Automatic User Testing and Emotion Detection in Interactive Urban Devices

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Abstract. Automated testing and evaluation of interfaces is a well-established reality supported by many tools that shorten the time to deploy new software versions to the user. However, exploring users' emotions while interacting with interfaces as a tool to further increase the quality of traditional usability evaluation methods is still far from being a reality. This work uses the automatic analysis of users' emotions while interacting with touchable interactive urban devices to detect usability issues. To this end, a coupled approach is implemented: the data is acquired from the interaction, and user emotions are extracted and processed to determine the emotional status during the interaction. This data is integrated into a web application so that designers can further improve the quality of the interface in the presence of negative emotions. Results show that the experimental tests showed that different users manifest similar negative emotions in the same contexts, which is a clear sign of usability issues that are to be corrected by the design team.

Keywords: User Testing · Emotion Detection · User Experience · Automation Processes · Evaluation

1 Introduction

Interactive urban devices have spread with the evolution of smart cities and become an immersive interaction point that brings cities closer to people who live, work, and travel to them. At the city level, they are a unique way to promote multiple activities and points of interest, such as tourism, culture, local commerce, and public services. At the citizen level, they have to be user-friendly and have a way to interact with the dynamics of a city based on information gathered by it. Inside hospitals, parking lots, and industry, these kiosks have been used as a pertinent medium to deal with services and information. However, some kiosks are not easy to use or understand, and people require specific computer skills to find what they need [1,2]. Smart cities face the challenge of implementing easy-yo-use technologies, infrastructures, and best practices [3]. With the use of interactive urban devices that spread across cities all over the world, there

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is a need to create user-friendly interfaces, that is, interfaces that are simple, pleasant, and easy to understand but that still maintain all the functions for which they were intended [4,5].

Interaction usability problems can be identified using techniques varying from empirical to analytic methods. While the first focus on the subjective opinion of users and experts [6–9], the second focus on automated testing [10–12], and presents several advantages, when compared to traditional techniques. One of the approaches explored in this paper is identifying usability issues by automatically detecting users' facial expressions while interacting with the interfaces.

This paper proposes an open-source facial recognition application that correlates user emotions and interactions with interactive urban devices. This provides valuable information to identify improvements to introduce in the device interface. The major contribution of this paper is to detect emotions in the interaction with touchscreen devices to determine the problems in the interface. To this end, several requirements were specified:

- Create a facial recognition application to accurately detect emotions
- Analysis on the accuracy of obtained results
- The storage of detected emotions synchronized with the interactions carried out by users during interface tests on the outdoor device database
- Express the interactions correlated with the emotions detected, graphically, in a web application, for possible identification of points of improvement.

The remainder of this paper is organized as follows. Section 2 presents a review of techniques for facial recognition and APIs on emotion detection. Section 3 presents a view of the high-level architecture and the frameworks that support the data visualizer that is presented in Sect. 4. In Sect. 5, user scenarios are created, and the visualizer is applied to real interaction contexts. Finally, Sect. 6 presents the major conclusions and some hints of future work.

2 Background

This section reviews the state of the art in two fundamental contexts related to the work presented in this paper: facial recognition and emotion detection API. Moreover, a view of interactive urban devices is also presented.

Using interactive systems to access information or services is a well-known challenge. The first interactive system was based on the Plato Computing System [13]. Since then, these systems have evolved and are used to communicate with citizens in the context of smart cities [14]. Several projects are implemented in real scenarios. The LinkNYC project [15] is a digital Kiosk that contains WiFi hotspots for the city of New York. Citizens can connect their devices for free WiFi access, and provide services in the city. The system has an interactive tablet on its side, and two fifty-five-inch screens on both sides, which display public service announcements and publicity. IKE Smart City [16] is another example of a digital kiosk available in several locations. It aims to create value for municipal customers and the cities it serves through smart city solutions and

is similar to a city guide with information about its location. The system has two sides, one interactive and the other aimed at promoting communication and video advertising. The interactive side promotes city information such as where to eat, shop or sleep, events, and fun games. The TOMI [17] interactive urban device can be compared to a city guide with information about the urban region where it is located. TOMI works in a very interactive way between the user and the machine, allowing several actions, such as consulting news, booking events and accommodation, searching for places and means of transport, and even the possibility of creating an animated gif and taking a picture to post on social media. Many other solutions are available in the market (Partteam [18], Moobo [19], and Lamasatech [20], just to cite some). However, they all have one point in common: to bring together the city and the citizen.

For human beings, recognizing a person by his face is an involuntary act, performed naturally that provides information used in communication, and developing interaction between human beings. For a machine, the process is quite different. With the evolution of computer technology came the interest in video and image processing in terms of security and entertainment. A facial recognition system has as its main function to map the human face, using algorithms and programs as a resource, in order to be able to collect information, such as facial expressions [21,22]. The human face has a composition of common characteristics from person to person, such as eyes, nose, and distance from nose to mouth, among others. The systems can read and map these common points, which are assembled into geometric and/or algorithmic shapes. In a way, face recognition methods act to compare a person's facial features in a certain image with faces already existing in a database [23,24].

