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Research Article

Forecasting The Adoption Rate of Students to the E-Learning Platforms Using Multilayer Recurrent Neural Network with Long Short-Term Memory

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ABSTRACT

E learning platform has increased learning outcomes of the students in the education environment. Recent advances in technologies have increased potential of e learning system on offering student centric materials through recommendation and forecasting approach to increase their user adoption rate. Despite of several advantages of machine learning and deep learning approaches in e- learning platform, those approaches fails to accurately forecast the adoption rate of the student to their learning different modules due to evolving dynamic user behaviors and perception. To meet above objective, a deep learning model from artificial intelligence has to be incorporated. In this paper, long short term memory mechanism integrated multilayer recurrent neural network has been employed as deep learning model to forecast adoption rate of the students to different modules in the e learning platforms. Initially data is preprocessed using stop word removal, stemming, tokenization and token weighting mechanism. Weighted Tokens of the user feedback in form of vector is applied to recurrent neural network. Recurrent Neural Network processes each weighted token in hidden layer. Hidden layer uses activation function to identify the relationship between the sequences of token and organizes as dependency map in association of the long short term memory model. Long short term memory model uses gating mechanism to store the different state of the hidden layer of RNN in different states as hidden state and forget state. In particular, LSTM model compute the long dependency between the tokenized vectors effectively. Finally those dependency maps is processed in the dense layer of the model using softmax function to predict user opinion or feedback as positive (High Adoption Rate) or negative (Low Adoption Rate) effectively. Experimental analysis of the model is performed using Contextual e learning learner interaction dataset extracted from kaggle repository in the Google colab environment incorporating tensorflow to obtain GPU capabilities. Performance analysis of model using cross fold validation of the test data proves that proposed model attains 97.4% accuracy which found to be better compared to conventional fraud detection approaches.

Keywords: Contextual E learning learner Interaction Dataset, Recurrent Neural Network, Long Short Term Memory, Deep Learning, Learner Adoption Rate, E- Learning Platform

1. INTRODUCTION

Nowadays many schools and universities across the world have started using e –learning platform as education platform to enhance potential of their students. Especially after covid -19 pandemic, huge transformations can be observed in students using e learning platform towards skill development and career advancement. In particular, advances in technologies has enabled multiple solutions to increase learner attentions on offering student centric materials. Despite of several advantageous of the technologies, still there exist some challenges in forecasting the adoption rate of the learners to the specified materials in the e learning platform with respect to evolving dynamic user behaviors and perception. To meet mentioned objective, it is mandatory to design a deep learning based artificial intelligence approaches to forecast the adoption rate of the learners to the customized learning materials deployed in the e learning platform.

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In this paper, a long short term memory mechanism integrated multilayer recurrent neural network has been employed as deep learning model to forecast adoption rate of the students to different modules in the e learning platforms. Initially data is preprocessed using stop word removal, stemming, tokenization and token weighting mechanism. Weighted Tokens of the user feedback in form of vector is applied to recurrent neural network. Recurrent Neural Network processes each weighted token in hidden layer. Hidden layer uses activation function to identify the relationship between the sequences of token and organizes as dependency map in association of the long short term memory model. Long short term memory model uses gating mechanism to store the different state of the hidden layer of RNN in different states as hidden state and forget state. In particular, LSTM model compute the long dependency between the tokenized vectors effectively. Finally those dependency maps is processed in the dense layer of the model using softmax function to predict user opinion or feedback as positive (High Adoption Rate) or negative (Low Adoption Rate) effectively.

Rest of the article is segmented into section as follows section 2 defines review of literatures related to the user adoption prediction approaches from machine and deep learning architectures. Section 3 defines a design of accurate adoption rate forecasting model using recurrent neural network with long short term memory model with preprocessing process such as stop word removal, stemming, tokenization and token weighting and embedding. Section 4 mentions experimental and performance results of the proposed model against conventional approaches on cross fold validation of the contextual e learning learner interaction dataset in accurately forecasting user adoption rate to the e learning platforms. Finally section 5 concludes the article with major findings and suggestions.

2. RELATED WORK

In this section, review of literatures related to the different user opinion or feedback classification approaches from machine and deep learning architectures has been analyzed on basis of its performance and architecture capabilities is as follows

2.1. Convolution Neural Network for user feedback classification

In this literature, convolution neural network is employed to classify the user feedback to the e learning materials. Model composed of multiple convolution layers to extract low level and high level features from weighted tokenized vector of the user feedback and establishes feature map with respect to its associations. Those feature maps is processed in dense layer through activation function and softmax function to classify the user feedback to the e learning materials. Experimental analysis and performance analysis using learner feedback dataset proves that model produces 92.1% detection accuracy but it leads to class imbalance issues [8].

