International Journal of Aquatic Science
ISSN: 2008-8019
Vol 12, Issue 03, 2021

A Multi-Level Adaptive Loot Box Recommendation System for Video Games

[1]S. Balapriya, [2]Dr N. Srinivasan

[1]Research Scholar, Sathyabama University, Chennai
[2]Sr. Consultant, Bassure Solutions Pvt. Ltd, Chennai

Email: [1]s.balapriya@gmail.com, [2]srinin@bassure.com

Abstract: Loot Box is one of the most important economies in video Games especially in massively multiplayer online (MMO) games. With Free to Play games growing in popularity, loot boxes became a primary monetisation technique. Loot boxes consist of virtual items that are consumed by players. The items vary from a new weapon to a skin. Loot boxes are one of the reward elements that create continuous interest among players to play games. On the other hand, publishers can generate revenues even after the game is released. These advantages have made loot boxes quite popular in the video game industry. Loot boxes have become one of the monetizing methods for video games. An online multiplayer accommodates different types of players and also the design incorporates opportunities for different types of fun. Considering this design philosophy, defining loot boxes with predefined items in it may cause disappointments to players as the item does not fit for them. In addition to causing negative engagement, such scenarios will not favor purchases that affect the game economy. Recommending loot items adaptive to the traits of the players and their play style could be a desired solution. We recommend a novel approach based on machine learning algorithms to solve this problem. The approach couples to Machine learning solutions together to generate loot item suggestions. The system uses Random Multimodal Deep Learning based classification approach to identify player profile and classification. The system identifies the player trait and the play style using sentiment analysis. The model employs Bartle player classification to evaluate the results. The multi-level approach helps the system to deliver results with minimal resource utilization.

Keywords- Machine Learning, Sentiment Analysis, Play style, Recommender systems, Loot boxes, Video Games.

1. INTRODUCTION

Video games are growing as the primary entertainment medium over the globe. Video games have evolved into various forms of entertainment with the growth of technology. With internet and machine learning techniques, games provide new forms of experience for players. The big titles are emerging as games that could be played by different player personalities (Medler 2009). Attempting to design games that are appealing to varying audiences is challenging for designers. The core game experience cannot be varied from players to players. Many designers attempted to define a game system that is reflective of the players' interests. It means, players can achieve the fun they are looking for. Grand Theft Auto is one of such titles that contain such design elements in it.

Online games are gaining more popularity and they are aiming to provide varying levels of experience to people. Online games have opened new markets to games where there is a high need for precisely targeting their audience. Every game will have a different context and all games do not accommodate a gameplay system that provides varying experiences to different players. Loot boxes are found to be one interesting way to handle this problem. Designers define Loot boxes with different items relevant to the context of the game. Loot boxes, even though it is contextual, have less to do with gameplay and progression of the player. Loot boxes are used to deliver the fun that the core game is not dealing with. Skins are a good example of that.

Loot boxes emphasize the chance factor of the player. Loot boxes typically reward players with virtual items that can be used only inside the game. These items are not useful anywhere else. The items can be picked for free / paid and it depends on the item and the game model. Many games emphasize this monetisation method. Other than money making, looting and using the items have also brought new fun for players while playing a game, which is another important factor to be noted. The excitements, show-offs favoured by loots are enjoyed by many players, even though it sounds simple.

Recommending Loot items with respect to the player preferences is found to be a promising solution to drive engagement and economy in games. Recommendation systems are deployed in various applications to define personalized and meaningful services for people. It has been used by designers widely in various sectors (Enríquez et al. 2019). Recommendation involves classifying the game data into patterns. This pattern detection system will further help game systems to generate effective emergence in games. The key elements with which a player could be classified are with his/her Play style, Choices, Attitude, Standards, Taste, Economy, Exposure, Learning ability, Social skills, etc.

One of the famous theories of player classification with respect to what type of content they enjoy is the taxonomy presented by Bartle (1996). Bartle classified players into Killers, Achievers, Explorers and Socializers. This theoretical classification helped designers to build exclusive experiences for their audience. The classification also concluded that no human being is strictly typed - Every player is a combination of various such player types and crafting experiences for these huge numbers of combinations is complex. Looking at the micro level by considering more specific interest factors of a player such as attack style, kills, would be more complex.