The first stage of facial recognition begins by locating a face in an image or video containing one or more people simultaneously. The second stage consists of collecting and analyzing a face from the image or video. In this situation, the software is responsible for making the geometric reading of the faces, identifying their main characteristics, called nodal points, such as the shape of the lips, the chin, the distance and depth of the eyes, and the length of the face, the latter being the distance between forehead and chin. A grid on the identified face usually marks these features. After collecting and analyzing the collected face, if facial detection aims to collect emotions, the position of the nodal points is analyzed, which depending on the algorithm analyzes the contractions of the facial muscles marked with the nodal points, this recorded information is transformed into data via a mathematical formula, which gives rise to a unique numerical code, which, like a fingerprint, is unique. Finally, the numerical code obtained is compared with others from faces stored in different datasets. Emotions datasets are a kind of collection of data, in this case, emotions are stored in the form of a table, where each column represents a variable and the rows, in this case, correspond to values of emotions.

The performance of machine learning models is deeply dependent on the volume of data available for training models. For that reason, the most accurate models are provided by giants of software that have access to large volumes of data

for training models capable of accurately detecting emotions from images. Fortunately, these models are widely available through an Internet-accessible API like the IBM Watson [25], Face API [26], Kairos [27], and Amazon AWSRekognition [28]. In this paper, the API has to be adequate to detect emotions in real-time and is open source. For that purpose, several emotion detection APIs are analyzed, and results are presented in Table 1.

Table 1. List of API tested.

APIs	Cost	JSON Format	Emotion Detection	Emotions detected (anger, fear, surprise..)	Dataset used	Accuracy	Real Time
Kairos	Freemium	yes	yes	4	KairosDB	0,62	yes
Animetrics	Freemium	yes	yes	3		0.99	
Lambda Labs	Freemium	yes	no	1		0.99	no
Google Cloud Vision	Freemium	yes	yes	8	local or cloud		
Luxand.cloud	Freemium	yes	yes	8		0.94	yes
EyeRecognize	Freemium	no	no			0.99	
Face++	Freemium	yes	yes	8	LFW and others	0,99	yes
Macgyver	Freemium					0,74	
Computer Vision	Freemium	yes	no		local or cloud	0.96	yes
BetaFace	Freemium	yes	yes		LFW	0.81	yes
Deep Face	Free	yes	yes	7	LFW	0.94	yes
EmoVu	Freemium		yes	7			yes
AWSRekognition	Freemium	yes	yes	9	local or cloud		yes
OpenFace	Free	yes	no		LFW		yes
Keras	Free	yes	yes	5	Fer+ and AffectNet		yes

Of the APIs presented in Table 1, two were chosen for testing: Keras (with the FER+ and AffectNet datasets, and with the FER2013 dataset), and the DeepFace API. The inclusion criteria were the ability to detect emotions and are free to use in all functionalities present in the API, unlike the others that are only free in a basic plan (real-time detection and free use).

3 Materials and Methods

This section presents the process of integrating emotion detection APIs with user interaction in devices to detect negative and positive emotions during the interaction. This can assist the designer of interfaces in improving them based on emotions. It presents a high-level architecture description and a detailed view of its components.

3.1 High-Level Architecture

The high-level architecture description provides a general view of integrating separate components that result in the interaction interface. The system must detect emotions in real-time while users interact with an interactive urban device, as illustrated in Fig. 1. The overall view of the architecture can be interpreted in three stages: data gathering, data storage, and the data visualizer.

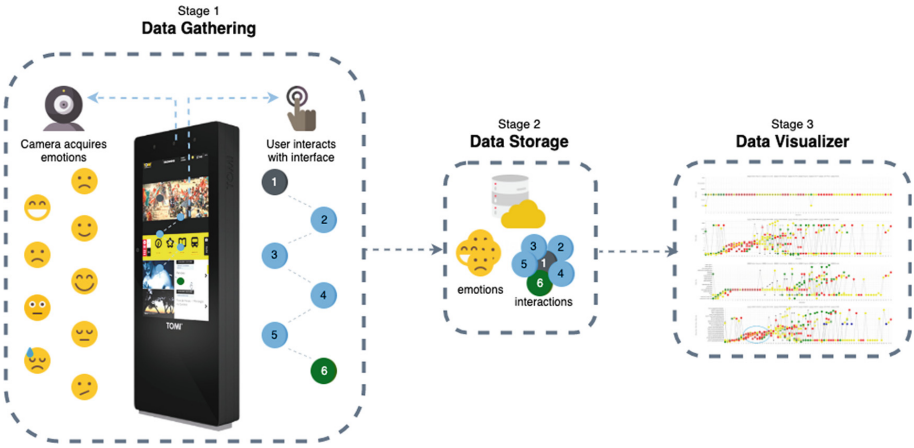


Fig. 1. High-level view of the proposed architecture.

