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Movie Recommendation using CNN& ANN

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ABSTRACT: In the context of such an era where nearly everything is based on big data, personalized recommendation systems are becoming increasingly valuable for research. Deep learning has attained great achievements in numerous fields by virtue of its powerful computing power and extraordinary nonlinear transformation capabilities. Applying deep learning to a recommendation system that needs to mine and extract features from massive amounts of data will not only help the development of recommendation algorithms, but also improve the algorithm performance and thus improve the user experience. This project introduces a recommendation algorithm based on CNN-ANN and applies it to the recommendation of movies by mining user behaviour data and recommending movies with higher ratings to them. It is testing set and training set that the data is divided into, and Top-N recommendation list is produced for the training set, while the algorithm is evaluated on the testing set. It is the features of the data that CNN-ANN can effectively extract and complete the recommendation from the results.

1.INTRODUCTION:

As information technology develops, at present information overload has already replaced information shortage. In current era, faced with exponentially increasing information, what really confuses people is no longer how to obtain information, but how to quickly extract useful information from massive information. With this dilemma, recommendation system came into being and became an important tool for connecting users and data. A successful recommendation system not only accurately predicts user behaviour based on data, but also discovers users 'potential interests, helping them find things that are not easy to find but meet their preferences. In fact, in daily life, recommendation systems are already everywhere. For example, our commonly used shopping platforms:

Amazon, Tmall; social networks: Facebook, Twitter, WeChat. It is precisely because of the existence of the recommendation system that we can quickly find the items we need among countless products, and we can also surprise in the recommendation list to find the products that we are interested but unexpected. It is also because of the existence of the recommendation system that we can successfully find our favorite bloggers and browse the content we are interested in from time to time. There is no doubt that the recommendation system is becoming a very significant part of our daily lives and brings us great convenience. In recent years, with its powerful data mining capabilities, deep learning has been well received in many fields[[1],[2]]. How to apply deep learning to recommend products that are of real interest to specific people more efficiently has also received attention. RecSys, an international conference, has also actively held seminars to encourage the research on this direction. Hence, it is undeniable that deep learning will be the new trend and future direction of recommendation systems.

2. LITERATURE SURVEY

[1] Raglio A, Imbriani M, (2019), Machine learning techniques to predict the effectiveness of music therapy: A randomized controlled trial in computer methods programs in biomedicine

Background. The literature shows the effectiveness of music listening, but which factors and what types of music produce therapeutic effects, as well as how music therapists can select music, remain unclear. Here, we present a study to establish the main predictive factors of music listening's relaxation effects using machine learning methods. Methods. Three hundred and twenty healthy participants were evenly distributed by age, education level, presence of musical training, and sex. Each of them listened to music for nine minutes (either to their preferred music or to algorithmically generated music). Relaxation levels were recorded using a visual analogue scale (VAS) before and afterthe listening experience. The participants were then divided into three classes: increase, decrease, or no change in relaxation. A decision tree was generated to predict the effect of music listening on relaxation. Results. A decision tree with an overall accuracy of 0.79 was produced. An analysis of the structure of the decision tree yielded some inferences as to the most important factors in predicting the effect of music listening, particularly the initial relaxation level, the combination of education and musical training, age, and music listening frequency. Conclusions. The resulting decision tree and analysis of this interpretable model makes it possible to find predictive factors that influence therapeutic music listening outcomes. The strong subjectivity of therapeutic music listening suggests the use of machine learning techniques as an important and innovative approach to supporting music therapy practice. Music listening is a widespread technique used by music therapists in various clinical settings [1-6]. A recent survey administered to a sample of music therapists from around the world underlined that 42.7% of these professionals use music listening in therapeutic interventions [7]. Music listening can be administered as self-selected or experimenter-selected music [8]. In the first case (individualized music listening), patients/clients select their preferred music to listen to at various moments, while in the second condition, the experimenter selects playlists, considering music parameters and structures in relation to therapeutic aims. Music listening is mainly aimed at reducing behavioral and psychological symptoms, such as agitation, anxiety, stress, or