**ARTIFICIAL INTELLIGENCE-BASED BUSINESS STRATEGY FOR OPTIMIZED ADVERTISING**

**2021-152**

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**Individual Final Project Thesis**

**Kumara G.D.S.H**

**B.Sc. (Hons) Degree in Information Technology**

**Specialization: Information Technology**

**Department of Information Technology**

**Sri Lanka Institute of Information Technology**

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

# DECLARATION OF THE CANDIDATES & SUPERVISOR

I declare that this is my own work and this Research thesis does not incorporate without acknowledgment any material previously submitted for a degree or diploma in any other university or institute of higher learning and to the best of our knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgment is made in the text.

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| --- | --- | --- |
| **Name** | **IT Number** | **Signature** |
| Kumara G.D.S.H | IT18041408 | Shape  Description automatically generated with medium confidence |

The above candidates are carrying out research for the undergraduate Dissertation under my supervision.

Signature of the supervisor: ………………….............. Date: 10/08/2021

(Ms. Dinuka Wijendra)

Approved for Research Project:

…………………..............

Research Project Coordinator, SLIIT

Ms. Jenny Kishara

# ABSTRACT

Advertising plays a significant role in marketing. Traditional media is defined as media that existed before the rise of the internet. That includes TV and radio broadcasts, newspapers, magazines, and billboards. Digital media advertising includes advertising in social media, digital platforms, websites, etc. With the emerging technology, advertising strategies in digital media have been more successful than traditional media advertising. Therefore, our main goal was to adapt the digital advertising strategies to traditional media television advertisements. In this study, we built a recommender system based on facial features and we were able to predict the most likable ad for the audience across four different age groups with 87% accuracy. In the analysis, we identified the best facial features for the classifier and showed the best and worst places for displaying the ads. Further, we showed that sometimes people enjoy watching ads than some movie parts.

# ACKNOWLEDGMENT

Our research group created the proposed concept prototype "Artificial intelligence-based business strategy for optimized advertising" as a final year project to show only the advertisements that people really want and to increase the efficiency of the advertising agency; in this concept prototype, "Human Emotional Analysis while watching advertisement and feedback generation" is my individual implemented part. The biggest support, courage, and excitement that we received from our supervisor, Ms. Dinuka Wijendra, and our co-supervisor, Ms. Jenny Kishara, during the implementation of this research and the entire study are difficult to measure and describe in words. It was a tremendous relief to have such a wonderful supervisor for the duration of the project.

Mr. Jagath Wickramarathne of our course coordinator deserves special thanks for his great support in supplying course materials and for sharing his extensive expertise of the module and also want to thank my parents and teammates for helping me while I developed the prototype, as well as my SLIIT colleagues who helped me with assignments and other elements of the project on several occasions. Definitely, my heartfelt gratitude goes out to everyone who contributed in any manner to the study's success, even if their names aren't included above.

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# LIST OF ABBREVAITIONS

|  |  |
| --- | --- |
| Abbreviation | Description |
| CNN | Convolutional Neural Network |
| EEG | Electroencephalogram |
| SAE | Sparse Auto-Encoder |
| SDFA | Salient Discriminative Feature Analysis |
| LIF | Local Invariant Features |
| SER | Speech Emotion Recognition |
| SVM | Support Vector Machine |

# **INTRODUCTION**

Feelings or emotions take a significant role in human existence, and we may deduce what the user is attempting to convey through those feelings and emotions. This is a common occurrence. Understanding human emotions and sentiments will be extremely beneficial to us. If we categorize these human emotions, we can divide them into numerous divisions. Happy, Sadness, Anger, Fear, Disgust, Joy, Surprise, and a variety of other emotions are just a few examples.

The majority of the world's population now watches television. Nowadays, almost every home has a television. As a result, everyone, regardless of age, watches television. People in front of the television might be of several types. We may classify them as relatives, friends, children under the age of 18, and so on if we categorize them. They use their many emotions and reactions to respond to ongoing TV shows/films/advertisements/songs. In this case, the attention was mostly on television commercials. As a result of these facts, we're attempting to integrate human emotions with technology to capture consumers' emotions in television advertising.

Tracking incoming video footage and capturing people's emotions and reactions comes first and Capturing people's emotions and reactions using Affectiva because of Manage data processing time and have to be very careful about user privacy. Then, compare the presented commercial to the video data to discover how the advertisement has an impact. After the movie clip is over a response from the user is taken regarding the most remembered advertisement. After that, it generates a report and sends it to the advertising firm. The advertising agency will be able to determine how individuals reacted to the relevant advertisement as a result of this. It gives them the option of deciding whether or not to turn up initially.

Incoming video data is tracked, and people's emotions and reactions are captured. Then, when the commercial is presented, compare it to the video data to determine how it makes an impression. After that, it generates a report and sends it to the advertising firm. The advertising agency will be able to determine how individuals reacted to the relevant advertisement as a result of this. It gives them the option of whether or not to show.

In today's culture, there are a lot of advertising agencies and also a lot of very busy people. As a result, the advertising firm airs fictitious commercials on TV at various times throughout the day. Some individuals in front of the television are watching the commercials, while others are not. Also, we can see that some advertising is relevant to this person while others are not. Because the advertising agency failed to present an effective advertisement to the user, that undesired advertisement is a waste of the user's time as well as a weakness of the advertising agency. We provide the finest solution based on these data. We're launching a new system that will benefit both the advertising agency and the end-user. For an advertising agency, this is quite effective. Because they can observe what sort of impact their advertisement has on people and choose which advertisement to display them.

## Background and Literature Survey

In today's world, there is a lot of research done using emotion analysis. But my research area it’s has been a little bit of research that has been done using emotion detection and facial expression analysis for television advertisement classification. Various attempts by researchers to determine human emotions have been documented in the previous literature.

In addition, the literature review discovered numerous applications that have been utilized to identify human mood. Some of that are listed below.

Desmet, Bart, and Veronique Hoste have been researched “Emotion Detection in Suicide Notes”[1]. This research provides Binary support vector machine classifiers that were used to create a system for automated emotion identification. They hypothesized that lexical and semantic features because this features could be an adequate way to represent the data. What they have done in this research is to identify the emotion in a particular text. When taking a snap or a screenshot of paragraphs there is a word set in the dataset of the AI algorithm that is related to emotions. if those words match with the words in the algorithm data set it gives a percentage that how many words are in a particular paragraph. In this research paper, there is another key feature that is when there is a spelling error in a paper it will re-correct that spelling errors too. Also have different 15 emotions.

Yanghui Raoa, Qing Li, Liu Wenyin, Qingyuan Wu, and Xiaojun Quan have conducted a research “Affective topic model for social emotion detection”[2]. The purpose of this research is to examine how social media can be used to detect emotions in readers. When applied to social media, analysis from the reader's perspective can be more useful than traditional sentiment analysis conducted from the writer's perspective. They propose an emotional topic model that introduces an intermediate layer to bridge the gap between social media materials and a reader's emotions. The suggested methodology may be used to categorize unlabeled documents' social emotions and create a social emotion lexicon. Extensive tests utilizing real-world data have proven that the proposed approach is effective in each of these applications.

Two researchers Lubis and Nurul have conducted a study “Emotion Recognition on Indonesian Television Talk Shows” [3]. They have used TV shows recordings as input and emotion recognition from that input. The first study on emotion recognition in Indonesians is presented in this paper. They are using a support vector machine algorithm to extract the emotions. To get the best possible result, feature selection and parameter optimization are added to this algorithm. Finally, they can have got the result of recognition accuracy of 68.31% at best. They built their corpus utilizing recordings from television talk shows on a variety of themes, resulting in colorful emotive utterances.

