Integration of PSO with LSTM to Enhance Accuracy of Movie Recommendation System

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***Abstract*−Recommender systems considered in the paper is making use of LSTM based learning in order to perform prediction considering previous experiences. It has been observed that previous researches in field of recommender system took lot of time and provided solution with less accuracy. Proposed work is making use of PSO based optimization mechanism in order to filter out the dataset of movies dataset. The dataset considered in research has been taken from kaggle and it consists of records of 45466 movies with 24 attributes. Major attributes of dataset is original_title and vote average. The optimizer would filter the dataset and get the records where vote average is more than optimized value. Then filtered dataset is trained by LSTM model where this model is making use of hidden layers in order increase the accuracy. During simulation it has been observed that accuracy of model is depending on hidden layer count, batch size, and epoch size. Moreover the length of data set required for training and testing has also a significant impact on accuracy as well as time consumption. Hybrid approach, which is integration of optimization mechanism and LSTM, is capable to provide more accurate recommendation for movie considering vote count attribute.**

Keywords: ***Recommender systems, LSTM, PSO, Hybrid approach.***

I. Introduction

The proposed work is making use of Kaggle dataset and applying PSO algorithm on it to get the optimized voting. The movies that are having more average voting than optimized votes would be considered for training. The LSTM mechanism has been used to train and test the model. The Hybrid approach that is making used of PSO before training and applying LSTM model on dataset is supposed to provide more accuracy in result. Moreover due to filtering of useless record the time consumption of training is also reduced.

A. Recommender System

A recommender system tries to predict or filter preferences depending on the preferences of the user. Movies, music, news, books, research papers, and general products are all examples of applications where recommender systems are utilized. The user's information is used as input in a recommendation system. The recommendation system is often implemented using an artificial intelligence system. The popularity of recommender systems is growing all the time. Machine learning has been utilized in many recommender systems to generate predictions based on previous experiences. A dataset is still needed to offer a machine learning system experience. Predictions have been encoded into the recommender system. However, time limitations and accuracy problems have hindered previous research in area of recommender systems. In order to perform training and get the proper output, the dataset must still be filtered to eliminate the values below optimum value. To filter the movie dataset, the suggested method uses an optimization approach. This filtered dataset would be used to train the LSTM model. The LSTM model employs hidden layers to get a more accurate result. The number of hidden layers, batch size, and epoch size used affect the model's accuracy. The size of the data collection used for training and testing has an impact on accuracy and time consumption. To put it another way, the research uses a hybrid approach that combines an integrated optimization mechanism with LSTM to provide accurate movie suggestions in the quickest time possible.

B. Dataset

The dataset considered in research has been taken from kaggle and it consists of records of 45466 movies with 24 attributes. Major attributes of dataset is original_ title and vote average.

Source of dataset: https://www.kaggle.com/rounakbanik/the-movies-dataset
Number of records : 45466
Number of fields: 24

C. Particle Swarm Optimizaton (PSO)

PSO has been considered a technique to optimize issues by repeatedly choosing to enhance candidate's solution based on a quality metric. It is resolving issue by producing population of potential solutions. This solution are termed as particles. These particles move in search space by making use of mathematical equation. This equation is based on location and velocity of particles. Movement of every particle has been influenced by its local best known location. Particle is directed toward best known positions in search space. Its position is updated when better places are found by other particles.

D. Long Short-Term Memory(LSTM)

The LSTM [22] has long been thought to be a well-known artificial RNN. In the field of deep learning, this is often used. Feedback connectivity is included in the LSTM [23]. It's not the same as a standard feed-forward neural network. LSTM doesn't simply deal with single data points like graphics. It also completes information sequences such as audio and video. LSTM networks are thought to be good for categorization. It is processing data as well as generating predictions based on time-series data. In important occurrences throughout time series, there may be duration delays that are unknown. In the instance of the sequence prediction issue, LSTM has been shown to be capable of learning order dependency. LSTM is a behaviour that is required in complex problem areas such as machine translation. Long Short-Term Memory has long been thought to be a difficult area of deep learning. LSTM is a difficult concept to grasp.

