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Movie Automatic Recommendation System Using Optimal Deep Learning Model

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Abstract
The Recommendation System is a concept for client-bearing data load problem of sites that allows evaluation of a particular movie. In this paper, to develop Optimal Deep Learning Model (ODLM) for automatic movie recommendation system. The proposed model is developed to predict the best rated movies and automatic movie recommendation system. This ODLM is combination of Recurrent Neural Network (RNN) and Aquila Optimization Algorithm (AOA). In the RNN, the AOA is utilized to select optimal weighting parameters. The proposed methodology is a utilized the last search information of a user related references and movie category this to develop the recommender engine, based on that, the list of predictions for top rating is computed. The collaborative filtering is utilized along with proposed techniques to enable efficient movie recommendation system. To validate the proposed methodology, the movie databases isgathered from the online solutions. The proposed methodology isexecuted in MATLAB in addition performances can beassessed by performance measureslike recall, precision, accuracy, recall, specificity, sensitivity and F_Measure. The projected methodology can be compared with the conventional methods such as Artificial Neural Network (ANN), Support Vector Machine (SVM), and Recurrent Neural Network – Particle Swarm Optimization (RNN-PSO) respectively.

Keywords: *movie recommendation system, rating, machine learning, collaborative filtering, recurrent neural network and aquila optimization algorithm*

1. Introduction

Recommendation systems are tools that separate data from current content in terms of customer preferences and behavior, for example, logical documents or ideas about music that a customer may like. In light of what we have said, in the development of software engineering, we have begun to look at great information and have noticed how it is used to find customer interest, we have noticed that more research is being done in place of the recommendation and there are strong structures [1]. Accessible. In the 1990s, proposal structures became a popular subject of choice. Memory in the referral framework is filled on a late basis, and proposal frameworks currently play a major role in business platforms and significant companies such as Spotify, Facebook, LinkedIn and IMdb. Sell and sell more upgraded products or increase client fulfillment. This interest in this type of structure has led researchers to develop stronger structures, and some research has been done in this area [2].

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 [3]. 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 [4]. 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 [6\.

The section and information built-in proposal framework deals with district transparent information filtration and clear information filtration. The hybrid recommendation framework can be designed by taking at least one set of RSs of one type or another [7]. The most widely used referral framework is Cooperative RS. After all, it's a cold-start (no recommendation list for new customer and new things) [8], lack of information (customer structure has low ratings), bad attacks (customer ratings are copied, triggering intimacy between other customer customers) and the Gray-Sheep issue (customer taste is exceptional). The resulting proposal structure weakens the proposal structure). Due to the limitations and difficulties of the Collaborative (CF) proposal, the trust and similarity between the clients is considered for better advice than the comparatively [9] based client. Without a trace of information evaluation, social interaction between customers can be seen as a factor of trust between them [10].

The main contribution of the paper is presented as follows,

- In this paper, to develop ODLM for automatic movie recommendation system. The proposed model is developed to predict the best rated movies and automatic movie recommendation system.
- This ODLM is combination of RNN and AOA. In the RNN, the AOA is utilized to select optimal weighting parameters. The proposed methodology is a utilized the last search information of a user related references and movie category this to develop the recommender engine, based on that, the list of predictions for top rating is computed.
- The collaborative filtering 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 ANN, SVM, and RNN-PSO respectively.

The extra portion of the paper can be pre-planned as follows; section 2 given the detail review section. The projected model is deliberated in the section 3. The outcomes of the projected approach are presented in the section 4. The conclusion in addition future implications can be presented in the section 5.

2. Literature Review

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.

Afoudi yassine *et al.*, [11] have introduced a new intensive recommendation framework that integrates the co-sieve sieve (CF) with the well-known unaided machine learning computation K clustering group. In addition, use specific client segment credits, for example, Orientation for creating partial client profiles and progress over the years, when products (films) are grouped by categories categorized using K-meansin addition clients can beconsidered by the inclination of things. The class they want to see. To suggest things to the active user, the collective filtering technique is used for the group where the client should be. Following trial and error for significant images, we show that the proposed structure fulfills the consistency of the CF calculation in the group lens. Furthermore, the proposed framework operates at the exposure in addition time reaction speed of a conventional collaborative filtering process in addition content-based strategy.

Jiang Zhang *et al.*, [12] have introduced a customized continuous movie recommendation framework. In this paper, consider these two issues. Initially, a basic and high-tech consulting calculation was proposed, which divides the customer's profile into a few modules. Aimed ateverycluster, a virtual valuation prototype was considered to speech the whole set, with the ultimate goal being to reduce the components based on the first client content network, and then, at that point, a weighted slope a-VU technique was planned and applied to the virtual evaluation prototype subject phase to obtain the proposed results. In contrast to the conventional bunching-based CF proposal plot, our technique minimizes time consuming execution of equivalent advice. Besides, have developed a truly personalized online movie proposal framework, Movie Watch, opening it to the general public, collecting customer reviews on recommendations, and evaluating the achievability and accuracy of our framework considering this credible information.

Bushra Ramzan *et al.*,[13] have introduced an original CF proposal approach in which evaluation-based feedback was used to accomplish abode highlight lattice with peak identification. This approach combines lexical inquiry, language structure study, and semantic inquiry into a customized proposal. The built-in structure cannot handle multifaceted information using bulky information;however, it also indorses accommodation class depending on the kind of visitor utilizingfuzzy guides. Various studies were conducted on this current reality database obtained from two accommodation sites. In addition, the overlaps of accuracy and revision and F-measurement were determined, and the results were spoken up to basically improved accuracy and reaction time than conventional methods.