Two researchers Brynielsson and Joel have been published a research paper on the topic “Emotion Classification of Social Media Posts for Estimating People’s Reactions to Communicated Alert Messages during Crises”[4]. As mentioned in this research they detect emotion in social media posts. That From tweets on Twitter. This system is built to classify the emotion that comes from tweets. They have used the Support Vector Machine algorithm because, On the multi-classification task, the results suggest that a support vector machine provides the best results, with roughly 60% accuracy. Initially, they have labeled Twitter by emotions particularly but in this research, they have trained support vector machine to detect emotions automatically on Twitter. Most probably they have used crisis-related tweets in here they have gone through the Sandy Harikin crisis Twitter. Initially, they have promised the research to 59% accuracy but after the training process, they have achieved 75% accuracy.

Nomura, Tomomi, and Yasue Mitsukura have conducted a research “Detection of Latent Emotion Using TV Commercial Evaluation”[5].In this study, By analyzing Japanese TV advertising, they were able to discover hidden emotions. They detect emotions on both, Tv advertisements and people who watched that advertisement but not in real-time. As a result, they use an electroencephalogram (EEG) and a questionnaire to examine consumers' underlying emotions while watching TV commercials that they later remembered favorably. In Japan, they work on both award-winning and non-award-winning television ads. They also looked at the effects of positive TV advertising on consumers' recollections across time: immediately after seeing and a month later and get the result of the questionnaires, In the long term, both award-winning and non-award-winning TV ads had nearly identical memory retention rates.

Mao and Qirong have been published a research paper on the topic “Learning Salient Features for Speech Emotion Recognition Using Convolutional Neural Networks” [6]. This system for SER, studying salient, discriminatory characteristics is an important research issue. The key contribution of this study is two-fold. First, SER implements feature learning, in which CNN automatically learns the best feature set for SER by two-stage training: SAE and SDFA. Second, we propose a novel objective feature in SDFA that encourages Saliency, orthogonality, and segregation are attributes. As a consequence, our methodology will isolate effect-salient properties from other noisy variables, such as speakers and vocabulary. Our emphasis in this paper is on the identification of prototypic. Based on demonstrated emotional utterances in experimental environments, manifestations of many specific emotions. In naturalistic and real-world environments, subtle, persistent, and context-specific interpretations of affective utterances are more relevant and more complex research concerns. Feature learning is well-suited to overcome these problems, as an innovative methodology to learn a transformation of raw inputs to a representation that can be easily used by a classifier.

## Research Gap

|  |  |  |
| --- | --- | --- |
| **Research** | **Affect of emotional factors for television advertising(Sri Lankan Context)** | **Effects of Facial Expression for Advertisement Classification**  **(Sri Lankan Context)** |
| Emotion Detection in Suicide Notes | NO | NO |
| Affective Topic Model for Social Emotion Detection. | NO | NO |
| Emotion Recognition on Indonesian Television Talk Shows | NO | NO |

**Table 1: Research Gap**

Advertising plays a significant role in marketing. Traditional media is defined as media that existed before the rise of the internet. That includes TV and radio broadcasts, newspapers, magazines, and billboards. Digital media advertising includes advertising in digital platforms especially emerged with the internet.

Day by day, more people divert from traditional media and head towards digital platforms to fulfill their entertainment, information acquiring needs. Moreover, with the rapid development of technology and easy accessibility of equipment, it is convenient for people to satisfy their needs from digital media and platforms.

Like traditional media, the main income of digital media is from advertising. Moreover, regardless of the media type audience is always forced to consume advertisements. But digital platforms serve more personalized ads for the users, so the frustration over user interruption caused by the ads is limited.

TV broadcasting plays a major role in traditional media in Sri Lanka. Even though Sri Lankans are still in a transition phase for digital content, the majority of the people still consume traditional media a lot. Especially TV. But still, advertisers target TV audiences mostly by the demography and the time. In our study, we showed that there is almost no correlation between ad likability and demography. In other words, it is not successful in suggesting ads only based on the demography. Since ad targeting in digital advertising is more successful, we proposed to study the feasibility of suggesting ads based on the users' emotions, facial features, and demography. We built a recommender system for suggesting advertisements to the audience based on their facial expressions, emotions, and demography. We tested each component individually, and we reported the accuracy. Our analysis showed that the ensemble method of suggesting ads is more successful than suggesting ads based on one component.

Even though people may not like to get interrupted their experiences with advertisements, they don’t have much of a choice other than consuming advertisements. As we described earlier, It is easier to recognize the audience and deliver the most appropriate content to the most suitable audience in digital advertising. As a result, advertising platforms and firms more often gather user behavior data and analyze it to categorize the users based on their preferences. But in traditional advertising still, the advertisers broadcast ads based on demography and time. So we thought of developing a system that suggests advertisements to the audience based on their emotions, facial expressions, and demography data.

## Research Problem

Our main research problem is adapting digital advertising practices to traditional advertising, in this case, TV broadcasting. Mainly the digital advertisers focus on the following for advertising the brands on e-platforms.

1) Identify the Target Audience.

2) Develop a Content Marketing Strategy.

3) Build Relevant Content.

4) Incorporate SEO Tactics.

5) Try Omnichannel Marketing.

6) Use Accurate Data.

7) Employ Email Campaigns.

8) Utilise Chatbots.

Advertisers put a lot of effort into identifying the target audience in target advertising because some ads are more relevant for a subset of the population. In addition, identifying the target audience helps businesses to sell their products and brand their name more efficiently. Therefore, we mainly focused on identifying the audience and deliver the ads based on the audience. We identify the relevant audience by tracking their facial features and emotions while they are watching a movie.

My contribution to the overall research question is as follows.

* Design and implement a web platform for acquiring emotional and facial features while the user is watching a particular video while preserving the user's privacy.
* Identify the most mattered facial features and emotional features for recommending advertisements.
* Recrute and gather the emotional and facial features of the users while they are participating in the study.

## Research Objectives

We describe the objectives of the study in this part, and this part consists of 5 sections as follows.

1. The focus of the study
2. Variables to be measured.
3. Step by step guide of the prototype and data gathering
4. List down the limitations of the study and the prototype

## The focus of the study

This part of the thesis is about an individual contribution towards the full research goal. As mentioned earlier, the main research goal is: identifying the audience and delivering the ads based on the audience and identifying the relevant audience by tracking their facial features and emotions while watching a movie.

1. The individual focus was on implementing a system to acquire emotional and facial features without violating users' privacy.

In this information era, most of the datasets are available on the internet. But our system is specially customized for Sri Lankans. But Sri Lankan dataset with emotion and facial features are not available on the internet for the necessary age groups. Because of this, we needed to gather data.

Since we started our research in this pandemic, it was challenging for us to interview users personally. Considering all of these factors, we decided to implement a web platform to gather data while watching a video. We made sure to embed popular ads in the video as well. The embedded ads were carefully chosen for each age group. When considering the practical aspect of the application, no one likes to observe their faces by a human while the user is engaging on something, in this case, the video. So we needed a clever solution to extract the emotions and facial features without human interference.

Since there isn't any point in reinventing the wheel, and also as suggested by the previous, we decided to integrate "AFFECTIVA”. AFFECTIVA is a very well-known lightweight library that extracts facial features and emotions. Also, AFFECTIVA runs on the frontend as a JavaScript library, and it doesn’t store the facial images of the users. Instead, AFFECTIVA detects the main key points of the faces and classifies the emotions and facial features based on the key points.

1. Identify the most mattered facial and emotional features for recommending advertisements.

AFFECTIVA outputs a number of emotions and facial features. Instead of throwing all the parameters to the recommender system or any deep or machine learning algorithm, it is always recommended to analyze the data and extract only the most mattered parameters. Supplying only the fined tuned and most mattered parameters causes the deep learning algorithms to learn faster. Also, this causes to simplify the final trained model. Simple models can be deployed in embedded systems as well. Simplifying the recommended system would be an added advantage since our final product is also a small device with very limited computational capability.

1. Recrute and gather the emotional and facial features of the users while they are participating in the study.

Due to the lack of Sri Lankan emotional tracing data on the internet, we decided to collect the data by ourselves. Moreover, recruiting and gathering data was more challenging because the entire country was in lockdown, and personally, we were responsible for the health of our participants. So we decided to implement the web application as well. We contacted the participants remotely and set up everything virtually. We tried our best to keep the environmental factors steady for all the participants.