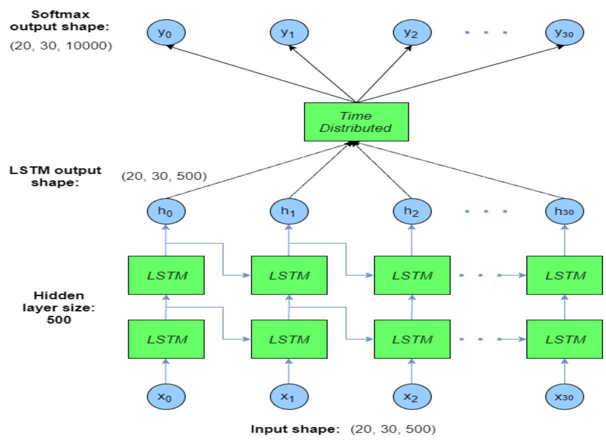

Fig. 1: Working of LSTM[32]

II. Literature Review

Many researches in field of recommendation system are conducted. Multiple recommendation systems were made for various objectives. Moreover technology and mechanism used in those researches also vary. Some of the existing researches have been mentioned considering their objective, methodology and limitation. Previous recommendation systems made use of collaborative filter [1], Context-aware recommender systems [2]. Some author tried to give novel approach depending on multi-view reliability measures in order to alleviate data sparsity in recommender systems [3]. Howeer some of them were performing survey on recommendation system considering effective crowd sourcing [4]. Some of author continued to deal with recommendations using a distributed collaborative filtering architecture [5] and some of them focused on application of recommender systems in a multi site, multi domain environment [6]. Hybrid recommender mechanism [7], intelligent fuzzy dependent recommendation mechanism used in case of consumer electronic products [8], commercial-strength parallel hybrid movie recommendation engine [9], User-centric evaluation of recommender systems [10] came in existence. Several researchers are considering context-aware mechanism for recommender systems [11] while some researches considered keyword extraction as well as clustering in case of document recommendation in conversations [12]. Survey of state of art as well as future research challenges along with opportunities in case of Interactive recommender systems [13], music similarity and recommendation from music context data [14], Recommender system application developments [17], and recommendation system mechanism [19] are conducted. Online partitioning of large graphs to enhance the scalability in recommender systems [15] as well as RNN recommendation [16] are proposed. Studies and analysis to present effects of personal characteristics when explaining music recommendations [18] and recommendation systems in case of location dependent social network with big data [20] have been made.

III. Problem Statement

However, time limitations and accuracy problems have hindered previous research in the field of recommender systems. Many researchers simply conducted surveys or reviews of suggesting systems, while others worked on recommender systems for consumer products, music, and

Table 1: Comparison chart

	Context-aware recommender systems [2]	Fuzzy-based recommendation system [8]	Hybrid recommender systems [7]	Recurrent Neural Network Based Recommendation System [16]	Proposed work
Recommender system	Yes	Yes	Yes	Yes	Yes
Neural Network	No	No	Yes	Yes	Yes
Accuracy	No	No	No	No	Yes
Time consumption	No	No	No	No	Yes
Optimization	No	No	No	No	Yes
Hybrid approach	No	No	Yes	No	Yes

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other media. In the case of movies, the proposed approach has taken into account a recommender system. The goal of research is to come up with a more precise answer. Furthermore, the aim is to offer a solution in the shortest possible period.

IV. Proposed Model

Major objective of our research is to consider the existing researches in field of recommendation system, machine learning and optimization mechanism. Present work is investigating the issues and challenges faced by methodologies used in previous research such as lack of accuracy and time consumption. Hybrid model that would integrate optimization mechanism and learning approach in order to provide more accurate and high performance system, is supposed to build. Finally proposed model is performing comparative analysis between traditional and proposed recommender system. The proposed work is considering PSO based optimization technique to filter out the movie dataset before performing training and testing operation to reduce the time consumption. The LSTM model would be used to train his filtered dataset. Hidden layers of LSTM model would allow modeling of more accurate solution. Research is considering influencing factors for accuracy such as number of hidden layers, batch size, and epoch size utilized. The accuracy and time consumption are also influenced by the size of the data set used for training and testing. In other words, the study employs a hybrid method that combines an integrated optimization mechanism with LSTM to get correct movie recommendations in the shortest amount of time.

A. LSTM and its Training Mechanism

The technology saves the trained network "net" for future testing. To create a trained network, the LSTM was implemented using two LSTM layers. During a training operation, the proposed model employs two LSTM layers as well as a drop out layer. To conduct training, 70% of the dataset is used for training and the remaining 30% is used for testing. The LSTM dependent neural is trained based on the feature. Batch size is one of the variables that influences training time. In order to improve accuracy, hidden layers and dropout layers are used extensively. Following the acquisition of an IDS dataset, the selection of characteristics is carried out in order to train the dataset. After that, the training and testing ratios are established, with the LSTM1 layer having twelve hidden layers and the LSTM2 layer having five hidden layers. To address the problem of overfitting, dropout layers are employed, followed by a fully connected layer and a softmax layer. The classification operation is used to make decisions in order to anticipate incursion.

