RECOMMENDATION SYSTEM FOR MOVIES USING RECURRING NEURAL NETWORKS (RNN) WITH GATED RECURRENT UNITS (GRU) AND LONG SHORT-TERM MEMORY (LSTM)

Mahesh Sankaran[1], Dr E.N. Ganesh[2]

Article History: Received: 12.12.2022 **Revised:** 29.01.2023 **Accepted:** 15.03.2023

Abstract

Recommender frameworks have become widespread of late because they manage the data overload problem by recommending the most important items to customers through a smorgasbord of information. As for the media item, online collaborative movie propositions make efforts to help customers get preferred motion pictures by accurately capturing relative neighbors among customers or by capturing motion pictures from their verifiable normal ratings. However, due to the lack of information, the rapid expansion of movies and customers makes choosing neighbors more complicated. This paper proposes deep learning Recurrent Neural-Networks to recommend movies & listing and users interests. We have used publicly available the movie databases. The proposed methodology is executed in MATLAB in addition performances can be assessed by performance measures like recall, precision, accuracy, recall, specificity, sensitivity and F_Measure. The projected methodology can be compared with the conventional methods such as SDLM, ODLM, Recurrent Neural Network (RNN) and Artificial Neural Network (ANN) respectively.

Keywords: movie recommendation system, Gated Recurrent Units (GRUs); Recurrent Neural Network-Long Short-Term Memory, Time Series Analysis

[1]Department of Computer Science, Phd Scholar, Vels Institute of Science Technology and Advanced Studies, Chennai, India
[2]School of Engineering, Dean, Vels Institute of Science Technology and Advanced Studies, Chennai India

Email: [1]mahesh.smahesh@gmail.com, [2]dean.se@velsuniv.ac.in

DOI: 10.31838/ecb/2023.12.s3.252

1. Introduction

Two central issues in the actual movie recommendation framework are often neglected: adaptability and Fair use input/confirmation considering actual performance. The Major need of the Users were to get a recommendation that will cover their behavior, previous watched movies, tv shows, suggestions for new coming movies. Secondly how long it would take to view the recommendations. Recently due to availability of abundant data, Machine Learning and deep learning techniques have gained immense interest. These techniques are very helpful for obtaining the relationships from data without defining them earlier [22]. Further these techniques are also capable of recommending the trends based on reported time-series data over a known period. Several researchers have used the machine learning and deep learning models to recommend movies & tv shows for the users. Collaborative filtering (CF) is one the most involved calculations for generating rating expectations within CF [1]. It depends on the center Doubt that customers who have communicated comparable interests in the past will now share common interests. Thus, the potential for cooperative segmentation is to internally recognize customers who share an appreciation for comparable items [2]. Naturally, if two customers have evaluated the same or practically the same things, they have comparative preferences, and then they can be sent to a converging or intimate area [3]. A customer can get proposals for things he/she has not evaluated before, although they are currently being judged by customers in his/her area. As the number of clients and subjects grows, CF-based recommendation frameworks require more assets to handle data and framework proposals. Most of these assets are used in determining customers with relative preferences and comparable depictions [4]. Then, CF calculations face a versatile problem, which becomes a significant variable for a proposal framework. In case the problem is not resolved, it is problematic to make continuous recommendations [5].

The rapid growth of innovation has led to tremendous expansion of information due to internet administrations, e-commerce area, film, music and comedy and many more. The framework restores old-fashioned data suggestion in view of the client's recorded behavior instead of specifying any customer question [6]. Different types of consulting strategies can be named as demographic recommendation filter, knowledge-inbuilt recommendation approach, collaborative recommendation approach, content enabled recommendation approach. In which hybrid strategies are preferred to develop a collaborative, content-based and integrated process, i.e., recommendation systems [7]. Material Reinforced Proposal Approach explores different characteristics of things and items such as supporters for interested customers. The Collaborative recommendation approach looks at the customer comparison list [5], taking into account the customer's previous ratings, with the assumption that the solution buyers will have to make relevant decisions in the coming periods that are comparable to the results of the previous period [8].

Whether in diversion, training or in different fields, consulting structures have been gradually gaining popularity recently. Already, buyers had to decide what books to buy, what music to focus on, and which movies to watch. Commercial movie libraries are now in large numbers, surpassing the visual capacity of any individual [9]. By browsing an incredible number of movies like this, individuals can sometimes gain power. Accordingly, a strong proposal framework is needed for film professional cooperatives and clients to be empowered. Due to the improvement of referral frameworks, customers will have no problem judging options, and efforts will continue to attract their clients to their site and help client fulfillment attract new customers. Besides, current developments, for example, machine learning and deep improvement now play a significant role in improving adaptations that can be converted to everyday activities [10].

- In this paper, to develop PCAADLM for automatic movie recommendation system. The projected technique is developed to identify the best rated movies and automatic movie recommendation system.
- This PCAADLM is a combination of RNN-LSTM, PCA and CMO. In the RNN-LSTM, the CMO is utilized to select optimal weighting parameters. The PCA is utilized along with proposed techniques to enable efficient movie recommendation system.
- To validate the proposed methodology, the movie databases is gathered from the online solutions. The proposed methodology is executed in MATLAB in addition performances can be assessed by performance measures like recall, precision, accuracy, recall, specificity, sensitivity and F_Measure.
- The projected methodology can be compared with the conventional methods such as SDLM, ODLM, Recurrent Neural Network (RNN) and Artificial Neural Network (ANN) respectively.

The remaining portion of the paper is pre-arranged as follows; section 2 provides the detail literature review of movie recommendation system. Section 3 given the proposed system model. Section 4 outcomes of the projected system. The conclusion of the research is presented in the section 5.