## Variables to be measured

A widely accepted theory developed by Paul Ekman suggests six basic emotions. The six basic emotions can be list down as follows:

* Happiness
* Sadness
* Fear
* Anger
* Surprise
* Disgust

The theory suggests that complex emotions are a consequence or derived from the above-described emotions. Therefore, we decided to acquire this set of emotions from users while watching the video.

Apart from the emotions, we also were interested in extracting the facial features as well. Therefore, for facial features, we acquired the full set suggested from AFFECTIVA. Later we analyzed the data and identified the most mattered facial features. The extracted facial features are as below.

'smile','innerBrowRaise','browRaise','browFurrow','noseWrinkle','upperLipRaise','lipCornerDepressor', 'chinRaise', 'lipPucker', 'lipPress', 'lipSuck', 'mouthOpen', 'smirk',  'eyeClosure','lidTighten', 'jawDrop', 'dimpler', 'eyeWiden',  'cheekRaise', 'lipStretch'[7]

## Step by step guide of the prototype and data gathering

We implemented the user study as a within-subject study. Therefore, we let all the users experience all the ads as in a within-subjet experiment design; all the participants should experience all the study conditions in a within-subject study. Also, the data is gathered while the user is watching the advertisement.

We chose a within-subject design because we wanted to analyze the dominant emotions for each age group. And we wanted to analyze the most mattered emotional and facial features. So all the participants should have undergone all the conditions. We can’t do this analysis if we have done a between-subject design, as in a between-subject design, each individual goes only through one condition. In this case, each individual will see only one advertisement. Then we would need more participants and also, it will be harder to compare the emotional variances across the movie and advertisements.

It is necessary to have a within-subject experiment design to compare the emotional and facial features across the movie and ads, We implemented the frontend with the help of AFFECTIVA.AFFECTIVA is a lightweight JavaScript library. It detects the visual features on the face and predicts the emotional features and facial features based on the extracted visual features. It is an added advantage for users’ privacy since it doesn’t need to send the images for the classification.

We chose a Sri Lankan family drama as our video and chose well-known four ads targeted for different age groups. The ads were embedded in the video in constant lengths, and we made sure to choose ads in the same duration. The chosen ads are as follows:

1. 1st ad => targeted age group
2. 2nd ad => targeted age group
3. 3rd ad => targeted age group
4. 4th ad => targeted age group

We uploaded the created video on YouTube and embedded it on our designed website. First, web applications access the camera while the user is watching the video. Then, AFFECTIVA will access the camera feed, detect features from each frame, and classify emotion and facial features. Finally, the system stores the timestamp when the user hits the play button and all the emotional and facial features until the end of the video.

At the end of the video, each user was given a small survey, asking the most memorable ad among the four ads. Finally, all the data will be sent to the backend and saved on a mongo database.

## List down the limitation of the study and the prototype

Due to the pandemic, it was harder to maintain the same environment for all the users. However, we were careful to choose a similar environment as much as possible for all the users. The web application was served on each user’s personal computer. Sometimes the resolution of the displays was not the same. Internet speed was not the same for every participant. The speed of the connection directly influenced the quality of the video and also the quality of the user experience. We removed all the participants who had connection troubles while preprocessing.

Sometimes AFFECTIVA fails to assign values to emotions and facial features. We removed those timestamps while preprocessing.

# METHODOLOGY

## 2.1. Methodology

When designing user studies, there are mainly three design concepts.

* Between-subject design
* Within-subject design
* mixed subject design.

In the between-subject design, the participant will face only a one-factor level. In a within-subject design, the user will expose to all the factor levels. And finally, in mixed design, the participant will be exposed on some factor levels only. But overall, the participants will cover across all the factor levels.

We chose the within-subject design because we wanted to compare and analyze the facial and emotional features across the four advertisements. However, we can't compare the emotional or facial features across the ads for the between-subject design.

## 2.1.1. The design of the application.

Nowadays, plenty of datasets are out there on the internet. But we couldn’t find any Sri Lankan dataset with tracked emotions and facial features. So, we went ahead and made our own dataset. Due to the lockdown situation, it was difficult for me to collect data. In order to identify the user's emotions, The goal was to obtain a huge data set in order to train my own dataset. I took part in collecting this data from my campus friends and their family members because I wanted different people's emotions. As a result, we have data across 77 participants after preprocessing in 1 million data points after preprocessing.

A screenshot of a computer

Description automatically generated with medium confidence

frontend view of web application

Fig . 1 frontend view of web application

With the travel restriction at that time, it became very difficult to collect data. So, I implemented a web application to collect data from home. The implemented web application is hosted on a server because that all users can access it. To execute the web program, I used my social media accounts and forwarded the instruction document to my friends. Fig 1 represents a front-end application that was created to collect data on a user's emotions. First need to enter the user’s name, age, and gender and then press the start button. When the start button is pressed, the user's permission to launch the cam is requested. After giving access, the camera preview will display. Then the cam detects the user's face and takes the required data. Before watching a YouTube video, the user must take note of the start time stamp, and after watching the video, the user must take note of the finish time stamp. Fig 2 below shows how the instructions for running a web application are given.

A screenshot of a computer

Description automatically generated

Fig . 2 Instructions to use web application

After doing these instructions, the user needs to click the stop and submit button to end this process. When the user click the stop and submit button the user's emotional data has been saved in our database and A message will pop up at the top in few seconds.

The web platform lets the user watch a video and track the user’s emotional and facial features once every 20 milliseconds. AFFECTIVA extracts the emotional and facial features and saves the output in the memory. Once the user finished the study, the stored emotional and facial features are updated to the server via the backend.

AFFECTIVA is a lightweight JavaScript library that classifies emotions and outputs facial features. This library is so useful due to its lightweight implementation. The privacy of the users is safer since AFFECTIVA doesn’t store or send the images to the cloud.

We made sure to keep a constant time between all the advertisements, and also the duration of the ads was the same 30 seconds. We uploaded the video on youtube. We implemented an iframe on the website and embedded the youtube link. So the user can play along. The platform logs the starting time of each user. The web application will ask the user to mark the most remembered ad at the end of the video. All the saved data will be sent to the backend and saved into a mongo database.

## 2.1.2. Data collection

We collected the following emotional and facial features.

Emotional Features:

* Happiness
* Sadness
* Fear
* Anger
* Surprise
* Disgust

Facial Features:

'smile', 'innerBrowRaise', 'browRaise', 'browFurrow', 'noseWrinkle',

'upperLipRaise', 'lipCornerDepressor', 'chinRaise', 'lipPucker',

'lipPress', 'lipSuck', 'mouthOpen', 'smirk', 'eyeClosure', 'attention',

'lidTighten', 'jawDrop', 'dimpler', 'eyeWiden', 'cheekRaise','lipStretch'[7]

The data was saved in the mongo instance as JSON objects in demographies, users, and emotions collections.

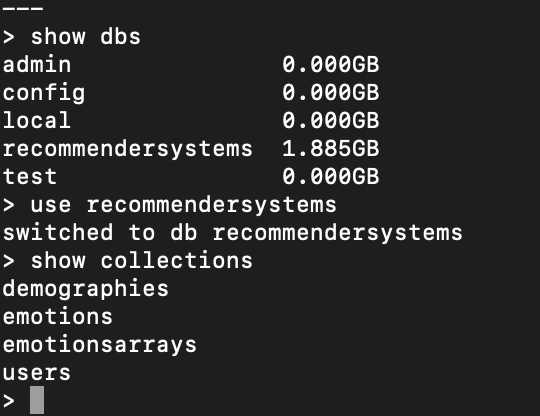


Fig . 3 Db Storage

We dumped the whole emotions and demographies collections into CSV after the data-gathering phase.

We interviewed 100 users in total across all the age segments. We only left with 77 users after preprocessing and clearing data. AFFECTIVA has failed to classify emotions in some people and it causes have N/A values in the database. We cleared all N/A values in the CSV.

