

Bi-LSTM Deep Learning Approach for Employee Churn Prediction

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ABSTRACT

Employee churn prediction also known as 'attrition' or 'turnover' is referred to as the identification of employees planning to quit the organization in the future. Organizations invest time, effort, and money in employees' training. Therefore, an experienced employee is an asset to the organization. If organizations could predict employee churn using machine learning techniques and can take timely measures, then they can prevent long-term loss. Several machine learning models have been used for churn prediction of employees, such as Logistic Regression, Support Vector Machine, and MLP (Multi-Layer Perceptron). This study aims to find the optimal algorithm of classification for the prediction of the churn employee rate. A deep learning approach based on B-LSTM (Bi-Directional Long Short-Term Memory) is being proposed and tested. The accuracy of B-LSTM is 97.5% during the consistency test. A comparative analysis with other machine-learning techniques is also performed and it is concluded that B-LSTM has proved more effective than other machine learning techniques investigated in this study.

Keywords: Churn Prediction, MLP (Multi-Layer Perceptron), Bidirectional LSTM (B-LSTM), Gradient Boosting, Naïve Bayes, Organization

Author's Contribution

¹ Data analysis, interpretation and manuscript writing, Active participation in data collection, ²Conception, synthesis, planning of research, ³ Interpretation and discussion

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INTRODUCTION

Churn prediction is referred to as the identification of persons planning to quit an organization process in the future [1-3]. Churn prediction has two types, customer churn, and employee churn. Churn customer is a prediction of when and which customer stops buying products. This study focuses on employee churn prediction. Employee churn prediction is also known as 'attrition' or 'turnover' is referred to as the identification of

employees planning to quit the organization in the future [4]. Human asset is the most critical and vulnerable asset of organizations. In a competitive and rapidly changing business era, employees tend to find better job opportunities for growth and they leave their organization easily for a better perspective. Churn is very difficult to control and it is a nearly unavoidable process in any field. Therefore, organizations are

focusing nowadays on prior identification of employees who might have a high tendency to leave [1, 5, 6].

Organizations taking timely measures to reduce churn problems are more effective in executing long-term business plans. Employee churn prediction could be helpful for an organization to avoid a high churn rate of valuable employees [7]. It is affected by several factors such as growth potential, pays, promotions, working environment, working hours, and job satisfaction [8]. Some employees leave involuntary for reasons like retirements, internal transfers, and performance issues [9-12]. Hiring new employees to replacement of churn employees costs a lot in terms of training and hiring process [13, 14]. The new employee requires more time to learn processes and gain experience. It affects the performance of other employees as well. They get demotivated by the unexpected resignation of a senior co-worker. Similarly, working in an organization for a long time without any increments also pushes the workers to resign after some duration. This phenomenon makes organizations suffer in the long term as they invest time, human effort, and money to train their workers and convert them into organizational assets [15]. Employee churn is the main hassle in telecom, IT, and many other sectors now a day [16]. Therefore, employers want to retain employees and want to prevent worker turnover.

Several machine learning classification models have been used for churn prediction such as gradient boosting, Naïve Bayes, MLP (Multi-Layer Perceptron), logistic regression, SVM (Support Vector Machines), KNN (K-Nearest Neighbor), Random Forest, Decision Trees [6, 15-24]. However, the accuracy of recent churn prediction techniques is not optimal and there is room for improvement. Deep learning is an emerging subset of machine learning approaches that need to be extensively explored yet to resolve the employee churn problem. This research has investigated the behavior of the above-mentioned classification models using public research dataset of employees. Further, the potential of deep learning is explored for employee churn prediction and a novel deep learning-based approach is proposed for churn prediction with enhanced performance and accuracy. Moreover, a comparative analysis between the above-mentioned models and the proposed model is also presented.

The main contributions of this paper are summarized as follows:

- A deep learning approach based on RNN/LSTM is proposed and implemented by using bi-directional properties to predict the optimal accuracy of churn employees.
- Multiple state of art machine learning approaches such as MLP and Naïve Bayes is implemented for better implementation with parameter tuning.
- Quantitative performance comparison among all implemented approaches is presented.

The rest of the paper is organized as follows: Section 2 describes the literature review. Section 3 explains the research methodology. Section 4 presents the experimental results and discussions followed by the conclusion in Section 5.

