**ARTIFICIAL INTELIGENCE BASED BUSINESS STRATEGY FOR OPTIMIZED ADVERTISING**

**2021-152**

**A picture containing text, clipart, vector graphics

Description automatically generated**

**Individual Final Project Report**

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**Submitted on the 13th of October 2021**

October 2021

I certify that I have read this thesis and that it is entirely acceptable, in content and quality, as a Bachelor of Science thesis.

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Research Project Coordinator, SLIIT

Ms. Jenny Kishara

# DECLARATION OF ORIGINALITY

I declare that this is our work, and that this proposal does not contain any material previously submitted for a degree or diploma at any other university or institute of higher learning without acknowledgment, and that it does not contain any material previously published or written by another person, except where acknowledgement is made in the text. In addition, I hereby give to Sri Lanka Institute of Information Technology the nonexclusive right to reproduce and distribute my dissertation in whole or in part in print, electronic, or other media, in whole or in part. I maintain the right to incorporate this information into future works in whole or in part (such as articles or books).

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# ABSTRACT

Technology and algorithms are used in recommendation systems to propose "relevant" content to consumers. In an ideal world, the suggested things would be as relevant to the user as feasible, allowing the user to interact with them. This method is presently in use in a variety of places, including social networking platforms, movie websites, and so on. This method has never been utilized in TV commercials. The system may choose the most appropriate and relevant advertising for the user viewing television using a theme of recommendation algorithm.

# ACKNOWLEDGEMENT

The history of all great achievements shows that no great attempt has ever been achieved without the active or passive support of one's immediate surroundings. As a consequence, I'd want to express my gratitude to the project supervisor, Ms. Dinuka Wijendra, and the co-supervisor, Ms. Jenny Kishara for the  direction and support offered throughout the study period, as well as the happy attitude, resulted in the research being completed in a pleasant and stress-free working atmosphere. As a result, without his essential support, expert guidance, and encouragement, the effort would not have been a success.

I'd like to express my gratitude to our course coordinator, Mr. Jagath Wickramarathne, for his invaluable assistance in providing course materials and for sharing his vast knowledge of the module. Finally, I'd want to express my gratitude to my parents and group members for guiding me and supporting me in solving problems I faced when developing the system, as well as my SLIIT colleagues who supported me often when working on the assignments and other aspects of the project. Of course, my deepest appreciation goes out to everyone who helped in any way to the success of this study, even if their names aren't included above.

# DEDICATION

I would want to dedicate this research to my University, Parents, and friends, who have been an everlasting source of inspiration to me. They have given us courage, spirit, and direction.

My heartfelt gratitude also goes to everyone who assisted in various ways; without their love and support, this project would not have been possible.

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# INTRODUCTION

## Background and Literature Survey

## Background

Marketing of a product, brand, or service to viewership to generate attention, interaction and sales is an advertisement (often shortened to advertising or ads). Ads come in many ways, interactive videos, and have grown to become a core aspect of the marketplace. Advertising varies from other marketing forms because it is paid for what is received.

We use the internet or any other means to search for a product, and the only way to find the product we think of is through a platform that uses a recommendation system. This system provides users with a lot of things like any product they like. In addition, this process also provides other products related to the product you are looking for or related to that product brand

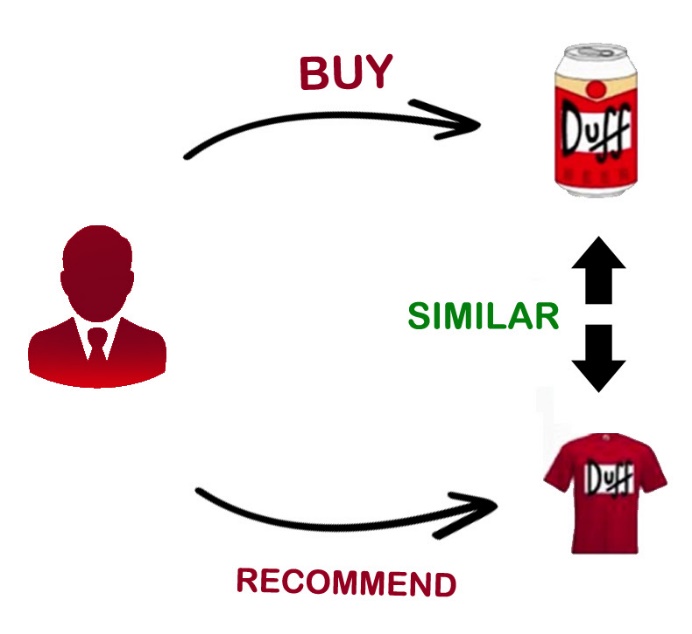
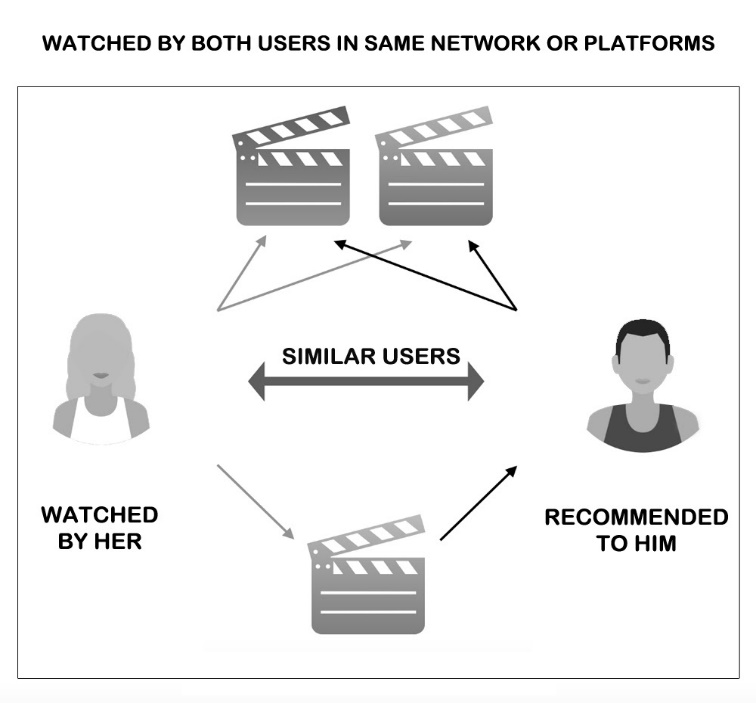


Fig . Consumers selection

This type of process is also used for movie recommendations. But the way it happens is a little different than product recommendations. The brand name of the product is unique and so are the movies and videos. We also analyze viewers' preferences and their pre-searched data. This movie recommendation system also allows users to choose the movies they want and the movies they like best.

Also, if you think of two users connected to the same network, it is more likely that they will have different opinions, but sometimes there is a possibility of matching similar ideas. Then if they both use the same platform this recommendation system will work to give both of them the same movies.