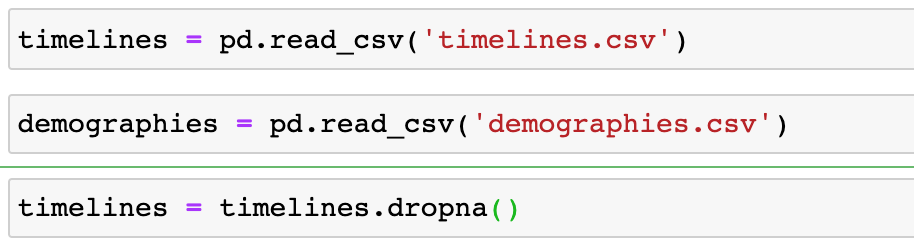


Fig . 4.CSV files

## 2.1.3. Format of the data

AFFECTIVA classifies the emotions and facial expressions once every 20 milliseconds. So for one user, we have about 30,000 data points per video. The video clip has four movie parts and four ad parts. We filtered all the emotional and facial features that belong to a particular movie part and ad part. Then we got the mean value for each movie or ad part. We created our processed dataset by doing the same for all the users.



Fig . 5.DataSet

The number of the part represented by the ‘num’ variable and ‘part’ variable represents the type of the part, whether it is a movie or an ad.

We created ‘favAd’ CSV to hold survey information. Survey information contains the user preferred ads for each user.

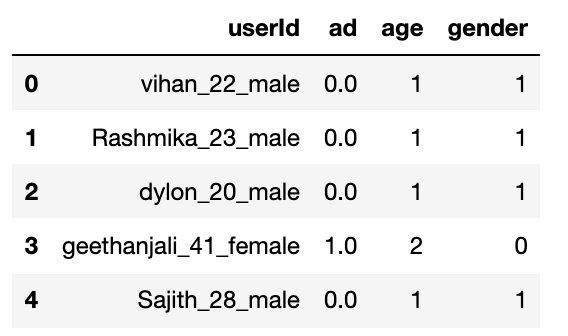


Fig . 6.favAd data

We extracted emotional feature means, and facial feature means belongs to the favorite ad of the particular user. We did this for all the users and made the final dataset for training the machine learning models.

We developed a supervised machine learning algorithm. Each emotion and facial feature set was labeled by the user’s favorite ad among the four ads. We considered standard machine learning algorithms as the starting point, and we developed the deep learning models considering the machine learning models as the baseline.

For classification first, we used the Random Forest classifier and Support vector machine. Before inputting data, we split the data into two partitions as train and test. We trained the classifiers on the training set. Once the training was done, we validated the model with the testing set.

Random forest classifier is a standard machine learning classifier. Most of the deep learning models take these standard machine learning models as the baseline. Then they implement the deep learning models further. Random forest classifiers consisted of many decision trees. It uses a bag of features algorithm to build the decision trees. Bag of feature algorithms uses clustering algorithms to group similar features together. So in the end, a random forest classifier groups the similar features together with the help of clustering algorithms and build the trees based on the similarity of each feature.

The earliest reference for bag-of-words was in Zellig Harris's Distributional Structure. Since then, the Bag-of-words model has been used in different document classification methods. Each word's frequency (number of occurrences) is used as a feature for training a classifier. Bag-of-features (bag-of-visual-words) model is influenced by the bag-of-words model and is used to classify images by treating image features as words.

Sivic J. et al. first introduced Bag of Features (BoF) for matching objects in videos. This paper investigated whether it is possible to retrieve a video scene containing a particular object. So the team can embed the most relevant part of the video to appear in google search results. They used the “bag of features” text retrieval approach to find and track the objects in the video. Furthermore, Yu et al. created an image retrieval system based on the Bag of Features method. In their study, image-based SIFT-LBP integration by weighted k-means[8] clustering achieved the best performance. The bag of features can be used in object identification, transcribing speech into text, matching news items, products with user interests, selecting relevant search results[9], and many more.

Support vector machine is a linear model for classification and regression. Basically, support vector machines also do clustering. SVM is very good at clustering data points in linear spaces and also in hyperspaces. After the clustering, it is easier to find the closest cluster for an input. Once it finds the nearest group, then that is the class prediction of SVM. Support vector machine is a supervised machine learning algorithm. Apart from classification output, SVMs can be used to get regression outputs as well. Another critical use case of the support vector machine is outlier detection. Even though SVM is widely recognized as a supervised learning algorithm, it behaves as an unsupervised learning algorithm for outlier detection.

We trained a random forest classifier on the facial features data set. The final accuracy was 0.43.

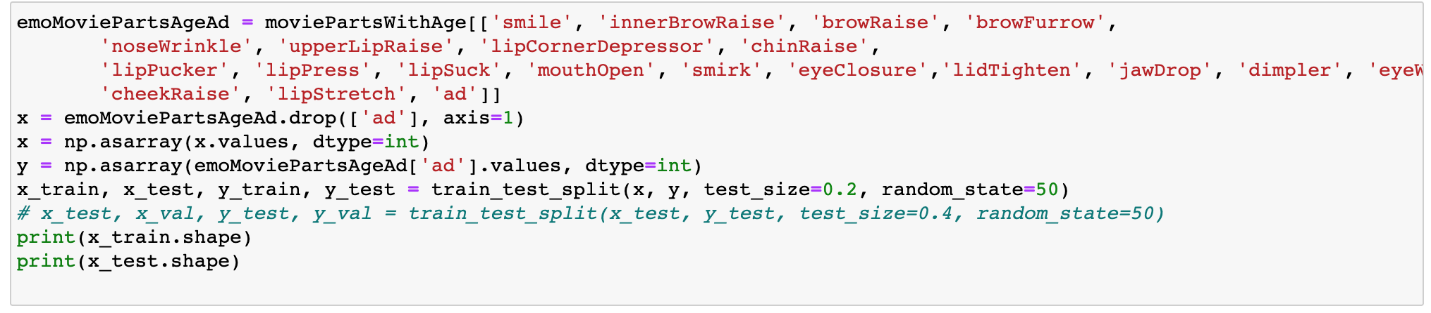


Fig . 7.Facial Features data set

First, we selected the facial features from the dataset. Then removed the classification value from the input x and assigned the classification value for y. We converted the input vector into a NumPy array and they value as well. Then the dataset was split as train and test sets. Before splitting the data we made sure to shuffle the dataset randomly.



Fig . 8.Test set result

We initialized the random forest classifier, set the max depth as two levels and also the initial state to 0. Then, we trained the classifier by fitting the data and predicted to evaluate the accuracy. We chose Keras’s classification report for reporting the accuracy and performance of the model. Further, we plot the confusion matrix to identify the point where the classifier loses its performance.

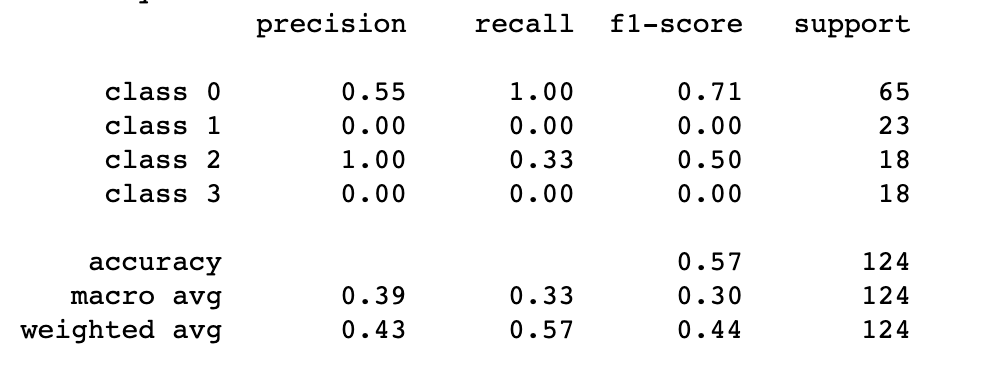


Fig . 9.Average Accuracy

According to the classification report, the average accuracy is much lower. It is almost like random accuracy gained by chance.