BACKGROUND

In literature, several researchers have investigated the problem of employee churn. In a study, the XGBoost classifier is used which proved to be a superior algorithm with high accuracy and low runtime, and it predicted employee turnover with 95% accuracy [18]. In another study, Yigit et al. [22] evaluated multiple classifiers and presented results as logistic regression with 87.1% and SVM 89.7% accuracy rate. Naïve Bayes is also used in another study by Yedida et al. [17] with 85.6% accuracy. Feature selection methods can be utilized to build many models with special subsets of train datasets and decide these aspects that are and are no longer relevant to building a dependable and accurate model [25]. Alamsyah et al. [17] conducted a survey that includes 38 questions like overall satisfaction, loyalty, motivation, gender, age, and salary is highlighted as key distinguished parameters helpful for the training of machine learning models to predict employee churn. They have used Naïve Bayes-based prediction model with 10-fold cross-validation for evaluation.

In another study, C4.5 classifiers are used with 90% training data and 10% testing data. They evaluated the accuracy of C4.5 classifiers as 77 % [26]. In another study, the classification technique used is based on 10-fold cross-validation training and a test dataset. They used data mining tools such

as WEKA and ROSETTA toolkit in their experiment [26, 27]. Their experiment resulted in 95% accuracy to train C4.5 classifiers. Sisodia et al. trained the KNN model on the HR dataset with 96% accuracy [28]. Naïve Bayes classifier reported 72.7% accuracy and SVM reported 51.2% accuracy on customer churn data of Twitter [29]. In another study, traditional machine learning predictive models did not perform well in predicting the churn of workers however, they pointed out the factors contributing to the worker's churn or worker's motivations for staying longer in the organization [30]. In another study, a method to approach worker retention has been proposed using general machine learning strategies such as SVM and it gives a ROC of 80%. They observed and reported that for the information at hand, the maximum efficient retention exercise became to broaden skills mobility throughout positions [31]. Further, other strategies such as decision tree, SVM, and neural network are also investigated using an open-source software program called WEKA [32] and their experiment reported performance of decision tree at 77.9%, neural networks at 83.7%, and SVM at 83.7% accuracy. A method to approach worker retention has been proposed using general machine learning strategies such as logistic regression accuracy is 90.1% in IT sector, telecom sector has 82.9% and in banking sector 86.3% accuracy [33]. In another study, SVM accuracy is 70.9%, Naïve Bayes has 77.4% and random forest has acquired 77.4% accuracy [34].

Yang et al. proposed an approach for churn time prediction of players using linear regression. They used the datasets of six free online games: Thirty-six Stratagems (TS), Thirty-six Stratagems Mobile (TSM), Game of Thrones Winter is Coming (GOT), Woman land in Journey to the West (WJW), League of Angels II (LOA II), and Era of Angels (EOA). Their proposed approach acquired 78.9% accuracy [35]. Khalid et al. proposed an approach to attract future customers and to investigate churning rate of current customers. They employed their investigation on employee data of the Telecom industry using Decision Tree to prevent the loss of potential customers while retaining the happiness level of the current customers with 94% accuracy [36].

Li et al. used Gradient Boosting Decision Tree (GBDT) and applied hyper-parameter tuning to acquire 94% accuracy for churn prediction [37]. Kassem et al. used

proposed an approach to highlight the factors of customer churn using the attribute-selection classifier algorithm. Two datasets have been used. They used Random forests with 95% accuracy [38]. In another study bagging, MLP is used on two benchmark datasets obtained from GitHub for evaluation of the proposed model with 94% accuracy [39]. In another study, the dataset is collected from one of China's largest online professional social network websites. The dynamic Bipartite Graph Embedding (DBGE) method is used, which learns low-dimensional vector representations. They acquired 89% accuracy by applying DBGE random forest [40]. Jain et al. [33] used datasets of banking, telecom, and IT to predict employee churn. They acquired 86.3% accuracy in the banking sector using random forest, 82.9% accuracy in the telecom sector using XGBoost, and 90% accuracy in the IT sector using logistic regression. Lalwani et al. [41] applied ANN for employee churn and acquired 86.5% accuracy. Castellini et al collected employee data from an American Telecom Company named 'Orange' and acquired 85.2% accuracy using logistic regression. Khodadadi et al. [42] acquired 95% accuracy using XGBOOST on structured and semi-structured data of the company. Jain et al. [43] trained logistic regression using a telecom dataset with 80% accuracy. In another study, a large amount of professional social data from one of the largest workplace social platforms in China used Cox-Random Forest with 85.6% [44]. Hu et al. [45] acquired 81% accuracy training Adaboost classifier on customer dataset.