The LSTM method is being explored in the study to train the network, which employs deep learning and feedback connectivity. With the use of hidden layers, dropout layers, fully connected layers, and classification layers, LSTM networks were utilised to conduct movie recommendation in the suggested model. On the basis of the provided movie dataset, the LSTM mechanism was utilized to conduct processing and generate predictions.

Different anomalies are classified by the trained model. The movie recommender was modeled using two LSTMs that were connected in a sequential order. Each has a distinct number of hidden levels, namely 12 and 5. These hidden layers have improved accuracy, but they can induce over fitting. Over fitting occurs during the training of neural network models. If the training is prolonged, the model will develop its own quirks.

1. Dropout Layer

During plotting, the validation loss may be used to detect overfitting. Dropout layer is used to deal with overfitting.

2. Layer that is Completely Interconnected

The input is multiplied by a weight matrix in a fully linked layer. After that, it adds a bias vector. The completely Connected Layer (output size) method returns a fully connected layer and specifies the Output Size property in the proposed work.

3. Softmax

In the case of a neural net, the activation layer is applied to the final layer. It replaces the ReLU, sigmoid, and tanh activation functions. The Softmax layer is required because it converts the output of the previous layer to the neural network. Softmax is typically run using the neural network layer as a backend right before the output layer. The number of nodes in the output layer should be counted precisely in this layer.

4. Layer of Classification

The categorization of neural networks has long been regarded the most active research and application field. Classification is an important feature for decomposing large datasets into classes and generating a rule.

5. Size of the Batch

The batch size examined in this research is 512. When the batch size is raised, training time is lowered; however, when the batch size is decreased, training time rises.

6. Threshold for Gradients

This parameter is taken into account since there is a risk of exploding gradients, which occurs when substantial error gradients build and result in large changes in neural network model weights during training. It is insecure and unable to learn from prior training data.

7. *Epoch*

Every sample in the dataset used for training has altered to adjust parameters in the internal model, which is referred to as an epoch. At the period of the model's training, there are 30 epochs.

8. *Rate of Learning*

The model's adaptation problems are controlled by the learning rate. In the instance of the suggested task, the learning rate is 0.001. The process flow of proposed work has been discussed below:

V. Result And Discussion

A. *Get the Dataset*

The dataset considered in research has been taken from kaggle and it consists of records of 45466 movies with 24 attributes. Major attributes of dataset is original_ title and vote average. The Source of dataset is https://www.kaggle.com/rounakbanik/the-movies-dataset and Number of records is 45466 with 24 fields. Following figure is showing the considered dataset.