2. Related works

The eminence of the recommendation structure can be operated by various systems. It is basically in two different ways. In light of the trust between clients, regular referral structures and trust-appreciative referral structures. Some of the techniques are revealed in this portion. Ghoshal et all.[23] has used the liner regression and multiple linear regression to predict the data for upcoming six weeks. Authors have recommended the data if the parameters are unchanged.

Parbat and Chakraborty [24] have used the support Vector Regression (SVR) for recommendation data for certain days based on the time series data. Their model has ~97% accuracy in recommending the data and has ~87% accuracy in predicting the daily data.

Maleki et al. [25] have employed autoregressive time-series models based on two-piece scale mixture normal distributions to recommend data. Their model performed well in recommendation.

Ram Kumar Singh et al. [26] applied holt-winter models and Susceptible Infected and Recovered (SIR) model on data of India . They used particle spam optimization to estimate the parameters of the SEIR model.

Ribeiro et al. [27] have used ARIMA, Cubist regression, Random Forest, Ridge Regression, SVR and Stacking-ensemble learning for short-term forecasting This paper reveals best to worst performing models, best performing models are found to be SVR and ARIMA.

Ardabili et al.[28] have used the Machine Learning techniques for predicting the data,they found that the multi-layer perceptron model and adaptive network based fuzzy interface system are found to give promising results.

Chimmula and Zhand[29] have used the deep learning model using Long short-term Memory (LSTM) network to recommend data.

Salgotra et al [30] have developed models based on genetic programming for forecasting the data. Authors have reported their model is less sensitive to variables and highly reliable in recommending.

Qi et al[31] have used the generalized adaptive model to understand the association of various parameters.

Ismail et al[32] conducted a comparative study based on ARIMA, LSTM, Non-linear Autoregressive Neural Networks (NARNN) models. Combined LSTM based(RNN) model provided a better recommendation when compared to the individual models.

Anuradha Tomar et al[33] have used LSTM and curve fitting for the recommendation data.

Mehdi et al[34] have used RNN, LSTM, Seasonal Autoregressive Integrated Moving Average(SARIMA) and Holt winder’s exponential smoothing and moving average method to recommend data. Their comparative study on these methods showed that LSTM model outperformed other models in terms of less error values

3. Proposed System Model

Based on the reports, the models proposed in the literature survey confined to very less data points. We still have room to develop geo specific deep learning models to recommend data, provide trends that are highly impactful. Hence aim is to recommend future trends of the data using RNN along with Gated Recurrent Units (GRUs) and Long Short Term Memory cells. These models are trained on the training data and tested on the testing data, ultimately, the validated models have used to recommend data in several geos.

The complete architecture of the proposed system is presented in figure 1.

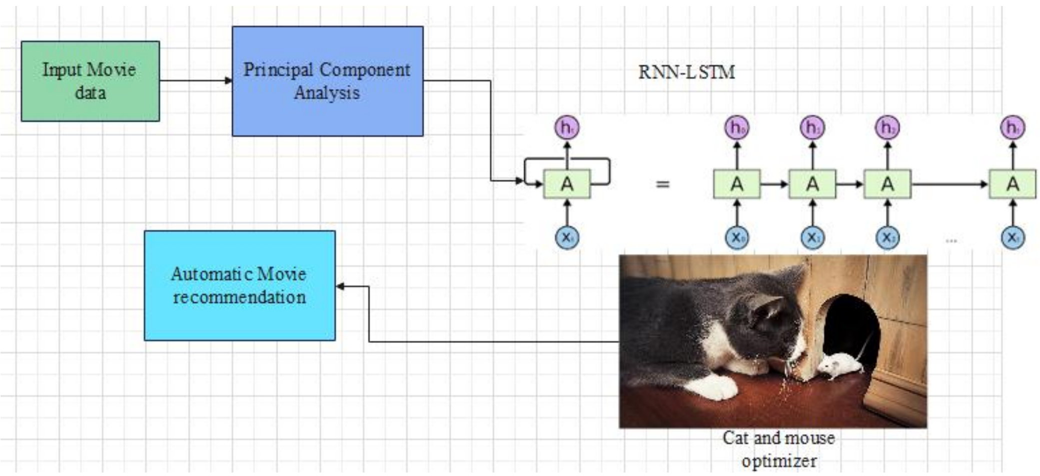

Figure 1: Block diagram of the proposed methodology

In this paper, to develop PCAADLM for automatic movie recommendation system. The projected technique is developed to identify the best rated movies and automatic movie recommendation system. This PCAADLM is a combination of RNN-LSTM, Principal PCA and CMO. In the RNN-LSTM, the CMO is utilized to select optimal weighting parameters. The PCA is utilized along with proposed techniques to enable efficient movie recommendation system. To validate the proposed methodology, the movie databases is gathered from the online solutions. The proposed methodology is executed in MATLAB in addition performances can be assessed by performance measures like recall, precision, accuracy, recall, specificity, sensitivity and F_Measure.

3.1. Recurrent neural networks

Recommendation involving time-series data can be mainly two types, machine learning and deep learning methods. Deep learning models are superior over machine learning models for recommendation on non-linear applications such as weather, stock prices, electro cardiogram recordings and oil prices etc. Feed forward neural networks(FFNNs) and Recurrent Neural networks (RNNs) are two widely used deep learning techniques. FFNNs are not suitable for recommendations as they are not capable of considering the trends in the time-series data. RNNs are powerful and robust type of artificial neural networks that uses existing time-series data to recommend future data. RNNs are promising techniques due to the internal memory that can remember important features of sequential data. FFNNs information flows strictly In one direction from layer to layer, in RNNs the output from previous time stamp along within put from present time stamp will fed into RNN cell, so the current state of model is influenced by its previous states.