Modern computational systems facilitate gathering and processing large data. Video games generate huge amounts of data and technologies favored gathering and mining them for better services. Player - centric game design methods were evolved based on these technologies. Video games used the potential of machine learning technologies in various aspects of its development. Diversification, increased user engagement, and communities have all brought together new problems that can be solved by leveraging the power of technologies like machine learning (Cheuque et al. 2019).

Video game industry has seen various recommendation systems to suggest game titles that they would like to play. This application is more like the movie/video suggestion that we could see in any video playing applications. A system proposed by Cheuque et al. (2019) uses Deep Neural Networks and Factorization Methods to recommend games for players. A system to generate recommendations in real time - while the game is being played is an area that is not being visited often.

Sentiment analysis is one of the key applications of machine learning where the sentiments (expressions) expressed by users through text and media. Mittal, Sharma and Joshi (2018) proposes a sentiment analysis system and extract predictions based on the image shared with the user over the web.They used Deep Neural Network and Convolutional Neural Network to perform sentiment analysis.

Every user is different and classifying them is a critical task. But behaviors of users tend to change with respect to their interests and likings. In games, players express their interest, likings through the choices they make. They play games as long the choices are appealing to their likings.

Progressive game play design is an overall design goal where players can experience the gameplay with respect to their performance and preferences. One area where we are focussing is the adaptive loop system for players. The problem we have chosen is to develop an efficient and operational system that generates appropriate loot items for players with respect to their performance and preferences.

2. LITERATURE REVIEW

According to Adomaviciuns and Tuzhilin (2005), recommendation systems gather and generate sets of information about the problem context, filter and produce meaningful patterns. Figure 1 describes the classification of Recommender Systems. The patterns can be further used to produce relevant suggestions / recommendations for the player. Classical recommendation systems are based on the following three approaches:
Content - based recommendation - Users past preference will be filtered out and items will be recommended based on that.
Collaborative recommendation - This recommendation method will infer knowledge from similar user's choices and produce recommendations based on that.
Hybrid recommendation method - It is a combination of both the above methods to deliver more precise recommendations.