pain. [5, 9- 15]. In this light, one of the most frequent and important objectives of music listening in clinical settings is psychophysical relaxation (deactivation). Relaxation can be defined as an absence of physical and emotional tension and stress, a deactivation of the mind that promotes general wellbeing. We can consider this a possible cross-cutting outcome that involves many clinical areas: pain medicine [16], hospitalization conditions [5], psychological symptoms [4,17], behavioral disturbances [9], etc. The literature has shown the effectiveness of music listening, but what types of music produce which effects remains unknown, as well as how music therapists can select music while keeping therapeutic aims in mind. Moreover, the complexity of music structures and parameters makes it difficult to find a connection between music elements (rhythm, melody, and harmony but also intensity, pitch, timbre, etc.) and therapeutic results [5]. Thus, the relationship between music characteristics and their effects on therapeutic outcomes has not been thoroughly explored. In this study, we hypothesized that algorithmic music with specific characteristics (Melomics-Health music) [18] can activate neutral music listening, bypassing cultural and aesthetic references and promoting relaxation and deactivation. Algorithmic music creates the possibility to study therapeutic music impact using music structures and parameters created for specific therapeutic aims. Many studies have also shown a link between musical styles and personality [19-23] or cognitive styles [24]. Cultural aspects were implicitly present, as they influenced the musical tastes of the participants. In all cases, the therapeutic effects of music were not considered. Other studies have used machine learning (ML) techniques: Vempala and Russo [25] studied the link between musical listening and emotion judgments using various ML methods, such as (ensembles of) artificial neural networks, linear regression, and random forests. In that study, the relationship between music listening and therapeutic outcomes remained unexplored. The present study compared algorithmic music (based on sonorous music features aimed at therapeutic effects) and individualized music listening (based on subjective choices) to find possible predictivity factors of effectiveness related to these two types of music listening approaches. For this comparison, we relied on decision trees: this choice is motivated by the ability of this machine learning technique in extracting complex relations among the dependent variables while producing a human-readable model that can be fully understood by a domain expert. This property distinguishes decision trees from other machine learning methods that provide a black-box-like model. From such a model, it is impossible (or at least difficult and time-consuming) to extract meaningful information that can support the domain experts in their daily activities. Aims and Research Hypotheses The main aim of the present study was to use ML techniques to investigate how personal factors (age, sex, education, music training, preferred music genre, music listening frequency) can predict/classify the effectiveness of two music listening approaches (individualized and Melomics-Health music listening) for relaxation. We used decision trees, a well-known ML method [26-30]. Material and Methods Participants Three hundred and twenty healthy volunteer participants were recruited and allocated to two homogeneous groups (with and without musical training or practice) stratified by sex, age and education. Each final subgroup was formally randomized to individualized or Melomics-Health music listening. Table 1 shows the actual age distribution of the participants, while Table 2 shows the distributions of education levels, musical training, and sex. To select only healthy participants, before starting the questionnaire, the examiners asked the participants for the presence of any health-related problem. Participants with deafness/hypoacusis problems or severe neurological/psychiatric diseases in the last year and participants that showed a low level of cooperation/refusal were excluded from the study. Measurement Instruments A discrete VAS with a range of 0 to 10 was used to evaluate the participants' relaxation levels. The variation of the relaxation level, obtained comparing VAS scores before and after music listening, was considered as a dependent variable, with three possible categories (increase, decrease, or no variation). For the classification of music effects, three classes were selected: positive effect (prelistening relaxation lower than post-listening relaxation), no effect (no change in relaxation), and negative effect (a decrease in relaxation). Design This study is a Randomized Controlled Trial. For each participant, the information about musical training/practice, sex, age, education level, and listening habits were collected as independent variables. Figure 1 summarizes the study's design and the distribution of musical training/practice, sex, age (in two categories), and education level, that was planned during the selection of the participants. Procedure After randomization, the participants underwent one of the two music listening conditions (with earphones) in a state of comfort. Each music listening session lasted approximately 9 minutes. In the individualized music listening group (IMLG), before the experiment, the researcher asked each subject to select a list of 2-3 preferred relaxing pieces of music; the only restriction was a total length of 9 minutes at the most. In the Melomics-Health group (MHG) participants listened to 3 relaxing pieces of music, with a total length of 9 mi