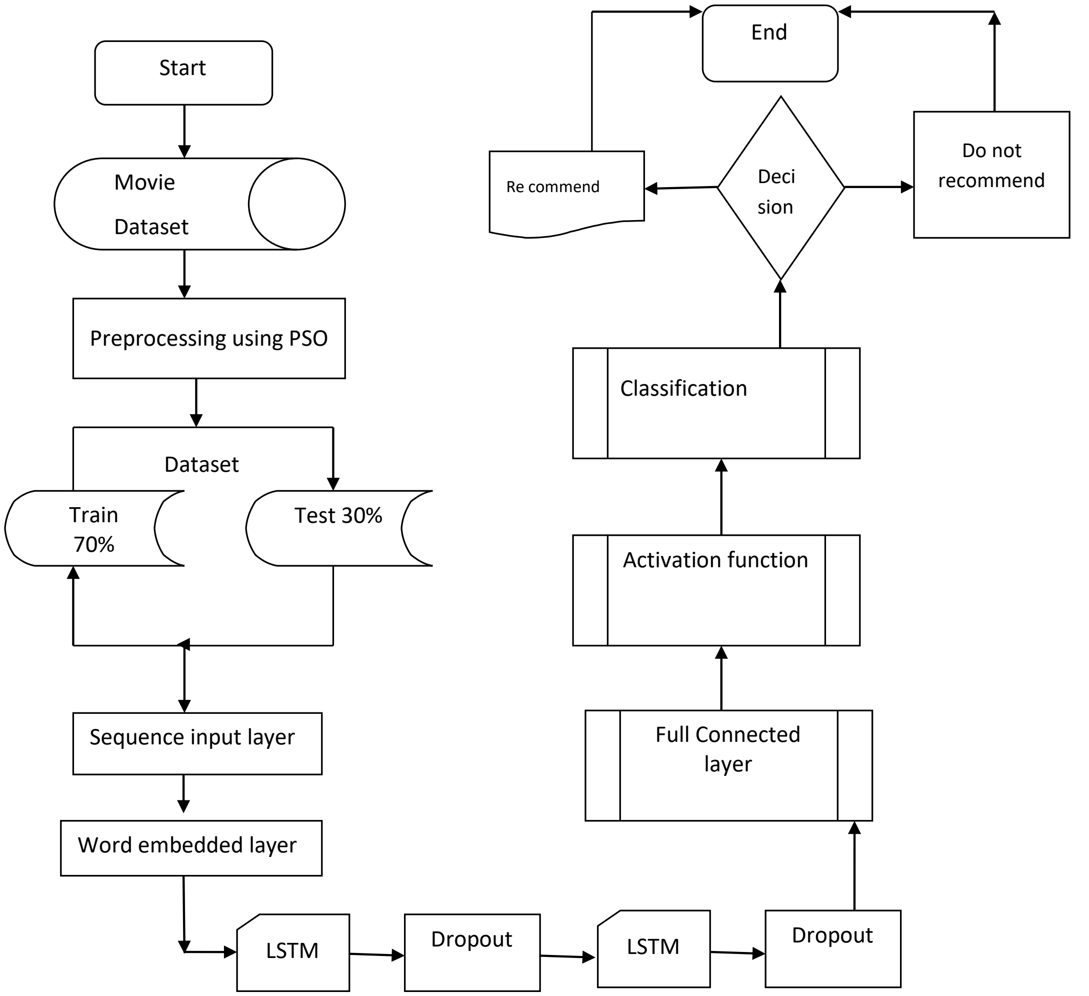
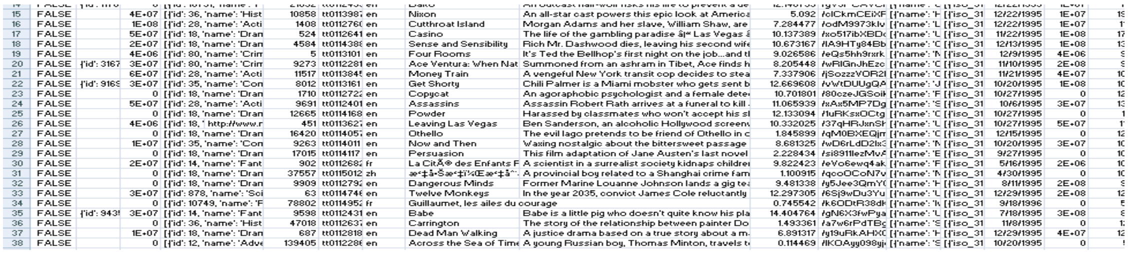