RESEARCH METHODOLOGY

Dataset Acquisition and Pre-processing

An employee churn dataset named HR_comma_sep.csv dataset [8] from Kaggle is used. It comprises fifteen thousand (15,000) employees' samples and provides ten (10) features/attributes. It includes features like satisfaction, evaluation, project count, average monthly hours, years at the company, work accident, promotion, department, turnover, and salary as shown in Table 1. Department and salary were in strings then convert into numbers through a label encoder. Department has 10 categories and salary has 3 categories including low, medium and high.

Label encoder is used for feature scaling. Normalization is applied using the Min-Max Scaler method. We have used an automated convenient feature selection technique Principal Component Analysis (PCA), which is a dimensionality reduction method to predict the accurate result of employee churn. The assumption in deep learning relies on the principle that data was generated by a composition of factors that can be represented in some hierarchical form.

Proposed Approach

A deep learning model based on B-LSTM and LSTM is proposed. LSTM [46] are modified form of the RNN model. A recurrent neural network (RNN) is an effective and well-known type of neural network. It can remember

records through its memory and it's efficient due to its internal memory. RNNs are used to understand records in sequential traits. They use patterns to predict the subsequent probable scenario. RNNs are widely used in developing deep learning models. Its bidirectional model has applications in speech recognition and prediction. Recurrent neural networks are good to remember important things about the input received, which enables them to predict what is coming next. RNN produces predictive consequences sequentially that other algorithms cannot perform [24].

Table 1. Details of HR Dataset			
S. No.	Attributes	Data Type	Value Range
1	Satisfaction	Numeric	0.38-0.9
2	Evaluation	Numeric	0.53-1
3	Project Count	Numeric	2-7
4	Average Monthly hours	Numeric	157-306
5	Years at Company	Numeric	3-6
6	Work Accident	Numeric	0-1
7	Turnover	Numeric	1-0
8	Promotion	Numeric	0-1
9	Department	Categorical	Sales(Different other department)
10	Salary	Categorical	Low/High/Medium

RNN has three gates; input gate, forget gate, and output gate. Forget gate finds out values to be discarded from the block. It is determined by the sigmoid function. The input and the memory of the block are used to figure out the output. It trains the model by back-propagation of weights and bias. It can process data from initial input to final output. It has a forward as well as a backward

process. It has at least one feedback loop. RNN can model the sequence of data so that each sample can be assumed to be dependent on previous ones. RNN is even used with convolutional layers to extend the effective pixel neighborhood. However, it cannot process long sequences if used with the ReLU activation function.

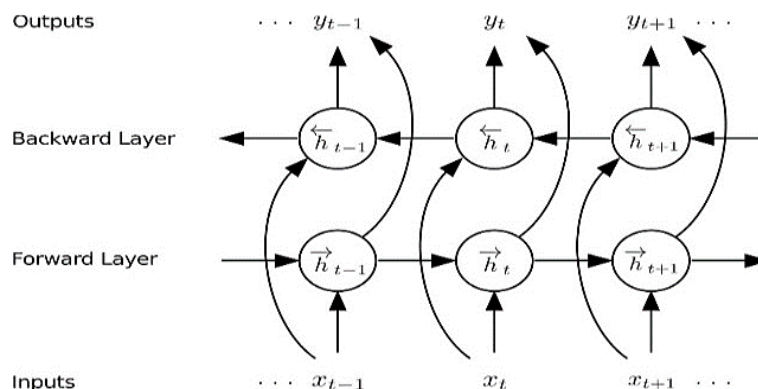


Figure 1. Bidirectional RNN Framework [47]

A Bidirectional RNN known as LSTM is a sequence processing model comprising of two RNNs: one takes the input in a forward direction, and another one takes it in a backward direction. It duplicates the first recurrent layer in the network to develop two layers side-by-side. Then first input sequence is provided as input to the first layer and a reversed copy of the input sequence is provided to the second layer. In contrast to standard feed-forward neural networks, LSTM has feedback connections. This enables it not only to process single data points, but also entire sequences of data. Bidirectional LSTM works in both directions forward as well as backward. It has input, hidden and output layers which are shown in Figure 1 [47].