Data gathering comprises the acquisition of user emotions while interacting with the touchable device. This stage generates data stored in a database where emotions are associated with each interaction. Next, this data is processed to generate visual representations of the execution of tasks that allow for the determination of negative emotions. These are the most important since they infer usability issues on the interface.

3.2 Emotion Detection Framework

There are several parameters associated with emotions returned by facial recognition systems, namely anger (A_p), contempt (C_p), disgust (D_p), fear (F_p), happiness (H_p), neutral (N_p), sadness (S_p) and surprise (Su_p). These emotions are related to positive, negative, and neutral emotions. To determine the weights to consider in each of the emotions, an empirical study was carried out with users that were asked to express several emotions that were compared to the results obtained from the API, to determine the level of accuracy (comparison between 8th and 9th columns of Tables 7, 8, and 9, presented in Appendix A). For the Deepface API, the accuracy of measurements is 68.29%, and typical measurement errors occur when the real emotion is negative, which is detected as neutral, as shown in Table 7 of Appendix A. On the other hand, the accuracy of the Keras API with Fer+ and AffectNet is 70.73%, where more inaccuracy is present on positive emotions, as shown in Table 8 of Appendix A. Finally, considering the Fer2013 dataset, the accuracy increases to 87.80%; however, errors still occur in the detection of negative emotions that are processed as neutral emotions (see Table 9) of Appendix A. These results are summarized in Table 2.

Table 2. Accuracy and detection issues in selected APIs for emotion detection.

	API - analysis of general values of emotions		
	DeepFace	Keras with Fer and AffectNet	Keras with Fer2013
Accuracy	68.29%	70.73%	87.80%
Detection issues	Negative as neutral	Positive as neutral	Negative as neutral

Given the lack of precision of the results presented in the previous section, and considering that this paper aims to measure positive and negative emotions while interacting with an interface, the final classification focuses on these three categories (positive, negative, and neutral). This is carried out in two manners: first, emotions reduce to these categories, where *happy* and *surprise* define a *positive* emotion ($P_i = (H_p)_i + (Su_p)_i$); *sad*, *fear*, *anger* and *disgust* define the *negative* emotion ($NE_i = (S_p)_i + (F_p)_i + (A_p)_i + (D_p)_i$), and *neutral* maintains its definition. This is depicted in columns 10–12 of Tables 7, 8, and 9, while column 13 presents the resulting value based on categories of emotions.

In the second stage, several metrics are applied to refine the values of emotions to obtain a correct reading of the emotion. This approach improved the accuracy of the emotion detection for each API, which is presented in Table 3.

Table 3. Refinement on accuracy in three categories: positive, negative, and neutral emotions

	API - analysis of three categories		
	DeepFace	Keras with Fer and AffectNet	Keras with Fer2013
Accuracy	90.48%	92.85%	100.0%

From the results, the API Keras with Fer2013 provided the best detection results and is used for emotion detection in the interaction with the interface. After the correct specification of the emotion analysis framework, the next step is to focus on the interaction framework.

3.3 Interaction Framework

TOMI [17] are devices for public use, with dimensions that allow them to integrate a touch screen of 47 to 55 in. and that provide various services, of which we highlight the provision of local information and communication functionalities for residents and tourists of the cities where they are located. Due to their characteristics, they classify as Urban Furniture for Information (MUPI). However, in addition to being digital, they are also interactive; that is, the services they provide depend on users' actions through the interface. Users can use all these features through touches on the TOMI touch panel, as shown in Fig. 2.



(a) News (b) Event Detail (c) Restaurants

(d) Photo feature (e) Transportation

Fig. 2. TOMI graphic user interface.

With regard to interactions on the TOMI device, each touch on the touch panel identifies a user interaction, which is stored in the device's database (developed in *SQLite*) containing information about where the touch was made in the touch panel. This new entry to the database is automatically generated with several data obtained from the device as illustrated in Table 4. The acquired

data vary from interaction coordinates (denoted by x and y); *menu_slug* is the category where the touch was carried out; *create_date* corresponds to the date and time of the user touch in the device, and is used to synchronize with the timestamp of emotions;*meta_tag* that marks the touches in objects like buttons, dialogues, or text events. The *objective* is the goal defined by the user and is used for tests in the interface, where users have to carry out tasks. The *objective* is reached when its value matches the concatenation of *menu_slug*, *meta_tag*, and *meta_value*.