Fig. 2: Process flow of proposed work



15	FALSE		4E+07	[{'id': 36, 'name': 'Hist	10858	tt0113987	en	Nixon	An all-star cast powers this epic look at America	5.092	/cICkmCEiXF	[{'name': 'H	[{'iso_31	12/22/1995	1E+07
16	FALSE		1E+08	[{'id': 28, 'name': 'Acti	1408	tt0112760	en	Cutthroat Island	Morgan Adams and her slave, William Shaw, are	7.284477	/odM9973klv	[{'name': 'L	[{'iso_31	12/22/1995	1E+07
17	FALSE		5E+07	[{'id': 18, 'name': 'Dran	524	tt0112641	en	Casino	The life of the gambling paradise â¦“ Las Vegas â	10.137389	/xo517ibXBDc	[{'name': 'L	[{'iso_31	11/22/1995	1E+08
18	FALSE		2E+07	[{'id': 18, 'name': 'Dran	4584	tt0114388	en	Sense and Sensibility	Rich Mr. Dashwood dies, leaving his second wife	10.673167	/lA9HTy84Bb	[{'name': 'C	[{'iso_31	12/13/1995	1E+08
19	FALSE		4E+06	[{'id': 80, 'name': 'Crim	5	tt0113101	en	Four Rooms	It's Ted the Bellhop's first night on the job...and th	9.026586	/eQs5hh9rxrk	[{'name': 'M	[{'iso_31	12/9/1995	4E+06
20	FALSE	{'id': 3167	3E+07	[{'id': 80, 'name': 'Crim	9273	tt0112281	en	Ace Ventura: When Nat	Summoned from an ashram in Tibet, Ace finds h	8.205448	/wRlGnJhEzc	[{'name': 'C	[{'iso_31	11/10/1995	2E+08
21	FALSE		6E+07	[{'id': 28, 'name': 'Acti	11517	tt0113845	en	Money Train	A vengeful New York transit cop decides to stea	7.337906	/jSozzzVOR2l	[{'name': 'C	[{'iso_31	11/21/1995	4E+07
22	FALSE	{'id': 9169	3E+07	[{'id': 35, 'name': 'Con	8012	tt0113161	en	Get Shorty	Chili Palmer is a Miami mobster who gets sent b	12.669608	/vWtDUUgQA	[{'name': 'J	[{'iso_31	10/20/1995	1E+08
23	FALSE		0	[{'id': 18, 'name': 'Dran	1710	tt0112722	en	Copycat	An agoraphobic psychologist and a female detec	10.701801	/80czeJGSoik	[{'name': 'F	[{'iso_31	10/27/1995	0
24	FALSE		5E+07	[{'id': 28, 'name': 'Acti	9691	tt0112401	en	Assassins	Assassin Robert Rath arrives at a funeral to kill	11.065939	/xAx5MP7Dg	[{'name': 'S	[{'iso_31	10/6/1995	3E+07
25	FALSE		0	[{'id': 18, 'name': 'Dran	12665	tt0114168	en	Powder	Harassed by classmates who won't accept his sl	12.133094	/1uRKsxOCtg	[{'name': 'C	[{'iso_31	10/27/1995	0
26	FALSE		4E+06	[{'id': 18, ' http://www.r	451	tt0113627	en	Leaving Las Vegas	Ben Sanderson, an alcoholic Hollywood screenw	10.332025	/37qHRJxnSh	[{'name': 'L	[{'iso_31	10/27/1995	5E+07
27	FALSE		0	[{'id': 18, 'name': 'Dran	16420	tt0114057	en	Othello	The evil Iago pretends to be friend of Othello in c	1.845899	/qM0BXEQjm	[{'name': 'C	[{'iso_31	12/15/1995	0
28	FALSE		1E+07	[{'id': 35, 'name': 'Con	9263	tt0114011	en	Now and Then	Waxing nostalgic about the bittersweet passage	8.681325	/wD6rLdD2lx3	[{'name': 'N	[{'iso_31	10/20/1995	3E+07
29	FALSE		0	[{'id': 18, 'name': 'Dran	17015	tt0114117	en	Persuasion	This film adaptation of Jane Austen's last novel	2.228434	/si8911lezMvA	[{'name': 'E	[{'iso_31	9/27/1995	0
30	FALSE		2E+07	[{'id': 14, 'name': 'Fant	902	tt0112682	fr	La CitÃ© des Enfants F	A scientist in a surrealist society kidnaps children	9.822423	/eVo6ewq4ak	[{'name': 'F	[{'iso_31	5/16/1995	2E+06
31	FALSE		0	[{'id': 18, 'name': 'Dran	37557	tt0115012	zh	æ‹‡å•Šæ‹‡ï¼Œæ‹‡å˜·	A provincial boy related to a Shanghai crime fam	1.100915	/qcoOCoN7v	[{'name': 'N	[{'iso_31	4/30/1995	0
32	FALSE		0	[{'id': 18, 'name': 'Dran	9909	tt0112792	en	Dangerous Minds	Former Marine Louanne Johnson lands a gig tea	9.481338	/y5Jee3QmYC	[{'name': 'H	[{'iso_31	8/11/1995	2E+08
33	FALSE		3E+07	[{'id': 878, 'name': 'Sci	63	tt0114746	en	Twelve Monkeys	In the year 2035, convict James Cole reluctantly	12.297305	/6Sj9wDu3Yu	[{'name': 'L	[{'iso_31	12/29/1995	2E+08
34	FALSE		0	[{'id': 10749, 'name': 'F	78802	tt0114952	fr	Guillaumet, les ailes du courage		0.745542	/k6ODtR38dk	[{'name': 'I	[{'iso_31	9/18/1996	0
35	FALSE	{'id': 9435	3E+07	[{'id': 14, 'name': 'Fant	9598	tt0112431	en	Babe	Babe is a little pig who doesn't quite know his pla	14.404764	/gN6X3fwPya	[{'name': 'L	[{'iso_31	7/18/1995	3E+08
36	FALSE		0	[{'id': 36, 'name': 'Hist	47018	tt0112637	en	Carrington	The story of the relationship between painter Do	1.493361	/a7w6rPdTBg	[{'name': 'S	[{'iso_31	11/8/1995	0
37	FALSE		1E+07	[{'id': 18, 'name': 'Dran	687	tt0112818	en	Dead Man Walking	A justice drama based on a true story about a m	6.891317	/y19uRkAHXC	[{'name': 'H	[{'iso_31	12/29/1995	4E+07
38	FALSE		0	[{'id': 12, 'name': 'Adve	139405	tt0112286	en	Across the Sea of Time	A young Russian boy, Thomas Minton, travels to	0.114469	/lKOAyy098yj	[{'name': 'S	[{'iso_31	10/20/1995	0