We also tried an SVM classifier. This classifier was trained the same way as the random forest classifier. Data was split the same way as well. We kept all the things the same, so it is much easier to compare.

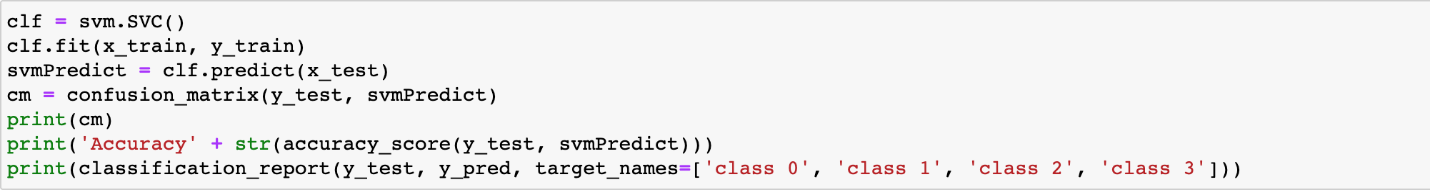


Fig . 10. SVM Classifier

The SVM was initialized with the default parameters. Once initialized, the classifier was trained on the same dataset and same split as before. We tested the test dataset on the trained classifier. As usual, at last, we reported the classifier’s performance with the help of the classification report method. The performance of the SVM classifier is as below.

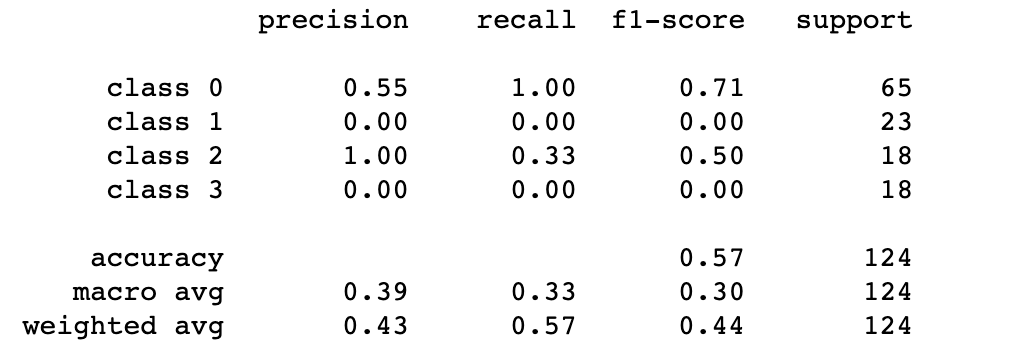


Fig . 11.Performance of the SVM Classifier

The accuracies were the same for both machine learning classifiers. But this is a good starting point. According to the confusion matrices of both, SVM’s confusion matrix showed higher performance because the classification was not random like in the random forest classifier.

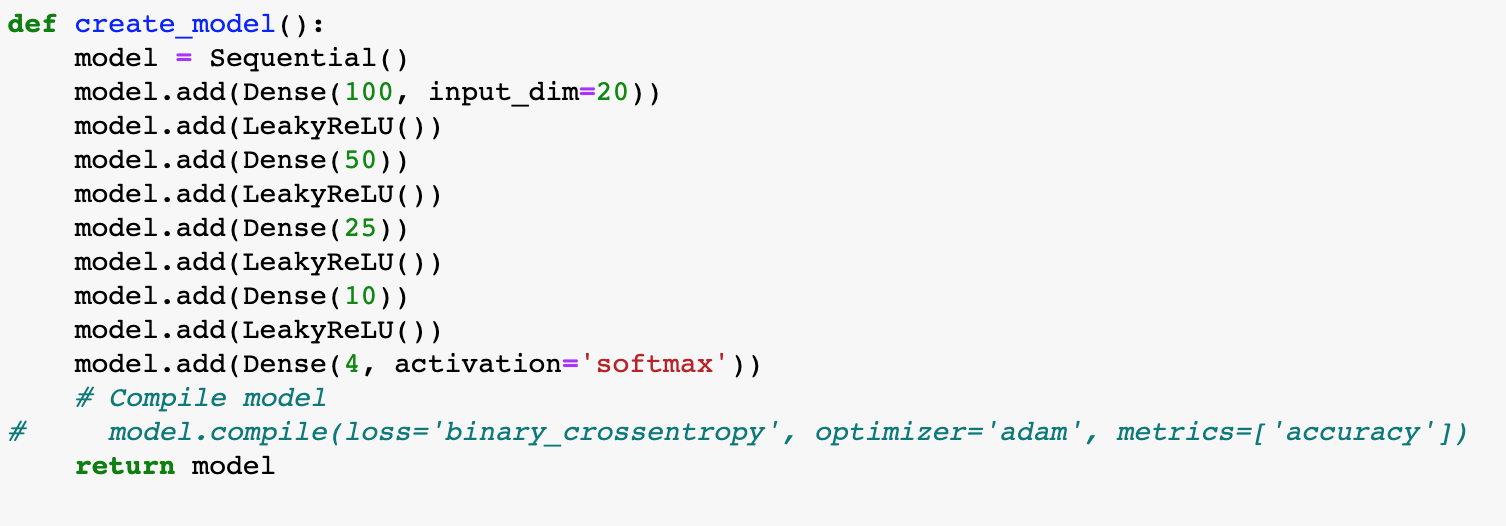


Fig . 12.create\_model

At last, we implemented a deep learning algorithm by taking the above two classifiers as the baseline. The deep learning architecture was influenced by the sequential model. We equipped the sequential model with three fully connected dense hidden layers. As usual, we added a dense layer at first with an input dimension of 20 and 100 output dimensions. The first dense layer is followed by the LeakyRelu activation function and then stacked the first fully connected dense layer with 50 neurons. The activation function of this layer is also LeakyRelu. Another two fully connected layers were stacked, and LeakyRelu was the activation function for those as well. Finally, we added a dense layer with four neurons with softmax activation because our classifier classifies them into four classes.

The sequential model comes in Keras machine learning library. It is one of the easiest ways to build deep learning models. This model allows the user to build their model by adding new layers sequentially on top of each other[7]. The weights of each layer correspond to the layer that follows it. Significantly, the sequential models are convenient for transfer learning. As in transfer learning, the users can use the trained weight set from another model, freeze some of the layers and then adapt the existing model for a new task.

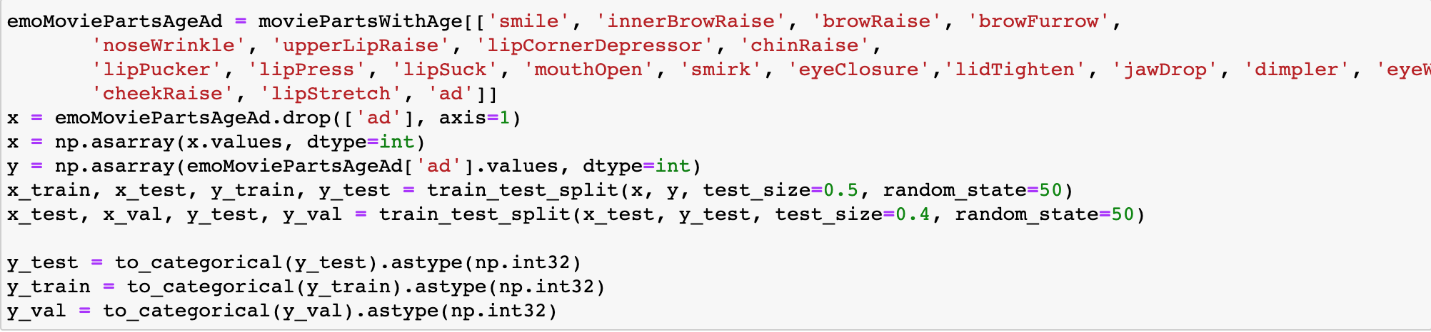


Fig . 13.existing model

As usual, first, we extracted the facial features from the dataset. Then made the x\_train variable by dropping the class variable. Next, assigned the class variable for y\_train and converted both x\_train and y\_train into NumPy arrays. With the help of the train\_test\_split method, we partitioned the entire dataset into train, validation, and test sets. The data were partitioned in the proportion of 50%, 20%, and 30% among train, validation, and test sets. After partitioning, y\_train, y\_val, and y\_test variables were encoded as one-hot vectors. We used the to\_categorical method to represent the y data as a one-hot vector. The class variable only has one value usually, that is the number of the class. But this value can’t be input as the value to deep learning networks as the final layers expect an array. Because of this, we need to encode the class variable as a one-hot vector. In a one-hot encoded array, the appropriate class number index is one while the rest of the cells are 0’s.