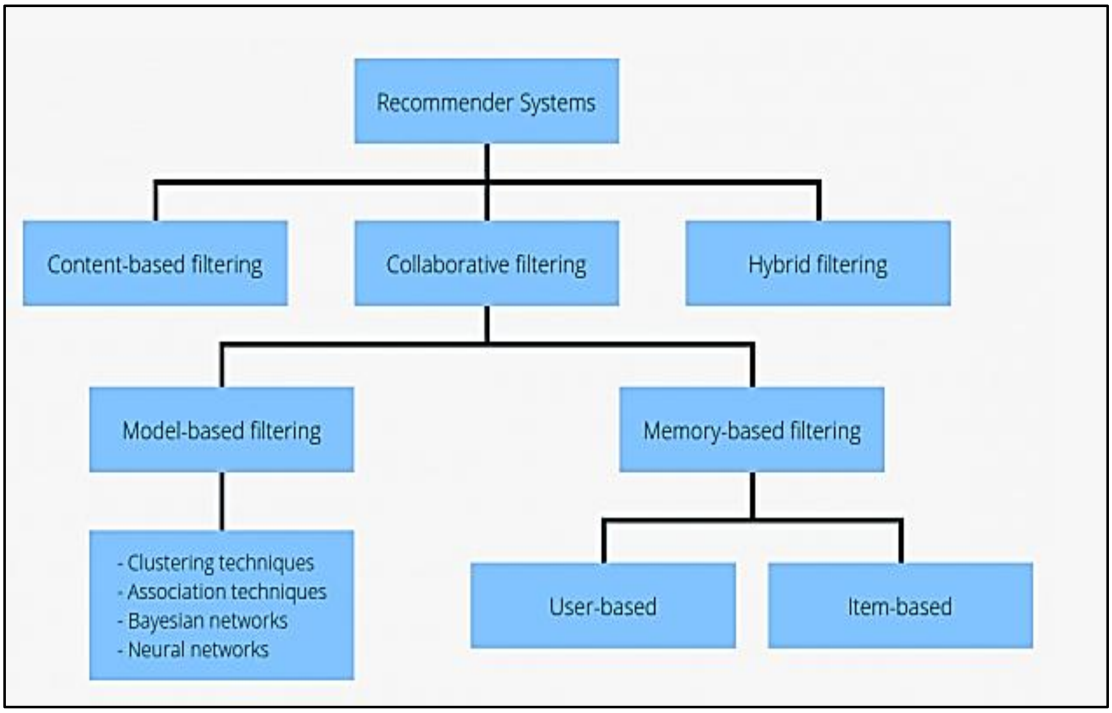

Figure 1: Classification of Recommender Systems

Content-Based Filtering

This filtering system is based on the preferences of users and the similarity of features the user previously purchased. This approach is used in many platforms for item recommendation. The content based filtering recommends titles based on various parameters such as the game name, genre, studio, etc (Naumov et al 2019).

User preference can be recognized by retrieving information from the user - mainly demographic data, views, watch history, purchase history, etc. The start of the system will be poor as there won't be any information on the user choices and interactions. This scenario could be solved once a user spends enough time with the system. Objective of a recommendation system is defining scores for items not rated by the users. The process will happen based on the feature detection (Kläs and Vollmer 2018).

Collaborative Filtering

This filtering overcomes the limitations of content based filtering especially on the quality of suggestions. This mainly eliminates the problem of suggesting recommendations in the earlier stage of the product. This filtering collects the behavior information from the user. This process is the most complex part of the system as information cannot be extracted easily. Information such as how they rate items, approaching items (Yıldız, 2016). This method emphasizes the user behavior and not on the content of the product. As many similar users can be found, it is easy to gather information and easy for systems to recommend. The system uses the metadata of the product and user behavior and gathering this information is critical.

Hybrid Recommender Systems Based On User-Recommender Interaction

Employing a particular type of recommendation system has different setbacks as discussed above. Hybrid systems function by blending both the filtering approaches to produce results. This approach in addition to recording the paes information, it also records the user-recommended interaction and evaluates the performance of it. The approach devises metrics to achieve it. The system collects request information from users and processes it and produces items based on that. It records the user's choices and tracks the further browsing information (Kläs and Vollmer 2018).

Various researchers were carried out in the video game industry to deploy recommender systems in it. The earlier one among them would be the attempted adaptive systems based on player types by Bartle (2003). Later it was used as a means to classify and model players and define gameplay according to it, Togelius et al. (2007). The systems function similarly to content recommendation systems that model players, process inputs and predict results out of it.

Interactive Drama Architecture (IDA) is a system based on the top of player model to keep the player focused and bound into the game story. (Magerko and Laird 2003) The system builds an AI agent as a Director. The director manages all the player data recordings and the flow of the story. The director keeps track of player actions to determine whether any negative effect on the story could be caused and present events in order to prevent the negative actions by the player.

Passage system is another similar approach built by Thue et al. (2007) based on Never Winter Nights engine and Aurora in Bioware, 2002 - 08. The system functions based on Role - Playing Game (RPG) genre and records the player’s action. The system attempted to classify players into several traits based on the context of the game such as - Powerful, Fighter, Scientist, Demonstrator and Storyteller. Based on the traits, quests were designed and recommended to the player.

Togelius et al. (2007) built a system exclusively for racing games. The system involves procedurally generated race tracks for players with respect to the skill levels. The player's performance will be calculated and an appropriate challenge level will be made and delivered through race tracks in the game.

Further, several recommendation systems were built as follows. Most of the video game based recommendation system works to suggest game titles for players to play next. This system uses the data shared by video game platforms and identifies the trend of games coming out. The model employs Factorization Machines and Deep Neural Network, mixing them together to present accurate recommendations to the users.

There are models developed to generate in-game recommendations to players contextual to the game. The model discusses a method based on two algorithms - ensemble based model using randomized trees and a deep neural network. The model attempted to generate in - game items based on the results generated by machine learning algorithms (Bertens et al. 2018).

Mittal, Sharma & Joshi, 2018 proposes deep learning based solutions to analyse the sentiments of users. They have produced a system that converse critical information on user sentiment using the visual data exchanged by users over social networks. Their experiment on using CNN for sentiment analysis with various social media image datasets have yielded successful results.

3. PROBLEM STUDY

The problem is the lack of an inclusive recommendation system for games. Even though several game titles have recommendation systems, they are contextual and specific to the design of the game. This provides a big research place to explore and define an efficient recommendation system that could help game developers recognize the player state and spawn items based on that.