Advertising on social media is a very popular service today and these social media platforms have been very helpful to a large number of merchandisers. It also makes it very easy for buyers to buy or search for the products or services they want. These social media platforms are extremely helpful for the sellers to publish their product on these platforms and to have a strong understanding of how their product behaves in the seasons and what products sell best. When a buyer searches for a product of his choice, he is shown related products to the product he is looking for and is also shown as ads.

The advertising industry is made up of advertising firms, advertising agencies, advertising media, and a host of people such as copy editors, visualizers, brand managers, researchers, creative heads, and designers who carry the customer or recipient to the last mile. An advertising agency is employed by a corporation that wants to promote itself and/or its products.[[1]](#_References) The business briefs the brand, its imagery, the beliefs and values behind it, the target segments, and so on to the agency.

Currently, there are more than billions of internet users, interact with Social networking, visiting a site, reading a blog, etc. The majority of the world today uses social media for advertising purposes. Advertising can be done using the internet or television, but it can also be done through conversations between people which is also known as recommendations.

A Recommendation System(RS) is a smart computer technique that forecasts the acceptance and use of users and helps them choose products from a wide body of knowledge online. Most internet users are sure to have happened to the RS in some way. For example, for future friends, Facebook recommends that YouTube recommend the videos accordingly, that Glassdoor advises us for matching jobs, that TripAdvisor recommends us appropriate holiday destinations, that Goodreads recommend us interesting books, etc. The RS has gained phenomenal acceptance in the e-business scenario. [[2]](#_References)RS has created a new dimension in the communication approach between users and online service providers. Nowadays, many companies are using RS techniques as an added value to enhance their client services. Although the implementation of the RS depends on the specific recommendation approach adopted by the application, the core work of the RS remains more or less the same for all applications. The main objective of RS is to support users in their decision-making processes to select an online item.

The potential of RS in different domains has attracted researchers to explore the possibilities exhaustively. People from various disciplines such as data mining, information retrieval, knowledge discovery, artificial intelligence (AI), approximation theory, forecasting theory, information security and privacy, and business and marketing have contributed extensively with diverse research approaches. Several technological challenges were addressed by new methodologies and algorithms, including more precision recommendations while reducing computational time online. Several recommendation algorithms were proposed and implemented successfully in different fields. These algorithms mainly follow demographic filters, CBFs, hybrid approaches, and collaborative filters. RS has recently expanded its research into social networks and contextual information in the recommendation to generate the dynamic features

## Literature Survey

**Machine Learning algorithms for recommender systems – A comparative analysis[4]**

The recommendation system is one of the foremost popular applications of computing which attracts many researchers everywhere in the world. The appearance of the web era has brought a wide implementation of recommendation systems in our everyday lives. Many machine learning techniques may be accustomed realize the recommendation system. Among these techniques we are addressing Content-Based Filtering, Collaborative Based Filtering, Hybrid Content-Collaborative Based Filtering, k-mean clustering, and Naive Bayes classifier. We've exploited these algorithms to their extreme to attain the most effective possible precision and have presented a comprehensive comparative analysis. The strength of all these algorithms is often clearly realized by the significant enhancement within the accuracy, depicted by the experimental analysis considering the cold start problem.

This has been done by Sahu, Satya & Nautiyal, Anand & Prasad, Mahendra. In this research, they have shown what kind of result the algorithm can get as an output using 5 algorithms. The algorithm used here is the main algorithm used for the recommendation system. They describe the analysis of the experiments performed and the comparison of all modern technologies.

They used MovieLens datasets in 10K, 50K, and 100K to compare their accuracy. For example, the 100K MovieLens database has 100K ratings, 943 users, and 19 variations of 1682 movies

Varieties. This algorithm was used to measure the accuracy of the demonstration based on the analysis. For each test user, the algorithm is implemented, 30% of the movies seen by the user are converted into invisible movies. Out of the total number of recommendations, the recommendations contained in them are the correct recommendations for the converted movies. The results of their analysis are as follows.

|  |  |  |  |
| --- | --- | --- | --- |
| **Algorithm/Size** | **10K** | **50K** | **100K** |
| Content Base | 18.45 | 18.66 | 19.10 |
| Collaborative | 17.97 | 18.69 | 19.95 |
| Hybrid | 20.31 | 21.03 | 22.20 |
| K-Mean | 21.05 | 21.93 | 22.67 |
| Naive Bayes | 24.62 | 25.19 | 25.73 |

Fig . Comparison of algorithms

This analysis by them is very helpful for many recommendation system developers and to get an idea to choose the required algorithm.

**Application of machine learning in recommendation systems[5]**

The research provides fundamental knowledge and descriptions of machine learning and recommendation systems. The subject of machine learning algorithms, which are used in such programs, was more widely discussed. The paper focused mainly focuses on filtering algorithms based on users' or objects' demographics, and based on content. The overview of these algorithms includes similarities, drawbacks, and advantages, algorithm evaluation steps, and the sample value estimation of the prediction of the evaluation. The architecture part of the work starts with the definition from the MovieLens portal of the databases used. The technologies and realistic application of the above-described algorithms are then discussed afterward. The next section includes an overview of the findings and assumptions based on the computer-based simulations to determine how the algorithms operate. After the work, there is a review, an assessment of the success of the suggestion systems and lessons learned from the research, as well as a plan for more work on the problem of those systems.

This study has focused on the same areas of function and research.

Many companies use big data to make super-relevant recommendations and revenue for growth. Data scientists need to select the right one according to the constraints and demands of an organization from a variety of recommendation algorithms.

**A Recommender System for Online Advertising[6]**

In the online advertising environment, recommendation systems are now evolving as essential marketing and decision-supporting tools, because many customers dealing with e-commerce and related domains are often overloaded with challenging and unprocessed data-driven by dynamic operations, processes, and business guidelines.

Recommendation systems will systematically analyze and filter complex data to provide clients with essential and useful information (in e-commerce). We have proposed an effective recommender algorithm based on user browsing behavior. This algorithm will understand the characteristics, interests, and other parameters of users when they browse the web to present relevant ad(s) to them. The Ad recommendation system uses feedback information about an advertisement and historical website visitation behavior to run dynamically. Advertising positioning and appearance are determined by these inputs. The algorithm solves the issue of "recommending more similar ad(s)" offering an incentive to produce greater user response, providing more value for time and resources with user satisfaction. Our tests and outcomes indicate that up to 92.47 percent of 1900 instances had the importance of the dynamically suggested Advertisements by the recommender system.