[2]N.N. Vempala, F.A. Russo, Modeling music emotion judgments using machine learning methods, Front. Psychol. 8 (2017) 2239, doi: 10.3389/fpsyg.2017.02239.

People experience stress due to various factors like work pressure, emotional problems, disaster, violence, etc in their day to day life. This stress leads to many physical and mental health risk such as Asthma, Headaches, Anxiety, heart disease, Depression, Asthma, Alzheimer's disease, etc. Music therapy has the ability to balance both the physical and mental fitness of humans.

Music therapy is a healing process that uses music to an inscription the emotional, physical, cognitive needs of a self one or a group. Here we aimed to establish the music classification and prediction for music therapy using a machine learning algorithm- Random forest. This study involves factors such as people's age, education status, music interest, preferences of music in both individual and therapist aspects, and their respective relaxation scale before and after music therapy. Our study reveals the important features involved in music prediction for music therapy and the accuracy performance of about 89 is achieved by this classification. Therapy is one of the types of treatments that aims to improve one's physical and mental fitness.

3.PROPOSED SYSTEM

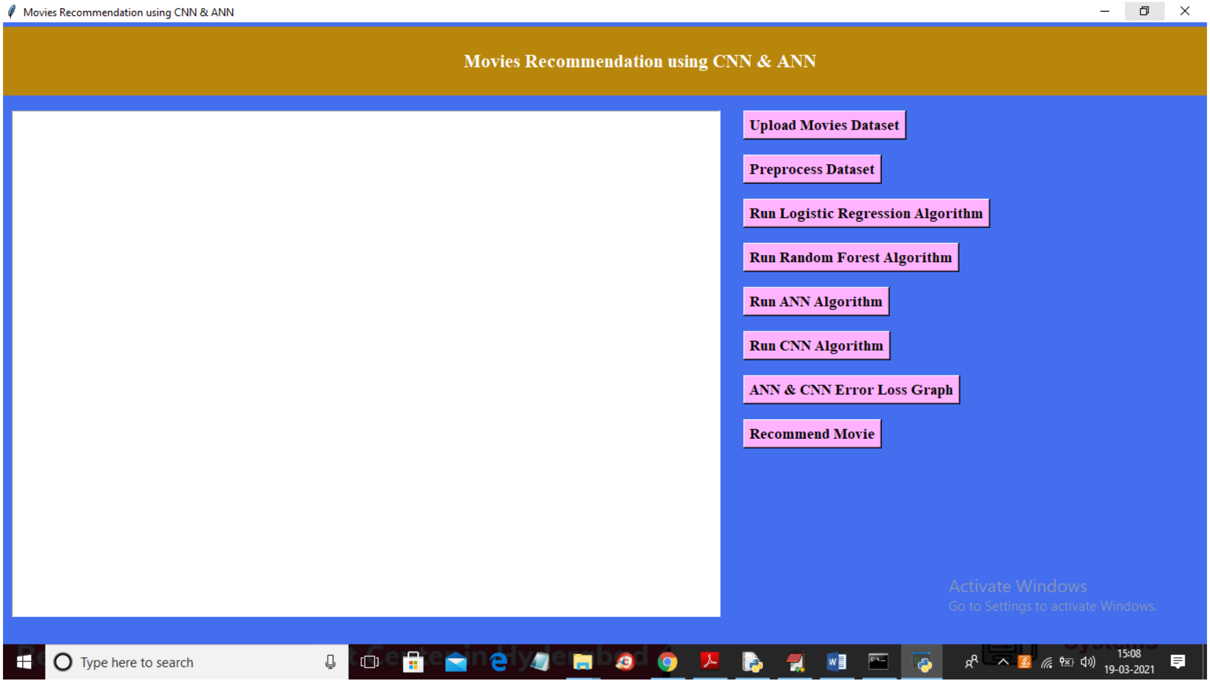
In this project, the CNN-ANN is applied to extract features from the data. For the movie data set, the CNN-ANN is applied to process the movie name. The general process is to get the embedding vector of each word corresponding to the movie name from the embedding matrix. Because the movie name is a bit special, the name length is limited. Here, when using the filter size, the length of 2, 3, 4 and 5 is chosen. Then the text embedding layer is convoluted and pooled by using convolution kernels of sliding 2-, 3-, 4- and 5-word sizes, and then the dropout operation is used to output the full connection layer.

The feature vectors generated in the above steps are connected by two full connection layers. The first full connection layer is the full connection of movie ID features and movie type features, and then the full connection of CNN generated movie name features to generate the final feature set.

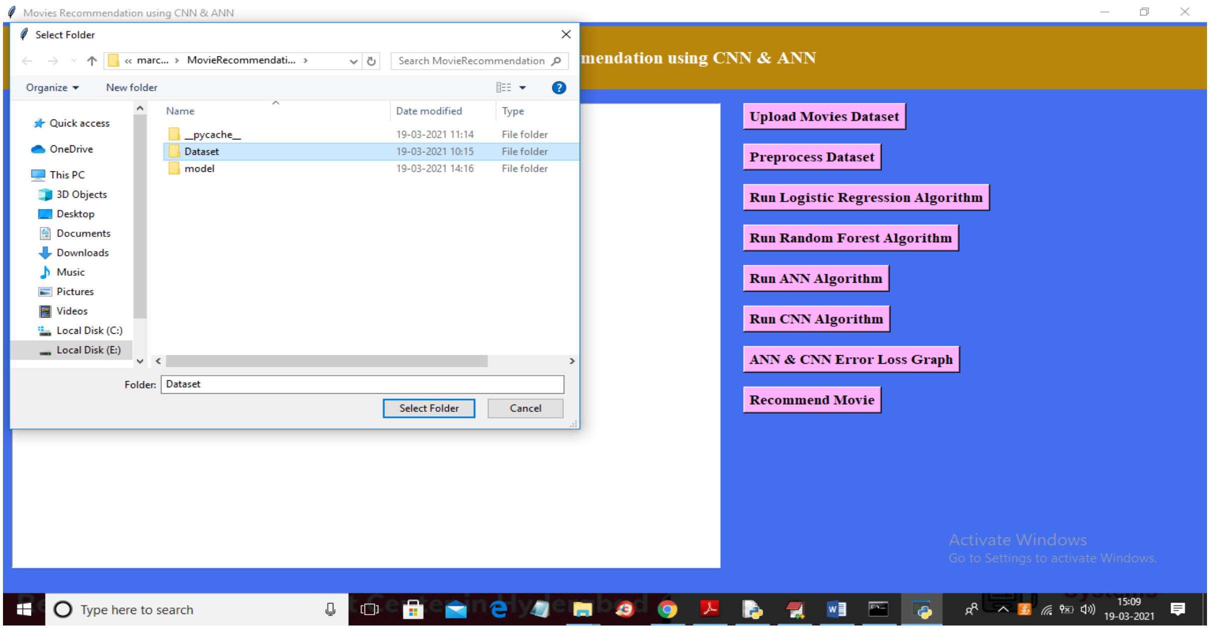
3.1 ADVANTAGES:

- Accuracy is Very high.
- In this project, two features are taken as input and are passed into the fully connected layer again till a value is output. The output value is then returned to the real score, and Mean Squared Error (MSE) is used to optimize the loss. Mean Absolute Error (MAE) is applied to evaluate the recommended model.
- The smaller the value of the two indicators, the better the prediction result.

