

# Movie Recommendation System Using Deep Learning

**Nandamudi Anil Kumar**

PG scholar, Department of MCA, DNR College, Bhimavaram, Andhra Pradesh.

**A.Naga Raju**

(Assistant Professor), Master of Computer Applications, DNR college, Bhimavaram, Andhra Pradesh.

*Abstract: A recommendation system is being used by several streaming services to suggest new content that is relevant to currently available content. This project uses a movie dataset to train a deep learning model, which can then be used to predict which movies users will be recommended to watch next. In this project, a deep learning model was trained utilizing both the user ID and the movie ID as input features, and the ratings as the class label. A deep learning model built on the highest rated movies would suggest new movies to the same user. The suggested approach demonstrates the implementation of many functions covered in depth in the section on result analysis. To create a movie recommendation module, we have loaded a number of Python packages, including NumPy, SKLEARN, pandas, SNS, and many more. Accuracy parameters and the confusion matrix are computed to obtain the performance analysis. Performance metrics demonstrate that the suggested model outperforms cutting-edge methods in terms of performance.*

**Keywords:** Deep Learning Model, New Movie Recommendations, Highest Ratings, Features.

## I. INTRODUCTION

Recommending those movies that a certain user is most likely to wish to view is the main objective of movie recommendation systems. A fancy term for a system that attempts to infer your preferences based on you or people who are similar to you is a movie recommendation system. To put it simply, a recommendation system is a programme that anticipates or filters items based on user activity. In today's digital age, the abundance of available

content can be overwhelming for consumers. With countless movies being produced and distributed across various platforms, users often find it challenging to discover new movies that align with their preferences.

These recommendation systems' machine learning algorithms make use of this user's information from the database. Because deep learning-based recommender systems can handle non-linear data, they perform better than traditional ones. Sequence modelling, representation learning, non-linear transformation, and flexibility are the main advantages of using DL for recommendations. Recommender systems improve sales, reinvent the online browsing experience for users, provide users with personalised recommendations, and assist users in making wise selections in their online transactions.

There are three main objectives of our development.

- One is the study of existing techniques for movie recommendation and their drawbacks and limitations.
- The second is the study of deep learning architecture for the proposed methodology.
- The third is to design a proposed algorithm using Python and show improved accuracy over state-of-the-art techniques.

Design and analysis of a movie recommendation system for recommending new movies to the user based on ratings with Python software. Because of information overload, we can call the recommendation system the information filter system. It has a significant impact on how we interact with the world—music (Spotify), shopping (Amazon), video (Netflix, YouTube), etc. To create a recommendation system that can serve millions of

users with millions of items. Users can spend lots of hours or time scrolling through hundreds, if not thousands, of songs, movies, or items without ever finding something they like.

Movie recommendation systems employ deep learning techniques to analyse complex patterns in user behaviour and movie attributes, thereby providing highly tailored suggestions to users. Deep learning models excel at extracting intricate features from vast amounts of data, making them particularly well-suited for movie recommendation tasks. Deep learning models can capture intricate patterns and relationships in user behaviour and movie attributes, leading to more accurate and personalised recommendations compared to traditional recommendation approaches.

Deep learning models can efficiently handle large-scale datasets and complex feature spaces, making them well-suited for recommendation tasks on platforms with millions of users and movies. Deep learning-based recommendation systems are highly flexible and adaptable to various data modalities, including textual data, images, and user interactions. This flexibility allows for the incorporation of diverse sources of information to improve recommendation quality.

Based on the featurization recommendation system, it can be divided into the following categories:

1. Collaborative Filtering-Based Recommendation System
2. Content-based Filtering-Based Recommendation System
3. Combined/Hybrid Recommendation System

These days, a movie recommendation system plays a significant role in our social interactions due to its capacity to deliver higher-quality entertainment. This kind of technology might suggest a collection of movies to viewers based on their preferences or the films' level of popularity. Despite the fact that many movie recommendations have been made, most of the movies are not in any way suitable for either new or returning users. Our proposal in this study is a movie recommendation system that can suggest a movie to

both current and potential viewers. The movie databases must have all pertinent data, including popularity and attractiveness, in order to make recommendations.