Table 4. Example of an event inserted in the database.

id	x	y	menu_slug	create_date	meta_tag	meta_value	objective	Emotion	user
3358	790	795	TRANSPORTATION	1624460415	subFilterClick	onde-comer	SEARCH openDirections car	Negative	User 1
3360	495	1314	TRANSPORTATION	1624460420	keyPressSearchDialog	V	SEARCH openDirections car	Negative	User 1

As an example, if the column *objective* is defined by *Transportation KeyPressSearchDialog V* and the columns *menu_slug*, *meta_tag*, and *meta_value* contain the values *Transportation*, *KeyPressSearchDialog* and *V*, respectively, then the goal is reached in the interaction.

Finally, the columns *emotion* and *user* correspond to the interactions of the test user and the emotion in each interaction (where the emotion detection process is applied, as described in Sect. 3.2).

4 Emotion-Interaction Visualizer

This section approaches the web implementation of the emotion-interaction visualizer, which accounts for the overlap of emotions and interaction timelines to detect usability issues. The data is represented in a line chart, using the Chart.js library [29]. The yy axis represents the category of the interaction, and the xx axis is the value of the interaction. In the (x, y) coordinate, the associated emotion is represented (green for the positive emotion, yellow for the neutral, and red for the negative). Finally, the blue color represents the interaction where the user has reached the goal, as shown in Fig. 3.

Data visualization requires a pre-processing stage. To this end, for the accurate representation of the interaction with the TOMI device, the database contains the *menu_slug*, *meta_data*, and *meta_value* columns, as presented in Sect. 3.3. The representation of data from the database requires that these values are synchronized in the chart so that a correct match can be established between the xx and the yy axis. Moreover, it is required that the yy axis does not contain repeated values. With the yy axis prepared, it is necessary to treat the values of each user interaction. In this process, each user interaction will be

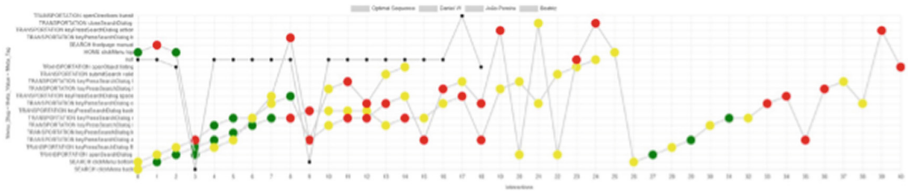
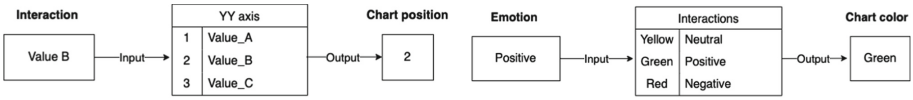


Fig. 3. The emotion-interaction visualizer.

compared with the different values of the *yy* axis where, if applicable, that value will be changed by the integer corresponding to the position of the *y* value on the axis, as shown in Fig. 4a. Later, this value will be the correct position of the interaction on the chart.



(a) Data (b) Emotion

Fig. 4. Data and emotion treatment for axis representation.

Regarding the treatment of emotions obtained from the database, the method is different, since in the chart the data correspond to colors. Instead of collecting integer numbers, there will be a collection of colors corresponding to the emotion, changing the value by the color that represents the emotion, as shown in Fig. 4b.

5 Results

In order to verify the existence of usability errors in the interaction with the TOMI device, some tests are created with goals to be achieved. These tests are carried out by test users who do not know or know very little about the device's interface, thus enabling secure data collection regarding the application's usability. During the tests, the emotion detection application was used simultaneously with TOMI to collect the users' facial expressions. The interaction scenario of the tests is presented in Table 5.

After the execution of tasks with users, data is generated to be processed by the web application. A general view of the results is presented in Table 6, which allows an understanding of the number of interactions required for a user to complete their goal and also the percentage of emotions predominant in the interactions.

Table 5. Scenarios for the interaction with the TOMI device.

#	Goal	Tasks
1	You have just arrived in <city>, hungry, and it is close to lunchtime. You found a TOMI in the middle of the street and heard that it has information on restaurants in the city	1. Find a restaurant close to you 2. Meanwhile, your friend Joana, who is a vegetarian, called and said she would like to have lunch with you. Look for the nearest vegetarian restaurant and calculate the driving distance there 3. Share the restaurant location with your friend José through WhatsApp, so that he can join you
2	Your friend José has told you that you can take photos in a TOMI. Try it	1. Take a photo in the TOMI device, and send it to your friend José 2. Try to make a video, instead of taking a photo 3. Since you are a fan of emojis, you use them a lot. Try to add an emoji to your video 4. You have created an amazing video. Share it on Instagram
3	You are going to spend the day in <city> and have three yours available in the afternoon.	1. Find an event and save the event in the calendar on your phone. Try to find an easy way to do it 2. Since you are also staying in <city> to sleep, see if there is a hotel near the event location 3. Check if there is any traffic congestion at the event 4. Since there is not much traffic, send the location of the event to your phone

Table 6. General view of emotions in user testing.