**Context-aware advertisement recommendation for high-speed social news feeding [7]**

Ad on social media is a multi-billion dollar market that has been the main source of income for Facebook and Twitter. These social network systems learn a prediction model for and users based on their personal preferences to distribute advertisements to potentially interested users. However, the consumer can end up seeing repeat ads as user preferences sometimes change slowly. We suggest a context-aware advertisement system in this paper that takes into account the relatively static personal interests, as well as the diverse friends' news, feeds to drive ad click-through rate rise. To satisfy the real-time requirement, we first suggest an online retrieval technique that identifies the most appropriate advertisements that fit the complex context when a read operation is triggered. We suggest a protected area approach to rapidly decide when a user's top-k advertisements are altered to prevent repeated retrieval when the meaning changes marginally. Finally, by studying the dynamism of news streams to assess an acceptable retrieval approach, we consider a hybrid model to incorporate the merits of both approaches. The feasibility and robustness of our hybrid model have been confirmed by comprehensive research carried out on several actual social networks and ad datasets.

**Collaborative Filtering Systems (CF)[8]**

CF modifications are one of the most commonly used recommendation algorithms. Even data scientist beginners can use it to build their movie recommender system. There are two foundational methods in CF: collaborative user-based filtering and collaborative item-based filtering, respectively.

**Component Procedures of a Recommender System[8]**

* Candidate Generations: This method is responsible for generating smaller subsets of candidates to recommend to views, given a huge pool of thousands of advertisements.
* Scoring Systems: Candidate generations will be implemented by different generators, so we need to standardize each one and try to assign a score to each of the items in the sub-sets. The Scoring System does this.
* Re-Ranking Systems: After the scoring is finished, the system considers some external requirements to create the final rankings.

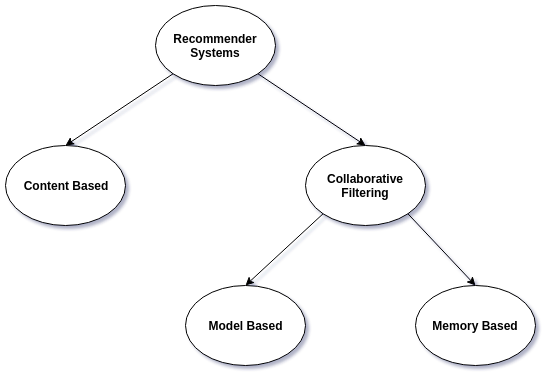


Fig . Types of recommender systems

## Research Gap

**Research Gap**

In today's world, social networking, word quest, online shops (Amazon, eBay, AliExpress), movies, and videos (Netflix, YouTube) are indispensable. That's why a lot of media associations are paying a lot of money for their advertisements. Many internet-based platforms are used for the display of advertisements.

The main reason for this is that when someone goes to the Internet base platforms to watch a product, service, video, or movie they prefer to be notified of the items they wish to buy. This occurs due to their preferences, Therefore, only people who view ads have to pay for advertising companies. It's not a waste of money for the advertising company. It also does not show ads to those who do not want ads. Only the ads that the user wants will be displayed. With the use of an RS, these platforms are capable of recommending relevant advertisements.

Although this feature is in use on social media, Video streams platforms, and e-commerce applications this is not currently available in television advertising.

## Research Problem

How to view ads when not using internet platforms? Advertising companies have to use a traditional method. There is no internet but Television is a great medium for this.

On internet platforms, these companies can display something related to the user's preference, or if it shows up before searching for any item that the user is trying to buy. This RS delivers ads to users tailored to the individual's desires and age group to provide the most appropriate product or service.

TV and advertising agencies broadcast commercials. The advertisement industry even pays the TV channels a lot of money. The goal of this study is to reduce the amount of money that TV viewers and advertising companies pay for advertising and to show advertisements that are more realistic and relevant to the TV viewer with the aid of a Recommendation System.

## Research Objectives

### 1.3.1 Main objective

This project's major goal is to promote user preferences by optimizing user-preferred and user-centric ads. This implies that the viewers can see advertising that are relevant to their interests. When choosing the most appropriate advertising on the TV during a commercial break, elements such as demographics, emotional characteristics, and face features are taken into account. This project will benefit both the audience and the advertising firm by allowing the audience to develop an interest in the goods that will be advertised and giving advertising firms the ability to create advertisement content based on age, gender, and peer group, all of which will have a direct impact on the users in purchasing goods and services.

**1.3.2 Specific objectives**

* Organize demographic content in a csv format
* Organize facial and emotional data into a csv
* Conduct separate analysis with Machine Learning and deep learning models to find the most appropriate approach.
* Recommend the user preferred advertisement using all the factors demography , emotional and facial features.

A recommendation system based on advanced video data analysis techniques. Once we have gathered the interaction data and created a dataset, we handle the challenge of transforming an original dataset from a real component-based application to an optimal dataset to apply machine learning algorithms by using feature engineering techniques and methods of feature selection.

The recommender can be used on its own. The unique ad suggestion system, which reduces users' efforts in identifying the most appropriate advertisements based on current viewings without the need for a large number of TV watchers, like typical recommenders do.

Advertisement tagging has grown in popularity as a convenient tool for users to organize, manage, present, and search for a variety of materials. These tagging methods give a wealth of valuable information, such as tag, which is an expression of the advertisement's preference for a certain resource, and time, which is a denotation of an advertisement's drifting interests.

# METHODOLOGY

## Methodology

### Approach

The proposed research component is **“The Recommendation System**”. Explaining the overview of the process;

The initial step is the collection of data from the results obtained from human object detection and recognition using the implemented API (Application Programming Interface). The data relating to the audience such as demographics , emotions and facial features will be considered in this phase. Moreover, the advertisements and the tags (a category to which the advertisement belongs) are also considered in this step.

The advertisements(ads) received from the advertising firms are been classified with the use of programming languages like Python and algorithms like CF (Collaborative Filtering). When classifying the Ads, user all the features mentioned above are taken into account to analyze the user's preferences.

When further classifying, the advertisements are classified considering the tags which have been generated by the contents in the advertisement. For example, advertisements with food-related content will be given the tag as food.

Depending on the predictions and analysis of the above algorithm the most appropriate advertisement will be displayed on the television.