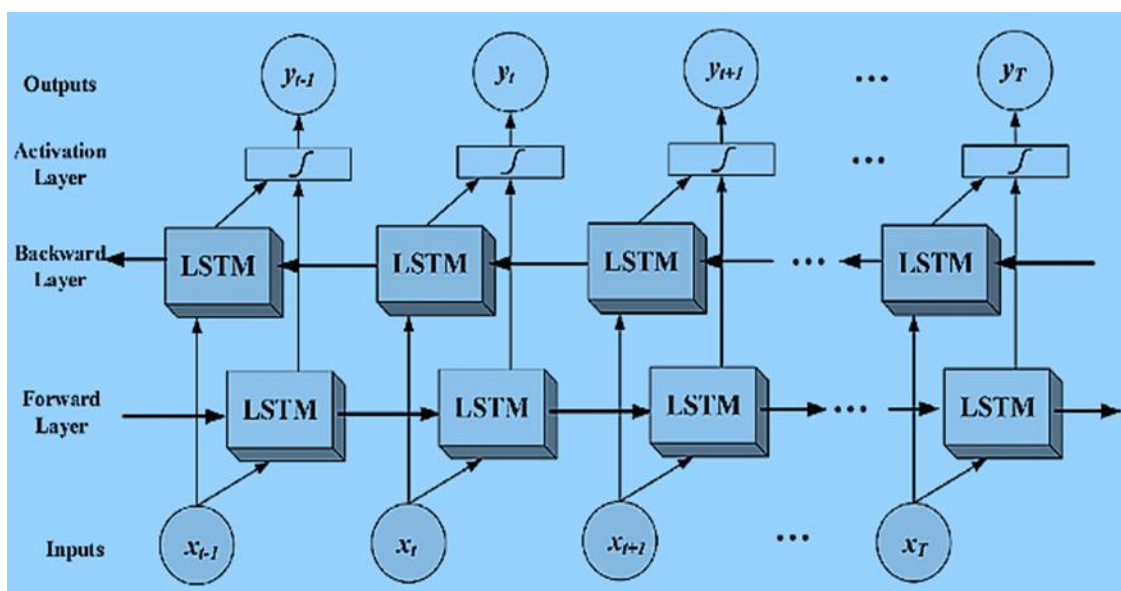


Figure 2. BI-LSTM Structure

The bottom LSTM nets are used for the forward feature. The top LSTM nets are used for backward. The two networks connect at a common activation layer to produce outputs. Neurons in a forward state of BLSTM behave like a unidirectional LSTM structure. Thus, the neurons in both networks are not directly connected as shown in Figure 2. A backward pass is performed for output neurons and the forward states. Finally, all weights are revised and updated. Hence, BLSTM structures provide better results than other network structures. Internal architectural detail is shown in Figure 3.

Detailed Architecture

The architecture of the proposed model is defined as a total number of neurons in the input layer being 9, one hidden layer includes 21 neurons and one neuron in the output layer. Adam optimization algorithm is used to find the weights and the accuracy metric is calculated and reported each epoch. Min-max scaler is used for normalization. ReLU is used as a classification function in the hidden layer. Sigmoid is used as an activation function in the hidden layer. The B-LSTM is trained for 1000 epochs. BI-LSTM block diagram with input layers, hidden layers, and an output layer which is shown in Figure 2.

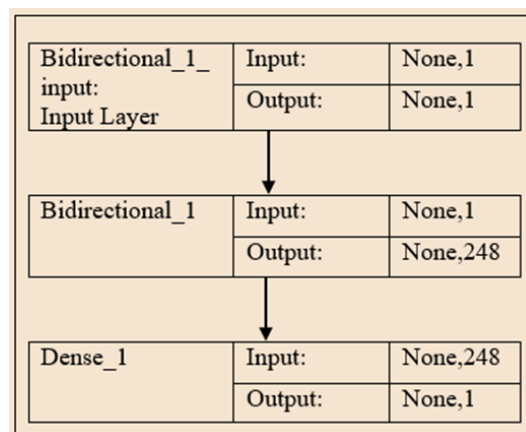


Figure 3. Architecture Diagram

Implementation and Experimental Setup

Google COLAB Python3 is used for implementation. TensorFlow's deep learning framework is used for implementation. RNN (Bidirectional LSTM) has been used to implement on the same dataset. The test train split ratio is 70%-30%. Further, during training 10 Fold Cross-validation is applied to manage to overfit.