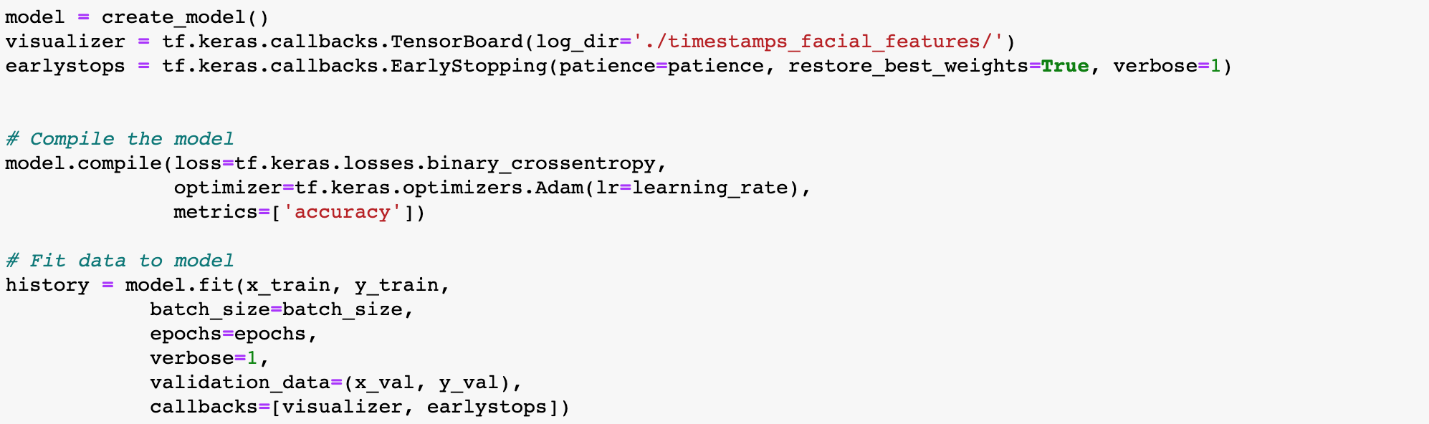


Fig . 14.Compile the model

We started training the model once we finished preparing the dataset and the deep learning architecture. When training we added two middleware to the model.

1. Visualizer
2. Early stop

We added the visualizer to save the train, test accuracies, and loss values after each iteration. The Early stopping middleware monitors the gradient of the loss curve; when the gradient isn’t changing significantly for each epoch, the early stopping middleware stops the training and restores the best weight set. Thus the early stopping middleware prevents the model from overfitting[7].

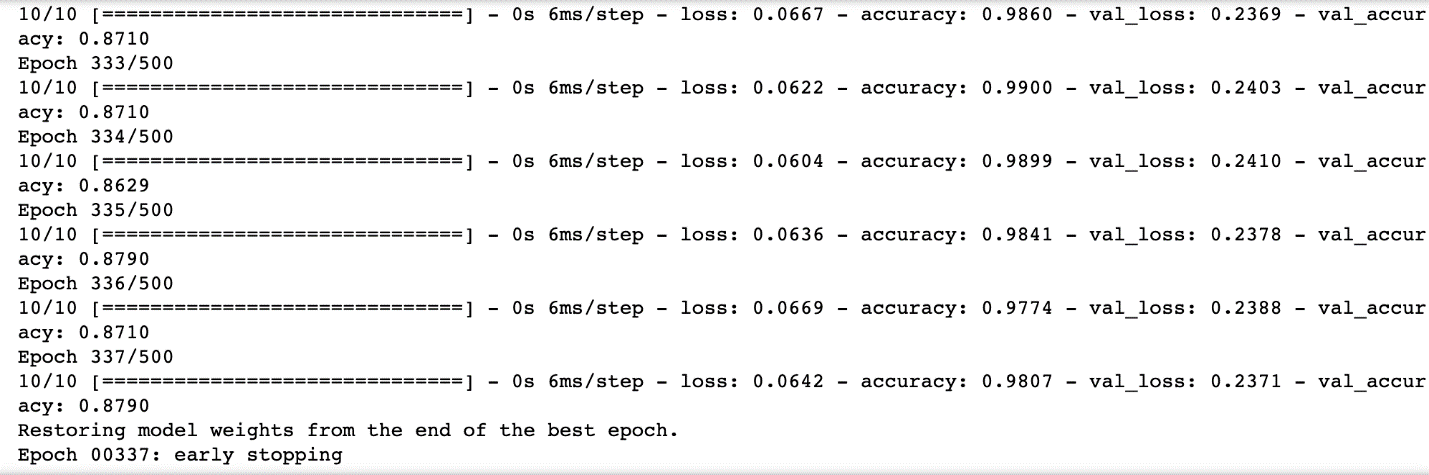


Fig . 15.Training middleware to the model

We used categorical cross-entropy and adam optimizer as the loss function and the optimizer. The learning rate[7] of the optimizer was 0.001. Initially, we set the number of epochs to 500[10]. But early stopping middleware stopped training at epoch 337 and restored the best weight set.

The accuracy of the sequential model was around 87% on the facial feature set.

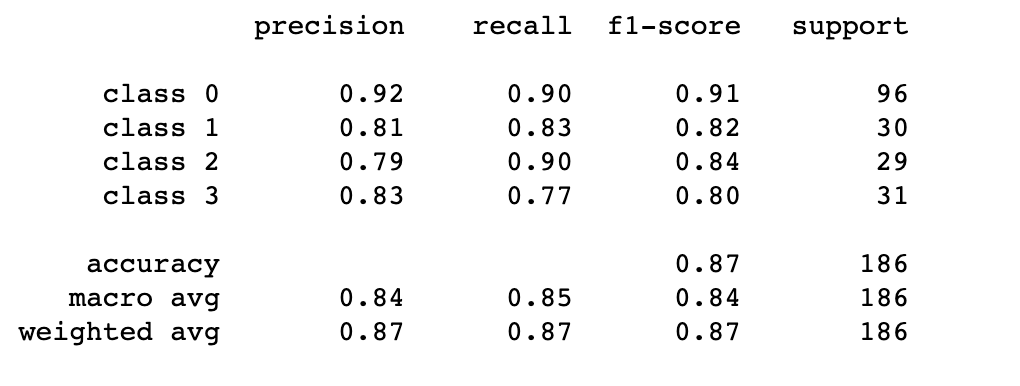


Fig . 16.accuracy of the sequential model

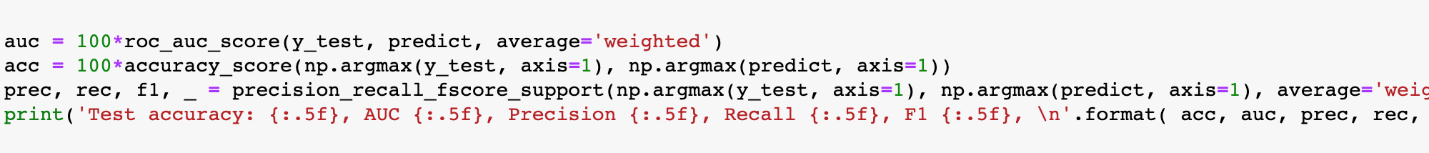


Fig . 17.Accuracy results

We calculated accuracy, AUC, roc, and f1 scores, and those scores are as follows.

Test accuracy: 86.55914, AUC 94.99042, Precision 0.86813, Recall 0.86559, F1 0.86601.