We presented a movie recommendation system in that paper that can recommend a movie to both new and returning customers. It is necessary to gather primary data on popularity and attractiveness in order to propose movies. It produces an abundance of films, which serves as both a suggestion for movies and a valuable resource for movie producers to plan future projects. The suggested system is shown by the experiment's outcome using real-world data. It creates an abundance of movies that are helpful for both movie recommendations and film makers' new project planning. Experimentation using real-world data shows how successful and efficient the suggested systems are.

## II. LITERATURE SURVEY

In Our social life, movie recommendation is essential because we have to get a lot of entertainment. The uses of that system to the user are it can suggest to the user based on their choice and popularities of the movie. There are many movie recommendations, and different sets of movie recommendations are proposed. Some users are prime so they can watch a film of their choice on their own time, but if the user is new, they cannot recommend a movie as per their choice. In that paper, we proposed a movie recommendation system that can suggest a film to existing and new users. For movie recommendations, there is a need to collect primary information for attractiveness and popularity. It creates a swarm of movies, which is not only the value for the producer of movies for the planning of new films but also the recommendation of the movie. The result of the experiment in the accurate -world data reveals the proposed system. In the whole world, there are lots of movies available. It isn't easy to user search for a movie according to their choice. The various users are there. They like different actors or movies. So, it is necessary to find a relevant movie that users require, known as a movie recommendation system. Many system results are inspired by various domains like Tv programs, jokes,

books, and news articles. Digital television is significant to research. The recommendation system is based on content and collaborative filtering (CF). From the active users then, the CF tries to find the same users' automatic groups using the correlation measure. These can see similarities between the users. After that, they recommend an item to users based on their choice. CF is succeeding in various fields because of its shortcomings like scalability and sparsity. CF uses a user rating to find dissimilar users, but it is not possible easily because some movies have a rating. For movie recommendations in that paper, we can discuss two methods. Using Movie Lens Data Sets, we demonstrated the efficacy of our proposed approaches.

1. For the planning of a new film, the movie swarm mining is used to produces
2. Some item recommendations, such as exciting and popular movies, solve the problem of unique users. [1]

The recommendation system is essential in the modern area and is employed in various famous applications. The recommendation system has resulted from the construction of a global village, the expansion of rich information, and the accumulation of apps. This paper views us based on the recommendation system in the collaborative filtering, the techniques generated and the approaches. The recommended system consists of 3 methods: content, hybrid, and collaborative filtering. In this paper, we study classifying collaborative filtering using several methodologies such as user-based recommendation, item-based recommendation, and matrix factorization. For the research purpose that survey is used in this area. We analyze the aspect based on detailed ratings from the recommendation and reviews based on rating trends and similarities. And lastly, for the multiple criteria, the suggested movie recommendation system is validated, and the proposed approach outperforms existing methods. [2]

As business demands expand, there is a greater reliance on extracting relevant information from massive amounts of raw data to drive business solutions. The same may be said about computerized recommendation systems, which are becoming commonplace in consumer industries such as music,

apparel, books, movies, news items, locations, utilities, and so on. That system collects information from the users to improve suggestions for the future. This paper describes two collaborative filtering algorithms and the movie implementation system using the Apache Mahout. Furthermore, using Matplotlib, this study will analyze the data to acquire insights into the movie dataset.[3]

A recommendation system is a program that suggests specific resources—like books, movies, music, and so on—to consumers based on a set of data. Generally, movie recommendation algorithms predict the types of movies a user would appreciate based on the features of previously enjoyed movies. Businesses that collect a lot of customer data and wish to efficiently provide the best recommendations may benefit from these recommendation systems. A multitude of factors can be considered while developing a movie recommendation system, including the genre of the movie, the actors in it, and even the director. The systems can recommend movies based on a combination of one, two, or more factors. This paper's recommendation system is predicated on the genres that the user could find most appealing. This is accomplished by content-based filtering based on genre connection. The dataset that the system utilises is called Movie Lens. R is the data analysis tool that is utilised. [4]

In our social life, the recommendation of the movie plays an important role. Based on how popular the movie is and the users' choice, the movie recommendation gives a set of movies to the user—the use of a recommendation system to purchase the object and view that object. They collect much more information to steer consumers to complete the user needs. In that paper, we can see the different algorithms for the movie recommendation that have been used in recent research. We have described the movie recommendation system's benefits, approach and drawbacks. Also, in this paper, we discussed the movie recommendations system. [5]