RESULTS AND DISCUSSION

After the training a testing phases, results are analyzed by following metrics to evaluate the performance of the proposed model and previous methods: -

Accuracy: It is the number of correct predictions divided by the total number of predictions.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \dots\dots (1)$$

Precision: It is the ratio of correctly predicted positive observations to the total predicted positive observations.

$$Precision = \frac{TP}{TP+FP} \dots\dots\dots (2)$$

F1-Score: The F1 Score is the weighted average of precision and recall. Therefore, this score takes both false positives and false negatives.

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} \dots\dots\dots (3)$$

Matthew's Correlation Coefficient: The Matthews correlation coefficient is used in machine learning as a measure of the quality of binary classification.

$$MCC = \frac{(TP*TN-FP*FN)}{\sqrt{(TP+FP)*(TP+FN)*(TN+FP)*(TN+FN)}} \dots\dots\dots (4)$$

10 Folds are used for cross-validation by partitioning the training set to train the model, and a test set to evaluate it. The training set is the one on which we train and fit our model basically to fit the parameters whereas test data is used only to assess the performance of the model. Training data's output is available to the model whereas testing data is the unseen data for which predictions have to be made. The training part of the dataset comprises 70% and the remaining 30% of the dataset is preserved for a testing phase in independent testing. By using similar data for training and testing, you can minimize the effects of data discrepancies and better understand the characteristics of the model. After a model has been processed by using the training set, you test the model by making predictions against the test set. We find the accuracy and other parameters of

different algorithms on our dataset by using COLAB. These accuracies are better than the previous accuracy found by different researchers.

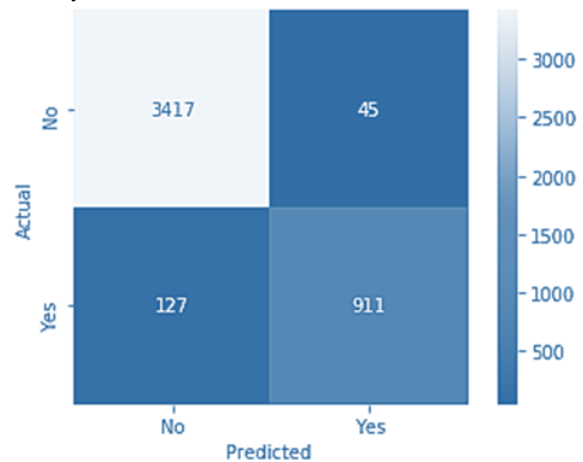


Figure 4. Confusion Matrix of Bidirectional LSTM

The confusion matrix of Bidirectional LSTM true positive is 911 which is the percentage of actual positives which are correctly identified, the true negative is 3417 which is the percentage of actual negatives which are correctly identified, false positive is 45 which incorrectly predicts the positive class and false negative is 127 which is incorrect which is shown in Figure 4.

True / Actual			
		No	Yes
Predicted	No	TN = 98.7%	FP = 1.29%
	Yes	FN = 12.2%	TP = 87.7%

Figure 5. Confusion Matrix of Bidirectional LSTM in Percentage

Confusion matrix of Bidirectional LSTM true positive is 87.7% which is the percentage of actual positives which are correctly identified, the true negative is 98.7% which is the percentage of actual negatives which are correctly identified, false positive is 1.29% which incorrectly predicts the positive class and false negative is 12.2% which is incorrect which is shown in Figure 5.