Fig. 3: Movie Dataset

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The size of dataset could be checked by its properties. The name of file is "movies_metadata" and size of file is 32.8 MB. This dataset would take longer time during training by LSTM model.

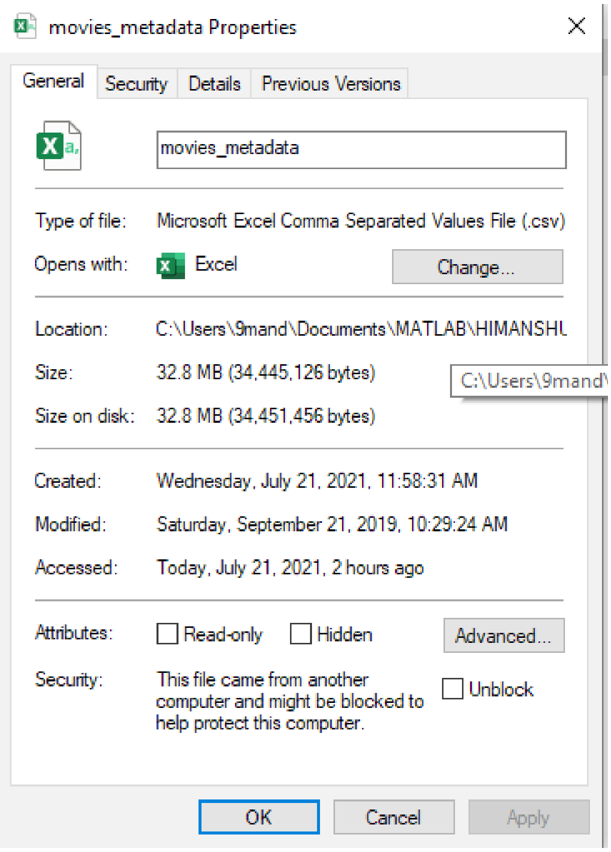

Fig. 4: Property of movies_metadata

The remark field has been added at the end of all fields considering 4 cases

TABLE 2: CONDITIONS FOR REMARK

Sno	Range of voting	Remark
1	<7	Normal
2	7 to 8	Good
3	8 to 9	Very Good
4	>9	Superb

B. *Get the Voting Data from Movie Dataset*

The voting field is copied to a text file and is named voting.txt. This file is kept with PSO module where dataset is captured to find the optimized value.

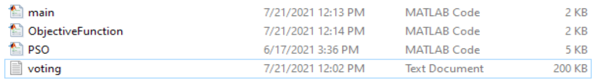

Fig. 5: PSO modules

The PSO module is consisting following files

1. *Main.m*

This file is fetching upper and lower bound data of voting dataset. Then it is invoking objective function. Finally after creating problem object, main function passes it to PSO function.

2. *Objectivefunction.m*

This function is getting data from voting.txt and assists in finding the best solution.

```
function [ o ] = ObjectiveFunction(x)
fid=fopen('voting.txt','r');
C=textscan(fid,'%f');
btc=C{1};
aS3=btc'
for j=1:45466
bS3(j)=sum((x'-aS3(:,j)).^6);
end
o=(1/500+sum(1./([1: 45466]+bS3))).^(-1);
end
```

3. *PSO.m*

This script is implementing the functionality of particle swarm optimization in technical manner.

4. *Voting.txt*

It is text file that is consisting values. These values are captured by main.m and objectivefunction.m during simulation operations.