User	Interactions	Positive	Negative	Neutral	Goal Reached
1	112%	32.61%	26.09%	41.30%	Yes
2	129%	41.51%	22.64%	35.85%	Yes
3	176%	5.56%	37.50%	56.94%	Yes
4	134%	45.45%	30.91%	23.64%	Yes
5	80%	9.09%	30.30%	60.61%	Yes
6	129%	30.19%	30.19%	39.62%	Yes
7	107%	15.91%	56.82%	27.27%	Yes
Average	124%	25.76%	33.49%	40.75%	–

Results show that it is possible to infer that in relation to the goal, the number of interactions is higher than 100% of the optimal interaction and that all users managed to reach the intended goal. As far as emotions are concerned, on average several negative emotions were detected, which suggests that there is a usability problem, given that users presented negative emotions. By refining the information in the chart format presented in Fig. 5, it is possible to understand the interactions that gave emphasis to the negative emotions and are to be analyzed by the design team. In Fig. 5, several users had negative emotions between interactions 8–19 which were analyzed by the research team and revealed effective problems of interaction.



Fig. 5. Results for tasks.

6 Conclusions

This paper addresses the analysis of emotions to detect usability issues in a touchable user interface. The methodology followed was based on two essential frameworks: the implementation of an emotion detection system based on facial recognition and a recorder of interactions that account for the objects the user has touched in a graphical user interface. These two frameworks are matched in a timeline, which allows the evaluation of both interactions and associated emotions with the interaction. With this, it is possible to measure the state of mind of a user when interacting with an interface.

The overlapping of interactions and emotions is represented in a timeline using a web application for the correct identification of emotions in the interactions with components, following a baseline of the optimal interaction. The relationship between both is presented in a chart format.

Results show that most users reached the goal but exceeded the number of interactions and did not follow the path defined by the optimal interaction for the task. Several negative emotions were detected in the same context of

interaction, which were later identified as usability issues of the interface by the design team.

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A Tests with APIs

As presented in Sect. 3.2, several tests were carried out with two APIs: Keras (with the FER+ and AffectNet datasets, and with the FER2013 dataset), and the DeepFace API. Differences in emotions when compared to real emotions are represented with a different color.

Table 7. Deepface API test.