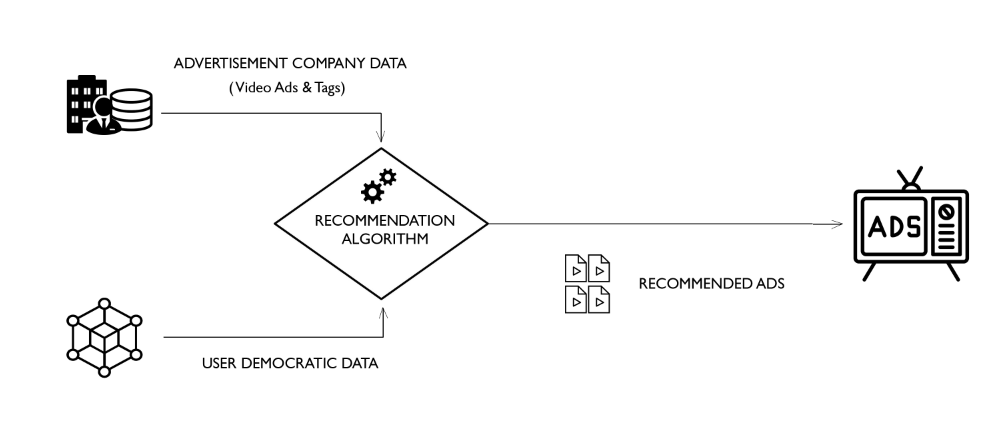


Fig . System overview diagram

To implement this recommendation, I first had to learn some selected algorithms and languages. Of those, I especially had to work hard to find a suitable algorithm. Accordingly, special attention had to be paid to support vector machine algorithms, random forest algorithms, deep learning algorithms. This was due to the data used to obtain TV viewer data. It is very important to know this to analyze the data used here.

**The Support Vector Machine,** or SVM, is a common Supervised Learning method that may be used to solve both classification and regression issues. However, primarily, it is used for Classification problems in Machine Learning. The objective of the SVM algorithm is to create the best line or decision limit that can divide N-dimensional spaces into classes so that we can easily include the new data point in the correct category in the future. This best decision-making limit is called a high-speed aircraft[].

The extreme points/vectors that assist create the hyperplane are chosen via SVM. Support vectors are extreme examples, and the method is called a Support Vector Machine. Consider the picture below, which shows how a decision boundary or hyperplane is used to classify two separate categories:

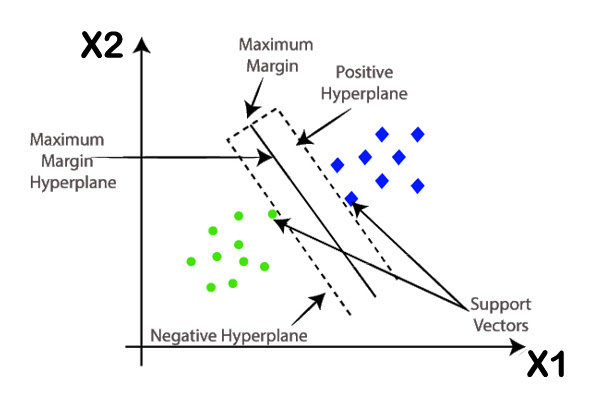


Fig . Hyperplane

Using this algorithm, it is possible to do things like Face detection, image classification, text categorization.

**Random forest** is a supervised learning algorithm. It creates a "forest" out of an ensemble of decision trees, usually trained with the “bagging” method. The bagging method is that a combination of learning models increases the overall result for classification problems.

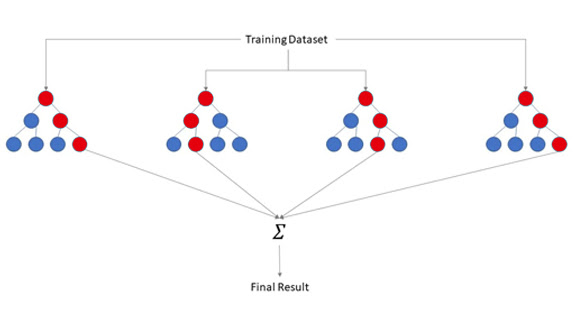


Fig . RF architecture

The random forest has the benefit of being able to solve classification and regression issues, which make up the majority of contemporary machine learning systems. Let's take a look at the random forest in categorization, which is frequently referred to as the "building block" of machine learning.

**Deep learning** is a machine learning and artificial intelligence technique that represents how people acquire knowledge. Data science, which includes statistics and predictive modeling, incorporates deep learning as a key component. Deep learning is particularly useful for data scientists who are responsible for gathering, analyzing, and interpreting large volumes of data, it speeds up and simplifies the process. Here deep learning is used for computer vision. That allowing computers to recognize objects and classify, rebuild, and segment images with exceptional precision.

**A Dense Layer** in a neural network is deeply linked to the layer before it, meaning that the layer's neurons are connected to every node in the layer before it. In deep learning systems, this layer is the most often utilized. In a model, the dense layer's node gets input from every node in the previous layer, and the dense layer's nodes execute matrix-vector multiplication. The row vector of the output from the preceding layers is identical to the column vector of the dense layer in matrix-vector multiplication. In matrix-vector multiplication, the row vector must have the same number of lines as the column vector.

**Fully Connected Layers** are those where all of the inputs from one layer are connected to every activation unit of the following layer. The last few layers in most common machine learning models are full connected layers that assemble the data collected by preceding layers to produce the final output. It takes the second most time to render, behind the Convolution Layer.

Such methods had to be used. Furthermore, **Adam Optimizer** do substitutes for a static sequential origin for in-depth learning model training. Adam Adgrad and RMSProp combine the best features of the optimization system to create an algorithm that can handle rare sequences in noisy situations.

Using a large number of such algorithms, it was possible to select the most suitable algorithm after analyzing the data obtained. A large amount of data means the data in the unique data set that we have collected. That being said, it took a lot of hard work to find an algorithm capable of analyzing that data in real-time. After sorting the data in that data set and providing the data for the relevant algorithm, the recommendation process was able to be successful. That process enabled models and analytics to be accurately obtained.

Collected data sets are used for this. The data set guesses the TV viewers' emotions, age, and how they will react to the show. That data is collected by the other component. The data set that is collected is a large amount. But after the sorting process of those data sets, the recommendation system is easy to apply to the process. The results obtained from the data analyzed here are very high in the ability to perform the task of finding the most accurate television advertisement. This data is divided into some main categories. This recommendation system process is done to get the most effective output. It is also important to remove unwanted and non-existent data rows from the data set as these other data can read its contents. Another database also traces the age gap, gender, and type of people watching television. It is possible to make another recommendation using that data set. All this is used to give the most suitable advertisement.

### Procedure of implementation

The optimized data is used as input by two modules before the data is set to the recommendation system. The data set used for this purpose is a collection of data unique to Sri Lanka, which enables us to accurately give advertisement recommendations. A new capturing system was set up to collect that data. In addition, due to the Covid pandemic, it was huge challenge collecting a dataset. But as an alternative, we enlisted the help of family members and computer savvy people to collect this data. With their help, they were able to successfully collect data. The collected data was analyzed using python. Python is a computer language used for deep learning algorithms.