2.2. Recurrent Neural Network for user feedback classification

In this literature, recurrent neural network is employed to classify the user feedback to the e learning materials. Model composed of input layer, hidden layers and output layer with feedback loop. Input layer receives input and creates as input state and those input sequence projected to hidden layer to extract features or patterns from sequences. Those patterns are processed in hidden layer through activation function to predict attack occurrence in the transactions. Further those predicted information represent cell state and it is reiterated for next sequences of input. Experimental analysis and performance analysis proves that model produces 93.1% detection accuracy but it leads to high complexity [9].

3. PROPOSED MODEL

In this section, design of learning feedback processing model using recurrent neural network with long short term memory model with preprocessing process such as stop word removal, stemming, tokenization and token weighting and embedding is performed.

3.1. Data pre-processing

Data Preprocessing is initial phase of the model which transforms textual dataset to numerical dataset with several processing methods is as follow

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3.1.1. Stop Word Removal

Stop word removal is a pre-processing step performed to eliminate the stop words in form of noun, pronouns articles, preposition and conjunctions in the user opinion to produce reduced opinion data. Further it eliminates punctuation, whitespaces, and delimiters in the sentences for further processing Stop word removal from dataset never impacts prediction outcomes.

3.1.2. Stemming process

Stemming is another pre-processing step performed to reduce character length of the opinion phrases or words as it mostly affixed to suffixes and prefixes.

3.1.3. Tokenization

Tokenization is primary step in pre-processing as it splits the user opinion words as separate tokens which is referred as word based tokenization. Figure 1 represents architecture of the proposed user adoption forecasting model.

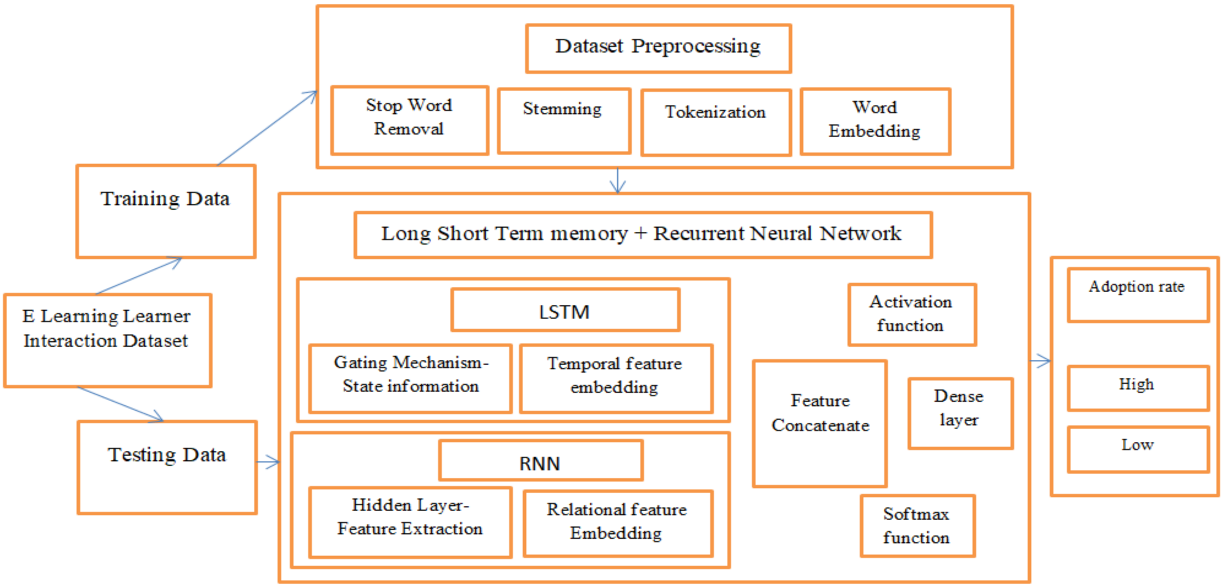

Figure 1: Proposed deep learning Architecture

3.1.4. Word Embedding or Weighted Tokenization

Word Embedding or weighted tokenization transforms the text into numerical format. It assigns numerical vector to each token with weight reflecting word importance. In this work, term frequency is used for word embedding which is defined as ratio of number of occurrence of the term or word in the specified opinion to total number of words in the opinion. Term frequency computation for word embedding is as follows

$$\text{TF (Token)} = \frac{No\ of\ occurence\ of\ the\ Specified\ word\ in\ the\ opinion}{Total\ number\ of\ words\ in\ the\ opinion}$$