### III. PROPOSED METHOD

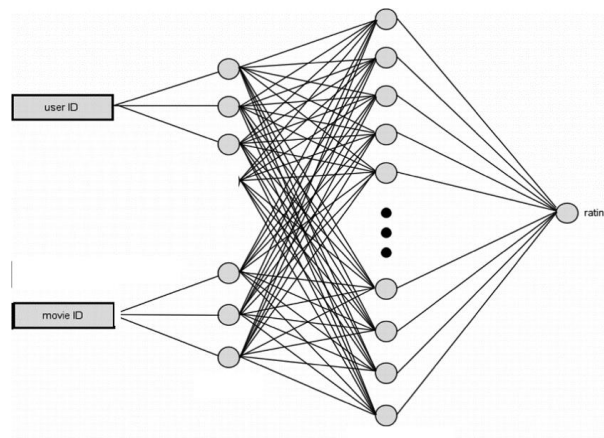
This project uses a movie dataset to train a deep learning model, which can then be used to predict which movies the viewer will be recommended to

view next. In this project, a deep learning model was trained utilising both the user ID and the movie ID as input features, and the ratings as the class label. A deep learning model built on the highest rated movies would suggest new films to the same user. The suggested approach demonstrates the implementation of many functions covered in depth in the section on result analysis. To create a movie recommendation module, we have loaded a number of Python packages, including SKLEARN, NumPy, pandas, SNS, and many more. Below is a detailed explanation of the proposed deep learning model.

The three main steps in the neural network construction are as follows:

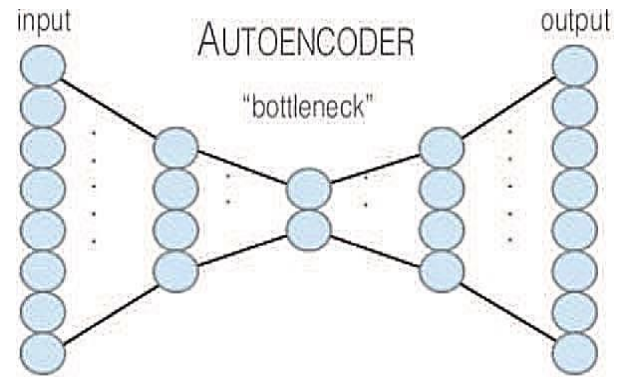
- Input layer
- Hidden layer
- Output layer

User ID and movie ID are the features for the suggested methodology that make up the input layer. We employed the deep learning technique for processing-based hidden layer creation.



**Fig. 3.1 Proposed Deep Learning Movie Recommendation System**

The proposed system, depicted in the above image, uses user ID and movie ID as input features, and rating is represented by a class label.



**Fig. 3.2 Architecture of a movie recommender**

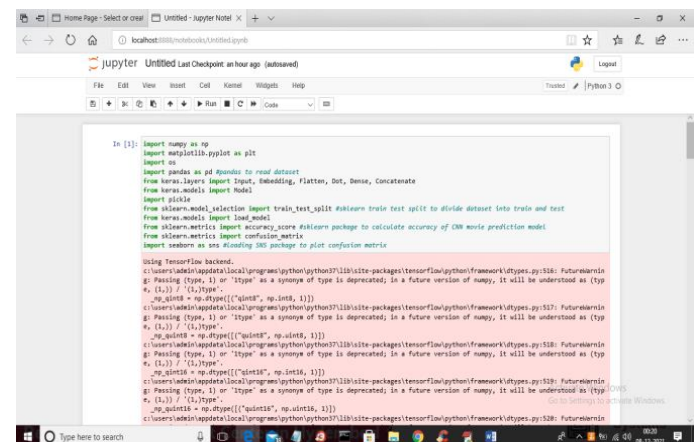
The rating details in this user profile are obtained through the usage of neural network architecture. There must be extreme caution while choosing a certain layer component.

### 3.1 Advantages of proposed Method

- In order to choose comparable neighbours for the target user and service, the system uses the location data of both users and services.
- To analyse the information about the videos and the users, as well as the past interactions between them.