Priyank Thakkar *et al.*,[14] have introduced a way to integrate forecasts from UbCF and IbCF through multiple linearregression (MLR) in addition support vector regression (SVR). The consequences of the proposed approach are different and the effects of the other combination are approaching. Communication shows the prevalence of the projectedtechnique. Each of the experiments was performed on a large public accessible database. CF is usually used to refer those things to a client. item-based collaborative filtering (IbCF) and User-basedcollaborative filtering (UbCF) were two types of CF that have a common goal of evaluating the objective client's objective content. This article explores the different approaches to integrating forecasts from UbCF and IbCF.

Yashar Deldjoo *et al.*, [15] have introduced another movierecommendation structure that creates new content in the film space movie Genetics; (ii) Utilization of a successful database strategy of permitted relationship investigation. The study was approved using a massive scope, certified film proposal database, a complete virus startup and a framework-based study on both cold and hot progress; And customer-driven web-based analysis that complements and evaluates different emotional perspectives such as variety. The results show that the advantages of this approach are inconsistent with existing methods.

3. Proposed System Model

The recommendation framework is a mechanized structure that filter a few components. These items can be any products, movies, songs, books, people and ads. It is computed based on complete platforms daily from eHarmony, YouTube, Pandora, Amazon to Netflix. Three various methods are utilized generally for recommender engines. One can be a collaborative filtering in additionremaining is a content-based filtering, and a system that additionally uses a portion of the referral structure is a combination of these two methods. This study developed an RS in the light of the co-operative segment by creating and evaluating different models that rank first in the series for clients.

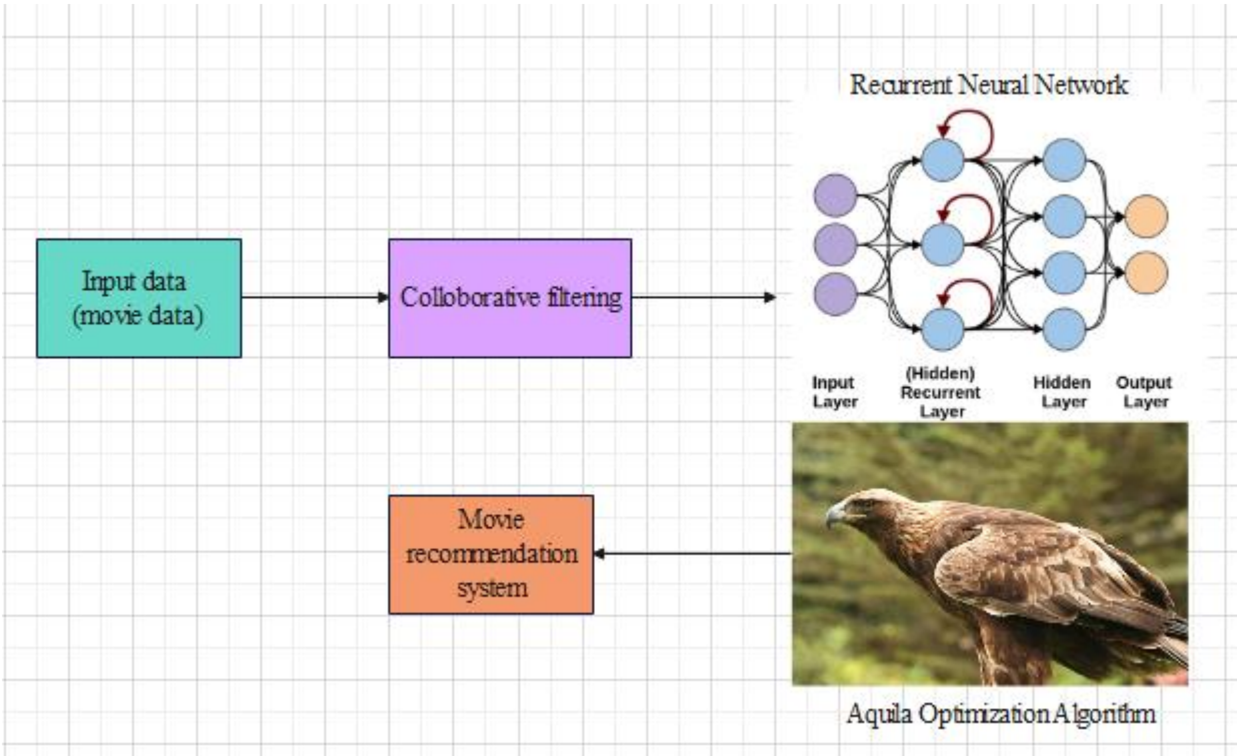

Figure 1: Block diagram of the projected technique

3.1. Collaborative filtering

This collaborative filtering can be a technique by recommendation structures. This filter is utilized to filters out parameters the user may be reacted to. With the consideration of similarities, it computes various large clusters of people in addition a smaller number of users; after that, the parameters are generating a list of variations. This collaborative filter is integrating the similar users in addition their selection to generate a list of variations. These variations which given by this filtering method can be generate an automatic cooperation of various users in addition their close interest. complete user selections are contrasted and they achieve a recommendation. Additionally, the user sees any movie, they are giving rating of the movie with one to five starts. Based on the rating, the large companies can give the recommendation with the assistance of collaborative filtering [16].

Table 1: Collaborative Filtering

User 1		**User 1 with User 2**	**User 2**	
Movie	**Ratings**	**Similarity computation**	**Movie**	**Ratings**
Jurassic Park	4		Jurassic Park	-
Tangled	1		Tangled	2
Shrek	-		Shrek	4
Finding Nemo	2		Finding Nemo	3
Ironman	4		Iron Man	5
The notebook	-		The notebook	-
Dark knight	5		Dark knight	5

To this end, customers initially purchase their managements and channels. Then, at that point, customers with comparable options are collected, in addition the novel well-known video will formerly be suggested to a specific crowd of customers. Many clients use the co-op section, and each part in this film demonstrates the number of movies viewed by the number of clients. Assuming that a user has seen The Dark Knight in addition Iron Man and given them a larger position, User B, who likes Dark Knight and

Iron Man, will not like things like Finding Nemo and Tangles and have comparative gradients; In the event that single of them gives a hugescore to a movie, can guess that the other customer who has not seen it yet can be going towards participate in that movie as well. In light of this rationale, can propose a suggestion. Based on this, the suggestion table is sent to the classifier to provide movie automatic recommendation system.