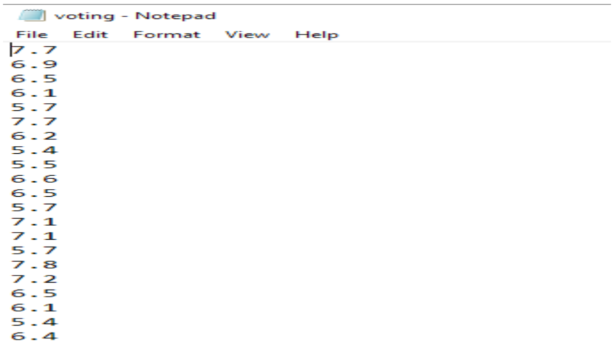

Fig. 6: Voting.txt File

C. *Apply PSO on Voting Dataset to Get Optimized Voting*

Iteration(gbest) 10 Swarm.GBEST.O = 0.097766
Best solution found
ans =
 6.8862
Best objective value
ans =
 0.0978
Elapsed time is 7.932216 seconds.
The optimized voting value is 6.8862.

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D. Filter the data of movie dataset and get new file "filtered_movies_metadata"

The records having voting value above optimized are considered in this file.

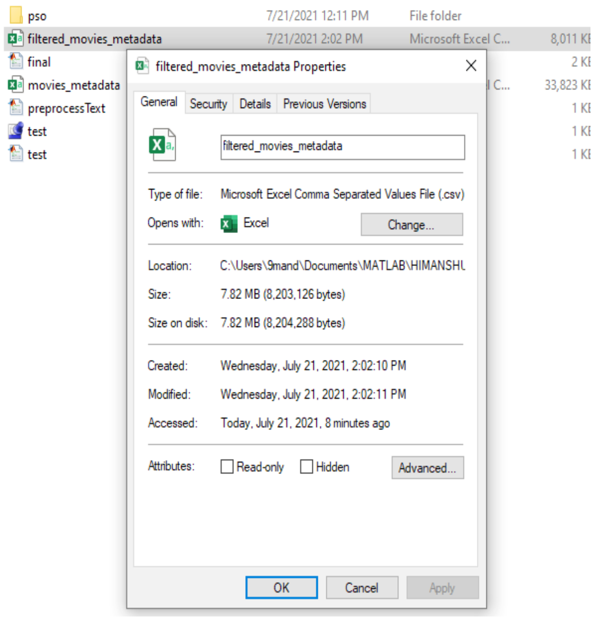

Fig. 7: Property of "filtered data"

E. Train the "movies_metadata" using LSTM model

The training of dataset of movies_metadata has been performed using LSTM model. The figure 8,9,10 are showing class distribution, Training data, Training progress of "movies_metadata"