RNN can recollect the recent information but cannot recollect the earlier information. Though the RNNs can be trained by back propagation, it will be very difficult to train them for long input sequences due to vanishing gradients.

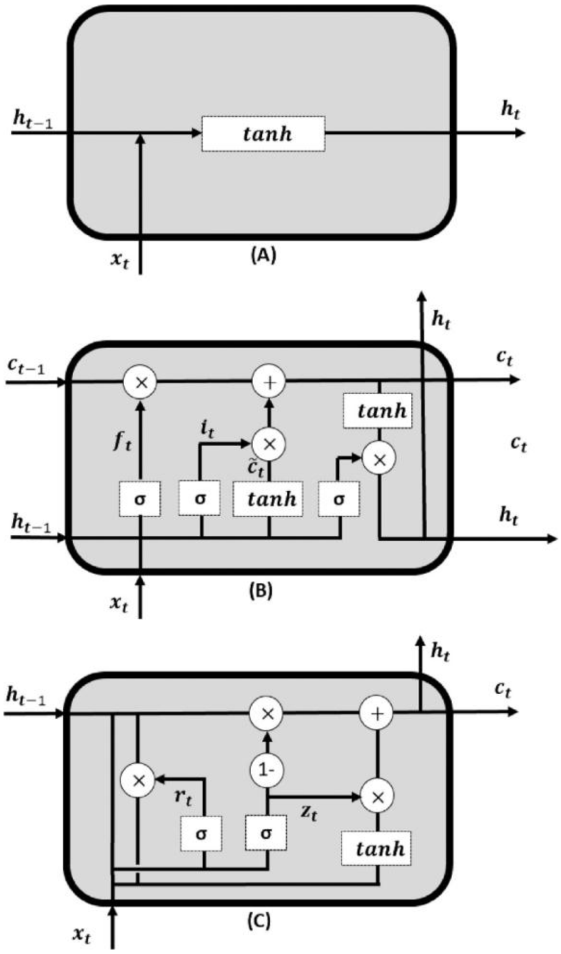

Figure 1: Representation of (A) simple Recurrent Neural Network(RNN) (B) Long-short term Memory (LSTM) cell (C) Gated Recurrent Unit (GRU) cell

3.2. RNN-LSTM

ANN is a correlation technique and analyzed with direct mapping among output and input data. The ANN application in time series forecasting is limited. To solve this issue, RNN generate sequence to sequence mapping through connecting neurons in the cycles. The input of the last time period may be affects by the output of the next time period. The utilization of contextual data for connecting among output and input can be a key parameter of the RNN. The RNN affect by loss of the efficient removed input data. Moreover, RNN affect by problem of gradient vanishing as with ANN. The variables can be optimized in a wrong path when the BP theory updates the parameters. The gradient disappears, in addition network cannot be updated. The validation of the conventional RNN design can be improved by utilizing LSTM. The RNN-LSTM is developed for reducing the problem of regression with machine learning techniques, ANFIS and ANN. The RNN layered LSTM design is illustrated in figure 2. The regression output layer, fully connected layer, LSTM layer and sequence input layer are designed in the proposed classifier model.

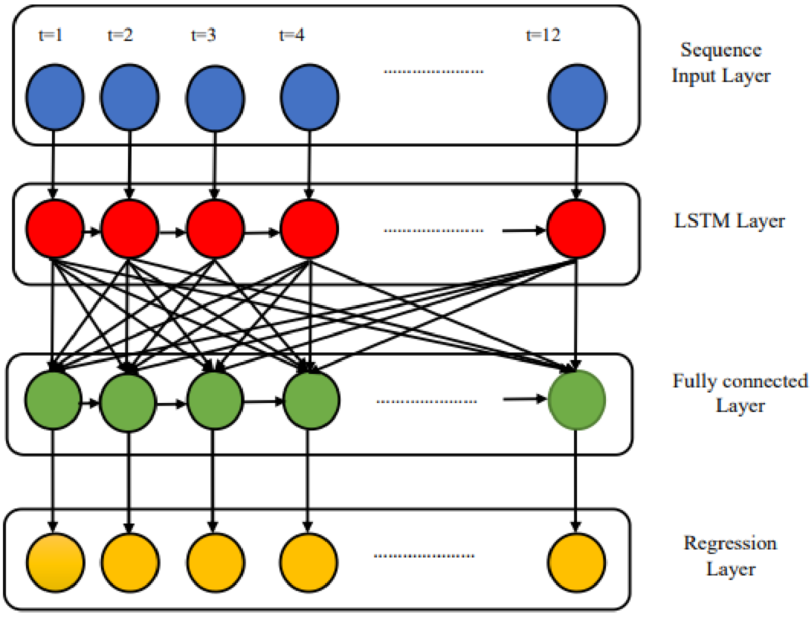

Figure 2: Architecture of the proposed RNN-LSTM

The hyperparameters can be efficiently managed to enhance the proposed system accuracy. Various combinations of this hyperparameter parameter within the specific period can be connected for implementation to compute accuracy of the projected technique. However, the constraints of the hyperparameters (hidden units, epochs) can be defined due to the response remains almost the similar higher than maximum parameter. It causes only wastage of resources and time. The efficient combination with low RMSE can be selected for efficient performance [17].