3.1. Recurrent Neural Network

In the RNN, the AOA is utilized to select optimal weighting parameters for enabling efficient human actions recognition from the images. The detail description of the RNN and AOA is presented in this section. The proposed RNN is developed by six fully connected layers. Normally, the RNN model trained with the help of back propagation. In this proposed RNN, it is achieved with the assistance of AOA. The proposed RNN consist of five neurons in the input layers, 1024 neurons in every four hidden layers in addition one neuron in the output layer. From datasets, the attributes are sent to the RNN [17] input section. RNN is a variation of general feed forward neural networks with their hidden layers. In the RNN, each hidden layer achieves input not only from the previous layer but also from initiations of itself for preceding input. The recurrent neural network is designed with the MLP and consists of hidden unit activations feeding back in the system which considered with the inputs. In this RNN, the time T can be discretized with the initial updating process at every time period. The time period may be varied to the function of real neurons or intended for reproduction methods. In the proposed RNN function, two activation functions are utilized such as exponential linear unit (ELU) and rectified linear activation unit (ReLU). The ELU function is mathematically formulated as follows,

$$F(x) = \alpha(e^{X} - 1), X < 0, otherwise\ F(x) = X \qquad (1)$$

Where, α can be described as a parameter and x can be described as input to a neuron.
The RLU function can be mathematically formulated as follows,

$$F(x) = \max(0, x) \qquad (2)$$

Where, x can be described as input to the neuron.
to mitigate the overfitting, dingo optimizer is utilized in the RNN network for training process. Additionally, dropout layer is utilized in among fully connected layers to mitigate overfitting. Normally, the dropout ratio is 0.5. The RNN training is contains two parts such as training objective and a dingo optimizer to reduce this objective function. In this research, utilized a dingo optimizer to reduce the Mean Square Error (MSE). In this proposed approach, the learning rate is considered as 0.001. The proposed RNN structure is illustrated in figure 2.

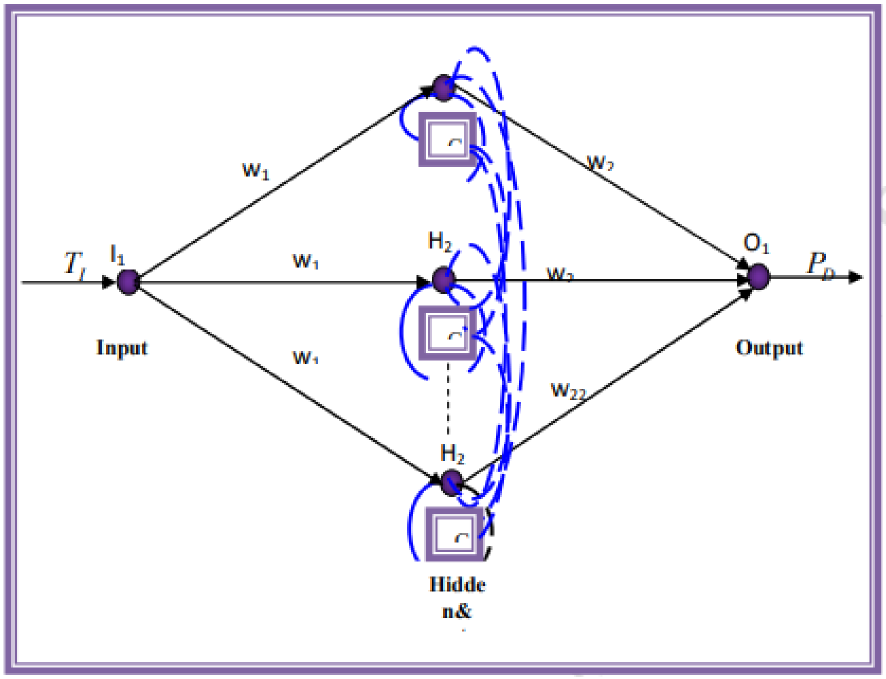

Figure 2: RNN architecture of the proposed methodology

The neuron in the output layer is related to and differentiated from the expected human activity recognition and the pre-defined human activity recognition (target data). The evaluation of the model performance depends on the rail-clearance test (80/10/10) plot. The actual product of the method was completed in the product database, while the approved database was used to adjust the hyper-boundaries; The general presentation of the model was evaluated in the experimental dataset. Teachable loads were introduced by the dingo optimizer. Weight updates were performed in small clusters and the size of the experiments for a group was set to 20. Production ends when the company does not work on its exhibition, subject to approval for a pre-defined number of ages. The figure was set at 80 and the execution was rated as unlucky and accurate. The misfortune is the MSE, which is the difference in the approximate output distribution from the actual distribution of the names.