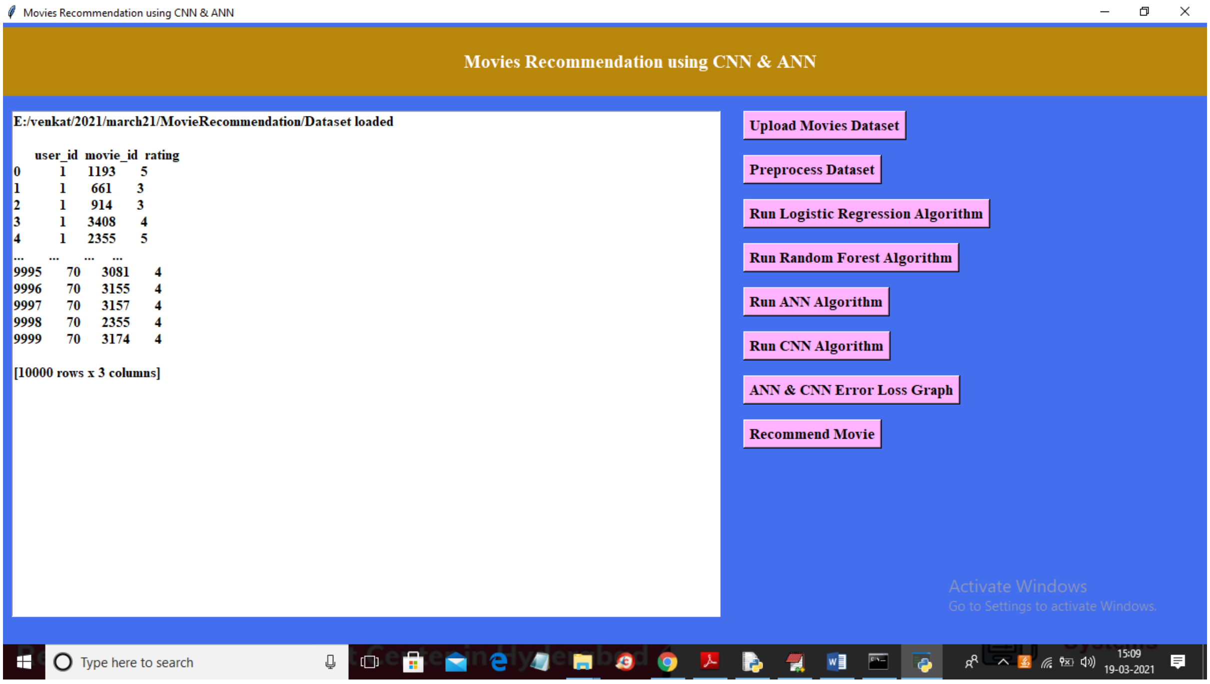
4.RESULTS AND DISCUSSIONS



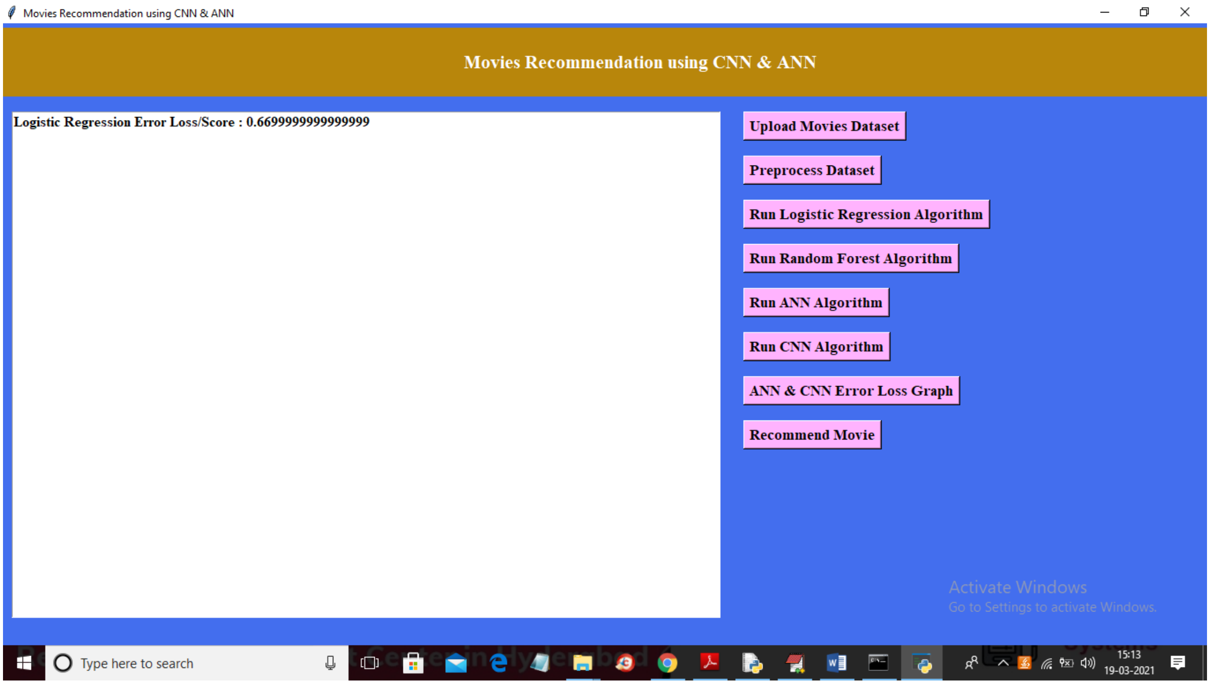
In above screen click on 'Upload Movies Dataset' button and then load dataset