Recommending items based on the interest and taste of the player is an important area to be explored. As it forms a solid base for the engagement curve and business design of the game, solving this problem can bring more possibilities.

The advantages of video games present is the access of data. As the problem lies in a virtual space where all the player actions are stored and managed by the game manager program, access to data is available easily. The issues regarding a video game system is the effective utilization of data and giving sufficient operational power to the other systems.

4. PROPOSED SOLUTION

A recommender system that suggests / spawn loot items based on studying the player’s interest. The proposed system is a combination of classification and recommended system. The purpose of defining such a model is to produce reusable data sets and recommendations.

The classification model will be defining players into different patterns. The pattern data will be passed to the publisher. Further, players of the same patterns may have different interests and likings -sentiments. A sentiment analysis system is created that identifies the interest of the player and recommends loot items specific to it. Sentiment analysis outcomes can help generate more personalized and appealing loot items to the player.

Every time a new player accesses the game, his performance will be tracked and matched with the existing defined patterns. Based on the results, the recommendation system produces results. If the player does not fit into a pattern, the recommendation system filters out results for the player based on the activity and context of the game. The system uses Convolution Neural Networks at its core to achieve the expected results.

The system proposed in this paper is built on the Random MultiModel Deep Learning Method (RMDL) proposed by Kowsari et al. (2018) for classification. It further uses CNN - Convolution Neural Networks for sentiment analysis. With the above approach, the system derives the personality and interest of the player. The system further uses these findings to recommend loot items. The proposed loot item recommendation model will be used as a reusable recommendation system that presents efficient results and consumes minimal resources thus not affecting the in-game performance.

Classification System

Video game systems handle data in the form of text. Games generate programmable data. All games can accommodate such systems which makes the extraction easy. The model applied here for classification is RMDL. The key aspects of the RMDL model are feature extraction, Techniques for classification, and learning methods. As mentioned above, video games are generating programmable data; it will be easy to extract information from them. Naïve Bayes Classification techniques are used to extract features in this implementation. Deep Learning Networks are commonly used in classification systems. Neural networks represent the structure and functionality of a human brian with an architecture that contains hidden layers. Convolutional Neural Networks (CNN) uses feed-forward networks. The CNN has convolutional layers with local and pooling layers. Recurrent Neural Network is a kind of iterative neural network where the output is fed back to the network as input again that makes the processing more intensive. RMDL relies on a Neural Network that is a combination of all the above three forms. As we are working on programmable data which is structured already and a small scale game system, feature extraction can be achieved easily.

This helped us to achieve the results with a minimal version of RMDL that uses only Deep Neural Networks without CNN and RNN. However, in the case of large scale games and also to produce reusable patterns, implementation of complete RMDL will be recommended.

Recommendation System

The Item recommendation system is based on the work done by (Bertens et al. 2018). The system works on top of functions such as games played by the player, reviews and ratings suggested by the player, play time in games, purchase history, preferred genres, gaming social identity, etc. These attributes are critical in identifying the major expectations of a player in a game. As several online hybrid games are evolving, games are designed to deliver different types of fun altogether. This challenge can be solved with the inference derived from the data sets.

The RMDL model is trained with such data sets. This model used Steam datasets for the experimentation. Steam is a popular video games store. The profile information of players is fed into the system. The system classifies the player into patterns based on the different attributes mentioned above. This data is sampled and passed to training. Table 1 describes the items and corresponding factors.

Player Types	Factors
Achievers	No of Games Completed, Leaderboard Stats, Competitive Gaming, Challenge levels
Explorers	Incomplete games, Storytelling games, Puzzle Solving, More comments published in forums
Killers	No of games completed, Competitive gaming, No of kills, Action games
Socilaizers	Online games, Active in Social groups, Incomplete games

Table 1: Player Types and corresponding factors

Sentiment Analysis

As players are classified based on their play history and other factors outside the games, the model further applied sentiment analysis to identify the interest of the player in the game. In-game desires are very often with respect to the plot and the mood of the player. In-games loot items should be aligned to that too. The model performs a short term data analysis based on the decisions players have made while playing the games. The decisions reflect the play style,actions taken, loot items purchased, time to solve challenges, skill level lifetime, involvement, daily play time. The system will extract features from the player data based on the above parameters. It will produce inferences based on which loot items will be recommended.