Formulation of RNN

The design of RNN presented on last information $(T-1)$ to make output of data for present time (T). The conventional three-layer Elman network is considered. The input can be sent to the hidden layer with the basis of learning function. It is a connection to collect the last data of the hidden unit in the context information. The formula is presented as follows,

$$H_T = \varphi_H(U_{IN}X_T + V_H H_{T-1} + B_H) \quad (1)$$

$$Y_T = \varphi_Y(W_{out}H_T + B_Y) \quad (2)$$

Here, W_{out} can be defined as the weight matrix among output layer and hidden layer, B_Y can be defined as the biases of output layer, B_H can be defined as the bias of hidden layer, V_{in} can be defined as the weight matrix among the hidden layers, U_{IN} can be defined as the weight matrix, φ_Y and φ_H can be defined as output layer and hidden layer activation functions, H_T can be defined as the vector of present time [19], H_{T-1} can be defined as vector of previous time. Conventional activation functions can be considered as sigmoid function which used for RNN implementation. The formulation is defined as follows,

Power sigmoid activation function:

$$\varphi(X) = \begin{cases} \dfrac{(1+e^{-\epsilon x})(1+e^{-\epsilon})}{(1+e^{-\epsilon})(1+e^{-\epsilon x})} & |X| < 1 \\ X^a & |X| \geq 1 \end{cases} \quad (3)$$

Here, $a \geq 3$ and $\epsilon > 2$.

Bipolar sigmoid activation function,

$$\varphi(X) = \frac{1-e^{-\epsilon x}}{1+e^{-\epsilon x}} \quad (4)$$

Here, $\epsilon > 2$

Formulation of LSTM

The LSTM network contains the advantage to manage time series information due to its ability to connect among output and input sequences with contextual data. The workflow design of output gate, input gate and forget gate of LSTM network is presented as follows,

Memory cell

A tanh layer generates a vector of novel candidate parameters which can be added in the state.

$$\widetilde{C_T} = \tanh(W_C \times [H_{T-1}, X_T] + B_C) \quad (5)$$

$$H_T = O_T * tanh(C_T) \quad (6)$$

The state of the old memory cell can be upgraded to novel memory cell,

$$C_T = F_T * C_{T-1} + I_T * \widetilde{C_T} \quad (7)$$

Output gate

The memory cell output can be managed by the output gate is presented as follows,

$$O_T = \varphi_a(W_{out} \times [H_{T-1}, X_T] + B_{OUT}) \quad (8)$$

Input gate

The data flowing into the cell can be managed by the input gate.

$$I_T = \varphi_a(W_{IN} \times [H_{T-1}, X_T] + B_{IN}) \quad (9)$$

Forget gate

This forgets gate considers the latest input and last output of memory block. the activation function of the forget gate can be selected to be logistic sigmoid as general practice, computes how much data can be reserved the upper cell.

$$F_T = \varphi_a(W_{IN} \times [H_{T-1}, X_T] + B_F) \quad (10)$$

The RNN-LSTM is utilized to automatic movie recommendation system. In the RNN-LSTM, the optimal weighting parameter is selected with the assistance of CMBO [18].

3.3. Gated Recurrent unit (GRU)

GRU is a simplified version of LSTM and requires less training time with improved network performance. The Operation of a GRU cell is similar to the operation of LSTM cell but GRU cell use one hidden state that mergers the forget gate and the input gate into a single update gate. Further it combines the cell state and hidden state into one state and hence the total number of gates in LSTM. Hence it is popular and simplified variant of LSTM cell. ,

4. Performance Evaluation

To recognize the presence of the projected image segment, the proposed strategy is implemented on the Intel Core i5-2450M CPU 2.50GHz PC in addition 6GB RAM. This technique is carried out on MATLAB programming R2016b. To authorize the exhibition of the proposed strategy, data are collected from collections [21], which include more than 1500 movie name with rating. Optimizing the set of hyper parameters such as number of nodes in each layer, number of hidden layers and the learning rate is very important for achieving the best sequential prediction.Adam optimizer is used for iteratively optimize the network weights with the mean squared error(MSE) function as loss function. RNNs are very sensitive to the fluctuations in the time series data and to capturing the trends in time series data, the data has to be normalized before feeding it to the neural network. MinMaxscaler was used to normalize the data. MinMaxScaler retaings the shape of original distribution of the data and does not alter the information which is embedded within the original data even after transforming the data.

The training time-series data is divided into several data sequences each of length 20. Each sequential data is fed to the RNN (i.e the data from day 1 to day 20) to predict the 21st data point. In consequent step, the next sequence of the data is fed to RNN to complete one set of recommendations and which also is complete one epoch. The process was repeated for each country and for each of time-series dataset to propose a customized RNN models. Mean Square Error(MSE) and Root Mean Square Error(RMSE) were used to evaluate performance of proposed models

The projected technique is contrasted with the traditional techniques like ODLM, RNN in addition ANN respectively.

Table 1: Parameters of projected technique

S. No	**Technique**	**Description**	**Value**
1	Proposed Method	Number of Decision Variables	5
2		Number of Populations	50
3		Upper bound	5.12
4		Lower bound	-5.12
5		Iteration	100