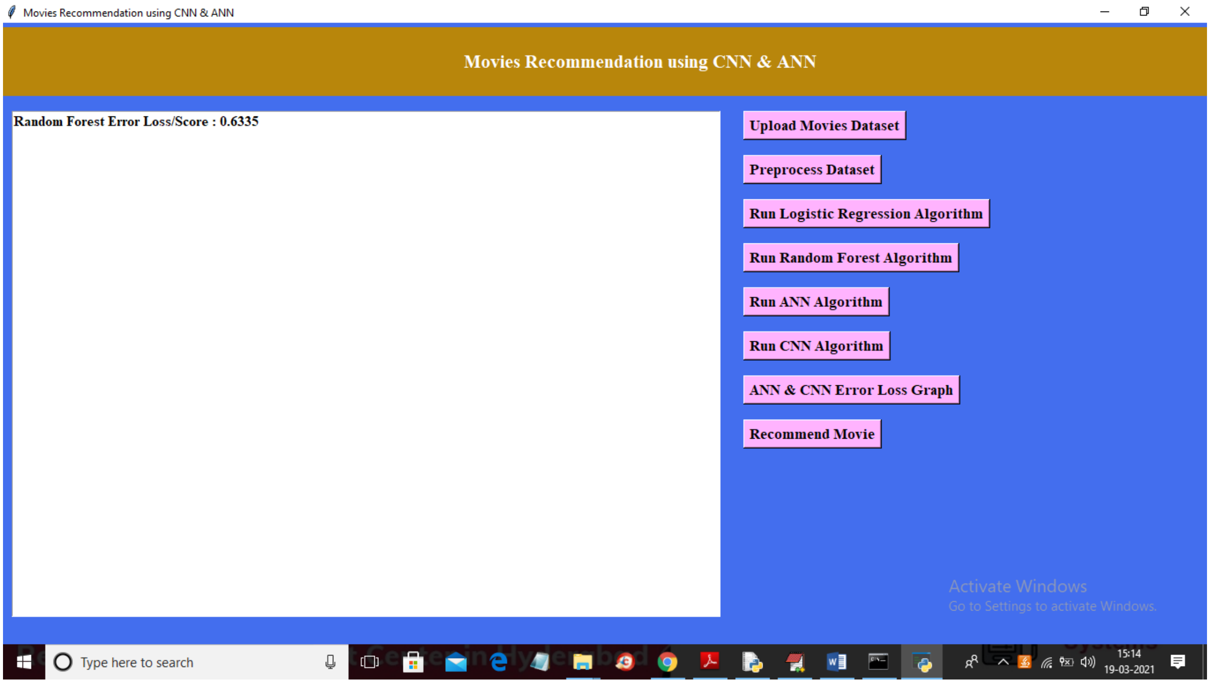
In above screen selecting and uploading 'Dataset' folder and then click on 'Select Folder' button to load dataset and to get below screen



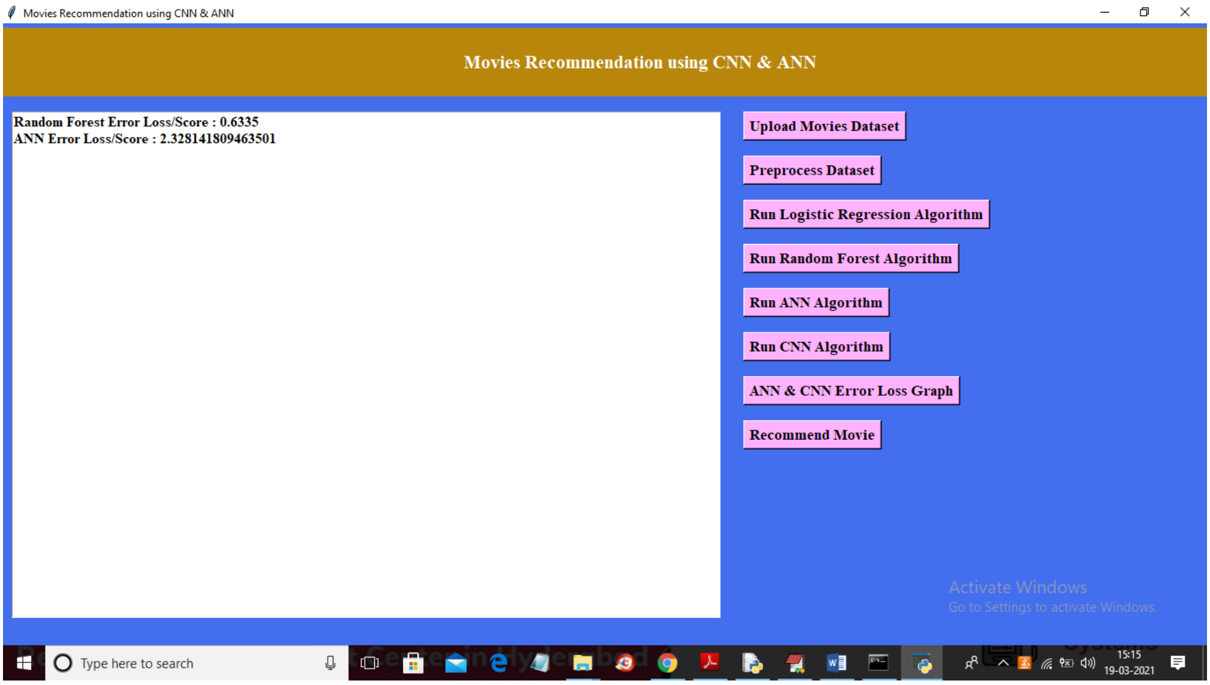
In above screen dataset loaded and displaying few values from dataset and now click on 'Preprocess Dataset' button to split dataset into train and test