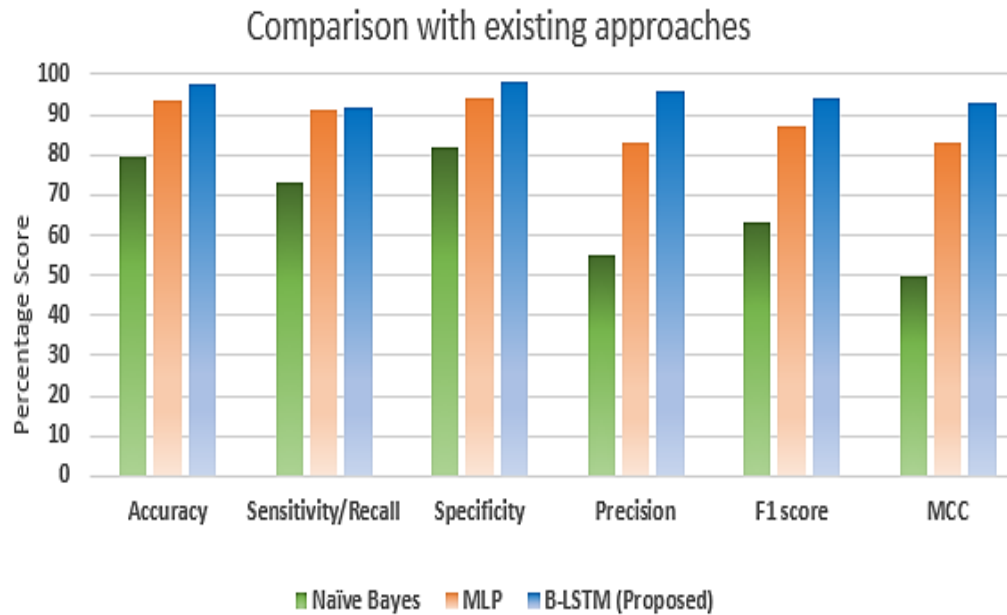


Figure 6. Comparison of Consistency Test Parameters

A consistency test is performed when the model is fully trained on given training data. Inconsistency test accuracy of B-LSTM is 97.5%, specificity is 98%, precision is 96%, sensitivity is 92%, Mathew's correlation coefficient is 93%, and F1 score is 94% as shown in Figure 6.

The Receiver Operating Characteristic (ROC) curve is a trade-off between sensitivity and specificity and tells about the true positive rate and false-positive rate. If it is nearest to the diagonal, then it is not a good curve. Classifiers that give curves closer to the top-left corner indicate better

performance. The closer the curve comes to the 45-degree diagonal of the ROC space, the less accurate the model is. The ROC curve of B-LSTM is shown in Figure 6. Its ROC is 95% and it shows the true positive and false positive rate of B-LSTM for an independent test. It means there is a 95% chance that the model will be able to distinguish between positive class and negative class which is shown in Figure 7.

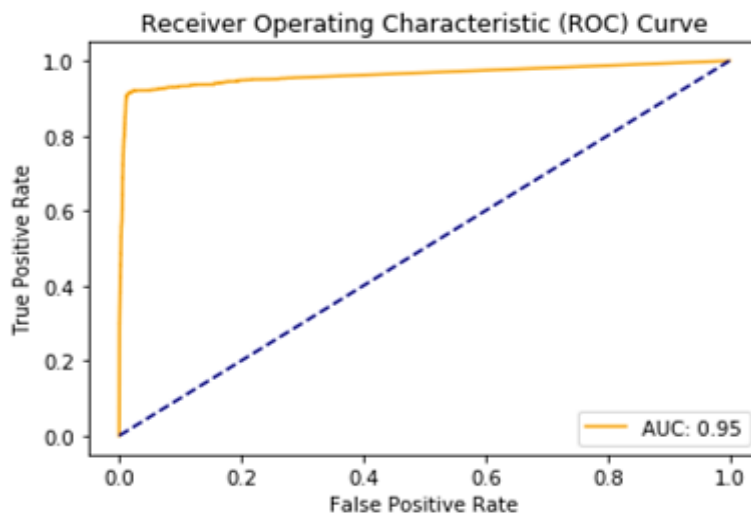


Figure 7. B-LSTM Consistency Test ROC Curve

CONCLUSION

The prediction of employee churn is useful for HR of any organization to take necessary action for the retention of employees predicted to be at risk of leaving. Machine learning algorithms like Naïve Bayes, MLP, and a proposed model based on BILSTM are used to predict the employee churn problem. We have implemented the above-mentioned algorithms and Bidirectional LSTM (B-LSTM). B-LSTM's accuracy is 97.5%, sensitivity is 92% specificity is 98%, precision is 96%, F1 score is 94% and MCC is 93%. On a larger dataset, B-LSTM will outperform even better because deep learning-based approaches need huge data sets to reach their full potential. Therefore, it is evident that B-LSTM will be more effective in if huge training is provided either using data augmentation techniques or a larger dataset is available. Further experiments are planned as future work to discover the full potential and performance optimality of the proposed B-LSTM-based model by applying text augmentation techniques to the employee dataset.

Data Availability

The data set download link is already shared in references. Model implementation code and detailed experimental results will also be available soon on Github.

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