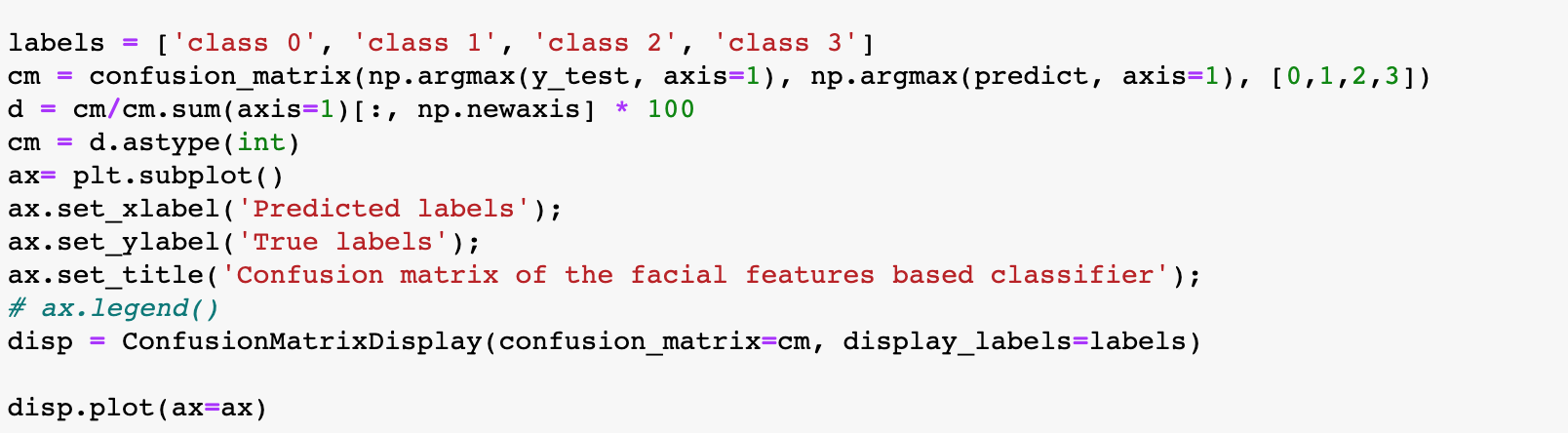


Fig . 18.Accuracy Scores

We plotted the confusion matrix after calculating the accuracy scores. Even though the standard machine learning algorithms failed to recommend ads based on facial features, the deep learning algorithm was successful.

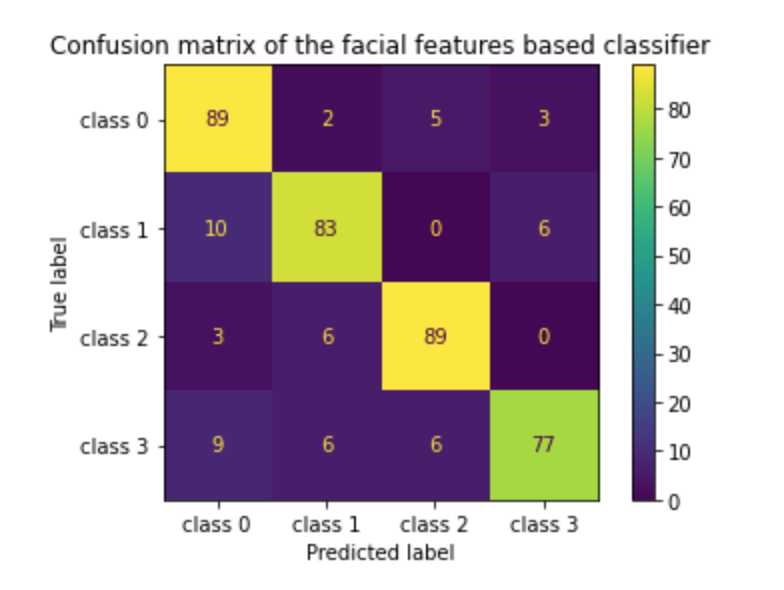


Fig . 19.confusion matrix

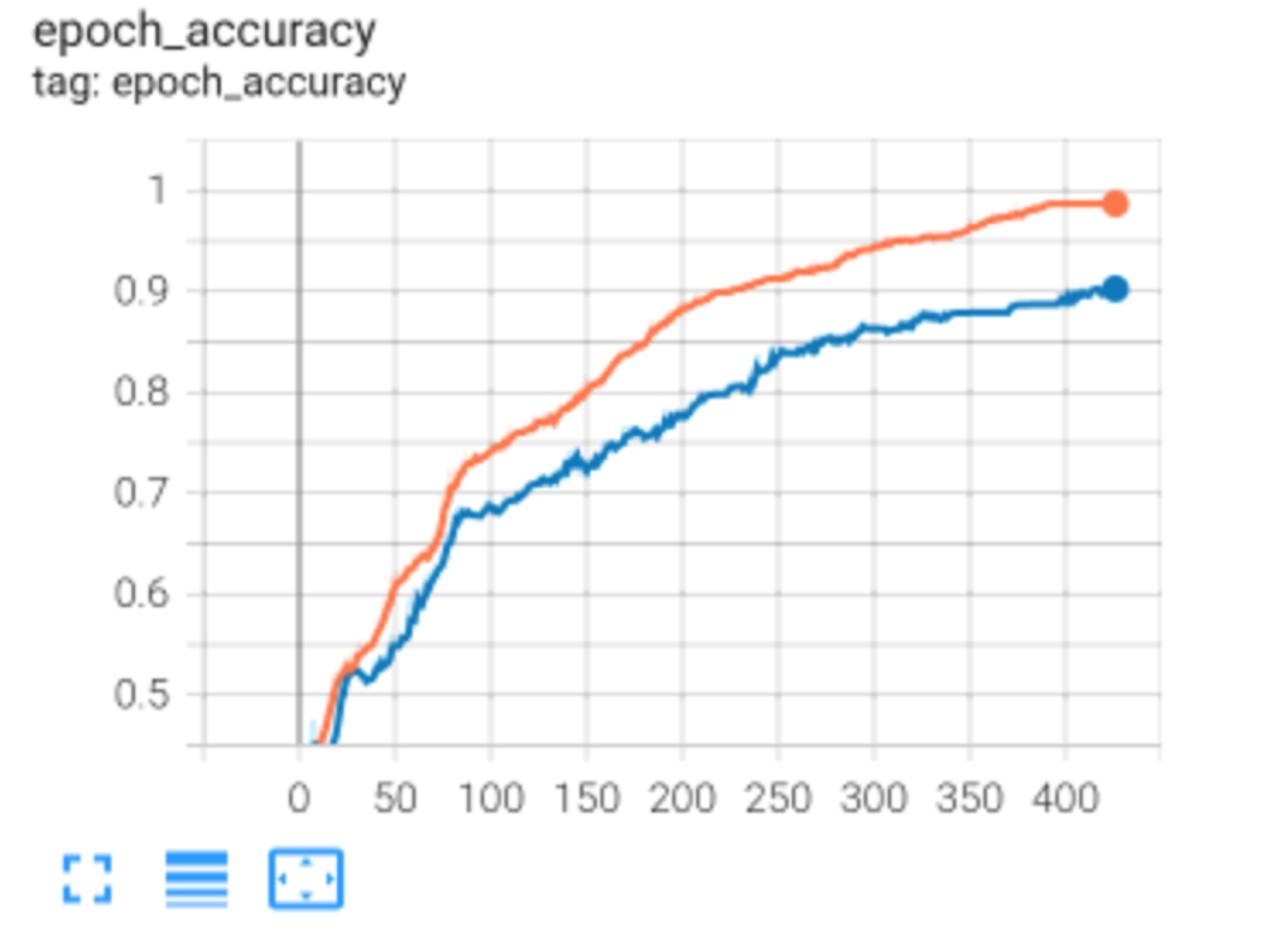


Fig . 20.epoch\_accuracy

The orange curve shows the training accuracy for each epoch, and the blue curve shows the validation accuracy curve[11].