3.2. Aquila Optimization Algorithm

In the Northern Hemisphere, the most popular fly is considered as a aquila. The most well-known types of spread are Aquila. Like all birds, Aquila is featured with the "Acebridae" herd.Typically, the aquila can be lighter gold-clay feathers on the back of the neckand dull brown. The young Aquila of this herd can be a white tone on the tail in addition, in general, their annexes have small white markings. Aquila usages its agility and speed to get different prey with durable paws and large, polished claws, mainly rabbits, deep sea creatures, marmots, squirrels and other terrestrial creatures. Akila and their specific patterns of behavior can be found in nature.Reveals hunting tactics for Aquila is presenting follows [18],

- The main technique is to fly high with an upward stop, which is used to hunt birds in flight, where the aquila climbs significantly above the ground. As it explores its prey, Akilah enters a long, low-angle beach that climbs at speed as the wings close further. For this strategy to progress, Aquila needs heights above its prey. Shortly beforehand the dedication, the wings in addition tail can be stretched out in addition the legs can be pushed forward to receive prey towards match the applause of the thunder.
- The next technique, travel with short float attack, can be considered the maximum commonly utilized technique through Aquila, here Aquila climbs to a low section on the ground. Whether the prey can

be running or flying, stare at the prey. This technique can be used to hunt ground squirrels and to raise cruises or seabirds.

- The third technique is low travel with a sluggish drop attack. In it, Aquila lands on the ground and turns on the next invading prey. Aquila tries to infiltrate by selecting locations in the neck and back of her prey and prey. This hunting technique can be used aimed at slow prey like diamond vertebrates, foxes, hedgehogs, in addition turtles or slightly prey that lacks aseepage reaction.
- The fourth technique can be surfing in addition plucking prey, in thataquila roams the land and tries to catch prey. It is used to pull young prey (i.e., sheep or deer) out of the covered locations.

Step 1:Initialization

It is a population scheme; the optimization law starts with the candidate population answers (X). The random population is generated based on lower bound and upper bound of the assumedproblematic. The optimal solution, so far can be achieved as the best solution in every iteration.

$$X=\begin{bmatrix} X_{1,1} & \dots & X_{1,J} & X_{1,}Dim-1 & X_1,Dim \\ X_{2,1} & \dots. & X_{2,J} & \dots & X_{2,}Dim \\ \dots & \dots & X_{I,J} & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ X_{N-1,1} & \dots & X_{N-1,J} & \dots & X_{N-1,}Dim \\ X_{N,1} & \dots & X_{N,J} & X_{N,Dim-1} & X_{N,Dim} \end{bmatrix} \quad (3)$$

Here, Dim can be described as the dimension size of the problem, N can be described as the total number of candidate solutions, X_I can be denoted as the decision values of the ith solution, X can be described as set of candidate solutions that can be randomly generated.

$$X_{IJ}=Rand\times\left(ub_J-lb_J\right)+lb_J, I=1,2\dots N\ and\ J=1,2,\dots,Dim \quad (4)$$

Here, ub_J can be described as the upper bound of the jth upper bound, lb_J can be described as the lower bound of the jth lower bound and $Rand$ can be described as the random number.

Step 2:Expanded Exploration

In the first technique, the aquila identifies the prey location in addition choose the optimal hunting location by vertical stoop with a high soar. Additionally, the in-height soar to compute the location of the search location. This expanded exploration can be presented as follows,

$$X_1(T+1)=X_{Best}\left(1-\frac{T}{t}\right)\times X_{best}(T)+(X_M(T)-X_{best}(T)*Rand) \quad (5)$$

Here, $X_M(T)$ can be described to the sites mean parameter of the present answers at Tth iteration, $\left(1-\frac{T}{t}\right)$ can be described as the switch the expanded search (exploration) by the maximum iterations, $X_{best}(T)$ can be described as optimal achieved solution till Tth iteration, $X_1(T+1)$ can be described as the solution in the upcoming iteration of T that can created with the first search technique, T and t can be described as the present iteration in addition the maximum number of iteration.

$$X_M(T)=\frac{1}{N}\sum_{I=1}^{N}X_I\,(T),\forall_{J=1,2,\dots,Dim} \quad (6)$$

Where, N can be described as the number of candidate solution and $Dim$is described as the measurement size of the issue.

Step 3: Narrowed Exploration

In the second technique, the prey location is identified from a tall soar, the aquila ringsoverhead the final prey, start the land afterwards bouts. This narrowed exploration is formulated as follows,

$$X_2(T+1)=X_{Best}(T)\times Levy\ (D)+(X_R(T)+(Y-X)*Rand) \quad (7)$$

Here, $Levy\ (D)$ can be described as the levy flight distribution function, D can be described as the dimension space, $X_2(T+1)$ can be described as the solution of the next iteration of T that can be created with the consideration of second search technique. The levy function can be computed as follows,

$$Levy\ (D) = S \times \frac{U \times \sigma}{|V|^{\frac{1}{\beta}}} \qquad (8)$$

Here, V and U can be described as the random number among 0 to 1, S can be considered as the constant variable which is fixed among 0.01.

$$\sigma = \left(\frac{\Gamma(1+\beta) \times sine\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right) \qquad (9)$$

Here, β can be described as the constant parameter which fixed as 1.5. The parameter Y and X can be utilized to searching space in spiral shape [19] which presented as follows,

$$Y = R \times cos(\theta) \qquad (10)$$
$$X = R \times sin(\theta) \qquad (11)$$
$$R = R_1 + U \times D_1 \qquad (12)$$
$$\theta = -\omega \times D_1 + \theta_1 \qquad (13)$$
$$\theta_1 = \frac{3 \times \pi}{2} \qquad (14)$$

Here, R_1 can be described as the constant parameter within the parameter among 1 to 20, ω can be described as the small parameter value fixed is 0.005, D_1 can be described as the integer variables from 1 to search space length and U can be described as the small parameter fixed to 0.00565.