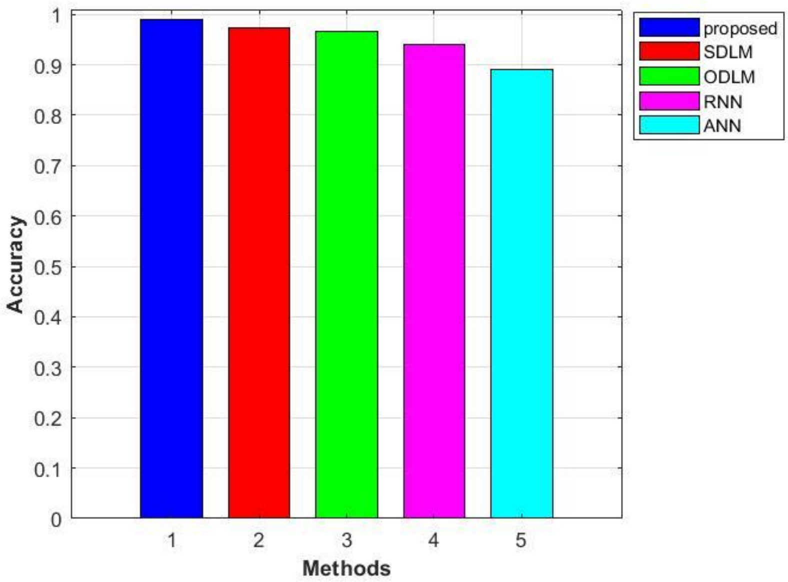

Figure 3: Accuracy

The performance metric of accuracy is utilized to evaluate the projected technique which is illustrated in figure 3. The projected technique is contrasted with the traditional techniques like SDLM, ODLM, RNN in addition ANN respectively. The proposed methodology is attained the 0.99 accuracy. Similarly, the SDLM, ODLM, RNN, ANN is attained the 0.98, 0.93, 0.90 and 0.87 accuracy. With the analysis of the accuracy, the projected technique is achieved efficient accuracy in the movie recommendation system. The performance metric of precision is utilized to evaluate the projected technique which is illustrated in figure 4. The projected technique is contrasted with the traditional techniques like SDLM, ODLM, RNN in addition ANN respectively. The proposed methodology is attained the 0.97 precision. Similarly, the ODLM, SVM, ANN is attained the 0.91, 0.87 and 0.85 precision. With the analysis of the precision, the projected technique is achieved efficient precision in the movie recommendation system.

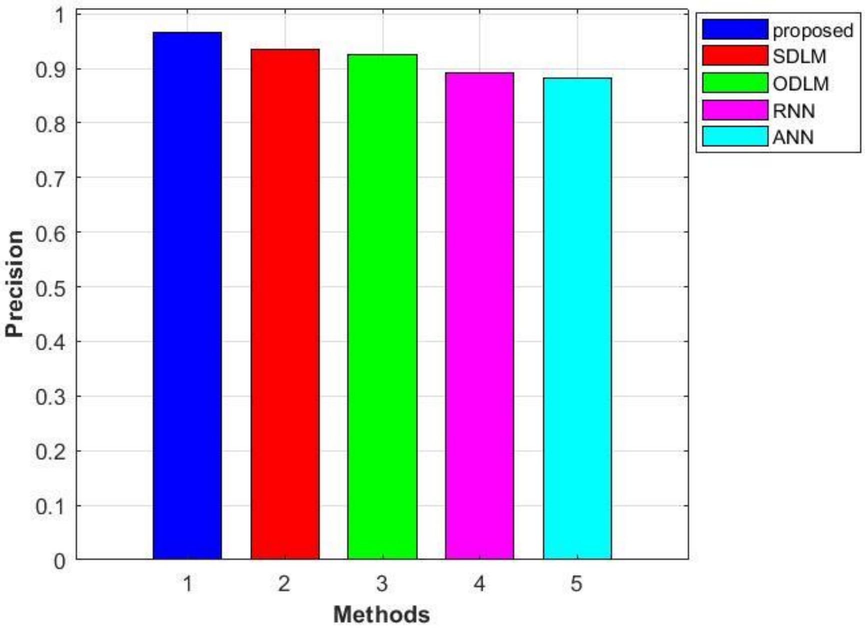

Figure 4: Precision

The performance metric of recall is utilized to evaluate the projected technique which is illustrated in figure 5. The projected technique is contrasted with the traditional techniques like SDLM, ODLM, RNN in addition ANN respectively. The proposed methodology is attained the 0.95 recall. Similarly, the SDLM, ODLM, RNN, ANN is attained the 0.93, 0.91, 0.90 and 0.87 recall. With the analysis of the recall, the projected technique is achieved efficient precision in the movie recommendation system. The performance metric of sensitivity is utilized to evaluate the projected technique which is illustrated in figure 6. The projected technique is contrasted with the traditional techniques like SDLM, ODLM, RNN in addition ANN respectively. The proposed methodology is attained the 0.94 sensitivity. Similarly, the SDLM, ODLM, RNN, ANN is attained the 0.93, 0.92, 0.87 and 0.85 sensitivity. With the analysis of the sensitivity, the projected technique is achieved efficient sensitivity in the movie recommendation system.