The collected demography data and timelines data CSV files were first imported and then the data columns were checked. There we were able to find out what kind of data is received through those components. Fig .7 demonstrates the libraries import for the initial data processing

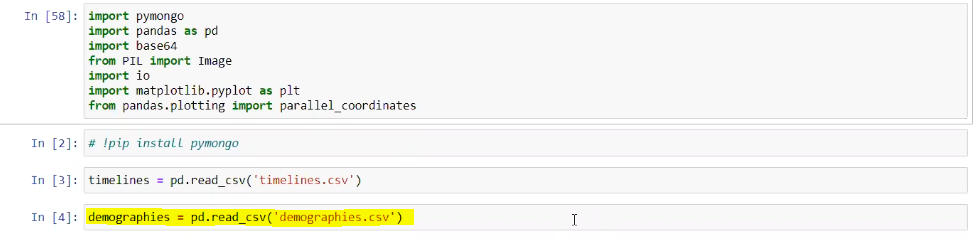


Fig . : Imported libraries



The read data is put into a panda frame. At the same time, data rows with null values ​​in that database were removed. This process is called data preprocessing.

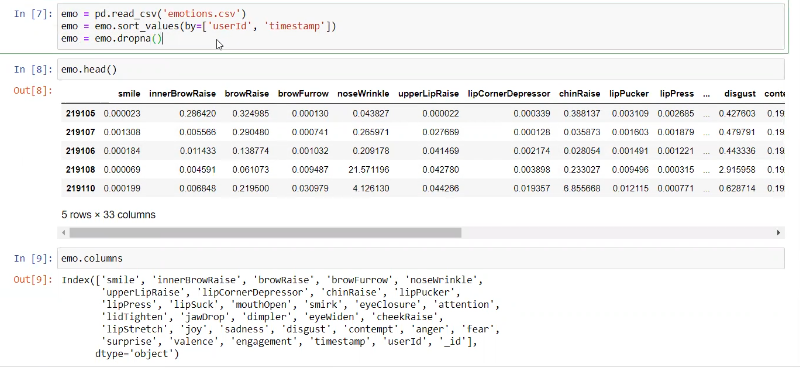


Fig . : Emotional data processing

Fig .9 is a screenshot of the implemented python code to the emotion data set and preprocessing the data as before. Also does emotion sorting. Separation is also done for all timestamps in the userId during sorting. Column names are also taken into consideration. There are a lot of timestamps so they are grouped. Here the name of the data row required for recommendation is searched using the relevant userId.



Fig . : Save image data in the csv

In the capturing process, images are captured but saved in string data type. It is possible to recommend using that data type but it is not possible to do it as required. Therefore, the string photos in the required CSV are saved as png image type. To do this, I have decoded the base64 string and assign a file name to the converted image and then save it to png. In the same way, demography data and related captured images are retrieved from the database as mentioned earlier.



Fig . : Implementation for splitting the data

The above Fig.10 represents the code base implemented to preprocess the video data frame which is used for the analysis. Initially the movie part is defined as an empty data frame and take the columns of the emotional data . Next step is to iterate through the time stamp row to get the start time. This only done if the start time is defined. Then the for loop is used to iterate through the emotional column and time row to find matching user Ids.All the columns representing User Id’s one by one is located. In the timeline , the timestamp is calculated in milliseconds , but the video frame uses seconds so the timestamps should be also converted to seconds. . For that purpose the initial time stamps are divided by 1000.

The video used for this analysis is a Sri Lankan comedy teledrama known as “Yes Boss” and in between the video there consists 4 advertisements. In the video an advertisement is 30 seconds long and the first advertisement stats after 60 seconds of the movie part. The movie parts are declared as ‘M’ and the to identify which movie part a numeric number stating from 1 is declared. Following the above steps the mean value of all emotions to a specific user is append to the movie part.

As the next step which is to find the advertisement and the emotional response towards the advertisement. The same method used to find the movie part is utilized to find the first advertisement. Time frame for the first add will be the duration ending the first movie part. Then again the mean values of the emotional responses are append to the advertisement part.The same method is continued until the timestamps of all movie parts and add parts are found and append into the emotional response of each user. Fig .11 illustrated the rest of the code implemented to find the movie and advertisement parts.

Graphical user interface, text, application

Description automatically generated

Fig . :Video frame preprocessing

## 2.1 Implementation of the ensemble models

The ensemble model uses the data collected for every component to conduct the analysis. By initializing the model , demographic data, emotional and facial features are being loaded to the models. All the csv files are cleaned and optimized to obtain the best result out of it.The Fig.12 depicts the variable initialized for the ensemble model.



Fig . Input variables

### SVM and RF Models

SVM and RF classifiers were used to carry out this study using the above implemented code segments. A total of 31 parameters two from demography , 9 from emotions and 20 from facial features . We divided the data set into two segments  as  training and testing sets before entering the data. On the training set, we trained the classifiers by using the testing set to validate the model once it had been trained.The bellow Fig .13 represents the code segment of the Random Forest classifier.

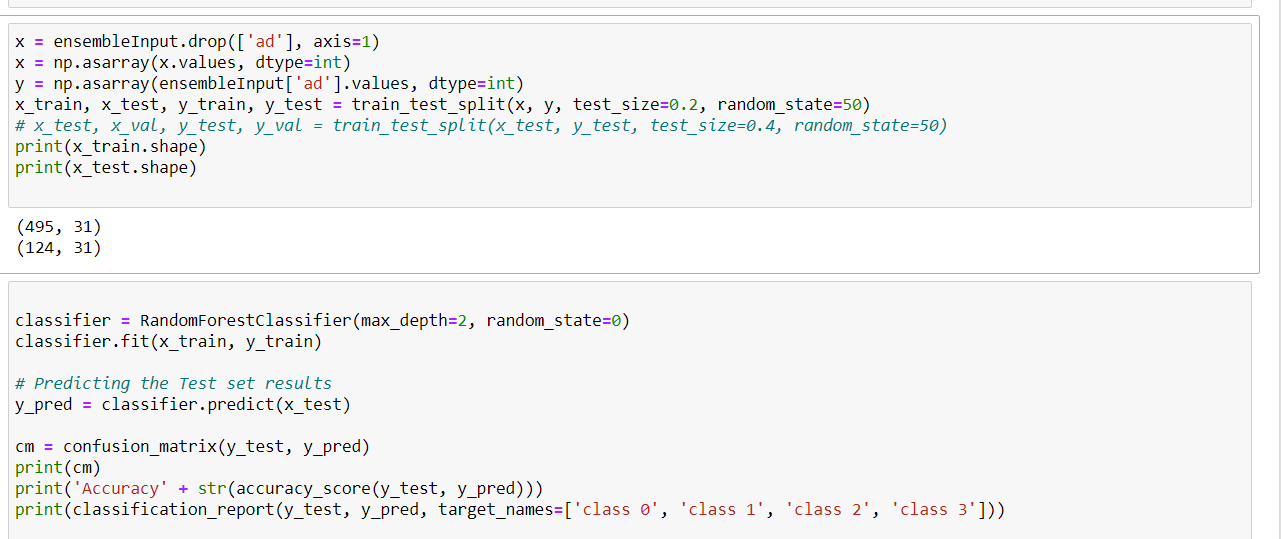


Fig . Random Forest Classifier

To train the model and make the actual prediction, we utilize both train and test data. The data are then visualized using a confusion metric. The same procedure was used with the SVM model to ensure and receive a higher level of accuracy, however both models were unable to obtain a better level of accuracy .But the classifiers both achieved the same accuracy. Implementation of the SVM Classification model is shown in the code section Fig. 14