3.2. Recurrent Neural Network integrated Long Short Term Memory

Integrated Recurrent Neural Network with Long Short Term Model Network leverages the benefit of feature extraction and detection process to balanced dataset. Proposed model strengthens discriminative capabilities of the features to enhance the performance of the model to prediction task. Component of the model is as follows

3.2.1. Input layer

Input layer of the Recurrent Neural Network obtains the word embedding vector and transforms it into sequential data. Transformed sequential data vector composed of feature representation is projected to hidden layer of the model.

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3.2.2. Hidden Layer

Hidden layer of the recurrent neural network processes the sequential data through activation function which uses Pearson correlation coefficients to generate correlated features. Correlated feature in form of state information is projected to LSTM model. Table 2 represents the hyperparameter setting of the Recurrent Neural Network for optimal sequence length. Learning rate, batch size and epoch were employed for early stopping to prevent overfitting. Optimizer was used for efficient training and mean square error as loss function

Table 2: Hyperparameter setting of Recurrent Neural Network

Hyperparameter	Value
Learning rate	10^{-6}
Batch Size	15
Epoch	20
Loss function	Cross entropy
Activation function	ReLu
Dropout rate	L2 regularization

3.2.3. Long short term memory mechanism

Long Short Term Model Network is applied to capture long term dependency of the temporal features of the sequential data using gating mechanism and represents in form of cell states. Initially it processes the input sequence over optimized time windows. Further multiple LSTM layers were stacked to learn temporal patterns utilizing forget gate. Especially dense layer is interfaced to transform the LSTM output into feature vector. Table 2 represents the hyperparameter setting of the Long Short Term Model Network for optimal sequence length.

Table 2: Hyperparameter setting of LSTM Network

Hyperparameter	Value
Learning rate	10^{-5}
Batch Size	11
Epoch	10
Loss function	Mean Square Error
Optimizer	Adam

Learning rate, batch size and epoch were employed for early stopping to prevent overfitting. Optimizer was used for efficient training and mean square error as loss function

3.2.4. Dense layer

The temporal feature embedding from LSTM model in form of patterns and relational features embedding from RNN in form of relation were concentrated to form a unified feature vector. Further complex relations among the features is learned [14]. Finally dense layer with activation function linearizes the complex relations and softmax function with classifier function classifies the user feedback with class labels of adoption rate (High /Low) effectively. Algorithm steps of the integrated recurrent neural network with long short term memory is as follows

Algorithm: RNN+LSTM

Input: Contextual E learning Learner interaction Dataset – User feedbacks

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Output: Classes – {High Adoption Rate, Low Adoption Rate}
Process()
Preprocess_Dataset ()
S_t = Stop word Removal (Dataset)
S_s = Stemming (S_t)
T= Word based tokenization(S_s)
T_f = Term Frequency(T)
RNN_LSTM ()
Input layer
Transform Numerical Vector into Sequential vector
Hidden Layer ()
Compute Similarities between features of the Sequential Vector
Relational Embedding
LTSM ()
Gating (Association Pattern of Sequence vector)
Cell state = patterns of the sequence
Feature Vector of LSTM= Long Term Dependency
Temporal Embedding
Dense layer ()
Activation function _ReLu (feature map)
Linear feature map
Dropout layer_L2 Regularization (linear feature)
Feature Concatenation (Temporal Feature Vector + Relational Feature Vector)
Unified Aggregated feature vector
Softmax function _Classifier (feature Vector)
Class= {High Adoption Rate & Low Adoption Rate }

4. EXPERIMENTAL ANALYSIS

Experimental analysis of the proposed model is conducted in Google colab which provides high performance online python environment with tensor flow functionalities and multiple libraries such as NumPy and Pandas for data manipulation, scikit learn for baseline models and Matplotlib for data visualization. Panda's libraries for data processing using contextual e learning learner interaction dataset extracted from kaggle repository [15]. Dataset is portioned as 60 percent employed for model training and 40 percent for model testing. Grid search was conducted to identify the optimal hyperparameter for model training to LSTM and RNN.