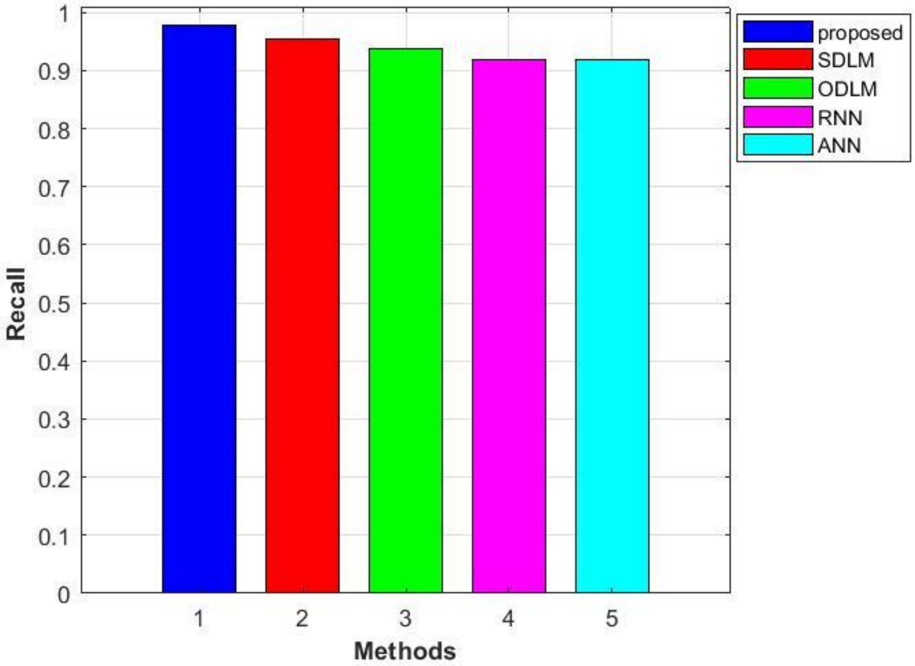

Figure 5: Recall

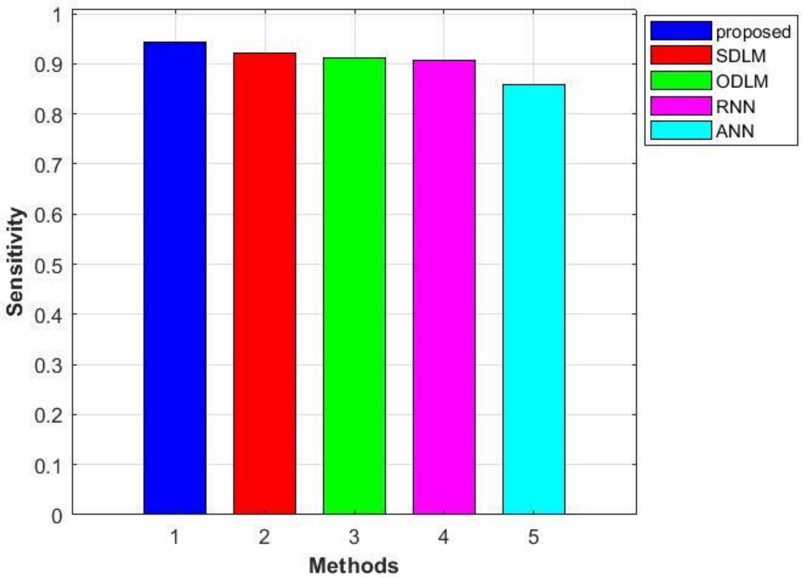

Figure 6: Sensitivity

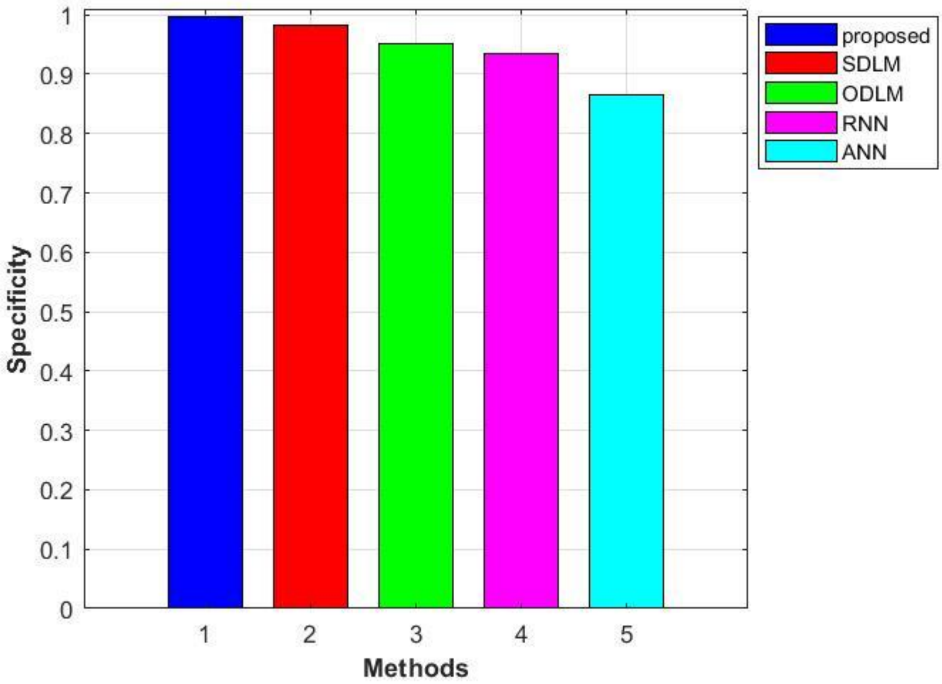

Figure 7: Specificity

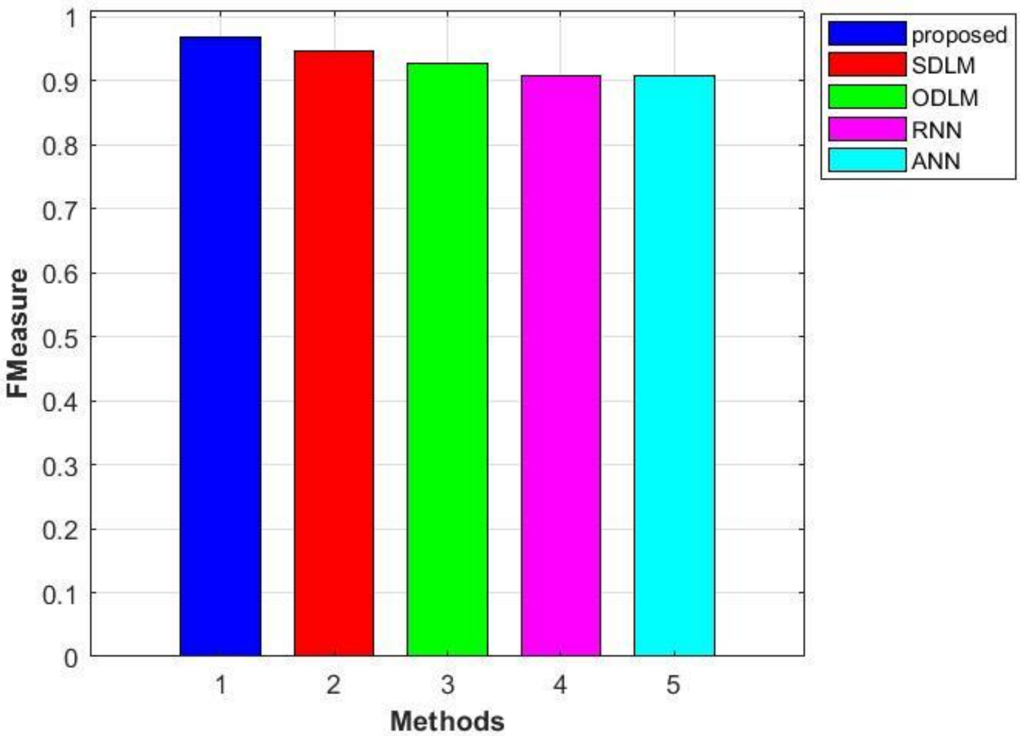

Figure 8: F_Measure

The performance metric of specificity is utilized to evaluate the projected technique which is illustrated in figure 7. The projected technique is contrasted with the traditional techniques like SDLM, ODLM, RNN in addition ANN respectively. The proposed methodology is attained the 0.97 specificity. Similarly, the SDLM, ODLM, RNN, ANN is attained the 0.96, 0.94, 0.89 and 0.85 specificity. With the analysis of the specificity, the projected technique is achieved efficient specificity in the movie recommendation system. The performance metric of F_Measure is utilized to evaluate the projected technique which is illustrated in figure 8. The projected technique is contrasted with the traditional techniques like SDLM, ODLM, RNN in addition ANN respectively. The proposed methodology is attained the 0.96 F_Measure. Similarly, the SDLM, ODLM, RNN, ANN is attained the 0.94, 0.93, 0.88 and 0.87 F_Measure. With the analysis of the F_Measure, the projected technique is achieved efficient F_Measure in the movie recommendation system.

2. Conclusion

In this paper, we had reported a recommendation data using RNN-LSTM and RNN-GRU models. Model with less values of MSE and RMSE is believed to be best model for recommendation. LSTM model performs better for few countries and other hand, GRU model performed better for other few countries. The projected technique is developed to identify the best rated movies and automatic movie recommendation system. LSTM model recommendations were much closed to users interest and was viewed well in few countries, but GRU provided a recommendations data which was rise in adaption over the time. For demographic related data recommendations, LSTM model can perform better for some counters and GRU model can perform better for some countries. Based on the results data, it is highly recommended to develop a deep learning model by feeding all various countries data sets simultaneously recommend the trends. More amount od data and