Table 1: Items and corresponding factor

Item	Factors
Weapon	Player Skill, Involvement on mission, playtime, current performance
Skin	Previous purchases, Tastes, Daily play time
Digital outfits	Learning ability, Previous purchases, Play styles
Cost of Loot	Current player position

Steps

1. Training the model with Steam data sets.
2. Fetching player profile and classifying the profile based on the RMDL.
3. Categorizing players into a defined pattern.
4. In-game activities will be recorded and analysed by the sentiment analysis system developed using CNN.
5. Player actions will be evaluated to decide which loot item to be spawned. Each user action will be processed and necessary decisions will be made and the most appropriate loot item will be spawned.

6. After spawning, the system evaluates whether the player bought the loot item and adds the result to the player data set.
7. The data set will be sampled for future usage as players cannot be studied closer immediately when the game starts.

Algorithm

- System records all player profiles and steam
- The records were stored in a programmable format
- K= P(s,c,a),
    - K stands for record, P stands for player, s - Scenario, c- Choice, a - Action
- Training of the system starts - Features are extracted from the player to infer knowledge
- Data classification
    - P(c | d) = P(d | c)P(c) P(d)
    - where d is a document, c indicates classes.
    - CMAP = агд max c ∈C P(d | c)P(c) = агд max c ∈C P(x1, x2, ..., xn | c)p(c)
    - P(cj | di ; ˆθ) = P(cj | ˆθ)P(di | cj ; ˆθj) P(di | ˆθ)
- Deep Neural Network Training for Recommendation
    - Input the player profile to the system
    - Infer decision based out of the knowledge - Filtering process
    - Create player profile based out of the knowledge
- Sentiment Analysis for In-game player interest identification
    - Capture the player actions and choices
    - Analyse and evaluate the results
    - Capture the longevity, reflex and commitment
    - Associate with player traits
    - Derive the current state of the player
    - Suggest Loot items in the game
- Model Recommendation Evaluation
    - Verify the accuracy of the suggested item.
        - Ti=P(A,E)
        - T stands for accuracy of item, P stands for Player, A - Item, E - Purchase flag
- Update Datasets

Observed Results

The solution was implemented using unity c# and the analysis of the implement reveals that spawning appropriate loot items enhances the gameplay experience of the player. The algorithm was evaluated by players with different play styles. Around 50 players were used for the testing of the solution. The players were identified and classified based on Bartle’s Taxonomy. The players were grouped according to their dominant play style.

Players were also further subdivided based on the other parameters. The other parameters are based on their demographic details. The solution did not focus much on this area as it should be reflective in the theme / context of the gameplay.

The table 2 illustrates the types of loots defined appropriate to the player skill types.

Table 2: Player types and loot items

S No	Player Type	Loot Items
1	Killer	Weapons, Operators, Weapon Upgrades
2	Achiever	Skins, Boosters, Renowns
3	Explorer	Badges, Treasures, Skins
4	Socializer	Skins, Boosters, Party invites

Various tests were carried out with different players as given above. The test results showed that the recommendation system suggests the right items that the player purchases.
The table 3 illustrates the precision of the recommendation system based on the demonstration results.

Table 3: Precision of the recommendation system

S No	Player actions	Player type	Suggested Item	Accuracy
1	Player collects for easter eggs	Achiever, Explorer	Charm	54.2
2	Player kill ratio is high	Killer	Weapons unlock	48.8
3	Long Play time	Achiever	Skins / Safe suits	62.1
4	Player active in chat	Socializer	Emojis	69.7

The classification of player and loot item opted will be recorded for further process.
The system relies a lot on the pre-analysis of the player - classifying players based on their profile information rather than the in-game identification. The design of the system is to minimize the computational resources. A multi level approach: pre-analysis and in-game analysis helped the system to provide results with minimal resources.

As games could produce huge data, few data sets were used for generic classification of players. Also, the earlier period of the game has challenges as we contain less information about the player, this sampled data helps the system to recommend items thereby studying more about the player gradually.

A multi-level approach minimizes the computational resources compromising the confidence of loot items in the early states of the game. As early stages of games are more naive to the player and they will be more interested in learning the game, the impact of the results are very minimal. The player classification based on their profile information adds values to the suggestions made with minimal cost.