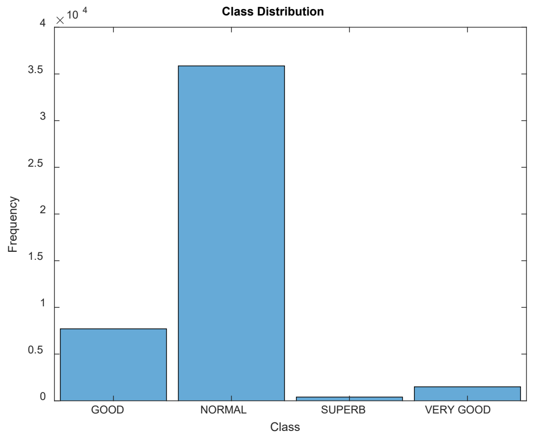

Fig. 8: Class distribution for movies_metadata

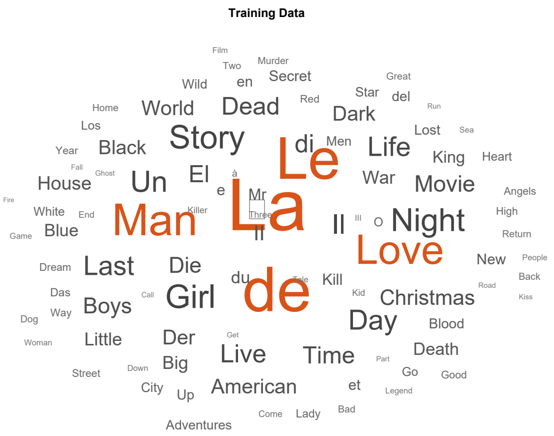

Fig. 9: Training Data for movies_metadata

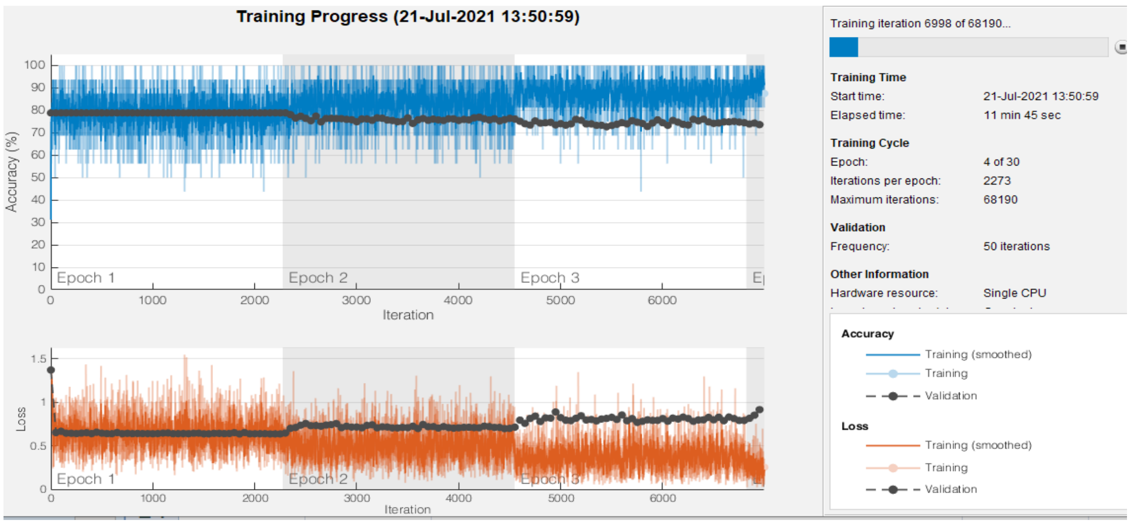

Fig. 10: Training progress of movies_metadata

The training simulation took 110 minutes.

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F. Train the "Filtered_Movies_Metadata" using LSTM Model

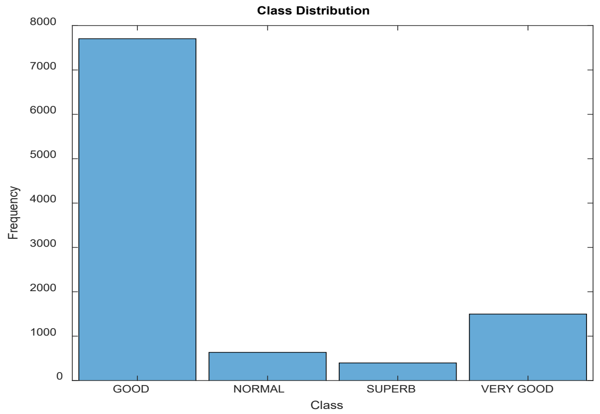

Fig. 11: Class distribution for filtered_movies_metadata

Fig. 12: Training Data for filtered_movies_metadata

G. Compare the Performance in Both Cases

Table 3 is presenting the comparative analysis in case of training of normal movie dataset and filtered movie dataset. The parameters considered for comparison are file size, Training time and number of total records in categorized manner.

TABLE 3: COMPARATIVE ANALYSIS

	Normal movies data	Filtered movie dataset
File size	32.8 MB	7.82
Training time	110 minutes	10 minutes
Total record	45466	10641
NORMAL	35864	1041
GOOD	7705	7705
VERY GOOD	1498	1498
SUPERB	397	397

VI. CONCLUSION

Simulation result conclude that use of PSO has reduced the size of dataset used for training and minimized the training and testing time. Moreover the filter dataset comprises most recommended movies because these movies have got better voting according to optimization. The comparative analysis concludes that integration of optimization mechanism in LSTM training has improved the performance. Moreover, number of recommended movies has been increased.

VII. SCOPE OF RESEARCH

Present recommender system is making use of PSO optimizer to filter the dataset. The process of filtering reduces the dataset to list of recommended movies. Dataset of Movies that have been voted more than optimized values would be considered for training using

Fig. 13: Training Process for filtered_movies_metadata

Simulation completed in 10 minutes

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LSTM Model. This would allow the training process to perform in better way. Such research could lay significant foundation for further researches in field of LSTM and recommendation system.

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