accurate data is needed to develop robust accurate models To validate the proposed methodology, the movie databases has been gathered from the online solutions. The proposed methodology is executed in MATLAB in addition performances can be assessed by performance measures like recall, precision, accuracy, recall, specificity, sensitivity and F_Measure. The projected methodology can be compared with the conventional methods such as SDLM, ODLM, RNN and ANN respectively.

3. References

Liu, Dan, and Hou-biao Li. "A Matrix Decomposition Model Based on Feature Factors in Movie Recommendation System." arXiv preprint arXiv:2206.05654 (2022).

Kale, Rohit, Saurabh Rudrawar, and Nikhil Agrawal. "Movie Recommendation System Using Hybrid Collaborative Filtering Model." In Computational Vision and Bio-Inspired Computing, pp. 109-117. Springer, Singapore, 2022.

Hui, Bei, Lizong Zhang, Xue Zhou, Xiao Wen, and Yuhui Nian. "Personalized recommendation system based on knowledge embedding and historical behavior." Applied Intelligence 52, no. 1 (2022): 954-966.

Daneshvar, Hirad, and Reza Ravanmehr. "A social hybrid recommendation system using LSTM and CNN." Concurrency and Computation: Practice and Experience (2022): e7015.

Sahu, Sandipan, Raghvendra Kumar, Pathan MohdShafi, Jana Shafi, SeongKi Kim, and Muhammad Fazal Ijaz. "A Hybrid Recommendation System of Upcoming Movies Using Sentiment Analysis of YouTube Trailer Reviews." Mathematics 10, no. 9 (2022): 1568.

Ramya, G. R., and Priyadarshini Bhatnagar. "Movie Recommendation System Using Color Psychology Based on Emotions." In Inventive Computation and Information Technologies, pp. 463-480. Springer, Singapore, 2022.

Pavitha, N., Vithika Pungliya, Ankur Raut, Roshita Bhonsle, Atharva Purohit, Aayushi Patel, and R. Shashidhar. "Movie Recommendation and Sentiment Analysis Using Machine Learning." Global Transitions Proceedings (2022).

Khatter, Harsh, Amit Kumar Gupta, Prabhat Singh, and Ruchi Rani Garg. "Smart Recommendation System for Hollywood Movies Using Cosine Similarity Index." In International conference on smart computing and cyber security: strategic foresight, security challenges and innovation, pp. 283-294. Springer, Singapore, 2022.