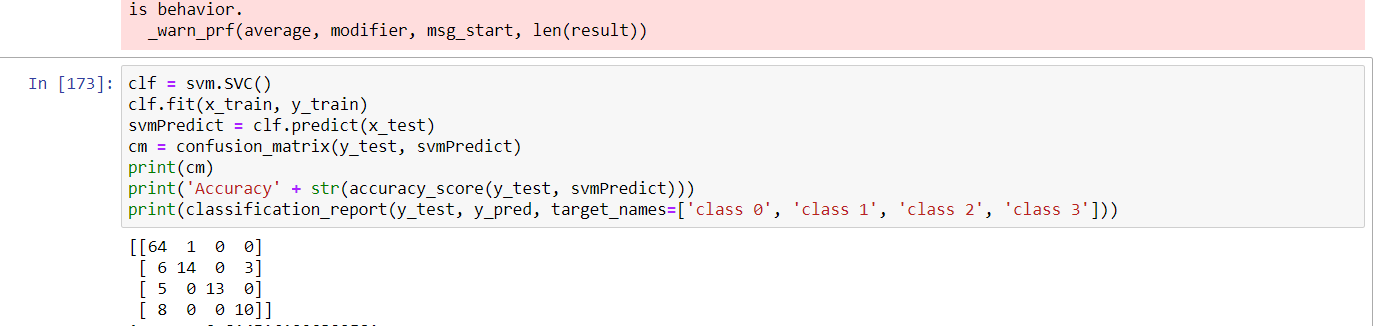


Fig . Support Vector Machine classifier

### Deep Learning Classifier

Because machine learning classifiers were unable to achieve higher accuracy, the experiment was taken to the next level which is to conduct the analysis with the deep learning model. Since we are using categorical data for the sequential deep learning model the data set has to be distributed as training , testing and validation data. The following code segments Fig .15 depicts the distribution of the data set.

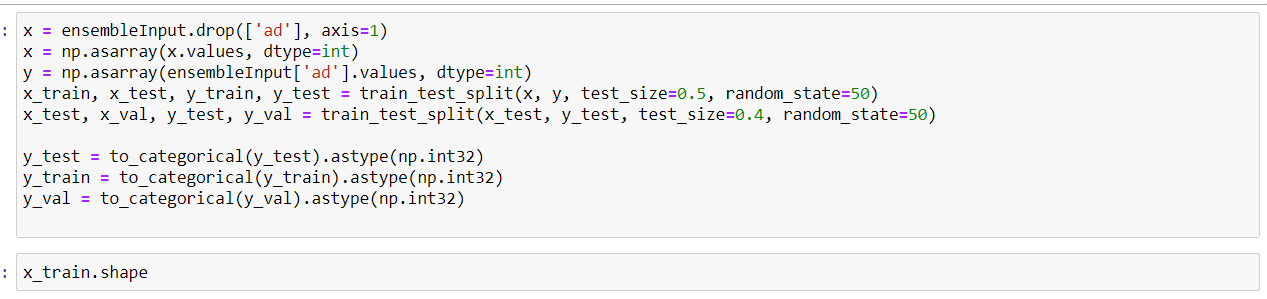


Fig . Distributing as Train ,Test & Validation

The exact same data set which was utilized for the machine learning classifier was  applied here. A total 31 variable containing demographics , emotions  and facial features were  used to train the data set again the most preferred advertisement according to the users response at the requirement gathering .These variables are also called the input dimensions of the model. Because of the categorical approach followed the output layer is set to 4 neurons and one hot encoder is used to store the categorical data in a binary format .The patience, learning rate, batch size, and epochs were all set to 50, 0.0001, 32, and 500.The sequential model also consist of 5 fully connected dense layers with 4 layers followed by LekyReLu activation function. The final layer is made up of four neurons that represent the four advertisements, using SoftMax as the activation function. Fig .16 depicts the code segment of the implemented deep learning model.



Fig . Deep learning model

At the training stage of the model, two middleware's visualizer and early stopper are been used. The validation and the test accuracies of the model are being saved using the visualizer. Early stopper checks for changes in validation accuracy after every epoch .If no such change is monitored for sometime , the early stopping criteria will terminate the training and the highest accuracy received will be restored. This will prevent the model from overfitting. Binary Cross Entropy and Adam Optimizer are the loss and optimization functions utilized in this model.

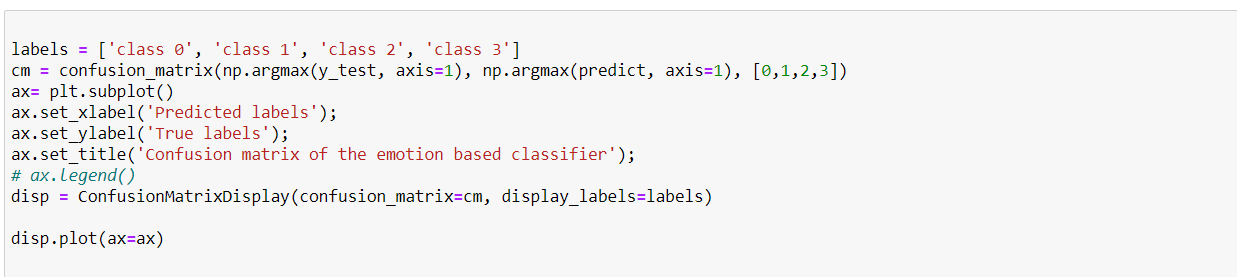


Fig . Visualizing results

To visualize the results obtained by the deep learning model a confusion matrix is  displayed .At the same time loss and accuracy curves are plotted.

## 2.2 Commercialization aspects of the product

The bulk of Sri Lankan media users still utilize traditional media. The majority of traditional media ads are targeted by place and time. A considerable amount of money is being squandered as a result of ineffective advertising. Not only the advertiser, but also the content user, suffers as a result of this loss. The customer is compelled to watch something he or she does not want to see.

Advertising's objective is to educate the audience about the product and the company, as well as persuade them that the advertisers' products are the best available. The success rate of digital advertisements is determined by the number of impressions and click through rate.