## 2.1.4. Process of implementation

The suggested approach is used to categorize advertisements based on demographic emotions and facial expressions. The below diagram shows a system overview diagram of this component.

Diagram, schematic

Description automatically generated

Fig . 20. system overview diagram

Fig . 21.system overview diagram

## 

## 2.1.5. Software and Language Requirements

**Jupyter Notebook**

**Company name

Description automatically generated**

Fig . 22. jupyter Notebook

Fig.22 Shows Jupyter notebook. This is an open-source, online web app that lets users create and share documents with interactive computations, scripts, and pictures, among other things. People may build interactive "stories" that they can modify and share by combining data, code, and visuals into a single notebook. Notebooks are documents that include both computer code (such as Python) and other text components including paragraphs, markdown, figures, and links, among other things. The Jupyter notebook is well-known and well-documented, with a simple interface for generating, editing, and executing notebooks. The notebook is accessed via a web application known as the "Dashboard" or "control panel," which displays local files and enables users to browse notebook pages and execute code snippets. The results are well-formatted and shown in the browser.

**Visual Studio Code**

**Icon

Description automatically generated**

Fig . 23. Visual Studio Code

Fig. 23. shows Visual studio code. This is a source code editing application by Microsoft that is available for Windows, Linux, and OS X. It's a program that helps with integrated git control, debugging, syntax highlighting snippets, intelligent code completion, and refactoring code. It's a lightweight, cross-platform, and multi-language editor that you can get straight from the Visual Studio website[12].

**jQuery Language**

jQuery is a free JavaScript framework that makes it easier to deal with HTML/CSS documents, namely the Document Object Model (DOM), and JavaScript.

jQuery facilitates HTML document traversal and manipulation, browser event handling, DOM animations, Ajax interactions, and cross-browser JavaScript programming, to name a few things.

**Text

Description automatically generated with medium confidence**

Fig . 24. jQuery

The concept of jQuery is well-known: "Write less, accomplish more." This philosophy may be broken down into three parts:

* Finding certain elements (using CSS selectors) and doing something with them (using jQuery methods), i.e. finding a collection of items in the DOM and then doing something with them.
* Using several jQuery methods on a group of items in a chain
* Using the jQuery wrapper and iteration implicitly
* On an HTML page, using the jQuery (JS) library
* There are a few different methods to get started using jQuery on your website.

To add a version of jQuery, use the Google/Microsoft-hosted content delivery network (CDN)[13].

Download your own jQuery version from jQuery.com and host it on your own server or local disk[14].

**Python Language**

**Graphical user interface, text

Description automatically generated**

Fig . 25. Python Language

Python is one of the most widely used programming languages. Guido van Rossum created it, and it was published in 1991.It is used for the following purposes on web development (server-side), software development, mathematics, and system scripting are all skills that may be learned[15].

What does Python have to offer?

* Python may be used to build web applications on a server.
* Python may be used to build workflows in conjunction with other applications.
* Python has the ability to connect to database systems. It also has the ability to read and edit files.
* Python may be used to work with large amounts of data and conduct complicated calculations.
* Python may be used for fast prototyping as well as the creation of production-ready applications[16].

## 2.1.6. Functional and User Requirements

## 2.1.6.1. Functional Requirements

* Detect human emotions accurately
* Ability to generate a report considering the emotions captured

## 2.1.6.2. User Requirements

* People with facial wearables such facial masks and helmets will not be detected
* Having a Smart TV with a Camera

## Commercialization aspects of the product

The majority of the Sri Lankan media consumers still rely on traditional media. The main way of targeting advertisements on traditional media is by the demography and the time. A huge amount of money is getting wasted because the advertising strategy is outdated. This loss is not only to affects the advertiser but the content consumer as well. The consumer has to watch something that the consumer doesn’t want to.

The purpose of advertising is to inform about the product and the company to the audience and convince them that these particular advertisers' products are the best in the market. In digital advertising, the ads’ success rate is measured by the number of impressions, click true rate, and direct purchases. But in traditional advertising, there isn’t still any robust, fast and reliable method for measuring these.

We propose to bring the digital advertising strategies into traditional advertising. Since most Sri Lankans are still handing on to traditional advertising, there is a huge opportunity for our product. Furthermore, we have shown in this research that our prototype is capable of recommending user-preferred advertisements.

Apart from these advantages, we can calculate the number of impressions and whether the audience liked the ad displayed to them in real-time with the help of the device that we are plugging into the tv.

# RESULTS AND DISCUSSION

## Data analysis

We used Affectiva to detect facial and emotional features during the movie watching. Affectiva outputs emotional and facial features for each timestamp. On average, there are 10 000 timestamps per user. Affectiva calculates facial and emotional features for each of the timestamps. After recording the data, we filtered the timestamps belongs each ad part and movie part. Then we averaged all the emotional values individually for each ad/movie part. We were left with mean values for all the emotional and facial features for each ad/movie part. Then we plotted each emotional feature against the ad/movie part to visualize the variation of each emotional feature during the watching time.

Chart, line chart

Description automatically generated

Fig . 26.Attention Value for each movie/AD part

Chart, line chart

Description automatically generated

Fig . 27.Joy Value for each movie/AD part

Chart, line chart

Description automatically generated

Fig . 28.Sadness Value for each movie/AD part

Chart, line chart

Description automatically generated

Fig . 29.Engagement Value for each movie/AD part

Fig 23 shows the averaged joy value for each ad/movie part for the entire population. And Fig 24 shows the averaged sadness values for each ad/movie part for the entire population. The maximum joy value and the lowest sadness value have been recorded at the beginning of the movie. So we propose that the best time for showing an advertisement is at the beginning of a movie.

According to Figures 23 and 24, the minimum joy and maximum sadness values were recorded during the first ad. After the first ad, users were not that sensitive to ads. The variation between ad and movie parts was not that high. Interestingly, the average joy value has increased in the second ad part than the second movie part. So people have enjoyed the ad part than the movie part. It is almost the same joy values that were recorded for the 3rd movie and the 2nd ad parts. After the first movie part, people were much happier during the second ad. This concludes that the users sometimes enjoy watching ads than movie parts.

The engagement has been decreased over time across the population. The highest engagement value has been observed during the first movie part. And then it has reduced accordingly regardless of the movie or ad part. Substantial reductions can be observed between the first movie part and the first ad part, then between the third movie part and the third ad part.

The maximum values were recorded in attention, engagement, and joy. But the same patterns were observed across most of the emotional features.

Best location to serve ads

Chart, line chart

Description automatically generatedPeople enjoy ads also.

Fig . 30.Smile, brow raise, nose wrinkle, upper lip raise, lip corner depressor.

According to fig 26, the maximum values were returned on smile among facial features. The most variable facial feature is the smile also. Brow raise values were similar across the watching time. Lip corner depressor and nose wrinkle reported the lowest values.

Chart, line chart

Description automatically generated

Fig . 31.values chin raiser, lip plucker, r lip press, eye closure, dimpler

The maximum variance can be observed in dimpler and eye closure from cross chin raiser, lip plucker lip press, eye closure, and dimpler. We explored the variances of facial features in Figures 26 and 27. It is enough to choose the higher varying parameters for the classifier. The chosen features are as below.

Smile

Upper lip raise

Lip plucker

Dimpler

Eye closure

Lip corner depressor

# CONCLUSION

It is possible to adapt the digital adverting strategies in television advertisements, and it causes the audience to enjoy the broadcasted ads as well. Enjoying watching the ad helps the users to retention the brand names in their minds. We showed that it is possible to build a recommender system solely based on the facial features to recommend likable user ads. In this study, we change the user’s perspective toward television ads by suggesting valuable ad content. The analysis showed that instead of 20 facial features, it is enough to gather the few most mattered facial parameters such as Smile, upper lip raise, lip plucker, dimpler, eye closure, and lip corner depressor. We identified the best and worse locations for displaying the ads during a movie. And also we showed that sometimes people enjoy watching ads more than watching the movie.

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# Appendix

## Similarity Index

Graphical user interface

Description automatically generated