4.1. Performance analysis

Performance analysis of the model is performed using test data through confusion matrix. Confusion matrix generates the values to the true positive, false negative, true negative and false positive parameters. Those parameter values of the matrix demonstrates strong performance of the LSTM +RNN model in classifying the user feedback of e learning system on integrating the time series data(processed by LSTM network) and relational data(processed RNN network). Model achieved enhanced prediction accuracy of 9.4 percent. Further precision analysis, recall analysis and accuracy analysis were performed as follows

4.1.1. Precision Analysis

Precision analysis is performed to determine no of the aggregated positive feature correctly classified into high adoption rate classes among the total aggregated features. Precision analysis represented on parameter of confusion matrix is as follows

$$\text{Precision} = \frac{TP}{TP+FP}$$

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Figure 2 represents precision analysis of the model against conventional approaches. It represents model ability towards identifying adoption rate of the user to learning module of the e learning system on continuously updating the user behavior and perceptions.

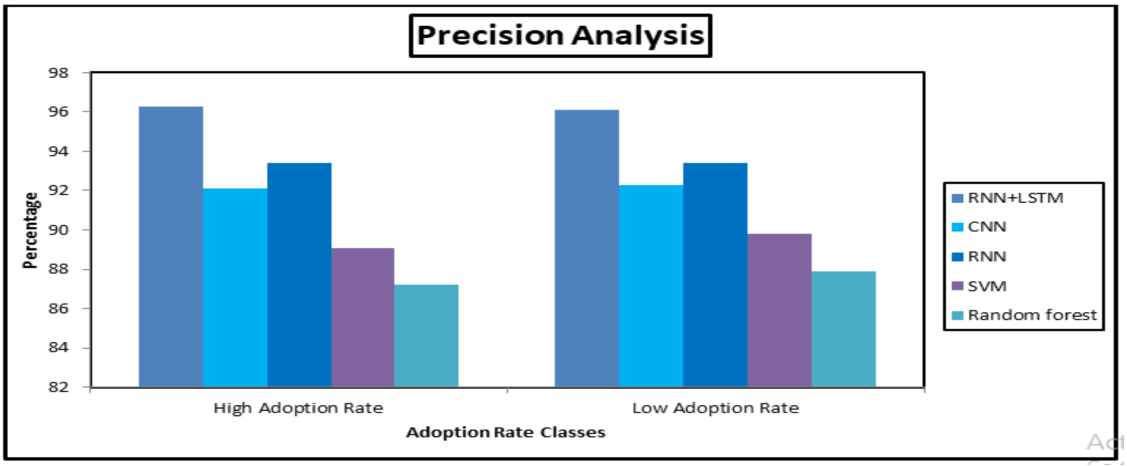

Figure 2: Precision Analysis

4.1.2. Recall Analysis

Recall analysis is performed to determine no of the aggregated feature incorrectly classified into financial transaction classes among the total aggregated features. Recall analysis represented on parameter of confusion matrix is as follows

$$\text{Recall} = \frac{TN}{TP+FP}$$

Figure 3 represents recall analysis of the model against conventional approaches. It represents model ability towards identifying adoption rate of the user to learning module of the e learning system on continuously updating the user behavior and perceptions.