Step 3: Expanded exploitation

In this technique, the prey location can be identified efficiently, the aquila can be preparedaimed at attack in addition landing. The aquila slopessheer with the consideration of initial attack towards compute the prey response. This technique is named as the slow descent attack with low flight. These characteristics are formulated as follows,

$$X_3(T+1) = X_{Best}(T) - X_M(T) + \alpha - rand + (ub - lb) \times rand + lb \times \delta \qquad (15)$$

Here, lb and ub can be described as the lower bound and upper bound, α and δ can be described as the exploitation change variables secure in this article towards a low parameter (0,1), $rand$ can be generated random variable among 0 and 1, $X_M(T)$ can be described as the mean parameter of the current solution, $X_{Best}(T)$ can be described as the approximate location of the prey until ith iteration, $X_3(T+1)$ can be described as the solution of the next iteration that can be generated with the assistance of third search technique.

Step 5: Narrowed Exploitation

In the fourth technique, the aquila achieve near to the prey, the aquila bouts the prey near the land related to their stochastic changes. This technique named as the walk-in addition grab prey. Additionally, the aquila bouts the prey in the final position. This condition is mathematically formulated as follows,

$$X_4(T+1) = QF \times X_{best}(T) - G_1 \times X(t) \times Rand) - G_2 \times Levy\ (d) + Rand \times G_1 \qquad (16)$$

Here, G_2 can be described as the different motions, G_1 can be described as the different motions which is track the prey with the consideration of the elope, QF can be described as the quality variable which is utilized to equilibrium the search techniques.

$$QF(T) = T^{\frac{2 \times rand(\ \ ) - 1}{(1-t)^2}} \qquad (17)$$
$$g_1 = 2 \times Rand(\ \ ) - 1 \qquad (18)$$
$$g_1 = 2 \times \left(1 - \frac{T}{t}\right) \qquad (19)$$

Here, $QF(T)$ can be described as the quality function parameter at the Tth iteration, T can be described as the current iteration and t isdefined as the maximum number of iterations, $Levy\ (D)$ can be described as the levy flight distribution function.

4. Outcome Evaluation

The exhibition of the projected technique canbe evaluated in addition legalized in this area. In this portion, planned strategic exhibitions are approved through implementation and communication inquiry. 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 [20], which include more than 1500movie name with rating. The planned strategy implementation boundaries can be presented in Table 1. The projected strategy can beappliedin addition approved utilizing presentation measureslikeaccuracy, specificity, precision, recall, F_Measure and sensitivity. The projected technique is contrasted with the traditional techniques like RNN-PSO, SVM 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

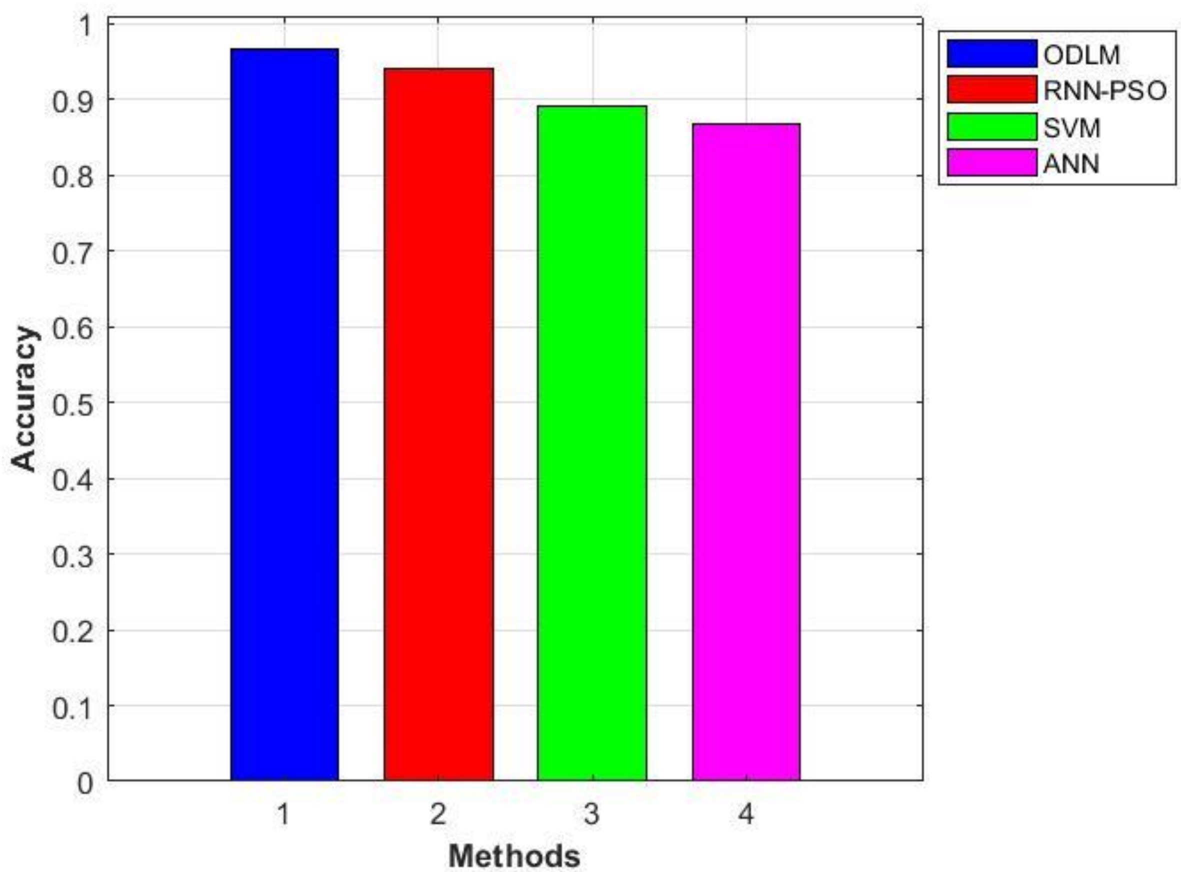

Figure 2: Accuracy

The performance metric of accuracy is utilized to evaluate the projected technique which is illustrated in figure 2. The projected technique is contrasted with the traditional techniques like RNN-PSO, SVM in addition ANN respectively. The proposed methodology is attained the 0.97 accuracy. Similarly, the RNN-PSO, SVMM, ANN is attained the 0.92, 0.89 and 0.85 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 3. The projected technique is contrasted with the traditional techniques like RNN-PSO, SVM in addition ANN respectively. The proposed methodology is attained the 0.95 precision. Similarly, the RNN-PSO, SVMM, ANN is attained the 0.88, 0.85 and 0.83 precision. With the analysis of the precision, the projected technique is achieved efficient precision in the movie recommendation system.