Anger (A_p)	Disgust (D_p)	Fear (F_p)	Happiness (H_p)	Neutral (N_p)	Sadness (S_p)	Surprise (Su_p)	Obtained API emotion	Real Emotion	Negative	Positive	Neutral	Emotion Value
96.5	0	0.07	0	2.6	0.76	0	Anger	Anger	97.33	0	2.6	Negative
51.6	3.1	0.8	0	18.79	25.2	0.2	Anger	Anger	80.7	0.2	18.79	Negative
79.8	0.12	0	0	7.6	11.6	0.6	Anger	Anger	91.52	0.6	7.6	Negative
32	0	0	3.98	41.79	21.93	0.2	**Neutral**	**Anger**	53.93	4.18	41.79	Negative
28	0	5.5	0.93	54.95	10.2	0	**Neutral**	**Anger**	43.7	0.93	54.95	Negative
35.2	0	7.7	3.77	45.7	5.58	1.9	**Neutral**	**Anger**	48.48	5.67	45.7	Negative
4.89	0	5	5.26	78.2	6.16	0.3	**Neutral**	**Anger**	16.05	5.56	78.2	**Neutral**
0.4	0.3	45.6	1.01	18.3	34.13	0	Fear	Fear	80.43	1.01	18.3	Negative
0	0.1	84.42	3.87	3.63	7.89	0	Fear	Fear	92.41	3.87	3.63	Negative
3.6	62.4	22.24	3.82	2.12	5.7	0	**Disgust**	**Fear**	93.94	3.82	2.12	Negative
6	13.6	28.5	4.65	39	7.85	0.15	**Neutral**	**Fear**	55.95	4.8	39	Negative
0.25	18.5	49.4	0.3	0.66	30.75	0	Fear	Fear	98.9	0.3	0.66	Negative
7.48	0	39.18	29.95	15.5	2.95	4.91	Fear	Fear	49.61	34.86	15.5	Negative
5.3	0	15.65	31.91	12.8	33.85	0.39	**Sadness**	**Fear**	54.8	32.3	12.8	Negative
0	0	0	99.99	0.0099	0	0	Happiness	Happiness	0	99.99	0.0099	Positive
0	0	0	99.99	0	0	0	Happiness	Happiness	0	99.99	0	Positive
0.03	0	0	96.9	0.29	2.75	0	Happiness	Happiness	2.78	96.9	0.29	Positive
0	0	0.4	86.92	0	12.66	0	Happiness	Happiness	13.06	86.92	0	Positive
0	0	0	99.43	0.54	0.02	0	Happiness	Happiness	0.02	99.43	0.54	Positive
0	0	0	49.22	50.77	0	0	**Neutral**	**Happiness**	0	49.22	50.77	Positive
0	0	0	97.63	0.01	2.35	0	Happiness	Happiness	2.35	97.63	0.01	Positive
3.16	1.33	0.03	1	28.17	66.23	0.04	Sadness	Sadness	70.75	1.04	28.17	Negative
0	0	0	0	0	99.99	0	Sadness	Sadness	99.99	0	0	Negative
0.2	0.02	0	35.71	16.53	47.5	0	Sadness	Sadness	47.72	35.71	16.53	Negative
0	0	0.02	0.02	0	99.95	0	Sadness	Sadness	99.97	0.02	0	Negative
0.43	0.1	0.01	13.86	42.22	43.35	0	Sadness	Sadness	43.89	13.86	42.22	Negative
0.96	0	0.33	59.95	7.71	31.03	0	**Happiness**	**Sadness**	32.32	59.95	7.71	Negative
0.35	3.37	0.32	5.08	7.07	83.77	0	Sadness	Sadness	87.81	5.08	7.07	Negative
10.83	0	43.86	0.33	7.17	18.22	19.55	**Fear**	**Surprise**	72.91	19.88	7.17	**Negative**
13.63	2.69	12.8	65.34	0.54	3.54	1.42	**Happiness**	**Surprise**	32.66	66.76	0.54	Positive
0.002	0	5.3	0	22.43	0.03	72.22	Surprise	Surprise	5.332	72.22	22.43	Positive
11.49	0	29.07	0.01	2.64	0.14	56.62	Surprise	Surprise	40.7	56.63	2.64	**Negative**
7	0.7	24.78	0.13	49.06	10.01	8.29	**Neutral**	**Surprise**	42.49	8.42	49.06	**Negative**
3.62	10.9	61.24	0.12	1.83	19.16	3.09	**Fear**	**Surprise**	94.92	3.21	1.83	**Negative**
0	0	0.05	0	80.11	16.53	3.28	**Neutral**	**Surprise**	16.58	3.28	80.11	**Neutral**
0.39	0	0	0.17	92.82	6.6	0	Neutral	Neutral	6.99	0.17	92.82	Neutral
0.6	0	0	0.91	80.07	18.39	0	Neutral	Neutral	18.99	0.91	80.07	Neutral
0.14	0	0	2.52	93.58	3.74	0	Neutral	Neutral	3.88	2.52	93.58	Neutral
0.04	0	0	2.39	96.23	1.32	0	Neutral	Neutral	1.36	2.39	96.23	Neutral
5.59	0	0.09	0	54.96	39.34	0	Neutral	Neutral	45.02	0	54.96	Neutral
1.29	0	0.18	0	78.46	20.05	0	Neutral	Neutral	21.52	0	78.46	Neutral
0.35	0	0	0	97.43	2.2	0	Neutral	Neutral	2.55	0	97.43	Neutral