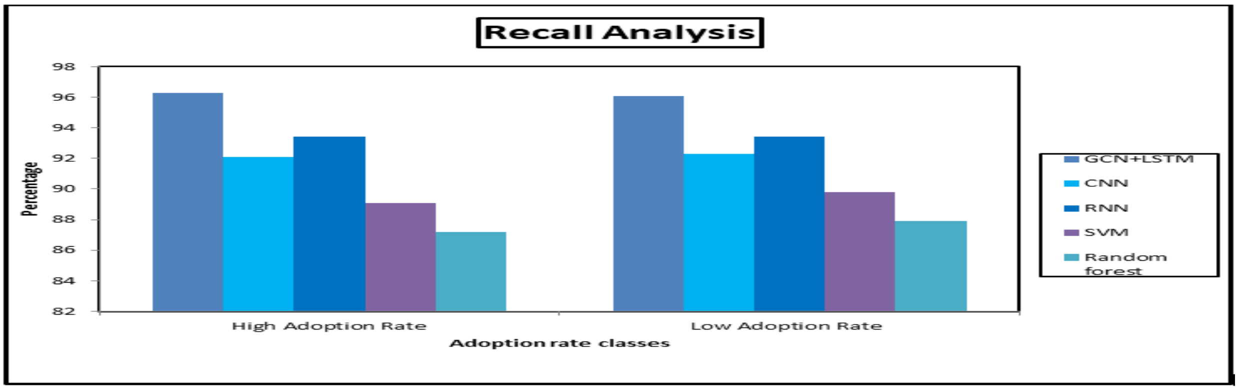

Figure 3: Recall Analysis

4.1.3. F-Measure Analysis

F-measure analysis is performed as aggregation of recall and precision towards detecting aggregated feature among total aggregated features into adoption rate classes. F-Measure analysis represented on parameter of confusion matrix is as follows

$$\text{F-Measure} = \frac{TP+TN}{TN+FN+TP+FP}$$

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Figure 4 represents F-Measure analysis of the model against conventional approaches. It represents model ability towards identifying adoption rate of the user to learning module of the e learning system on continuously updating the user behavior and perceptions.

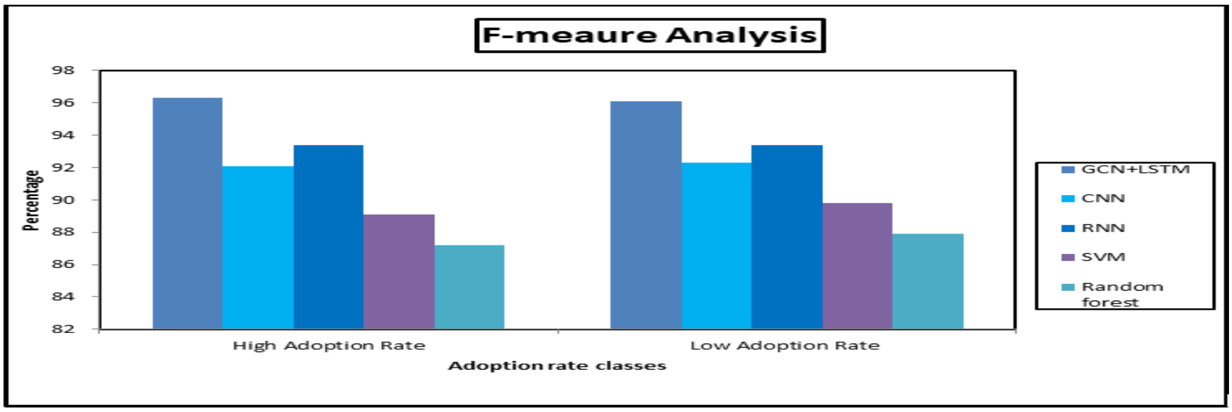

Figure 4: F-Measure analysis

Finally performance of RNN+LSTM architecture performs better with detection accuracy 96.4% on compared to conventional approaches. Table 2 mentions the performance evaluation of the deep learning architectures in adoption rate prediction

Table 2: Performance Evaluation of Deep learning architecture in forecasting adoption rate

Technique	Classes	Precision	Recall	F-Measure
GCN+LSTM – Deep learning	High Adoption Rate	96.1	94.2	96.4
	Low Adoption Rate	96.4	94.5	96.2
CNN-Deep learning	High Adoption Rate	93.4	91.7	93.7
	Low Adoption Rate	93.6	91.8	93.3
RNN – Deep learning	High Adoption Rate	91.6	90.1	91.6
	Low Adoption Rate	92.3	90.5	91.3
SVM-machine learning	High Adoption Rate	89.1	87.2	89.6
	Low Adoption Rate	89.8	87.3	89.2
Random Forest-machine learning	High Adoption Rate	87.2	86.3	87.8
	Low Adoption Rate	87.6	86.4	87.2

CONCLUSION

In this paper, a recurrent neural network with long short term memory model has been designed and implemented along group of preprocessing techniques such as stop word removal, stemming, tokenization and token weighting and embedding. Recurrent neural network extracts relational features on processing relational data in different layers of the network and long short term memory model extracts temporal features on processing time series data

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Research Article

in different layers of the network. Dense layer were concatenated feature vector in unified form and classified those feature vector into high adoption rate and low adoption rate. Experimental analysis defines efficiency of the configuration towards processing the user opinion on basis of interaction dataset and Performance analysis of model reports 96.4 % accuracy which is found to be better compared to accuracy value of the traditional architectures in user opinion classification. As a future work, accuracy of the opinion classification can be enhanced on employing federated architectures.

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