5. CONCLUSION

The problem of delivering appropriate loot items to players that generate adaptive gameplay is achieved using a Hybrid Receommender system based on Machine Learning. The system proposed by us classified players based on their profile information , play style, in-game decisions, previous purchases and other critical factors of their game session. The system employed deep learning methods to infer knowledge from the data sets to identify and classify the players. Further, sentiment analysis is performed during in-game to decide the right loot item for the player. The recommendation system was analyzed by people of various player types and the results were recorded. The results show a high accuracy on loot items spawned and player purchase. The system generates a better engagement and economy based on the loot items. The hybrid approach gives a better trade off between computational resources and recommendation quality. The research can further grow to produce adaptive gameplay scenarios in real time.

6. REFERENCES

1] Adomavicius, G., & Tuzhilin, A. 2005. Personalization technologies: a process-oriented perspective. Communications of the ACM, 48(10), 83-90.
2] Adomavicius, G., & Tuzhilin, A. 2005. Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. IEEE transactions on knowledge and data engineering, 17(6), 734-749.
3] Bartle, R. 1996. Hearts, clubs, diamonds, spades: Players who suit MUDs. Journal of MUD research, 1(1), 19.
4] Bartle, R. 2003. Hearts, clubs, diamonds, spades: players who suit MUDs. 1996. The Game Design Reader: A Rules of Play anthology, 754-787.
5] Bertens, P., Guitart, A., Chen, P. P., & Periáñez, Á. 2018. A machine-learning item recommendation system for video games. In 2018 IEEE Conference on Computational Intelligence and Games (CIG) (pp. 1-4). IEEE.
6] Cheuque, G., Guzmán, J., & Parra, D. 2019. Recommender systems for online video game platforms: the case of STEAM. In Companion Proceedings of The 2019 World Wide Web Conference (pp. 763-771).
7] Enríquez, J. G., Morales-Trujillo, L., Calle-Alonso, F., Domínguez-Mayo, F. J., & Lucas-Rodríguez, J. M. 2019. Recommendation and Classification Systems: A Systematic Mapping Study. Scientific Programming, 2019.
8] Hao, F., & Blair, R. H. 2016. A comparative study: classification vs. user-based collaborative filtering for clinical prediction. BMC medical research methodology, 16(1), 172.
9] Kläs, M., & Vollmer, A. M. 2018. Uncertainty in machine learning applications: A practice-driven classification of uncertainty. In International Conference on Computer Safety, Reliability, and Security (pp. 431-438). Springer, Cham.
10] Kowsari, K., Heidarysafa, M., Brown, D. E., Meimandi, K. J., & Barnes, L. E. 2018. Rmdl: Random multimodel deep learning for classification. In Proceedings of the 2nd International Conference on Information System and Data Mining (pp. 19-28).
11] Magerko, B., & Laird, J. E. 2003. Building an interactive drama architecture. In First International Conference on Technologies for Interactive Digital Storytelling and Entertainment (pp. 226-237).
12] Medler, B. 2009. Using recommendation systems to adapt gameplay. International Journal of Gaming and Computer-Mediated Simulations (IJGCMS), 1(3), 68-80.
13] Naumov, M., Mudigere, D., Shi, H. J. M., Huang, J., Sundaraman, N., Park, J., ... & Dzhulgakov, D. 2019. Deep learning recommendation model for personalization and recommendation systems. arXiv preprint arXiv:1906.00091.

14] Ojha, R. K., & Nayak, B. 2018. Application of Machine Learning in Collaborative Filtering Recommender Systems. International Journal of Engineering & Technology, 7(4.38), 213-215.
15] Thue, D., Bulitko, V., Spetch, M., & Wasylishen, E. 2007. Interactive Storytelling: A Player Modelling Approach. In AIIDE (pp. 43-48).
16] Togelius, J., De Nardi, R., & Lucas, S. M. 2007. Towards automatic personalised content creation for racing games. In 2007 IEEE Symposium on Computational Intelligence and Games (pp. 252-259). IEEE.
17] Yıldız, O. T., Irsoy, O., & Alpaydın, E. 2016. Bagging soft decision trees. In Machine Learning for Health Informatics (pp. 25-36). Springer, Cham.
18] Mittal, Sharma, Joshi, 2018, Image Sentiment Analysis using Deep Learning, ACM International Conference on Web Intelligence, IEEE.