## IV. RESULT

Proposed method showing implementation of different functions discussed in this section in detail. we have loaded various python packages such as pandas, NumPy, SNS, SKLEARN and many more to build movie recommendation module.



```

In [1]: import numpy as np
import matplotlib.pyplot as plt
import os
import pandas as pd
from keras.layers import Input, Embedding, Flatten, Dot, Dense, Concatenate
from keras.models import Model
import pickle
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.metrics import confusion_matrix

# Using TensorFlow backend
user_embeddings = Embedding(1000, 10)
movie_embeddings = Embedding(1000, 10)
def get_embeddings(user_id, movie_id):
    user_embedding = user_embeddings.get_weights()[user_id]
    movie_embedding = movie_embeddings.get_weights()[movie_id]
    return user_embedding, movie_embedding

# Defining the model
def build_model():
    user_input = Input(shape=(1,))
    movie_input = Input(shape=(1,))
    user_embedding = user_embeddings(user_input)
    movie_embedding = movie_embeddings(movie_input)
    dot_product = Dot([user_embedding, movie_embedding])
    output = Dense(1)(dot_product)
    model = Model([user_input, movie_input], output)
    model.compile(optimizer='adam', loss='mse')
    return model

# Training the model
def train_model():
    # Load data
    data = pd.read_csv('data.csv')
    # Split data into training and testing sets
    train_data, test_data = train_test_split(data, test_size=0.2, random_state=42)
    # Train the model
    model = build_model()
    model.fit(train_data[['user_id', 'movie_id']], train_data['rating'], epochs=100)
    # Save the model
    pickle.dump(model, open('model.pkl', 'wb'))

# Evaluating the model
def evaluate_model():
    # Load test data
    test_data = pd.read_csv('data.csv')
    # Load the model
    model = pickle.load(open('model.pkl', 'rb'))
    # Predict ratings
    predictions = model.predict(test_data[['user_id', 'movie_id']])
    # Calculate accuracy
    accuracy = accuracy_score(test_data['rating'], predictions)
    # Print accuracy
    print('Accuracy: {}'.format(accuracy))

# Main function
def main():
    train_model()
    evaluate_model()

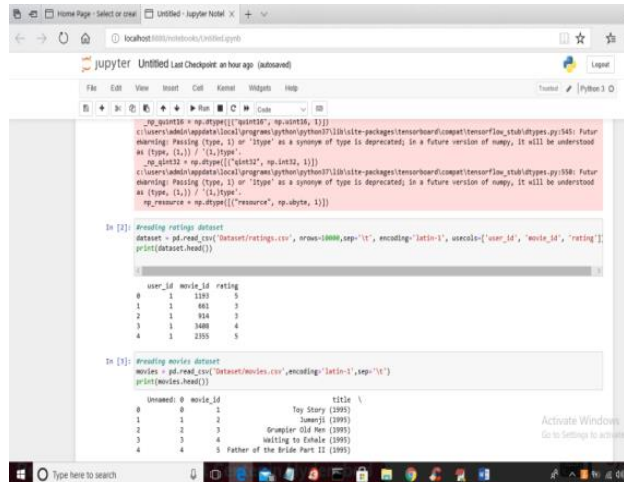
if __name__ == '__main__':
    main()

```



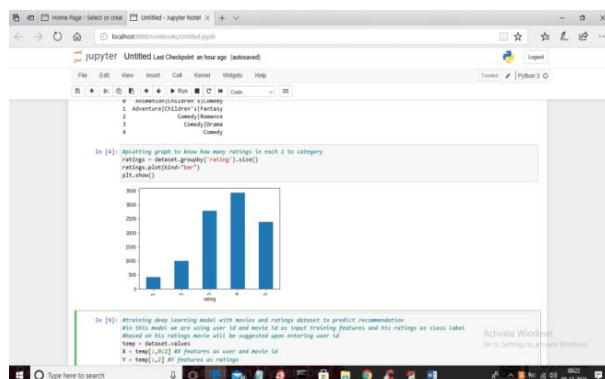
### Fig.4.1 Loading Python Packages

In above screen we have loaded various python packages such as pandas, numpy, SNS, SKLEARN and many more to build movie recommendation module. In above screen you can read light blue colour comments starting with # symbol to know code functionality. In below screen we are showing code to read movie and ratings dataset.



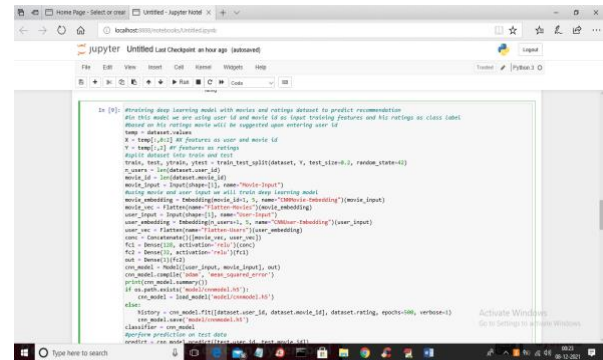
### Fig4.2 Read Movie and Rating Dataset

Here we are importing dataset which consists of movies and ratings of movies.