Parthasarathy, Govindarajan, and Shanmugam Sathiya Devi. "Hybrid Recommendation System Based on Collaborative and Content-Based Filtering." Cybernetics and Systems (2022): 1-22.

Shrivastava, Vineet, and Suresh Kumar. "Movie Recommendation Based on Fully Connected Neural Network with Matrix Factorization." In Applications of Artificial Intelligence and Machine Learning, pp. 545-556. Springer, Singapore, 2022.

A. F. O. U. D. I. Yassine, L. A. Z. A. A. R. Mohamed, and Mohammed Al Achhab. "Intelligent recommender system based on unsupervised machine learning and demographic attributes." Simulation Modelling Practice and Theory 107 (2021): 102198.

Bhalse, Nisha, and Ramesh Thakur. "Algorithm for movie recommendation system using collaborative filtering." Materials Today: Proceedings (2021).

Bushra Ramzan, Imran Sarwar Bajwa, Noreen Jamil, Riaz Ul Amin, Shabana Ramzan, Farhan Mirza, and Nadeem Sarwar. "An intelligent data analysis for recommendation systems using machine learning." Scientific Programming 2019 (2019).

Behera, Dayal Kumar, Madhabananda Das, Subhra Swetanisha, and Prabira Kumar Sethy. "Hybrid model for movie recommendation system using content K-nearest neighbors and restricted Boltzmann machine." Indones. J. Electr. Eng. Comput. Sci 23, no. 1 (2021): 445-452.

Yashar Deldjoo, Maurizio Ferrari Dacrema, Mihai Gabriel Constantin, Hamid Eghbal-Zadeh, Stefano Cereda, Markus Schedl, Bogdan Ionescu, and Paolo Cremonesi. "Movie genome: alleviating new item cold start in movie recommendation." User Modeling and User-Adapted Interaction 29, no. 2 (2019): 291-343.

Lamichhane, Shyam, Gökhan Eğilmez, Ridvan Gedik, M. Khurrum S. Bhutta, and Bulent Erenay. "Benchmarking OECD countries' sustainable development performance: A goal-specific principal component analysis approach." Journal of Cleaner Production 287 (2021): 125040.

Chui, Kwok Tai, Brij B. Gupta, and Pandian Vasant. "A genetic algorithm optimized RNN-LSTM model for remaining useful life prediction of turbofan engine." Electronics 10, no. 3 (2021): 285.

Gill, Harmandeep Singh, and Baljit Singh Khehra. "An integrated approach using CNN-RNN-LSTM for classification of fruit images." Materials Today: Proceedings 51 (2022): 591-595.

Dehghani, Mohammad, Štěpán Hubálovský, and Pavel Trojovský. "Cat and mouse-based optimizer: a new nature-inspired optimization algorithm." Sensors 21, no. 15 (2021): 5214.

Alqahtani, Abdullah Saleh, P. Saravanan, M. Maheswari, and Sami Alshmrany. "An automatic query expansion based on hybrid CMO-COOT algorithm for optimized information retrieval." The Journal of Supercomputing 78, no. 6 (2022): 8625-8643.

http://deepyeti.ucsd.edu/jianmo/amazon/index.html

S. rekhaHanumanthu Role of Intelligent Computing in COVID-19 Prognosis: A State-of-the-Art Review, Chaos, Solitons& Fractals (2020), Article 109947

S. Ghosal, *et al.* Prediction of the number of deaths in India due to SARS-CoV-2 at 5–6 weeks Diabetes & Metabolic Syndrome: Clinical Research & Reviews (2020

D. Parbat, A Python based Support Vector Regression Model for prediction of Covid 19 cases in India, Chaos, Solitons & Fractals (2020), Article 10994

M. Maleki, *et al.* Time series modelling to forecast the confirmed and recovered cases of COVID-19, Travel Medicine and Infectious Disease (2020), Article 101742

D. Benvenuto, *et al.* Application of the ARIMA model on the COVID-2019 epidemic dataset,Data in brief (2020), Article 105340

F. Petropoulos, S. Makridakis, Forecasting the novel coronavirus COVID-19 PloS One, 15 (3) (2020), Article e0231236

R.K. Singh, *et al.* Short-term statistical forecasts of COVID-19 infections in India IEEE Access, 8 (2020), pp. 186932-186938

S. He, Y. Peng, K. Sun SEIR modeling of the COVID-19 and its dynamics Nonlin Dyn, 101 (3) (2020), pp. 1667-1680

M. Thäter, K. Chudej, H.J. Pesch ,Optimal vaccination strategies for an SEIR model of infectious diseases with logistic growth ,Math Biosci Eng, 15 (2) (2018), p. 485

J. Tolles, T. Luong Modeling Epidemics With Compartmental Models JAMA, 323 (24) (2020), pp. 2515-2516

P. Teles A time-dependent SEIR model to analyse the evolution of the SARS-CoV-2 epidemic outbreak in Portugal (2020) ,arXiv preprint arXiv:2004.04735

M.H.D.M. Ribeiro, *et al.* Short-term forecasting COVID-19 cumulative confirmed cases: Perspectives for Brazil Chaos, Solitons& Fractals (2020), Article 109853

P. Kumar, *et al.*Forecasting the dynamics of COVID-19 Pandemic in Top 15 countries in April 2020: ARIMA Model with Machine Learning Approach (2020) medRxiv

S.F. Ardabili, et al.Covid-19 outbreak prediction with machine learning(2020) Available at SSRN 3580188

K.E Arunkumar et al . Forecasting of COVID-19 using deep layer Recurrent Neural Networks (RNNs) with Gated Recurrent Units (GRUs) and Long Short-Term Memory (LSTM) cells, Chaos, Solitons & Fractals (2021), Article 110861