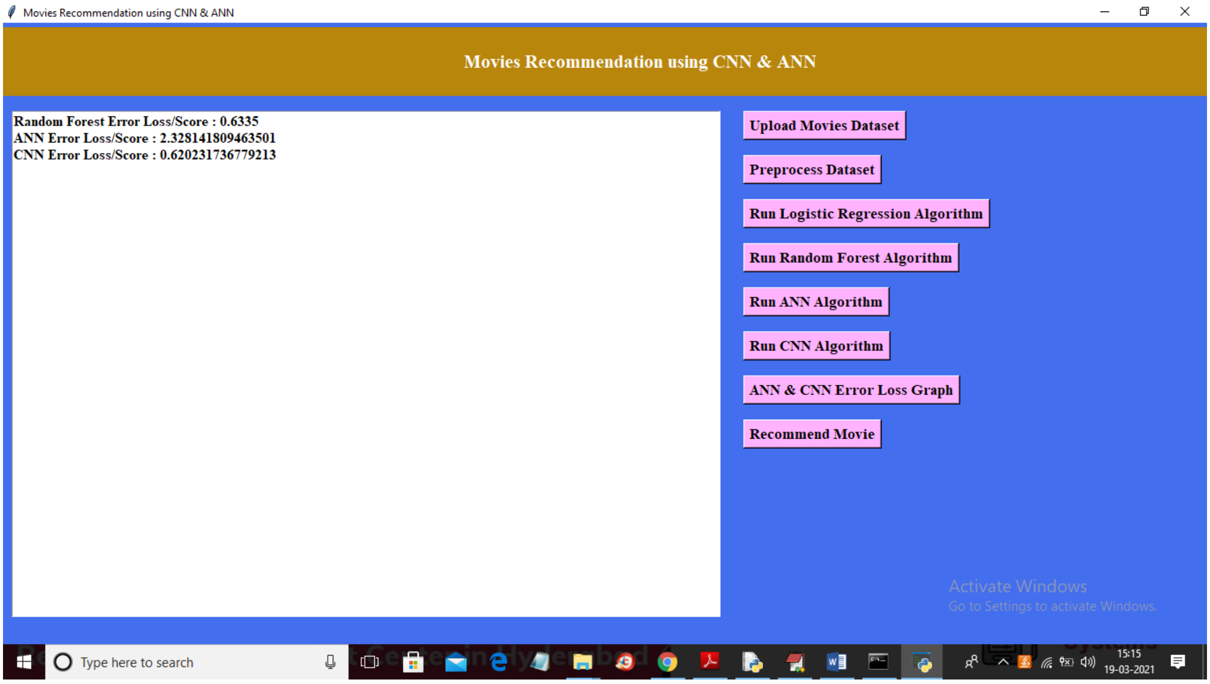
In above screen with logistic regression error rate is 0.66 and now click on 'Run Random Forest Algorithm' button to get its prediction error loss



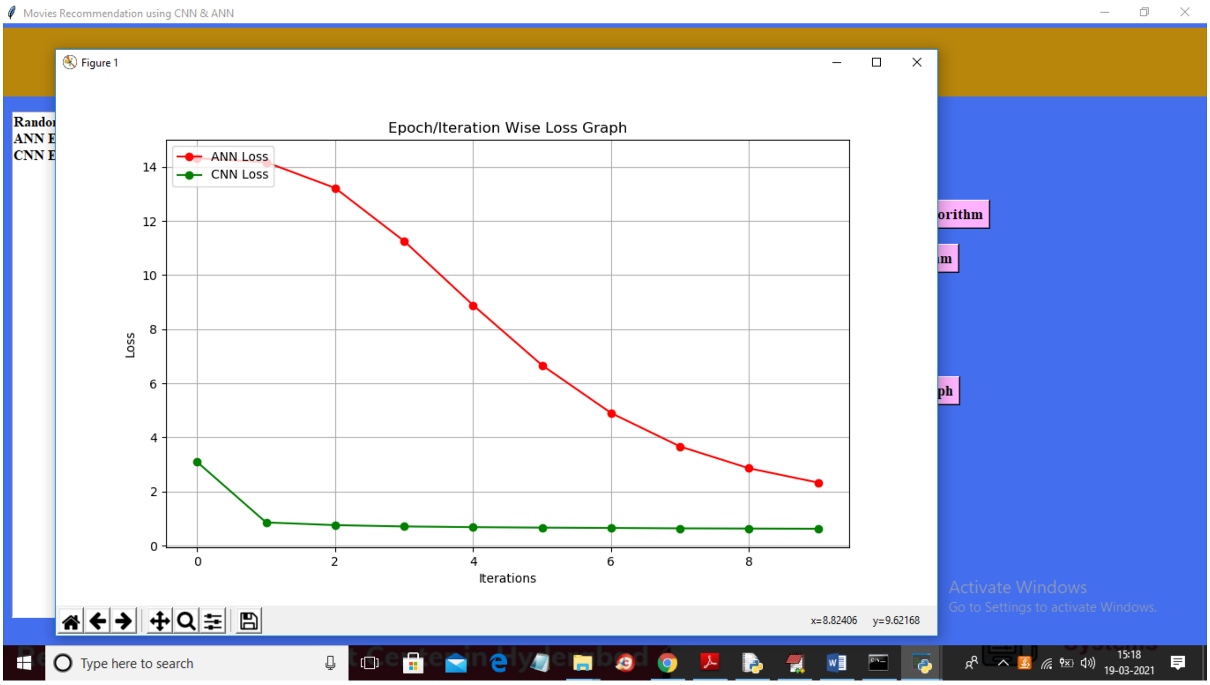
In above screen random forest error loss is 0.63 and now click on 'Run ANN Algorithm' button to train ANN algorithm