Traditional advertising, on the other hand, lacks a comprehensive, quick, or accurate means to quantify them. Digital ad techniques should be included into traditional ad campaigns, according to us. Because the majority of Sri Lankans still rely on conventional advertising, our products have a sizable market. Furthermore, we proved in this study that our prototype can propose user-favorite advertisements.

Apart from these advantages, we can analyze the amount of impressions and if the audience enjoyed the ad aired to them in real-time using the device we are plugged into the television.

We first picked social media as our marketing tool to present the notion to the public. Because the majority of individuals and businesses use Facebook on a regular basis, it is an excellent market place. We also set up a Facebook page since most of the sponsors needed to be aware of the notion for which they were providing support. We've been working on pitching this prototype concept to ad agencies and television businesses. The notion may be tested with a real audience for free during the introduction stage. The Facebook page used to market the concept is depicted in the diagram below

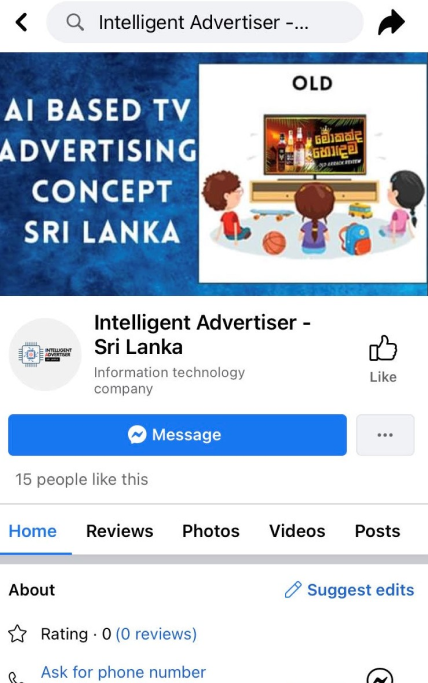


Fig . 18 Facebook Page

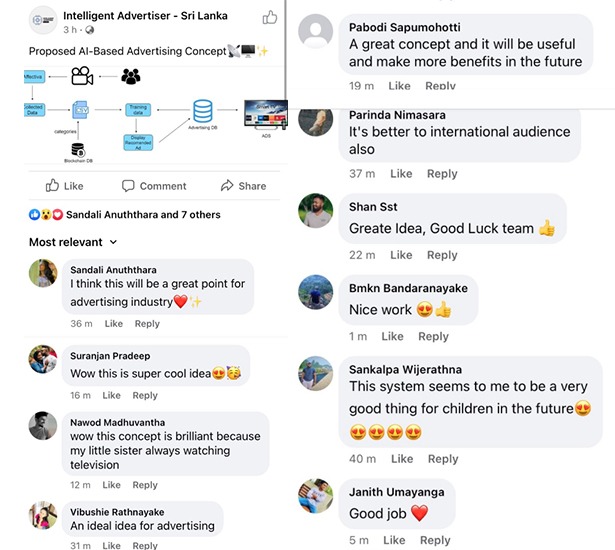


Fig . 19 Feedback

## 2.3 Testing of the product

A sample number of 100 people are allowed to watch the same movie clip used to collect data for testing reasons, but unlike the previous movie clip, this one does not have any advertising contained in it. Once the user has been identified, the machine learning model will examine the demographics, emotions and facial features of the user . The most favored advertising will be overlayed by halting the video clip, along with the criteria and findings derived from the study that was done. Marking the end of the video clip, the prediction will be further reviewed by a poll. Table 2 shows some of the test cases that were utilized during the testing process.

|  |  |  |
| --- | --- | --- |
| **Test Case** | **Test Case** | **Expected Result** |
| Advertisement recommendation considering the ensemble model | Consider demographics, emotions and facial features when recommending | Predict the correct ad according to the predicted results |
| Classify ads based on tags | Consider tags to predict advertisements | Predict the correct advertisement |

Table :Test Cases

# Results and Discussion

## Results

The analysis was conducted using 3 methods considering the same data points .Although the data points were same the results obtained from each model was different since the deep learning model is much more accurate than the machine learning models.

### Accuracy of models

Because of the pandemic situation which was the main obstacle faced throughout the study, there were problems which we had to face due to shortage of data points. Somehow Random Forest model, was able to achieve a validation accuracy of 43 percent. Fig . 18 depicts a comprehensive report on the categorization model.

Table

Description automatically generated

Fig . 20 Classification report for RF model

Since the accuracy of the RF could not obtain an average accuracy the analysis was further carried out with SVM model, but the accuracy was same as 43%. The next step was to undertake the study using a deep learning method, as deep learning algorithms have been shown to achieve greater accuracy than machine learning models. The results of the deep learning model trained on commercials to determine the most appealing advertisement for the ensemble model is demonstrated by the Fig .19.

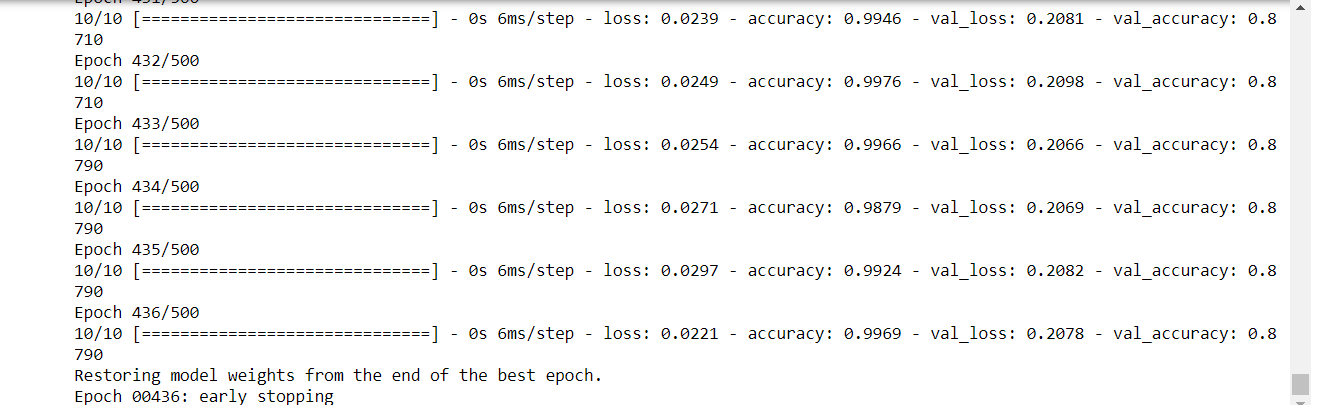


Fig . 21 Deep learning Model Training

When the model is being trained the accuracy is checked at each epoch up to the last epoch .If any significant change in the accuracy of the model is not detected for a period of 50 epoch’s the training will be automatically stopped with the aid of the early stopper, and the model will restore the accuracy of the epoch containing the highest accuracy. An accuracy over 90% was obtained by training this model. The Fig .20 represents a detailed report of the classification model.