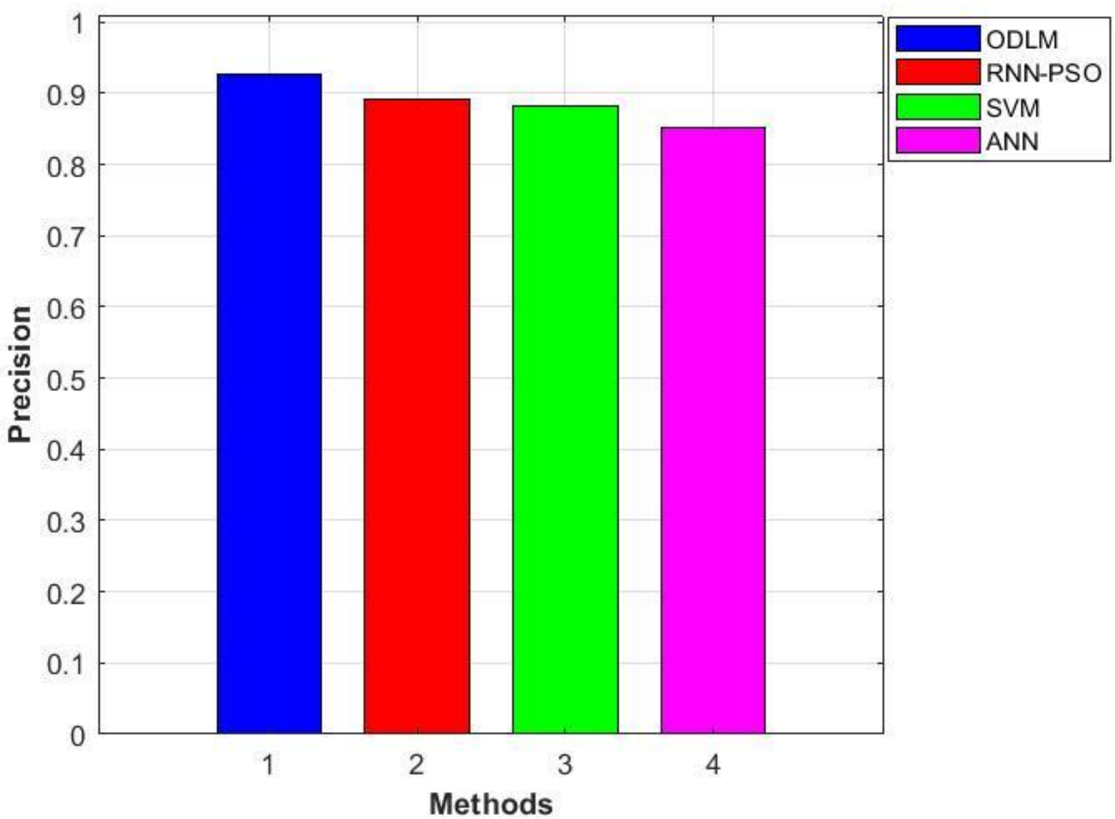

Figure 3: Precision

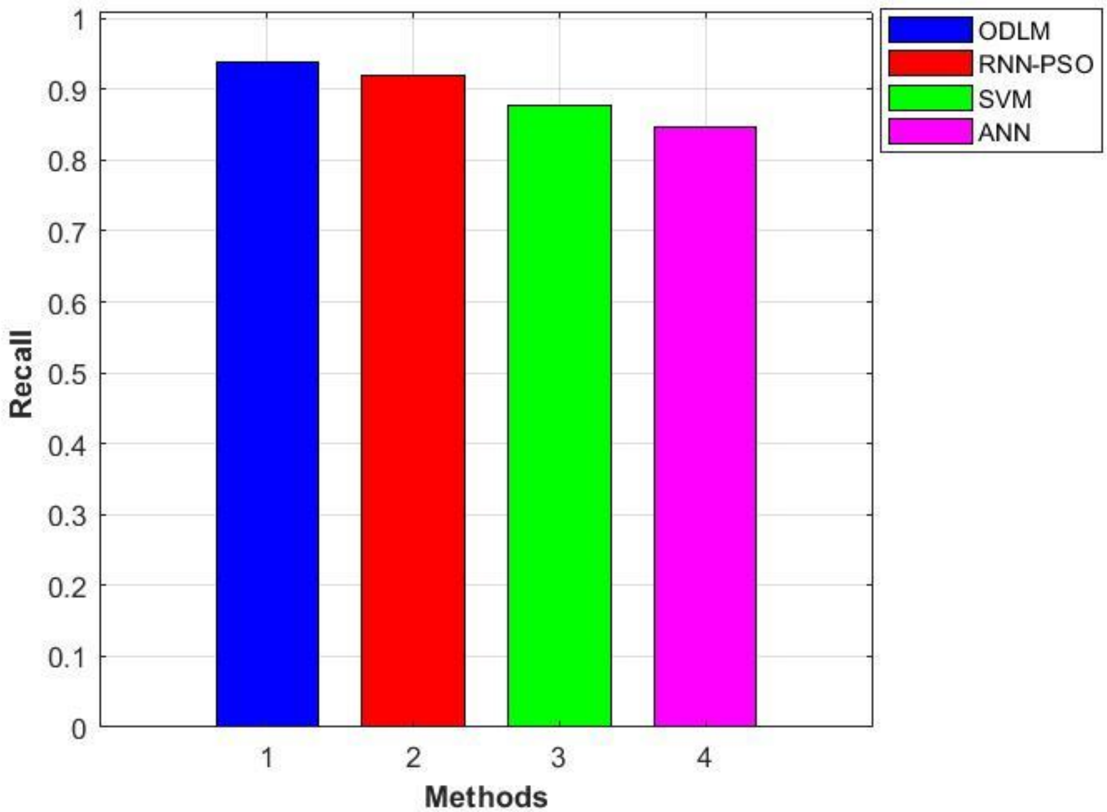

Figure 4: Recall

The performance metric of recall is utilized to evaluate the projected technique which is illustrated in figure 4. The projected technique is contrasted with the traditional techniques like RNN-PSO, SVM in addition ANN respectively. The proposed methodology is attained the 0.91 recall. Similarly, the RNN-PSO, SVMM, ANN is attained the 0.90, 0.88 and 0.85 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 5. The projected technique is contrasted with the traditional techniques like RNN-PSO, SVM in addition ANN respectively. The proposed methodology is attained the 0.91 sensitivity. Similarly, the RNN-PSO, SVMM, ANN is attained the 0.90, 0.85 and 0.82 sensitivity. With the analysis of the sensitivity, the projected technique is achieved efficient sensitivity in the movie recommendation system.