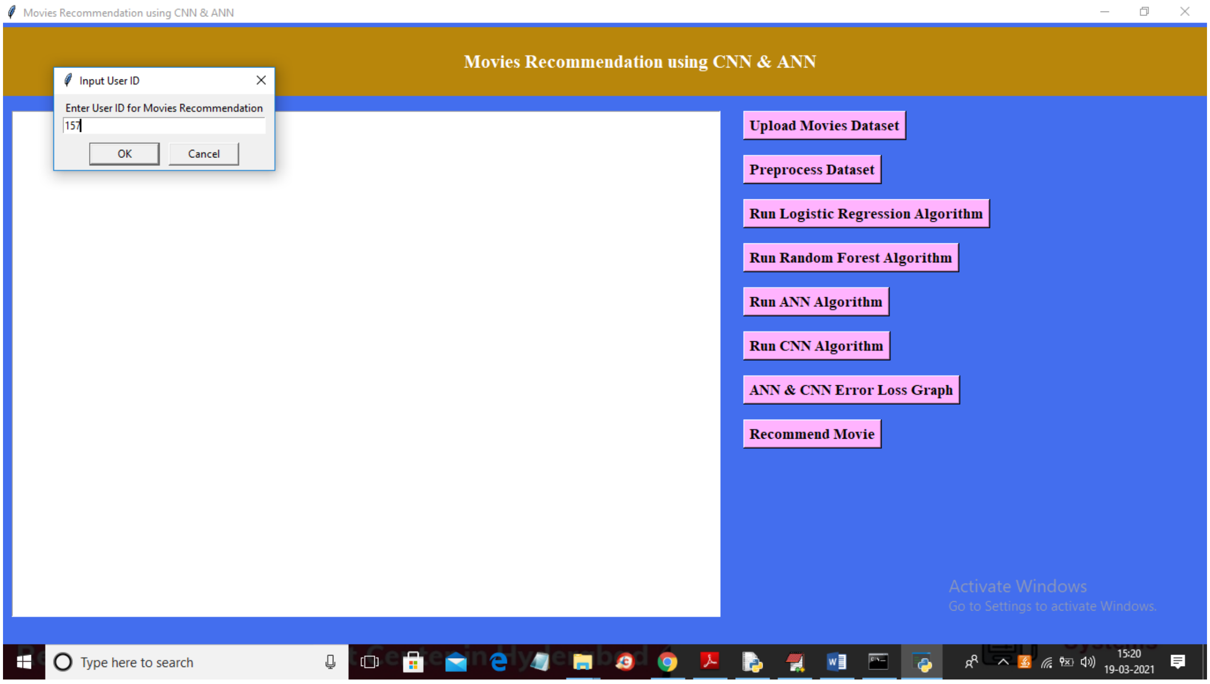
In above screen ANN error loss is 2.32% and now click on 'Run CNN Algorithm' button to get its loss value



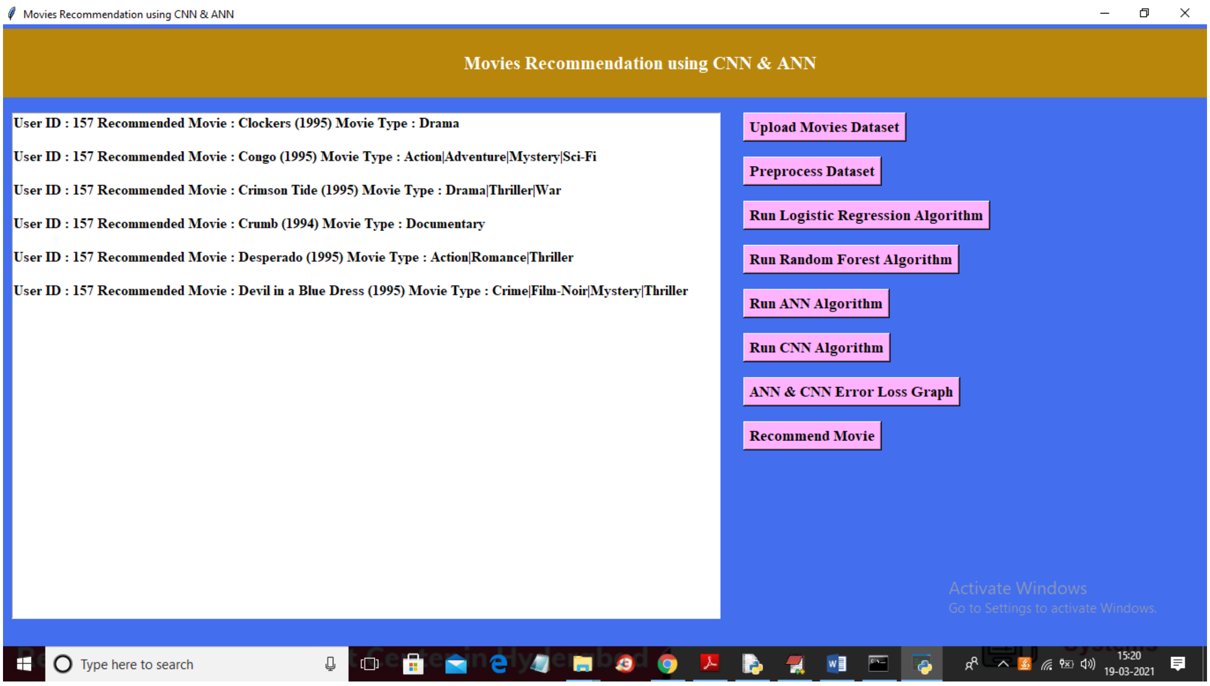
In above screen CNN got 0.62% error loss and the model with less error loss rate will be consider as best model and below screen showing summary of both models