Table

Description automatically generated

Fig . 22 Classification model for DL

The following graphs Fig.21 and Fig.22 illustrates the accuracy and loss curves of the deep learning model.

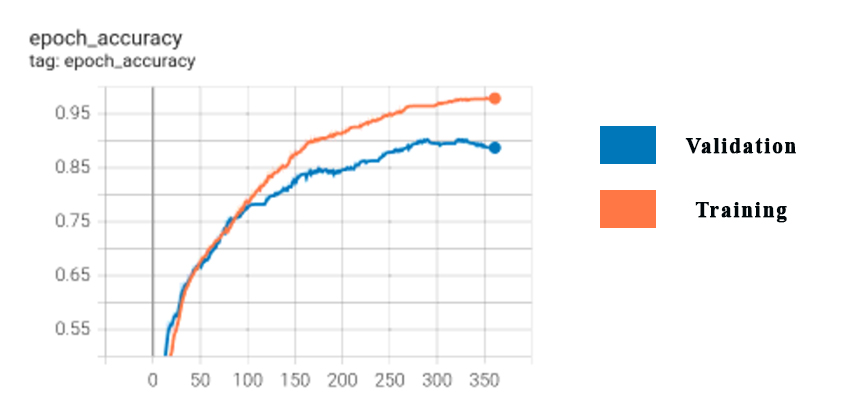


Fig . 23 Accuracy curve

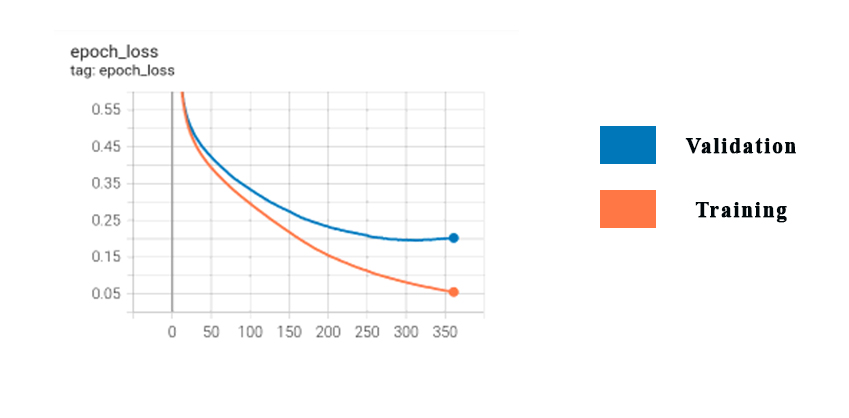


Fig . 24 Loss Curve

## Research findings

In this component I have analyzed the video clip containing the 4 advertisement against the factors demographics , emotions and facial features together. Also the results obtained from the previous analysis done using demographics and emotions are taken into consideration. However the model I created was able to obtain an accuracy of 90 % which adds a novel finding to this study as other than every other factor individually , advertisement can be recommended with a higher validation accuracy when all the factors are put together. The comparison of model Table states more clearly that the ensemble model is the best model for recommendation.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Model** | **Test Accuracy %** | **AUC %** | **Precision** | **Recall** | **F1** |
| Age & Gender | 52 | 70 | 0.27 | 0.52 | 0.36 |
| Emotion | 65.05 | 80.15 | 0.66 | 0.65 | 0.64 |
| Facial | 86.55 | 94.99 | 0.86 | 0.86 | 0.86 |
| Ensemble | 90.32 | 97.38 | 0.90 | 0.90 | 0.90 |

Table : Comparison of models

### Discussion

This research is primarily aimed at determining how the ensemble model consisting all the 31 factors influence in recommending advertisements.  According to recent research, almost everyone in Sri Lanka watches live television, despite their lack of knowledge of other modern technology. Television commercials have a significant influence on consumer choice, and it is also a medium that reaches a large audience.  Advertisers charge for ads depending on when they are broadcast. The study done for this component is very significant to take benefit of this problem since it has unique findings to give to the television advertising domain.

# CONCLUTION

This novel study was done to find out how affectively tv advertisements can be recommended by considering the demographic features (age, gender and peer groups), facial features and emotional features. Therefore a sample of 100 users was let to watch a short movie clip with four advertisement and was able to gather their emotional, facial and demographic features. Then at the end of the movie, the user was asked a questioner “what was the most memorable advertisement played?” as if to verify the collected data when training. All the three factors was trained against the advertisement data using a deep learning model and the results obtained were that there is no strong correlation between the three factors against the user-preferred advertisement. In the end ensemble model outperformed all with 97% accuracy. Therefore it is concluded that an ensemble model with demographic, emotional and facial features is best at recommending preferred advertisements.

# APPENDIX

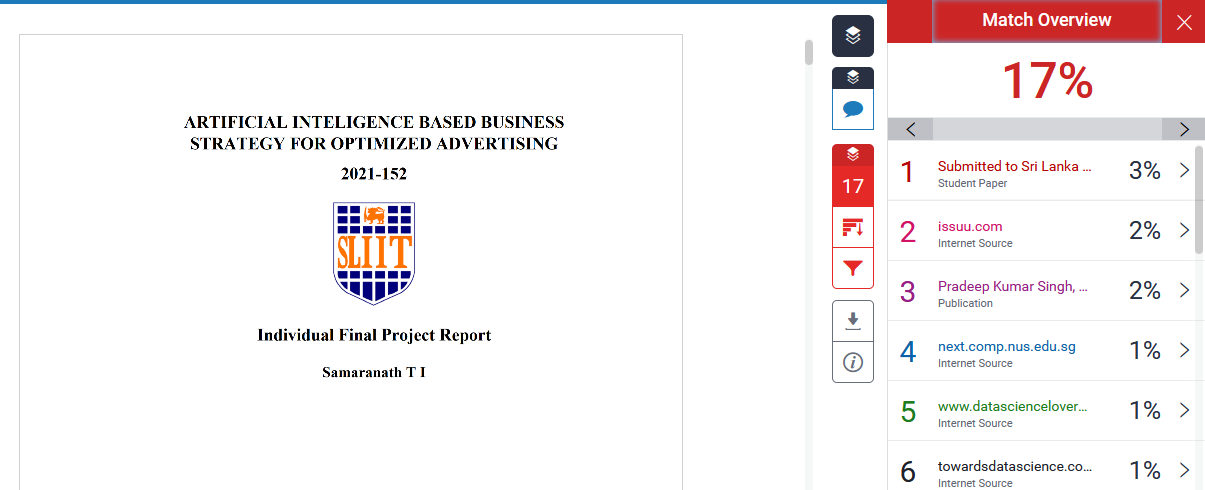


Fig. 25 Similarity index

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