Table 8. Keras API with Fer+ and AffectNet

Anger (A_p)	Disgust (D_p)	Fear (F_p)	Happiness (H_p)	Neutral (N_p)	Sadness (S_p)	Surprise (Su_p)	Obtained API emotion	Real Emotion	Negative	Positive	Neutral	Emotion Value
0.52	0.02	0.03	0.01	0.15	0.28	0.01	Anger	Angry	0.85	0.02	0.15	Negative
0.18	0	0.01	0	0.5	0.3	0.01	**Neutral**	**Angry**	0.49	0.01	0.5	Negative
0.49	0	0.11	0	0.15	0.25	0.01	Anger	Angry	0.85	0.01	0.15	Negative
0.81	0	0	0	0.03	0.14	0.01	Anger	Angry	0.95	0.01	0.03	Negative
0.98	0	0	0	0.01	0.01	0	Anger	Angry	0.99	0	0.01	Negative
0.41	0	0.02	0.02	0.14	0.39	0.02	Anger	Angry	0.82	0.04	0.14	Negative
0.7	0	0.01	0.01	0.1	0.14	0.04	Anger	Angry	0.85	0.05	0.1	Negative
0.09	0	0.61	0.01	0.03	0.07	0.19	Fear	Fear	0.77	0.2	0.03	Negative
0.09	0	0.8	0.01	0	0.01	0.08	Fear	Fear	0.9	0.09	0	Negative
0.27	0	0.66	0.01	0.01	0.02	0.03	Fear	Fear	0.95	0.04	0.01	Negative
0.11	0	0.78	0.01	0.01	0.02	0.07	Fear	Fear	0.91	0.08	0.01	Negative
0.17	0	0.51	0	0.03	0.15	0.14	Fear	Fear	0.83	0.14	0.03	Negative
0.1	0	0.07	0.01	0.39	0.25	0.17	**Neutral**	**Fear**	0.42	0.18	0.39	Negative
0.17	0	0.39	0.03	0.05	0.32	0.05	Fear	Fear	0.88	0.08	0.05	Negative
0.12	0	0.07	0.38	0.22	0.19	0	Happiness	Happiness	0.38	0.38	0.22	Positive
0.16	0	0.08	0.09	0.54	0.12	0.01	**Neutral**	**Happiness**	0.36	0.1	0.54	**Neutral**
0.42	0	0.03	0.19	0.24	0.12	0	**Anger**	**Happiness**	0.57	0.19	0.24	**Negative**
0.17	0	0.02	0.19	0.51	0.1	0	**Neutral**	**Happiness**	0.29	0.19	0.51	Positive
0.07	0.02	0.04	0.83	0.01	0.03	0	Happiness	Happiness	0.16	0.83	0.01	Positive
0.02	0	0.01	0.75	0.15	0.07	0.01	Happiness	Happiness	0.1	0.76	0.15	Positive
0.15	0.01	0.09	0.18	0.28	0.28	0.05	**Sadness**	**Happiness**	0.53	0.23	0.28	Positive
0.1	0	0.03	0.01	0.39	0.48	0	Sadness	Sadness	0.61	0.01	0.39	Negative
0.08	0	0.02	0.02	0.55	0.32	0	**Neutral**	**Sadness**	0.42	0.02	0.55	Negative
0.16	0	0.21	0.02	0.23	0.38	0	Sadness	Sadness	0.75	0.02	0.23	Negative
0.02	0	0.01	0.01	0.29	0.67	0	Sadness	Sadness	0.7	0.01	0.29	Negative
0.13	0	0.2	0.01	0.24	0.4	0.02	Sadness	Sadness	0.73	0.03	0.24	Negative
0.09	0	0.02	0.17	0.43	0.28	0.02	**Neutral**	**Sadness**	0.39	0.19	0.43	Negative
0.23	0	0.13	0.05	0.34	0.24	0.01	**Neutral**	**Sadness**	0.6	0.06	0.34	Negative
0.02	0	0.59	0.01	0.1	0.07	0.21	**Fear**	**Surprise**	0.68	0.22	0.1	Positive
0.05	0	0.63	0.15	0.02	0.02	0.13	**Fear**	**Surprise**	0.7	0.28	0.02	Positive
0.06	0	0.25	0.29	0.01	0.01	0.37	Surprise	Surprise	0.32	0.66	0.01	Positive
0	0	0.13	0	0	0	0.87	Surprise	Surprise	0.13	0.87	0	Positive
0	0	0.4	0.01	0.06	0.04	0.49	Surprise	Surprise	0.44	0.5	0.06	Positive
0	0	0.15	0	0	0	0.85	Surprise	Surprise	0.15	0.85	0.0	Positive
0.06	0	0.16	0.03	0.29	0.3	0.16	**Sadness**	**Surprise**	0.52	0.19	0.29	**Negative**
0.1	0	0.02	0.04	0.61	0.22	0	Neutral	Neutral	0.34	0.04	0.61	Neutral
0.01	0	0.02	0	0.79	0.18	0.01	Neutral	Neutral	0.21	0.01	0.79	Neutral
0.05	0	0.01	0.07	0.71	0.13	0.02	Neutral	Neutral	0.19	0.09	0.71	Neutral
0.01	0	0.01	0.25	0.52	0.19	0.01	Neutral	Neutral	0.21	0.26	0.52	Neutral
0.01	0	0.01	0.31	0.4	0.31	0.01	Neutral	Neutral	0.33	0.32	0.4	**Positive**
0.03	0	0.01	0.27	0.59	0.27	0.03	Neutral	Neutral	0.31	0.3	0.59	Neutral
0.01	0	0.01	0.16	0.73	0.16	0.03	Neutral	Neutral	0.18	0.19	0.73	Neutral

Table 9. Keras API with Fer2013.