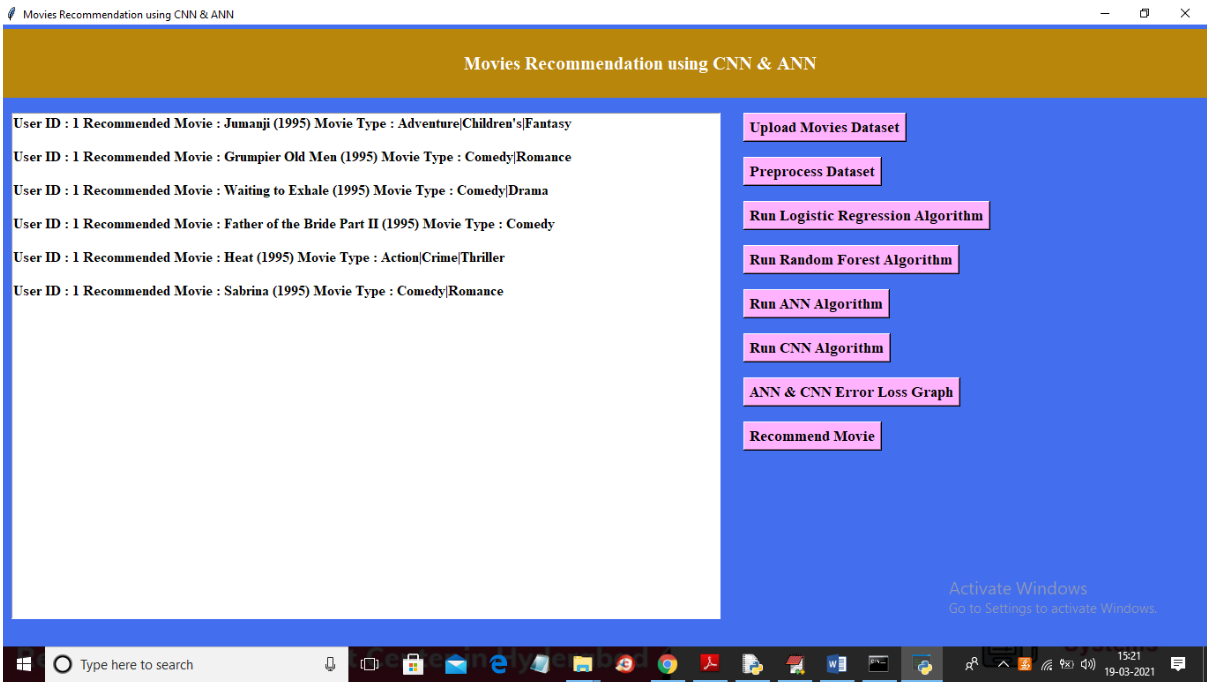
In above graph x-axis represents epoch and y-axis represents loss rate and red line refers to ANN and green line refers to CNN and when epoch increases both model loss get decreased but CNN loss is lower than ANN. Now click on 'Recommend Movie' button and enter user id to get movie recommendation



In above screen entered user id as 157 and then click OK button to get below recommendation



Now try with user is 1



Similarly you can enter any user id and if this user id exists in CNN model then it will predict and recommend new movies to user and u can enter user id from 1 to 1000 and if user exists then u will get output

5.CONCLUSION

In this project we are using Random Forest, Logistic Regression, ANN and CNN neural network to build movie recommendation model and to build this trained model we are using MOVIELENS dataset and after building model CNN is giving less error rate compare to other algorithms. Dataset saved inside 'Dataset' folder. This recommendation system recommends different movies to users. Since this system is based on a collaborative approach, it will give progressively explicit outcomes contrasted with different systems that are based on the content-based approach. Content-based recommendation systems are constrained to people, these systems don't prescribe things out of the box.

FUTURE SCOPE

This algorithm is still inadequate in solving the problems of cold start and sparsity, so future research will focus on solving these two problems.

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