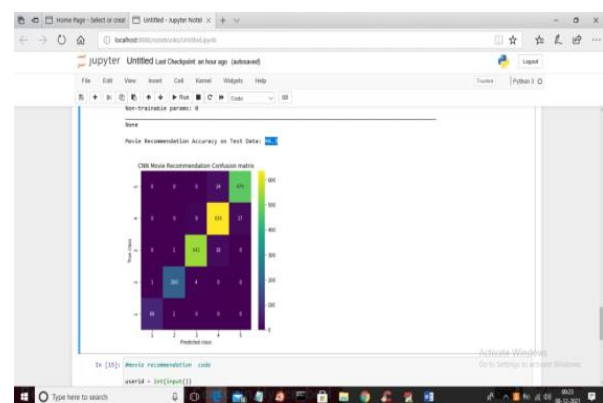


### Fig4.3 Graph for movie ratings

In above two screens we read movie and ratings dataset and then plot graph with various ratings and in below screen using both movies and ratings dataset we are training deep learning model

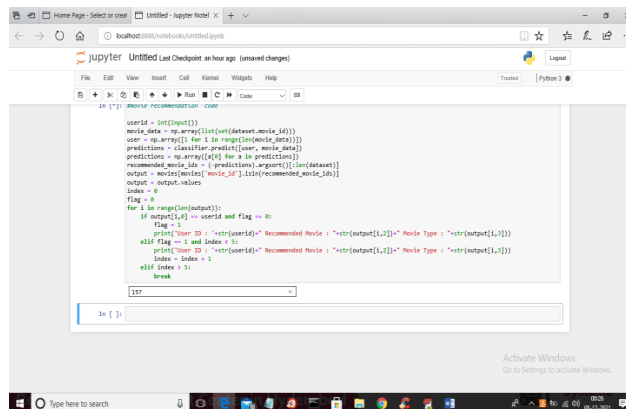


**Fig4.4 Prosed model got 96% accuracy for predicting recommended movies**



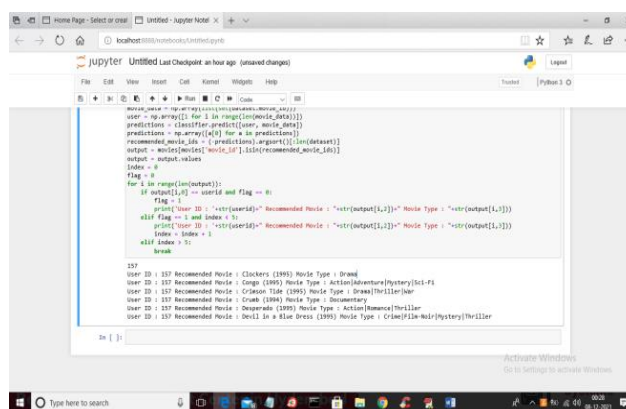
**Fig4.5 confusion matrix for classification**

In above screen in blue colour text, we can see we got 96% accuracy for predicting recommended movies and in confusion matrix graph we can see all classes are correctly classified except very few are incorrectly classified. In above graph x-axis represents Predicted class and y-axis represents TRUE class and we can see a greater number of predictions are matching with TRUE values. In below screen we are performing movie recommendation.



**Fig.4. 6 Entered user ID for his new movie recommendation**

In above screen I entered user id as 157 which means I want to recommend new movies for user id 157 by analysing ratings given by him in past and these past ratings we read from dataset and now press enter key to get below list of recommendation movies.



**Fig.4.7 Top 5 recommendations for user ID 157**

In above screen for user id 157 we recommended top 5 ratings movies and similarly you can enter any user id and get recommendation list

## V. CONCLUSION

For getting new recommendations proposed model used 2 features such as movie ID and user ID. For movie recommendation gives 96% using deep learning-based architecture. For getting movie recommendation under deep learning basic neural network architecture is used. Comparing with other techniques result analysis proves that proposed methodology of deep learning gives better performance. To show the performance analysis of

proposed model is better we calculated accuracy parameter which gives accuracy of 96%.

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