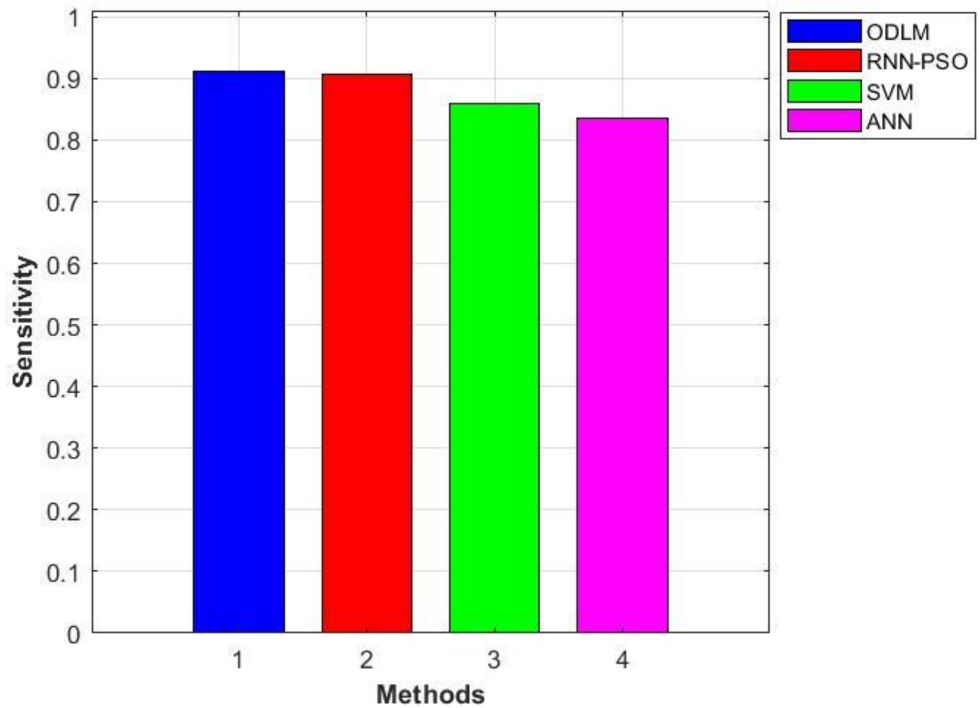

Figure 5: Sensitivity

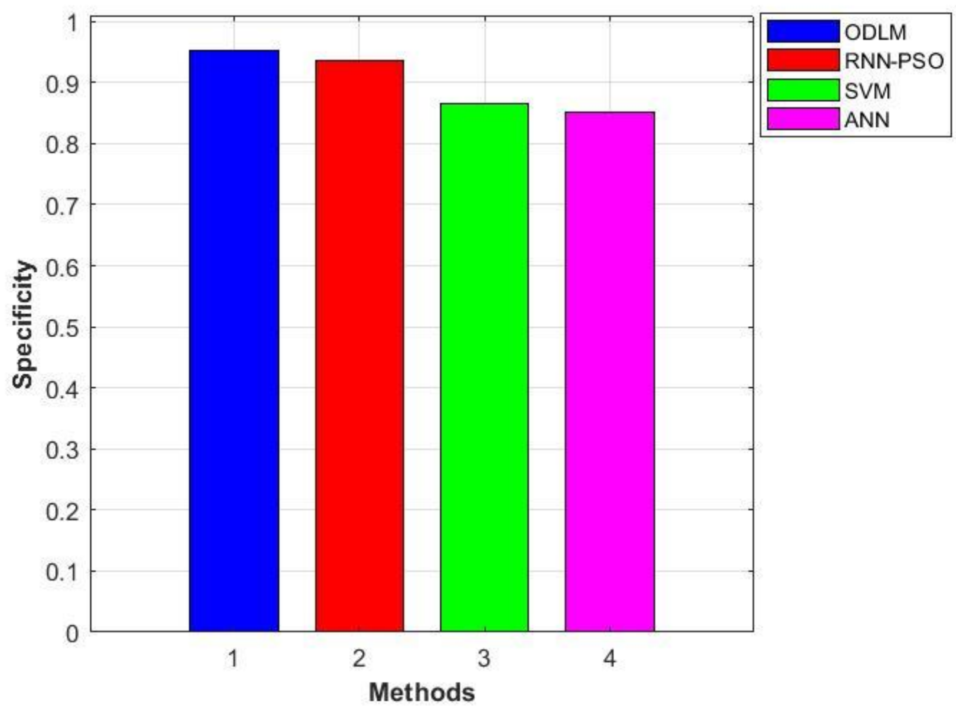

Figure 6: Specificity

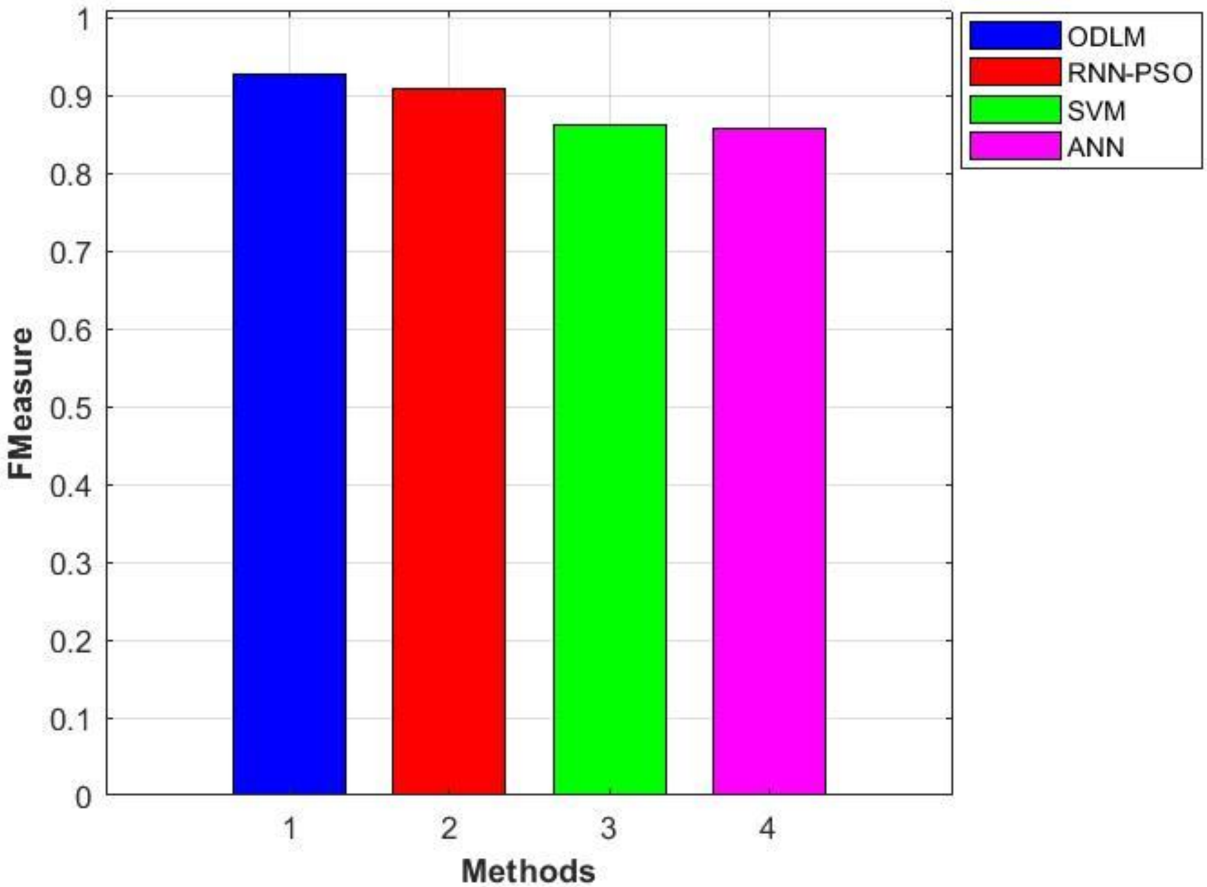

Figure 7:F_Measure

The performance metric of specificity is utilized to evaluate the projected technique which is illustrated in figure 6. The projected technique is contrasted with the traditional techniques like RNN-PSO, SVM in addition ANN respectively. The proposed methodology is attained the 0.94 specificity. Similarly, the RNN-PSO, SVMM, ANN is attained the 0.92, 0.87 and 0.83 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 7. The projected technique is contrasted with the traditional techniques like RNN-PSO, SVM in addition ANN respectively. The proposed methodology is attained the 0.92 F_Measure. Similarly, the RNN-PSO, SVMM, ANN is attained the 0.91, 0.85 and 0.84 F_Measure. With the analysis of the F_Measure, the projected technique is achieved efficient F_Measure in the movie recommendation system.

5. Conclusion

In this paper, to develop ODLM for automatic movie recommendation system. The proposed model is developed to predict the best rated movies and automatic movie recommendation system. This ODLM is combination of RNN and AOA. In the RNN, the AOA is utilized to select optimal weighting parameters. The proposed methodology is a utilized the last search information of a user related references and movie category this to develop the recommender engine, based on that, the list of predictions for top rating is computed. The collaborative filtering is utilized along with proposed techniques to enable efficient movie recommendation system. To validate the proposed methodology, the movie databases isgathered from the online solutions. The proposed methodology isexecuted in MATLAB in addition performances can be assessed by performance measureslike recall, precision, accuracy, recall, specificity, sensitivity and F_Measure.The proposed methodology is compared with the conventional techniques such as ANN, SVM, and RNN-PSO respectively. Based on the analysis, the projected approach is attained efficient outcomes in relationships of accuracy, precision, recall, specificity, sensitivity in addition F_Measure. In future, the content-basedmovie automatic recommendation system will be developed.

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