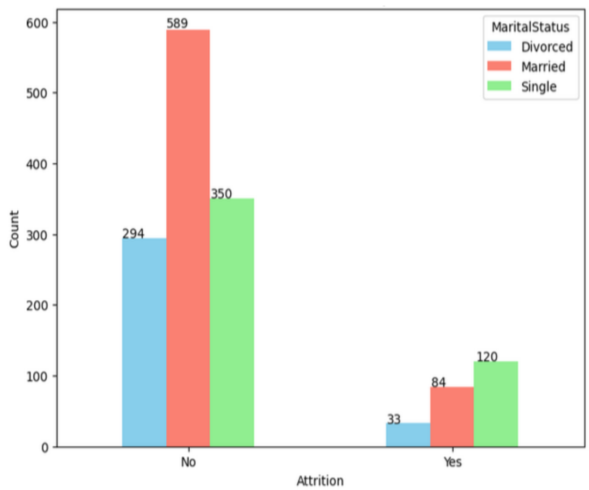


Fig.13 Marital status with Attrition

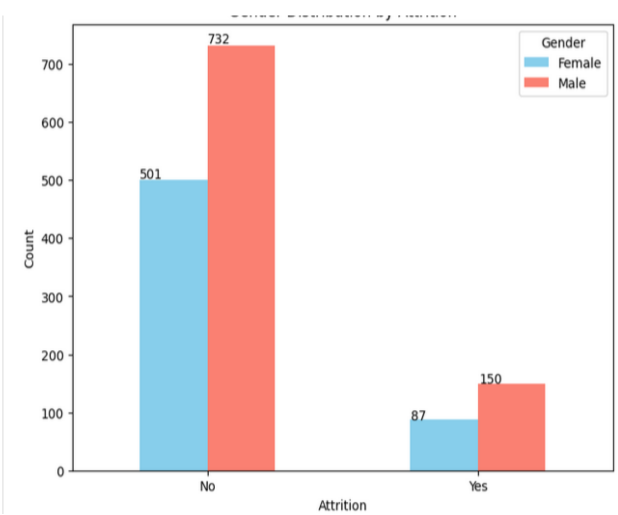


Fig.14 Gender with Attrition

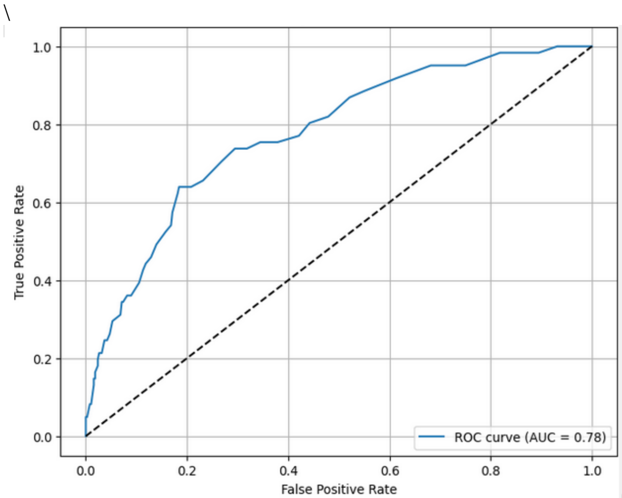


Fig 15 ROC

**Result and Discussion**

The training and testing process of RF model, the accuracy score results were measured and it was found the model attained 86 % of accuracy. The Accuracy score of BI LSTM SVM and LSTM were found to be 87%, 88% and 87% respectively as seen in Table 7 and Fig.9. The indication is that all the four models performed excellent but SVM perform better than RF, BI LSTM and LSTM Models in term of Accuracy. Precision focus on minimizing false positive and increase the positive instances predicted. From the stimulation, Precision values of 0.87, 0.87, 0.91 and 0.90 for RF, BILSTM, SVM and LSTM respectively as seen in Fig.10. The study then revealed the four models perform well as the precision value is closer to 1 but SVM outperform other models. The model also demonstrated high recall value and Fi score value as seen in Table 7 which shows that the model is reliable for the prediction. The confusion matrix analysis of the model as seen in Fig. 5 shows that 221 samples were classified as TP and 4 samples were identified as TN. So also, 34 samples were classified as FP and 35 were identified as FN. The confusion Matrix result validated the model. The higher the value of the area under the curve the higher the performance of the model. The ROC analysis in Fig. 15 revealed the Model performed well. The training loss graph shows the value closer to zero which revealed that model is reliable as seen in Fig. 11. The Analysis carried on the attrition dataset revealed that marital status has effect on attrition as seen Fig. 13. It is revealed that higher percentage of married people is likely to say no attrition and higher percentage of singles are like to vacate their place of work. It is also revealed that the average number of companies worked for affects attrition as higher percentage of people like to move from one company to another in search for greener pasture see Fig. 12. Gender also analysed as a factor that caused attrition as higher percentage of male are like to no attrition compare with female as seen Fig. 14

**Conclusions**

The paper concluded by developing attrition predictive model using four machine and deep learning techniques which are RF , BILSTM , SVM and LSTM. The PCA applied on the datset increase the accuracy of the Model. The model developed achieved higher performance in term of accuracy value, precision value; recall value and F1 score values which show that the model is reliable. The study revealed that SVM perform better than BILSTM RF and LSTM in terms of the validating metric used. The ROC curve validate that model is reliable. The analysis carried on the Dataset shows that Gender, Marital Status and No of Company worked for affect attrition. The future work can be done using another dataset and more deep learning techniques can be applied. The future on the attrition predictive model can be treated as regression problem to see the performance. The Model can be used in decision making as regards to attrition issues.

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