Anger (A_p)	Disgust (D_p)	Fear (F_p)	Happiness (H_p)	Neutral (N_p)	Sadness (S_p)	Surprise (Su_p)	Obtained API emotion	Real Emotion	Negative	Positive	Neutral	Emotion Value
29.06	0.4	19.99	23.95	15.79	8.43	2.32	Anger	Anger	57.88	26.27	15.79	Negative
41.11	0.1	25.66	1.6	24.34	5.05	2.08	Anger	Anger	71.92	3.68	24.34	Negative
37.53	0.3	29.49	4.22	17.35	10.03	0.9	Anger	Anger	77.35	5.12	17.35	Negative
35.16	0.1	23.1	7.3	23.51	10.14	0.6	Anger	Anger	68.5	7.9	23.51	Negative
37.09	0.3	34.07	8.52	12.55	6.38	1.04	Anger	Anger	77.84	9.56	12.55	Negative
27.09	0.3	51.54	5.87	0.52	2.02	7.92	**Fear**	**Anger**	80.95	13.79	0.52	Negative
27.09	0.2	32.31	12.87	19.31	3.2	0.49	**Fear**	**Anger**	62.8	13.36	19.31	Negative
7.57	0.1	51.65	4.56	18.43	12.03	5.62	Fear	Fear	71.35	10.18	18.43	Negative
6.99	0	49.96	7.12	20.01	11.4	4.43	Fear	Fear	68.35	11.55	20.01	Negative
13.43	0	31.94	17.84	22.97	10.7	3.03	Fear	Fear	56.07	20.87	22.97	Negative
27.92	0.1	28.43	6.02	23.59	13.57	0.3	Fear	Fear	70.02	6.32	23.59	Negative
13.36	0	48.14	8.77	19.52	8.05	2.05	Fear	Fear	69.55	10.82	19.52	Negative
8.92	0.1	58.82	12.31	4.68	10.1	4.99	Fear	Fear	77.94	17.3	4.68	Negative
27.93	0.1	48.56	5.67	10.11	6.96	0.5	Fear	Fear	83.55	6.17	10.11	Negative
7.27	1.08	10.07	58.26	14.2	7.74	1.34	Happiness	Happiness	26.16	59.6	14.2	Positive
3.77	0.5	16.19	55.68	11.96	10.98	0.8	Happiness	Happiness	31.44	56.48	11.96	Positive
4.86	0.1	32.63	35.28	3.73	11.03	12.32	Happiness	Happiness	48.62	47.6	3.73	Positive
2.43	0.1	24.83	47.37	7.37	8.7	9.16	Happiness	Happiness	36.06	56.53	7.37	Positive
3.17	0	21.81	51.04	8.69	4.27	10.91	Happiness	Happiness	29.25	61.95	8.69	Positive
15.76	0	16.95	40.81	13.96	4.39	8.05	Happiness	Happiness	37.1	48.86	13.96	Positive
11.82	0	10.3	34.08	26.99	9.31	7.42	Happiness	Happiness	31.43	41.5	26.99	Positive
8.71	0	17.61	11.68	25.74	28.45	7.75	Sadness	Sadness	54.77	19.43	25.74	Negative
10.38	0	23.39	3.36	29.45	32.81	0.52	Sadness	Sadness	66.58	3.88	29.45	Negative
12.91	0.11	17.61	7.59	35.26	25.51	0.99	**Neutral**	**Sadness**	56.14	8.58	35.26	Negative
11.44	0	19.63	5.29	34.49	28.08	0.97	**Neutral**	**Sadness**	59.15	6.26	34.49	Negative
12.61	0.12	19.68	6.05	30.9	29.99	0.62	**Neutral**	**Sadness**	62.4	6.67	30.9	Negative
12.46	0	18.07	3.49	32.71	32.91	0.29	Sadness	Sadness	63.44	3.78	32.71	Negative
9.39	0	32.23	2.1	22.24	33.8	0.16	Sadness	Sadness	75.42	2.26	22.24	Negative
4.61	0	33.94	6.66	7.14	2.15	45.42	Surprise	Surprise	40.7	52.08	7.14	Positive
5.65	0	30.97	1.73	23.08	3.68	34.83	Surprise	Surprise	40.3	36.56	23.08	Positive
7.28	0	27.49	3.7	7.02	3.49	50.98	Surprise	Surprise	38.26	54.68	7.02	Positive
5.21	0	22.72	1.56	1.64	1.18	67.67	Surprise	Surprise	29.11	69.23	1.64	Positive
3.15	0	26	1.91	5.05	1.86	61.99	Surprise	Surprise	31.01	63.9	5.05	Positive
2.31	0	24.79	1.9	1.66	0.78	68.53	Surprise	Surprise	27.88	70.43	1.66	Positive
2.34	0	29.1	0.66	0.89	0.75	66.24	Surprise	Surprise	32.19	66.9	0.89	Positive
9.08	0	25.79	0.23	49.71	15.16	0.01	Neutral	Neutral	50.03	0.24	49.71	Neutral
11.65	0	16.75	0.71	57.07	13.75	0	Neutral	Neutral	42.15	0.71	57.07	Neutral
14.78	0	17.67	0.3	55.1	12.1	0.02	Neutral	Neutral	44.55	0.32	55.1	Neutral
15.23	0	16.56	0.39	55.58	12.17	0	Neutral	Neutral	43.96	0.39	55.58	Neutral
14.83	0	13.57	0.32	59.9	11.33	0.02	Neutral	Neutral	39.73	0.34	59.9	Neutral
13.89	0	16.07	0.24	57.85	11.9	0.01	Neutral	Neutral	41.86	0.25	57.85	Neutral
15.58	0	14.25	0.29	57.33	12.5	0.03	Neutral	Neutral	42.33	0.32	57.33	Neutral

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